

Introduction to Phrase-based Statistical Machine Translation

Fabienne Cap



**UPPSALA
UNIVERSITY
SWEDEN**

Where are we?

Type	Date	Time	Place	Topic	Reading / Assignments
F	2016-03-30	10-12	6-K1031	Introduction (SS)	Koehn 1; JM 25.1-2; Hutchins; CFMF
F	2016-03-30	14-16	6-K1031	MT evaluation (SS)	Koehn 8; JM 25.9
F	2016-04-04	10-12	2-0076	MT in practice (Convertus) - guest lecture	
L	2016-04-06	10-12	Chomsky	MT in practice (AS)	lab report 1
F	2016-04-11	10-12	2-0076	Introduction to SMT (FC)	Koehn Ch 4, Ch 7, KK97
L	2016-04-13	10-12	Chomsky	Word-based SMT (SS)	lab report 2
L	2016-04-18	10-12	Chomsky	Word-based SMT (SS)	lab report 2
F	2016-04-18	14-16	2-1077	Machine translation at Semantix, a translation provider - guest lecture	
F	2016-04-20	10-12	6-K1031	Parallel Corpora, Alignment (AS)	Koehn 2-4, JT 3-4, KK97, KK99
L	2016-04-25	10-12	Chomsky	Parallel corpora & alignment (AS)	lab report 3
F	2016-04-27	10-12	2-0076	Phrase-based SMT (FC)	Koehn Ch 5
L	2016-05-02	10-12	Chomsky	Phrase-based SMT (AS)	lab report 4
F	2016-05-04	10-12	6-K1031	Decoding (CH)	Koehn Ch 6
L	2016-05-09	10-12	Chomsky	Phrase-based SMT (AS)	lab report 4
F	2016-05-11	10-12	2-0076	Tree-based SMT & MT for morphologically rich languages (SS, FC)	Koehn 10.2, 11
F	2016-05-16	10-12	2-0076	Document-wide decoding & Neural MT (CH)	
L	2016-05-18	10-12	Chomsky	Document-wide decoding lab (AS)	oral lab report 5
S	2016-05-23	10-12	2-0076	Seminar - master student presentations	
S	2016-05-25	10-12	6-K1031	Seminar - master student presentations	

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Goals for Today

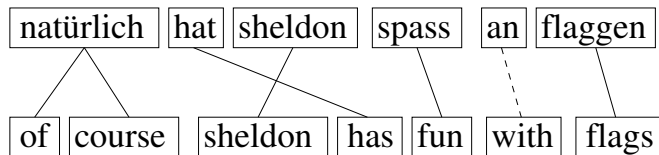
Why phrases?

Symmetrisation of word alignment

Phrase extraction and scoring

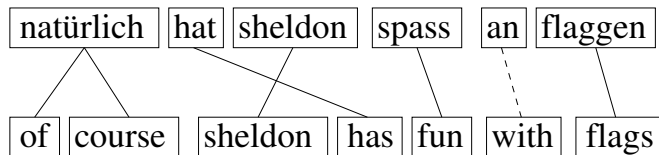
Log-Linear Model

Word-based vs. Phrase-based SMT

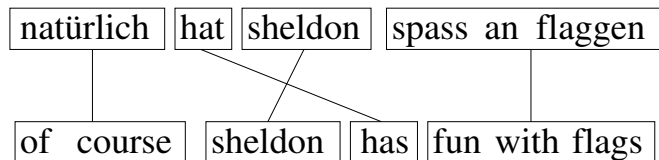


Word-based models translate **words** as atomic units

Word-based vs. Phrase-based SMT



Word-based models translate **words** as atomic units



Phrase-based models translate **phrases** as atomic units

Phrase-based SMT

- A phrase is a **continuous** sequence of words
- Not necessarily a linguistic phrase (!):
Spass an - fun with the
→ using only linguistic phrases **hurts** translation quality!
- State-of-the-art for many language pairs
- Used by Google Translate and others

