Phrase-Based MT



Machine Translation Lecture 8

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Website: mt-class.org/penn

• Task: translate this sentence from German into English

er geht ja nicht nach hause

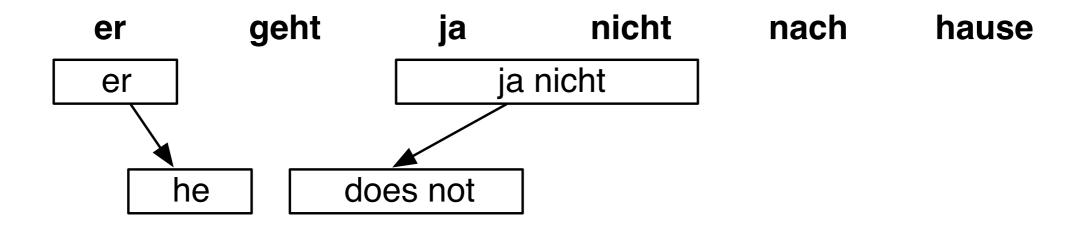
Chapter 6: Decoding

• Task: translate this sentence from German into English



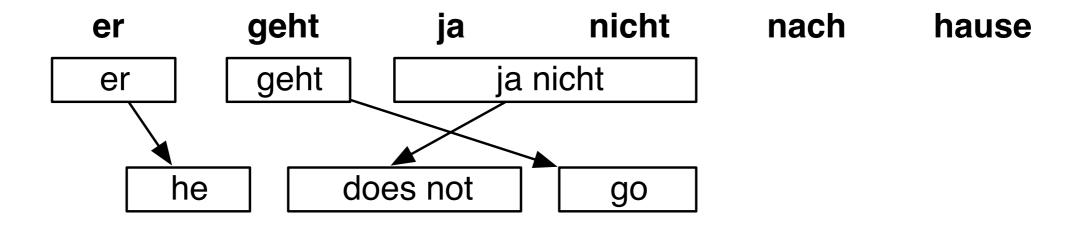
• Pick phrase in input, translate

• Task: translate this sentence from German into English



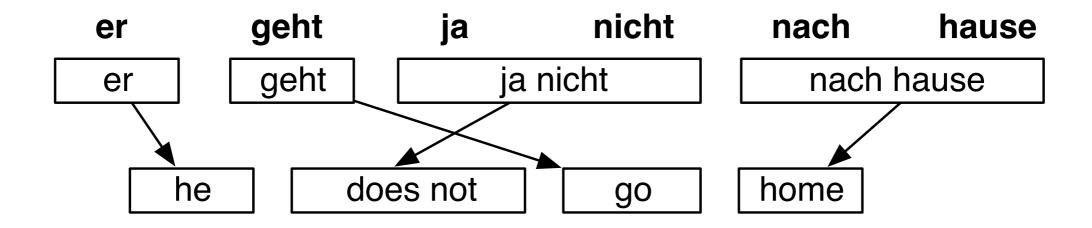
- Pick phrase in input, translate
 - it is allowed to pick words out of sequence reordering
 - phrases may have multiple words: many-to-many translation

• 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

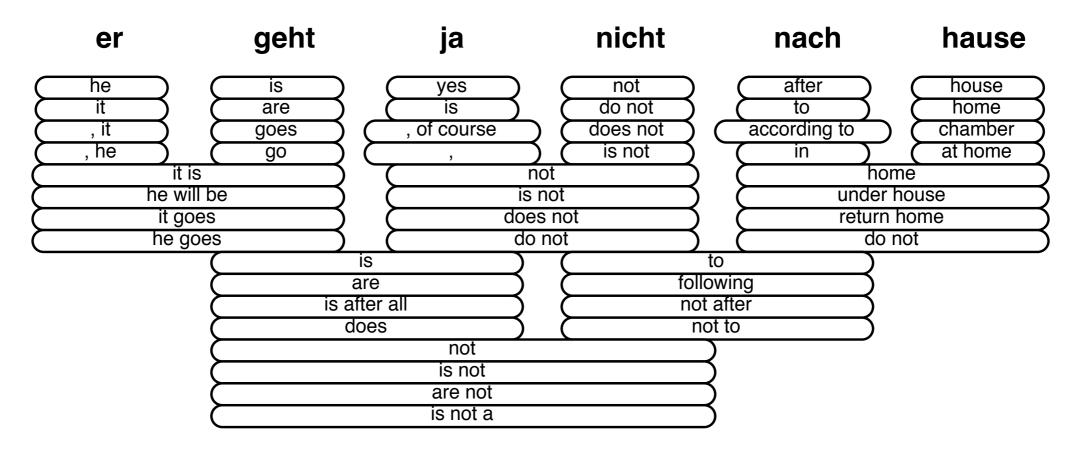
 \rightarrow look up score $\phi(\bar{f}_i|\bar{e}_i)$ from phrase translation table

