CSE 517
Natural Language Processing
Winter 2013

Phrase Based Translation

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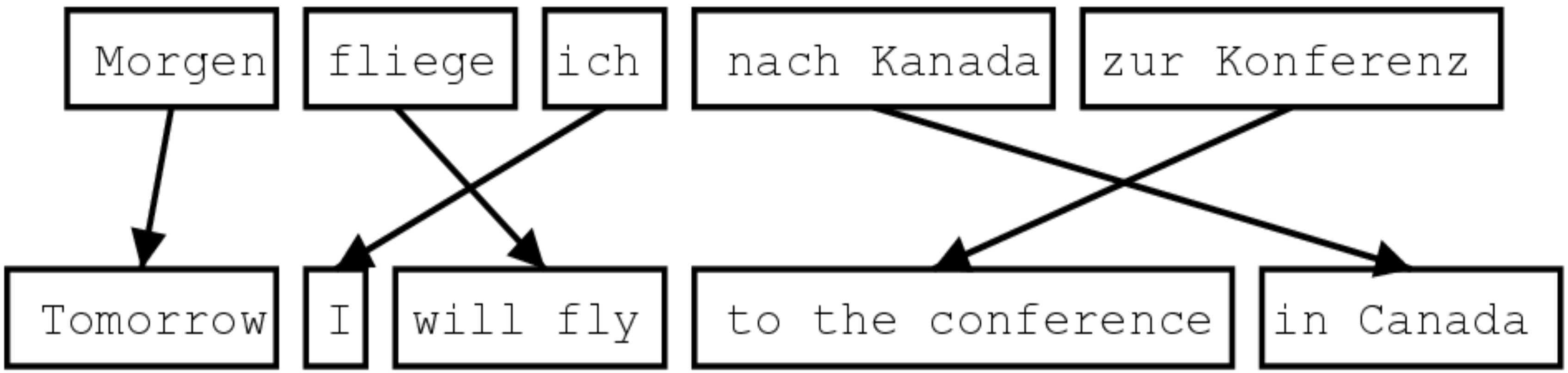
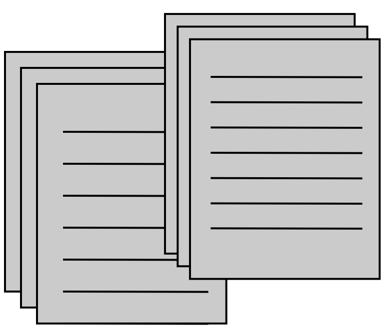
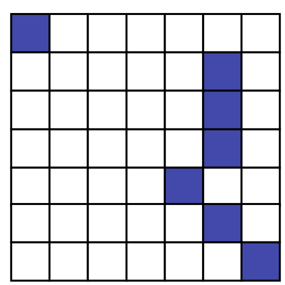
Slides from Philipp Koehn and Dan Klein

Phrase-Based Systems





Sentence-aligned corpus



Word alignments

cat ||| chat ||| 0.9
the cat ||| le chat ||| 0.8
dog ||| chien ||| 0.8
house ||| maison ||| 0.6
my house ||| ma maison ||| 0.9
language ||| langue ||| 0.9
…

Phrase table
(translation model)

Phrase Translation Tables

- Defines the space of possible translations
  - each entry has an associated “probability”
- One learned example, for “den Vorschlag” from Europarl data

English	$\phi(\bar{e}\|\bar{f})$	English	$\phi(\bar{e}\|\bar{f})$
the proposal	0.6227	the suggestions	0.0114
’s proposal	0.1068	the proposed	0.0114
a proposal	0.0341	the motion	0.0091
the idea	0.0250	the idea of	0.0091
this proposal	0.0227	the proposal ,	0.0068
proposal	0.0205	its proposal	0.0068
of the proposal	0.0159	it	0.0068
the proposals	0.0159	...	...

  - This table is noisy, has errors, and the entries do not necessarily match our linguistic intuitions about consistency….

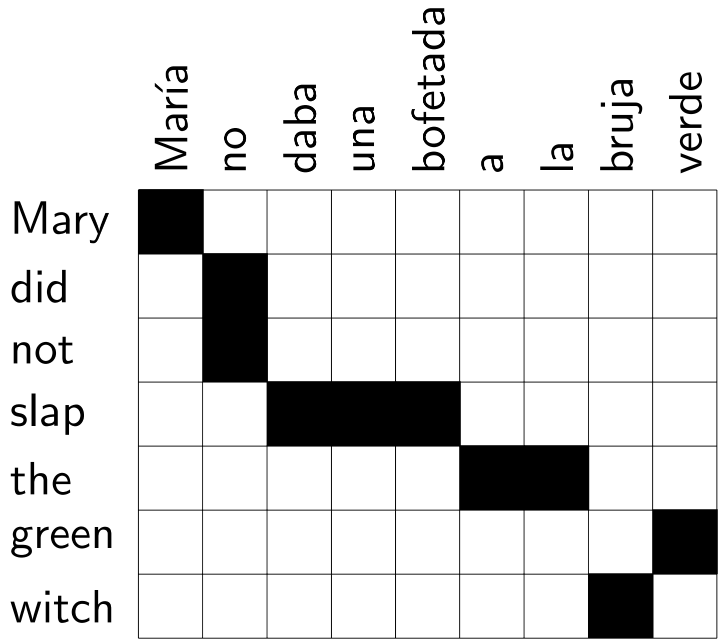
Phrase-Based Decoding

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]

Extracting Phrases

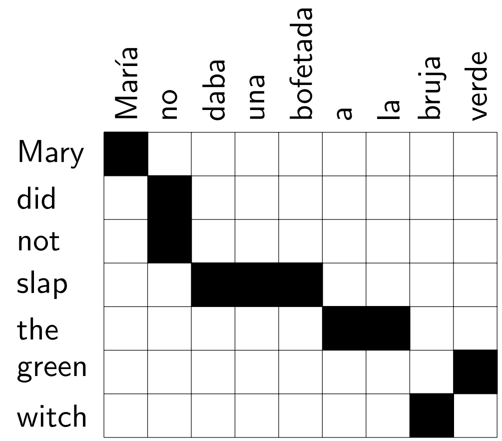
- We will use word alignments to find phrases

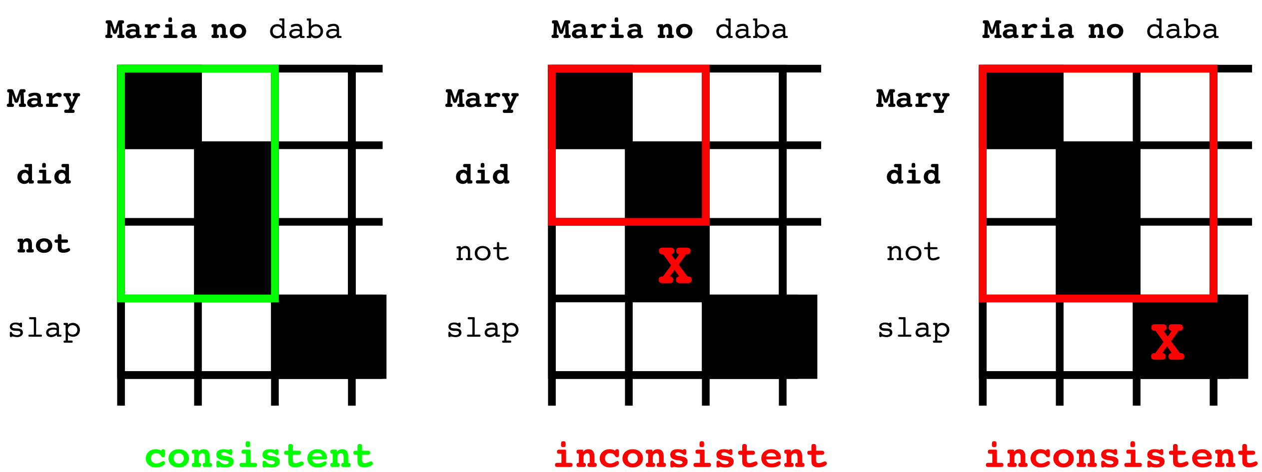


- Question: what is the best set of phrases?

Extracting Phrases

- Phrase alignment must
  - Contain at least two aligned words
  - Contain all alignments for phrase pair





- Extract all such phrase pairs!

