

Modelling Syntactic Gradience with Loose Constraint-based Parsing



*Modélisation de la gradience syntaxique
par analyse relâchée à base de contraintes*

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Motivation

Graded Grammaticality

- Je soutiens ma thèse de doctorat
- *Je soutiens mon thèse de le doctorat
- *Moi thèse soutenir de le doctorat mon

- *I am the chair of my department*
- **Me are the chair of my department*
- **Me are chair the me's department of*

(Pullum and Scholz, 2001)

Motivation

An adequate linguistic theory will have to recognize degrees of grammaticalness

(Chomsky, 1975)

Anyone who knows a natural language knows that some utterances are not completely well formed. (...) experienced users of a language are also aware that some ungrammatical utterances are much closer to being grammatical than others.

(Pullum and Scholz, 2001)

Motivation

- How to represent and analyse graded syntactic phenomena?

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- How to represent and analyse graded syntactic phenomena?
- How to automate the computation of the degree of acceptability of an utterance?

Outline

- 1 Background
 - Gradience
 - Modelling Gradience
 - Classification
- 2 Intersective Gradience and Optimality
 - Knowledge Representation
 - Loose Satisfaction Chart Parsing
 - Evaluation
- 3 Subjective Gradience and Acceptability
 - Predicting Acceptability
 - Empirical Investigation
 - Interpretation
- 4 Conclusion

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Gradience

- Graded phenomena,

Gradience

- Graded phenomena,
- in classification problems

Example

- Is a three-legged horse a horse?
- Is a *penguin* less of a bird than a *robin*?

Modelling Gradiance

Bas Aarts, 2007

- Intersective Gradiance (IG)

- Subsective Gradiance (SG)

Modelling Gradiance

Bas Aarts, 2007

- Intersective Gradiance (IG)

Example

- Is a *tomato* a *fruit* or a *vegetable*?
- Is a *van* a *car* or a *truck*?
- Subjective Gradiance (SG)

Modelling Gradience

Bas Aarts, 2007

- Intersective Gradience (IG)

Example

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- Is a *van* a *car* or a *truck*?

- Subjective Gradience (SG)

Example

- Is a *penguin* less of a *bird* than a *robin*?
- Is a three-legged horse a horse?

Intersective Gradiance

Optimality

*Marie a emprunté un très long chemin pour

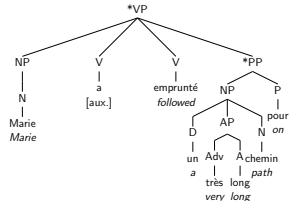
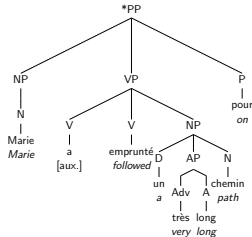
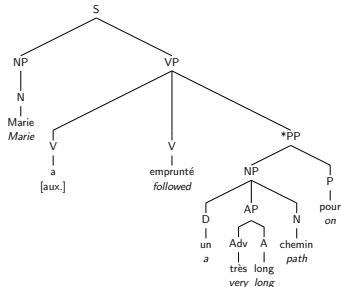
**Marie [aux.] took a very long path on*

Intersective Gradience

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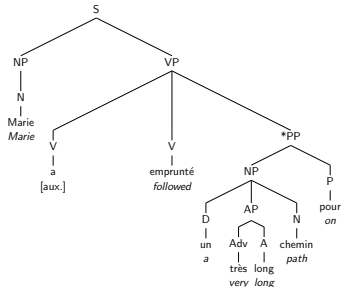


Intersective Gradience

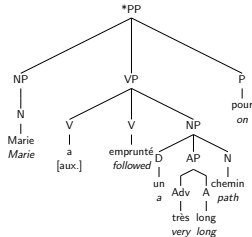
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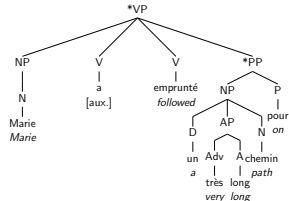
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merit



merit



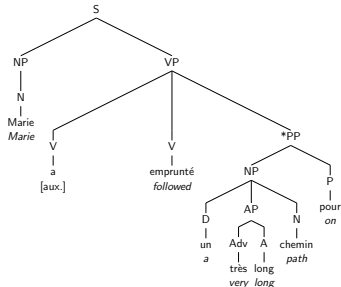
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merit

