Moses

Machine Translation with Open Source Software

Philipp Koehn and Hieu Hoang

1 November 2012



Outline



09:30-10:00 Introduction

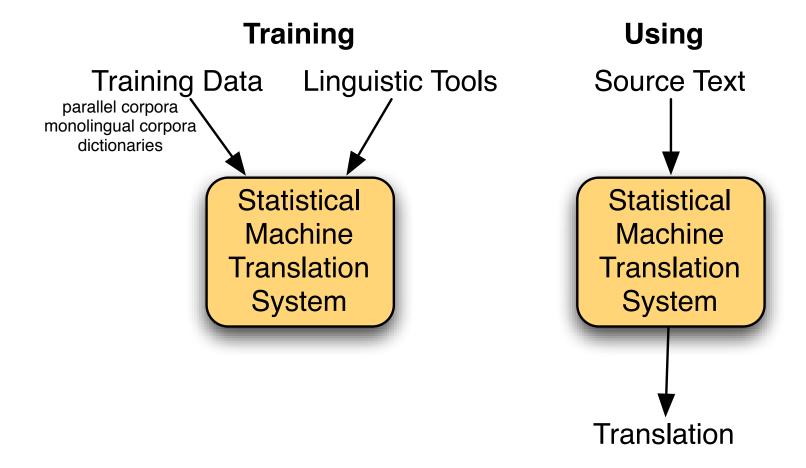
10:00-11:00 Hands-on Session — you will need a laptop

11:00-11:30 Break

11:30-12:30 Advanced Topics

Basic Idea





Statistical Machine Translation History



around 1990

Pioneering work at IBM, inspired by success in speech recognition

1990s

Dominance of IBM's word-based models, support technologies

early 2000s

Phrase-based models

late 2000s

Tree-based models



Moses History

- 2002 Pharaoh decoder, precursor to Moses (phrase-based models)
- 2005 Moses started by Hieu Hoang and Philipp Koehn (factored models)
- **2006** JHU workshop extends Moses significantly
- since late 2006 Funding by EU projects EuroMatrix, EuroMatrixPlus
- **2009** Tree-based models implemented in Moses
- 2012 MosesCore project. Full-time staff to maintain and enhance Moses

Moses in Academia



- Built by academics, for academics
- Reference implementation of state of the art
 - researchers develop new methods on top of Moses
 - developers re-implement published methods
 - used by other researchers as black box
- Baseline to beat
 - researchers compare their method against Moses

Developer Community



- Main development at University of Edinburgh, but also:
 - Fondazione Bruno Kessler (Italy)
 - Charles University (Czech Republic)
 - DFKI (Germany)
 - RWTH Aachen (Germany)
 - others...
- Code shared on github.com
- Main forum: support and developer mailing lists
- Main event: Machine Translation Marathon (next: September 2011, Trento)
 - annual open source convention
 - presentation of new open source tools
 - hands-on work on new open source projects
 - summer school for statistical machine translation



Open Source Components

- Moses distribution uses external open source tools
 - word alignment: GIZA++, Berkeley aligner
 - language model: SRILM, IRSTLM, RANDLM
 - scoring: BLEU, TER, METEOR
- Other useful tools
 - sentence aligner
 - syntactic parsers
 - part-of-speech taggers
 - morphological analyzers



Other Open Source MT Systems

- Joshua Johns Hopkins University http://joshua.sourceforge.net/
- CDec University of Maryland http://cdec-decoder.org/
- Jane RWTH Aachen http://www-i6.informatik.rwth-aachen.de/jane/
- Very similar technology
 - Joshua implemented in Java, others in C++
 - Joshua and Jane support only tree-based models
 - Phrasal supports only phrase-based models
- Open sourcing tools increasing trend in NLP research





- Distributed with LGPL free to use
- Competitive with commercial SMT solutions (Language Weaver, Google, ...)
- But:
 - not easy to use
 - requires significant expertise for optimal performance
 - integration into existing workflow not straight-forward

Case Studies



European Commission —

uses Moses in-house to aid human translators

Autodesk —

showed productivity increases in translating manuals when post-editing output from a custom-build Moses system

Systran —

developed statistical post-editing using Moses

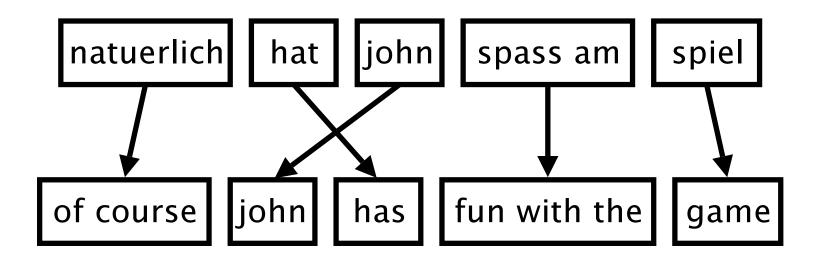
Asia Online —

offers translation technology and services based on Moses

Many others... World Trade Organisation, Adobe, Symantec, WIPO, Sybase

Phrase-Based Model

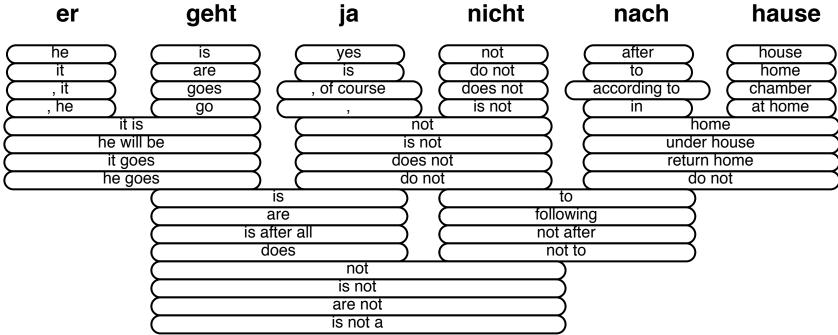




- Foreign input is segmented in phrases
- Each phrase is translated into English
- Phrases are reordered