Phrase Pair Extraction Example

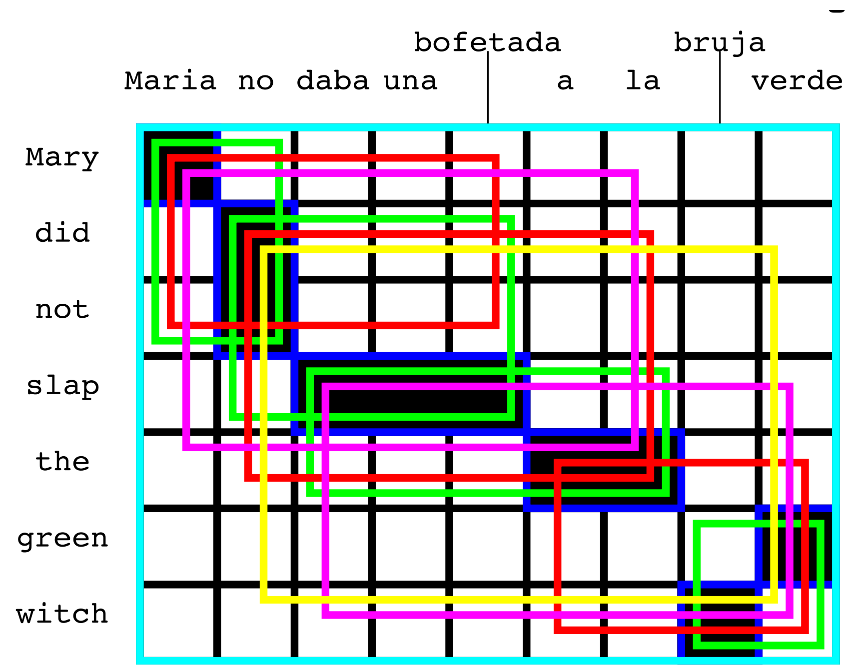
(Maria, Mary), (no, did not), (slap, daba una bofetada), (a la, the), (bruja, witch), (verde, green)

(Maria no, Mary did not), (no daba una bofetada, did not slap), (daba una bofetada a la, slap the), (bruja verde, green witch)

(Maria no daba una bofetada, Mary did not slap), (no daba una bofetada a la, did not slap the), (a la bruja verde, the green witch)

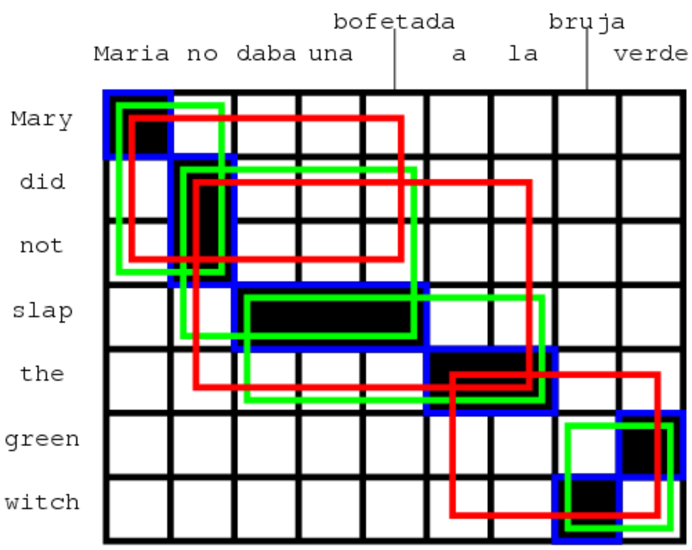
(Maria no daba una bofetada a la, Mary did not slap the), (daba una bofetada a la bruja verde, slap the green witch)

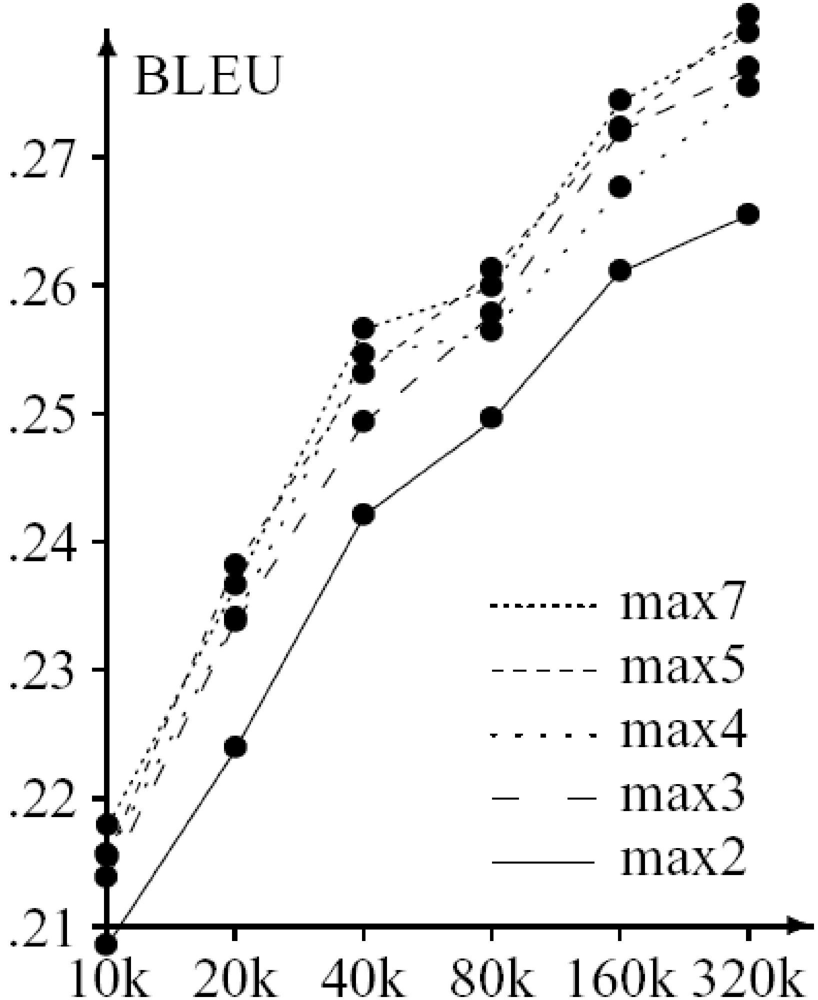
(Maria no daba una bofetada a la bruja verde, Mary did not slap the green witch)



