Hierarchical Machine Translation

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May 2, 2018

Content

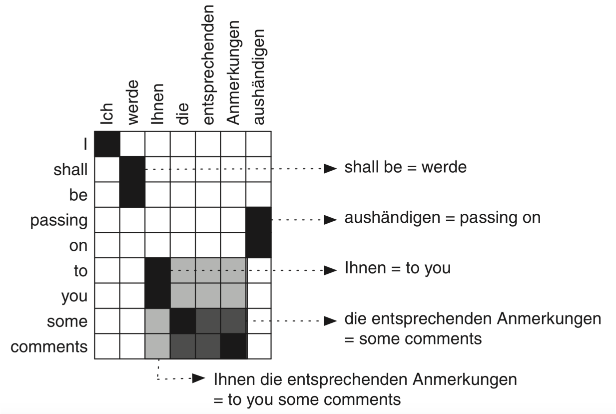

Figure: Koehn [2010]

werde X aushändigen | shall be passing on X

Why hierarchical structure?

Better generalisation

- compositionality
- reordering

Why is reordering important?

Monotone translation is unrealistic

- languages differ wrt word-order

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  e.g. different syntactic structure

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  e.g. rich morphology

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Reordering is arguably one of the hardest problems in MT

Why is reordering important?

Monotone translation is unrealistic

- languages differ wrt word-order
  e.g. different syntactic structure
  e.g. rich morphology

Reordering is arguably one of the hardest problems in MT

- part of the model of translational equivalences
  the part that determines the space of translations

Key aspects

Expressiveness

- how much can two languages differ wrt word order?

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Expressiveness

- how much can two languages differ wrt word order?

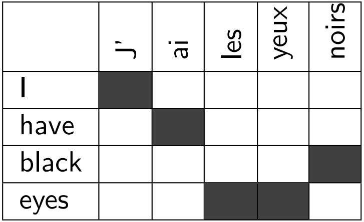
Modelling

- how many parameters do we have to estimate?

Content

Hierarchical phrase-based - Motivation

Local Reordering



Hierarchical phrase-based - Motivation

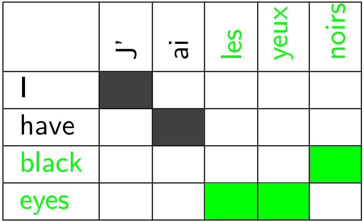
Local Reordering

	J'	ai	les	yeux	noirs
I	■				
have		■			
black					■
eyes			■	■	

- Monotone
  J'$_1$ ai$_2$ $\rightarrow$ I$_1$ have$_2$

Hierarchical phrase-based - Motivation

Local Reordering



- Swap
  les yeux$_4$ noirs$_5$ $\rightarrow$ black$_3$ eyes$_4$

Hierarchical phrase-based - Motivation

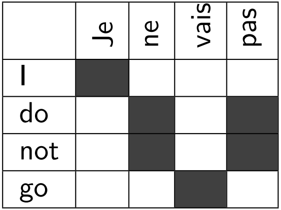
Local Reordering

	J'	ai	les	yeux	noirs
I	■				
have		■			
black					■
eyes			■	■	

- Discontinuous
  ai$_2$ X_{3-4} noirs$_5$ $\rightarrow$ have$_2$ black$_3$ X_4

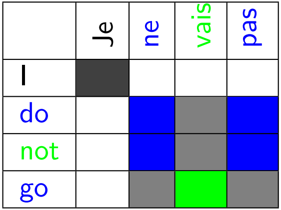
Hierarchical phrase-based - Motivation

Discontiguous Phrases



Hierarchical phrase-based - Motivation

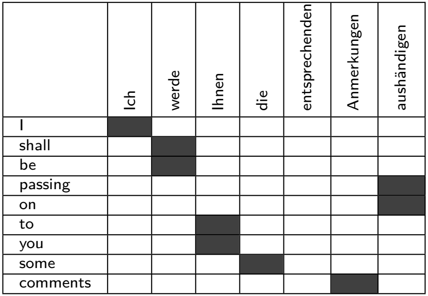
Discontiguous Phrases



- Gappy phrase
  ne vais pas $\rightarrow$ do not go
  ne X_{vais} pas $\rightarrow$ do not X_{go}

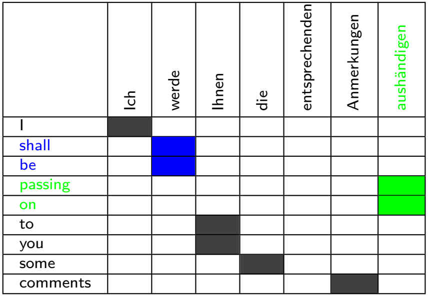
Hierarchical phrase-based - Motivation

Long Distance Reordering



Hierarchical phrase-based - Motivation

Long Distance Reordering



- How can we extract a biphrase for **shall be passing on**?