Phrase Translation Options



Many translation options to choose from



Phrase Translation Options



- 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





consult phrase translation table for all input phrases

Decoding: Start with Initial Hypothesis 15 G



er 	geht	ja 	nicht	nach	hause ———
		-			

initial hypothesis: no input words covered, no output produced



Decoding: Hypothesis Expansion

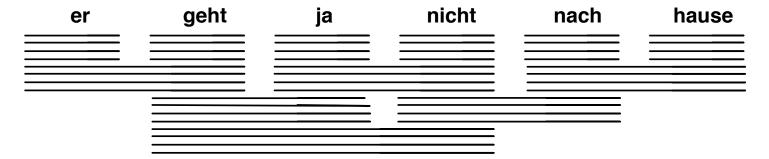


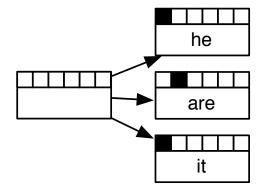


pick any translation option, create new hypothesis



Decoding: Hypothesis Expansion

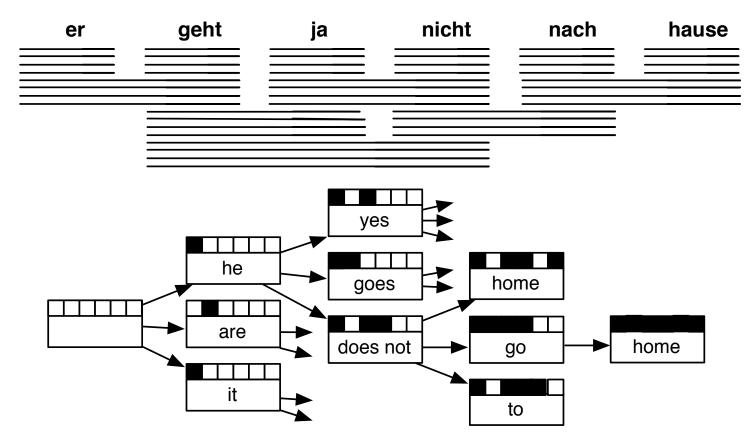




create hypotheses for all other translation options



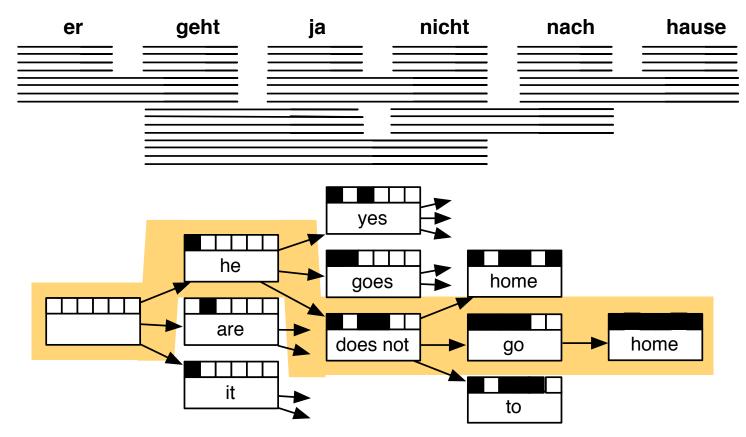
Decoding: Hypothesis Expansion



also create hypotheses from created partial hypothesis



Decoding: Find Best Path



backtrack from highest scoring complete hypothesis



Computational Complexity

- The suggested process creates exponential number of hypothesis
- Reduction of search space: pruning
- → Decoder may not find the model-best translation





Factored represention of words

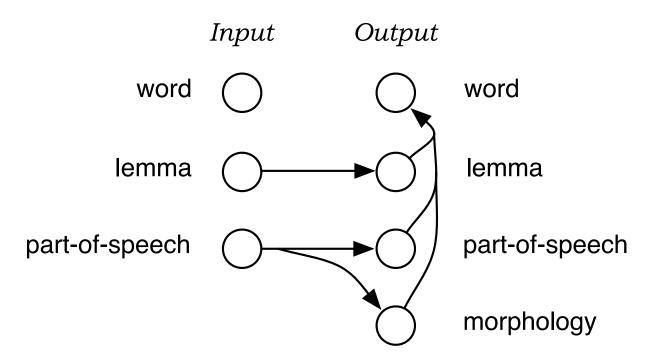
	Input	Output	
word	\bigcirc		word
lemma	\bigcirc		lemma
part-of-speech	-		part-of-speech
morphology			morphology
word class	\bigcirc		word class

- Goals
 - generalization, e.g. by translating lemmas, not surface forms
 - richer model, e.g. using syntax for reordering, language modeling)



Factored Model

Example:



