Algorithms for NLP

Machine Translation III

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Phrase-Based Translation Overview

Input:	lo haré | rápidamente | .	
Translations:	I'll do it | quickly | .	
	quickly | I'll do it | .	

The decoder...

tries different segmentations,

translates phrase by phrase,

and considers reorderings.

Objective:

$$\arg\max_{\mathbf{e}} \left[P(\mathbf{f}|\mathbf{e}) \cdot P(\mathbf{e}) \right]$$

$$\arg\max_{\mathbf{e}} \left[\prod_{\langle \bar{e}, \bar{f} \rangle} P(\bar{f}|\bar{e}) \cdot \prod_{i=1}^{|\mathbf{e}|} P(e_i | e_{i-1}, e_{i-2}) \right]$$

Phrase-Based Decoding

这	7人	中包括	来自	法国	和	俄罗斯	的	宇航	员	.
the	7 people	including	by some		**and**	the russian	**the**	the astronauts		,
it	7 people included		by france		and the	the russian		international astronautical	of rapporteur .	
this	7 out	including the	**from**	the french	and the russian		the fifth		.	
these	7 among	including from		the french and		of the russian	of	space	members	.
that	7 persons	including from the		of france	and to	russian	of the	aerospace	members .	
	7 include		from the	of france and		russian		**astronauts**		. the
	7 numbers include		**from france**		and russian		of astronauts who			. "
	7 populations include		those from france		and russian			astronauts .		
	7 deportees included		come from	**france**	**and russia**		in	astronautical	personnel	;
	7 philtrum	including those from		**france and**		**russia**	a space		**member**	
		including representatives from		france and the		**russia**		astronaut		
		include	came from	**france and russia**			by cosmonauts			
		include representatives from		french	**and russia**			cosmonauts		
		include	came from france		and russia 's			cosmonauts .		
		includes	coming from	french and		russia 's		cosmonaut		
				french and russian			's	astronavigation	member .	
				french	**and russia**		**astronauts**			
					and russia 's				special rapporteur	
					, and	**russia**			rapporteur	
					, and russia				rapporteur .	
					, and russia					
					or	russia 's				

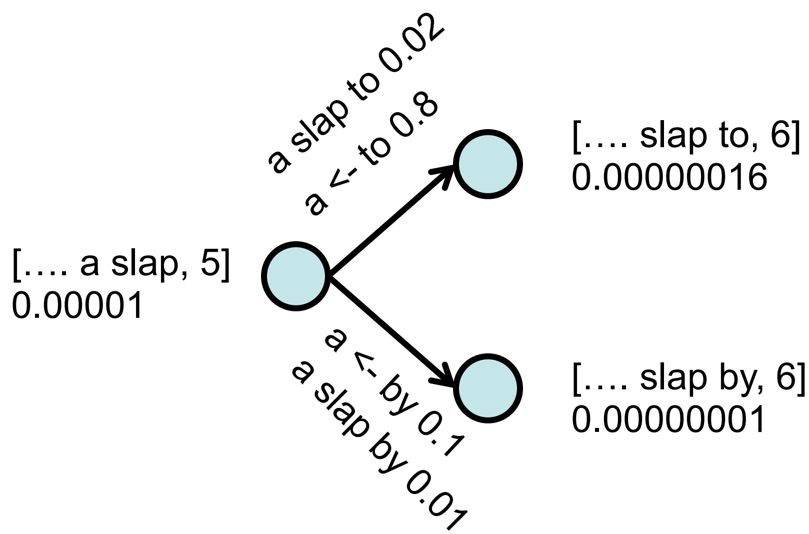
Decoder design is important: [Koehn et al. 03]

Phrase-Based Decoding

Monotonic Word Translation

Maria	no	dio	una	bofetada	a	la	bruja	verde
Mary	not	give	a	slap	to	the	witch	green
	did not				by			
	no							

- Cost is LM * TM
- It's an HMM?
  - $P(e|e_{-1},e_{-2})$
  - $P(f|e)$
- State includes
  - Exposed English
  - Position in foreign
- Dynamic program loop?



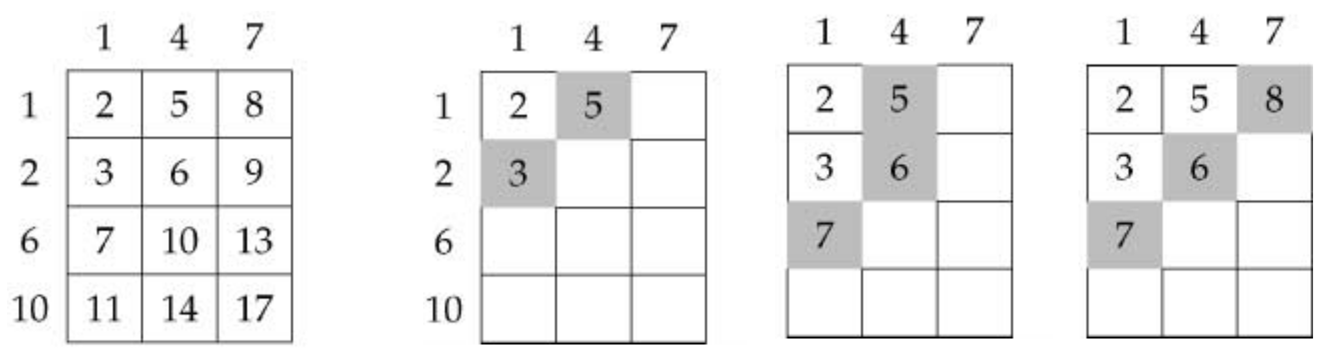

```
for (fPosition in 1…|f|)
  for (eContext in allEContexts)
    for (eOption in translations[fPosition])
      score = scores[fPosition-1][eContext] * LM(eContext+eOption) * TM(eOption, fWord[fPosition])
      scores[fPosition][eContext[2]+eOption] =max  score
```

Beam Decoding

- For real MT models, this kind of dynamic program is a disaster (why?)
- Standard solution is beam search: for each position, keep track of only the best k hypotheses

```
for (fPosition in 1…|f|)
  for (eContext in bestEContexts[fPosition])
    for (eOption in translations[fPosition])
      score = scores[fPosition-1][eContext] * LM(eContext+eOption) * TM(eOption, fWord[fPosition])
      bestEContexts.maybeAdd(eContext[2]+eOption, score)
```

- Still pretty slow… why?
- Useful trick: cube pruning (Chiang 2005)



Example from David Chiang

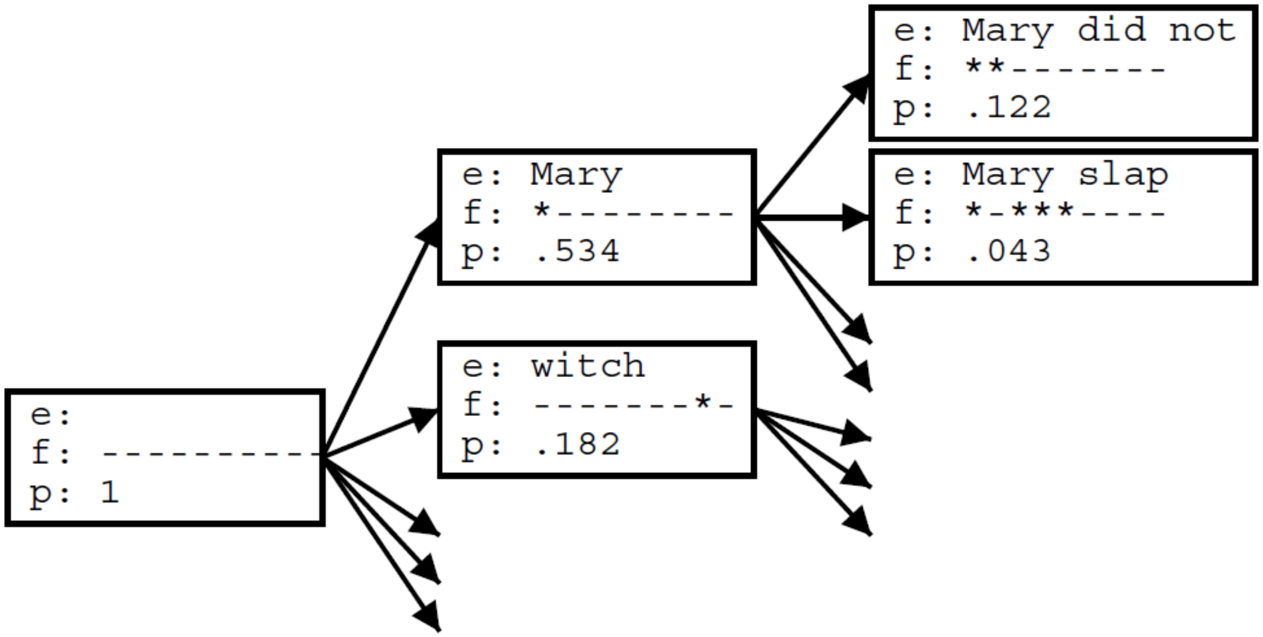
Phrase Translation

- If monotonic, almost an HMM; technically a semi-HMM

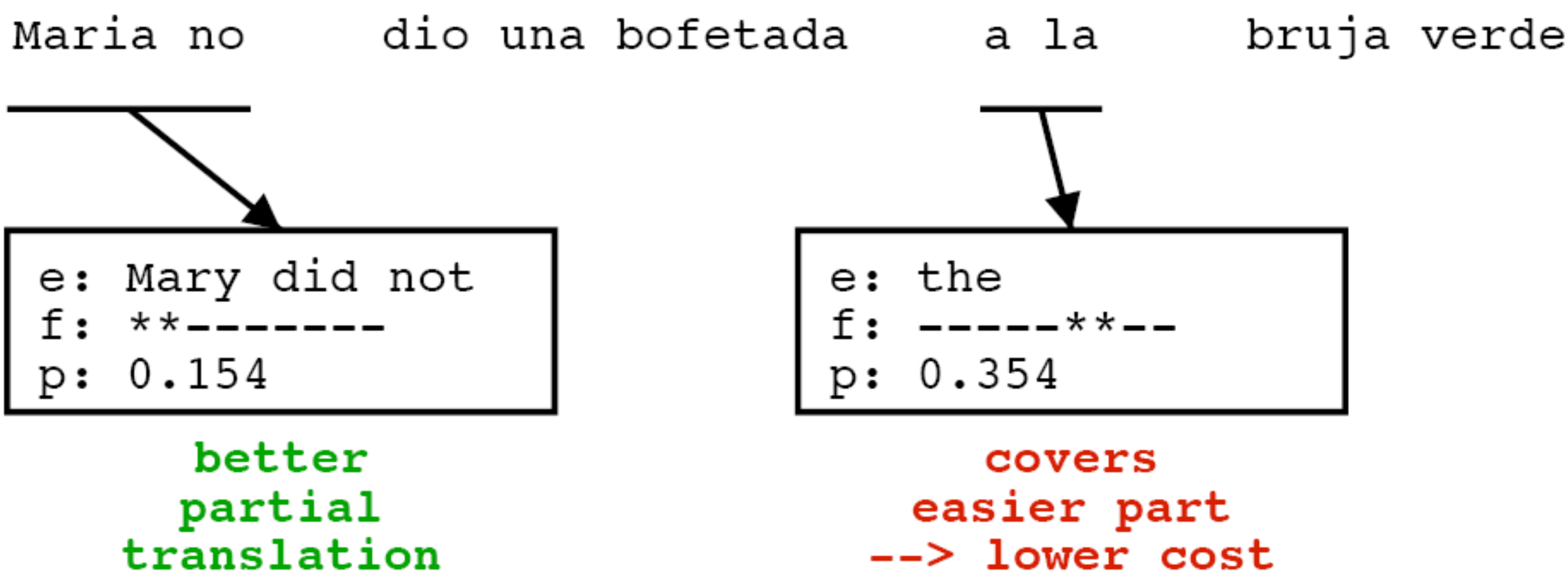
```
for (fPosition in 1…|f|)
  for (lastPosition < fPosition)
    for (eContext in eContexts)
      for (eOption in translations[fPosition])
         … combine hypothesis for (lastPosition ending in eContext) with eOption
```

- If distortion… now what?

Non-Monotonic Phrasal MT



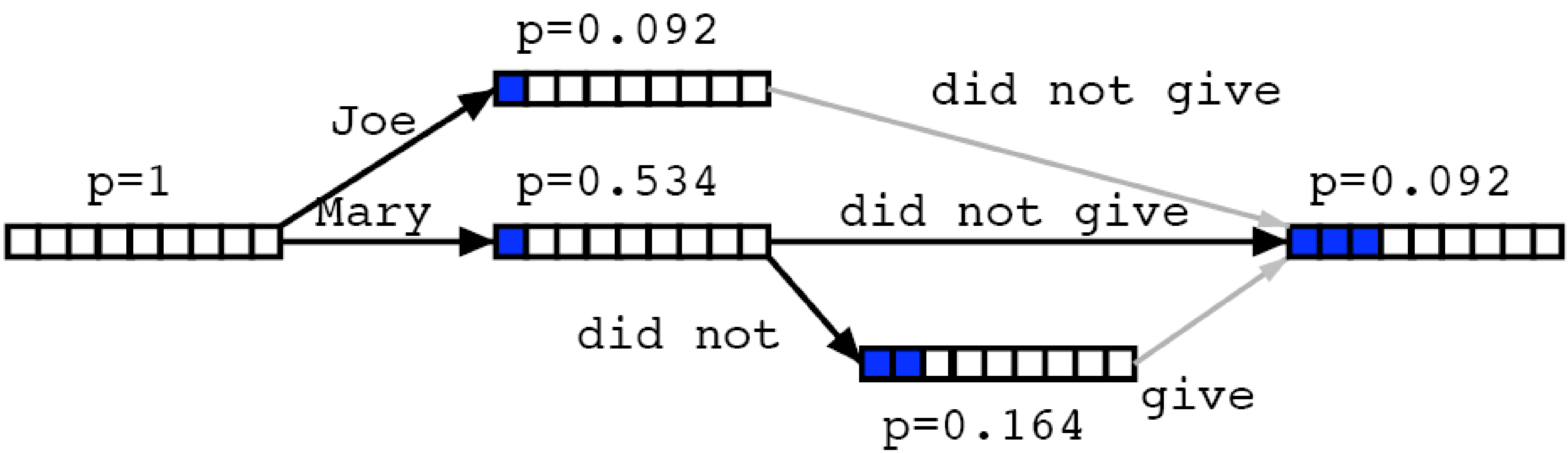
Pruning: Beams + Forward Costs



- Problem: easy partial analyses are cheaper
  - Solution 1: use beams per foreign subset
  - Solution 2: estimate forward costs (A*-like)

The Pharaoh Decoder

Hypotheis Lattices



Parameter Tuning

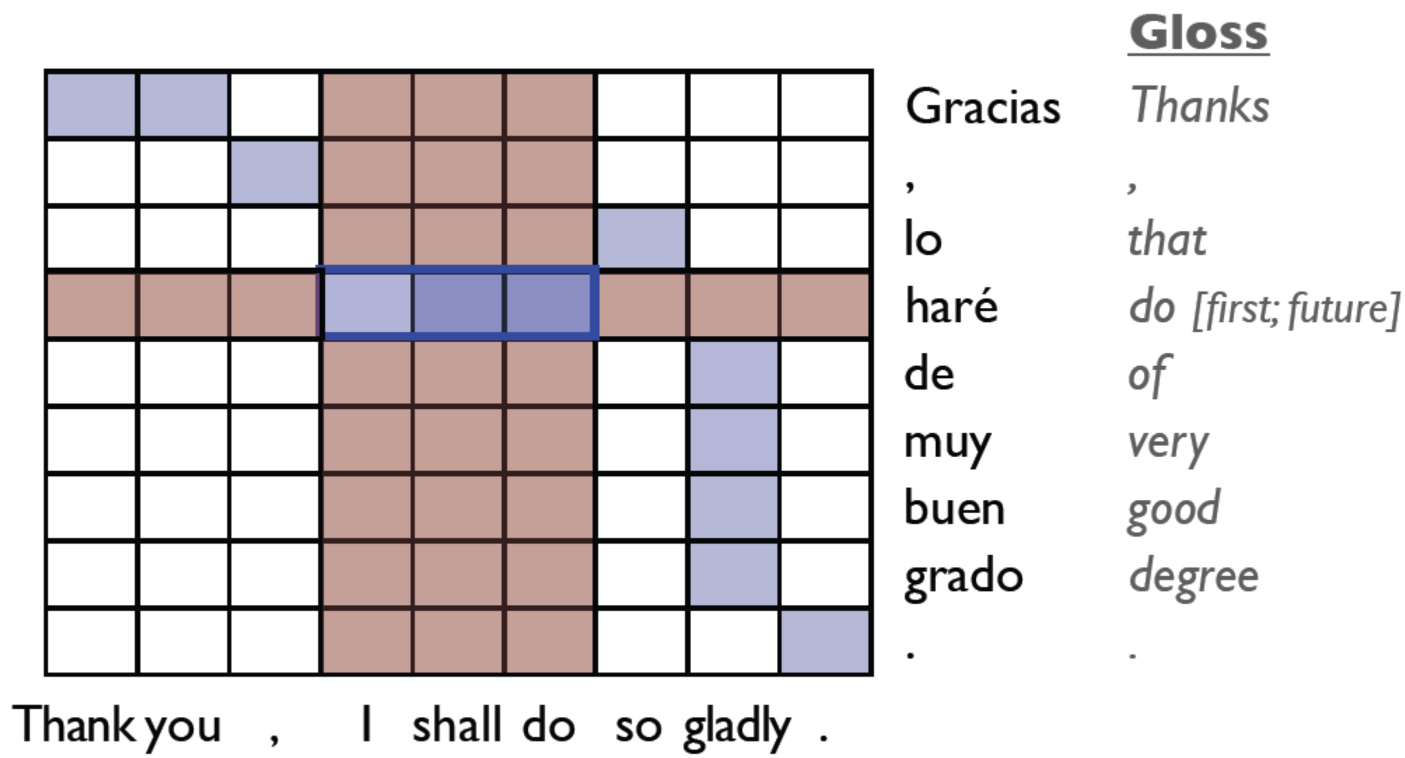
Counting Phrase Pairs

Input:

Gracias , lo haré de muy buen grado .
Thank you , I shall do so gladly .