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

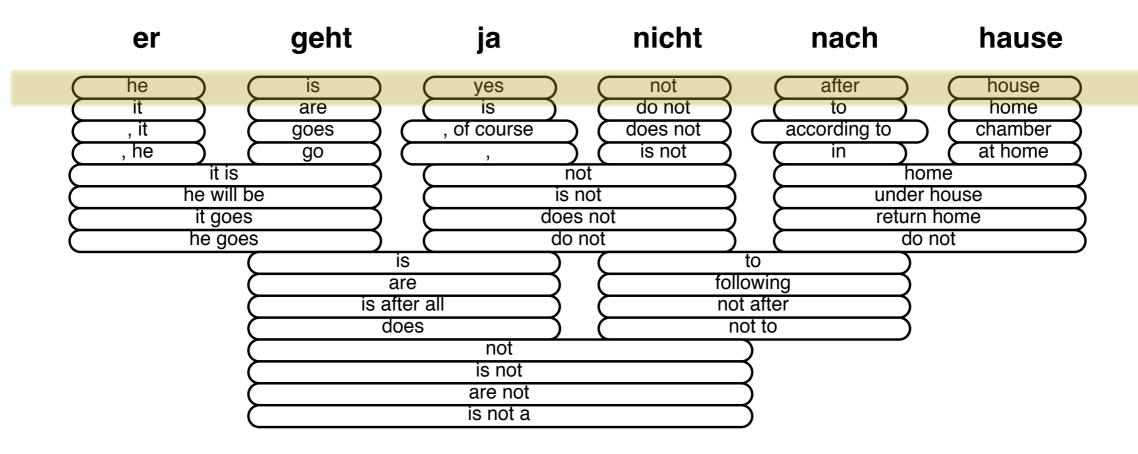
 \rightarrow compute $d(start_i - end_{i-1} - 1)$

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

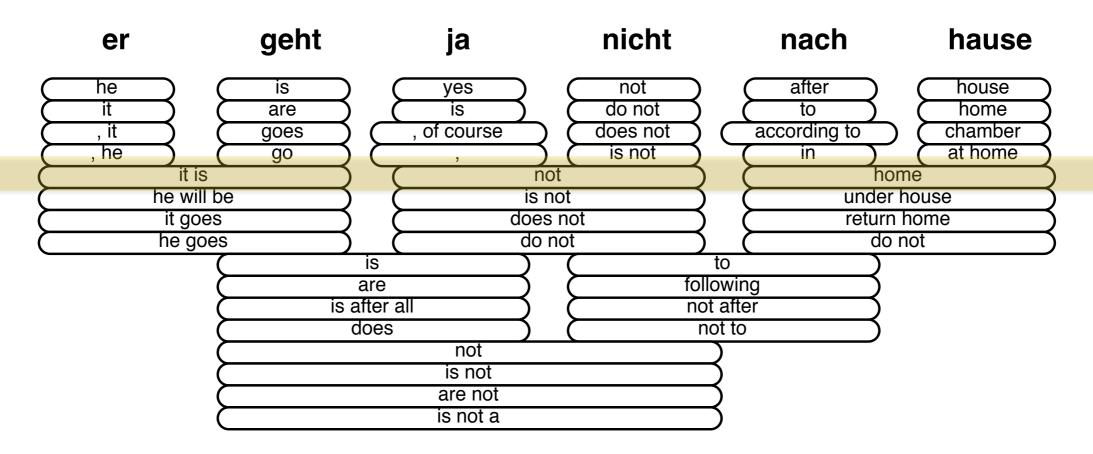
 \rightarrow compute score $p_{\text{LM}}(w_i|w_{i-(n-1)},...,w_{i-1})$ for added words w_i



