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# Machine learning for human behavioral discovery

Anna Aniszewska-Stepień

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Normandie Université



## THÈSE

Pour obtenir le diplôme de doctorat

Spécialité INFORMATIQUE

Préparée au sein de l'INSA Rouen Normandie

Machine learning for human behavioral discovery

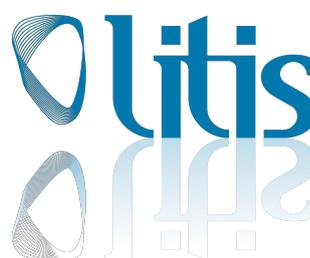
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**ANNA ANISZEWSKA-STEPIEN, NÉ·E STEPIEN**

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# THÈSE

Pour obtenir le diplôme de Docteur de Normandie Université

Spécialité Informatique

Préparée au sein de l'École Doctorale Mathématiques, Information, Ingénierie des Systèmes

**Machine learning for human behavioral discovery**  
Apprentissage automatique pour la découverte du comportement humain

Présentée et soutenue par  
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**CETAPS**

# Machine learning for human behavioral discovery

A DISSERTATION PRESENTED  
BY  
ANNA ANISZEWSKA-STĘPIEŃ  
TO  
THE DEPARTMENT OF INSA LITIS

IN FULFILLMENT OF THE REQUIREMENTS  
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DOCTOR OF PHILOSOPHY  
IN THE SUBJECT OF  
COMPUTER SCIENCE

NORMANDY UNIVERSITY  
ROUEN, FRANCE  
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Thesis advisor: Professor Gilles Gasso

Thesis co-advisor: Professor Ludovic Seifert

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## Machine learning for human behavioral discovery

### ABSTRACT

The research is part of a multidisciplinary project that combines advances in computational science and in the humanities to understand and explain the role of visuomotor exploration strategies in a climbing task during a learning protocol. We seek to model the dynamics of learning to understand how the frequency of novelty and the complexity of the learning situation affect the learning outcome. Modeling from machine learning and human movement science has been used to design optimal practice environments to train climbers to exploit adaptive behaviors that invite them to safely explore novel and functional patterns. This framework involves working with a behavioral signal that is a representation of the climber in the movement; this signal is multidimensional, has complex dynamics and has two main characteristics that limit its application in statistical learning: it is sparse (has missing measurements) and scarce in the number of samples. As a part of our work, in order to facilitate the creation of new qualitative metrics to assess the climbers' performance, we first proposed a novel model for annotation of a behavioral signal trained on partially labeled sequences. This part of the thesis dealt with the first type of constraints. In the second part of the dissertation, we focused on adapting machine learning to evaluate the type of practice (control, variable and self-controlled) in order to apply a predictive modeling of transfer to compare them. In the pipeline design, we had to handle a small dataset (second type of constraints) to demonstrate higher predictive stability for self-controlled practice.

**KEYWORDS:** machine learning, behavioral signal, human motor learning, missing values, small sample

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## Apprentissage machine pour la découverte du comportement humain

### RÉSUMÉ

Notre recherche s'inscrit dans le cadre d'un projet multidisciplinaire qui combine les avancées des sciences humaines et des sciences informatiques pour comprendre et expliquer le rôle des stratégies d'exploration visuo-motrice dans la tâche d'escalade lors d'un protocole d'apprentissage. Nous cherchons à modéliser la dynamique de l'apprentissage pour comprendre comment la fréquence de la nouveauté et la complexité de la situation d'apprentissage influent sur le résultat de l'apprentissage. La modélisation dans la science du mouvement humain et l'apprentissage automatique ont été utilisés pour concevoir des environnements de formation optimaux afin d'apprendre aux grimpeurs à utiliser un comportement adaptatif, en les encourageant à explorer en toute sécurité des modèles nouveaux et fonctionnels. Ce cadre implique de travailler avec un signal comportemental qui est une représentation du grimpeur dans le mouvent; ce signal est multidimensionnel, possède une dynamique complexe et deux caractéristiques principales qui limitent son utilisation dans l'apprentissage statistique : il est clairsemé (des mesures sont manquantes) et limité dans le nombre d'échantillons. Dans le cadre de notre travail, afin de faciliter la création de nouvelles métriques qualitatives pour évaluer les performances des grimpeurs, nous avons d'abord proposé un nouveau modèle d'annotation du signal comportemental entraîné sur des séquences partiellement étiquetées. Cette partie de la thèse traite du premier type de contraintes. Dans la deuxième partie de la thèse, nous nous sommes concentrés sur l'adaptation de l'apprentissage automatique pour évaluer le type d'entraînement (contrôle, variable et autocontrôle) afin d'utiliser une modélisation prédictive du transfert pour les comparer. Dans le pipeline proposé, nous avons dû traiter un petit ensemble de données (le deuxième type de contrainte) pour montrer une plus grande stabilité prédictive pour la pratique autocontrôlée.

**MOTS-CLÉS :** apprentissage automatique, signal comportemental, apprentissage moteur humain, valeurs manquantes, petit ensemble de données

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TO MY CHILDREN WHO ARE THE ESSENCE OF MY LIFE.

TO MY SCIENCE-LOVING DAD,  
MY INSPIRATIONAL AND SUPPORTIVE SISTER WITH HER FAMILY AND MY MUM.

TO MY LOVE.

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---

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<sup>†</sup>The current 2nd version is a modified version of the reviewed manuscript i.e. it contains the modifications of the following type: correction of typos, new version of Figure 2 and 4 (better resolution), extension with footnote Chapter 3 (*Predictivity* definition in Introduction 3.1) and one sentence translocation in Conclusion 4 (semi-last); plus it includes defence remarks of the Reviewers or Jury Members: re-naming the position coordinates axis (Subsection 1.2.3), added one sentence in general Conclusion 4 (end of paragraph MODEL INTERPRETABILITY).

together with their individual level of knowledge and dedication. I learned this from the whole team of professors and Litis staff, together with the extremely professional and at the same time very personal, most respectful approach to the student.

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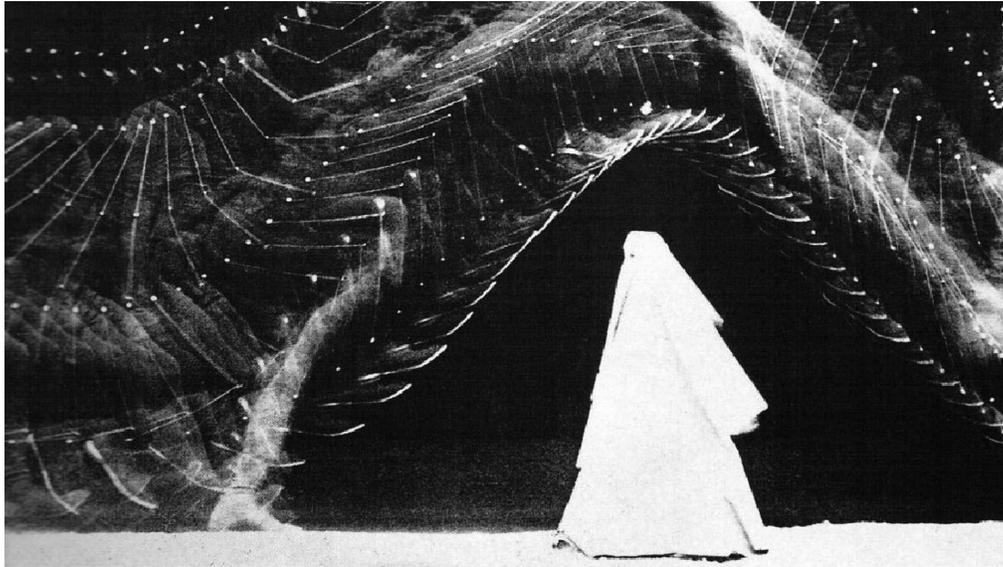
## Introduction

BEHAVIORAL DISCOVERY is of paramount importance to both the human-oriented sciences and the advancement of technology. The human movement domain requires new reliable and quantifiable modeling methods to explain the latent structure and organization of dynamic patterns in ever-increasing data; while the technology can be inspired by the evolutionary advances. Leveraging simplicity and complexity in the methodology becomes critical in the implementation process.

## 0.1 CONTEXT AND MOTIVATION

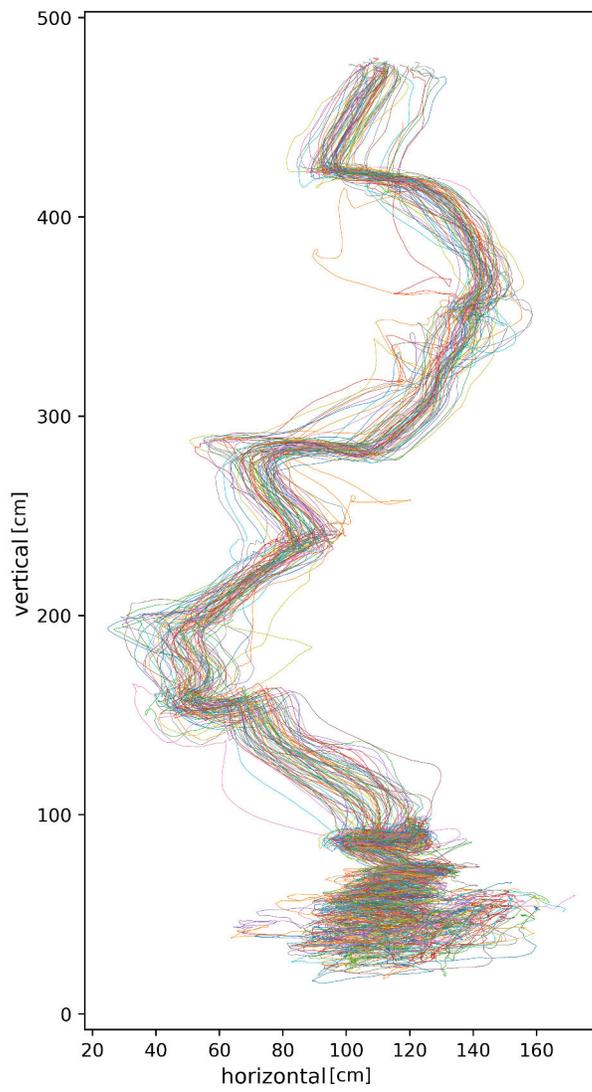
Part of our established knowledge of human psychology is the theory that the internal states are reflected in physiological processes (James [1890]). At the macro-scale this is the essence of the subdivision of neuroscience that investigates how the hidden working of the mind controls the coordinated production of rich, complex behaviors. The living creature in motion is an extremely convoluted system operating on manifold of dimensions. Even when mental states are covered, they produce a measurable behavioral signal, embedded in multidimensional space and evolving in time. Due to these characteristics, we can identify signals based on their functionality or provenance. Across different domains of study we can differentiate a huge subdomain of multiple biological or medical signals such as proxies for brain activity (functional magnetic resonance imaging and electrophysiological signals: electroencephalography, magnetoencephalography, electromyography, etc.) or bodily function sensing (heart monitoring, temperature detection, blood pressure capture). Another is the social signal in all its diversity, based on the ephemeral cues, both visual and auditory (e.g. gestures, facial expressions, pitch, prosody propagation, Narayanan and Georgiou [2013]), that result from the human interactions or from the human relations with personified parts of the world (machines, animals, etc.). These signals are multifaceted, extremely difficult to process and require huge amounts of high quality and high consistency data to distill their digital representation.

The motion signal can be placed somewhere in between these two subdomains, when it comes to its accessibility. Movement is overt and likely to be detected. It can be measured by the external sensors and wearable technology, or by visual markers that can be captured by high-resolution film or dedicated devices (Figure 1). However it is multimodal and encoded at different temporal scales, which requires reducing its complexity or finding signal-specific processing methods in order to translate the qualitative characteristics we see into computationally tractable representations. Taking advantage of the fact that movement can be produced in response to the manipulated stimulus or condition, we



**Figure 1** – Chromophotograph of human movement (E.J. Marey, public domain).

can aim to collect the data that map a particular neural function. Traditionally, in experimental research most of the motor signals are action-based responses of the organism measured as frequency (success/failure rate) or duration in a designed stimulation task. They can then be subjected to aggregate statistics, which provide information about the relationships between participants; however this method does not account for the manner how they evolved. Due to its complexity, but also due to its deterministic character (originating from the neural processes), human movement can be described in a dynamical rather than a representational context (Favela [2021]). Dynamical methods, being mostly qualitative, are able to reveal underlying patterns of behavior. However, they may not give us the access to quantitative information, and it is therefore reasonable to explore novel techniques that will support the qualitative findings. We can also notice that the mental-sourced signal would lead to the variability within a person (Figure 2) and across individuals, it would also be contaminated by the external sources of noise. Therefore the methods used to study movement must thus be robust



**Figure 2** - Two-dimensional recording of the hip position trajectories during 84 climbing ascents (same route) by the same climber. Data taken from the experimental protocol.

to the noisy component and at the same time they must refine the intertwined valuable information integrated in these variabilities (Hérault [2020]).

Machine learning algorithms come in handy as they can handle multiple sources of variability: inter-participant and intra-participant. The challenge is to find an appropriate pipeline that maps the primary noisy signals to behavioral features (through the signal processing tools) and further, to the psychological constructs (such as learning) from which emergent behavior can be inferred. In addition, data-driven, bottom-up algorithms, do not require any non-objective expert knowledge, thus no bias of any kind would be involved. Neither the traditional statistical analysis nor hand-selected features meet this requirement to provide measurable means to compare learning patterns, for example. In contrast, by using machine learning, we would be able to optimise the objective function in a way that preserves the sensitivity and specificity at the same time (Bone et al. [2017]).

In the Thesis, the primary avenue for evaluating these ideas is through an in-depth study of the machine learning methods used to analyse behavioral signals (Chapter 1). We have attempted to present machine learning as a response to the demands of behavioral discovery, to illustrate how to implement it in actual applications and what further challenges this implementation may pose. In doing so, our primary goal was to answer the most pressing questions drilling into the field of human movement science. With the example of two cases (Chapter 2 and Chapter 3), we have demonstrated the problem-specific solutions that the supervised methods offer to the human movement science field. But the use of machine learning itself rises some methodological questions. The specific requirements make its deployment in the context of the behavioral sciences thrilling, as the algorithms cannot be applied in a straightforward manner, but must be customized. In general, and in addition to their sequential nature, human behavioral signals are marked by constraints of two types: they are sparse (i.e. they have missing data in the measurements) and they are scarce (i.e. they are constrained in size), due to the numerous limitations resulting from the fact that humans, with their error-prone and finite nature, are involved in the measurements. These challenges are further commented on in the Thesis as

the limitations of the first and second type; we devote Chapter 2 and Chapter 3 respectively, to tackle them. Generally, we aim to examine different types of behavioral signals and to explore and create machine learning solutions, respectively, due to their usefulness.

Finally, through all the previously explained steps, we would like to elucidate how the two prominent areas of research can motivate each other and positively drive each other's progress.

## 0.2 MANUSCRIPT OUTLINE

The Thesis is divided into four Chapters as follows.

- Chapter 1 introduces the background of the fields under study, and is intended as a basic theoretical presentation. First, it presents the machine learning theory that is required to comprehend the main parts of the thesis, thus it includes the main concepts and the pillars of the field with an emphasis on the supervised methods and sequential learning. The state of the art in the motor control and learning theory is also described in this Chapter. This is followed by an overview of the machine learning algorithms that are currently used to learn and discover behaviors in humans. The subsequent section details the data collection conditions and the limitations that the structure of the measurements imposes on the analysis.
- Chapter 2 addresses the problem of some data missing in measurements of behavioral signal. It presents and discusses the theory of semi-supervised learning framework, which is a context for introducing the hidden Markov model in the partially labeled scenario, that is defined together with the Viterbi algorithm traditional scheme. The further body of the Chapter provides a demonstration of the proposed algorithm along with a description of the evaluation methods and results.
- Chapter 3 investigates the solution to the small sample size issue in the behavioral data studies. It attempts to find an unbiased pipeline for evaluating the practice set generalization-purpose ability in human skill acquisition by comparing it to the machine learning predictivity measure. These two measures in parallel serve to indicate the transfer process effect for various types of practice in skill learning.
- Chapter 4 offers some more concluding remarks and the perspectives.

### 0.3 CONTEXTE ET MOTIVATION

Une partie de notre compréhension bien établie de la psychologie humaine est la théorie selon laquelle l'état interne se reflète dans les processus physiologiques (James [1890]). À l'échelle macro, c'est l'essence même d'une subdivision des neurosciences qui étudie comment le fonctionnement implicite de l'esprit contrôle la production coordonnée de comportements riches et complexes. Un être vivant en mouvement est un système extrêmement alambiqué qui fonctionne sur de multiples dimensions. Même lorsque les états mentaux sont implicites, ils produisent un signal comportemental mesurable, inscrit dans un espace multidimensionnel et évoluant dans le temps. Grâce à cette caractéristique, nous pouvons identifier les signaux en fonction de leur fonctionnalité ou de leur origine. Dans divers domaines scientifiques, il est possible de distinguer d'importants sous-domaines de nombreux signaux biologiques ou médicaux, tels que les proxies de l'activité cérébrale (imagerie par résonance magnétique fonctionnelle et signaux électrophysiologiques : électroencéphalographie, magnétoencéphalographie, électromyographie, etc.) ou la détection du fonctionnement du corps (surveillance du cœur, détection de la température, capture de la pression sanguine). Le signal social, avec toute sa diversité, est un autre de ces sous-domaines, s'appuyant sur des indices éphémères, tant visuels qu'auditifs (par exemple, les gestes, les expressions faciales, la hauteur du son, la propagation de la prosodie, Narayanan and Georgiou [2013]), qui résulte des interactions humaines ou des relations de l'homme avec des parties personnifiées du monde (machines, animaux, etc.). Ces signaux sont multidimensionnels, extrêmement difficiles à traiter et nécessitent une énorme quantité de données de haute qualité et cohérentes pour distiller leur représentation numérique.

Les signaux de mouvement peuvent être placés quelque part entre ces deux sous-domaines en termes d'accessibilité. Le mouvement est manifeste et susceptible d'être observé. Il peut être mesuré par des capteurs externes et des technologies portables, ou par des marqueurs visuels, ce qui permet de le capturer avec des vidéos haute résolution ou des dispositifs spécifiques (Figure 3). Cependant, il est multi-

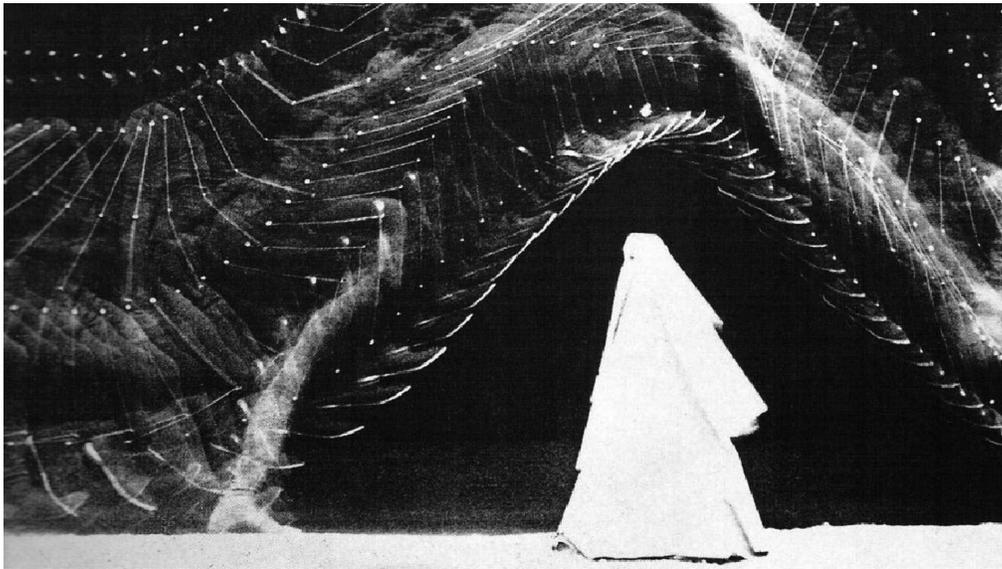


Figure 3 – Photo du mouvement humain (E.J. Marey, domaine public)

modale et codée à différentes échelles de temps, ce qui nécessite de réduire sa complexité ou de trouver une méthodologie de traitement spécifique au signal pour traduire la caractéristique qualitative que nous observons en représentations calculables. En exploitant le fait que le mouvement peut être produit en réponse à un stimulus ou à une condition manipulée, nous pouvons chercher à collecter des données qui cartographient une fonction neuronale spécifique.

Traditionnellement, dans les études expérimentales, la plupart des signaux moteurs sont des réponses dérivées de l'action, mesurées en termes de fréquence (taux de réussite/échec) ou de durée dans une tâche de stimulus conçue. Ceux-ci peuvent ensuite être soumis à des statistiques agrégées qui fournissent des informations sur les relations entre les participants, mais cette méthode ne tient pas compte de leur évolution. En raison de sa complexité, mais aussi compte tenu de sa nature déterministe (dérivée des processus neuronaux), le mouvement humain peut être décrit dans un contexte dynamique plutôt que représentationnel (Favela [2021]). Les méthodes dynamiques, qui sont essentiellement qualitatives, permettent de découvrir des modèles de comportement sous-jacents. Cependant, ils ne nous

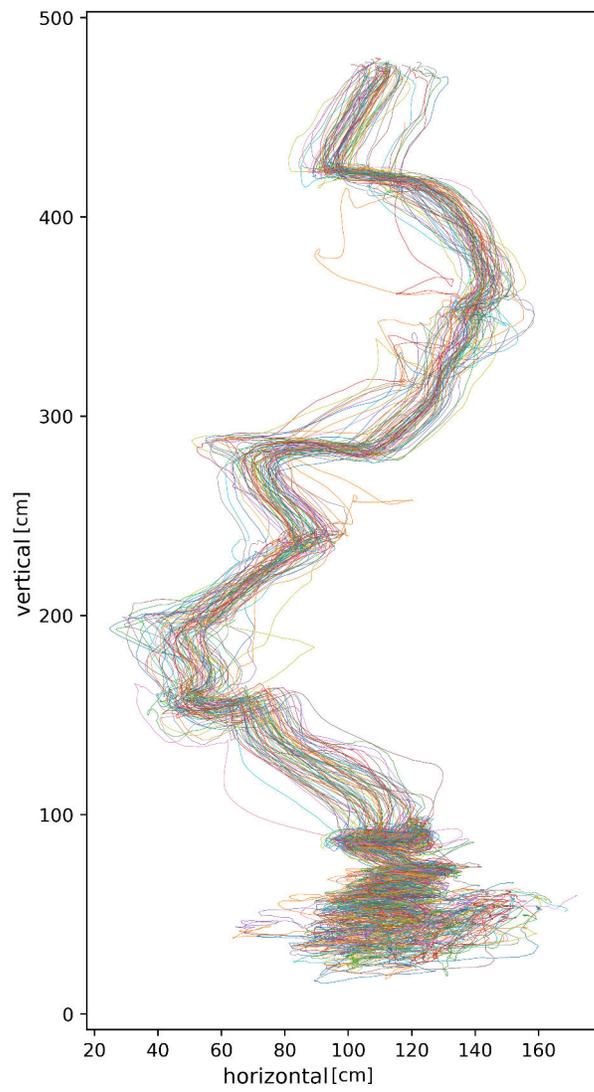
permettent pas toujours d'accéder à des informations quantitatives, et il est donc logique de rechercher de nouvelles techniques permettant d'étayer les résultats qualitatifs. Nous pouvons également noter que le signal provenant de l'esprit entraîne une variabilité au sein d'une personne (Figure 4) et entre individus, et sera également contaminé par des sources de bruit externes. Les méthodes de recherche sur le mouvement doivent donc être robustes aux composantes bruyantes, tout en affinant les précieuses informations entrelacées intégrées dans ces variabilités (Héroult [2020]).

Les algorithmes d'apprentissage automatique sont très utiles car ils peuvent gérer de multiples sources de variabilité : inter- et intra-participants. Le défi consiste à trouver un pipeline approprié qui transforme les signaux bruyants d'origine en caractéristiques comportementales (via des outils de traitement du signal) et en constructions psychologiques (comme l'apprentissage) à partir desquelles il est possible de déduire un comportement émergent. En outre, les algorithmes ascendants fondés sur les données ne nécessitent pas de connaissances spécialisées impartiales, et il n'y a donc aucun risque de biais.

Ni l'analyse statistique traditionnelle, ni les caractéristiques sélectionnées à la main ne répondent à cette exigence de fournir des dispositifs mesurables pour, par exemple, comparer des modèles d'apprentissage. En revanche, en utilisant l'apprentissage automatique, nous serions en mesure d'optimiser la fonction objectif de telle sorte que la sensibilité et la spécificité soient maintenues en même temps (Bone et al. [2017]).

Dans la Thèse, le principal moyen d'évaluer ces idées est une étude approfondie des méthodes d'apprentissage automatique utilisées pour analyser les signaux comportementaux (Chapitre 1). Nous avons essayé de présenter l'apprentissage automatique comme une réponse aux exigences de la découverte comportementale, d'illustrer comment il peut être mis en œuvre dans des applications du monde réel et quels défis supplémentaires cette mise en œuvre peut apporter.

Ce faisant, nous voulions avant tout répondre aux questions les plus pressantes qui percent dans le domaine de la science du mouvement humain. À l'aide de deux exemples de cas (Chapitre 2 et Chapitre 3), nous démontrons les solutions spécifiques aux problèmes que les méthodes supervisées offrent au



**Figure 4** - Enregistrement bidimensionnel de la trajectoire de la position de la hanche pendant 84 ascensions (même voie) par le même grimpeur. Données extraites du protocole expérimental.

domaine de la science du mouvement humain. Toutefois, l'utilisation de l'apprentissage automatique soulève en soi certaines questions méthodologiques. Les exigences spécifiques rendent son utilisation passionnante dans le contexte de la science comportementale, car les algorithmes utilisés ne peuvent être simples, mais doivent être conçus sur mesure. En général, en plus de leur nature séquentielle, les signaux de comportement humain sont caractérisés par des limitations de deux types : ils sont éparpillés (c'est-à-dire qu'ils comportent des données manquantes dans les mesures) et limités (c'est-à-dire qu'ils ne sont pas nombreuses) en taille, en raison des nombreuses contraintes découlant du fait que des humains, avec leur nature finie et sujette aux erreurs, sont impliqués dans les mesures. Ces défis sont commentés plus loin dans la dissertation comme des contraintes de première et de deuxième nature ; nous consacrons respectivement les Chapitres 2 et Chapitre 3 à leur solution. En général, notre objectif est d'explorer différents types de signaux comportementaux et, par conséquent, d'explorer et de créer des solutions d'apprentissage automatique en raison de leur utilité.

Enfin, à travers toutes les étapes expliquées précédemment, nous aimerions expliquer comment ces deux domaines de recherche peuvent se motiver mutuellement et faire progresser leurs travaux de manière positive.

#### 0.4 PLAN DE LA THÈSE

Le manuscrit est divisé en quatre Chapitres comme suit.

- Le Chapitre 1 introduit le contexte des domaines étudiés et est conçu comme une présentation de la théorie sous-jacente. Tout d'abord, il introduit la théorie de l'apprentissage automatique, nécessaire pour comprendre les principales parties de la Thèse, et inclut donc les principaux concepts et piliers du domaine en mettant l'accent sur les méthodes supervisées et l'apprentissage séquentiel. Ce Chapitre décrit également l'état de l'art en matière de théorie du contrôle et d'apprentissage moteur. Cette partie est suivie d'un aperçu des algorithmes d'apprentissage

automatique qui sont actuellement utilisés pour apprendre et découvrir le comportement des humains. Le Chapitre détaille ensuite les conditions de collecte des données et les limites que la structure de mesure introduit dans l'analyse.

- Le Chapitre 2 aborde le problème de l'absence de certaines données dans les mesures de signaux comportementaux. Il présente et discute la théorie du cadre d'apprentissage semi-supervisé, qui fournit le contexte pour l'introduction d'un modèle de Markov caché dans le scénario partiellement étiqueté qui est défini avec le schéma traditionnel de l'algorithme de Viterbi. Le reste du Chapitre présente une démonstration de l'algorithme proposé ainsi qu'une description des méthodes d'évaluation et des résultats.
- Le 3ème Chapitre explore une solution au problème de la petite taille des échantillons dans la recherche de données comportementales. Il tente de trouver un pipeline non biaisé pour évaluer la généralisabilité des ensembles de formation dans l'acquisition de compétences humaines en la comparant à une mesure de la prévisibilité de l'apprentissage automatique. Ces deux mesures sont utilisées en parallèle pour indiquer l'efficacité de l'effet du processus de transfert pour différents types de pratique dans l'apprentissage.
- Le Chapitre 4 offre quelques remarques supplémentaires et perspectives.

## 0.5 NOTATIONS

Notation, that is brought in here, launches elemental mathematical notions that will be used throughout the whole manuscript; it will be supplemented with some basic definitions.

The simple scalar is denoted by the lowercase letter in italics as in the case of  $x$ , the vector is similarly denoted by the bold font  $\mathbf{x}$ , and the matrix or tensor is denoted by the uppercase bold font  $\mathbf{X}$ . The  $i$ th entry of the vector  $\mathbf{x}$  is denoted as  $x_i$ . Then, the set of these elements is signed with bold italic uppercase font  $\mathbf{X}$ , while the space is signed with the double uppercase font  $\mathbb{X}$  (e.g.  $\mathbb{X}^{d \times d}$  is a space of dimension  $d \times d$ ).

For statistical models with parameter  $w$ , the candidate for an optimal parameter is signed with a tilde  $\tilde{w}$ , the estimate is signed with a hat  $\hat{w}$ , and the optimal parameter is signed with an asterisk  $w^*$ .

Moreover, the  $l_p$ -norm will be signed  $\|\mathbf{w}\|_p = \left( \sum_{j=1}^p |w_j|^p \right)^{\frac{1}{p}}$ , where vector  $\mathbf{w} \in \mathbb{R}^p$ ,  $p \in [1, \infty)$ .

For the sequences we will use the notation  $a_{1:T}$ , where  $T$  is the length of the sequence.

The model is denoted usually by the capital letter  $\mathcal{M}$ .

The notation will be systematically completed as it becomes more precise in the following Chapters.

*It is not knowledge, but the act of learning,  
not possession but the act of getting there,  
which grants the greatest enjoyment.*

Carl Friedrich Gauss

# 1

## Machine learning for neuroscience of motor learning

THEORETICAL BACKGROUND of machine learning applied to human motor learning with a literature overview will be presented here, together with the description of characteristic behavioral data context.

