Shared-Neighbours methods for visual content structuring and mining

Amel Hamzaoui

UNIVERSITÉ PARIS-SUD 11
Faculté des sciences d'Orsay

P H D T H E S I S

Shared-Neighbours methods for visual content structuring and mining

Submitted for the degree of "docteur en sciences"
of the University Paris-Sud 11
Speciality: Computer Science

By

Amel HAMZAOUI

May 2012

INRIA Paris-Rocquencourt, IMEDIA Team
ED Informatique de Paris Sud

Thesis committee:

Reviewers:	Patrick GALLINARI	-	Prof. at University of Pierre et Marie Curie (FR)
	Arjen Paul DE VRIES	-	Prof. at Delft University of Technology (NL)
Director:	Nozha BOUJEMAA	-	Director of the INRIA-Saclay Center (FR)
Advisor:	Alexis JOLY	-	Researcher at INRIA-Rocquencourt (FR)
Examinator:	Sid Ahmed BERRANI	-	Head of " the Multimedia Content Analysis Technologies R & D " team (FR)
President:	François YVON	-	Prof. at University of Paris-Sud 11 (FR)

To my dear parents
To my dear husband

Acknowledgements

I would like to deeply thank the various people who, during the several years, provided me with useful and helpful assistance. Without their care and consideration, this thesis would likely not have matured.

First, I offer my sincerest gratitude to my Ph.D. supervisor, Nozha Boujemaa, who has supported me throughout my thesis with her patience and knowledge from the very early stage of this research.

I am eternally grateful to my advisor, Alexis Joly, for his guidance and expertise. This thesis would not have been possible without him. His endless enthusiasm and energy towards research has been truly inspiring.

Thanks are due to everyone in Imedia Team, past and present. Their wisdom and guidance helped with many of the ideas presented in this thesis and steered me through some difficult problems.

I wish to thank my friend Ibtihel Ben Gharbia at Inria Rocquencourt for helping me get through the difficult times, and for all the emotional support, entertainment, and caring she provided.

Where would I be without my family ? My parents deserve special mention for their inseparable support and prayers, thanks for being supportive and caring siblings. They bore me, raised me, supported me, taught me, and loved me. To them I dedicate this thesis.

I wish to thank my entire extended family for providing a loving environment for me. My brother and my sisters were particularly supportive.

Words fail me to express my appreciation to my husband Anouar khamassi whose dedication, love and persistent confidence in me, has taken the load off my shoulder.

Finally, I would like to thank everybody who was important to the successful realization of thesis, as well as expressing my apology that I could not mention personally one by one.

Abstract

Unsupervised data clustering remains a crucial step in many recent multimedia retrieval approaches, including for instance, visual objects discovery, multimedia documents suggestion or event's detection across different media. However, the performance and applicability of many classical data clustering approaches often force particular choices of data representation and similarity measures. Such assumptions are particularly problematic in a multimedia context that usually involves heterogeneous data and similarity measures. This thesis investigates new clustering paradigms and algorithms based on shared nearest-neighbours (SNN), i.e. any two items are considered to be well-associated not by virtue of their pairwise similarity value, but by the degree to which their neighbourhoods resemble one another. As most other graph-based clustering approaches, SNN methods are actually well suited to deal with data complexity, heterogeneity and high-dimensionality. But unlike to state-of-the-art graph partitioning algorithms they do not attempt to minimize a global cost function based on pairwise similarities. Rather, they consider local optimizations in the neighbourhood of each item based on ranking considerations.

The first contribution of the thesis is to revisit existing shared neighbours methods in two points. We first introduce a new SNN formalism based on the theory of *a contrario* decision. This allows us to derive more reliable connectivity scores of candidate clusters and a more intuitive interpretation of locally optimum neighbourhoods. We also propose a new factorization algorithm for speeding-up the intensive computation of the required shared neighbours matrices.

The second contribution of the thesis is a generalization of the SNN clustering approach to the multi-source case, i.e. each input object is associated with a set of top-k lists coming from different sources instead of a single list of nearest neighbours. Whereas SNN methods appear to be ideally suited to sets of heterogeneous information sources, this multi-source problem was surprisingly not addressed in the literature beforehand. The main originality of our approach is that we introduce an information source selection step in the computation of the candidate cluster scores. Any arbitrary

item's set is thus associated with its own optimal subset of modalities maximizing a normalized multi-source significance measure. As shown in the experiments, this source selection step makes our approach widely robust to the presence of locally outlier sources, i.e. sources producing non relevant nearest neighbours (e.g. close to random) for some input objects or clusters. This new method is applied to a wide range of problems including multi-modal structuring of image collections and subspace-based clustering based on random projections.

The third contribution of the thesis is an attempt to extend SNN methods to the context of bipartite *k*-NN graphs, i.e. when the neighbours of each item to be clustered lie in a disjoint set. We introduce new SNN relevance measures revisited for this asymmetric context and show that they can be used to select locally optimal bipartite clusters. Accordingly, we propose a new bipartite SNN clustering algorithm that is applied to visual object's discovery based on a randomly precomputed matching graph. Experiments show that this new method outperform state-of-the-art object mining results on the Oxford Building dataset. Based on the objects discovered, we also introduce a new visual search paradigm, i.e. object-based visual query suggestion. The idea is to suggest to the user some relevant objects to be queried as they are the most frequent to appear in the full dataset or in a subset filtered by previous queries.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 General introduction and contributions

With the steady growth of the Internet and the falling price of storage devices, the amount of data continues to increase. Finding tools to manipulate large repositories of digital information is becoming a necessity. Who has never come back from holiday and found himself with a large set of pictures taken during the stay in different places and with different people? Keeping pictures in a single repository makes browsing very long and particularly when we are looking for pictures of a specific place or specific people. Structuring similar pictures in a set of groups makes visiting the collection very friendly and efficient. But, personal photo collections is not the only application that requires a structuring of data : scientific images collections (satellites, plants, medical) also have a great need for discovering patterns, clustering, summarizing, mining and even recommending.

Despite 40 years of research on data clustering, there is still no agreement on which clustering is the best solution. Each clustering method represents some advantages/limitations and is applied for limited problems and data. For that reason, there are as many solutions as problems, and as clustering methods. Users have multiple clustering algorithms but do not know which one is the most suitable. There is no generic tool that can be applied for any application, or any data, using any modality. The heterogeneity of the data from one application to another is one of the causes of this problem. Even in a single application, we can find heterogeneous information sources that can be explored to take advantage from each one. In some cases, the heterogeneity of the data and the use of different modalities lead to the use of different similarity functions, which is not very convenient. However, some clustering algorithms need *adhoc* parameters to produce relevant results which can be very difficult

for the user to tune when he uses different databases. Some others produce specific shapes of clusters and cannot deal, for example, with clusters of different densities. All these constraints make the user lost in his choice of the right clustering method. Shared neighbours clustering strategy appears to be promising and deal with the above problems. Shared neighbours information seems to be suitable to deal with different natures of the data, different similarity functions, and diverse modalities.

This PhD builds upon this idea. We propose a novel theoretical shared nearest neighbours clustering framework based on the *a contrario* approach. Thanks to the selection of the optimal neighbourhood of each item, we show by using synthetic data how our method is robust against outliers and noisy neighbours. To accelerate the calculation of shared neighbours, we propose a new factorisation algorithm based on the recursion of the calculation. The proposed method is compared to spectral clustering and we show by experiment that our method is more robust to the size of the graph.

The next challenge addressed in this work is the extension of our method to a multi-source shared neighbours clustering. Each object in this case is not associated with a single ordered list of nearest neighbours but a set of lists from different sources of information. The availability of different sources of information in some applications are not always operated properly.

We suggest a generic multi-source shared neighbours method that can be applied to any multimedia sources including text, image, videos and audio documents. The fact that only nearest neighbours lists are used as input of our clustering method makes this possible. Whereas SNN methods appear to be ideally suited to sets of heterogeneous information sources, this multi-source problem was surprisingly not addressed in the literature beforehand. Our contribution concerns two points. First, we introduce an information source selection step in the computation of the candidate cluster scores. Any arbitrary item's set is thus associated with its own optimal subset of modalities maximizing a normalized multi-source significance measure. As shown in the experiments, this source selection step makes our approach widely robust to the presence of locally outlier sources, i.e. sources producing non relevant nearest neighbours (e.g. close to random) for some input objects or clusters.

Second, in this multi-source case, we propose, applying the reshaping step of the clusters during the construction of candidate clusters. Missing items are not recovered only during the elimination of redundant clusters as is done in the mono-source case, but also from the other available lists of K-nearest neighbours belonging to the optimal selected sources of each cluster. Thanks to the synthetic data, we demonstrate the effectiveness and the robustness of our method against noisy sources. Our proposed

multi-source shared neighbours clustering method is applied to multi-modal search results clustering, visual object mining and image clustering based on multiple randomized visual subspaces.
Finally, we investigate the case where the nearest neighbours of an item belong to another another set. In this bipartite case, the similarity of two objects is evaluated by their shared nearest neighbours belonging to a disjoint set. We propose a new bipartite shared nearest neighbours clustering method and we apply it to object-based visual query suggestion. We aim to resolve user perception issues by applying our bipartite framework to object's seeds to group visual object's instances of the same object. We address the problem of suggesting only the object's queries that actually contain relevant matches in a dataset. Experiments show that this new method outperforms state-of-the-art object mining and retrieval results on the Oxford Building dataset. We also describe two object-based visual query suggestion scenarios using the proposed framework.

1.2 Thesis outline

This thesis is organized in three parts. The first part reviews some past and current methods in clustering and in visual content structuring and mining.
The chapter 2 explains the clustering problem and reviews some existing clustering methods. We focus particularly on graph-based clustering methods because they are related to our contributions in this PhD. Open problems and latest trends in data clustering are also presented.
Chapter 3 explores the state-of-the-art in visual content structuring and mining as they use generally the clustering techniques.
The second part covers the contributions we propose, including a Chapter on the suggested shared neighbours clustering method based on the *a contrario* approach, a second Chapter on the multi-source version and a last Chapter on the bipartite case. Chapter 4 presents our proposed shared nearest neighbours clustering framework and chapters 5 and 6 extend our proposed method respectively to the multi-source case and the bipartite case.
Finally, the third part presents some applications in structuring visual contents with multi-source shared-neighbours clustering and with bipartite shared-neighbours clustering.
Chapters 7 and 8 describe the application of our methods to visual content structuring.

In particular, the first presents some experiments including multi-modal search results clustering, visual object mining and image clustering based on multiple randomized visual subspaces. The second presents an application of our proposed bipartite shared-neighbours clustering to object-based visual query suggestion.
Finally, Chapter 9 summarizes our contributions, sets out the major conclusions and suggests some possible perspectives.

Part I

State-of-the-art

Chapter 2

Clustering Methods

2.1 The Clustering problem

Clustering is used in a wide variety of scientific fields and applications : image segmentation for instance can be formulated as a clustering problem [146], Connell *et al.* [29] use clustering to discover subclasses in a handwritten character recognition application, where a search engine clusters the search results for a better visualization. Biologist have applied clustering to analyse large amounts of genetic information and find groups of genes that have similar functions [176]. In the business domain, clustering can be used to segment customers into groups for additional analysis and marketing activities [2]. Clustering therefore relates to techniques from different disciplines including mathematics, statistics, computer science, artificial intelligence and databases.

In addition to the growth of the amount of data and applications, the variety of available data (text, image and video) has also increased. The Web and digital devices such as Tablet PCs, PDAs (personal digital assistants), and Smart Phones (cell phones with PDA capabilities) create new data every day, many of them are unstructured, which makes them difficult to analyse. Automatically understanding, processing and summarizing this data is one of the biggest challenge of the modern computer sciences.

Organizing data into natural groupings is a fundamental mode of understanding and learning. The absence of categories of information (class labels) distinguishes data clustering (unsupervised learning) from classification or discriminant analysis (supervised learning). The aim of clustering is to group data into classes or clusters, in such a way that objects within a cluster have a high similarity in comparison with each other but are dissimilar to objects in other clusters [66]. It can be used to extract models describing large data classes or to predict categorical labels [41]. Such analysis can

help us to achieve a better understanding of the data because cluster analysis provides an abstraction from individual data objects to the clusters.
In many applications, the notion of a cluster is unfortunately not well defined. In fact, the definition of a cluster depends on the nature of the data, the desired results and the goal of the application. Not surprisingly, there are several different notions of clusters [157]:

- Well-separated : A set of clusters is said to be well-separated when each object in a cluster is closer to every other object in the same cluster than to any object belonging to the other clusters. This idealistic definition of a cluster is satisfied when the data contains natural clusters (regardless of the shape) that are far from each other. However, in many sets of data, a point on the edge of a cluster may be closer (or more similar) to some objects in another cluster.
- Prototype-based : Some clustering techniques represent each cluster by a representative object called a *cluster prototype* [182] which is used as the basis for data processing techniques (summarization, compression, etc). For data with continuous attributes, the prototype of a cluster is often a centroid (the average of all the points in the cluster). In the case of categorical attributes, the prototype is often a medoid (the most representative point of all the objects in a cluster). Not surprisingly, such clusters tend to be spheric because they focus on the cluster's centers (the cluster surrounds the center).
- Graph based : If the data is represented by a graph where the nodes are the objects and the edges represent the similarity between them, a cluster can be defined as a connected component: a group of objects that are connected to one another but that have no connection to objects outside the group [144]. In some clustering techniques, a cluster is defined as a *clique* : a set of nodes in a graph that are completely connected to each other. Like prototype-based clusters, such clusters tend to be globular.
- Density-based : In density-based clustering methods, a cluster is defined as a dense region of objects that is surrounded by a region of low density. This definition of a cluster makes it robust to the presence of noise and outliers [46].
- Shared-property : In this case, a cluster is defined as a set of objects that share some property. For instance, a *shared-neighbours* cluster contains objects that share their nearest neighbours [44]. Objects in a *center-based* cluster share the property that they are all closest to the same centroid or medoid. This definition encompasses all the previous definition of a cluster.

The diversity of cluster definitions is not the only cause of the increasing number of clustering methods. Features representing the different measures of the properties of an object are not appropriate for all types of data. The better the choice of the feature, the more compact the clusters are and a simple clustering algorithm such as K-means [67] can be used to find them. Unfortunately, no universally appropriate features seem to exist, the choice of the feature must be related to the domain knowledge, the purpose of the clustering and the nature of the data set to be clustered.

2.2 Clustering evaluation

How to evaluate the relevance of a clustering result is a central point in any clustering method. For the case of unsupervised clustering, a standard evaluation can be made when a ground truth is available. The evaluation measure depends on the goal of the application. While it is possible to develop various numerical measures to assess the different aspects of the cluster's validity, there are a number of issues: i) a measure of cluster validity may be quite limited in the scope of its applicability, ii) we need a framework to interpret any measure.
A variety of different evaluation measures have been suggested recently in [19, 30]:

- **F-measures**: introduced by Larsen *et al.* [101] and combines the precision and recall measures. It considers that each cluster is the result of a query and that each class is the desired answer to that query.
- **Rand Index**: proposed by Hubert *et al.* [75] to compare two partitions. It can be used to compare the resulting partition of a clustering algorithm with the ground truth classes or to compare two partitions resulting from different clusterings.
- **Purity**: proposed by Zhao *et al.* [187] to measure the percentage of objects in a cluster that belong to the largest class of objects in this cluster. The larger the value of the purity, the better the clustering solution is.
- **Cosine Measure**: used by [73] and combines the precision and the recall of each cluster. A low precision score of clustering is an indication of cluster fusion, which often occurs when too few clusters are produced, whereas a low recall indicates cluster fragmentation, which occurs when too many clusters are generated. A high cosine measure value can be interpreted that the clustering avoids extremes fusion and cluster fragmentation, and that the number and sizes of the clusters roughly conform with those of the classes.

All these measures will be described in detail in Section 4.6.1. Recently, a different way to evaluate clusters has been proposed. Cao *et al.* [20] present a measure of the meaningfulness of clusters. This measure is derived from a background model assuming no class structure in the data. It provides a way to compare clusters, and leads to a cluster validity criterion. This criterion, inspired by the *a contrario* approach, is applied to every cluster. The Helmholtz principle [36] states that if an observed arrangement of objects is highly unlikely, the occurrence of such an arrangement is significant and the objects should be grouped together into a single structure. Hence, clusters are detected *a contrario* to a null hypothesis or background model (no class structure in the data). This notion will be used in this PhD to compute the *a contrario* significance measures of clusters.

2.3 Data clustering methods

As mentioned above, so many clustering algorithms have been proposed in the literature, in many different scientific fields and applications, that is would be extremely difficult to review all the proposed methods. These methods differ in the choice of data, the objective function, heuristics and hypotheses.
Here, we will not detail all the existing clustering methods. In the next Section 2.3.1, we present an overview of some clustering methods and the particular properties of each one. Thereafter in Section 2.3.2, we review some open problems and recent trends in data clustering. Finally, in Section 2.4, we focus particularly on graph based methods and especially on spectral clustering and shared nearest neighbours clustering methods *SNN*. Our contributions are related to *SNN* methods and we use spectral clustering for comparison and positioning.

2.3.1 Overview

Comprehensive surveys on clustering have been published, such as the well-known papers by Jain *et al.* [9], Jian *et al.* [82] and Xu *et al.* [179] where a large variety of algorithms are detailed.
One of the most important points that can be helpful in selecting a clustering algorithm is the nature of the data and the nature of the desired clusters. Data dimensionality and the size of the dataset are also important criteria since no stable clustering algorithm exists [47] and might be restricted to low dimensionality [1, 155].
Traditionally, clustering methods are divided into *hierarchical* and *partitioning* tech-

niques. While hierarchical algorithms are subdivided into *agglomerative* and *divisive*, partitioning algorithms are subdivided into 2 types : i) methods that tend to build clusters of proper convex shape and look how items fit into their clusters (K-medoid, K-means, probabilistic clustering), ii) density based methods that define clusters as high density regions in the feature space separated by low density regions.
The density-based algorithm *DBSCAN* [46] introduced a frequency count within the neighbourhood to define a concept of a core point. In fact, while density-based methods are attractive because of their ability to deal with arbitrarily shaped clusters and are less sensitive to outliers, they have limitations in handling high-dimensional data. They are usually used with low-dimensional data of numerical attributes because the feature space is usually sparse when the data is high-dimensional. This is due to the fact that it is difficult to distinguish high-density regions from low-density regions in high-dimension.
To overcome this limitation, subspace clustering algorithms such as *CLIQUE* [3] try to find clusters embedded in low-dimensional subspaces of the given high-dimensional data. When the dimension grows, a problem arises from the decrease in metric separation (*curse of dimensionality*). Two solutions exist : either reducing the dimension by transforming the attributes (PCA [128], wavelets [93], Discrete Fourier Transform DFT [94]) or using clustering techniques for high dimensional data (subspace clustering [126], multi-clustering techniques [137]).
When the data points are represented by nodes in a weighted graph and the weight of the edges connecting the nodes represents the pair-wise similarity, the clustering is referred to graph clustering. The most popular graph clustering is spectral clustering. The main idea of such clustering is to partition the nodes into subsets such that the sum of the weights assigned to the edges connecting two subsets is minimized. We detail spectral clustering techniques in Section 2.4.

2.3.2 Open problems and latest trends in data clustering

While new clustering algorithms continue to be developed, some issues still have to be resolved. Some problems and research directions as pointed by [76] have to be addressed:

– There is a need to achieve tighter integration between clustering algorithms and application requirements. Each application has its own requirements: some of them just need a global partition of the data while others need to have the best partition with great precision. Generally, in mining applications, the goal is

not to provide all the clusters of the search results but a summarized list of the different topics of the query. Users can after easily figure out what they are exactly searching for by selecting the target topic. Showing images from the target category in which the user is truly interested is much more effective and efficient than returning all the clusters or all the mixed images.

- There is a need for clustering algorithms that lead to computationally efficient solutions for large scale data. Not all clustering algorithms can deal with large scale issues.
- There is a need for stable and robust clustering algorithms that lead to stable solutions even in the presence of noisy data.
- There is a need to use any available *a priori* information concerning the nature of the dataset and the goal/domain of the application in order to decide which data representation is the most suitable and which clustering method is the most appropriate.
- There is a need to have generic clustering that can be applied for any type of data.
- There is a need for benchmark data with available ground truths and diverse data sets from various domains to evaluate any kind of clustering algorithm because current benchmarks are limited to a small dataset that can be applied only for a limited choice of clustering methods.

As said above, the growing amount of data leads to diverse data (both structured and unstructured). Raw images, text, video are considered as unstructured data because they do not follow a specific format, in contrast to structured data where there is a semantic relationship between objects. Generally, clustering approaches are applied without taking into account the structure of the data. It is precisely for these reasons, that new algorithms are being developed. Recently, [76] presents an overview of clustering techniques and highlights some emerging, and useful, trends in data clustering, some of which are presented below :

- Clustering ensembles [58] : The idea here is that by combining multiple partitions (clustering ensembles) of the same data, we can obtain a better data partitioning. For example, we can obtain a set of clustering ensembles by taking a different value of K in a K-means clustering with each time a random initialization, and then, combining these partitions using a co-occurrence matrix which results in a good separation of the clusters, as was done in [56]. Applying the same clustering algorithm with different parameter values is not the only way to generate a clustering ensemble. We can apply different clustering algorithms on

the same data which leads to different clusters or even use different data representations of the data with different clustering algorithms.

– Large scale clustering : A number of clustering algorithms have been developed to handle large size dataset. Some of them are based on efficient nearest neighbours search and use trees as in [119] or random projections as in [16]. Some others first, try to summarize a large data set into small subset and then apply the clustering algorithms to the summarized dataset as with the BIRCH algorithm [186] in contrast to sampling based methods like CURE algorithm [64] which sub-sample a large dataset selectively and perform clustering over the small set, which is later transferred to the larger dataset.
– Multi-way clustering [18] When a set of objects to be clustered is formed by a combination of heterogeneous components, a classical clustering method leads to poor performances. *Co-clustering* treats this problem, and has been successfully applied to document clustering (clustering both documents and words belonging to documents at the same time [38]). This *Co-clustering* framework was extended to multi-way clustering in [7] to cluster a set of objects by simultaneously clustering their heterogeneous components.

2.4 Graph-based clustering methods

A graph is classically defined by a set of nodes or vertices and a set of edges linking some pairs of nodes. Graphs are a nice way to represent the data when we do no have more information than the similarity between objects. In this case, the weight associated to the edge connecting two nodes is equal to the similarity between these nodes. Graph clustering tends to group vertices of a given input graph into clusters taking into consideration the edge structure of the graph. Vertices belonging to the the same group are connected by high weight while edges between different groups have very low weights.

As the field of graph clustering has become quite popular, the number of clustering algorithms as well as the number of applications have become high. Graph clustering algorithms serve as a tool for analysis, model and predict in many different domains [144]. In social networks for instance, groups of people (such as friends or families) can be connected by means of their profile as done in collaborative filtering recommendation systems [145].

Representing data by a graph also helps in the biological domain to study for example

the spread of epidemics. Newman [120] studied susceptible, infective and recovered type epidemic processes and found that clustering decreases the size of epidemics.
Generally, the goal of graph based clustering is to group items into clusters such that connected or similar items are assigned to a same cluster. But each application defines its own desirable cluster properties. In some applications, the density of edges within the cluster is more important than the edges with the rest of the graph [86]. Some graph structures are hierarchical and other graphs can simply computed by flat clustering.
Different kinds of graphs can be computed from a given unstructured set of data items:

- **The fully connected graph**: Every pair of distinct vertices is connected by a unique edge. As the goal is to model the local neighbourhood relationships between items, the edges have to be weighted. The similarity plays the role to detect partitions with high weights. The choice of the similarity function, used to compute the weights between objects, is very important for this kind of graph since all pairs are connected and only the edge weights are discriminant.
- **The ε-neighbourhood graph**: Only vertices whose dissimilarity is smaller than ε are connected. The difficulty lies in choosing this parameter. The produced graph and the resulting clustering are actually very sensitive to the choice of ε. To determine the smallest value of this parameter, we can consider it as the length of the longest edge in a minimal spanning tree of the fully connected graph of the data items. The disadvantage of this method of determining ε is that if the data contains outliers, this leads to choosing a larger ε , so that some vertices will be connected even if they are dissimilar.
- **The k-nearest neighbours graph**: A vertex is only connected to its k-nearest neighbours. The resulting graph is directed as the nearest neighbour relation is not a symmetric one, i.e., if an item q is among the k-nearest neighbours of a point p, this does necessarily mean that p is a nearest neighbour of q. To make the graph undirected, we can consider that two points are connected if one of the pair is among the k-nearest neighbours of the other and we ignore the direction of the edge. A second way is to connect a pair of items only if they are among the k-nearest neighbours of each other. By this restrictive method, we obtain a *mutual k-nearest neighbour graph* which has the property of connecting nodes within regions of constant density as well as points within different scale of density. When the clusters are from different densities, this kind of graph is very useful.

  The choice of k is crucial in order to achieve good performances. A small k makes the graph too sparse or disconnected. On the other hand, by choosing a

large k, dissimilar points are related on the graph. The advantage of this kind of graph is that points belonging to different level of density can be connected. The similarity function is only used to connect the points to their k nearest neighbours in the graph. [14] suggests guaranteeing the good connectivity of this graph by choosing k in the order of $log(n)$ with n being the number of the data items. As for the *mutual k-nearest neighbour graph* [124], the number of edges is more limited than for the standard k-nearest neighbour graph and this suggests choosing a large value of k. No theoretical study has clearly resolved the problem.

– **The Bipartite graph**: The set of vertices is divided into two subsets and all the edges lie between these two subsets [177]. Such graphs are natural for many applications involving 2 types of objects such as documents and words. A word belongs to a set of documents and at the same time, a document contains a set of words. The motivation can be to regroup documents having common words. To achieve this, we simultaneously obtain the clustering of words and of documents. To evaluate the similarity of two vertices of the same side of the graph can be done only by evaluating the overlap of their neighbourhood on the other side and vice versa.

Over the years, there has been a huge amount of work on graph-based clustering [54, 91]. Rather than giving an exhaustive description of all the methods, we focus on two widely used divisive categories of graph-based methods: "spectral clustering" that is probably the most well-known one and "shared nearest neighbours clustering" that is related to our work.

2.4.1 Spectral clustering

Graph-based divisive clustering [51] is a class of hierarchical methods that tends to divide the graph recursively into clusters in a top-down manner. The division should not break a natural cluster but rather separate connected clusters from other clusters. Among this type of clustering, we find the spectral clustering [110] that is very popular and used extensively in many studies.

The main idea of this clustering is that by computing the eigenvectors corresponding to the second smallest eigenvalue of the normalised Laplacian, the clustering can be determined by using the eigenvector as vertex-similarity values.

The success of spectral clustering is mainly based on the fact that it does not need to have assumptions on the form of the clusters unlike the popular K-means algorithm

for example which leads to a convex form of clusters. However, spectral clustering depends on the choice of similarity graph (choosing the right parameter of connectivity of the graph representation of items).
A comprehensive tutorial on spectral clustering was given by Ulrike Von Luxburg [110] and a broad overview of the different methods is available in [166] where an evaluation of what features make a spectral clustering more valuable is provided.

Spectral clustering as a graph partitioning approach

The goal of graph clustering is to divide data into some clusters such that the elements in the same cluster are highly connected and the edges between the different clusters have low weights. This means that we aim to separate groups of elements from each other with the minimum of cuts (often called *the min-cut problem*) [89].
The clustering problem is then configured as a graph cut problem where an appropriate objective function has to be optimized.
Let us define by $C_1, C_2, ..., C_k$ the partition of a data set on k groups that we want to achieve with the minimum of cuts.
As the objective function that has to be minimized, we can find the normalized association [146], the conductance [87], or the ratio cut [37]. But the most widely used is the normalized cut (Ncut) [146]:

$$Ncut(C_1, C_2, ..., C_k) = \sum_{i=1}^{k} \frac{cut(C_i, \bar{C_i})}{vol(C_i)}. \tag{2.1}$$

where $\bar{C_i}$ is the complement of C_i and $vol(C_i)$ is the sum over the weights of all the edges attached to vertices in C_i.
Because spectral clustering techniques have a strong connection with Laplacian Eigenmaps [8], spectral concepts and graph analysis is the way to solve the relaxed version of this NP hard problem of *the min-cut problem* [167, 146].
This relaxation can be formulated by introducing the Laplacian matrix [28]. The resulting balanced groups with low edges between them have another property : a random walk (jumping randomly from one vertex to another [107]) on a group stays long before jumping to another groups. By this property, spectral clustering can also be interpreted as trying to find a partition that random walks have more chance of staying on the same cluster than jumping to another cluster. [112] analyse the relation with the Normalized cut (NCut) and the random walk: when we minimize the Ncut, we are actually looking for the partition with a frequent random walk within the clusters and

hardly from C_i to $\bar{C_i}$.
The most popular spectral clustering algorithms are those of [121] and [146]. The core of these algorithms is the eigenvalue decomposition of the Laplacian matrix **L** of the weighted graph obtained from data to solve the relaxed problem of objective functions like the Ncut. In fact, the second smallest eigenvalue of L is related to the graph cut [50] and the corresponding eigenvector can cluster together similar items [13, 28, 146]. The main difference between [146] and [121] is the way the normalized graph Laplacian is used.
In the next Section, we describe these two algorithms and some relative properties of each.

Normalized spectral clustering according to Shi and Malik [146]

This spectral clustering was initially proposed for image segmentation problems [146]. In the original framework each node is a pixel and the definition of adjacency between them is suitable for image segmentation purposes. Each pixel of the image is considered as a point having a feature vector which takes into account several of its attributes (e.g. intensity, color and texture information). The goal is to regroup similar pixels describing a same region.
Given a set of points $x_1, x_2, ..., x_n$ of size n, by using the similarity matrix S, we want to cluster the data into k groups. To do so:

1. construct the affinity matrix A (also called the adjacency matrix) defined by $A_{ij} = exp(-\frac{\|s_i - s_j\|^2}{2\sigma^2})$ for $i \neq j$ and $A_{ii} = 0$.
2. form the degree matrix D as the diagonal matrix defined by $D_{ii} = \sum_{j=1}^{n} A_{ij}$.
3. compute the unnormalized Laplacian matrix $L = D - A$.
4. compute the first k eigenvectors $v_1, v_2, ..., v_k$ of the generalized eigen problem $Lv = \lambda Dv$.
5. form the matrix V containing the eigenvectors as columns elements.
6. consider each row i of V as a point y_i and apply K-means algorithm on Y.
7. assign each point x_i to cluster j if y_i was assigned to the cluster j.

Note that this algorithm uses the generalized eigenvectors of L, hence is called normalized spectral clustering. The next algorithm also uses a normalized Laplacian. As we will see, this algorithm needs to introduce an additional row normalization step which is not needed in the other algorithms [110].

Normalized spectral clustering according to Ng, Jordan and Weiss [121]

Given a set of points $x_1, x_2, ..., x_n$ of size n, by using the similarity matrix S, we want to cluster the data to k groups. To do so:

1. construct the affinity matrix A defined by $A_{ij} = exp(-\frac{\|s_i - s_j\|^2}{2\sigma^2})$ for $i \neq j$ and $A_{ii} = 0$.
2. form the degree matrix D as the diagonal matrix defined by $D_{ii} = \sum_{j=1}^{n} A_{ij}$.
3. compute the normalized Laplacian matrix $L = D^{-0.5} A D^{-0.5}$.
4. find the first k eigenvectors $v_1, v_2, ..., v_k$ of L
5. form the matrix V by letting as columns the eigenvectors.
6. form the matrix Y from V by normalizing each row to have unit length i.e. $Y_{ij} = \frac{V_{ij}}{(\sum_j V_{ij}^2)}$.
7. consider each row of Y as a point and cluster into k clusters them via K-means.
8. assign each point x_i to cluster j if the row i of Y was assigned to the cluster j.

The two algorithms given above look rather similar, apart from the fact that they use two different graph Laplacians. If the graph is regular and most vertices have approximately the same degree, then all the Laplacians are very similar to each other, and will work equally well for clustering. The main trick is to change the representation of the abstract data items x_i to feature vector $y_i \in R^k$. This change of representation enhances the cluster-properties in the data, so that clusters can be trivially detected in the new representation. In particular, the simple K-means clustering algorithm has no difficulty detecting the clusters in this new representation [110]. Note that there is nothing principled about using the K-means algorithm in this step. In fact, this step should be very simple if the data contains well-expressed clusters and the Euclidean distance between the points y_i is meaningful enough .

Bipartite spectral graph partitioning

This kind of spectral graph partitioning is applied on bipartite graphs. By modelling a document collection, for example, as a bipartite graph with the two sets *documents* and *words*, we want to have a document clustering and at the same time a word clustering [177, 38]. This problem is called *dual clustering* or *co-clustering* [104]. Most existing algorithms handle each one separately. By using bipartite spectral graph partitioning, the similarity between two documents is computed by using

their corresponding words, and the similarity between two words is computed by using the information of documents in which they occur.
Failing to take into consideration the similarity of the words they contain leads to some problems when we cluster documents and vice-versa: two documents d_1 and d_2 are considered to be similar because they share a set of words S_w but it can happen that the words in S_w are never clustered together.
Dhillon [38] proposed a spectral approach to approximate the optimal normalised cut of a bipartite graph, which was applied for document clustering. This involved computing a truncated singular value decomposition (SVD) of a suitably normalised term-document matrix, constructing an embedding of both terms and documents, and applying K-means to this embedding to produce a simultaneous k-way partitioning of both documents and terms. The usefulness of this approach was however limited and [97] proposed an adapted bipartite spectral graph partitioning approach to successfully cluster micro array data simultaneously in clusters of genes and conditions.
Wieling *et al.* [173] proposed applying a bipartite spectral graph partitioning to a new sort of data, namely dialect pronunciation data to recognize groups of varieties in this sort of data while simultaneously characterizing the linguistic basis of the group. Such a study demonstrates that spectral clustering gives sensible clustering results in the geographical domain as well as for the concomitant linguistic basis.
Is is not necessarily to have different kind of objects to form a bipartite graph. Simultaneous inputs of data from two sensory modalities can be modelled by a bipartite graph [34]. Each sensory modality is considered as a view and a spectral clustering is applied to cluster each side while taking the other side into account with the goal of minimizing the disagreement between the clusterings.
To get a better idea of the principle of bipartite spectral graph partitioning algorithm, we present here the first one proposed by [38] to cluster documents and words: Given a set of documents $D = d_1, d_2, ..., d_n$ and a set of words $W = w_1, w_2, ..., w_m$. We construct the bipartite graph $G = (D, W, E)$ where E is the set of edges $d_i, w_j : d_i \in D, w_j \in W$. By considering the $m \times n$ word-by-document matrix A such as A_{ij} is equal to the edge-weight E_{ij}, we want to have a set of word-document dual clusters $C = C_1, C_2, ..., C_k$ such that the cut of k-partitioning the bipartite graph is minimized. Minimizing the normalized-cut is equivalent to maximizing the proportion of edge weights that lie within each partition such as [146] and [121]. Finding a globally optimal solution to such bipartite graph partitioning is NP-complete but by using the left and right singular vectors, we can relax the discrete optimization problem and find an optimal solution. We present here the bipartite spectral clustering algorithm proposed by Dhillon [38] :

1. calculate the diagonal matrices D_w and the D_d of A defined by $D_w(i,i) = \sum_{j=1}^{n} A_{ij}$ and $D_d(j,j) = \sum_{i=1}^{m} A_{ij}$
2. form the new normalized matrix of A denoted $A_n = {D_w}^{-0.5} A {D_d}^{-0.5}$.
3. perform SVD (Singular Value Decomposition) operation on A_n to obtain the left and the right k singular vectors L_w and R_d and combine the transformed row and column vectors to create a new projection matrix Z.
4. run a clustering algorithm as K-means on the Z matrix and return the co-clusters $C_j = (w_j, d_j), j = 1, ..., k$.