- 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

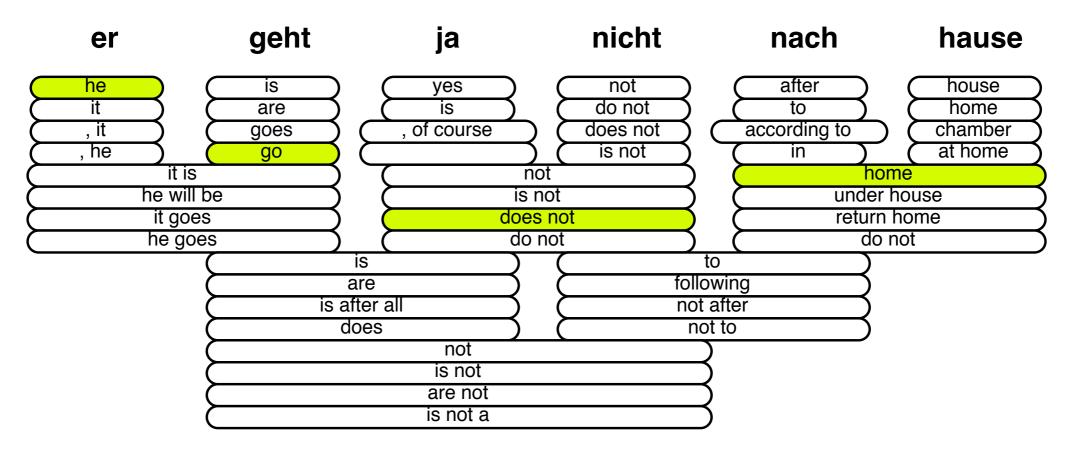


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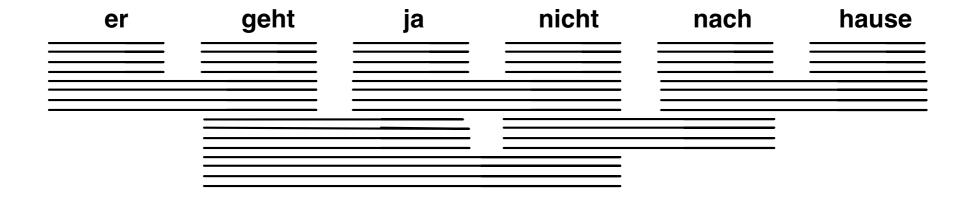
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Chapter 6: Decoding



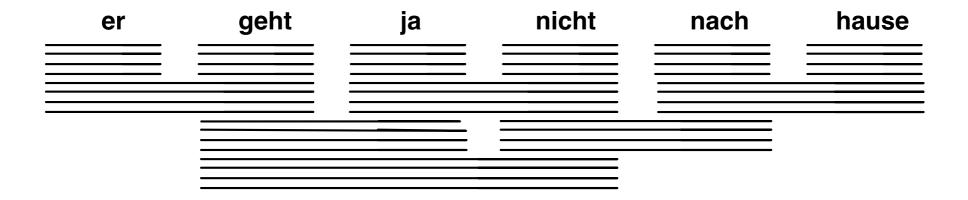
- The machine translation decoder does not know the right answer
 - picking the right translation options
 - arranging them in the right order
- → Search problem solved by heuristic beam search

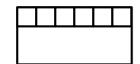
Decoding: Precompute Translation Options