Decomposing the translation step

Translating lemma and morphological information more robust

Syntax Models



String to String

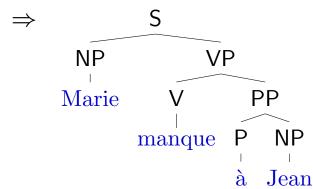
John misses Mary

⇒ Marie manque à Jean

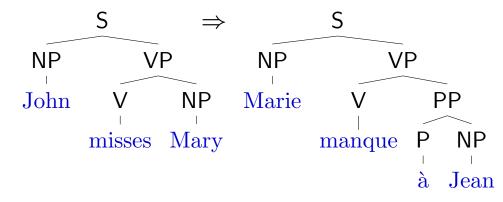
Tree to String

String to Tree

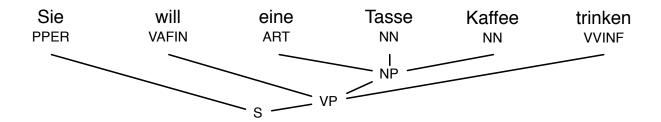
John misses Mary



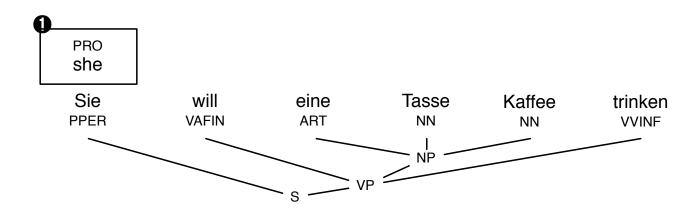
Tree to Tree



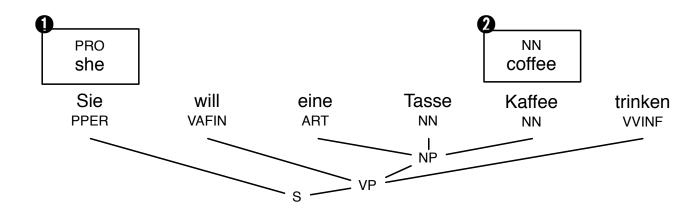




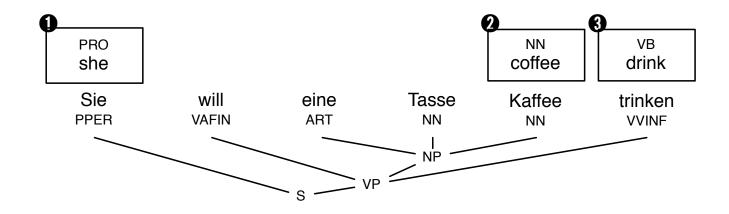




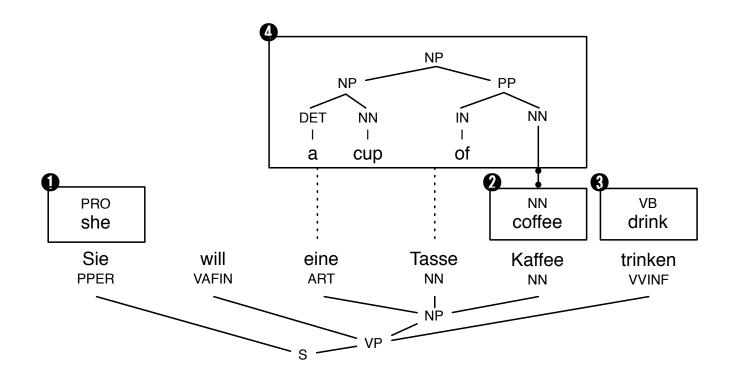




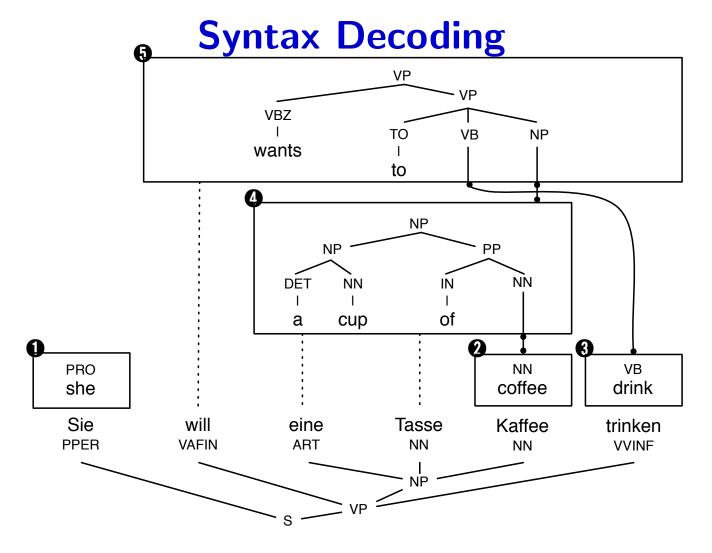


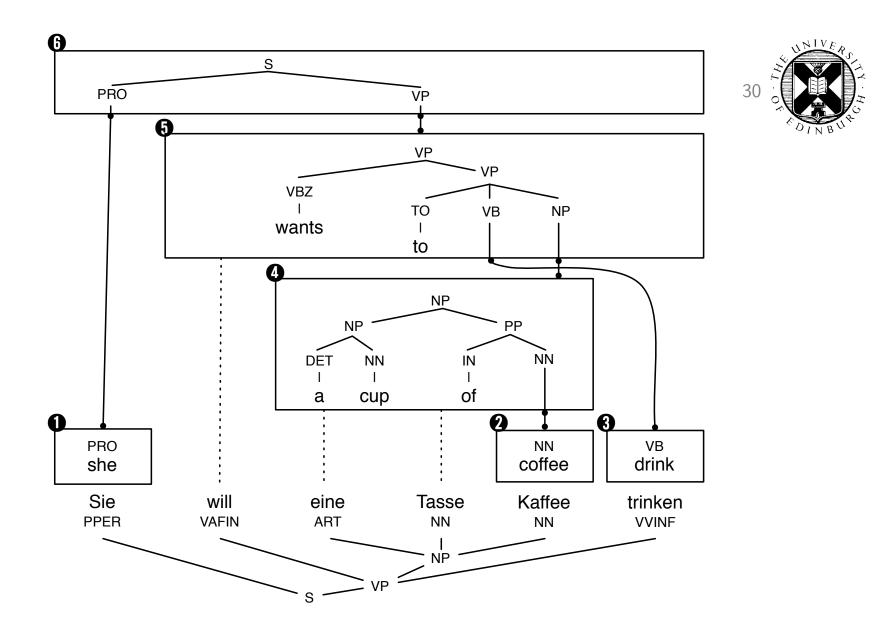












Advanced Topics



- Data and domain adaptation
- Speed vs. quality
- Speed vs. memory use
- Language models
- Instructions to decoder
- Input formats
- Output formats
- Minimum Bayes risk decoding
- Translation models
- Experiment management system



Hands-On Session



Advanced Topics

Advanced Features



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Data



- Parallel corpora → translation model
 - sentence-aligned translated texts
 - translation memories are parallel corpora
 - dictionaries are parallel corpora
- Monolingual corpora → language model
 - text in the target language
 - billions of words easy to handle

Domain Adaptation



- The more data, the better
- The more in-domain data, the better (even in-domain monolingual data very valuable)
- Multiple models
 - train a translation model for each domain corpus
 - train a language model for each domain corpus
 - use all, tune weights for each model
 - alternative: interpolate language model
- Always tune towards target domain

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Speed



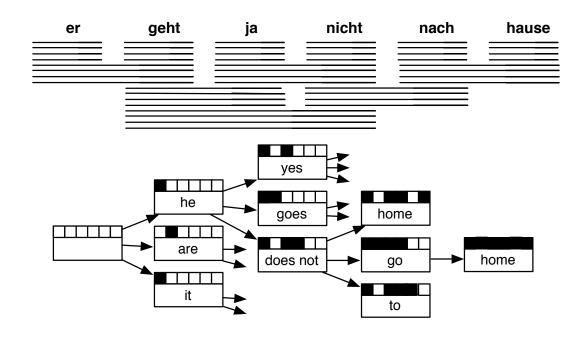
• Easy speed-up: multi-threaded decoding

--threads NUM

- Requires boost library
- Does not currently work for:
 - syntax-based decoding
 - IRSTLM
 - randLM



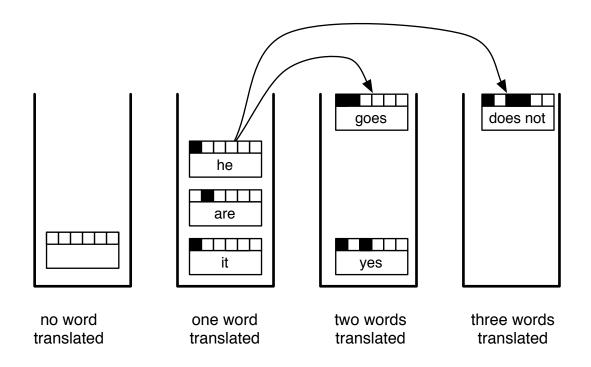
Speed vs. Quality



- Decoder search creates very large number of partial translations ("hypotheses")
- ullet Decoding time \sim number of hypotheses created
- ullet Translation quality \sim number of hypothesis created



Hypothesis Stacks



- Phrase-based: One stack per number of input words covered
- Number of hypothesis created = sentence length \times stack size \times applicable translation options

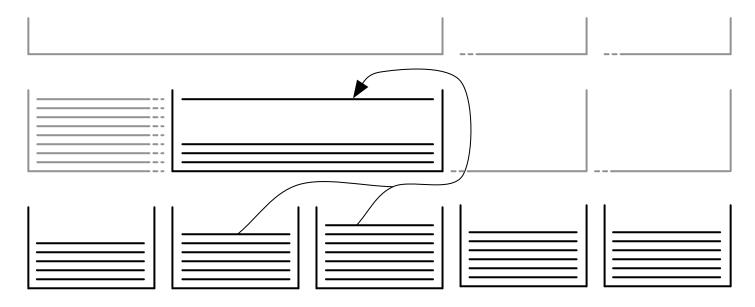
Pruning Parameters



- Regular beam search
 - --stack NUM max. number of hypotheses contained in each stack
 - --ttable-limit NUM max. num. of translation options per input phrase
 - search time roughly linear with respect to each number
- Cube pruning (fixed number of hypotheses are added to each stack)
 - --search-algorithm 1 turns on cube pruning
 - --cube-pruning-pop-limit NUM number of hypotheses added to each stack
 - search time roughly linear with respect to pop limit
 - note: stack size and translation table limit have little impact in speed

