Automatically Improved Category Labels for Syntax-Based Statistical Machine Translation

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Language Technologies Institute

Ph.D. Thesis Proposal
January 18, 2011

Thesis Committee
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Carnegie Mellon

Syntax-Based Statistical MT

- In this thesis, means MT systems that
  - Acquire syntax in a supervised manner from constituency parse trees
  - Model it with a synchronous context-free grammar (SCFG)

$$\text{NP} \rightarrow \text{DET}\ \ \text{N}\ \ \text{ADJ} \quad (\text{“la voiture bleue”})$$

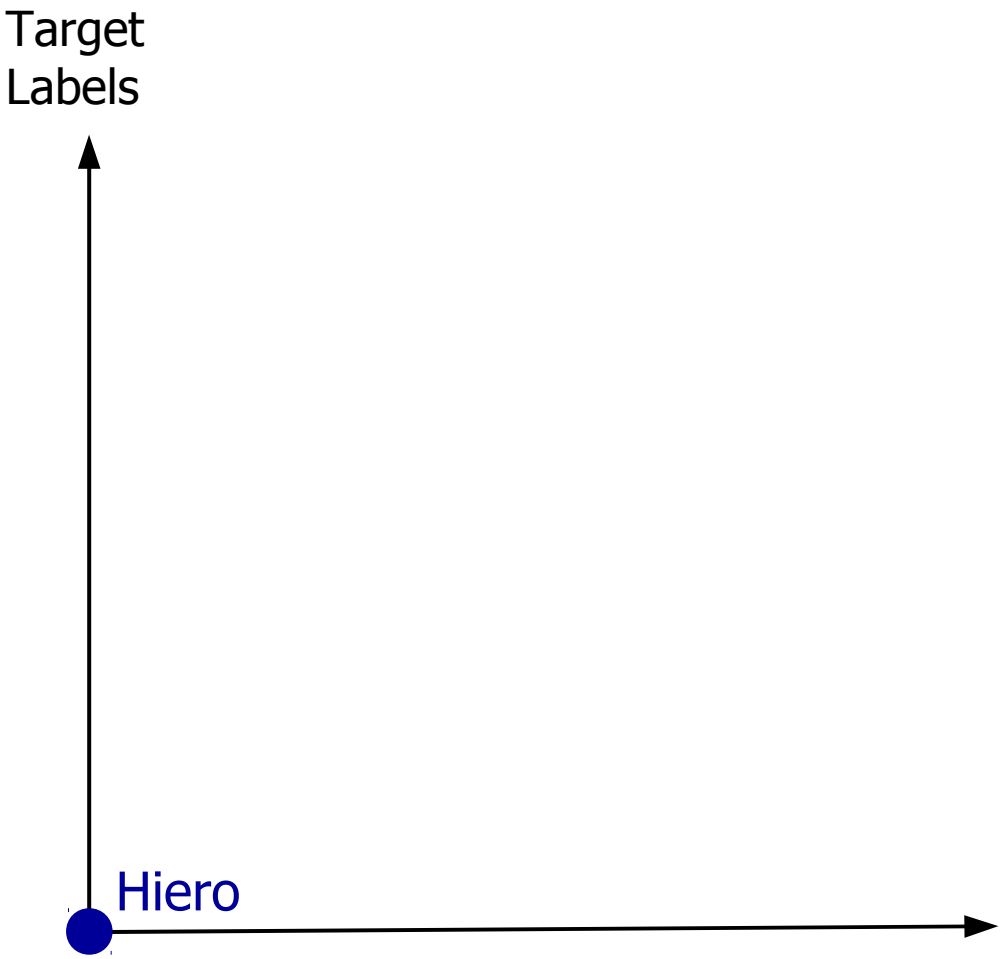
$$\text{NP} \rightarrow \text{DT}\ \ \text{JJ}\ \ \text{NN} \quad (\text{“the blue car”})$$

$$\text{NP::NP} \rightarrow [\text{DET}^1\ \text{N}^2\ \text{ADJ}^3]::[\text{DT}^1\ \text{JJ}^3\ \text{NN}^2]$$

SCFG Labeling Schemes

$$X::X \rightarrow [X^1 \text{ de } X^2]::[X^2\ X^1]$$

[Chiang 2005]



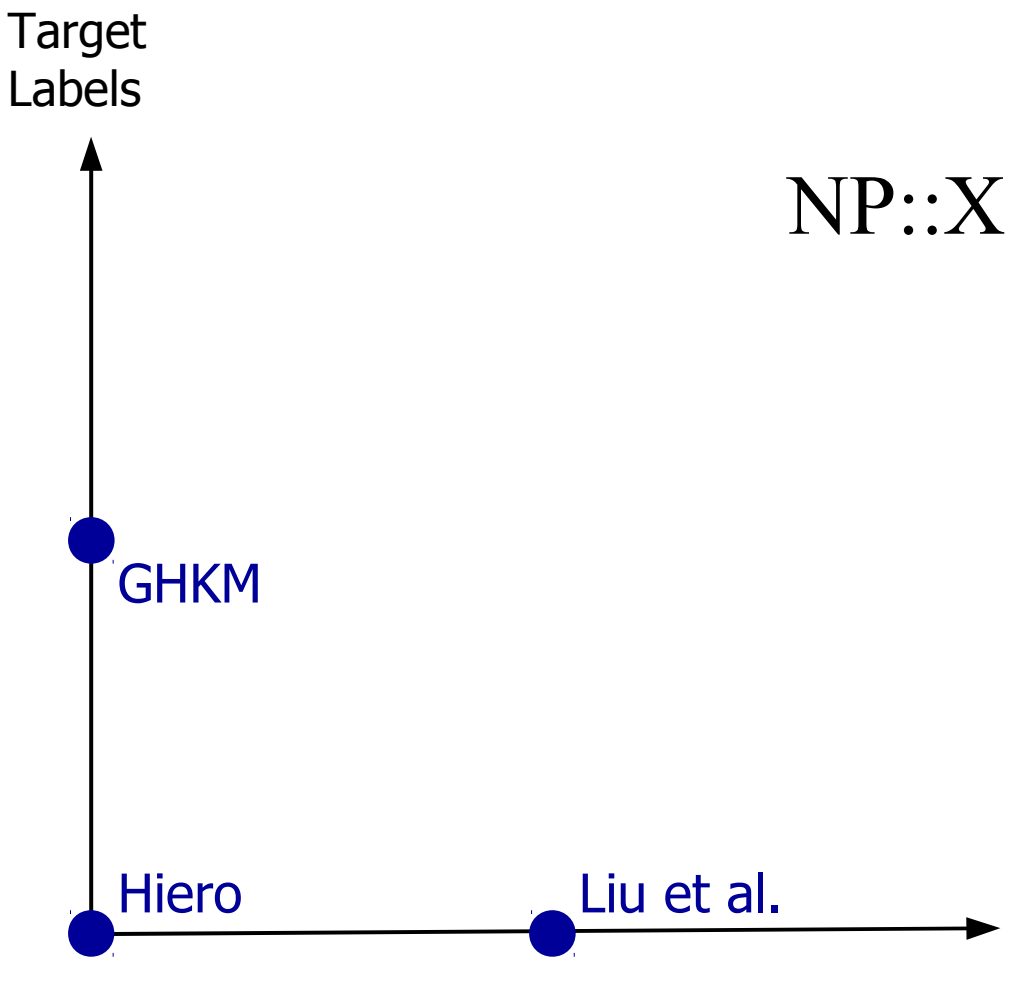
SCFG Labeling Schemes

$$\text{X::NP} \rightarrow [\text{X}^1 \text{ de } \text{X}^2]::[\text{N}^2 \text{ NP}^1]$$

[Galley et al. 2004]

$$\text{NP::X} \rightarrow [\text{NP}^1 \text{ de } \text{N}^2]::[\text{X}^2 \text{ X}^1]$$

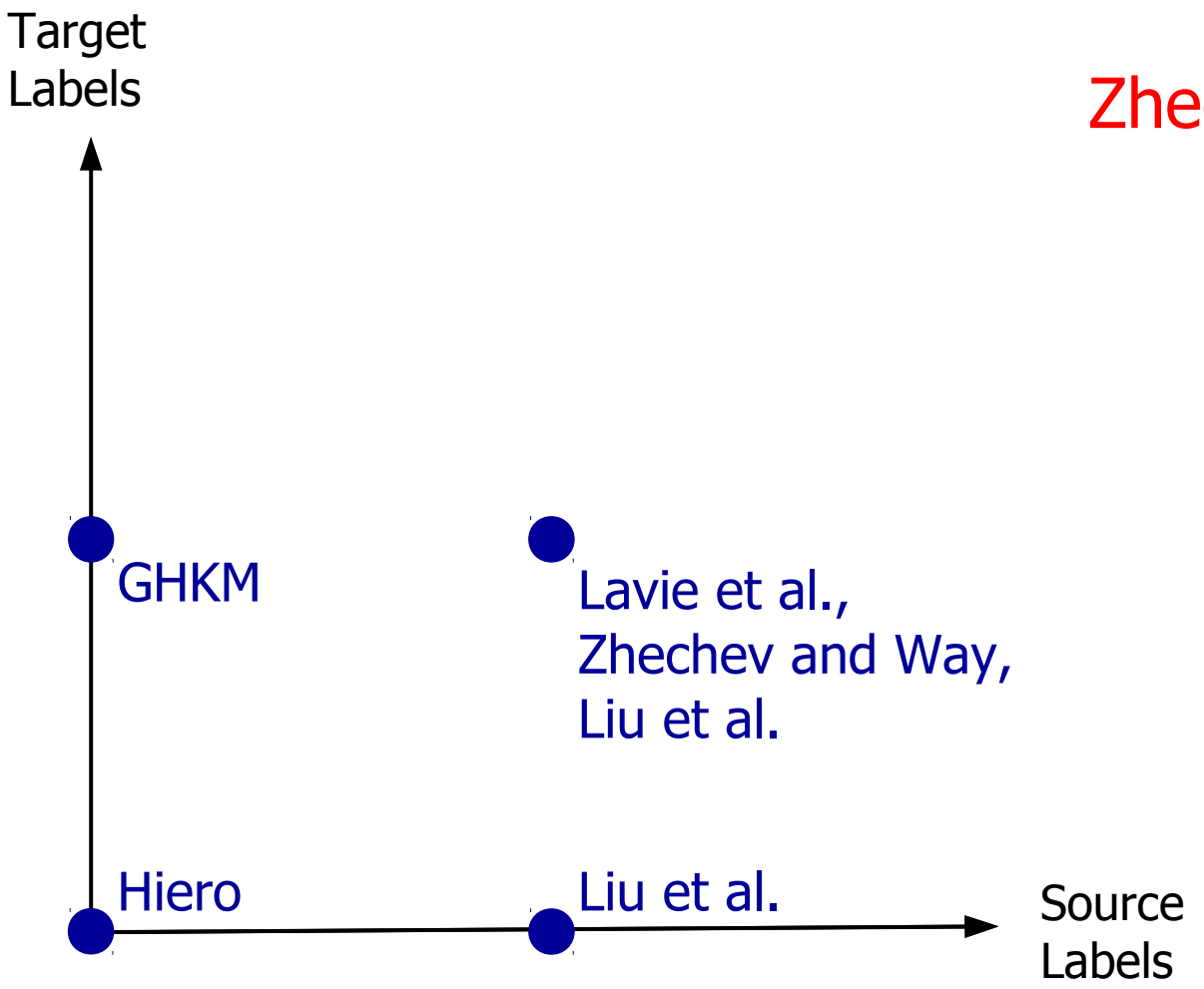
[Liu et al. 2006]



SCFG Labeling Schemes

$$\text{NP::NP} \rightarrow [\text{NP}^1 \text{ de } \text{N}^2]::[\text{N}^2 \text{ NP}^1]$$

[Lavie et al. 2008;
Zhechev and Way 2008;
Liu et al. 2009]

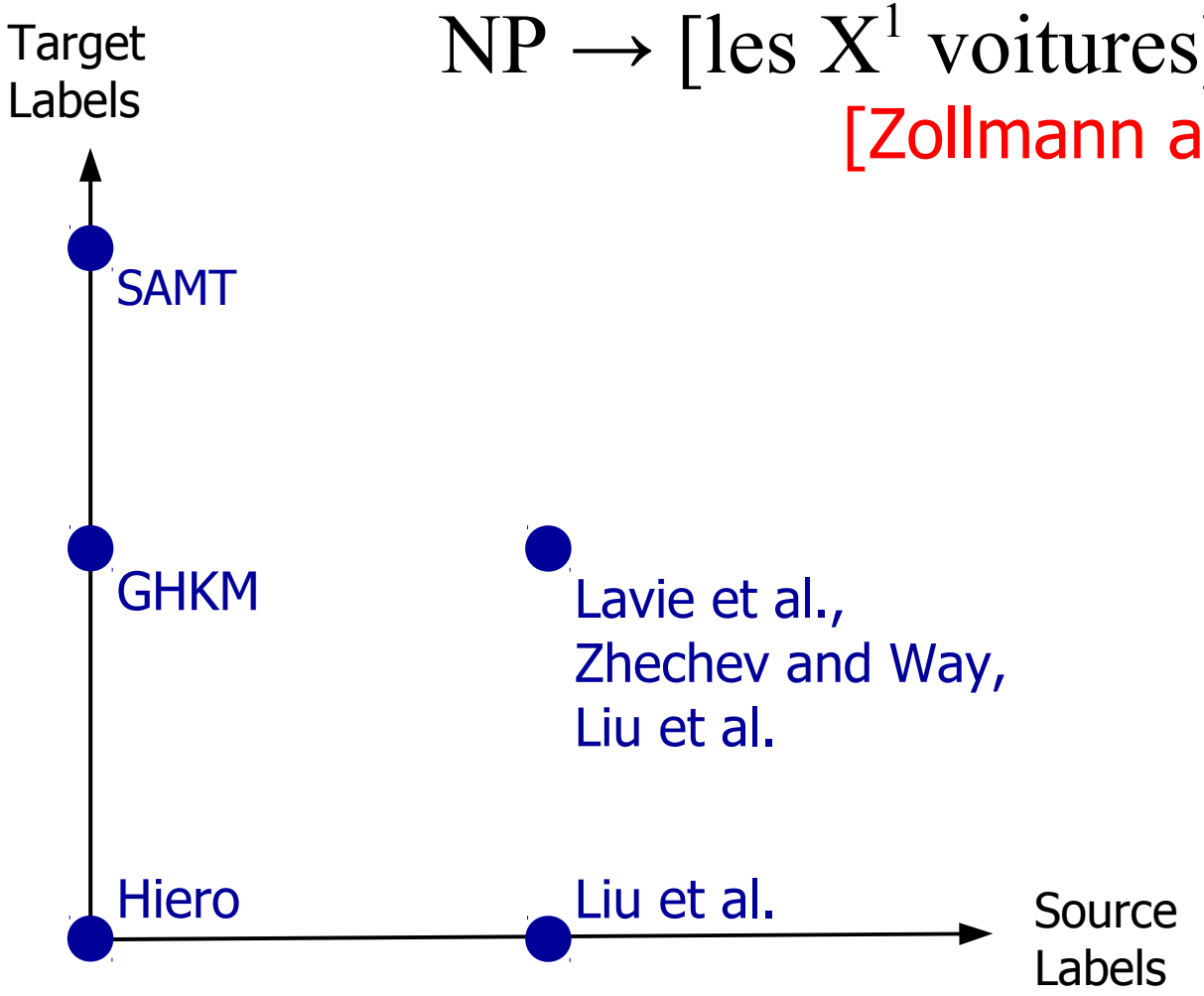


SCFG Labeling Schemes

$$S \rightarrow [\text{il y a } X^{1}]::[\text{there is } S/NP^{1}]$$

$$NP \rightarrow [\text{les } X^{1} \text{ voitures}]::[\text{the } JJ{+}JJ^{1} \text{ cars}]$$

