Phrase-Based MT: Decoding



February 7, 2013

Phrase Based MT

$$\mathbf{e}^* = \arg \max_{\mathbf{e}} p(\mathbf{e} \mid \mathbf{f})$$

$$= \arg \max_{\mathbf{e}} p(\mathbf{f} \mid \mathbf{e}) \times p(\mathbf{e})$$

$$\approx \arg \max_{\mathbf{e}} p(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) \times p(\mathbf{e})$$

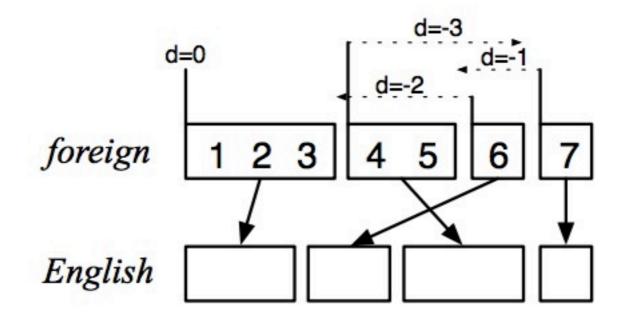


- Recipe
 - Segmentation / Alignment model
 - Phrase model
 - Language Model

Phrase Tables

$ar{\mathbf{f}}$	$\overline{\mathbf{e}}$	$p(\overline{\mathbf{f}} \mid \overline{\mathbf{e}})$
	the issue	0.41
das Thema	the point	0.72
das i liellia	the subject	0.47
	the thema	0.99
oo eiba	there is	0.96
es gibt there are	there are	0.72
morgen	tomorrow	0.9
fliege ich	will I fly	0.63
	will fly	0.17
	I will fly	0.13

Reordering Model



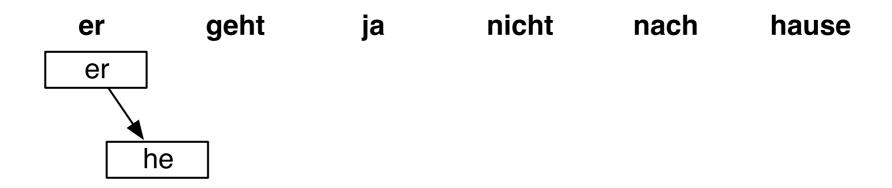
phrase	translates	movement	distance
1	1–3	start at beginning	0
2	6	skip over 4-5	+2
3	4–5	move back over 4-6	-3
4	7	skip over 6	+1

Scoring function: $d(x) = \alpha^{|x|}$ — exponential with distance

• Task: translate this sentence from German into English

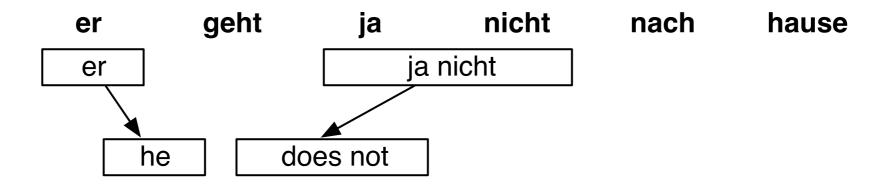
er geht ja nicht nach hause

• Task: translate this sentence from German into English



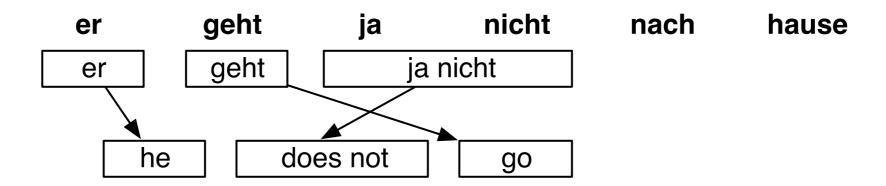
• Pick phrase in input, translate

• Task: translate this sentence from German into English



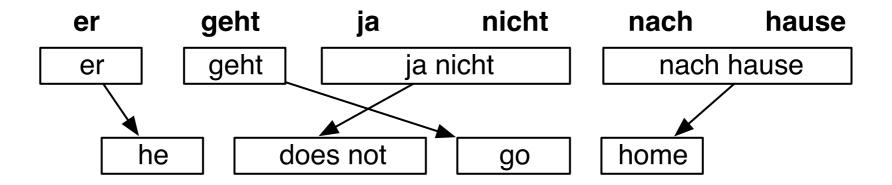
- Pick phrase in input, translate
 - it is allowed to pick words out of sequence reordering
 - phrases may have multiple words: many-to-many translation

• Task: translate this sentence from German into English



• Pick phrase in input, translate

• Task: translate this sentence from German into English



• Pick phrase in input, translate

Computing Translation Probability

Probabilistic model for phrase-based translation:

$$\mathbf{e}_{\mathsf{best}} = \mathsf{argmax}_{\mathbf{e}} \ \prod_{i=1}^{I} \phi(\bar{f}_i | \bar{e}_i) \ d(start_i - end_{i-1} - 1) \ p_{\scriptscriptstyle \mathrm{LM}}(\mathbf{e})$$

- Score is computed incrementally for each partial hypothesis
- Components

Phrase translation Picking phrase \bar{f}_i to be translated as a phrase \bar{e}_i

ightarrow look up score $\phi(\bar{f}_i|\bar{e}_i)$ from phrase translation table

Reordering Previous phrase ended in end_{i-1} , current phrase starts at $start_i$

 \rightarrow compute $d(start_i - end_{i-1} - 1)$

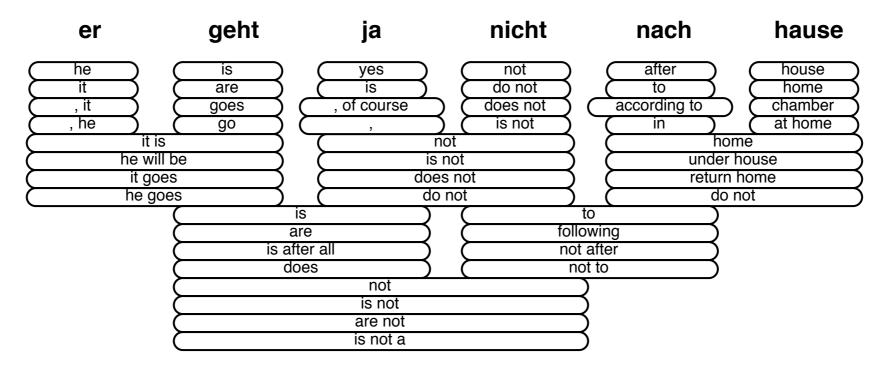
Language model For n-gram model, need to keep track of last n-1 words

