Moses

Machine Translation with Open Source Software

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Outline

09:30-10:15 **Introduction**

10:15-11:00 **Hands-on Session** — you will need a laptop

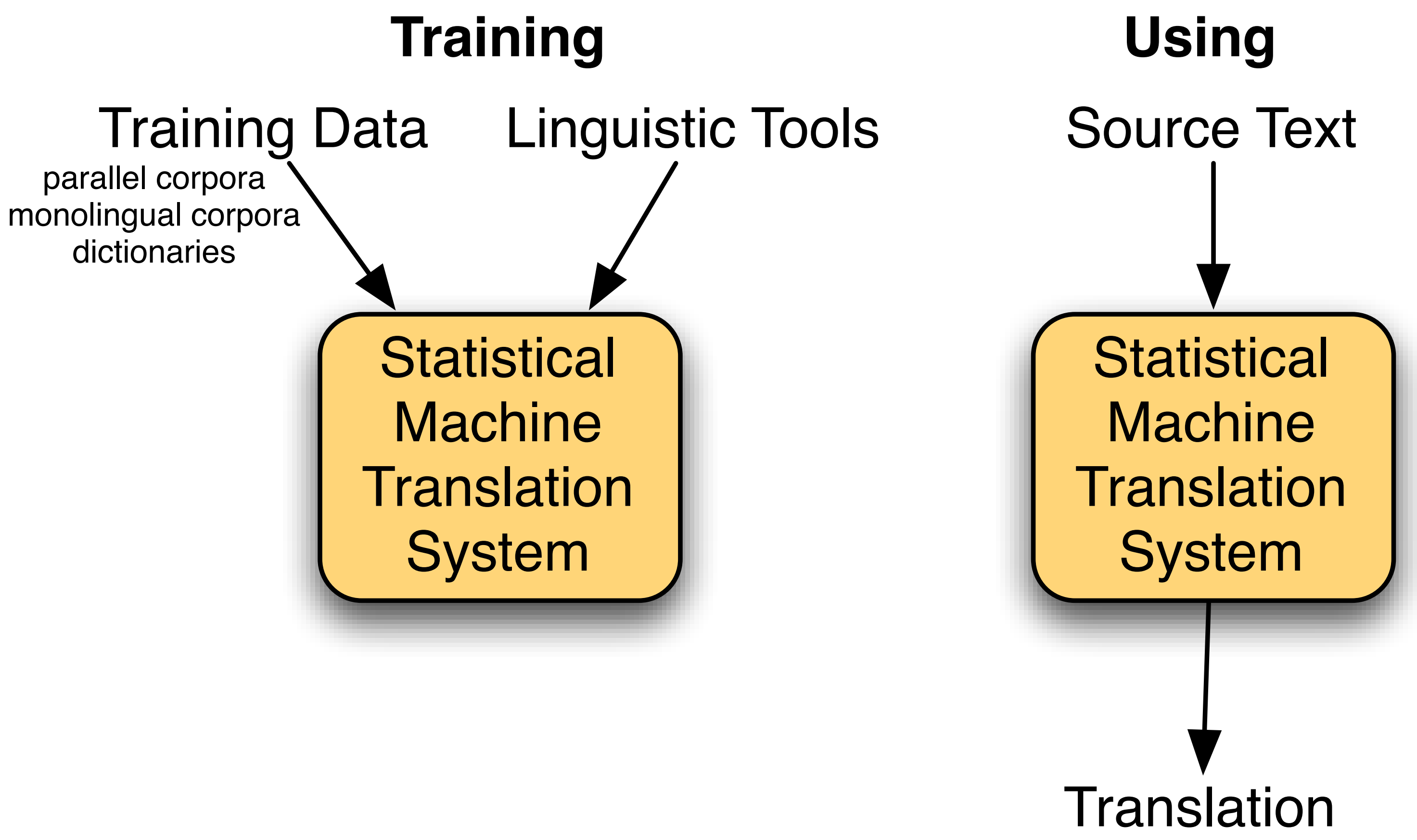
11:00-11:30 Break

11:30-12:30 **Advanced Topics**

Slides downloadable from

```
http://www.statmt.org/moses/amta.2014.pdf
```

Basic Idea


Training
Using
Training Data
parallel corpora
monolingual corpora
dictionaries
Linguistic Tools
Source Text
Statistical Machine Translation System
Statistical Machine Translation System
Translation

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

2006-2012 Funding by EU projects EuroMatrix, EuroMatrixPlus

2009 Tree-based models implemented in Moses

2012-2015 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: Moses support mailing list
- Main event: Machine Translation Marathon
  - 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++, MGIZA, BerkeleyAligner, FastAlign
  - language model: SRILM, IRSTLM, RANDLM, KENLM
  - 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.hltpr.rwth-aachen.de/jane/`
- **Phrasal** — Stanford University
  `http://nlp.stanford.edu/phrasal/`
- Very similar technology
  - Joshua and Phrasal implemented in Java, others in C++
  - Joshua supports only tree-based models
  - Phrasal supports only phrase-based models
- Open sourcing tools increasing trend in NLP research

Moses in Industry

- Distributed with LGPL — free to use
- Competitive with commercial SMT solutions
  (Google, Microsoft, SDL Language Weaver, . . .)
- 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

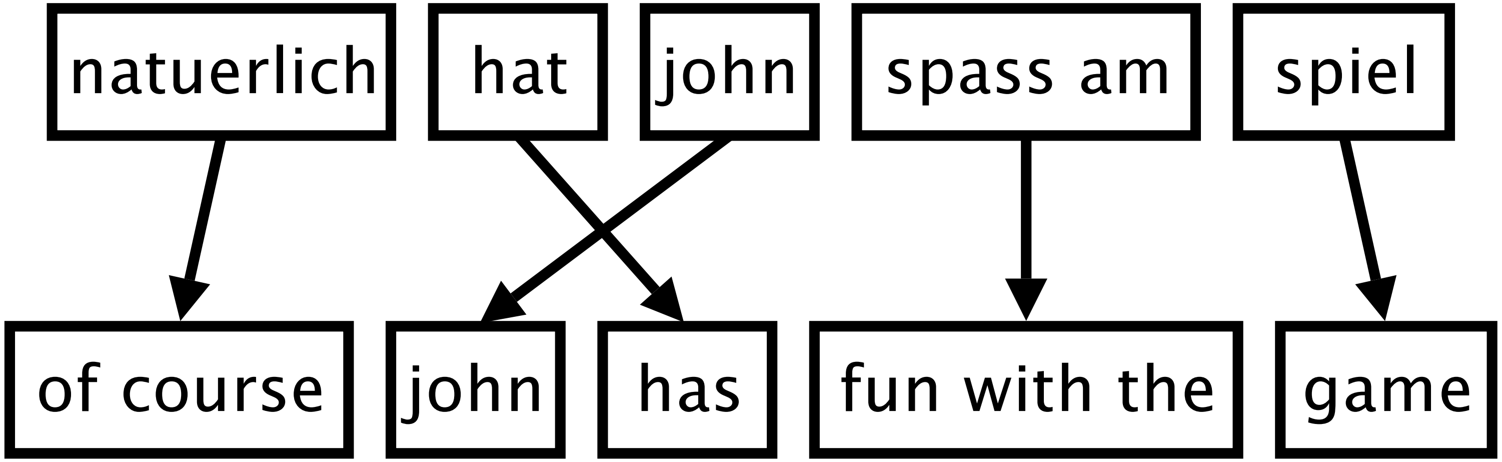
Autodesk —
showed productivity increases in translating manuals when post-editing output from a custom-build Moses system