Linear Optimality Theory

Keller, 2000

- Based on Optimality Theory (Prince and Smolenski, 1993)

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- Based on Optimality Theory (Prince and Smolenski, 1993)
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- Optimality-Theoretic Grammaticality
 - Grammatical structure = optimal structure
 - Grammaticality vs. ungrammaticality?

Subjective Gradience

Rating

Marie a emprunté un très long chemin pour le retour	4
<i>'Marie took a very long path on the way back'</i>	
*Marie a emprunté emprunté un très long chemin pour le retour	3.9
<i>*'Marie took took a very long path on the way back'</i>	
*Marie a emprunté un très long chemin pour	2.7
<i>*'Marie took a very long path on'</i>	
*Marie un très long chemin pour le retour	1.3
<i>*'Marie a very long path on the way back'</i>	

Classes: Construction

- English Caused-Motion Construction

Chloe sneezed the tissue off the table

'Chloé a éternué le mouchoir hors de la table'

- Phrases: NP, VP, D, A

'le juge', 'a octroyé', 'un', 'bref'

- Lexical Constructions: words

Construction Specification

Property Grammars (Blache, 2001)

S (Utterance)	
Feat.	Prop. Type : Properties
[AVM]	<i>obligation</i> : Δ VP (P1)
	<i>uniqueness</i> : NP! (P2)
	<i>linearity</i> : NP \prec VP (P3)
	<i>dependency</i> : NP \rightsquigarrow VP (P4)

NP (Noun Phrase)	
Feat.	Prop. Type : Properties
[GEND] [NUM]	<i>obligation</i> : Obl(N \vee PRO) (P5)
	<i>uniqueness</i> : D! (P6)
	<i>linearity</i> : D \prec N (P7)
	<i>requirement</i> : N \Rightarrow D (P8)
	<i>exclusion</i> : N \nleftrightarrow PRO (P9)
	<i>dependency</i> : N $\begin{matrix} \text{[GEND 1]} \\ \text{[NUM 2]} \end{matrix} \rightsquigarrow$ D $\begin{matrix} \text{[GEND 1]} \\ \text{[NUM 2]} \end{matrix}$ (P10)

Modelling Syntactic Gradience

Proposed Solution

- Characterise a well formed or ill formed sentence

Modelling Syntactic Gradiance

Proposed Solution

- Characterise a well formed or ill formed sentence
- Generate an optimal full parse

Modelling Syntactic Gradience

Proposed Solution

- Characterise a well formed or ill formed sentence
- Generate an optimal full parse
- Rate the syntactic acceptability of the utterance

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Model

Intuitively, a constituent is a model of an utterance, which satisfies the grammar

Model-Theoretic Syntax (MTS)

- Domain: constituents
- Grammar: set of pairs
 - Constraint: a well-formed formula ϕ in FOL

Example

obligation : ΔVP
linearity : $NP \prec VP$

- Projection Rule:

$$r.CAT = C \rightarrow \phi$$

Example

$$r.CAT = NP \rightarrow \text{obl}(r) \wedge \text{lin}(r)$$

Constraint Satisfaction

Definition (Strict Satisfaction)

$$\mathcal{M} \models \bigwedge_{i \in \{1, \dots, n\}} \phi_i$$

Constraint Satisfaction

Definition (Strict Satisfaction)

$$\mathcal{M} \models \bigwedge_{i \in \{1, \dots, n\}} \phi_i$$

Definition (Loose Satisfaction)

$$\mathcal{M} \models \bigwedge_{i \in \{1, \dots, n\}} \phi_i$$

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Definition (Strict Satisfaction)