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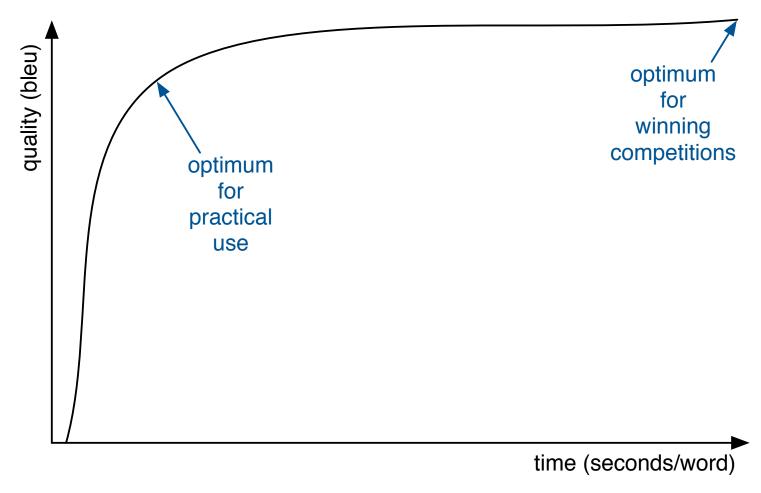
Syntax Hypothesis Stacks



- One stack per input word span
- $\begin{array}{l} \bullet \ \, \text{Number of hypothesis created} = \\ \text{sentence length}^2 \times \text{number of hypotheses added to each stack} \\ \text{--cube-pruning-pop-limit NUM} \quad \text{number of hypotheses added to each stack} \\ \end{array}$



Trade-Off Speed vs Quality

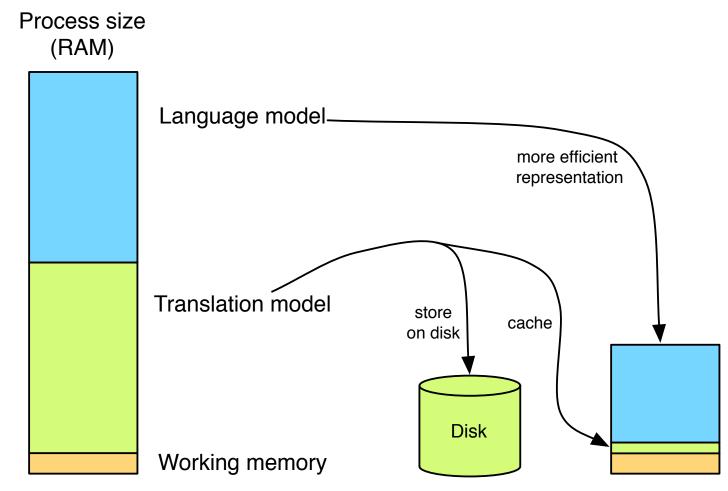


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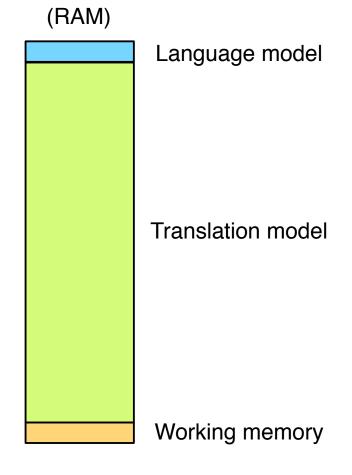




Process size

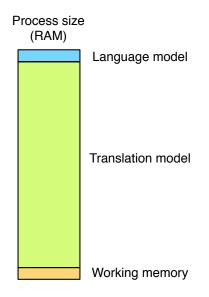
Typical Europarl file sizes:

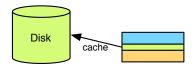
- Language model
 - 170 MB (trigram)
 - 412 MB (5-gram)
- Phrase table
 - 11GB
- Lexicalized reordering
 - 9.4GB
- \rightarrow total = 20.8 GB





- Load into memory
 - fast decoding
 - large memory usage
 - large load time
- Load-on-demand
 - store indexed model on disk
 - binary format
 - minimal start-up time, memory usage
 - slower decoding







Phrase Table:

Phrase-based

```
export LC_ALL=C
cat pt.txt | sort | ./processPhraseTable -ttable 0 0 - \
    -nscores 5 -out out.file
```

Hierarchical / Syntax

```
export LC_ALL=C
./CreateOnDiskPt 1 1 5 100 2 pt.txt out.folder
```

Lexical Reordering Table:

```
export LC_ALL=C
processLexicalTable -in r-t.txt -out out.file
```

Language Models (later)



Change ini file

Phrase-based

[ttable-file]
1 0 0 5 out.file

Hierarchical / Syntax

[ttable-file]
2 0 0 5 out.folder

Lexical Reordering Table

[distortion-file]
0-0 wbe-msd-bidirectional-fe-allff 6 out.file

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Language Models



- Probability of the output
- \bullet Very important in MT, for all SMT models \rightarrow improve fluency
- Huge amount of training data easy to obtain
 - monolingual
 - can scrape from websites etc.
- But:
 - training takes a long time
 - large memory requirement during decoding
 - large load time
- IRSTLM and RandLM especially designed to tackle large data issues

IRSTLM



- Developed by FBK-irst, Trento, Italy
- Create a binary format which can be read from disk as needed
 - reduces memory but slower decoding
- Quantization of probabilities
 - reduces memory but lose accuracy
 - probability stored in 1 byte instead of 4 bytes

IRSTLM in Moses



• Compile the decoder with IRSTLM library

```
./configure --with-irstlm=[root dir of the IRSTLM toolkit]
```

• Change ini file to use IRSTLM implementation

```
[lmodel-file]
1 0 3 file/path
```

IRSTLM: Training



- Specialized training for large corpora
 - parallelization
 - reduce memory usage
- Training:

- − -n 3 = n-gram order
- -k 10 = split training procedure into 10 steps

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IRSTLM: Binary Format

• Create binary format:

compile-lm language-model.srilm language-model.blm

• Load-on-demand:

rename file .mm

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Randomized language model

- For huge corpora (e.g. 100 billion words)
- Lossy compression
 - Makes false positive mistakes
 - frequency of mistakes can be varied with a parameter
- Typically $\frac{1}{10}$ size of SRI / IRST language model
- Maybe use as secondary LM to complement conventional LM
 - out-of-domain data scraped from the web
 - high-order n-gram, eg. 6-7 gram



RandLM: Use in Moses

Compile the decoder with RandLM library

```
./configure --with-randlm=[root dir of the RandLM toolkit]
```

Change ini file to use RandLM implementation

```
[lmodel-file]
0 0 3 /path/to/file  # conventional lm
5 0 7 /path/to/file  # rand lm
```



RandLM: Training

• Train from text corpus

```
./buildlm -struct BloomMap -falsepos 8 -values 8 -order 3
   -output-prefix model
   < corpus.txt</pre>
```

Convert SRILM language model

```
./buildlm -struct BloomMap -falsepos 8 -values 8 -order 3
   -output-prefix model
   -input-path lm.srilm -input-type arpa
```

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Specifying Translations with XML

• Translation tables for numbers?