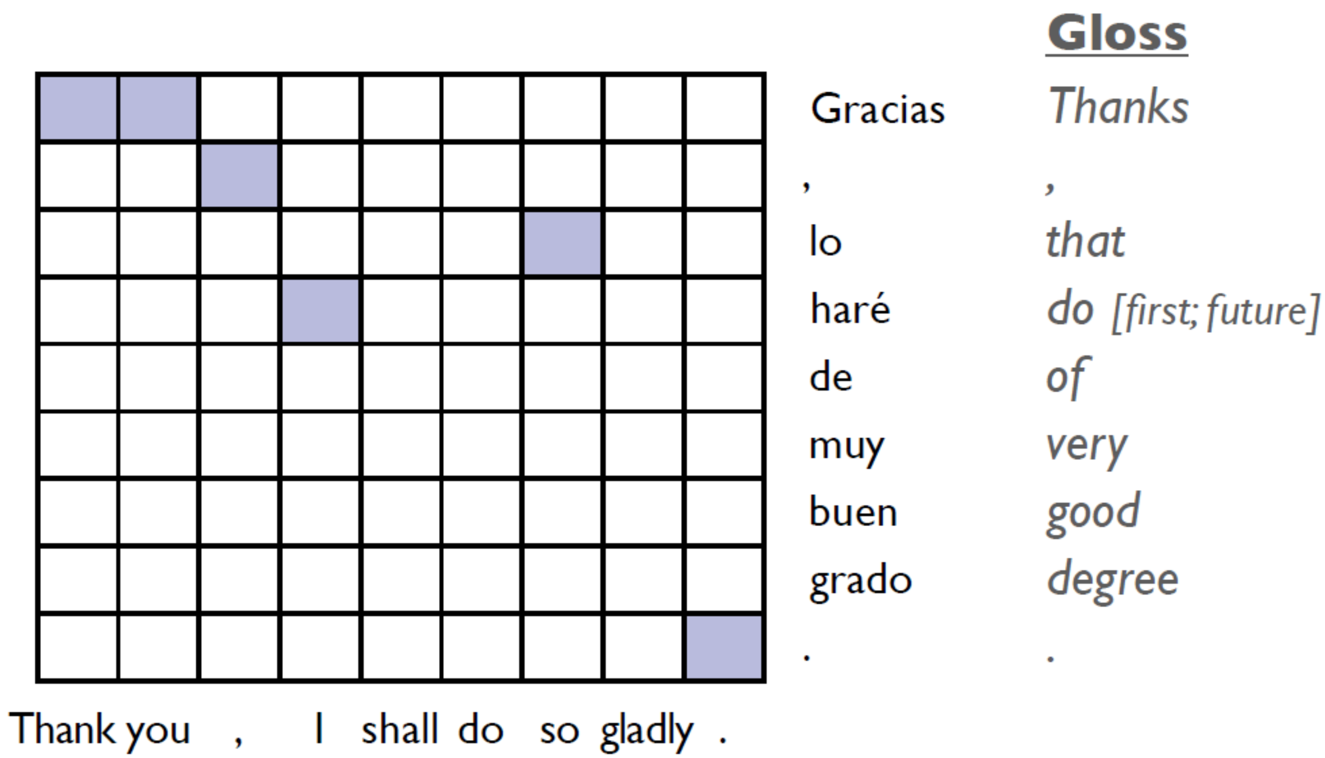
First, we learn word alignments,

then we infer aligned phrases.



What Happens in Practice

A real word alignment
(GIZA++ Model 4 with
grow-diag-final combination)



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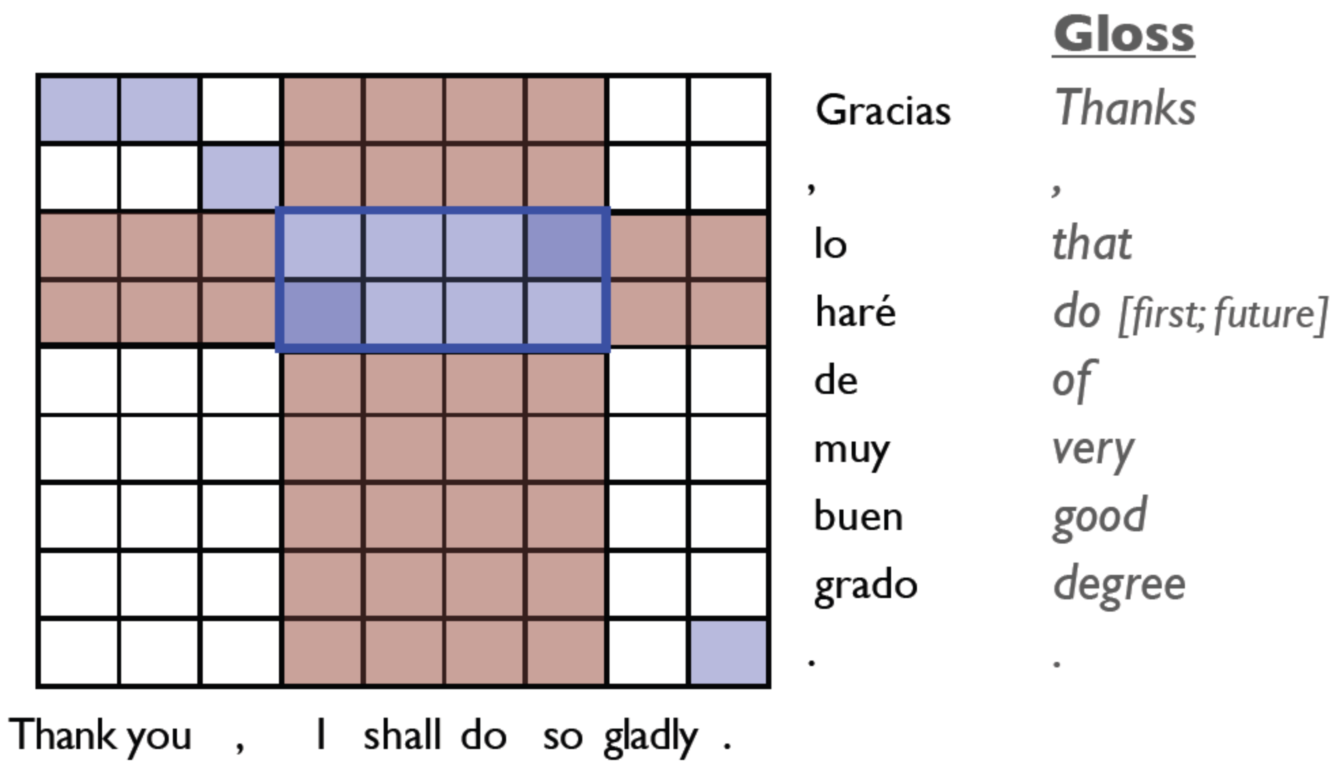

What Happens in Practice

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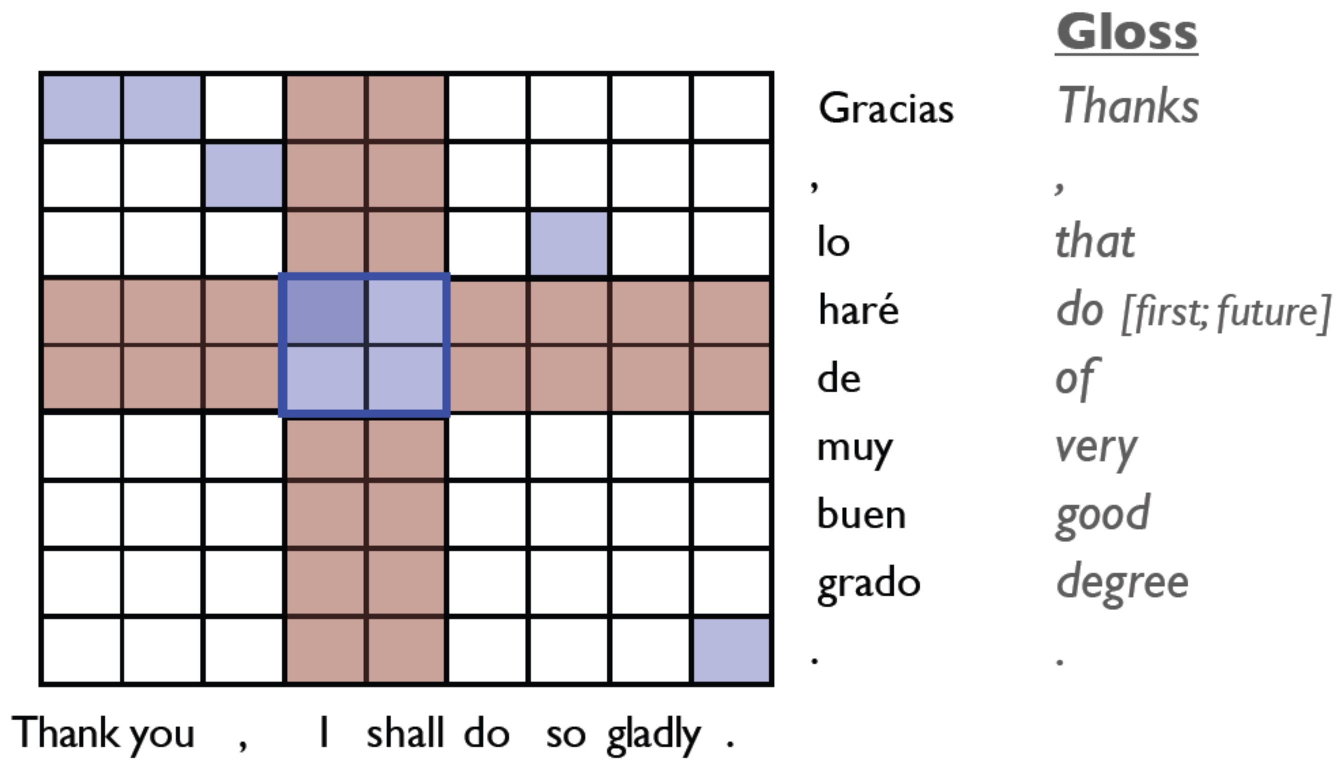
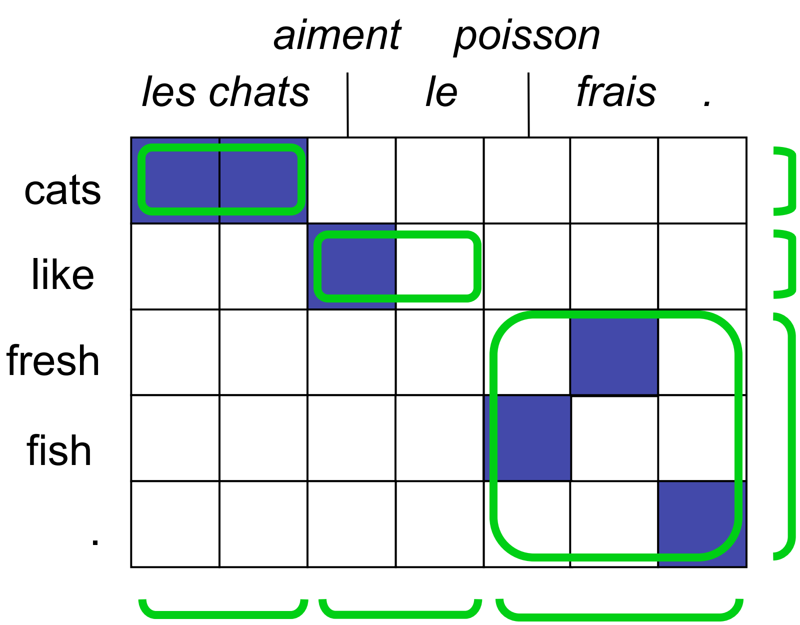


Phrase Scoring

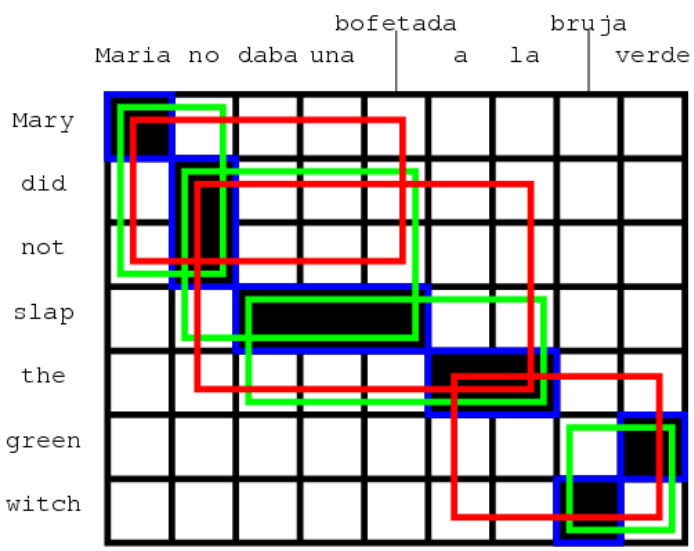
$$\phi_{new}(\bar{e}_j|\bar{f}_i) = \frac{c(\bar{f}_i, \bar{e}_j)}{c(\bar{f}_i)}$$

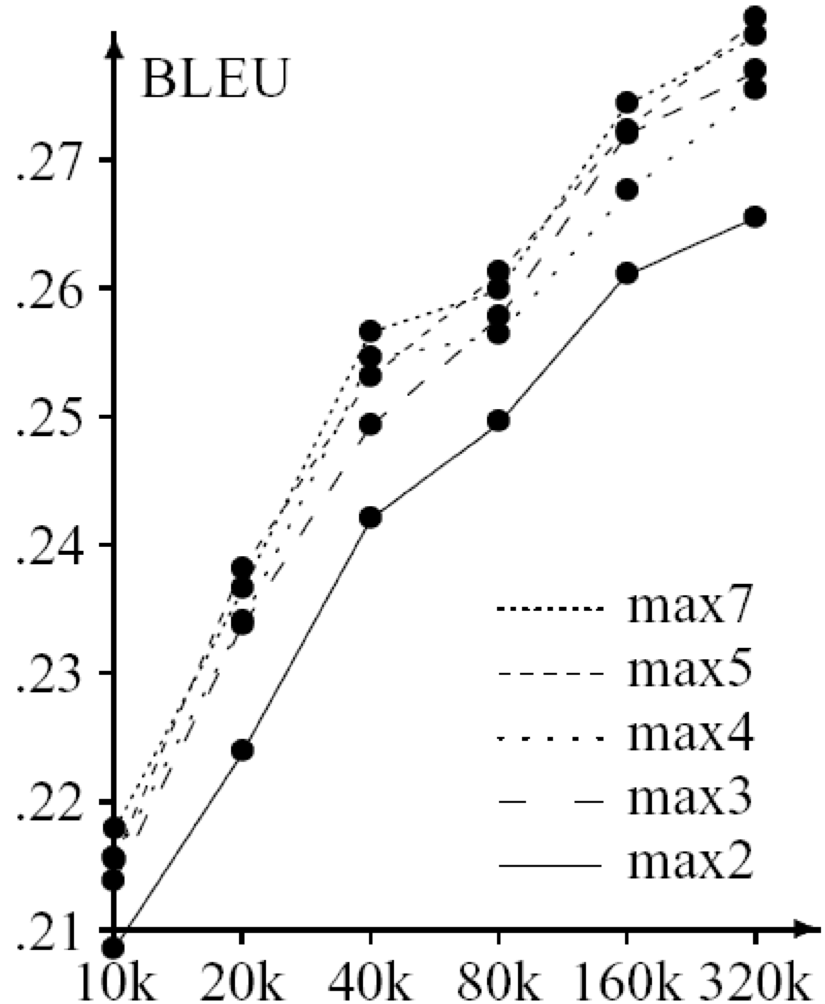


- Learning weights has been tried, several times:
  - [Marcu and Wong, 02]
  - [DeNero et al, 06]
  - … and others
- Seems not to work well, for a variety of partially understood reasons
- Main issue: big chunks get all the weight, obvious priors don't help
  - Though, [DeNero et al 08]

Phrase Size

- Phrases do help
  - But they don't need to be long
  - Why should this be?



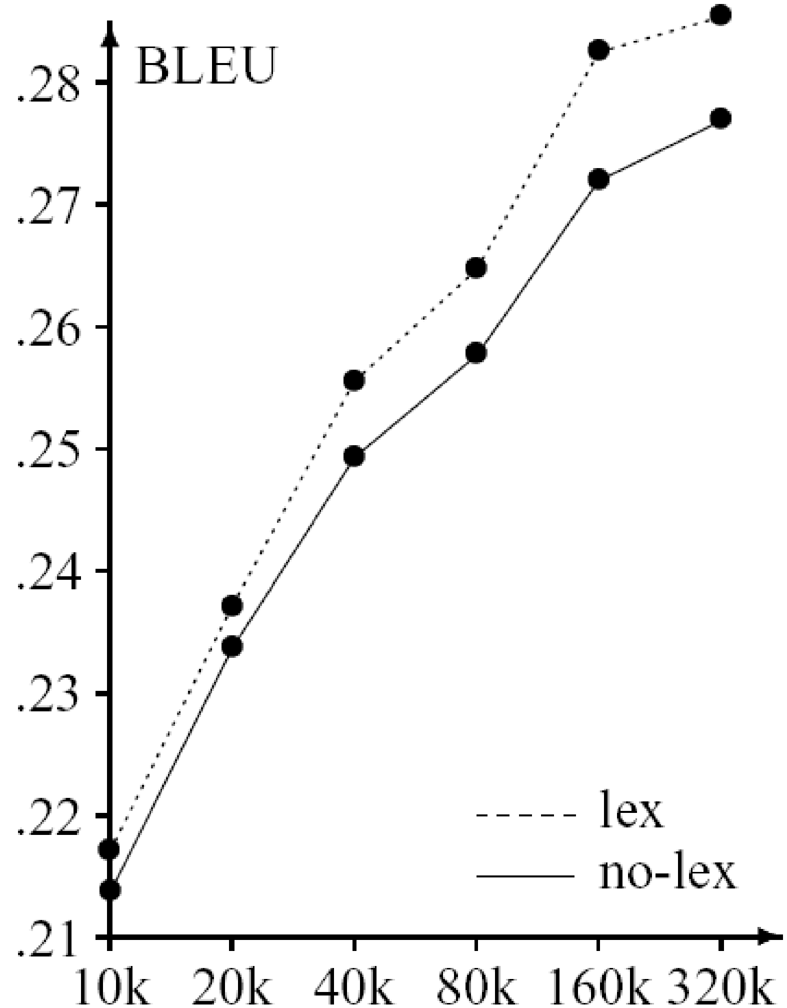


Lexical Weighting

$$\phi(\bar{f}_i|\bar{e}_i) = \frac{count(\bar{f}_i, \bar{e}_i)}{count(\bar{e}_i)} p_w(\bar{f}_i|\bar{e}_i)$$

```
      f1 f2 f3
NULL  -- -- ##
  e1  ## -- --
  e2  -- ## --
  e3  -- ## --
```

$$\begin{aligned} p_w(\bar{f}|\bar{e}, a) &= p_w(f_1 f_2 f_3 | e_1 e_2 e_3, a) \\ &= w(f_1|e_1) \\ &\quad \times \frac{1}{2}(w(f_2|e_2) + w(f_2|e_3)) \\ &\quad \times w(f_3|\text{NULL}) \end{aligned}$$

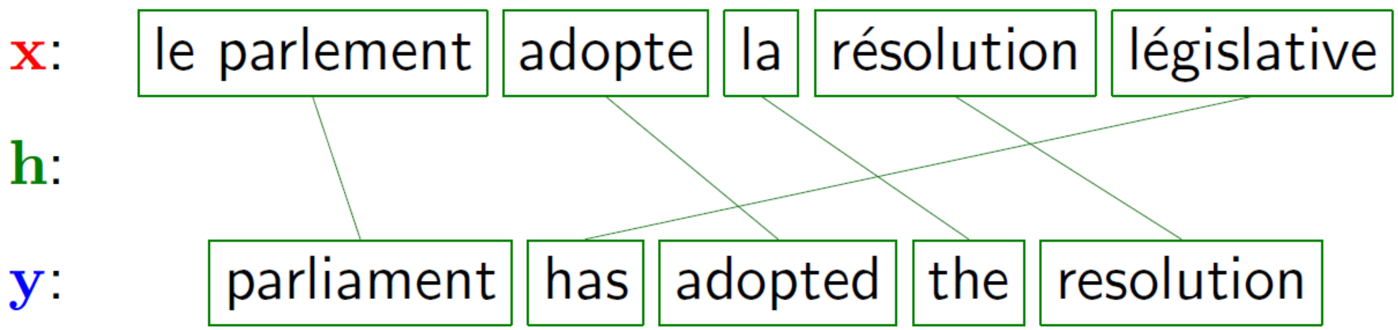


Tuning for MT

- Features encapsulate lots of information
  - Basic MT systems have around 6 features
  - P(e|f), P(f|e), lexical weighting, language model
- How to tune feature weights?
- Idea 1: Use your favorite classifier