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Definition (Loose Satisfaction)

$$\mathcal{M} \models \bigwedge_{i \in \{1, \dots, n\}} \phi_i$$

$$\mathcal{M} \models \bigwedge_{i \in \{1, \dots, n\} \setminus I_k} \phi_i \wedge \bigwedge_{j \in I_k} \neg \psi_j$$

Parsing

Characterisation and Optimality

- Loose Constraint Satisfaction
- Dynamic Programming (CKY skeleton)
 - Chart (Dynamic Programming Table)
 - Memoization

Loose Satisfaction Chart Parsing (LSCP)

Algorithm

```
for (span=1 to num_words)
  for (offset=1 to num_words-span+1)
    for (every assignment A in [offset..end])
      X ← characterisation(A)
      C ← projection(X)
      for (every x in C)
        if (merit(x) >= pi[offset, span, C]) then
          pi[offset, span, C] ← {x,merit(x)}
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Example

*Le juge octroie bref entretien à ce plaignant

**The judge grants brief interview to this plaintiff*

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LSCP

Walkthrough

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LSCP

Walkthrough

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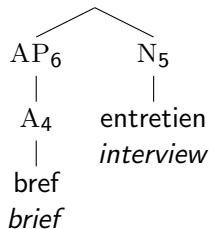
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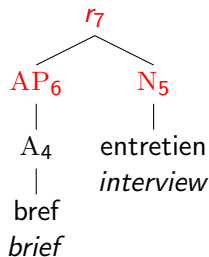


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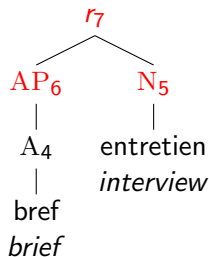


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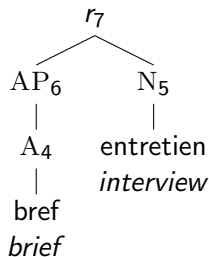
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$$\mathcal{A} = \langle \parallel r_7 \parallel = R_7, AP_6, N_5 \rangle$$

Grammar Lookup

NP (Noun Phrase)	
Feat.	Prop. Type: Properties
[AVM]	<i>obligation</i> : Obl(N ∨ PRO) (P11)
	<i>uniqueness</i> : D! (P12)
	: N! (P13)
	: PP! (P14)
	: PRO! (P15)
	<i>linearity</i> : D < N (P16)
	: D < PRO (P17)
	: D < AP (P18)
	: N < PP (P19)
	<i>requirement</i> : N ⇒ D (P20)
	: AP ⇒ N (P21)
	<i>exclusion</i> : N ⇏ PRO (P22)
	<i>dependency</i> : N $\begin{matrix} \text{GEND [1]} \\ \text{NUM [2]} \end{matrix}$ ∼ D $\begin{matrix} \text{GEND [1]} \\ \text{NUM [2]} \end{matrix}$ (P23)