[Zollmann and Venugopal 2006]

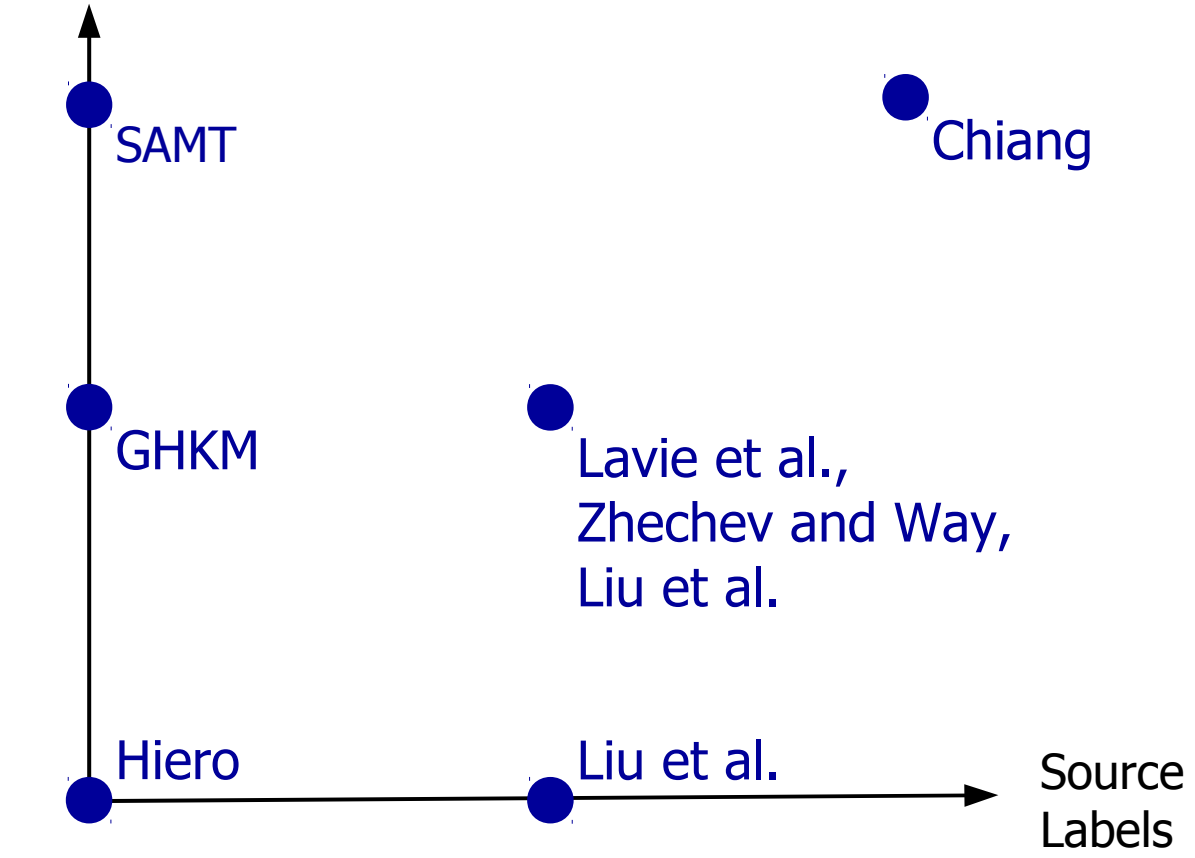


SCFG Labeling Schemes

$$\text{S::S} \rightarrow [\text{il y a S/NP}^1]::[\text{there is S/NP}^1]$$

$$\text{NP::NP} \rightarrow [\text{les D+A}^1 \text{ voitures}]::[\text{the JJ+JJ}^1 \text{ cars}]$$

[Chiang 2010]



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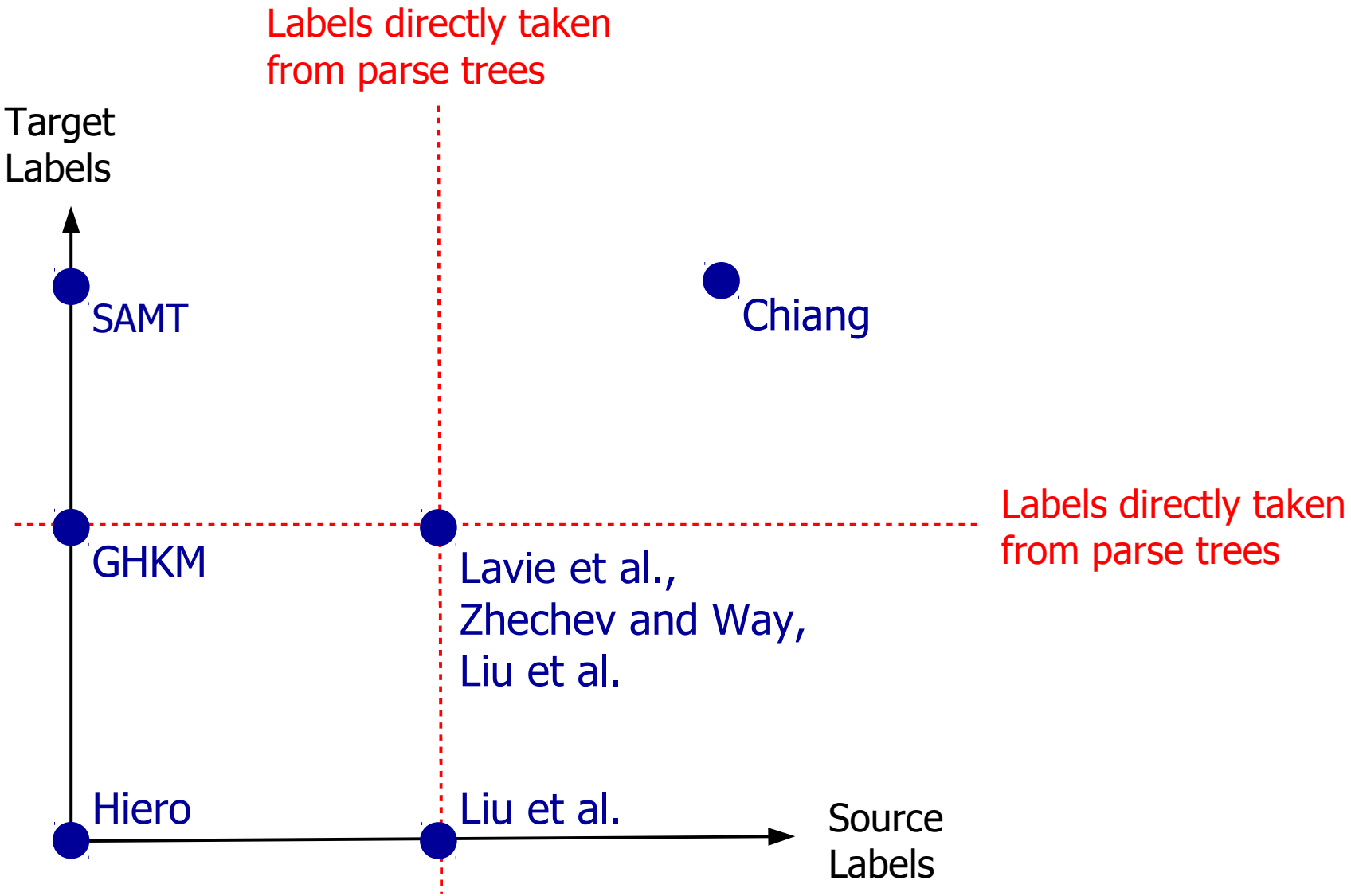
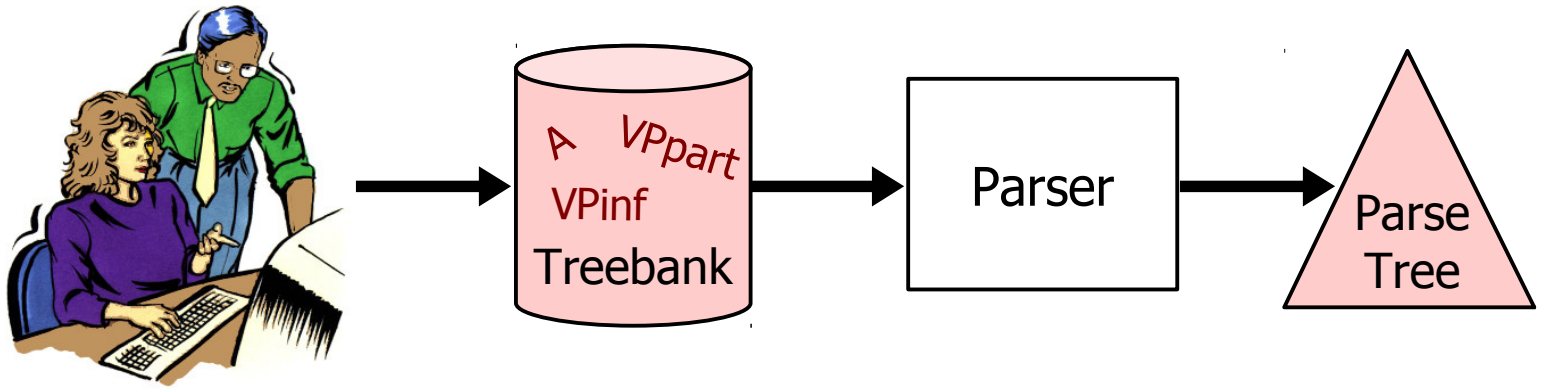


Parse Tree Labels Assume a Lot



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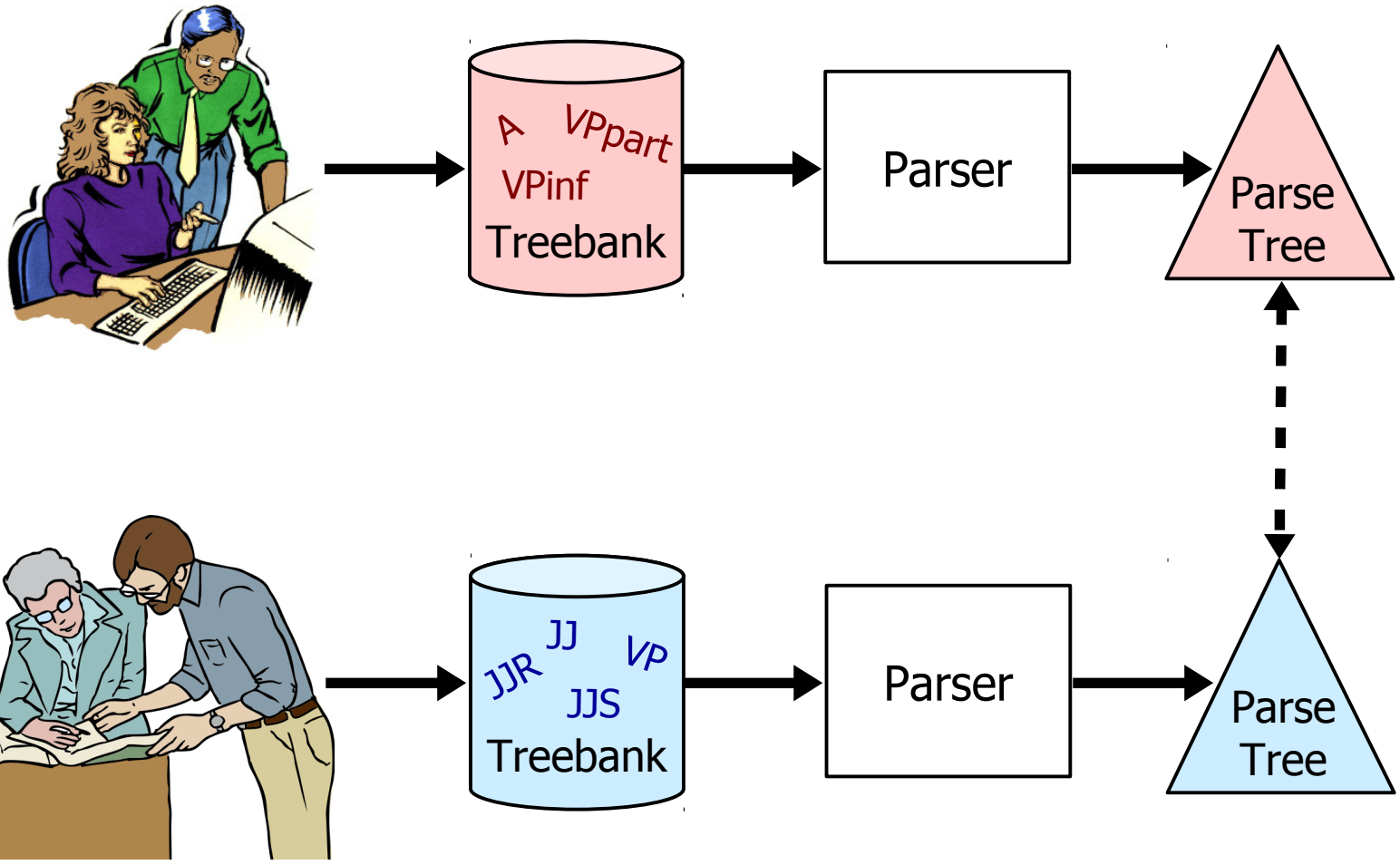
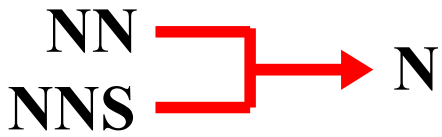


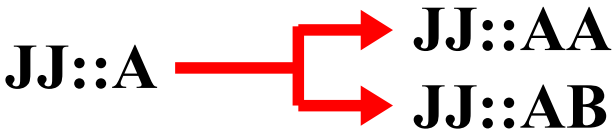
Thesis Statement

The nonterminal set used in SCFG-based MT is important.

Using category labels from treebanks is suboptimal for MT, but we can make labels better automatically.