Systran —
developed statistical post-editing using Moses

Asia Online —
offers translation technology and services based on Moses

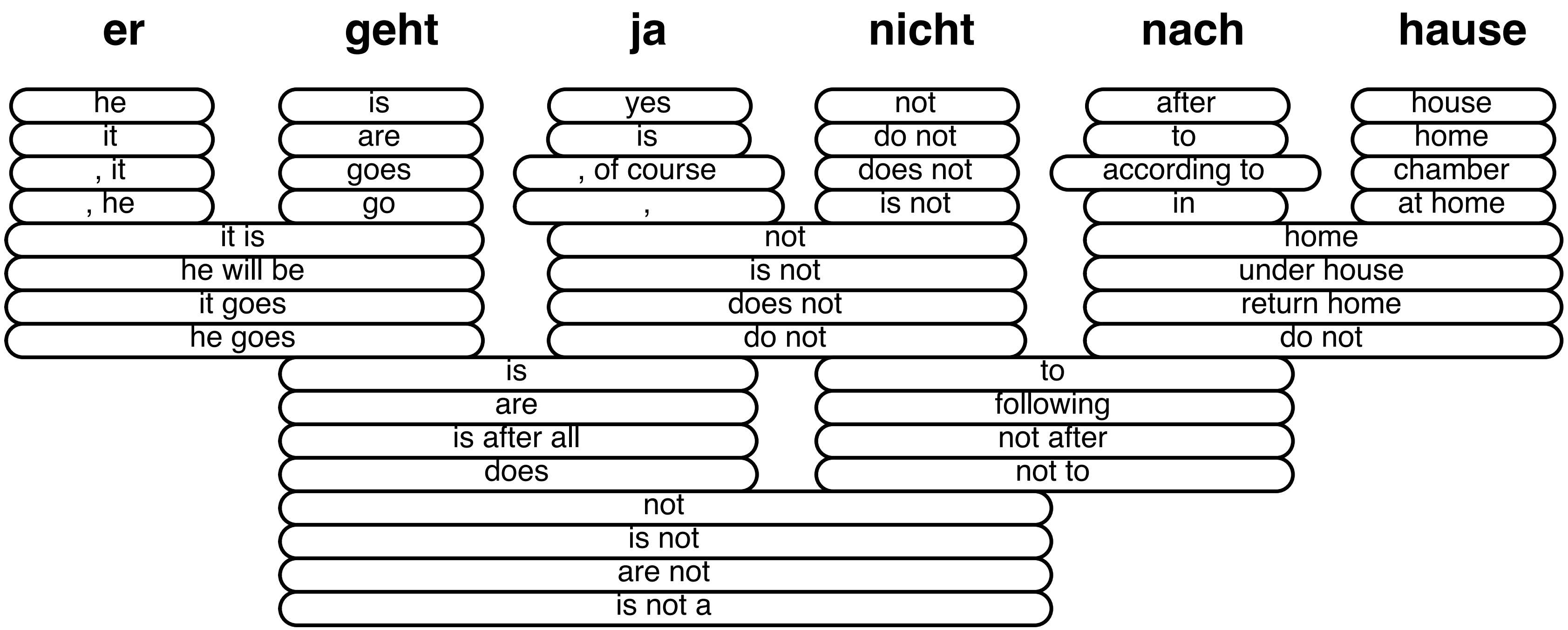
Many others . . .
World Trade Organisation, Adobe, Symantec, WIPO, Sybase, Safaba, Bloomberg, Pangeanic, KatanMT, Capita, . . .

Phrase-based Translation



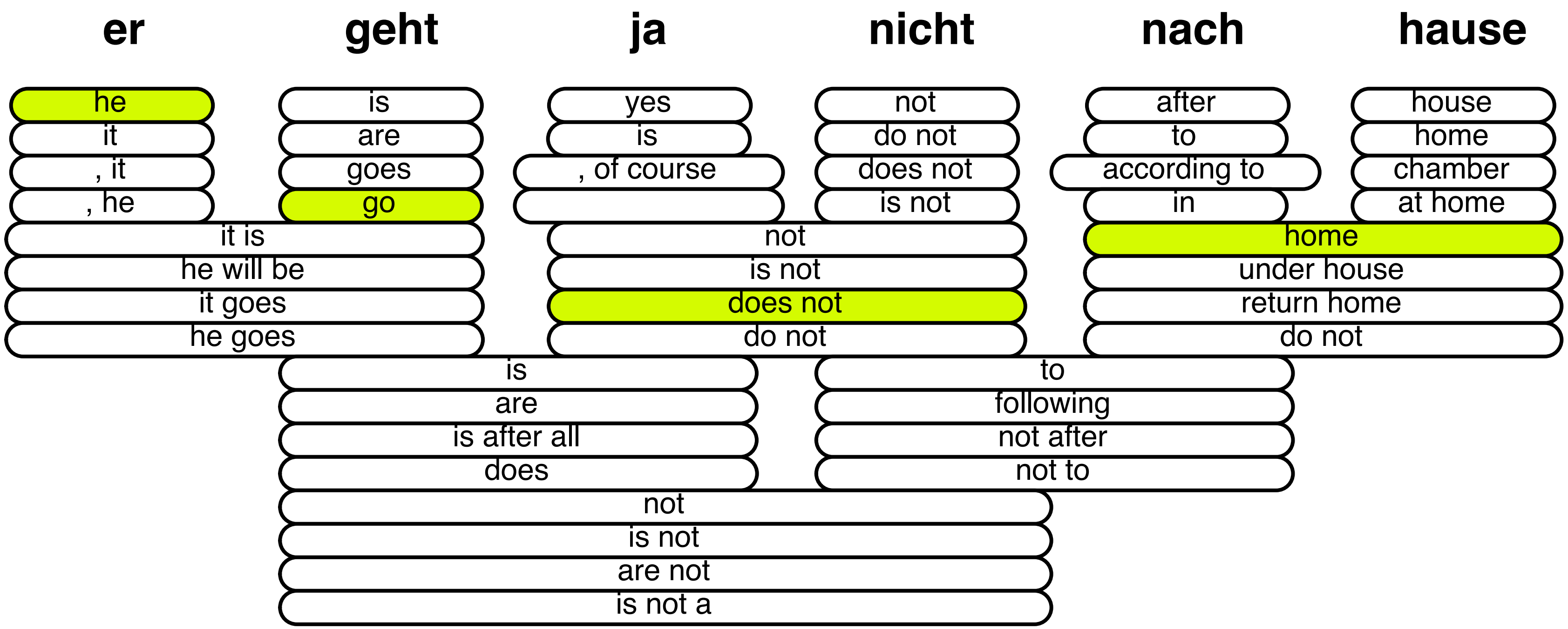
- Foreign input is segmented in phrases
- Each phrase is translated into English
- Phrases are reordered