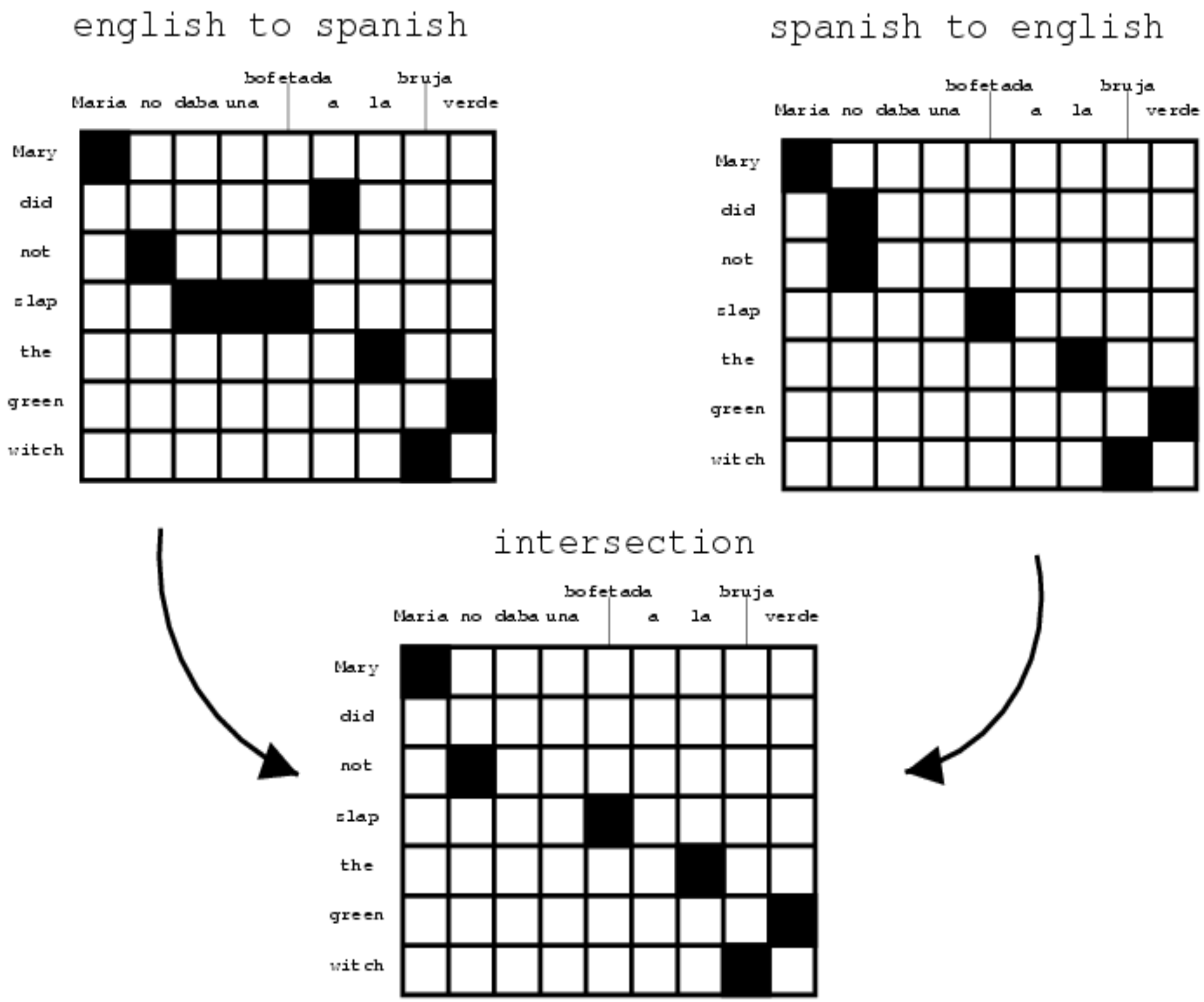
Phrase Size

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

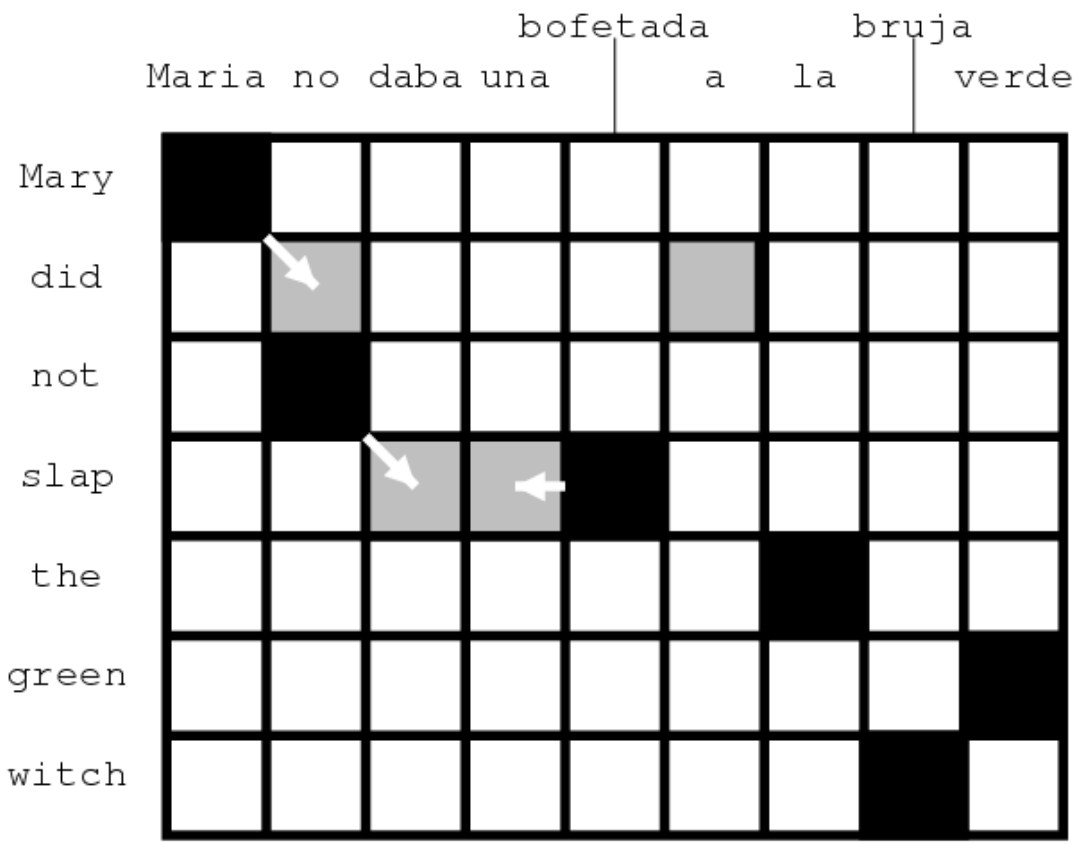


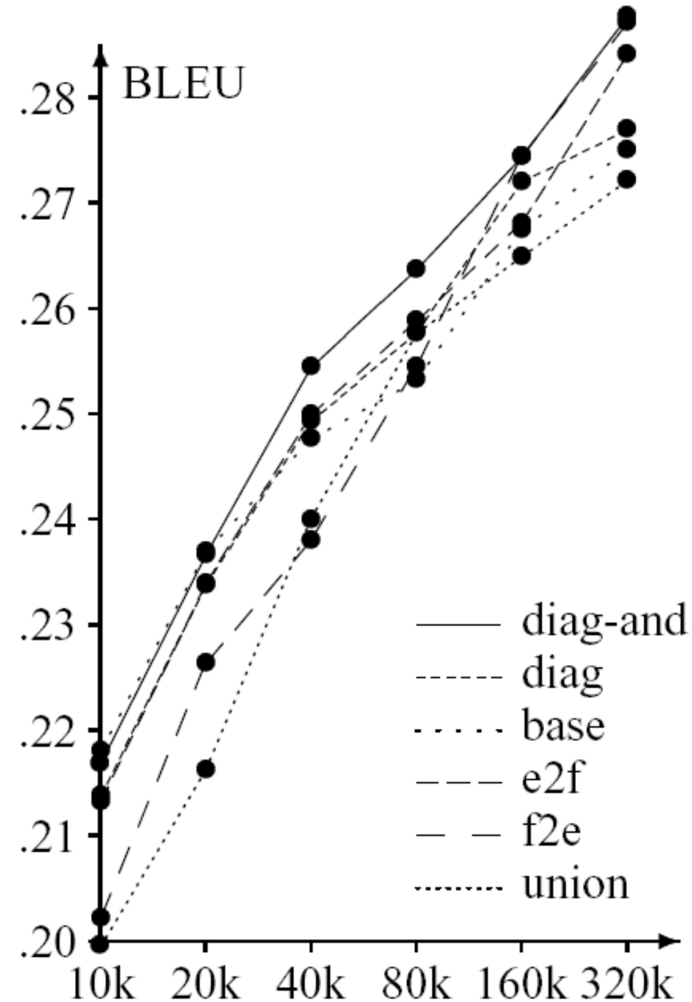


Bidirectional Alignment



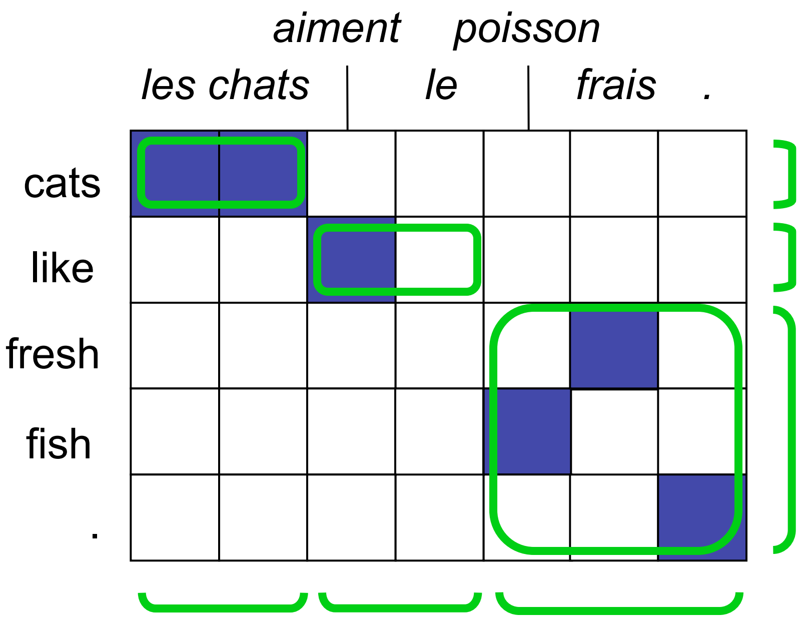
Alignment Heuristics





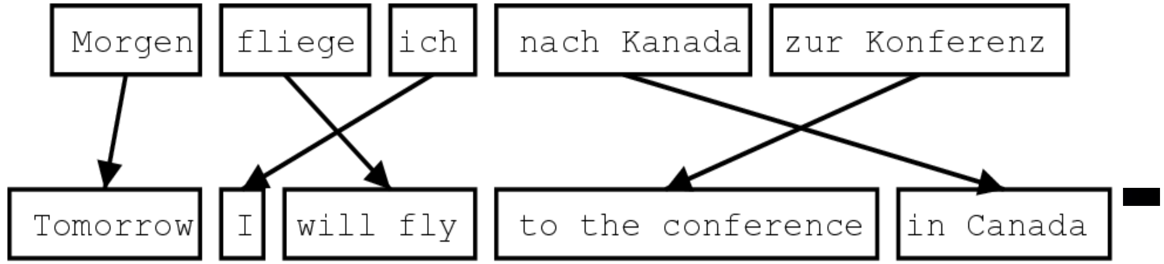
Phrase Scoring

$$g(f, e) = \log \frac{c(e, f)}{c(e)}$$



- 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]

Scoring:



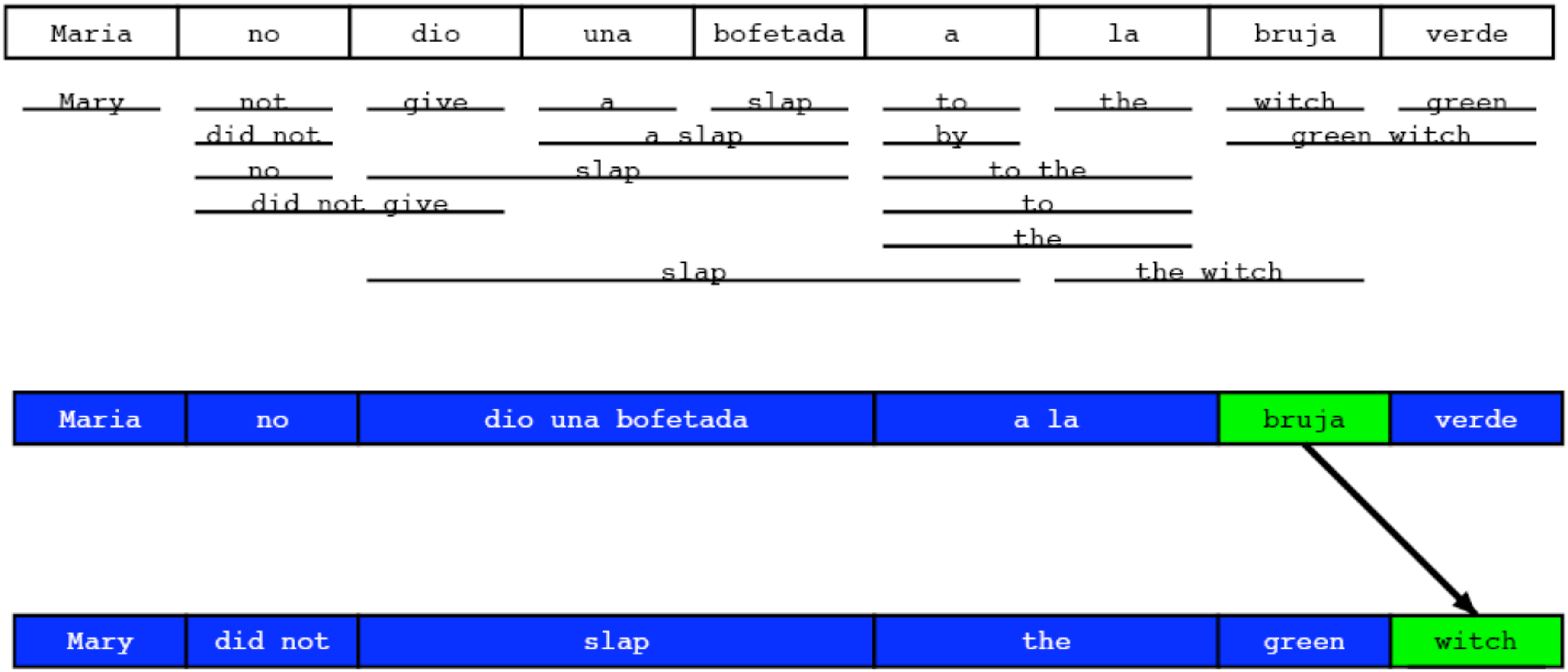
- Basic approach, sum up phrase translation scores and a language model
  - Define $y = p_1 p_2 \ldots p_L$ to be a translation with phrase pairs p_i
  - Define e(y) be the output English sentence in y
  - Let h() be the log probability under a tri-gram language model
  - Let g() be a phrase pair score (from last slide)
  - Then, the full translation score is:

$$f(y) = h(e(y)) + \sum_{k=1}^{L} g(p_k)$$

- Goal, compute the best translation

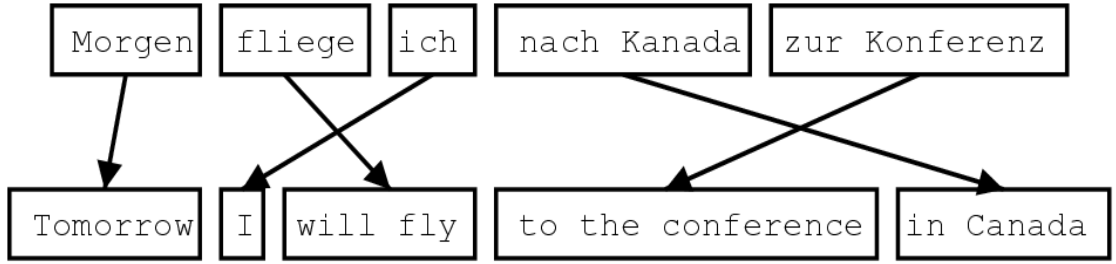
$$y^*(x) = \arg \max_{y \in \mathcal{Y}(x)} f(y)$$

The Pharaoh Decoder



- Scores at each step include LM and TM

Scoring:



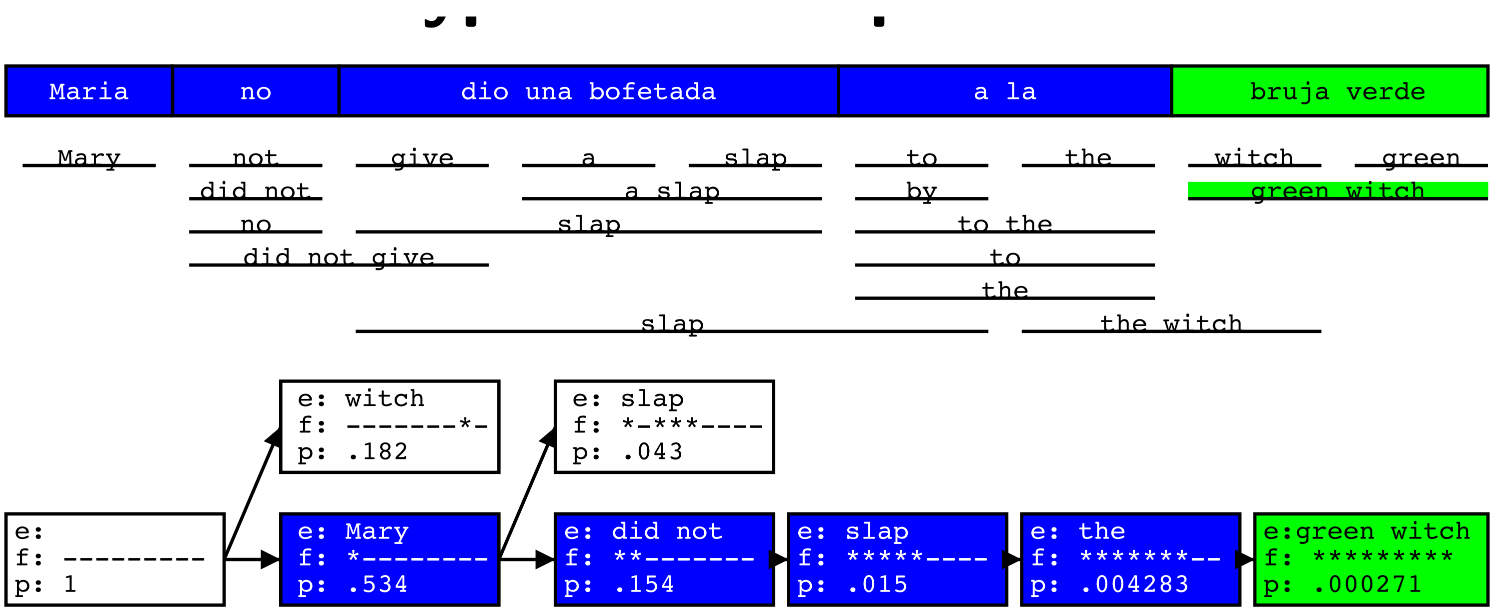
- In practice, much like for alignment models, also include a distortion penalty
  - Define $y = p_1 p_2 \ldots p_L$ to be a translation with phrase pairs p_i
  - Let $s(p_i)$ be the start position of the foreign phrase
  - Let $t(p_i)$ be the end position of the foreign phrase
  - Define η to be the distortion score (usually negative!)
  - Then, we can define a score *with distortion penalty*:

$$f(y) = h(e(y)) + \sum_{k=1}^{L} g(p_k) + \sum_{k=1}^{L-1} \eta \times |t(p_k) + 1 - s(p_{k+1})|$$

- Goal, compute the best translation

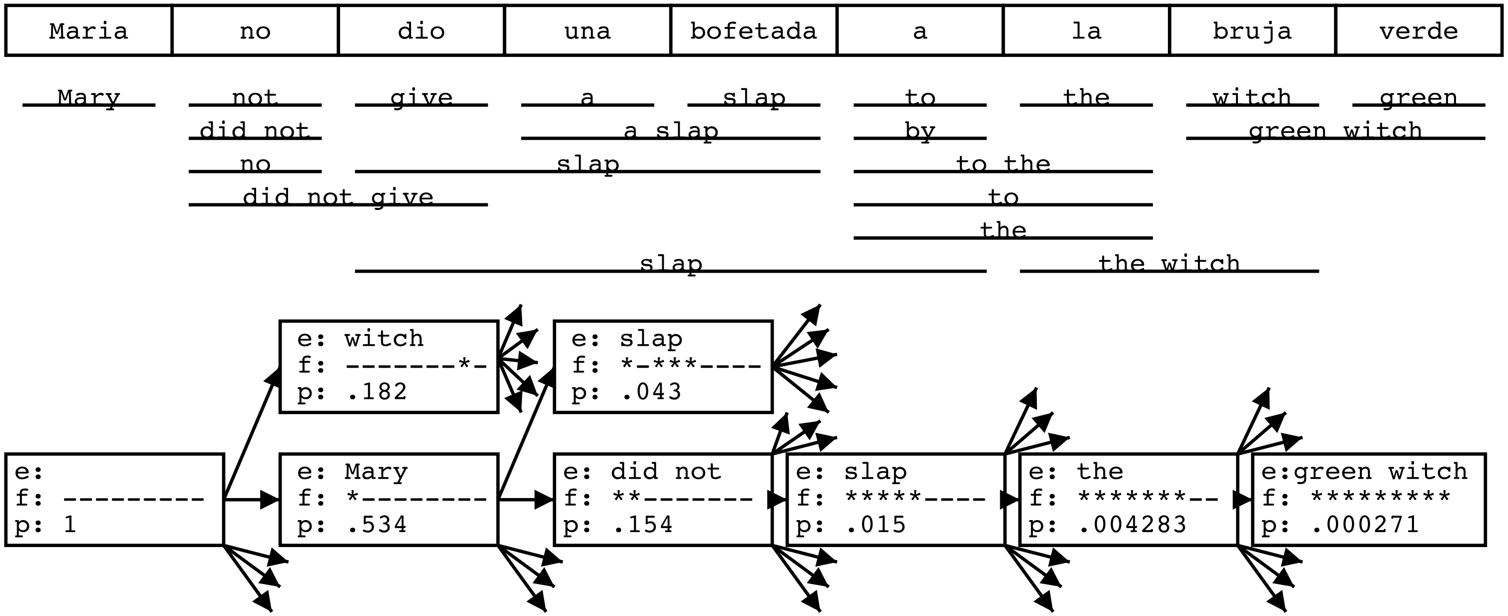
$$y^*(x) = \arg \max_{y \in \mathcal{Y}(x)} f(y)$$