Advantages of Phrase-based SMT

- Many-to-many translation can handle
non-compositional phrases:
kick the bucket - ins Gras beissen (lit. into the grass bite)
compounds:
blättderblocksblad - flipchart paper
- Local context can be taken into account:
local word order:
affaires extérieure - external affairs
local agreement issues:
*Vorlesung **am** Mittwoch - lecture **on** Wednesday*
*Spass **am** Spiel - fun **with the** game*

Advantages of Phrase-based SMT II

- Translating phrases helps to reduce translation ambiguities
- Phrases of arbitrary length:
sometimes the **entire sentence** might be covered by a phrase
- Simpler model:
no more need to explicitly model the concepts of **fertility**, **insertion** and **deletion** of words

Real Example

Phrase translations for **begreppet** taken from EUROPARL

English	$\phi(\bar{t} \bar{s})$	English	$\phi(\bar{t} \bar{s})$
the	0.226415	the news	0.012816
told	0.169811	the report	0.008544
announcement	0.075472	the information	0.008544
message	0.056604	the back	0.004272
news	0.056604	the suspension	0.004272
information	0.037736	the death	0.004272
informed	0.037736	this announcement	0.002848
learnt	0.037736	this news	0.002136
peace of mind by ensuring	0.027778	a message	0.001539
insight	0.018868	his answer	0.000356
the announcement	0.017088	were told	0.000229
the message	0.012816	the back and	2.917e-05

- lexical variation (announcement, message, news, told, ...)
- Morphological variation (information, informed)
- Included function words (the, a, were, this)
- Noise (the, the back and)

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Why phrases?

Symmetrisation of word alignment

Phrase extraction and scoring

Log-Linear Model

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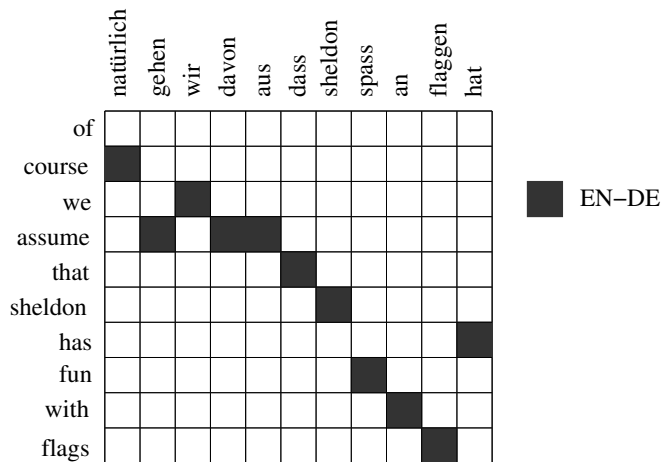
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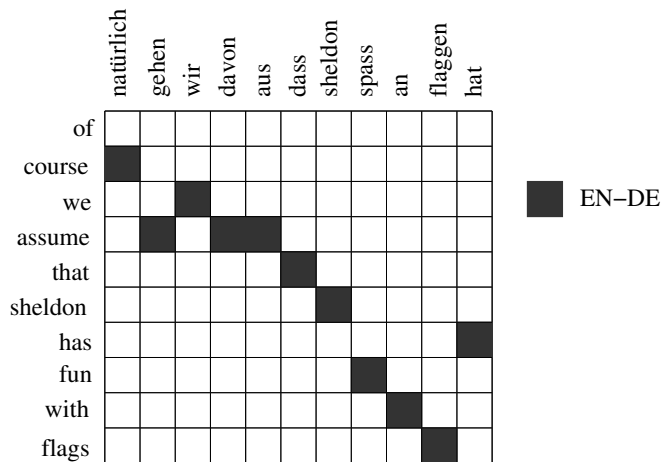
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Directional Word Alignment Matrix

