Machine Translation

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Language Technology II
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Decoding

- The decoder …
  - uses source sentence *f* and phrase table to estimate $P(e|f)$
  - uses LM to estimate $P(e)$
  - searches for target sentence *e* that maximizes $P(e)*P(f|e)$

Decoding

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- Decoding is:
  - translating words/chunks (equivalence)
  - reordering the words/chunks (fluency)
- For the models we‘ve seen, decoding is **NP-complete**, i.e. enumerating all possible translations for scoring is too computationally expensive.
- Heuristic search methods can approximate the solution.
- Compute scores for partial translations going from left to right until we cover the entire input text.

Beam Search

1. Collect all translation options:
   a) der Hund schläft
   b) der = the / that / this; Hund = dog / hound / puppy / pug ; schläft = sleeps / sleep / sleepy
   c) der Hund = the dog / the hound
2. Build *hypotheses*, starting with the empty hypothesis:
   1. der = {the, that, this}
   2. der Hund = {the + dog, the + hound, the + puppy, the +pug, that + dog, that + hound, that + puppy, that +pug, this + dog, this + hound, this + puppy, this +pug, the dog, the hound}
   3. ...

Beam Search II

- In the end, we consider those hypotheses which cover the entire input sequence.
- Each hypothesis is annotated with the probability score that comes from using those translation options and the language model score.
- The hypothesis with the best score is our final translation.

Search Space

- Examining the entire search space is too expensive: it has exponential complexity.
- We need to reduce the complexity of the decoding problem.
- Two approaches:
  - Hypothesis recombination
  - Pruning

Hypothesis Recombination

- Translation options can create identical (partial) hypotheses:
  - the + dog vs. the dog
- We can share common parts by pointing to the same final result:
  - [the dog] ...
- But the probability scores will be different: using two options will yield a different score than using only one (larger) option.
  - → drop the lower-scoring option
  - → can never be part of the best-scoring hypothesis

Pruning

- If we encounter a partial hypothesis that‘s apparently worse, we want to drop it to avoid wasting computational power.
- But: the hypothesis might redeem itself later on and increase its probability score.
- We don‘t want to prune too early or too eagerly to avoid search errors.
- But we can only know for sure that a hypothesis is bad if we construct it completely.
- We need to make some educated *guesses*.

Stack Decoding

- Organise hypotheses in stacks.
- Order them e.g. by number of words translated.
- Only if the number grows too large, drop the worst hypotheses.
- But: is the sorting (number of translated words, ...) enough to tell how good a hypothesis is?

Pruning Methods I

- Histogram pruning:
  - Keep *N* hypotheses in the stack
- We have stack size N, a number of translation options T and the length of the input sentence L:
  - $O(N*T*L)$
- T is linear to L ➔ $O(N*L^2)$

Pruning Methods II

- Threshold pruning:
  - Considers difference in score between the best and the worst hypotheses in the stack.
- We declare a fixed threshold α by which a hypothesis is allowed to be worse than the best hypothesis.
- α declares the *beam width* in which we perform our search.

Future Cost

- To avoid pruning too eagerly, we cannot solely rely on the probability score.
- We approximate the future cost of creating the full hypothesis by the outside cost (rest cost) estimation:
  - Translation model: look up the translation cost for a translation option from the phrasetable
  - Language model: compile score without context (unigram, ...)
- We can now estimate the cheapest cost for translating any input span.

  ➔ combine with probability score to sort hypotheses

Other Decoding Algorithms

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- A* Search
  - Similar to beam search
  - Requires cost estimate to never *over*estimate the cost
- Greedy Hill-Climbing Decoding
  - Generate a rough initial translation.
  - Apply changes until translation can‘t be improved anymore.
- Finite State Transducers

Search Errors vs. Model Errors

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- We need to distinguish error types when looking at wrong translations.
- Search error:
  - the decoder fails to find the optimal translation candidate in the model
- Model error:
  - the model itself contains erroneous entries

Advanced SMT models

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- Word-based models (IBM1-5) don‘t capture enough information.
- The unit word is too small: use phrases instead.
- Phrase-based models are doing better ➔ can capture collocations and multi-word expressions:
  - *kick the bucket = den Löffel abgeben*
  - *the day after tomorrow = übermorgen*

Phrase-Based SMT

- $E^* = \text{argmax}_E \; P(E|F) = \text{argmax}_E \; P(E) * P(F|E)$
- In word-based models (IBM1):
  - P(F|E) is defined as $\Sigma p(f_i|e_j)$ where f_i and e_j are the i-th French and j-th English word

- In the phrase-base models, we no longer have words as the basic units, but phrases which may contain up to n words (current state of the art uses 7-gram phrasetables):
  - P(F|E) is now defined over phrases f_i^n and e_j^m where f_i^n contains the span of the i-th to the n-th French word and e_j^m the j-th to the m-th English word:
  - $P(F|E) = \Pi \; \phi(f_i^n|e_j^m) \; d(start_i - end_{i-1} - 1)$

Phrase Extraction

- Phrases are defined as *continuous* spans.