Phrase Translation Options



- Many translation options to choose from

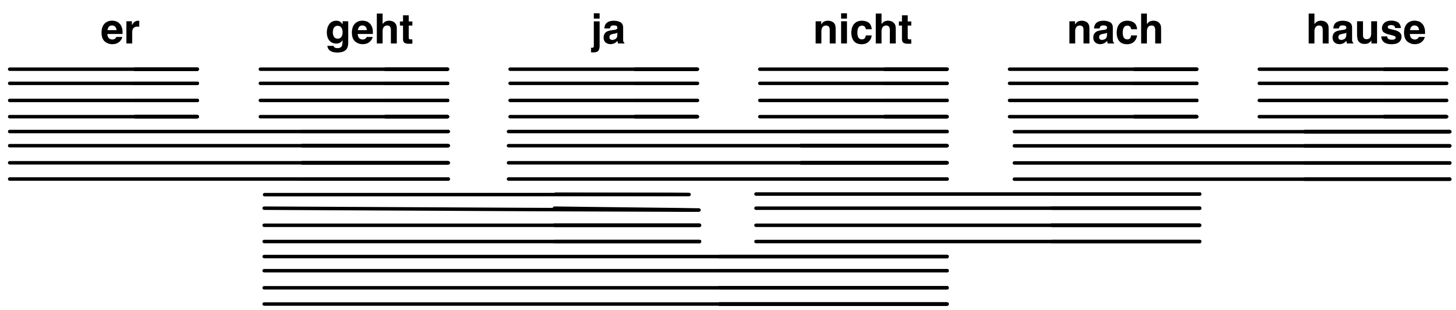
Phrase Translation Options



- The machine translation decoder does not know the right answer
  - picking the right translation options
  - arranging them in the right order

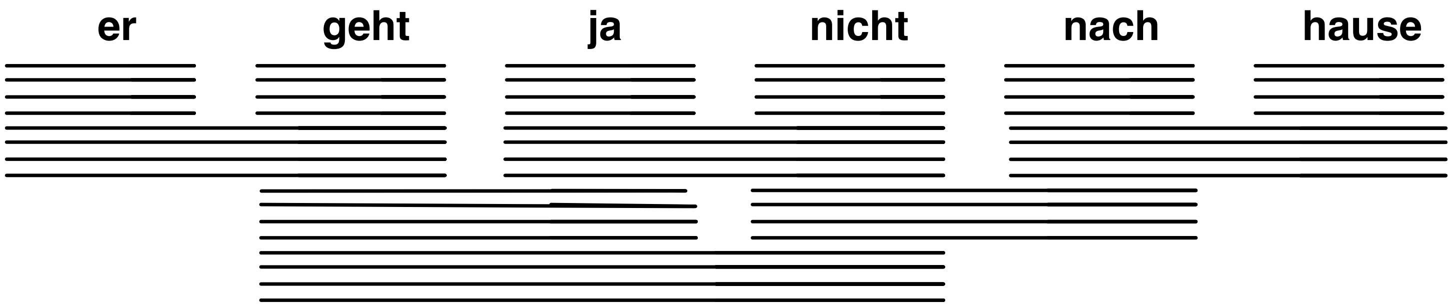
→ Search problem solved by beam search

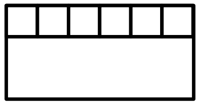
Decoding: Precompute Translation Options