In the first chapter we will describe the machine learning notions (Section 1.1) that are either mentioned or presented in the next sections and chapters. Here we will introduce as well the human movement approaches (Section 1.2) that provide the ideas that led us to investigate the motor learning particular concepts. The chapter will be extended with a literature review of common machine learning applications in motor learning (Section 1.3). Finally, we will characterize the climbing experimental data (Section 1.4), with the peculiarities, that both inspire and limit our research.

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## 1.1 MACHINE LEARNING

Machine learning (ML) is a large branch of artificial intelligence (AI) area of science, that focuses on inferring the general patterns present in data through statistical exploration of data samples. In our introductory presentation, we will focus on a few concepts that are most relevant to human movement science and our research, starting with a characterization of the unsupervised and supervised learning - the two approaches that apply depending on the knowledge we have about the data and the type of information we would like to infer from our data. This basic division will lead us to sequential learning, where we will introduce other (mixed) types of machine learning.

### 1.1.1 UNSUPERVISED METHODS

In the unsupervised case, we learn only from the data samples  $\mathbf{x} \in \mathcal{X}$  (with no labels and no a priori knowledge about the target of learning), and we try to find the patterns present in them. We distinguish here two types of learning: representation learning (related to feature selection and extraction) and clustering of the data (establishing rules of the neighborhood that allow to divide the data set into the subsets).

REPRESENTATION LEARNING is aimed at finding a new representation of the data, that will facilitate further data analysis. We can distinguish several types of methods, that reduce the dimension of the data for this purpose (variants of principal component analysis or embeddings, autoencoders), however we will focus principally on two of them.

- **Principal component analysis** (PCA, Jolliffe [2002]) is a technique of *linear dimension reduction*, that allows to indicate the components that contribute to the variability of the data. By finding the largest eigenvectors and eigenvalues of the covariance matrix of the standardized data points, it allows to reduce the dimension of the data to the desired size.

- **Embedding techniques**, like stochastic neighbor embedding (SNE, Hinton and Roweis [2003]) or its t-distributed version (tSNE, van der Maaten and Hinton [2008]), is another statistical technique used in human movement analysis to map the high-dimensional data to a low-dimensional structure. It is a *non-linear dimension reduction* technique, in which the cost function (minimized with gradient descent) is the sum of all the Kullback-Leibler divergences for the probabilities describing the similarities between the data points in the reduced dimensional space. The similarity is based on the neighborhood relationship of two data points\*, described as a Gaussian distribution (or student t-distribution, for tSNE) centered on a given data point.

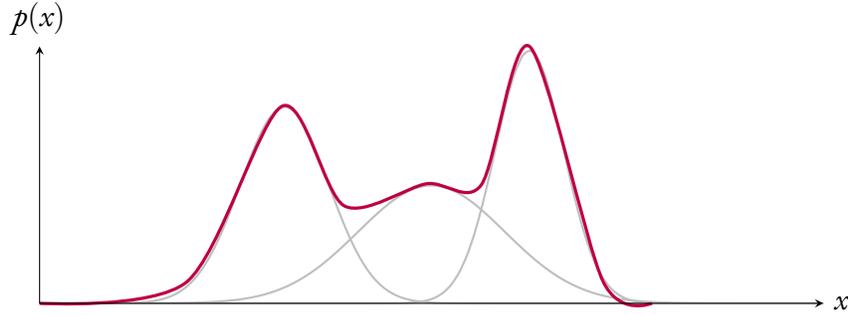
Variants of embedding techniques may include multi-scale (due to the multi-similarity including different structural scales present in the data) Jensen-Shannon embedding using a mixture of KL divergences (Lee et al. [2013]).

CLUSTERING involves dividing the sample set  $X = \{\mathbf{x}_i, i = 1, \dots, n\}$  into subsets, called clusters. Clustering is meant to find the structure or pattern in data. The relationship of belonging to a particular cluster is based on the similarity (or closeness) of the samples. In general, the number of clusters is not known and becomes a hyperparameter of the clustering task - it is usually evaluated by standard model selection criteria such as Bayesian information criterion (BIC, Schwarz [1978]) or silhouette score (Rousseeuw [1987]) among others. The most common clustering methods are described below.

- **Gaussian mixture model** (GMM, McLachlan and Basford [1988]) is a simple way to describe the patterns present in the data by summing Gaussian distributions (Figure 1.1), where for each cluster  $c$  we find the parameters  $\theta_c = (\pi_c, \mu_c, \Sigma_c)$  of the basic Gaussian subdistributions (the mean  $\mu_c$  and

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\**Similarity* of data point  $\mathbf{x}_i$  to data point  $\mathbf{x}_j$  is the conditional probability, that  $\mathbf{x}_i$  would choose  $\mathbf{x}_j$  as its neighbor.



**Figure 1.1** - Gaussian mixture: the gray lines are separate distributions, that contribute to the mixture in red.

the variance  $\Sigma_c$ ) together with the weight ( $\pi_c$ ), which determines its share in the Gaussian mixture  $p(\mathbf{x}) = \sum_{c=1}^k \pi_c \mathcal{N}(\boldsymbol{\mu}_c, \Sigma_c)$  (where  $k$  is the number of clusters and  $\sum_{c=1}^k \pi_c = 1$ ).

GMM is a generative framework, in which we estimate the parameters by likelihood maximization; it can be used to sample new elements, once we have learned the parameters  $\theta_c$ .

The parameter search (due to the impossibility of computing the closed-form solution directly), can be found with **expectation-maximization algorithm** (EMA, [Dempster et al. \[1977\]](#)).

If we define the posterior probability that the data point  $\mathbf{x}_i$  belongs to the  $c$ th mixture component as in Equation 1.1,

$$\gamma_{ic} = \frac{\pi_c \mathcal{N}(\mathbf{x}_i | \boldsymbol{\mu}_c, \Sigma_c)}{\sum_{j=1}^k \pi_j \mathcal{N}(\mathbf{x}_i | \boldsymbol{\mu}_j, \Sigma_j)} \quad (1.1)$$

then  $\gamma_{ic}$  is proportional to the likelihood  $p(\mathbf{x}_i | \pi_c, \boldsymbol{\mu}_c, \Sigma_c) = \pi_c \mathcal{N}(\mathbf{x}_i | \boldsymbol{\mu}_c, \Sigma_c)$ .

In EMA for the Gaussian mixture model, we choose initial values for  $\pi_c$ ,  $\boldsymbol{\mu}_c$ ,  $\Sigma_c$  and alternate until convergence between 1) E-step: evaluate the  $\gamma_{ic}$  (posterior probability that the data point  $i$  belongs to the mixture component  $c$ ) and 2) M-step: use the updated  $\gamma_{ic}$  to reestimate the parameters  $\pi_c$ ,  $\boldsymbol{\mu}_c$ ,  $\Sigma_c$  ([Hastie et al. \[2009\]](#)).

The EMA can be applied in a general case of *latent variables* (Figure 1.2), in the probabilistic framework, if we assume, that each data point  $\mathbf{x}_i$  has been generated by a latent variable  $\mathbf{z}_i \in \mathbb{R}^k$ . In this form, EMA is described in the Algorithm 1 ([Deisenroth et al. \[2020\]](#)).

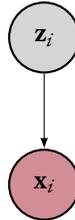


Figure 1.2 – Latent variable model:  $\mathbf{z}$ -latent,  $\mathbf{x}$ - generated variable .

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**Algorithm 1** Expectation-maximization algorithm for hidden variable version

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- 1: **repeat** STEP 1 and STEP 2 alternately **until** *convergence*
- 2: **STEP 1** ▷ Expectation
- 3: **procedure** CALCULATE EXPECTED LOG-LIKELIHOOD given a current iteration setting of model parameters  $\theta_t$ ,

$$\mathbb{P}(\theta|\theta_t) = \mathbb{E}_{(\mathbf{z}|\mathbf{x},\theta_t)}[\log p(\mathbf{x}, \mathbf{z}|\theta)] = \int \log p(\mathbf{x}, \mathbf{z}|\theta) p(\mathbf{z}|\mathbf{x}, \theta_t) d\mathbf{z}, \quad (1.2)$$

where the expectation of  $\log p(\mathbf{x}, \mathbf{z}|\theta)$  is taken with respect to the posterior  $p(\mathbf{z}|\mathbf{x}, \theta_t)$  of the latent variables  $\mathbf{z}$ ,  $p(z_c = 1|\mathbf{x}_i)$  is the posterior probability.

- 4: **end procedure**
  - 5: **STEP 2** ▷ Maximization
  - 6: **procedure** SELECT AN UPDATED SET OF MODEL PARAMETERS  $\theta_{t+1}$  by maximizing the log-likelihood (Equation in line 3 herewith).
  - 7: **end procedure**
-

We must notify, that while EMA guarantees to increase the log-likelihood in the current step, it does not necessarily drive to the global maximum likelihood (proof in Bishop [2007]).

A variant of EMA is **Fisher-EMA** (Bouveyron and Brunet [2012]), which is an iterative clustering algorithm that allows to project the data into a new subspace, where the cluster Fisher information is maximized (it maximizes the inter-cluster distance, while the same time minimizing the intra-cluster distance).

- **K-means algorithm** (KMA, Lloyd [1982]) is another method, that allows to divide the observed sample set into clusters; in this case the similarity is based on the distance of the samples (given the metrics) from the cluster mean (called *centroid*). At each step the new mean is calculated and the new set membership relation is established for the samples. In KMA, the number of clusters  $k$  is not known *a priori* and is a hyperparameter to be determined.

- **Hierarchical cluster analysis** (HCA, Hastie et al. [2009]) is another clustering technique based on distance connectivity. It can be either a top-down (divisive, from the root to the leaves) or a bottom-up (agglomerative, from the individual leaves to the whole set) technique, that establishes the tree-like hierarchy between the clusters. Thanks to the creation of the hierarchy (easily displayed as a dendrogram), this method allows an easier data interpretation than the flat clustering (KMA); however, as being non-parametric (it does not assume the number of clusters), it can increase the computational complexity and, being based on the distances, it can cause the *curse of dimensionality*.

### 1.1.2 SUPERVISED METHODS

By *supervised learning* we understand the case where we dispose a pair (the examples) of input and target data  $(\mathbf{x}, \mathbf{y})$  - here we use two vectors  $\mathbf{x} \in \mathbf{X}, \mathbf{y} \in \mathbf{Y}$  - which allows us to establish the relationship (modeling function)  $\mathcal{M}$  between the elements of the observation set  $\mathbf{X}$  and the set of labels  $\mathbf{Y}$ . We can compose a rule for the supervision, in which the model  $\mathcal{M}$  - with respect to the parameters  $\mathbf{w}$  - learns from the examples  $(\mathbf{x}, \mathbf{y})$ , where  $n$  is the number of them.

The pair  $(\mathbf{x}, \mathbf{y})$  is assumed to be drawn randomly (independently and identically distributed) from the unknown distribution  $P(\mathbf{x}, \mathbf{y})$ .

CLASSIFICATION is an example method of the supervised learning, where the mapping  $(\mathbf{x}, \mathbf{y})$  is learned, when the label space  $\mathbb{Y}$  is discrete, so we obtain categorical data partitioning.

Generally, we aim to predict the label  $\hat{\mathbf{y}}$  associated with the observation  $\mathbf{x}$ , so that  $\hat{\mathbf{y}} = M_{\mathbf{w}}(\mathbf{x})$ . Then, the *loss function*  $L$  calculates the difference (an error) between the true label  $\mathbf{y}$  and the predicted one  $\hat{\mathbf{y}}$  as  $L_{\mathbf{y}, \hat{\mathbf{y}}} = L(\mathbf{y}, \hat{\mathbf{y}})$ . In general,  $L_{\mathbf{y}, \hat{\mathbf{y}}} = 0$  if  $\mathbf{y} = \hat{\mathbf{y}}$  and  $L_{\mathbf{y}, \hat{\mathbf{y}}} > 0$  otherwise. An example of a loss function is the Euclidean metrics  $l_2$  (for regression):  $L_{\mathbf{y}, \hat{\mathbf{y}}} = \|\mathbf{y} - \hat{\mathbf{y}}\|_2^2 = \|\mathbf{y} - M_{\mathbf{w}}(\mathbf{x})\|_2^2$  or the cross-entropy loss (for classification [Hastie et al. \[2009\]](#)).

We can define *empirical risk* (ER) as the weighted sum of the errors for all the examples  $\mathbf{x}_i$ .

Then, the best model  $M$  is found by determining the parameter  $\mathbf{w}$  that minimizes the ER value

$$\mathbf{w}^* = \arg \min_{\mathbf{w}} \frac{1}{n} \sum_{i=1}^n L(\mathbf{y}_i, M_{\mathbf{w}}(\mathbf{x}_i)) \quad (1.3)$$

i.e. by the EMPIRICAL RISK MINIMIZATION.

So far we have trained our model  $M$  with the given examples, i.e. with the *training set*. However, the goal of the model is not to find the relation for the known samples, but possibly to discover a general rule to label any sample  $\mathbf{x}$ . Otherwise, if the data sample is not sufficient enough, the model may be *overfitted* (i.e., phenomena related to overly complicated models, that fit the noise rather than the essential properties of the data). Undoubtedly, there is a necessity to increase the model *generalization* (ability of the model to perform well on unseen data), which requires using new examples for model validation and testing. The *validation set* is an additional set of unseen data examples, that serves for model hyperparameter tuning. Subsequently, the *test set*, allows to finally evaluate the model (trained on the training set and validated on the validation set), i.e. to find its performance on the different

set of unseen data. We can say, however, that the model performs well in general if its prediction performance is similar for the training set and for the test set.

UNDERFITTING AND OVERFITTING are the two phenomena that lead to poor predictive performance of the statistical model. They can occur when the learned model produces high accuracy on the training set, but gives poor prediction on the unseen data (overfitting), or produces high errors on both the training and validation sets (underfitting). In the case of underfitting, the model is improperly learned e.g. due to missing values or an inappropriate model type; conversely, overfitting results from fitting the model to the noise present in the samples rather than to important information. Therefore, an optimal model finding procedure (solving the so-called *bias-variance dilemma* Hastie et al. [2009], where bias accounts for overly simple models and variance accounts for overly complicated, overfitted models), concerns the control of model *complexity* (the number of model parameters or the model degrees of freedom, Figure 1.3).

In order to avoid overfitting, we could ideally get more data for training, however if this is not possible (as in the case of motor learning behavioral data, commented on in Section 1.2), we can use regularization to limit the complexity of the model.

REGULARIZATION is a technique to penalize the impact of the coefficient assignment in the model, in order to mitigate the phenomena that deteriorate the prediction with the new data. Imposing a cost on the model coefficients, results in making the distribution of the weight values more regular in the case of *ill-posed problem* (when there is no exact solution for  $M(\mathbf{x}) = \mathbf{y}$  or the solution is not stable).

The general aim of the addition of TIKHONOV REGULARIZATION (Tikhonov and Arsenin [1977]) is to reformulate of the minimization problem present in the least squares problem (linear regression)

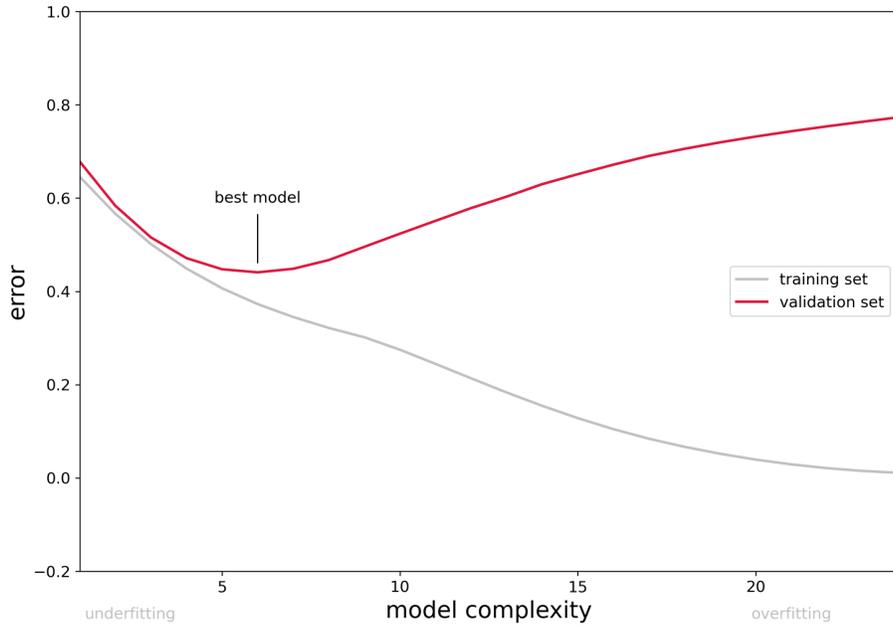


Figure 1.3 - Underfitting vs. overfitting: error evaluation for training and validation set.

by adding a term with an appropriately chosen Tikhonov matrix  $\Gamma$

$$\min_{\mathbf{w}} \|\mathbf{y} - M_{\mathbf{w}}(\mathbf{x})\|_2^2 + \|\Gamma \mathbf{w}\|_2^2, \quad (1.4)$$

where the solutions prioritize smaller norms (i.e., the solution is found even in the presence of large statistical noise in the data samples). It is similar to the ER stabilization method.

Likewise, the STRUCTURAL RISK, introduces a regularization (penalty term) into the previous ER scheme (Equation 1.3), so that we could find the solution to the STRUCTURAL RISK MINIMIZATION PROBLEM in the following way

$$\hat{\mathbf{w}} = \arg \min_{\mathbf{w}} \frac{1}{n} \sum_{i=1}^n L(\mathbf{y}_i, M_{\mathbf{w}}(\mathbf{x}_i)) + \lambda l_p(\mathbf{w}). \quad (1.5)$$

The  $l_p$  norm on  $\mathbf{w}$  serves as the regularization term, and  $\lambda \geq 0$  is the regularization parameter. Besides, if the output  $\mathbf{y}$  is a vector, then  $\mathbf{w}$  is likely to be a matrix that can be vectorized to apply the  $l_p$  norm regularization. This approach is well tailored for the small data sets and leads to an increase in generalizability. Depending on the metrics  $l_p$ , we speak of different types of regularization. To illustrate them, we find it convenient to introduce regression problems in supervised learning.

REGRESSION learns the assignment in the pair  $(\mathbf{x}, \mathbf{y})$ , if the output space  $\mathbb{Y}$  is continuous. A regression model is usually trained by minimizing the objective function formed by the least squares error and appropriate regularization. For the human movement applications, we will focus on Ridge and Lasso regressions, which are the structural risk minimization examples with different  $l_p$  norms. The popular metrics used in the penalty term are  $l_1$  and  $l_2$  respectively:  $\|\mathbf{w}\|_1 = \sum_i |w_i|$  and  $\|\mathbf{w}\|_2 = \sqrt{\sum_i (w_i)^2}$ .

- **Ridge regression** (Hoerl and Kennard [1970]) includes the regularization term with  $l_2$  norm in the model, in order to reduce the weights of the features (provides shrinkage).

It solves the problem

$$\hat{\mathbf{w}} = \arg \min_{\mathbf{w}} \frac{1}{n} \sum_{i=1}^n \|y_i - M_{\mathbf{w}}(\mathbf{x}_i)\|_2^2 + \lambda \|\mathbf{w}\|_2^2. \quad (1.6)$$

- **Least absolute shrinkage and selection operator** (Lasso, Tibshirani [1996]), concerns the  $l_1$  norm, which introduces sparsity (zeroing out of some coefficients, as a result of using the absolute value)

$$\hat{\mathbf{w}} = \arg \min_{\mathbf{w}} \frac{1}{n} \sum_{i=1}^n \|y_i - M_{\mathbf{w}}(\mathbf{x}_i)\|_2^2 + \lambda \|\mathbf{w}\|_1 \quad (1.7)$$

and is intended to eliminate some features (not just to reduce their weights). It is thus able to lead to sparse models and, due to this property, can be used for model selection, as it reduces the number of features to the most important ones.

### 1.1.3 SEQUENTIAL LEARNING

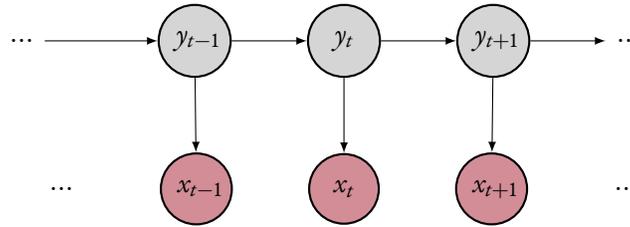
In machine learning we can work with different types of data; it can be images, signals, sequences.

Sequential learning is a special case of machine learning that is dedicated to *sequences* - the structures, in which the observation variables are arranged (for instance) in time. Sequences are thus useful for behavioral signal processing and pattern recognition in behavioral signal applications. We can divide the sequential learning into supervised one for a labeled sequence  $\{(x_t, y_t)\}_{t \in \{1, \dots, T\}}$  or unsupervised one for an unlabeled sequence of observations  $\{x_t\}_{t \in \{1, \dots, T\}}$ .

Due to the specificity of the sequences, such as the degree of interaction in the sequential structure, the discrete or continuous observations, or our knowledge of the labeling, standard machine learning approaches are not optimal. Therefore, we need to find the models that incorporate the time dependence (Dietterich [2002]), such as recurrent neural networks (RNN) with LSTM cells (long-short-term-memory for the networks with memory, Hochreiter and Schmidhuber [1997]; Sutskever et al. [2014]), hidden Markov models (HMM, Rabiner [1989]), conditional random fields (CRFs, Lafferty et al. [2001]), autoencoders (Cho et al. [2014]; Kramer [1991]). In the human movement application, however, we will focus on the HMM and its varieties, to finally introduce the basics of neural networks at the end of the current Section.

THE HIDDEN MARKOV MODEL (Figure 1.4) is a generative model, that represents the probability  $\mathbb{P}(x_{1:T}, y_{1:T})$  defined by the *transition probability*  $Q(y_t | y_{t-1})$  (which describes the relationship between the hidden states  $y_t$  - a set of values for different labels) and the *observation probability*  $P(x_t | y_t)$  (which describes how the observation values  $x_t$  are related to the hidden values  $y_t$ ).

The HMM hallmark is that the current observation  $x_t$  depends only on the previous one  $x_{t-1}$ , which is called the *Markov property* (formally defined in Chapter 2 as Equation 2.1.2). We can distinguish types of learning within the HMM framework and use them in different ways, depending



**Figure 1.4** – Hidden Markov model generation scheme for a labeled sequence. Note that here, to preserve the machine learning notations, the hidden states are the labels and are therefore written as  $y_{1:T}$  and the observations are the model inputs, and are therefore written as  $x_{1:T}$  (in contrast to standard HMM notations).

on our knowledge about input and output or the learning goal. We will briefly present four of them here: generation, labeling, supervised training and unsupervised training, two of which are aimed at an already trained HMM, and the last two, at training the HMM.

- **Generative HMM** is used when we know the HMM distributions of transition and observation probabilities ( $P$  and  $Q$ ) and want to generate the sequences of observations  $x_{1:T}$  and labels  $y_{1:T}$ .

- **Labeling with HMM** is intended for labeling of the given sequence  $x_{1:T}$ ; for this task the maximum of all the joint probabilities  $\mathbb{P}(x_t, y_t)$  can be found with *Viterbi algorithm* (commented in Chapter 2 and in Algorithm 2).

- **Supervised HMM training** can be used if we dispose of the knowledge about the sequences  $x_{1:T}$  and  $y_{1:T}$ , but not about the distributions ( $P$  and  $Q$ ), that are to be computed by counting.

- **Unsupervised HMM training** is designed for a case where we only know the observation sequence  $x_{1:T}$  and we intend to estimate  $P$  and  $Q$  using the EMA-like, *Baum-Welsh algorithm*, described as follows:

Step 1). using the (assumed to be known) HMM distributions  $P$  and  $Q$  and the given sequence  $x_{1:T}$  to find the labels  $y_{1:T}$ ,

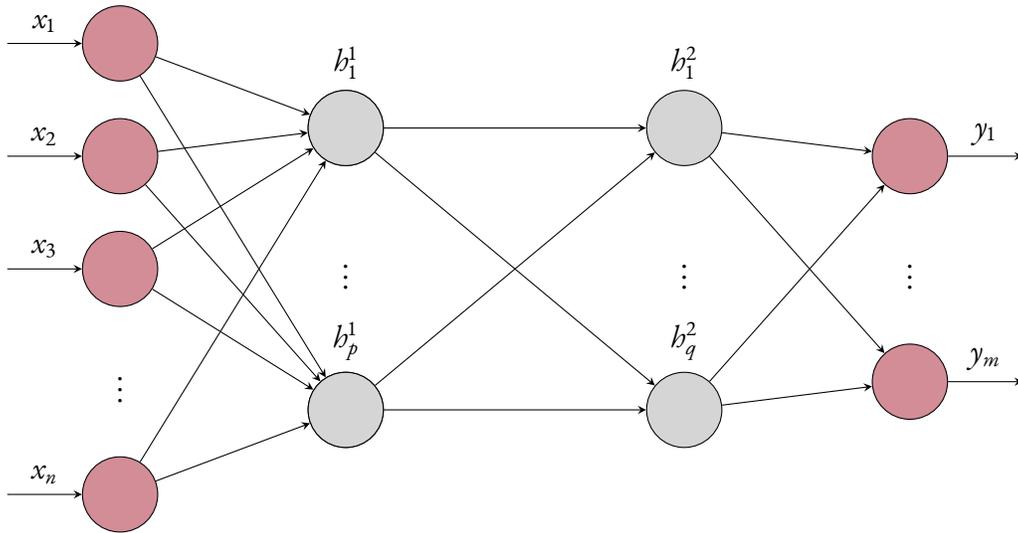
Step 2). using  $x_{1:T}$  and  $y_{1:T}$  (with the labels found in the previous step, this is a supervised learning step), compute the HMM distributions  $P$  and  $Q$ .

→ repeat Step 1).

A more difficult task is the one, when we do not know the parameters of the HMM (distributions  $P$  and  $Q$ ) and the labels are only partially known (for some chunks of the observation sequence  $x_{1:T}$ ). This last approach, in combination with the Viterbi algorithm (acting on the unlabeled, constrained chunks), was used to solve the case of learning the partially labeled sequence and inspired our first contribution (Chapter 2).

NEURAL NETWORKS, which constitute the *deep learning* subdivision of machine learning, are the structures built with *artificial neurons* (McCulloch and Pitts [1943]), in which the input vector  $\mathbf{x}$  of length  $n$ , after being processed by the activation function  $f$ , produces the output  $y$  described by the rule  $y = f(\sum_{i=1}^n w_i x_i - b)$ , where  $\mathbf{w}$  is a weight vector of length  $n$  and  $b$  is a bias term. The activation function is usually a linear function, a sigmoid function or a hyperbolic tangent function. Artificial neurons are combined in several layers to form *multilayer perceptron* (Rosenblatt [1957]), where each neuron of layer  $l$  is connected to each neuron of the following layer  $l+1$  in such a way, that the outputs of the layer  $l$  become the inputs of layer  $l+1$ . For two-layer neural network, where the number of neurons in each layer is the same, the structure is displayed in the Figure 1.5. In order to correct for errors in the process of training, the weights are modified based on the known value of the output  $y$  with backpropagation (Werbos [1974]): the error is calculated as the difference between the obtained value of the network processing  $\hat{y}$  and the ground true value  $y$ . The smallest error value guarantees the best prediction. The layers that are not the input or output layers, are called *hidden layers*. The depth of the network depends on the number of the hidden layers.

The recurrent connections of the neurons in the feedforward network (the self-connections of the neuron) form the recurrent neural network (RNN, Rumelhart et al. [1986]). RNN can serve for instance for sequential learning as a Long-Short Term Memory system (LSTM, Hochreiter and Schmidhuber [1997]; Sutskever et al. [2014]).



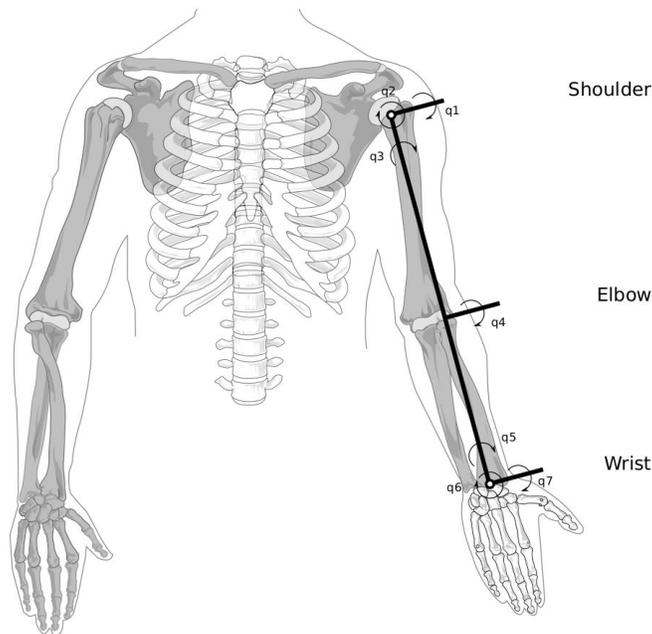
**Figure 1.5** – Sample design of a neural network with  $n$  inputs,  $m$  outputs and respectively  $p$  and  $q$  neurons in each of the two hidden layers. The strength of the connections between the neurons is described by the adjusted weights  $w$ .

## 1.2 HUMAN LEARNING

Learning as an optimization of the learner’s motor control is a complex process of a multidimensional nature. In the second Section of the current Chapter we will explain how the dynamical systems theory helps to limit and manage the number of variables that describe movement, and how, by embedding the individual in the environment, he is constantly invited to act and improve the actions based on the ecological dynamics principles (Button et al. [2021]).

### 1.2.1 ECOLOGICAL DYNAMICS

MOVEMENT CONTROL in the mechanical standpoint, concerns the handling of the infinite possibilities, that the body (as a complex of smaller executional physical units like limbs or muscles and joints, that undergo the particular transformations with angles or dimensional transformations) has to move towards the goal (Figure 1.6).



**Figure 1.6** – Schematic of the human upper limb, with joints governed by muscles, whose functional units limit the DOF manifold (based on the theory of [Bernstein et al. \[1996\]](#)); figure adapted from [Hérault \[2020\]](#) with the author's permission.