f	e	p(f e)
2003	2003	0.7432
2003	2000	0.0421
2003	year	0.0212
2003	the	0.0175
2003	•••	•••

Instruct the decoder with XML instruction

```
the revenue for <num translation="2003"> 2003 </num> is higher than ...
```

Deal with different number formats

```
er erzielte <num translation="17.55"> 17,55 </num> Punkte .
```

Walls and Zones



- Specification of reordering constraints
- Zone
 sequence to be translated without reordering with outside material
- Wall hard reordering constraint, no words may be reordered across
- Local wall wall within a zone, not valid outside zone

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Walls and Zones: Examples

• Requiring the translation of quoted material as a block

```
He said <zone> " yes " </zone> .
```

Hard reordering constraint

```
Number 1 : <wall/> the beginning .
```

Local hard reordering constraint within zone

```
A new plan <zone> ( <wall/> maybe not new <wall/> ) </zone> emerged .
```

Nesting

```
The <zone> " new <zone> ( old ) </zone> " </zone> proposal .
```





How do you translate this:

• Solution 1: XML translations, walls and zones

```
<x translation="<h1>"/> <wall/> My Home Page <wall/>
<x translation="</h1>"/>

I really like to <zone><x translation="<b>"/> <wall/> eat <wall/>
<x translation="</b>"/> </zone> chicken!
```

(note: special XML characters like < and > need to be escaped)

Preserving Markup



- Solution 2: Handle markup externally
 - track word positions and their markup

I	really	like	to	<b $>eat$	chicken	!
1	2	3	4	5	6	7
_	_	_	_		_	_

translate without markup

I really like to eat chicken!

- keep word alignment to source

re-insert markup

Ich esse wirklich gerne Hühnchen!

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• Misspelt sentence:

The room was *exellent but the hallway was *filty.

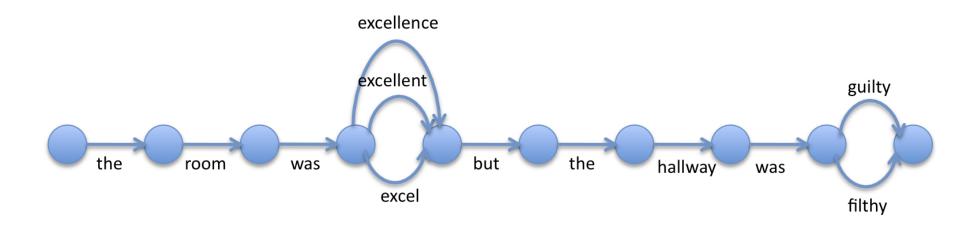
- Strategies for dealing with spelling errors:
 - Create correct sentence with correction
 - × problem: if not corrected properly, adds more errors
 - Create many sentences with different corrections
 - × problem: have to decode each sentence, slow



Confusion Network

The room was *exellent but the hallway was *filty .

Input to decoder:



Let the decoder decide





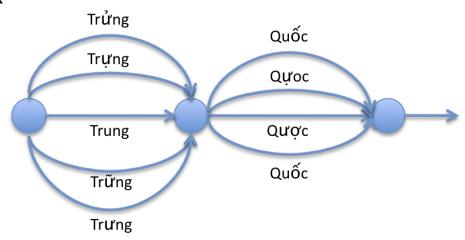
Correct sentence

Trung Quốc cảnh báo Mỹ về luật tiền tệ

Something a non-native person might type

Trung Quoc canh bao My ve luat tien te

• Confusion network





Confusion Network Specification

Argument on command line

```
./moses -inputtype 1
```

Input to moses

```
the 1.0
room 1.0
was 1.0
excel 0.33 excellent 0.33 excellence 0.33
but 1.0
the 1.0
hallway 1.0
was 1.0
guilty 0.5 filthy 0.5
```

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Lattice

Example: Chinese Word Segmentation

Unsegmented sentence

硬质合金号称"工业牙齿"

Incorrect segmention

硬质 合 金 号称 "工 业牙 齿 "

• Correct segmention

硬质合金号称"工业牙齿"

Lattice



Input to decoder:



Let the decoder decide



Example: Compound Splitting

• Input sentence

einen wettbewerbsbedingten preissturz

Different compound splits



• Let the decoder decide



Lattice Specification

Command line argument

./moses -inputtype 1

Input to Moses (PLF format - Python Lattice Format)

```
(
 ('einen', 1.0, 1),
  ('wettbewerbsbedingten', 0.5, 2),
 ('wettbewerbs', 0.25, 1),
  ('wettbewerb', 0.25, 1),
),
 ('bedingten', 1.0, 1),
),
 ('preissturz', 0.5, 2),
 ('preis', 0.5, 1),
 ('sturz', 1.0, 1),
),
```

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N-Best List



Input

es gibt verschiedene andere meinungen.

• Best Translation

there are various different opinions.

Next nine best translations

```
there are various other opinions.

there are different different opinions.

there are other different opinions.

we are various different opinions.

there are various other opinions of.

it is various different opinions.

there are different other opinions.

it is various other opinions.

it is a different opinions.
```

Uses of N-Best Lists



- Let the translator choose from possible translations
- Reranker
 - add more knowledge sources
 - can take global view
 - coherency of whole sentence
 - coherency of document
- Used to tune component weights



N-Best Lists in Moses

Argument to command line

./moses -n-bestlist n-best.file.txt [distinct] 100

Output

```
0 ||| there are various different opinions . ||| d: 0 lm: -21.6664 w: -6 ... ||| -113.734  
0 ||| there are various other opinions . ||| d: 0 lm: -25.3276 w: -6 ... ||| -114.004  
0 ||| there are different different opinions . ||| d: 0 lm: -27.8429 w: -6 ... ||| -117.738  
0 ||| there are other different opinions . ||| d: -4 lm: -25.1666 w: -6 ... ||| -118.007  
0 ||| we are various different opinions . ||| d: 0 lm: -28.1533 w: -6 ... ||| -118.142  
0 ||| there are various other opinions of . ||| d: 0 lm: -33.7616 w: -7 ... ||| -118.153  
0 ||| it is various different opinions . ||| d: 0 lm: -29.8191 w: -6 ... ||| -118.222  
0 ||| there are different other opinions . ||| d: 0 lm: -30.426 w: -6 ... ||| -118.236  
0 ||| it is various other opinions . ||| d: 0 lm: -32.6824 w: -6 ... ||| -118.395  
0 ||| it is a different opinions . ||| d: 0 lm: -20.1611 w: -6 ... ||| -118.434
```

Search Graph



Input

er geht ja nicht nach hause

• Return internal structure from the decoder



• Encode millions of other possible translations (every path through the graph = 1 translation)

Uses of Search Graphs



- Let the translator choose
 - Individual words or phrases
 - 'Suggest' next phrase
- Reranker
- Used to tune component weights
 - More difficult than with n-best list