consult phrase translation table for all input phrases

Decoding: Start with Initial Hypothesis

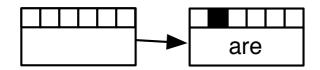




initial hypothesis: no input words covered, no output produced

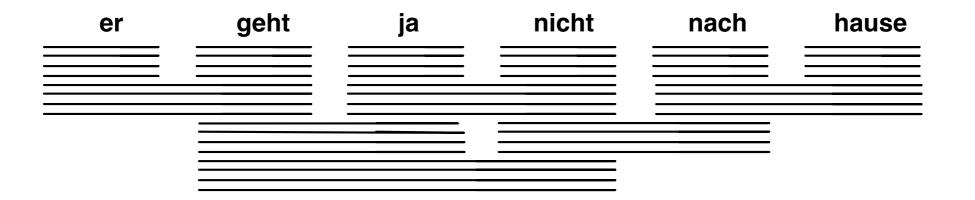
Decoding: Hypothesis Expansion

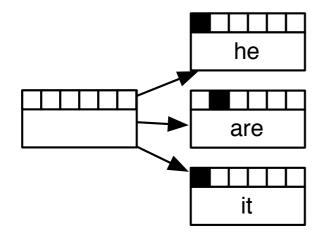




pick any translation option, create new hypothesis

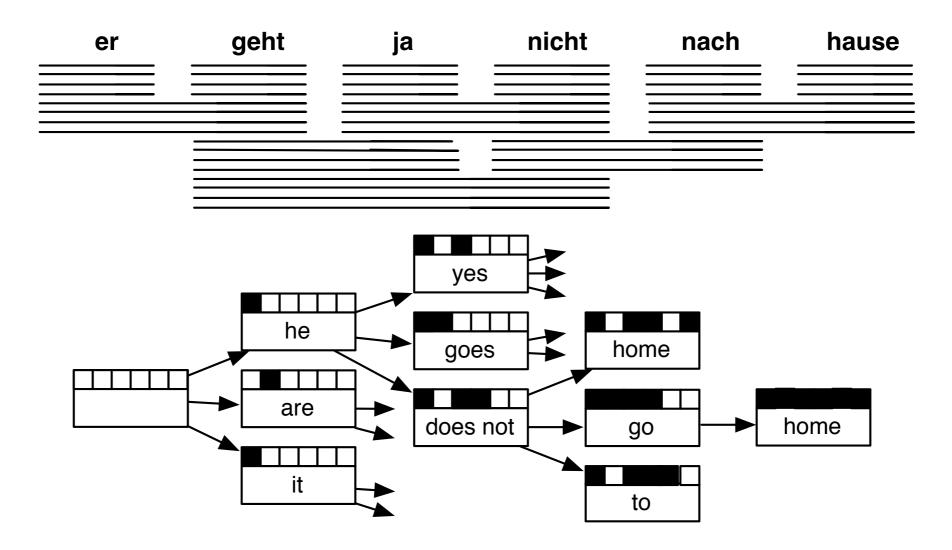
Decoding: Hypothesis Expansion





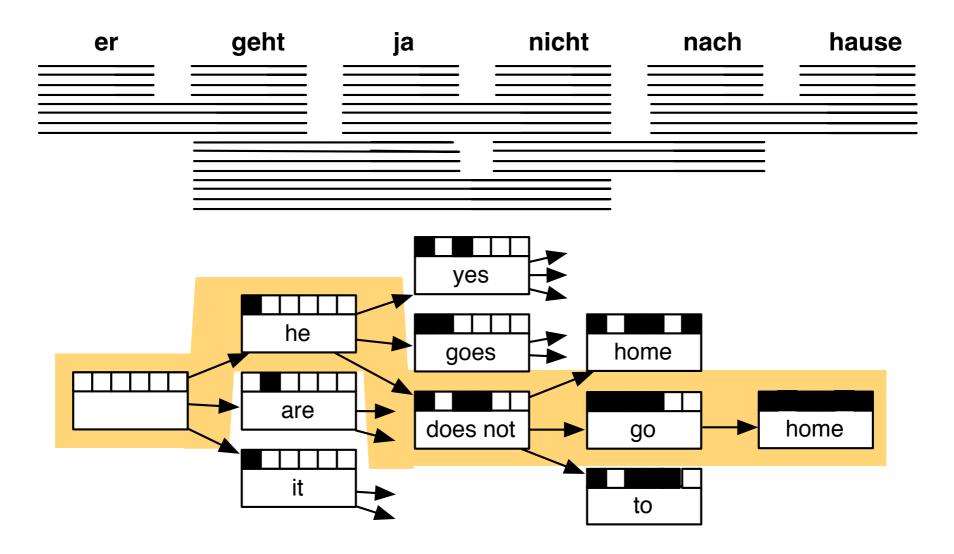
create hypotheses for all other translation options

Decoding: Hypothesis Expansion



also create hypotheses from created partial hypothesis

Decoding: Find Best Path



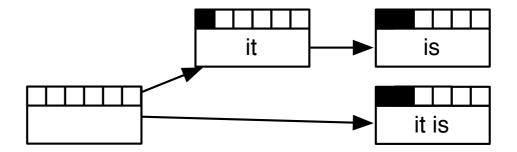
backtrack from highest scoring complete hypothesis

Size of the search space

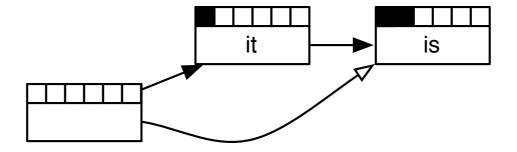
- Decoding is an NP-complete problem
- The search space is exponential
- How can we reduce the search?
- Dynamic programming (risk free)
- Heuristic search (risky)