Discussion

The main advantage of spectral clustering is that it can transform any graph-based problem into a linearly separable problem that can be easily solved by an algorithm such as K-means. Its success is essentially based on the fact that it does not need strong assumptions on the form of clusters as opposed to K-means where the resulting clusters have a convex form. Because it is easy to implement and avoids having a local minima, spectral clustering represents a powerful tool to produce good results.
On the other hand, one drawback of spectral clustering is that it depends on the type of the graph. [111] demonstrate theoretically and through practical examples that minimising NCut on a k-nearest neighbour graph leads to different results than minimising the NCut on a ε-neighbourhood graph. This means that by using a given data and an spectral clustering algorithm, we obtain different results if we construct the underlying graph differently and we use different neighbourhood size.
Another critical parameter that has to be fixed is the number of clusters as in most clustering problems. Guidelines are proposed in the literature such as the ratio of the intra/inter cluster similarity and many other *adhoc* measures [100, 55] but there is a particular one used for spectral clustering based on the eigen-gap heuristic. Justifications based on spectral graph theory and perturbation theory allow us to conclude that there is a large gap between the k-th eigenvector and the $k+1$-th eigenvector, which is not the case between the first k eigenvectors where the gap is very small. In the presence of noise or overlaps between clusters, this heuristic is less effective: the gap is not significant and the k-th eigenvector cannot be found precisely. We can conclude that to achieve good results by using spectral clustering, some parameters have to be considered carefully: the number of clusters, the choice of graph, and the parameter of connectivity on the graph. Each of these parameters

influence consistently the clustering results and is a potential source of instability.

2.4.2 Shared nearest neighbours clustering methods

In this Section, we focus on another kind of graph-based clustering i.e *shared nearest neighbours clustering methods*. In these methods, the edge between two nodes represents the rank of a node in the nearest neighbours list of another node. The rank is computed using a primary similarity measure that will be discussed in the next paragraph. Unlike spectral clustering, the goal is not necessarily a global graph cuts optimization but a local optimization cut. The use of a similarity based on the shared nearest neighbours makes the graph less sensitive to the different parameters seen in the previous section. Let us begin by presenting the effects of high data dimensionality on a range of popular distance measures and explain why a shared nearest neighbours measure is more appropriate.

Shared nearest neighbours measure

To support clustering, a measure of similarity or a distance is needed between data objects but clustering then depends critically on density and similarity. These concepts become more difficult to define when dimensionality increases. Similarity measures based on distances are sensitive to variations within a data distribution or the dimensionality of a data space. These variations can limit the quality of the clustering solution.

In low dimensions, the most common distance metric used is the Euclidean distance or the L_2 norm. While it is useful in low dimension, it does not work well in high dimensions. One of the reasons is that the Euclidean distance considers missing attributes to be as important as the present attributes. Often, in high dimensions, data points are actually sparse vectors and the presence of an attribute has to be more important than the absence of an attribute.

Even the traditional Euclidean notion of density, which is the number of points per unit volume, in high dimensional data is meaningless. As the number of dimensions increases, the volume increases rapidly and if the number of points does not grow exponentially with the number of dimensions, the density tends to 0. Thus, in high dimensions, we cannot differentiate between high density regions and low density regions.

To solve this problem, the cosine measure and the *Jaccard coefficient* were suggested.

The cosine similarity between two data points is equal to the dot product of the two vectors divided by the norm of each vector. The *Jaccard coefficient* is equal to the number of intersecting attributes (if the attributes are binary of course) divided by the number of spanned attributes by the two vectors.
Even if *cosine* and *Jaccard* measures can provide relevant similarity measures, they cannot handle high dimensionality well: there are cases where using such measures still does not eliminate all the problems of similarity in high dimensions [139]. This problem is not due to the lack of a good similarity measure but to the fact that in high dimensions direct similarity cannot be trusted when the similarity between pairs of points is very low [44].
In fact, [10] demonstrates that in high dimensions, the proportional difference between the farthest point distance and the closest point distance tends to be equal to 0. As the dimension increases, the contrast of distance between data points decreases: this is one of the aspects of the so-called *curse of dimensionality* [40]. The distance measure does not become discriminant unless the data is composed of natural well-separated clusters, each one following its own distribution. This is a fundamental problem studied in detail in [1, 69].
An interesting alternative to direct similarity is to define a secondary measure based on the rankings induced by a specified primary measure. This primary similarity measure can be any function that determines a ranking of the data objects relative to the query. The most basic form of a secondary measure is the similarity between pairs of points in terms of their shared nearest neighbours SNN.
While we cannot rely on the absolute values of the distance because the *curse of dimensionality*, it is still viable to use distance values to derive a ranking of data objects. By using a ranking of the nearest neighbours, we are not dependent on the value of similarity but we retrieve the top k-nearest neighbours independently of their absolute distance values. In some cases, when dimensionality increases, the ranking improves significantly [10]. [74] demonstrate that the quality of the ranking may not necessarily depend on the data dimensionality but on the number of relevant attributes in the data set. In other words, if the dimensionality increases but the number of relevant attributes is high, the relative contrast between points tends to decrease but the separation among different clusters can increase. But if the data dimensionality is high and the number of relevant dimensions is low, the *curse of dimensionality* comes into effect. In the same study, an evaluation of the performance of a secondary similarity measure based on SNN information is done empirically and compared to the primary distances from which the rankings were derived. The experiments suggest that using an SNN simi-

larity measure can significantly boost the quality of the ranking compared to the use of the primary distance measure alone. In particular, the secondary distance performs very well at high dimensionality, and is robust if we respect the neighbourhood size : for two points from a common cluster, if we consider their neighbourhoods of a large size but always lower than the real size of the class, the overlap will increase. But if we use neighbourhoods larger than the size of the class, many others objects from different groups will be contained in the neighbourhoods of the two points and the performance of the secondary measure will become less predictable.

Shared nearest neighbours based algorithms

For high dimensional data clustering, traditional clustering algorithms like K-means, for example, show their limitations to deal with outliers and do not work well when the clusters are of different sizes, shapes and densities. Agglomerative hierarchical clustering, known to be better than K-means for low-dimensional data, also has the same problems. To solve this problem, an alternative similarity based on shared nearest neighbours was first proposed by Jarvis and Patrick [77]. A similar idea was later presented in the hierarchical algorithm ROCK [139]. In Jarvis and Patrick's clustering method, a graph is constructed as follows: a link is created between a pair of items x and y if and only if x and y belong to their respective closest k nearest neighbours lists. The weight of the link can represent the number of shared neighbours between x and y or a weighted version that takes into account the ordering of the neighbours. All edges with weights less than a user predefined threshold are removed and all the connected components in the resulting graph are the final clusters. Defining this threshold is the major drawback of this method : if the threshold is too high, two distinct sets of points can be merged into the same group even if there is one link between them. On the other hand, if the threshold is too small, then natural clusters can be split into many small clusters. Despite this drawback, this algorithm presents some advantages: noise points and outliers will have their link broken because they are not in the nearest neighbours lists of their own neighbours. Uniform regions will keep their links until transition regions break the ones (we can say that the graph is independent of the density of the regions, only links are important).
For low to medium dimensional data, density-based algorithms such as DBSCAN [46] have been proposed to find clusters of different sizes and shapes but not of different densities. This method introduced the idea of *representative* or *core* points that become the origin of the clusters. In DBSCAN, the density associated with a point is

obtained by counting the number of points in a region of a specified radius around the point. Points with a density higher than a specified threshold are considered as core points and clusters will grow around these points. In this way, this method can find clusters of different shapes but not of different densities. For this reason, an SNN clustering algorithm [44] was proposed to deal with this problem by using a density based approach to find core points: by computing the sum of links strengths for every point in the SNN graph, points that have high total link strength then become candidates for the representative core points, while the others become noise points.
It is not difficult to see that there are many disadvantages of this method: the definition of thresholds for core points and outliers is not clearly provided (core points may belong to identical clusters while core points had better be as disperse as possible). The performance of the SNN greatly depends on the tuning of several non-intuitive parameters specified by the user and it is difficult to determine their appropriate values on real datasets.
In conclusion, a common need of the previous shared neighbours algorithms is that a fixed neighbourhood size (in terms of the number of neighbours k as in Jarvis-Patrick and SNN or in terms of the radius r of the neighbourhood in ROCK or DBSCAN) has to be chosen in advance by the user and applied equally to all items of the dataset to cluster which leads to bias in the clustering process.
Recently, an SNN-based clustering method was proposed by Houle [73] that allows the variation of the neighbourhood size. The *Relevant Set Correlation* (RSC) model defines the relevance of the data point x to a cluster C in terms of the correlation between items in C with the $|C|-$nearest neighbours set of x. The model does not require the user to choose the neighbourhood size or to specify a target number of clusters. The clustering process is not guided by a global optimization criterion but by only a local criterion for the formation of cluster candidates. For each item, an optimal radius that maximizes the quality of the cluster is selected. A greedy strategy is then applied to keep the clusters according to their qualities and their overlap with the other clusters.
In this work, we provide several contributions and insights into SNN clustering by firstly revisiting shared nearest neighbours metrics using the *a contrario* approach, then we extend SNN approach to the multi-source case and finally to the bipartite case. For each case, theoretical contributions and experimental applications are provided. We will focus particularly on visual content which seems an interesting application of our method. For this reason, in the next Chapter, we provide a short overview of visual content structuring and mining techniques.

Chapter 3

Visual Content Structuring and Mining

The steady growth of the Internet, the falling price of storage devices and an increasing pool of available computing power make it necessary and possible to manipulate very large repositories of digital information efficiently. Analysing this huge amount of multimedia data to discover useful knowledge or even just browse is a challenging problem. The task of developing data mining methods and tools is to discover hidden knowledge in unstructured multimedia data. The data is often the result of different outputs from various kinds of information sources, each one with its own modality. The fact of organizing, searching, managing, clustering and more generally structuring helps to improve decision making. These tools have been applied in different domains such as medical data, news, consumer purchasers of a store as well as user generated contents (UGC).

The typical data mining process consists of several stages and the overall process is inherently interactive and iterative. The main stages of the data mining process are [48]: (1) Domain understanding; (2) Data selection; (3) Data preprocessing, cleaning and transformation; (4) Discovering patterns; (5) Interpretations; and (6) Reporting and using discovered knowledge [127].

At the heart of the entire data mining process lies pattern discovery. This includes clustering, classification and visualization. Summarizing a huge amount of data so as to be able to browse it is not a trivial task.

Many intelligence agencies and low enforcement bodies now employ this technology to fight against child pornography, the trafficking of cultural objects and counterfeiting. Various fields ranging from Commercial to Military want to analyse data in an efficient and fast manner.

In this PhD, we particularly interested in “visual contents mining” which is a complex domain with different challenges that are sometimes specific to images [95]. Visual mining is not just an extension of data mining to image domain. It deals with the extraction of hidden knowledge, image data relationships, or other patterns not explicitly stored in the images. The goal is to determine how low-level pixel representations can be processed to identify high-level objects and relationships. For example, many pictures of various persons once stored and mined can reveal interesting images of the same music concert because some patterns have been detected and shared in these collections of data. Clearly, visual contents mining does not aim to extract and/or to understand features from images but to discover and to extract significant visual patterns in a collection of visual documents such as images, videos, etc.
We will not review all the problems here but focus on the following issues related to the applicative experiments of our work in this PhD: (1) Browsing and summarization; (2) Building visual vocabularies; (3) Visual object discovery; (4) Multi-cue and multi-modal image clustering.

3.1 Browsing and summarization

There has been a wide variety of innovative ways to browse and summarize multimedia information from the visual content. The first idea was to cluster visually similar images in the same cluster and then convert image clusters to a video in sequential order based on their inter-cluster similarities. Image cluster contents can be viewed separately by selecting an index frame from the global overview and by showing a video loop of cluster frames in a minimum variance order [154]. Hari Sundaram *et al.* [156] presented a novel framework for condensing computable scenes. The solution consists in analysing visual complexity and film syntax, then robust audio segmentation and significant phrase detection via SVM’s and finally determining the duration of the video and audio segments via a constrained utility maximization. The aim is to make the user able to have an abstract of the story in video format.
For summarising video, Snoek *et al.* [153] propose grouping by categories and browsing by category and in time. [175] group similar images and explore the use of a nearest neighbour network to facilitate interaction with the users.
All these solutions, at some point require a clustering phase based on different visual or multi-modal features. For more details, the readers can refer to the interesting survey [103].

3.2 Building visual vocabularies

The visual vocabulary is a strategy issued from the text retrieval community. A document is a distribution of words and all the different tasks related to a document such as indexing, retrieving documents in which a query word exists, can be done with relevant results. By considering an image as a visual document, we can consider local features descriptors as visual words. A feature vector can be expressed in terms of the region of the feature space to which it belongs. Each visual document is represented by a distribution of visual words (BOW) over a fixed vocabulary. Work on object based image retrieval [151] has imitated simple text-retrieval systems using the analogy of "visual words".
The building of a standard visual vocabulary consists in:

- Collecting a corpus of images and selecting a set of features: The most accurate results are generally obtained when using the same data to create the vocabulary. Generally, the goal is to construct a generative vocabulary with a corpus and this vocabulary has to deal with any other data and not be an application-specific vocabulary. For this purpose, [125] proposed collecting images from WWW clustering them and eliminating irrelevant ones.

- Clustering the sampled features in order to quantize the space into a discrete number of visual words. Usually, a simple K-means clustering is used [88]. The number of clusters has to be given as user-supplied parameter and the centers of the clusters represent the visual words. The problem is that the size of the data essentially rules out methods such as mean-shift, spectral and agglomerative clustering. It is true that K-means clustering is effective but it is difficult to scale to large vocabularies. Some work [42] has been done on accelerating the k-means but it requires $O(K^2)$ extra storage, where K is the number of cluster centers, rendering it impractical. More recent work has used cluster hierarchies [115] and greatly increased the visual-word vocabulary size by using them. [122] generates a "vocabulary tree" using a hierarchical K-means clustering scheme where a branching factor and number of levels are chosen and then hierarchical K-means is used to recursively subdivide the feature space. Philbin *et al.* [132] propose scaling K-means to a large vocabulary using of approximate nearest neighbour methods. The method has similar complexity to the vocabulary tree, but far superior performance.
  Another problem to take into account is the size of the vocabulary. It has been

observed in [31, 85, 129] that even with databases containing a limited number of categories, the best performances are obtained with a large vocabulary. Because the cost of histogram computations depends on the size of the vocabulary, one way to reduce the computational cost is to have a more compact vocabulary. Winn *et al.* [174] studied the problem of defining and estimating descriptive and compact visual models of object classes for efficient object class recognition. They proposed an approach based on the information bottleneck principle (a technique introduced to find the best trade-off between accuracy and complexity) [159]. A vocabulary inatially containing several thousand words was reduced to 200 words without any lose of performance. A tree structure, as the Extremely Randomized Clustering Forests, was also proposed in [117] to organise the vocabulary with the goal of reducing the computational cost.

In short, building a visual vocabulary depends on the type of visual features, the input set of features, the number of words to be selected and the type of clustering algorithm. The lack of geometry in BOW can be both an advantage or a disadvantage. By counting only the occurrence of visual words and not considering the relative geometry, we obtain a flexibility to variation (view point, pose changes). At the same time, the geometry between features can represent a discriminant factor. Furthermore, by incorporating a post processing spatial verification step [132] or by considering the neighbourhood of words, one can achieve a better representation of the geometry.

Given a new image, each local feature region is assigned to the nearest visual word. Thus, the image is represented with a list of words number. Such representations are equivalent to standard vector-space models in text information retrieval allowing to efficiently measure the similarity between items with classical operators. Such similarities only consider global statistics of the image which is a problem when the goal is to discover very small objects representing a small part of an image.

When dealing with small objects, the solution is to use a method based on probing local query regions. Many studies [132, 78] use this second type of strategy and consider each local feature of an image independently. Joly *et al.* [84] show that using each local feature is effective in retrieving small objects, such as trademark logos.

The disadvantage of this accurate local description of image strategy is that the number of candidate local regions can be huge. Even with the most efficient indexing structures that drastically reduce the computational costs, the overall complexity remains expensive.

Chum *et al.* [27] propose automatically selecting *Regions Of Interest* (ROI) with a very low computational cost. Their method combines BOW models with a geometric

Min-Hash [15] and can be considered as a trade-off between global and local strategies.
Adopting another solution to avoid querying all possible regions of interest while keeping a good coverage of the contents, Letessier *et al.* [102] propose a weighted and adaptive sampling strategy aiming at selecting the most relevant query regions. A concept of consistent visual words is proposed and the experiments demonstrate that these consistent visual words largely overcome the usual visual words and are very effective to describe and retrieve local visual contents. To generate consistent visual words (CVW), they developed a framework based on Adaptive Sampling and Priors. The core idea is that the visual vocabulary produced by an adaptive sampling method might be adapted to what the user is searching for. A CVW is a set of image patches. These patches are described by local feature sets. A CVW models a small rigid object, or a piece of a bigger object and is defined by the geometric consistency between the feature points of the patches considered. In Section 8.1, we propose a visual objects discovery and object-based visual query suggestion based on this method.
While there are studies on supervised refinement of visuals words [113, 118], Rongrong *et al.* [81] propose using correlative semantics labels to guide the quantizer in building more semantically discriminative codewords. By using Hidden Markov Random Field, they generatively model the relationships between correlative Flicker labels and the local image patches to build a supervised vocabulary.
Concerning the multi-modal side of a vocabulary, very little work has been carried out on multi-modal or multi-cue vocabularies [106]. Shared nearest neighbours methods introduced in this PhD could help to build such vocabularies.

3.3 Visual object discovery

The success of data mining techniques in semi-structured data (e.g. xml data) has generated interest in applying them to many computer vision tasks : object retrieval [149], categorization [168], object discovery [135, 160]. To discover visual objects, tools from the statistical text analysis community have been borrowed [150]. All the methods using these tools generally start from the same image representation: they extract some local visual primitives (interest points [109] or regions [114]) and consider their “visual words” as input to text-based data mining. The image is then described in terms of a set of quantized local image patch descriptors. The images are treated as documents, each image being represented by a “bag of words”.

One major issue highlighted by [138], is that "visual words" are not always as descriptive as their text counterparts. Visual words do capture high-level object parts as well as many others encoding simple oriented corners. Consequently, there is ambiguity regarding two aspects: synonym and polysemy. A synonymous visual word describing the same object or object part, and, more problematically, the polysemous visual word mean different things in different contexts. One way to reduce the ambiguity of polysemous visual words is to consider the spatial context. Indeed, all visual words in an image are generally embedded into a single histogram, losing all spatial and neighbourhood relationships. This could provide further improvement. We revisit this later.
Probably, the first work that studied the problem of object discovery is [172]. They presented ideas for learning mixture models of objects from unhomogeneous training images in an unsupervised setting. In their work, distinctive features of the object class are selected automatically and the joint probability density function encoding the object's appearance is learnt. This allows the automatic construction of an object detector which seems robust to clutter and occlusion.
Thereafter, probabilistic models interested several authors. Sivic *et al.* [147] proposed a model developed in the statistical text literature: probabilistic Latent Semantic Analysis (pLSA) [71]. In text analysis, this is used to discover topics in a corpus using the bag-of-words document representation but in the context of images, they consider object categories as topics. Thus, an image containing instances of several categories is described as a mixture of topics like a term-document occurrence matrix with classical models used in text-based information retrieval. [105] extend the PLSA model with the integration of a temporal model to discover objects in a video. Others such as [12, 158, 170] use another Latent Topic Models : Latent Dirichlet Allocation (LDA) or hierarchical LDA [148].
The idea underlying these methods is to use common Bags-of-visual-Words models (BOW) and to analyze the resulting term-document occurrence matrix with classical models used in text-based information retrieval. Some object discovery methods such as [170, 161] started by including spatial information to improve their results. Also, the method of [133] makes a step forward by augmenting the topics of the LDA model with the spatial position of the visual words. Latent topic models are a favourite choice for object category recognition and retrieval. But their generalization ability is rather a disadvantage when searching for particular object instances. The underlying models tend to be dense rather than sparse and fail to discover accurate clusters of object instances.
Most other methods rely on graph-based clustering methods. The majority of these

methods are based on two steps: matching graph construction, and analysing this graph.

To build a matching graph, they need to discover an object's seeds, i.e. spatially stable image regions in the collection. Nodes of the matching graph typically represent images whereas edges correspond to common matching regions between the images.

A method that combines BOW models with a Min-Hash hashing scheme [15] is proposed by [26, 27] and has a very low computational cost. The MinHash scheme may be seen as an instance of locality sensitive hashing, a collection of techniques for using hash functions to map large sets of objects down to smaller hash values in such a way that, when two objects have a small distance to each other, their hash values are likely to be the same. Applied on visual words, it can efficiently discover very discriminant candidate visual sketches that are likely to be parts of more reliable objects.

The drawback of this method is that it does not deal with small objects, as pointed out by [25] who proposed a new Min-Hash based strategy called Geometric Min-Hash. This version is able to discover more relevant local sketches and is therefore a very efficient way to discover candidate query regions that are likely to contain object instances.

Once the matching graph has been constructed, graph-based object mining methods differ in the way they analyse or post-process the graph. One of the simplest operations for splitting a graph is to find connected components as proposed in [134, 24, 4]. However, as pointed by [134], the main problem is that many disjoint objects are grouped in the same component due to under-segmentation.

Grauman *et al.* [63] propose a method based on spectral clustering. They aim to separate the objects from the background and propose a semi-supervised extension. A great disadvantage of spectral clustering is the need to specify the number of clusters, whereas in some cases it is impossible to know *a priori* how many objects could be found.

More recently, [134] also used a spectral clustering approach but in the context of spatially verified objects. They automatically estimate the optimal number of clusters by performing multiple clustering, leading to a consistent cost overhead. Furthermore, the clusters produced suffer from over-segmentation and therefore require some additional heuristics to merge them into consistent clusters.

Tuytelaars *et al.* [163] evaluated the performance of different unsupervised methods of object discovery based on bag-of-visual words image representation. The authors conclude that to maximize the performance, it is important to select the right image representation (interest points, dense patches, or both). They also conclude that cor-

rectly normalizing the bag-of-words histograms is also important in order to improve results. Moreover, these design choices are different for latent variables models than for spectral clustering based methods.
In this PhD, we introduce an alternative object discovery method based on our shared nearest neighbours clustering algorithm and consistent visual words [102].

3.4 Mono-source, multi-cue and multi-modal image clustering

3.4.1 Web image clustering

In the beginning, clustering and classification received less attention than feature extraction and similarity computation of images. With the explosion in the growth of the World Wide Web, the public has been able to gain access to massive amounts of information, and the need for practical systems to manage this data has become crucial. For example, in response to the user's query, current image search engines return a ranked list of images and present them as a sorted thumbnail grid (up to 1 million images).
For this reason, it is usually difficult to identify the specific images which the user is interested in. Users are forced to sift through a long list of images. Moreover, internal relationships among the images in the visual search result are rarely presented and are left up to the user. One of the alternative approaches is to automatically group the search results into thematic groups (clusters). The display groups similar images, enabling users to quickly scan for the most relevant images. This visualization allows users to exploit the location of images and to use thumbnails to preview potentially relevant images.
The problem is the same when a user has a personalized collection of heterogeneous images that he wants to structure into groups of similar images which facilitates archiving and retrieval of large image repositories. Browsing and the searching become easier and more efficient.
Web images have received particular attention from the multimedia community, and the reader may refer to these studies for comprehensive reviews: [171, 57, 17, 32].
Classifying images with complex scenes is a challenging task because of the variability of illuminations, scale condition, geometric transformation, etc. The availability of image annotations makes them advantageous compared to unlabelled images.
In [61], the authors discuss how to apply appropriate processing to different types of

images (landmark images and images coming from webcams) and to decide which clustering and classification approaches are appropriate.

3.4.2 Multi-cue and multi-modal image clustering

There are different kinds of media on the WWW, including text, images, videos, and audio. Unfortunately, most existing search engines support only one type of media, and little work has been done on integrating different kinds of media in the same framework. In 2006, among the major research challenges cited in the state-of-the-art and challenges of content-based multimedia information retrieval of [103] (and declared before in 2004 in [95] as an issue to be studied), we can quote: *"Multi-modal analysis and retrieval algorithms especially towards exploiting the synergy between the various media including text and context information"*.
An image has many properties which are quite different from one information source to another. Relying purely on the keywords around the images produces a lot of noise in the search result. One possible solution is to benefit from all available sources of information which might help to have more meaningful information concerning the images. By considering all information sources as simple oracles returning ranked lists of relevant objects, we can carry out a multi-modal analysis and clustering towards exploiting the above-mentioned synergy between the various media including text and visual information or between any other sources of information.
Multi-modal mining tends to combine different features or to generate more semantically meaningful features.
The healthcare industry, for example, is producing massive amounts of multi-modal data : Wang *et al.* [168] present a new multi-modal mining-based clinical decision support system that brings together patient data captured in various way to provide a holistic presentation of a patient's exam data, diseases, and medications. In addition, it offers a disease-specific similarity search based on various data modalities to assemble statistically similar patient cohorts summarizing possible diagnoses, their associated medications,and other demographic information. The key idea explored is that by finding similar patients based on a disease-specific analysis of their raw data, they can make inferences about similarities in their diagnosis and hence their treatments and outcomes.
[33] is an overview of technologies that support media retrieval in a way that is complementary to visual analysis. Authors aim to emphasize that technology based

on linguistic and contextual sources can bring more than basic keyword search in collateral text. They illustrate how linguistic, knowledge-based, and visual resources can be combined to detect high-level concepts, and how contextual information can improve retrieval results obtained via visual analysis.

The issue for multi-modal data mining is how to merge the different features. The classifiers can run either on concatenated feature vectors coming from the different available modalities or by combining the result of multiple classifiers on each modality to make a final decision. The first option is usually not recommended due to *the curse of dimensionality*, there is a need for an efficient way to apply mining techniques on multi-modal data while keeping the correlation among different modalities intact. The second option has to apply a relevant fusion in order to have a successful result. In this approach, by processing each modality separately, we discard the inherent associations between different modalities. [143] demonstrate the effectiveness of combining three multi-modal classifiers. They model the problem of combining classifiers as a reclassification of the judgement made by each classifier. The experiments show that they obtain better results than the traditional approaches like "majority voting" or "linear interpolation" because these two methods ignore generally the relative quality among the classifiers.

The problem of combining different classifiers, each one with its own modality, is that generally the synergy between the modalities is not exploited as done in [180] where common sources of spam images are revealed by a two-level clustering algorithm. At the first level, they calculate visual similarities between images and similar images are grouped into some clusters. At the second level, the textual similarities between images is calculated to refine the clustering results from the first level. Exploiting some mining algorithm based on association rule could enhance the effectiveness of the results obtained [11].

Chen *et al.* [23] propose a decision tree-based multi-modal data mining framework for soccer goal detection from soccer videos because different modalities have different contributions to the soccer goal detection application domain.

In [116], the authors propose a method for extracting meaningful and representative clusters that is based on a shared nearest neighbours (SNN) approach. They treat both content-based features and textual descriptions (tags) but they produce two sets of clusters (an image could be an element of a tag-based cluster and a content-based cluster). By displaying the two cluster sets with their representative form, users can browse a cluster and switch from one cluster set to another. When they combine the two clusterings (by a simply summing the visual and textual similarity matrix), they

lose the particularities of each modality and produce clusters that are more ambiguous and hardly understandable by a user.

[17] propose three representations of web images (visual, textual and link information) and apply spectral techniques to cluster the search results into different semantic categories. In [141], the authors address the problem of web image clustering by simultaneous integration of visual and textual features from a graph partitioning perspective. They propose a CIHC (Consistent Isoperimetric High Order Co-clustering) framework. More recently, [39] have organized image search results by a hierarchical clustering based navigation. First, the K-lines based semantic clustering organization is applied. Second, the resulting images corresponding to each phrase are clustered with the Bregman Bubble Clustering (BBC) algorithm. Bekkerman *et al.* [7] develop an effective multi-modal clustering using the Combinatorial Markov Random Field. They allow more flexibility in their approach (the modalities are not fixed, there is no limitation in the number of modalities and they take into account other modalities which do not have to be clustered).

Sabrina Tollari *et al.* [162] studied how to automatically exploit visual concepts in an image retrieval task. Authors use Forest of Fuzzy Decision Trees (FFDTs) to automatically annotate images with visual concepts and show that automatic learning of visual concepts and then its exploitation, by filtering of text-based image retrieval is effective.

Recently, Young-Min *et al.* [96] proposed a new multi-view clustering method which uses clustering results obtained on each view as a voting pattern in order to construct a new set of multi-view clusters. The proposed approach is an incremental algorithm which first groups documents having the same voting patterns assigned by view-specific PLSA (Probabilistic Latent Semantic Analysis) models [72]. Working in the concatenated feature spaces, the remaining unclustered documents are then assigned to the groups using a constrained PLSA model.

Generally in the state-of-the-art of multimedia data mining, studies do not pay attention to the accuracy of sources. In some cases, a feature of a modality can be extracted with some errors due to the semantic gap or to the breakdown of the source of the information that produces the feature. We need a way to make multi-modal fusion accurate and robust against noisy or near random source of information.

Most previous work on multimedia clustering has focused on specific modalities but not on the genericity and the robustness of the clustering algorithm itself when it is used in a multi-source approach.

Part II

Contributions to shared nearest neighbours clustering

Chapter 4

Revisiting shared nearest neighbours clustering

4.1 Introduction

Unsupervised data clustering remains a crucial step of many recent multimedia retrieval approaches, e.g. web objects and events mining [136], search results clustering [92] or visual query suggestion [185]. However, the performance and applicability of many classical data clustering approaches often force particular choices of data representation and similarity measures. Some methods, such as k-means and its variants [90], require the use of L_p metrics or other specific measures of data similarity; others, such as the hierarchical methods BIRCH [186] and CURE [64], pay a prohibitive computational cost when the representational dimension is high, due to their reliance on data structures that depend heavily upon the data representation. Such assumptions are particularly problematic in a multimedia context that usually involves heterogeneous data and similarity measures.

An interesting alternative approach to clustering that requires only comparative tests of similarity values is the use of so-called shared-neighbours information [77, 70, 181, 45, 139, 73] as discussed in chapter 2. Here, we present our first contribution to the clustering paradigm : we introduce a new SNN formalism based on the theory of *a contrario* decision. This allows us to derive more reliable connectivity scores of the candidate clusters and a more intuitive interpretation of locally optimum neighbourhoods.

4.2 Basic principles, Notations and Definitions

The basic principle of SNN clustering methods is to consider that a perfect cluster is composed of items that have their all neighbours in the same cluster. Two elements are considered involved, not in relation to their similarity value but rather by the degree of similarity of their respective neighbours. This means that if two elements have a high proportion of neighbours in common, it is reasonable to put them in the same group. The advantage is that no hypothesis is made on the shape, density or metric. Figure 4.1 illustrates this in the Euclidean space. It shows four clusters of different size, density and shape. With most clustering methods, these clusters would have different significance measures but according to the principles of shared neighbours clustering methods, all the clusters are considered to be perfect clusters. Every item in each cluster has its all neighbours in the same cluster. Let us consider in the following,

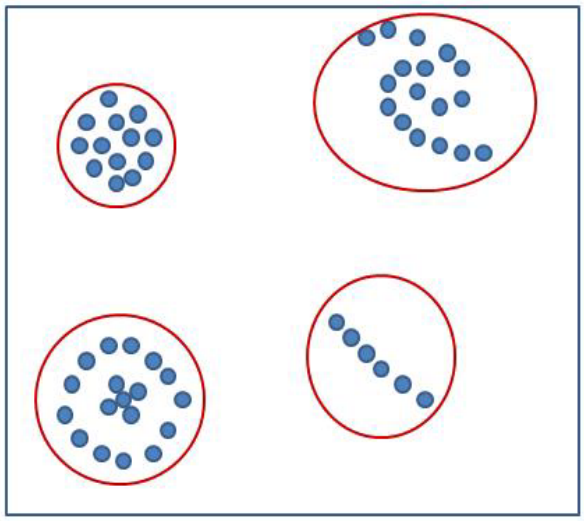


Figure 4.1: Four clusters of different size, shape and density considered as perfect clusters in shared neighbours clustering

a set X of N items from some domain D. The feature of these elements can be of any type. We assume the existence of a function F_K that associates to any item x from X its K nearest neighbours with respect to some similarity or distance measure. Notice that this metric might be totally unknown. Only the ranking it produces is known.
Let us denote as $nn_k(x) \in X$ the k-th nearest neighbours of $x \in X$ with respect to some distance metric. The F_k is defined as:

Definition 1. *K-nearest neighbours function F_K:*

$F_K(x) = \{nn_k(x) | 0 < k \leq K\}$
For any $i < j$, the item $nn_i(x)$ is more relevant or similar to x than $nn_j(x)$.

We sometimes refer to F_K as an *oracle* or an *information source* that returns a ranked list of relevant items to a query. During this work, we will consider a few different kinds of oracles. Since no hypothesis is made on the nature of the items or the similarity metric used to compare items between each other, we define the similarity between a pair of items x_1 and x_2 in terms of their shared nearest neighbours. That is the intersection between their K-NN :

$$Sim(x_1, x_2) = |F_K(x_1) \cap F_K(x_2)|. \tag{4.1}$$

But though the initial metric and the shared neighbours similarity are both used for similarity assessment, they do not share the same fundamental properties. Metrics (sometimes called distance function or simply distance) satisfy four basic properties:

- non-negativity: d(x,y) $\geq$ 0
- identity: d(x,y) = 0 if and only if x = y
- symmetry: d(x,y) = d(y,x)
- triangle inequality: d(x,z) = d(x, y) + d(y, z)

Shared neighbours similarity is non-negative and symmetric, however it does not require to satisfy the triangle inequality. In addition, the fact that two items x_1 and x_2 have elements in common, does not necessarily mean that x_1 belongs to the K-NN of x_2 and vice versa.

4.3 *a contrario* SNN significance measures

4.3.1 Raw SNN measures

The primary shared neighbours similarity measure of any set $A \subset X$ is defined similarly to [73] as :

Definition 2. ***Intra-significance measure :***

$$\begin{aligned} I(A) &= \frac{1}{|A|} \sum_{x \in A} (A \cap F_{|A|}(x)) \\ &= \frac{1}{|A|} \sum_{x \in A} I_A(x) \end{aligned} \tag{4.2}$$

Intuitively, $I(A)$ measures the average number of common neighbours between A and the $|A|$ nearest neighbours of any of its items. Unfortunately it has the disadvantage of a bias related to the size of the set. When the size of the set is large, it is much easier to achieve a high value by chance than when the size of the set is small. This can be easily illustrated by a short synthetic experiment. Let us consider an initial set of 100 items denoted as x_{100}. We produce 10000 random subsets of items of different sizes from x_{100} and we use a random oracle to produce a random list of nearest neighbours in x_{100} for each item of the subsets.
As this notion of random oracle will be re-used many times in this PhD, we define it here formally.

Definition 3. ***Random Oracle :***
Given a dataset X composed of N items , we define a random oracle $R_K(x)$ as a function returning K items selected uniformly at random from X for each item x.

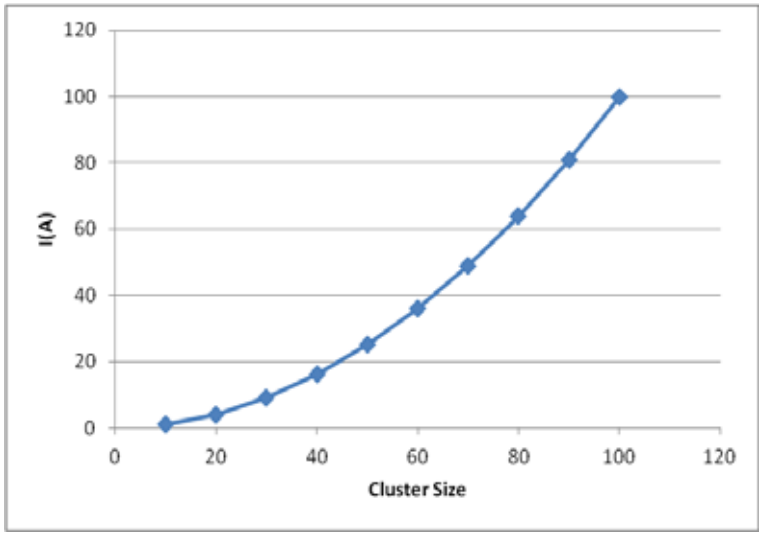


Figure 4.2: Illustration of the intra-significance measure I(A)

Figure 4.2 shows how the intra-significance measure increases when the size of the cluster increases. When the size of the cluster size approaches that of the dataset (100 items) the intra-significance measure reaches its maximum value and is equal to the size of the cluster.
To compare two sets with different sizes, we need to find a way to remove this bias.