In the neurophysiological approach to motor control, [Bernstein \[1966\]](#) was the first to address the problem of action of moving the body as both, a feed-forward path of information (addressing the goal of action) and an antagonistic (sensory-related) information feedback path. In his view, the infinite number of the *degrees of freedom* (DOF) is reduced by the constant refinement of action-perception information, which makes the issue of too many opportunities for motor task (which are assumed redundant and characterized by the term *degeneracy*, [Edelman and Gally \[2001\]](#)) that are solvable for the nervous system in an on-line fashion. Moreover, we may note that perception-action bounding induce information flux between the counterparts of the system as well as their modification and thus motivating the functional role (and certainly not an adverse role) of the system's inherent variability (cf. Subsection 1.2.2).

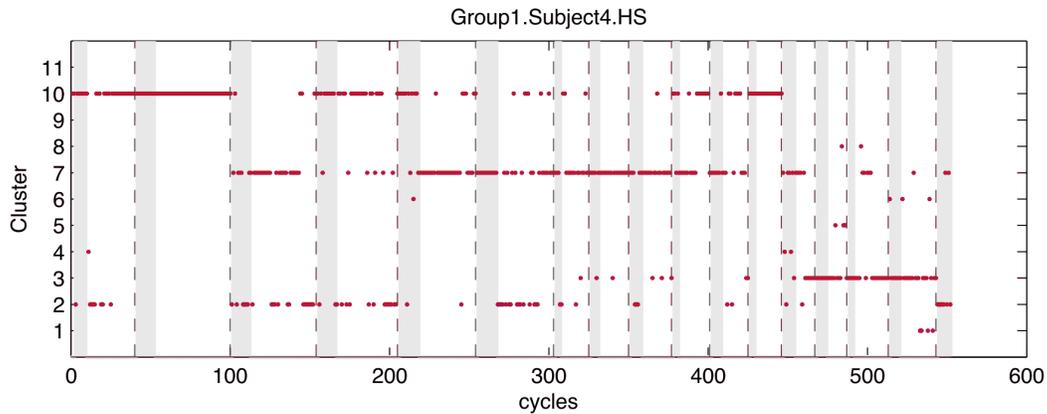
If we want to attempt to describe the nature of the mentioned interaction qualitatively, it is most suitable to apply the perspective of *ecological dynamics* (Button et al. [2021]), which allows to study an individual (i.e. organism with its abilities and the intention to act, i.e. goal), who is embedded in the environment, externally shaping its *intrinsic dynamics* (Zanone and Kelso [1992]). We can notify, that the human movement system can acquire an efficient action through variable paths (Newell [1986]), and that the constraints imposed by the organism, the task and the external physical world limit the DOF, restricting the manifold of possible actions (Newell et al. [1991]; Newell [1996]). However, the environmental possibilities (*affordances*, as defined by Chemero [2003]; Gibson [1979]) are not all equally accessible to the individual at any given moment in time. The landscape of affordances (Rietveld and Kiverstein [2014]) that is continuously explored by a human in movement is a term that probably most appropriately captures its temporal and transient (but also its personal, skill-based) nature.

We can summarize that ecological dynamics describes the possibilities of an individual embedded in an environment (which forms a basic dynamical system) to attune to the information flowing from constantly changing conditions, with a system-regulating perception-action loop. We will show how these foundations of the theory, described by the three dynamical properties (1. ecological unit, with 2. the forces acting on it, and 3. self-regulation mode, Seifert et al. [2017, 2018]), with all the consequences that this description entails (such as variability, sensitivity to initial conditions, nonlinearity), facilitate the investigation of the complexity of human learning.

LEARNING in ecological dynamics theory furnishes the human movement science with the starting point to study the different phases of behavioral adaptation, with the variability as one of the main actuators, which can stem from external forces (environmental constraints) or various neurobiological strategies (operating on the different levels of *skill adaptation* timeline, which can be divided into novice, expert and elite stages, Seifert et al. [2011]). The process of learning involves a destabiliza-

tion of the existing repertoire of movements that leads to a reorganization of this repertoire in a functional way. Given that learning is not an integrative process during which the learner accumulates or acquires skills, but an *adaptive process* that changes over time the coordinative structure of the elements composing that repertoire. Indeed, the human motor system may rather navigate between decreasing and increasing the degrees of freedom (freezing and releasing their number) in the coordination task (Newell et al. [2001]), so that different timescales (Newell et al. [2009]) may be crucial in determining the variability level required for stable coordination as well as for the flexible adaptation to the novel behavioral information (Mayer-Kress et al. [2006], cf. Chapter 3, Section 3.3).

The optimization of movement, that takes place during learning, operates on the current dynamics of the individual and the behavioral information that enters the system as a function of external factors; both of which will determine the direction of further reorganization of individual's behavioral repertoire. Zanone and Kelso [1992] described its nature as follows. When the intrinsic dynamics and the new information are similar, they cooperate to rise a gradual, continuous refinement of an existing behavioral pattern. If the degree of dissimilarity is significantly higher, the new information begins to compete with an existing dynamics, which leads to instability and an abrupt appearance of a new pattern may occur, as a result of a bifurcation (phase transition). This happens when the level to be learned and the level of the existing pattern do not present a large gap and is, in a dynamical sense, a sign of the appearance of a new attractor. If the new pattern does not emerge in a stable way, another behavior of the system may be an intermittent regime. In this regime, if it persists and the patterns interchange for some time, it may elicit multistability (coexistence of attractors), but if its nature is transient, we can observe metastability (Bruineberg et al. [2021]). In the metastable regime the learner is challenged to explore the new patterns and safely backup to the previous pattern (Orth et al. [2018]; Seifert et al. [2015]). Inducing metastability in the learner's learning is a way to learn effectively by introducing a small amount of variability in the stable, exploitative behavior (which uses



**Figure 1.7** – Patterns of coordination exhibited by a swimmer. We observe transitions between different clusters over the course of training, and the stabilization within a session (dashed lines are separations between the training sessions). Figure adapted from Komar [2013] with the permission of the author.

the existing behavioral pattern in the intrinsic dynamics) by manipulating the affordance landscapes in order to elicit exploratory behavior (new behavioral patterns).

The example of navigating between different patterns of learning dynamics can be studied thanks to the performance clustering. For the dynamic analysis of the swimmers, that is illustrated in the Figure 1.7, we can observe that after 100 cycles, the dominant pattern 10th switched to patterns 2nd and 7th, which coexisted, with the returning to include pattern 10th, leaving only separate visits to 2nd cluster after 200 cycles (and before final stabilization). Thus between 280 and 480 cycles the two predominant patterns 10th and 7th (occasionally with patterns 2nd and 3rd and with a marginal role of the rest of the clusters) drive multistability and oscillations in behavior. Interestingly, we observe the return to the initial pattern 10th, during learning (around 420 cycles), i.e. the stabilization of the previously visited pattern through learning (exploitation), even in the face of predominant phenomena of switching between the state patterns (exploration). The routine appears as the 2nd pattern at the end of the performance study, however the rare visits to this cluster, present from the very beginning of learning, are a sign of exploration of the pattern before the final stabilization. Metastability

appears when *there is an attractiveness, but no attractor* (Kelso and Engström [2006]) and this regime cannot be identified with mere transitions between successive patterns (Komar et al. [2023]).

As we have demonstrated, ecological dynamics (supported by unsupervised statistical learning) allows the study of exploitation-exploration transitions in the strategies of the learner, which could be used to create the safe learning conditions (Orth et al. [2018]).

### 1.2.2 ROLE OF VARIABILITY IN MOTOR LEARNING

With respect to the intra- and interdependent differences in movement realization by individuals, the learning process may be explained by managing the amount and the type of variability used during the action performance. In order to acknowledge its desirable and undesirable effects on skill acquisition, it is important to distinguish the variability of behavior from the variability of the performance outcome, each of which operates on a different time scale.

THE VARIABILITY OF THE PERFORMANCE OUTCOME (e.g. climbing fluency, climbing duration, or number of falls/stops) is the variability of the first type. It can be reduced by adjusting the pattern of behavior during practice. In this case, the pattern varies only due to different (and constantly changing) body constraints, and is expressed as the DOF of the smallest possible size. This variability size is inversely proportional to proficiency.

THE VARIABILITY OF BEHAVIOR is the second kind of variability. It allows for exploration of the redundant set of possibilities for action, leaving room for flexible adaptation to the novel contexts. This variability could be related to either a low-order behavioral parameter (such as stride frequency or stroke length in walking) or to a high-order behavioral parameter (i.e. the level of the coordination of elements). In the latter case, low variability could be a refinement of an existing pattern (level of low order parameter) or a transition from one pattern to another pattern of coordination (e.g. from

walking to running). It results in keeping the DOF of a reasonable number (not too small and not too large) in order to provide optimal coordination in the face of unpredictable changes in constraints (not previously experienced) or for the discovery of the novel patterns of action (changing the strategy for a more efficient one).

Ultimately, these two types of variability emerge from exploration and adaptation on a fast scale and from learning on a long time scale, but both reflect the continuous coupling of the human movement system with the performance environment. Examining the variability of learning within the framework of ecological dynamics is not just about accepting that multiple ways of performing an action have a functional role (allowing adaptation to changing and interacting constraints: to new conditions, to fatigue and in extreme situations, to injury, etc.). Since different behavioral patterns may occur during skill acquisition, the behavioral variability may be a sign of critical fluctuations prior to the transition between different learning patterns (Chow et al. [2008b], van Emmerik and van Wegen [2000]).

VARIABILITY CAN BE INDUCED by intervention by designing different forms of variable practice compared to constant practice (Ranganathan and Newell [2013]). It can be seen as a method of perturbation (for stable behavior of exploiting nature) by forcing to find novel skill patterns (exploration). Ranganathan et al. [2014] tested that the protocol with induced variability in the task during learning has a positive influence on performance by the measure of adaptability of the learner to the novel context (*skill or learning transfer*, commented later). For this reason, modifying the learning protocol (depending on the skill acquisition level of the individual) could be the way in which the instructor increases the learning ability during training, by externally manipulating the task constraints (e.g., by applying an environmental change in one dimension of the structured task, such as modifying the route in the climbing task).

A SEPARATE QUESTION is how to apply the variability in the learning schedules, or, in a more general framework, how to gradually manage the difficulty level of the task. Apart from the traditional criterion of changing condition based on the choice of the instructor, we can recognize the case of self-control during learning. There is an evidence that learner self-regulation has a beneficial effect on learning outcomes (Liu et al. [2012]; Wulf and Lewthwaite [2016]), however there is a debate about the timing and extent of the autonomy granted to the learners (Andrieux et al. [2016]).

Overall, the behavior becomes more stable in the face of fatigue and emotional transients (such as anxiety) during the learning process. The simplest way to analyze this is to examine changes in performance over time (Button et al. [2021]); we will review some methods in the next Subsection.

### 1.2.3 METHODS OF MOTOR LEARNING PERFORMANCE EVALUATION

There are several methods used for general performance assessment. In the following subsection we will first describe the particular metrics used in climbing, and then proceed to the tests used in general progress evaluation.

#### FLUENCY IN CLIMBING

The measures of motor performance use to depend on the type of activity. For motor learning evaluation purpose, using the right metrics is key to comparing pre- and post-practice effects, as well as the progress of practice across the sessions. One of the most popular metrics for evaluating the performance in almost any activity is the task duration (e.g. such as the time it takes to climb a given route). However the simplicity of the time measure, and its application as well as processing, does not entirely correspond to the climbing goals. In the technical mastery of climbing, the most important thing, instead of time, is the fluency or smoothness of movements, which not only allows to move forward in the most efficient manner, but is also the measure of energy economy during the whole route climbing

- how the energy may serve for the continuation of climbing (e.g. the next route in a row), or how to limit potential injuries. For this reason, the improvement of climbing techniques, includes not only the temporal factor, but also the spatial one, because the frugality of the space in which the climbing unfolds, designates the training effectiveness, as opposed to the time measure, which is much more influenced by the external of learning factors, such as total strength before training or other purely body dependent individual factors (which are difficult to average out). The proper choice of the evaluation metrics, due to the assumptions of ecological dynamics theory, must also reflect the instruction type given to the learners prior to the task (e.g., more attention given to fluent climbing than to fast climbing). Here is a brief list of the metrics used to evaluate climbing.

GEOMETRIC INDEX OF ENTROPY is undoubtedly the most popular and most established way of evaluating fluency, used in most of climbing studies. It is a purely spatial measure, that characterizes the spread of the climbing trajectory (measured as the hip position relative to the climbed route) over time.

According to [Cordier et al. \[1994\]](#) it is defined as

$$GE = \ln\left(\frac{2 \cdot l}{c}\right),$$

where  $l$  is the length of the climbing trajectory and  $c$  is the perimeter of the convex hull of the trajectory. In the entropy calculation, low values indicate behavioral stability (certainty of a climber), while higher values indicate behavioral instability reflected in chaotic movements ([Orth et al. \[2016\]](#)).

JERK is a popular physical measure that is used across different domains to describe the spatial and temporal dependencies at once (for a multidisciplinary review cf. [Hayati et al. \[2020\]](#)). It can be calculated either as the third time derivative of position or as the rate of change of acceleration.

As in Seifert et al. [2014] the jerk of the hip acceleration is defined as

$$JE_s(T) = C \int_0^T ||l_s||^2 ds,$$

where  $l_s : [0, T]$  is a smooth trajectory (developed in time),  $C = \frac{T^5}{(\Delta l)^2}$  is a normalization constant, and  $T$  is the duration of the climb. The jerk defined here is a dimensionless measure.

In climbing it is a measure that describes the smoothness of the climbing trajectory. Indeed, avoiding jerky movements (which appear as the *knots* on the trajectory line), which are a sign of anxiety in postural regulation and are detrimental to performance, leads to an improvement in climbing fluency.

Jerk of hip rotation is an alternative view of this spatiotemporal measure as the number of saccadic movements during climbing.

IMMOBILITY RATIO is a purely temporal metrics based on the ratio of time spent immobile to time spent in motion.

From Orth et al. [2017, 2018], for a trajectory  $l : [O, T] \rightarrow \mathbb{R}^2$ , we find the threshold-based immobility to mobility ratio as:

$$IM(l) = \frac{\sum_{i=1}^n p_i}{n},$$

$$p_i = \begin{cases} 1 & \text{for } q_i < \text{threshold}, \\ 0 & \text{for } q_i \geq \text{threshold}, \end{cases}$$

$$q_i = t_i \sqrt{(h_i)^2 + (v_i)^2}.$$

where  $i = \{1, \dots, n\}$  ( $n$  is the number of time intervals) and  $(h_i, v_i)$  symbolizes the coordinates of the center of the body in two-dimensional space (horizontal and vertical), which change with time  $t_i$ .

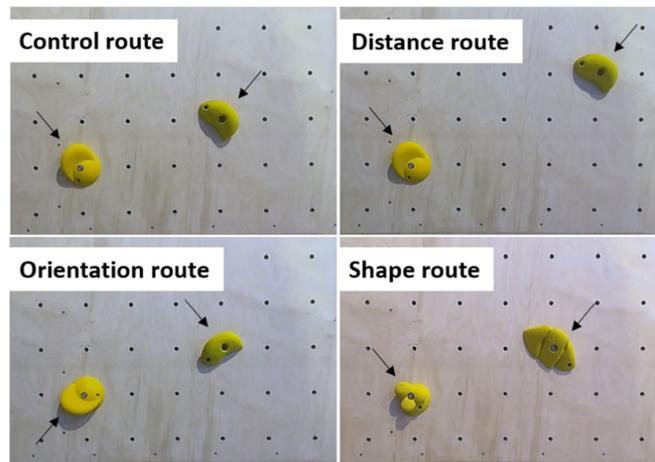
We may notice that, in the energy cost calculation, time spent immobile may induce unnecessary fatigue to the climber (while it may also be a sign of some exploratory behavior).

Moreover, the *threshold* level that distinguishes movement from immobility state is an arbitrary value of velocity (with  $[\frac{m}{s}]$  units) and as such could be considered a drawback of this fluency measure calculation. It also makes the immobility ratio a discrete measure, unlike the entropy and jerk, which are both continuous.

It has been shown, that the fluency metrics in climbing are correlated (Orth et al. [2017]; Seifert et al. [2014]) and could presumably substitute each other. However studying them separately, could shed light on whether the temporal or spatial aspect of fluency dominates the behavior. It is worth mentioning however, that the above defined metrics are of different scales when we consider the raw computations and for the comparison, they should undergo the unification technique (as for e.g. standardization) in the pre-processing stage (prior to analysis or machine learning).

#### GENERALIZATION TRANSFER AS MOVEMENT ASSESSMENT

The performance of the individual during the *transfer test* is necessary for calculation of the skill or learning transfer to the new context (Oppici and Panchuk [2022]). In this experimental test, the skill is evaluated under conditions that differ from the practiced ones (e.g. new route in climbing). The measure of transfer to the new context is the most important for calculating the practice effectiveness in climbing (Seifert et al. [2019]), in particular, to determine the degree of generalization acquired by the climber. The concept of *generalization transfer* unites in the present work the skill (short-term) transfer and the learning (long-term) transfer. However, the difference between these two types of transfer is not only related to the time scale. In *learning transfer*, learning is related to active improvement of cognitive abilities such as decision making (Araújo et al. [2017]). Conversely, *skill transfer* refers to skill refinement according to a different context, as presented in the research of Hacques et al. [2021],



**Figure 1.8** – Manipulating the handholds to create the transfer routes. The arrows indicate the preferred grip enabled by the handhold; figure adapted from [Hacques et al. \[2021\]](#) with permission of the author.

where skill transfer was studied by manipulating the distance between holds, hold orientation, and hold shape (Figure 1.8).

More specifically, in sports science we can distinguish three types of learning assessments. The first one is an *adaptation* evaluation, obtained by comparing pre- and post-tests (measurements taken before and after the practice) or even a trial-to-trial analysis. This measure can give us an illustration of the basic learning dynamics of the individual throughout the practice. Another example is the assessment of learning by comparing post-test and retention test (measurements taken immediately after and some time after the practice); this is the *memorization* evaluation. The third one, is the aforementioned generalization transfer, which is attained by comparing either post-test to transfer test, or retention test to transfer test. This relation may manifest itself as a positive effect on performance outcome (increase) or a negative effect on performance (decrease); it may also manifest as an intermittent, neutral effect. Thus, generalization transfer is not a direct function of time (like memorization, which depends on the retention period), but rather the measure of how well the learning protocol for the acquired skill allows for performance in an unfamiliar environment ([Newell \[1996\]](#)). Transfer reflects the most general ability of the learner to adjust the acquired skill as a function of the organismic

capabilities in the confrontation with the environmental properties, perceived in a continuous way. From the point of view of ecological dynamics (Bruineberg et al. [2021]), generalization transfer is a post-learning process that allows for the interaction with novelty (exploration) in order to reshape the landscape of affordances. From a temporal perspective, the necessity of continuous modification of one's skills in a new environment, determines the dynamic and time-dependent nature of the transfer.

There is a dimension of specificity-generality of transfer, which refers to how specific is the information present in the practice environment that is transferred, for instance between two types of climbing: indoor climbing and ice climbing (e.g. learning to handle the texture-specific ice-hold or using ice tools is specific compared to general capacities that are learned in both types of climbing such as body management or finger/foot exploratory actions, Seifert et al. [2016]). But there is also the volume perspective (the gap), that allows to determine how different are the tasks that allow the transfer of the learned skill, i.e. how much the affordances overlap between the two tasks, the mastered task and the novel one (reflected in near and far transfer types as in Issurin [2013]). The spectrum of novelty on which the transfer operates is described by the *learning-to-learn* phenomena, which can be measured between different tasks, such as different sports (Oppici and Panchuk [2022]) or different developmental stages of infants (Adolph [2008]).

To put our considerations in a more global perspective, it should be emphasized that the use of information-theoretic terminology, whose vehicle is the concept of generalization, is not accidental here, since the same mechanisms that are present in the machine learning, also operate in the case of motor learning (Hérault [2020]). In the general point of view, we can see the moderate adaptation to the error-free modeling in human learning, as a form of regularization analogous to the one that allows to counteract the overfitting in machine learning model building. The question is what kind of (structured) variability in motor learning might reflect the use of the regularization term in information theory. Several attempts have been made to test different degrees of similarity (on the structural

level, referring to the modeling weights in the optimal model finding in machine learning) and sizes of variability (that refers to the hyperparameter adjustment in the regularization scheme). Some experimental protocols in human learning address the issue of variability adaptation, depending on the task (as demonstrated for instance in [Hacques et al. \[2021\]](#) for the climbing task).

### 1.3 MACHINE LEARNING FOR BEHAVIORAL SIGNALS

The behavioral signal is specific. First, it evolves in time, so we are often concerned with analyzing the sequences and the time series of data. Second, these data are bounded in time dimension (and thus in size), since the recordings can only be as long as the experiment duration, which in turn must be limited by the body constraints (such as fatigue). The third limitation is the missing data, which is often present in the record, so the policy of ignoring or imputing the missing data must be applied with all its consequences.

IN THE THEORY OF SKILL ACQUISITION APPLIED TO HUMAN MOVEMENT, machine learning in behavioral pattern analysis has mainly been employed to 1) recognize patterns, 2) analyze learning profiles and 3) assess levels of expertise. These applications involve unsupervised learning utilized to analyze training data (time series) of performance indicators (in the case of climbing, these are fluency indicators).

Pattern recognition is based on the identification of learning styles through segmentation and cluster analysis (most frequently the hierarchical clustering of an agglomerative nature) and explores the transitions between them in the course of learning (cf. Figure 1.7 together with the interpretation of the Fisher-EM clustering in [Komar \[2013\]](#); Figure 1.9). The variability comparison (the critical fluctuations or the lack of them) allows to study the behavioral dynamics in the learning process ([Chow et al. \[2008b\]](#)) and, in general, it helps to identify at the individual level different behavioral states

(clusters), that the learner goes through during the learning process. Furthermore, by recording the evolution of the patterns of an individual learner, it is possible to access the learning profile, which is paramount to address the intra-individual variability. Learning profile analysis of different learners helps to track the cluster transitions over time - i.e. the behavioral states (patterns) that the learner prefers in the course of practice (Chow et al. [2008a]). Comparing the learners from this perspective not only addresses the universal constraints related to task structure, but also respects the personal constraints of each individual learner. An attempt at such an analysis for the climbing task is included in an exploratory study by Hacques et al. [2018].

Similarly, in the expertise analysis (Seifert et al. [2011]), clustering allows to identify different profiles of learners (novices, experts, elite performers) without using any a priori knowledge about the datasets. This type of analysis helps to find the real and unbiased weight of each performance-dependent feature (such as gender, age, sport specialty, anthropometry, etc.). Therefore overall, clustering provides a more powerful approach to tracking individual particularities than group comparisons based on averaging.

SOME OF THE OTHER APPLICATIONS OF MACHINE LEARNING IN SKILL ACQUISITION use the dimension reduction methods such as PCA or embeddings to select the factors (limiting DOF) that are most important for performance (PCA: Hong and Newell [2006] in learning a skiing task, Pacheco and Newell [2018a,b] in a fine motor task, embeddings: H erault et al. [2017] in climbing). In addition, there are multiple applications of statistical learning in the predicting of individual performance, using supervised learning techniques (these applications involve frequently regression methods or interpolation) or the unsupervised ones (e.g. Gaussian processes Leroy et al. [2020]).

THE MISSING DATA ISSUE in motor recordings is often not recognized as a problem, resulting in it being ignored in the analysis (as in Pacheco and Newell [2018a]). The voids in the measurements are

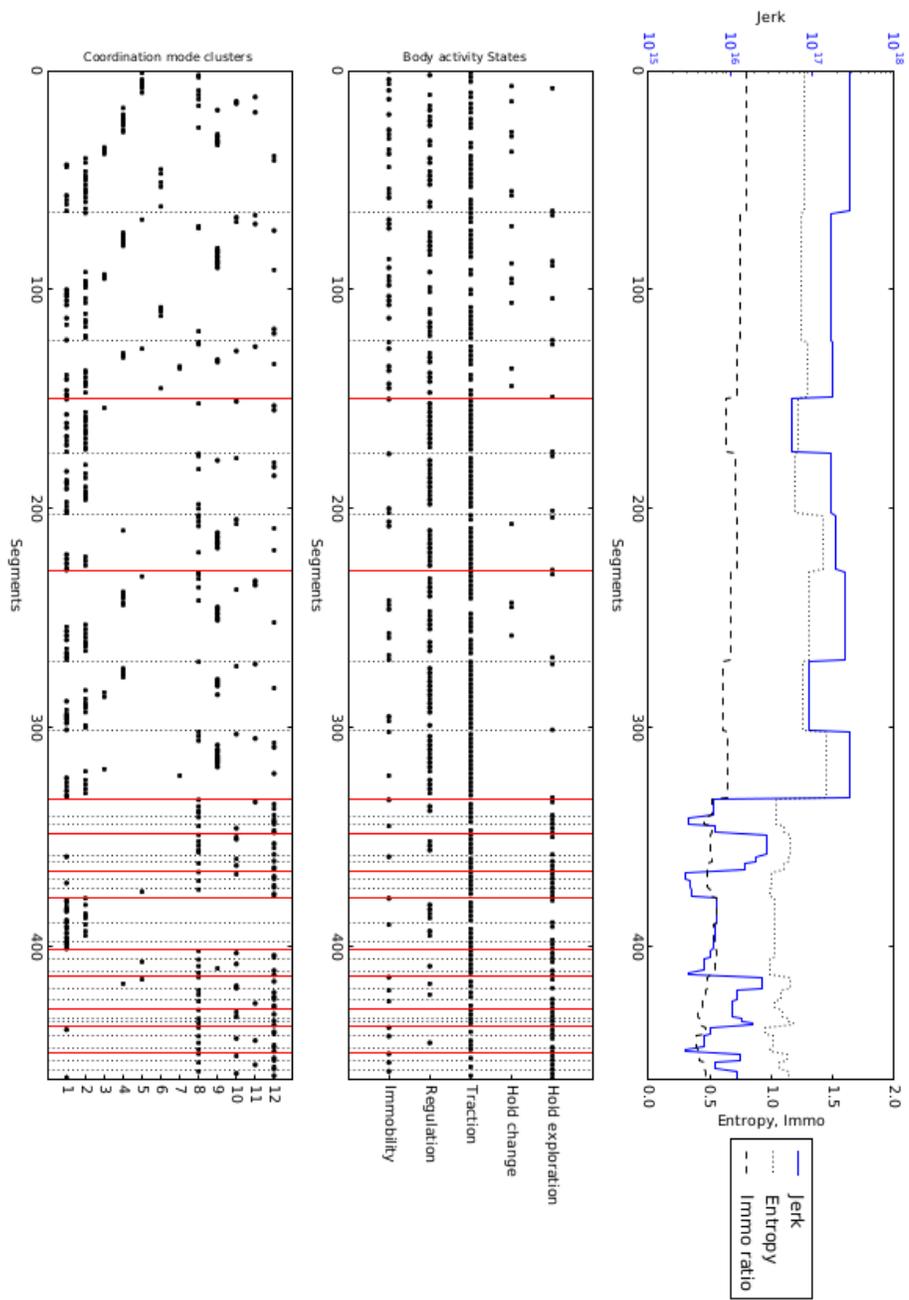


Figure 1.9 – An example of clustering and segmentation compared to fluency values, along multiple trials during the climber's practice. Figure from [Héroult et al. \[2017\]](#) used with permission of the author.

usually the consequence of a malfunction of the measuring device (physical or software error), human error in the recording or the individual participant indisposition (injury, absence or dismissal).

Generally in signal processing, we can encounter different types of missing data (Rubin [1976]): missing at random (MAR), missing not at random (MNAR), missing completely at random (MCAR), and depending on the type, we can use different strategies to treat them. One strategy is to ignore the existence of voids, and focus on the remaining complete data sequences. However, if we have to tackle the missing values present in the data - depending on the size of the missing data and the data type - we can enumerate methods of deleting voids in a sequence (only the non-void elements remain), imputation (e.g. based on the mean, interpolation, multiple imputation Murray [2018]), and machine learning (e.g. k nearest neighbors KNN, multi-layer perceptron MLP, self-organization maps SOM Kohonen [1982]). We faced the problem of missing data in one of our contributions (Chapter 2, Aniszewska-Stępień et al. [2020]) and mentioned it in the second one (Chapter 3, Aniszewska-Stępień et al. [2023]). By studying the data collection protocol in climbing (next Section), we will see how easily information deficits can appear in the behavioral signal.

#### 1.4 CLIMBING DATA

Anchored in the ecological dynamics framework (Button et al. [2021]), our main objective is to assess how learners functionally adapt their behavior during constant and variable practice through a learning protocol in a climbing task, and then to predict how different forms of variable practice could help them to transfer their skills more efficiently to a new situation. The goal of the climbing task was to climb as fluently as possible because in climbing, fluency has been found to be related to an indicator of efficiency, that reflects attunement to relevant information for action (in climbing jargon, this is called *route* or *path finding*) and calibration of the perceptual-action system. Therefore our first goal in machine learning was to assess the climbing fluency at the hip level (as it reflects the center of

mass) through different indicators (spatial, i.e. geometric of entropy; temporal, i.e. immobility-to-motion ratio; spatiotemporal, i.e. jerk) and the subsequent actions of the four limbs. To reach this goal, the task was designed to allow either alternating grasping actions with the right and left hand (called *alternation grasping pattern*) or repeated grasping actions with the same hand (called *repetition grasping pattern*). Therefore, the first key challenge in machine learning presented in Chapter 2 was to recognize both alternation and repetition grasping patterns, as well as foot supports, and then associate these patterns with fluency indicators. Second, to test whether variable practice (vs. constant practice) helps to transfer acquired skills more effectively to a new situation, we designed two types of variable practice: variability induced by the instructor, which corresponds to the *imposed variability* group of participants, and variability chosen by the participants, which corresponds to the *self-controlled variability* group of participants. In both cases, the variability is related to the pace of the route changes. In terms of machine learning, the challenge presented in Chapter 3 was to model the learning curve based on the fluency indicators, then predict skill transfer to a new route and compare whether the imposed and/or self-controlled variability groups exhibited higher transfer than the constant practice group.

The source of the raw data for the analysis were the measurements collected by the procedure described below, followed by preprocessing and precalculation.