Why Tuning is Hard

- Problem 1: There are latent variables
  - Alignments and segementations
  - Possibility: forced decoding (but it can go badly)

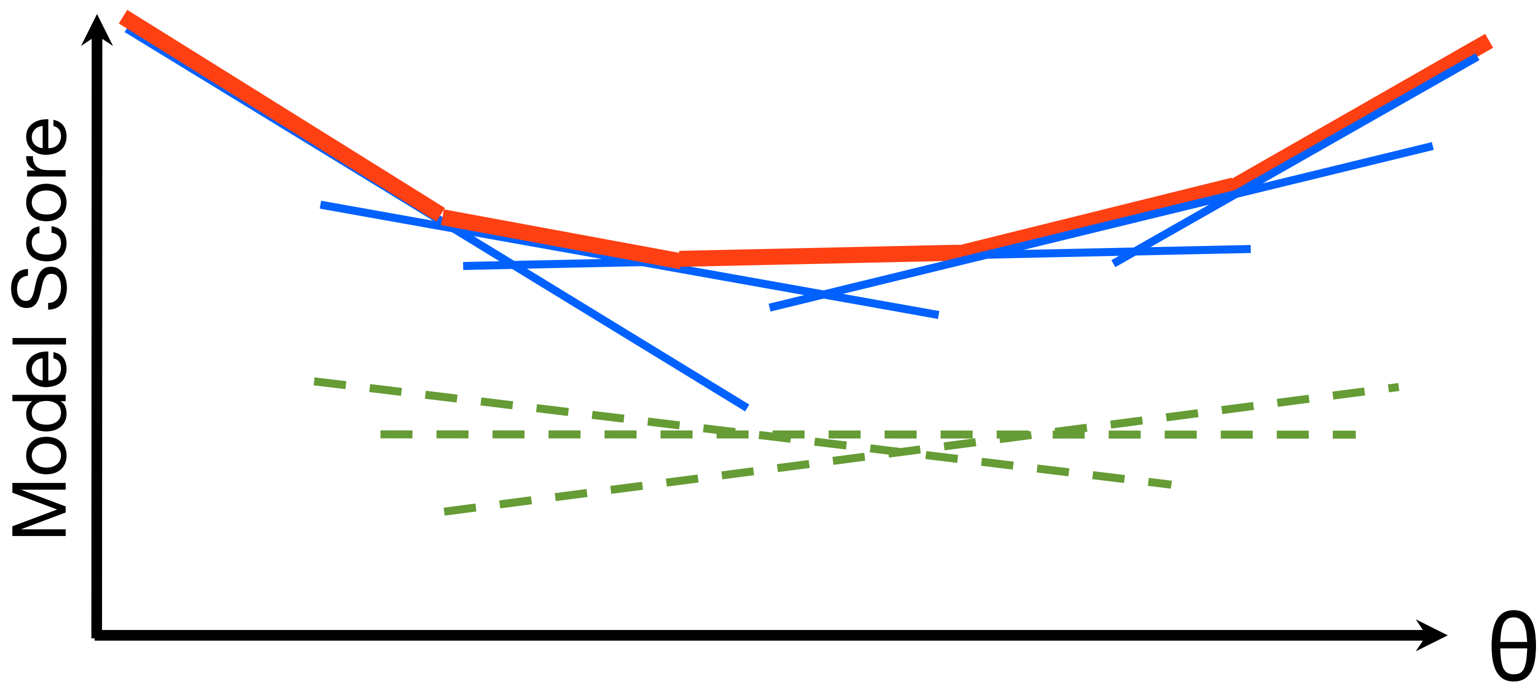


Why Tuning is Hard

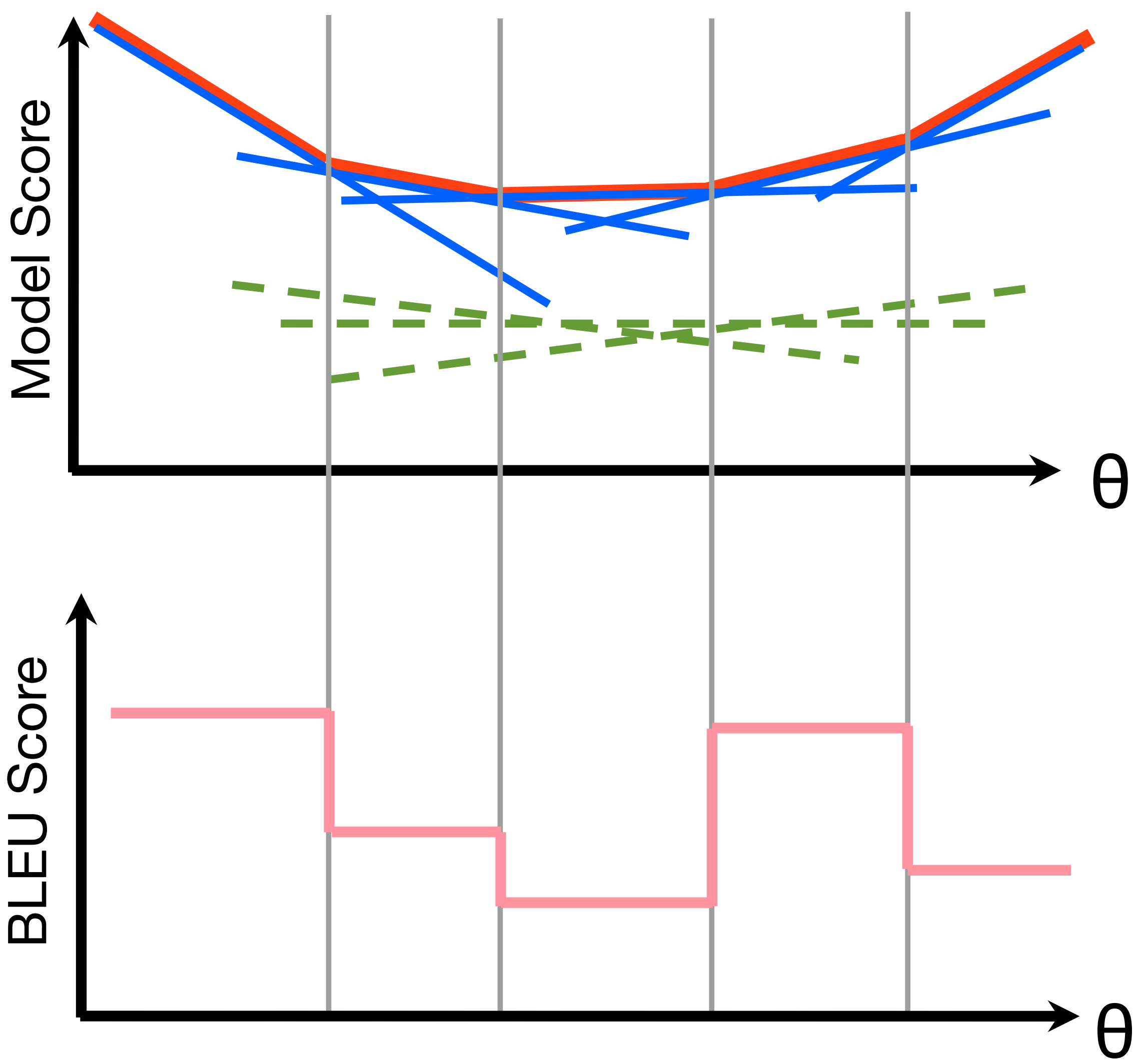
- Problem 3: Computational constraints
  - Discriminative training involves repeated decoding
  - Very slow! So people tune on sets much smaller than those used to build phrase tables

Minimum Error Rate Training

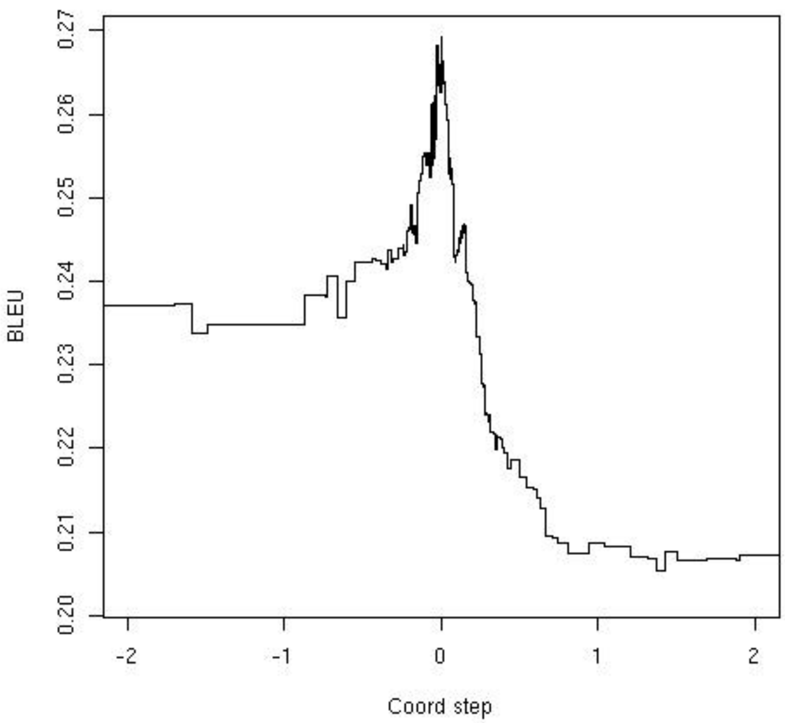
- Standard method: minimize BLEU directly (Och 03)
  - MERT is a discontinuous objective
  - Only works for max ~10 features, but works very well then
  - Here: k-best lists, but forest methods exist (Machery et al 08)
  - Recently, lots of alternatives being explored for more features

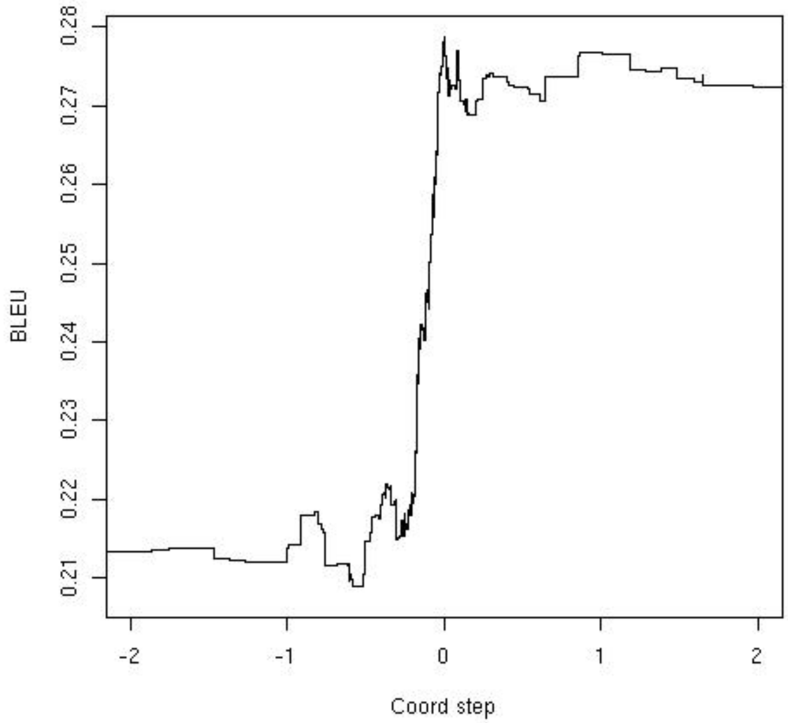


MERT



MERT


BLEU
0.20
0.21
0.22
0.23
0.24
0.25
0.26
0.27
-2
-1
0
1
2
Coord step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0.21
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0.28
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0
1
2
Coord step

Syntactic Models

Translating with Tree Transducers

Input

Output

lo haré de muy buen grado .

Grammar

Translating with Tree Transducers

Input

Output

lo haré de muy buen grado .

Grammar

ADV → ⟨ de muy buen grado ; gladly ⟩

Translating with Tree Transducers

Input

ADV

lo haré de muy buen grado .

Output

ADV

gladly

Grammar

ADV → ⟨ de muy buen grado ; gladly ⟩

Translating with Tree Transducers

Input

ADV

lo haré de muy buen grado .

Output

ADV

gladly

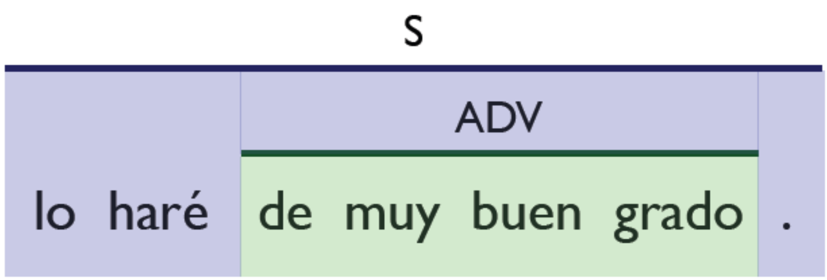
Grammar

S $\rightarrow$ $\langle$ lo haré ADV . ; I will do it ADV . $\rangle$

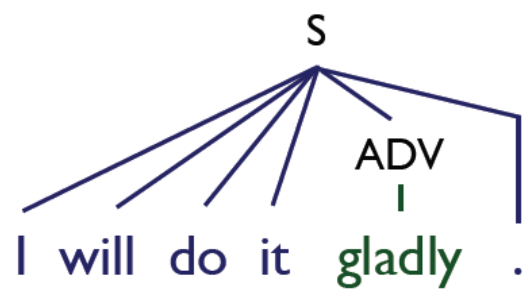
ADV $\rightarrow$ $\langle$ de muy buen grado ; gladly $\rangle$

Translating with Tree Transducers

Input



Output



Grammar

S → ⟨ lo haré ADV . ; I will do it ADV . ⟩

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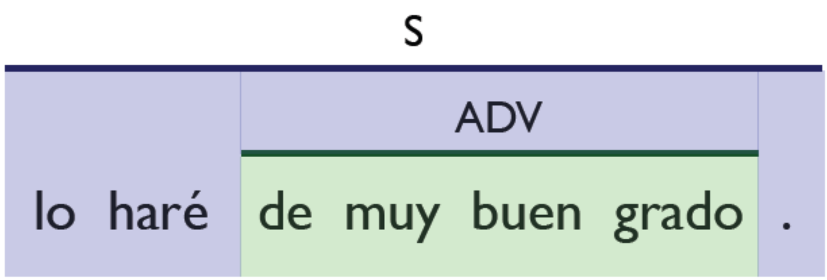
Translating with Tree Transducers

Input



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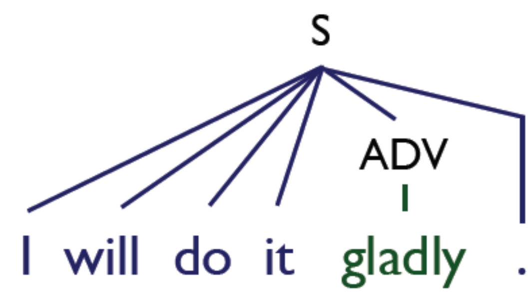
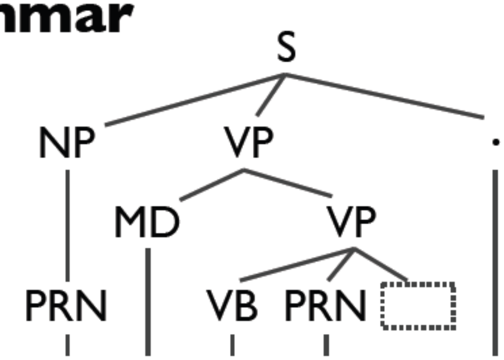


Grammar



S → ⟨ lo haré ADV . ; I will do it ADV . ⟩

ADV → ⟨ de muy buen grado ; gladly ⟩

Translating with Tree Transducers

Input

Output

ADV

lo haré de muy buen grado .

ADV

gladly

Grammar

S → ⟨ lo haré ADV . ; I will do it ADV . ⟩

ADV → ⟨ de muy buen grado ; gladly ⟩

Translating with Tree Transducers

Input

ADV

lo haré de muy buen grado .

Output

ADV

gladly

Grammar

VP → ⟨ lo haré ADV ; will do it ADV ⟩

S → ⟨ lo haré ADV . ; I will do it ADV . ⟩

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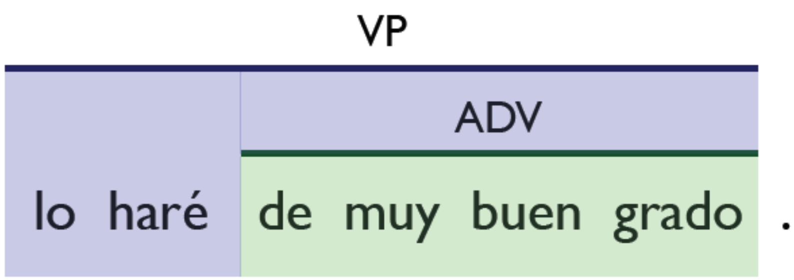
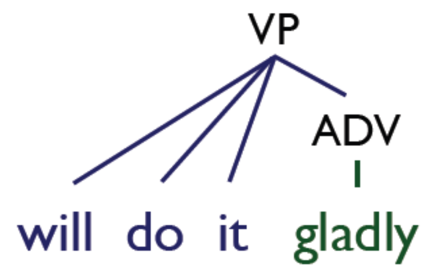
Translating with Tree Transducers

Input



Output



Grammar

VP → ⟨ lo haré ADV ; will do it ADV ⟩

S → ⟨ lo haré ADV . ; I will do it ADV . ⟩

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Translating with Tree Transducers

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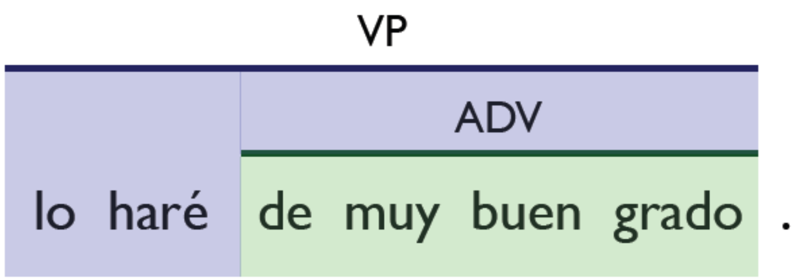

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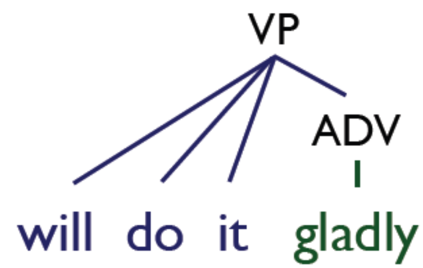

Grammar

S → ⟨ VP . ; I VP . ⟩

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Translating with Tree Transducers

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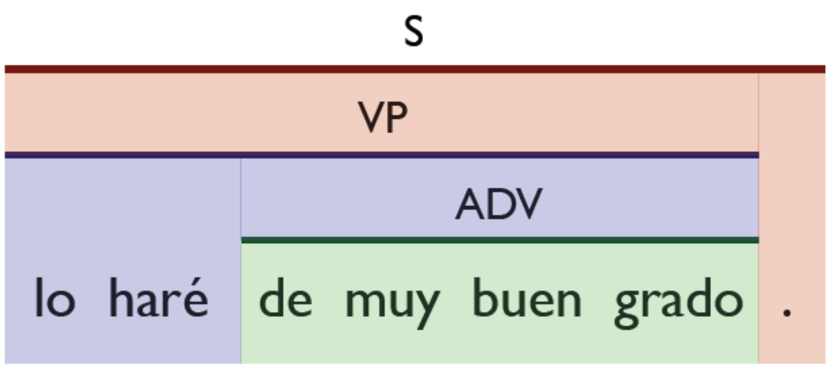