4.3.2 *a contrario* normalization

To remove the bias of the raw measure, we propose using the *a contrario* principle [35]. Such *a contrario* normalization has already been proposed for clustering [20, 165], but not for SNN. The *a contrario* approach is a mathematical formalization of a perceptual grouping principle. The more a set of objects is highly unlikely, the more the occurrence of such an arrangement is significant and the more the objects should be grouped together into a single group. Clusters are detected *a contrario* to a null hypothesis or *background model*. The meaningfulness of a group of objects is measured by the *number of false alarms* (NFa) that would have been produced under the null hypothesis. The lower the NFa is, the more significant the group is considered to be. This measure is used for example in [20] to rank clusters and to decide whether a cluster is a natural group in which outliers have been discarded.

Let us call $\mathscr{H}$ a null hypothesis where a list of neighbours is produced by a random oracle, i.e. generated by means of uniform random selection from the available items. Under this null hypothesis, the number of shared neighbours $I_A(x)$ between a set $A \subset X$ and the $|A|$ nearest neighbours of an item x selected uniformly at random from X is a hypergeometrically distributed random variable with expectation:

$$\mathbf{E}[I_A(x)] = \frac{|A|^2}{N} \tag{4.3}$$

and variance:

$$\mathbf{Var}[I_A(x)] = \frac{|A|^2(|N|-|A|)^2}{N^2(N-1)} \tag{4.4}$$

Deriving the formal distribution of the intra-significance measure $I(A)$ is unfortunately a tricky task. But we can approximate it thanks to the central limit theorem. This theorem says that the mean of a sufficiently large number of independent random variables, each with finite mean and variance, will be approximately normally distributed [142]. By applying this theorem, we can assume that the measure $I(A)$ follows a normal distribution $\mathscr{N}(\mu_A, \sigma_A^2)$ with:

$$\begin{aligned} \mu_A = \mathbf{E}[I(A)] &= \mathbf{E}[I_A(x)] \\ &= \frac{|A|^2}{N} \end{aligned} \tag{4.5}$$

and

$$\begin{aligned}\sigma_A^2 = \mathbf{Var}[I(A)] &= \frac{|A|}{|A|^2}\mathbf{Var}[I_A(x))] \\ &= \frac{|A|(N-|A|)^2}{N^2(N-1)} \end{aligned} \tag{4.6}$$

As it is possible to relate all normal random variables to a standard normal, we can standardize the normal distribution $I(A)$ to a normal distribution function with expectation 0 and variance 1.
We can therefore define a new shared-neighbour measure Z as:

$$\begin{aligned} Z(A) &= \frac{I(A)-\mathbf{E}[I(A)]}{\sqrt{\mathbf{Var}[I(A)]}} \\ &= \frac{\sqrt{N^2(N-1)}}{\sqrt{|A|(N-|A|)^2}}(I(A)-\frac{|A|^2}{N}) \\ &= \sqrt{|A|(N-1)}\frac{N}{|A|(N-A)}(I(A)-\frac{|A|^2}{N}) \end{aligned} \tag{4.7}$$

With expectation:

$$\begin{aligned}\mathbf{E}[Z(A)] &= \sqrt{|A|(N-1)}\frac{N}{|A|(N-A)}(\mathbf{E}[I(A)]-\frac{|A|^2}{N}) \\ &= 0\end{aligned}$$

and variance:

$$\begin{aligned}\mathbf{Var}[Z(A)] &= \mathbf{Var}[\sqrt{|A|(N-1)}\frac{N}{|A|(N-A)}(I(A)-\frac{|A|^2}{N})] \\ &= (\sqrt{|A|(N-1)}\frac{N}{|A|(N-A)})^2\mathbf{Var}[I(A)] \\ &= 1\end{aligned}$$

Directly using this standardized measure rather than the I measure would be equivalent to what Houle [73] called a "standard score" expressed in terms of the Pearson correlation:

$$Z_{Houle}(A) = \sqrt{|A|(N-1)}SR_1(A) = Z(A) \tag{4.8}$$

Where $SR_1(A)$ is the expected correlation between A and the relevant set of size $|A|$ based at randomly selected items of A:

$$SR_1(A) = \frac{1}{|A|}\sum_{x\in A} R_{Houle}(A, F_{|A|}(x)) \tag{4.9}$$

and a normalised set correlation R defined as:

$$R_{Houle}(A,B) = \frac{|\,A \cap B\,| - \frac{|A||B|}{N}}{\sqrt{|\,A\,||\,B\,|\,(1-\frac{|A|}{N})(1-\frac{|B|}{N})}} \tag{4.10}$$

It is in favour of this method that the same result can be obtained from another methodology (*a contrario*). But, we can still go a step further in our *a contrario* model.
Now that we have estimated the distribution of our intra-significance measure Z under the null hypothesis H, we can estimate the precision score *a contrario* to H as follows:

$$\begin{aligned} P_{Z(A)}(z) &= \int_{-\infty}^{z} \frac{1}{\sqrt{2\Pi}} e^{-\frac{t^2}{2}}\,\mathrm{d}t \\ &= 1-\phi(z) \end{aligned} \tag{4.11}$$

Where $\phi()$ is the cumulative distribution function of the standard normal distribution that describes probabilities for a random variable to fall within the interval $]-\infty, z]$.
$P_{Z(A)}(z)$ is the probability that $Z(A)$ does not exceed a threshold z under the null hypothesis H. So that , $Pfa(z) = 1 - P_{Z(A)}(z)$ is the likelihood that A is not a false alarm (i.e the likelihood that the subset A was not generated by a random oracle).
$Pfa(z)$ can also be expressed in terms of the error function **erf** as follows:

$$Pfa(z) = \frac{1}{2} - \frac{1}{2}\mathbf{erf}(\frac{z}{\sqrt{2}}) \tag{4.12}$$

Having this likelihood of a false alarm under the null hypothesis, we can now determine our *a contrario* significance score as the complement of the Pfa :

Definition 4. *a contrario significance:*

$$\begin{aligned} S(A) &= 1 - Pfa(z) \\ &= 1-\phi(z) \\ &= \frac{1}{2} + \frac{1}{2}\boldsymbol{erf}(\frac{z}{\sqrt{2}}) \end{aligned} \tag{4.13}$$

Looking closely at S line according to Z given in Figure 4.3, we can see that for intra-significance score $Z = 0$, the *a contrario* significance score is equal to 0.5.
Let us considerer a set of N_c clusters all having a score above a threshold z. The expected number of clusters under the null hypothesis H is $Pfa(z) \times N_c$ so we can estimate the precision of our cluster set A as $\frac{N_c - (Pfa(z) \times N_c)}{N_c} = S(A)$.

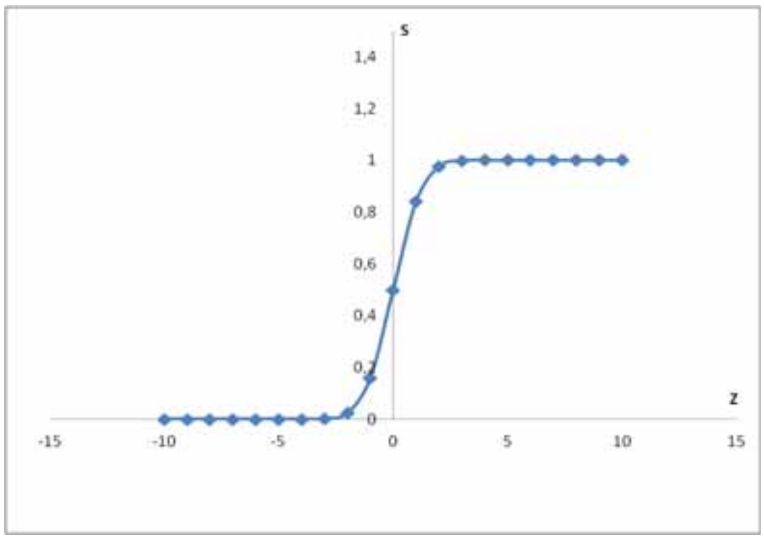


Figure 4.3: Illustration of the *a contrario* significance measure S and the standard Zscore Z

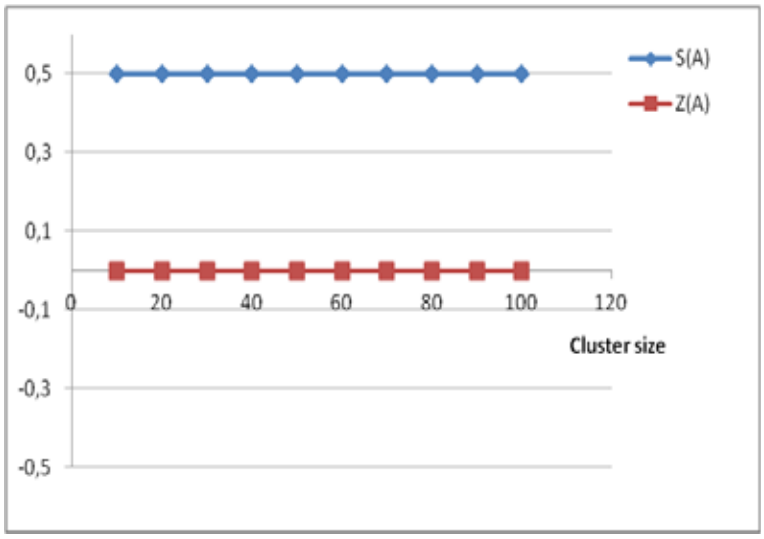


Figure 4.4: Illustration of the *a contrario* significance measure S and the standard Zscore Z according to the size

Figure 4.4 shows that the standard normal score Z and the *a contrario* significance score S are not biased relative to the size of the cluster. We carried out this experiment with the same data used for the experiment illustrated in Figure 4.2.

After showing in Figure 4.4 that the *a contrario* precision score S is not biased relative to the size of the clusters, we illustrate in Figure 4.5 that the number of clusters

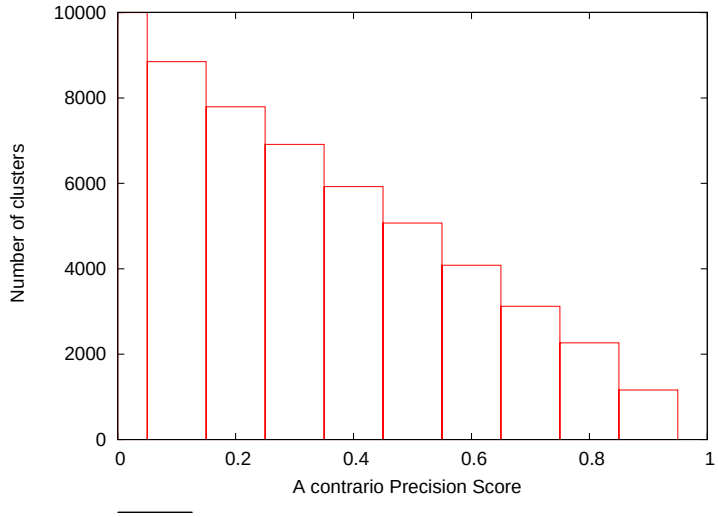


Figure 4.5: Number of clusters Vs *a contrario* precision score of 10000 random clusters $(S \geq x)$

is equally distributed for each value of *a contrario* precision score S: 5000 clusters from 10000 clusters have *a contrario* precision score S more than 0.5. We can see also that 2000 clusters have S more than 0.8.
The advantage of using this *a contrario* significance score S rather than simply staying with the standard score Z, as done in [73], is two folds:

1. our score is bounded in $[0,1]$
2. our score is more interpretable

Let us discuss a few values:

- $S(A) = 1$ means a perfect cluster.It is not possible that it has been generated randomly.
- $S(A) = 0.5$ means that the cluster with such a score is likely to be random.
- $S(A) > 0.5$ means that the number of shared neighbours within A is larger than would be expected randomly. Therefore A is potentially a cluster.
- $0 < S(A) < 0.5$ means that there are abnormally few intersections between A and the neighbours of its elements. Therefore A is composed of dispersed items.
- $S(A) \simeq 0$ means that it is a perfectly unclustered set of items.

To illustrate this, Table 4.1 on the left gives some *a contrario* significance score values of the ground truth clusters of Holidays database [79]. This database is composed of 1491 images and 500 groups. Some images from this base are presented in Figure 4.6. We use two different features: a bag-of-words constructed from SIFT [108] (L1

distance), and a HSV Histogram [49].
On the right of the same Table 4.1, we illustrate the result for 500 random clusters built from the 1491 images with a random size for each cluster.

The *a contrario* score somehow measures the difficulty to cluster a dataset. If, on the true clusters, the *a contrario* score for HSV histogram is on average equal to 0.86, it means that one cannot expect results better than this in a clustering result using the same feature. So that, 14 of discovered clusters might be random ones. At the same time, the results can not be worse on average than those of the random clusters using the same feature (0.55).

Figure 4.6: Some images from Holidays database [79]

We can conclude that for those clusters and for this experiment, the HSV feature is more structuring than the *Bag of words* feature.

Ground truth clusters	Min	Max	Avg
Bow	0.55	1	0.71
HSV Histogramme	0.67	1	0.86976

Random clusters	Min	Max	Avg
Bow	0.51	0.6	0.56
HSV Histogramme	0.53	0.57	0.55

Table 4.1: Holidays Database's *a contrario* significance scores of the ground truth clusters (left) and of random clusters (right) by using bag-of words and HSV histogram features.

Out of curiosity, we do the same experiment with another database: *Corel1000*

database [169]. The database contains 10 image classes with 100 images each. The classes are: Africa, beach, buildings, buses, dinosaurs, flowers, elephants, horses, food and mountains. This database was used in various scientific articles in the past for content-based image retrieval systems. For this experiment, we use the HSV histogram and the local feature SIFT. We present the *a contrario* score in Table 4.2.
For the ground truth clusters, the average of the *a contrario* score is equal to 0.98, which means that, by using HSV histogram, this database is easier to cluster than the *Holidays database* which is coherent with the fact that this dataset is known to be "easy" for CBIR (Content-Based Image Retrieval) methods . Note that, by demonstrating these two experiments, we do not claim in any way to say that HSV histogram is better than Bow or SIFT. We rather want to show that having a target database and a set of features, by means of computing the *a contrario* scores, we can select the more structuring feature and having an idea about the difficulty of the database to be clustered using the selected features.

Ground truth clusters	Min	Max	Avg
Sift	0.81	1	0.78
HSV Histogram	0.96	1	0.98

Random Clusters	Min	Max	Avg
Sift	0.56	0.84	0.66
HSV Histogram	0.53	0.79	0.68

Table 4.2: Corel1000 Database's *a contrario* significance scores of the ground truth clusters (left) and of random clusters (right) by using SIFT and HSV histogram features.

4.3.3 Partial contributions to a set

Now that we have a normalised measure $S(A)$ to qualify any set A, how would this measure behave if a new element x_i joins A? An item x_i can have a greater contribution to improve the quality of a cluster. Two cases are possible:

- if $(S(A \cup x_i) - S(A) > 0)$ then the contribution of the item x_i increases the intra-significance measure of the cluster, this means that this item is relevant to the cluster and should be added to it. We call this *Cluster reshaping*.
- if $(S(A \cup x_i) - S(A) < 0)$ then the item is not relevant to the cluster. It has not improved the quality of the cluster A.

However, recomputing the whole score S(A) for any new item x_i would be inefficient in a clustering framework. Fortunately $S(A \cup x_i)$ can be computed more efficiently from $S(A)$. We first show it with the intra-significance measure and the other measures

as $Z(A)$ and $S(A)$ will be calculated as seen in Section 4.3.2.

$$\begin{aligned}
I(A\cup x_i)-I(A) &= \frac{1}{|A+1|}\sum_{x\in(A\cup x_i)}|(A\cup x_i)\cap F_{|A+1|}(x)| \\
&\quad -\frac{1}{|A|}\sum_{x\in A}|A\cap F_{|A|}(x)| \\
&= \frac{1}{|A+1|}[\sum_{x\in A}|A\cup x_i)\cap F_{|A+1|}(x)| \\
&\quad +|(A\cup x_i)\cap F_{|A+1|}(x_i)|] \\
&\quad -\frac{1}{|A|}\sum_{x\in A}|A\cap F_{|A|}(x)| \\
&= \frac{1}{|A+1|}[\sum_{x\in A}|(A\cup x_i)\cap F_{|A+1|}(x)| \\
&\quad +|(A\cup x_i)\cap F_{|A+1|}(x_i)|] \\
&\quad -\frac{1}{|A|}\sum_{x\in A}|A\cap F_{|A|}(x)| \\
&= \frac{1}{|A+1|}[\sum_{x\in A}|A\cap F_{|A|}(x)| \\
&\quad +\sum_{x\in A}|(A\cup x_i)\cap nn_{|A+1|}(x)| \\
&\quad +|(A\cup x_i)\cap F_{|A+1|}(x_i)|] \\
&\quad -\frac{1}{|A|}\sum_{x\in A}|A\cap F_{|A|}(x)| \\
&= [\frac{1}{|A+1|}-\frac{1}{|A|}]\sum_{x\in A}|A\cap F_{|A|}(x)| \\
&\quad +\frac{1}{|A+1|}[\sum_{x\in A}|(A\cup x_i)\cap nn_{|A+1|}(x)| \\
&\quad +|(A\cup x_i)\cap F_{|A+1|}(x_i)|] \qquad (4.14)
\end{aligned}$$

If we denote:

$$I_1(A)=[\frac{1}{|A+1|}-\frac{1}{|A|}]\sum_{x\in A}(A\cap F_{|A|}(x)) \qquad (4.15)$$

and

$$I_2(A,x_i)=\frac{1}{|A+1|}[\sum_{x\in A}((A\cup x_i)\cap nn_{|A+1|}(x)) +((A\cup x_i)\cap F_{|A+1|}(x_i))] \qquad (4.16)$$

Then, the difference of intra-significance scores will be expressed as:

$$I(A\cup x_i)-I(A) = I_1(A)+I_2(A,x_i) \qquad (4.17)$$

We do not recalculate all terms when adding a new item x_i. The term $I_1(A)$ has already been calculated earlier and it only remains to calculate the second term $I_2(A)$ which is very easy and fast to calculate. Thanks to this development, we avoid a time-consuming computation.

4.3.4 Optimal neighbourhood

As we will see later, selecting the optimal neighbourhood of an item is an important step in our clustering algorithm. It can be done by running through all the k-nearest neighbours from 1 to K and selecting the optimal rank k_{opt} that maximizes the *a contrario* score of the neighbourhood:

$$k_{opt}(x) = \underset{k}{\operatorname{argmax}}\, S(F_k(x)) \tag{4.18}$$

By this, we select only relevant neighbours among the k-NN list and we make our method robust against noisy neighbours.

4.4 An efficient algorithm for building the shared-neighbours matrix

During the computation of the intra-significance measure, the most costly part is calculating the number of shared neighbours between pairs of items for every $k = [1..K]$ to select the best neighbourhood. Therefore, we need an efficient way to compute and to save the shared neighbours matrix *(SNN Matrix)* for any k.
The naive way would be to compute the intersection of K-NN of the entire set for every $k = [1..K]$. This approach is time consuming and cannot be applied for most applications due to its high complexity.
We propose a new factorisation algorithm to accelerate the calculation of shared neighbours based on the same optimisation of the cluster reshaping computing as seen in the previous section. As $nn_p(x)$ is the p-th nearest neighbour of an item x and $F_k(x)$ is the set of the k-nearest neighbours of x, we can define the intra-significance measure of a

neighbourhood $F_k(x_i)$ of an item x_i as:

$$\begin{aligned} I(F_k(x)) &= \frac{1}{k}\sum_{x_j \in F_k(x)} |F_k(x) \cap F_k(x_j)| \\ &= \frac{1}{k}[\sum_{x_j \in F_{k-1}(x)} |F_{k-1}(x) \cap F_{k-1}(x_j)| \\ &\quad + \sum_{x_j \in F_{k-1}(x)} |nn_k(x_j) \cap nn_k(x)| \\ &\quad + |F_k(x) \cap F_k(nn_k(x))|] \\ &= \frac{1}{k}[I(F_{k-1}(x)) \\ &\quad + \sum_{x_j \in F_{k-1}(x)} |nn_k(x_j) \cap nn_k(x)| \\ &\quad + |F_k(x) \cap F_k(nn_k(x))|] \end{aligned} \tag{4.19}$$

Computing $I(F_k(x))$ for $k = [1..K]$ is very time consuming, and the key idea of our algorithm is to compute it recursively. We remark here that in Equation 4.19 that the intra-significance measure of a neighbourhood $F_k(x)$ of size k can be computed from the previous intra-significance measure of the neighbourhood of x of size $|k-1|$ and it only remains to compute the rest, which is very simple.
The final shared neighbours algorithm can be summarized in:
Input:the K-nearest neighbours matrix of size $(N \times K)$.
Init: T = Zeros(N), I = zeros(N,K).
Output: $I(F_k(x))$

Algorithm 1 Fast shared neighbours of a variable neighbourhood from $k = 1toK$

```
for x = 1 to N do
  for k = 1 to K do
    for p = 1 to k do
      T(nn_p(nn_k(x))) += 1
    end for
    for p = 1 to k-1 do
      T(nn_p(nn_k(x))) += 1
    end for
    for q = 1 to k do
      I(F_k(x)) += T(nn_q(x))
    end for
  end for
end for
```

4.5 Clustering framework

4.5.1 Possible scenarios

The main goal of clustering is to identify distinct groups in a dataset. However, in some applications, user wants to have the control in some aspects of groups. The number of distinct groups N_c in the data is a parameter that the user in some cases want to fix as *a prior*. For most applications, this parameter is unknown, the clustering method has to determine by itself the number of clusters by several strategies. Our proposed clustering method is able to work in both cases.
Resulting clusters can present some intersection between them. Some clustering methods [183] of the state-of-the-art allow the overlap between clusters (**soft clustering**) but others like [88] require elements to belong to a single cluster (**hard clustering**). The maximum allowed overlap between two clusters is fixed by a parameter $\theta_{Overlap}$. Typically clusters sharing more than $\theta_{Overlap}$ elements, are considered redundant and have to be merged efficiently.
In some cases, the quality of resulting clusters is limited to a minimum allowed threshold $\theta_{Quality}$. Clusters having less than $\theta_{Quality}$ are not accepted in the final list of clusters. In our clustering method, the user can set this parameter $\theta_{Quality}$ of **minimum *a contrario* score of a cluster** from the beginning. If this parameter has no importance for the user, $\theta_{Quality}$ will be equal to 0.
In summary, we dispose of 3 optional parameters (N_c, $\theta_{Overlap}$ and $\theta_{Quality}$) that lead to different scenarios of clustering. Thanks to the *a contrario* score, the rate of quality allowed is rather interpretable which facilitates the task of the user to fix it. The impact of these parameters and their impact on the clustering result will be described in the next Section.

4.5.2 Clustering method

Now that we have defined our new shared neighbours significance measures based on the *a contrario* approach, we can describe our clustering. The goal is to find the optimal clusters that maximize the *a contrario* scores.
This combinatorial problem cannot be solved exactly. In practice, we use a greedy solution to reduce the number of solution by first considering each item as the center of a candidate cluster. The following steps depend on the scenario that the user selects. Our clustering algorithm is based on two main steps, *candidate cluster construction* and *final clusters selection*. The first step is shared by the 3 scenarios and only the

second step depends on which parameter is fixed or not.
Our proposed shared neighbours clustering is as follows:

- **Candidate cluster construction**: Each item $x \in X$ is considered as a candidate cluster center and an optimal candidate cluster $C(x)$ needs to be computed for it. We first compute an optimal neighbourhood $F_{k_{opt}}(x)$ by varying the neighbourhood size k from 1 to K and selecting the neighbourhood size that maximizes our new *a contrario* score S (Eq.4.13):

  $$k_{opt}(x) = \underset{k}{\operatorname{argmax}}\, S(F_k(x))$$

  Among the K neighbours of the item x, we finally keep the candidate cluster $C_{opt}(x)$ which has the maximum S score:

  $$C_{opt}(x) = F_{k_{opt}}(x)$$

  We obtain N candidate clusters of different qualities.
- **Final clusters selection**: After the candidate cluster selection, we obtain some potentially relevant clusters for each item but many of these clusters are still very similar because close items might generate approximately the same candidate cluster. Therefore, redundant clusters have to be eliminated and only different seeds have to be selected.
  For this step, we use a simple heuristic based on the overlap between candidate clusters. The parameter $\theta_{Overlap}$ is generally used for this step. For that, first, we sort all candidate clusters in decreasing order of their *a contrario* score and then iterate on them. If an encountered cluster has an overlap (on percentage) less than $\theta_{Overlap}$ with at least one of the previously retained clusters, it is added to the final list of clusters.
  If not, the encountered cluster is considered as similar to the retained cluster and has to be used to reshape the retained cluster. For this: the contribution of all items of both clusters to the retained cluster is computed (see Section4.3.3) and sorted in decreasing order. The final retained cluster will be built from items that increase the quality of the original retained cluster. This reshaping step is useful because some relevant items from the original retained cluster may be greater than others. It replaces poor associated items by other more strongly associated items in order to yield a new improved retained cluster.

If the parameter $\theta_{Overlap}$ is equal to zero, then a cluster is retained only if it doesn't share any item with the other retained clusters. Similar clusters are affected to these different retained clusters and used to reshaping them. Note that, in this case, an item is only assigned to one cluster.
In addition, for each retained cluster, we have its *a contrario* score in $[0,1]$. If the user had limited the minimum allowed *a contrario* score to $\theta_{Quality}$, all clusters having less than $\theta_{Quality}$ will be eliminated from this list of final clusters.
In the case of knowing the number of clusters N_C in advance, when iterating on cluster to retain different clusters, we stop when achieving the target number of clusters. The rest of clusters are assigned to one of the N_C clusters according to their intersection of them. They are used to reshape the N_C retained clusters.

Overall, we remark here that our clustering framework requires essentially to know the parameter $\theta_{Overlap}$ to decide if two clusters are similar which can be fixed by default or done by the user. It can be chosen in a natural way with no knowledge of the nature of the data set or its distribution. The other parameters are optional and used only if the user has prior knowledge.

4.6 Experiments

4.6.1 Evaluation metrics

As discussed in Chapter 2, the choice of an evaluation metric depends on the goal of the clustering experiment. In some applications, we evaluate the ability of the clustering algorithm to discover the true categories (in a data mining perspective) whereas in other application, we evaluate the quality of the clusters produced.
The metrics used in the experiments are as follows:

– **AvgPurity**: To measure the quality of the clusters produced, we measure the Average Purity of all returned clusters. The Purity of a cluster C is defined according to [22] by

$$Purity(C) = \frac{1}{\mid C \mid} max \mid C_h \mid$$

where C_h are the sub clusters composed of all the items of C coming from the same ground truth category. $max \mid C_h \mid$ is thus the dominant category of the cluster.

– **F1** measure: To measure the ability of the clustering algorithm to retrieve the

initial categories, we define the F1 measure by:

$$F1 = 2 * \frac{PREC \times REC}{PREC + REC}$$

with

$$PREC = \frac{\#ofdistinctclusters}{\#ofretrievedclusters}$$

and

$$REC = \frac{\#distinctclusters}{\#ofClasses}$$

Two clusters are considered to be distinct if their dominant categories differ.

– **AvgCM**: we measure the overall effectiveness of the clustering with the average cosine measure (AvgCM) of all returning clusters based on the usual precision and recall measures. To assess the quality of the clustering, we treat every center q of a cluster C as a query returning the cluster and we compare it to the unique class G of the ground-truth to which it belongs. **The Cosine Measure CM** of a cluster in terms of its center q is defined by :

$$CM(q) = \sqrt{Prec(q).Recall(q)}$$

with

$$Prec(q) = \frac{\mid G \cap C \mid}{\mid G \mid}$$

and

$$Recall(q) = \frac{\mid G \cap C \mid}{\mid C \mid}$$

– The Rand index or Rand measure is a measure of the similarity between two data clusterings : the ground truth clusters that we denote as X and the resulting clusters that we denote as Y. We define :
  – a, the number of pairs of elements that are in the same set in X and in the same set in Y
  – b, the number of pairs of elements that are in different sets in X and in different sets in Y
  – c, the number of pairs of elements that are in the same set in X and in different sets in Y
  – d, the number of pairs of elements that are in different sets in X and in the same set in Y

  The Rand index, R, is:

$$R = (a+b)/(a+b+c+d)$$

The Rand index has a value between 0 and 1, with 0 indicating that the two data clusters do not agree on any pair of points and 1 indicating that the data clusters are exactly the same.

4.6.2 Synthetic oracles definitions

Using synthetic data allows us to study individual effects separately, whereas using real data sets usually makes it more difficult to isolate the various influences. In Section 4.3.1, we introduced one synthetic oracle i.e the random oracles. Here, we already introduce other synthetic oracles attempting to model real systems in a generic way (independently from metrics):

Definition 5. ***Perfect oracle:***
Given a dataset X composed of N items, we define a ***perfect oracle*** *as a function returning the true K relevant nearest neighbours for each item.*

Definition 6. ***No-perfect oracle:***
Given a dataset X composed of N items, we define a ***no-perfect oracle*** *as a function returning, for each item x, r% of the true K nearest neighbours and* $(1-r)\%$ *of K are items selected uniformly at random from X. All of the perfect neighbours and the random neighbours are mixed together.*

We define also an alternative of the **no-perfect oracle** that we call the **Best first oracle** and which we define as follows:

Definition 7. ***Best first oracle:***
Given a dataset X composed of N items, we define a ***best first oracle*** *as a function returning, for each item x, r% of the true K nearest neighbours and* $(1-r)\%$ *of K are items selected uniformly at random from X.*

Unlike the **no-perfect oracle**, perfect neighbours are returned first, followed by the random neighbours.

Definition 8. ***Unstable oracle:***
Given a dataset X composed of N items, we define an ***unstable oracle*** *as a function returning random neighbours for the* $(1-t)\%$ *of items. For the other t% of items, it returns the true K-nearest neighbours.*

Definition 9. ***No-perfect and unstable oracle:***
Given a dataset X composed of N items, we define a ***no-perfect and unstable oracle***

as a function returning random neighbours for $(1-t)\%$ *of the items. For the other* $t\%$ *of items, it returns* $r\%$ *of the true K nearest neighbours and* $(1-r)\%$ *of K are items selected uniformly at random from* X.

Note that with t=0 and/or r=0, we get a **random oracle** and with with t=1 and r=1, we get a **perfect oracle**.

4.6.3 Synthetic oracles experiments: impact of parameters r and t

We built a synthetic set of 5000 items clustered in 30 categories with category sizes varying between 20 and 260 items. In the rest of this thesis, we refer to this dataset as X_{5000}. In this experiment, we study the influence of parameters r and t. With each value of the couple (r,t), we use a **no-perfect and unstable oracle** to generate a set of K nearest neighbours for all the items and we compute the *a contrario* score of the clusters returned by our method. We repeat that 150 times for each value of (r,t) and take the average at the end. The *a contrario* score of clusters is equal to 0.5 only when the cluster is likely to be random items that do not represent any correlation between them. When the *a contrario* score is greater than 0.5, it means that the cluster contains elements that represent a certain correlation between them (i.e that shares more neighbours than a random oracle).
We can see in Table 4.3 that even for very noisy oracles $(t = 8\%, r = 40\%)$, our resulting clusters are not completely random sets of items.
Tables 4.4, 4.5 and 4.6 demonstrate the impact of the parameters r and t on *average purity AvgPurity, F1 measure* and *AvgCM* on the resulting clusters of our proposed clustering algorithm. For a fixed r, when t increases the number of items having their true nearest neighbours increases and consequently the ability to return true classes increases (i.e F1 measure increases). On the other side, for a fixed t, when r increases this means that the quantity of true nearest neighbours for the t percent items increases and the number of random neighbours decreases. So the quality of clusters is improved when the parameter r increases.

Globally, the results show that our method is likely to be highly robust to the two kinds of noise considered (unstability and noise in the items returned by an oracle). For example, with $(t = 8\%, r = 60\%)$, excellent scores are obtained: F1=0.94, AvgPurity=0.92, AvgCM=0.70.

	t=8%	t=10%	t=12%	t=20%	t=40%	t=60%	t=80%
r=20%	0.5	0.5	0.5	0.5	0.5	0.5	0.51
r=40%	0.7	0.79	0.81	0.87	0.88	0.92	0.97
r=60%	0.92	0.95	0.96	0.97	0.98	0.99	1
r=80%	0.97	1	1	1	1	1	1
r=100%	1	1	1	1	1	1	1

,

Table 4.3: Impact of r and t noise parameters on the *a contrario* score of the resulting clusters.

	t=8%	t=10%	t=12%	t=20%	t=40%	t=60%	t=80%
r=20%	0.44	0.50	0.54	0.78	0.92	0.95	0.99
r=40%	0.68	0.76	0.78	0.85	0.94	0.98	1
r=60%	0.92	0.94	0.95	0.97	0.98	1	1
r=80%	0.98	0.99	1	1	1	1	1
r=100%	1	1	1	1	1	1	1

,

Table 4.4: Impact of r and t noise parameters on the AvgPurity measure of the resulting clusters

	t=8%	t=10%	t=12%	t=20%	t=40%	t=60%	t=80%
r=20%	0.42	0.44	0.48	0.49	0.52	0.56	0.60
r=40%	0.74	0.79	0.8	0.86	0.87	0.91	0.95
r=60%	0.94	0.95	0.96	0.97	0.97	0.98	0.99
r=80%	0.98	1	1	1	1	1	1
r=100%	0.99	1	1	1	1	1	1

,

Table 4.5: Impact of r and t noise parameters on the F1 measure of the resulting clusters

	t=8%	t=10%	t=12%	t=20%	t=40%	t=60%	t=80%
r=20%	0.07	0.09	0.11	0.21	0.37	0.41	0.42
r=40%	0.30	0.40	0.42	0. 48	0.50	0.53	0.64
r=60%	0.70	0.71	0.72	0.73	0.74	0.75	0.80
r=80%	0.86	0.88	0.89	0.9	0.92	0.96	0.99
r=100%	0.99	0.99	1	1	1	1	1

,

Table 4.6: Impact of r and t noise parameters on the AvgCM measure of the resulting clusters

4.6.4 Optimal radius for computing candidate clusters

To validate that our approach tends to select the optimal neighbourhood of any candidate clusters, we use the same dataset X_{5000} from the previous experiment and the **best first oracle** with parameters $(r = 80\%, t = 100\%)$ to generate the K-nearest neighbours. This means, that each item x_i has as its neighbours $r = 80\%$ of the cluster $C(x_i)$ to which it belongs and the rest is a set of items selected uniformly at random of $X_{5000} - C(x_i)$. It is important to note that items from the $r = 80\%$ of the cluster $C(x_i)$ are also selected randomly, so two items from the same cluster may not have the same neighbours.

In the **Candidate cluster construction** step of our clustering framework, we obtain for each item x_i, the optimal neighbourhood size k_{opt} (see Section 4.5) equal to the $r = 80\%$ of the cluster to which x_i belongs. This confirms that only relevant items are selected when looking for the optimal neighbourhood size.

After this step, for each item , we obtain a candidate cluster containing only relevant items from the cluster to which it belongs. By using the second step of our clustering framework i.e. **final clusters selection**, we obtain at the end 30 different clusters that represent all the categories of the ground truth and we eliminate redundant clusters.

4.6.5 Impact of the overlap parameter

The overlap parameter is the only parameter that the user has to fix in our algorithm. To evaluate the impact of this parameter, we use the same dataset X_{5000} and a **no-perfect and unstable oracle** to generate two lists of K nearest neighbours of items. The first one is computed with $(r = 40\%, t = 8\%)$ and the second one with $(r = 60\%, t = 8\%)$. We vary the parameter of overlap $\theta_{Overlap}$ when eliminating the redundant clusters and we compute the F1 measure and the AvgCM of resulting final clusters. Figure 4.7 shows how the F1 measure remains stable until a particular value (40% for the square and triangle lines and 50% for dots and crosses lines). When the $\theta_{Overlap}$ increases, we allow more overlap between clusters so the number of clusters considered as different increases which decreases the $F1$ measure. In the case of a small value of $\theta_{Overlap}$, we select the most different clusters which represent the initial classes. When the goal of a user is to have the more representative clusters of a dataset, we recommend to choose a small value of $\theta_{Overlap}$. We generally fix this parameter to 50% when no constraints are required.