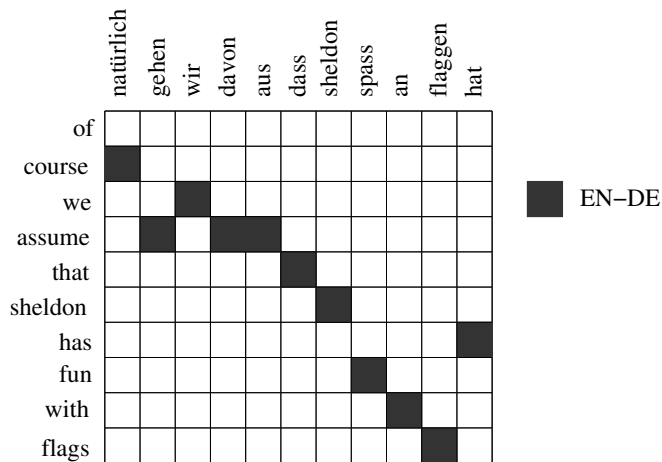


Directional Word Alignment Matrix



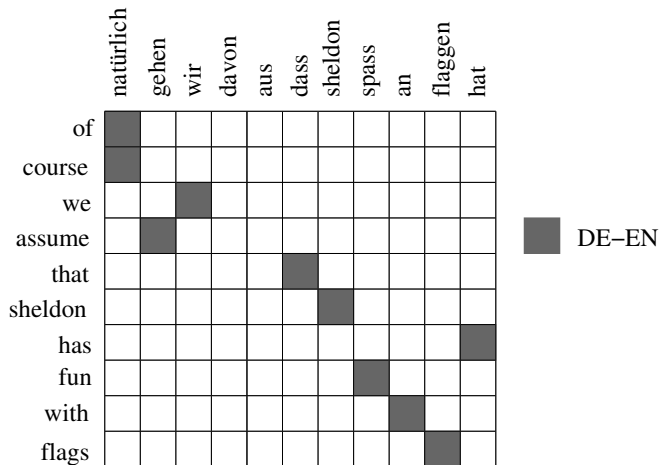
Each target word can be aligned to at most one source word

Directional Word Alignment Matrix



Each target word can be aligned to at most one source word
But: a source word can be aligned to more than one target word

Directional Word Alignment Matrix



Each target word can be aligned to at most one source word

But: a source word can be aligned to more than one target word

Word Alignment Do-it-Yourself

- Languages available:
Swedish, German, Spanish, French, Chinese
- Do **not** fill out all matrices!
- Start with the language you know best!

SWEDISH I

	min	kraft	den	flödar	genom	luft	och	genom	mark
my									
power									
flurries									
through									
the									
air									
into									
the									
ground									

Swedish → English

	min	kraft	den	flödar	genom	luft	och	genom	mark
my									
power									
flurries									
through									
the									
air									
into									
the									
ground									

English → Swedish

SWEDISH I

	min	kraft	den	flödar	genom	luft	och	genom	mark
my	■								
power		■							
flurries				■					
through					■				
the						■			
air						■			
into								■	
the									■
ground									■

Swedish → English

	min	kraft	den	flödar	genom	luft	och	genom	mark
my	■								
power		■	■						
flurries				■					
through					■				
the						■			
air						■			
into								■	
the									■
ground									■

English → Swedish

SWEDISH II

	och	de	rädslar	som	har	styr	mig
and							
the							
fears							
that							
once							
controlled							
me							

Swedish → English

	och	de	rädslar	som	har	styr	mig
and							
the							
fears							
that							
once							
controlled							
me							

English → Swedish

SWEDISH II

	och	de	rädslar	som	har	styrt	mig
and	■						
the		■					
fears			■				
that				■			
once							
controlled						■	
me							■

Swedish → English

	och	de	rädslar	som	har	styrt	mig
and	■						
the		■					
fears			■				
that				■			
once							
controlled					■	■	
me							■

English → Swedish

GERMAN I

	keine	Spuren	sind	zu	sehen
not					
a					
footprint					
to					
be					
seen					

German → English

	keine	Spuren	sind	zu	sehen
not					
a					
footprint					
to					
be					
seen					

English → German

GERMAN I

	keine	Spuren	sind	zu	sehen
not	■				
a	■				
footprint		■			
to				■	
be					■
seen			■		