 \rightarrow compute score $p_{\text{LM}}(w_i|w_{i-(n-1)},...,w_{i-1})$ for added words w_i

Chapter 6: Decoding

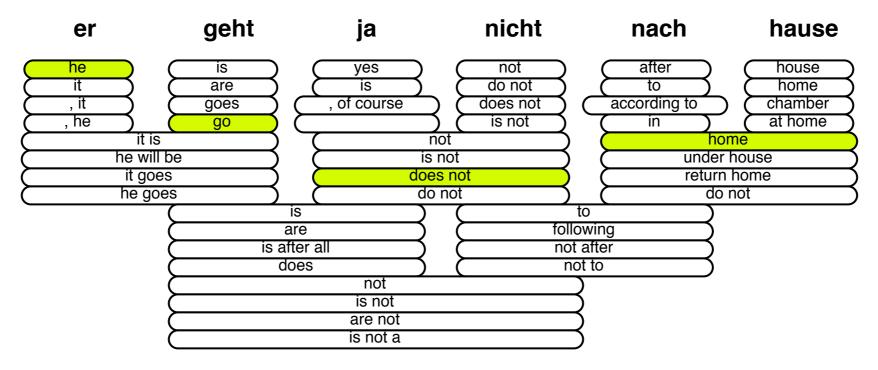
7

Translation Options



- Many translation options to choose from
 - in Europarl phrase table: 2727 matching phrase pairs for this sentence
 - by pruning to the top 20 per phrase, 202 translation options remain

Translation Options



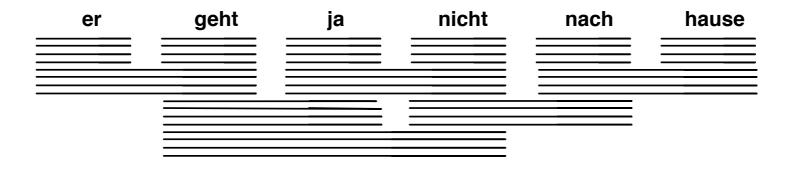
- The machine translation decoder does not know the right answer
 - picking the right translation options
 - arranging them in the right order
- \rightarrow Search problem solved by heuristic beam search

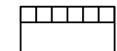
Decoding: Precompute Translation Options



consult phrase translation table for all input phrases

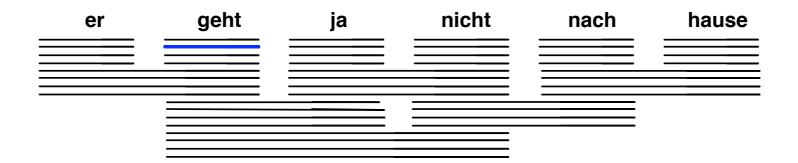
Decoding: Start with Initial Hypothesis

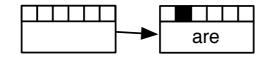




initial hypothesis: no input words covered, no output produced

Decoding: Hypothesis Expansion

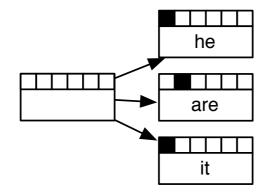




pick any translation option, create new hypothesis

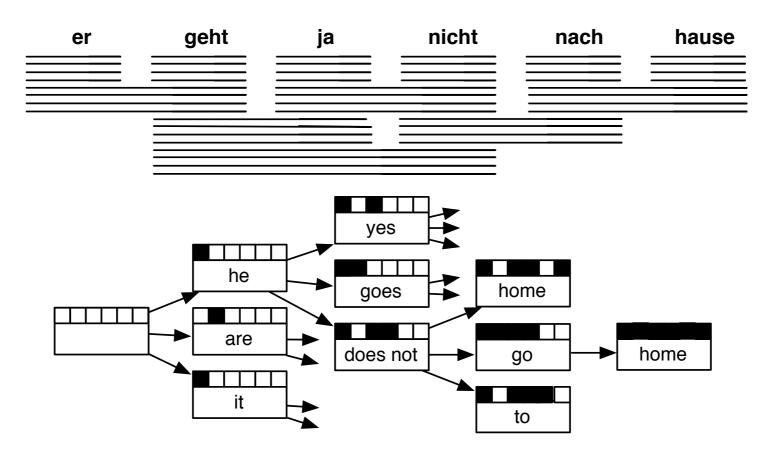
Decoding: Hypothesis Expansion





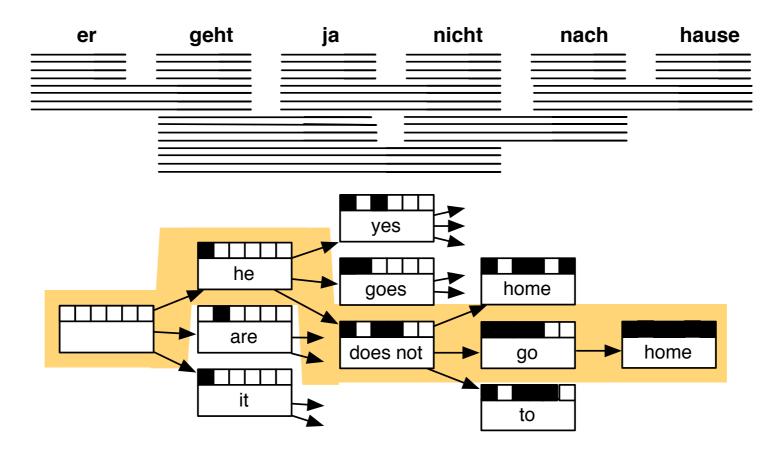
create hypotheses for all other translation options