- The word alignment is key:
  - we only extract phrases that form continuous spans on both sides

- Translation probability $\phi(f|e)$ is modeled as the relative frequency:
  - $\phi(f|e) = \text{count}(e, f) / \Sigma_{fi} \text{count}(e, f_i)$

All Problems Solved?

- But phrase-based models have one big constraint: the length of the phrases: currently we work with 7-grams for phrases and 5-gram LMs in state of the art systems
  - The larger the n-gram, the more data you need to prevent data sparseness
  - We always need more and more data

- We need to make better use of the data we have

Factored Models

- In factored models we introduce additional information about the surface words:
  - dangerous dog → dangerous|dangerous|JJ|n.sg dog|dog|NN|n.sg
  - instead of the word use word|lemma|POS|morphology

- Factors allow us to generalise over the data: even if a word is unseen, if we have seen similar factors, this works in our favour:
  - Haus|Haus|NN|n.sg ➔ house|house|NN|n.sg
  - Hauses|Haus|NN|g.sg?

More And More Possibilities

- Can use different translation models:
  - lemma to lemma
  - POS to POS

- We can even build more differentiated models:
  - Translate lemma to lemma
  - Translate morphology and POS
  - Generate word form lemma and POS/morphology

Linguistic Information

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- Complete freedom which information you use:
  - lemma, morphology
  - POS
  - named entities
  - ...

- But which information do we really need?
  - In Arabic you can get results from using stems (first 4 characters) and morphology → cannot be generalised
  - To get good factors/a good setup, you need to know your language(s) well

Factored Models - Problems

- To get the factors, you need a list of linguistic resources:
  - lemmatiser
  - part of speech tagger
  - morphological analyser
  - ...

- These resources may not always be available for your language pair of choice.
- Depending on which factors you use, your risk of data sparseness increases.
- Still suffers from many of the problems of phrase-based SMT

Tree-Based Models

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- There are two sorts of tree-based models:
  - hierarchical phrase-based
  - syntax-based

- Syntax-based models make use of a grammar:
  - ne X_1 pas → not X_1
  - read X_1 → habe X_1 gelesen

- We now have non-terminals (X_1) which can be substituted by any phrase in our grammar/phrase-table.
- Syntax-based models require a corpus that has already been parsed as training input.

Syntax-based Models

- The decoder automatically learns a mapping between source and target side annotation:
  - you can parse both or only one side
  - score(tree, e, f) = Π_i rule$_i$
- The basic syntax structures are supposed to capture especially long-distance dependencies
- Data sparseness:
  - „relax“ the rules

Grammars

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- Usually uses phrase structure grammars.

- Dependency grammars can also be used, but:
  - Are trees in different languages really isomorphic?

- In SMT:
  - PSG: synchronous context free grammar (SCFG)
  - A SCFG consists of pairs of trees, one for each language.

Scoring

- We can consider different probability distributions:
  - Joint rule probability:

    $p(\text{LHS}, \text{RHS}_f, \text{RHS}_e)$
  - Rule application probability:

    $p(\text{RHS}_f, \text{RHS}_e \mid \text{LHS})$
  - Direct translation probability:

    $p(\text{RHS}_e|\text{RHS}_f, \text{LHS})$
  - Noisy channel probability:

    $p(\text{RHS}_f|\text{RHS}_e, \text{LHS})$
  - Lexical translation probability:

    $\Pi_{e \text{ in RHSe}}\ p(e_i|\text{RHS}_f, a)$

Hierarchical Phrase-Based

- If we don‘t have a parser ready, can we learn rules automatically?
  - Yes: $R : X \rightarrow (\gamma, \alpha, \sim)$
  - $X \rightarrow$ dangerous X_1 ||| gefährlicher X_1 ||| f_1 f_2 f_3

- Hierarchical models don‘t put any restrictions of which words/phrases can be replaced by a non-terminal:
  - John likes Anna → John mag Anna
  - John likes X → John mag X
  - John X Anna → John X Anna
  - X likes → X mag