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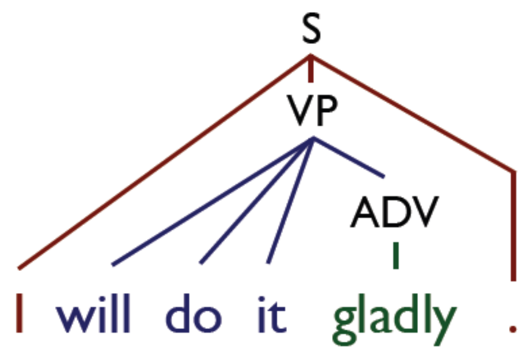

Grammar

S → ⟨ VP . ; I VP . ⟩

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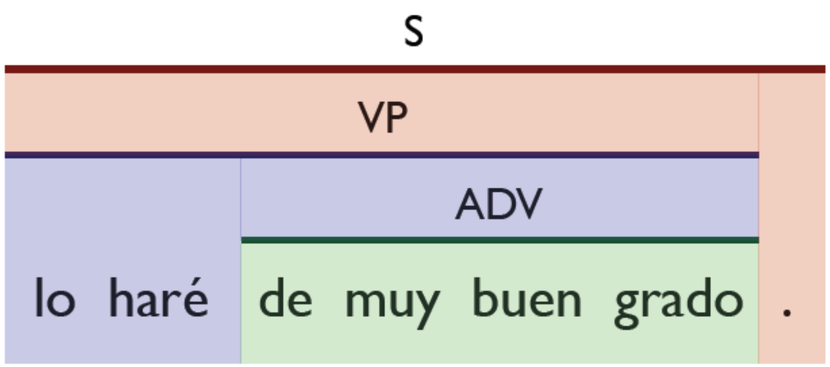

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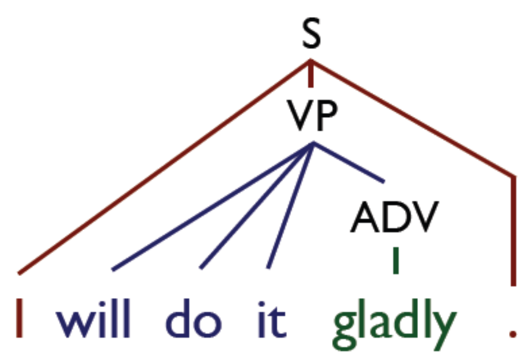


Grammar

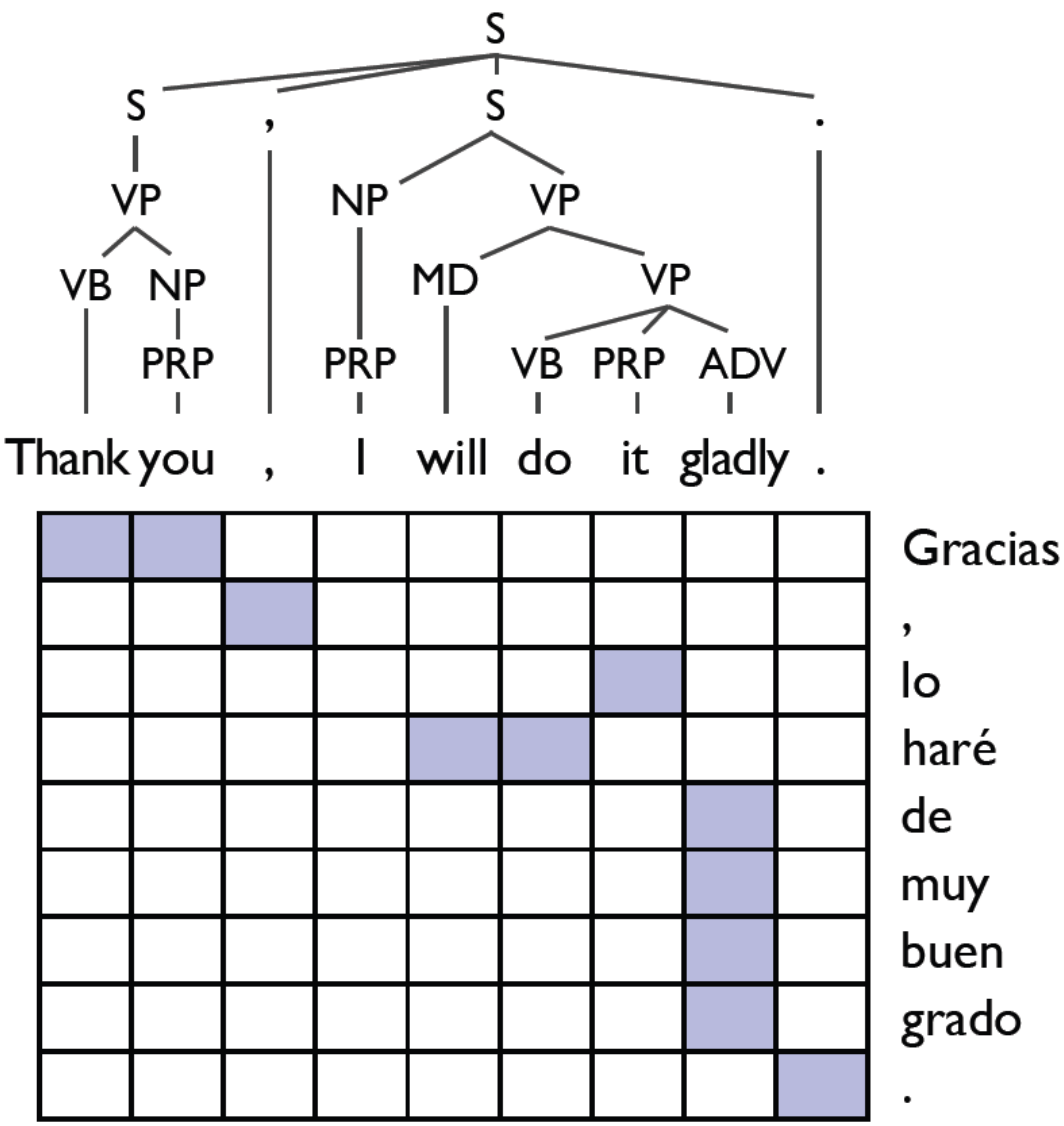
S → ⟨ VP . ; I VP . ⟩ **OR** S → ⟨ VP . ; you VP . ⟩

VP → ⟨ lo haré ADV ; will do it ADV ⟩

S → ⟨ lo haré ADV . ; I will do it ADV . ⟩

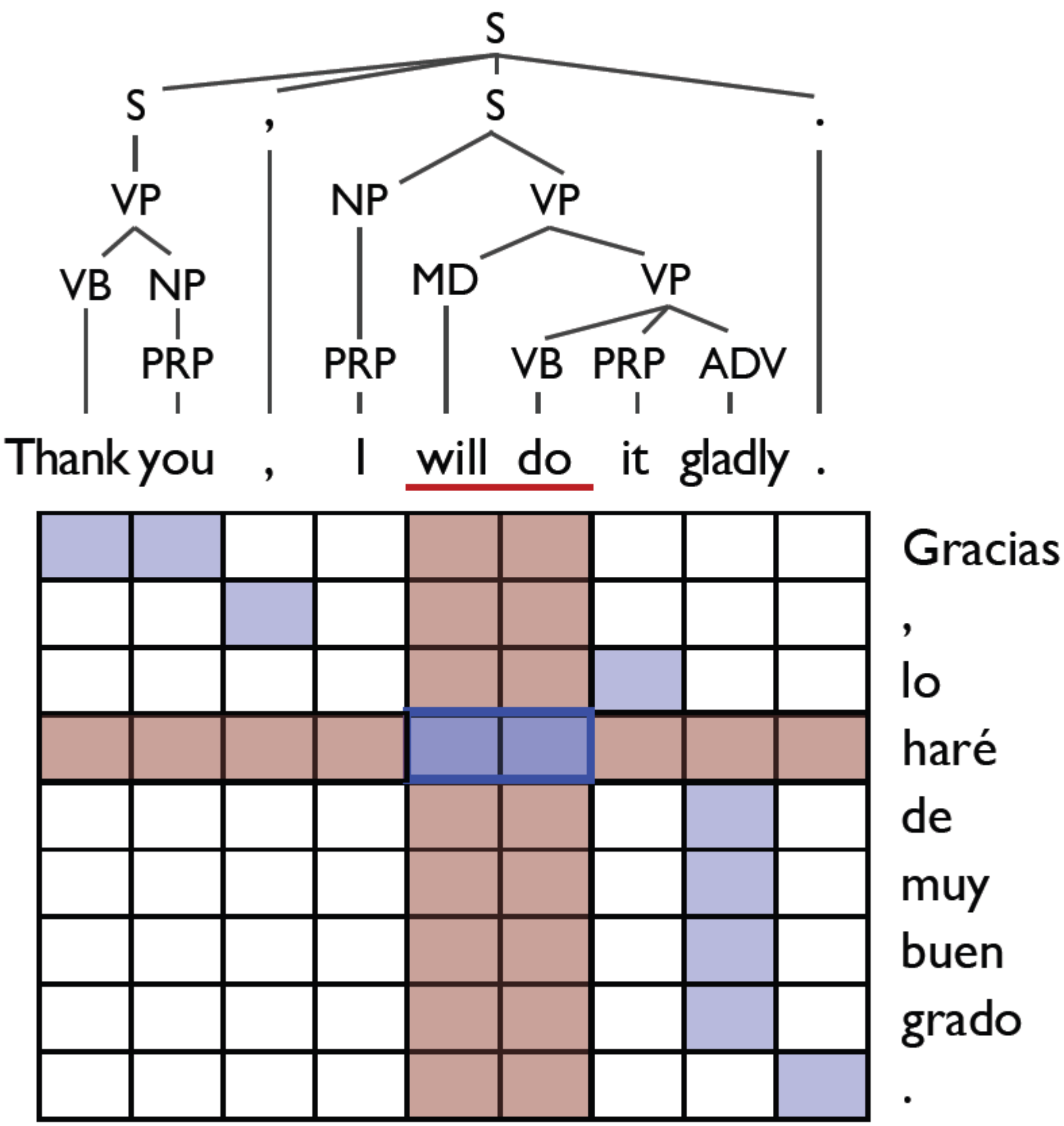
ADV → ⟨ de muy buen grado ; gladly ⟩

Learning Grammars for Translation



Grammar Rules

Learning Grammars for Translation



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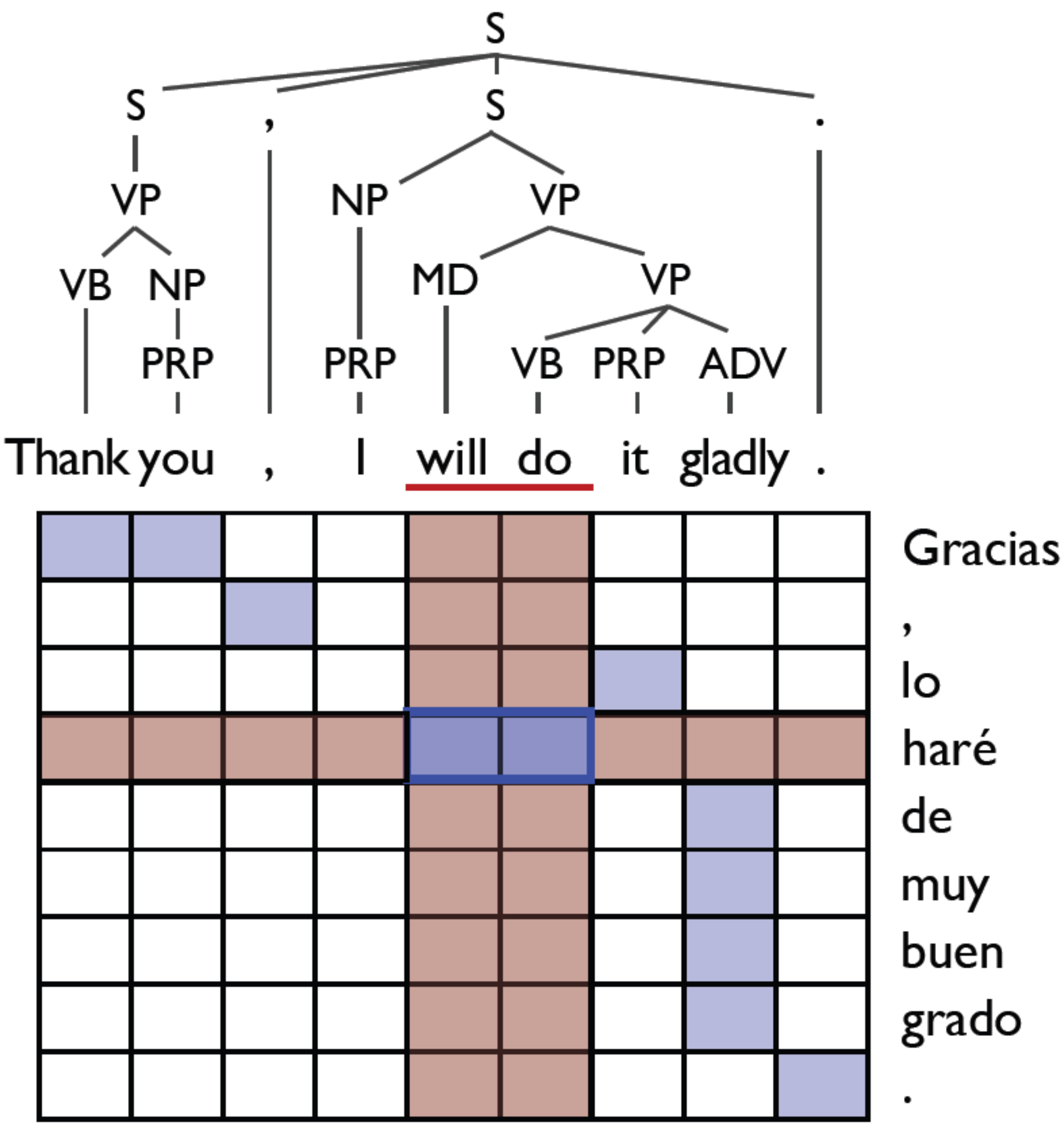

Grammar Rules

⟨haré ; will do⟩

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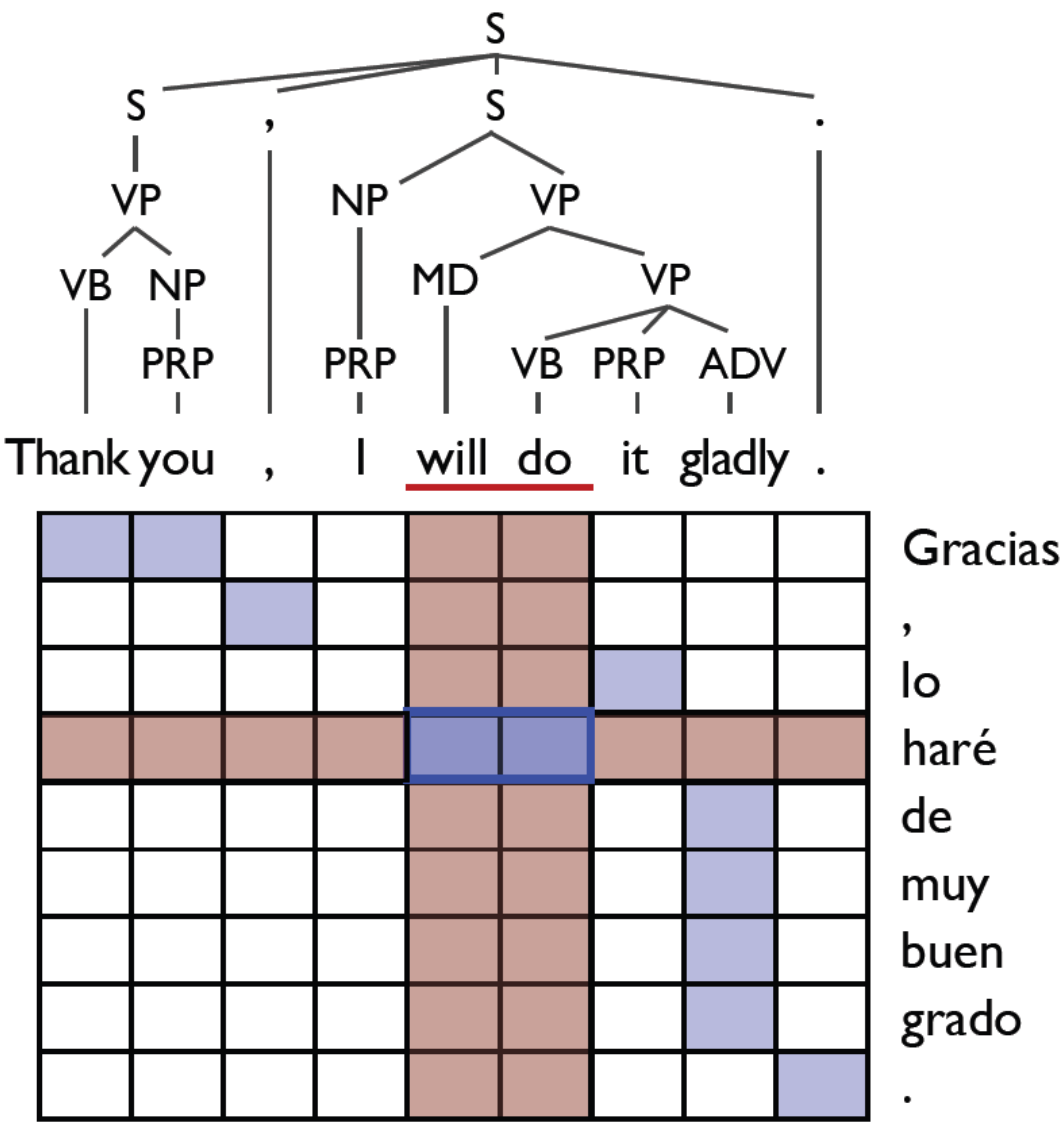