#### 1.4.1 DATA COLLECTION

A group of 34 student volunteers from the University of Rouen Normandy (11 females and 23 males) were recruited to participate in this study. On average, the participants were  $20.3 \pm 1.2$  years old,  $172.3 \pm 6.8$  cm tall,  $66.4 \pm 9.8$  kg and had an arm span of  $172.7 \pm 8.6$  cm. Five participants were left-

handed and the remaining 29 were right-handed. One participant withdrew from the study during the training sessions due to injury, thus there were 33 complete data tracks <sup>†</sup>.

Participants in the experiment climbed designed routes on an indoor artificial wall. They were novice climbers who completed learning consisting of 84 trials divided into 10 practice sessions.

It is important to notify (especially for the approach presented in Chapter 3) that the participants were divided into 3 practice groups according to the instructions they followed: 9 of them (constituting the constant practice group CP) followed the practice on the very same route (called *control route*) during the whole learning. The remaining 21 climbers (constituting the variable practice group VP) have been climbing the same route (control route) only in the first 3 trials of each session, while the other trials of the session (three in the sessions 1 and 10 and six in sessions 2 to 9) were performed on different routes (called *variant routes*). Furthermore, the variable practice group was divided according to the type of route alternation, into the induced variability group VP<sub>1</sub>, in which the pace of the route changes from trial to trial was externally controlled by the instructor, and the self-controlled variability group VP<sub>2</sub>, in which the participants experienced route modifications only when they explicitly expressed their willingness to tackle the novelty. The two variability practicing groups consisted of 9 participants (VP<sub>1</sub>) and 12 participants (VP<sub>2</sub>), respectively.

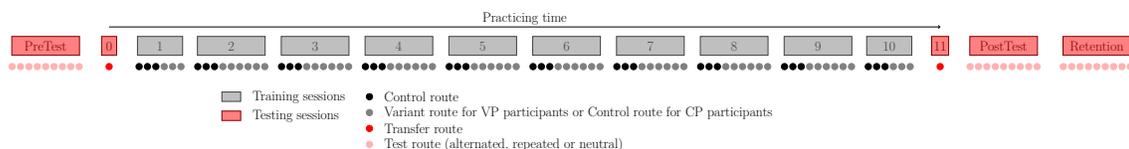
Regarding the type of route, it should be noted, that the practicing protocol began (i.e., the first ascent of the 1st practice session) and ended (i.e., the last ascent of the 10th session) with an attempt on a *transfer route* for which the participants had no additional practice during the learning sessions. This route was designed to assess whether the participants were able to find an adapted chain of movements on new routes with learning.

The protocol is illustrated by the Figure 1.10 and the climbing route examples by the Figure 1.11. By examining the route modifications, we can clearly discern the differences in the route designs. The

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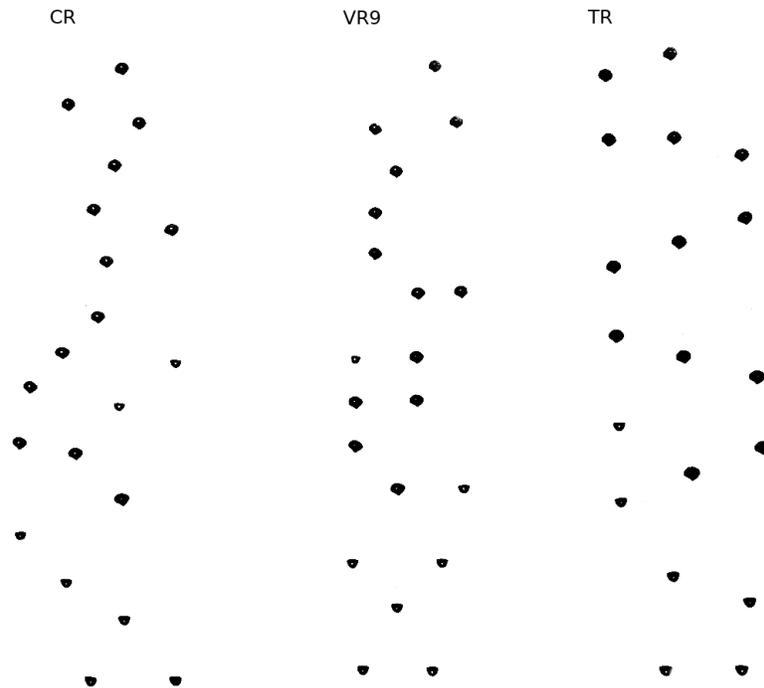
<sup>†</sup>In one condition, the exponential divergence of data from 3 participants eliminated these participants (Chapter 3).

route conversions did not account for the handle shape modifications nor the rotation of the handle, but focused mainly on its displacement (which is consistent with climbing variability detailed study Hacques et al. [2021]).



**Figure 1.10** – The protocol of data collection. The rectangular blocks in the upper figure indicate the type of session. The black dots in the lower figure represent the *control route*, which was the same for all participants in each of the 10 sessions. The gray dots remained the same throughout the training for the constant practice group CP (followed *control route* climbing until the end of the training); however, they varied in the case of the variable practice group VP (became *variant routes*). The red dots (signed with 0 and 11, however included in the adjacent sessions 1 and 10, respectively) represent the *transfer route* (different from the control or variant routes) and are not considered as practice routes, but were used only to evaluate the participants' progress in a novel context. The test sessions (pre-test, post-test and retention test sessions) each consist of 3 alternating, 3 retention and 3 neutral routes each one, in random order (here marked with pale red dots).

In addition to the ten practice sessions described above, there were three *test sessions* (as explained in Hacques et al. [2018]; Figure 1.10). The purpose of the test sessions was to scan the behavioral repertoire of the participants. More specifically, to assess the extent to which the participants could perform hand alternations (using two different hands for two consecutive movements) and hand repetitions (using the same hand for two consecutive movements). For this purpose, they had to climb three different routes (Figure 1.12) that either encouraged them to perform alternations (*alternation route*), repetitions (*repetition route*), or both grasping patterns (*neutral route*). Furthermore, during the test sessions, participants climbed these three routes in three different instruction conditions: a free condition (to observe the spontaneous behavior), an alternation condition (i.e., they were invited to perform as many alternations on the routes as possible), and a repetition condition (i.e., they were invited to perform as many repetitions as possible).



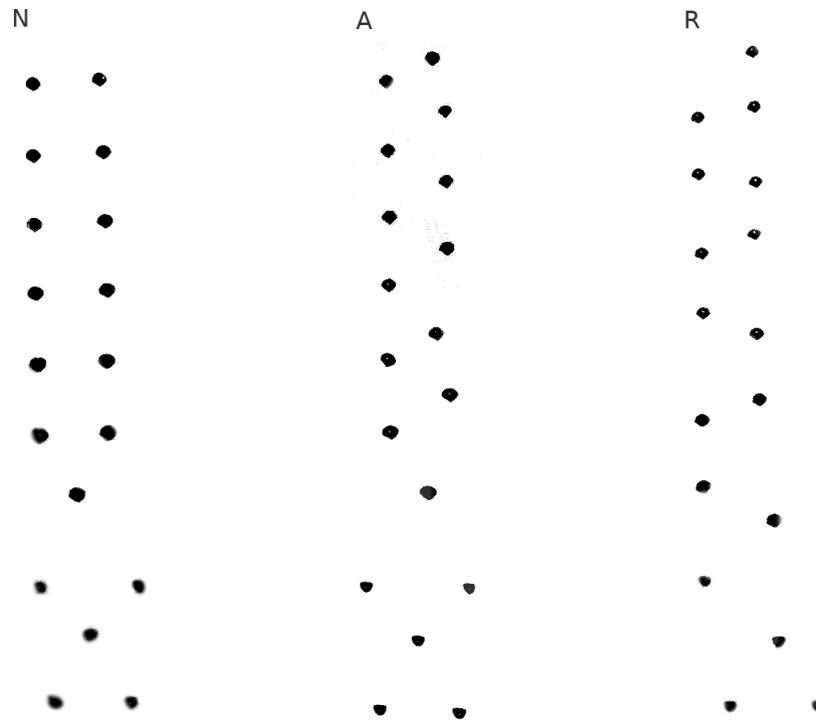
**Figure 1.11** – The examples of climbing routes used in the experiment. Left: constant route, center: one of the variant routes (last variant applied during the practice), right: transfer route.

The protocol followed the guidelines of the Declaration of Helsinki<sup>‡</sup>. The procedures were explained to the participants who then gave their written consent to participate.

**DATA RECORDING** The hip coordinates of the participants were registered from the red light trajectory, that has been provided by the LED lamp attached to the climbing harness (a video recording). In addition, the participants wore a Hikob IMU (inertial measurement unit) placed on their backs. The IMU contains an accelerometer, a gyroscope and a magnetometer (Figure 1.13(a)).

The position and acceleration registered from the video and IMU were used to calculate the fluency indicators for each of the learning session trials (separately for each of the 84 trials divided into

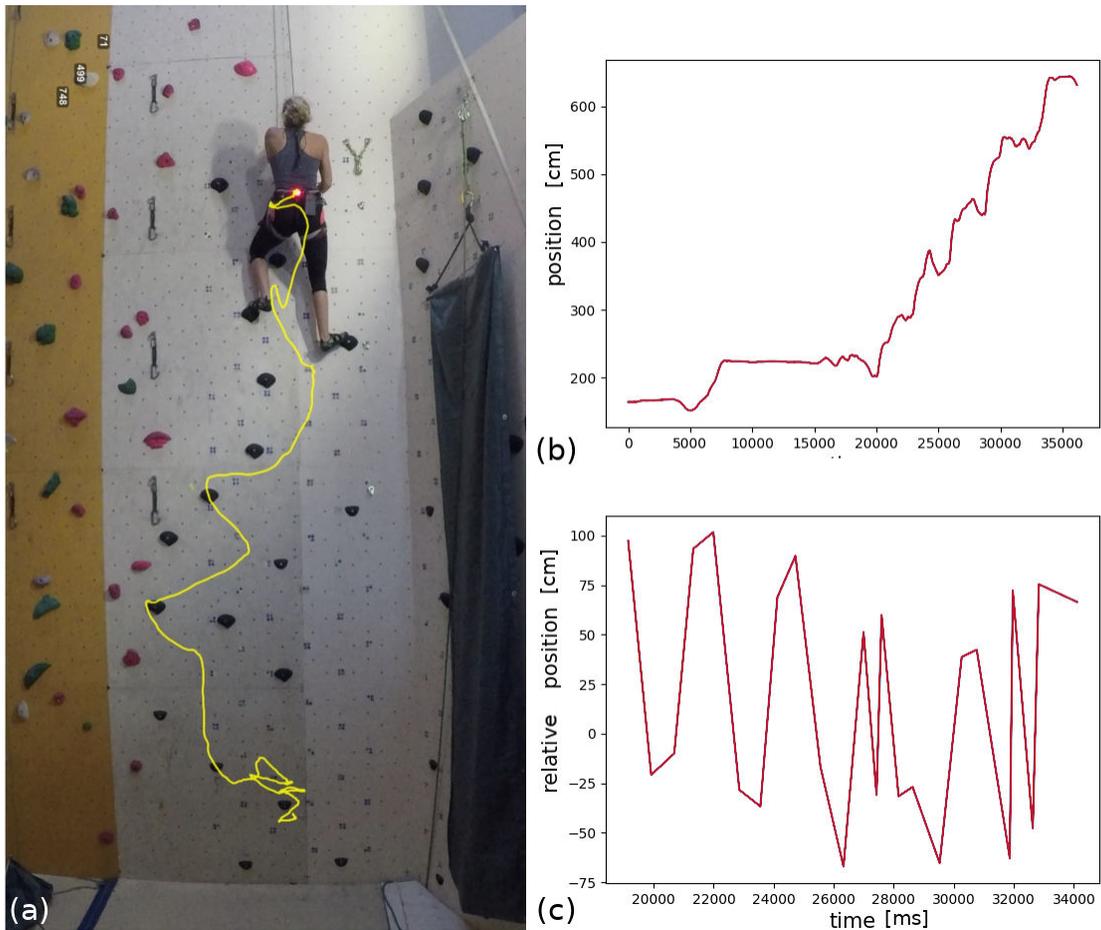
<sup>‡</sup><https://www.wma.net/what-we-do/medical-ethics/declaration-of-helsinki/doh-oct2000/>



**Figure 1.12** - The three simple routes used during the test sessions. Left: neutral, center: alternation, right: repetition route.

ten sessions climbed by each participant) and for a post-practice transfer route. The duration of the participant's touch was registered by the Luxov®Touch system.

Before the start of each session, the climbers were given feedback on their climbing fluency (jerk, entropy and immobility ratio) during the previous session (the example of the given feedback Figure B.1 can be found in the Appendix B). Some climbers also participated in the separate phenomenological study to comment on their activity during the self-confrontation interviews (Rochat et al. [2020]), but we made no correction for the secondary effect that participation in the phenomenological study might have had on the progress of these participants.



**Figure 1.13** – Experimental setup for climbing of the artificial wall: the LED lamp light for tracking the trajectory of the climber’s center of mass is attached to the harness along with the IMU. The handholds on the artificial wall were all equipped with sensors. (a) The trajectory of the climber is marked by the yellow line. The signal is composed of the time series of the distance between the climber’s hip and limb position, when touching the hold. (b) Position of the climber’s body center collapsed to 1D by summing the horizontal and vertical position ( $b_i + v_i$ ) evolution in time. (c) Observation signal as the position of the body center relative to the limb that is touching the hold (collapsed to 1D by summation), evolution in time.

#### 1.4.2 LIMITATIONS AND DATA PREPROCESSING

Prior to analyzing the behavioral signal, we faced several issues due to the signal specificity: 1) incompleteness of the data recordings - due to malfunction or error of the measurement system, or participant withdrawal due to injury (especially in cases of extreme sports, and when the recordings consist

of many trials spanning over a long period of time) - and 2) avoidance of averaging over group data, to preserve the individual variability of participants. The first limitation, the incompleteness of the data can be addressed in many ways, depending on its nature, and will be described further on for the different types of missing elements in the following chapters (Chapter 2, Chapter 3). With respect to the second limitation, we have used the data standardization instead of averaging, for instance in the case of the fluency comparison (to unify the different scaling of the fluency indicators as shown for the raw values in the Figure 1.14).

THE BEHAVIORAL SIGNALS that we analyzed, were mostly based on the position of the climber on the wall during the ascent, and were the following.

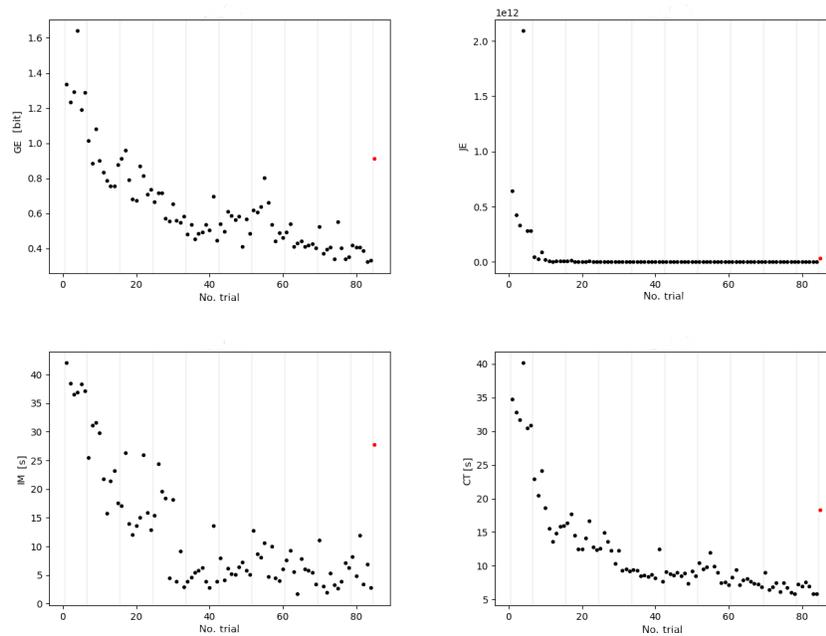
- **Relative position of the support limb throughout the trial**

The behavioral signal to be labeled in the first contribution (Chapter 2), was based on the climbers' body position relative to the limb position while touching the handhold (Figure 1.13(b), (c)). This measure takes into account the distance from the center of mass (hip coordinates) to the particular limb used for support during the ascent and was calculated from the video recording (for the climb trajectory) and the handhold touch time recording.

- **Fluency time series**

To evaluate the performance of the participants during the climbing of each route in the second contribution (Chapter 3), there were three fluency indicators, that were precalculated for the study from the climber's trajectory: geometric index of entropy (GE), jerk of the hip acceleration (JE) and the ratio of hip immobility (IM), as in Subsection 1.2.3. All of these are classical measures employed in the evaluation of motor performance in climbing (Cordier et al. [1994]; Orth et al. [2017]; Seifert et al. [2014]) and describe the smoothness of movement during the climbing of each route (spatial fluency for GE, spatio-temporal fluency for JE, or purely temporal fluency for IM). Additionally, as

an auxiliary measure<sup>§</sup>, we used climbing time (CT). The Figure 1.14 presents the examples of behavioral signals obtained by computing the fluency indicators of each trial for a participant's learning progress. They constitute the practicing session scores, which together, for a single climber shape the (exponential-like) *learning curve* that reflects the learning dynamics.



**Figure 1.14** – Four metrics (GE, JE, IM, CT) from one participant in the VP group (the ordinate axis indicates the raw value scale, i.e. the values before standardization). The black dots represent parts of the signal of each indicator that correspond to the practice routes. The red dot corresponds to the post-practice *transfer* route. The gray vertical lines indicate the sessions partition.

The experimental data for our analyses were collected at the CETAPS of the University of Rouen and provided by Guillaume Hacques, who also archived the experimental conditions (present in the photographs in this manuscript), operated the measurement equipment, and provided the calculations of the fluency measures.

<sup>§</sup>Participants were not instructed to climb quickly, but as *smoothly* as possible, i.e. avoiding movement saccades.

## 1.5 CHAPTER CONCLUSION

The interdisciplinary research that we present in this Thesis is not easy to follow without a background consisting of definitions and introductions to the core problems of both machine learning and human learning. In the current Chapter we have merely scratched the surface of the main concepts of machine learning, together with the motivation stemming from the human movement science, to use them, which is both functional and formal. From the formal point of view, we highlight the commonalities between the two fields exemplified by the use of the notions of optimality, variability and generalization. From the functional point of view, we present the specificity of the considered signal, i.e. its sequential character, with the integrated two kinds of constraints: the voids/artifacts present in the recorded data or the small sample size, both provided with the related machine learning solutions to address the requisites and limitations. Both aspects, functional and formal, will guide us in revealing the methodology in the following Chapters of the Thesis manuscript, through scrutinizing the approaches used for each task.

In the following Chapters, where we present our contribution to facing the current challenges in the field of human movement, we will in parallel emphasize the importance of the formal dimension of the approaches used.

Our first study (Chapter 2) formally establishes a new generative approach, which is the HMM-CVA, to label missing values of the ascent trajectory (relative position on the wall) with the kind of limb used for support by the climber. It is intended to be useful to the human movement scientists in constructing new metrics for assessing climbing expertise. The so-called alternation-repetition rate (A-RR) is intended to be used by coaches to improve the climbing learning protocols and hopefully would lead to more efficient, personalized practice schedules.

The second work (Chapter 3), which applied linear regression furnished with Lasso selection to predict post-learning test (transfer) based on learning dynamics (fluency curve), aimed to compare

different types of practice and find the one in which the relationship between the performance history (the input) and the transfer (the output) is the strongest. In this way, we deliberate how to introduce statistical learning when data are scarce; at the same time, however, we contribute to the discussion on the most profitable contexts in terms of the role of diversity in the learning process.

In this view, through the present work, we overall show how machine learning can be a supportive tool in motor science research and our global knowledge of human learning.

*ELEVEN*

*Thirty spokes share the wheel's hub;*

*It is the center hole that makes it useful.*

*Shape the clay into a vessel;*

*It is the space within that makes it useful.*

*Cut doors and windows for a room;*

*It is the holes that make it useful.*

*Therefore profit comes from what is there;*

*Usefulness from what is not there.*

Tao te ching / Lao Tsu

# 2

## Learning from partially labeled sequences for behavioral signal annotation

IN THIS CHAPTER will be presented a first contribution, which is a method to label the sequences by training the classifier in the missing data framework.

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## 2.1 CHAPTER INTRODUCTION

In the Chapter 1 we described the background of the present contribution: a hidden Markov model (HMM) and its application to structural learning in human movement science (Section 1.1.3). In the current Chapter, we will present the rationale for using the sequential learning in the framework of motor learning and will show the challenge that the context of use dictates for the application of specific methods. For this, we will first describe the human movement science objectives (Subsection 2.1.1) matched with the character of the data to be used (Section 2.2) and secondly present our model and its evaluation for the given problem solution (Subsection 2.4.1). Meanwhile, we will also review previous attempts to handle the issue of partially labeled training data and compare these approaches in a more specific bibliographic study (Subsection 2.1.2).

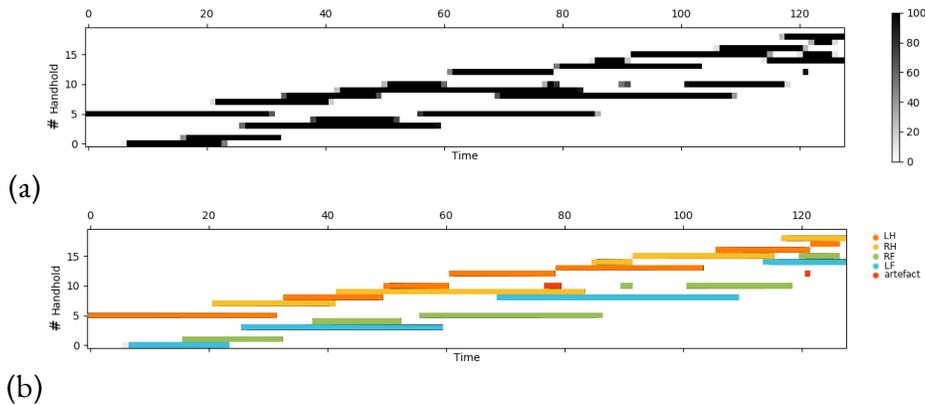
### 2.1.1 CLIMBING PROFICIENCY EVALUATION

The collection of data within sport protocols (in terms of design and modification) makes it easy to compare the progress of learning and movement strategy between different individuals, facilitating both the evaluation of performance (inter-individual analysis) and the improvement of an individual performer throughout the process (intra-individual analysis). For the qualitative evaluation of the climbing activity, one of the pieces of information that can be extracted from the data is the identification of the type of posture and the succession of postures. Namely, by knowing the sequence of postures (or *engrams*, that represent the muscle memory) throughout the ascent, sports specialists are able to analyze the climber's pattern while facing a particular route design. Postural recognition can be characterized by patterns such as immobility, traction, postural regulation, hold interaction (exploration, change) as in [Boulanger et al. \[2016\]](#). Such knowledge is helpful to access the individual strategy evolution all along a climbing ascent.

Conversely, a simpler evaluation of movement patterns could be the alternation/repetition ratio (A-RR). In the case of this metrics, the implicit assumption would be that the alternation pattern (alternating the hands or the legs used for support, as in the walking up pattern) characterizes the early stage of climbing learning, while the repetition grasping pattern (repeatedly using the same hand for support on the wall; this style never occurs in unconstrained walking up) would be a marker of growing climbing expertise. Indeed, when constrained by the route design (a situation that often occurs in outdoor climbing on natural walls), the expert climber is able to increase the repetition/alternation ratio according to the constraints of the route (e.g. in the case of two close handholds). The change in the climbing grasping pattern may occur in the later stages of climbing acquisition as a result of improved on-line judgment of the required action (environmental challenge) combined with increased physical ability (muscle strength) to use the same limb twice in a row. Thus, the A-RR would become a proficiency indicator, similar to fluency metrics (Subsection 1.2.3), and would inform about the chain of movements produced by the climber (Hacques et al. [2018]). However, this hypothesis requires in-depth analysis, for which it is crucial to know the annotation of the support limb used during the ascent, in order to determine the order and frequency of use of each grasping pattern (A-R).

To study limb order, the sequence of supporting limbs for each ascent is required, but this data is not easy to obtain and the simplest method would require manual annotation, which is tedious and time consuming. A more efficient and automated labelling method is therefore essential.

In order to classify the evolution of human movement patterns, we will annotate the behavioral signal with discrete labels (Figure 2.1) based on the two-dimensional trunk position recording (with manually annotated limbs) and the automated hand-touch time registration. To do this, we will first extract the important sequence of events from the measurement data, focusing on the spatial position of the supporting limb relative to the trunk *at the moment of contact with the handhold*, which will become our sequence of observations (two-dimensional input). The labels, i.e. the description of the type of limb used for support at that moment (right hand RH, left hand LH, right foot RF and left



**Figure 2.1** – Performance and learning dynamics achieved with the instrumented holds. The abscissa indicates the number of the climbing holds pressed (sensor activated in time). An example of the unannotated duration of limb contact with a hold for an ascent is shown in panel (a). The corresponding color-coded annotated version is displayed below in panel (b), which is our desired goal in the task. The time series (a) is labeled with the type of limb used for support: left hand (LH), right hand (RH), left leg (LL) and right leg (RL) in (b).

foot LF), will become the output and will also form the sequence, aligned with the former. Thus, we are operating in the framework of sequence-to-sequence learning, which can be fully supervised (if we have the complete sequences of labels in our training set) or semi-supervised (if not all elements are labeled: some sequences are missing or some tokens in sequences are missing, so we have only partial annotations).

Before describing our annotation algorithm, we will characterize sequential data learning, in order to be able to match the data (the limb sequences for simple routes, which are our input) with the respective data desired to be labeled (the trials of the training session).

### 2.1.1.2 SEQUENTIAL DATA LEARNING

Sequences are the popular types of data, commonly present in linguistic applications (natural language processing NLP), in biology (in genomics and proteomics), or - and precisely as in our case - in the time series of any process evolution. Sequential data learning is therefore a separate branch of machine learning, involving different types of algorithms from the traditional ones: those that are not

only aimed at simple classification or labeling tasks (as in the supervised framework), but are able to learn with potentially multiple variables (the elements of the sequence) and an unfixed dimension on at least one axis. The algorithms must therefore reflect the interactions between the tokens in each sequential data sample. The relationship within a sequence can be of different nature, namely the sequence tokens can be locally dependent on each other (the adjacency relation), or the dependence can concern more distant sectors and elements. The most local relation, where the tokens in the sequence depend only on their nearest neighbors, is known as the *Markov property*. Formally, in the case of a discrete stochastic process, for any total time duration  $T > 0$  and for any sequence of states of that process  $x_{1:T}$ , the future depends only on the present, and not on the past:

$$\mathbb{P}\left(x_{T+1} \mid x_0, x_1, \dots, x_{T-1}, x_T\right) = \mathbb{P}\left(x_{T+1} \mid x_T\right). \quad (2.1)$$

Intuitively, this kind of relationship seems to be unrealistic, as it ignores the complexity of potential global signal properties, especially in the case of linguistic applications (reach structural interaction of words/letters in a sentence). In some cases, the assumption of a Markov property allows a first rough analysis. Sometimes, however, a wider spectrum of interactions seems to be an unnecessary complication, as it seems to be in our case when we pursue the investigation of the successive nature of postures in movement: whether there was a repetition or a change in a successive development of behavior.

In the same vein we can qualify the degree to which two sequences are similar in the process of learning: we can distinguish the diversification of separate tokens in the sequences, or we can treat a sequence as an entire entity. Depending on the assumed degree of similarity, we can define the accuracy condition that is used in the optimization function in the sequential learning task. Most generally, the supervised sequential data learning task (Dietterich [2002]) is to predict the sequence of labels  $\hat{y}_{1:T}$  that pair with the input observation sequence  $x_{1:T}$ , based on the  $n$  learning samples  $\{(x_{1:T}^i, y_{1:T}^i)\}^{i=1, \dots, n}$ ,

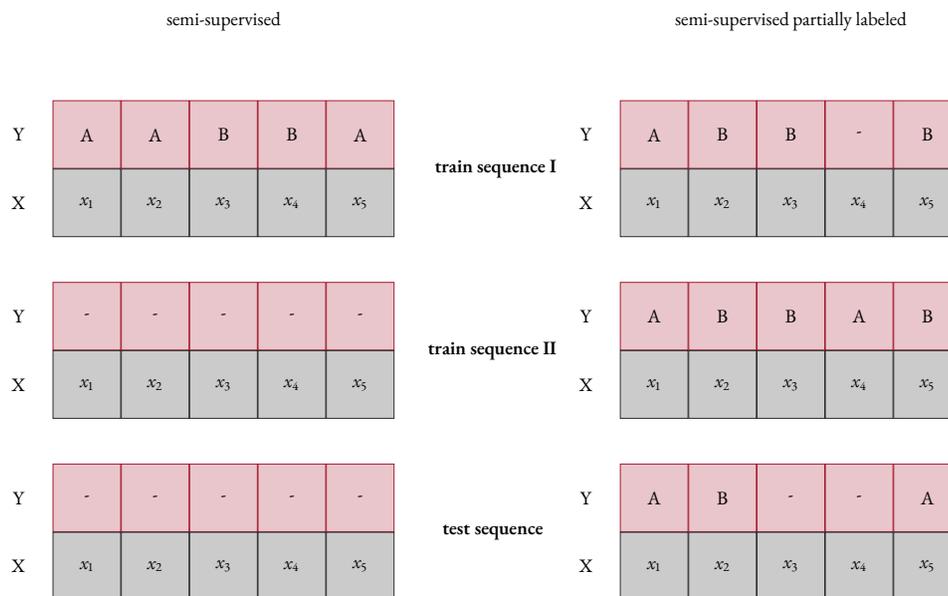
where each  $y_t \in \{Y_1, Y_2, \dots, Y_n\} = L$  and only one label  $y_t$  from the set  $L$  is correct (partial label learning as described in Cour et al. [2011]). In this configuration our model  $M$  would need to correctly assign the labels to the new data  $\hat{y}_{1:T} = M(x_{1:T}^i)$ . One way to find the optimal parameters of the model is to maximize the joint conditional probability of two sequences:

$$\hat{y} = \arg \max_y \mathbb{P}(y_{1:T} | x_{1:T}). \quad (2.2)$$

The above loss function (Equation 2.2) is not the only possible choice in sequential learning, but it does allow to deal with the issue of finding the separate attributions  $(x_t^i, y_t^i)$  in each learning sequence, which limits the computational load. Moreover, there are supervised and semi-supervised learning approaches that process entire sequences; the HMM used with the Viterbi algorithm to find the optimal path between elements in the sequence is one of them.