Chart Parsing

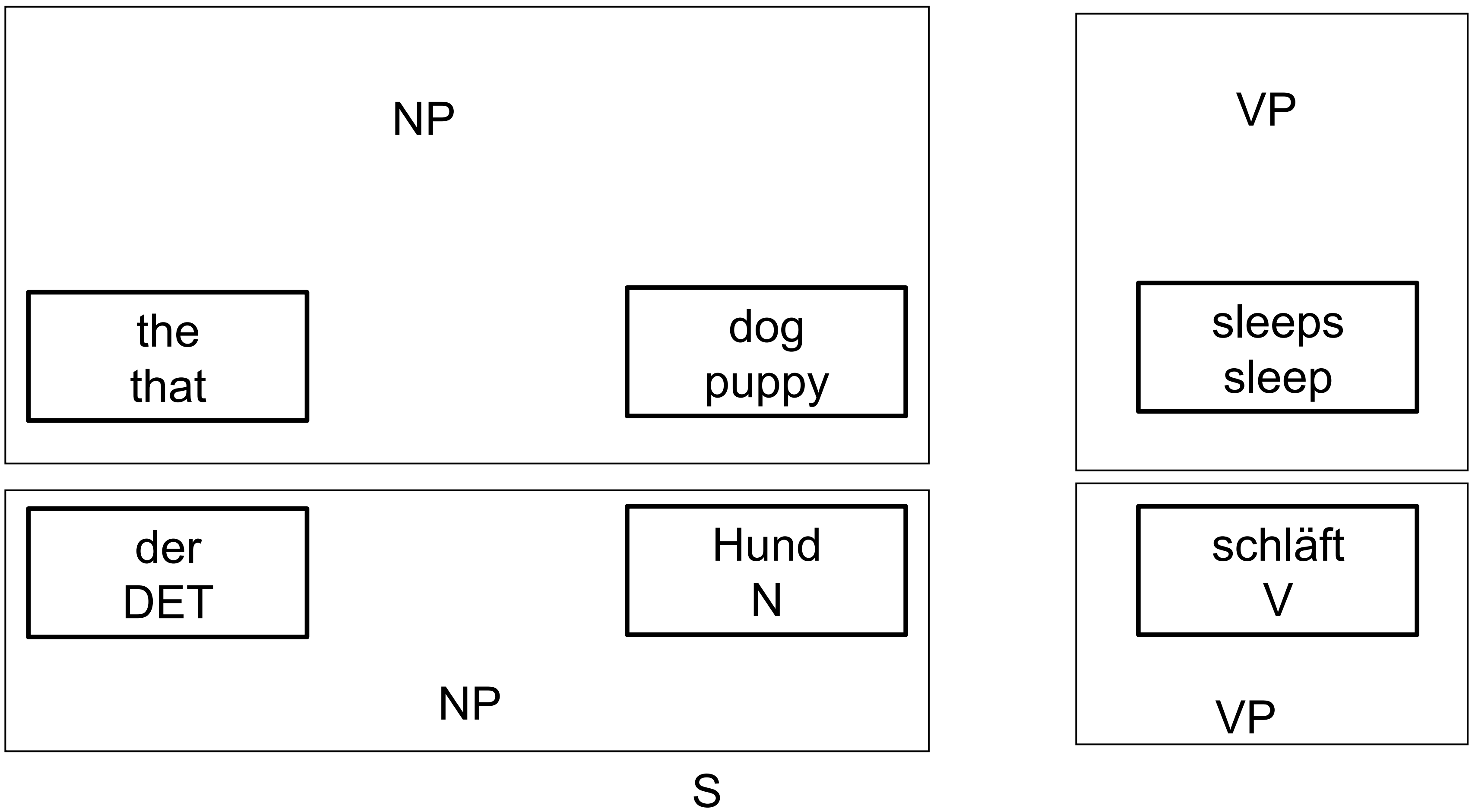
- Instead of using beam search, we apply an algorithm initially developed for chart parsing in our decoder.

Grammar:

DET → der | the	N → Hund | dog	V → schläft | sleeps
DET → der | that	N → Hund | puppy	V → schläft | sleep
S → NP VP	NP → DET N	VP → V NP
V → V		

Input: der Hund schläft

Chart Parsing



Tree-Based Models - Problems

- Data sparseness: especially for syntax-based models you need enough data.
  - How much does the parser influence translation quality?

- Tree-based models focus on getting a better sentence structure, but what about morphology?