consult phrase translation table for all input phrases

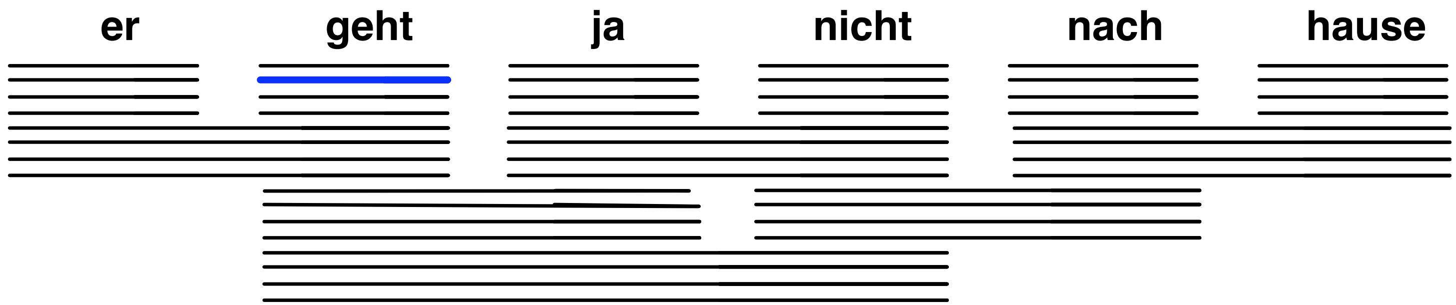
Decoding: Start with Initial Hypothesis

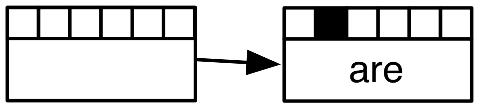




initial hypothesis: no input words covered, no output produced

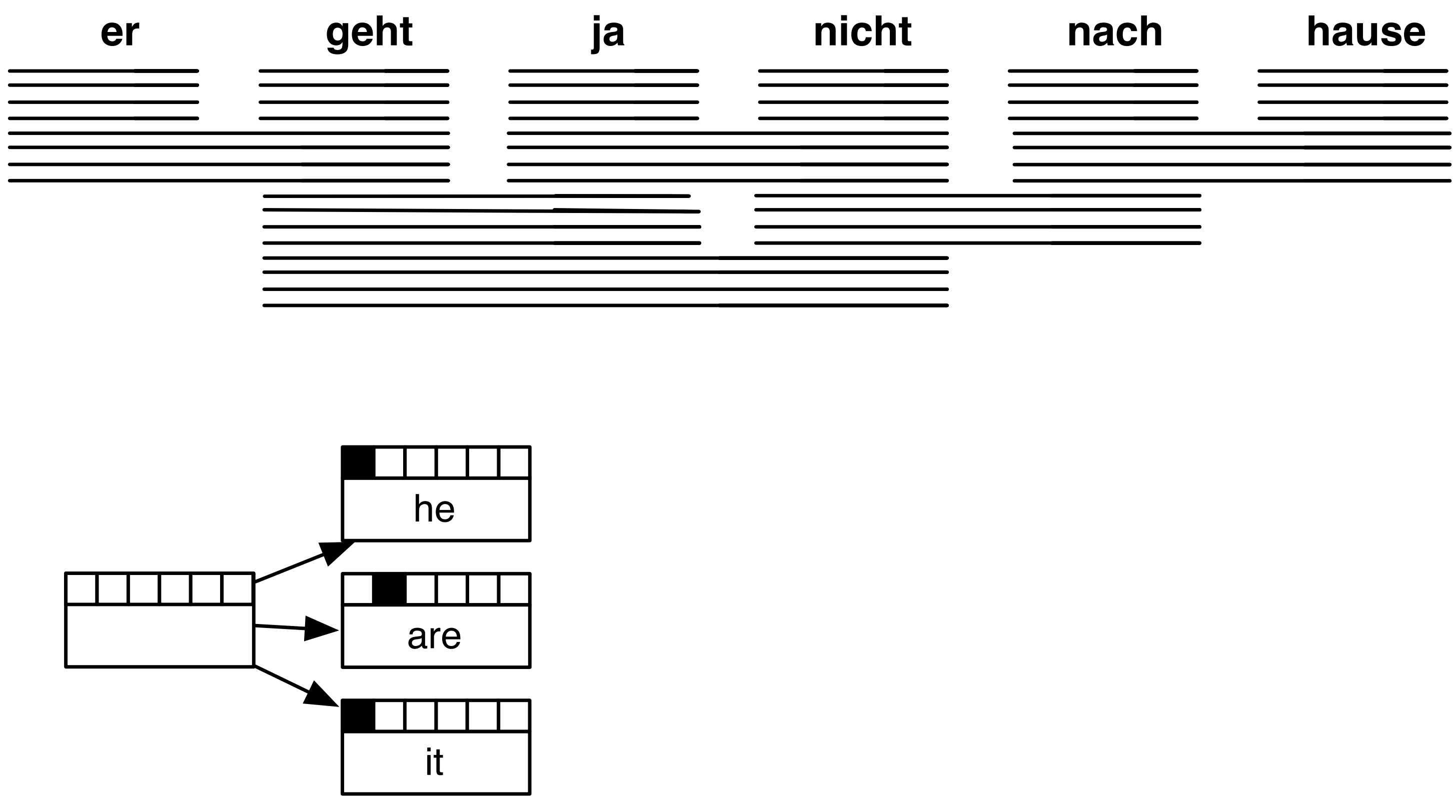
Decoding: Hypothesis Expansion





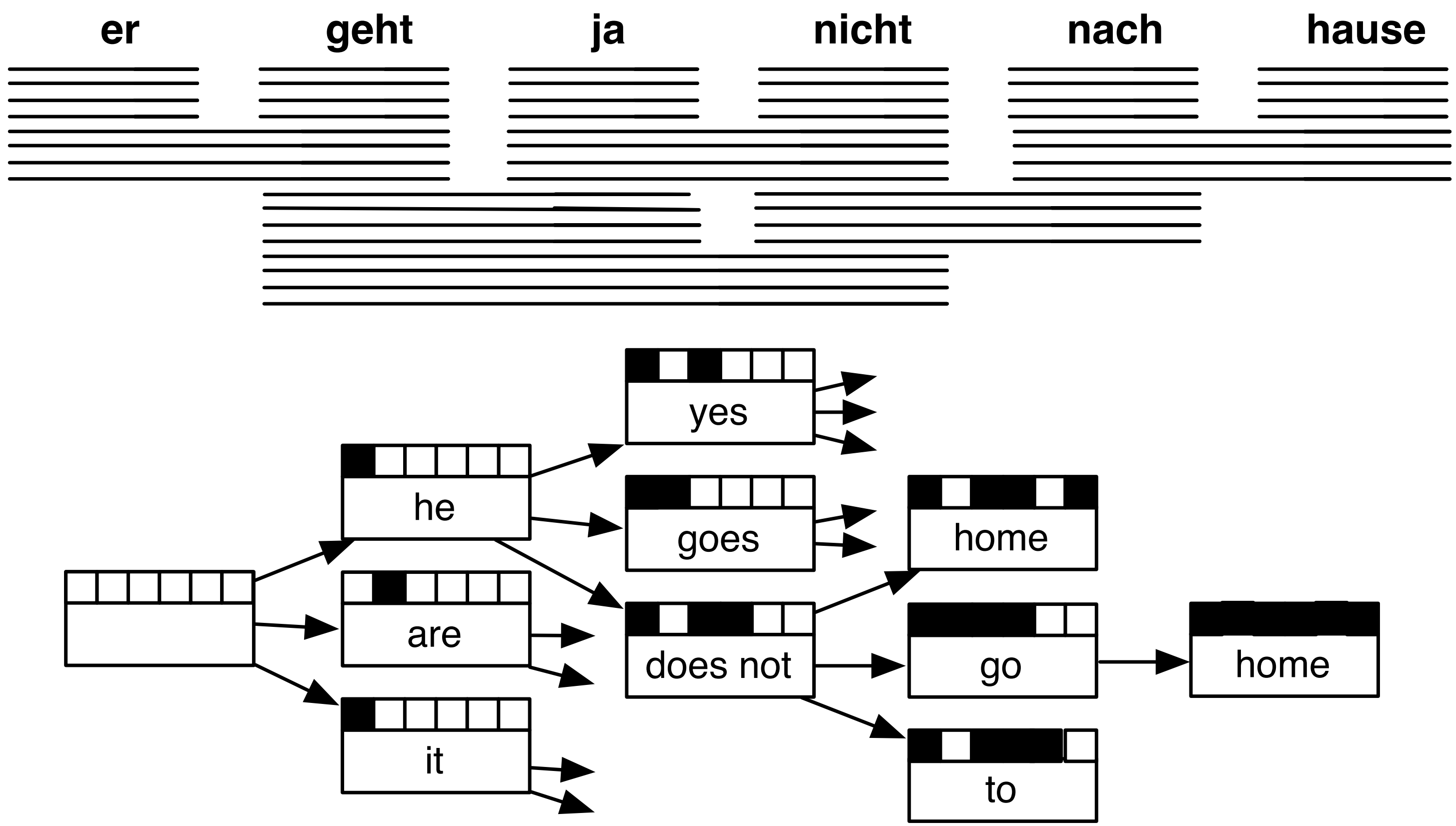
pick any translation option, create new hypothesis