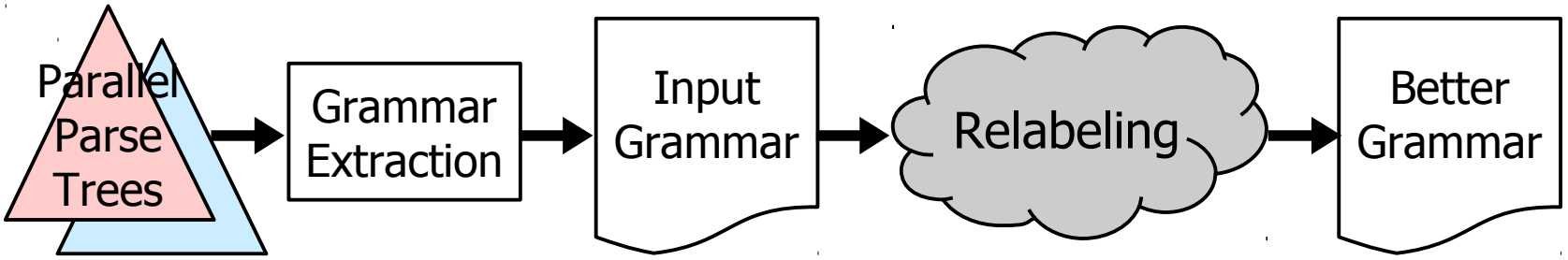
Thesis Proposal

- Define and measure the effect labels have
  - Spurious ambiguity, rule sparsity, and reordering precision
- Explore the space of labeling schemes
  - Collapsing labels 

  - Refining labels 

  - Correcting local labeling errors 

Thesis Claims

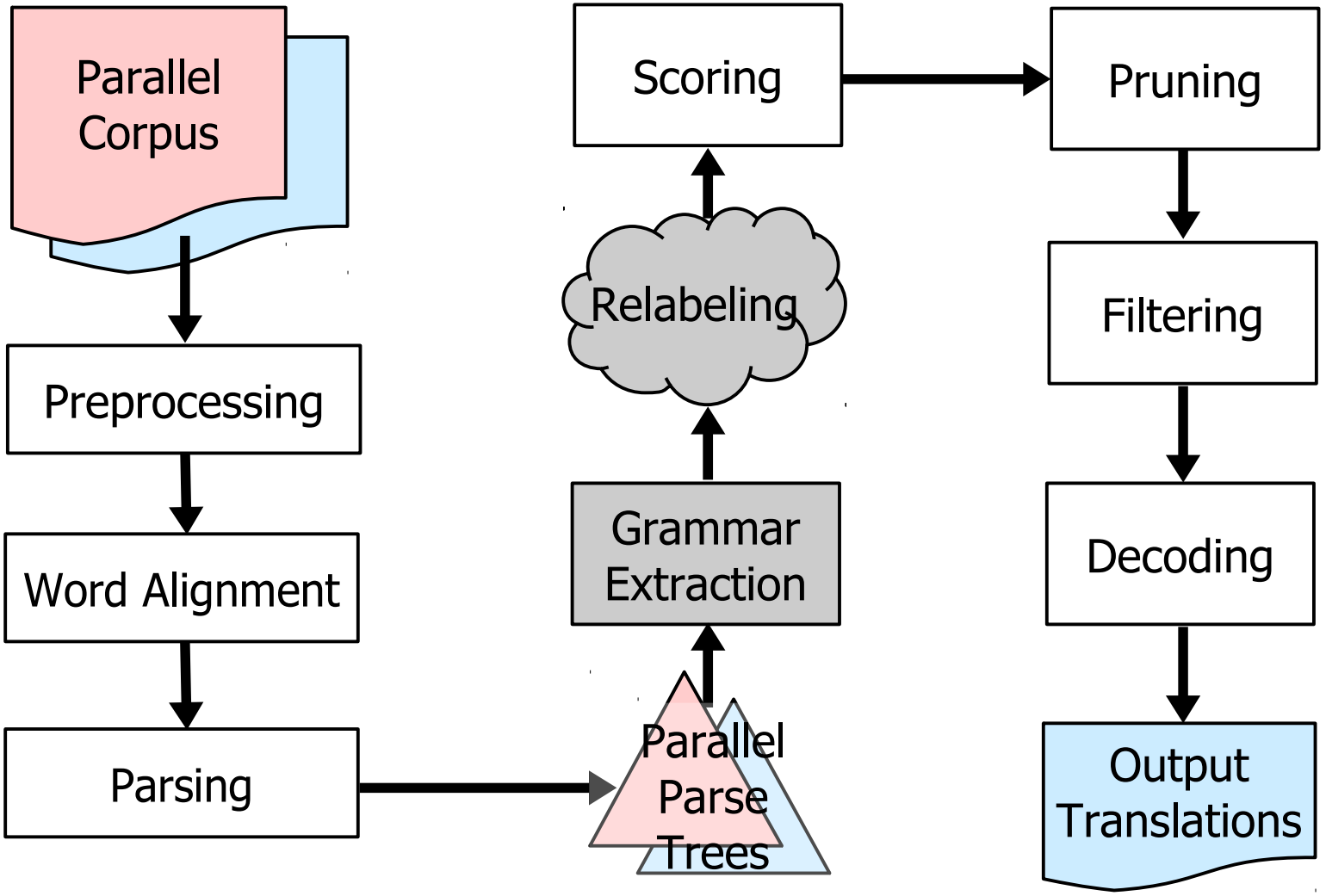


- "Better" will be defined by
  - Significant improvement on automatic metrics
  - Reduced spurious ambiguity and rule sparsity
  - Maintained or improved reordering precision
- Improvements will be demonstrated on at least two language pairs

Outline

- Introduction
- Baseline system and experimental setup
- Label-based system properties
- Extraction and relabeling techniques
- Putting it all together

Experimental Setup



Baseline System

[Hanneman et al. 2010]

- French–English, based on WMT 2010 data
  - 8.6 million sentence pairs of Europarl, news commentary, and UN document text
- Stanford and Berkeley parsers
- Extracted 14 million unique hierarchical rules and 41 million unique phrase pairs
- Pruned to 10,000 most frequent rules and all phrase pairs matching test set
- Joshua SCFG-based decoder

Language Pairs and Data

- French–English
  - Millions of sentence pairs of Europarl, news commentary, UN document, and Web text
  - Annual WMT evaluation
- Arabic–English and Chinese–English
  - Millions of sentence pairs released from LDC
  - Periodic NIST evaluation
- Chinese–English proving ground
  - FBIS corpus of 300,000 sentence pairs

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- Introduction
- Baseline system and experimental setup
- Label-based system properties
  - Spurious ambiguity
  - Rule sparsity
  - Reordering precision
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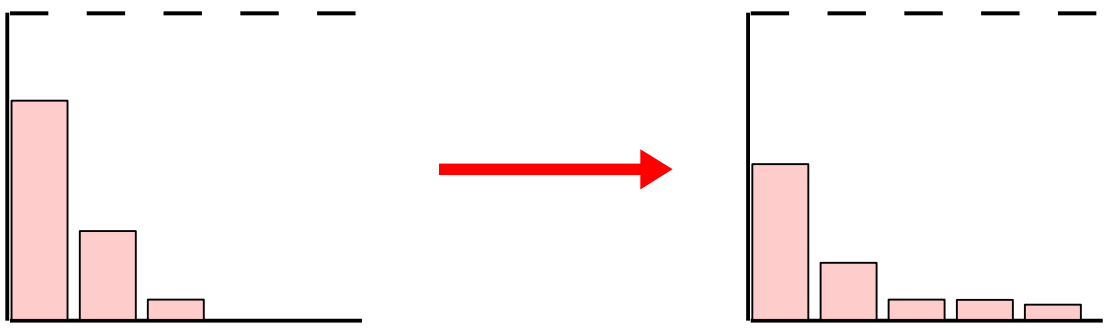
(1) Spurious Ambiguity

- "Many derivations that are distinct yet have the same model feature vectors and give the same translation" [Chiang 2005]
- Weakens conditional probabilities

$$\mathrm{P}(\ell_s, \ell_t, r_s \mid r_t) \quad \mathrm{P}(\ell_s, \ell_t \mid r_s) \quad \mathrm{P}(\ell_s, \ell_t \mid r_s, r_t)$$
$$\mathrm{P}(\ell_s, \ell_t, r_t \mid r_s) \quad \mathrm{P}(\ell_s, \ell_t \mid r_t) \quad \mathrm{P}(r_s, r_t \mid \ell)$$



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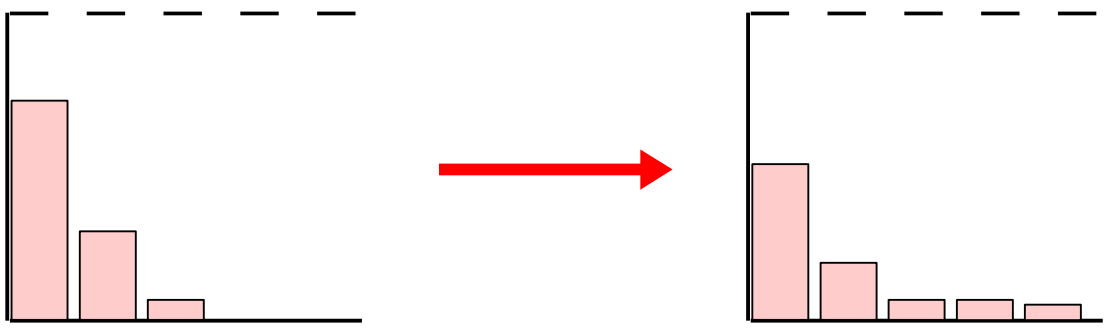

(1) Spurious Ambiguity

- Generates duplicate chart entries with varying left-hand-side labels

une employée spéciale

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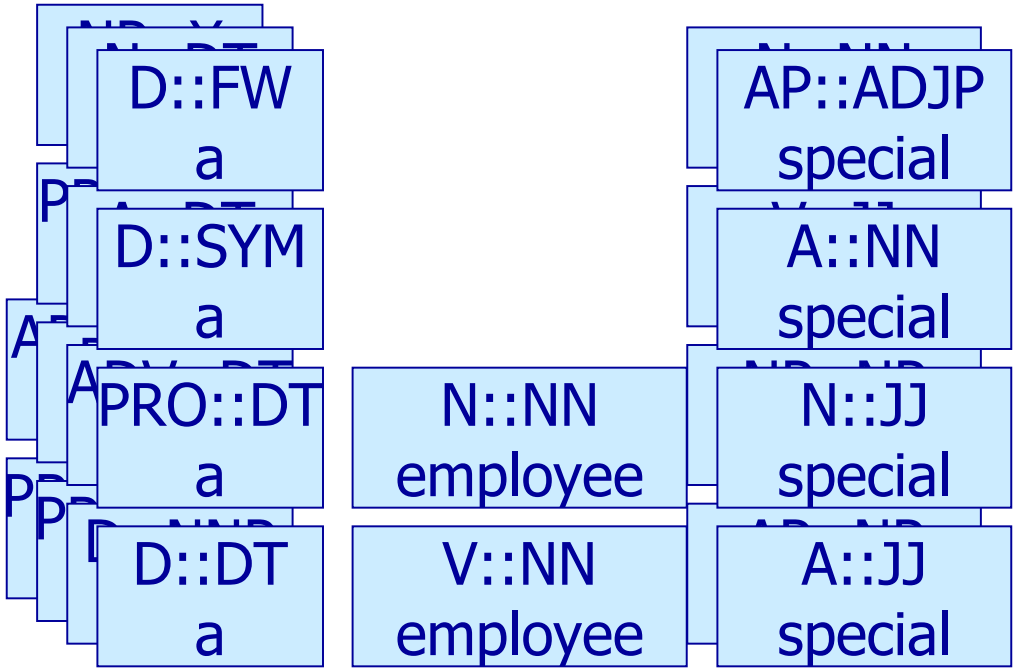

(2) Rule Sparsity

- Necessary rule not found in grammar
- Prevents building of translation fragment

l’ office monétaire de Hongkong

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$$\text{NP::NP} \rightarrow [\text{NP}^1 \text{ de } \text{NP}^2]::[\text{NP}^2 \text{ NP}^1]$$
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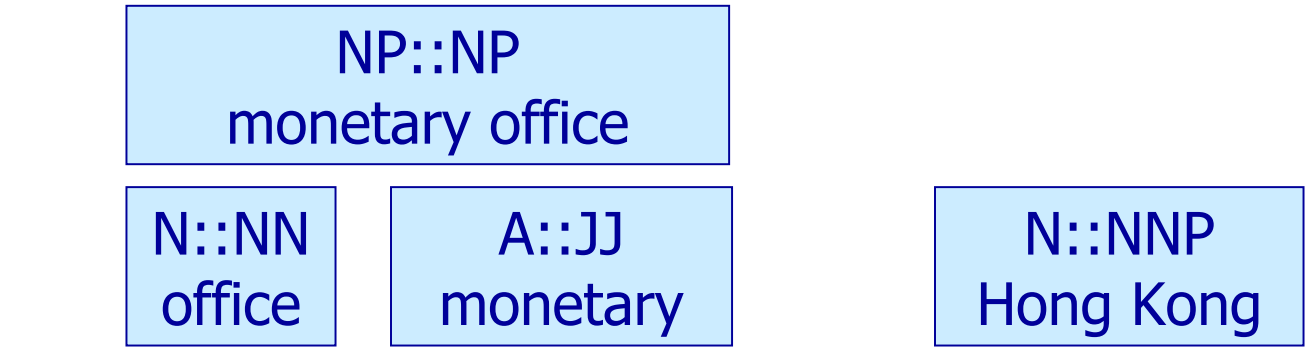

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$$\text{NP::NP} \rightarrow [\text{NP}^1 \text{ de } \text{N}^2]::[\text{NN}^2 \text{ NP}^1]$$

Need an NP::NP or an N::NN

(3) Reordering Precision

- Restricts rules to only apply in contexts specified by their labels

$$X::X \rightarrow [X^1 \text{ de } X^2]::[X^1\ X^2]$$
$$X::X \rightarrow [X^1 \text{ de } X^2]::[X^2\ X^1]$$

$$PP::X \rightarrow [P^1 \text{ de } NP^2]::[X^1\ X^2]$$
$$NP::X \rightarrow [N^1 \text{ de } N^2]::[X^2\ X^1]$$

$$PP::PP \rightarrow [P^1 \text{ de } NP^2]::[IN^1\ NP^2]$$
$$NP::NP \rightarrow [N^1 \text{ de } N^2]::[NN^2\ NNS^1]$$

Measuring These Properties

- Simple counting in the grammar
  - Left-hand-side labels per right-hand side
  - Fraction of possible labelings that instantiate a reordering pattern
- Counting within runtime system
  - Cell contents in completed decoder charts
  - Words out of order on a test set
- Constrained decoding [Auli et al. 2009]
  - Reference reachability

