# Statistical Machine Translation Lecture 2 Theory and Praxis of Decoding

Philipp Koehn

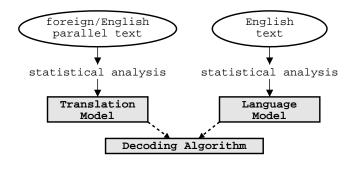
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# Statistical Machine Translation

• Components: Translation model, language model, decoder



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### **Phrase-Based Systems**

- A number of research groups developed phrase-based systems (RWTH Aachen, Univ. of Southern California/ISI, CMU, IBM, Johns Hopkins Univ., Cambridge Univ., Univ. of Catalunya, ITC-irst, Univ. Edinburgh, Univ. of Maryland...)
- Systems differ in
  - training methods
  - model for phrase translation table
  - reordering models
  - additional feature functions
- Currently best method for SMT (MT?)
  - top systems in DARPA/NIST evaluation are phrase-based
  - best commercial system for Arabic-English is phrase-based

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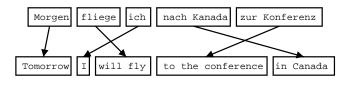
### Phrase Translation Table

• Phrase Translations for "den Vorschlag":

English	$\phi$ (e f)	English	$\phi$ (e 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		

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# **Phrase-Based Translation**

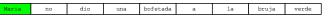


- Foreign input is segmented in phrases
  - any sequence of words, not necessarily linguistically motivated
- Each phrase is translated into English
- Phrases are reordered

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# **Decoding Process**



- Build translation left to right
  - select foreign words to be translated

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Statistical Machine Translation — Lecture 2: Theory and Praxis of Decoding Statistical Machine Translation — Lecture 2: Theory and Praxis of Decoding **Decoding Process Decoding Process** no dio una bofetada Maria no dio una bofetada la bruja verde la bruja verde a a Build translation left to right Build translation left to right - select foreign words to be translated - select foreign words to be translated - find English phrase translation - find English phrase translation - add English phrase to end of partial translation - add English phrase to end of partial translation - mark foreign words as translated Philipp Koehn, University of Edinburgh 7 Philipp Koehn, University of Edinburgh 8 Statistical Machine Translation — Lecture 2: Theory and Praxis of Decoding Statistical Machine Translation — Lecture 2: Theory and Praxis of Decoding **Decoding Process Decoding Process** dio una bofetada Maria no la bruja verde bruja verde a la • One to many translation Many to one translation Philipp Koehn, University of Edinburgh 9 Philipp Koehn, University of Edinburgh 10 Statistical Machine Translation — Lecture 2: Theory and Praxis of Decoding Statistical Machine Translation — Lecture 2: Theory and Praxis of Decoding **Decoding Process Decoding Process** dio una bofetada bruja verde bruja did not did not Reordering Many to one translation

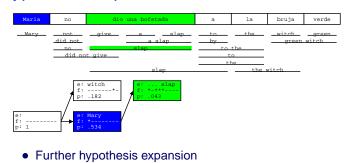
Statistical Machine Translation — Lecture 2: Theory and Praxis of Decoding Statistical Machine Translation — Lecture 2: Theory and Praxis of Decoding **Decoding Process Translation Options** Maria no dio una b Maria no dio una bofetada bruja did not give the Look up possible phrase translations • Translation finished - many different ways to segment words into phrases - many different ways to translate each phrase Philipp Koehn, University of Edinburgh 13 Philipp Koehn, University of Edinburgh 14 Statistical Machine Translation — Lecture 2: Theory and Praxis of Decoding Statistical Machine Translation — Lecture 2: Theory and Praxis of Decoding Hypothesis Expansion Hypothesis Expansion Maria no dio una bofetada no dio una bofetada bruja verde bruja did did not give did not give the Start with empty hypothesis • Pick translation option - e: no English words Create hypothesis - f: no foreign words covered e: add English phrase Mary - f: first foreign word covered - p: probability 1 - p: probability 0.534 Philipp Koehn, University of Edinburgh 15 Philipp Koehn, University of Edinburgh 16 Statistical Machine Translation — Lecture 2: Theory and Praxis of Decoding Statistical Machine Translation — Lecture 2: Theory and Praxis of Decoding Hypothesis Expansion A Quick Word on Probabilities • Not going into detail here, but... Maria dio una bofetada Translation Model did not give to - phrase translation probability p(Mary Maria) - reordering costs

- phrase/word count costs
- ...
- Language Model
  - uses trigrams:
  - p(Mary did not) = p(Mary | <s>) \* p(did | Mary, <s>) \* p(not | Mary did)



• Add another hypothesis

## Hypothesis Expansion



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# Hypothesis Expansion



- ... until all foreign words covered
  - find best hypothesis that covers all foreign words

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• Number of hypotheses is exponential with respect to