On the other hand, we can see that the AvgCM measure is not very sensitive to the overlap parameter because we use a greedy strategy to eliminate redundant clusters in

our clustering algorithm so that selected clusters are always the best clusters of our clustering.
Generally, the eliminated clusters are those of poor quality. As we do not keep all the candidate clusters ($\theta_{Overlap} < 100\%$), we can say that the resulting clusters represent the best clusters among the candidate clusters.

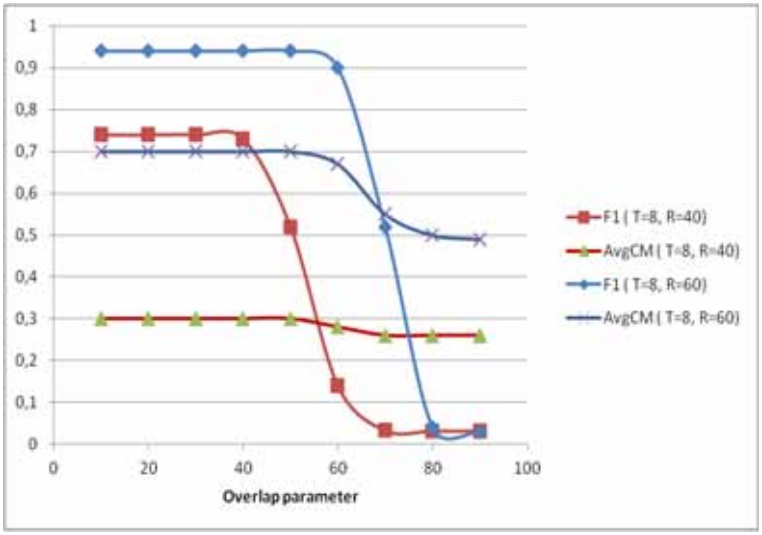


Figure 4.7: Impact of the overlap parameter $\theta_{Overlap}$ on F1 and AvgCM measures.

4.6.6 Comparison with spectral clustering

Qualitative comparison

Graph-based clustering algorithms are particularly suited for dealing with data that do not come from a Gaussian or a spherical distribution. In particular, spectral clustering can deal with arbitrary distribution datasets and metric. Compared to our approach, they are however more sensitive to variations of cluster density. The parameters must be selected cautiously. From spectral clustering algorithm, we can see that two parameters influence the final clustering result: the scale parameter σ in the affinity function and the number of clusters.
Because the use of the K-means step in the spectral clustering (any other clustering can be applied but generally K-means is used for its simplicity), the results can be different from one iteration to another according to the initialisation. The results depend on the initial clusters, it is common to run it multiple times with different starting condition to have stable results.
The main idea of the spectral clustering is to optimize the overall cut of the graph

while in our proposed SNN method, we aim to select an optimal neighbourhood for each item and to merge redundant clusters by simple heuristics.
In spectral clustering, the choice of the graph, as described in Section 2.4, influences the results [111]. If a K-nearest neighbour graph is chosen, the parameter K is critical and has to be fixed carefully: if K is very limited, some relevant neighbours are disconnected, whereas if K is very large, outliers are connected to relevant neighbours. In our proposed clustering method, note that thanks to the selection of the optimal neighbourhood even if K is large, only relevant nearest neighbours that maximize the quality of the neighbourhood are selected: outliers are ignored and not considered as relevant neighbours even if the parameter K has allowed it to be connected to the item. In the case of a limited K, thanks to the reshaping step, we recover the elements that we missed.
Another difference with spectral clustering is that in our method, an item can belong to different clusters, whereas spectral clustering is generally a hard clustering, because ultimately K-means selects one cluster for each item.
Although some recent works [180, 21] propose methods to tune the scale parameter and the number of clusters automatically, the results remain sensitive to the choice of the method or the heuristic whereas in our method the number of clusters is produced automatically and the only predefined overlap threshold can be determined without any knowledge of the data to cluster.
A last difference with spectral clustering is the robustness of our method. If the source that produce the K nearest neighbours of an item is noisy or contains some errors, the spectral clustering will take the generated graph as it is and look for the optimal cut, which obligatory lead to irrelevant results. In our case, thanks to the selection of the optimal neighbourhood and the reshaping steps, irrelevant neighbours, even those having a low rank by mistake, will not be considered as relevant because by including them, they did not improve the quality of the cluster.

Quantitative comparison

To compare our proposed clustering method to spectral clustering algorithms, we choose the two standard versions described in the state-of-the-art (see Section 2.4.1): the normalized spectral clustering according to Shi and Malik [146] and the normalized spectral clustering according to Ng, Jordan and Weiss [121].
For this, we use two common datasets: the Iris Plants Database [53] and the Wine

dataset usually used in papers dealing with spectral clustering issues. Iris Dataset is perhaps the best known database to be found in the pattern recognition literature. It can be download on [1]. The data set contains 3 classes of 50 instances each, where each class refers to a type of iris plant. One class is linearly separable from the other 2; the two others are not linearly separable from each other. The Number of Attributes is equal to 4 numeric predictive attributes and the class:

- sepal length in cm
- sepal width in cm
- petal length in cm
- petal width in cm
- classes: Iris Setosa, Iris Versicolour, Iris Virginica

The scope of "Wine Data Set" is related to chemical analysis. The task consists in regrouping 178 items from the same origin of wines in 3 classes. Created by [164] and available on [2], this dataset is the results of a chemical analysis of wines grown in the same region in Italy but derived from three different cultivators. The analysis determined the quantities of 13 constituents found in each of the three types of wines. All attributes are continuous:

- Alcohol
- Malic acid
- Ash
- Alcalinity of ash
- Magnesium
- Total phenols
- Flavanoids
- Nonflavanoid phenols
- Proanthocyanins
- Color intensity
- Hue
- OD280/OD315 of diluted wines
- Proline

The number of instances per class is respectively : 59, 71, 48. For all methods, the Euclidean distance was used as a pairwise similarity measure. For tested spectral clustering methods , the number of clusters is given as input whereas our method finds by itself automatically the right number of clusters for the two data sets. We can say that

1. http://archive.ics.uci.edu/ml/datasets/Iris
2. http://archive.ics.uci.edu/ml/datasets/Wine

in this experimentation, the spectral clustering has more advantages than our method from the start.
Concerning the scale parameter σ needed in the spectral clustering, we use the method proposed by [146]. They gave a range of the scale parameter as:

$$\sigma = c \times (max(dist) - min(dist)) \tag{4.20}$$

with c $\in [0.1, 0.2]$.
For the overlap parameter of our proposed shared nearest neighbours clustering, we fix it to 50% as discussed earlier in Section 4.5. We remember that this parameter is the maximum overlap allowed between two clusters to be considered as two different clusters. If the overlap exceeds 50%, the two clusters are considered as similar and have to be grouped on a relevant single cluster by reshaping.
For the evaluation, we use two metrics : the *Rand Index* [140] and the *Average Purity* (see Section 4.6.1). The results of the two datasets are reported in Tables 4.7and 4.8. Note that as spectral clustering use K-means the results differ from an iteration to another, we iterate 50 times and take the average.

	Ng, Jordan and Weiss	Shi and Malik	Our SNN clustering
Rand index	0.87	0.75	0.83
Avg Purity	0.9	0.8	0.87

Table 4.7: The Iris Plants Database clustering results

	Ng, Jordan and Weiss	Shi and Malik	Our SNN clustering
Rand index	0.62	0.48	0.72
Avg Purity	0.81	0.78	0.70

Table 4.8: The Wine Database clustering results

Through this experimentation, we want to show that the performances our SNN clustering results do not differ greatly from those of the two spectral clustering methods tested here although that we did not give any *a priori* information to our clustering (i.e the number of clusters). By keeping the overlap threshold to 50% which can be kept for all experiments in this PhD. Our clustering method finds automatically the right number of clusters and the results are very promising. For standard spectral clustering that we tested, it was necessary to give the number of clusters as input, computing the best value of the scale parameter for the affinity matrix and finally iterating

several times to have stable results.

We then studied the impact of the neighbourhood size on our SNN clustering compared to the spectral clustering of Ng, Jordan and Weiss. For this, we used the synthetic data X_{5000} build from 5000 items clustered in 30 categories with different size between 20 and 260 items. We vary the value of the k nearest neighbours and we compute the AvgPurity and the Rand Index. Results are reported in Figures 4.8 and 4.9.

For spectral clustering [121], we can denote that by increasing the neighbourhood size, the average purity and the rand index values increase smoothly for the spectral clustering with the best tuning (the right number of clusters is done and we take the best scale parameter). For $k = 50$, the used spectral algorithm diverges : items are disconnected and the algorithm cannot find the 30 categories. This is why we had to begin with $K = 100$ in the experiment.

This is not the case for our proposed clustering, which deals with a small neighbourhood (for $k = 50, AvgPurity = 1$ and $RandIndex = 0,98$). Thanks to the reshaping step during the elimination of the redundant clusters, even with small neighbourhood, our clustering adds relevant missing items to their relative clusters.

By this experiment, we can conclude that our SNN clustering is robust and less sensitive to the neighbourhood size than the spectral clustering [121]. It also shows, that our method is globally more robust to the kind of noises considered in this experiment (unstability and noisy returned items).

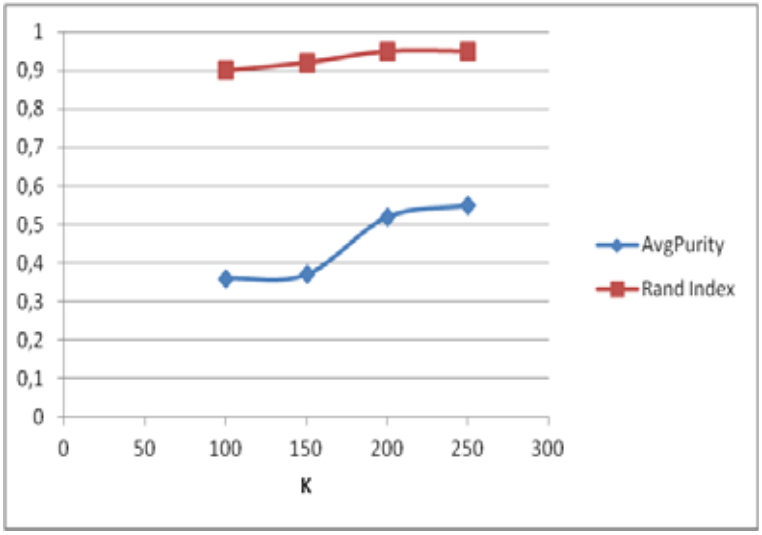


Figure 4.8: Impact of the neighbourhood size on the AvgPurity and the Rand Index values when using the spectral clustering [121]

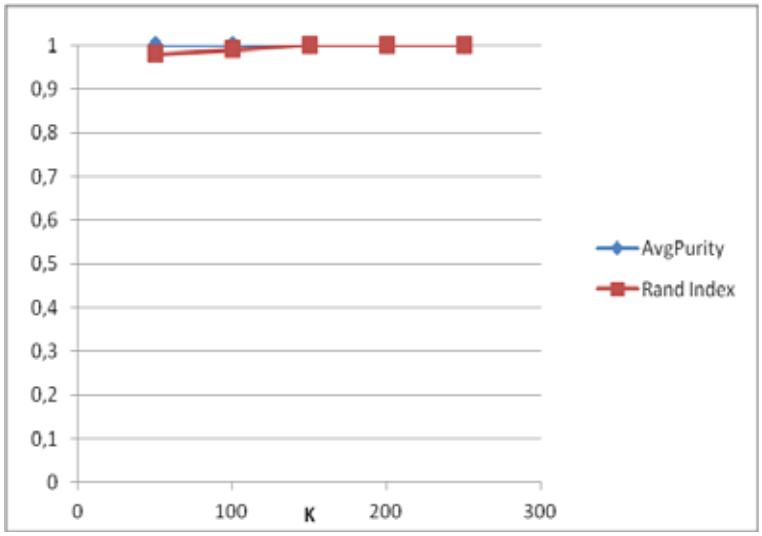


Figure 4.9: Impact of the neighbourhood size on the AvgPurity and the Rand Index values when using our proposed SNN clustering

4.7 Conclusion

In this chapter, we revisited an existing shared neighbours methods in two points. We first introduced a new SNN formalism based on the theory of *a contrario* decision. This allows us to derive more reliable connectivity scores of candidate clusters and a more intuitive interpretation of locally optimum neighbourhoods. We also proposed a new factorization algorithm for speeding-up the intensive computation of the required shared neighbours matrices. We compared our proposed method to a spectral clustering [121]. We showed that our method is globally more robust to the kind of noises considered in the experiment (unstability and noisy returned items).
This chapter is the basis for the second and the third contributions of this work.

Chapter 5

Multi-source shared nearest neighbours clustering

5.1 The multi-source SN problem

The increasing availability of devices (laptops, smart phones, camera) has led to an explosion in the amount of information that user must confront in order to use them efficiently. We are often given unsupervised data originating from different sources. For example, images have many properties (color, texture, etc) and meta-data (textual annotation, EXIF, etc) which are quite different from one source of information to another. The goal is to benefit from all available sources of information so as to be able to have more meaningful information concerning the images. To harness the strengths of that, multi-modality processing has become an attractive strategy.
It is known that processing data from a single irrelevant information source will contribute to the creation of a bad result. Does the use of multiple data sources had more chance to improve the result? How can we deal with sources when some of them are characterized uncertain information ? We need an efficient combination of sources and not just a trivial fusion. An effective combination is crucial.
In order to deal with uncertainty in the available data, we propose to determine a clustering that is consistent not with all sources but with the optimal subset of sources. For each cluster, we need to select relevant information sources and ignore irrelevant ones. In this way, noise can be reduced by combining sources effectively and can overcome the bad quality of sources by correcting the errors produced by each individual source. Imagine that a search engine asks M decentralized servers to return the K first responses to a user's query and it merges the M lists to produce a final ranking of results. What happens if one or multiple servers return junk results ? Will the search

engine find that one source of information returns results with no significance ? This can be avoided if we merge not only the results of all available sources but we select the optimal subset of sources ? We will try to answer these questions in this Chapter.
A second problem is how to group observations that belong to different physical spaces with different dimensionalities, e.g., how to group visual data with textual data ? To do this, shared neighbours clustering seems appropriate because even in heterogeneous contexts in which underlying features and similarity values do not have a straightforward unique interpretation, two items having a high proportion of neighbours in common can be assigned to the same group. Two items are considered to be well-associated not by virtue of their pairwise similarity value, but by the degree to which their neighbourhoods resemble one another.
Shared nearest neighbours (**SNN**) methods thus appear to be ideally suited to **multi-modal** clustering. Because they are based on conexity information only and not on densities or metrics in some feature spaces, heterogeneous information sources can be embedded identically and easily compared or fused. **SNN** method, as stated before, are able to overcome several shortcomings of traditional clustering approaches: they do not suffer from *the curse of dimensionality*, they are robust to noisy data, they do not need to initially fix the number of clusters, and, last but not least, they do not require any explicit knowledge of the nature or representation of the data. These properties make them widely generic for multimedia mining or structuring purposes, whatever the targeted objects and the required similarity measures.
In this chapter, we introduce, a new generic **multi-source** SNN framework including new multi-source measures for arbitrary object sets and information sources. The main originality of our approach is that we introduce **an information source selection step** in the computation of these measures thanks to an *a contrario* standardization of the sum of the individual SNN scores. In addition to a usual conexity score, any arbitrary object set is thus associated with its own optimal subset of modalities maximizing the multi-source *a contrario* score. All resulting clusters do not necessarily have the same selected sources in contrast to other previous work.

5.2 A contrario multi-source SNN significance measures

To generalize a shared neighbours clustering to a multi-source environment, several issues have to be solved. Whereas in a single source model, each item of the dataset

$X = \{x_i\}_{i=[1..N]}$ to be clustered is associated with a single nearest neighbours list, in the multi-source environment, each item is associated with m nearest neighbours lists where m corresponds to the number of sources. In the following, we denote as O the set of available information sources and $m = |O|$ the number of sources. Any information source $o \in O$ is defined only by its nearest neighbours response function $F_K(x,o)$:

$$F_K(x,o) = \{nn_k^o\}_{k\in[1,K]}$$

where x represents any item of the whole dataset X to be clustered and $nn_k^o \in X$ the k-th nearest neighbour of the item x according to the source o.

5.2.1 Raw multi-source SNN significance measures

We first generalise the *intra-significance measure* (Equation 4.2) seen in Chapter 4.3 to the multi-source case, by measuring the expectation of the inter-set correlation between a set A and the nearest neighbours set of an item x selected uniformly at random from A according to an information source o selected uniformly at random from O.
As a primary multi-source intra-set significance measure for any set $A \subset X$, we have:
Definition: Multi-source intra-significance measure

$$\begin{aligned} I(A,O) &= \frac{1}{|A||O|}\sum_{o\in O}\sum_{x\in A}(A \cap F_{|A|}(x,o)) \\ &= \frac{1}{|A||O|}\sum_{o\in O}\sum_{x\in A} I_A(x,o) \end{aligned} \tag{5.1}$$

Comparing the multi-source intra-set significance measure of sets of different sizes and different amounts of information sources is biased. It is not only regarding the size as in the mono-source case (see the section 4.2) but also concerning the number of sources. How can we normalize this measure to be able to compare and sort the sets of items regardless of their size and their selected sources ?

5.2.2 *A contrario* normalization

As in the mono-source case, we propose to remove the bias of the raw measure by the *a contrario* principle. Let us call $\mathscr{H}'$ the null hypothesis that all sources are i.i.d and uniformly distributed, i.e. each source returns nearest neighbours selected uniformly at random from X (all sources are independent **random Oracles**). Under the hypothesis $\mathscr{H}'$, *the multi-source intra-significance measure* is normally distributed

and the $I_A(x,o)$ is a hypergeometrically distributed random variable with expectation :

$$\mathbf{E}[I_A(x,o)] = \frac{|A|^2}{N} \tag{5.2}$$

and variance :

$$\mathbf{Var}[I_A(x,o)] = \frac{|A|^2(|N|-|A|)^2}{N^2(N-1)} \tag{5.3}$$

by using the central limit theorem, we can conclude that $I(A,O)$ is assumed to follow a normal distribution $\mathscr{N}(\mu_A,\sigma_A^2)$ with:

$$\begin{aligned} \mu_A = \mathbf{E}[I(A,O] &= \mathbf{E}[I_A(x,o)] \\ &= \frac{|A|^2}{N} \end{aligned} \tag{5.4}$$

Because of the independence of $I_A(x,o)$ variables, we obtain for the variance:

$$\begin{aligned} \sigma_A^2 = \mathbf{Var}[I(A,O)] &= \frac{\mathbf{Var}[I_A(x,o)]}{|O||A|} \\ &= \frac{|A|(N-|A|)^2}{|O|N^2(N-1)} \end{aligned} \tag{5.5}$$

Note that in Equation 5.5, for a fixed size set $|A|$, the more sources we have, the smaller the variance is. $I(A,O)$ can therefore be standardized to a multi-source standard normal distribution $Z(A,O)$ with parameters $\mathscr{N}(0,1)$ under the hypothesis $\mathscr{H}'$ as follows:

$$\begin{aligned} Z(A,O) &= \frac{I(A,O)-\mathbf{E}[I(A,O)]}{\sqrt{\mathbf{Var}[I(A,O)]}} \\ &= \sqrt{|O|}\frac{|A|(N-|A|)^2}{N^2(N-1)}(I(A,O)-\mathbf{E}[I(A,O)]) \\ &= \sqrt{|O|}[\frac{I(A,O)-\mathbf{E}[I(A)]}{\sqrt{\mathbf{Var}[I(A)]}}] \\ &= \sqrt{|O|}[\frac{\frac{1}{|O|}\sum_{o=1}^{|O|} I(A,o)-\mathbf{E}[I(A)]}{\sqrt{\mathbf{Var}[I(A)]}}] \end{aligned} \tag{5.6}$$

As we have now a multi-source standard significance measure Z under the null hypothesis $\mathscr{H}'$, we can estimate the precision score *a contrario* to $\mathscr{H}'$ as follows:

$$\begin{aligned} P_{Z(A,O)}(z) &= \int_{-\infty}^{z} \frac{1}{\sqrt{2\Pi}} e^{-\frac{t^2}{2}}\,\mathrm{d}t \\ &= 1-\phi(z) \end{aligned} \tag{5.7}$$

where $\phi()$is the cumulative distribution function of the standard normal distribution that describes probabilities for a random variable to fall within the interval $]-\infty, z]$.
$P_{Z(A,O)}(z)$ is the probability that the multi-source standard significance measure $Z(A,O)$ does not exceed a threshold z under the null hypothesis $\mathscr{H}'$ in the multi-source case.
So that , $Pfa(z) = 1 - P_{Z(A,O)}(z)$ is the likelihood that A is not a false alarm (i.e the likelihood that the subset A was not generated by a subset of random oracles).
$Pfa(z)$ can also be expressed in terms of the error function **erf** as follows:

$$Pfa(z) = \frac{1}{2} - \frac{1}{2}\mathbf{erf}(\frac{z}{\sqrt{2}}) \tag{5.8}$$

Having the probability of a false alarm under the null hypothesis, we can now determine our multi-source *a contrario* significance score as the complement of the Pfa :
Definition Multi-source *a contrario* significance score:

$$\begin{aligned} S(A,O) &= 1 - Pfa(Z(A,O)) \\ &= 1 - \phi(Z(A,0)) \\ &= \frac{1}{2} + \frac{1}{2}\mathbf{erf}(\frac{Z(A,O)}{\sqrt{2}}) \end{aligned} \tag{5.9}$$

5.3 Cluster-centric selection of optimal sources

Now that we have a precision score that is unbiased relative to the number of information sources, we can describe our approach to select the optimal subset of sources of any input set A. If we denote as $\theta \subseteq O$ an arbitrary subset of sources, then we are

searching for the optimal subset $\theta_{opt}(A) \subseteq O$ maximizing $S(A,\theta)$:

$$\begin{aligned}
\theta_{opt}(A) &= \underset{\theta\subseteq O}{\operatorname{argmax}}\,(S(A,\theta)) \\
&= \underset{\theta\subseteq O}{\operatorname{argmax}}\left(\frac{1}{2}+\frac{1}{2}\mathbf{erf}(\frac{Z(A,\theta)}{\sqrt{2}}\right) \\
&= \underset{\theta\subseteq O}{\operatorname{argmax}}\,Z(A,\theta) \\
&= \underset{\theta\subseteq O}{\operatorname{argmax}}[\frac{I(A,\theta)-\mathbf{E}[I(A,\theta)]}{\sqrt{\mathbf{Var}[I(A,\theta)]}}] \\
&= \underset{\theta\subseteq O}{\operatorname{argmax}}\sqrt{|\theta|}[\frac{1}{|\theta|}\sum_{o\in\theta} I(A,o)] \\
&= \underset{\theta\subseteq O}{\operatorname{argmax}}\frac{1}{\sqrt{|\theta|}}\sum_{o\in\theta} I(A,o) \\
&= \underset{i<|O|}{\operatorname{argmax}}\ \underset{\theta\subseteq O\setminus|\theta|=i}{\operatorname{argmax}}\frac{1}{\sqrt{|\theta|}}\sum_{o\in\theta} I(A,o) \\
&= \underset{i}{\operatorname{argmax}}\frac{1}{\sqrt{i}}\underset{\theta\setminus|\theta|=i}{\operatorname{argmax}}\sum_{o\in\theta} I(A,o) \\
&= \underset{i}{\operatorname{argmax}}\frac{1}{\sqrt{i}}\sum_{o\in\hat{\theta}_i} I(A,o) \qquad (5.10)
\end{aligned}$$

In this way, we are not only seeking the best number of sources i but also selecting the best combination of sources of size i . $\hat{\theta}_i$ is the optimal combination of sources of size i.

What seemed at first glance to be a combinatorial problem can indeed be solved extremely easily by pre-sorting single-sources intra-significances in decreasing order and finding the optimal number of top sources θ_{opt}.

Our final selected-source intra-significance measure of any arbitrary set A is finally given by:

$$I_{opt}(A,\theta_{opt}(A)) = \frac{1}{\sqrt{|\theta_{opt}|}}\sum_{o_i\in\theta_{opt}(A)} I(A,o_i) \qquad (5.11)$$

This indicates that if the intra-significance measures for A are available with respect to individual oracles and have been presorted from highest to lowest, then the most significant sub collection of oracles describing A, over a desired range of sub collection sizes, can be determined in linear time.

In the same way, the optimal multi-source *a contrario* score $\hat{S}$ can be computed by combining the individual *a contrario* scores according to the optimal subset of sources

θ_{opt}:

$$\hat{S}(A,\theta) = S(A,\theta_{opt}(A)) \tag{5.12}$$

The goal of selecting the optimal subset of sources is to avoid outlier sources in O. Unlike methods that use all available sources to compute the significance of a set whatever the quality of the information sources, we only select sources that maximize the quality of the set A and ignore the rest.

5.4 Clustering framework

Now that we have defined our new multi-source shared nearest neighbours significance measures we can describe our multi-source clustering procedure. It is based on three main steps, unlike the mono-source case which was based in only two steps. The three steps are: *candidate cluster construction*, *candidate cluster reshaping* and *final clusters selection*.

– **Candidate cluster construction**: Each item $x \in X$ is considered as a candidate cluster center and an optimal candidate cluster $C(x)$ needs to be computed for it. For each source $o_i \in O$, every item has a list of K-NN. For that, we have to select the optimal neighbourhood in each K-NN that maximizes our multi-source *a contrario* score S (Equation 5.9).
Note that an optimal source selection is performed for each iteration on the neighbourhood size k and the selected subset $\theta_{opt}(F_k(x,o_i))$ of sources may differ from one value of k to another.
The optimal neighbourhood $\hat{k}_{o_i}(x,O)$ for the item x according to the source $o_i \in O$ is defined by:

$$\begin{aligned} \hat{k}_{o_i}(x,O) &= \underset{k}{\operatorname{argmax}}\, \hat{S}(F_k(x,o_i),O) \\ &= \underset{k}{\operatorname{argmax}}\, S(F_k(x,o_i),\theta_{opt}(F_k(x,o_i))) \end{aligned} \tag{5.13}$$

Unlike the mono-source case, where each item is represented by a single neighbourhood, in the multi-source case, for each source $o_i \in O$, we obtain the optimal neighbourhood. Among the m list of optimal neighbourhoods $\hat{k}_{o_i}(x,O)$ of the item x according the each single source o_i, we finally keep as a candidate cluster

$C_{opt}(x)$ the neighbourhood of the source o_j that has the maximum multi-source *a contrario* score S:

$$C_{opt}(x) = F_{\hat{k}}(x, \theta_{opt}(F_{\hat{k}}(x, o_j))$$

Each candidate cluster is defined by its own optimal subset of sources that are the most relevant for it.

– **candidate cluster reshaping**: After selecting the single optimal neighbourhood with its own optimal subset of sources, some neighbours provided by each source of the selected sources may be more relevant to $C_{opt}(x)$. The candidate cluster $C_{opt}(x)$ is the best set of K-NN provided by a source o_j because it has the maximum multi-source *a contrario* score. By selecting just one neighbourhood, some other relevant neighbours provided from the other sources (selected in the optimal subset of sources) may be missing. The contribution of some relevant items from the other neighbours of x can improve the quality of $C_{opt}(x)$.
For this reason, each candidate cluster $C_{opt}(x)$ has to be reshaped by adding only the strongly associated items provided from the remaining optimized neighbourhoods, those from sources included in the selected subset $\theta_{opt}(x, o_j)$ of sources. We denote these items as K'-NN. For each item y in K'-NN, we compute its own contribution $c(y, C_{opt}(x) \setminus \theta_{opt}(x, o_j))$ to the candidate cluster $C_{opt}(x)$ centred on x and provided by the source o_j. This contribution is based on the selected optimal subset of sources $\theta_{opt}(x, o_j)$ as described in the following equation:

$$c(y, C_{opt}(x) \setminus \theta_{opt}(x, o_j)) = \frac{1}{|C_{opt(x)}||\theta_{opt}(x, o_j)|} \sum_{o \in \theta_{opt}(x, o_j)} |(C_{opt}(x) \cap F_{|C_{opt}(x)|}(y, o)| \quad (5.14)$$

We sort in decreasing order the contribution of each y in K'-NN to $C(x)$ and we select those who decrease the quality of the candidate cluster $C_{opt}(x)$ i.e that maximize the final multi-source precision score $S(C_{opt}(x, \theta_{opt}))$ as seen in

Section 4.3.3 but in multi-source case:

$$
\begin{aligned}
I(C_{opt}(x)\cup y) - I(C_{opt}(x)) \;=\; & \frac{1}{|\theta_{opt}(x,o_j)|}\Big(\\
& \Big[\frac{1}{|C_{opt}(x)+1|} - \frac{1}{|C_{opt}(x)|}\Big] \\
& \sum_{o\in\theta_{opt}(x,o_j)} \sum_{x\in C_{opt}(x)} |C_{opt}(x)\cap F_{|C_{opt}(x)|}(x,o)| \\
& + \frac{1}{|C_{opt}(x)+1|}\Big[\\
& \sum_{o\in\theta_{opt}(x,o_j)} \sum_{x\in C_{opt}(x)} |(C_{opt}(x)\cup y)\cap nn_{|C_{opt}(x)+1|}(x)| \\
& + \sum_{o\in\theta_{opt}(x,o_j)} |(C_{opt}(x)\cup x_i)\cap F_{|C_{opt}(x)+1|}(y,o)|\Big]\Big)
\end{aligned}
\tag{5.15}
$$

– **Final clusters selection**: After the candidate cluster selection and the reshaping step, we obtain potentially relevant clusters. However, some of them are similar because close items will have approximately the same candidate cluster which leads to redundant clusters. Therefore we use the same technique as that used in the **Final clusters selection** of the mono-source schema (see Section 4.5). The only difference is that for each final cluster, we also have the information of the optimal subset of sources selected for this cluster. This information can generate knowledge about the sources: a source that is never selected for any cluster can be considered as irrelevant.

5.5 Synthetic oracles experiments

In this section, we use the synthetic oracles defined in section 4.6.2.

5.5.1 Impact of outlier sources

Our first experiment consists in combining one **perfect oracle** as described in the section 4.6.2 with m **non-perfect and unstable sources** with parameters ($r = 0$ and $t = 0$) as described in Section 4.6.2, to validate the robustness of our source selection algorithm. We used these sources and the X_{5000} dataset. As theoretically expected, our method is fully invariant to the inclusion of random outlier sources and both F1 measure and AvgPurity are equal to 1.0 whatever the value of m.

5.5.2 Impact of source precision and stability parameters

Our second experiment is to study the influence of parameters t and r when combining several **non-perfect and unstable information sources**. For this experiment, we used $m = 4$ **oracles** and we varied the value of r and t. We use the same dataset X_{5000} described in 4.6.3 but the difference of this experiment relative to the experiment done in 4.6.3 is that here we are evaluating the *a contrario* score, the F1 measure, the AvgPurity and the AvgCM of our resulting clusters in a multi-source case. By this experiment, we aim to show the interest of using multiple sources even if they are non-perfect and unstable. The results of the **F1** measure and the average cosine measure (AvgCM) in multi-sources case are reported in Tables 5.2 and 5.3, the *a contrario* scores of clusters are reported in 5.1.
Note that thanks to the oracle selection and the reshaping steps, all produced clusters present $AvgPurity = 1$, this means that only relevant items are kept in clusters.
The a contrario scores even with low quality of K-nearest neighbours of cluster's items $(r = 20\%, t = 8\%)$ still relevant clusters (*a contrario* score=0.97) which means that the clusters are far from random sets. Compared to the mono-source case (Table 4.3), the score has almost doubled.
Tables 5.2 and 5.3 show that our method is robust to both kinds of noise, i.e imprecision and unstability. Compared to the results showed in the mono-source case described in the section 4.6.3, we can see how results are improved by combining 4 non-perfect and unstable oracles. For example, even with low quality of nearest neighbours ($r = 40\%$ and $t = 8\%$), the **F1** measure increases from 0.74 in the mono-source case to 0.99 in the multi-source case. For the same parameters, the AvgCM increases from 0.30 to 0.62 by using 4 sources. That means that our method is able to compensate the weak quality of very noisy independent sources by combining them effectively even with only 4 sources.
Note that all these results could be more improved if we had used more sources as done in the next section.

5.5.3 Impact of the number of sources

We study the impact of the number of sources on the effectiveness of our method. For this experiment we fixed r and t and we varied the number of **unstable and no-perfect oracles** from 1 to 14. We do that by using a couple of parameters $(r = 40\%, t = 10\%)$. The results are provided in Figure 5.1. It shows that increas-

,	t=8%	t=10%	t=12%	t=20%	t=40%	t=60%	t=80%
r=20%	0.97	0.98	1	1	1	1	1
r=40%	0.98	0.99	1	1	1	1	1
r=60%	1	1	1	1	1	1	1
r=80%	1	1	1	1	1	1	1
r=100%	1	1	1	1	1	1	1

Table 5.1: Impact of r and t noise parameters on the a contrario scores of our resulting clusters in the multi-sources case (4 sources).

,	t=8%	t=10%	t=12%	t=20%	t=40%	t=60%	t=80%
r=20%	0.64	0.81	1	1	1	1	1
r=40%	0.98	0.99	1	1	1	1	1
r=60%	0.99	1	1	1	1	1	1
r=80%	1	1	1	1	1	1	1
r=100%	1	1	1	1	1	1	1

Table 5.2: Multi-sources case: impact of r and t noise parameters on the F1 measure of resulting clusters.

,	t=8%	t=10%	t=12%	t=20%	t=40%	t=60%	t=80%
r=20%	0.43	0.58	0.85	0.96	1	1	1
r=40%	0.62	0.72	0.93	0.98	1	1	1
r=60%	0.76	0.81	0.97	0.99	1	1	1
r=80%	0.89	0.95	0.99	1	1	1	1
r=100%	0.99	1	1	1	1	1	1

Table 5.3: Multi-sources case : impact of r and t noise parameters on the AvgCM measure of resulting clusters.

ing the number of sources is **always** profitable, which is a very consistent result for our multi-source shared nearest neighbours method. The errors induced by each individual source are very well compensated by combining the information sources.
We can conclude that by combining more sources, the AvgCM is more improved thanks to the reshaping steps that add relevant items from the selected optimal sources. So the more the number of sources increases, the more the quality of clusters is improved.
The AvgPurity is still good thanks to the optimal selection of neighbourhood that always selects homogeneous and correlated items of a same clusters. The reshaping steps support the quality of clusters.

Finally, the F1 measure is still also good thanks to the correlated steps: the elimination of redundant clusters and the use of poor clusters to reshape relevant ones.

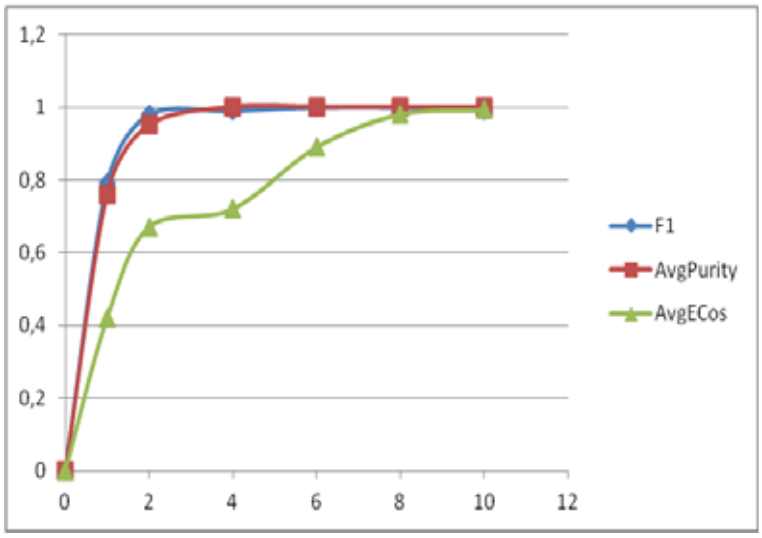


Figure 5.1: Impact of the information sources number on AvgPurity, F1 measure and the AvgCM.