VP (Verb Phrase)	
Feat.	Prop. Type: Properties
[AVM]	<i>obl.</i> : ΔV (P24)
	<i>uniq.</i> : V _[main part.] ! (P25)
	: NP! (P26)
	: PP! (P27)
	<i>lin.</i> : V < NP (P28)
	: V < Adv (P29)
	: V < PP (P30)
	<i>req.</i> : V _[part.] ⇒ V _[aux.] (P31)
	<i>excl.</i> : PRO _[acc.] ⇏ NP (P32)
	: PRO _[dat.] ⇏ PRO _[acc.] (P33)
<i>dep.</i> : V $\begin{matrix} \text{TYPE: pers} \\ \text{PERS [0]} \\ \text{NUM [0]} \end{matrix}$ ∼ PRO $\begin{matrix} \text{CASE: nom} \\ \text{PERS [0]} \\ \text{NUM [0]} \end{matrix}$ (P34)	

S (Utterance)	
Feat.	Prop. Type: Properties
[AVM]	<i>obl.</i> : ΔVP (P35)
	<i>uniq.</i> : NP! (P36)
	: VP! (P37)
	<i>lin.</i> : NP < VP (P38)
	<i>dep.</i> : NP ∼ VP (P39)

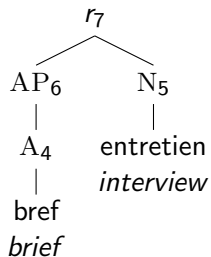
AP (Adjective Phrase)	
Feat.	Prop. Type: Properties
[AVM]	<i>obl.</i> : Obl(A ∨ V _[part.]) (P40)
	<i>uniq.</i> : A! (P41)
	: V _[part.] ! (P42)
	: Adv! (P43)
	<i>lin.</i> : A < PP (P44)
	: Adv < A (P45)
	<i>excl.</i> : A ⇏ V _[part.] (P46)

PP (Prepositional Phrase)	
Feat.	Prop. Type: Properties
[AVM]	<i>obl.</i> : ΔP (P47)
	<i>uniq.</i> : P! (P48)
	: NP! (P49)
	<i>lin.</i> : P < NP (P50)
	: P < VP (P51)
	<i>req.</i> : P ⇒ NP (P52)
<i>dep.</i> : P ∼ NP (P53)	

LSCP Walkthrough

Characterisation

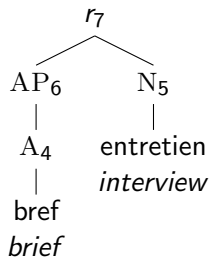
$$\mathcal{A} = \langle \|\| r_7 \| = R_7, AP_6, N_5 \rangle$$



LSCP Walkthrough

Characterisation

$$\mathcal{A} = \langle \|r_7\| = R_7, AP_6, N_5 \rangle$$



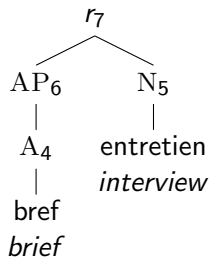
$$\mathcal{A} \models (P11) \wedge (P21) \wedge (P22) \quad (1)$$
$$:= \chi_{\mathcal{A}}^+$$

$$(2)$$

LSCP Walkthrough

Characterisation

$$\mathcal{A} = \langle \|r_7\| = R_7, AP_6, N_5 \rangle$$



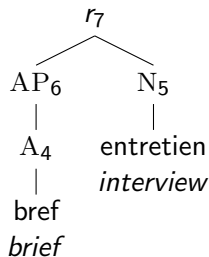
$$\mathcal{A} \models (P11) \wedge (P21) \wedge (P22) \quad (1)$$
$$:= \chi_{\mathcal{A}}^+$$

$$\mathcal{A} \not\models (P20) \quad (2)$$
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LSCP Walkthrough

Projection

Algorithm