Decoding: Hypothesis Expansion



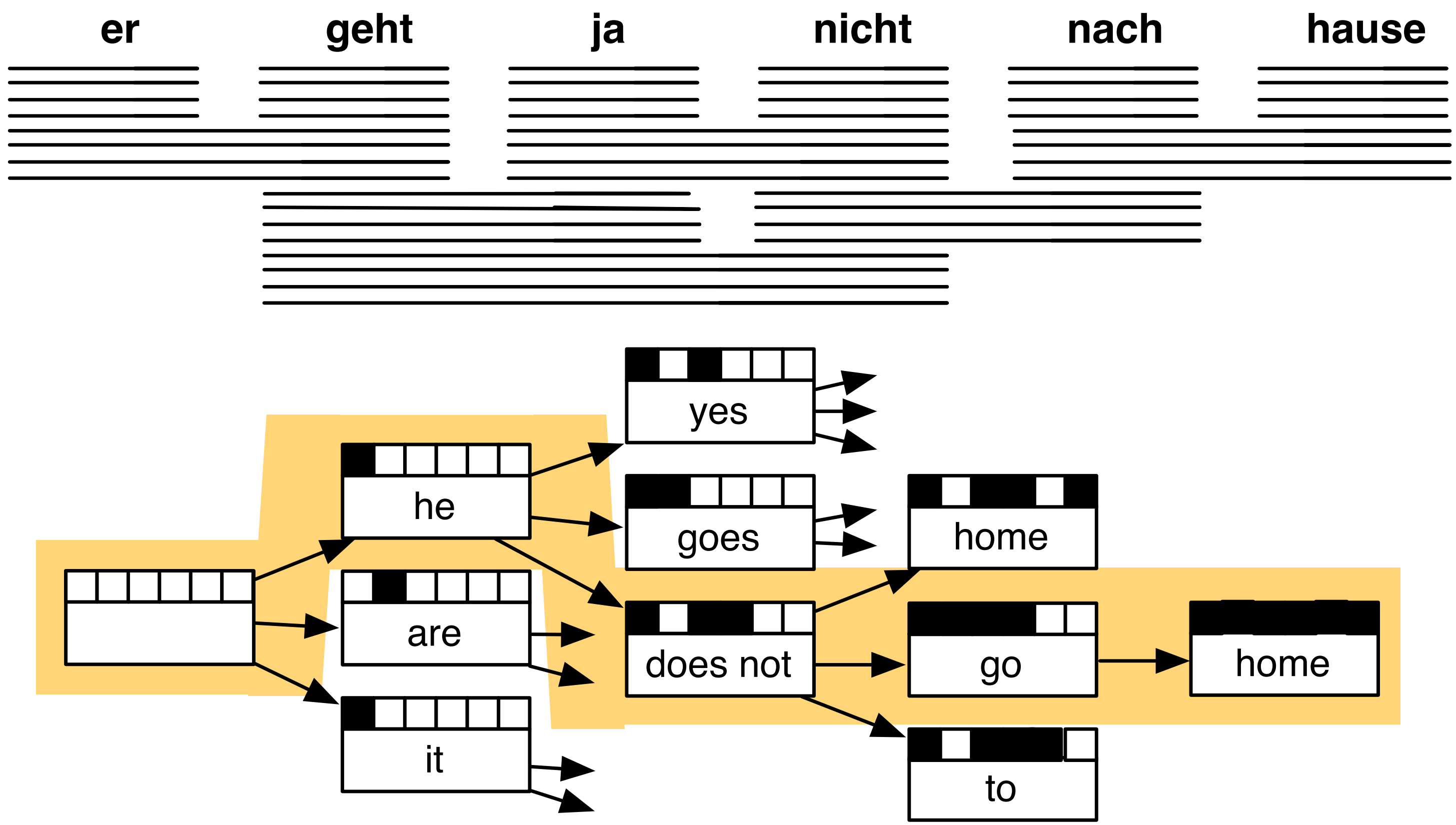
create hypotheses for all other translation options