Decoding: Hypothesis Expansion



also create hypotheses from created partial hypothesis

Decoding: Find Best Path



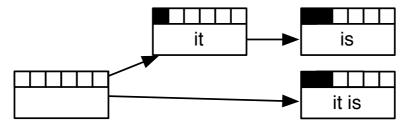
backtrack from highest scoring complete hypothesis

Complexity

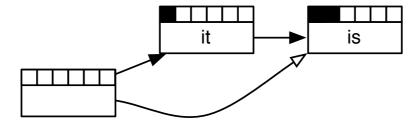
- This is an NP-complete problem
 - Reduction to TSP (sketch)
 - Each source word is a city
 - A bigram LM encodes the distance between pairs of cities
 - Knight (1999) has careful proof
- How do we solve such problems?
 - Dynamic programming [risk free]
 - The state is the current city C & the set of previous visited cities
 - Doesn't matter the order the previous list was visited in as long as we keep the best path to C through
 - How many states are there?
 - Approximate search [risky]

Recombination

- Two hypothesis paths lead to two matching hypotheses
 - same number of foreign words translated
 - same English words in the output
 - different scores

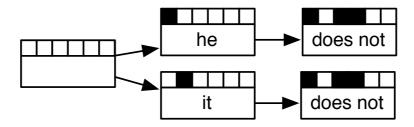


• Worse hypothesis is dropped

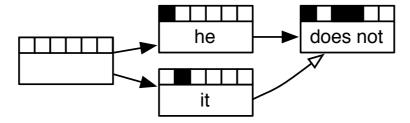


Recombination

- Two hypothesis paths lead to hypotheses indistinguishable in subsequent search
 - same number of foreign words translated
 - same last two English words in output (assuming trigram language model)
 - same last foreign word translated
 - different scores



Worse hypothesis is dropped



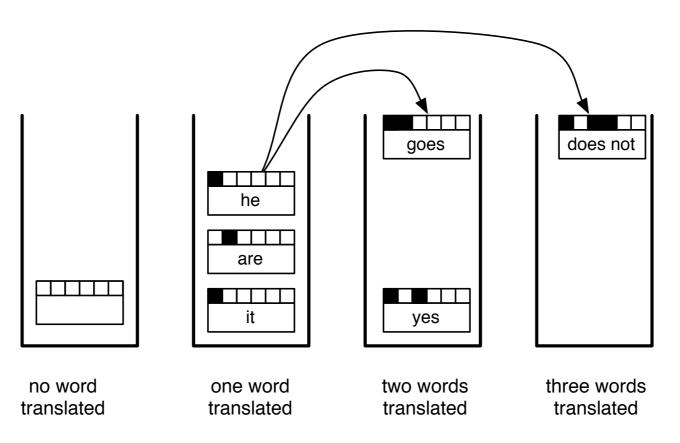
Restrictions on Recombination

- Translation model: Phrase translation independent from each other
 - → no restriction to hypothesis recombination
- Language model: Last n-1 words used as history in n-gram language model
 - \rightarrow recombined hypotheses must match in their last n-1 words
- Reordering model: Distance-based reordering model based on distance to end position of previous input phrase
 - → recombined hypotheses must have that same end position

Pruning

- Recombination reduces search space, but not enough (we still have a NP complete problem on our hands)
- Pruning: remove bad hypotheses early
 - put comparable hypothesis into stacks
 (hypotheses that have translated same number of input words)
 - limit number of hypotheses in each stack

Stacks



- Hypothesis expansion in a stack decoder
 - translation option is applied to hypothesis
 - new hypothesis is dropped into a stack further down

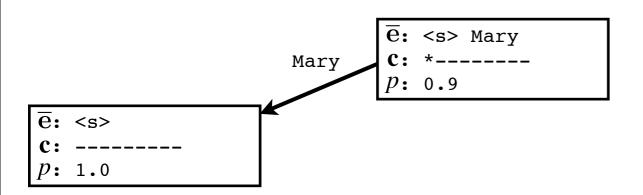
Stack Decoding Algorithm

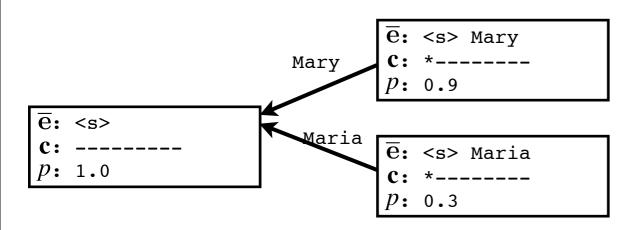
```
1: place empty hypothesis into stack 0
2: for all stacks 0...n-1 do
      for all hypotheses in stack do
          \  \, \text{for all translation options } \  \, \text{do} \\
4:
           if applicable then
5:
              create new hypothesis
              place in stack
7:
              recombine with existing hypothesis if possible
8:
              prune stack if too big
9:
           end if
10:
         end for
11:
      end for
13: end for
```