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- Introduction
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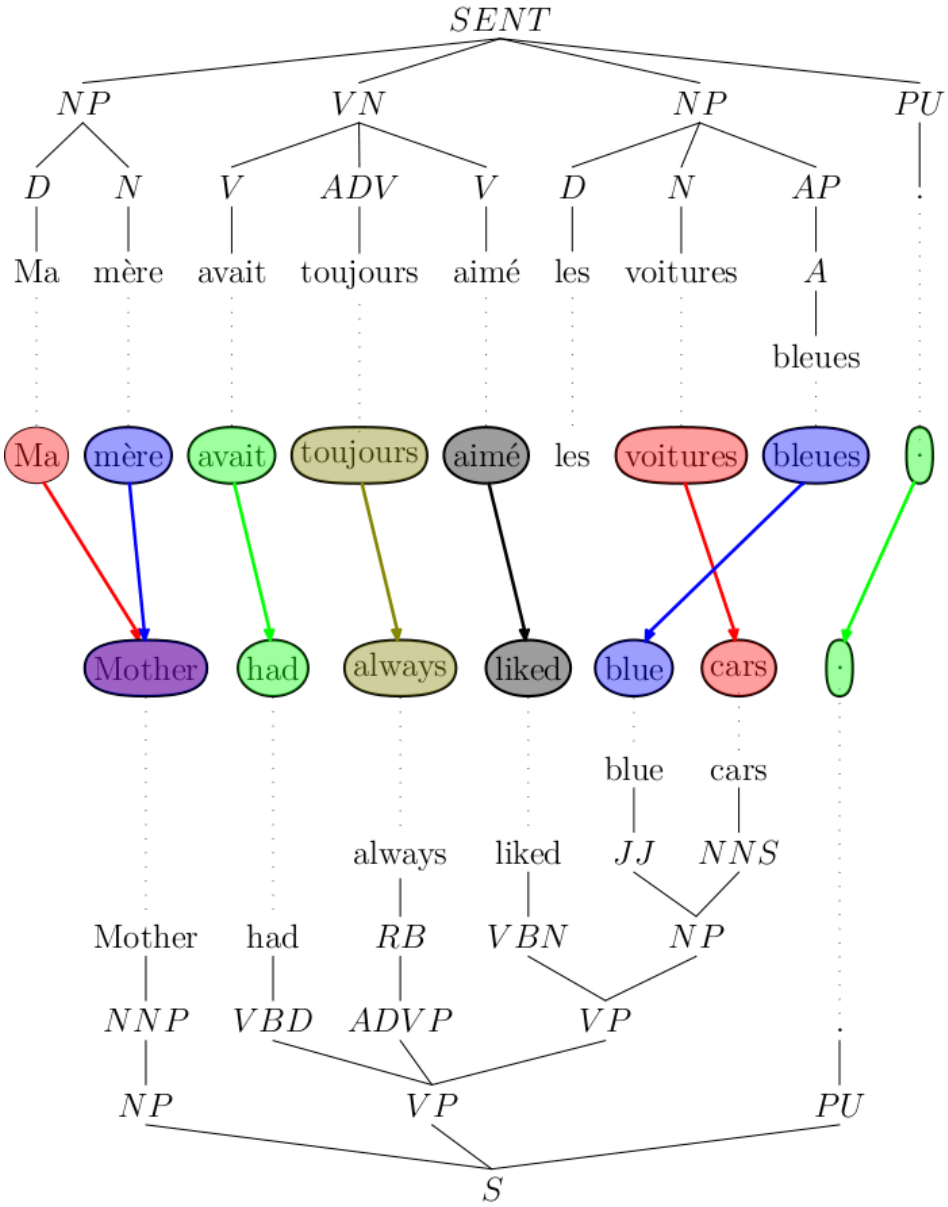
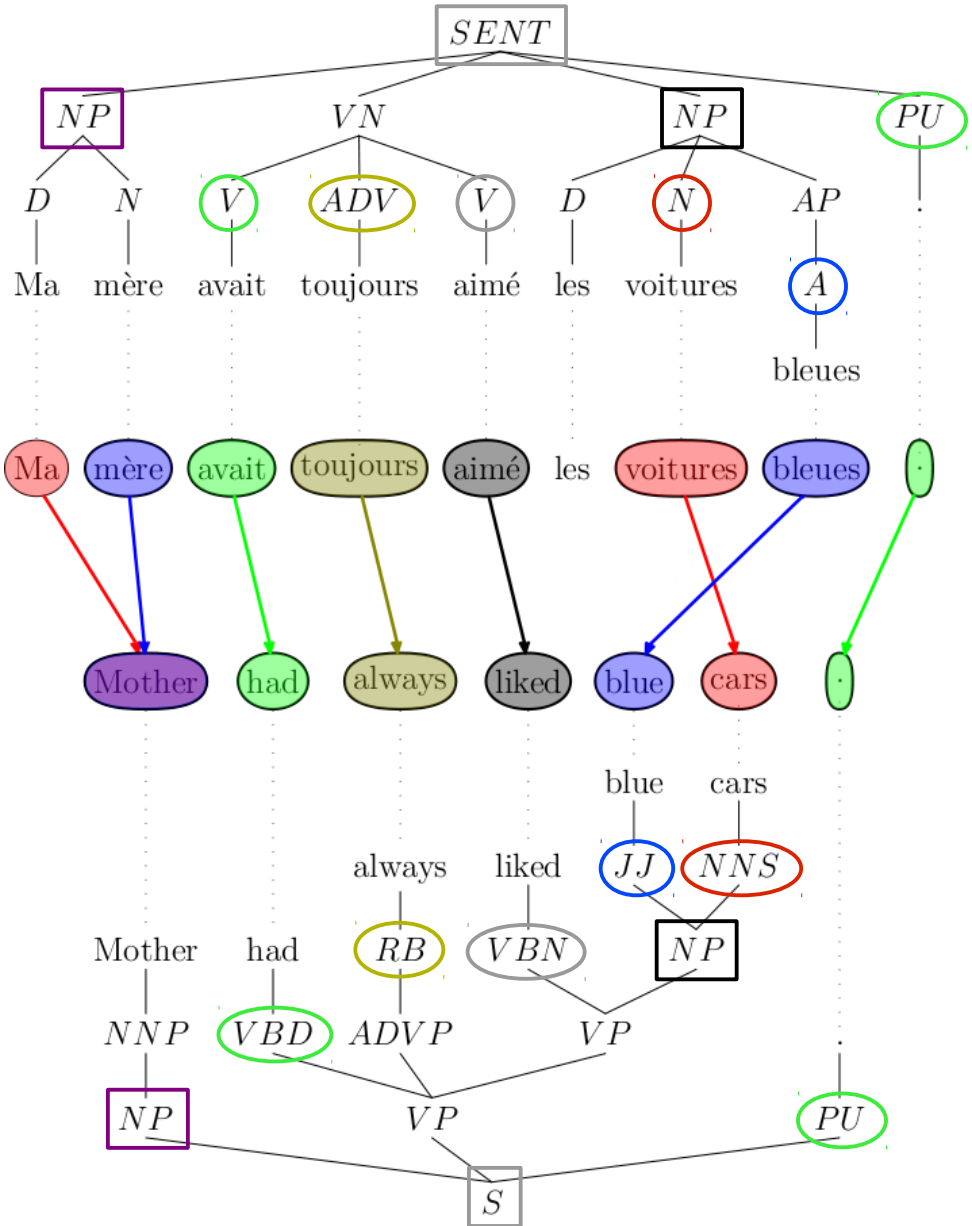
- Extraction and relabeling techniques
  - General-purpose rule extractor
  - Label collapsing
  - Label refining
  - Correcting local labeling errors
- Putting it all together

(1) General Rule Extractor



Baseline Extraction Method

[Lavie et al. 2008]



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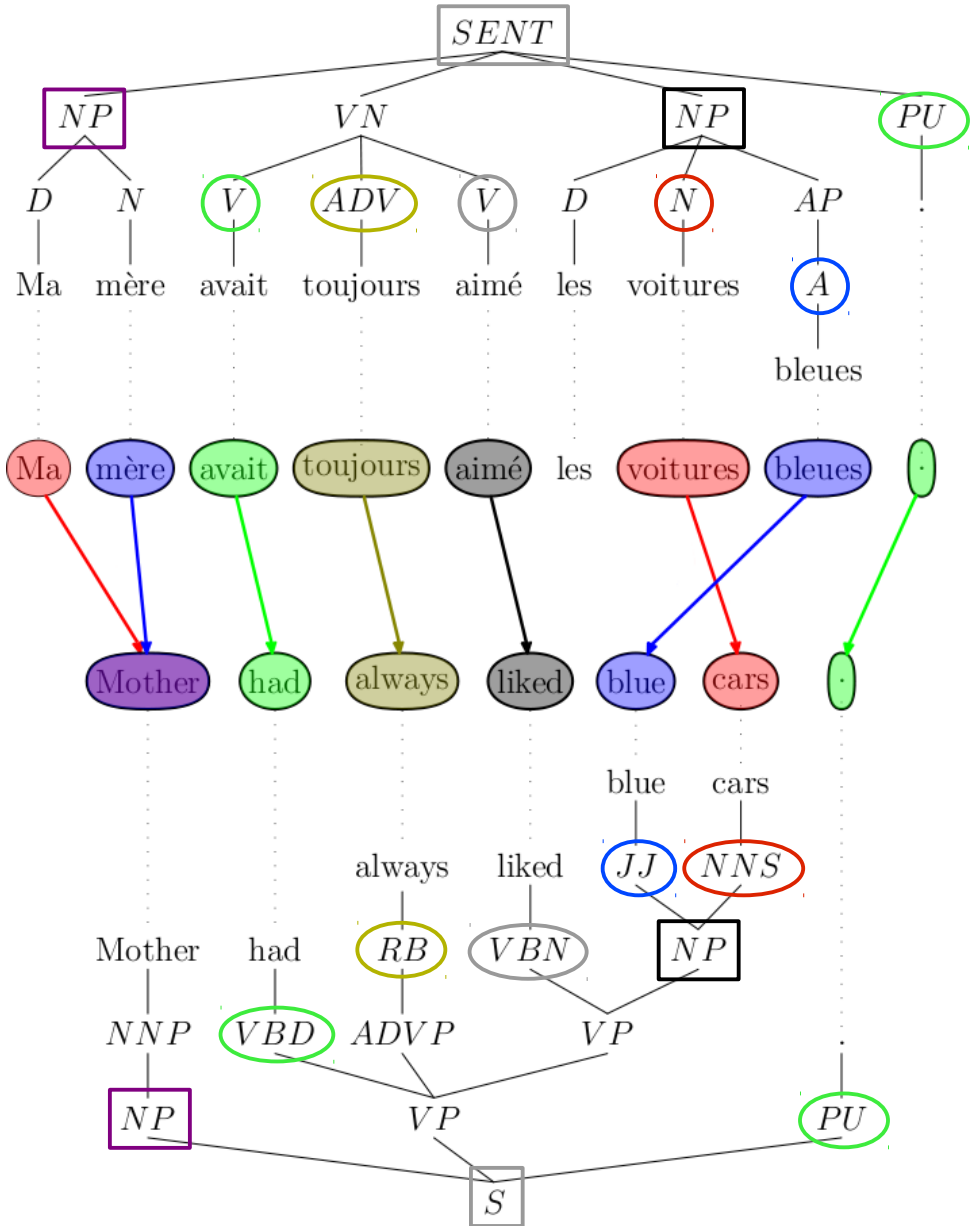


NP::NP → [les voitures bleues]::
[blue cars]

NP::NP → [les N^1 A^2]::
[JJ^2 NNS^1]

Proposed Extensions

- Node alignment
  - Remove constraints on ambiguous alignments
  - Align single node to sequence of sibling nodes
- Rule extraction
  - Produce multiple tree decompositions

$$\text{NP::NP} \rightarrow \text{[les voitures bleues]::[blue cars]}$$

$$\text{NP::NP} \rightarrow \text{[les voitures A}^{2}\text{]::[JJ}^{2}\text{ cars]}$$

$$\text{NP::NP} \rightarrow \text{[les N}^{1}\text{ bleues]::[blue NNS}^{1}\text{]}$$

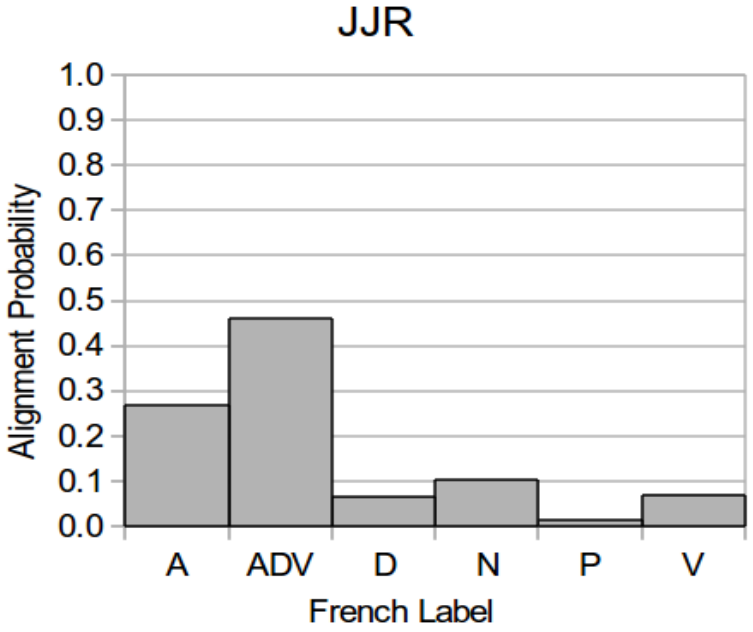
$$\text{NP::NP} \rightarrow \text{[les N}^{1}\text{ A}^{2}\text{]::[JJ}^{2}\text{ NNS}^{1}\text{]}$$

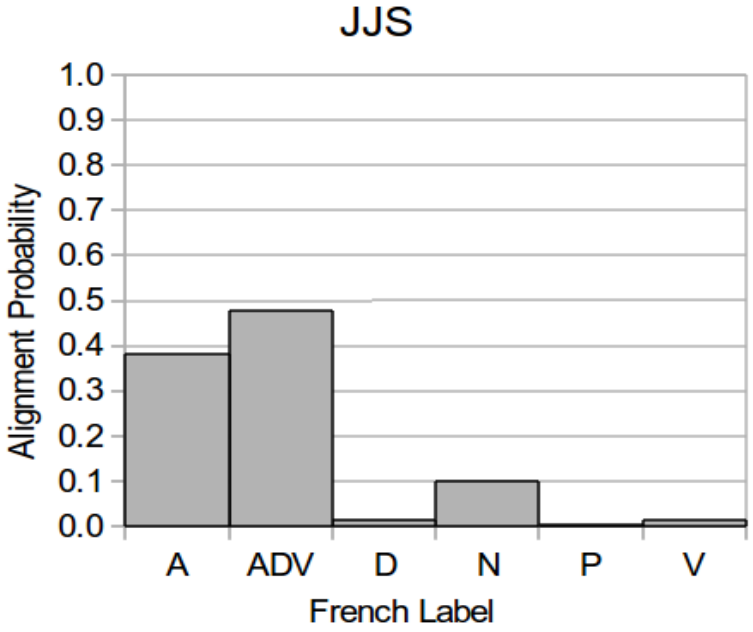
(2) Label Collapsing

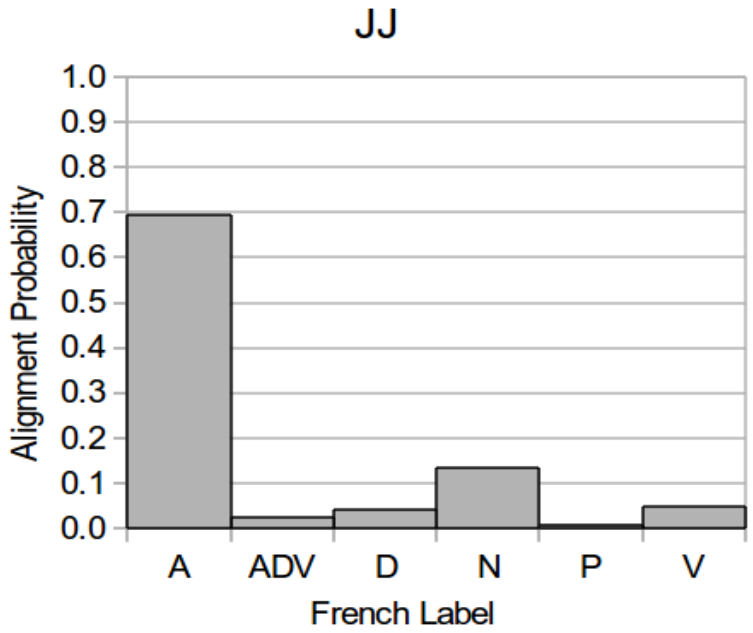
- Spurious ambiguity and rule sparsity caused by large label sets
- Idea: Cluster and collapse the label set
- Intuition: Categories that translate differently still "deserve" different labels
  - English JJ vs. JJR and JJS

the large car	la grande voiture
the larger car	la plus grande voiture
the largest car	la voiture la plus grande

Alignment Distribution Difference







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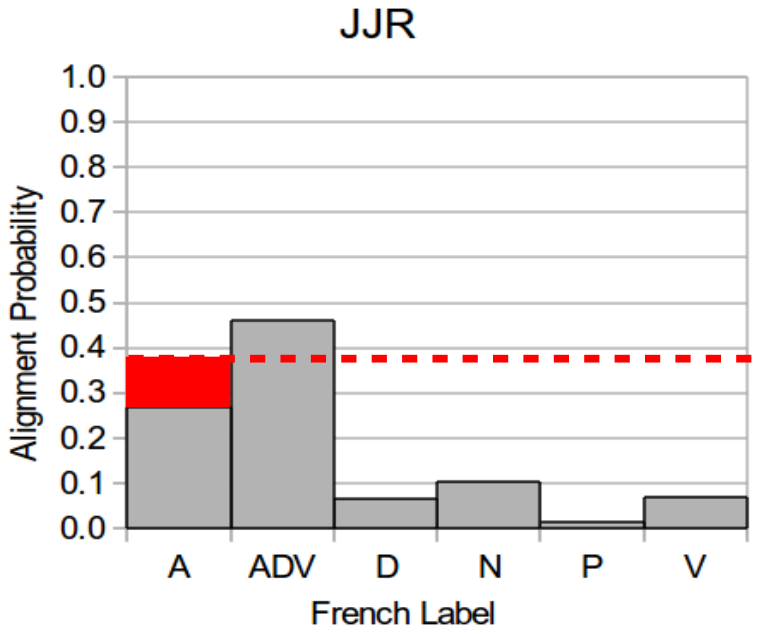