German → English

	keine	Spuren	sind	zu	sehen
not	■				
a					
footprint		■			
to				■	
be					■
seen			■		

English → German

GERMAN II

	ein	einsames	Königreich	und	ich	bin	die	Königin
a								
kingdom								
of								
isolation								
and								
it								
looks								
like								
I								
'm								
the								
queen								

German → English

	ein	einsames	Königreich	und	ich	bin	die	Königin
a								
kingdom								
of								
isolation								
and								
it								
looks								
like								
I								
'm								
the								
queen								

English → German

GERMAN II

	ein	einsames	Königreich	und	ich	bin	die	Königin
a	■							
kingdom	■		■					
of		■						
isolation		■						
and				■				
it								
looks								
like								
I					■			
'm					■	■		
the							■	
queen								■

German → English

	ein	einsames	Königreich	und	ich	bin	die	Königin
a	■							
kingdom	■		■					
of		■						
isolation		■						
and				■				
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I					■			
'm					■	■		
the							■	
queen								■

English → German

SPANISH I

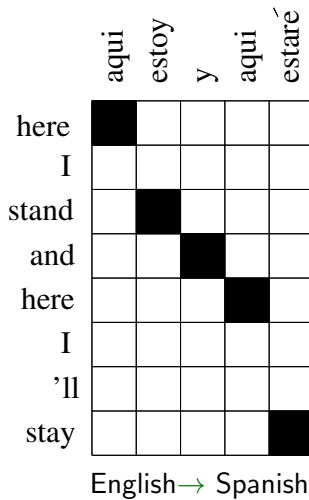
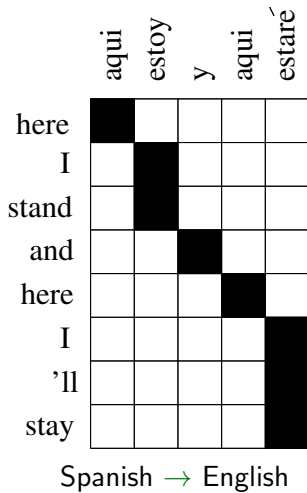
	aquí	estoy	y	aquí	estaré
here					
I					
stand					
and					
here					
I					
'll					
stay					

Spanish → English

	aquí	estoy	y	aquí	estaré
here					
I					
stand					
and					
here					
I					
'll					
stay					

English → Spanish

SPANISH I



SPANISH II

	el	frío	a	mi	nunca	me	molesto
the							
cold							
never							
bothered							
me							
anyway							

Spanish → English

	el	frío	a	mi	nunca	me	molesto
the							
cold							
never							
bothered							
me							
anyway							

English → Spanish

SPANISH II

	el	frío	a	mi	nunca	me	molesto
the	■						
cold		■					
never					■		
bothered							■
me						■	
anyway							

Spanish → English

	el	frío	a	mi	nunca	me	molesto
the	■						
cold		■					
never					■		
bothered							■
me						■	
anyway							

English → Spanish

FRENCH

	je	ne	reviendrai	pas	le	passé	est	passé
I								
'm								
never								
going								
back								
the								
past								
is								
in								
the								
past								

French → English

	je	ne	reviendrai	pas	le	passé	est	passé
I								
'm								
never								
going								
back								
the								
past								
is								
in								
the								
past								

English → French

FRENCH

	je	ne	reviendrai	pas	le	passé	est	passé
I	■							
'm			■					
never				■				
going			■					
back			■					
the					■			
past						■		
is							■	
in								■
the								■
past								■

French → English

	je	ne	reviendrai	pas	le	passé	est	passé
I	■							
'm								
never		■		■				
going			■					
back								
the					■			
past						■		
is							■	
in								■
the								■
past								■