Hierarchical phrase-based - Motivation

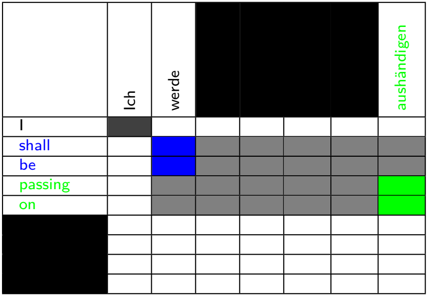
Long Distance Reordering

	Ich	werde	Ihnen	die	entsprechenden	Anmerkungen	aushändigen
I							
shall							
be							
passing							
on							
to			X				
you			X				
some				X			
comments						X	

- How can we extract a biphrase for **shall be passing on**?
- We cannot, we need to extract **to you some comments** along

Hierarchical phrase-based - Motivation

Long Distance Reordering



- How can we extract a biphrase for **shall be passing on**?
- We cannot, we need to extract **to you some comments** along
- Unless we replace all those words by a variable

Hierarchical phrase-based - Motivation

Long Distance Reordering

shall be passing on to you some comments

$\updownarrow$

werde Ihnen die entsprechenden Anmerkungen aushändigen

Hierarchical phrase-based - Motivation

Long Distance Reordering

shall be passing on ~~to you some comments~~

$\updownarrow$

werde ~~Ihnen die entsprechenden Anmerkungen~~ aushändigen

Hierarchical phrase-based - Motivation

Long Distance Reordering

shall be passing on X

$\updownarrow$

werde X aushändigen

Hiero

Extends phrase-based MT with hierarchical rules [Chiang, 2005]

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- conditions on word alignment

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Motivation

- long-distance reordering

Hiero

Extends phrase-based MT with hierarchical rules [Chiang, 2005]

- conditions on word alignment
- heuristic rule extraction
- heuristic scoring by relative frequency counting
- log-linear model
- SCFG decoding

Motivation

- long-distance reordering
- lexicalised reordering

Heuristic rule extraction

Initial phrase pairs created with same heuristic as PBSMT.

shall be passing on to you some comments

$\updownarrow$

werde Ihnen die entsprechenden Anmerkungen aushändigen

Heuristic rule extraction

Initial phrase pairs created with same heuristic as PBSMT.

shall be passing on ~~to you~~ some comments

↕

werde ~~Ihnen~~ die entsprechenden Anmerkungen aushändigen

Heuristic rule extraction

Initial phrase pairs created with same heuristic as PBSMT.

shall be passing on X_1 some comments

$\updownarrow$

werde X_1 die entsprechenden Anmerkungen aushändigen

Heuristic rule extraction

Initial phrase pairs created with same heuristic as PBSMT.

shall be passing on X_1 ~~some comments~~

$\updownarrow$

werde X_1 ~~die entsprechenden Anmerkungen~~ aushändigen

Heuristic rule extraction

Initial phrase pairs created with same heuristic as PBSMT.

shall be passing on X_1 X_2

$\updownarrow$

werde X_1 X_2 aushändigen

Heuristic rule extraction

Initial phrase pairs created with same heuristic as PBSMT.

$[X] \rightarrow$ shall be passing on X_1 X_2 | werde X_1 X_2 aushändigen

$[X] \rightarrow$ shall be passing on X_3 | werde X_3 aushändigen

$[X] \rightarrow$ to you | Ihnen

$[X] \rightarrow$ some comments | die entsprechenden Anmerkungen

$[X] \rightarrow$ to you some comments | Ihnen die entsprechenden Anmerkungen

Hiero - Scoring

Relative frequency: assume all fragments have been "observed"
Give a count of one to phrase pair occurrence, then distribute its weight equally among the obtained rules.