5.5.4 Computational time analysis

Finally, we study the time execution of the fast shared neighbours computation step and the candidate cluster selection (including the first reshaping). We use the synthetic data X_{5000} and we vary some parameters: the number of oracles and the size of the dataset. Results in Figure 5.2 show that the greatest amount of time is consumed by the fast shared neighbours computation step when the number of oracles increases from 2 to 20. The execution time of the candidate cluster selection and reshaping step, even if we compute the cluster candidate for every source and reshape according to the oracle selection, is still linear. The fast shared neighbours computation time is quadratic for the number of oracles.

When we vary the size of the dataset for a fixed number of oracles (5 oracles) and a fixed number of nearest neighbours allowed (Kmax), the time of the fast shared neighbours computation is linear in dataset, as it is shown in Figure 5.3. To decrease the time of the candidate cluster selection, the size of the dataset to be clustered has to be limited, so we can apply it on on-line applications.

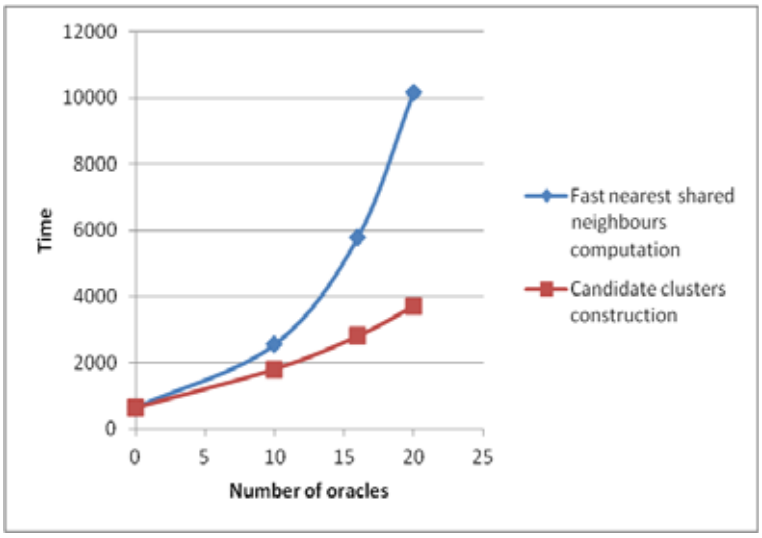


Figure 5.2: Running time in seconds vs. number of oracles for the fast nearest shared neighbours computation, the candidate cluster selection using Kmax=200 for the synthetic data set X_{5000}.

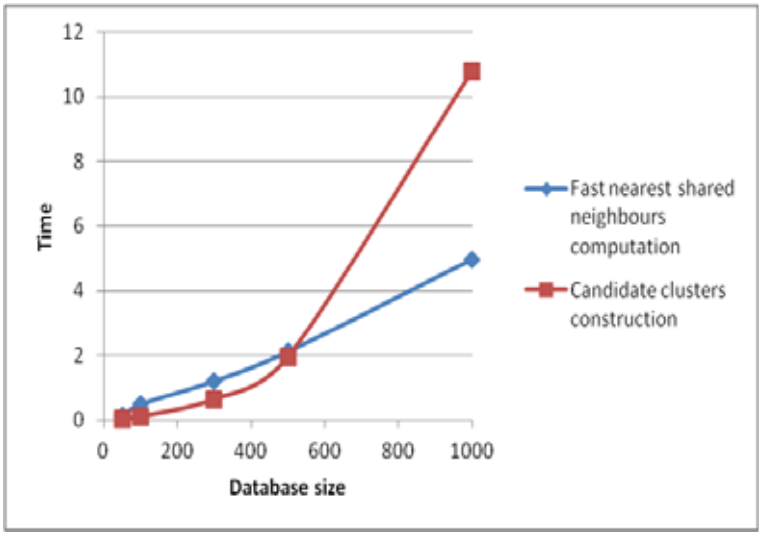


Figure 5.3: Running time in seconds vs. the dataset size or the fast shared neighbours computation , the candidate cluster selection using 5 oracles and Kmax=30 for the synthetic data set X_{5000}

5.6 Conclusion

Shared Nearest Neighbours (SNN) techniques are well known to overcome several shortcomings of traditional clustering approaches, notably high dimensionality and metric limitations. However, previous methods were limited to a single information

source in spite of such methods appear to be very well suited for heterogeneous data, typically in multi-modal contexts. In this chapter, we introduced a new **multi-source** shared neighbours scheme applied to multi-modal image clustering. We first extend the existing SNN-based similarity measures to the case of multiple sources and we introduced an original automatic source selection step when building candidate clusters. The key point is that each resulting cluster is built with its own optimal subset of modalities which improves the robustness to noisy or outlier information sources. We experimented our method with synthetic data involving different information sources. We demonstrated the effectiveness and the robustness to noisy sources of our proposed method.

Chapter 6

Bipartite shared-neighbours clustering

6.1 The bipartite SNN problem

In this section, we are interested in the bipartite graph in which the nodes are not considered as a single group but are divided into two groups. The k-nearest neighbours of a set *A* of items to be structured belong to a second disjoint set *B*. Nodes from the same group are not connected to each other, only edges between nodes from different groups are connected. The relation between the nodes of the same group is expressed by the number of shared nodes in the second group.
In [98], bipartite graphs are employed to capture the relationship between users and their interests, the users and their queries, the page and ads and the photo and tags. They developed an algorithm to compute the connected components of the k-neighbourhood graph and hence a *K-neighbour connectivity plot* called *KNC-plot* that is used to understand the macroscopic properties of the graph. On the other hand, in this thesis, we are interested in the clustering aspect of such graphs. We study the bipartite graph clustering by Shared Nearest Neighbours (SNN) clustering methods. The principle of SNN algorithms is to group items not by virtue of their pairwise similarity, but by the degree to which their neighbourhoods resemble one another. This property is suitable for our bipartite graph clustering problem. To the best of our knowledge, SNN clustering methods have not yet been studied in the case of bipartite nearest neighbours graphs, as done in this thesis.
As we do not have more information than connection with rank between data points of the two different groups, given a bipartite graph, the intuitive goal of clustering is to divide the data nodes into several groups such that nodes in the same group are similar and nodes in different groups are dissimilar to each other as illustrated by an example in Figure 6.1.

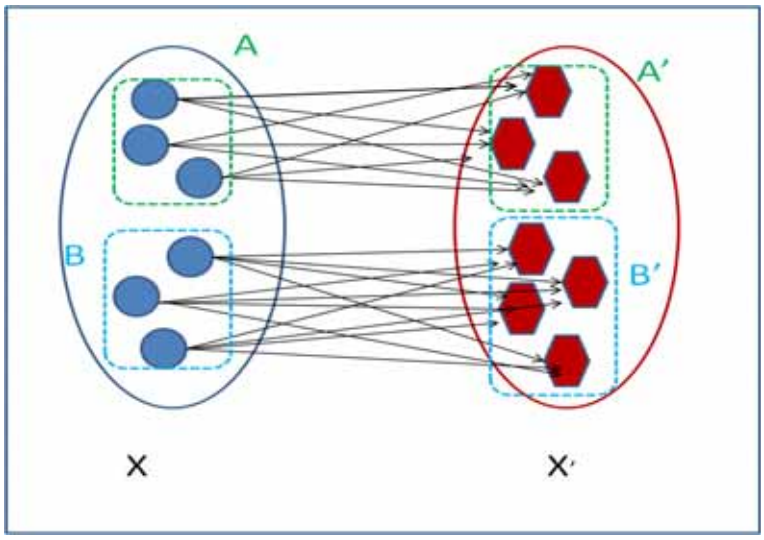


Figure 6.1: An example of bipartite graph with two perfect bipartite clusters.

Such graph are natural for many application such as documents and words. A word belong to a set of documents and in the same time, a document contains a set of words. The motivation can be to regroup documents having common words.
Another example of bipartite graph is a job matching problem. Suppose we have a set P of people and a set J of jobs. We can model this as a bipartite graph. If a person p_x is suitable for a job j_y, there is an edge between p_x and j_y in the graph. The clustering of this bipartite graph provides groups of persons who can possibly work on a group of jobs. This structuring can help considerably a recruiter's job who received person's applications for a list of jobs.

6.2 Notations

We denote as $G(X,X';E)$ a bipartite graph composed of two different sets of nodes X and X' and a set E of directed edges $e_{i,j}$ with a starting point in X, an endpoint in X' and a weight $w_{i,j}$ corresponding to a matching score ($w_{i,j}=0$ means that no edge connects item x_i to item x'_j).
Any bipartite set (A,A') in (X,X') is composed of an extension set $A \in X$ and an intention set $A' \in X'$. The size of X is denoted N and the one of X' as N'. Note that $A \cap A' = \emptyset$ which means that there are no duplicated items.
We define the norm of a bipartite cluster (A,A') as:

– $|(A,A')| = |A||A'|$. It quantifies the number of possible connections between all

items of A and A'.

- $(A,A') \cap (B,B') = (A \cap B, A' \cap B')$. It denotes the intersection between two bipartite clusters.
- $|(A,A') \cap (B,B')| = |(A \cap B, A' \cap B')| = |A \cap B|.|A' \cap B'|$. It quantifies the intersection between two bipartite clusters.

We define the bipartite function $F_k(x_i)$ as the nearest neighbouring set of items in X' of size k connected to the item $x_i \in X$:

$$F_k(x_i) = \{x'_j = nn_j(x_i), \forall j \in [1..k]\} \text{ where } x'_j \in X'.$$

Note that the reverse nearest neighbours in X' of an item x'_j is denoted by :

$$\bar{F_k}(x'_j) = \{x_i | x'_j \in F_k(x_i)\} \text{ where } x_i \in X.$$

The advantage of this bipartite representation is that it allows us to formulate our clustering objective as a *co-clustering* problem (or *dual subset clustering* [178]).
Indeed we aim to find clusters $C = (A,A')$. An ideal dual cluster (A,A') is one in which the reverse neighbours of all items in A' match all the items in A and in the same time the neighbours of items in A belong to A':

- $F_{|A'|}(x_i) = A', \forall x_i \in A$ i.e the nearest neighbours of items in A match A'.
- $\bar{F_{|k|}}(x'_j) = A, \forall x'_j \in A'$ i.e the reverse nearest neighbours of items in A' match A.

6.3 Bipartite shared nearest neighbours significance measures

6.3.1 bipartite *a contrario* significance measures

As primary bipartite shared neighbours similarity measure for any dual cluster (A,A'), we define the *bipartite intra-significance* measure as:

$$\begin{aligned} I(A/A') &= \frac{1}{|A||A'|} \sum_{x \in A} \sum_{x' \in A'} |(F_{|A'|}(x), \bar{F}_{|A|}(x')) \cap (A,A')| \qquad (6.1) \\ &= \frac{1}{|A||A'|} \sum_{x \in A} \sum_{x' \in A'} \frac{|F_{|A'|}(x) \cap A'|}{|A'|} . \frac{|\bar{F}_{|A|}(x') \cap A|}{|A|} \\ &= \frac{1}{|A||A'|} \sum_{x \in A} \sum_{x' \in A'} I_{A,A'}(x,x') \end{aligned}$$

where

$$I_{A,A'}(x,x') = \frac{|F_{|A'|}(x) \cap A'|}{|A'|}.\frac{|\bar{F}_{|A|}(x') \cap A|}{|A|}$$

For a perfect cluster, $\forall x,x' \in (A,A'), (F_{|A'|}(x), \bar{F}_{|A|}(x')) = (A',A)$. This means that all shared neighbours of each $x \in A$ matches with the set A' and , all reverse shared neighbours of each item $x' \in A'$ matches with the set A. The bipartite intra-significance measure is equal to:

$$\begin{aligned} I(A/A') &= \frac{1}{|A||A'|} \sum_{x\in A} \sum_{x'\in A'} |(F_{|A'|}(x), \bar{F}_{|A|}(x')) \cap (A,A')| \\ &= \frac{1}{|A||A'|} \sum_{x\in A} \sum_{x'\in A'} |(A,A') \cap (A,A')| \\ &= \frac{1}{|A||A'|} \sum_{x\in A} \sum_{x'\in A'} |A'|.|A| \\ &= |(A,A')| \end{aligned} \tag{6.2}$$

Note that this result is similar to $I(A) = |A|$ in the mono-source case.
Under the null hypothesis $\mathscr{H}$ where a list of neighbours is produced by a random oracle i.e. generated by means of uniform random selection from the available items, the number of shared items between the $|A'|$ nearest neighbours of x and A' is selected uniformly at random from X' and in the same time the number of shared items between the $|A|$ reverse shared neighbours of x' and A is selected uniformly at random from X. Intuitively, the intersection measure $I_{AA'}(x,x')$ is the product of two random independent variables and it follows the hypergeometric distribution with parameters :

$$\begin{aligned} \mathbf{E}[I_{AA'}(x,x')] &= \mathbf{E}[I_{A'}(x)].\mathbf{E}[I_A(x')] \\ &= \frac{|A|^2|A'|^2}{NN'} \end{aligned} \tag{6.3}$$

and the variance of their product is given by [60]:

$$\begin{aligned}
\mathbf{Var}[I_{AA'}(x,x')] &= \mathbf{Var}[I_{A'}(x).I_A(x')] \\
&= \mathbf{E}[I_{A'}(x)]^2.\mathbf{Var}[I_A(x')] + \mathbf{E}[I_A(x')]^2.\mathbf{Var}[I_{A'}(x)] \\
&+ \mathbf{Var}[I_A(x')].\mathbf{Var}[I_{A'}(x)] \\
&= \frac{|A'|^2}{N'}.\frac{|A|^2(N-|A|)^2}{N^2(N-1)} \\
&+ \frac{|A|^2}{N}.\frac{|A'|^2(N'-|A'|)^2}{N'^2(N'-1)} \\
&+ \frac{|A'|^2(N'-|A'|)^2}{N'^2(N'-1)}.\frac{|A|^2(N-|A|)^2}{N^2(N-1)} \\
&= \frac{|A|^2.|A'|^2}{NN'}[\frac{(N-|A|)^2}{N(N-1)} + \frac{(N'-|A'|)^2}{N'(N'-1)} \\
&+ \frac{(N-|A|)(N'-|A'|)}{NN'(N'-1)(N-1)}]
\end{aligned} \tag{6.4}$$

By using the central limit theorem, we can conclude that the measure $I(A/A')$ could be approximated by a normal distribution $\mathcal{N}(\mu_{AA'}, \sigma^2_{AA'})$ defined by the expectation :

$$\begin{aligned}
\mu_{AA'} = \mathbf{E}[I(A/A')] &= \frac{1}{|A||A'|}\sum_{x\in A}\sum_{x'\in A'}\mathbf{E}[I_{A,A'}(x,x')] \\
&= \frac{(|A||A'|)^2}{NN'}
\end{aligned} \tag{6.5}$$

and the variance

$$\begin{aligned}
\sigma^2_{AA'} &= \mathbf{Var}[I(A/A')] \\
&= \mathbf{Var}[\frac{1}{|A||A'|}\sum_{x\in A}\sum_{x'\in A'} I_{A,A'}(x,x')] \\
&= \frac{1}{|A|^2|A'|^2}\mathbf{Var}[I_{A,A'}(x,x')] \\
&= \frac{1}{|A|^2|A'|^2}.[\frac{|A|^2.|A'|^2}{NN'}(\frac{(N-|A|)^2}{N(N-1)} \\
&+ \frac{(N'-|A'|)^2}{N'(N'-1)} + \frac{(N-|A|)(N'-|A'|)}{NN'(N'-1)(N-1)})] \\
&= \frac{1}{NN'}[\frac{(N-|A|)^2}{N(N-1)} \\
&+ \frac{(N'-|A'|)^2}{N'(N'-1)} + \frac{(N-|A|)(N'-|A'|)}{NN'(N'-1)(N-1)}]
\end{aligned} \tag{6.6}$$

As it is possible to relate all normal random variables to a standard normal, we can standardize the normally distributed variable $I(A/A')$ to a normal distribution function with expectation 0 and variance 1. The standard normal distribution Z will be defined by :

$$\begin{aligned} Z(A/A') &= \frac{I(A/A') - \mathbf{E}[I(A/A')]}{\sqrt{\mathbf{Var}[I(A/A')]}} \\ &= \frac{1}{\sqrt{\mathbf{Var}[I(A/A')]}}(I(A/A') - \frac{|A|^2|A'|^2}{NN'}) \end{aligned} \tag{6.7}$$

With expectation :

$$\begin{aligned} \mathbf{E}[Z(A/A')] &= \frac{1}{\sqrt{\mathbf{Var}[I(A/A')]}}(\mathbf{E}[I(A/A')] - \frac{|A|^2|A'|^2}{NN'}) \\ &= 0 \end{aligned} \tag{6.8}$$

And variance :

$$\begin{aligned} \mathbf{Var}[Z(A/A')] &= \mathbf{Var}[\frac{1}{\sqrt{\mathbf{Var}[I(A/A')]}}(I(A/A') - \frac{|A|^2|A'|^2}{NN'})] \\ &= (\frac{1}{\sqrt{\mathbf{Var}[I(A/A')]}})^2\mathbf{Var}[I(A/A')] \\ &= 1 \end{aligned} \tag{6.9}$$

Now that we have estimated the distribution of our intra-significance measure Z under the null hypothesis $\mathscr{H}$, we can estimate the precision score *a contrario* to $\mathscr{H}$ as follows :

$$\begin{aligned} P_{Z(A,A')}(z) &= \int_{-\infty}^{z} \frac{1}{\sqrt{2\Pi}} e^{-\frac{t^2}{2}} \, \mathrm{d}t \\ &= 1 - \phi(z) \end{aligned} \tag{6.10}$$

Where $\phi()$ is the cumulative distribution function of the standard normal distribution that describes probabilities for a random variable to fall within the interval $]-\infty, z]$.
$P_{Z(A,A')}(z)$ is the probability that $Z(A,A')$ does not exceed a threshold z under the null hypothesis $\mathscr{H}$. So that , $Pfa(z) = 1 - P_{Z(A,A')}(z)$ is the likelihood that A and A' are not a false alarms (i.e the likelihood that the subset A and A' were not generated by a random oracle).
$Pfa(z)$ can also be expressed in terms of the error function **erf** as follows:

$$Pfa(z) = \frac{1}{2} - \frac{1}{2}\mathbf{erf}(\frac{z}{\sqrt{2}}) \tag{6.11}$$

Having this likelihood of a false alarm under the null hypothesis, we can now determine our bipartite *a contrario* significance score as the complement of the Pfa :
Definition Bipartite *a contrario* significance :

$$\begin{aligned} S(A,A') &= 1 - Pfa(Z(A,A')) \\ &= 1 - \phi(Z(A,A')) \\ &= \frac{1}{2} + \frac{1}{2}\mathbf{erf}(\frac{Z(A,A')}{\sqrt{2}}) \end{aligned} \tag{6.12}$$

6.4 Clustering framework

Now that we have defined our extend significance measures for a bipartite graph, we can describe our clustering procedure. It is based on two main steps, *candidate cluster creation* and *redundant clusters merging*.

– **Candidate object cluster creation**: Any item $x_i \in X$ is considered as a candidate cluster center . For each item x_i selected as a candidate center, we would like to build a relevant bipartite candidate cluster C_i from the set of *neighbouring* items having at least one match in $F_{|k|}(x_i)$, i.e all the reverse shared neighbours of $F_k(x_i)$. Let us first denote as $R_k(x_i)$ this full set of candidate *neighboring* seeds:

$$R_k(x_i) = \left\{ x_j \in X \mid F_k(x_i) \cap F_k(x_j) \neq \emptyset \right\} \tag{6.13}$$

All these items in $R_k(x_i)$ matched on X' at least once as x_i, it is meaningful to consider them as candidate items for the object's cluster. However, many of them might match more to other items in X' than $F_k(x_i)$. We therefore would like to build the candidate cluster C_i as the optimal subset of $R_k(x_i)$ maximizing the significance measure. For that, we use an increasing value of k. By this, we begin by selecting the more efficient x'_j that maximize the bipartite *a contrario* significance. This means that in the same time, we progress one by one in $F_k(x_i)$ and for each one, first, not all items in $\bar{F_k}(x'_1)$ will be considered, but only the ones for which x'_1 belong to their F_1. If x_i belongs afterwards to a candidate cluster $|C_i|$, we will consider items if we select only its $|C_i|$ reverse nearest neighbours. This way, for example, if x_i match x'_1 as $\bar{F_k}(x'_1)$ for which x'_1 belongs to their $F_{|C_i|}$.
This is unfortunately a combinatorial problem that cannot be solved efficiently. We therefore propose to relax this objective by a greedy heuristic that locally selects optimal subsets of X when iterating on the neighbouring in X'.

For this, all neighbours in $F_k(x_i)$ are first ranked in decreasing order of their matching score $w_{i,j}$. The candidate cluster C_i is initialized by the central candidate seed x_i, i.e $C_i^0 = x_i$. The algorithm then iterates on the ranked items $F_k(x_i)$ by means of a counter t' from 1 to k and build locally the optimal cluster of a progressive size t as:

$$C_i^t = C_i^{t-1} \cup \underset{C_i \subset R_k(x_i)}{\operatorname{argmax}} \frac{1}{\sqrt{|C_i^{t-1}|}} \sum_{x_h \in \bar{F}_{t-1}(\forall x'_j \in F_{t'}(x_i))} SI(x_h, C_i^{t-1}/F_{t'}(x_i)) \qquad (6.14)$$

where the contribution SI is equal to:

$$SI(x_h, C_i^{t-1}/F_{t'}(x_i)) = \sqrt{\frac{X-1}{t}} \sum_{x_j \in C_i^{t-1}} (F_{t'}(x_j) \cap F_{t'}(x_h)) \qquad (6.15)$$

Intuitively, each step simply selects the optimal set of x_h that matched in their $F_{t'}$ on $F_{t'}(x_i)$ as x_i. The full algorithm stops when $C_i^t = C_i^{t-1}$ meaning that no improving items have been found from the ones matching the t'-th x'_j in $F_{t'}(x_i)$. At this step, any item $x_i \in X$ is associated with an approximate optimal cluster C_i. Candidate clusters are however still highly redundant since all similar items might produce very similar clusters. Next step is aimed at merging these candidate clusters.

– **Redundant object clusters merging**: For this step, we use a greedy strategy similar to the one in [73]. First, we sort all candidate clusters C_i by decreasing order of their bipartite *a contrario* significance score $S(C_i, F_{t'}(x_i))$ (Equation 6.12) and then iterate on them. If an encountered cluster has an intersection greater than a user-defined threshold with one of the previous clusters, it is merged with it. If not, it is considered as a new object cluster. To improve the quality of the final cluster when an encountered cluster has to be merged, we use a reshaping strategy: only the items of the new cluster that increase the intra-significance of the resulting cluster are kept as new items.

6.5 Contribution to the cluster : fast computing

In the mono-source shared neighbours clustering, when selecting the optimal neighbourhood, we needed to introduce a fast shared neighbours algorithm to compute the sum of intersection between an item and its variable neighbours from $k = [1..K]$.

In the bipartite case, the neighbours $x'_1, x'2, ..., x'_N$ of an item x_i belong to another disjoint set X'. During the clustering, we need to compute the contribution of an item x_h to the cluster C_i having as center the item x_i and this when iterating in the t' nearest neighbours in X' :

$$SI(x_h, C_i/F_{t'}(x_i)) = \sqrt{\frac{X-1}{|C_i|}} \sum_{x_j \in C_i} (F_{t'}(x_j) \cap F_{t'}(x_h))$$

We have to take into consideration the intersection of x_j with each item in the cluster C_i according to their nearest neighbours of size $t' = [1..k]$. The size of the cluster can increase as the size of nearest neighbours, when an item improve the quality of the cluster.

To avoid the repetitive computation of the intersection of an item to another item belonging to a cluster, we propose a new factorisation to accelerate the calculation of shared neighbours based on the same optimisation done in Section 4.4.

By this, the shared neighbours of two items for a variable size of neighbours from 1 to k is available and can be pre-computed once and used for the different experimentations with the same dataset.

Let us consider a bipartite graph (X, X') of size respectively N and N'. Each item $x \in X$ has list of K nearest neighbours in X'. The final shared neighbours algorithm can be summarized in :

Input: NN: the K-nearest matrix of size $(N \times K)$.

Init: $SNN = zeros(N, N, K)$.

Output: SNN

Algorithm 2 Fast shared neighbours from $k = 1$ to K

```
for x_i = 1 to N do
  for x_j = 1 to N do
    T = Zeros(N')
    for k = 1 to K do
      SNN(x_i, x_j, k) = SNN(x_i, x_j, k-1) { Initialisation from the k-1 iteration}
      T(NN(x_i, k)) += 1
      T(NN(x_j, k)) += 1
      if (NN(x_i, k) != NN(x_j, k)) then
        if (T(NN(x_i, k)) == 2) then
          SNN(x_i, x_j, k) += 1
        end if
        if (T(NN(x_j, k)) == 2) then
          SNN(x_i, x_j, k) += 1
        end if
      else
        if (T(NN(x_i, k)) == 2) then
          SNN(x_i, x_j, k) += 1
        end if
      end if
    end for
  end for
end for
```

We can remark that by using the recursion, we have just to compute the occurrence of the neighbours of the current rank.

6.6 Synthetic data experiments

In this experiment, we use synthetic data to illustrate the potential of our method compared to a spectral bipartite method from the state-of-the-art. Experiments on real data will be done in Section 8.1.

We built a synthetic bipartite graph $G(X, X'; E)$. The set X is composed of 1500 items clustered in 10 classes , each one composed of 150 items. In the other side, X' is composed of 1000 items, each item $x_i \in X$ match 100 items in X'.

To evaluate our bipartite shared neighbours clustering, we decided to compare it to another bipartite clustering algorithm. For this, we have chosen the well-known bipartite spectral graph partitioning algorithm of Dhillon [38]. The author studied the problem of clustering documents and words simultaneously. To solve the partitioning

problem, a spectral co-clustering algorithm is proposed that uses the second left and right singular vectors of an appropriately scaled word-document matrix to yield good bi-partitionings.

To understand more effectively, the impact of the neighbourhood size and quality on the two bipartite methods, we study the influence of parameters r and t. With each value of the couple (r,t), we use a **no-perfect and unstable oracle** to generate a set of K nearest neighbours for all the items.

We use $\theta_{Overlap}$ equal to 50% for our method. The number of classes is given to the used bipartite spectral clustering.

We compared the produced clusters with F1, AvgPurity and AvgCM applied on the extension parts of the bipartite clusters. We repeat the experiment several times for each value of (r,t) and take the average of evaluation measures at the end. Results are described respectively on Table 6.1, Table 6.2 and Table 6.3.

Our proposed bipartite shared nearest neighbours clustering returns automatically 10 clusters whereas this information is given as input for the bipartite spectral clustering method.

We can note that for each couple of (r,t), our bipartite SNN clustering outperforms the spectral clustering of Dhillon [38]. We can conclude that our method is more robust against noisy and unstable K-NN.

Even with $(r = 100\%, t = 100\%)$, this spectral clustering cannot find the perfect clusters whereas in with our bipartite SNN clustering, we obtained an optimal neighbourhood for each item. This confirms that only relevant items are selected when looking for the optimal neighbourhood. By eliminating redundant candidate clusters, we obtained all the classes.

	t=40%	t=60%	t=80 %	t=100 %
r=40%	0.39	0.48	0.87	1
r=60%	0.50	0.83	0.96	1
r=80%	0.68	0.91	0.98	1
r=100%	0.73	0.96	0.99	1

	t=40%	t=60%	t=80 %	t=100 %
r=40%	0.24	0.3	0.38	0.55
r=60 %	0.29	0.5	0.52	0.93
r=80 %	0.58	0.67	0.73	0.95
r=100 %	0.65	0.79	0.83	0.96

Table 6.1: AvgPurity measures of our bipartite SNN clustering (left) and of spectral bipartite clustering (right) on synthetic data.

6.7 Conclusion

In this chapter, we extend SNN methods to the context of bipartite k-NN graphs, i.e. when the neighbours of each item to be clustered lie in a disjoint set. We intro-

	t=40%	t=60%	t=80 %	t=100 %
r=40%	0.33	0.54	0.91	1
r=60 %	0.6	0.91	1	1
r=80 %	0.83	1	1	1
r=100 %	0.88	0.96	1	1

	t=40%	t=60%	t=80 %	t=100 %
r=40%	0.33	0.4	0.42	0.6
r=60 %	0.37	0.54	0.61	0.83
r=80 %	0.53	0.60	0.8	0.86
r=100 %	0.73	0.8	0.82	0.93

Table 6.2: F1 measures of our bipartite SNN clustering (left) and of spectral bipartite clustering (right) on synthetic data.

	t=40%	t=60%	t=80 %	t=100 %
r=40%	0.3	0.38	0.71	0.91
r=60 %	0.39	0.66	0.86	1
r=80 %	0.48	0.7	0.88	1
r=100 %	0.51	0.74	0.89	1

	t=40%	t=60%	t=80 %	t=100 %
r=40%	0.23	0.28	0.35	0.52
r=60 %	0.25	0.43	0.46	0.86
r=80 %	0.39	0.51	0.71	0.88
r=100 %	0.49	0.66	0.74	0.94

Table 6.3: AvgCM measures of our bipartite SNN clustering (left) and of spectral bipartite clustering (right) on synthetic data.

duce new SNN relevance measures revisited for this asymmetric context and show that they can be used to select locally optimal bipartite clusters. By using synthetic data, we compared our method to a the well-known bipartite spectral clustering [38]. We demonstrated that our method is more robust against noisy and unstable K-NN.
This contribution is still prospective and we believe it possible to find better algorithms for building optimal bipartite neighbourhoods for any item x. This would improve the intention part of our bipartite cluster.

Part III

Applications to visual content structuring

Chapter 7

Structuring visual contents with multi-source shared-neighbours clustering

7.1 Why use multi-source shared neighbours clustering ?

Exploiting the relationships of items according to an ensemble of modalities is very interesting : Two items can be closely related according to a specific source and completely disconnected according to another source. By using a multi-source shared neighbours representation, we can take advantage of these relationships on the same time and not by combining different classifiers. Our proposed multi-source shared neighbours clustering considers each modality as an oracle. These oracles are like a black box producing for each item its K nearest neighbours according to the feature and similarity measure of the oracle. The advantage of our multi-source SNN clustering algorithm is that the only input needed is these lists of neighbours without the need of knowing any information about the modality used. This point makes the clustering very useful whatever the modality. The interpretation of the result is another advantage of our clustering. By analysing the selected sources for each cluster, we can understand why a group of items is put together. By this, we can determine which sources are the mostly selected and which sources are discarded of the optimal selection of sources for each cluster. The relevancy of sources is then determined and can be used as *a priori* to eliminate or to keep it.

In the following section, we experiment our multi-source shared neighbours clustering in different applications to show how it can be used to structure items by using the

available sources of information.

7.2 Tree leaves Experiments

7.2.1 Motivation

To enable the accurate description and the identification of a plant species, one of the work of botanists for centuries is to observe and study the morphology of plants. They typically aim at finding visual elements characteristic of a group of plants to regroup them and separate them from other groups of plants at different levels of a taxonomic hierarchy (species, genus, family). Once these morphological categories are established, each species can be described as a composition of character states, including some memberships to morphological categories. The main goal of this experiment is to assist the construction of these characters and later to help building new identification keys or methods (e.g a sketch (robot portrait) [1]).

Discriminant botanical characters are generally difficult to define because they are very diverse (Figure 7.1). Indeed, they may concern different organs or parts of the plants: sometimes it is the bark that can be characteristic like the white trunk that is very marked of a birch, or rather the appearance of flowers such as the huge flowers of the *Magnolias*. These features can be sometimes very remarkable as for example the constant number 4 petals for all species of the family *Brassicaceae*. However, in some cases, the characteristic elements are much more difficult to be accessible for the novice such as cutting hair in an *oak leaf* pubescent to distinguish from other species of oak in the same form lobed leaf. In addition, when a group of botanist enters a new flora, such as trees of Guyana, we cannot know in advance what is the number and nature of morphological categories involved in the characterisation of these plants. For example, it is not relevant to distinguish a range of categories of types of teeth of leaf edges for a flora that is mostly not toothed edges. Note that botanists may miss relevant morphological characters that are not yet formalized.

The biggest difficulty is related to the amount of data to be analysed. Our proposed multi-source shared nearest neighbours clustering may reveal unsupervised classes considered as homogeneous in a completely automatic way, thereby assisting the botanists to identify and formalize the useful morphological categories to distinguish species. By using different visual sources, we aim to take advantage from each modality and to combine them efficiently to produce clusters. We do not use a concatenation

1. http://idao.cirad.fr/home

of features as done generally to cluster leaves but we look for homogeneous leaves groups that share some morphological properties. Each cluster represents correlated leaves thanks to an optimal subset of available sources.

7.2.2 Data and annotations

To illustrate the interest of our approach to this botanical problem, we were interested in the study of tree leaves, common in France. Leaves have several advantages to help identify a plant because they are often in large numbers on a plant for a long period of years, they are easy to pick, and are often flat which allows to acquire images in a controlled manner for instance with a scanner.
The advantage of studying the common trees of the French flora is that it has been well described for several centuries, and the main morphological categories can be used as ground truth for evaluating our method. Morphological attributes typically affect the overall shape of the leaves (round, elliptical, ovoid ...) as the shape of a sub part of the leaves (top, base, edges ...), or also the analysis of the rib, size, color,.., [43]. The purpose of this experiment is to see if we are able to find automatically the same categories established by botanists and this by unsupervised analysis of the visual content of leaves scans. If this experiment is successful, then we can consider replicating our approach on other flora, other organs.

The data used for this experiment comes from the *PlantLeaves* dataset [59], built

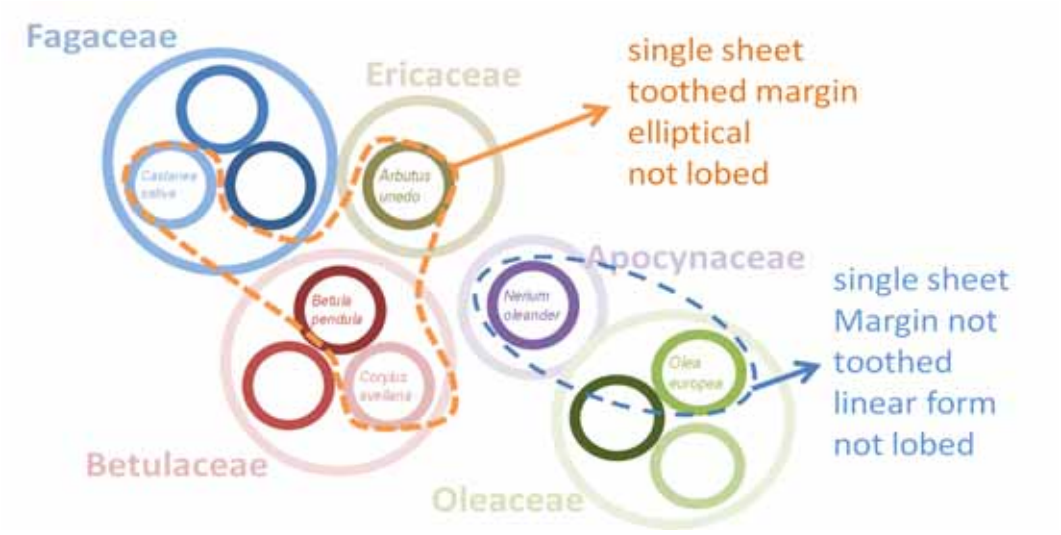


Figure 7.1: Example of categories sharing some morphological characters

collaboratively in the research project in computer-Botanical **Pl@ntNet** [5], and

used in the plant identification task organized within the international competition **ImageCLEF2011**. Initially, this dataset is dedicated to content-based identification of plant species but we benefit here only from the provided data. Morphological attributes of the leaves were actually not provided. We thus collaborate with some botanists to describe the morphological attributes of each species.
This experiment focuses on a sub part of the base *PlantLeaves*, more precisely the part containing only scans of leaves of 55 species and total number of 2228 images. Scans of leaves were collected over two seasons, between June and September, in 2009 and 2010, thanks to the work of active contributors from Tela Botanica social networks, which introduces a significant degree of morphological variability related to the different collection sites, like whose contributors have scanned the leaves, related to different devices, etc.
To assess the relevance of the results produced by our proposed method, we asked professional botanists to establish a *ground truth* focusing on the morphological aspects of the 55 species. They produce a state table of characters (0 or 1) under different aspect of a leaf. For example, a leaf of *Judea* is simple, non-toothed margin smooth, orbicular, not lobed, etc. The leaves of the same species may belong to several sub categories, especially in the case of single sheets or rather it expresses a range of possible states, even on the same tree such as leaves of laurel which leaves are from elliptic shape to lanceolate shape. The hierarchical list of the morphological aspects are described in the annexe Section 10.1.