Recombination

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

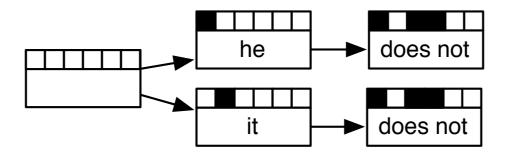


Worse hypothesis is dropped

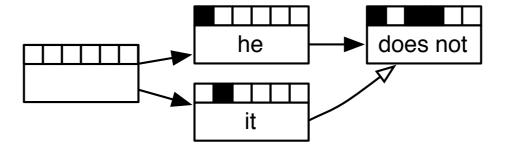


Recombination

- 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



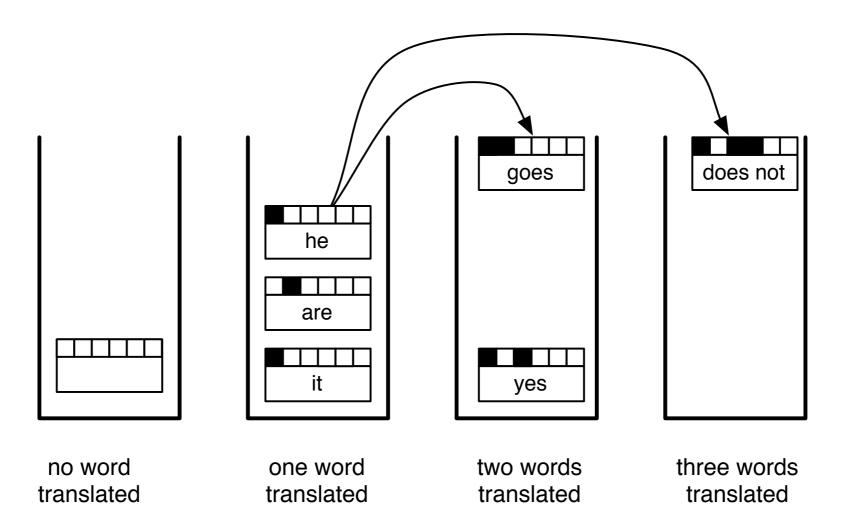
Restrictions on Recombination

- 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
- Other feature function may introduce additional restrictions