[1] New probe into US attorney affair >>
Neuer Vorstoß in den USA Anwalt neue Affäre sonde (9 edits)

neue sonde						
ent	er in E	×.				
new	probe	into	US	attorney	affair	
neue	Sonde		in	Anwalt	die	
die	testet	in	dle	Staatsanwalt	Affäre	
		in	in	Anwälte	dle	
		in	dle	Testamentsvollstreckers	sle	
		In	dle	Vollmachten	Angelegenheit	
		auch	in	Anwalt	um	
		In	der		Sache	

nach die

das



Search Graphs in Moses

Argument to command line

./moses -output-search-graph search-graph.file.txt

Argument to command line

```
0 hyp=0 stack=0 forward=36 fscore=-113.734
0 hyp=75 stack=1 back=0 score=-104.943 ... covered=5-5 out=.
0 hyp=72 stack=1 back=0 score=-8.846 ... covered=4-4 out=opinions
0 hyp=73 stack=1 back=0 score=-10.661 ... covered=4-4 out=opinions of
```

- hyp hypothesis id
- stack how many words have been translated
- score total weighted score
- covered which words were translated by this hypothesis
- out target phrase

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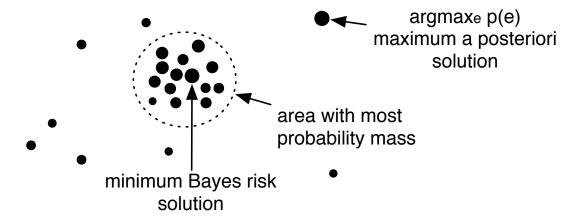
Minimum Bayes Risk Decoding

Normal (MAP) decoding:

$$\hat{t} = argmax_t \ p(t|s)$$

MBR decoding:

$$\hat{t} = argmax_t \sum_{t' \in T} p(t'|s) \times bleu(t', t)$$





Minimum Bayes Risk Decoding

• Set of translations $t' \in T$

$$\hat{t} = argmax_t \sum_{t' \in T} p(t'|s) \times bleu(t', t)$$

• Using n-best list:

• Using lattice:

lmbrgrid ... -f moses.ini -i input.txt

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Phrase-Based Model



- Advantages
 - fast: under half a second per sentence for fast configuration
 - low-memory requirement
 - * 200-300MB for lowest configuration
 - * suitable for netbooks and mobile devices
 - outperform more complicated models for many language pairs
 - * especially for related languages pairs
- Command line

./moses -f moses.ini -i in.txt > out.txt

Output

there are various different opinions .

Hierarchical Models



Advantages

- able to model non-contiguous phrases
 - ne..pas \rightarrow not
- low-memory requirement
 - 200-300MB for lowest configuration
 - suitable for netbooks and mobile devices
- outperform phrase-based models when translating between widely different languages
 - Chinese-English consistently better with hierarchical model
 - better at medium range re-ordering
- Linguistically motivated

Disadvantages

- slower
 - 0.5 2 sec for fastest configuration
- more memory requirement
 - 1-2GB ram
- more disk usage
 - translation model $\times 10$ larger than phrase-based

Command line

./moses-chart -f moses.ini -i in.txt > out.txt

Syntax Models



- Hierarchical model + use of syntactic information (constituency parser, chunkers)
- Advantage
 - Can use outside linguistic information
 - promises to solve important problems in SMT, eg. long-range reordering
- Disadvantages
 - difficult to get right
 - for many language pairs still worse than phrase-based and hierarchical models
 - need syntactic parse information
 - * unreliable
 - * available only for some languages
 - * not designed for machine translation



Moses Tree Representation

```
NP PUNC
NE ADJA NN ?
Musharrafs letzter Akt
```

```
- <tree label="TOP">
    - <tree label="NP">
        <tree label="NE"> Musharrafs </tree>
        <tree label="ADJA"> letzter </tree>
        <tree label="NN"> Akt </tree>
        </tree>
        <tree label="PUNC"> ? </tree>
        </tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree></tree>
```



Phrase-Based Model Training

Command line

Model

```
Bndnisse ||| alliances ||| 1 1 1 1 2.718 ||| ||| 1 1 General Musharraf appeared on ||| 1 1 1 1 2.718 ||| || 1 1
```

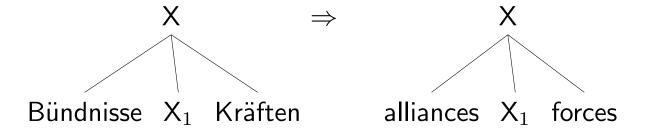
Hierarchical Model Training



Command line

Example rule from model

Bündnisse [X][X] Kräften [X] ||| alliances [X][X] forces [X] ||| 1 1 1 1 2.718 ||| 1-1 ||| 0.0526316 0.0526316



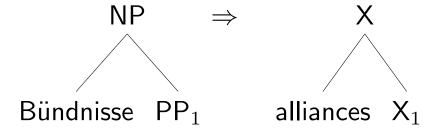


Tree-to-String Model Training

• Command line

Example rule from model

Bündnisse [PP][X] [NP] || alliances [PP][X] [X] || 1 1 1 1 2.718 || 1-1 || 1 1



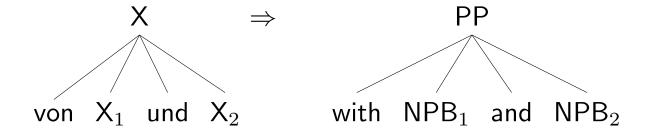
92 OF DINBUTE

String to Tree Model Training

Command line

Example rule from model

```
von [X][NPB] und [X][NPB] [X] ||| with [X][NPB] and [X][NPB] [PP] ||| ...
```



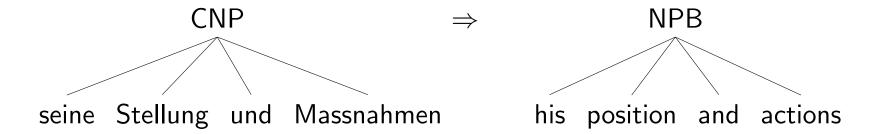
Tree-to-Tree Model Training



• Command line

Example rule from model

```
seine Stellung und Manahmen [CNP] \mid \mid \mid his position and actions [NPB] \mid \mid \mid ...
```





Syntax Models Decoding in Moses

String-to-string (hierarchical) or string-to-tree

```
./moses-chart -f moses.ini -i in.txt > out.txt
```

• Tree-to-string or tree-to-tree

```
./moses-chart -f moses.ini -i in.txt -inputtype 3 > out.txt
```

Advanced Features



- Data and domain adaptation
- Speed vs. quality
- Speed vs. memory use
- Language models
- Instructions to decoder
- Input formats
- Output formats
- Minimum Bayes risk decoding
- Translation models
- Experiment management system



Running Experiments

Execute a lot of scripts

```
tokenize < corpus.en > corpus.en.tok
lowercase < corpus.en.tok > corpus.en.lc
...
mert.perl ....
moses ...
mteval-v13.pl ...
```

Change a part of the process, execute everything again

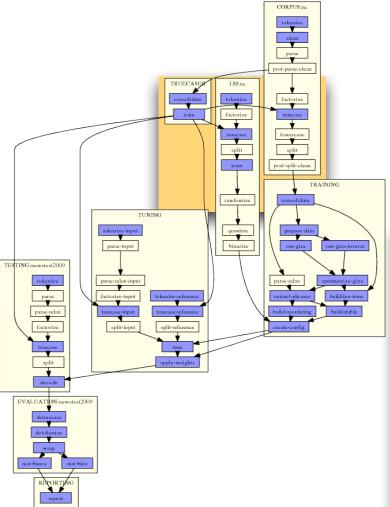
```
tokenize < corpus.en > corpus.en.tok
lowercase < corpus.en.tok > corpus.en.lc
...
mert.perl ....
moses ...
mteval-v13.pl ...
```