SEMI-SUPERVISED SEQUENTIAL DATA LEARNING has typically been applied to very large and mostly unlabeled data, containing a very small fraction of labeled samples. Usually, this fraction is obtained manually, which is costly and limited (requiring some expertise in the data domain and time for annotation). However, having even this small amount of annotated data is crucial for using supervised methods to annotate the entire dataset. As a result, the sample sequences are either fully labeled or completely unlabeled. Below we mention some of them, however the number of techniques that vary depending on the type of sequences, is huge. For traditional semi-supervised learning (Chapelle et al. [2006]), when the training set contains a small amount of labeled data with and a large amount of unlabeled data, we dispose many well-known and well-studied techniques. Some of them, through iterative refinement, predict the labels of the unlabeled set from the small annotated set (self-training Clark et al. [2018]; Dai and Le [2015]) or from multiple labeled samples (co-training Blum and Mitchell [1998], graph-based training Hassan et al. [2006]). The idea of starting with a small *gold* amount

of manually annotated data is also used in the semi-supervised learning of conditional random fields (CRFs) training in order to extract highly accurate and non-redundant data (Veeramachaneni and Liao [2009]). Deep learning methods can also rely on some pre-trained sources of information (Mikolov et al. [2013]), and these approaches increase the number of learning samples for supervised learning. A separate group are generative methods (HMM, multivariate Gaussians), which in search for general distributions of labels (closest to the real one), improve the distribution parameters with multiple techniques. The semi-supervised example of traditional sequential learning is illustrated in the Figure 2.2 (left column).



**Figure 2.2** – Comparison of semi-supervised sequential learning problems (Y - label sequence, X - signal sequence). The left column exemplifies the typical semi-supervised (fully labeled or fully unlabelled) training sequence (top two sequences) and the typical sequence to be annotated (bottom). In semi-supervised partially labeled learning (right column), the training sequence (top two sequences) may (or may not) contain voids. The sequence to be annotated may also contain voids.

SPARSE LABEL SEMI-SUPERVISED LEARNING poses a greater challenge than traditional semi-supervised methods, because in this case we are not handling a mixture of unlabeled and labeled sequences, but

rather partially labeled sequences in which the voids are randomly distributed within the sequence. For this endeavor, the prediction algorithm must recognize the labeled and unlabeled parts of the sequence, and address them differently. The example is illustrated in the Figure 2.2 (right column).

Notably, hidden Markov models have been used in similar tasks for the NLP applications [Juang and Rabiner \[1991\]](#). The HMM alone can be used for the labeled chunks of the sequences, but not for the unlabeled chunks. The unlabeled parts require applying another algorithm to refill the gaps, most commonly in an EMA-like fashion, by interleaving the two algorithms at each iteration step. There are several candidates for the auxiliary algorithm. For instance [Fernandes et al. \[2016\]](#) used HMM supported with Baum and Welsh algorithm (BWA, [Baum et al. \[1970\]](#)). Another method, which is discriminative for a change (and more difficult than HMM) is the simple transductive loss-augmented perceptron (STLP) furnished with the constrained Viterbi algorithm (CVA, [Fernandes and Brefeld \[2011\]](#)).

Conditional random field method (CRF, [Lafferty et al. \[2001\]](#), [Lafferty et al. \[2004\]](#) [Veeramachaneni and Liao \[2009\]](#)), is another structured learning approach (undirected graphical model, that is discriminative) that allows for prediction with incompletely labeled sequences. An example of this particular application is an improved version of the STLP and HMM methods in the framework of CRF. Specifically, in [Jie et al. \[2019\]](#) the authors investigated the probability of distribution in the unannotated chunks, that have been originally introduced by [Bellare and McCallum \[2007\]](#) as missing label linear chain CRF (in which each prediction depends only on its adjacent neighbors).

Structural support vector machines ([Altun et al. \[2003\]](#), [Tschantaridis et al. \[2005\]](#)), maximum entropy Markov models (MEMMs, [Mccallum et al. \[2001\]](#); [Punyakanok and Roth \[2001\]](#)), or max-margin Markov ([Taskar et al. \[2004\]](#)) methods are other examples of alternative architectures for partially labeled sequential learning.

One of the discriminative alternatives to the HMM model in addressing the sparse labeling task could be the introduction of the connectionist temporal classification (CTC, [Graves et al. \[2006\]](#))

within sequential learning in LSTM, which allows the direct computation of conditional probabilities. The superiority of this method over the HMM, lies in the fact, that it does not require alignment, since it operates with the extra token that replaces any other token. However, as a drawback, we can mention that the method cannot assume for partially labeled sequences of significant missing ratio (70 %). However this shortcoming can be overridden by a similar approach such as star temporal classification (STC, [Pratap et al. \[2022\]](#)). Other alternative methods include the encoder-decoder approach with attention, autoencoders and LSTM with partially labeled sequences [Hochreiter and Schmidhuber \[1997\]](#).

To have a complete picture of the situation we are confronted with, in the partially labeled framework, since the voids populate all the sequences, we do not dispose of the ground true annotations to verify the precision of the proposed algorithm. Therefore, we have developed special ways to evaluate our method (by deleting the known annotations and by log-likelihood evolution), which are explained further below (Subsection 2.4.3).

As a part of the traditional sequential learning, we find useful the approaches that recognize an adjacency relationship (temporal succession of the limb-trunk positions), which does not imply the long range dependence. Therefore, we have chosen hidden Markov model, which is particularly well tailored for such a case, and which offers the possibility of highlighting the most local relationship within the sequence. The important caveat is the prerequisite of pairwise *alignment* of the two sequences: sequence of observations and sequence of labels (as implemented in Subsection 2.2.2).

## 2.2 CLIMBING DATA COLLECTION AND PRE-PROCESSING

The data was collected using the protocol described in Section 1.4. More specifically, the signal analyzed in this Chapter is the relative position of the climber on the wall, which was calculated as the difference between the position of the hip and the position of the limb touching the handhold at a given

instant (for vertical and horizontal positions respectively, the signal analyzed is two-dimensional). As a result we dispose of the sequence of the observations in the hidden Markov model, denoted in the following formulas as  $x_{1:T}$ .

### 2.2.1 DATA SPECIFICITY

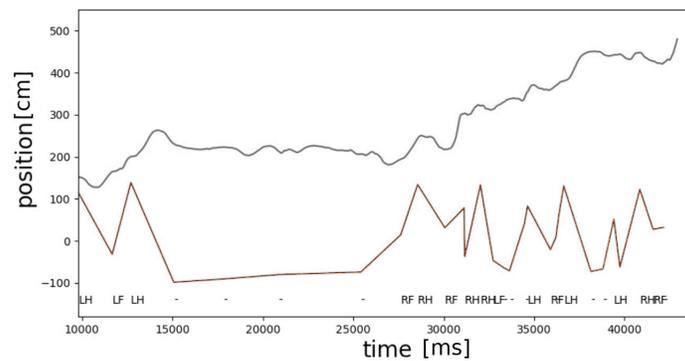
In our task we are interested in the annotation of each behavioral signal with the sequences of the support limb used during the ascent (Figure 2.1). From the total number of 13 sessions of recorded ascents, we first process the subset of the data (the simple routes in test sessions 1, 12 and 13) which were annotated by a human on the basis of the video recordings. Nevertheless, most of the training sessions were not processed manually (sessions 2-11) due to the difficulty and cost of in such a process (it is time consuming and can be imprecise). The manual annotation process resulted in sequences of labels, that were of different in length from the analyzed time series (mostly based on the handheld touch system); moreover, the two types of sequences were not aligned (the time had a different base in each of the paired sequences case and the only reliable information was the order of events).

In fact, we were faced with a situation, where 1) there were some voids in the sequence, that were not labeled by the human (missed) when the touch event was unnoticed because the hand/foot was covered by the body/cloth, another limb or when the touch event was very brief, 2) there were artifacts, because some hold recordings could have been made by, for example, the trunk, cloth or knee and were not related to a deliberate hold touch action made by the climber. The Table 2.1 contains an illustration of the sample sequences available for processing and the Figure 2.3 depicts the sparse sequence resulting from the alignment.

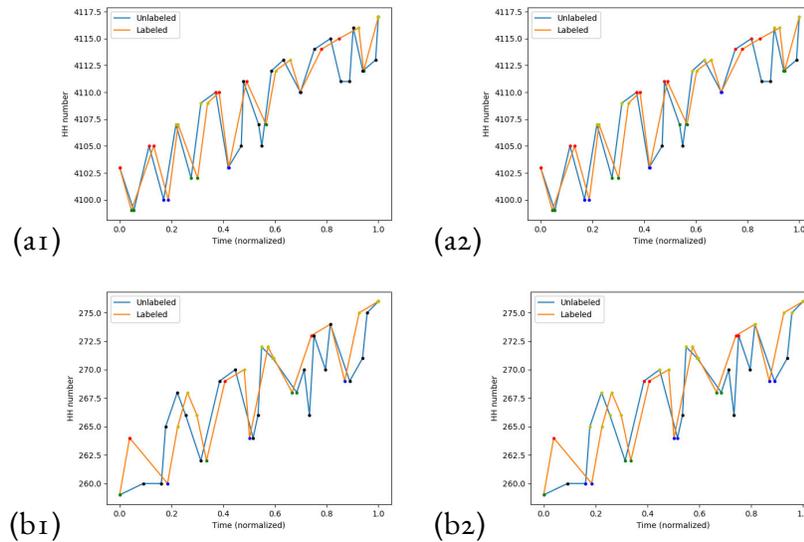
The challenge of the task was therefore twofold: 1) the labeling did not cover the entire set of experimentally collected recordings and 2) the annotations carried the errors or gaps in the descriptive sequences. Handling these two difficulties (as well as possible noise) was not a trivial task. Another difficulty we encountered in learning the annotations, is the supposed difference in the distributions

	time	hh number	time	x	y		time	hh number	limb
	...	...	...	...	...		...	...	...
(a)	4673	9	(b) 35.02	1.2	0.1	(c)	36.467	10	RH
	5895	4	35.04	1.3	0.6		37.211	4	LF
	6346	12	35.06	1.1	1.1		37.581	11	LH
	...	...	...	...	...		...	...	...

**Table 2.1** – The sample of data available in the experiment. The observations are depicted in (a) hold sensor data, and (b) hip tracking data (note that sensors and tracking use different time codes). The annotation/target examples are presented in (c). In (a) and (b), the data was captured automatically, while the (c) was manually annotated (the abbreviations describe the right R or left L, foot F or hand H).



**Figure 2.3** – Example of a climbing trial with signals during the entire ascent: the gray top line approximates the position (the horizontal and vertical coordinates collapsed to one dimension by summation), while the red line (bottom) represents the relative limb position. The letters LH, RH, LF, RF in the sequence (beneath) abbreviate the limb type, if assigned (otherwise it is reported as null '-'). The time resolution is 1 ms, but it should be noted that the position, is not the one used in the experiment (as it was two-dimensional) and is displayed here for illustrative purposes only.



**Figure 2.4** – Examples of aligned data (a1), (b1). Some data matching in the signals have been copied (a2), (b2). The color code indicates for different limbs (red: LH, yellow: RH, blue: LF, green: RF, black - not aligned, unlabeled).

between the annotated and the unannotated sets, since the observed sequences were not stationary due to the evolution of the climbing learning protocol.

As a first step, we attempted to align the manually annotated sequences with the touch time records registered by the sensors on the wall, based (mostly) on the number of handholds (illustrated in the Figure 2.4 ). The resulting sequences (containing voids) would consist of our (presumably) sparse label sequences to pair them with the climbing behavioral signal (combination of hip position and the coordination of the hold touched). These counterparts would constitute the training data in order to label the gaps (and subsequently annotate new potential observations).

### 2.2.2 PAIRWISE ALIGNMENT

We have implemented a dynamic programming method (Needleman and Wunsch [1970]) for global alignment of two sequences. These two sequences are 1) manually labeled handhold time series based on video recording with type of limb in use, 2) handhold time series based on sensor recording (un-

labeled). In the case of errors in assigning handhold numbers, we gave priority to the sensor-based sequence, which was more reliable. The task was complicated by the fact that the time formats in both time series were different (Table 2.1).

More formally, given two time series of length  $m$  and  $n$ , we construct the matrix  $D$  of size  $[m \times n]$  in which we find the best fit. The algorithm has two stages:

- forward phase (recurrence) to compute the  $D[i, j]$  elements of the matrix  $D$ ,
- traceback to find the optimal alignment.

There are three rules for choosing the values to construct the elements of the matrix: The tokens in both time series match, a gap is introduced in the first time series, a gap is introduced in the second time series.

The algorithm retains the property, that it is not possible to add a gap to both related time series in the same iteration step (which minimizes the number of gaps). The maximum of the three scores is chosen as the optimal score and is written in the matrix element  $D[i, j]$ .

The second phase is to construct the optimal alignment by tracing back in the matrix any path from  $D[m, n]$  (last element) to  $D[0, 0]$  (first element) that led to the highest score.

An alternative dynamic programming method is the [Dijkstra \[1959\]](#) algorithm.

We used the implementation of the algorithm for limb sequences in both subsets (labeled and unlabeled) with the following rules: identical tokens have a score of 1, otherwise 0; gap penalty equals to zero (Figure 2.4). However we verified that with different hyperparameters (different scores for matching and mismatching tokens, different gap penalties and gap penalty lengths), the result did not differ significantly (was stable).

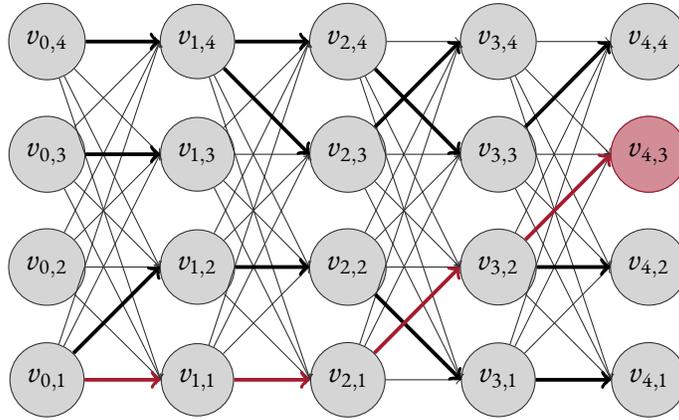
### 2.3 HMM WITH VITERBI TRAINING

Exploring the sequential data learning task (Equation 2.2), in our application we have additionally assumed that the sequences  $x_{1:T}$  are continuous series of two-dimensional measurements and the label set is the alphabet of all the limb states that can be used for support  $L = \{LH, RH, LF, RF\}$ . In this vein we end up with sequences  $x_{1:T} = (x_1, x_2, \dots, x_T)$  and its pair label sequence  $y_{1:T} = (y_1, y_2, \dots, y_T)$ , where each  $y_t \in L$ . Both sequences are aligned (have the same length  $T$ ). In the following theoretical description we will first focus on supervised HMM learning, and then proceed to the semi-supervised case in the next Section 2.4.

HMM SUPERVISED LEARNING FRAMEWORK (Rabiner [1989]) with fully labeled pairs of sequences  $(x_{1:T}, y_{1:T})$ , describes their relationship with a generative model  $\mathcal{M}$ . The model  $\mathcal{M}$  is subsequently applied to new sequences of observations using the Viterbi [1967] algorithm to find the most likely corresponding label sequences (Figure 2.5). Note that by applying the Viterbi algorithm we obtain a *hard* label assignment, whereas by using the Baum-Welsh algorithm we would obtain the probabilistic one (cf. Algorithm in Section 1.1.3). In our case, the former, hard assignment, is necessary for the next step of the processing in the human movement science application (which is our specific requirement and is not always the case).

Apparently, there is a relationship within each pair  $(x_t, y_t)$  all along the sequences, which we describe by the probability of observation emission  $e_s(x_t) = \mathbb{P}(x_t | y_t = s)$ . In the case of a Markov process, there is no dependence between non-adjacent labels, while there is one between the adjacent labels in the sequence  $y_{1:T}$ , which is described by the probability of transition  $f_{rs} = \mathbb{P}(y_{t+1} = r | y_t = s)$ . Both kinds of probabilities (observation and transition) form a part of the parameters of the model  $\mathcal{M} = (p_s, E, F)$ . Particularly, they are the elements of the matrices  $E = (e_s(x_t))_{s \in L, 1 \leq t \leq T}$  and  $F = (f_{rs})_{r, s \in L}$ . The first parameter of  $\mathcal{M}$  is an initial probability  $p_s = \mathbb{P}(y_1 = s)$ . We find the optimal

parameters of the model, by maximizing the joint probability  $\mathbb{P}(x_{1:T}, y_{1:T})$ . Once the model parameters are found, we predict new labels for the unlabeled observations  $x_{1:T}$  using the Viterbi algorithm (Figure 2.5).



**Figure 2.5** – Standard Viterbi algorithm. The red path is the optimal one, ending with the maximum  $v$  value (red circle). All the possible paths (in gray) are explored. At each tracing (forward) step the most likely path to each state is recorded (bold). In the end, only the path that leads to the most likely final state is retained (red). The most likely transitions to each state are marked in bold (e.g. from  $v_{0,1}$  to  $v_{1,2}$ ); note that they need not be part of the final most optimal (red) path.

The algorithm, starting from  $p$  and propagating through the observation sequence  $x_{1:T}$ , stores the probabilities of the most likely path of labels  $y_{1:T}$  that generated  $x_{1:T}$  and at the same time, the most likely label sequence. The resulting optimal  $\hat{y}_{1:T}$  is the sequence of argmax, once we have found all the probabilities. First, in the framework of hidden Markov model, we compute the joint probability for the sequence of observations  $x_{1:T}$  and the sequence of labels  $y_{1:T}$  as

$$\mathbb{P}(x_{1:T}, y_{1:T}) = p_s \prod_{t=1}^T \mathbb{P}(x_t | y_t) \prod_{t=1}^{T-1} \mathbb{P}(y_{t+1} | y_t) \quad (2.3)$$

and we estimate the parameters of the model  $\mathcal{M}$  by maximizing the log-likelihood

$$\hat{\mathcal{M}} = \arg \max_M \log \mathbb{P}(x, y | \mathcal{M}). \quad (2.4)$$

Subsequently, by means of the Viterbi algorithm, the parameters are used in a recursive manner and in  $T$  steps, serve to compute the maximum-likelihood label sequence  $\hat{y}_{1:T}$  given the observation sequence  $x_{1:T}$ .

The recurrence is used to compute the intermittent variables  $v$  and  $w$  :

$$v_{0,s} = p_s \quad (2.5)$$

$$v_{t,s} = \max_r v_{t-1,r} f_{rs} e_s(o_t) \quad (2.6)$$

$$w_{t,s} = \arg \max_r v_{t-1,r} f_{rs} \quad (2.7)$$

and that for the last estimated label element

$$\hat{y}_T = \arg \max_r v_{T,r} \quad (2.8)$$

by backtracking we find the entire sequence of estimates

$$\hat{y}_t = w_{t+1, \hat{y}_{t+1}}. \quad (2.9)$$

Thus, the final sequence  $\hat{y}_{1:T}$  is the optimal sequence of labels.

The Algorithm 2 describes all the algorithmic steps. The optimality of the Viterbi algorithm can be shown as in [Omura \[1969\]](#).

#### 2.4 MISSING LABELS IN A SEQUENCE

The sequence alignment that was performed allowed us to label some chunks of the sequences that we will use for training. However, some sequences chunks were left unlabeled. Overall, the sequence that is an example of the training set sample is exemplified in Figure 2.6. This type of partially labeled

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**Algorithm 2** Viterbi algorithm

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- 1: **procedure** FINDING THE OPTIMAL SEQUENCE OF LABELS  
Complete the label sequences with the Viterbi algorithm (parameters computed with model  $\hat{M}$ ), to obtain fully labeled estimates  $(x_{1:T}, \hat{y}_{1:T})$
  - 2:     **Input** unlabeled observation sequence  $x_{1:T}$  and randomly initialized model  $\hat{M} = (p_s, E, F)$
  - 3:     **Output** optimal sequence of labels  $\hat{y}_{1:T}$
  - 4:     Trace the maximum probabilities of going from each state to another (by computing the intermittent variables  $v$  and  $w$  in a recursive mode)
  - 5:     Compute the last element of the optimal sequence of labels  $\hat{y}_T$
  - 6:     Find estimates  $\hat{y}_t$  (elements of the optimal path/sequence) by backtracking (from  $\hat{y}_T$  to  $\hat{y}_1$ ).
  - 7: **end procedure**
- 

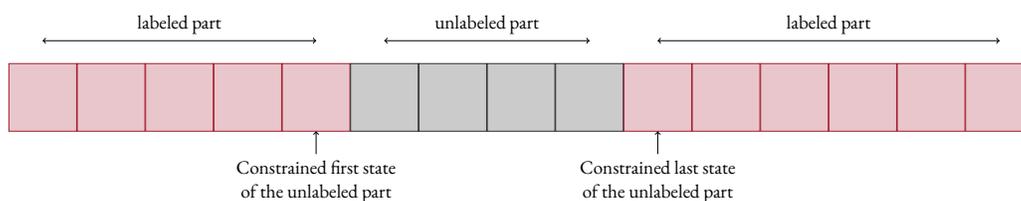
sequence consists of a large number of the unlabeled chunks, making the learning task inaccessible to the traditional supervised learning algorithms. The semi-supervised method described below, allowed us to address this challenge in a simple fashion.

#### 2.4.1 HMM WITH CONSTRAINED VITERBI TRAINED ON PARTIALLY LABELED SEQUENCES

In the case of partially labeled sequences in the training set, we need to adapt the basic supervised HMM procedure in order to train only from the labeled chunks of the sequences. For this purpose, we will use the constrained Viterbi algorithm (CVA). CVA has previously been used for images (Cao and Chen [2003]) and for linguistic purposes (Fernandes and Brefeld [2011]), but has never been applied in the HMM context before (although an unconstrained version of the Viterbi algorithm is regularly used in this context). The use of HMM to derive the observation and transition probabilities used in a dynamic programming of CVA is a hallmark of our approach, which also accounts for its simplicity. For instance we can note that, in a fully unsupervised learning framework (when all the observations are unlabeled, cf. Chapter 1), we can randomly initialize the model parameters  $M = (p_s, E, F)$  in the

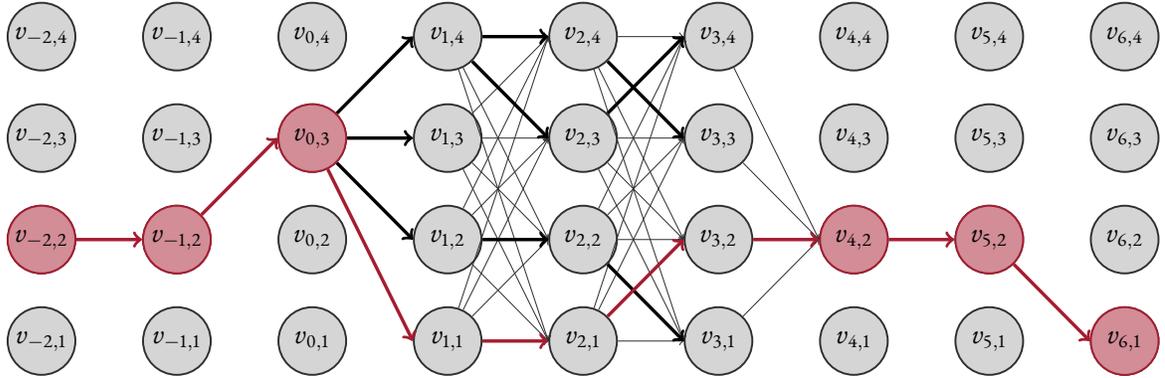
first step (provided that the Markov property of the observation probability matrix  $E$  is respected). Subsequently, in the E-step, having the parameters fixed, we can recover the optimal sequence of states  $\hat{y}_{1:T}$  by applying Viterbi decoding. Then, in the M-step, the new elements of the matrices  $E$  and  $F$  are being calculated, so that the maximum likelihood corresponds to the fraction of the time we were in one state that we transitioned to another one. In this way, by iterating the E and M-steps, we obtain both: the model  $M$  parameters and the sequence of labels (states).

The unsupervised HMM-CVA learning is thus simple, but intuitively its speed should be increased if we could take advantage of the labeled chunks of the sequences and constrain the unsupervised scenario. The technique proposed here combines the supervised and unsupervised learning in semi-supervised framework.



**Figure 2.6** – Example of a partially annotated sequence. Constrained Viterbi is applied to the gray chunk taking into account the last red token of the first labeled chunk and the first red token of the second labeled chunk.

Namely, we initialize the model with random parameters or with pre-training held on only labeled chunks of the sequences  $(x_{1:T}, y_{1:T})$ , for which we obtain interim parameters  $\hat{M}$ . In the next step, we find the interim labels  $\hat{y}_{1:T}$  for the partially labeled sequence (Figure 2.6) with the use of constrained Viterbi, that is enforced to move through the already known label chunks, by maximizing the probability of the most likely label path. Indeed, in the constrained scheme, the traditional Viterbi algorithm operates on the unlabeled segments of the sequences, but with the first and the last states labeled (which are the fixed adjacent tokens of the unlabeled chunk), treating each chunk sequence independently (Figure 2.7).



**Figure 2.7** - Illustration of the constrained Viterbi algorithm. The red states are constrained. We start with the constrained state (the red one in the zero column); we apply the Viterbi algorithm and backpropagate from the constrained state (the red one in the fourth column). The left labeled chunk (left hand side of the zero column) and the right labeled chunk (right hand side of the fourth column) form the hard assignment path (hence in red) and are not used in the CVA computation. The most likely transitions between the states are marked in bold, while the optimal final path is marked in red.

Subsequently, we use the predicted (fully labeled) sequences  $\hat{y}_{1:T}$  to generate new model parameters  $\hat{\mathcal{M}}$  and further adjust the labeling on the initially unlabeled parts of the sequences. While EMA finds the local optimum, we iterate until convergence to find the best representation in terms of log-likelihood of the label sequence joint probability  $\mathbb{P}(x_{1:T}, \hat{y}_{1:T})$  (Algorithm 3).

---

**Algorithm 3** HMM with the constrained Viterbi

---

1: **initialization** annotated sequence chunks (or random)  
2: **repeat** STEP 1 and STEP 2 alternating **until** *convergence* or *number of iterations*  
3: **STEP 1** ▷ Expectation  
4: **procedure** RUNNING INFERENCE ALGORITHM  
    Fill in the unlabeled tokens given the labeled ones: complete the gaps in the sequences of labels with the constrained Viterbi algorithm (using parameters of model  $\hat{\mathcal{M}}$ ) to obtain fully labeled estimates  $(x_{1:T}, \hat{y}_{1:T})$   
5:     **Input** partially labeled observations  $x_{1:T}$  and trained or pre-trained model  $\hat{\mathcal{M}}$   
6:     **Output** labeled data  $(x_{1:T}, \hat{y}_{1:T})$   
7:     Compute new labels  $\hat{y}_{1:T}$  with a model  $\hat{\mathcal{M}}$   
8: **end procedure**  
  
9: **STEP 2** ▷ Maximization  
10: **procedure** OBTAIN THE IMPROVED VALUES  
11:     **Input** labeled data  $(x_{1:T}, \hat{y}_{1:T})$   
12:     **Output** new model  $\hat{\mathcal{M}}$   
13:     Update model  $\hat{\mathcal{M}}$  based on new labels  $(x_{1:T}, \hat{y}_{1:T})$   
14: **end procedure**

---

### 2.4.2 EXPERIMENTAL ANALYSIS

We test the proposed procedure with the data as in Table 2.2.

For the synthetic data generation we used the Gaussian bi-variate distribution for the four label states. All the four states have the same covariance  $\Sigma$ , they differ in their mean  $\mu$ . For each of the two dimensions of the mean, we used either  $-\mu$  or  $\mu$ , leading to 4 possible states as shown in Equation 2.10:

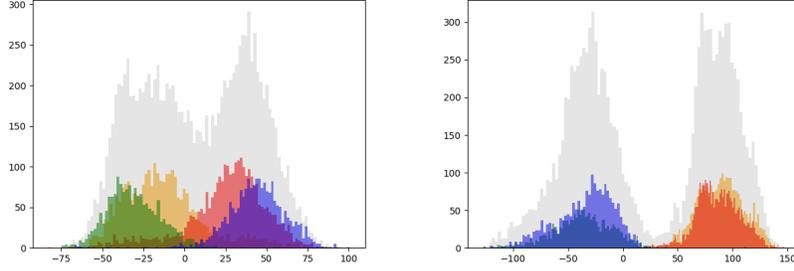
$$\mu_1 = \begin{pmatrix} \mu \\ \mu \end{pmatrix}, \mu_2 = \begin{pmatrix} \mu \\ -\mu \end{pmatrix}, \mu_3 = \begin{pmatrix} -\mu \\ \mu \end{pmatrix}, \mu_4 = \begin{pmatrix} -\mu \\ -\mu \end{pmatrix}, \Sigma = \sigma \mathbf{I}. \quad (2.10)$$

The synthetic data distribution defined in this way (Figure 2.9) should approximate the statistics of the climbing data (Figure 2.8).

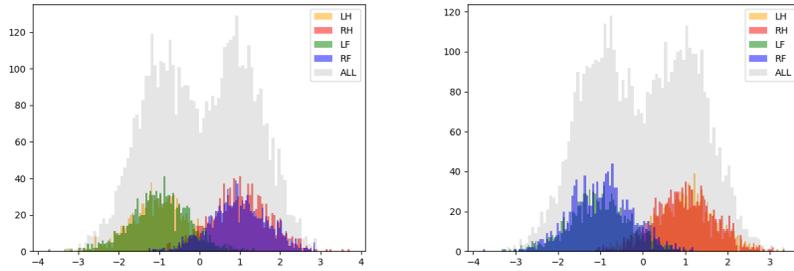
To apply random label discarding in fully labeled sequences, the level of gap ratio  $\tau$  was fixed (Table 2.2). For the experimental climbing data set (DATA1 and DATA2), we disposed the manually annotated sequences of observations (simple sessions routes), which were divided into training and test sets. Finally, the established model will be used to annotate a total number of about 3700 unlabeled sequences recorded with touch sensors (practice sessions routes). In order to evaluate the performance of the model on the datasets DATA2 and DATA3 (where the ground truth labeling was initially fully

DATA	Type	Description	Average length	Number of items (train:test)	Gap ratio $\tau$
1	climbing	partially labeled	about 20 tokens	497 (400:97)	about 0.3
2	climbing	fully annotated sequences with labels randomly discarded	less than 20 tokens	497 (400:97)	0.25
3	synthetic	$\mu = 1.5, \sigma = 0.2$	about 20 tokens	2000 (1000:1000)	0.25

**Table 2.2** – Experimental datasets DATA1, DATA2 and DATA3.



**Figure 2.8** – Distribution of labels over the original climbing data for the horizontal coordinate (left) and vertical coordinate (right). The color code accounts for different limbs (yellow: LH, red: RH, green: LF, blue: RF, grey: all including gaps).