7.2.3 Visual features

We use 5 different visual features to describe the scan of leaves, none of them being specialised for plant leaves recognition. We actually want to demonstrate that even without knowledge concerning the morphological attributes, we want to discover if our multi-source SNN clustering is able to produce meaningful categories from a botanical point of view.
Concretely, we used different types of local features:

- DIPOLE: refers to dissociated dipoles [83] around Harris points:It is mostly used in near duplicate search applications and is robust to many image distortions including partially affine transformation.
- SURF on Harris points: a successful state-of-the-art descriptor used in object recognition [6]. The source code of SURF was provided by the OpenSURF

library [2] on Harris point.

- SURF on SURF points: SURF is used for interest point detector and descriptor (By using a Hessian matrix-based measure for the detector, and a distribution-based for the descriptor).
- Differential invariant descriptor on Harris points: This feature is based on a characterization of the points of interest based on the differential invariants of Hilbert, with the color information. It involves the invariants first order and only two invariants specific color to ensure the invariance in translation and in rotation and a certain numerical stability [62].
- A concatenation of three standard histograms, usually used globally but used here locally: EOH, Fourier and Hough [49]. The Hough feature is a 16 dimensional histogram based on ideas inspired from the Hough transform and is used to represent simple shapes in an image. The Fourier feature is a Fourier histogram used as a texture descriptor describing the distribution of the spectral power density within the complex frequency plane. It can differentiate between the low, middle and high frequencies and between different angles the salient features have in a patch. Eoh feature is a 8 dimensional classical Edge Orientation Histogram used for describing shapes in images and gives here the distribution of gradients on 8 directions in a patch. They are extracted around each Harris point from an image patch oriented according to the principal orientation and scaled according to the resolution at which the Harris corner was detected. These features are computed in a fixed window size 65 centred with respect to interest points extracted using the Harris detector.

7.2.4 Matching schema and SNN parameters

Once the candidate features have been matched to their similar features in the database, we perform a geometric matching between the candidate image and the retrieved images. The parameters of a geometric transformation model are estimated for each retrieved image and the final similarity measure is computed by counting the number of matches that respect this model. The choice of the model characterizes the tolerated transformations. In this experiment, we considered resize, rotation, and translation for the spatial transformations. The parameters of this model are estimated for each retrieved image thanks to a random sample consensus algorithm (RANSAC [52]). Concerning the SNN clustering parameters, we used as maximum overlap be-

2. http://www.chrisevansdev.com/computer-vision-opensurf.html

tween clusters $\theta_{Overlap} = 20\%$ to have the more disjoint clusters representing the more representative categories in the base.

7.2.5 Results

The visual result 7.2 represent the 14 resulting clusters formed automatically with our clustering method. We show some scans of leaves in each cluster and we link them to the categories of ground truth. In green are indicated the states identified in the ground truth. In red, we suggested that states were not expressed in the ground truth in the goal to offer which would be visually remarkable and that would distinguish the clusters C11, C10, C0 and C4.
Some clusters contain many species, other single species. One can note a certain homogeneity at a first glance to each cluster. The organization as hierarchical tree is not computed automatically by our method but the one produced by the botanists themselves. We provide it only to show that the clusters produced by our method correspond to leaf-nodes of this tree.

It is important to note that all images of a cluster do not meet 100% of the indicated state, the majority state is used. For example, the cluster number 4 (C_4) contains 13 composed leaves and 255 simple leaves, which allows us to associate this cluster to the branch *simple leaves* in the visualization of results.
It was interesting groupings of species: maple leaf lobes are associated with the plane, which is quite consistent in terms of botany (a species of maple acer also called pseudo-Platanus, an another Acer platanoides). The morphological attribute trees for the cluster C_4 and C_2 are represented respectively in 7.3 and 7.4.
This experiment allows us to advance the interests of our clustering method for multi-modal analysis of morphological categories of plants. We have shown that by the analysis of multi-modal proximities of the visual content, we can find by totally unsupervised and fully automatic way the categories formalized by botanists gradually over the centuries.
During the clustering, each cluster selects the optimal combination of sources. By analysing the selected sources for each cluster, we discover the following result:

- The source 1 (the DIPOLE feature) is selected 13 times.
- The source 2 (the SURF feature on Harris points) is selected 14 times.
- The source 3 (the SURF feature on SURF points) is selected 14 times.
- The source 4 (the Differential invariant descriptor on Harris points) is selected 4 times.

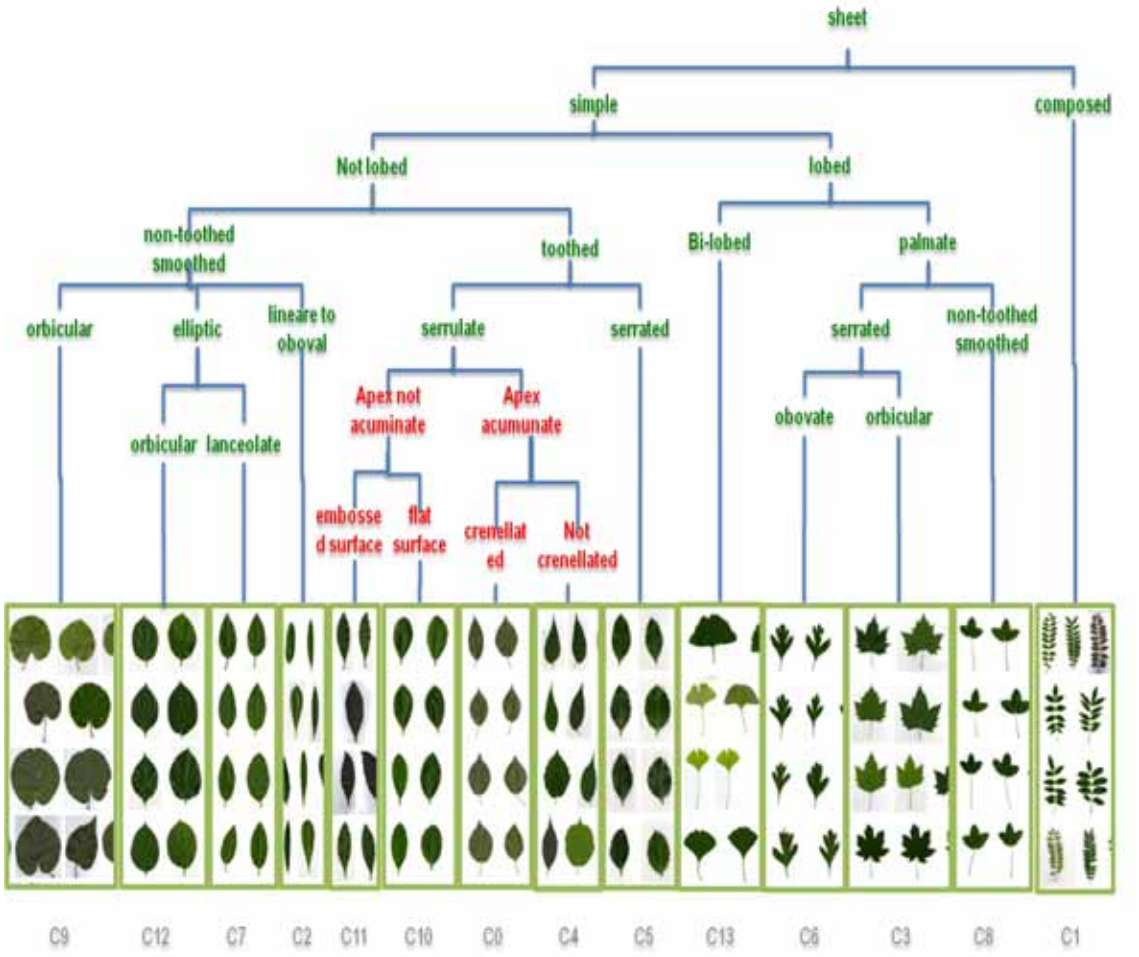


Figure 7.2: Hierarchical tree organization of the clusters produced by our SNN clustering method

– The source 5 (the concatenation of three standard histograms) is selected 14 times.

We can remark that the source 4 is selected only 4 times which is very low compared to the rest of sources. Two causes are possible :

– the source 4 is a redundant source and selecting it adds nothing to the cluster. The source is then ignored.
– the source 4 is irrelevant when is combined with the other sources and selecting it decreases the quality of the cluster. The source is discarded.

The approach requires additional validation of a larger amount of data, including more species in the goal of producing a finer division of the large amount of existing morphological categories. Ultimately, this approach could be integrated into a helper

application to the analysis and into the establishment of morphological categories of flora, including the flora being found in the tropics where a large number of species remains to discover.

A second perspective would be to integrate this clustering method in an identification system of species. The idea is to build as many binary classifiers as there are clusters estimated by the clustering method. An image to be identified would be associated with a set of outcomes. Afterwards each classifier measures the membership of the image to the morphological categories. The following results could then be exploited to develop a list of species most likely, those sharing the greatest number of similar morphological categories.

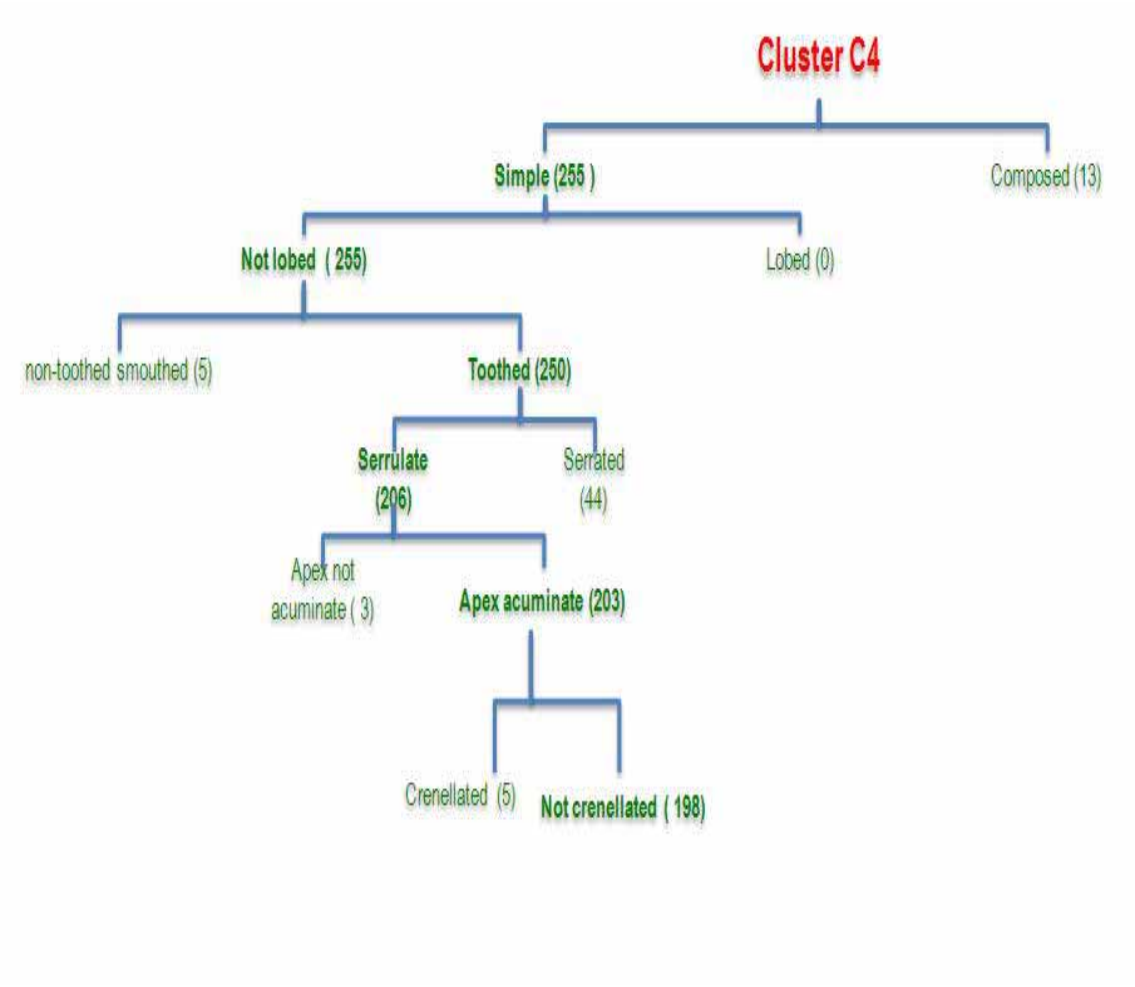


Figure 7.3: This cluster brought together mostly these species : Celtis australis species(54), Corylus avellana species(53), Castanea sativa species(44), Carpinus betulus species(33), Betula pendula species(14) because they shared essentially these morphological attributes (simple, not lobed, toothed, serrulated, apex accumulate, not crenellated).

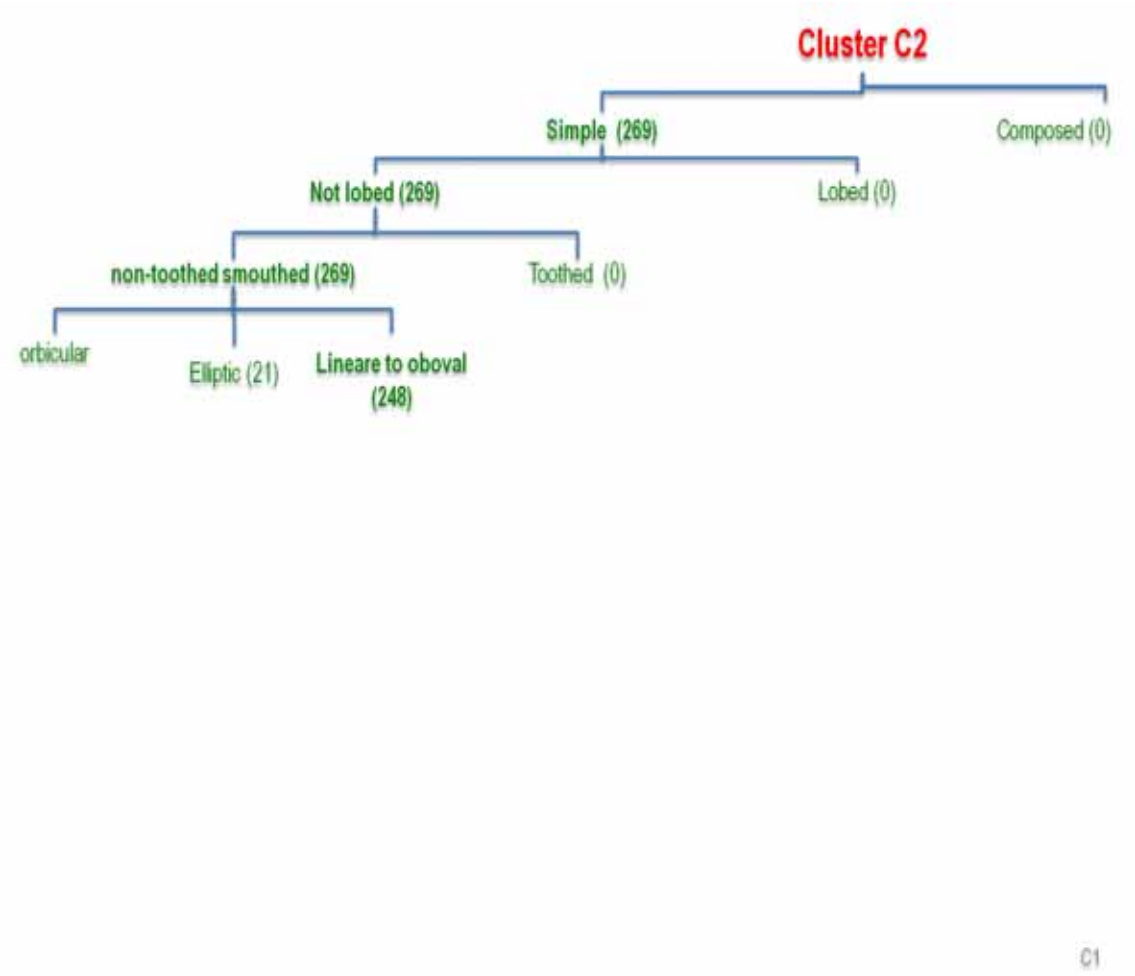


Figure 7.4: This cluster brought together mostly these species : Olea europaea species (131), Nerium oleander species (68), Pittosporum tobira (49) because they shared essentially these morphological attributes (simple, not lobed, non-toothed smoothed, lineare to oboval).

7.3 Multi-modal search result clustering

In this experiment, we suppose that a multi-modal search engine has *m* search services to which we can submit query objects, without any knowledge on underlying methods. The predominant method for image search results browsing is ranking-based list presentation. Due to the unsatisfactory performance of current ranking algorithm, it is time-consuming process for users to find images of interest in the returned garbage of images. Images can be re-organised and automatically structured into different clusters and presented to the user. In this manner, user is allowed to view the search results

through a few clusters rather than mixed images. Such re-organisation is very effective for browsing the search results. In the multi-modal case, images have a lot of properties which are quite different from a source of information to another. The goal is to benefit from all available sources of information which helps to have more meaningful information concerning the images. By considering all search services (information sources) as simple oracles returning ranked lists of relevant objects, we can do a multi-modal analysis and clustering especially towards exploiting the synergy between the various media including text and visual information or between any other sources of information.
Clustering approaches applied on different features have been studied severely before but the originality of our work is the use of the shared neighbourhood clustering that presents a lot of advantages (see Section 2.4.2) compared to the other clustering methods in a multi-source case where all the sources of information are tested with the intention of selecting the optimal combination of sources for each cluster. All resulting clusters have not necessarily contrary to other previous work the same selected sources. Figure 7.5 is an illustration of a multi-modal search clustering using only two sources of information : visual and textual services.

Because it is difficult to have ground truth on real search engine, we simulate the multi-modal clustering on the **Wikipedia** image dataset of ImageClef 2009 [3]. Initially, this dataset is dedicated to multi-modal *retrieval* evaluations but we benefit here from the provided annotations to build a text-image search results clustering task.
Among the full 150K images dataset, we keep only the images that have been effectively annotated during the pooling procedure, i.e the images that have been manually controlled as positive for at least one of the 44 query topics. The resulting dataset is composed of 1582 images categorized in 44 clusters. Each image is associated with textual information extracted from the initial Wikipedia web page (title, description, etc).
We used two information sources, one textual information source based on the *TF/IDF* similarity measure of *PF/Tijah* system [68]. One visual information source based on 5 global visual features (HSV Histogram [49], Hough histogram [49], Fourier histogram [49], edge orientation histogram [49] and probability weighted RGB histogram) and L1 metric as similarity measure.
We used the same F1 and AvgPurity metric as described before. Results are given in Table 7.1. Using visual source, the clustering return more relevant categories than

3. http://www.imageclef.org/2009/wiki

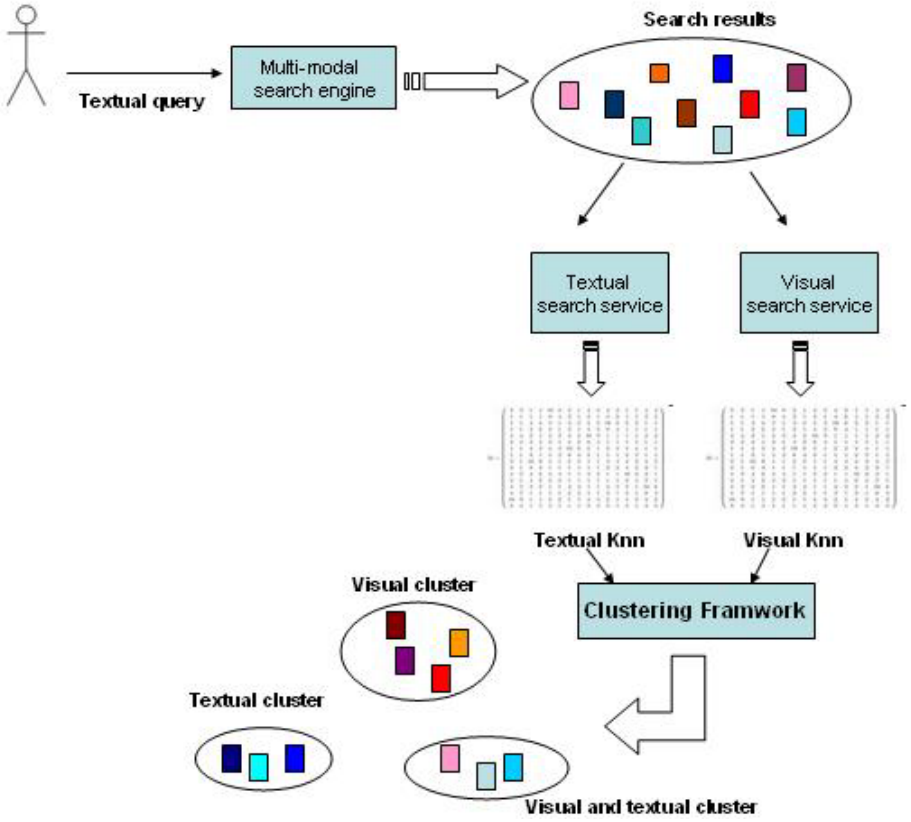


Figure 7.5: Illustration of a multi-modal search result clustering using visual and textual sources of information.

using textual source but clusters are less coherent. However, by combining the two modalities, the F1 measure and the average purity increase. The source selection step during the clustering process makes the results better than each single source. Clusters produced by selecting both of visual and textual sources are more semantically and visually coherent. The remaining clusters that select the visual source are visually coherent but not semantically while clusters using textual source are visually heterogeneous but semantically relevant.

Figure 7.6 is a part of the clustering result (the first four clusters) ranked in decreasing order quality. The oracle selection step opt for the optimal sources for every cluster. As it is shown, the first cluster (a) is semantically and visually coherent. For the second cluster (b), the textual source is selected because it is considered better than the combination with the visual source. Images are visually different but refer all to the keyword "Stamp". However, the third cluster (c) is visually consistent by semantically have a little sense. In the last cluster (d), images refer to the word "Dog" but are visually very

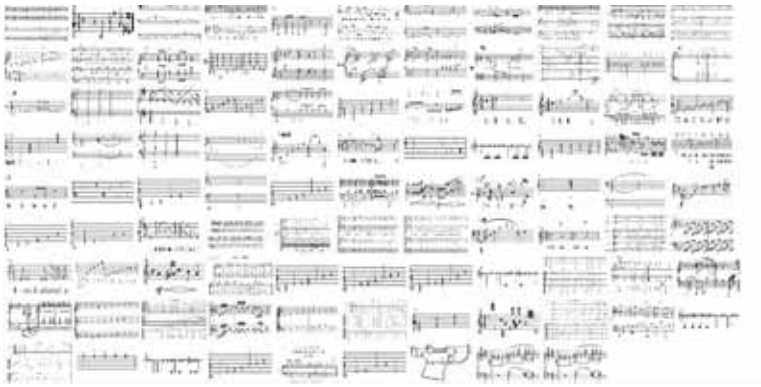
heterogeneous.

	Visual and Textual sources	Textual source	Visual source
F1	0.63	0.30	0.62
AvgPurity	0.55	0.51	0.35

Table 7.1: F1 and AvgPurity measures for the Sub set of Wikipedia ImageClef 2009.

7.4 Visual object mining

Keyword queries are usually ambiguous especially when they are short. This ambiguity often leads to unsatisfying search results. Many queries like “apple” covers several different topics: fruit, computer, smart-phone,and so on. In some cases, users prefers to have a list of the different categories returned in the search result than a mixed images with divers categories. The goal in this application is not to provide all clusters of the search results but a summarized list of the different topics of the query. Users can after easily figure out what they are exactly searching by selecting the target topic. Showing image from the target category in which the user is truly interested is much more effective and efficient than returning all clusters or all mixed images.
We performed a visual object mining experiment based on **Caltech256** dataset. Initially, this dataset was dedicated to supervised objects classification so that unsupervised clustering over the 256 classes provides too weak results for consistent analysis. We thus used this dataset in a different way to evaluate visual objects discovery in small image sets. This experiment is a simulation of a visual object mining and the goal is to evaluate the ability of our method to retrieve the categories. We collected 5 subsets of the Caltech256 dataset. Each subset is constructed from 10 random categories and 20 random images selected from the whole database. Each subset is typically like images that we could get from a previous textual search. The size of each subset is respectively 1792, 1581, 1221, 2098 and 1390 images. We used the same 5 global visual features as described in the previous experiment. Table 7.2 shows the performance comparison of our method and each visual feature. By combining the global visual features together, the F1 measure is better than that of each source. The “Fourier Histogram” performs better than the others mono-sources but remains lower than multi-source case.
The average selection of each visual global feature is reported in Table 7.3. As it is shown, the “HSV Histogram feature” is the most selected feature on average in this experiment. However, the “Prob-weighted Histogram RGB” feature is never selected



(a) Cluster Number 1: Oracle selection = Textual and visual sources , SSI(C1,F)= 328.936

(b) Cluster Number 2: Oracle selection = Textual source

(c) Cluster Number 3: Oracle selection = visual source

(d) Cluster Number 4: Oracle selection = Textual source

Figure 7.6: First four Clusters of the Wikipedia's subset clustering using visual and textual sources .

when it is combined with all the visual features because it provides no more relevance to the clusters.

	DB1	DB2	DB3	DB4	DB5	Avg
Multi-source	**0.38**	**0.37**	**0.56**	**0.27**	**0.57**	**0.43**
HSV Histogram	0.36	0.21	0.42	0.13	0.53	0.33
Hough Histogram	0.36	0.24	0.31	0.22	0.47	0.32
Fourier Histogram	0.35	0.34	0.54	0.24	0.50	0.39
Edge Orientation Histogram	0.35	0.24	0.35	0.15	0.54	0.32
Prob-weighted Histogram RGB	0.36	0.21	0.42	0.13	0.46	0.31

Table 7.2: Clustering results on F1 measure for the Sub sets of Caltech256.

Visual global feature	Average selection
HSV Histogram	0.56
Hough Histogram	0.26
Fourier Histogram	0.14
Edge Orientation Histogram	0.17
Prob-weighted Histogram RGB	0

Table 7.3: Average selection of each global visual feature in the Caltech Experiment.

7.5 Image clustering based on multiple randomized visual subspaces

7.5.1 Proposed method

Recently, researchers have begun paying attention to combine a set of individual classifiers in order to improve the overall classification accuracy. An ensemble of classifiers must be both diverse and accurate in order to improve the accuracy of the whole. Most of them use a simple vote from the output of each classifier to decide the final result. However, in our case, we combine the lists of K-NN and apply our single classifier once.

The idea of our method is to determine multiple K-NN lists. Every K nearest neighbours list is based on a random subset features selection. Then our oracle selection step selects the best K nearest neighbours among the available list of K-NN and thanks to the reshaping operation increases the accuracy of the class prediction.

We select the random subset of features by sampling from the original set of features. Each of the nearest neighbours list is computed using the same number of features, has access to all the patterns in the original training set but only to a random subset of

features.
Selecting different feature subsets is an attempt to make different and hopefully uncorrelated errors. However, there is no guarantee that using different features sets will decorrelate the error because in high dimensional data, many of the dimensions are often irrelevant. These irrelevant dimensions can confuse clustering algorithms by hiding clusters in noisy data but we think that our oracle selection step will make irrelevant sources less selected than relevant ones which increase cluster's quality.
In contrast to other dimensionality reduction techniques, like those based on projection (e.g. principal component analysis) or compression (e.g. using information theory), feature selection techniques do not alter the original representation of the variables, but merely select a subset of them. Thus, they preserve the original semantics of the variables, hence, offering the advantage of interpretation by a domain expert.
By using multiple subsets of features, our clustering approach tries to find clusters that exist in multiple possibly overlapping subspaces. The corresponding sources of clusters would indicate the key concept of the domain (keywords that are relevant for each cluster). This information can be very useful for the user and help him to have an idea of the cluster's category.
Generate K-NN on a high-dimensional feature tends to be computationally complex. For this reason, we search for a multiple K-NN on a subset of features instead of searching the K-NN on all the features. A high-dimensional feature like Bag-Of-Features allows to represent every image as a set of visual words, hence making it possible to describe them with a weighted vector. We choose this high-dimensional feature to experiment our method. The oracle selection and reshaping steps combine neighbours from multiple subset features to build the best K-NN in order to increase the quality of the candidate cluster. The redundant clusters elimination is then applied on the final K-NN lists to produce final clusters. Each cluster is constructed according to its optimal subset of features.

7.5.2 Experiment

We tested our proposed multiple random subset features clustering on a small subset of the large hand-labelled ImageNet dataset. ImageNet is an image dataset organized according to the WordNet hierarchy. Each meaningful concept in WordNet, is described by multiple words or word phrases. It is used on "PASCAL Visual Object Classes Challenge 2010" (VOC2010) [4].

4. http://www.image-net.org/challenges/LSVRC/2010/index

We use bag of visual words as features for our experiment. We extract 30 random subset features of the bag-of-words. Each subspace represents 10% of the full space. We use a sampling with replacement (a feature can be selected more than once). We then compute the k-nearest neighbours of each image according to the corresponding subset of features. Each *K*-NN according to a random subset feature is considered as a source of information.
We extract from the validation database of ImageNet (that consists of 200,000 photographs, collected from flickr and other search engines, hand labelled with the presence or absence of 1000 object categories) 500 items clustered in 10 categories

Table 7.4 reports the clustering results using on the one hand the full space and on the other hand a multiple random subset features varying from 2 to 30 sources. The results demonstrate that using multiple subset features is better than using the whole high dimensional feature. By using a number of sources at least equal to nearly 4 sources, the F1 measure, the average purity and the cosine measure exceed those of full space. As expected the performance of our method greatly increase by combining different source of information even if they are produced from the same feature. The reshaping step improves the quality of clusters by adding other elements from other sources. With 30 subspaces, The F1 measure, the average purity measure and the Average Cosine (F1=0.66, AvgPurity=0.26, AvgCosine = 0.33) increase and particularly the F1 measure was approximately doubled compared respectively to F1 measure of the full space (F1=0.30).

	F1	AvgPurity	AvgCosine Measure
Full Space	0.30	0.23	0.20
2 sources	0.17	0.17	0.16
4 sources	0.32	0.19	0.21
6 sources	0.54	0.21	0.23
8 sources	0.53	0.20	0.25
10 sources	0.66	0.21	0.28
20 sources	0.66	0.23	0.29
30 sources	0.66	0.26	0.33

Table 7.4: Multiple Random Subset features clustering result on ImageNet subset

Chapter 8

Structuring visual content with bipartite shared-neighbours clustering

8.1 Visual objects Discovery and Object-based Visual Query Suggestion

8.1.1 Introduction

State-of-the-art visual search systems allow to retrieve efficiently small rigid objects in very large datasets. They are usually based on the query-by-window paradigm: a user selects any image region containing an object of interest and the system returns a ranked list of images that are likely to contain other instances of the query object. User's perception of these tools is however affected by the fact that many submitted queries actually return nothing or only junk results (complex non-rigid objects, higher-level visual concepts, etc).

In this chapter, we address the problem of suggesting only the object's queries that actually contain relevant matches in the dataset. This requires to first discover accurate object's clusters in the dataset (as an off-line process); and then to select the most relevant objects according to user's intent (as an on-line process). We therefore introduce a new object's instances clustering framework based on a major contribution: a bipartite shared-neighbours clustering algorithm that is used to gather object's seeds discovered by matching adaptive and weighted sampling. We study a bipartite graph in the context of object's discovery. Experiments show that this new method outperforms state-of-the-art object mining and retrieval results on the Oxford Building dataset. We finally describe two object-based visual query suggestion scenarios using the proposed framework and show examples of suggested object queries.

8.1.2 New visual query suggestion paradigm

Large-scale object retrieval systems have demonstrated impressive performance in the last few years. The underlying methods, based on local visual features and efficient indexing models, can retrieve accurately small rigid objects such as logos, buildings or manufactured objects, under varying view pose and illumination conditions [131, 130, 80, 99, 132, 25, 84]. Therefore online object retrieval is now achievable up to 1 M images with a state-of-the-art computer [80].

From the usage point of view, these methods are usually combined with a *query-by-window* search paradigm. The user can freely select a region of interest in any image, and the system returns a ranked list of images that are the most likely to contain an instance of the targeted object of interest [132]. This paradigm has however several limitations related to user's perception: (i) When no (or very few) other instances of the query object exist in the dataset, the system mostly returns false positives making the user uncomfortable with the results. Indeed, he does not know if there are actually no other instances of the query object or if the system did not work correctly. (ii) When the user selects a deformable or complex object that the system is actually not able to retrieve, the system mostly returns false positives as well. As the user can freely select any object, this appears very frequently leaving the user with a bad impression of the effectiveness of the tool.

The second remark is even more critical if the user believes that the system can retrieve any semantically similar objects (e.g. object categories or visual concepts such as *cats* or *cars*). We do not argue here that such queries will never be solved effectively in the future. We just emphasize that bridging the gap between user's understanding of the system and the actual capabilities of the underlying tools is essential to make it successful in a real world search engine. A first possible solution to address these limitations would be to use some adaptive thresholding method, allowing only relevant results to be filtered, and possibly returning no results if none are found. The *a contrario* method of [84], for instance, allows the actual false alarm rate of rigid object instances retrieval to be controlled very accurately. But still, as the user can select any region of interest, the system might return no results in many cases and leave the user disappointed.

We propose to solve these user perception issues by a new visual query suggestion paradigm. Rather than letting the user select any region of interest, the system will suggest only visual query regions that actually contain relevant matches in the dataset. By mining offline object instances in the dataset, it is indeed possible to suggest to

the user only query objects having at least a prefixed number of instances in the collection. Figure 8.1 illustrates such suggested objects in several images. When a user clicks on a highlighted region, the system returns only the images containing other object instances of the same discovered cluster. From a user perception point of view, the proposed paradigm is very different to the window query paradigm. Indeed, since all suggested objects mostly return correct results, the user might rather perceive them as visual links (or *hyper-visual* links by analogy to hypertext links). To the best of our knowledge, this is the first work to detail a method for object-based visual query suggestion. Unlike existing approaches, the links produced by our method are not similarity links between images, but rather links between automatically localized images containing instances of the same rigid object. These object-based visual links can be used in many different retrieval paradigms. In this paper, we focus on two visual query suggestion scenarios showing the potential of the proposed method :

Mouse-over visual objects suggestion: when the user moves or *hovers* the mouse cursor over a particular image, the system suggests object queries by highlighting the object instances present in the image. The suggested objects do not depend on the preliminary textual query but are guaranteed to match some other instances in the collection (when the user clicks on one of them).

Text-aware visual objects suggestion: After a user submits a text query, the most frequent visual items discovered in the result list are suggested as new object-based visual queries (typically displayed as some clickable thumbnails on top of the result GUI). Images containing other instances of the suggested object are returned if the user clicks one.

Simple as it seems to be, moving from the free window-query paradigm to the object's suggestion paradigm is not trivial. Indeed, it first requires to discover accurate object's clusters in the dataset (typically as an off-line process), without any supervision and without knowledge on the location and the extent of the objects.

Therefore, this chapter introduces a new object's instances clustering framework based on two main steps:

Object's seeds discovery with adaptive weighted sampling: this step, proposed in [102], allows to discover small and rigid repeated patterns in the collection by randomly querying small image patches with an efficient geometric matching. In the next section 8.1.4, we summarize the work done by [102] and we use their result as input for our experimentations.