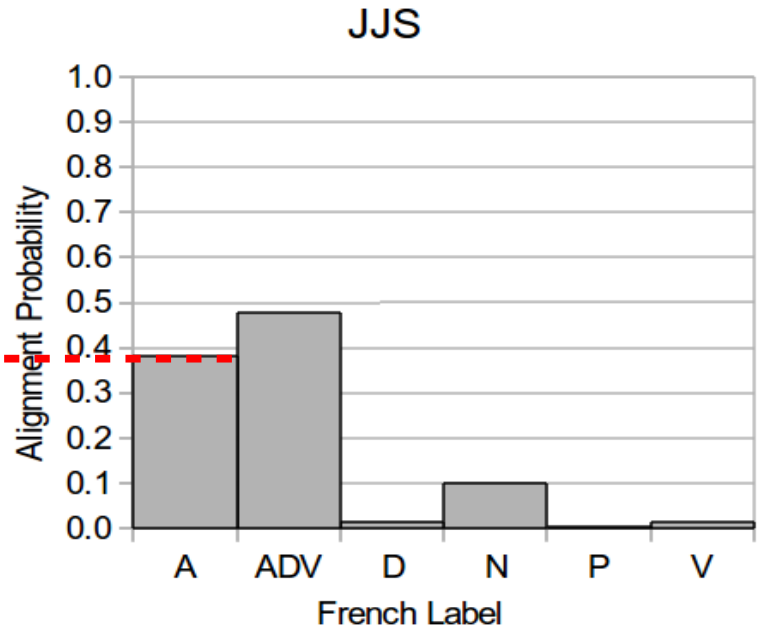

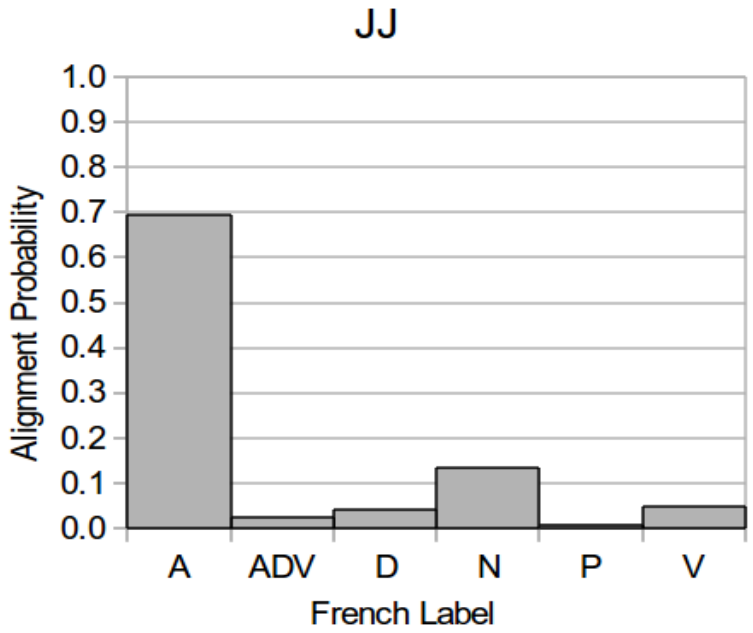

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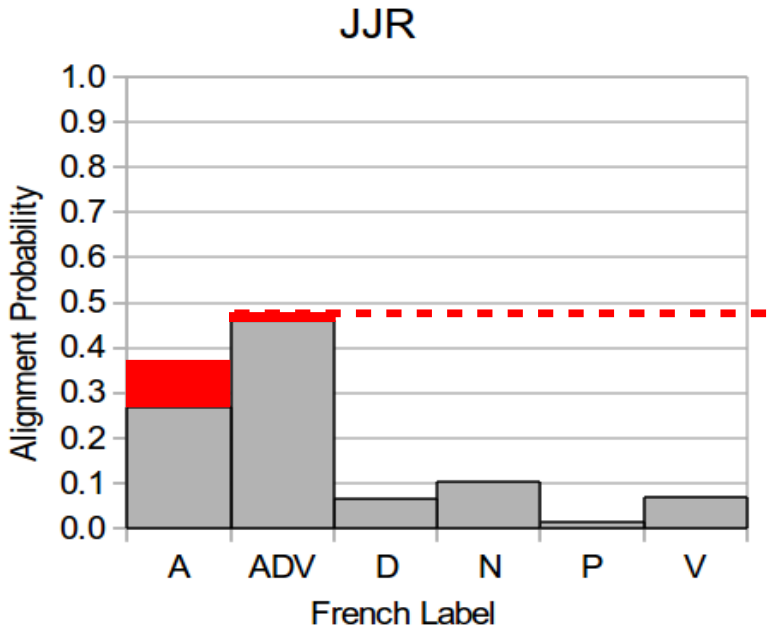

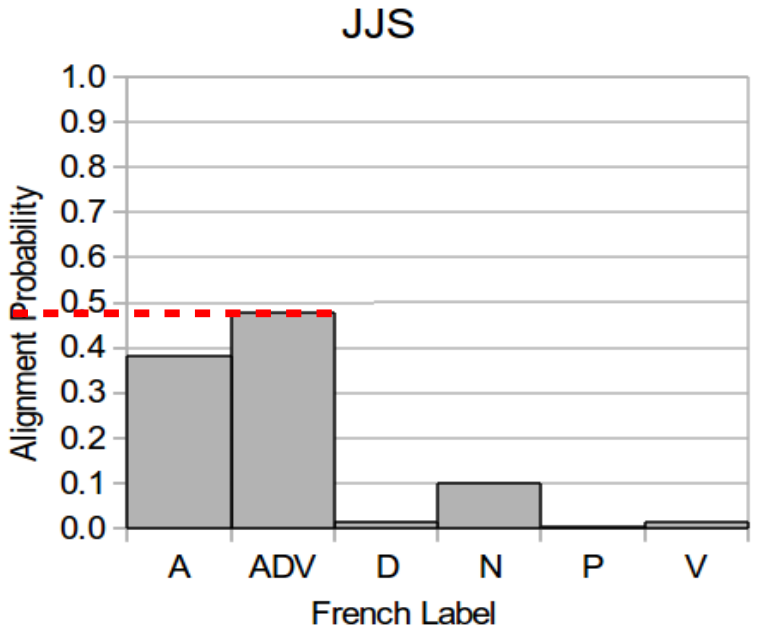

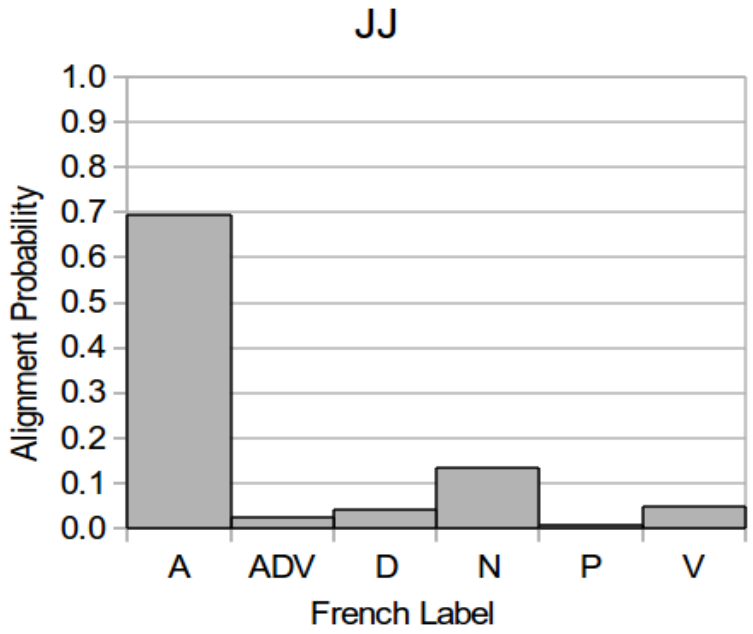

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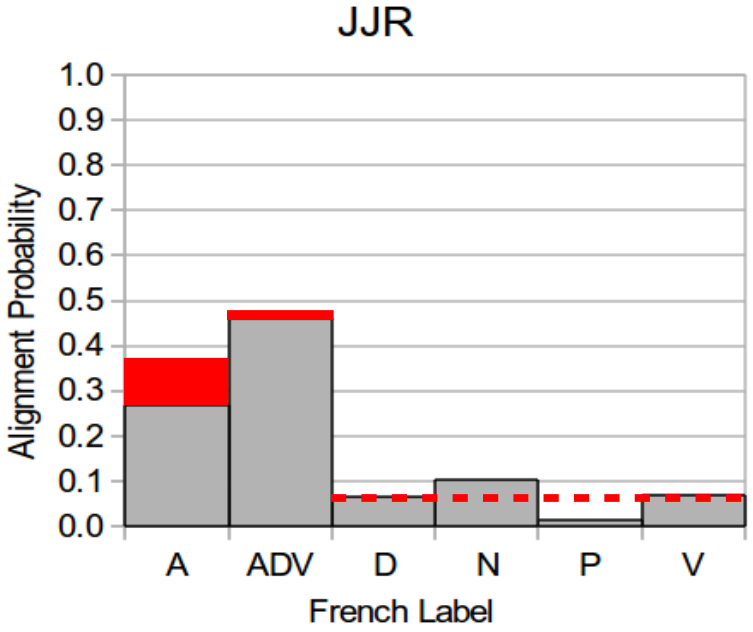

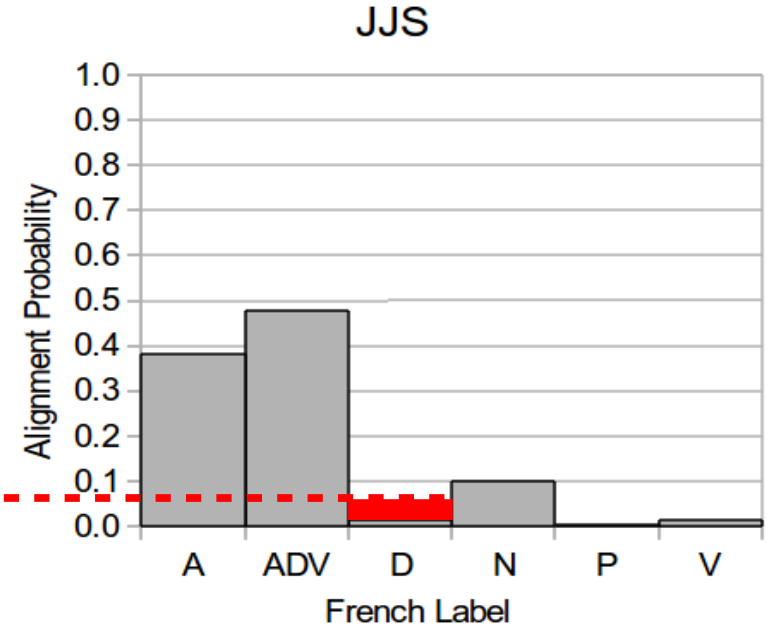

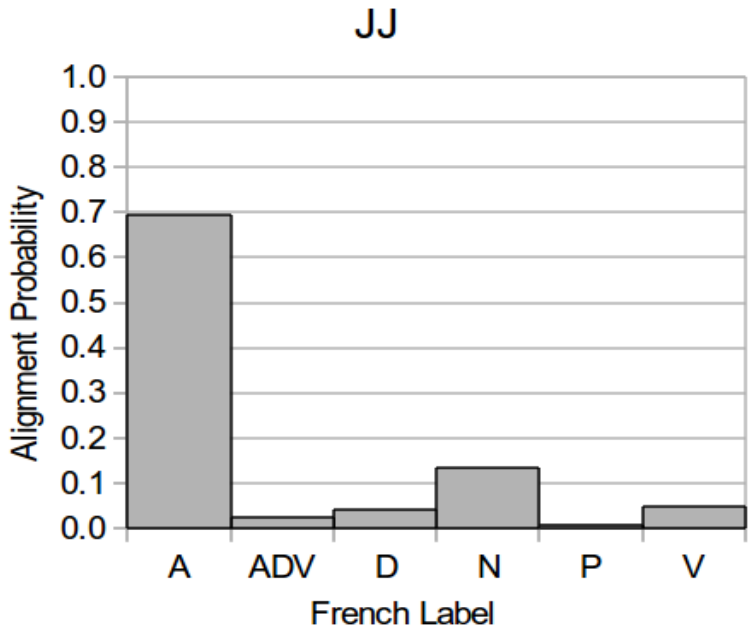

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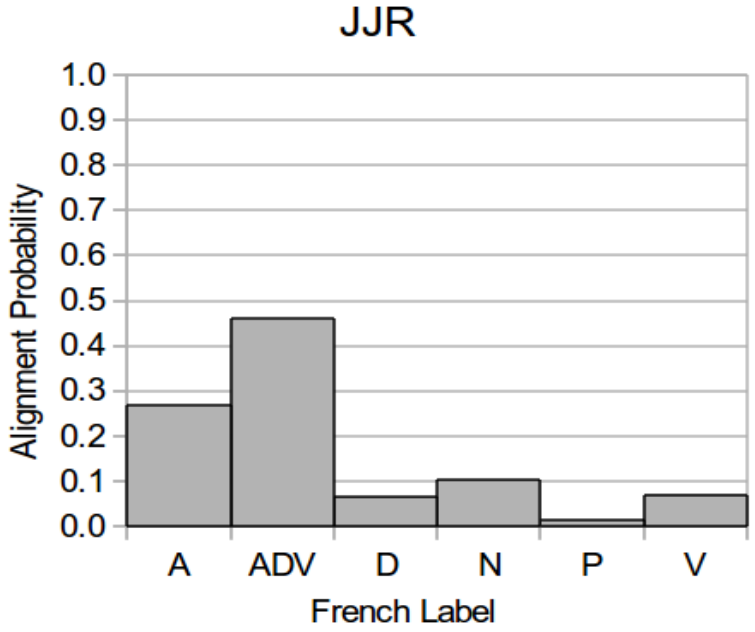

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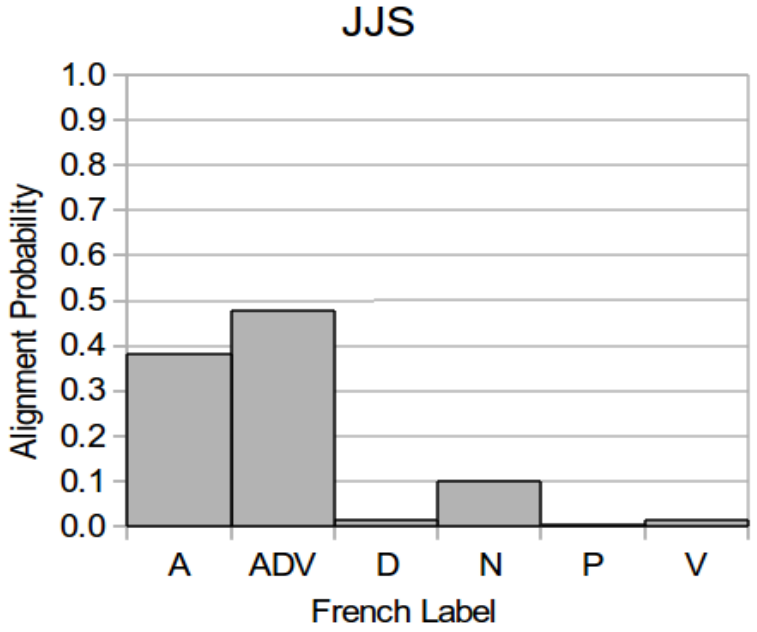
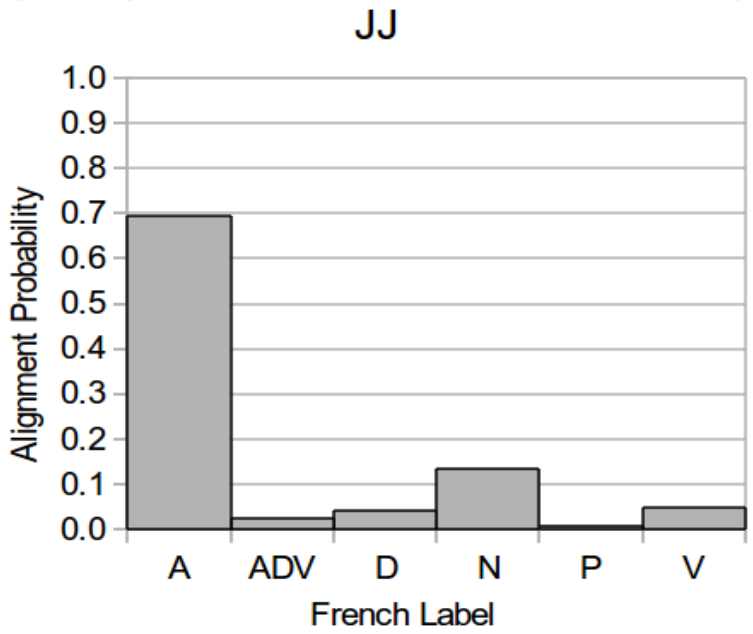