**Figure 2.9** – Distribution of the synthetically generated data labels for horizontal (left) and vertical coordinates (right); color coding as in Figure 2.8.

known), we computed an accuracy measure which is the similarity ratio (averaged sum over the entire sequence, with a score of 0 for mismatch and 1 for match for each token in the sequence) employed on the fully labeled initial sequence  $y_{1:T}$  (before label removal) to the sequence estimated by the model  $\hat{y}_{1:T}$ . Thus, the evaluation score for an entire sequence  $y_{1:T}$  and its prediction  $\hat{y}_{1:T}$  reads

$$d(y_{1:T}, \hat{y}_{1:T}) = \frac{1}{T} \sum_{t=1}^T d_t(y_t, \hat{y}_t) \quad (2.11)$$

with the loss function  $d_t$  defined over two tokens  $y_t$  and  $\hat{y}_t$  as

$$d_t(y_t, \hat{y}_t) = \begin{cases} 1 & \text{for } y_t = \hat{y}_t, \\ 0 & \text{otherwise.} \end{cases} \quad (2.12)$$

To test the hidden Markov model with constrained Viterbi we used synthetically generated data with known parameters (as in Table 2.2 case DATA<sub>3</sub>). The missing labels level was set to  $\tau = 0.25$ .

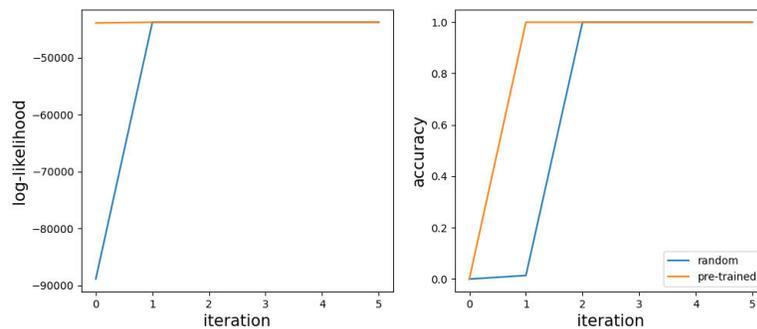
We compared the predicted model parameters with the original counterpart as well as the scoring in two sequences: the label sequence generated with the original model and the label sequence predicted with the estimated model parameters. The same way of evaluation procedure was employed for experimental data with full annotation (DATA<sub>2</sub>). In these cases we were able to compare the resulting fully labeled sequences with the initial true labels, before label removal. For all the datasets however, the likelihood of the observation sequences knowing the model parameters was always accessible regardless of whether the true labels were fully known, partially known or completely unknown. To summarize, in the case of fully labeled sequences altered artificially to partially labeled ones (DATA<sub>2</sub> and DATA<sub>3</sub>), we can compute a similarity ratio comparing the estimated labels with the true ones. Otherwise (DATA<sub>1</sub>), only the likelihood of the HMM is accessible as an evaluation measure.

### 2.4.3 EVALUATION METHODS FOR SPARSE DATA

**SYNTHETIC DATA SET** (DATA<sub>3</sub> in Table 2.2) is the first one to apply the learning procedure. The artificially generated data contained either random initialization or a pre-trained model.

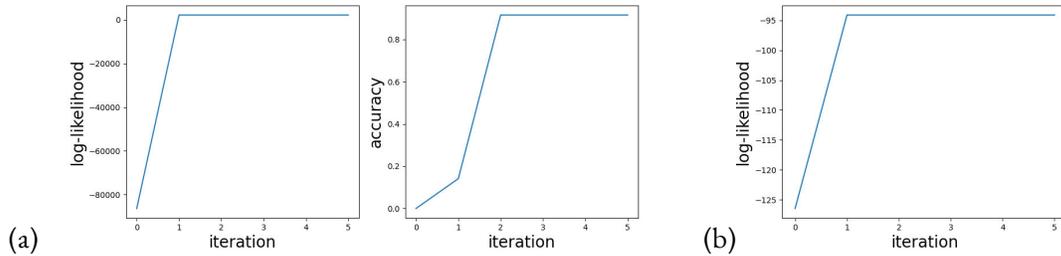
We analyze the log-likelihood over the joint probability of observation and labeling sequences which evolves over the iterations for the label distribution with known model parameters (Figure 2.10). This score determines how well the label sequence describes its pairwise observation sequence, based on the label distribution. As expected, we observe a monotonic increase of the log-likelihood over the itera-

tions, as well as for the similarity score computed for unannotated chunks. Stability is reached after the second iteration. The log-likelihood evolution proves that the model fits to the experimental data well, and at the same time it leads to the generation of optimal labels. Likewise, the score analysis confirms an increasing recognition of the labels, when compared to the ground truth annotations in the subsequent steps.



**Figure 2.10** - Synthetic data set (generated with  $\mu = 1.5$  and  $\sigma = 0.2$ ): log-likelihood values evolution (left) and similarity ratio (right). The labels were discarded with the ratio  $\tau = 0.25$ . The applied initialization was either random (blue) or pre-trained (orange) on the labeled chunks.

CLIMBING DATA was applied to test the model in two distinct modes. First, we explore the real experimental dataset of concatenated full chunks of sequences with the annotations artificially deleted (with the deletion rate set to 0.25). In this way, we do have knowledge of the true labeling in the artificially deleted slots, so we can compute the similarity ratio. After the alteration, we first pre-trained the HMM on the fully labeled chunks of the sequences, bypassing the voids. Then, the HMM was trained using the constrained Viterbi method as described in the Algorithm 3, with all the partially labeled sequences (Table 2.2 DATA<sub>2</sub>). In the Figure 2.11(a), we observe the learning progress through iterations (growing log-likelihood), and at the same time (Figure 2.11(b)) - the annotations of the labels are mostly correct (the maximum similarity ratio is above 0.9).



**Figure 2.11** - Evaluation of climbing datasets. (a) Sequences originally fully labeled but with artificial label deletion: log-likelihood evolution (left) and similarity ratio (right). In order to apply the model, the labels were synthetically discarded with the ratio  $\tau = 0.25$ . (b) Climbing data, partially labeled with a gap ratio of about 0.3: log-likelihood evolution.

Based on this fact, the second mode of testing the sport data, involved partially labeled original sequences registered by touch sensors (with original voids as described in  $DATA_1$ ). Similarly (Figure 2.11 (b)), for the experimental climbing data we observe a monotonic growth of the log-probability function, which is - as in the synthetic data case and the artificially discarded labels in the climbing data - represents learning over iterations. While the ratio of unannotated labels was around 0.3 in all three experimental data cases, we can expect the results to be comparable between the sets. As in the previous data sets, the log-likelihood of the model converges very quickly, within two iterations. In this case, unlike the previous two, the similarity ratio is not accessible, as the true labels remain unknown. The final values of the log-likelihood function, however, are lower than in the case of artificially labeled discarded climbing data. We might suppose that this fact might have an impact on the quality of the label prediction. Although we do not dispose of any other objective evaluation method, the convergence of the model could be a proof that it leads to a relevant solution. We suspect that the artifacts that occur in the collected data (e.g. when the sensor registers a touch that is not made by the hand or foot) may have the largest contribution to incorrect label assignment.

To complete the analysis, we followed the machine learning evaluation method, where for the synthetic data, the ratio of the training set to the test set was 1000:1000, and for the annotated sequences of the sports data, we split the data set with a ratio of 400:97. Namely, we verified the accuracy of

the model trained on one subset of partially labeled data (training set) when applied to the previously unused subset of unlabeled data (test set). In this setting, the similarity score evaluated on the new test sequences did not differ significantly from the previously observed training score, confirming correct label assignment. Table 2.3 summarizes the results.

DATA	Accuracy
2	0.90
3	0.99

**Table 2.3** – Predictive accuracy (similarity score) for DATA2 climbing data set and DATA 3 synthetic data set (test data as in Table 2.2).

## 2.5 CHAPTER SUMMARY

In the current Chapter we have discussed the challenging but common issue of sequence annotation based on sparsely labeled data with significant but moderate missing data ratio, and we have analyzed it with the example of a behavioral signal with discrete labels.

Our contribution is the following:

1. We have shown that the temporal registration of the combined positions of the trunk and the supporting hand can be used for annotation and prediction of the supporting limb sequence.
2. We have presented a simple method (HMM-CVA) that allows to train on the partially labeled sequences for the annotation of unlabeled sequences. The model converged quickly and while annotating the voids, took into account the constraints. The implementation of the HMM allowed to simplify the previous similar approach proposed by [Fernandes and Brefeld \[2011\]](#).
3. We have demonstrated different methods to evaluate the model on the partially labeled set, depending on the data availability by using the accuracy score on the labeled chunks and the log-likelihood for those for which ground true labels were not accessible. We found that the

two methods match (we observe monotonic growth in both cases), and can be used alternatively.

Although, the presented approach was applied to a particular signal, it can probably be applied to any discrete-data sequential learning with missing data. One difficulty that should be considered (and is present in our case) is the difference in the distribution between the annotated and the unannotated sets. The lack of stationarity was also potentially present in our case as the difference between the routes used for training (test climbing routes) and the unlabeled routes (practice sessions routes) and should be acknowledged. Considering the fact that human annotation is very laborious and the visual attribution is not precise (the missing ratio for manually labeled sequences was 0.7), our method appears to be a solid first method. However, because it is relatively easy to implement, HMM-CVA can be used as a baseline that, by also providing the distributions of the labels, allows for an insight that can potentially facilitate further interpretation of the results in the human movement science application (action chains).

In the next Chapter 3, we will see if we always need to target the missing values in behavioral data, and consider other means to handle the missing measurements in the analysis.

*They must often change,  
who would be constant in happiness or wisdom.*

Confucius

# 3

## Prediction of transfer in motor skill acquisition

THE SECOND CONTRIBUTION which is an adaptation of machine learning to the research in the variability impact for motor learning will be presented here.

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### 3.1 CHAPTER INTRODUCTION

In behavioral neuroscience, one of the most important questions is how to learn. Any human activity is an interaction of the internal dynamics of the learner with the external conditions that foster this process (Button et al. [2021]). Thus, individual capacities and their dynamics of change over time (Zanone and Kelso [1992]) are crucial in the performance, as they are the determinants of the individual's goal.

Human learning, as an optimization of one's actions, could help to understand the mechanistic laws that govern the behavior. In the process of learning, we could observe how, by advancement of motor control, the learner's dynamics determine which direction of change is preferred and which are the main factors to be modified in order to improve the learning outcome. The choice of the elements for optimization that lie behind the adapted movement, is crucial for learning, as we could be interested in increasing expertise in a particular task or skill in similar tasks that differ by a certain amount of variability. We could ask whether the variability of the task or goal during practice is advantageous or detrimental to the learning effect, or which type of practice, constant or variable, is more profitable in terms of performance and skill transfer to novel conditions.

In addition, we could also ask about the role of the instructor in the learning process (Ranganathan et al. [2014]) and about the benefits of trusting in one's own abilities: the ability to objectively assess one's own level of competence and to manage one's emotional state during the learning process. Therefore, it is interesting to measure quantitatively the phenomena known from practice: whether the possibility of controlling the level of novelty by the learner (self-controlled or free condition Liu et al. [2012]) supports the willingness to undertake new challenge and fosters one of the main factors influencing the speed and sustainability of the effects of learning, namely motivation. These questions inspired our research in Chapter 3, even if we do not claim that we aimed to answer them.

In particular, in the current Chapter we are interested in indicating which learning condition used in the experiment (control, instructed, or self-controlled, as explained in Section 1.4 of Chapter 1) prevails in terms of predicting the knowledge transfer to novel situations. To this end, we would study the skill acquisition data (the fluency indicators computed all along each climber training) from the temporal perspective (how they evolve from trial to trial, in the learning dynamics framework) and how this dynamics contributes to the overall transfer effect. Assuming that learning dynamics can be informative for the transfer effect, we will use statistical learning modeling to investigate the improvement of generalization in human learning. With regard to the generalization ability of the machine learning algorithms, we claim that prediction can be used to evaluate the post-practice effect of retention and transfer (e.g. skill and learning transfer, Section 2.4). Moreover, the appropriate choice of the prediction model could allow us not only for a simple application of the method that in an unbiased way matches the evolution of learning fluency with the post-learning evaluation, but also for the interpretation of the modalities that influence the underlying process.

Nevertheless, the choice and adaptation of an appropriate method, especially given the data constraints, was our issue. An important adversity in our study is the sample size, which is quite limited due to the complexity of data collection and measurement methods. In machine learning, a small sample size is a factor that strongly undermines the effectiveness of the methods used and reduces their reliability. For this reason, it has been a noteworthy challenge to handle prediction with the large number of features compared to the small number of samples in the datasets. Additionally, our task involved model selection in the usual machine learning sense: choosing the most salient features for statistical prediction.

As one of the most important points, we claim that by introducing machine learning to the analysis of experimental data, we also hope to overcome the fundamental disadvantage of relying on the assumption of group homogeneity, which carries the risk of averaging out the variability inherent in the behavioral signals of the individuals participating in the study. Through training methods (by

linking input and output data), machine learning allows for a divergence of the samples and thus a statistical diversification of the participants due to their inter-individual variability.

For the above stated objectives we studied several machine learning prediction models altogether with different methods of feature extraction. In the following sections we will thus first describe the specificity of the data explored (Section 3.2), motivate the choice of the best pipeline for our purpose (Section 3.3) in order to finally interpret the results in view of the human learning theory (Sections 3.4 and 3.5).

Machine learning algorithmic machinery will be used thus twofold: as a means to find the best model for transfer prediction and as an evaluation of data quality. The data quality due to its *predictivity*<sup>\*</sup>, can later be interpreted in the context of human learning theory by comparing different datasets due to the conditions of practice that were used during data collection.

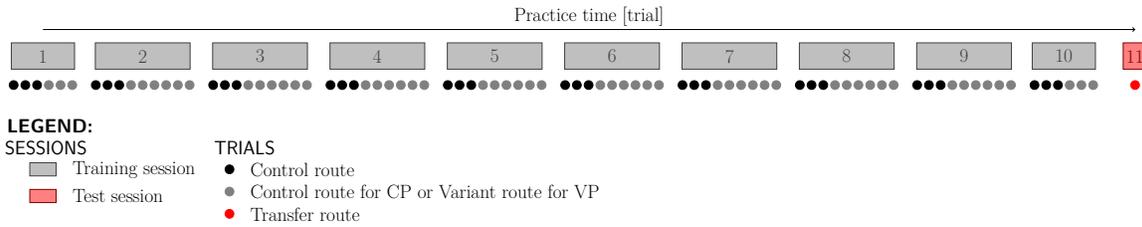
### 3.2 DATA PREPROCESSING

The data used for this experiment concerned the training sessions 1-11 (all sessions with post-test transfer, without pre-test transfer and test sessions, Figure 3.1); the climbing routes are exemplified in Fig. 1.11. The conditions of climbing were as explained in Section 1.4 in Chapter 1 with data synthesis in Tables 3.1 and 3.2.

There measures of fluency (Subsection 1.2.3 in Chapter 1) and the climbing duration were used as initial signals in the analysis. The Figure 1.14 presents the examples of behavioral signals obtained by computing the fluency indicators of each trial for one training participant. The trials' fluency constituted the training session scores and were taken into account as training features in the machine learning algorithm. They shape the *learning curve*; whereas the transfer trial fluency (post-training evaluation score), which appears each time as a single red dot, accounted for the prediction target in

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<sup>\*</sup> *Predictivity* is understood here as a property of the dataset that provides the match between input and output as measured by the size of the error.



**Figure 3.1** – The data acquisition protocol for acquiring a behavioral signal (as in Figure 1.10). The rectangular blocks in the top figure count the sessions. The dots in the bottom figure illustrate the number of trials in the sessions, which was the same for all the groups (CP, VP1, VP2). The color of the dots distinguishes the variability that was introduced. The black dot represents the route that was identical for all the climbers in all the sessions and which was the *control* route. The gray dot represents either 1) the control route in the case of the CP group, or 2) the *variant* route in the case of the VP1 and VP2 groups. The last red dot symbolizes the *transfer* route (test route that was different from the control route or variant routes), which was used to assess participants’ progress in a novel context; session 11 immediately followed session 10.

	number
climbers	33
fluency metrics	4
climber data with voids	13
climber groups	3
climbers per group (initial)	$I_1(\text{CP}), I_0(\text{VP}_1), I_2(\text{VP}_2)$
trials in practice sessions	84
features (initial)	$336(=4*84)$

**Table 3.1** – Summarization of the experimental data in numbers (CP - constant practice, VP1 - variable instructed practice, VP2 - variable self-controlled practice). These are initial values, since some data have been processed or eliminated according to the analysis and the chosen pipeline.

the statistical learning. We can observe that the transfer fluency is of a completely different nature than the learning function curve. Moreover, since the climbing raw fluency values for the different indicators demonstrate a large range of discrepancies (from  $10^{-12}$  for jerk to  $10^1$  for immobility and duration time), we applied a standardization of the data, prior to any processing.

TO ADDRESS THE PREDICTIVITY of the transfer score, we wanted to evaluate the statistical model performance based on the fluency metrics computed for the data measured during the practice sessions. This evaluation would allow us to compare different types of practice (participant groups CP, VP1,

	GE	JE	IM	CT
number of samples	33	33	33	33
full samples	27	20	27	30
practice session routes	2762	2715	2762	2767
voids	10	57	10	5
single void samples	6	8	6	3
sequential void samples	0	5	0	0
missing ratio	0.9964	0.9794	0.9964	0.9982

**Table 3.2** - The experimental data in numbers (per indicator) with analysis of the corrupted data extent (cf. Figure B.3).

VP<sub>2</sub>). The fluency metrics practice series data was composed of our  $p$  training features,  $\mathbf{X} \in \mathbb{R}^{n \times p}$ , where  $n$  is the number of samples. Then, the prediction output  $\mathbf{y} \in \mathbb{R}^n$  is the  $n$  dimensional vector of the transfer values in our model  $\hat{\mathbf{y}} = \mathcal{M}_{\mathbf{w}}(\mathbf{x})$ . We will train our model by minimizing the loss function  $L_{\mathbf{y}, \hat{\mathbf{y}}} = \|\mathbf{y} - \hat{\mathbf{y}}\|_2^2 = \|\mathbf{y} - \mathcal{M}_{\mathbf{w}}(\mathbf{x})\|_2^2$  (Chapter 1, Section 1.1.2). Depending on the number of features  $p$ , for a constant number of samples  $n$ , it is feasible for  $p \leq n$ . We explored different loss functions and different ways to select the features, also manipulating different types of inputs (fluency metrics).

THE EXPLORATORY STUDY allowed to select the pipeline for our prediction purpose due to the main challenges of the data that we dispose of: large number of features (Table 3.1) compared to the small set of samples and missing measurements (Table 3.2). We were studying different ways to address these problems.

In the preliminary feature selection study, we compared different prediction models (linear regression and Ridge regression). In these calculations, we investigated whether the full set of features (336) could be reduced to satisfy the learning condition ( $p \leq n$ ), so that we reduced the signal to single sessions (two first sessions) or to fitting function terms (exponential fitting). We tested different dimensions of the data, e.g. how the inclusion of climber group information (due to the conditions applied during climbing practice) changes the prediction. We examined same-domain data (fluency

Features (computed on training phase)								Targets (transfer phase)
$a^{GE}$	$e^{GE}$	$a^{JE}$	$e^{JE}$	$a^{IM}$	$e^{IM}$	$a^{CT}$	$e^{CT}$	$y^{GE}$
								$y^{JE}$
								$y^{IM}$

**Table 3.3** - The set of 8 features used to predict the 3 targets ( $y^I, I = \{GE, JE, IM\}$ ).

data for control routes only) and different-domain data (fluency data for control and variant routes); we studied separate (i.e. only one indicator data used as input) and mixed-indicator (two or more indicator data used as an input) data for their influence on feature selection and prediction error size. In constructing the pipeline, we have paid particular attention to how the chosen method would simultaneously address the problem of missing data. Finally, we chose to model the behavioral data with an exponential function; the input-output data is detailed in Table 3.3.

Notably, we utilized four fluency indicators for the input data (including climbing duration CT), while only three of them were our prediction outputs (GE, JE, IM). Thus, we employed four types of metrics as features and three as targets.

### 3.3 MODELING CLIMBING LEARNING DYNAMICS

The exponential curve has been postulated as a function that reflects the learning progress of the trainees and provides the best fit to the learning data. In the comparative study of [Newell et al. \[2009\]](#), the authors referred to established training data (data from tests of fine visual-motor skills: pursuit rotor task [Adams \[1952\]](#) and mirror tracing task [Snoddy \[1926\]](#)) and evaluated the power law and exponential models with single and double time dynamics. In the rationale, they mention (as in [Mayer-Kress et al. \[2006\]](#)) that the slow learning dynamics evolution, which accounts for general memory involvement, was additionally furnished with another time parameter. This parameter represents the adaptation process within the ongoing session in order to grasp the fast changes that usually predominate during the rest periods (outside the scope of the measurements, thus their immediate presence

STAGE	INPUT	OUTPUT (TARGET)	MODELING
1	video / sensors of a climb	fluency indicator for a climb	skill proficiency
2	fluency indicators along the climb	exponential fit $(a, c)$	learning dynamics
3	terms $(a, c)$ from exponential fit	transfer route fluency indicator	learning generalization

**Table 3.4** – Table of modeling stages.

remains unregistered). However, even if the slow time dynamics progression is undeniably present in our data (reflecting the stability of the learning dynamics), patterns that reflect fast time scale (adaptation), cannot be captured in a task that induces high fatigue, such as climbing (thus we dispose too few trials per session to reflect the fast scale effect). Hence, in our study we focus on modeling the slow dynamics using a decreasing exponential function. The Figure 3.2 further explains all stages of modeling, together with the Table 3.4.

Exponential curve fitting is intended to summarize the climbing training dynamics in a few features. Thus, by focusing on the dominant tendency and reducing the number of components involved in the exponential models, we could approximate the dynamics as closely as possible with a simple exponent that could ultimately be symbolized by only two terms.

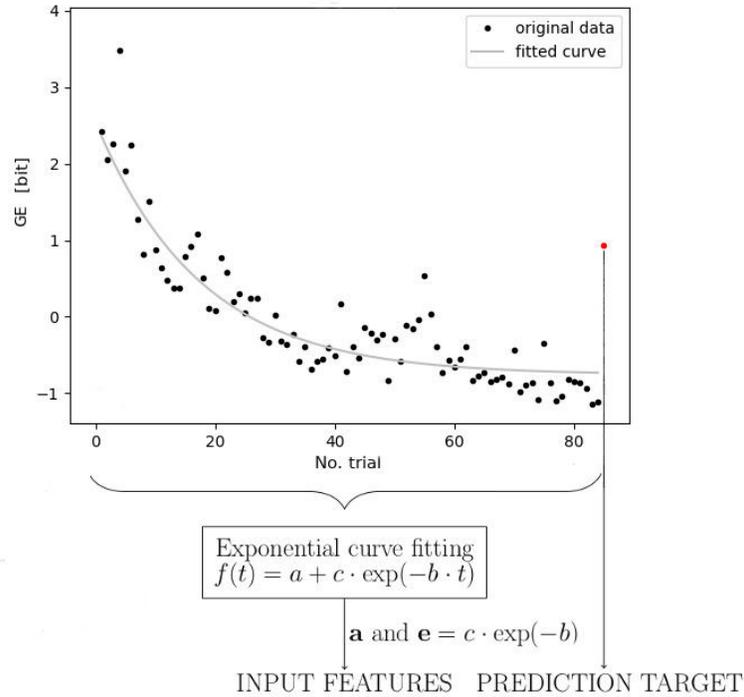
### 3.3.1 FEATURE EXTRACTION

The exponential model we employ to represent the climbers dynamics is

$$f(t) = a + c \cdot \exp(-b \cdot t) \quad (3.1)$$

with parameters  $a$ ,  $b$  and  $c$  (Fig. 3.2).

In our approach, the first component (an additive term  $a$  present in the Equation 3.1) would refer to the maximum performance of each participant (understood as the inverse of the fluency measure) achieved during practice (the asymptotic minimum of the exponential decay, which is an *inverted*



**Figure 3.2** - Diagram of the modeling stages. The *first stage*, illustrated as black dots in the figure, depicts the fluency of one participant, and the last red dot symbolizes the climbing fluency for the transfer route in the post-test trial. In the *second stage* (learning dynamics modeling), the exponential function is fitted to the training data signal (gray line), except for the transfer test value (not fitted). Subsequently, the exponential function parameters of all metrics (entropy, jerk, immobility ratio and climbing duration) are utilized in the prediction algorithm (*third stage*) as the input set of features, while the transfer value is utilized as the output (target). This stage models the learning generalization. The example entropy data in the graph has been standardized beforehand.

*plateau* and a stable state of the learning dynamics); while the second one (the exponential term in the Equation 3.1, *i.e.*  $e = c \cdot \exp -b$ ) would depict the individual learning rate of each participant. In this way, the simplified two-term approach satisfies both: motor description exhaustion (using as many parameters as necessary) and machine learning convenience (using the least number of features).

For each climber and each of the associated fluency indicators (GE, JE, IM), we fit the exponential model by solving

$$\min_{a,b,c} \frac{1}{n} \sum_t (a + c \cdot \exp(-b \cdot t) - I(t))^2$$

where  $I$  denotes the fluency indicator (GE, JE, or IM) and  $n$  is the number of climbing sessions. Hence, for each climber the estimated terms of the fitting functions serve as features to predict the outcome of learning progress in the post-training *transfer test* fluency. Specifically, we consider  $a$  (an additive term) and  $e = c \cdot \exp^{-b}$  (an exponential term) as features associated with each fluency indicator (Table 3.3).

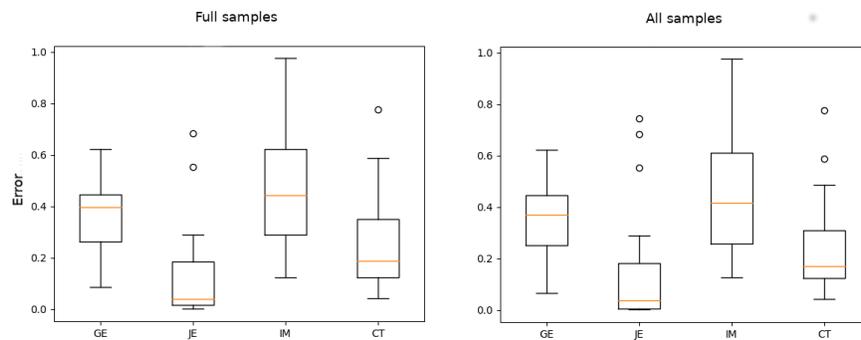
Even though the exponential model adopted here is justified for learning curve modeling, we must be cautious, since the individual intrinsic dynamics (the inter-participant differences in pre-training dynamics [Kostrubiec et al. \[2012\]](#)) and the context of motor activity (e.g. the different sports) may promote different learning functions, as explained in [Newell and Liu \[2012\]](#).

### 3.3.2 EXPONENTIAL FITTING EVALUATION

Measurement-based analysis is often challenged by incomplete data. Given that the protocol consisted of hundreds of recordings per participant, it is likely that the equipment will sometimes fail, as was the case with our recorded data (Table 3.2). The voids were of two kinds: isolated random missing fluency values and the missing sequences corresponding to a session (for jerk measurements, Figure B.3). To handle the voids in the recordings, we started the analysis by comparing the fit accuracy for the complete data samples of the (selected) participants with all (sometimes incomplete) participants. There were a total of 33 *incomplete* measured tracks from participants, for which we performed fitting of the exponential function, whereas there were a variable number of *full* training track evaluations, depending on the fluency score (GE: 27, JE: 20, IM: 27, CT: 30, Table 3.2). Obviously, we aimed

at including the incomplete samples into the study, in order to increase the sample size and thus the reliability of the prediction.

In the Figure 3.3 we can observe, that the difference in fitting accuracy for incomplete and complete training tracks was in favor of complete training tracks (with the exception of the time indicator CT, which, however, was not considered as a valid measure of fluency in our study, as mentioned at the beginning of this Section). For this reason, we might expect that, by imputing appropriate data to the



**Figure 3.3** – Exponential evaluation fit for the complete track data (left) and for the incomplete tracks of all the participants (right). The Figure indicates the median of the mean squared error (MSE).

voids (e.g. using a machine learning algorithm to reconstruct missing data), we could achieve a more accurate prediction. It is worth noting, however, that the two statistical tests Mann-Whitney U Test and Kruskal-Wallis H Test (applied separately to each indicator), performed on the full track data and the data with voids, did not manifest any statistically significant difference in the distributions of the fitting results. For this reason and for the sake of simplicity (since the difference in fitting accuracy was not substantial), we assumed in the following analysis that we could rely on the curve fit to the corrupted signals (i.e., without reconstructing the data).

Additionally, in both cases (complete and incomplete datasets), three samples whose dynamics did not reflect the pattern of exponential learning evolution, were eliminated due to the divergence prob-

lems of the fitting algorithm. Based on the initial results, we were not reluctant to proceed with the 30 samples based on the incomplete data sets.

### 3.4 PREDICTION OF TRANSFER

To predict the post-training transfer fluency score, we used the terms of the exponential function fitted to the climbers' performance based on all the four metrics (entropy, jerk, immobility and duration). Therefore, after reducing the number of terms to 2 for each metrics (one additive term,  $a$ , and one exponential term,  $e = c \cdot \exp(-b)$ ), we applied a total of 8 features to predict the transfer score of each indicator for the data sets consisting of 9 (CP: control practice protocol) and 21 (VP: variable practice protocol) samples (9 in VP1 and 12 in VP2).

We emphasize that in the prediction, as in the exponential fitting procedure, our priority was to reduce the number of features, without losing the essential information (according to Table 3.3).

#### 3.4.1 PREDICTION ALGORITHM

In our approach we applied the linear model, suspecting a linear relationship between input (the joint exponential parameters of the learning dynamics for all the indicators) and output (test transfer fluency). For this aim, as mentioned in Section 3.1, we evaluated the model predictions on each set of practice separately (VP1, VP2 or CP).