Hypothesis Expansion



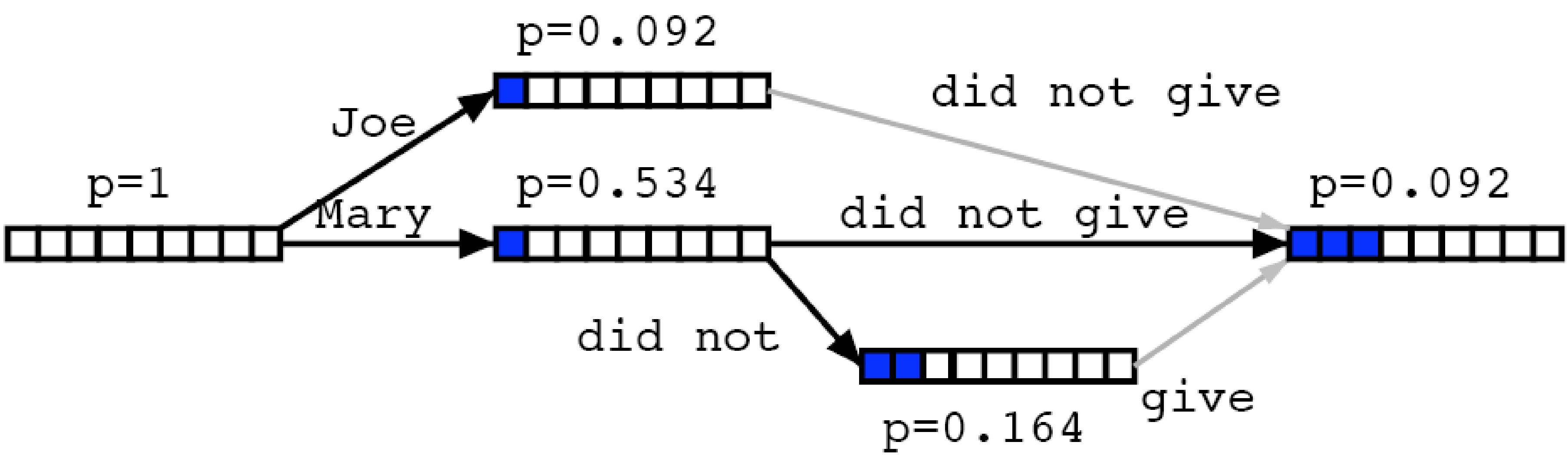
- ... until all foreign words *covered*
  - find *best hypothesis* that covers all foreign words
  - *backtrack* to read off translation

Hypothesis Explosion!

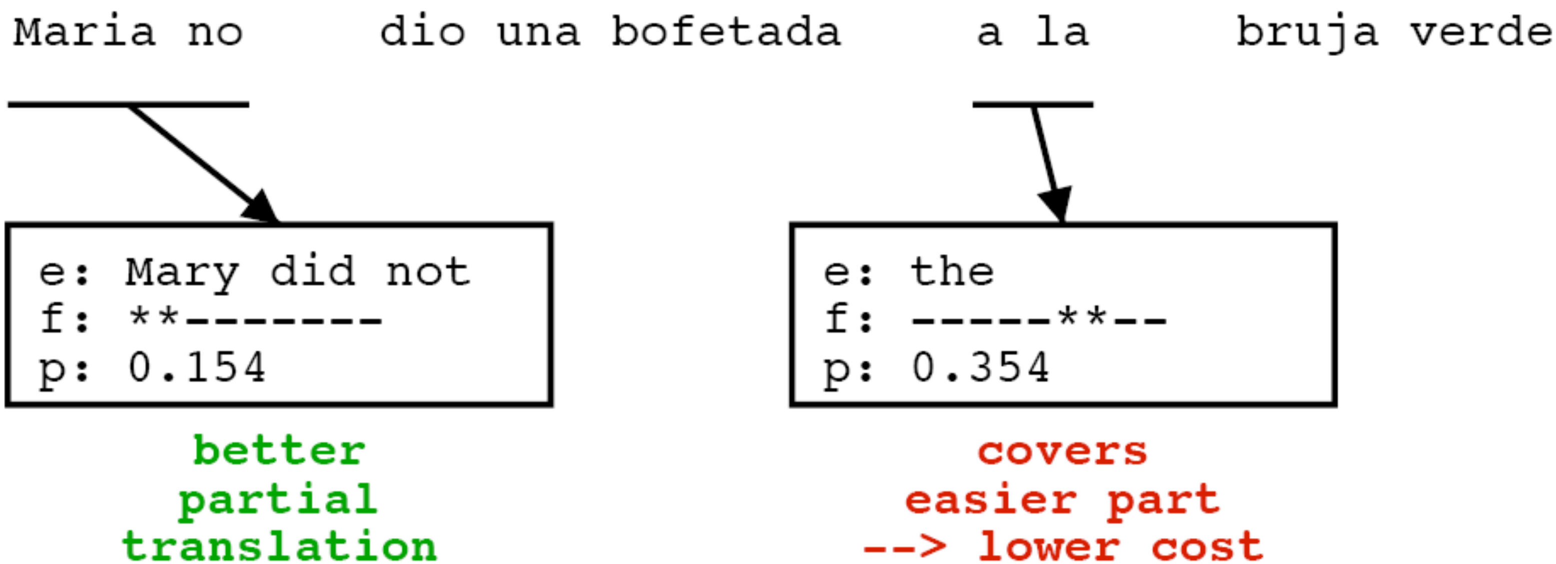


- Q: How much time to find the best translation?
  - NP-hard, just like for word translation models
  - So, we will use approximate search techniques!

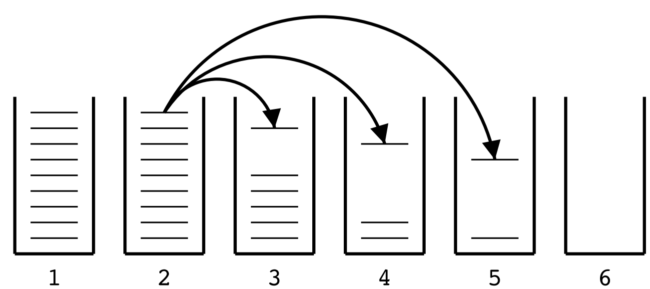
Hypothesis Lattices



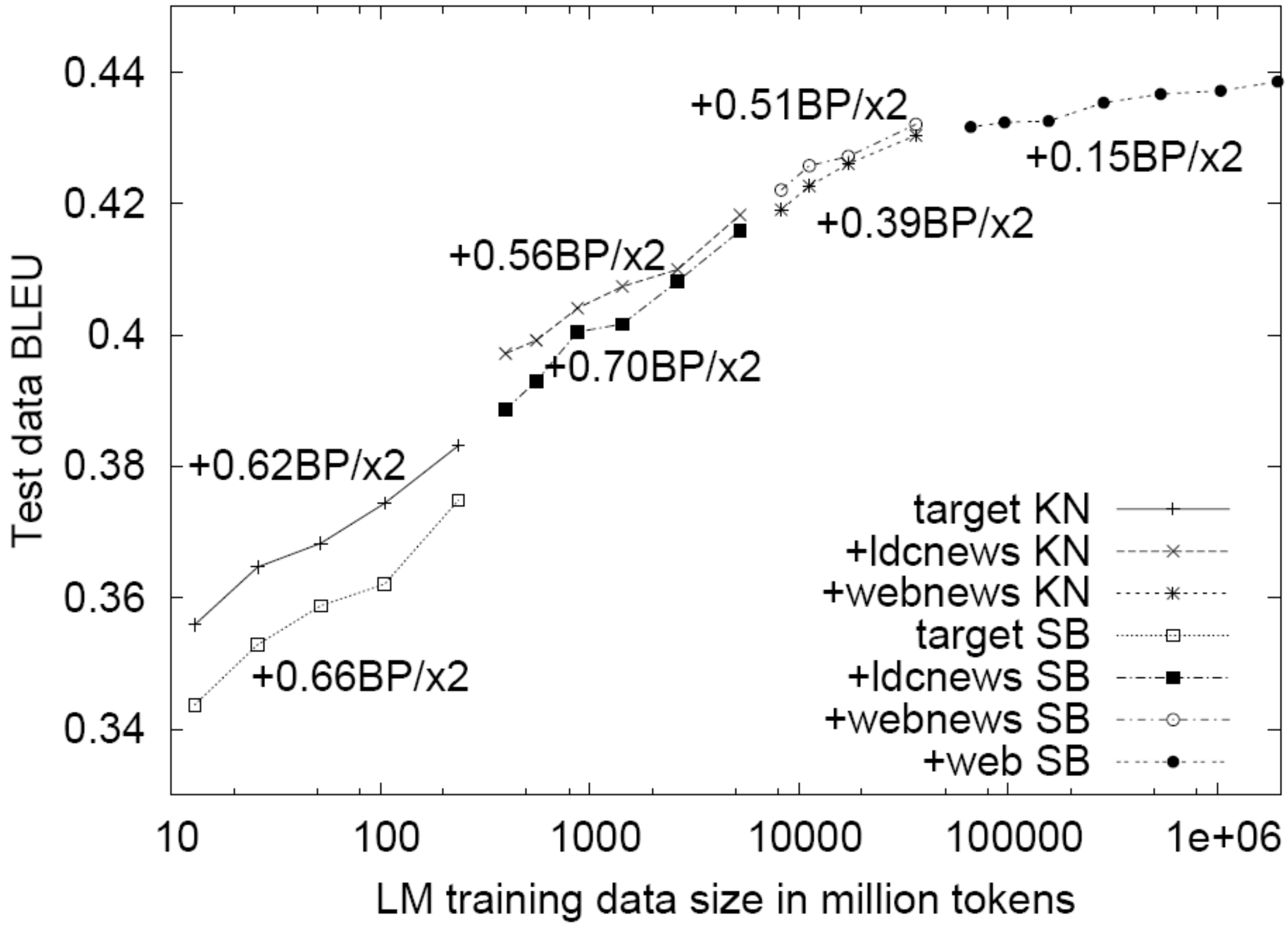
Pruning



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



Tons of Data?