```
for (span=1 to num_words)
  for (offset=1 to num_words-span+1)
    for (every assignment A in [offset..end])
      X ← characterisation(A)
      C ← projection(X)
      for (every x in C)
        if (merit(x) >= pi[offset, span, C]) then
          pi[offset, span, C] ← {x,merit(x)}
```

$$\mathcal{A} \models \text{NP}_7.\text{CAT} = \mathbf{NP} \rightarrow \chi_{\mathcal{A}}^+ \wedge \chi_{\mathcal{A}}^-$$

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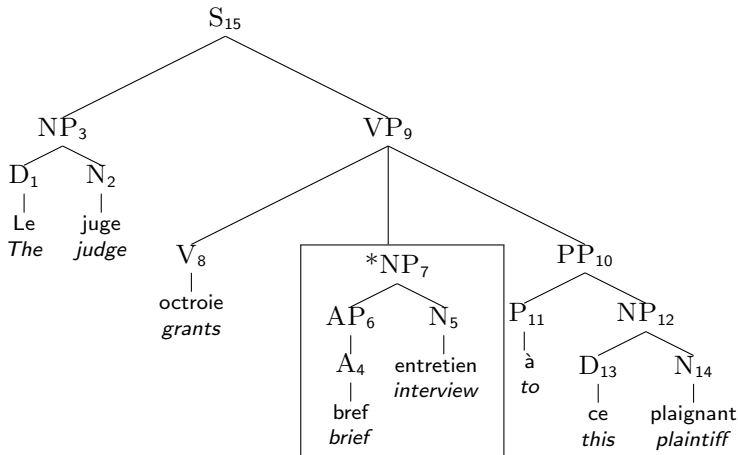
LSCP Walkthrough

Memoization

...								
2				$ \begin{array}{c} *NP_7 \\ \swarrow \quad \searrow \\ AP_6 \quad N_5 \\ \\ A_4 \end{array} $				
1				A_4, AP_6	N_5			
	Le <i>The</i>	jugé <i>judge</i>	octroie <i>grants</i>	brief <i>brief</i>	entretien <i>interview</i>	à <i>to</i>	ce <i>this</i>	plaignant <i>plaintiff</i>

LSCP

Solution Parse



Evaluation of *Numbat*

EASY

	Precision	Recall	F_1
<i>Numbat</i>	78.4%	70.6%	74.2%

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	Precision	Recall	F_1
<i>Numbat</i>	78.4%	70.6%	74.2%
LPL Shallow parser	78.5%	83.8%	81 %
LPL stochastic parser	90.1 %	89.8%	89.9%

Evaluation of *Numbat*

EASY

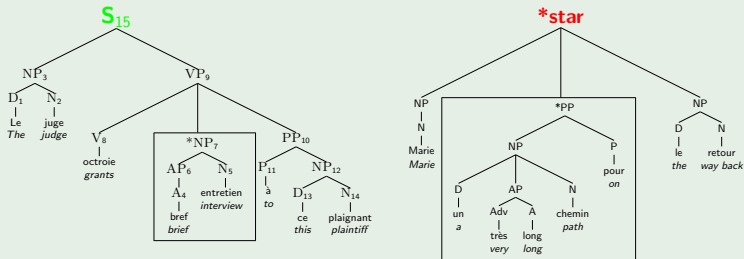
Example

j'entendais	encore,	au fond	du pavillon,	monsieur	qui	essayait	d'ébranler	la porte.
NV	GR	GP	GP	GN	GN	NV	PV	GN
VP	AdvP	PP	PP	NP	NP	VP	Prep. VP	NP

'I was still hearing, at the back of the house, Sir, who was trying to shake the door.'

Evaluation of *Numbat*

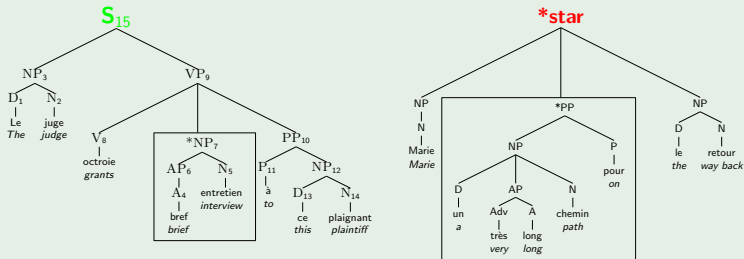
Quasi-expressions



Evaluation of *Numbat*

Quasi-expressions

	Precision $\frac{\text{correct}}{\text{complete}}$	Recall $\frac{\text{correct}}{\text{total}}$	F_1
<i>Numbat</i>	74%	68%	71%



Summary

- Automated syntactic parsing (LSCP)
- Well formed or ill formed utterance
- Intersective Gradience:
 - Optimal parse (constituent structure)
 - Characterisation of maximum merit for a given grammar

Outline

- 1 Background
 - Gradience
 - Modelling Gradience
 - Classification
- 2 Intersective Gradience and Optimality