0.9952

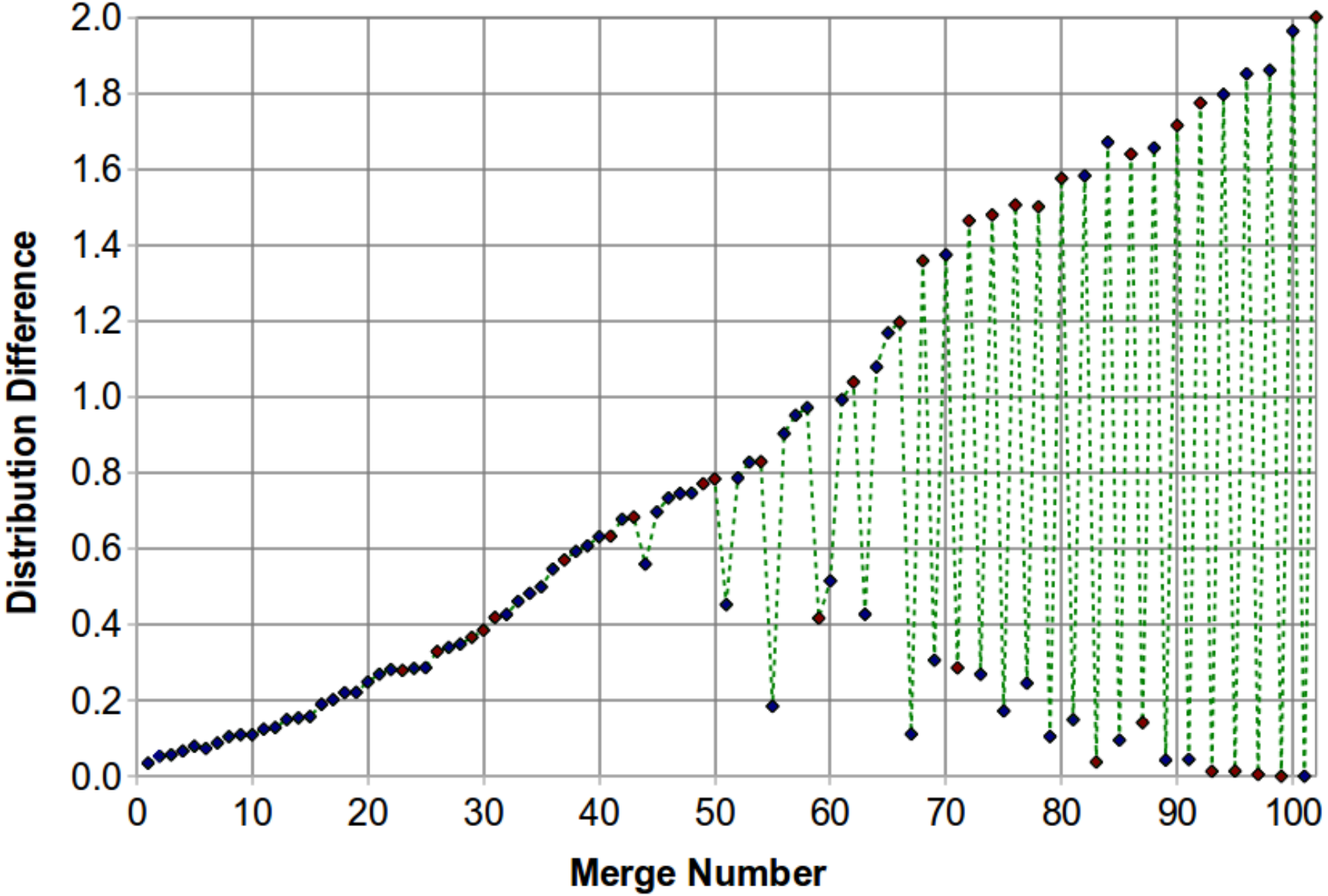


0.9114

Label Collapsing Algorithm

- Greedy procedure
  - Compute distribution difference between all pairs of source and target labels
  - Merge the label pair with smallest value
  - Update alignment statistics
  - Repeat
- Stopping criterion...?

Label Collapsing Algorithm



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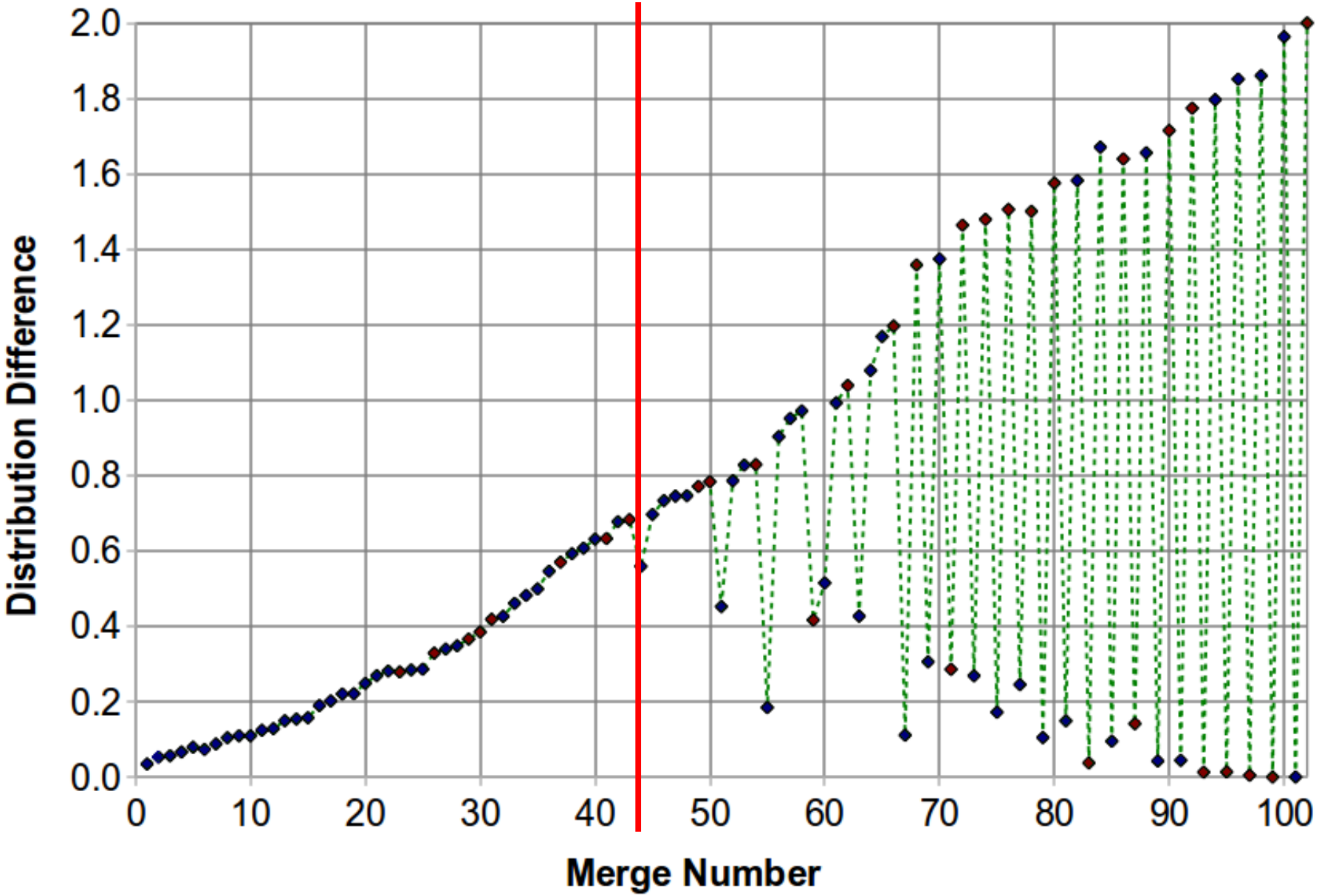


Results: Grammar

- Label set
  - Before: 33 French × 72 English ⇒ 1134 joint
  - After: 25 French × 37 English ⇒ 502 joint
- Spurious ambiguity
  - 1000 most frequent phrase pairs have 21% fewer left-hand-side labels
- Rule sparsity
  - Label sequences 7 times more likely to fit 10 frequent reordering patterns
  - More rule applications in MT test sets

Results: MT Output

- Collapsing the label set improves scores
  - news-test2009

	BLEU	METR	TER
Original	21.75	51.96	59.44
Collapsed	22.78	53.00	59.16

  - news-test2010

	BLEU	METR	TER
Original	22.03	53.13	58.00
Collapsed	23.14	54.03	57.86

Proposed Work

- Investigate choice of
  - Stopping criterion
  - Distance metric
  - Greedy collapsing vs. all at once
- Run collapsing from different initial label granularities [Petrov et al. 2006]
  - Default: S, NP, NNS, A, VPinf
  - Refined: S-1, S-4, NP-2, NP-17, NNS-8, A-11, A-13, VPinf-3, etc.

(3) Label Refining

- Bilingual SCFG rules encode knowledge not used in monolingual parsers
- Idea: Split existing labels using reordering information
- Intuition: Rules that differ only in target-side order indicate hidden categories

$$\text{NP::NP} \rightarrow [\text{DT}^1\ \text{JJ}^2\ \text{NN}^3]::[\text{D}^1\ \text{N}^3\ \text{A}^2]$$

$$\text{NP::NP} \rightarrow [\text{DT}^1\ \text{JJ}^2\ \text{NN}^3]::[\text{D}^1\ \text{A}^2\ \text{N}^3]$$

Proposed Algorithm

- Identify rule set of interest

$$\text{NP::NP} \rightarrow [\text{DT}^1\ \text{JJ}^2\ \text{NN}^3]::[\text{D}^1\ \text{N}^3\ \text{A}^2]$$

$$\text{NP::NP} \rightarrow [\text{DT}^1\ \text{JJ}^2\ \text{NN}^3]::[\text{D}^1\ \text{A}^2\ \text{N}^3]$$

- From parsed corpus, tabulate what plugs into the rules at each extracted instance
- Items much more likely to plug into one rule than other form a category subtype

Refining Example

$$NP::NP \rightarrow [DT^1\ JJ^2\ NN^3]::[\ \_\_\_\_\_\ ]$$

$D^1\ N^3\ A^2$	
un	0.3165
une	0.2654
la	0.1288
le	0.0815
cette	0.0428
l’	0.0371
ce	0.0368
…	…

$D^1\ A^2\ N^3$	
une	0.2545
un	0.2067
la	0.1688
le	0.1054
cette	0.0563
Le	0.0515
La	0.0435
…	…

Refining Example

$$NP::NP \rightarrow [DT^1\ JJ^2\ NN^3]::[\ \_\_\_\_\_\ ]$$

$D^1\ N^3\ A^2$			$D^1\ A^2\ N^3$	
un	0.3165	0.4154	une	0.2545
une	0.2654	⟷	un	0.2067
la	0.1288		la	0.1688
le	0.0815		le	0.1054
cette	0.0428		cette	0.0563
l’	0.0371		Le	0.0515
ce	0.0368		La	0.0435
…	…		…	…

Refining Example

$$NP::NP \rightarrow [DT^1\ JJ^2\ NN^3]::[\ \_\_\_\_\_\ ]$$

$D^1\ \mathbf{N^3}\ A^2$		$D^1\ A^2\ \mathbf{N^3}$	
rôle	0.0349	fois	0.0397
position	0.0241	temps	0.0355
question	0.0213	point	0.0258
communauté	0.0212	majorité	0.0212
solution	0.0172	question	0.0199
situation	0.0171	chose	0.0193
base	0.0154	problème	0.0174
…	…	…	…

Refining Example

$$NP::NP \rightarrow [DT^1\ JJ^2\ NN^3]::[\ \_\_\_\_\_\ ]$$

$D^1\ N^3\ A^2$		$D^1\ A^2\ N^3$	
commune	0.0338	même	0.0957
important	0.0286	nouvelle	0.0837
politique	0.0285	première	0.0676
internationale	0.0267	bonne	0.0593
européenne	0.0218	nouveau	0.0521
européen	0.0186	deuxième	0.0509
juridique	0.0144	bon	0.0406
…	…	…	…

Refining Example

$$NP::NP \rightarrow [DT^1\ JJ^2\ NN^3]::[D^1\ N^3\ \mathbf{AA^2}]$$

$$NP::NP \rightarrow [DT^1\ JJ^2\ NN^3]::[D^1\ \mathbf{AB^2}\ N^3]$$

AA: commune, politique, internationale, européenne, européen, juridique, ...

AA & AB: important, importante, ...

AB: même, nouvelle, première, bonne, nouveau, deuxième, bon, autre, ...