Decoding: Hypothesis Expansion



also create hypotheses from created partial hypothesis

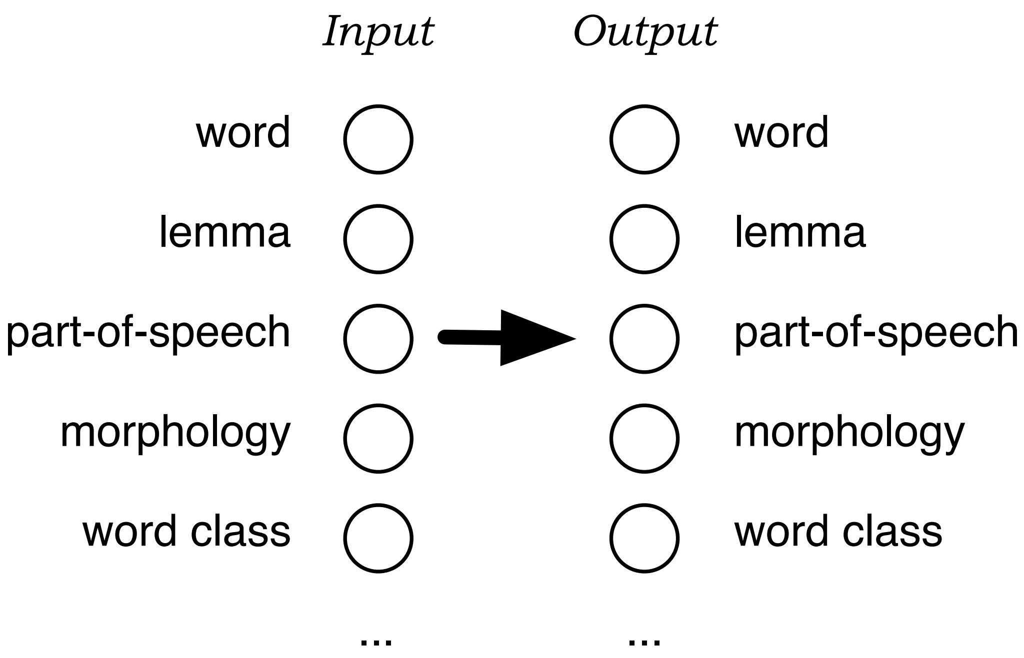
Decoding: Find Best Path



backtrack from highest scoring complete hypothesis

Factored Translation

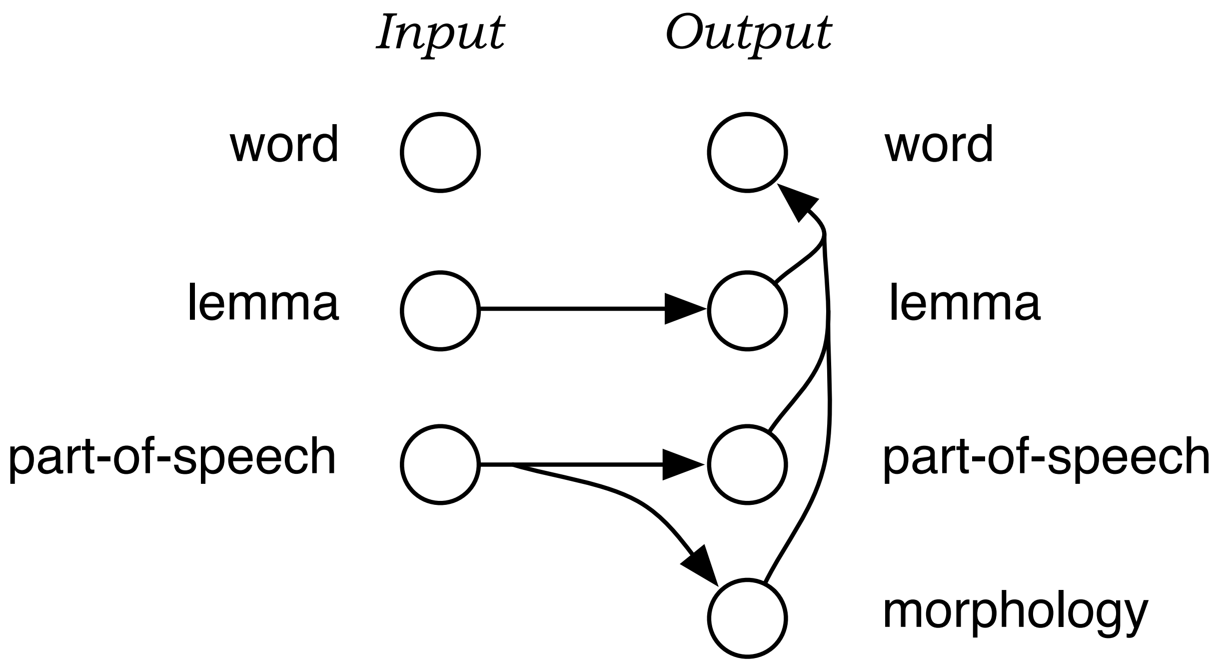
- Factored represention of words