- Joint rule probatility: $p(LHS, RHS_{source}, RHS_{target})$

$$p(X, \text{la maison } X_1, \text{the } X_1 \text{ house})$$

- Rule application probability: $p(RHS_{source}, RHS_{target}|LHS)$

$$p(\text{la maison } X_1, \text{the } X_1 \text{ house}|X)$$

- Direct translation probability: $p(RHS_{target}|RHS_{source}, LHS)$

$$p(\text{the } X_1 \text{ house}|\text{la maison } X_1, X)$$

- Noisy-channel translation probability: $p(RHS_{source}|RHS_{target}, LHS)$

$$p(\text{la maison } X_1|\text{the } X_1 \text{ house}, X)$$

- Lexical translation probability

$$\prod_{t_i \in RHS_{target}} p(t_i|RHS_{source}, a) \qquad \prod_{s_i \in RHS_{source}} p(s_i|RHS_{target}, a)$$

Hiero - Model

Log-linear combination of features

Hiero - Model

Log-linear combination of features Linear model

$$S_\theta(e,d,f) = \theta^T \sum_{r_{s,t} \epsilon d} h_i(r_{s,t}|e,f)$$

where s is a span over F,
t is a span over E
and r is a rule.
Weighted synchronous CFG.
LM.

Content

Decoding

Phrase-based

Tree-based

Decoding

Phrase-based

- Left-to-Right

Tree-based

- Bottom-Up

Decoding

Phrase-based

- Left-to-Right
- Beam Search

Tree-based

- Bottom-Up
- Chart Parsing (In the next Lab.)

Decoding

Phrase-based

- Left-to-Right
- Beam Search
- Formally intersection:

Tree-based

- Bottom-Up
- Chart Parsing (In the next Lab.)
- Formally intersection:

Decoding

Phrase-based

- Left-to-Right
- Beam Search
- Formally intersection:
- FST (TM) $\times$ FSA (LM)

Tree-based

- Bottom-Up
- Chart Parsing (In the next Lab.)
- Formally intersection:
- SCFG (TM) $\times$ FSA (LM)

Content

Discriminative Model

- model consists of features.

Discriminative Model

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- each feature has a weight.

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- supervised learning: tune feature weights wrt. an evaluation metric on development data

Discriminative Model

- model consists of features.
- each feature has a weight.
- supervised learning: tune feature weights wrt. an evaluation metric on development data
- Which objective?
  Bilingual Evaluation Understudy metric BLEU

Tuning

Task: find weights so that the model ranks best translations first.

- Translate development corpus using model with current feature weights,
  N -best list of translations (N = 100, 1000, . . .)

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Tuning

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- Translate development corpus using model with current feature weights,
  N -best list of translations ($N = 100, 1000, \ldots$)
- Evaluate translations with the objective
- Adjust feature weights to increase the gain
- Iterate translation, evaluation, and adjustment of feature weights

MERT

Minimum error rate training (MERT)

- coordinate ascent, where the search updates a feature weight which appears most likely to offer improvements.

MERT

Minimum error rate training (MERT)

- coordinate ascent, where the search updates a feature weight which appears most likely to offer improvements.
- Highest point in a hilly city with a grid of streets, like San Francisco. [Koehn, 2008]
  We start along a certain street.
  Find its highest point and continue along the cross-street.
  Also in this cross-street we find the highest point.

MERT

- Line search for best feature weights
  given: sentences with n-best lists of translations

MERT

- Line search for best feature weights
  given: sentences with n-best lists of translations
- iterate n times
  randomize starting feature weights

MERT

- Line search for best feature weights
  given: sentences with n-best lists of translations
- iterate n times
  randomize starting feature weights
  for each feature

MERT

- Line search for best feature weights
  given: sentences with n-best lists of translations
- iterate n times
  randomize starting feature weights
  for each feature
    - find best feature weight

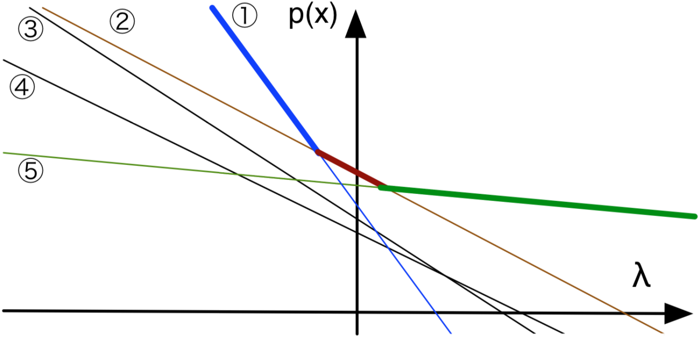
MERT

- Line search for best feature weights
  given: sentences with n-best lists of translations
- iterate n times
  randomize starting feature weights
  for each feature
  - find best feature weight
  - update if different from current

MERT

- Line search for best feature weights
  given: sentences with n-best lists of translations
- iterate n times
  randomize starting feature weights
  for each feature
  - find best feature weight
  - update if different from current
- return best feature weights found in any iteration

MERT



Questions?

References I

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Philipp Koehn. *Statistical Machine Translation*. Cambridge University Press, New York, NY, USA, 1st edition, 2010. ISBN 0521874157, 9780521874151.