 - Knowledge Representation
 - Loose Satisfaction Chart Parsing
 - Evaluation
- 3 Subjective Gradience and Acceptability
 - Predicting Acceptability
 - Empirical Investigation
 - Interpretation
- 4 Conclusion

Problem

Subjective Gradience

Can we predict how grammatically acceptable an utterance is?

Central Claim

The degree of acceptability of an utterance can be predicted by factors derivable from the outcome of LSCP

Predicting Acceptability

Postulates

- 1 Failure Cumulativity
 - Violated constraints
 - N_c^-

Predicting Acceptability

Postulates

- 1 Failure Cumulativity
 - Violated constraints
 - N_c^-
- 2 Success Cumulativity
 - Satisfied constraints
 - N_c^+

Postulates

3 Constraint Weighting

- $W_c^+ = \sum_c w^+$
- $W_c^- = \sum_c w^-$

Postulates

3 Constraint Weighting

- $W_c^+ = \sum_c w^+$
- $W_c^- = \sum_c w^-$

4 Constructional Complexity

- T_c : Total number of constraints **specifying** the construction \mathcal{C}
- E_c : Total number of constraints **evaluated** for the constituent c

Postulates

- Propagation
 - Acceptability of the whole depends on acceptability of the parts
 - $f(c) = k \cdot f(c_i)$

Predicting Acceptability

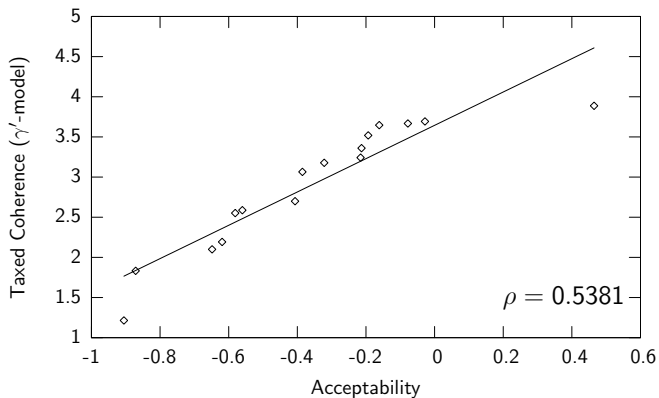
Numerical Models

- Cohesion (γ)
- Taxed Cohesion (γ')

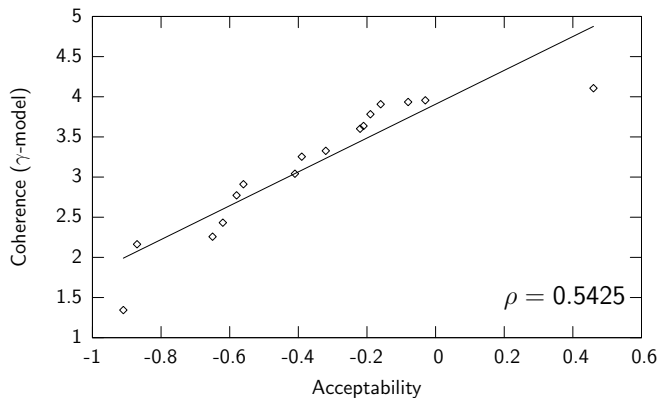
Human Judgements by Error Patterns

No violations		
1.1	Marie a emprunté un très long chemin pour le retour <i>Marie [aux.] followed a very long path on the way back</i>	0.465
NP-violations		
2.1	Marie a emprunté très long chemin un pour le retour <i>Marie [aux.] followed very long path a on the way back</i>	-0.643
...		
AP-violations		
3.2	Marie a emprunté un très long long chemin pour le retour <i>Marie [aux.] followed a very long long path on the way back</i>	-0.216
...		
PP-violations		
4.3	Marie a emprunté un très long chemin le retour <i>Marie [aux.] followed a very long path the way back</i>	-0.213
...		
VP-violations		
5.4	Marie emprunté un très long chemin pour le retour <i>followed a very long path on the way back</i>	-0.322