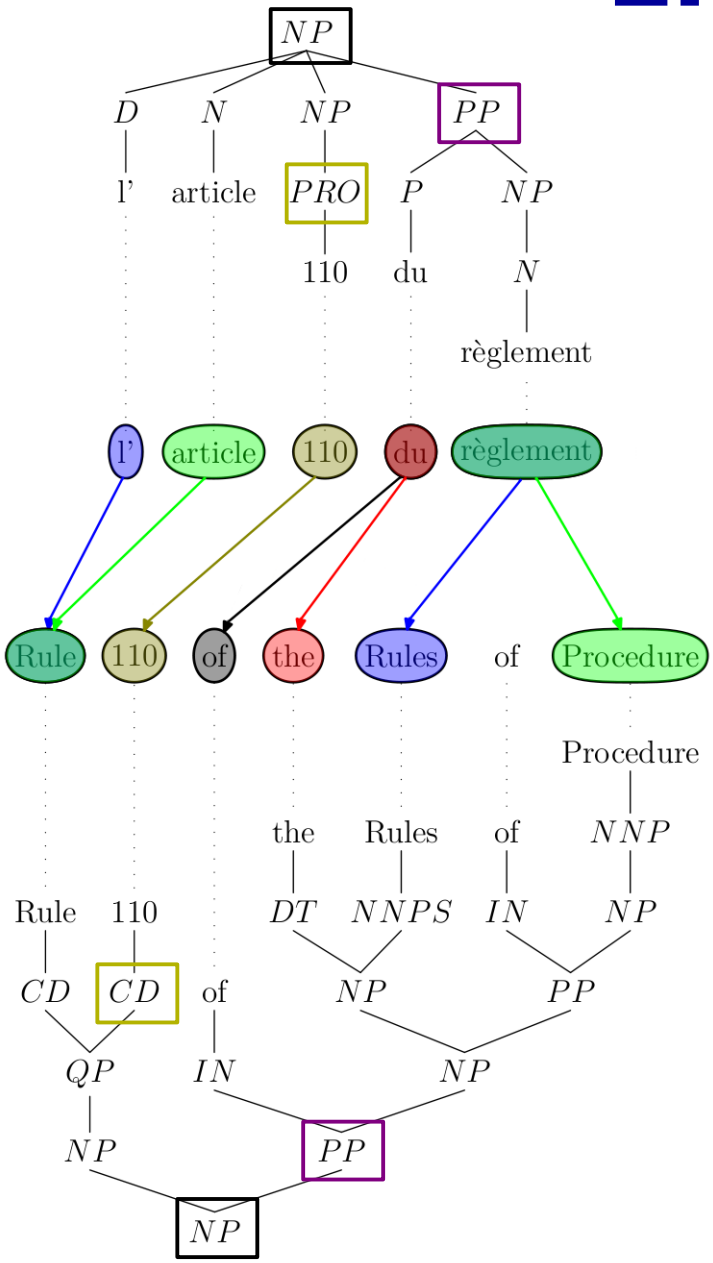
(4) Correcting Local Label Errors

- Sentences parsed independently may contain local labeling errors
- Idea: Correct them using rules extracted from the entire parsed parallel corpus
- Intuition: Rule probabilities from whole corpus can fix label errors; fixing local label errors improves rule probabilities

Proposed Algorithm

- EM algorithm
  - Initial grammar extraction: compute P(LHS | RHS) for each rule
  - E step: Re-derive most likely labeled version of each aligned tree pair using rule scores
  - M step: Re-extract grammar from modified trees and re-compute rule scores
  - Repeat E and M steps until grammar doesn't change

EM Example

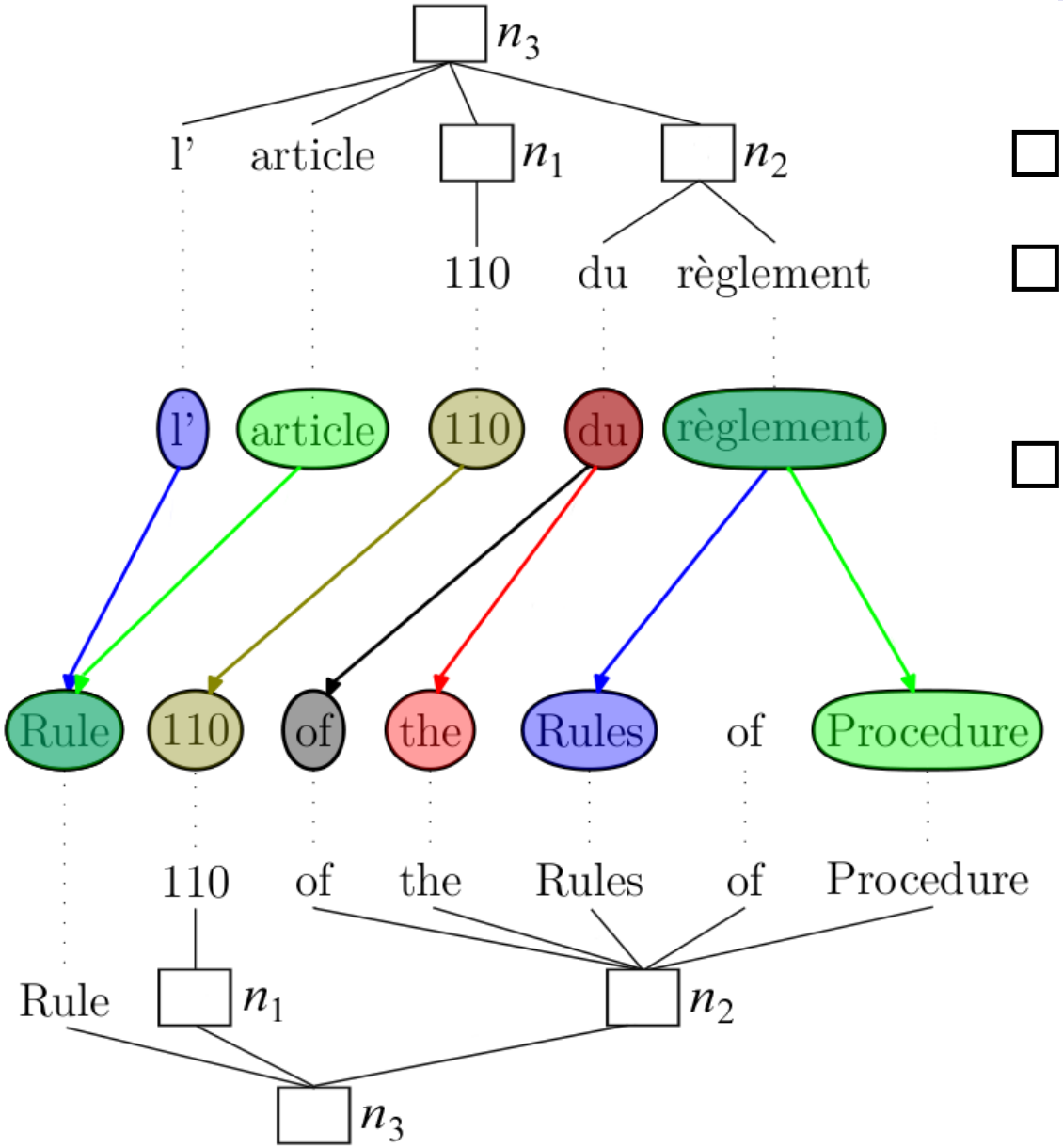


PRO::CD → [110]::[110]

PP::PP → [du règlement]::
[of the Rules of Procedure]

NP::NP → [l' article **PRO**^{1} PP^{2}]::
[Rule CD^{1} PP^{2}]

EM Example

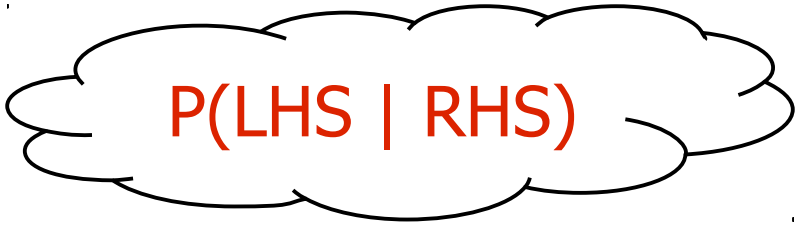


$\square::\square \rightarrow$ [110]::[110]

$\square::\square \rightarrow$ [du règlement]::
[of the R. of P.]

$\square::\square \rightarrow$ [l' article $\square^1$ $\square^2$]::
[Rule $\square^1$ $\square^2$]

EM Example



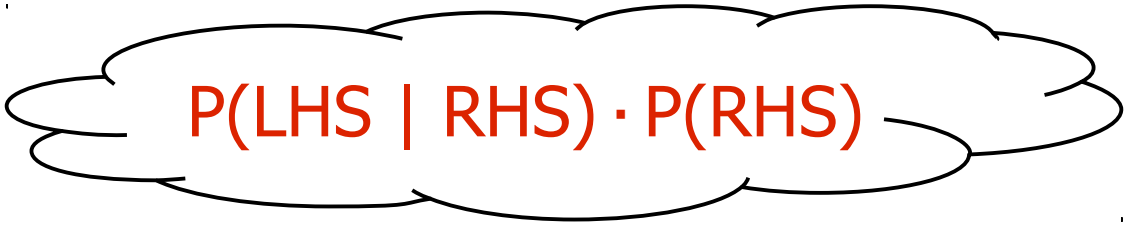
n_1: □::□ → [110]::[110]

D::CD	0.5081
PRO::CD	0.2789
N::CD	0.1004
…	…

n_2: □::□ → [du règlement]::[of the Rules of Procedure]

PP::PP	0.7736
NP::PP	0.2264

EM Example



n_3: $\square::\square \rightarrow [\text{l' article } \square^1\ \square^2]::[\text{Rule } \square^1\ \square^2]$

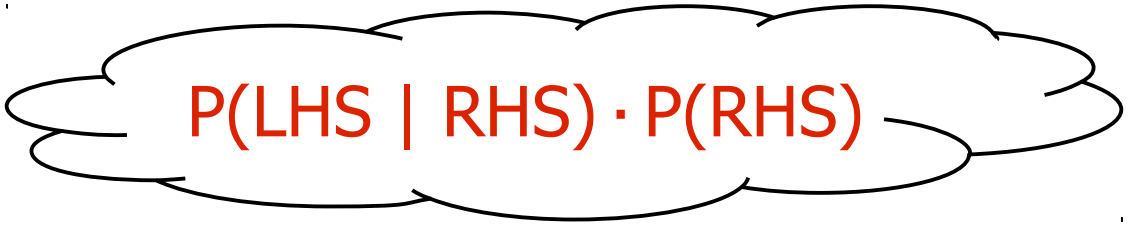
NP::NP → [l' article PRO^1 PP^2]::[Rule CD^1 PP^2]

1 · 0.2789 · 0.7736 = 0.2158

D::CD	0.5081
PRO::CD	0.2789
N::CD	0.1004
…	…

PP::PP	0.7736
NP::PP	0.2264

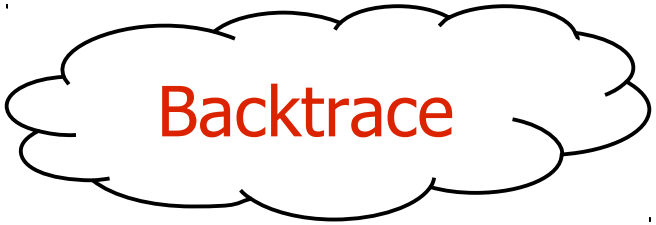
EM Example



n_3: $\square::\square \rightarrow$ [l' article $\square^1$ $\square^2$]::[Rule $\square^1$ $\square^2$]

NP::NP 0.7018
NP::VP 0.0023

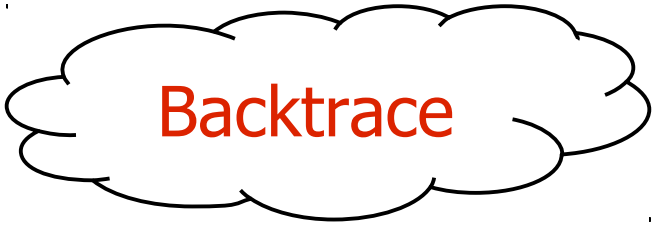
EM Example



n_3: NP::NP → [l' article □[1] □[2]]::[Rule □[1] □[2]]

NP::NP	0.7018
NP::VP	0.0023

EM Example

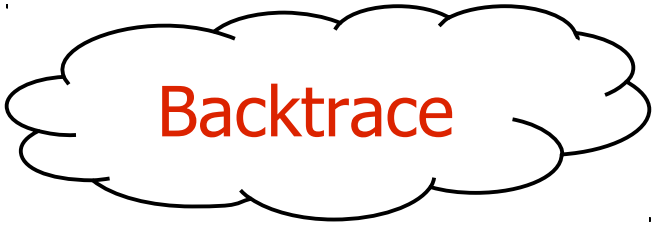


n_3: NP::NP → [l' article D^1 PP^2]::[Rule CD^1 PP^2]

NP::NP 0.7018
NP::VP 0.0023

NP::NP → [l' article D^1 PP^2]::[Rule CD^1 PP^2]
$1 \cdot 0.5081 \cdot 0.7736 = 0.3931$

EM Example



n_3: NP::NP → [l' article D^1 PP^2]::[Rule CD^1 PP^2]

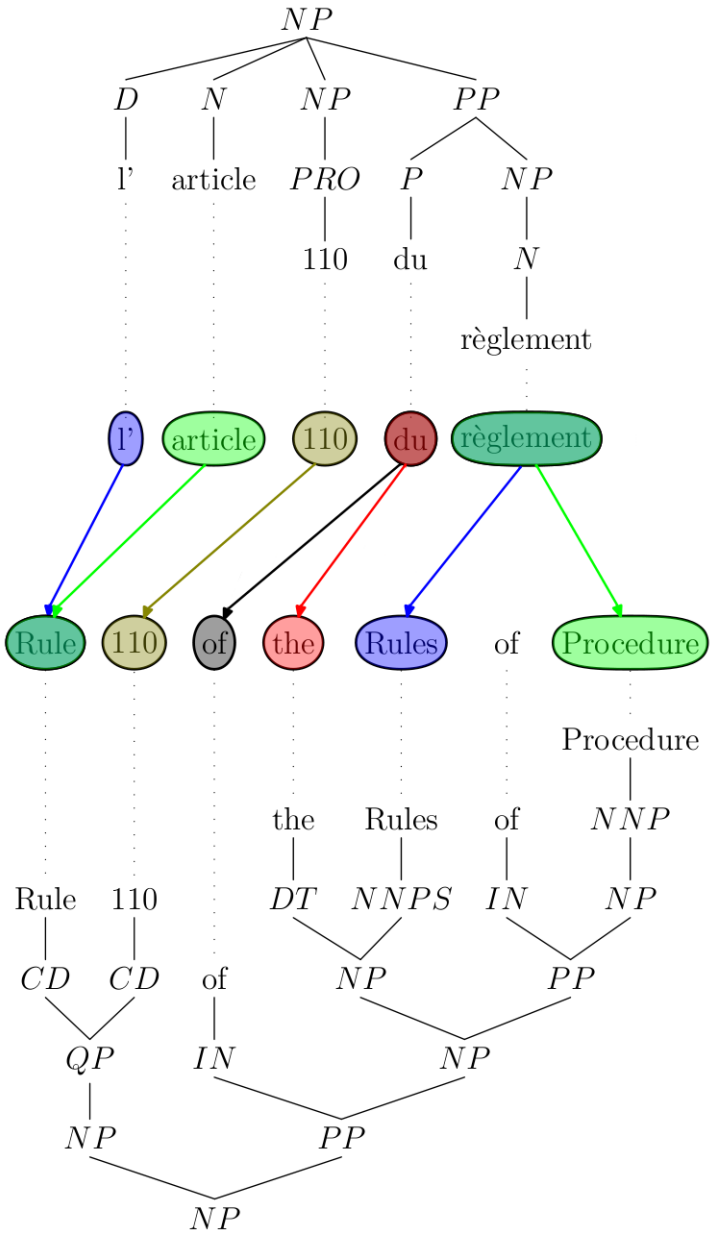
NP::NP 0.7018
NP::VP 0.0023

NP::NP → [l' article D^1 PP^2]::[Rule CD^1 PP^2]
$1 \cdot 0.5081 \cdot 0.7736 = 0.3931$

n_1: D::CD → [110]::[110]

n_2: PP::PP → [du règlement]::[of the Rules of Procedure]

EM Example



D::CD → [110]::[110]

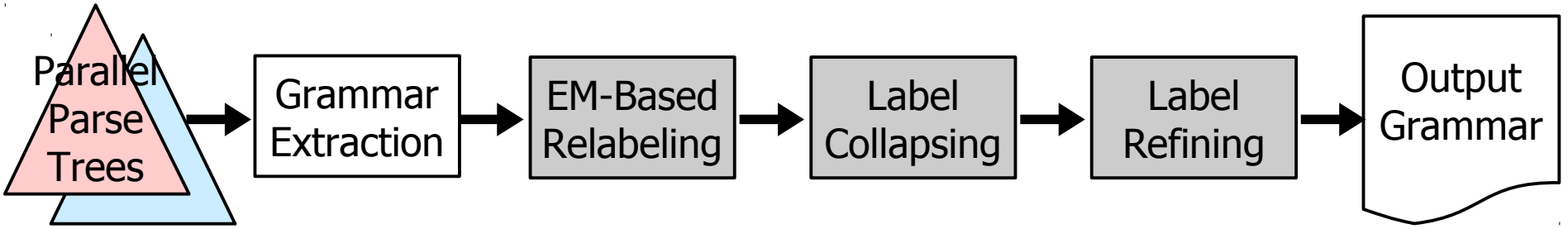
PP::PP → [du règlement]::
[of the Rules of Procedure]