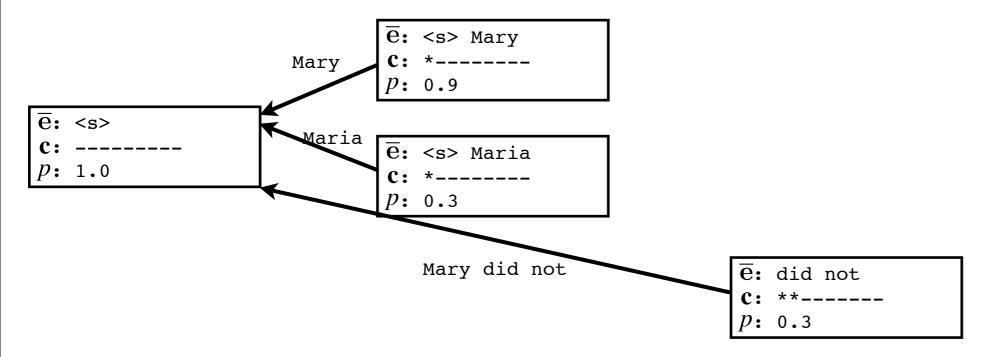
 ē: <s>

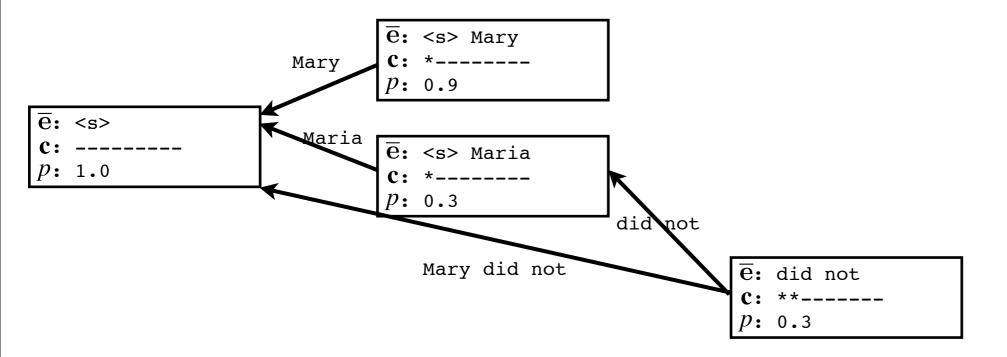
 c: ----

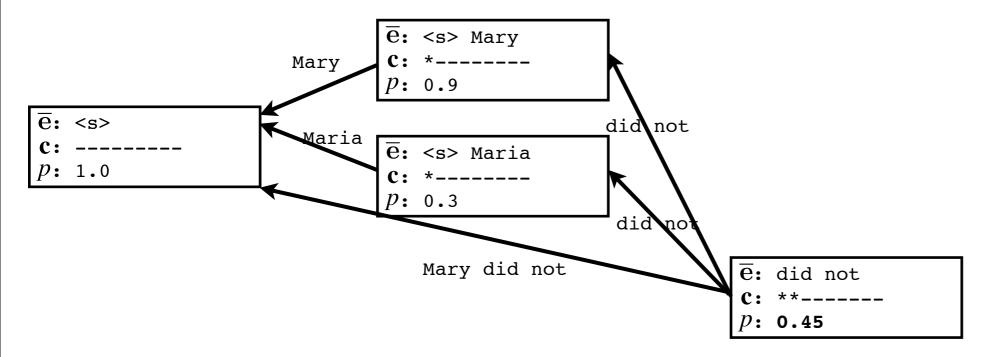
 p: 1.0

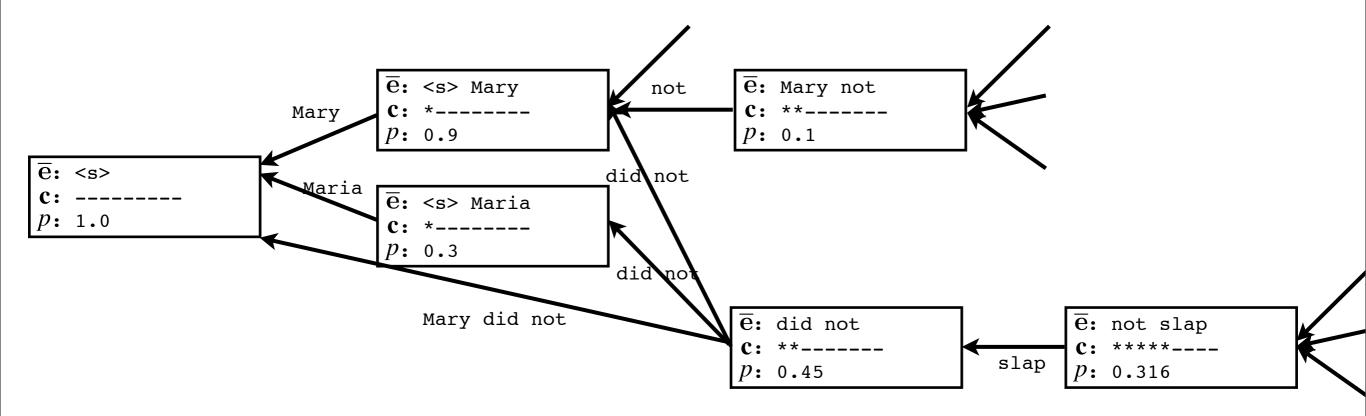












Pruning

- Pruning strategies
 - histogram pruning: keep at most k hypotheses in each stack
 - stack pruning: keep hypothesis with score $\alpha \times$ best score ($\alpha < 1$)
- Computational time complexity of decoding with histogram pruning

 $O(\max \text{ stack size} \times \text{translation options} \times \text{sentence length})$

• Number of translation options is linear with sentence length, hence:

 $O(\text{max stack size} \times \text{sentence length}^2)$

• Quadratic complexity

Reordering Limits

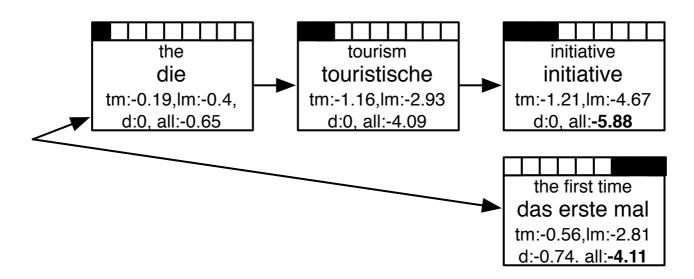
- Limiting reordering to maximum reordering distance
- Typical reordering distance 5–8 words
 - depending on language pair
 - larger reordering limit hurts translation quality
- Reduces complexity to linear

 $O(\max \text{ stack size} \times \text{ sentence length})$

• Speed / quality trade-off by setting maximum stack size

Translating the Easy Part First?