...		

Model Fit



Model Fit



Scale of γ -scores

Type	2.3	1.1	5.2	3.2	4.2	3.1	2.2	4.3
γ	4.11	3.96	3.93	3.91	3.78	3.64	3.60	3.33
Ref. Rank	15	1	5	7	3	10	4	6
Rank	1	2	3	4	5	6	7	8

Type	2.4	3.3	5.4	4.1	2.1	5.1	4.4	5.3
γ	3.25	3.042	2.91	2.77	2.43	2.26	2.16	1.34
Ref. Rank	2	13	8	12	14	11	9	16
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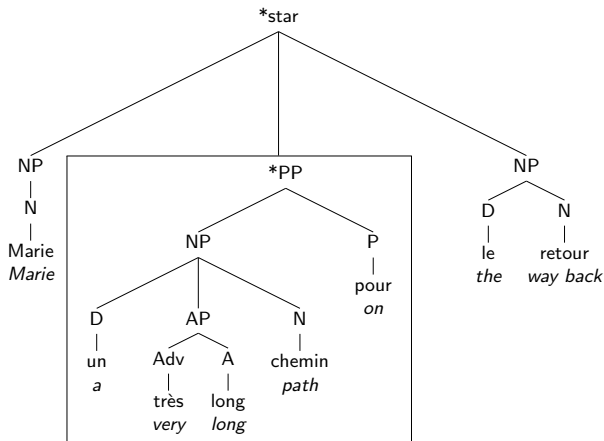
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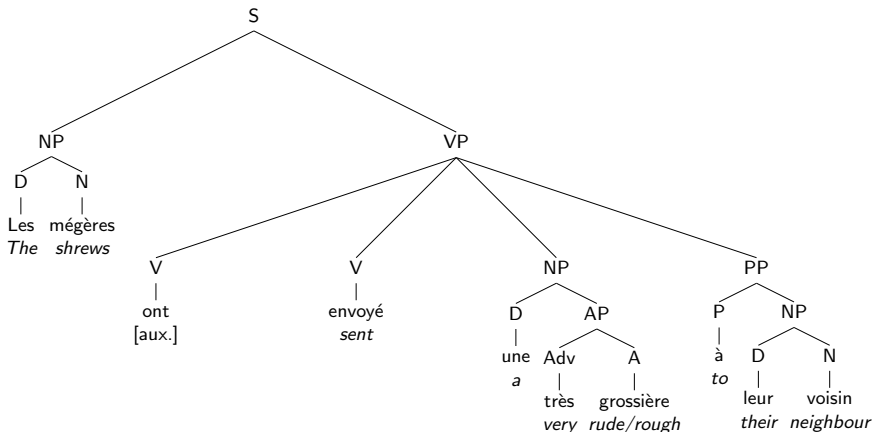
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Missing VP (5.3)



Missing NP (2.3)



Ranking

Rank diff.	Occurrences	% of total
≥ 6	3	18.75%
$= 4$	1	6.25%
≤ 3	12	75%

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Conclusion

- Model of syntactic gradience

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 - well formed and ill formed language
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Conclusion

- Model of syntactic gradience
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 - Intersective Gradience: Optimality

Conclusion

- Model of syntactic gradience
 - Extended IG/SG
 - well formed and ill formed language
 - at the constructional level
 - Intersective Gradience: Optimality
 - Subjective Gradience: Rating

Conclusion

- Automated solution

Conclusion

- Automated solution
 - Characterises a well formed or ill formed sentence

Conclusion

- Automated solution
 - Characterises a well formed or ill formed sentence
 - Generates an optimal full parse

Conclusion

- Automated solution
 - Characterises a well formed or ill formed sentence
 - Generates an optimal full parse
 - Predicts the utterance's syntactic acceptability by rating it

Conclusion

Contribution

- Specification of a basic Model-Theoretic framework for PG
- Implementation of LSCP
- Investigation of numeric models for predicting acceptability

Further Works

- Scaling up the model
 - To a large-coverage grammar
 - To non-artificial sentences
- Generalisation of constraint-based parsing to configuration

The End

Thank You