Bipartite shared-neighbours clustering: This proposed algorithm allows building full object's models by clustering the previously discovered object's seeds (Section

8.1.4).
Object's clusters will be used for the object-based visual query suggestion and for the object retrieval. Note that shared neighbours clustering methods were never been studied before in the case of bipartite graph and never been applied to object's discovery either.

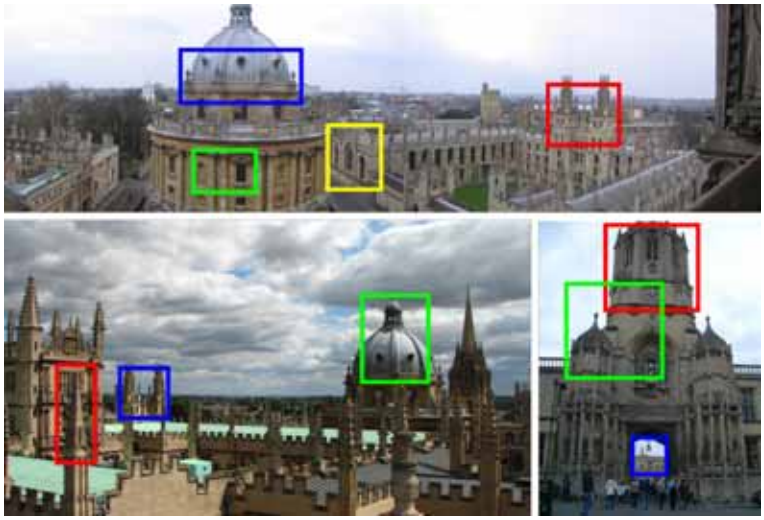


Figure 8.1: Discovered visual objects are displayed as links on which the user clicks to focus the retrieval on this specific object represented by a link-object.

8.1.3 Proposed visual query suggestion

Visual Query Suggestion was originally suggested in [184] by extension to Textual Query Suggestion methods that are now used in most existing search engines. The claim of the authors was that text-based predictive suggestion methods might sometimes not accurately express the intent of the users. By adding to the textual suggestion a set of representative pictures, the user can express his specific search intent more clearly. Their method was mainly based on global visual similarities using a joint text-image re-ranking for the retrieval. Our method differs in two main points: (i) we suggest purely visual queries (although the suggested queries can be computed according to the results of a textual query) (ii) the suggested visual queries represent object(s) in images and not global visual concepts associated to each image.
Beyond large-scale object retrieval methods discussed in the introduction [131, 130, 80, 99, 132, 25, 84], our work is more related to *object-based image clustering* and *unsupervised object mining* techniques [24, 133, 134, 163]. *Object-based image clus-*

tering attempts to cluster images that contain instances of the same object. Our objective differs in that we do not attempt to build image clusters but rather clusters of image *regions* containing instances of the same object. The problem to be solved is more challenging since the image regions to be clustered are not predefined entities (as images are). Therefore, image regions need to be segmented and clustered at the same time. This is basically what *object mining* methods are aimed at.
Many objects discovery method rely on graph-based clustering methods. They usually include a preliminary step allowing to discover object's seeds, i.e. spatially stable image regions in the collection. The main objective of this step is to build a matching graph that will be processed afterwards to cluster images or discover object instances. Similarly to some works using graph-based object mining mentioned in Section 3.3, our framework rely on two main steps: (i) building a matching graph by mining spatially consistent object seeds by using the method of [102] and (ii) post-processing the graph to build clusters of object's instances. But contrary to these methods, we formulate the problem as a bipartite graph clustering issue. Images are indeed considered as a first set of nodes, while object's seeds form a second disjoint one. Next section details the method used to discover object seeds and build the matching graph.

8.1.4 Building a matching graph and mining visual object seeds

As stated before, state-of-the-art large-scale object retrieval systems usually combine efficient indexing models with a spatial verification re-ranking stage to improve query performance [84, 130]. In the method that we used [102], authors suggested to use a such accurate two-stage matching strategy for building the input matching graph. The problem then rather becomes a sampling issue: how to effectively and efficiently select relevant query regions while minimizing the number of tentative probes. For this, they introduced an *adaptive weighted sampling* strategy.
Sampling is a statistical paradigm concerned with the selection of a subset of individual observations within a population of objects intended to yield some knowledge about the population without surveying it entirely. If all items have the same probability to be selected, the problem is known as uniform random sampling. In *weighted* sampling methods [123], the items might be weighted individually and the probability of each item to be selected is determined by its relative weight. In conventional sampling designs, either uniform or weighted, the selection for a sampling unit does not depend on the observations made during previous surveys. On the other hand, *Adaptive sampling* [152] is an alternative strategy aiming at selecting more relevant

sampling regions based on the results observed during the previous surveys.
The object seeds discovery method that we used is composed of three main stages processed at each iteration: *Adaptive Sampling* of a query image region, *Search* of the selected local query region and *Decision* of whether this query region might be considered as an object seed in the final output matching graph. The full algorithm repeats these 3 steps T times until a fixed number of seeds has been found.
More formally, let Ω be an input dataset of N images $\mathbf{I}_i$, $i \in 1,\ldots,N$.
Each image $\mathbf{I}_i$ is represented by a set of N_i local visual features $f_{i,j}$ (typically SIFT [108]) localized by their position $\mathbf{P}_{i,j}$. $N^f = \sum_{i=1}^{N} N_i$ is the total number of features $f_{i,j}$.
Each local feature $f_{i,j}$ is associated with a fixed candidate query region $\mathscr{R}_{i,j}$ defined as the bounding box centred around $\mathbf{P}_{i,j}$, with height $H_{i,j}$ and width $W_{i,j}$.
Finally, after T tentative probes, the algorithm outputs a set S of $|S| \leq T$ seeds S_j. Each seed corresponds to a spatially verified frequent visual pattern. A seed is associated with a query image region $\mathscr{R}_q^j$ and a set of M_j matching regions $\mathscr{R}_m^j$, $m \in 1,\ldots,M_j$.
The more the number of tentative probes is, the more a frequent object is likely to be considered as a seed. As this step of building matching graph is not our contribution, we will not detail more. See [102] for further explanation.

Although the discovered seeds correspond to consistent repeated patterns in the collection, they can still not be considered as full objects: (i) by construction, a seed usually covers only a subpart of an object instance with a loose localization, (ii) furthermore, due to the imperfect recall of the retrieval, a discovered seed matches only a subset of all instances in the dataset, (iii) finally, the more frequent an object is in the collection, the more redundant the discovered seeds are. Building accurate and complete object's model therefore requires to group all seeds belonging to the same object. This cannot be done according to the visual content of the seeds, since two seeds with distinct visual contents might still be two subparts of the same object. A more intuitive alternative is to group seeds that are matching correlated contents in the dataset, which can be formulated as a bipartite clustering problem. Figure 8.2 illustrates our proposed method to group seeds representing the same object.
Let us denote as $G = (X;E) = (I,S;E)$ the bipartite matching graph resulting from the object's seeds discovery, with

$$I = \{I_i\}_{i \in [1,N]}$$

the vertex set representing the images of the collection,

$$S = \{S_j\}_{j \in [1,|S|]}$$

the vertex set of the discovered seeds, $X = I \cup S$ and $I \cap S = \emptyset$. Each directed edge

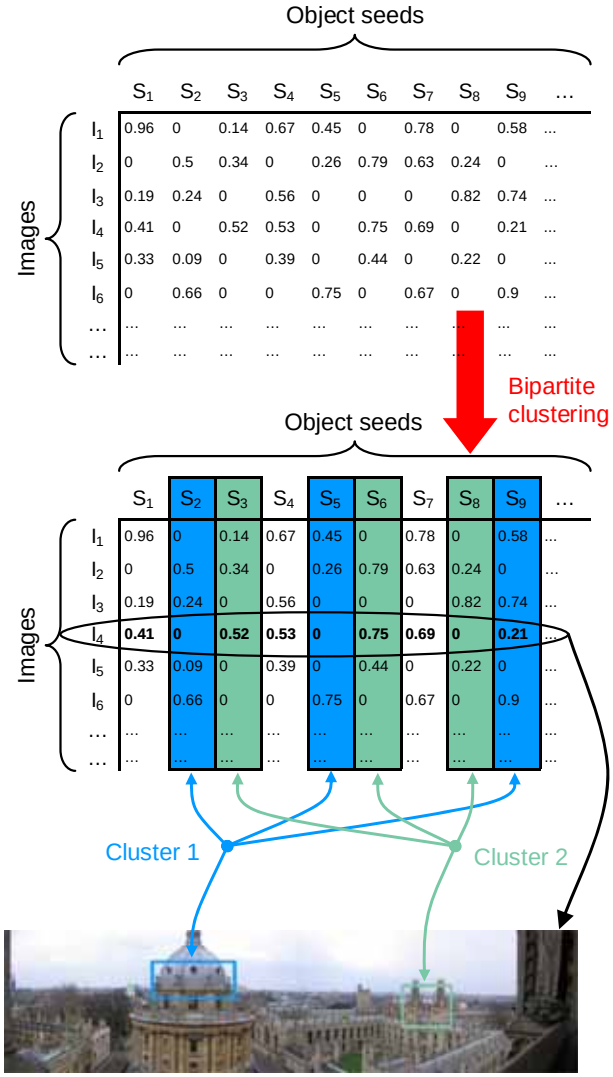


Figure 8.2: Illustration of the proposed method to suggest object-based visual queries in the image I_4. S_2, S_5 and S_9 belong to the cluster representig the same object by using the bipartite clustering. S_3, S_6 and S_8 represent seeds belonging to the second object in the image I_4.

$e_{i,j} \in E$ has a starting point in S, an endpoint in I and a weight $w_{i,j}$ corresponding to the matching score returned by the *a contrario* normalization method ($w_{i,j} = 0$ means that no edge connects seeds S_j to image I_i). The advantage of this bipartite representation it to allow formulating our seeds clustering objective as a *co-clustering* problem (or *dual subset clustering* [178]).

We indeed aim to find object clusters $O_n = (S^n, I^n)$ with $S^n \subset S$ being the subset of seeds modelling a given object and $I^n \subset I$ being the subset of images containing in-

stances of the object. An ideal object cluster is the one whose seeds are matching on the same images. It is important to notice the advantage over previous object mining methods using a single image-oriented matching graph [134, 24, 4, 63]: a given image can be accurately affected to several object clusters (when it contains instances of distinct objects). Furthermore, each object cluster is composed of a unique set of seeds associated with localized matching regions. As discussed in the next subsection, this will be useful for display purposes within our visual query suggestion scenarios.
Solving the bipartite clustering problem is not a trivial task. Some previous works proposed using spectral based techniques in the context of text documents clustering [177, 178]. These methods are useful to partition bipartite graphs in a prefixed number of balanced clusters but are not appropriated to our problem. The number of objects to be discovered as well as the number of seeds to be grouped within each object can indeed be highly variable. In addition, the results are very sensitive to the parameters used by these methods. This is why we proposed to use our new bipartite clustering algorithm described in Chapter 6 and inspired by Shared Nearest Neighbors (SNN) clustering methods [73, 65, 139].
The principle of our method as well as SNN algorithms in general is to group items not by virtue of their pairwise similarity but by the degree to which their neighbourhoods resemble one another. They are well known to overcome several shortcomings of classical clustering methods, notably high-dimensionality and similarity metrics limitation.

8.1.5 Object-based visual query suggestion

For each of the two visual query suggestion paradigms described in the introduction, we answer the following questions: What do we suggest? How do we display the suggestions? What do we return when the user clicks on a suggested object?

– **Mouseover visual objects suggestion** : For any image $I_j \in I$, we suggest queries. The number of these queries is equal to the number of clusters having I_j in their dual image set. Each cluster is represented by a rectangular window computed from the set of all regions that have been matched by the seeds of the cluster. Taking the bounding box of all matching regions would however be affected by outlier matches. We rather keep the bounding box of all pixels that are covered by at least 2 matching regions, as illustrated in Figure 8.3. When the user clicks on one of the suggested objects, we return a ranked list of images according to their intersection to the selected object (i.e. the number of seeds

matching with it or the sum of the corresponding matching weights).

Figure 8.3: Steps to obtain the suggested visual object on an image from BelgaLogos: i) selecting the bounding box, ii) intersection of bounding box , iii) keeping only the region that have been covered by at least two bounding box. The final result is the suggested object.

– **Text-aware visual objects suggestion**: We suppose that an external text-based search did already return a subset $I_x \subset I$ of images. We then select as suggested query objects the top M clusters of the dataset having the greatest intersection between the images in their dual representation and the text-based result list (i.e. the clusters representing the most frequent objects in the result list). Each suggested query object is displayed at the top of the search interface by a single representative thumbnail. This is done by first seeking the image that has the most intersection with the cluster (by mean of the number of seeds matching it) and then by cropping the object of interest in this image with the same procedure as the one described in the previous mouseover scenario. An illustration of resulting visual queries is given in Figure 8.4 for Oxford Buildings dataset. When the user clicks on one of the suggested object, we return as before a ranked list of images according to their intersection to the object.

8.2 Experiments

8.2.1 Experimental setup

Our method is demonstrated on three databases:

– Oxford Buildings: This dataset is described in [1] and consists of 5062 images of buildings from Oxford and miscellaneous images all retrieved from Flicker. A ground-truth is provided for 55 queries (11 different landmarks in Oxford). We describe the corpus with 30 million SIFT [108] features.

1. http://www.robots.ox.ac.uk/ vgg/data/oxbuildings/

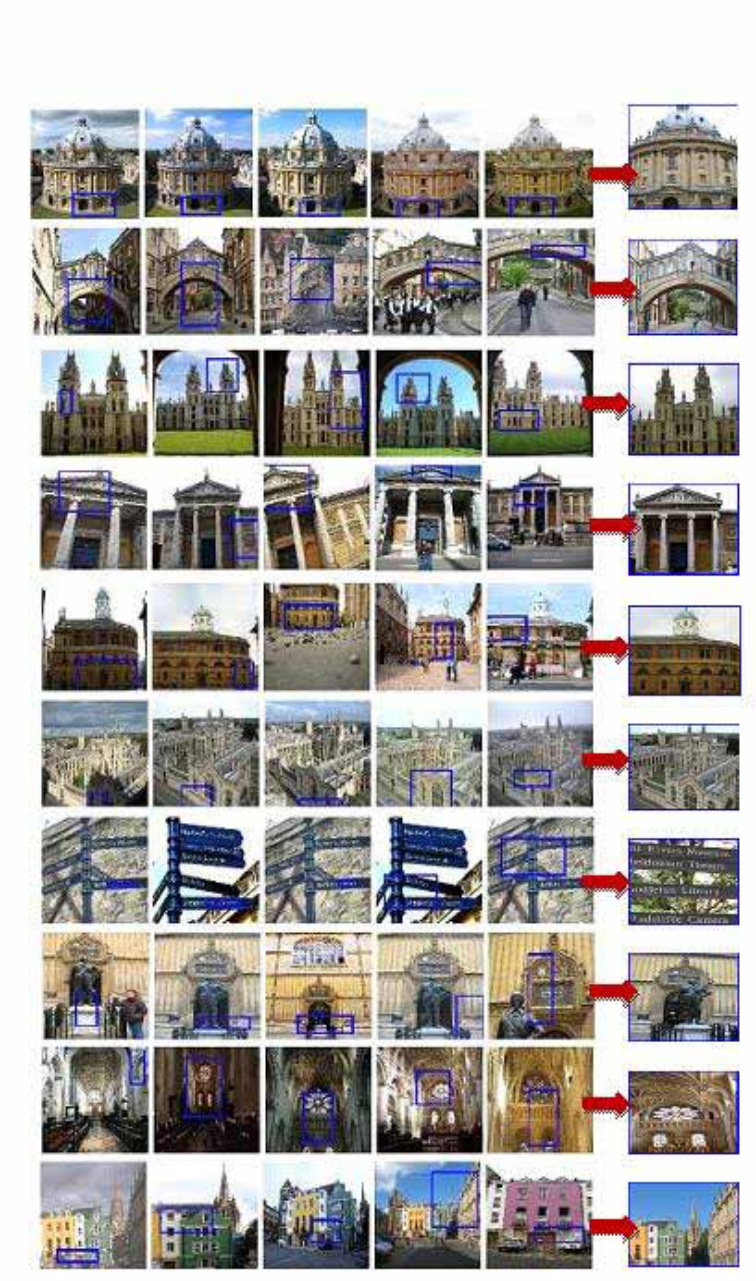


Figure 8.4: Some object clusters discovered in the Oxford Buildings Dataset. The top 4 rows clusters are in the ground truth. The fifth first columns are seeds examples of the cluster and the last column represents the suggested query object of each cluster.

– BelgaLogos: This dataset [2] is composed of 10,000 images. The images have been manually annotated for 26 logos. A given image can contain one or several

2. http://www-rocq.inria.fr/imedia/belga-logo.html

logos or no logo at all. We described this corpus with 38 millions of SIFT.

– GoogleCrawl: To illustrate the text-aware visual objects suggestion paradigm, we created a small dataset crawled from Google Image search engine using the five following queries: Metallica Concert, Green Peace, Disney, Khadafi, and World Cup. We described this dataset with 12 millions of SIFT.

For all experiments, the number of $|S|$ of seeds was set to 5K. Note that this vocabulary size is strongly lower than the sizes used by common bag-of-visual-word methods applied on Oxford Buildings dataset.

8.2.2 Clustering Performance evaluation

We first compared our clustering method to state-of-the-art objects mining methods [134, 24] on Oxford Buildings dataset. We used the same evaluation protocol as [134] and [24]: for each landmark, we found the cluster containing the most positive (Good and OK) images of that landmark and computed the fraction of positive ground truth images in this cluster.
Table 8.1 summarizes the results of our method and reproduces the results reported by Philbin *et al.* [134] and Chum *et al.* [24]. It shows that our method gives on average better performances than these two methods. It is clear that the overall gain of our method relies mainly on the two categories “Ashmolean” and “Magdalen” where other methods do not achieve good results. For “Ashmolean”, we scored a MAP of 0.9095 which is high compared to the best score (MAP= 0.68) of both Philbin *et al.* [134] and Chum *et al.* [24]. For “Magdalen” category, we scored a MAP of 0.7634 which is 3 times the score found by the best result (MAP =0.204) of both compared methods. The worst result we found is equal to 0.5847 for the “Balliol” category while the worst one for Philbin *et al.* [134] is equal to 0.204 and for Chum *et al.* [24] is equal to 0.0556 for the same category “Magdalen”.

This can be explained by the fact that these two methods combine bag-of-words indexing models with spatial verification re-ranking stage to improve query performance which gives a bad result if the initial results returned by the bag-of-words method are very bad while in our case we discover spatially verified visual words. The geometric consistency of the features points between patches make them consistent. So even if the building takes a small part in the image, by using small consistent objects, we can have cluster images that can be globally different but all containing the same object.

GroundTruth Object	Philbin *et al.* [134]	Chum *et al.* [24]	Our Proposed Method
All Souls	0.937	**0.9744**	0.9187
Ashmolean	0.627	0.68	**0.9095**
Balliol	0.333	0.3333	**0.5847**
Bodleian	0.612	**0.9583**	0.663
Christ Church	0.676	**0.8974**	0.599
Cornmarket	0.651	0.6667	**0.7449**
Heterford	0.705	**0.9630**	0.957
Keble	0.937	0.8571	**1**
Magdalen	0.204	0.0556	**0.7634**
Pitt Rivers	**1**	**1**	**1**
RadCliffe Camera	0.973	**0.9864**	0.9087
Average	0.696	0.7611	**0.8226**

Table 8.1: A comparison of the MAP clustering's results for the 5K Oxford Buildings dataset.

8.2.3 Retrieval performance evaluation

To evaluate the accuracy of our visual query suggestion method in terms of retrieval performances, we computed different MAP on Oxford Buildings dataset. We first evaluated the retrieval only for the common 55 queries, provided with their bounding boxes. We therefore select only the object's clusters discovered by our method that have one of the 55 image queries in their dual image set (as if the mouseover query suggestion scenario was applied to these images). In the first case, we considered as *clicked queries* only the object's clusters having a match within the bounding box. We then returned the list of matching images sorted by decreasing order of the matching score (i.e. the sum of weights $w_{i,j}$ over all seeds belonging to the selected clusters). Detailed results for each landmark are presented in Table 8.2. We also give in Table 8.3 the MAP over all queries compared to the retrieval results reported in Jegou et al. [80] and Philbin [130]. The results show that our method outperforms both methods.

To demonstrate that our proposed method is not only good for the common 55 queries but for any image, we then evaluated the retrieval in all images annotated to 1 in the groundtruth. Since we do not have bounding box with these images, we considered as *clicked queries* all objects suggested in these images. We also did the same for the 55 common queries for fair comparison. Results are reported in Table 8.4. They show that the MAP remains very good whereas some of the images belonging to the full groundtruth contain very small instances of the building, more partial views and more

GroundTruth Object	MAP
All Souls	0.967
Ashmolean	0.9045
Balliol	0.5594
Bodleian	0.922
Christ Church	0.8821
Cornmarket	0.7449
Heterford	0.9631
Keble	0.8736
Magdalen	0.7603
Pitt Rivers	1
RadCliffe Camera	0.9172
Average	0.8631

Table 8.2: Detailed MAP for the 12 landmarks of Oxford Buildings

	Jegou [80]	Philbin [134]	Our method
MAP	0.74	0.82	0.86

Table 8.3: A comparison of the MAP retrieval's results for the 5K Oxford.

complex view points. That is important in the sense that it proves the feasibility of our new object's suggestion paradigm. Whatever the object and the image in which we suggest a query, the returned results will be as good as if the user had selected himself one of the 55 windows queries.

	55 queries (with bounding box)	55 queries (without bounding box)	All images in ground truth
MAP	0.86	0.84	0.836

Table 8.4: MAP retrieval's results of the 55 queries compared to all images annotated to 1 of the ground truth. This means that whatever the object and the image in which we suggest a query, the returned results will be as good as if the user had selected himself one of the 55 windows queries

We finally computed some statistics on the produced clusters to evaluate the completeness of the suggested visual queries. Figure 8.5 gives the percentage of images

having equal or more than a number of suggested query objects denoted as *m*, for increasing values of m. It shows that when using only 5K seeds, 42 percent of the images have at least one suggested visual query. Remember that the number of seeds being a parameter of the method a more complete coverage can be simply obtained by running the seed's discovery algorithm longer. But, more we iterate, more we discover smaller and no frequent objects.

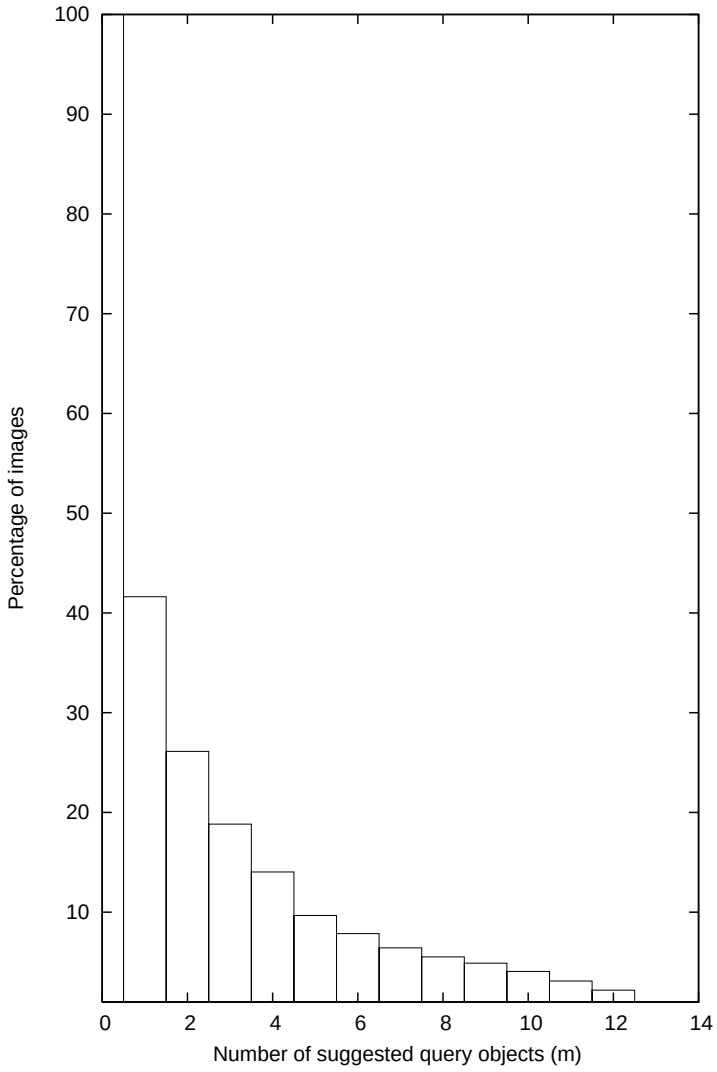


Figure 8.5: Histogram of the percentage of images that have more than m suggested query objects.

8.2.4 Visual query suggestion illustration

To illustrate qualitatively our suggested visual queries on other dataset, we used the BelgaLogos and GoogleCrawl datasets. The text-aware visual objects suggestion scenario is illustrated using the GoogleCrawl dataset. Figure 8.6 shows the top 3 suggested objects for each of the 5 text queries. To better understand what is *behind* such suggested objects we also provide in Figure 8.7, for 4 suggested queries, the top 3 images returned when the user clicks on them.

Figure 8.8 illustrates the Mouseover visual objects suggestion scenario on BelgaLogos dataset. The two first images are illustrations of images having two visual queries. The three last ones illustrate 3 other images with only one suggested visual query. The right column gives the top 3 returned images for each suggested query.

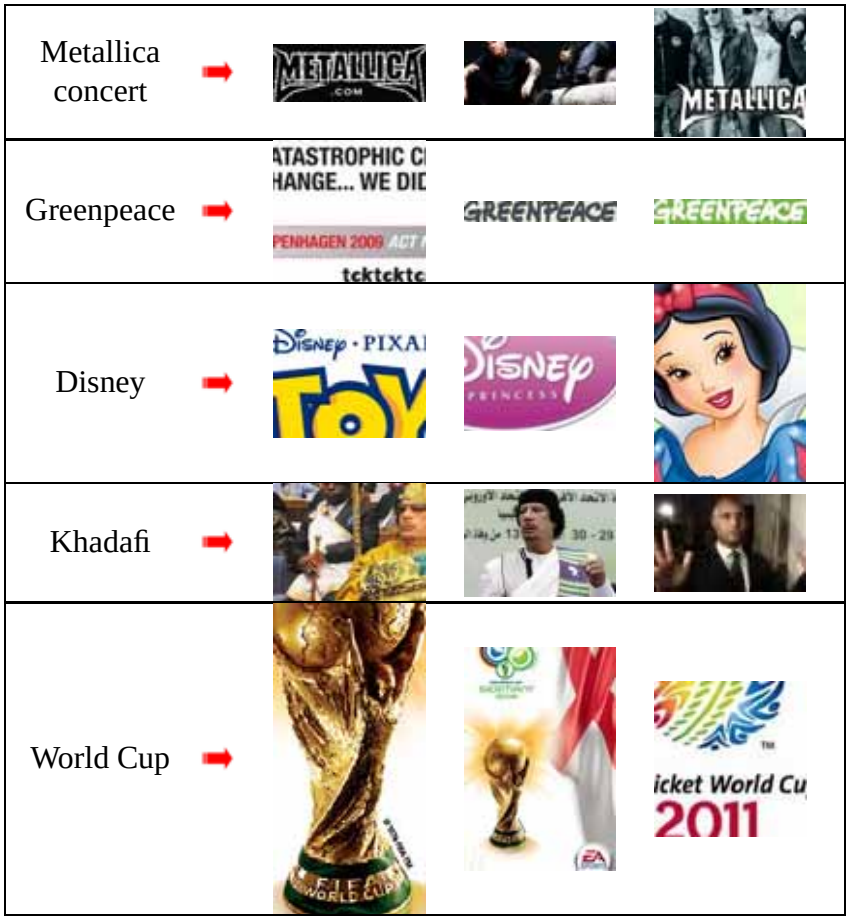


Figure 8.6: Some Suggested visual queries for each of the text-queries in the set of images crawled from Google Images.

Figure 8.7: Some suggested queries and the top three images returned for each one.

8.3 Conclusion

As future work, we plan to study the influence of the size and shape of the query region in the object seeds generation. Moreover, we plan to study the impact of the size of discovered seeds on the performance and accuracy of our approach.

Figure 8.8: Some discovered object clusters in BelgaLogos.

Part IV

Conclusion and perspectives

Chapter 9

Conclusion

9.1 Synthesis and conclusion

This thesis address the problem of content structuring and mining by using shared nearest neighbours clustering. Our motivation was that most classical data clustering often force particular choice of data representation and similarity measures. Such assumptions are particularly problematic in multimedia context that usually involves heterogeneous data and similarity measures. For this reason, we investigate new clustering paradigms and algorithms based on the principle of shared nearest neighbours (SNN) that are suitable to overcome data complexity, heterogeneity and high-dimensionality.

First, we proposed to revisit existing state-of-the-art shared neighbours methods in two points. We first introduce a new SNN formalism based on the theory of *a contrario* decision. This allows us to derive more reliable connectivity score that is used to select the optimum neighbourhoods. The advantage of using this *a contrario* significance score is that it not biased to the size of the clusters and it is interpretable. The idea is to select the best neighbourhood for each item and then to eliminate redundant candidate clusters by using a greedy strategy (beginning by the best ones) and a reshaping step that allows to add relevant items to final clusters from the deleted ones. We also proposed a new factorization algorithm for speeding-up the intensive computation of the required shared neighbours matrices. By using synthetic data, we demonstrated that our proposed method is able to select the best neighbourhood in presence of noisy source of K-nearest neighbours. Compared to the popular spectral clustering of Ng, Jordan and Weiss [121], we showed that our method is more robust and less sensitive to the size of the input graph.

The second contribution of this thesis is a generalisation of the proposed SNN cluster-

ing approach to the multi-source case. The main originality of our approach is that we introduced an information source selection step in the computation of the candidate cluster scores. Any arbitrary item set is thus associated with its own optimal subset of modalities maximizing a normalized multi-source significance measure. As shown in the synthetic data experiments, this source selection step makes our approach not only widely robust to the presence of locally outlier sources but also improves the quality of the clusters. We concluded that efficiently combining sources can compensate the weak quality of very noisy independent sources.

We applied our proposed multi-source shared nearest neighbours clustering to visual content structuring in different applications. In the tree leaves experiment, we aimed to help botanists to identify and formalize the useful morphological categories to distinguish species. The goal of our second multi-source application was to structure a content search results. By considering the visual and the textual informations of images, we obtained clusters that selected both of visual and textual sources and they were semantically and visually coherent. The remaining clusters that selected the visual source were visually coherent but not semantically while clusters using textual source were visually heterogeneous but semantically relevant. Such re-organisation is very effective for browsing the search results and very meaningful for users that has the information why images are grouped together. In the third experiment "visual object mining", we demonstrated that thanks to our source selection step, we can have some statistics about the used sources which can help users to select the best ones.

Finally, we focused our work to how extend SNN clustering to the context of bipartite k-NN graphs i.e. when the neighbours of each item to be clustered lie in a disjoint set. We introduced new SNN relevance measures revisited for this asymmetric context and showed that they can be used to select locally optimal bipartite clusters. By using synthetic data, we demonstrated that our bipartite SNN clustering performs the bipartite spectral clustering by selecting relevant items during the candidate object cluster creation. We applied our bipartite SNN clustering to visual object's discovery based on a randomly precomputed matching graph.

In comparison to recent work, experiments show that our method succeeds in increasing the clustering and the retrieval effectiveness by discovering frequent consistent visual objects seeds and grouping those that matched on the same images in the dataset. Based on the discovered objects, we also introduced a new visual search paradigm, i.e. object-based visual query suggestion. The idea is to suggest to the user some relevant objects to be queried as being the most frequent appearing in the full dataset or in a subset filtered by previous queries. Rather than letting the user select any region of in-

terest, the system will suggest only visual query regions that actually contain relevant matches in the dataset.
Along all these different applications in this PhD, we showed how the shared neighbours information has the potential to be used on different data representation and modalities and how our proposed methods whatever the context can deal with noisy data and produces relevant clusters.

9.2 Perspectives

As our shared nearest methods proposed in this PhD demonstrated their potential to select the optimal neighbourhood for each item, we plan to use these neighbourhood to construct the input graph for spectral clustering. By these way, we produce a graph easy to cluster and we improve the robustness of spectral method against noisy K-NN. Such optimal neighbourhood could be used in many application such as recommendation systems involving collaborative filtering or content-based filtering. P2P (peer to peer) recommendation systems could, for instance, allow to maintain efficiently the SNN graph through gossip-based operations.
In our next work, we will carry out more in-depth contribution on scalability which is the main limit of our proposed SNN method. We plan to test two idea : the first is to use hierarchical approach which deal with this problem and the second is to propose *a shared neighbour sensitive hashing*. The main idea is to use a hash function chosen such that points that share neighbours in the original space have a high probability of having the same hash value.
Finally, we want to extend our SNN method to supervised classification. Using SNN similarities might provide better performance than classical K-NN classifier, especially in multi-source context.

Chapter 10

Annexes

10.1 Hierarchical organisation of morphological properties of leaves

- margin
  - non-toothed and smooth
  - toothed
    - serrated
    - serrulated
    - crenellated
- Form sheet or leaflet
  - Elliptical
  - Orbicular
  - obovate
  - Linear
  - Lanceolate
  - Asymmetric
  - Lobed
- lobed form
  - not lobed
  - palmate
  - pinnate
  - lobed
- Color dark/clear
- Matt/gloss surface

- Presence of thorns
- Ribs
  - primary
  - secondary
- Apex
  - right
  - convex
  - acuminated
  - emarginated
  - lobed
- Base
  - right or Cune
  - concave
  - convex
  - concavo-convex
  - complex
  - decurrent
  - roped
  - lobed
  - runcinated
  - auriculated

Bibliography

[1] Charu C. Aggarwal, Alexander Hinneburg, and Daniel A. Keim. On the surprising behavior of distance metrics in high dimensional space. In *Lecture Notes in Computer Science*, pages 420–434. Springer, 2001.

[2] Vasilis Aggelis and Vasilis Christodoulakis. Customer clustering using rfm analysis. In *Proceedings of the 9th WSEAS International Conference on Computers*, ICCOMP'05, pages 2:1–2:5, Stevens Point, Wisconsin, USA, 2005. World Scientific and Engineering Academy and Society (WSEAS).

[3] Rakesh Agrawal, Johannes Gehrke, Dimitrios Gunopulos, and Prabhakar Raghavan. Automatic subspace clustering of high dimensional data for data mining applications. pages 94–105, 1998.

[4] A. Anjulan and N. Canagarajah. A unified framework for object retrieval and mining. *Circuits and Systems for Video Technology, IEEE Transactions on*, 19(1):63 –76, 2009.

[5] D. Barthélémy, N. Boujemaa, D. Mathieu, J.-F. Molino, A. Joly, Ph. Birnbaum, P. Bonnet, E. Mouysset, H. Goeau, and V. Roche. The pl@ntnet project: plant computational identification and collaborative information system. In *XVIII 18th International Botanical Congress*, Melbourne, Australia, Juillet 2011.

[6] Herbert Bay, Tinne Tuytelaars, and Luc Van Gool. Surf: Speeded up robust features. In *In ECCV*, pages 404–417, 2006.

[7] Ron Bekkerman and Jiwoon Jeon. Multi-modal clustering for multimedia collections. In *CVPR*. IEEE Computer Society, 2007.

[8] Mikhail Belkin and Partha Niyogi. Laplacian eigenmaps for dimensionality reduction and data representation. *Neural Computation*, 15:1373–1396, 2003.

[9] Pavel Berkhin. A survey of clustering data mining techniques. *Grouping Multidimensional Data*, pages 25–71, 2002.

[10] Kevin Beyer, Jonathan Goldstein, Raghu Ramakrishnan, and Uri Shaft. When is ”nearest neighbor” meaningful? In *In Int. Conf. on Database Theory*, pages 217–235, 1999.

[11] Chidansh Amitkumar Bhatt and Mohan S Kankanhalli. Multimedia data mining: state of the art and challenges. *Multimedia Tools and Applications*, 51(1):35–76, 2010.