the tourism initiative addresses this for the first time



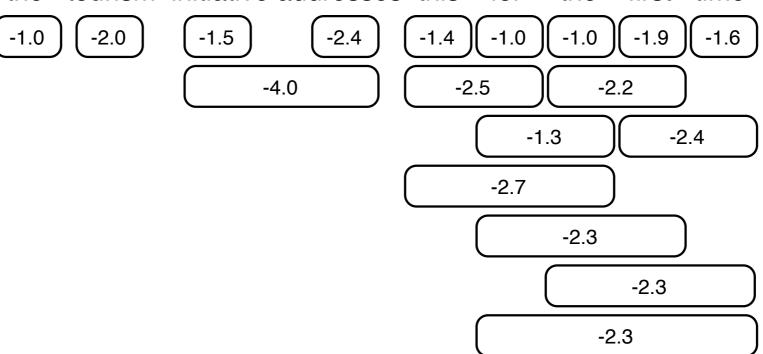
both hypotheses translate 3 words worse hypothesis has better score

Estimating Future Cost

- Future cost estimate: how expensive is translation of rest of sentence?
- Optimistic: choose cheapest translation options
- Cost for each translation option
 - translation model: cost known
 - language model: output words known, but not context
 - → estimate without context
 - reordering model: unknown, ignored for future cost estimation

Cost Estimates from Translation Options

the tourism initiative addresses this for the first time



cost of cheapest translation options for each input span (log-probabilities)

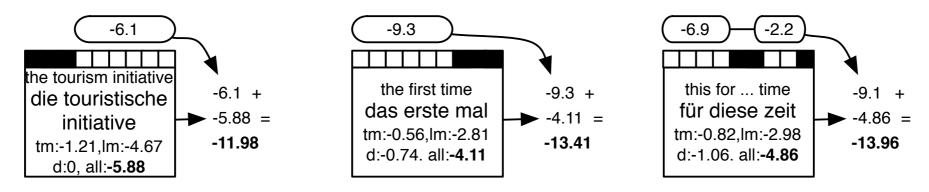
Cost Estimates for all Spans

• Compute cost estimate for all contiguous spans by combining cheapest options

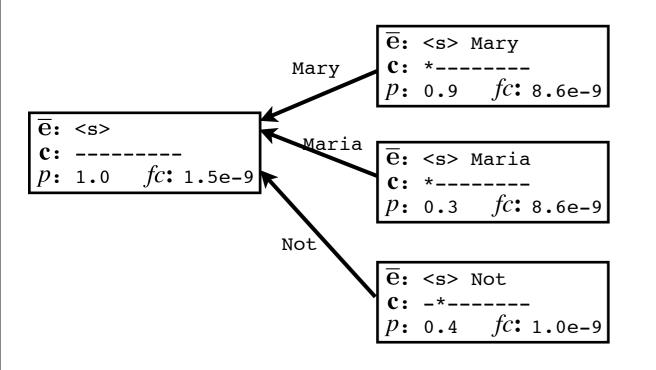
first	future cost estimate for n words (from first)								
word	1	2	3	4	5	6	7	8	9
the	-1.0	-3.0	-4.5	-6.9	-8.3	-9.3	-9.6	-10.6	-10.6
tourism	-2.0	-3.5	-5.9	-7.3	-8.3	-8.6	-9.6	-9.6	
initiative	-1.5	-3.9	-5.3	-6.3	-6.6	-7.6	-7.6		•
addresses	-2.4	-3.8	-4.8	-5.1	-6.1	-6.1		•	
this	-1.4	-2.4	-2.7	-3.7	-3.7				
for	-1.0	-1.3	-2.3	-2.3		•			
the	-1.0	-2.2	-2.3		•				
first	-1.9	-2.4		-					
time	-1.6		•						

- Function words cheaper (the: -1.0) than content words (tourism -2.0)
- Common phrases cheaper (for the first time: -2.3) than unusual ones (tourism initiative addresses: -5.9)

Combining Score and Future Cost



- Hypothesis score and future cost estimate are combined for pruning
 - left hypothesis starts with hard part: the tourism initiative score: -5.88, future cost: $-6.1 \rightarrow \text{total cost -}11.98$
 - middle hypothesis starts with easiest part: the first time score: -4.11, future cost: -9.3 → total cost -13.41
 - right hypothesis picks easy parts: this for ... time score: -4.86, future cost: $-9.1 \rightarrow \text{total cost } -13.96$



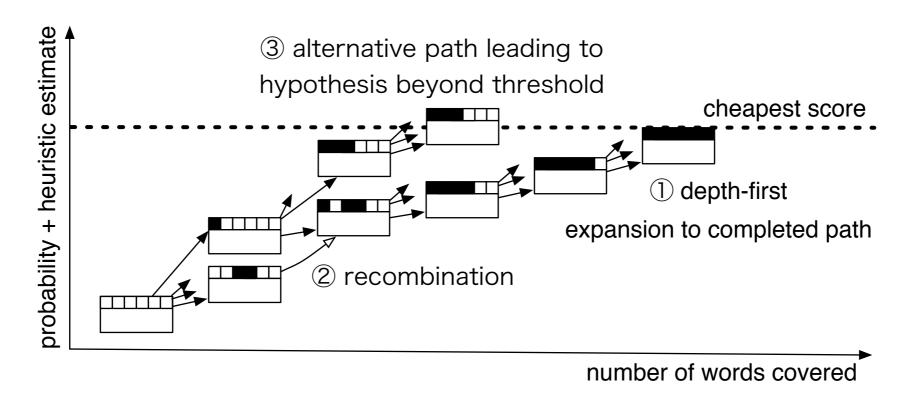


Future costs make these hypotheses comparable.