Experiment Management System

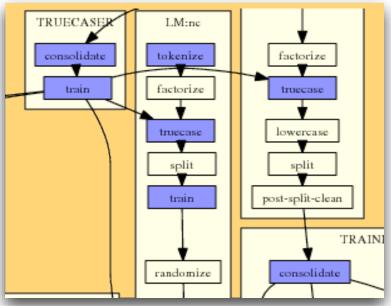


- One configuration file for all settings: record of all experimental details
- Scheduler of individual steps in pipeline
 - automatically keeps track of dependencies
 - on single machine, multi-core machines, GridEngine clusters
 - parallel execution
 - crash detection
 - automatic re-use of prior results
- Fast to use
 - set up a new experiments in minutes
 - set up a variation of an experiment in seconds





Workflow automatically generated by experiment.perl



How does it work?



• Write a configuration file (typically by adapting an existing file)

• Execute:

experiment.perl -config config

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Web Interface

All Experimental Setups

ID	User	Task	Directory
<u>97</u> j	pkoehn	Acquis Truecased	/group/project/statmt2/pkoehn/acquis-truecase
<u>96</u> j	pkoehn	Chinese-English AGILE 2008	/group/project/statmt2/pkoehn/agile08-chinese
<u>95</u> 1	miles	Randlm testing	/group/project/statmt7/miles/experiments /ep-enfr/work
<u>94</u> j	joseph	Proj2008 Impl.Adapted experiment(fr- en)for News Comm.	/group/project/statmt2/joseph/experimentJo/task6
<u>93</u> j	joseph	Proj2008 Impl.Baseline experiment(fr- en)for News Comm.	/group/project/statmt2/joseph/experimentJo/task5
92 j	jschroe1	FR-EN System Combination Components	/group/project/statmt9/josh/experiments /fr-syscomb/work

List of experiments

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List of Runs

Task: WMT10 German-English (pkoehn)

Wiki Notes | Overview of experiments | /fs/bragi2/pkoehn-experiment/wmt10-de-en

compare	ID	start	end	avg	newstest2009		newstest2010	
□ cfglparlimg	[1042-16] 11+analysis	16 May	16 May	BLEU-c: 21.74 BLEU: 22.91	21.03 (1.002) 22.30 (1.002)	<u>A</u>	22.45 (1.041) 23.51 (1.041)	<u>A</u>
□ cfglparlimg	[1042-15] 11+Internal emplus test set	21 Apr	crashed	-	-		-	
ecfglparlimg	[1042-14] 9+interpolated-tm.lm- weighted	21 Feb	21 Feb 9: 0.239258 -> 0.239296	-	20.81 (1.003) 22.06 (1.003)	<u>A</u>	-	
⊟ <u>cfglparlimg</u>	[1042-13] 9+only-ep	21 Feb	21 Feb 13: 0.235046 -> 0.235053	-	20.42 (1.002) 21.69 (1.002)	<u>A</u>	-	
efglparling	[1042-12] 9+only-nc	21 Feb	21 Feb 7: 0.222237 ->	-	18.96 (1.002) 20.16	<u>A</u>	-	



Analysis: Basic Statistics

Coverage	Phrase Segmentation				
model corpus	1 2 3 4+				
0 2047 (3.1%) 1708 (2.6%)	1 to 26897 (40.7%) 2145 (3.2%) 278 (0.4%) 90 (0.1%)				
1 738 (1.1%) 518 (0.8%)	2 to 4144 (6.3%) 14414 (21.8%) 2518 (3.8%) 432 (0.7%)				
2-5 1483 (2.2%) 818 (1.2%)	3 to 639 (1.0%) 3522 (5.3%) 4821 (7.3%) 1272 (1.9%)				
6+ 61745 (93.5%) 62969 (95.4%)	4+ to 158 (0.2%) 855 (1.3%) 1693 (2.6%) 2135 (3.2%)				
by token / by type /	by word / by phrase				
<u>details</u>					

• Basic statistics

- n-gram precision
- evaluation metrics
- coverage of the input in corpus and translation model
- phrase segmentations used



Analysis: Unknown Words

grouped by frequency in test set

unknown words

18 Eatonville	4:	-	2: Abfertigungen,	1: -Ach, -Minister, -Pakets, -weiss, .docx, .pptx, .xlsx, 1,45,
16 Hurston	Eatonvilles,		Albums, Alondra,	1.106,55, 1.983,73, 10.365,45, 10.579, 10.809,25, 106,85,
12 Barrick	Együtt,	BSA, Bayón,		11,9, 11.743,61, 12.595.75, 14,2, 14,7, 145.29, 16,8, 17.9,
	Garver,	Biztos, Bt.,		18,6, 18.286,90, 1802, 1834, 1880ern, 1920ern, 1925,
12 Hema	Harmadik,	Butch, Casado,	Bani, Baugesellschaften,	19252008, 199,61, 2,178, 2,37, 2.400, 26,3, 270.000, 29,2,
12 Stewards	Hurstons,	Dal, Embraer,	Bedienkomfort, Bento,	3,30, 3,632, 3,827, 3.0.0, 4,161, 4,357, 42,2, 43,4, 499,
11 Gebrselassie	Jobb, Jol,	FT, Faymann,	Bentos, Bingleys, Bojen,	49sten, 5.839, 506,43, 6,98, 684,81, 729,700, 75,5, 777,68,
	Jos, Jövőért,	Fiatal, Gregg,	Bowens, Bowery, Boyd,	8,25, 8,81, 9,14, 99.80, AAC, ADQ, ART, Aareal,
10 Flamenco	Kovalev,	Gélineau, HSV,	Bringley, Browser,	Abbremsens, Abhöraktion, Absenzen, Abwesenheiten,
10 Mango	Krever,	Hanzelka,	Bělohlávek, CBGB,	Abwiegen, Abwärtssog, Achronot, Actor, AdSense,
9 Glitter	Lados,	Illhäusern, Iván,	Carci, Cera, Charts,	AdWords, Aday, Adobe, Adressverzeichnisses, Adwards,
9 ÚOHS	Mercandelli,	Jansen, Jančura,	Chemical, Chigi,	Adélard, Agazio, Akku, Akron, Aktuálně.cz, Alameda,
9 ČTÚ	Stehplätze,	Joanne,	Cineast, Comics,	Alatriste, Alcolock, Aleš, Alhambra, Alleinregierer,
,	Tauro,	Kemrová, Kid,	Commerzbank, Coppola,	Amazonengebiet, Amil, Aminei, Amministrazione, Amway,
8 Coles	Tórtola,	Llamazares,	Corker, Cowon, DF,	Andalusierin, Andik, Android, Anděl, Angeklagtem, Ansa,
8 Deka	Zenobia,		Dinkins, Download,	Anthologie, Antiasthmatika, Apnoe, Aquel, Arabija,
8 Garci	fon,		Drehbewegung,	Arbeiternehmers, Arcandor, Arriaga, Asiana, Askale,
8 ITV	Évezredért,	Mobil.cz,	Drzewiecki, Drápal,	Astronomen, Aufeislegen, Augäpfel, Ausdrückstärke,
0 770	Ozd	Mutual,	Düsseldorfer, Ella,	Ausführungs-, Ausgeruhter, Ausscheidungsspiele,



Analysis: Output Annotation

[0.2152] This time was the reason for the collapse on Wall Street .