[12] David M. Blei, Andrew Y. Ng, and Michael I Jordan. Latent dirichlet allocation. *J. Mach. Learn. Res.*, 3:993–1022, March 2003.

[13] Matthew Brand and Kun Huang. A unifying theorem for spectral embedding and clustering. 2003.

[14] M. R. Brito, E. L. Chávez, A. J. Quiroz, and J. E. Yukich. Connectivity of the mutual k-nearest-neighbor graph in clustering and outlier detection. *Statistics & Probability Letters*, 35(1):33–42, Aug 1997.

[15] Andrei Z. Broder. On the resemblance and containment of documents. In *In Compression and Complexity of Sequences (SEQUENCES97)*, pages 21–29. IEEE Computer Society, 1997.

[16] Jeremy Buhler. Efficient large-scale sequence comparison by locality-sensitive hashing. *Bioinformatics*, 17:419–428, 2001.

[17] Deng Cai, Xiaofei He, Zhiwei Li, Wei-Ying Ma, and Ji-Rong Wen. Hierarchical clustering of www image search results using visual, textual and link information. In *Proceedings of the 12th annual ACM international conference on Multimedia*, MULTIMEDIA ’04, pages 952–959, New York, NY, USA, 2004. ACM.

[18] A. Colin Cameron, Jonah B. Gelbach, and Douglas L. Miller. Robust Inference with Multi-Way Clustering. Technical Working Paper 327, National Bureau of Economic Research, September 2006.

[19] Laurent Candillier, Isabelle Tellier, Fabien Torre, and Olivier Bousquet. Cascade evaluation of clustering algorithms. In Johannes Frnkranz, Tobias Scheffer, and Myra Spiliopoulou, editors, *17th European Conference on Machine Learning (ECML’2006)*, volume LNAI 4212 of *LNCS*, pages 574–581, Berlin, Germany, september 2006. Springer Verlag.

[20] Frederic Cao, Julie Delon, Agnes Desolneux, Pablo Muse, and Frederic Sur. An a contrario approach to hierarchical clustering validity assessment. Technical report, INRIA, 2004.

[21] Wen-Yen Chen, Yangqiu Song, Yangqiu Bai, Chih-Jen Lin, and Edward Y. Chang. Parallel spectral clustering in distributed systems. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 33(3):568–586, March 2011.

[22] Y. Chen, J. Z. Wang, and R. Krovetz. Content-based image retrieval by clustering. In *in Proceedings of the 5th ACM SIGMM international workshop on Multimedia information retrieval*, page pp. 193 to 200, 2003.

[23] Shu ching Chen, Mei ling Shyu, Min Chen, and Chengcui Zhang. A decision tree-based multimodal data mining framework for soccer goal detection. In *Proc. of IEEE International Conference on Multimedia and Expo*, pages 265–268, 2004.

[24] O. Chum and J. Matas. Large-scale discovery of spatially related images. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 32:371–377, 2010.

[25] O. Chum, J. Philbin, J. Sivic, M. Isard, and A. Zisserman. Total recall: Automatic query expansion with a generative feature model for object retrieval. In *Proceedings of the 11th International Conference on Computer Vision*, 2007.

[26] O. Chum, J. Philbin, and A. Zisserman. Near duplicate image detection: min-hash and tf-idf weighting. In *British Machine Vision Conference*, 2008.

[27] Ondrej Chum, Michal Perdoch, and Jiri Matas. Geometric min-hashing: Finding a (thick) needle in a haystack. In *CVPR 2009*, 2009.

[28] F.R.K. CHUNG. Spectral graph theory. *CBMS 92, Amer. Math. Soc., Providence, 1997*, 1997.

[29] Scott D. Connell and Anil K. Jain. Writer adaptation of online handwriting models. *IEEE Transaction PAMI*, 24:2002.

[30] Daniel Crabtree, Peter Andreae, and Xiaoying Gao. Qc4 - a clustering evaluation method. In *The 11th Pacific-Asia Conference on Knowledge Discovery and Data Mining (PAKDD'07)*, pages 59–70, 2007.

[31] Gabriella Csurka, Christopher R. Dance, Lixin Fan, Jutta Willamowski, and Cdric Bray. Visual categorization with bags of keypoints. In *In Workshop on Statistical Learning in Computer Vision, ECCV*, pages 1–22, 2004.

[32] Ritendra Datta, Dhiraj Joshi, Li Jia, and James Z. Wang. Image retrieval: Ideas, influences, and trends of the new age. *ACM Comput. Surv.*, 40:5:1–5:60, May 2008.

[33] Franciska M. G. de Jong, Thijs Westerveld, and Arjen P. de Vries. Multimedia search without visual analysis: The value of linguistic and contextual information. *IEEE Trans. Circuits Syst. Video Techn.*, 17(3):365–371, 2007.

[34] Virginia R. de Sa. Spectral clustering with two views. In *ICML (International Conference on Machine Learning),Workshop on Learning with Multiple Views*, 2005.

[35] A. Desolneux, L. Moisan, and J.-M. Morel. Maximal meaningful events and applications to image analysis. In *Annals of Statistics*, page 31(6), 2003.

[36] Agnès Desolneux, Lionel Moisan, and Jean-Michel Morel. Edge detection by helmholtz principle. *J. Math. Imaging Vis.*, 14:271–284, May 2001.

[37] Inderjit Dhillon, Yuqiang Guan, and Brian Kulis. A unified view of kernel k-means, spectral clustering and graph cuts. Technical report, 2004.

[38] Inderjit S. Dhillon. Co-clustering documents and words using bipartite spectral graph partitioning. pages 269–274, 2001.

[39] Haoyang Ding, Jing Liu, and Hanqing Lu. Hierarchical clustering-based navigation of image search results. In *Proceedings of the 16th ACM international conference on Multimedia*, MM '08, pages 741–744, New York, NY, USA, 2008. ACM.

[40] D.L Donoho. High-dimensional data analysis: the curses and blessings of dimensionality. In *American Mathematical Society Conf. Math Challenges of the 21st Century*. 2000.

[41] Richard O. Duda, Peter E. Hart, and David G. Stork. *Pattern Classification (2nd Edition)*. Wiley-Interscience, November 2001.

[42] Charles Elkan. Using the triangle inequality to accelerate k-means, 2003.

[43] Beth Ellis. *Manual of leaf architecture*. Cornell paperbacks. Published in association with the New York Botanical Garden, 2009.

[44] Levent Ertoz, Michael Steinbach, and Vipin Kumar. A new shared nearest neighbor clustering algorithm and its applications. In *Workshop on Clustering High Dimensional Data and its Applications at 2nd SIAM International Conference on Data Mining*, 2002.

[45] Levent Ertoz, Michael Steinbach, and Vipin Kumar. Finding clusters of different sizes, shapes, and densities in noisy, high dimensional data. In *in Proceedings of Second SIAM International Conference on Data Mining*, 2003.

[46] Martin Ester, Hans peter Kriegel, Jrg S, and Xiaowei Xu. A density-based algorithm for discovering clusters in large spatial databases with noise. pages 226–231. AAAI Press, 1996.

[47] Fredrik Farnstrom, James Lewis, and Charles Elkan. Scalability for clustering algorithms revisited. *SIGKDD Explor. Newsl.*, 2:51–57, June 2000.

[48] Usama M. Fayyad, Gregory Piatetsky-Shapiro, and Padhraic Smyth. Advances in knowledge discovery and data mining. chapter From data mining to knowledge discovery: an overview, pages 1–34. American Association for Artificial Intelligence, Menlo Park, CA, USA, 1996.

[49] M. Ferecatu. *Image retrieval with active relevance feedback using both visual and keyword-based descriptors*. PhD thesis, Université de Versailles Saint-Quentin-en-Yvelines, jul 2005.

[50] Miroslav Fiedler. Algebraic Connectivity of Graphs. *Czechoslovak Mathematical Journal*, 23:298–305, 1973.

[51] Maurizio Filippone, Francesco Camastra, Francesco Masulli, and Stefano Rovetta. A survey of kernel and spectral methods for clustering. *Pattern Recogn.*, 41:176–190, January 2008.

[52] Martin A. Fischler and Robert C. Bolles. Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. *Commun. ACM*, 24(6):381–395, June 1981.

[53] Ronald A. Fisher. The use of multiple measurements in taxonomic problems. *Annals Eugen.*, 7:179–188, 1936.

[54] Pasquale Foggia, Gennaro Percannella, Carlo Sansone, and Mario Vento. A graph-based clustering method and its applications. In *Proceedings of the 2nd international conference on Advances in brain, vision and artificial intelligence*, BVAI'07, pages 277–287, Berlin, Heidelberg, 2007. Springer-Verlag.

[55] Chris Fraley and Adrian E. Raftery. Model-based clustering, discriminant analysis, and density estimation. *JOURNAL OF THE AMERICAN STATISTICAL ASSOCIATION*, 97:611–631, 2000.

[56] Ana L. N. Fred and Anil K. Jain. Data clustering using evidence accumulation. In *ICPR (4)*, pages 276–280, 2002.

[57] Bin Gao, Tie-Yan Liu, Tao Qin, Xin Zheng, Qian-Sheng Cheng, and Wei-Ying Ma. Web image clustering by consistent utilization of visual features and sur-

rounding texts. In *Proceedings of the 13th annual ACM international conference on Multimedia*, MULTIMEDIA '05, pages 112–121, New York, NY, USA, 2005. ACM.

[58] R. Ghaemi, N. Sulaiman, H. Ibrahim, and N. Mustapha. A survey: Clustering ensembles techniques. *PROCEEDINGS OF WORLD ACADEMY OF SCIENCE, ENGINEERING AND TECHNOLOGY*, 38, February 2009.

[59] Hervé Goëau, Alexis Joly, Souheil Selmi, Pierre Bonnet, Elise Mouysset, and Laurent Joyeux. Visual-based plant species identification from crowdsourced data. In *MM'11 - ACM Multimedia 2011*, Scottsdale, États-Unis, Nov 2011. ACM.

[60] Leo A. Goodman. On the Exact Variance of Products. *Journal of the American Statistical Association*, 55(292):708–713, December 1960.

[61] Luc Van Gool, Michael D. Breitenstein, Stephan Gammeter, Helmut Grabner, and Till Quack. Mining from large image sets. In *Proceedings of the ACM International Conference on Image and Video Retrieval*, CIVR '09, pages 10:1–10:8, New York, NY, USA, 2009. ACM.

[62] V. Gouet, P. Montesinos, and D. Pel. A fast matching method for color uncalibrated images using differential invariants. In *proceedings of British Machine Vision Conference, BMVC*, pages 367–376, Southampton, Royaume-Uni, septembre 1998.

[63] Kristen Grauman and Trevor Darrell. Unsupervised learning of categories from sets of partially matching image features. In *In CVPR*, 2006.

[64] Sudipto Guha, Rajeev Rastogi, and Kyuseok Shim. Cure: an efficient clustering algorithm for large databases. *SIGMOD Rec.*, 27:73–84, June 1998.

[65] Amel Hamzaoui, Alexis Joly, and Nozha Boujemaa. Multi-source shared nearest neighbours for multi-modal image clustering. *Multimedia Tools Appl.*, 51:479–503, January 2011.

[66] Jiawei Han and Micheline Kamber. *Data Mining: Concepts and Techniques (The Morgan Kaufmann Series in Data Management Systems)*. Morgan Kaufmann, 2000.

[67] J. A. Hartigan and M. A. Wong. A K-means clustering algorithm. *Applied Statistics*, 28:100–108, 1979.

[68] Djoerd Hiemstra, Henning Rode, Roel Van Os, and Jan Flokstra. Pftijah: text search in an xml database system. In *In Proceedings of the 2nd International Workshop on Open Source Information Retrieval (OSIR*, pages 12–17, 2006.

[69] Alexander Hinneburg, Charu C. Aggarwal, and Daniel A. Keim. What is the nearest neighbor in high dimensional spaces? In *Proceedings of the 26th International Conference on Very Large Data Bases*, VLDB '00, pages 506–515, San Francisco, CA, USA, 2000. Morgan Kaufmann Publishers Inc.

[70] Irving Hofman and Ray Jarvis. Robust and efficient cluster analysis using a shared near neighbours approach. In *Proceedings of the 14th International Conference on Pattern Recognition-Volume 1 - Volume 1*, ICPR '98, pages 243–, Washington, DC, USA, 1998. IEEE Computer Society.

[71] Thomas Hofmann. Probabilistic latent semantic indexing. In *Proceedings of the 22nd annual international ACM SIGIR conference on Research and development in information retrieval*, SIGIR '99, pages 50–57, New York, NY, USA, 1999. ACM.

[72] Thomas Hofmann. Unsupervised learning by probabilistic latent semantic analysis. *Mach. Learn.*, 42(1-2):177–196, January 2001.

[73] Michael E. Houle. The relevant-set correlation model for data clustering. *Stat. Anal. Data Min.*, 1:157–176, November 2008.

[74] Michael E. Houle, Hans-Peter Kriegel, Peer Kröger, Erich Schubert, and Arthur Zimek. Can shared-neighbour distances defeat the curse of dimensionality ? In *Proceedings of the 22nd international conference on Scientific and statistical database management*, SSDBM'10, pages 482–500, Berlin, Heidelberg, 2010. Springer-Verlag.

[75] L. Hubert and P. Arabie. Comparing partitions. *Journal of Classification*, 2:193–218, 1985.

[76] Anil K. Jain. Data clustering: 50 years beyond k-means. *Pattern Recognition Letters*, 31(8), 2010.

[77] R.A. Jarvis and E.A. Patrick. Clustering using a similarity measure based on shared near neighbors. *IEEE Transactions on Computers*, 22:1025–1034, 1973.

[78] Hervé Jégou, Matthijs Douze, and Cordelia Schmid. Hamming embedding and weak geometric consistency for large scale image search.

[79] Hervé Jégou, Matthijs Douze, and Cordelia Schmid. Hamming embedding and weak geometric consistency for large scale image search. In Andrew Zisserman

David Forsyth, Philip Torr, editor, *European Conference on Computer Vision*, volume I of *LNCS*, pages 304–317. Springer, oct 2008.

[80] Hervé Jégou, Matthijs Douze, and Cordelia Schmid. Improving bag-of-features for large scale image search. *International Journal of Computer Vision*, 87:316–336, 2010.

[81] Rongrong Ji, Hongxun Yao, Xiaoshuai Sun, Bineng Zhong, and Wen Gao. Towards semantic embedding in visual vocabulary. In *CVPR*, pages 918–925, 2010.

[82] Daxin Jiang, Chun Tang, and Aidong Zhang. Cluster analysis for gene expression data: A survey. *IEEE Trans. on Knowl. and Data Eng.*, 16:1370–1386, November 2004.

[83] Alexis Joly. New local descriptors based on dissociated dipoles. In *Proceedings of the 6th ACM international conference on Image and video retrieval*, CIVR '07, pages 573–580, New York, NY, USA, 2007. ACM.

[84] Alexis Joly and Olivier Buisson. Logo retrieval with a contrario visual query expansion. In *Proceedings of the 17th ACM international conference on Multimedia*, MM '09, pages 581–584, New York, NY, USA, 2009. ACM.

[85] Frederic Jurie and Bill Triggs. Creating efficient codebooks for visual recognition. In *In Proceedings of the IEEE International Conference on Computer Vision*, 2005.

[86] R. Kannan, S. Vempala, and A. Veta. On clusterings-good, bad and spectral. *Foundations of Computer Science, Annual IEEE Symposium on*, 0:367, 2000.

[87] Ravi Kannan, Santosh Vempala, and Adrian Vetta. On clusterings: Good, bad and spectral. *J. ACM*, 51:497–515, May 2004.

[88] Tapas Kanungo, David M. Mount, Nathan S. Netanyahu, Christine D. Piatko, Ruth Silverman, and Angela Y. Wu. An efficient k-means clustering algorithm: Analysis and implementation. *IEEE Trans. Pattern Anal. Mach. Intell.*, pages 881–892, 2002.

[89] David R. Karger and Clifford Stein. A new approach to the minimum cut problem. *J. ACM*, 43:601–640, July 1996.

[90] L. Kaufman and P. J. Rousseeuw. Finding groups in data: an introduction to cluster analysis. New York, NY, USA. John Wiley and Sons.

[91] Hideya Kawaji, Yosuke Yamaguchi, Hideo Matsuda, and Akihiro Hashimoto. A graph-based clustering method for a large set of sequences using a graph partitioning algorithm. *Genome Informatics*, 12:93–102, 2001.

[92] Lyndon S. Kennedy and Mor Naaman. Generating diverse and representative image search results for landmarks. In *Proceeding of the 17th international conference on World Wide Web*, WWW '08, pages 297–306, New York, NY, USA, 2008. ACM.

[93] Eamonn Keogh, Kaushik Chakrabarti, Michael Pazzani, and Sharad Mehrotra. Dimensionality reduction for fast similarity search in large time series databases. *Knowledge and Information Systems*, 3(3):263–286, August 2001.

[94] Eamonn Keogh, Kaushik Chakrabarti, Michael Pazzani, and Sharad Mehrotra. Dimensionality reduction for fast similarity search in large time series databases. *Knowledge and Information Systems*, 3(3):263–286, aug 2001.

[95] M. L. Kherfi, D. Ziou, and A. Bernardi. Image retrieval from the world wide web: Issues, techniques, and systems. *ACM Comput. Surv.*, 36:35–67, March 2004.

[96] Young-Min Kim, Massih-Reza Amini, Cyril Goutte, and Patrick Gallinari. Multi-view clustering of multilingual documents. In *Proceedings of the 33rd international ACM SIGIR conference on Research and development in information retrieval*, SIGIR '10, pages 821–822, New York, NY, USA, 2010. ACM.

[97] Yuval Kluger, Ronen Basri, Joseph T. Chang, and Mark Gerstein. Spectral biclustering of microarray cancer data: Co-clustering genes and conditions. *Genome Research*, 13:703–716, 2003.

[98] Ravi Kumar, Andrew Tomkins, and Erik Vee. Connectivity structure of bipartite graphs via the knc-plot. In *Proceedings of the international conference on Web search and web data mining*, WSDM '08, pages 129–138, New York, NY, USA, 2008. ACM.

[99] Yin-Hsi Kuo, Kuan-Ting Chen, Chien-Hsing Chiang, and Winston H. Hsu. Query expansion for hash-based image object retrieval. In *Proceedings of the 17th ACM international conference on Multimedia*, MM '09, pages 65–74, oct 2009.

[100] Tilman Lange, Volker Roth, Mikio L. Braun, and Joachim M. Buhmann. Stability-based validation of clustering solutions, 2004.

[101] Bjornar Larsen and Chinatsu Aone. Fast and effective text mining using linear-time document clustering. In *Proceedings of the fifth ACM SIGKDD international conference on Knowledge discovery and data mining*, KDD '99, pages 16–22, New York, NY, USA, 1999. ACM.

[102] Pierre Letessier, Olivier Buisson, and Alexis Joly. Consistent visual words mining with adaptive sampling. In *Proceedings of the 1st ACM International Conference on Multimedia Retrieval*, ICMR '11, pages 49:1–49:8, New York, NY, USA, 2011. ACM.

[103] Michael S. Lew, Nicu Sebe, Chabane Djeraba, and Ramesh Jain. Content-based multimedia information retrieval: State of the art and challenges. *ACM Trans. Multimedia Comput. Commun. Appl.*, 2:1–19, February 2006.

[104] Cheng-Ru Lin, Ken-Hao Liu, and Ming-Syan Chen. Dual clustering: Integrating data clustering over optimization and constraint domains. *IEEE Trans. on Knowl. and Data Eng.*, 17:628–637, May 2005.

[105] David Liu and Tsuhan Chen. A topic-motion model for unsupervised video object discovery. In *CVPR*, 2007.

[106] Yi Liu, Joyce Y. Chai, and Rong Jin. Automated vocabulary acquisition and interpretation in multimodal conversational systems, 2008.

[107] Lszl Lovsz. Random walks on graphs: A survey. In *Combinatorics, Paul Erdős is Eighty*, volume 2, pages 353–398. János Bolyai Mathematical Society, Budapest, 1996.

[108] David Lowe. Object recognition from local scale-invariant features. pages 1150–1157, 1999.

[109] David G. Lowe. Distinctive image features from scale-invariant keypoints. *Int. J. Comput. Vision*, 60:91–110, November 2004.

[110] Ulrike Luxburg. A tutorial on spectral clustering. *Statistics and Computing*, 17:395–416, December 2007.

[111] Markus Maier, Ulrike von Luxburg, and Matthias Hein. How the result of graph clustering methods depends on the construction of the graph. Technical Report arXiv:1102.2075, Feb 2011.

[112] Marina Maila and Jianbo Shi. A random walks view of spectral segmentation. In *AI and STATISTICS (AISTATS)*, 2001.

[113] Julien Mairal, Francis Bach, Jean Ponce, Guillermo Sapiro, and Andrew Zisserman. Supervised dictionary learning. Research Report RR-6652, INRIA, 2008.

[114] K. Mikolajczyk, T. Tuytelaars, C. Schmid, A. Zisserman, J. Matas, F. Schaffalitzky, T. Kadir, and L. Van Gool. A comparison of affine region detectors. *Int. J. Comput. Vision*, 65:43–72, November 2005.

[115] Krystian Mikolajczyk. Multiple object class detection with a generative model. In *In CVPR*, pages 26–36, 2006.

[116] P.-A Moellic, J.-E. Haugeard, and G. Pitel. Image clustering based on a shared nearest neighbors approach for tagged collections. In *Proceedings of the 2008 international conference on Content-based image and video retrieval*, pages 269–278. ACM, 2008.

[117] F. Moosmann, W. Triggs, F. Jurie, and M. Vision. Randomized clustering forests for building fast and discriminative visual vocabularies.

[118] Frank Moosmann, Bill Triggs, and Frederic Jurie. Fast discriminative visual codebooks using randomized clustering forests. In *In NIPS*, 2007.

[119] Marius Muja and David G. Lowe. Fast approximate nearest neighbors with automatic algorithm configuration. In *In VISAPP International Conference on Computer Vision Theory and Applications*, pages 331–340, 2009.

[120] M. E. J. Newman. Properties of highly clustered networks. *Phys. Rev. E*, 68:026121, Aug 2003.

[121] A Y Ng, M I Jordan, and Y. Weiss. On spectral clustering: Analysis and an algorithm. *Advances in Neural Information Processing Systems*, 14(14):849856, 2001.

[122] David Nister and Henrik Stewenius. Scalable recognition with a vocabulary tree. In *Proceedings of the 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition - Volume 2*, CVPR '06, pages 2161–2168, Washington, DC, USA, 2006. IEEE Computer Society.

[123] Frank Olken. *Random Sampling from Databases*. PhD thesis, U.C. Berkeley, 1993.

[124] Kohei Ozaki, Masashi Shimbo, Mamoru Komachi, and Yuji Matsumoto. Using the mutual k-nearest neighbor graphs for semi-supervised classification of

natural language data. In *Proceedings of the Fifteenth Conference on Computational Natural Language Learning*, CoNLL '11, pages 154–162, Stroudsburg, PA, USA, 2011. Association for Computational Linguistics.

[125] Joohyoun Park and Jongho Nang. A novel approach to collect training images from www for image thesaurus building 2007. In *Computational Intelligence in Image and Signal Processing, 2007. CIISP 2007. IEEE Symposium on*, 2007.

[126] Lance Parsons, Ehtesham Haque, and Huan Liu. Subspace clustering for high dimensional data: a review. *SIGKDD Explor. Newsl.*, 6:90–105, June 2004.

[127] Nilesh Patel and Ishwar Sethi. Multimedia data mining: An overview. In Valery A. Petrushin and Latifur Khan, editors, *Multimedia Data Mining and Knowledge Discovery*, pages 14–41. Springer London, 2007.

[128] Karl Pearson. On lines and planes of closest fit to systems of points in space. *Philosophical Magazine*, 2:559–572, 1901.

[129] Florent Perronnin, Christopher Dance, Gabriela Csurka, and Marco Bressan. Adapted vocabularies for generic visual categorization. In *In ECCV*, pages 464–475, 2006.

[130] J. Philbin. *Scalable Object Retrieval in Very Large Image Collections*. PhD thesis, University of Oxford, 2010.

[131] J. Philbin, O. Chum, M. Isard, J. Sivic, and A. Zisserman. Lost in quantization: Improving particular object retrieval in large scale image databases. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2008.

[132] J. Philbin, O. Chum, J. Sivic, M. Isard, and A. Zisserman. Object retrieval with large vocabularies and fast spatial matching. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2007.

[133] J. Philbin, J. Sivic, and A. Zisserman. Geometric LDA: A generative model for particular object discovery. In *Proceedings of the British Machine Vision Conference*, 2008.

[134] J. Philbin and A. Zisserman. Object mining using a matching graph on very large image collections. In *Proceedings of the Indian Conference on Computer Vision, Graphics and Image Processing*, 2008.

[135] T. Quack, V. Ferrari, and L. Van Gool. Video mining with frequent itemset configurations. In *5th International Conference on Image and Video Retrieval, CIVR 2006, Phoenix, July 13-15, 2006*, July 2006.

[136] Till Quack, Bastian Leibe, and Luc Van Gool. World-scale mining of objects and events from community photo collections. In *Proceedings of the 2008 international conference on Content-based image and video retrieval*, CIVR '08, pages 47–56, New York, NY, USA, 2008. ACM.

[137] Thanh Tho Quan, Siu Cheung Hui, and Alvis Cheuk M. Fong. *Mining Multiple Clustering Data for Knowledge Discovery*. 2003.

[138] P. Quelhas, F. Monay, J.-M. Odobez, D. Gatica-Perez, T. Tuytelaars, and L. Van Gool. Modeling scenes with local descriptors and latent aspects. In *Proceedings of the Tenth IEEE International Conference on Computer Vision (ICCV'05) Volume 1 - Volume 01*, pages 883–890, Washington, DC, USA, 2005. IEEE Computer Society.

[139] Sudipto Guha Rajeev, Rajeev Rastogi, and Kyuseok Shim. Rock: A robust clustering algorithm for categorical attributes. In *Information Systems*, pages 512–521, 1999.

[140] William M. Rand. Objective Criteria for the Evaluation of Clustering Methods. *Journal of the American Statistical Association*, 66(336):846–850, 1971.

[141] Manjeet Rege, Ming Dong, and Jing Hua. Clustering web images with multimodal features. In *Proceedings of the 15th international conference on Multimedia*, MULTIMEDIA '07, pages 317–320, New York, NY, USA, 2007. ACM.

[142] John Rice. In *Mathematical Statistics and Data Analysis (Second ed.)*, 1995.

[143] Wei-Hao Lin Rong, Wei hao Lin, Rong Jin, and Er Hauptmann. Meta-classification of multimedia classifiers. In *in International Workshop on Knowledge Discovery in Multimedia and Complex Data*, 2003.

[144] S. Schaeffer. Graph clustering. *Computer Science Review*, 1(1):27–64, August 2007.

[145] J. Ben Schafer, Dan Frankowski, Jon Herlocker, and Shilad Sen. The adaptive web. chapter Collaborative filtering recommender systems, pages 291–324. Springer-Verlag, Berlin, Heidelberg, 2007.

[146] Jianbo Shi and Jitendra Malik. Normalized cuts and image segmentation. In *Proceedings of the 1997 Conference on Computer Vision and Pattern Recognition (CVPR '97)*, CVPR '97, pages 731–, Washington, DC, USA, 1997. IEEE Computer Society.

[147] J. Sivic, B. C. Russell, A. A. Efros, A. Zisserman, and W. T. Freeman. Discovering object categories in image collections. In *Proceedings of the International Conference on Computer Vision*, 2005.

[148] J. Sivic, B. C. Russell, A. Zisserman, W. T. Freeman, and A. A. Efros. Unsupervised discovery of visual object class hierarchies. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2008.

[149] J. Sivic and A. Zisserman. Video data mining using configurations of viewpoint invariant regions. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Washington, DC*, jun 2004.

[150] Josef Sivic, Bryan Russell, Alexei A. Efros, Andrew Zisserman, and Bill Freeman. Discovering objects and their location in images. In *International Conference on Computer Vision (ICCV 2005)*, October 2005.

[151] Josef Sivic and Andrew Zisserman. Video google: A text retrieval approach to object matching in videos. In *Proceedings of the Ninth IEEE International Conference on Computer Vision - Volume 2*, ICCV '03, pages 1470–, Washington, DC, USA, 2003. IEEE Computer Society.

[152] Thompson S.K. Adaptive sampling. In *The Survey Statistician*, pages 13–15, 1995.

[153] Cees G. M. Snoek, Marcel Worring, Jan Van Gemert, Jan mark Geusebroek, Dennis Koelma, Giang P. Nguyen, Ork De Rooij, and Frank Seinstra. Mediamill: Exploring news video archives based on learned semantics. In *In ACM Multimedia*, pages 225–226, 2005.

[154] J. A. Spierenburg and Dionysius P. Huijsmans. Voici: Video overview for image cluster indexing, a swift browsing tool for a large digital image database using similarities. In Adrian F. Clark, editor, *Proceedings of the British Machine Vision Conference 1997, BMVC 1997, University of Essex, UK, 1997*. British Machine Vision Association, 1997.

[155] Michael Steinbach, Levent Ertz, and Vipin Kumar. The challenges of clustering high-dimensional data. In *In New Vistas in Statistical Physics: Applications in Econophysics, Bioinformatics, and Pattern Recognition*. Springer-Verlag, 2003.

[156] Hari Sundaram, Lexing Xie, and Shih fu Chang. A utility framework for the automatic generation of audio-visual skims. In *ACM Multimedia*, pages 189–198. ACM Press, 2002.

[157] Pang-Ning Tan, Michael Steinbach, and Vipin Kumar. *Introduction to Data Mining*. Addison-Wesley, 2005.

[158] Jiayu Tang and Paul H. Lewis. Non-negative matrix factorisation for object class discovery and image auto-annotation. In *Proceedings of the 2008 international conference on Content-based image and video retrieval*, CIVR '08, pages 105–112, New York, NY, USA, 2008. ACM.

[159] Naftali Tishby, Fernando C. Pereira, and William Bialek. The information bottleneck method. pages 368–377, 1999.

[160] Sinisa Todorovic and Narendra Ahuja. Extracting subimages of an unknown category from a set of images. In *in CVPR*, pages 927–934, 2006.

[161] Sinisa Todorovic and Narendra Ahuja. Extracting subimages of an unknown category from a set of images. In *Proceedngs of the 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition - Volume 1*, pages 927–934, Washington, DC, USA, 2006. IEEE Computer Society.

[162] Sabrina Tollari, Marcin Detyniecki, Christophe Marsala, Ali Fakeri-Tabrizi, Massih-Reza Amini, and Patrick Gallinari. Exploiting visual concepts to improve text-based image retrieval. In *European Conference on Information Retrieval (ECIR)*, 2009.

[163] Tinne Tuytelaars, Christoph H. Lampert, Matthew B. Blaschko, and Wray Buntine. Unsupervised object discovery: A comparison. *IJCV*, 88(2), 2010.

[164] B. Vandeginste. Parvus: An extendable package of programs for data exploration, classification and correlation, m. forina, r. leardi, c. armanino and s. lanteri, elsevier. *Journal of Chemometrics*, 4(2):191–193, 1990.

[165] Thomas Veit, Frédéric Cao, and Patrick Bouthemy. Space-time a contrario clustering for detecting coherent motions. In *ICRA*, pages 33–39, 2007.

[166] Deepak Verma and Marina Meila. A comparison of spectral clustering algorithms. Technical report, 2003.

[167] Dorothea Wagner and Frank Wagner. Between min cut and graph bisection. In *Proceedings of the 18th International Symposium on Mathematical Foundations of Computer Science*, MFCS '93, pages 744–750, London, UK, UK, 1993. Springer-Verlag.

[168] Gang Wang and Ye Zhang Li Fei-fei. Using dependent regions for object categorization in a generative framework. In *CVPR*, pages 1597–1604. IEEE Computer Society, 2006.

[169] James Z. Wang, Jia Li, and Gio Wiederhold. Simplicity: Semantics-sensitive integrated matching for picture libraries. In *IEEE Trans. on Pattern Analysis and Machine Intelligence*, volume 23, pages 947–963.

[170] Xiaogang Wang and Eric Grimson. Spatial latent dirichlet allocation. *Advances in Neural Information Processing Systems*, 20:1–8, 2008.

[171] Xin-Jing Wang, Wei-Ying Ma, Qi-Cai He, and Xing Li. Grouping web image search result. In *Proceedings of the 12th annual ACM international conference on Multimedia*, MULTIMEDIA '04, pages 436–439, New York, NY, USA, 2004. ACM.

[172] M. Weber, M. Welling, and P. Perona. Towards automatic discovery of object categories. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2000.

[173] Martijn Wieling and John Nerbonne. Bipartite spectral graph partitioning to co-cluster varieties and sound correspondences in dialectology. In *Proceedings of the 2009 Workshop on Graph-based Methods for Natural Language Processing*, TextGraphs-4, pages 14–22, Stroudsburg, PA, USA, 2009. Association for Computational Linguistics.

[174] J. Winn, A. Criminisi, and T. Minka. Object categorization by learned universal visual dictionary. In *In ICCV*, pages 1800–1807. IEEE Computer Society, 2005.

[175] Marcel Worring, Ork de Rooij, and Ton van Rijn. Browsing visual collections using graphs. In *Proceedings of the international workshop on Workshop on multimedia information retrieval*, MIR '07, pages 307–312, New York, NY, USA, 2007. ACM.

[176] Xiang Xiao, Ernst R. Dow, Russell Eberhart, Zina Ben Miled, and Robert J. Oppelt. Gene clustering using self-organizing maps and particle swarm optimization. In *Proceedings of the 17th International Symposium on Parallel and Distributed Processing*, IPDPS '03, pages 154.2–, Washington, DC, USA, 2003. IEEE Computer Society.

[177] Hongyuan Zha Xiaofeng, Xiaofeng He, Chris Ding, Horst Simon, and Ming Gu. Bipartite graph partitioning and data clustering. In *In CIKM*, pages 25–32, 2001.

[178] Guandong Xu, Yu Zong, Peter Dolog, and Yanchun Zhang. Co-clustering analysis of weblogs using bipartite spectral projection approach. In *Proceedings of*

the 14th international conference on Knowledge-based and intelligent information and engineering systems: Part III, KES'10, pages 398–407, 2010.

[179] Rui Xu and Donald Wunsch. Survey of clustering algorithms. *Neural Networks, IEEE Transactions on*, 16(3):645–678, 2005.

[180] Zhang Yifei, Zhou Junlin, and Fu Yan. Spectral clustering algorithm based on adaptive neighbor distance sort order. In *Information Sciences and Interaction Sciences (ICIS)*, pages 444 – 447, 2010.

[181] Y.Q. Yu, D.R. Zhou, B. Meng., and H.B Wang. Fuzzy nearest neighbor clustering of high-dimensional data. In *International Conference on Machine Learning and Cybernetics*, 2003.

[182] Osmar R. Zaane, Andrew Foss, Chi hoon Lee, and Weinan Wang. On data clustering analysis: Scalability, constraints and validation. In *In Proceedings of the 6th Pacific-Asia Conference on Knowledge Discovery and Data Mining (PAKDD*, pages 28–39, 2002.

[183] Lotfi A. Zadeh. Fuzzy algorithm. *Information and Control*, pages 94–102, 1968.

[184] Zheng-Jun Zha, Linjun Yang, Tao Mei, Meng Wang, and Zengfu Wang. Visual query suggestion. In *Proceedings of the 17th ACM international conference on Multimedia*, pages 15–24, oct 2009.

[185] Zheng-Jun Zha, Linjun Yang, Tao Mei, Meng Wang, Zengfu Wang, Tat-Seng Chua, and Xian-Sheng Hua. Visual query suggestion: Towards capturing user intent in internet image search. *ACM Trans. Multimedia Comput. Commun. Appl.*, 6:13:1–13:19, August 2010.

[186] Tian Zhang, Raghu Ramakrishnan, and Miron Livny. Birch: an efficient data clustering method for very large databases. *SIGMOD Rec.*, 25:103–114, June 1996.

[187] Y. Zhao and G. Karypis. Criterion functions for document clustering: Experiments and analysis. In *Technical Report TR 01–40, Department of Computer Science, University of Minnesota, Minneapolis, MN*, 2001.