- backtrack to read off translation

**Explosion of Search Space** 

 $\Rightarrow$  Need to reduce search space

- risk free: hypothesis recombination

- risky: histogram/threshold pruning

 $\Rightarrow$  Decoding is NP-complete [Knight, 1999]

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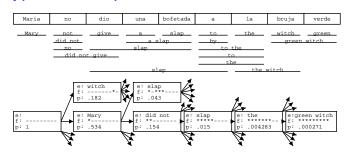
sentence length

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### Hypothesis Expansion



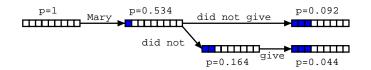
- Adding more hypothesis
- $\Rightarrow$  Explosion of search space

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# Hypothesis Recombination



• Different paths to the same partial translation

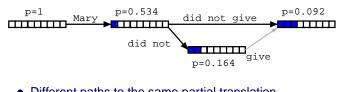
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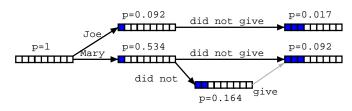
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# Hypothesis Recombination



- Different paths to the same partial translation
- $\Rightarrow$  Combine paths
  - drop weaker hypothesis
  - keep pointer from worse path

### Hypothesis Recombination



- Recombined hypotheses do not have to match completely
- No matter what is added, weaker path can be dropped, if:
  - last two English words match (matters for language model)
  - foreign word coverage vectors match (effects future path)

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### **Pruning**

- Hypothesis recombination is not sufficient
- $\Rightarrow$  Heuristically discard weak hypotheses
- Organize Hypothesis in stacks, e.g. by
  - same foreign words covered
  - same number of foreign words covered (Pharaoh does this)
  - same number of English words produced
- Compare hypotheses in stacks, discard bad ones
  - histogram pruning: keep top n hypotheses in each stack (e.g., n=100)
  - threshold pruning: keep hypotheses that are at most  $\alpha$  times the cost of best hypothesis in stack (e.g.,  $\alpha$  = 0.001)

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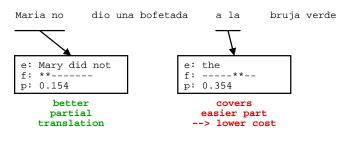
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# **Comparing Hypotheses**

• Comparing hypotheses with same number of foreign

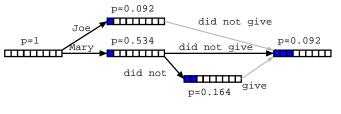
#### words covered



- Hypothesis that covers easy part of sentence is preferred
- $\Rightarrow$  Need to consider future cost of uncovered parts

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## Hypothesis Recombination



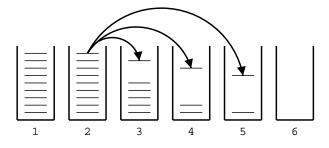
- Recombined hypotheses do not have to match completely
- No matter what is added, weaker path can be dropped, if:
  - last two English words match (matters for language model)
  - foreign word coverage vectors match (effects future path)
- $\Rightarrow$  Combine paths

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## Hypothesis Stacks



#### • Organization of hypothesis into stacks

- here: based on number of foreign words translated
- during translation all hypotheses from one stack are expanded
- expanded Hypotheses are placed into stacks

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# **Future Cost Estimation**



- Estimate cost to translate remaining part of input
- Step 1: estimate future cost for each translation option
  - look up translation model cost
  - estimate language model cost (no prior context)
  - ignore reordering model cost
  - $\rightarrow$  LM \* TM = p(to) \* p(the to) \* p(to the a la)

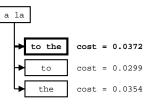
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## Future Cost Estimation: Step 2

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0.1

future



#### Step 2: find cheapest cost among translation options

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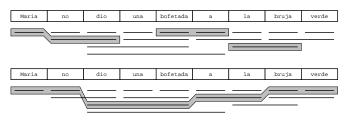
Future Cost Estimation: Application

covered

Use future cost estimates when pruning hypotheses

- look up future costs for each maximal contiguous uncovered span - factor them to actually accumulated cost for translation option for pruning Statistical Machine Translation - Lecture 2: Theory and Praxis of Decoding

# Future Cost Estimation: Step 3



- Step 3: find cheapest future cost path for each span
  - can be done efficiently by dynamic programming
  - future cost for every span can be precomputed

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## Pharaoh

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bruja

verde

33

la

future

- · A beam search decoder for phrase-based models
  - works with various phrase-based models
  - beam search algorithm
  - time complexity roughly linear with input length
  - good quality takes about 1 second per sentence
- Very good performance in DARPA/NIST Evaluation
- · Freely available for researchers

http://www.isi.edu/licensed-sw/pharaoh/

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# Phrase Translation Table

• Core model component is the phrase translation table:

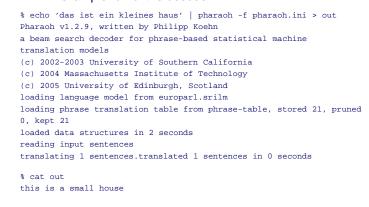
der	the	0.3
das	the	0.4
das	it	0.1
das	this	0.1
die 📗	the	0.3
ist	is	1.0
ist	's	1.0
das ist	:     i	t is     0.2
das ist	:     ti	his is     0.8
es ist	it	is     0.8
es ist	th	is is    0.2
ein	a	1.0
ein	an	1.0
klein		11     0.8
klein	lit	
kleines		mall     0.2
kleine	s     1	ittle    0.2
haus		e     1.0
alt	old	0.8
altes		0.2
gibt	give	s     1.0
es gibt	:     ti	here is     1.0

Statistical Machine Translation - Lecture 2: Theory and Praxis of Decoding Running the decoder

For each uncovered contiguous span:

# • An example run of the decoder:

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#### Trace

• Running the decoder with switch "-t"

% echo 'das ist ein kleines haus' | pharaoh -f pharaoh.ini -t
[...]
this is |0.014086|0|1| a |0.188447|2|2| small |0.000706353|3|3|
house |1.46468e-07|4|4|

- Trace for each applied phrase translation:
  - output phrase (there is)
  - cost incurred by this phrase (0.014086)
  - coverage of foreign words (0-1)

### **Reordering Example**

• Sometimes phrases have to be reordered:

% echo 'ein kleines haus ist das' | pharaoh -f pharaoh.ini -t -d 0.5
[...]
this |0.000632805|4|4| is |0.13853|3|3| a |0.0255035|0|0|
small |0.000706353|1|1| house |1.46468e-07|2|2|

• First output phrase (this) is translation of the 4th word

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### Hypothesis Accounting

• The switch "-v" allows for detailed run time information:

% echo 'das ist ein kleins haus' | pharaoh -f pharaoh.ini -v 2

HYP: 114 added, 284 discarded below threshold, 0 pruned, 58 merged. BEST: this is a small house -28.9234

- Statistics over how many hypothesis were generated
  - 114 hypotheses were added to hypothesis stacks
  - 284 hypotheses were discarded because they were too bad
  - 0 hypotheses were pruned, because a stack got too big
  - 58 hypotheses were merged due to recombination
- Probability of the best translation: exp(-28.9234)

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### **Future Cost Estimation**

• Pre-computation of the future cost estimates:

future	costs	from	0	to	0	is	-5.78855
future	costs	from	0	to	1	is	-10.207
future	costs	from	0	to	2	is	-15.7221
future	costs	from	0	to	3	is	-25.4433
future	costs	from	0	to	4	is	-34.7094
future	costs	from	1	to	1	is	-4.92223
future	costs	from	1	to	2	is	-10.4373
future	costs	from	1	to	3	is	-20.1585
future	costs	from	1	to	4	is	-29.4246
future	costs	from	2	to	2	is	-5.5151
future	costs	from	2	to	3	is	-15.2363
future	costs	from	2	to	4	is	-24.5023
future	costs	from	3	to	3	is	-9.72116
future	costs	from	3	to	4	is	-18.9872
future	costs	from	4	to	4	is	-9.26607

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# **Translation Options**

• Even more run time information is revealed with "-v 3":

[das;2]					
	the<1>, pC=-0.916291, c=-5.78855				
	it<2>, pC=-2.30259, c=-8.0761				
	this<3>, pC=-2.30259, c=-8.00205				
[ist;4]					
	is<4>, pC=0, c=-4.92223				
	's<5>, pC=0, c=-6.11591				
[ein;7]					
	a<8>, pC=0, c=-5.5151				
	an<9>, pC=0, c=-6.41298				
[kleines;9]					
	small<10>, pC=-1.60944, c=-9.72116				
	little<11>, pC=-1.60944, c=-10.0953				
[haus;10]					
	house<12>, pC=0, c=-9.26607				
[das ist;5]					
	it is<6>, pC=-1.60944, c=-10.207				
	this is<7>, pC=-0.223144, c=-10.2906				

• Translation model cost (pC) and future cost estimates (c)

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### Hypothesis Expansion

• Start of beam search: First hypothesis (das  $\rightarrow$  the)

```
creating hypothesis 1 from 0 ( ... </s> <s> )
    base score 0
    covering 0-0: das
    translated as: the => translation cost -0.916291
    distance 0 => distortion cost 0
    language model cost for 'the' -2.03434
    word penalty -0
        score -2.95064 + futureCost -29.4246 = -32.3752
new best estimate for this stack
merged hypothesis on stack 1, now size 1
```