English → French

CHINESE TO ENGLISH

白雪发亮今夜铺满山上

the									
snow									
glows									
white									
on									
the									
mountain									
tonight									

ENGLISH TO CHINESE

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the									
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CHINESE TO ENGLISH

	白	雪	发	亮	今	夜	铺	满	山	上
the		■								
snow		■								
glows		■	■							
white	■									
on										■
the									■	■
mountain									■	
tonight						■	■			

ENGLISH TO CHINESE

白 雪 发 亮 今 夜 铺 满 山 上

the									
snow		■							
glows		■	■	■					
white	■								
on									■
the									
mountain								■	
tonight				■	■	■			

Word Alignment Symmetrisation

How can we bring the two unidirectional alignments together?

- Intersection: high precision, but too few links
- Union: high recall, but too many links

- add diagonally adjacent links
- add links for unaligned words in a final step

Word Alignment Symmetrisation

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Solution:

start from the intersection and then "**grow**"
the alignment towards the union

- add diagonally adjacent links
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Word Alignment Intersection

	natürlich	gehen	wir	davon	aus	dass	sheldon	spass	an	flaggen	hat
of											
course	■										
we			■								
assume		■									
that						■					
sheldon							■				
has											■
fun								■			
with									■		
flags										■	

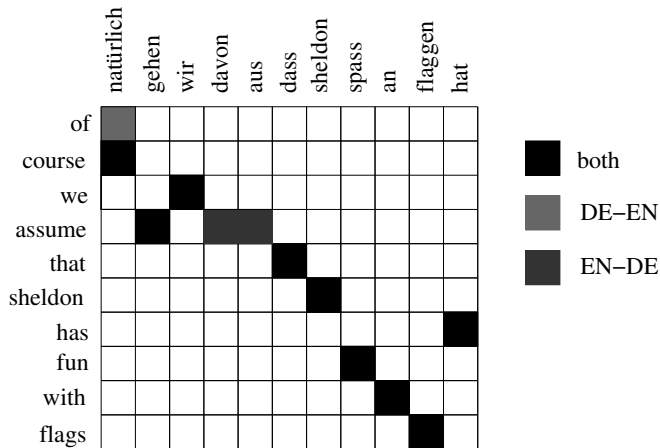
Intersection

Word Alignment Union

	natürlich	gehen	wir	davon	aus	dass	sheldon	spass	an	flaggen	hat
of	■										
course	■										
we			■								
assume		■		■	■						
that						■					
sheldon							■				
has											■
fun								■			
with									■		
flags										■	

Union

Word Alignment Symmetrisation



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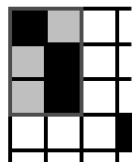
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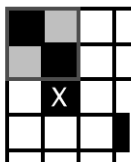
Consistent Phrase Pairs

All words of the phrase pairs have to align to each other



consistent

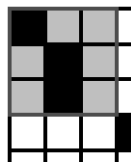
ok



inconsistent

violated

one alignment
point outside

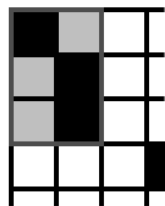


consistent

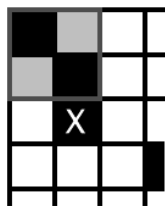
ok

unaligned
word is fine

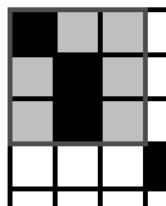
Phrase Extraction Definition



consistent



inconsistent



consistent

A phrase pair (\bar{t}, \bar{s}) is consistent with an alignment A , if all words s_1, \dots, s_m in \bar{s} that have alignment points in A have these with words t_1, \dots, t_n in \bar{t} and vice versa and at least one word in \bar{t} is aligned to at least one word in \bar{s} .

Phrase Extraction Example

	naturlich	gehen	wir	davon	aus	dass	sheldon	spass	an	flaggen	hat
of	■										
course	■										
we			■								
assume		■		■	■						
that						■					
sheldon							■				
has											■
fun								■			
with									■		
flags										■	

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Why Clickers?