- 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-based Translation

String-to-String

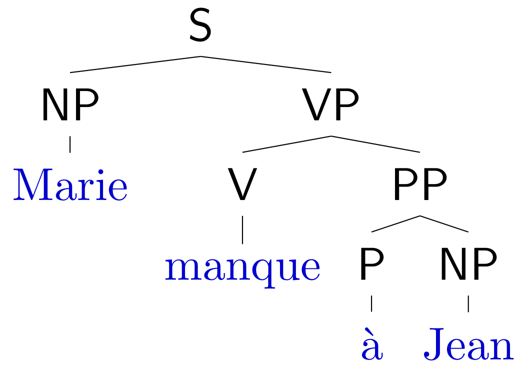
John misses Mary

⇒ Marie manque à Jean

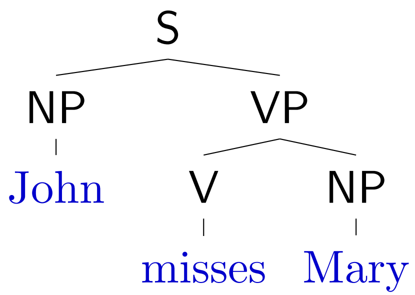
String-to-Tree

John misses Mary

⇒

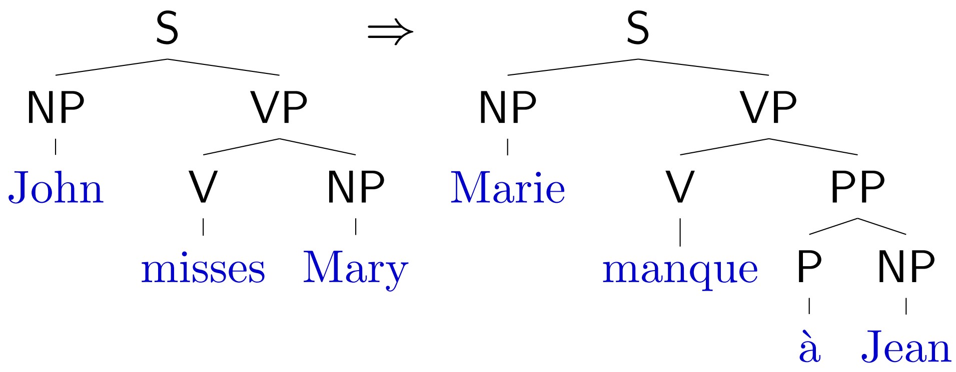


Tree-to-String

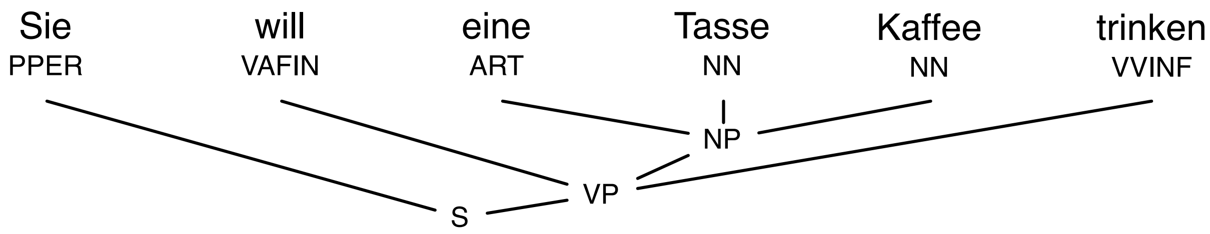