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### Hypothesis Expansion

#### • Another hypothesis (das ist $\rightarrow$ this is)

```
creating hypothesis 12 from 0 ( ... </s> <s> )
    base score 0
    covering 0-1: das ist
    translated as: this is => translation cost -0.223144
    distance 0 => distortion cost 0
    language model cost for 'this' -3.06276
    language model cost for 'is' -0.976669
    word penalty -0
    score -4.26258 + futureCost -24.5023 = -28.7649
new best estimate for this stack
merged hypothesis on stack 2, now size 2
```

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### Hypothesis Expansion

#### • Hypothesis recombination

```
creating hypothesis 27 from 3 ( ... <s> this )
        base score -5.36535
        covering 1-1: ist
        translated as: is => translation cost 0
        distance 0 => distortion cost 0
        language model cost for 'is' -0.976669
        word penalty -0
        score -6.34202 + futureCost -24.5023 = -30.8443
worse than existing path to 12, discarding
```

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### Hypothesis Expansion

#### • Bad hypothesis that falls out of the beam

```
creating hypothesis 52 from 6 ( ... <s> a )
    base score -6.65992
    covering 0-0: das
    translated as: this => translation cost -2.30259
    distance -3 => distortion cost -3
    language model cost for 'this' -8.69176
    word penalty -0
    score -20.6543 + futureCost -23.9095 = -44.5637
estimate below threshold, discarding
```

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### **Generating Best Translation**

- Generating best translation
  - find best final hypothesis (442)
  - trace back path to initial hypothesis

best hypothesis 442
[ 442 => 343 ]
[ 343 => 106 ]
[ 106 => 12 ]
[ 12 => 0 ]

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### **Translation Table Pruning**

- Limiting translation table size speeds up search
- Histogram pruning: keeping only top n entries
- Threshold pruning: keep only entries that score  $\alpha$  times worse than best

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### **Beam Size**

#### • Trade-off between speed and quality via beam size

% echo 'das ist ein kleines haus' | pharaoh -f pharaoh.ini -s 10 -v 2
[...]

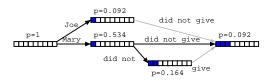
Collected 12 translation options HYP: 78 added, 122 discarded below threshold, 33 pruned, 20 merged. BEST: this is a small house -28.9234

Beam size	Threshold	Hyp. added	Hyp. discarded	Hyp. pruned	Hyp. merged
1000	unlimited	634	0	0	1306
100	unlimited	557	32	199	572
100	0.00001	144	284	0	58
10	0.00001	78	122	33	20
1	0.00001	9	19	4	0

### Limits on Reordering

- · Reordering may be limited
  - Monotone Translation: No reordering at all
  - Only phrase movements of at most n words
- Reordering limits speed up search
- · Current reordering models are weak, so limits improve translation quality

# Word Lattice Generation



- · Search graph can be easily converted into a word lattice
  - can be further mined for n-best lists
  - enables reranking approaches  $\rightarrow$
  - ightarrow enables discriminative training



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### Sample N-Best List

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#### • N-best list from Pharaoh:

Translation     Reordering LM TM WordPenalty     Score this is a small house     0 -27.0908 -1.83258 -5     -28.9234 this is a little house     0 -28.1791 -1.83258 -5     -30.0117 it is a small house     0 -28.1791 -1.83258 -5     -30.3268 it is a little house    0 -28.1696 -3.21888 -5     -31.4152 this is an small house     0 -31.7294 -1.83258 -5     -31.4152 it is an small house     0 -32.3094 -3.21888 -5     -35.5863 this is an little house     0 -31.7639 -1.83258 -5     -35.5965 this is a house small    -3 -31.6689 -1.83258 -5    -35.5965 this is a house small    -3 -31.5689 -1.83258 -5    -37.5628 it is an little house    0 -34.31.5689 -1.83258 -5    -37.7211 this is a house small    -3 -31.586 -3.21888 -5    -37.72121 this is an house small    -3 -32.9897 -1.83258 -5    -37.8049 this is an house little    -3 -32.9837 -1.83258 -5    -37.8163 the house is a little    -7 -28.5107 -2.52573 -5    -38.2156 is i a little house    0 -34.8557 -3.91202 -5    -38.2723 the house is a little    -7 -28.0443 -3.91202 -5    -38.7677 this house is a little    -7 -28.0443 -3.91202 -5    -38.566	
it 's a little house    0 -35.1446 -3.91202 -5    -39.0566 this house is a small    -7 -28.3018 -3.91202 -5    -39.2139	
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### Thank You!

Questions?

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## **XML** Interface

Er erzielte <NUMBER english='17.55'>17,55</NUMBER> Punkte

- Add additional translation options
  - number translation
  - noun phrase translation [Koehn, 2003]
  - name translation
- Additional options
  - provide multiple translations
  - provide probability distribution along with translations
  - allow bypassing of provided translations

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