Other Decoding Algorithms

- A* search
- Greedy hill-climbing
- Using finite state transducers (standard toolkits)

A* Search



- Uses admissible future cost heuristic: never overestimates cost
- Translation agenda: create hypothesis with lowest score + heuristic cost
- Done, when complete hypothesis created

Greedy Hill-Climbing

- Create one complete hypothesis with depth-first search (or other means)
- Search for better hypotheses by applying change operators
 - change the translation of a word or phrase
 - combine the translation of two words into a phrase
 - split up the translation of a phrase into two smaller phrase translations
 - move parts of the output into a different position
 - swap parts of the output with the output at a different part of the sentence
- Terminates if no operator application produces a better translation

Marginal Decoding

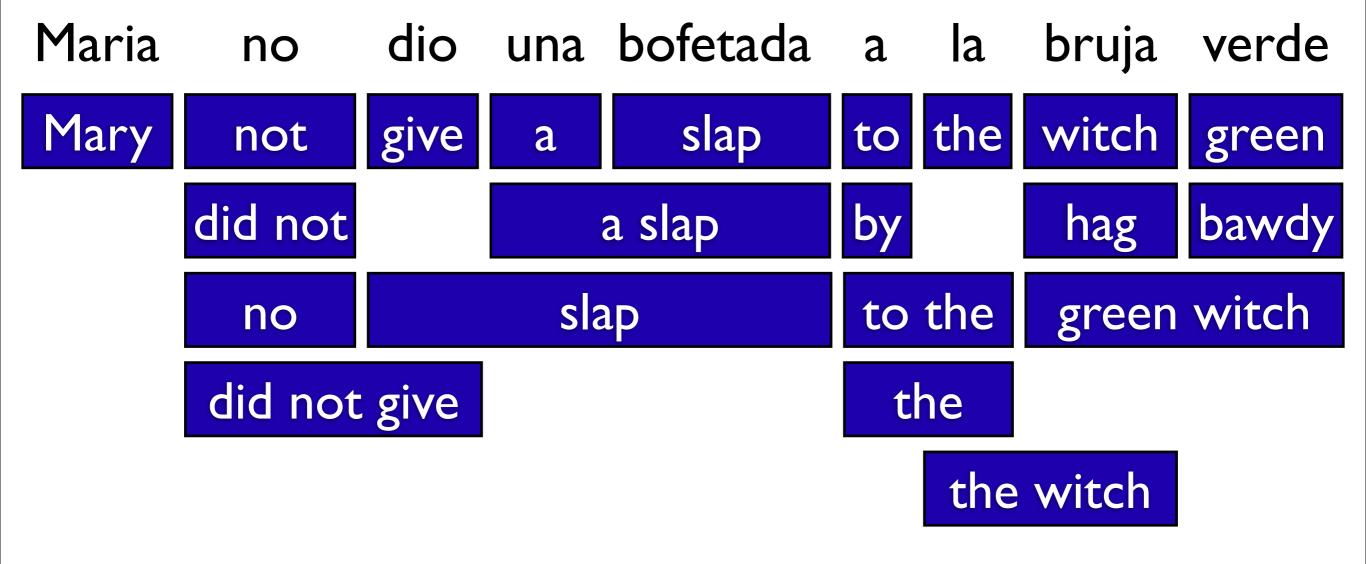
$$\mathbf{e}^* = \arg \max_{\mathbf{e}} p(\mathbf{e} \mid \mathbf{f})$$

$$= \arg \max_{\mathbf{e}} p(\mathbf{f} \mid \mathbf{e}) \times p(\mathbf{e})$$

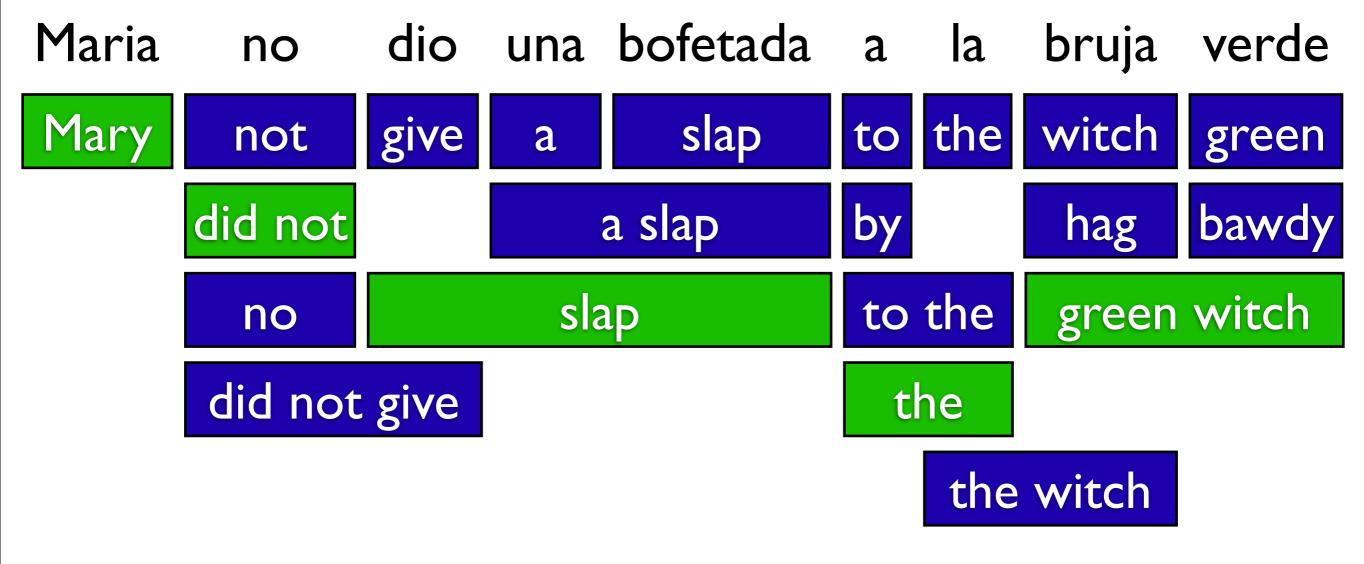
$$\approx \arg \max_{\mathbf{e}} p(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) \times p(\mathbf{e})$$

Does this last approximation matter?