Grammar Rules

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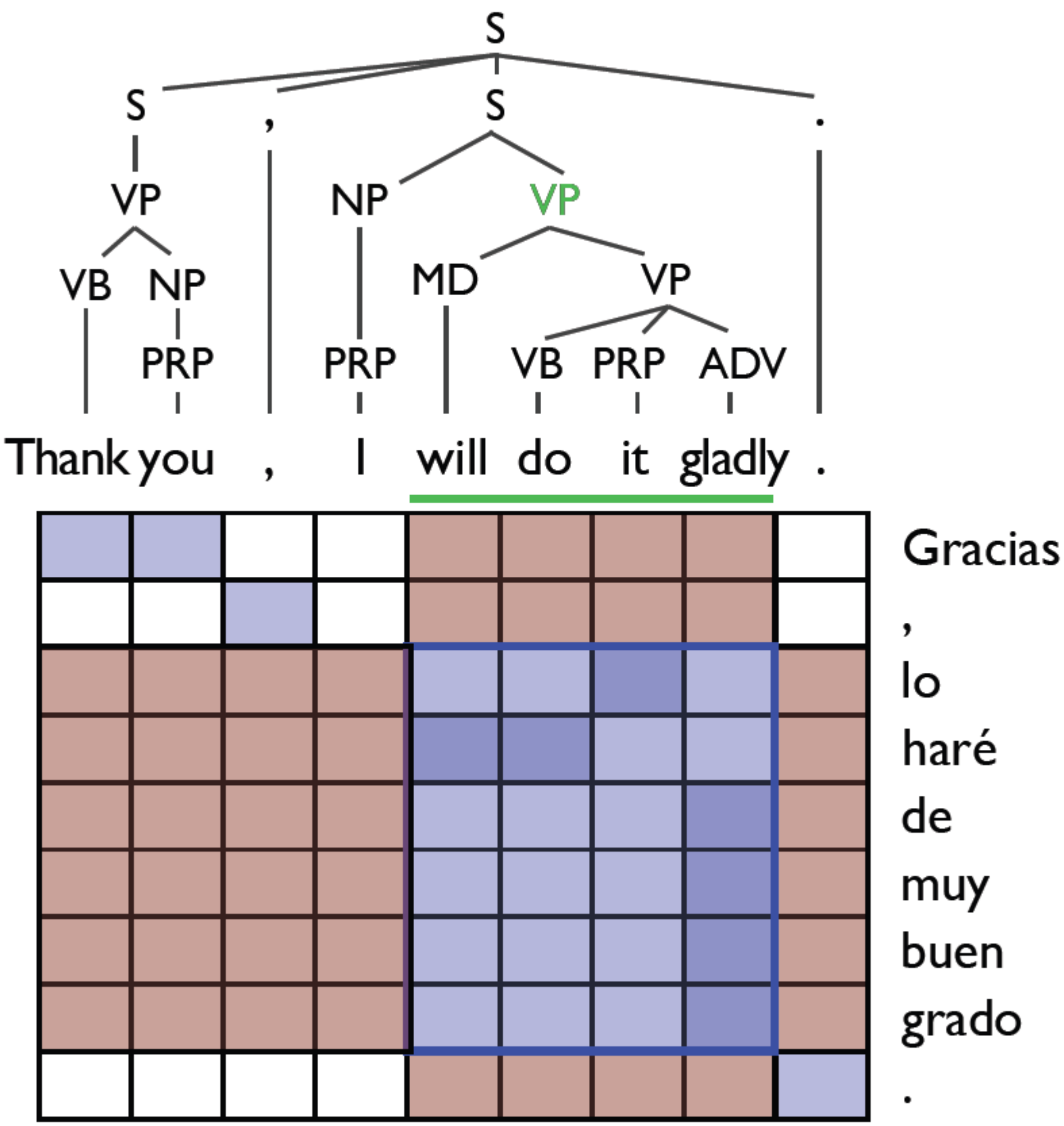

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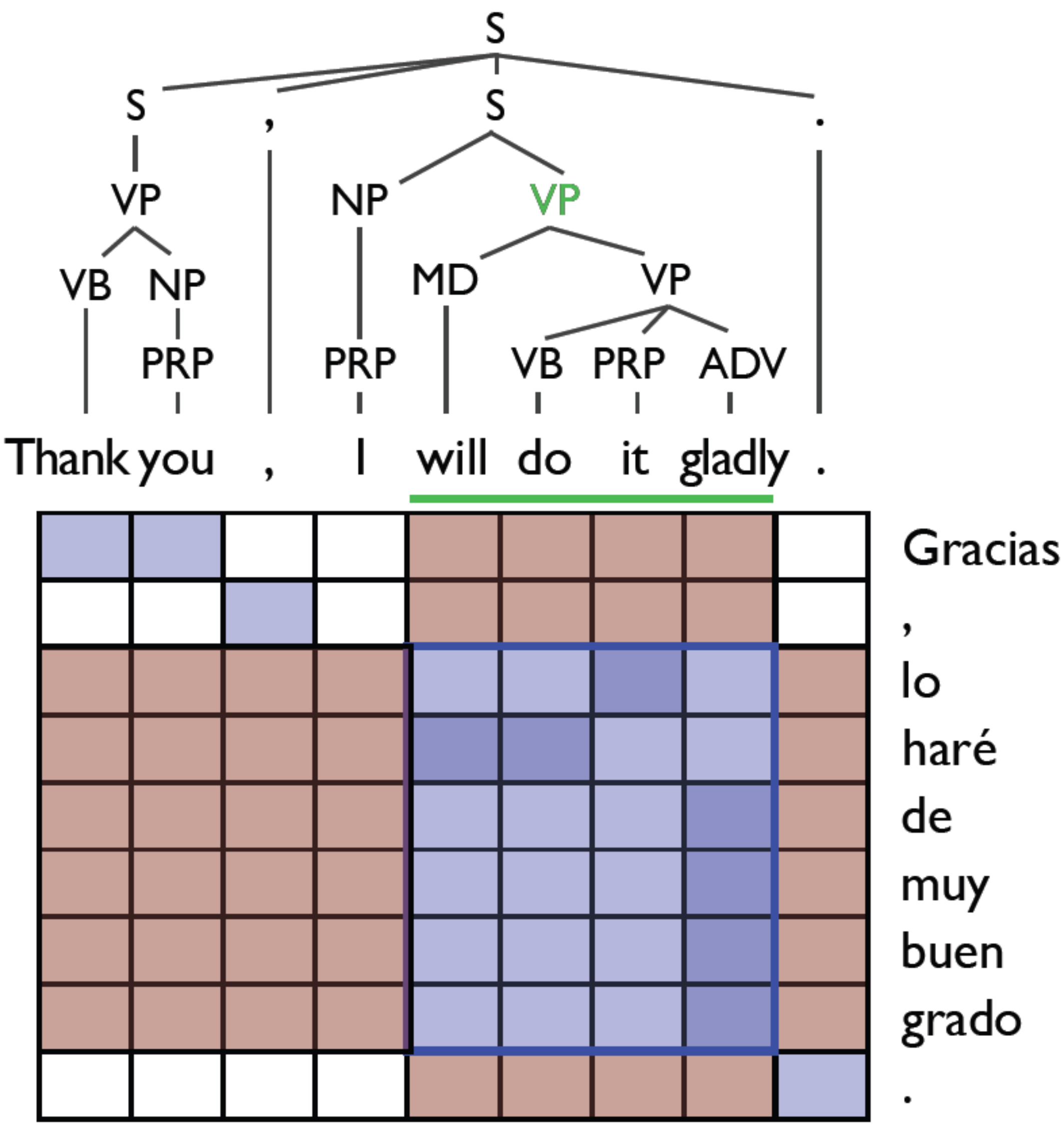


Grammar Rules

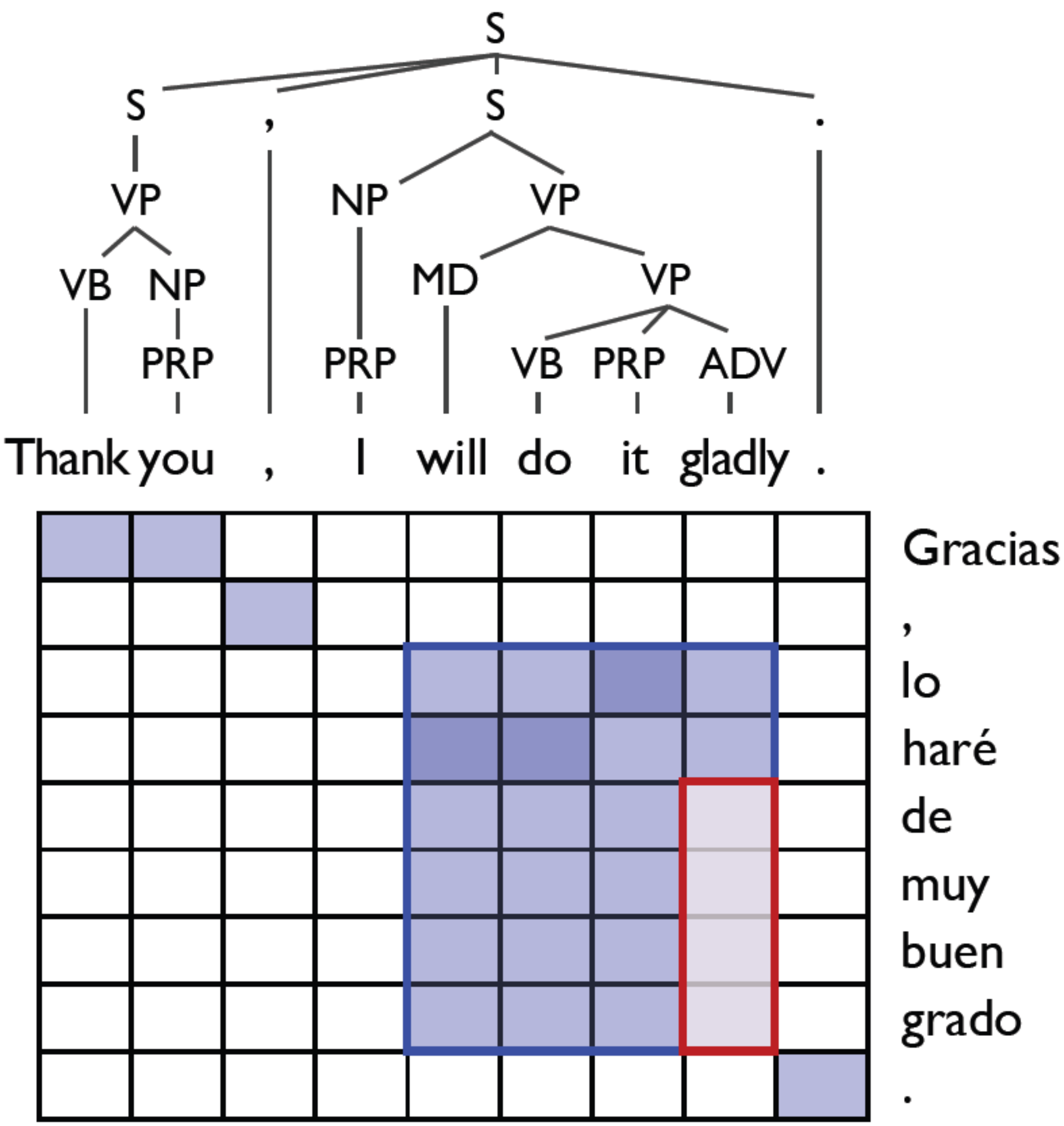
~~⟨haré ; will do⟩~~

VP →

⟨lo haré de ... grado ;

will do it gladly⟩

Learning Grammars for Translation



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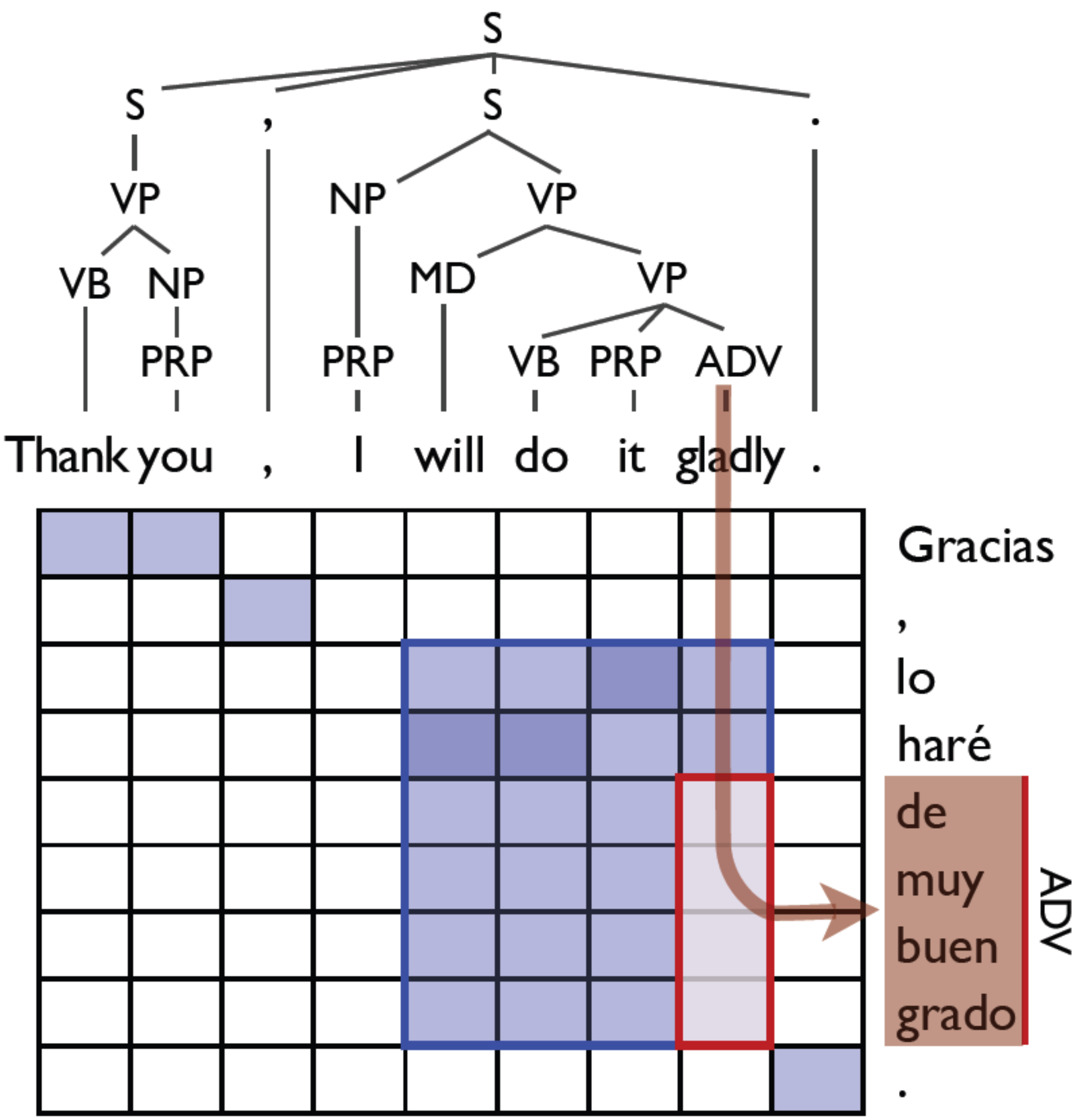
Learning Grammars for Translation



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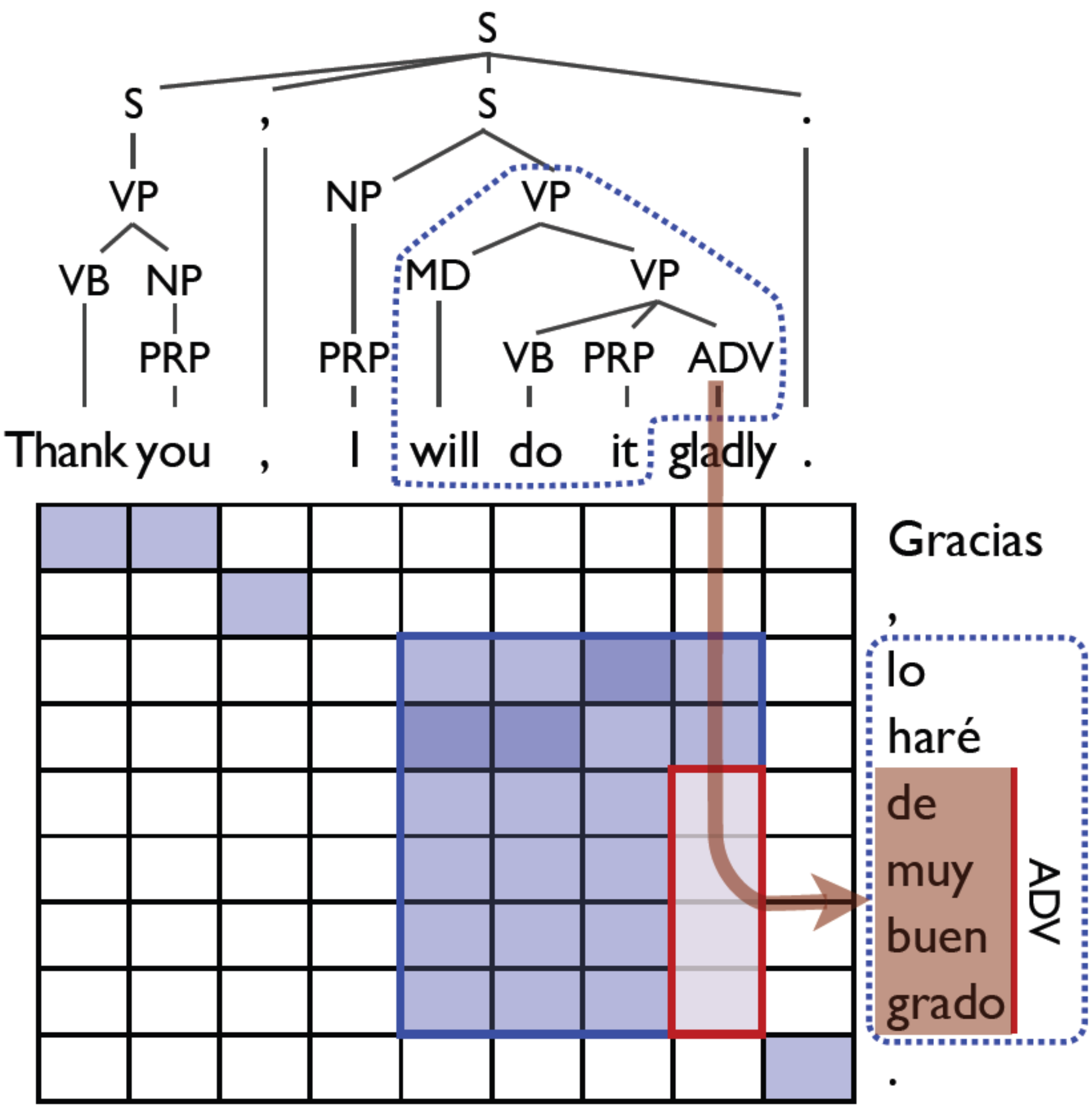
Learning Grammars for Translation