- **not:** teacher controlling individual students
- **no** influence on course examination
- **instead:**
 - voluntary exercises
 - learning by doing
 - self-assessment for the students

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Phrase Extraction Exercise 1

How many phrases can be extracted from this word alignment?

	a	b	c
1	■	□	□
2	□	■	□
3	□	□	■

Phrase Extraction Exercise 2

How many phrases can be extracted from this word alignment?

	a	b	c
1			
2			
3			

Phrase Extraction Exercise 3

How many phrases can be extracted from this word alignment?

	a	b	c
1	■	□	■
2	□	■	□
3	□	■	□

Phrase Extraction Exercise 4

How many phrases can be extracted from this word alignment?

	a	b	c	d
1	■	□	□	□
2	□	■	□	□
3	□	□	■	□
4	■	□	□	■

Phrase Extraction Exercise 5

How many phrases can be extracted from this word alignment?

	a	b	c	d
1	■			
2		■	■	
3			■	
4				■

Scoring Phrase Translations

- Phrase pair extraction: collect all phrase pairs from the data
- Phrase pair scoring: assign probabilities to phrase translations
- Score by relative frequency (MLE):

$$\phi(\bar{t}|\bar{s}) = \frac{\text{count}(\bar{s}, \bar{t})}{\sum_{\bar{t}'} \text{count}(\bar{s}, \bar{t}')}$$

- Potentially improve scoring by smoothing

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Goals for Today

Why phrases?

Symmetrisation of word alignment

Phrase extraction and scoring

Log-Linear Model

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Log-Linear Model

Weighted models

- The standard model consists of three sub-models:
 - Phrase translation model $\phi(\bar{s}|\bar{t})$
 - Reordering model d
 - Language model $p_{LM}(t)$

$$t_{best} = \arg \max_t \prod_{i=1}^l \phi(\bar{s}_i|\bar{t}_i) d(\text{start}_i - \text{end}_{i-1} - 1) \prod_{i=1}^{|t|} p_{LM}(t_i|t_{i-(n-1)} \dots t_{i-1})$$

- Some sub-models may be more important than others
 - Add weights $\lambda_{\phi}, \lambda_d, \lambda_{LM}$

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- Add weights $\lambda_\phi, \lambda_d, \lambda_{LM}$

- Such a weighted model is a log-linear model:

$$p(x) = \exp \sum_{i=1}^n \lambda_i h_i(x)$$

- Our feature functions:
 - three feature functions $n = 3$
 - random variable $x = (s, t, \text{start}, \text{end})$
 - feature function $h_1 = \log \phi$
 - feature function $h_2 = \log d$
 - feature function $h_3 = \log p_{LM}$

Weighted model as a log-linear model

$$\begin{aligned} p(t, a|s) = \exp(\lambda_\phi \sum_{i=1}^I \log \phi(\bar{s}_i | \bar{t}_i) + \\ \lambda_d \sum_{i=1}^I \log d(\text{start}_i - \text{end}_{i-1} - 1) + \\ \lambda_{LM} \sum_{i=1}^{|t|} \log p_{LM}(t_i | t_{i-(n-1)} \dots t_{i-1})) \end{aligned}$$

More feature functions

$$t^* = \arg \max_t \sum_i \lambda_i h_i(s, t)$$

- Easy and useful to add more feature functions
 - Bidirectional alignment probabilities $\phi(\bar{s}|\bar{t})$ and $\phi(\bar{t}|\bar{s})$
 - Lexical weighting of phrase pairs:
useful since rare phrase pairs have unreliable probability estimates

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- Language model has a bias towards short translations
 - word count: $wc(t) = \log |t|^\omega$
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Mid-Course Feedback

Sara asked me to ask you for feedback about the MT course so far

What did you like? What should be improved?

We will try to react to your feedback during the rest of the course!

Information for Bachelor's Students

Assignment 1 is now online.

You have 2 weeks from now to hand in this assignment.

Contact Sara if you have any further questions!