For the  $\mathbf{y} \in \mathbb{R}^n$ , which is the output (transfer test vector) and  $\mathbf{X} \in \mathbb{R}^{n \times p}$ , which is our input composed of the parameters of the exponential curve fitted to the fluency indicator history (learning dynamics), where  $n$  and  $p$  are the number of samples (30) and features (8) respectively, we can formulate a linear model. The linear regression reads :

$$\mathbf{y} = \mathbf{X}\mathbf{w} + \mathbf{e},$$

where  $\mathbf{e}$  is the vector of prediction models and  $\mathbf{w}$  is the vector of parameters. In order to apply the least squares linear regression model, a necessary condition is that  $p \leq n$ . According to Table 3.3 this is possible for VP<sub>1</sub>, VP<sub>2</sub> and CP, however to strengthen the transfer skill prediction performance (and to increase model interpretability), we implement a two-step modeling (Belloni and Chernozhukov [2013]):

STEP 1 performs feature selection,

STEP 2 learns a linear model for each group (CP, VP<sub>1</sub>, VP<sub>2</sub>) based on the features retained in STEP 1.

Specifically, at STEP 1 we rely on the full matrix  $X$  and the full vector  $y$  (with all practice groups) to learn a linear sparse model using the Lasso (Tibshirani [1996]), i.e. by solving

$$\min_{\mathbf{w}} \|\mathbf{y} - \mathbf{X}\mathbf{w}\|_2^2 + L\|\mathbf{w}\|_1.$$

$L > 0$  is the sparsity regularization parameter, that is tuned by a grid search (Hastie et al. [2009]). To consistently select the relevant features and circumvent our limited number of samples, we implement a leave-one-out cross-validation (LOO-CV, James et al. [2021]). The retained features are those that appear relevant across the sparse models generated by the LOO-CV. This illustrates STEP 1 in the Algorithm 4. Based on the previously selected features, STEP 2 estimates a classical linear regression for each practicing group CP, VP<sub>1</sub>, VP<sub>2</sub>. To assess the generalization performance for each group, a LOO error estimator is used as depicted in Algorithm 4 (STEP 2).

### 3.4.2 PREDICTIVITY EVALUATION

We aimed to examine the predictivity of the sets of each practicing group (VP<sub>1</sub>, VP<sub>2</sub> and CP), by evaluating the transfer test prediction stability (i.e. error variability).

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**Algorithm 4** Two-step model (one indicator case)

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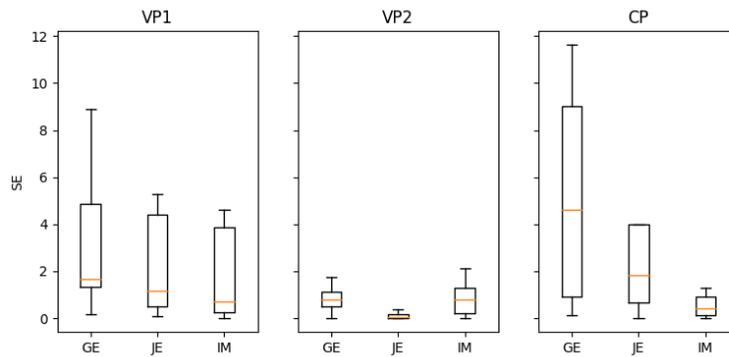
1: **STEP 1** ▷ feature selection  
2: **procedure** LASSO MODEL  
3:   **Input**  $\mathbf{X}, \mathbf{y}$   
4:   **Output**  $S$  ▷ the selected feature indices  
5:   **for**  $k=1$  **to**  $n$  **do** ▷ LOO-CV  
6:      $\mathbf{X}_k = \mathbf{X} \mid \{\mathbf{x}_k\}, \mathbf{y}_k = \mathbf{y} \mid \{y_k\}$  ▷  $\mathbf{X}_k$  is  $\mathbf{X}$  deprived of sample  $\mathbf{x}_k$   
7:     **solve**  
8:      $\hat{\mathbf{w}}_k = \arg \min_{\mathbf{w}} \frac{1}{2} \|\mathbf{y}_k - \mathbf{X}_k \mathbf{w}\|_2^2 + \hat{L}_k \|\mathbf{w}\|_1$  ▷  $\hat{L}_k > 0$  is selected with grid-search  
9:   **end for**  
10:   **average** over the estimates  $\bar{\mathbf{w}} = \frac{1}{n} \sum_{k=1}^n \hat{\mathbf{w}}_k$  ▷ most  $\hat{\mathbf{w}}_k$  are sparse  
11:   **select** the relevant features across models  
12:    $S = \{1_{\bar{\mathbf{w}}(i) \neq 0}\}_{i=1}^p$  ▷ indexes of the non-zero elements of  $\bar{\mathbf{w}}$   
13: **end procedure**

14: **STEP 2** ▷ prediction refinement  
15:  $pr = \text{VP}_1, \text{VP}_2$  or CP  
16:  $\tilde{\mathbf{X}} = [:, S]$  ▷ reduced to set of indices  $S$   
17: **procedure** LINEAR REGRESSION MODEL  
18:   **Input**  $\tilde{\mathbf{X}}^{pr}, \mathbf{y}^{pr}$   
19:   **Output** vector of errors  $err^{pr}$   
20:   **for**  $k=1$  **to**  $n$  **do** ▷ LOO error estimation  
21:     **estimate**  $\tilde{\mathbf{w}}^{pr} = \arg \min_{\mathbf{w}} \frac{1}{2} \sum_j (\mathbf{y}_j^{pr} - \mathbf{w}^T \tilde{\mathbf{x}}_j^{pr})^2$   
22:     **compute** error of prediction  $r_k^{pr} = (\mathbf{y}_k^{pr} - (\tilde{\mathbf{w}}^{pr})^T \tilde{\mathbf{x}}_k^{pr})^2$   
23:   **end for**  
24: **end procedure**

---

We evaluated the quality of the prediction with error  $r^{pr}$  defined in the Algorithm 4 (line 20). The final prediction performance is assessed as the median of the error vector that is the output of the Algorithm 4 (result of LOO procedure).

As the Figure 3.4 demonstrates, the VP2 group excelled the other two groups VP1 and CP in terms of the measure of squared error (SE) variability in prediction (i.e. the adjustment of the prediction to the true value) as well as by the SE median (except for the immobility measure for CP). We recognize



**Figure 3.4** – Comparison of the predictive power (by square error SE) for the variable practice (VP1, VP2) and the constant practice (CP) initial groups.

the lower variability of the entropy and jerk metrics as an effect of more appropriate attribution of the prediction result to the learning set, which would be accurate in the case of the variable practice data set VP2. The VP1 entropy SE is lower than CP entropy SE, but this pattern is reversed for jerk (CP jerk SE is lower than VP1 jerk SE). The immobility metric demonstrates superior prediction for CP SE, and higher SE for both variable practice groups. However, it is worth noting, that the algorithms that were utilized for the prediction are not designed for the discrete feature values. Since the immobility ratio is based on the (arbitrary) threshold for describing mobile and immobile actions (as defined in Chapter 1 Section 1.2.3), the machine learning procedure is not guaranteed to be properly adjusted to this discrete score, thereby demonstrating its low predictive reliability. To support the hypothesis that IM is different in nature from the remaining (continuous) metrics, we may also verify the result of the

<i>Target</i>	<i>Features</i>	GE		JE		IM		CT	
		a	e	a	e	a	e	a	e
$y^{GE}$		○	1	○	1	1	1	1	○
$y^{JE}$		1	○	1	1	○	○	○	1
$y^{IM}$		○	○	○	○	○	○	1	○

**Table 3.5** – Lasso feature selection result (*a*-additive term of fitting function = the maximum performance, *e* - exponential term of fitting function = the learning rate).

Lasso pre-train selection (STEP 1 in Algorithm 4). Namely, we found that the following number of features were retained for the second step (refinement of the model) GE: 5, JE: 4, IM: 1 (Table 3.5). Thus, in the case of IM, only one feature was kept as important (providing very sparse result), which confirms the fact that this particular fluidity indicator is not very informative and the output assigned to the input might be too elusive for the Lasso algorithm to be properly predicted. Another reason for the misbehavior of the immobility ratio, might be the sheer nature of this purely temporal indicator. Considering the nature of each one of the indicators, we might discuss about the fluidity aspects that each of them prioritizes: whether fluidity should reflect efficient movement towards the end of the route (ultimate goal), or with a general agility that allows to test different ways to complete a given stretch of route (exploration of multiple manners of goal reaching), even if, at the expense of efficient movement, it entails to temporarily move away from the goal. We can note that the fast movements (that are given priority in the temporal fluency indicators) might impede the overall smoothness evolution in climbing. From our result, we conclude that our approach is mainly appropriate for measures that carry the characteristics of displacement (entropy and jerk) and not merely the temporal ones (immobility)<sup>†</sup>.

To validate the results with statistical tests, we used the Kruskal-Wallis *H* Test (KW) [Kruskal and Wallis \[1952\]](#) and the Mann-Whitney *U* Test (MW) [Mann and Whitney \[1947\]](#). These tests are re-

<sup>†</sup>However this property may also be specific to our study due to the instructions given to the climbers not to omit the handholds and to follow their chronological order. Conversely, in a less constrained climbing task, we might observe that the temporal indicator is relevant because route finding would be an important perceptual-motor skill to succeed.

commended when the compared sample sizes vary. The initially applied (multiple group) KW test (for VP<sub>1</sub>, VP<sub>2</sub>, and CP; number of degrees of freedom  $df = 2$ ) demonstrated the only significant difference for the jerk score ( $p$ -value= 0.001 with test statistic  $H = 10.227$ ), even though it was close to significance for the entropy ( $p$ -value= 0.076,  $H = 3.157$ ); immobility exhibited no difference ( $p$ -value= 0.776,  $H = 0.081$ ). Further, the group pairwise MW test analysis revealed that only the entropy and jerk SE for the VP<sub>2</sub> group indicated a significantly different distribution compared to the other groups VP<sub>1</sub> and CP. The MW test values ( $p$ -value and associated test statistic  $U$  value) are illustrated in Table 3.6 (we did not find sufficient statistical significance in the distributions of our results for IM, as  $p$ -value > 0.05). These findings further support the fact that the prediction stability that was significantly higher for VP<sub>2</sub> in the case of GE and JE compared to the other groups (VP<sub>1</sub> and CP), should be valid, in contrast to the opposite result obtained for the IM (which provided higher prediction stability for the CP group), and unlike the comparison between the VP<sub>1</sub> and CP groups, Figure 3.4.

<i>p</i> -value ( <i>U</i> )	GE	JE	IM
VP <sub>1</sub> vs VP <sub>2</sub>	0.041 (29)	0.001 (9)	0.402 (50)
VP <sub>1</sub> vs CP	0.362 (36)	0.329 (35)	0.329 (35)
VP <sub>2</sub> vs CP	0.035 (28)	0.001 (10)	0.322 (47)

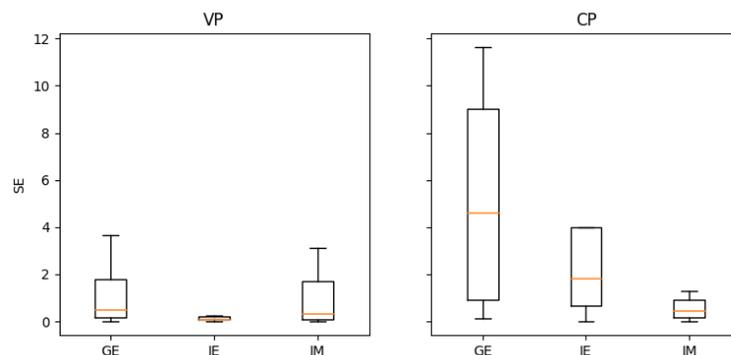
**Table 3.6** – Statistical significance  $p$ -value (with  $U$  value in the brackets) for the sets with Mann-Whitney  $U$  Test (MW).

#### CONSTANT VS. VARIABLE VP=VP<sub>1</sub>+VP<sub>2</sub> PRACTICE

The results provided here concern the variable practice group (VP, consisting of VP<sub>1</sub> and VP<sub>2</sub> together) compared to the control practice group (CP)<sup>‡</sup>. This result from another perspective demonstrates the differences between the unchanged and the modified practices.

<sup>‡</sup>It should be noted, that in this case the balance between the groups is affected, as there were 21 participants in the VP group vs. 9 participants in the CP group.

The Figure 3.5 reveals the overall lower squared error (SE) variability, as well as the SE median in the case of the VP dataset. We recognize the lower variability of the entropy and jerk metrics as an effect of a more appropriate assignment of the prediction score to the learning set, which would be more accurate in the case of the variable practice VP (VP<sub>1</sub>+VP<sub>2</sub>) data set. The two previously used statistical tests (MW and KW) yielded the following values; for entropy MW:  $p$ -value= 0.015 and KW:  $p$ -value= 0.028; for jerk MW:  $p$ -value= 0.002 and KW:  $p$ -value= 0.003, for immobility MW:  $p$ -value= 0.41 and KW:  $p$ -value= 0.803, thus, as in the case of a VP subgroup, we did not find sufficient statistical significance in the distributions of our results for IM ( $p$ -value > 0.05). These findings support the fact that the prediction stability that was much higher for VP in the case of GE and JE should be valid, in contrast to the opposite result obtained for the IM (higher prediction stability for CP group), Figure 3.5.



**Figure 3.5** - Comparison of the predictive power (according to squared error SE) for variable practice (VP = VP<sub>1</sub>+VP<sub>2</sub>) and constant practice (CP) groups.

TO SUMMARIZE, we have indicated the set of climbers VP<sub>2</sub> as more predictive of transfer, but additionally, by means of the Lasso selection method, we have revealed the fluency indicators (features are their parametric representation terms  $a$  or  $e$ ) that could affect the prediction of skill transfer fluency. Therefore, we might suspect that spatial metrics (entropy, jerk) are more adapted for this purpose, sug-

gesting their usefulness in future studies of dynamic variables that address the generalization property of the climber.

### 3.5 INTERPRETING THE RESULTS

In our analysis we attempted to quantify the effect of three different practice conditions on the transfer evaluation stability (the magnitude of the prediction error) with machine learning and its impact on attuning of the learner's dynamic variables to the most important information (Pacheco et al. [2019]).

FROM THE MACHINE LEARNING PERSPECTIVE, we paid special attention to the implementation of a reliable final pipeline for the movement science application given the small number of samples compared to the large number of features, which was our scientific challenge. Our solution to this problem was: 1) reducing long sequences of measurements to the parameters of the fitted curve, 2) introducing a pre-training step in the prediction algorithm. Nevertheless we may notify, that finding other ways of feature selection methods may result in other variants of the algorithm. Thus, further exploitation of other types of methods to reduce the complexity of the input data is highly desirable.

A similar issue is the heterogeneity of the sample, i.e. the inter-individual variability between participants, and how this has affected the generality of the statistical methods used. It is well known that the averaging (the standardization or normalization of data required by certain algorithms) in motor learning perspective can interfere with or falsify the individual dynamics of each participant (Newell and Liu [2012]). Although we may suspect that the our algorithm accounts for the subtle structure of the data, we did not focus on it in our analysis e.g. by clustering the different types of learning dynamics among the participants, thus this question remains open for future studies.

An important type of challenge in machine learning applied to behavioral signal analysis that should be highlighted, is the need to handle incomplete data problem, the need for data imputation. The ori-

ginal signal (entropy, jerk, immobility and climbing duration time sequences) to which we fitted the exponential function, contained missing data, so finding an imputation method for an approximate value instead of notifying the voids, could affect the results of our prediction accuracy. In this view, research on an adequate approach to address the missing data problem (although not applied here, but inspired by Figure 3.3) in the case of a behavioral signal would be beneficial to improve the quality of the final prediction.

Once the limitations of the method are known and we are confident that we have successfully addressed them in our approach, we are ready to discuss the results from a human movement science perspective.

FROM THE HUMAN MOVEMENT SCIENCE PERSPECTIVE, induced variability in climbing tasks is straightforward to apply through handhold manipulation, as in our case. In our study the task variants were designed by displacing the holds, i.e. the modifications were applied to only one dimension during the practice sessions. The same dimension was manipulated to design the transfer test, to take into account the same individual variables of the climbers' intrinsic dynamics. According to ecological dynamics (Button et al. [2021]), the climber learns to continuously adapt to a set of interacting constraints (task, environment, personal resources) and to attune to relevant opportunities for action. Therefore, ecological dynamics hypothesizes that variable practice further increases adaptive behavior in the sense that climbers would learn to adapt more functionally (i.e. facilitate generalization transfer). Attuning to variables that facilitate transfer to a new motor condition is considered a crucial part of the learning process, which in our case occurred during practice sessions. Then, the contextual change, that the learner faces in the transfer test trial, accounts for the adaptation of the learned variables within the reduced dimensionality, which supports the transfer to new contexts in the case of a well-trained climber.

In our study we expose that in the self-controlled practice (VP<sub>2</sub>), the climber's intrinsic dynamics cooperate in order to guarantee stable performance in the transfer trial (Smeeton et al. [2013]). In the light of our results, the self-controlled practice learners were able to generalize more effectively in the sense that their intrinsic dynamics constituted during practice allowed for reduced randomness in learning curve adjustment to the transfer fluency. These results might be explained by the fact that, variable practice actively led the climbers to successfully find more reliable information to tune to. However, the variable practice group (VP<sub>1</sub>) did not demonstrate improved predictions of their performance on the transfer test compared to the constant practice group (CP). Indeed, since VP<sub>2</sub> learners could decide to practice on the same route for several sessions, they would make improved exploitation of the route properties and optimize their behavior, whereas the rate of route changes in VP<sub>1</sub> may have been too high for some participants. Thus, these results confirm and extend the previously acknowledged positive effects of self-controlled practice schedules on skill acquisition (Liu et al. [2012]).

An important aspect of our climbing experimental protocol is that climbers not only attempted to climb the route (to reach the last handhold on the trial route), but also to improve their fluency according to the feedback score from the previous session. This caveat made it possible to quantify the learning effect with fluency measures, but at the same time emphasized the focus on the quality of the movements toward the goal, making it difficult to disentangle the effects of task and goal on the learners' functional dynamics (Pacheco et al. [2019]). However we could still question the extent to which the parameters of the exponential function of fluency history deployed in the study remain related to the subjects' intrinsic dynamics. Intuition would suggest, that they are strongly associated with the parameters of the jerk score exponential fit, for which we obtained the lowest level of prediction error. Moreover, the jerk and entropy values were the most prominent among the features selected in the pre-training step of the machine learning algorithm.

### 3.6 CHAPTER SUMMARY

Our results presented in this Chapter have pointed to the added value of the variable practice for skill acquisition and transfer. Furthermore, we confirmed that the positive effect of the variable practice was particularly significant when the variability of practice was self-controlled by the learner. Additionally, by means of the Lasso selection method, we revealed the fluency indicators (features are their parametric representation terms  $a$  or  $e$ ), that could affect the prediction of skill transfer fluency. Therefore, we might suspect that spatial metrics are more adapted for this purpose, suggesting their usefulness in future studies of dynamic variables that address the generalization property of the climber.

We can speculate that further research on how spatial fluidity corroborates particular aspects of dynamics during learning, may elucidate the details (particular movement types) that allow for contextual tuning of individual learners.

The methodology presented here (summarized beneath) allowed a statistical study of the behavioral signal with a small dataset, however some methodological improvements could help to constitutionalize the insights obtained, and in this direction (e.g., solving the problem of missing data or the selection method evolution) we envision potential for further development of research in machine learning applied to theory of learning in the behavioral neuroscience of human movement.

#### MACHINE LEARNING - pipeline construction

1. Reducing the dimensionality of the signal with fluency calculations (trial level)
2. Reducing the dimensionality of the time series with exponential curve fitting (session level)
3. Modeling with Lasso (feature selection)

#### HUMAN LEARNING SCIENCE - evaluation of predictivity

1. Prediction of learning progress (transfer value)
2. Evaluation of the prediction with median of the error (comparison of the sets predictivity)

# 4

## Conclusion and perspectives

In the Thesis we would like to underscore the importance of using machine learning in behavioral research. On the functional side, in our work we wish to respond to the specific demand of the theorists from human movement domain that we present in our two contributions. In the final Chapter we will reflect more on the formal implications and advancements of these approaches as well as on their utilization in different contexts.

## 4.1 CONCLUSION

Our aim in the Thesis was to exemplify that the use of machine learning has comprehensive benefits for behavioral discovery and opens up new avenues of analysis. Through the literature review and the introduction of the main concepts, we wanted to point out that applying statistical learning is not an entirely novel approach, as certain human learning phenomena have already been modeled using these methods. In particular, unsupervised learning has been successfully engaged to track emerging patterns, which is altogether a natural way of studying dynamic behavior of humans moving in an environment. However, we go further in our assumptions and, using semi-supervised and supervised algorithms (Aniszewska-Stępień et al. [2020]; Belloni and Chernozhukov [2013]), develop dormant possibilities of methodological interpretation.

## GENERATIVE MODELING

In the first approach (Chapter 2), we propose labeling based on a generative model. We have demonstrated, that HMM-CVA allows to annotate sequences based on a partially labeled training set. But the generative property brings an additional quality to the modeling, namely, a hidden Markov model explicitly provides a joint distribution over states and outputs  $P(x, y)$ . This means that it is possible to generate data that follows the same distribution as the inputs that are being modeled. This is not the case with a discriminative model, which only describes a conditional distribution of outputs given the current state  $P(y|x)$ . In a broader sense, having the access to the probability distribution over all the states, we can aim to interpret the relations between the states. In the contribution, we proposed a simple model for the particular task of labeling the climbing record with the type of hand or foot used during the practice trial (and only based on a small set of manually annotated examples), which not only fulfills the initial requirement and ensures correct labeling. Our model allows the access to

additional structural knowledge about the relationship between the attributed labels (limb type) and may be more informative for further analysis in human movement science.

#### SEMI-SUPERVISED LEARNING AND MISSING VALUES

In the Thesis we have demonstrated that semi-supervised methods (constrained Viterbi in HMM framework) in the case of sequential label learning (Chapter 2), can be more reliable (90% accuracy) than manual annotation made by human (about 70% accuracy) and are less costly. Our model performed well and learned quickly (in two iterations), despite the adversity of the missing values issue. The main idea we advocate is that missing data may provide additional measurement structure that is relevant and informative for analysis (we will elaborate on this concept in Perspectives). From the machine learning standpoint the excellent performance is an argument to support a mixed use type of learning (supervised and unsupervised), as some studies suggest that including unlabeled data does not compromise algorithmic efficiency (Ning et al. [2019]; Zhi et al. [2020]). For the humanities, the positive message is that the erroneous measurements do not have to be excluded from the dataset (one way of handling this is illustrated in Chapter 3), and missing values should not be ignored.

#### MODEL INTERPRETABILITY

In Chapter 3 we applied the bi-level strategy: first, to find the regularization parameter  $\lambda$  with LOO-CV, and second, to select the coefficients (weights) of the model by identifying the values that lead to the minimum of the optimization function. This technique using Lasso (Tibshirani [1996]) circumvents the small number of samples in the prediction stage (linear regression). Thanks to the bi-level strategy we were also able to trace which features are the most important for the prediction (have the highest weight) and identify which type of fluency metrics contribute to the prediction. Specifically, we found that the mixing of spatial and temporal information in the input data (which refers to the use of jerk fluidity) drives the most stable transfer prediction.

The complex nature of the human learning process can therefore be addressed by statistical learning, that is fully data-driven and induced, as opposed to traditional, deductive approaches, in which features are handcrafted and theoretical hypotheses are predetermined (Grimmer et al. [2021]). What makes the bottom-up (data-driven) approach useful for the humanities is that without any prior assumptions we could observe the interaction between the features (variables of the model), and attempt to drive an interpretation about the intrinsic dynamic process at work during the climbing learning protocol. Specifically, when we studied the behavioral signals collected under different experimental conditions, thanks to this approach we could observe that in the group of self-controlled learners, their intrinsic dynamics demonstrated high predictivity, i.e. throughout the practice they reduced the randomness in the learning curve adjustment to the transfer fluency (Section 3.5).

#### 4.2 PERSPECTIVES AND REMARKS

The interdisciplinary research illustrated here is particularly challenging, because it aims to be both meaningful for the application field and revolutionary in the computational domain, which is sometimes not so easy to combine. There are numerous issues that can be solved by basic statistical learning algorithms, and even if they require adaptation and structure-specific interpretation, the simplicity lies at the heart of their employment. Since generative approaches (Aniszewska-Stępień et al. [2020]; Pajot et al. [2019], Chapter 2) seem to best model behavioral dynamical phenomena, and in particular learning (Lake et al. [2016]) by accessing functional prior distributions of states, a generative model could be informative about the intrinsic dynamics of the learner or transitions between patterns and therefore subject strategy (detecting sources of stability and variability, Komar et al. [2023]). Furthermore, the presented methodology could be examined in a variety of similar sequential contexts with missing data.

However we can point to several directions in which statistical learning usage in movement analysis could be expanded. One is the further research on the missing data issue, which would help to discover the type of missingness present in the unrecorded measurements (i.e. random vs. structure based voids). One could also try to address different ways to incorporate the structure of the voids into the optimization algorithm (Descloux et al. [2020]). Another interesting idea is the broad exploration of multidimensional climber trajectory curves treating them as geometric entities, be it with unsupervised methods (revealing pattern dynamics) or supervised algorithms (including feature grouping Jacob and Obozinski [2009]). From another perspective our research may be limited by the fact that, according to the data collection protocol, we investigated movement learning on a single timescale. We suggest that further studies on the analysis of the learning paradigm could include an extension of the time dimensionality (Newell et al. [2005]).

It is an awesome endeavor to determine whether machine learning can be of practical use in identifying, for example, the most optimal (in terms of fluency) way for a given person to climb a particular route based on their current abilities. Given our knowledge of the neural system degeneration (Seifert et al. [2016]), the multistability of learning patterns and movement variability, it is doubtful that an artificial intelligence could ever create such a customized movement learning *program* for a single individual. Perhaps, human behavior will be a never-ending source of insight for those who wish to learn the reverse-engineering of an evolutionarily shaped human movement system. The abundance of bio-inspired branches of robotics that we see today is a natural consequence of this phenomenon. However in our case, by bringing together the machine learning and human movement science, we believe that our research contributes to the discovery of how adaptive motor strategies can be efficient while ensuring safety throughout the learning of complex tasks. Overall, the interdisciplinary combination of two learning areas, machine and human, gives us an amazing opportunity to present a supportive role of machine learning science, but also to discover its own ways to advance.



## Publications

The contributions presented in this doctoral Thesis, resulted in the following publications.

- **Peer-reviewed journal**

A. Aniszewska-Stępień, R. Hérault, G. Hacques, L. Seifert, and G. Gasso. Evaluating transfer prediction using machine learning for skill acquisition study under various practice conditions. *Frontiers in Psychology*, 13:8052, 2023. [Aniszewska-Stępień et al., 2023] *Material in this article appears in Chapter 3.*

### **Communications**

- **International conference workshop (peer-reviewed article)**

A. Aniszewska-Stępień, R. Hérault, G. Hacques, L. Seifert, and G. Gasso. Learning from partially labeled sequences for behavioral signal annotation. In *7th Workshop on Machine Learning and Data Mining for Sports Analytics ECML/PKDD 2020 Workshop, Ghent, Belgium*. Springer, 2020 [Aniszewska-Stępień et al., 2020] *Material in this article appears in Chapter 2.*

- **National conference**

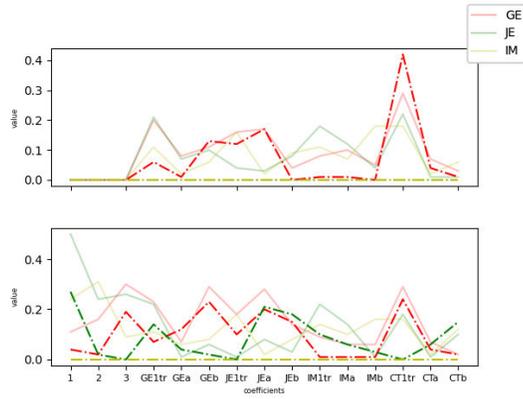
A. Aniszewska-Stępień, R. Hérault, G. Hacques, L. Seifert, and G. Gasso. An investigation on transfer in motor skill acquisition with machine learning. In *Conference Sports Physics 21*, page 34. ENS de Lyon, 12 2021. Abstract. [Aniszewska-Stępień et al., 2021] *Material in this article appears in Chapter 3.*

# B

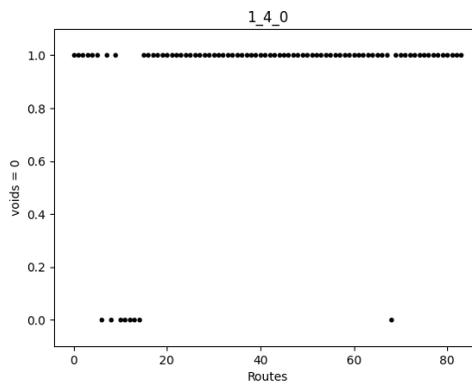
Additional figures



**Figure B.1** – Feedback was intended to provide participants with information about their climbing performance and to guide their learning. It should encourage participants to discover new ways of climbing the route and to fluently chain movements to lower their fluency scores to the greatest extent possible, without explicitly indicating how to do it (encouraging external focus of attention [Wulf and Shea, 2002]). Before starting a new session, the feedback from the previous session was described and explained to the participants. It was presented in the form of images of harness light trajectories on climbing routes during the session (one image per climb) and the corresponding values of three fluency scores labelled spatio-temporal fluency (JE), spatial fluency (GE) and immobility (IM). They were informed that the yellow line corresponded to the trajectory and that the more direct it was, the lower the spatial fluency score (GE) would be. The temporal fluency score (IM) was described as the percentage of climbing time spent immobile and the spatio-temporal score (JE) as the measure of saccadic movements during climbing ('knots' on the trajectory line). The participants were also informed that their aim was to reduce these scores to the greatest extent during training sessions.



**Figure B.2** – Exploratory analysis of data: x-axis represent coefficients (weights) of the features in LOO (above - with no group information, beneath - with group information included as a categorical value). Ridge regression is represented with solid line, Lasso with dotted-dashed line.



**Figure B.3** – Example of missing data in the measurements in one participant climbing learning protocol. Voids are depicted as value '0'. We can notify, that they are sequential or isolated in nature.