Grammar Rules

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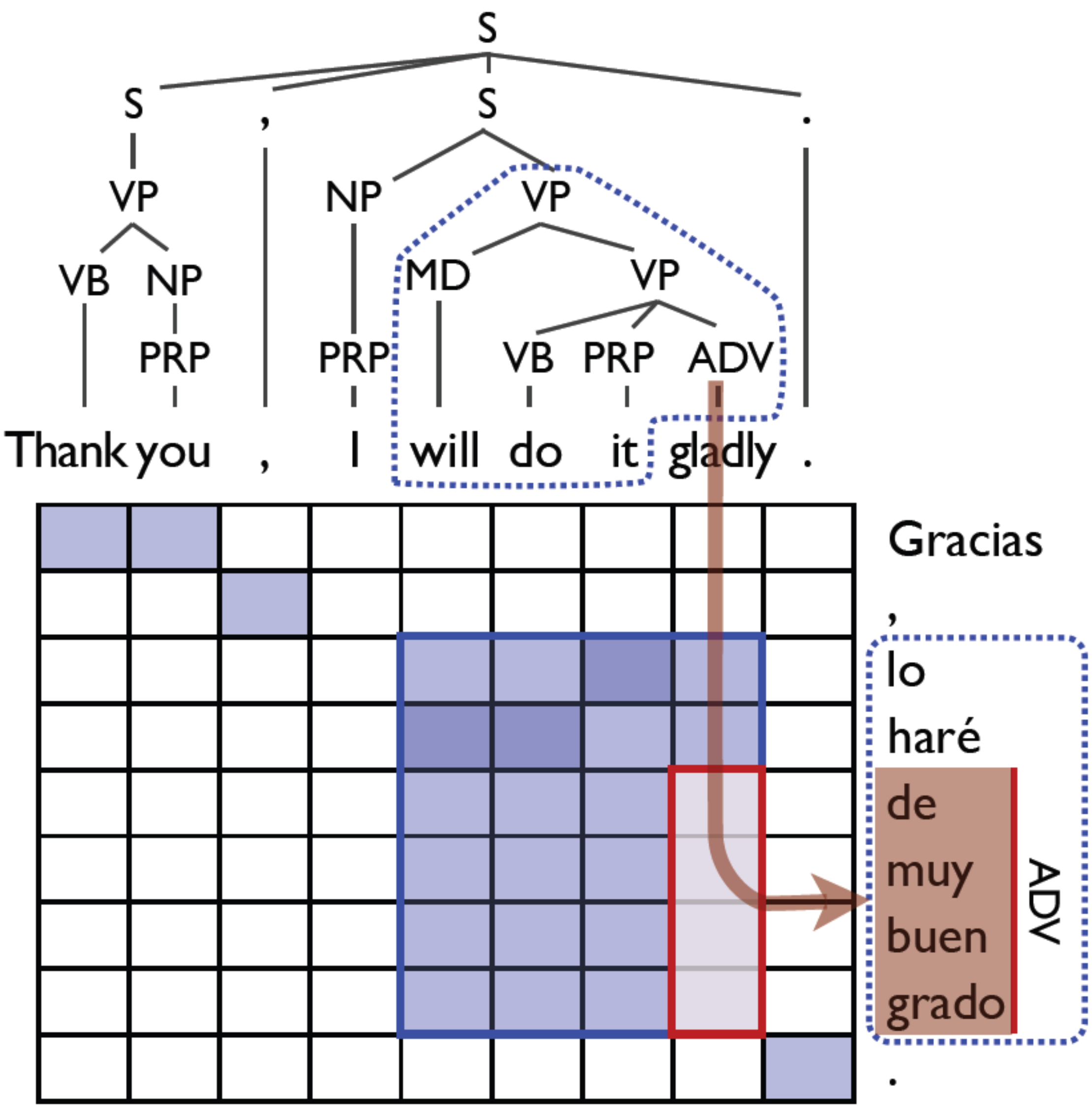


Grammar Rules

~~⟨haré ; will do⟩~~

VP → ⟨lo haré de … grado ; will do it gladly⟩

VP → ⟨lo haré ADV ; will do it ADV⟩

The Size of Tree Transducer Grammars

Extracted a transducer grammar from a 220 million word bitext

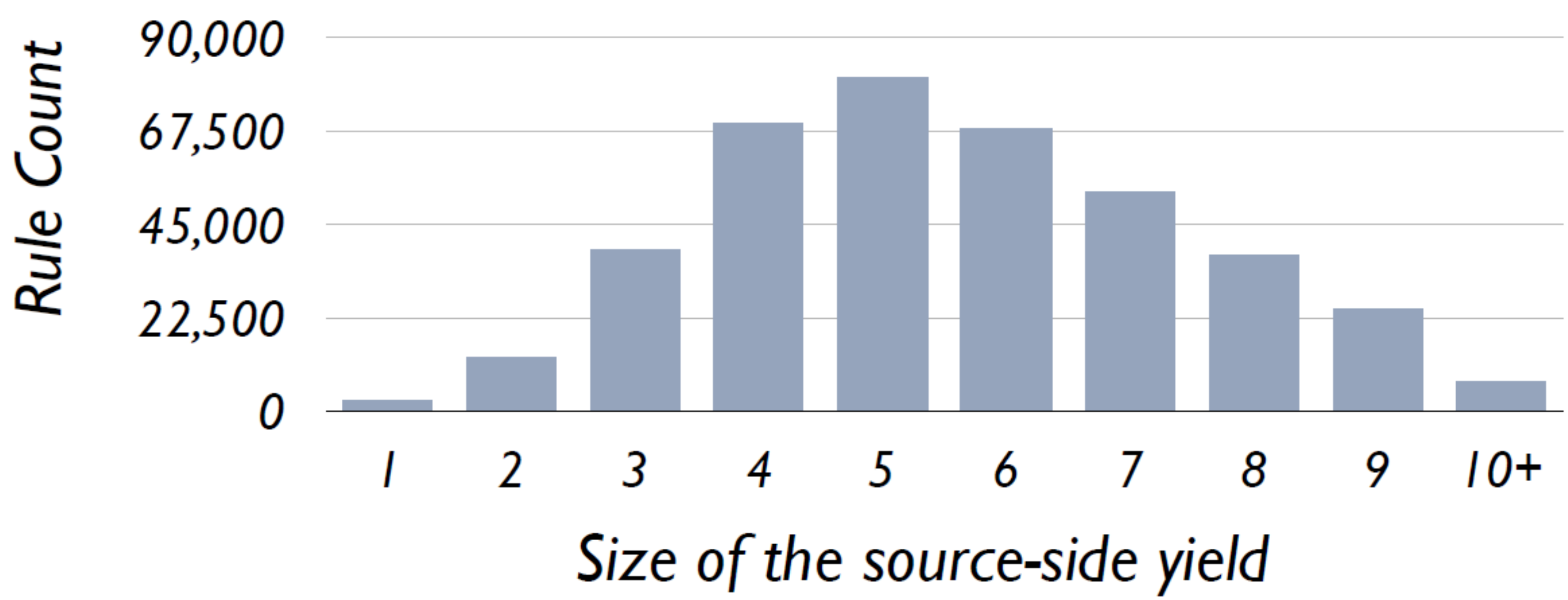
Relativized the grammar to each test sentence

Kept all rules with at most 6 non-terminals

The Size of Tree Transducer Grammars

Extracted a transducer grammar from a 220 million word bitext → Relativized the grammar to each test sentence → Kept all rules with at most 6 non-terminals

Rules matching an example 40-word sentence



The Size of Tree Transducer Grammars

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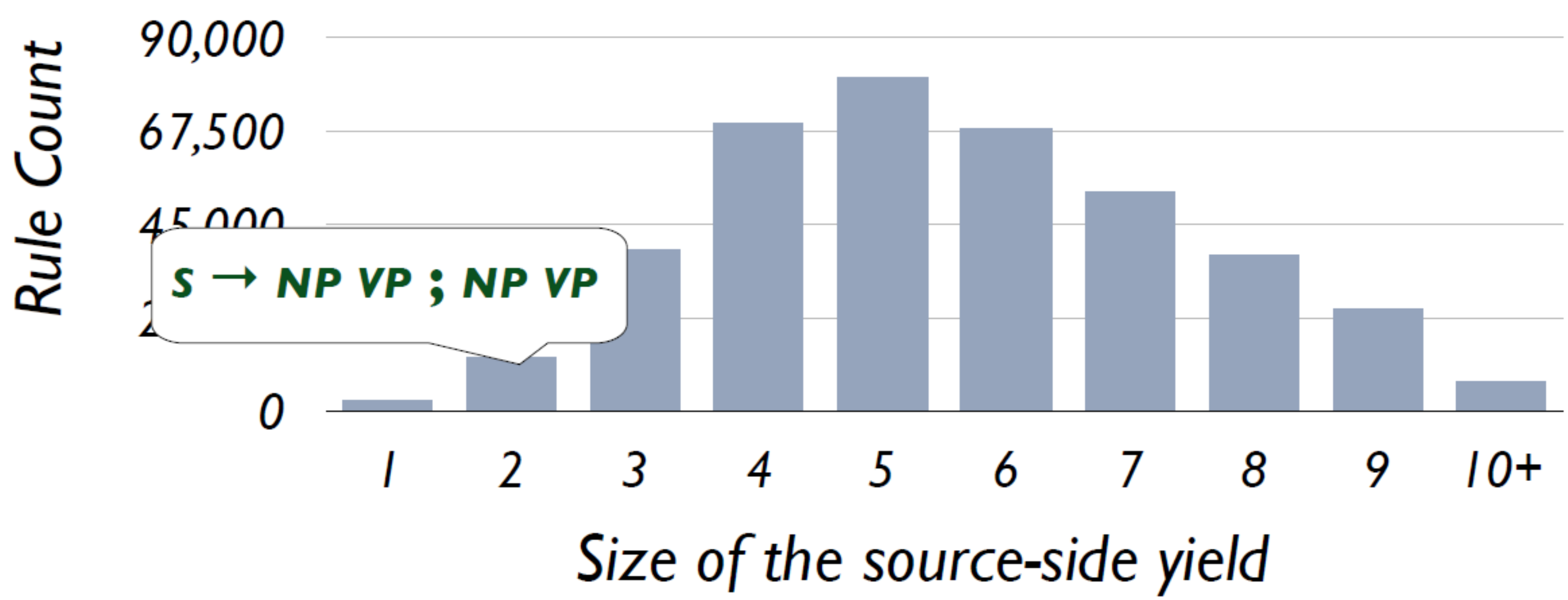

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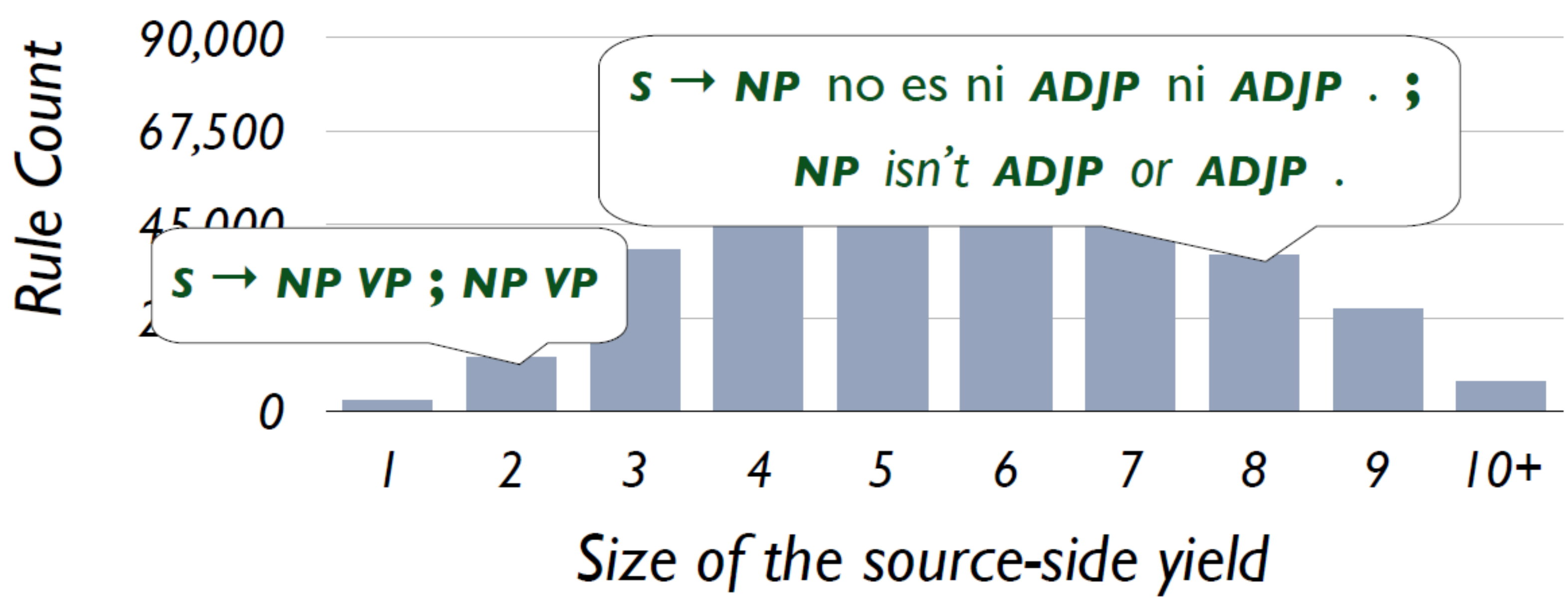

Syntactic Decoding

Tree Transducer Grammars

S

NN — NNP

No se olvide de subir un canto rodado en Colorado

Synchronous Grammar

NNP → Colorado ; *Colorado*

NN → canto rodado ; *boulder*

S → No se olvide de subir un ***NN*** en ***NNP*** ; *Don't forget to climb a* ***NN*** *in* ***NNP***

Output

S

NN — NNP

Don't forget to climb a boulder in Colorado

CKY-style Bottom-up Parsing

For each
span length:

CKY-style Bottom-up Parsing

For each span length:

For each span [i,j]:

CKY-style Bottom-up Parsing

For each span length:

> For each span [i,j]:
>
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For each span length:

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Binary rule: $X \rightarrow Y\ Z$

CKY-style Bottom-up Parsing

For each span length:

For each span [i,j]:

Apply all grammar rules to [i,j]

Binary rule:	$X \rightarrow Y\ Z$
Split points:	$i < k < j$
Operations:	$O(j - i)$
Time scales with:	Grammar constant

CKY-style Bottom-up Parsing

For each span length:

For each span [i,j]:

Apply all grammar rules to [i,j]

$_i$ No se olvide de subir un canto rodado en Colorado $_j$

CKY-style Bottom-up Parsing

For each span length:

For each span [i,j]:

Apply all grammar rules to [i,j]

S → No se ***VB*** de subir un ***NN*** en ***NNP***

$_i$ No se olvide de subir un canto rodado en Colorado $_j$

CKY-style Bottom-up Parsing

For each span length:

For each span [i,j]:

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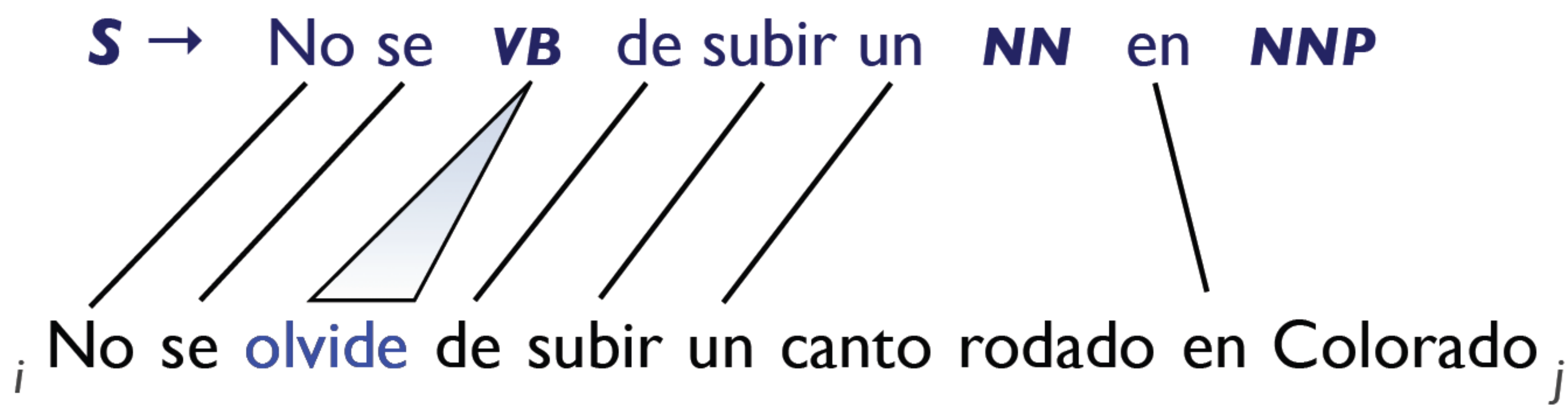

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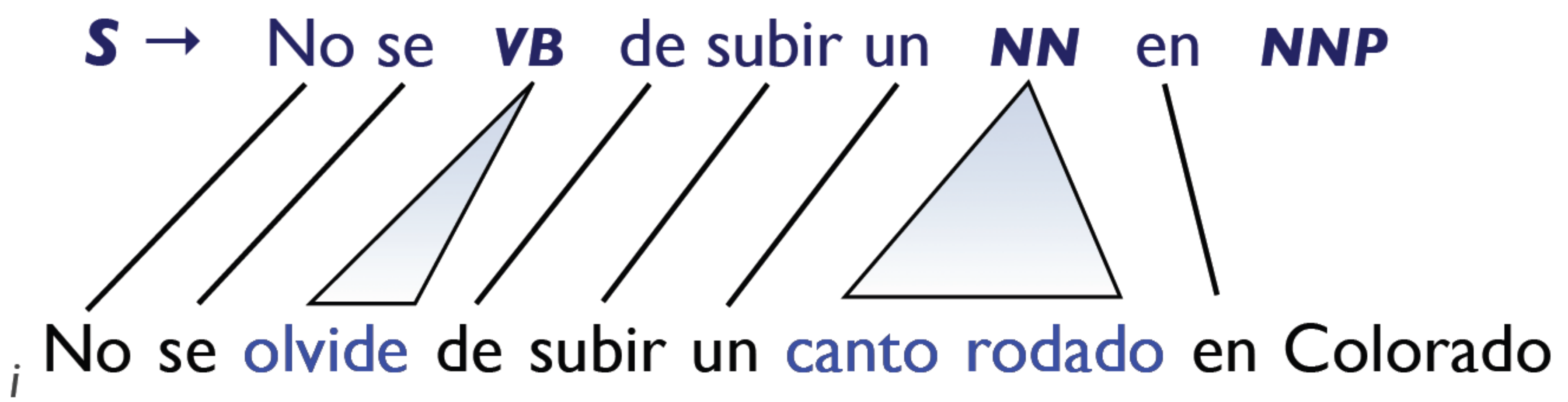

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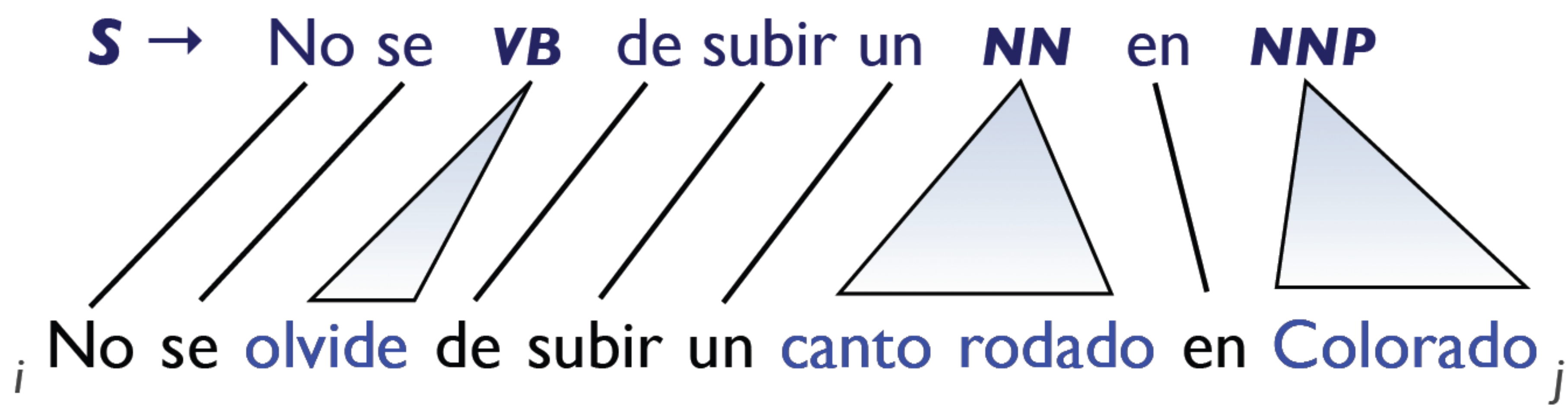