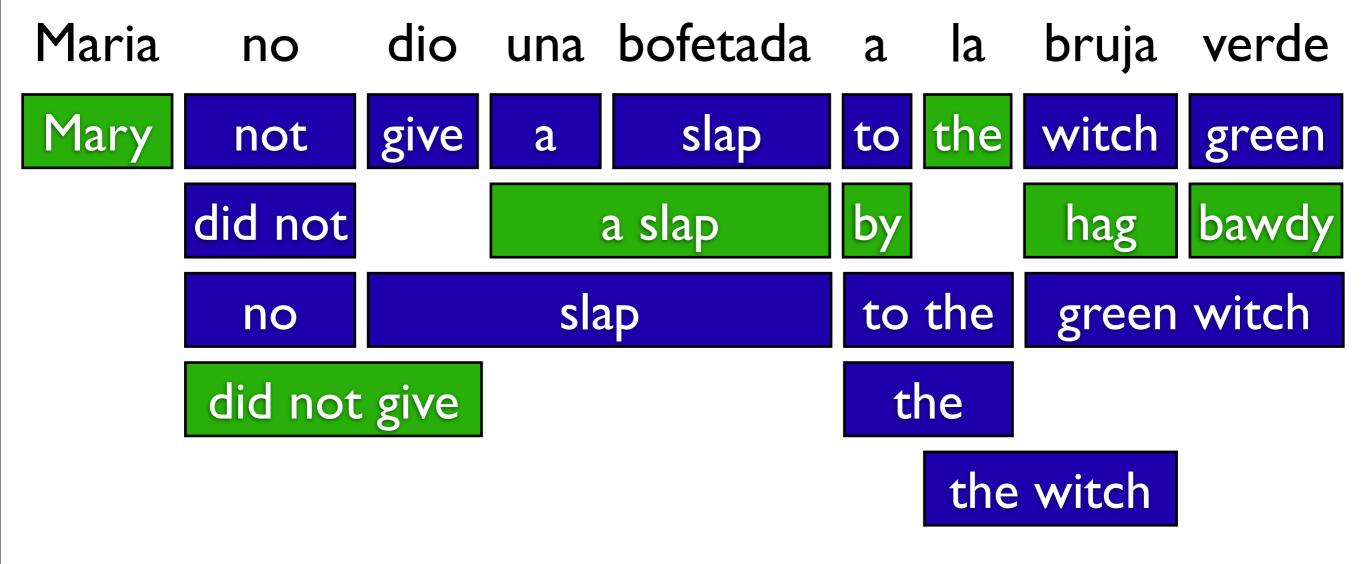
- Variational & MCMC explored
- marginal benefits, depending on training
- Really hard problem (Sima'an, 1997)



Adapted from Koehn (2006)



Adapted from Koehn (2006)



Adapted from Koehn (2006)

Decoding algorithm

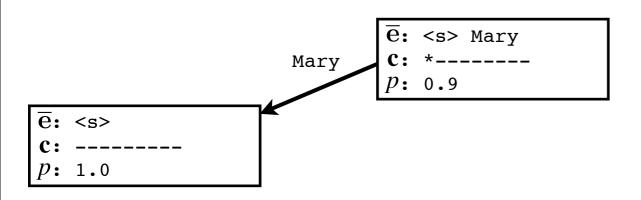
- Translation as a search problem
- Partial hypothesis keeps track of
 - which source words have been translated (coverage vector)
 - *n*-I most recent words of English (for LM!)
 - a back pointer list to the previous hypothesis + (e,f) phrase pair used
 - the (partial) translation probability
 - the estimated probability of translating the remaining words (precomputed, a function of the coverage vector)
- Start state: no translated words, E=<s>, bp=nil
- Goal state: all translated words

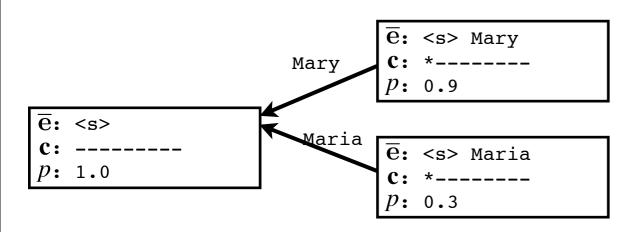
Decoding algorithm

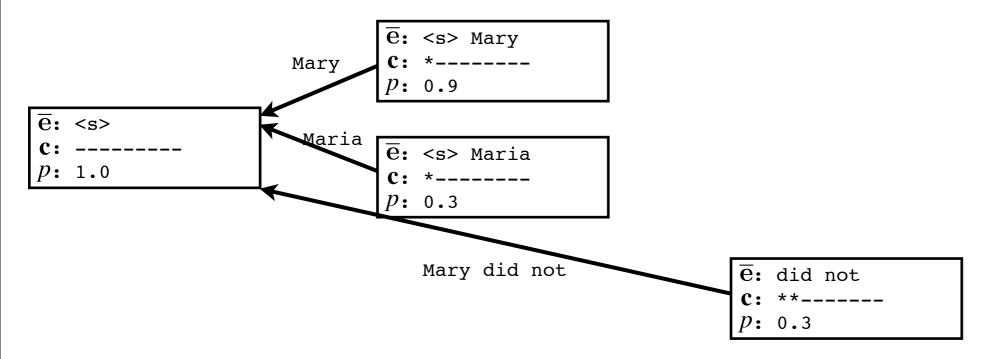
- Q[0] ← Start state
- for i = 0 to |**f**|-**l**
 - Keep b best hypotheses at Q[i]
 - for each hypothesis h in Q[i]
 - for each untranslated span in h.c for which there is a translation <e,f>in the phrase table
 - h' = h extend by <e,f>
 - Is there an item in Q[|h'.c|] with = LM state?
 - yes: update the item bp list and probability
 - no: $Q[|h'.c|] \leftarrow h'$
- Find the best hypothesis in $Q[|\mathbf{f}|]$, reconstruction translation by following back pointers