- Discussed for LMs, but can new understand full model!

Tuning for MT

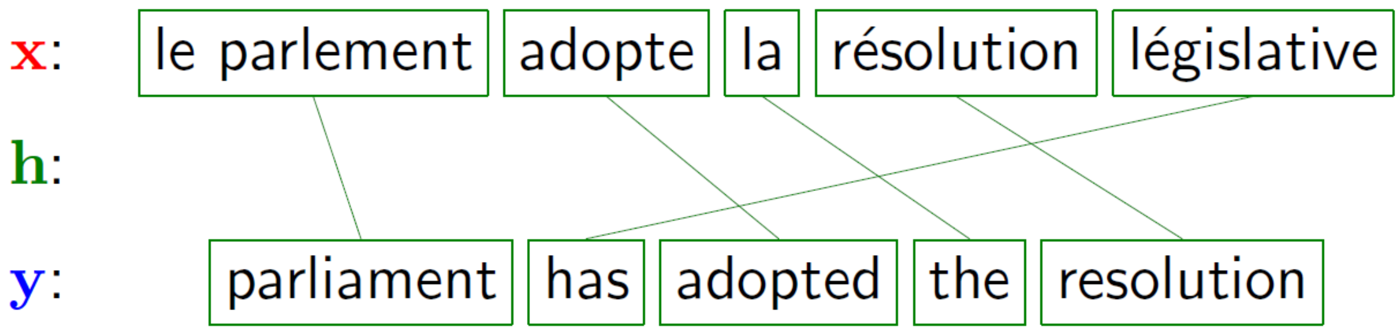
- Features encapsulate lots of information
  - Basic MT systems have around 6 features
  - $P(e|f)$, $P(f|e)$, lexical weighting, language model

- How to tune feature weights?

- Idea 1: Use your favorite classifier

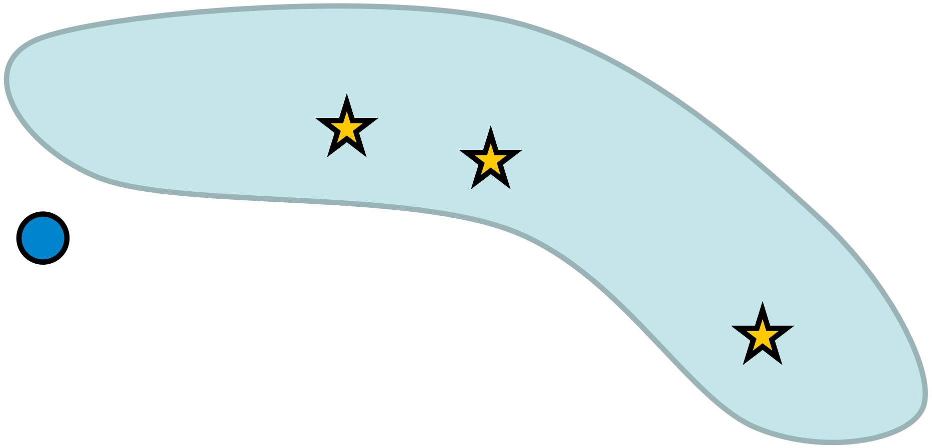
Why Tuning is Hard

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



Why Tuning is Hard

- Problem 2: There are many right answers
  - The reference or references are just a few options
  - No good characterization of the whole class



  - BLEU isn't perfect, but even if you trust it, it's a corpus-level metric, not sentence-level

Perceptron training

For each training example $(\mathbf{x}, \mathbf{y})$: [Collins '02]

$$\mathbf{w} \leftarrow \mathbf{w} \;\; +\Phi(\mathbf{x}, \mathbf{y}_{\mathsf{t}}) \qquad \Big| \; \mathbf{y}_{\mathsf{t}} = \mathbf{y}$$
$$\qquad\qquad -\Phi(\mathbf{x}, \mathbf{y}_{\mathsf{p}}) \qquad \Big| \; \mathbf{y}_{\mathsf{p}} = \textsc{Decode}(\mathbf{x})$$

$$\mathbf{w} \leftarrow \mathbf{w} \;\; +\Phi(\mathbf{x}, \mathbf{y}_{\mathsf{t}}, \mathbf{h}_{\mathsf{t}}) \qquad \Big| \; \mathbf{y}_{\mathsf{t}}, \mathbf{h}_{\mathsf{t}} = ???$$
$$\qquad\qquad -\Phi(\mathbf{x}, \mathbf{y}_{\mathsf{p}}, \mathbf{h}_{\mathsf{p}}) \qquad \Big| \; \mathbf{y}_{\mathsf{p}}, \mathbf{h}_{\mathsf{p}} = \textsc{Decode}(\mathbf{x})$$

Update strategies

$$\mathbf{w} \leftarrow \mathbf{w} + \Phi(\mathbf{x}, \boxed{\mathbf{y}_{\mathrm{t}}, \mathbf{h}_{\mathrm{t}}}) - \Phi(\mathbf{x}, \mathbf{y}_{\mathrm{p}}, \mathbf{h}_{\mathrm{p}})$$

Training example (reference)

$\mathbf{x}$: voté sur demande d ' urgence

$\mathbf{y}$: vote on a request for urgent procedure

Update strategies

$$\mathbf{w} \leftarrow \mathbf{w} + \Phi(\mathbf{x}, \boxed{\mathbf{y}_{\mathrm{t}}, \mathbf{h}_{\mathrm{t}}}) - \Phi(\mathbf{x}, \mathbf{y}_{\mathrm{p}}, \mathbf{h}_{\mathrm{p}})$$

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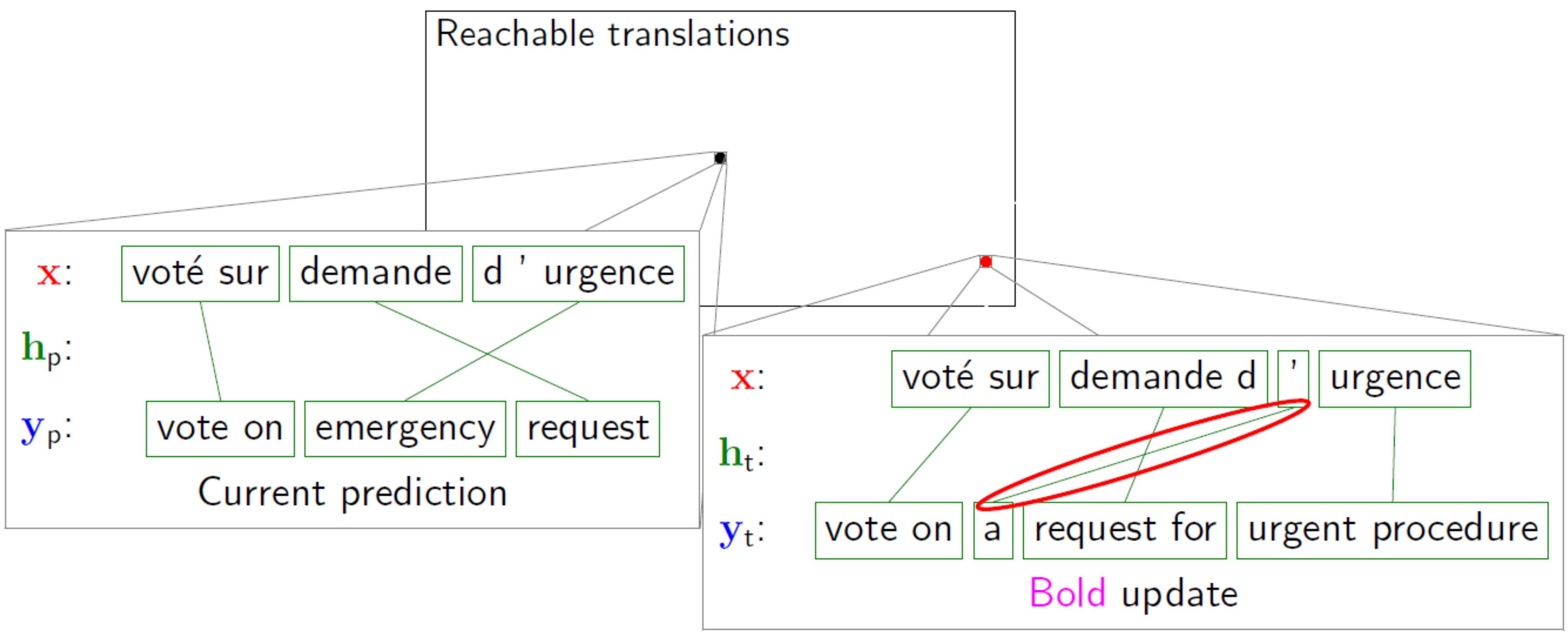