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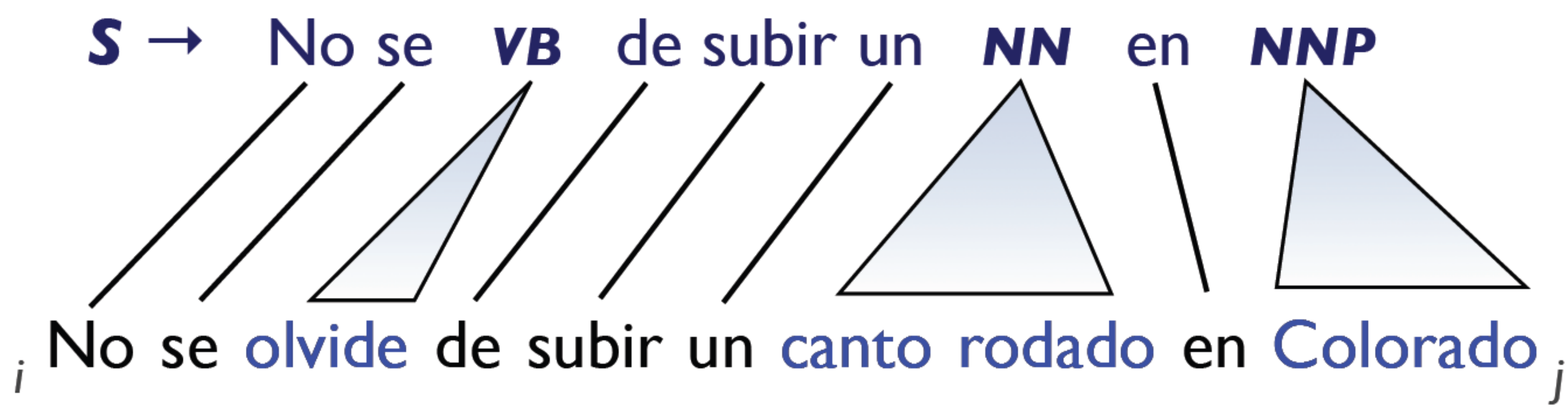

Many untransformed lexical rules can be applied in linear time

CKY-style Bottom-up Parsing

For each span length:

For each span [i,j]:

Apply all grammar rules to [i,j]

S → No se ***VP*** ***NP*** ***PP***

i No se olvide de subir un canto rodado en Colorado *j*

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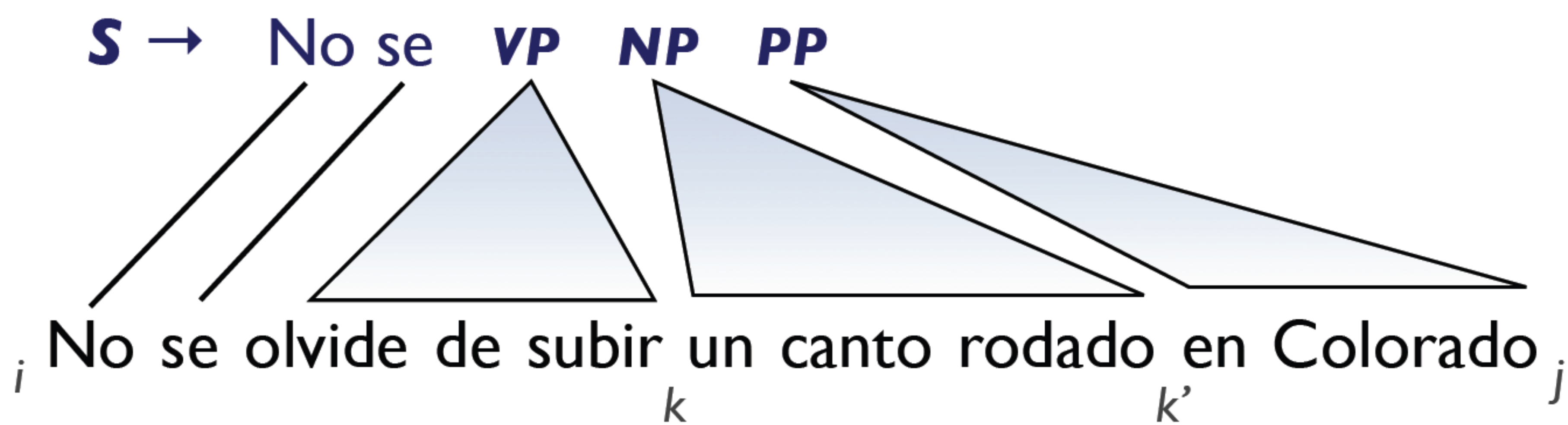

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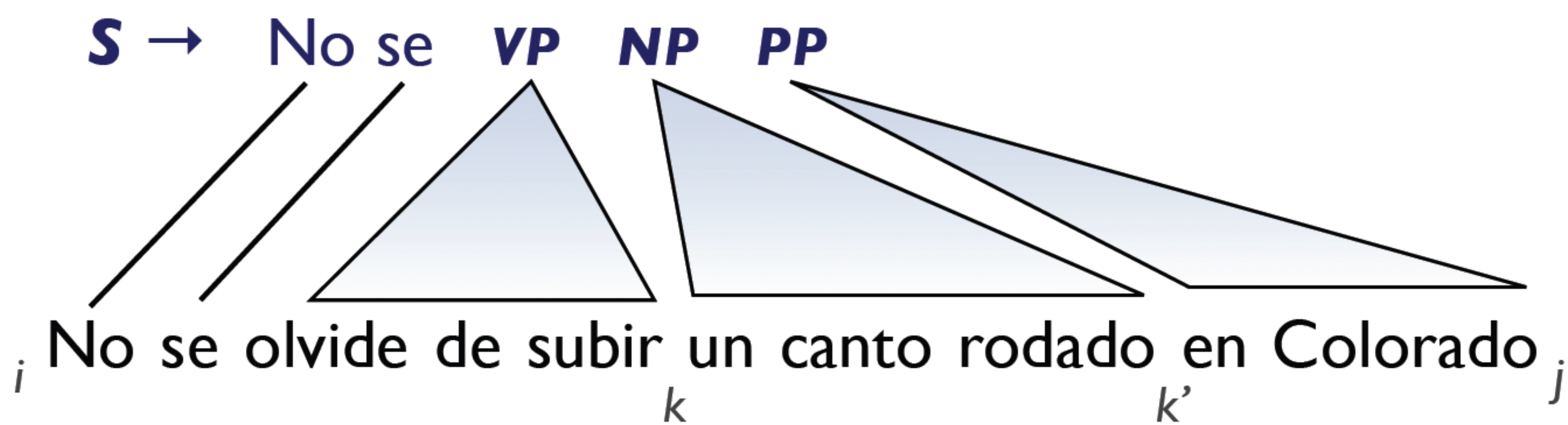


Problem: *Applying adjacent non-terminals is slow*

Eliminating Non-terminal Sequences

Lexical Normal Form (LNF)

(a) lexical rules have at most one adjacent non-terminal
(b) all unlexicalized rules are binary.

Original rule: ***S*** → No se ***VB*** ***VB*** un ***NN*** ***PP***

Transformed rules: ***S*** → No se ***VB~VB*** un ***NN~PP***

VB~VB → ***VB*** ***VB***

NN~PP → ***NN*** ***PP***

Parsing stages:

- Lexical rules are applied by matching
- Unlexicalized rules are applied by iterating over split points

Flexible Syntax

Soft Syntactic MT: From Chiang 2010

日本 文部 科学 省 官员 表示 , " 亚 伯拉罕 的 发言 , 令 我们 深感 鼓舞

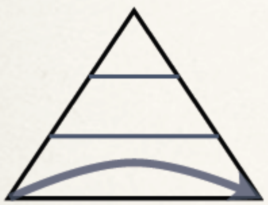
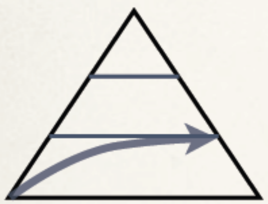
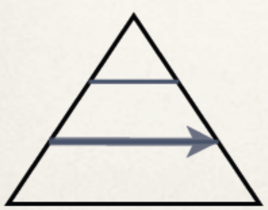
Japan MEXT official said , " Abraham 's comment make us deeply-feel courage

reference: An official from Japan 's science and technology ministry said , " We are highly encouraged by Abraham 's comment .

Hiero: Officials of the Japanese ministry of education and science , " said Abraham speeches , we are deeply encouraged by .

string-to-tree: Japan 's ministry of education , culture , sports , science and technology , " Abraham 's statement , which is most encouraging , " the official said .

Previous work

	string-to-string	ITG (Wu 1997)	Hiero (Chiang 2005)
	string-to-tree	Yamada & Knight 2001	Galley et al 2004/2006
	tree-to-string		Huang et al 2006 Y Liu et al 2006
	tree-to-tree	DOT (Poutsma 2000) Eisner 2003	Stat-XFER (Lavie et al 2008) M Zhang et al. 2008 Y Liu et al., 2009

Hiero Rules

$$S \rightarrow \langle S_{\boxed{1}} X_{\boxed{2}}, S_{\boxed{1}} X_{\boxed{2}} \rangle$$

$$S \rightarrow \langle X_{\boxed{1}}, X_{\boxed{1}} \rangle$$

$$X \rightarrow \langle \text{yu } X_{\boxed{1}} \text{ you } X_{\boxed{2}}, \text{have } X_{\boxed{2}} \text{ with } X_{\boxed{1}} \rangle$$

$$X \rightarrow \langle X_{\boxed{1}} \text{ de } X_{\boxed{2}}, \text{the } X_{\boxed{2}} \text{ that } X_{\boxed{1}} \rangle$$

$$X \rightarrow \langle X_{\boxed{1}} \text{ zhiyi, one of } X_{\boxed{1}} \rangle$$

$$X \rightarrow \langle \text{Aozhou, Australia} \rangle$$

$$X \rightarrow \langle \text{shi, is} \rangle$$

$$X \rightarrow \langle \text{shaoshu guojia, few countries} \rangle$$

$$X \rightarrow \langle \text{bangjiao, diplomatic relations} \rangle$$

$$X \rightarrow \langle \text{Bei Han, North Korea} \rangle$$

From [Chiang et al, 2005]

STSG extraction

1. Phrases
    - respect word alignments
    - are syntactic constituents on *both* sides
2. Phrase pairs form rules
3. Subtract phrases to form rules

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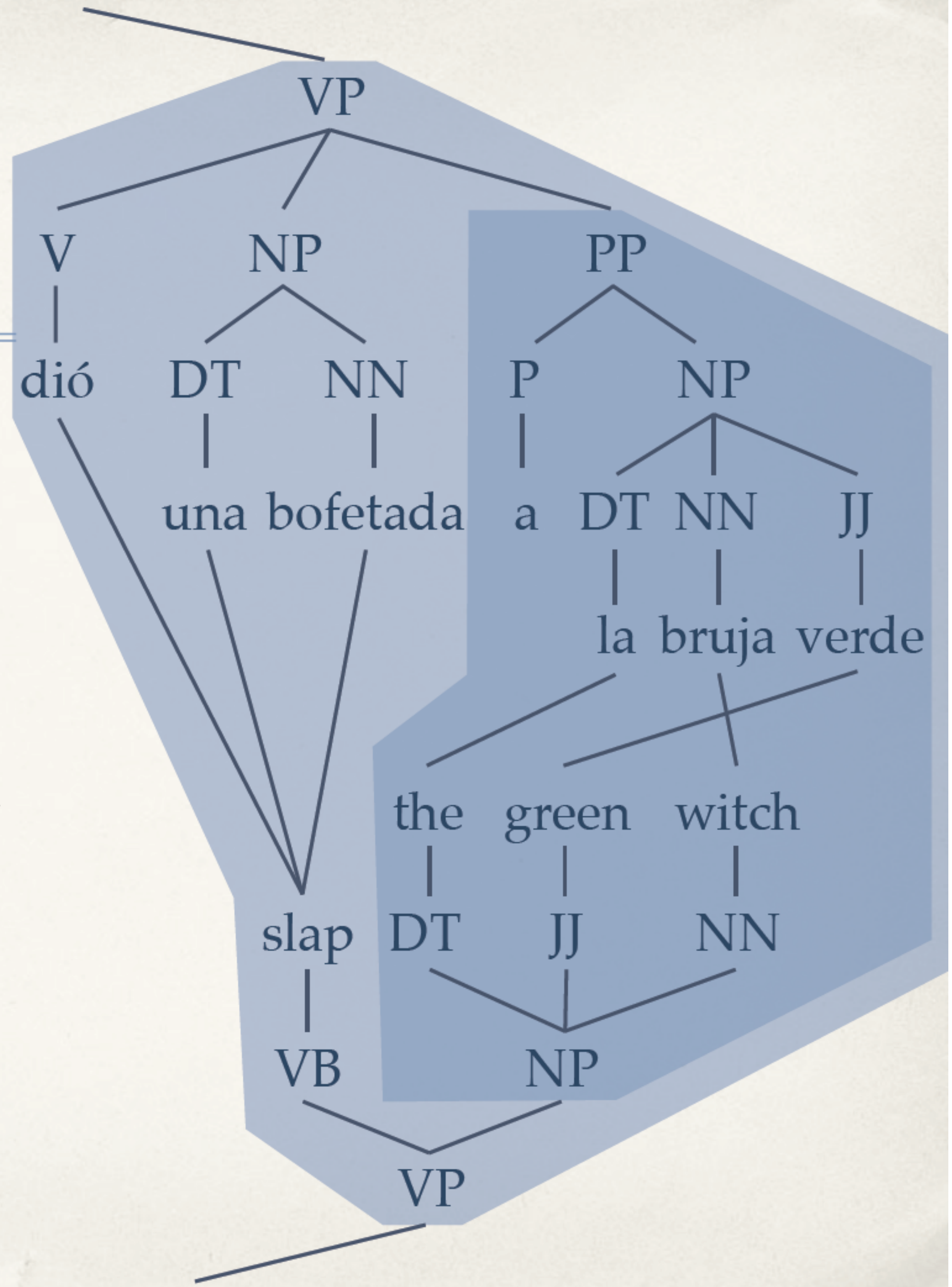

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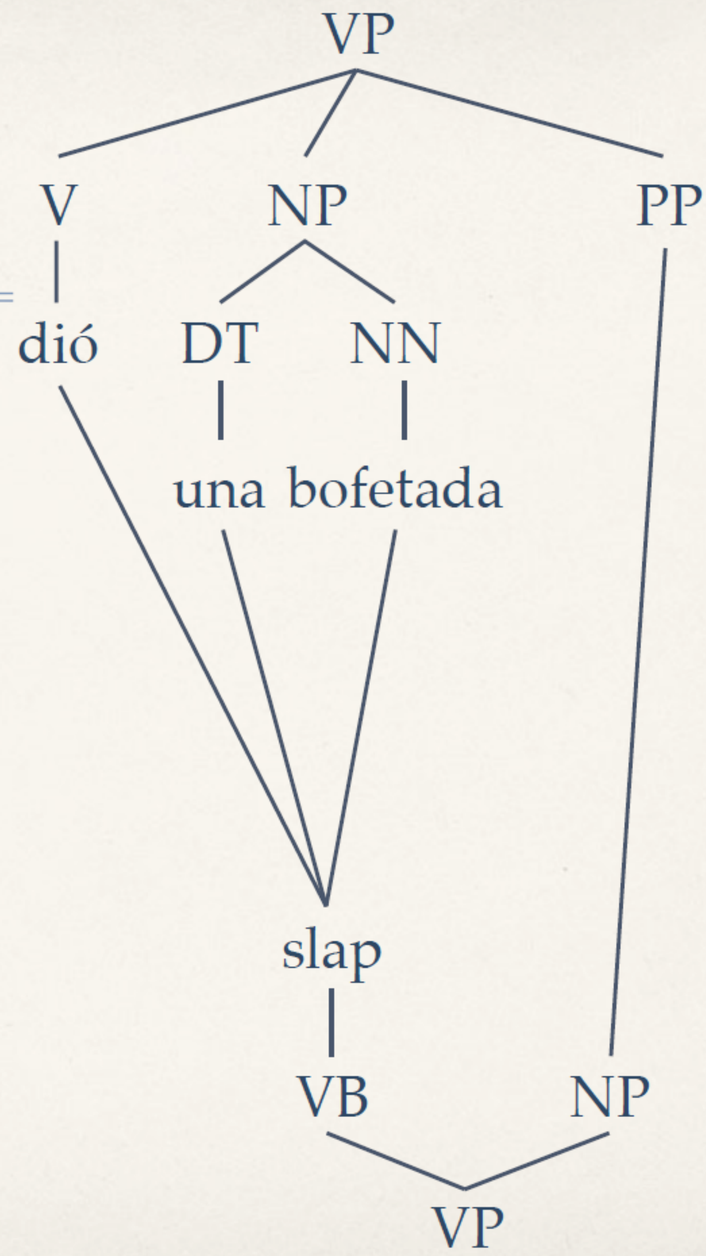
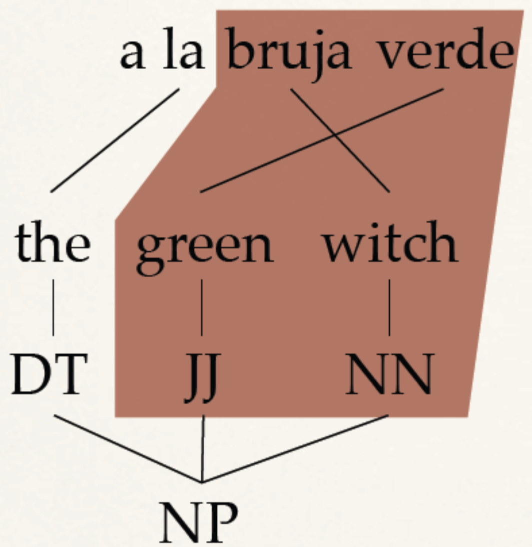
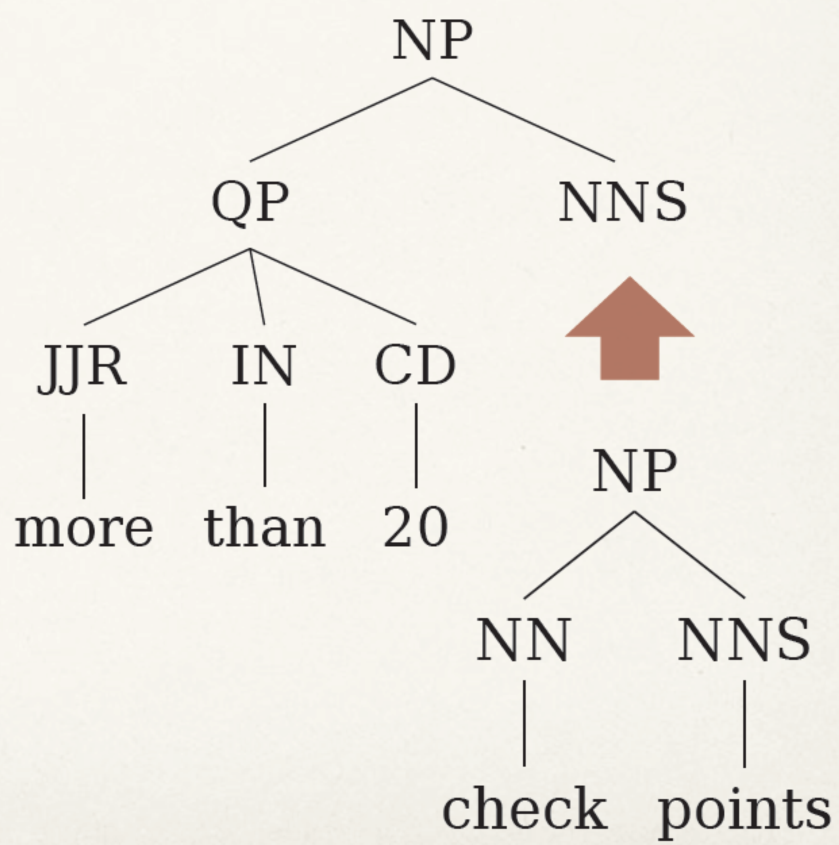


Why is tree-to-tree hard?