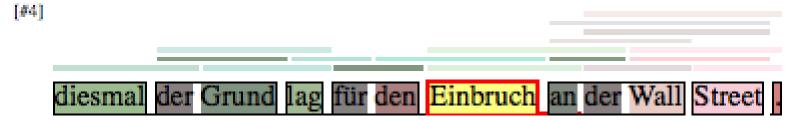
[ref] This time the fall in stocks on Wall Street is responsible for the drop .

Color highlighting to indicate n-gram overlap with reference translation darker bleu = word is part of larger n-gram match



Analysis: Input Annotation

100 occurrences in corpus, 52 distinct translations, translation entropy: 3.08447



- For each word and phrase, color coding and stats on
 - number of occurrences in training corpus
 - number of distinct translations in translation model
 - entropy of conditional translation probability distribution $\phi(e|f)$ (normalized)





entre autres(560/1554)

```
...d and made recommendations , " inter alia " , with respect to the follow...
...on (EC) No 1995 / 2000 imposing , inter alia , a definitive anti @-@ dumping dut...
...ervices . this increase , arising , inter alia , as a result of economic growth , ...
...of paragraph 1 the Commission may , inter alia , bring forward :
... of stocks of obsolete pesticides , inter alia , by supporting projects aimed at s...
...wn rules of procedure which shall , inter alia , contain provisions for convening ...
...uch specific agreements may cover , inter alia , financing provisions , assignment...
...he internal market and concerning , inter alia , health and environmental protecti...
...e product concerned ) originating , inter alia , in Belarus and Russia ( the count...
...e product concerned ) originating , inter alia , in India .
```

```
... des recommandations concernant , entre autres , les questions spécifiques suiva...
... 995 / 2000 du Conseil instituant , entre autres , un droit antidumping définitif ...
... nsports . cette augmentation , due entre autres facteurs à la croissance économi...
... aragraphe 1 , la Commission peut , entre autres , présenter :
... les stocks de vieux pesticides , entre autres en soutenant des projets à cet ef...
... lement intérieur , qui contient , entre autres dispositions , les modalités de c...
... ords spécifiques peuvent porter , entre autres , sur les mécanismes financiers s...
... hé intérieur et qui concernent , entre autres , la santé et la protection de l&...
... it concerné " ) originaire , entre autres , du Belarus et de Russie ( ci @-@...
... t concerné " ) originaires , entre autres , de l ' Inde .
```

notamment(447/1554)

```
... the EU budget by addressing " inter alia " the problems of accountabili...

...ates , the Commission has adopted , inter alia , Decision 2003 / 526 / EC ( 3 ) wh...

...d equitable development involving , inter alia , access to productive resources , ...

...ertain products which could be used inter alia , as equipment on board ships but w...

...nexes , taking into consideration , inter alia , available scientific , technical ...

...w that it is absolutely necessary , inter alia , because of enlargement , to find ...

...paragraphs 1 and 2 as appropriate , inter alia , by conducting studies and compili...

...liability and efficiency , caused , inter alia , by insufficient technical and adm...

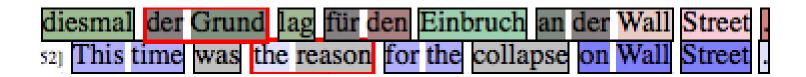
...in the Programme shall be pursued , inter alia , by the following means:
```

...get de l' Union , ce qui passe notamment par la résolution du problème de r...
...es États membres , la Commission a notamment arrêté la décision 2003 / 526 / C...
... durable et équitable , impliquant notamment l' accès aux ressources produc...
...usceptibles d' être utilisés notamment comme équipements mis à bord , mai...
...ion et à ses annexes , compte tenu notamment des informations scientifiques , tec...
...os; il est absolument nécessaire , notamment en raison de l' élargissement ...
...ragraphes 1 et 2 le cas échéant , notamment en menant des études et en compilan...
... et d' efficacité en raison , notamment , d' une interopérabilité tec...
...nis dans le programme , il convient notamment de mettre en oeuvre les moyens ci @-...

translation of input phrase in training data context



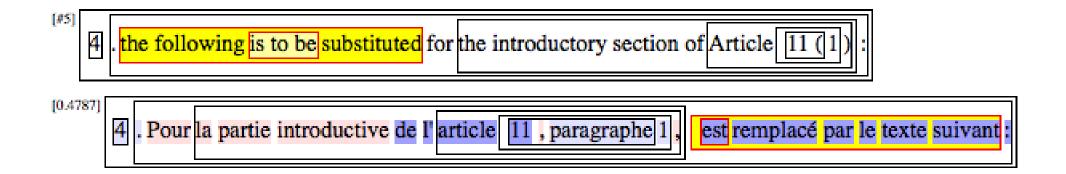
Analysis: Alignment



Phrase alignment of the decoding process (red border, interactive)



Analysis: Tree Alignment



Uses nested boxes to indicate tree structure (red border, yellow shaded spans in focus, interactive) for syntax model, non-terminals are also shown



Analysis: Comparison of 2 Runs

annotated sentences

sorted by order order worse display fullscreen showing 5 more all

identical same better worse

2348 51 57 69

93% 2% 2% 3%

[2143:0.2974] In Austria, Haider and Co. are ready to govern to prevent a red and black coalition.
[2143:0.1754] In Austria, Haider and Co. are prepared to rule to prevent a red and black coalition.

[ref] Haider and his party are ready to govern Austria in order to avoid red @-@ black coalition .

[2165:0.3174] The SPÖ wants to show that the cooperation of both parties is possible - in some countries and in the social partnership that is already the case.

[2165:0.2061] The SPÖ wants to show that a cooperation of both parties is possible - in some countries and in the social partnership that is already the case.

[ref] SPÖ would like to show that the cooperation of the two parties is possible - it does exist in some of the provinces as well as in social partnership.

Different words are highlighted sortable by most improvement, deterioration

Acknowledgements















Moses Developers



Abhishek Arun Amittai Axelrod Barry Haddow Christian Hardmeier Edmund Huber Frederic Blain Hieu Hoang Jean-Baptiste Fouet Abby Levenberg Mauro Cettolo Mark Fishel Nicola Bertoldi Phil Williams Joao Lus Rosas Sara Stymne Yizhao Ni Suzy Howlett Alexander Fraser

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Ales Tamchyna Anthony Rousseau Chris Callison-Burch Lane Schwartz Andreas Eisele Grace M. Ngai Holger Schwenk Jorge Civera Bo Fu Michael Auli Miles Osborne Pascual Martinez Raphael Payen Herve Saint-Amand Steven Buraje Poggel Sergio Penkale Yang Gao

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