NP::NP → [l' article **D**^{1} PP^{2}]::
[Rule CD^{1} PP^{2}]

Outline

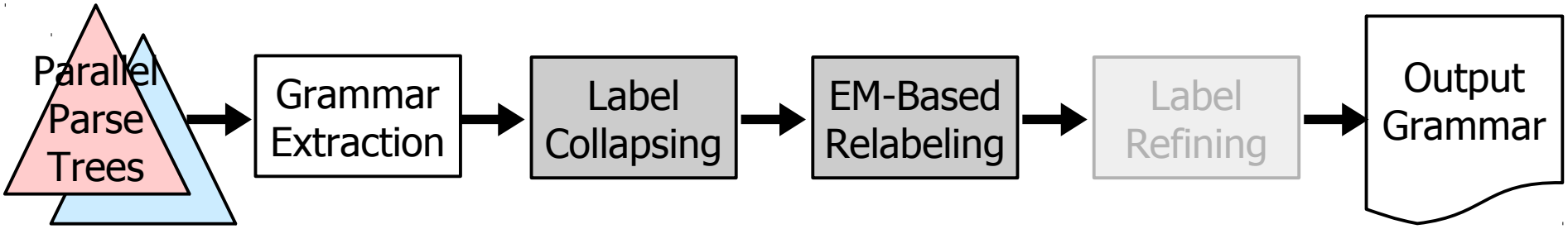
- Introduction
- Baseline system and experimental setup
- Label-based system properties
- Extraction and relabeling techniques
- Putting it all together

Proposed Combination: Default



- Large-scale system with standard labels
  - Remove easy-to-fix occasional labeling errors first (–SA)
  - Remove redundant labels next (–SA, –RS)
  - Add necessary latent categories (+RP)

Proposed Combination: Variants



- Fine-grained input categories
  - Move label collapsing to first (–fragmentation)
  - Remove label refining (focus on RS)
- Small-data systems
  - Remove label refining (focus on RS)

Work Summary

	Completed Work	Proposed Work
Spurious ambiguity, rule sparsity, reordering precision	Defined, measured by simple counting	Measured within system, constrained decoding
General-purpose grammar extractor	Node alignment stage	Rule extraction stage
Label collapsing	Basic algorithm, end-to-end experiments	Algorithm extensions
Label refining	Motivational example, basic approach	Scoping, end-to-end experiments
EM-based relabeling	Motivational example, basic approach	Implementation with grammar extractor, end-to-end experiments
Combined relabeling scheme	Default proposals for different systems	Experimentation

Timeline

Time Period	Work
Jan.-March 2011	Implementation of grammar extractor Full label collapsing experiments Tests of extensions to label collapsing algorithm Submission of EMNLP paper (March 23)
April-July 2011	Development of constrained decoding setup Development of label refining techniques Full label refining experiments French–English submission to WMT 2011
Aug.-Oct. 2011	Development of EM-based relabeling framework Full EM-based relabeling experiments Arabic or Chinese submission to NIST 2011
Nov.-Dec. 2011	Finalization of all individual-technique experiments
Jan.-March 2012	Development of combined-technique pipeline Finalization of systems and experiments
April-May 2012	Thesis writing Thesis defense

Grammar Pruning

- Hiero
  - Phrase pairs limited to length 10
  - Maximum two non-adjacent nonterminals in rules
  - No fully abstract rules
- GHKM
  - Phrase pairs filtered to sentence level
  - Save *n* most frequent translations per source RHS, or all rules extracted at least *k* times (*n* = 40, *k* = 50)
- Our systems
  - Phrase pairs filtered to test set level
  - Save *n* most globally frequent rules (*n* = 10,000)

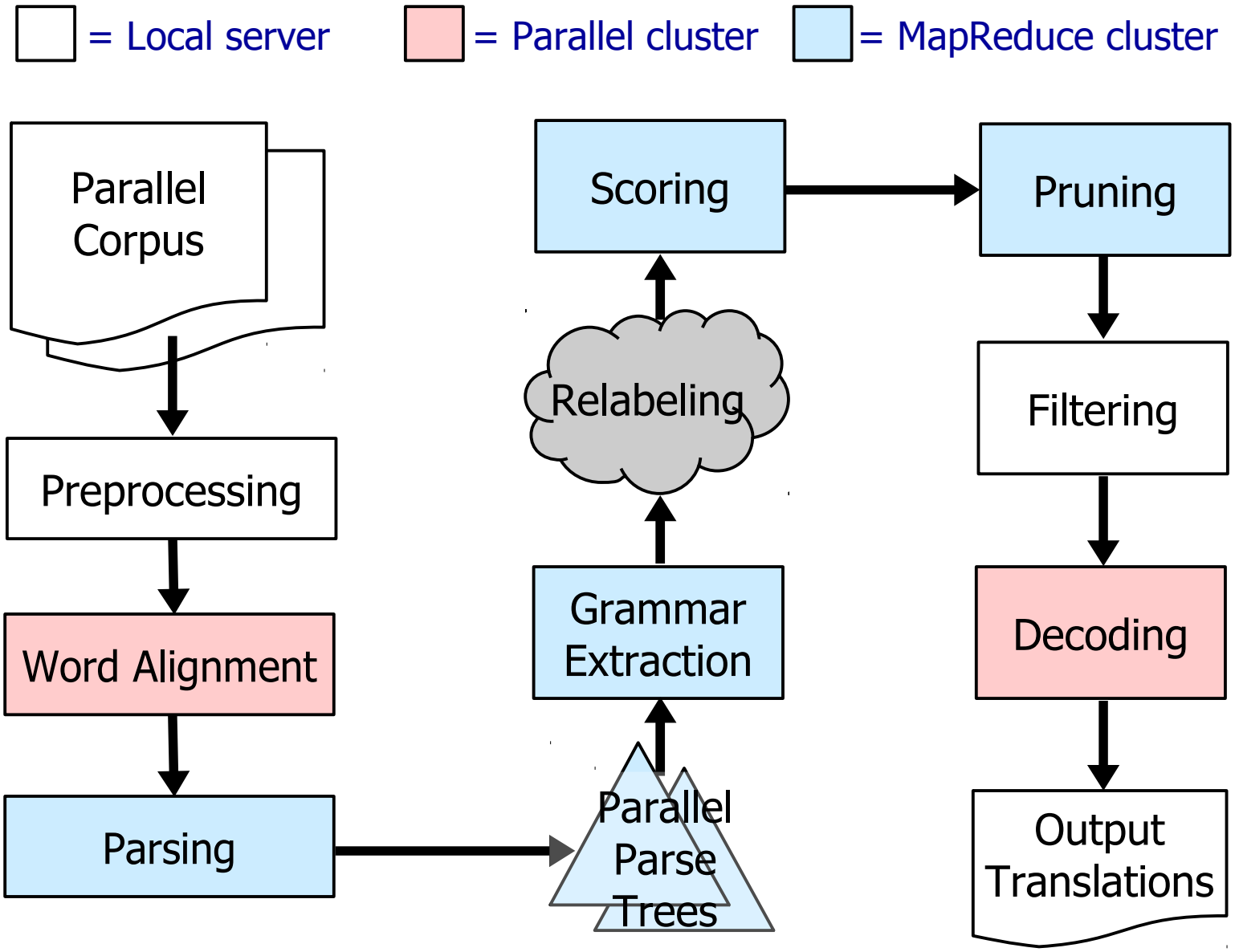
The State of the Art

- WMT news-test2010 test set

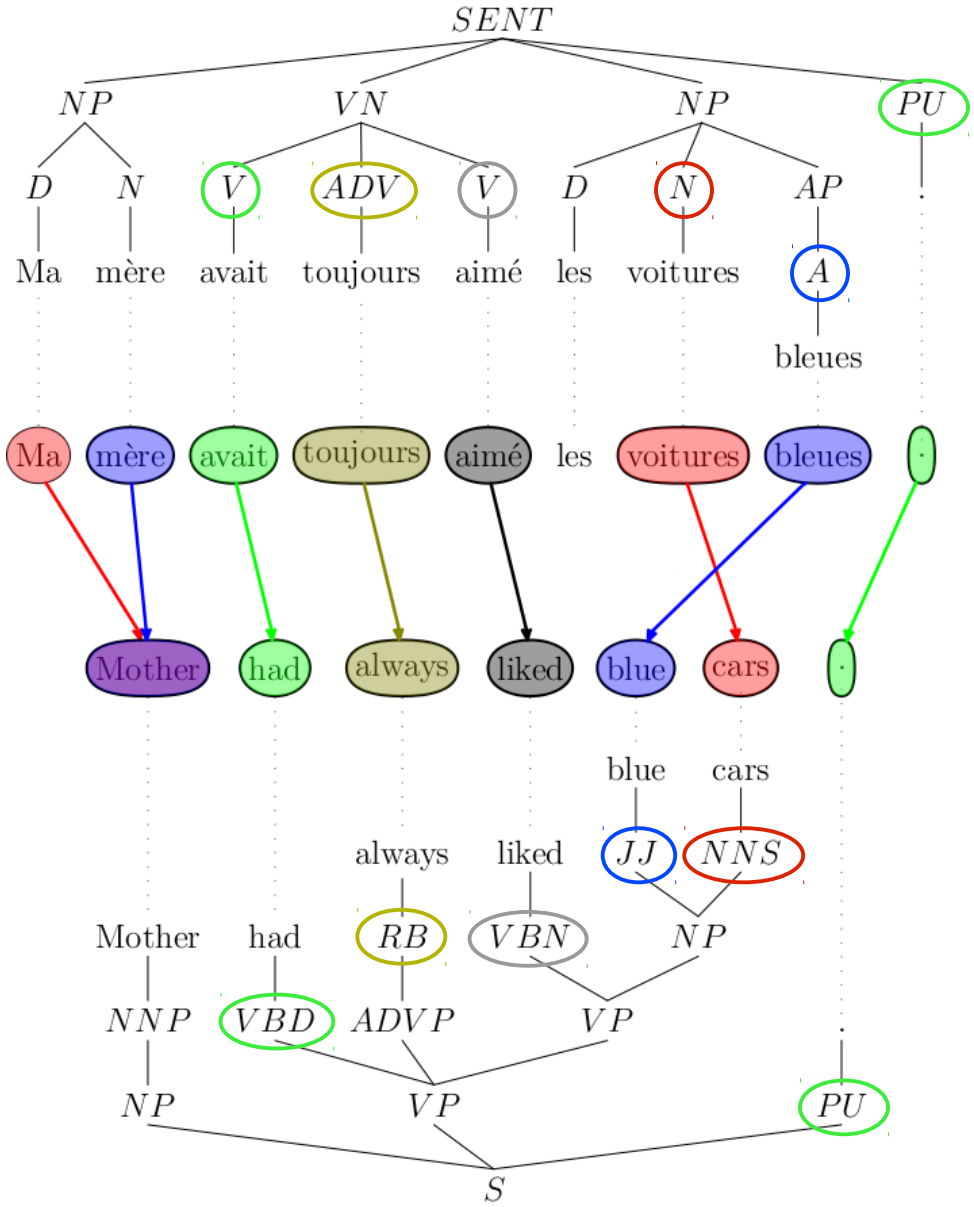
	BLEU	
Best Syntax-Only Baseline	24.1	+2.1
Best Overall Baseline	26.4	+1.2
Best WMT 2010 System	29.6	

- Syntax-only better for grammar analysis
- Expected improvements from improved grammar pruning and rule extraction

Computing Demands



Baseline Extraction Method



V::VBD → [avait]::[had]

ADV::RB → [toujours]::[always]

V::VBN → [aimé]::[liked]

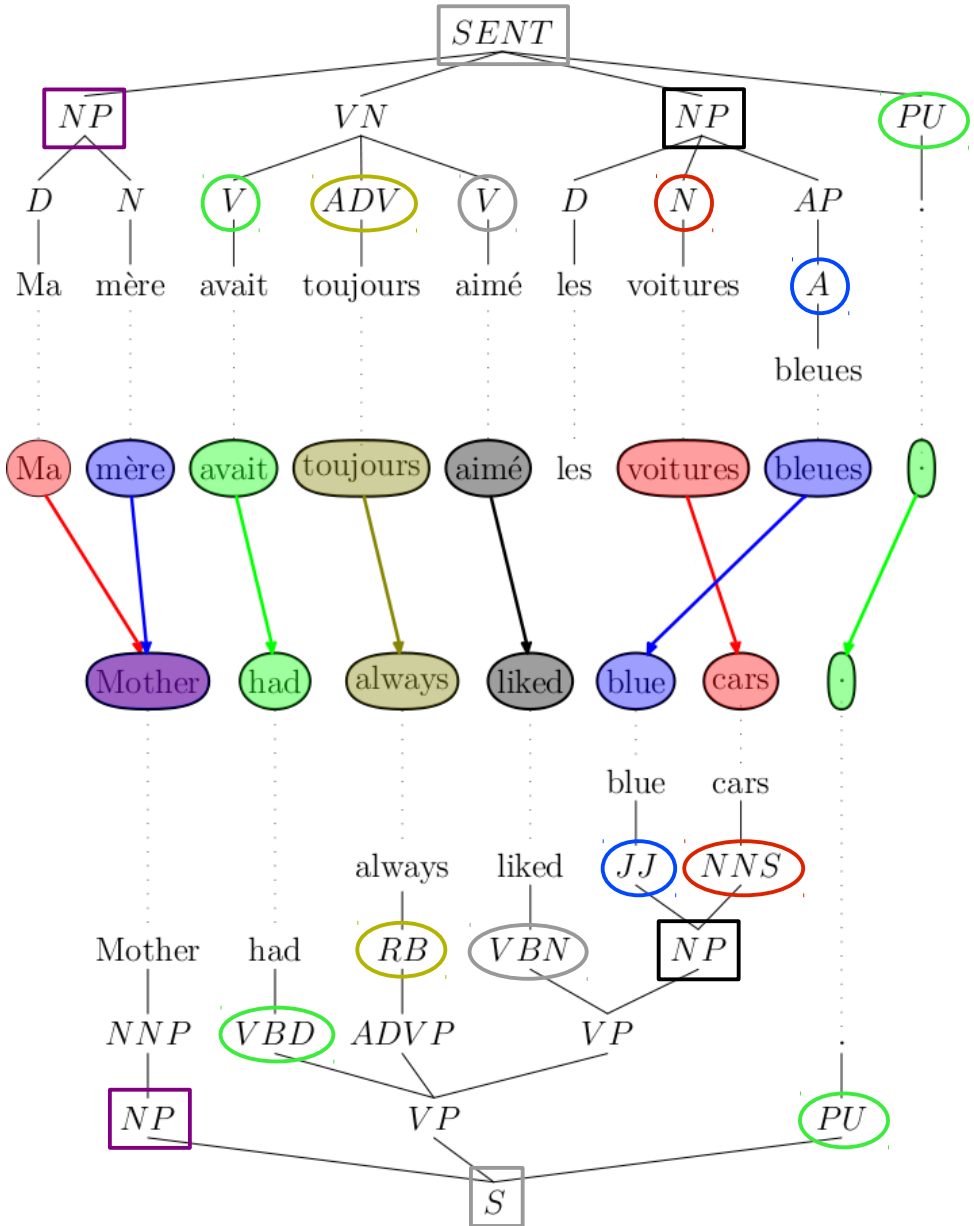
N::NNS → [voitures]::[cars]

A::JJ → [bleues]::[blue]

PU::PU → [.]::[.]

[Lavie et al. 2008]

Baseline Extraction Method



NP::NP → [Ma mère]::
[Mother]

NP::NP → [les voitures bleues]::
[blue cars]

NP::NP → [les N^1 A^2]::
[JJ^2 NNS^1]

SENT::S →
[NP^1 V^2 ADV^3 V^4 NP^5 PU^6]::
[NP^1 VBD^2 RB^3 VBN^4 NP^5 PU^6]

[Lavie et al. 2008]