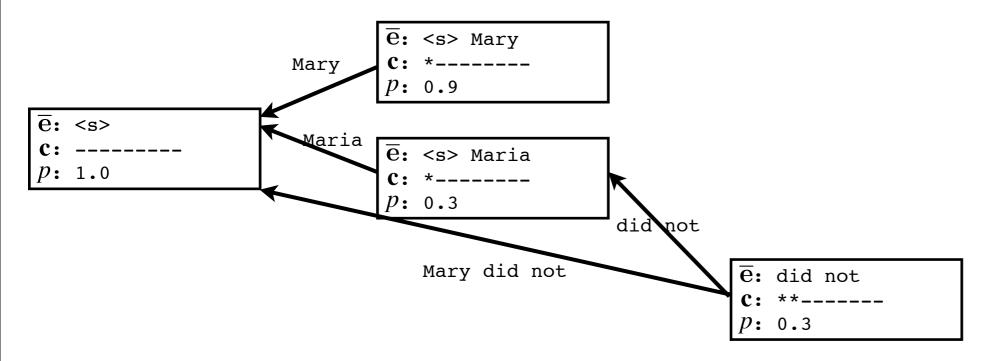
<u>e</u>: <s>

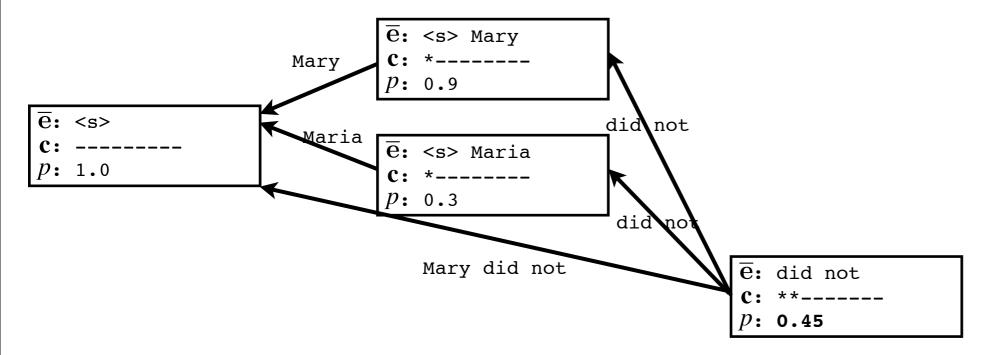
p: 1.0

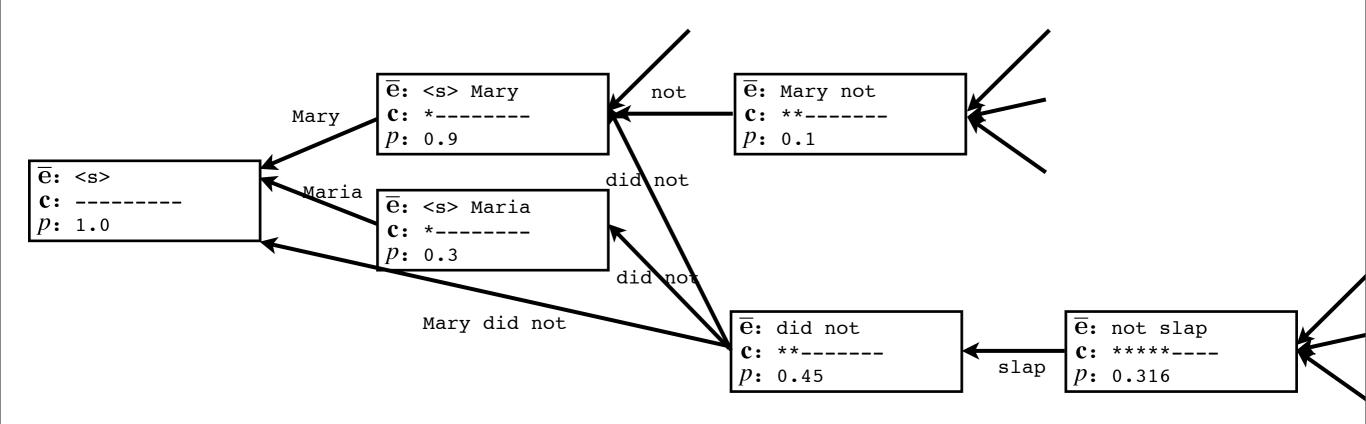






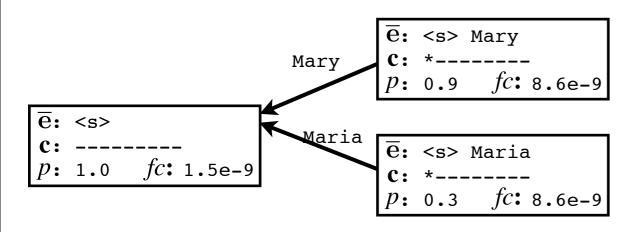


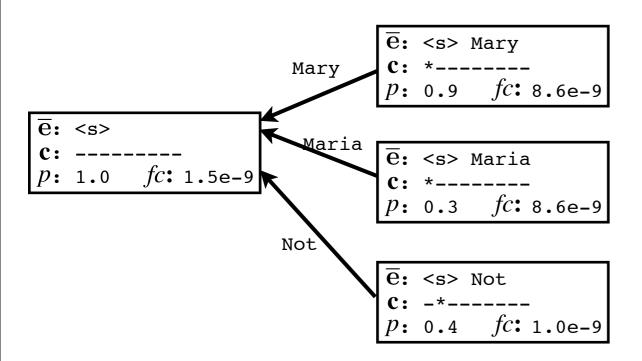


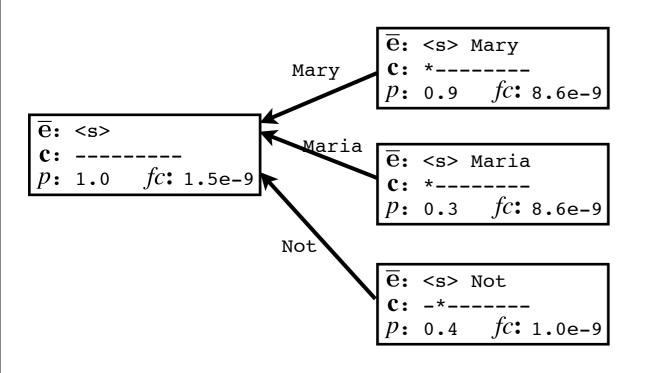


Reordering

- Language express words in different orders
 - bruja verde vs. green witch
- Phrase pairs can "memorize" some of these
- More general: in decoding, "skip ahead"
- Problem:
 - Won't "easy parts" of the sentence be translated first?
- Solution:
 - Future cost estimate
 - For every coverage vector, estimate what it will cost to translate the remaining untranslated words
 - When pruning, use p * future cost!









Future costs make these hypotheses comparable.

Decoding summary

- Finding the best hypothesis is NP-hard
 - Even with no language model, there are an exponential number of states!
 - Solution I: limit reordering
 - Solution 2: (lossy) pruning