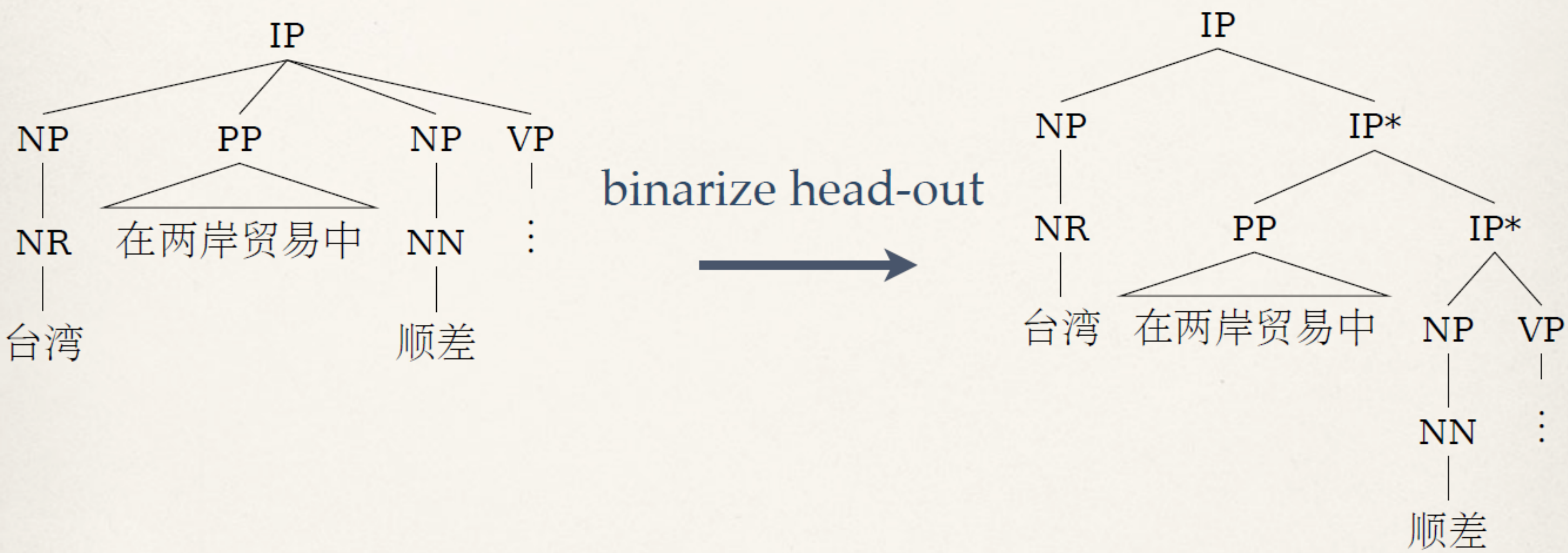
too few rules



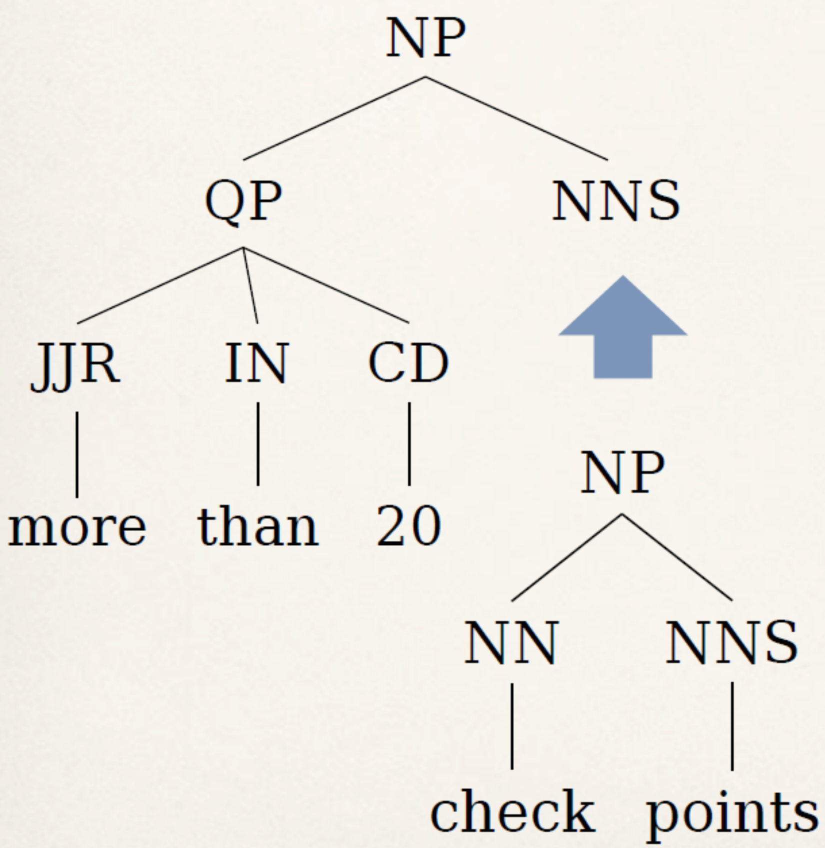
too few derivations



Extracting more rules

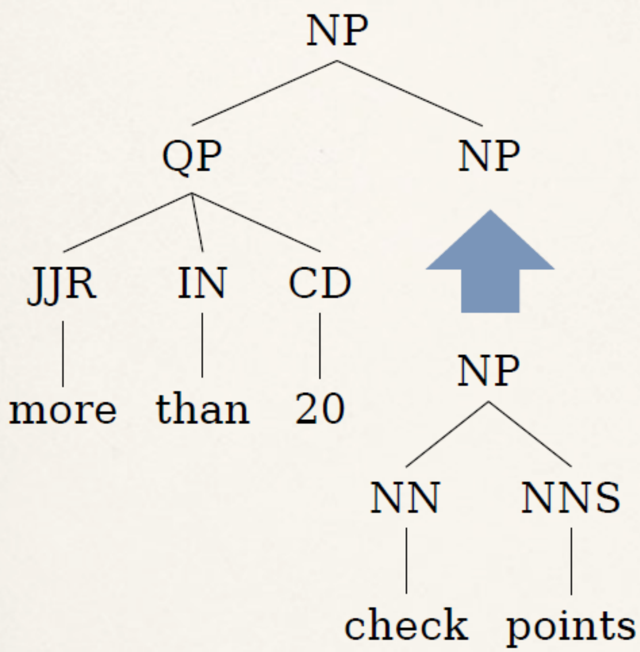


Allow more derivations

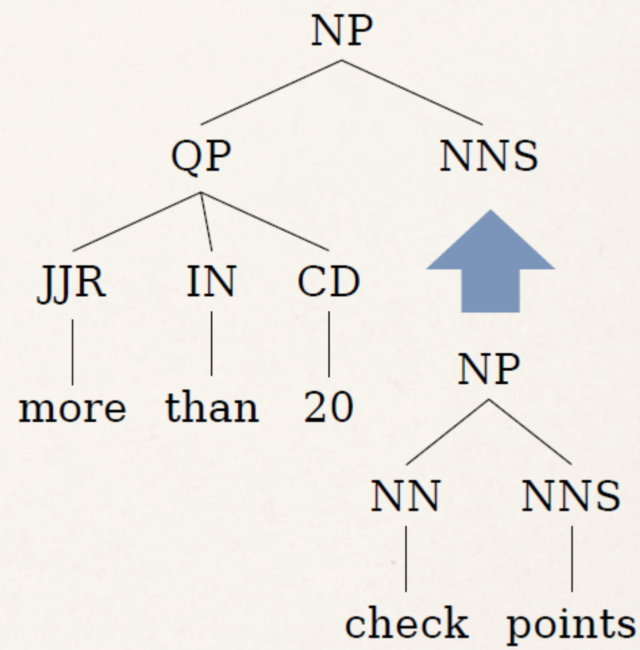


- STSG: allow only matching substitutions
- Hiero-like: allow any substitutions
- Let the model learn to choose:
  - matching substitutions
  - mismatching substitutions
  - monotone phrase-based

Allow more derivations



fire *subst*:NP→NP
fire *subst:match*



fire *subst*:NNS→NP
fire *subst:unmatch*

Allow more derivations

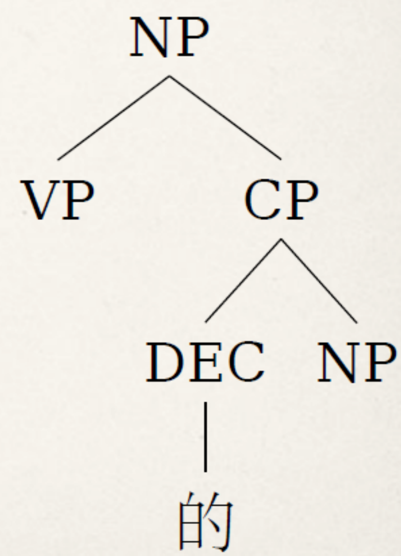
Hiero-like decoding

$$\frac{[\mathrm{X},i,j] \qquad [\mathrm{X},j+1,k]}{[\mathrm{X},i,k]}$$

$\mathrm{X} \rightarrow \mathrm{X}$ 的 X

STSG decoding

$$\frac{[\mathrm{VP},i,j] \qquad [\mathrm{NP},j+1,k]}{[\mathrm{NP},i,k]}$$



fuzzy STSG decoding

$$\frac{[A,i,j] \qquad [B,j+1,k]}{[\mathrm{NP},i,k]}$$

Results

	Chinese-English			Arabic-English		
extraction	rules	feats	BLEU	rules	feats	BLEU
Hiero	440M	1k	23.7	790M	1k	48.9
fuzzy STSG	50M	5k	23.9	38M	5k	47.5
fuzzy STSG +binarize	64M	5k	24.3	40M	6k	48.1
fuzzy STSG +SAMT	440M	160k	24.3	790M	130k	49.7

Example tree-to-tree translation

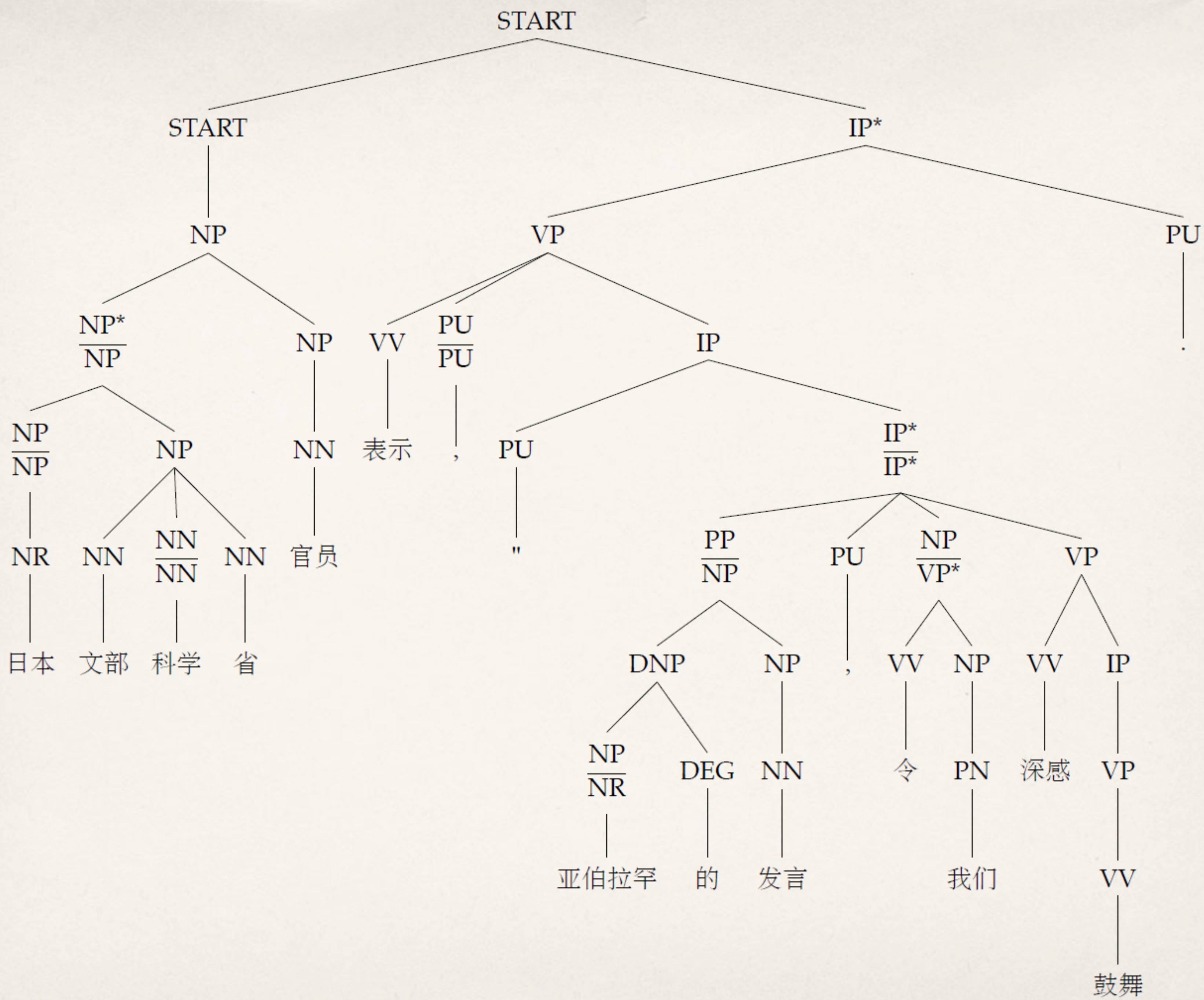
日本 文部 科学 省 官员 表示 , " 亚 伯拉罕 的 发言 , 令 我们 深感 鼓舞
Japan MEXT official said , “ Abraham ’s comment make us deeply-feel courage

reference: An official from Japan ’s science and technology ministry said , " We are highly encouraged by Abraham ’s comment .

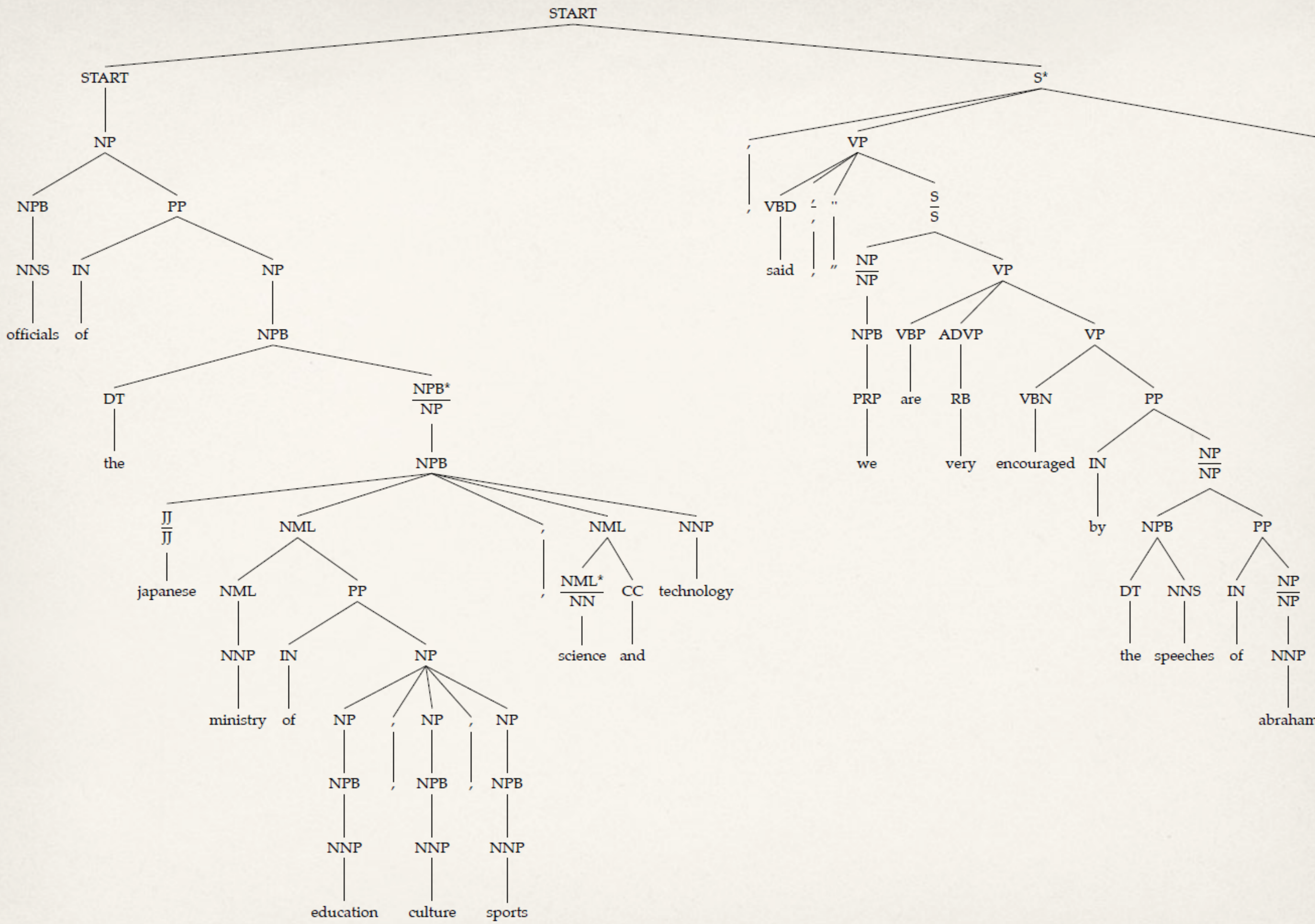
Hiero: Officials of the Japanese ministry of education and science , " said Abraham speeches , we are deeply encouraged by .

string-to-tree: Japan ’s ministry of education , culture , sports , science and technology , " Abraham ’s statement , which is most encouraging , " the official said .

Fuzzy STSG, binarize: Officials of the Japanese ministry of education , culture , sports , science and technology , said , " we are very encouraged by the speeches of Abraham .



START
START
IP*
NP
VP
PU
NP*
NP
NP
VV
PU
PU
IP
.
NP
NP
NP
NN
表示
，
PU
IP*
IP*
NR
NN
NN
NN
NN
官员
"
PP
NP
PU
NP
VP*
VP
日本
文部
科学
省
DNP
NP
，
VV
NP
VV
IP
NP
NR
DEG
NN
令
PN
深感
VP
亚伯拉罕
的
发言
我们
VV
鼓舞


START
START S*
NP , VP .
NPB PP VBD , " S/S
NNS IN NP said , " NP/NP VP
officials of NPB NPB VBP ADVP VP
DT NPB*/NP PRP are RB VBN PP
the NPB we very encouraged IN NP/NP
JJ/JJ NML , NML NNP by NPB PP
japanese NML PP NML*/NN CC technology DT NNS IN NP/NP
NNP IN NP science and the speeches of NNP
ministry of NP , NP , NP abraham
NPB NPB NPB
NNP NNP NNP
education culture sports