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
        for all translation options do
4:
          if applicable then
5:
             create new hypothesis
6:
             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
12:
13: end for
```

Chapter 6: Decoding

Decoding complexity

- Finding the best hypothesis is NP-hard
 - Even with no language model, there are an exponential number of states!
 - Solution 1: limit reordering
 - Solution 2: (lossy) pruning

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

Search Errors

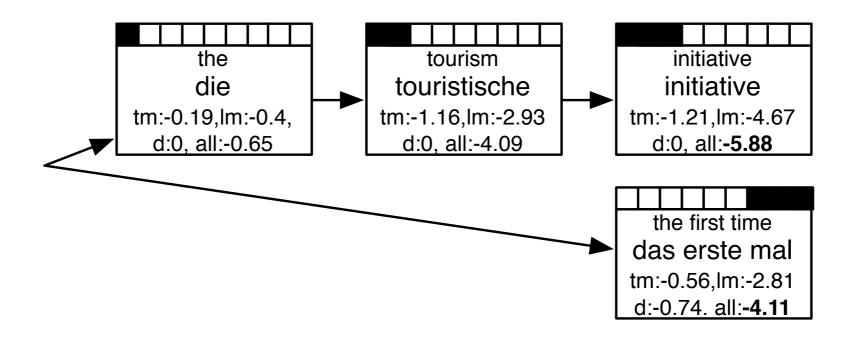
- We are using a heuristic search to prune the search space
- There are no guarantees of admissibility (like in A* search)
- We may therefore prune out a partial hypothesis that would have lead to the most probable translation, if we hadn't pruned it early on

Model Errors

- Model errors are different than search errors
- If the model scores an incorrect translation higher than higher than the correct translation, then it is the model's fault not the search strategy's fault
- How can these two interact?

Translating the Easy Part First?

the tourism initiative addresses this for the first time



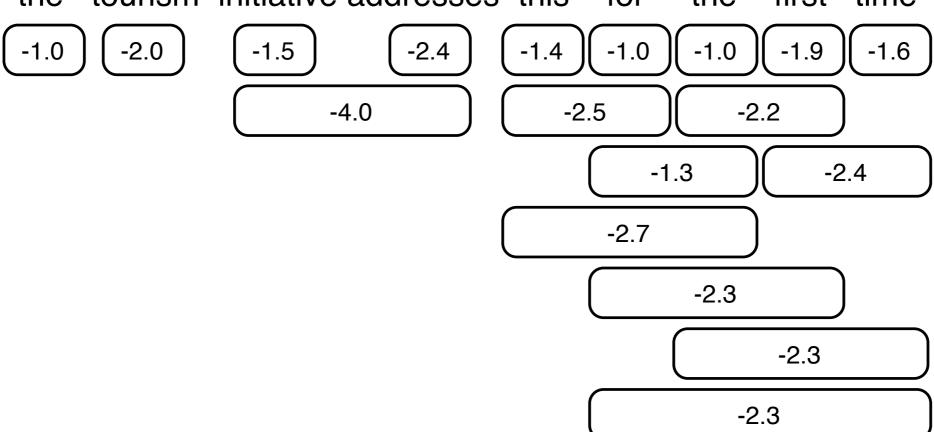
both hypotheses translate 3 words worse hypothesis has better score

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)

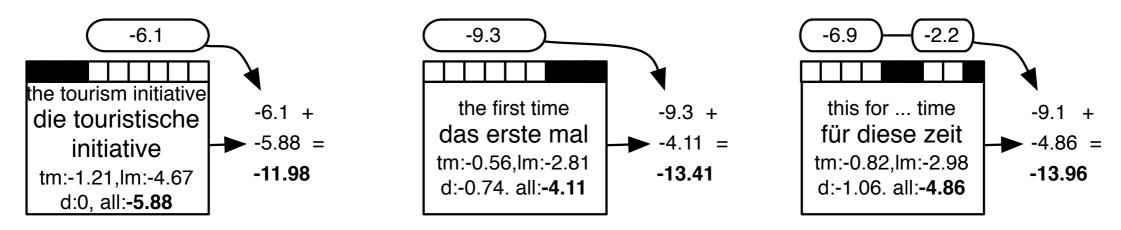
Cost Estimates for all Spans

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: $-9.3 \rightarrow \text{total cost } -13.41$
 - right hypothesis picks easy parts: this for ... time score: -4.86, future cost: $-9.1 \rightarrow \text{total cost } -13.96$

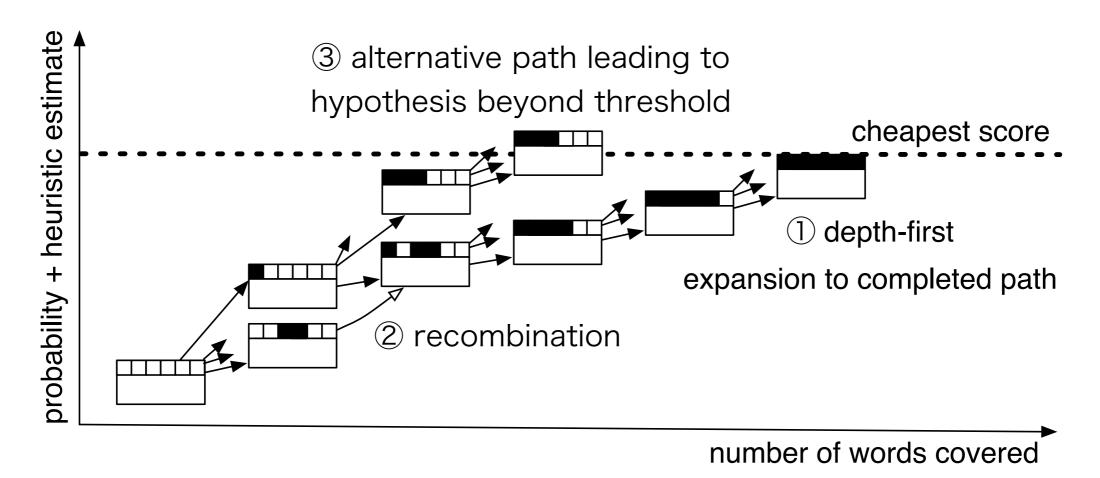
Alternate to Future Cost Estimation

- In the setup that we described so far, we had N stacks, N=number of source words
- Hypotheses were added to the stack based on how many source words they covered
- We could group hypotheses into stacked based on which source words they cover
- This eliminates the needs for FCE, but requires more stacks

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

Reading

Read 6 from the textbook