# Bibliography

- J. A. Adams. Warm-up decrement in performance on the pursuit rotor. *American Journal of Psychology*, 65:404–414, 1952.
- K.E. Adolph. Learning to move. *Current Directions in Psychological Science*, 17(3):213–218, 2008. doi: 10.1111/j.1467-8721.2008.00577.x. URL <https://doi.org/10.1111/j.1467-8721.2008.00577.x>. PMID: 19305638.
- Y. Altun, I. Tsochantaridis, and T. Hofmann. Hidden Markov support vector machines. *Proceedings, Twentieth International Conference on Machine Learning*, 1, 07 2003.
- M. Andrieux, A. Boutin, and B. Thon. Self-control of task difficulty during early practice promotes motor skill learning. *Journal of Motor Behavior*, 48(1):57–65, 2016. doi: 10.1080/00222895.2015.1037879. URL <https://doi.org/10.1080/00222895.2015.1037879>. PMID: 25961604.
- A. Aniszewska-Stępień, R. Hérault, G. Hacques, L. Seifert, and G. Gasso. Learning from partially labeled sequences for behavioral signal annotation. In *7th Workshop on Machine Learning and Data Mining for Sports Analytics ECML/PKDD 2020 Workshop, Ghent, Belgium*. Springer, 2020.
- A. Aniszewska-Stępień, R. Hérault, G. Hacques, L. Seifert, and G. Gasso. An investigation on transfer in motor skill acquisition with machine learning. In *Conference Sports Physics 21*, page 34. ENS de Lyon, 12 2021. Abstract.
- A. Aniszewska-Stępień, R. Hérault, G. Hacques, L. Seifert, and G. Gasso. Evaluating transfer prediction using machine learning for skill acquisition study under various practice conditions. *Frontiers in Psychology*, 13:8052, January 2023. doi: 10.3389/fpsyg.2022.961435.
- D. Araújo, R. Hristovski, L. Seifert, J. Carvalho, and K. Davids. Ecological cognition: expert decision-making behaviour in sport. *International Review of Sport and Exercise Psychology*, pages 1–25, 2017.
- L.E. Baum, T. Petrie, G.W. Soules, and N. Weiss. A maximization technique occurring in the statistical analysis of probabilistic functions of Markov chains. *Annals of Mathematical Statistics*, 41: 164–171, 1970.

- K. Bellare and A. McCallum. Learning extractors from unlabeled text using relevant databases. In *Proceedings of International Workshop on Information Integration on the Web.2007*,, pages 1–6, 2007.
- A. Belloni and V. Chernozhukov. Least squares after model selection in high-dimensional sparse models. *Bernoulli*, 19(2), 2013. ISSN 1350-7265. doi: 10.3150/11-bej410. URL <http://dx.doi.org/10.3150/11-BEJ410>.
- N. Bernstein. *The Co-Ordination and Regulation of Movements*. Pergamon Press Ltd, 1966.
- N.A. Bernstein, M.L. Latash, and M.T. Turvey. *Dexterity and Its Development*. Psychology Press, Taylor and Francis Group, New York London, 1996.
- Ch.M. Bishop. *Pattern Recognition and Machine Learning (Information Science and Statistics)*. Springer, 1 edition, 2007. ISBN 0387310738.
- A. Blum and T. Mitchell. Combining labeled and unlabeled data with co-training. *Proceedings of the Workshop on Computational Learning Theory*, pages 92–100, 1998.
- D. Bone, Ch-Ch. Lee, T. Chaspari, J. Gibson, and S. Narayanan. Signal processing and machine learning for mental health research and clinical applications [perspectives]. *IEEE Signal Processing Magazine*, 34:196–195, 09 2017. doi: 10.1109/MSP.2017.2718581.
- J Boulanger, L. Seifert, R. Héroult, and J.-F. Coeurjolly. Automatic sensor-based detection and classification of climbing activities. *IEE Sensors Journal*, 16(3):742–749, 2016.
- Ch. Bouveyron and C. Brunet. Simultaneous model-based clustering and visualization in the fisher discriminative subspace. *Statistics and Computing*, 22:301–324, 2012.
- J. Bruineberg, L. Seifert, E. Rietveld, and J. Kiverstein. Metastable attunement and real-life skilled behavior. *Synthese*, 199, 12 2021. doi: 10.1007/s11229-021-03355-6.
- Ch. Button, L. Seifert, J.Y. Chow, D. Araujo, and K. Davids. *Dynamics of Skill Acquisition: An Ecological Dynamics Approach, 2nd edition*. Human Kinetics, Champaign, IL, 01 2021. ISBN 9781492563228. doi: 10.5040/9781718214125.
- L. Cao and Ch.-W. Chen. A novel product coding and recurrent alternate decoding scheme for image transmission over noisy channels. *IEEE Transactions on Communications*, 51:1426 – 1431, 10 2003.
- O. Chapelle, B. Scholkopf, and A. Zien. *Semi-supervised Learning*. MIT Press, Cambridge, 2006.
- A. Chemero. An outline of a theory of affordances. *Ecological Psychology*, 15(2):181–195, 2003.
- K. Cho, B. van Merriënboer, C. Gülçehre, F. Bougares, H. Schwenk, and Y. Bengio. Learning phrase representations using RNN encoder-decoder for statistical machine translation. *CoRR*, abs/1406.1078, 2014. URL <http://arxiv.org/abs/1406.1078>.

- J.Y. Chow, K. Davids, Ch. Button, and M. Koh. Coordination changes in a discrete multi-articular action as a function of practice. *Acta Psychologica*, 127:163–176, 2008a.
- J.Y. Chow, K. Davids, Ch. Button, and R. Rein. Dynamics of movement patterning in learning a discrete multiarticular action. *Motor Control*, 12(3):219–40, 2008b.
- K. Clark, M.-T. Luong, C.D. Manning, and Q.V. Le. Semi-supervised sequence modeling with cross-view training. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1914–1925, Brussels, Belgium, 10 2018. Association for Computational Linguistics. doi: 10.18653/v1/D18-1217. URL <https://www.aclweb.org/anthology/D18-1217>.
- P. Cordier, M.M. France, J. Pailhous, and P. Bolon. Entropy as a global variable of the learning process. *Human Movement Science*, 13(6):745–763, 1994.
- T. Cour, B. Sapp, and B. Taskar. Learning from partial labels. *J. Mach. Learn. Res.*, 12(null):1501–1536, jul 2011. ISSN 1532-4435.
- A.M. Dai and Q.V. Le. Semi-supervised sequence learning. *Proceedings of Neural Information Processing Systems Conference*, pages 1–10, 2015.
- M.P. Deisenroth, A.A. Faisal, and Ch.S. Ong. *Mathematics for Machine Learning*. Cambridge University Press, 2020. URL <https://mml-book.github.io/book/mml-book.pdf>.
- A.P. Dempster, N.M. Laird, and D.B. Rubin. Maximum likelihood from incomplete data via the EM algorithm. *JOURNAL OF THE ROYAL STATISTICAL SOCIETY, SERIES B*, 39(1):1–38, 1977.
- P. Descloux, C. Boyer, J. Josse, A. Sportisse, and S. Sardy. Robust Lasso-Zero for sparse corruption and model selection with missing covariates, 2020. URL <https://arxiv.org/abs/2005.05628>.
- T.G. Dietterich. Machine learning for sequential data: A review. *Proceedings of the Joint IAPR International Workshop on Structural, Syntactic, and Statistical Pattern Recognition*, 1:1–15, 2002.
- E.W. Dijkstra. A note on two problems in connexion with graphs. *Numerische Mathematik*, pages 269–271, 1959.
- G. Edelman and J. Gally. Degeneracy and complexity in biological systems. *Proceedings of the National Academy of Sciences of the United States of America*, 98:13763–8, 12 2001. doi: 10.1073/pnas.231499798.
- L. Favela. The dynamical renaissance in neuroscience. *Synthese*, 199:2103–2127, 12 2021. doi: 10.1007/s11229-020-02874-y.
- E.R. Fernandes and U. Brefeld. *Learning from Partially Annotated Sequences*. Springer-Verlag Berlin Heidelberg 2011, 2011.

- E.R. Fernandes, U. Brefeld, R. Blanco, and J. Atserias. Using Wikipedia for cross-language named entity recognition. In Martin Atzmueller, Alvin Chin, Frederik Janssen, Immanuel Schweizer, and Christoph Trattner, editors, *Big Data Analytics in the Social and Ubiquitous Context*, pages 1–25, Cham, 2016. Springer International Publishing. ISBN 978-3-319-29009-6.
- J.J. Gibson. *Ecological approach to visual perception*. Houghton Mifflin, Boston, 1979.
- A. Graves, S. Fernandez, F. Gomez, and J. Schmidhuber. Connectionist temporal classification: Labelling unsegmented sequence data with recurrent neural networks. *Proceedings of the 23rd International Conference on Machine Learning, Pittsburgh, PA, 2006*, 1:1–8, 2006.
- J. Grimmer, M.E. Roberts, and B.M. Stewart. Machine learning for social science: An agnostic approach. *Annual Review of Political Science*, 24(1):395–419, 2021. doi: 10.1146/annurev-polisci-053119-015921. URL <https://doi.org/10.1146/annurev-polisci-053119-015921>.
- G. Hacques, J. Komar, J. Bourbousson, and L. Seifert. Climbers’ learning dynamics : an exploratory study. *4th International rock climbing congress (IRCRA). 12-15th July, Chamonix, France, 2018*.
- G. Hacques, J. Komar, and L. Seifert. Learning and transfer of perceptual-motor skill: Relationship with gaze and behavioral exploration. *Attention, perception and psychophysics*, 83(5):2303–2319, July 2021. ISSN 1943-3921. doi: 10.3758/s13414-021-02288-z. URL <https://doi.org/10.3758/s13414-021-02288-z>.
- H. Hassan, A. Hassan, and S. Noeman. Graph based semi-supervised approach for information extraction. In *Proceedings of TextGraphs: the First Workshop on Graph Based Methods for Natural Language Processing*, pages 9–16, New York City, June 2006. Association for Computational Linguistics. URL <https://aclanthology.org/W06-3802>.
- T. Hastie, R. Tibshirani, and J. Friedman. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Second Edition*. Springer, Verlag, 2009.
- H. Hayati, D. Eager, A.-M. Pendrill, and H. Alberg. Jerk within the context of science and engineering—a systematic review. *Vibration*, 3(4):371–409, 2020. ISSN 2571-631X. doi: 10.3390/vibration3040025. URL <https://www.mdpi.com/2571-631X/3/4/25>.
- R. Hérault. *Machine learning for high-dimensional and structured problems*. Habilitation à diriger des recherches, Université de Rouen-Normandie, December 2020. URL <https://hal-normandie-univ.archives-ouvertes.fr/tel-03104000>.
- R. Hérault, D. Orth, L. Seifert, J. Boulanger, and J.A. Lee. Comparing dynamics of fluency and inter-limb coordination in climbing activities using multi-scale Jensen–Shannon embedding and clustering. *Data Min Knowl Disc*, 31:1758–1792, 2017.

- G. E. Hinton and S. Roweis. Stochastic neighbor embedding. In S. Becker, S. Thrun, and K. Obermayer, editors, *Advances in Neural Information Processing Systems*, volume 15. MIT Press, 2003. URL <https://proceedings.neurips.cc/paper/2002/file/6150ccc6069bea6b5716254057a194ef-Paper.pdf>.
- S. Hochreiter and J. Schmidhuber. Long Short-Term Memory. *Neural Computation*, 9(8):1735–1780, 11 1997. ISSN 0899-7667. doi: 10.1162/neco.1997.9.8.1735. URL <https://doi.org/10.1162/neco.1997.9.8.1735>.
- A.E. Hoerl and R.W. Kennard. Ridge regression: Biased estimation for nonorthogonal problems. *Technometrics*, 12(1):55–67, 1970. ISSN 00401706. URL <http://www.jstor.org/stable/1267351>.
- S.L. Hong and K.M. Newell. Practice effects on local and global dynamics of the ski-simulator task. *Experimental Brain Research*, 169:350–360, 2006.
- V. Issurin. Training transfer: Scientific background and insights for practical application. *Sports medicine (Auckland, N.Z.)*, 43, 04 2013. doi: 10.1007/s40279-013-0049-6.
- L. Jacob and G. Obozinski. Group Lasso with overlaps and graph Lasso. In *In Proceedings of the 26th International Conference on Machine learning*, 2009.
- G. James, D. Witten, T. Hastie, and R. Tibshirani. *An Introduction to Statistical Learning with Applications in R. Second edition*. Springer, Verlag, 8 2021.
- W. James. *The Principles of Psychology*. New York Henry Holt and Company, 1890.
- Z. Jie, P. Xie, W. Lu, R. Ding, and L. Li. Better modeling of incomplete annotations for named entity recognition. In *Proceedings of the HLT-NAACL 2019, Vol.1*, pages 729–734, Minneapolis, Minnesota, 2019. Association for Computational Linguistics. doi: 10.18653/v1/N19-1079. URL <https://www.aclweb.org/anthology/N19-1079>.
- I. Jolliffe. *Principal component analysis. 2nd edition*. Springer, 2002.
- B.H. Juang and L. R. Rabiner. Hidden Markov models for speech recognition. *Technometrics*, 33(3):251–272, 1991. ISSN 00401706. URL <http://www.jstor.org/stable/1268779>.
- J.A.S. Kelso and D.A. Engström. *The complementary nature*. The MIT Press, Cambridge, MA, US, 2006.
- T. Kohonen. Self-organized formation of topologically correct feature maps. *Biological Cybernetics*, 43(1):59–69, January 1982. ISSN 0340-1200. doi: 10.1007/BF00337288. URL <http://dx.doi.org/10.1007/BF00337288>.

- J. Komar, L. Seifert, N. Vergne, and K. Newell. Narrowing the coordination solution space during motor learning standardizes individual patterns of search strategy but diversifies learning rates. *Scientific Reports*, 13, 02 2023. doi: 10.1038/s41598-023-29238-z.
- J.P. Komar. *Dynamique de l'apprentissage moteur : apprendre loin de l'équilibre*. PhD thesis, Université de Rouen-Normandie, 2013.
- V. Kostrubiec, P.-G. Zanone, A. Fuchs, and S.J.-A. Kelso. Beyond the blank slate: routes to learning new coordination patterns depend on the intrinsic dynamics of the learner-experimental evidence and theoretical model. *Frontiers in Human Neuroscience*, 6(22):1–14, 8 2012.
- M.A. Kramer. Nonlinear principal component analysis using autoassociative neural networks. *AICHE Journal*, 37(2):233–243, 1991. doi: <https://doi.org/10.1002/aic.690370209>. URL <https://aiche.onlinelibrary.wiley.com/doi/abs/10.1002/aic.690370209>.
- W.H. Kruskal and W.A. Wallis. Use of ranks in one-criterion variance analysis. *Journal of the American Statistical Association*, 47(260):583–621, 1952. doi: 10.1080/01621459.1952.10483441. URL <https://www.tandfonline.com/doi/abs/10.1080/01621459.1952.10483441>.
- J. Lafferty, X. Zhu, and Y. Liu. Kernel conditional random fields: Representation and clique selection. 01 2004.
- J.D. Lafferty, A. McCallum, and F. Pereira. Conditional Random Fields: Probabilistic models for segmenting and labeling sequence data. In *Proceedings of the 18th International Conference on Machine Learning 2001 (ICML 2001)*, pages 282–289, 2001.
- B.M. Lake, T.D. Ullman, J.B. Tenenbaum, and S.J. Gershman. Building machines that learn and think like people, 2016.
- J.A. Lee, E. Renard, G. Bernard, P. Dupont, and M. Verleysen. Type 1 and 2 mixtures of Kullback-Leibler divergences as cost functions in dimensionality reduction based on similarity preservation. *Neurocomputing*, 112:92–108, 2013. URL <http://dblp.uni-trier.de/db/journals/ijon/ijon112.html#LeeRBDV13>.
- A. Leroy, P. Latouche, B. Guedj, and S. Gey. Cluster-specific predictions with multi-task gaussian processes. pages 1–40, 2020.
- Y.-T. Liu, Z.-Y. Luo, G. Mayer-Kress, and K. M. Newell. Self-organized criticality and learning a new coordination task. *Human Movement Science*, 31(1):40–54, 2012. doi: 10.1016/j.humov.2011.06.005.
- S.P. Lloyd. Least squares quantization in PCM. *IEEE transactions on information theory*, 28(2): 129–137, 1982.
- H.B. Mann and D.R. Whitney. On a test of whether one of two random variables is stochastically larger than the other. *The annals of mathematical statistics*, pages 50–60, 1947.

- G. Mayer-Kress, Y.-T. Liu, and K.M. Newell. Complex systems and human movement. *Complexity*, 12(2):40–51, 2006. doi: <https://doi.org/10.1002/cplx.20151>. URL <https://onlinelibrary.wiley.com/doi/abs/10.1002/cplx.20151>.
- A. McCallum, D. Freitag, and F. Pereira. Maximum entropy Markov models for information extraction and segmentation. *ICML*, 03 2001.
- W.S. McCulloch and W. Pitts. A logical calculus of the ideas immanent in nervous activity. 5:115–133, 1943. doi: 10.1007/BF02478259.
- G.J. McLachlan and K. E. Basford. *Mixture Models: Inference and Applications to Clustering*. Taylor and Francis, Ltd, 1988.
- T. Mikolov, I. Sutskever, K. Chen, G.S. Corrado, and J. Dean. Distributed representations of words and phrases and their compositionality. *NIPS*, 2013.
- J.S. Murray. Multiple imputation: A review of practical and theoretical findings, 2018. URL <https://arxiv.org/abs/1801.04058>.
- S. Narayanan and P.G. Georgiou. Behavioral signal processing: Deriving human behavioral informatics from speech and language. *Proceedings of the IEEE*, 101(5):1203–1233, 2013.
- S.B. Needleman and C.D. Wunsch. A general method applicable to the search for similarities in the amino acid sequence of two proteins. *Journal of Molecular Biology*, 48(3):443–453, 1970. ISSN 0022-2836. doi: [https://doi.org/10.1016/0022-2836\(70\)90057-4](https://doi.org/10.1016/0022-2836(70)90057-4). URL <https://www.sciencedirect.com/science/article/pii/0022283670900574>.
- K. M. Newell and Y-T Liu. Functions of learning and the acquisition of motor skills (with reference to sport). *The Open Sport Sciences Journal*, 5, (Suppl 1-M3):17–25, 2012.
- K. M. Newell, P. V. McDonald, and P. N. Kugler. *The Perceptual-Motor Workspace and the Acquisition of Skill*, pages 95–108. Springer Netherlands, Dordrecht, 1991. ISBN 978-94-011-3626-6. doi: 10.1007/978-94-011-3626-6\_9. URL [https://doi.org/10.1007/978-94-011-3626-6\\_9](https://doi.org/10.1007/978-94-011-3626-6_9).
- K. M. Newell, G. Mayer-Kress, S. Lee Hong, and Y-T Liu. Adaptation and learning: Characteristic time scales of performance dynamics. *Human Movement Science*, 28:655–687, 2009.
- Karl Newell, Yeou-Teh Liu, and Gottfried Mayer-Kress. Learning in the brain-computer interface: Insights about degrees of freedom and degeneracy from a landscape model of motor learning. *Cognitive Processing*, 6:37–47, 03 2005. doi: 10.1007/s10339-004-0047-6.
- K.M. Newell. *Constraints on the Development of Coordination*. The Netherlands: Martinus Nijhoff, Dordrecht, Dordrecht, 1986.
- K.M. Newell. *Change in Movement and Skill: Learning, Retention, and Transfer*. Psychology Press, Taylor and Francis Group, New York London, 1996.

- K.M. Newell, Y.-T. Liu, and G. Mayer-Kress. Time scales in motor learning and development. *Psychological review*, 108(1):57–82, 2001.
- Q. Ning, H. He, C. Fan, and D. Roth. Partial or complete, that's the question. In *Proceedings of NAACL conference*, pages 2190–2200, 01 2019. doi: 10.18653/v1/N19-1227.
- J. Omura. On the Viterbi decoding algorithm. *IEEE Transactions on Information Theory*, 15(1): 177–179, 1969. ISSN 0018-9448.
- L. Oppici and D. Panchuk. Specific and general transfer of perceptual-motor skills and learning between sports: A systematic review. *Psychology of Sport and Exercise*, 59:102118, 2022. ISSN 1469-0292. doi: <https://doi.org/10.1016/j.psychsport.2021.102118>. URL <https://www.sciencedirect.com/science/article/pii/S1469029221002363>.
- D. Orth, K. Davids, and L. Seifert. Coordination in climbing: Effect of skill, practice and constraints manipulation. *Sports Medicine*, 46(2):255–268, February 2016. ISSN 0112-1642. doi: 10.1007/s40279-015-0417-5.
- D. Orth, G. Kerr, K. Davids, and L. Seifert. Analysis of relations between spatiotemporal movement regulation and performance of discrete actions reveals functionality in skilled climbing. *Frontiers in Psychology*, 8:1744, 2017. ISSN 1664-1078. doi: 10.3389/fpsyg.2017.01744. URL <https://www.frontiersin.org/article/10.3389/fpsyg.2017.01744>.
- D. Orth, K. Davids, J.-Y. Chow, E. Brymer, and L. Seifert. Behavioral repertoire influences the rate and nature of learning in climbing: Implications for individualized learning design in preparation for extreme sports participation. *Frontiers in Psychology*, 9:949, 2018.
- M.M. Pacheco and K.M. Newell. Transfer of a learned coordination function: Specific, individual and generalizable. *Human Movement Science*, 59:66–80, 2018a. ISSN 0167-9457. doi: <https://doi.org/10.1016/j.humov.2018.03.019>. URL <https://www.sciencedirect.com/science/article/pii/S016794571730951X>.
- M.M. Pacheco and K.M. Newell. Learning a specific, individual and generalizable coordination function: evaluating the variability of practice hypothesis in motor learning. *Experimental Brain Research*, 236(12):3307–3318, 2018b. doi: 10.1007/s00221-018-5383-3.
- M.M. Pacheco, C.W. Lafe, and K.M. Newell. Search strategies in the perceptual-motor workspace and the acquisition of coordination, control, and skill. *Frontiers in Psychology*, 10:1874, 2019. ISSN 1664-1078. doi: 10.3389/fpsyg.2019.01874. URL <https://www.frontiersin.org/article/10.3389/fpsyg.2019.01874>.
- A. Pajot, E. de Bézenac, and P. Gallinari. Unsupervised adversarial image reconstruction. *Proceedings of ICLR 2019*, pages 1–21, 2019.

- V. Pratap, A.Y. Hannun, G. Synnaeve, and R. Collobert. Star temporal classification: Sequence classification with partially labeled data. *CoRR*, abs/2201.12208, 2022. URL <https://arxiv.org/abs/2201.12208>.
- V. Punyakanok and D. Roth. The use of classifiers in sequential inference. In *Advances in Neural Information Processing Systems 13 - Proceedings of the 2000 Conference, NIPS 2000*, Advances in Neural Information Processing Systems. Neural information processing systems foundation, 2001. ISBN 0262122413. 14th Annual Neural Information Processing Systems Conference, NIPS 2000 ; Conference date: 27-11-2000 Through 02-12-2000.
- R.L. Rabiner. A tutorial on hidden Markov models and selected applications on speech recognition. *Proceedings of the IEEE*, 77(2):257–286, 1989.
- R. Ranganathan and K.M. Newell. Changing up the routine: Intervention-induced variability in motor learning. *Exercise and Sport Sciences Reviews*, 41(1):64–70, 2013. doi: 10.1097/JES.0b013e318259beb5.
- R. Ranganathan, J. Wieser, K.M. Mosier, F.A. Mussa-Ivaldi, and R.A. Scheidt. Learning redundant motor tasks with and without overlapping dimensions: Facilitation and interference effects. *Journal of Neuroscience*, 34(24):8289–8299, 2014. ISSN 0270-6474. doi: 10.1523/JNEUROSCI.4455-13.2014. URL <https://www.jneurosci.org/content/34/24/8289>.
- E. Rietveld and J. Kiverstein. A rich landscape of affordances. *Ecological Psychology*, 26(4):325–352, 2014. doi: 10.1080/10407413.2014.958035. URL <https://doi.org/10.1080/10407413.2014.958035>.
- N. Rochat, G. Hacques, C. Ganière, L. Seifert, D. Hauw, P. Iodice, and D. Adé. Dynamics of experience in a learning protocol: A case study in climbing. *Frontiers in Psychology*, 11:249, 2020. ISSN 1664-1078. doi: 10.3389/fpsyg.2020.00249. URL <https://www.frontiersin.org/article/10.3389/fpsyg.2020.00249>.
- F. Rosenblatt. The perceptron: a probabilistic model for information storage and organization in the brain. 65(6):386–408, 1957. doi: 10.1037/h0042519.
- P.J. Rousseeuw. Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics*, 20:53–65, 11 1987. doi: 10.1016/0377-0427(87)90125-7.
- D.B. Rubin. Inference and missing data. *Biometrika*, 63(3):581–592, 12 1976. ISSN 0006-3444. doi: 10.1093/biomet/63.3.581. URL <https://doi.org/10.1093/biomet/63.3.581>.
- D.E. Rumelhart, G.E. Hinton, and R.J. Williams. Learning representations by back-propagating errors. 323(6088):533–536, 1986. doi: 10.1038/323533a0.

- G. Schwarz. Estimating the Dimension of a Model. *The Annals of Statistics*, 6(2):461 – 464, 1978. doi: 10.1214/aos/1176344136. URL <https://doi.org/10.1214/aos/1176344136>.
- L. Seifert, H. Leblanc, R. Héroult, J. Komar, Ch. Button, and D. Chollet. Inter-individual variability in the upper-lower limb breaststroke coordination. *Human Movement Science*, 30(3):550–565, 2011. doi: 10.1016/j.humov.2010.12.003. URL <http://www.sciencedirect.com/science/article/pii/S016794571000182X>.
- L. Seifert, D. Orth, J. Boulanger, V. Dovgalecs, R. Héroult, and K. Davids. Climbing skill and complexity of climbing wall design: Assessment of jerk as a novel indicator of performance fluency. *Journal of Applied Biomechanics*, 50(5):619–625, 2014.
- L. Seifert, J. Boulanger, D. Orth, and K. Davids. Environmental design shapes perceptual-motor exploration, learning, and transfer in climbing. *Frontiers in Psychology*, 6, 2015. ISSN 1664-1078. doi: 10.3389/fpsyg.2015.01819. URL <https://www.frontiersin.org/article/10.3389/fpsyg.2015.01819>.
- L. Seifert, J. Komar, D. Araujo, and K. Davids. Neurobiological degeneracy: A key property for functional adaptations of perception and action to constraints. *Neuroscience & Biobehavioral Reviews*, 69, 08 2016. doi: 10.1016/j.neubiorev.2016.08.006.
- L. Seifert, D. Araujo, J. Komar, and K. Davids. Understanding constraints on sport performance from the complexity sciences paradigm: An ecological dynamics framework. *Human Movement Science*, 05 2017. doi: 10.1016/j.humov.2017.05.001.
- L. Seifert, D. Orth, B. Mantel, J. Boulanger, R. Héroult, and M. Dicks. Affordance realization in climbing: Learning and transfer. *Frontiers in Psychology*, 9, 2018. ISSN 1664-1078. doi: 10.3389/fpsyg.2018.00820. URL <https://www.frontiersin.org/article/10.3389/fpsyg.2018.00820>.
- L. Seifert, V. Papet, B.W. Strafford, E.K. Coughlan, and K. Davids. Skill transfer, expertise and talent development: An ecological dynamics perspective. *Movement and Sport Sciences*, pages 1–12, 2019.
- N.J. Smeeton, R. Huys, and D.M. Jacobs. When less is more: Reduced usefulness training for the learning of anticipation skill in tennis. *Plos ONE*, 8(11):1–11, 2013.
- G.S. Snoddy. Learning and stability. *Journal of Applied Psychology*, 10:40–51, 1926.
- I. Sutskever, O. Vinyals, and Q.V. Le. Sequence to sequence learning with neural networks. *CoRR*, abs/1409.3215, 2014. URL <http://arxiv.org/abs/1409.3215>.
- B. Taskar, C. Guestrin, and D. Koller. Max-margin Markov networks. *Advances in Neural Information Processing Systems 16: Proceedings of the 2003 Conference*, 16, 03 2004.
- R. Tibshirani. Regression shrinkage and selection via the Lasso. *Journal of The Royal Statistical Society. Series B (Methodological)*, 58(1):267–288, 1996.

- A.N. Tikhonov and V.Y. Arsenin. Solutions of ill-posed problems. 1977.
- I. Tsochantaridis, T. Joachims, T. Hofmann, and Y. Altun. Large margin methods for structured and interdependent output variables. *Journal of Machine Learning Research*, 6:1453–1484, 09 2005.
- L.J.P. van der Maaten and G.E. Hinton. Visualizing high-dimensional data using t-SNE. 2008.
- R.E.A. van Emmerik and E. van Wegen. On variability and stability in human movement. *Journal of Applied Biomechanics*, 16(4):394–406, 2000.
- W. Veeramachaneni and V. Liao. A simple semi-supervised algorithm for named entity recognition. *Workshop on Semi-supervised Learning for Natural Language Processing*, pages 58–65, 2009.
- A. Viterbi. Error bounds for convolutional codes and an asymptotically optimum decoding algorithm. *IEEE Transactions on Information Theory*, 13(2):260–269, 1967. ISSN 0018-9448. doi: 10.1109/TIT.1967.1054010.
- P. Werbos. *Beyond Regression: New Tools for Prediction and Analysis in the Behavioral Sciences*. PhD thesis, Harvard University, 1974.
- G. Wulf and R. Lewthwaite. Optimizing performance through intrinsic motivation and attention for learning: The optimal theory of motor learning. *Psychonomic bulletin & review*, 23(5):1382–1414, 2016.
- G. Wulf and C.H. Shea. Principles derived from the study of simple skills do not generalize to complex skill learning. *Psychonomic Bulletin & Review*, 9(2):185–211, 2002.
- P.G. Zanone and J.A. Kelso. Evolution of behavioral attractors with learning: nonequilibrium phase transitions. *Journal of Experimental Psychology: Human Perception and Performance*, 18(2):403–21, 05 1992. doi: 10.1037//0096-1523.18.2.403.
- S. Zhi, L. Liu, Y. Zhang, S. Wang, Q. Li, Ch. Zhang, and J. Han. Partially-typed NER datasets integration: Connecting practice to theory. *In press*, pages 1–13, May 2020.