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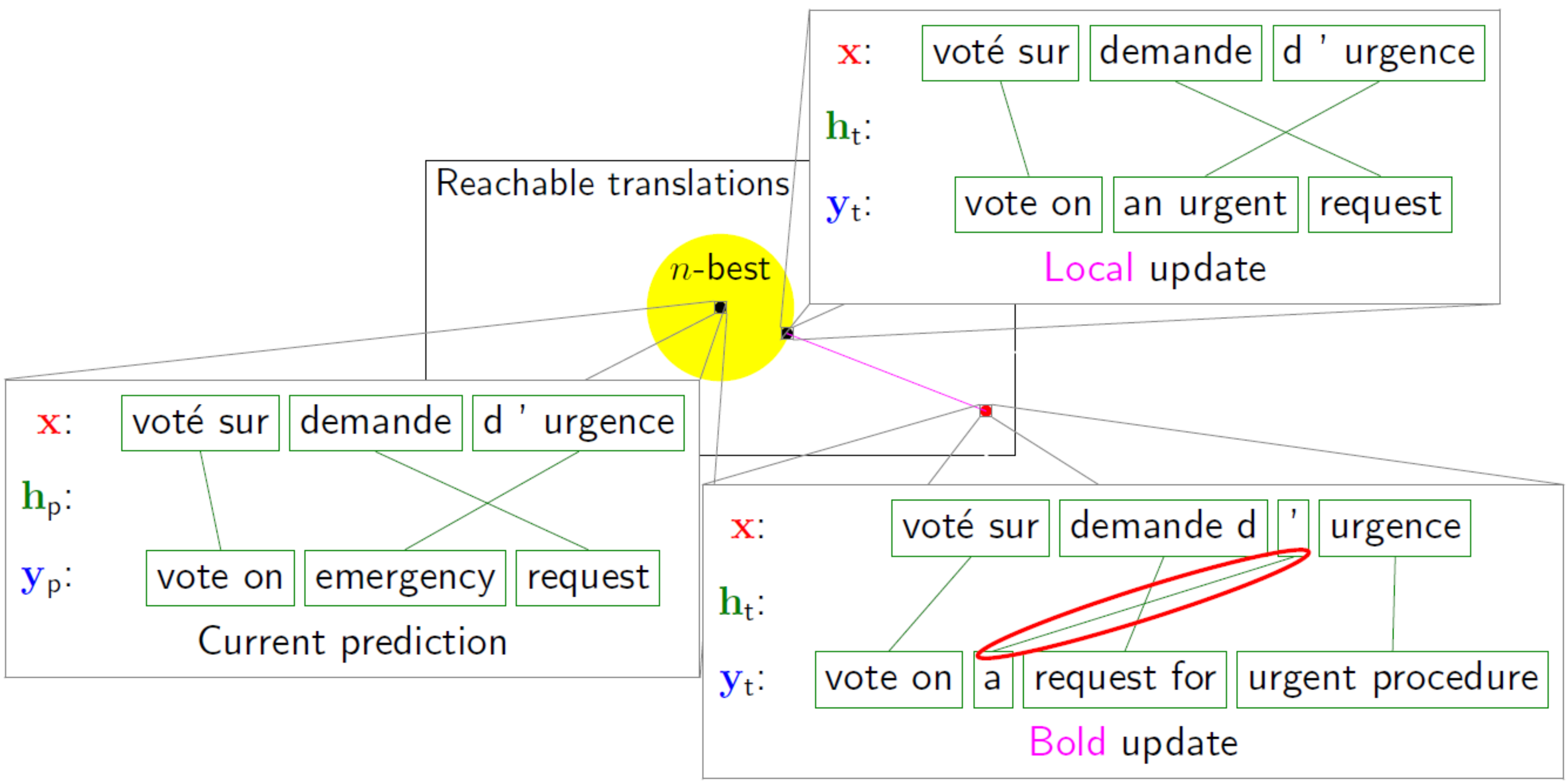


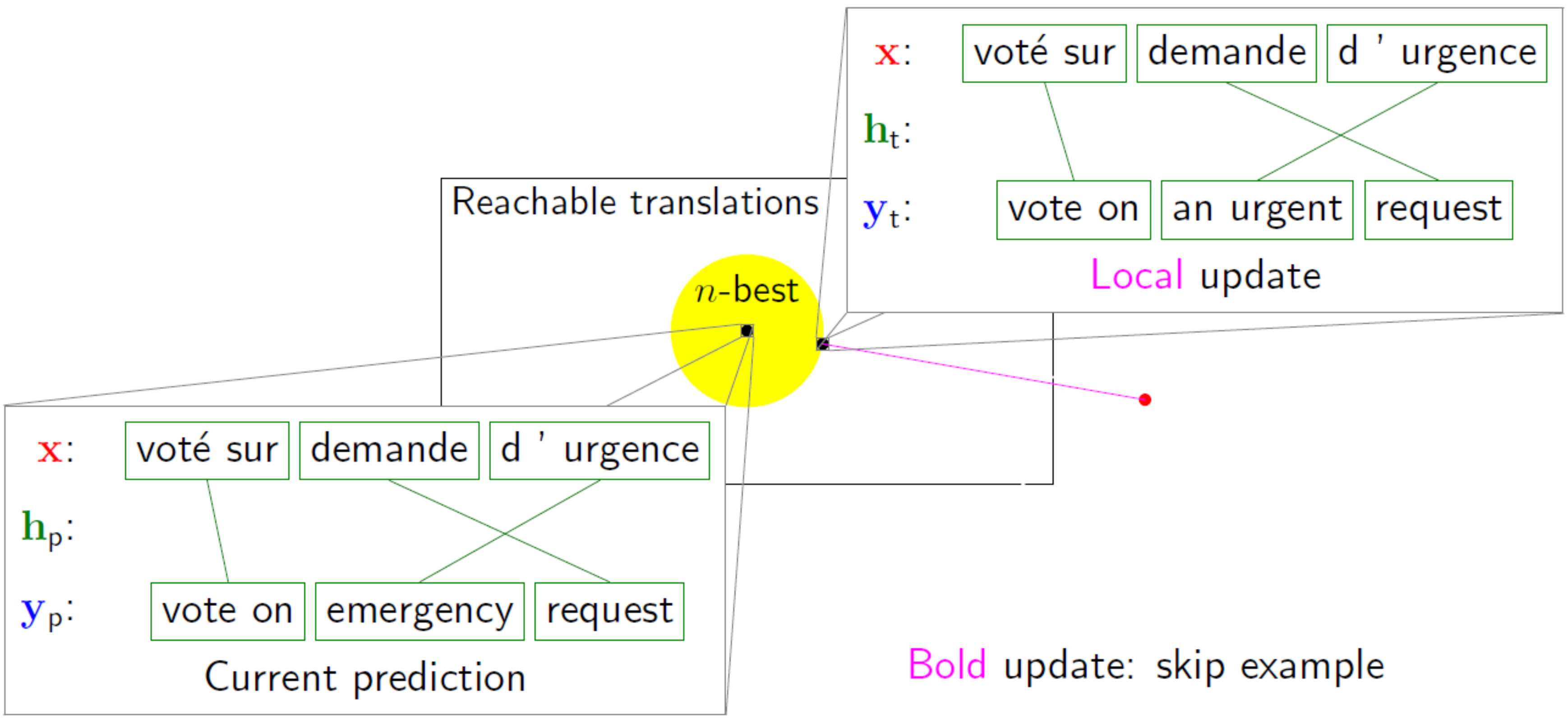
Update strategies

$$\mathbf{w} \leftarrow \mathbf{w} + \Phi(\mathbf{x}, \boxed{\mathbf{y}_{\mathrm{t}}, \mathbf{h}_{\mathrm{t}}}\,) - \Phi(\mathbf{x}, \mathbf{y}_{\mathrm{p}}, \mathbf{h}_{\mathrm{p}})$$

Training example (reference)

$\mathbf{x}$: voté sur demande d ' urgence

$\mathbf{y}$: vote on a request for urgent procedure



Update strategies

$$\mathbf{w} \leftarrow \mathbf{w} + \Phi(\mathbf{x}, \boxed{\mathbf{y}_t, \mathbf{h}_t}) - \Phi(\mathbf{x}, \mathbf{y}_p, \mathbf{h}_p)$$

Training example (reference)

$\mathbf{x}$: voté sur demande d ' urgence

$\mathbf{y}$: vote on a request for urgent procedure

$\mathbf{x}$:

$\mathbf{h}_t$:

te

Decoder	Bold	Local
Monotonic	34.3	**34.6**
Limited distortion	33.5	**34.7**

$\mathbf{x}$:

$\mathbf{h}_p$:

$\mathbf{y}_p$:

Current prediction

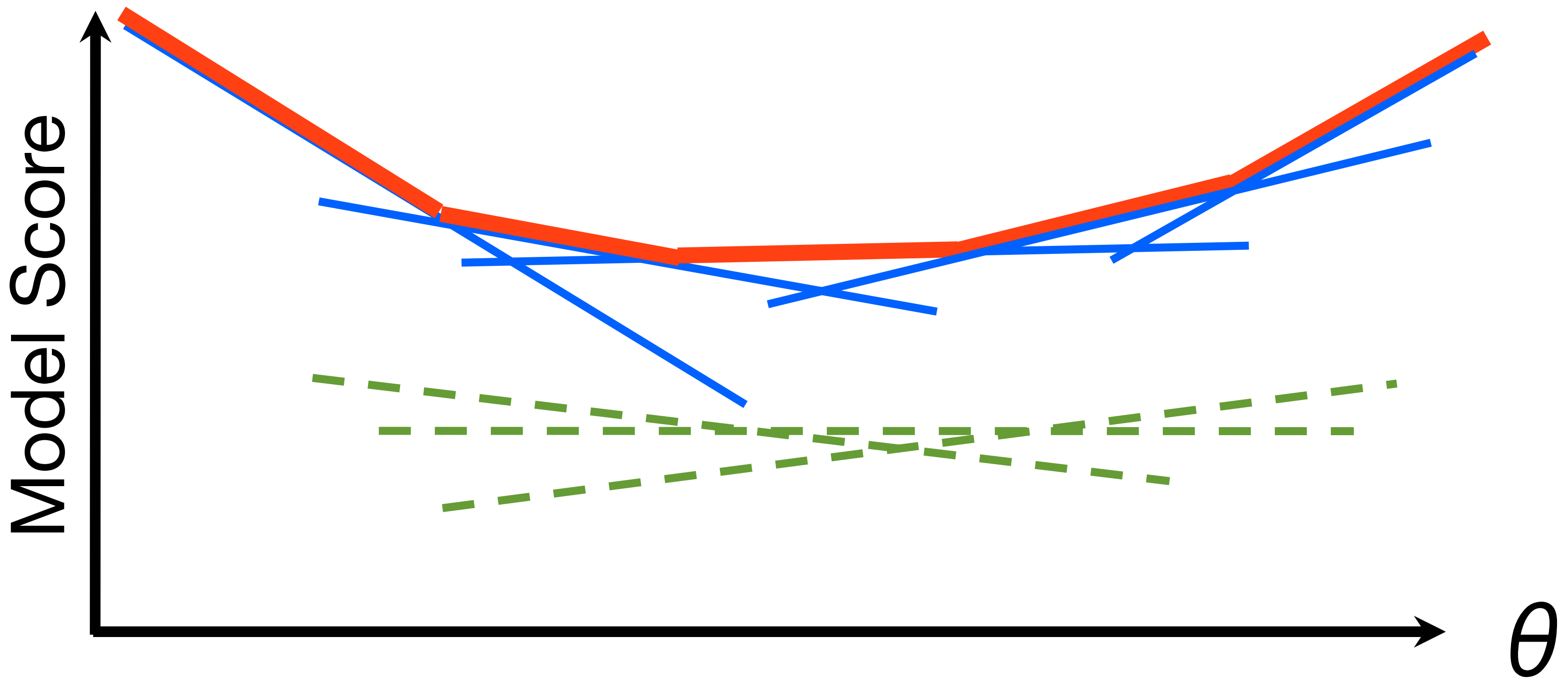
Bold update: skip example

Why Tuning is Hard

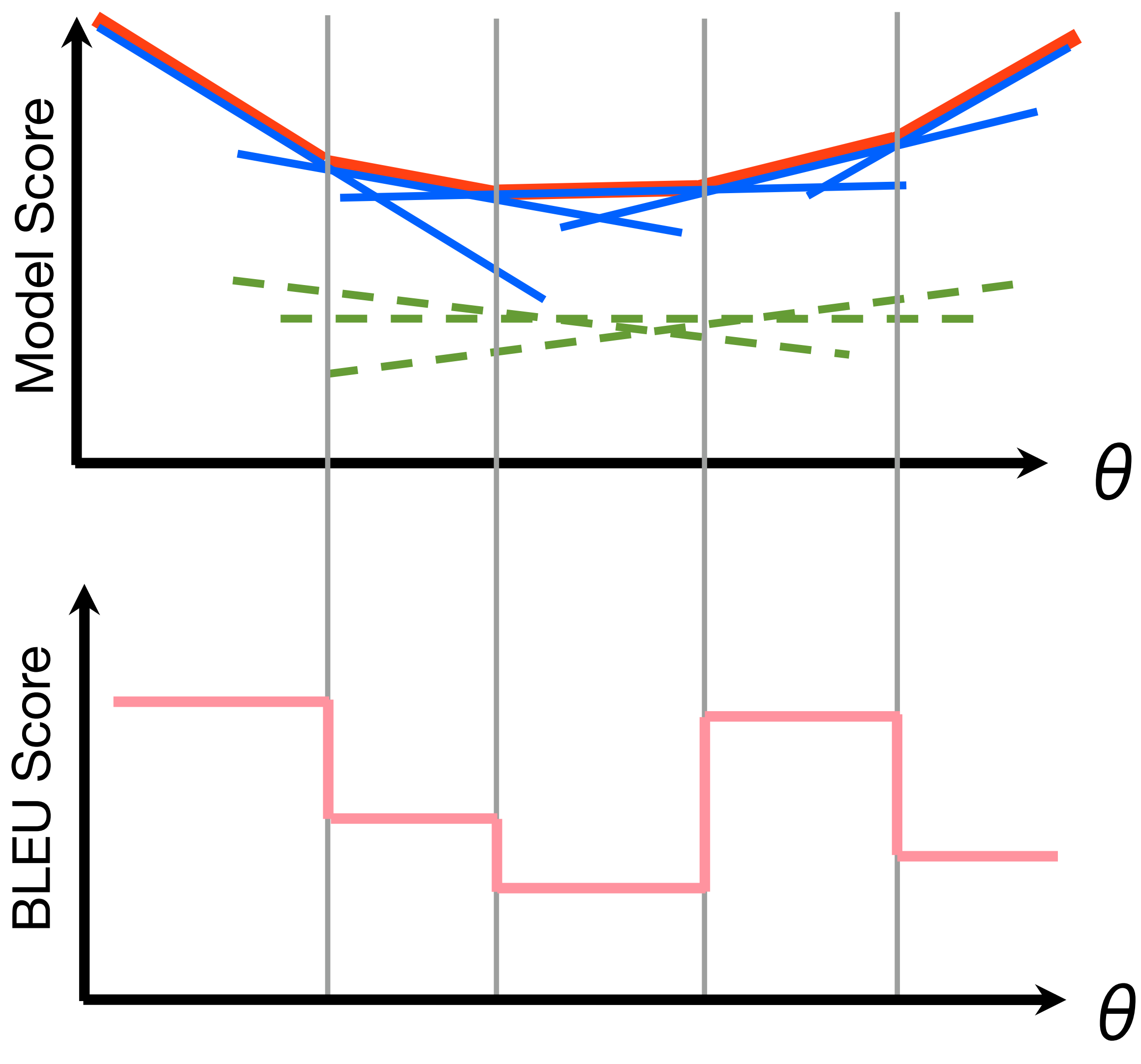
- Problem 3: Computational constraints
  - Discriminative training involves repeated decoding
  - Very slow! So people tune on sets much smaller than those used to build phrase tables

Minimum Error Rate Training

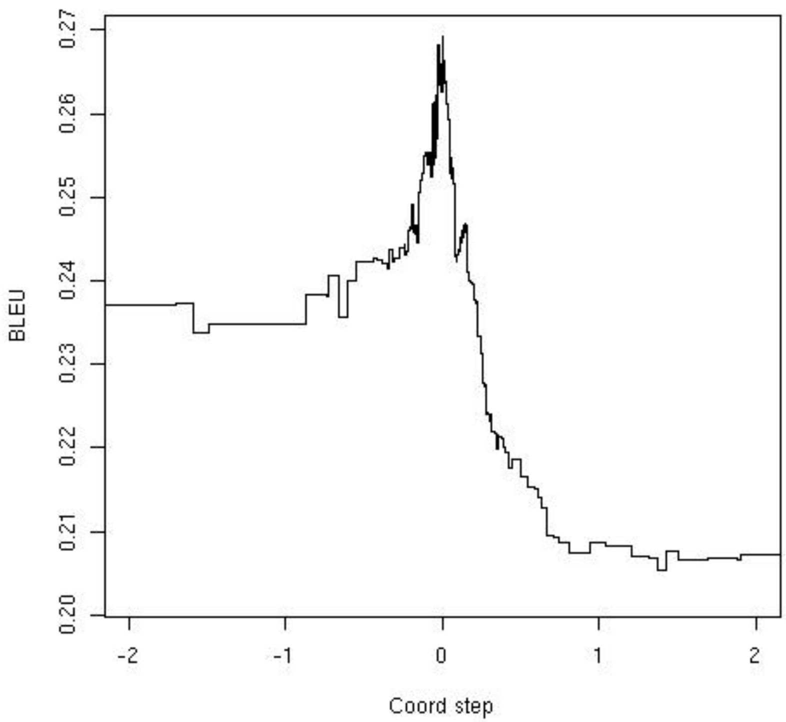
- Standard method: minimize BLEU directly (Och 03)
  - MERT is a discontinuous objective
  - Only works for max ~10 features, but works very well then
  - Here: k-best lists, but forest methods exist (Machery et al 08)



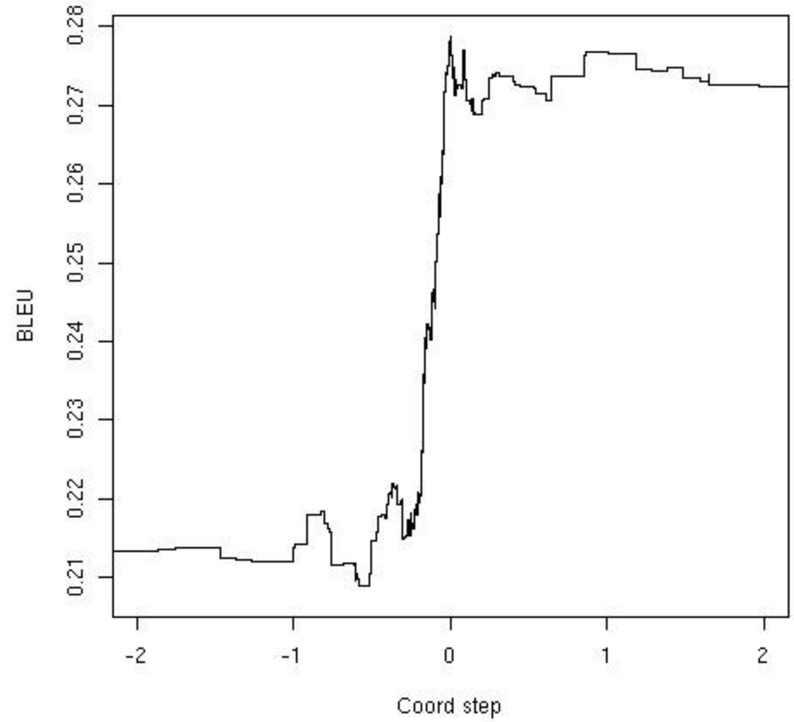
MERT



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



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