⇒ Marie manque à Jean

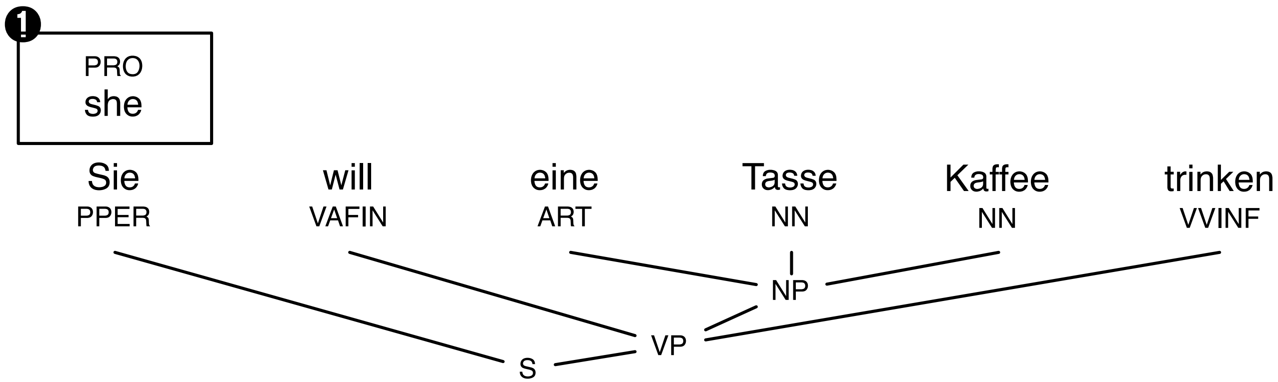
Tree-to-Tree



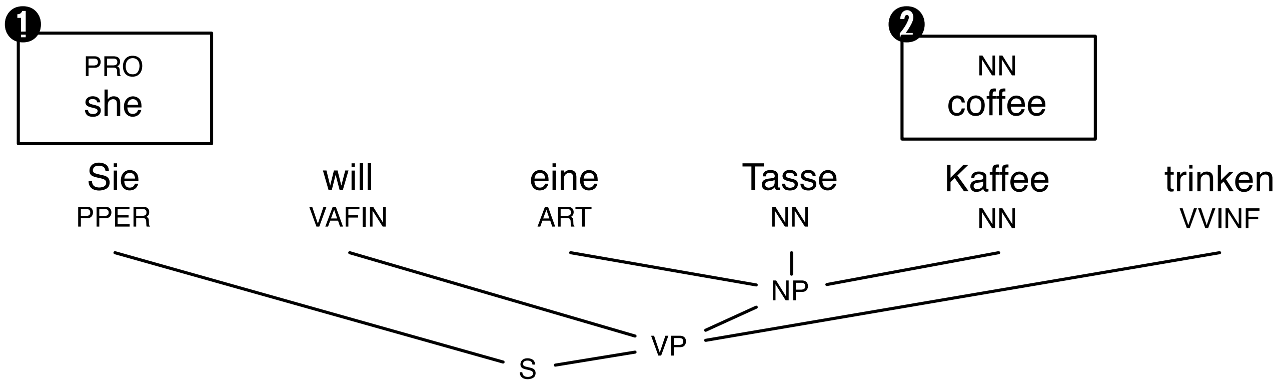
Syntax-based Decoding



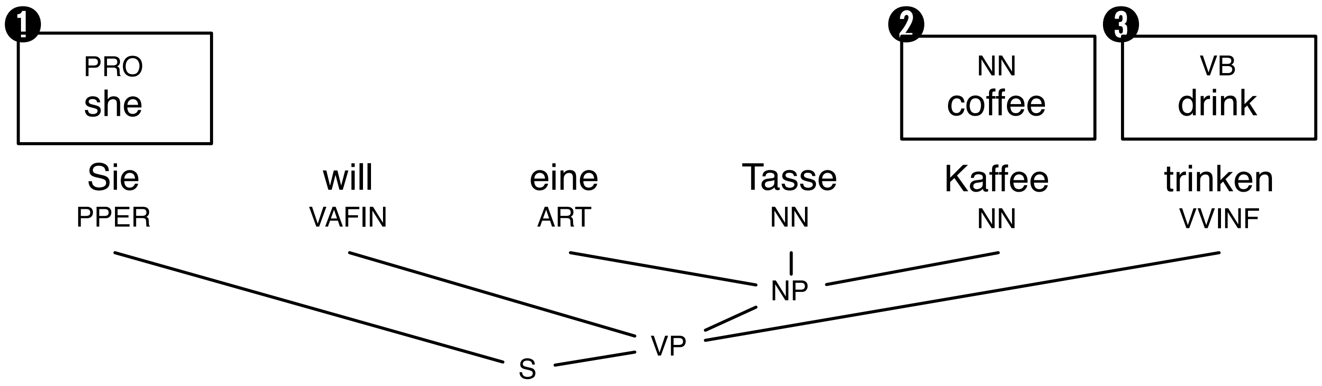
Syntax-based Decoding



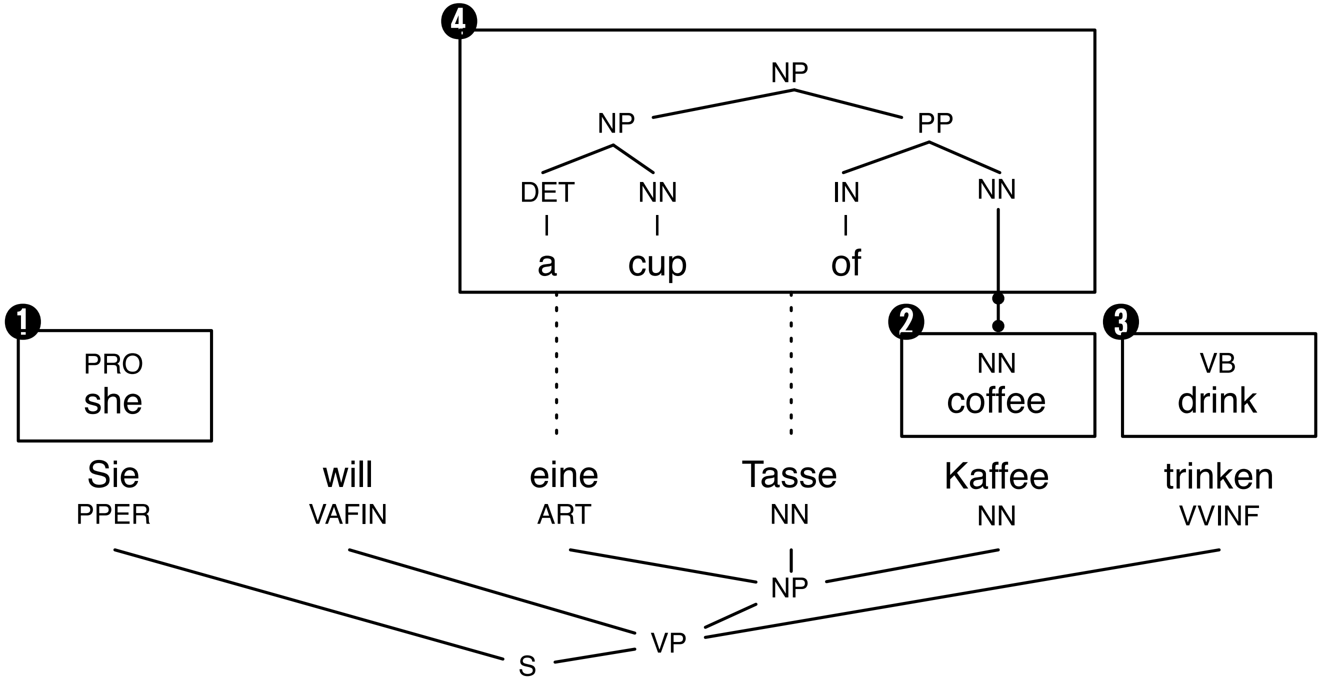
Syntax-based Decoding



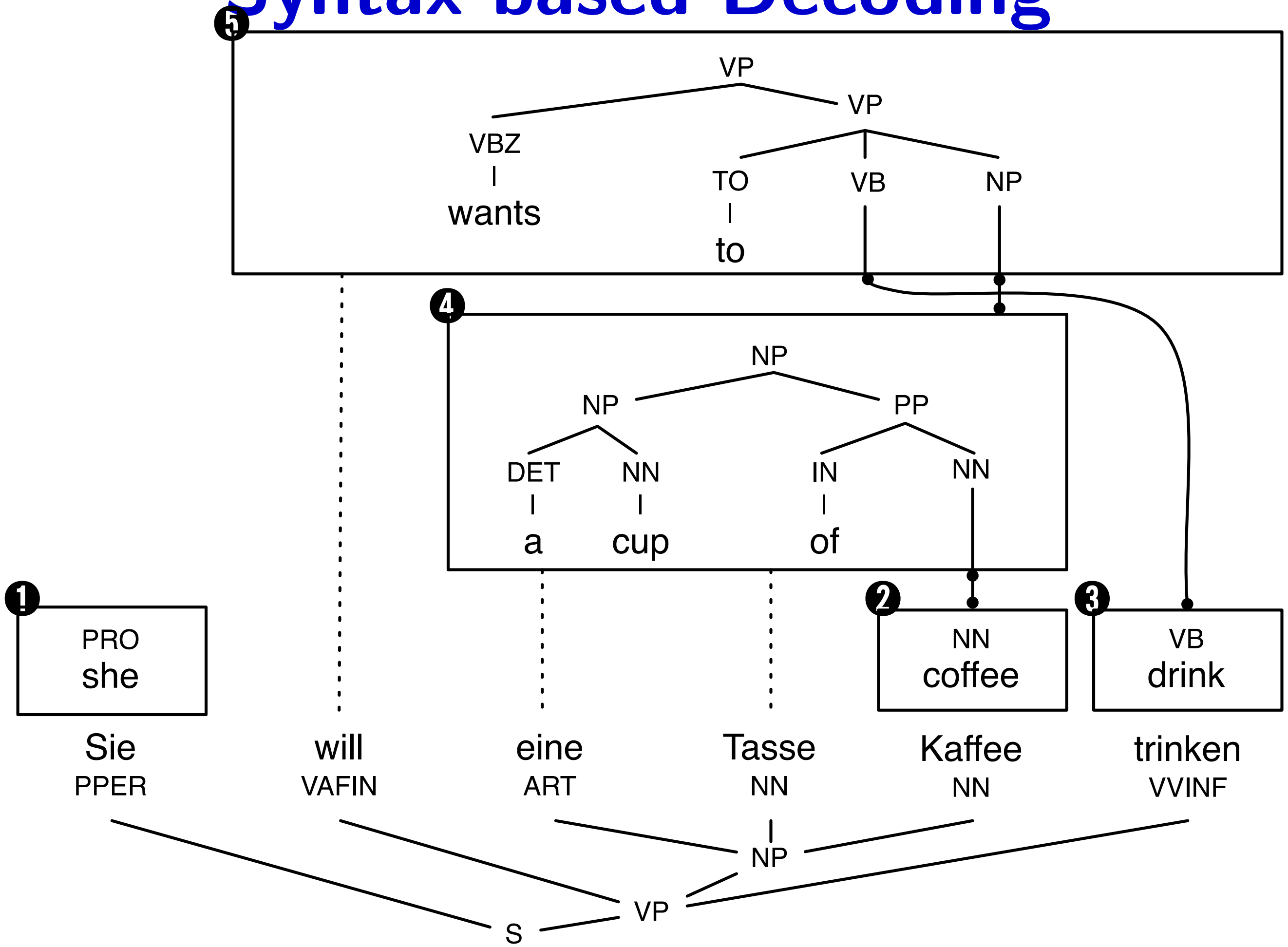
Syntax-based Decoding

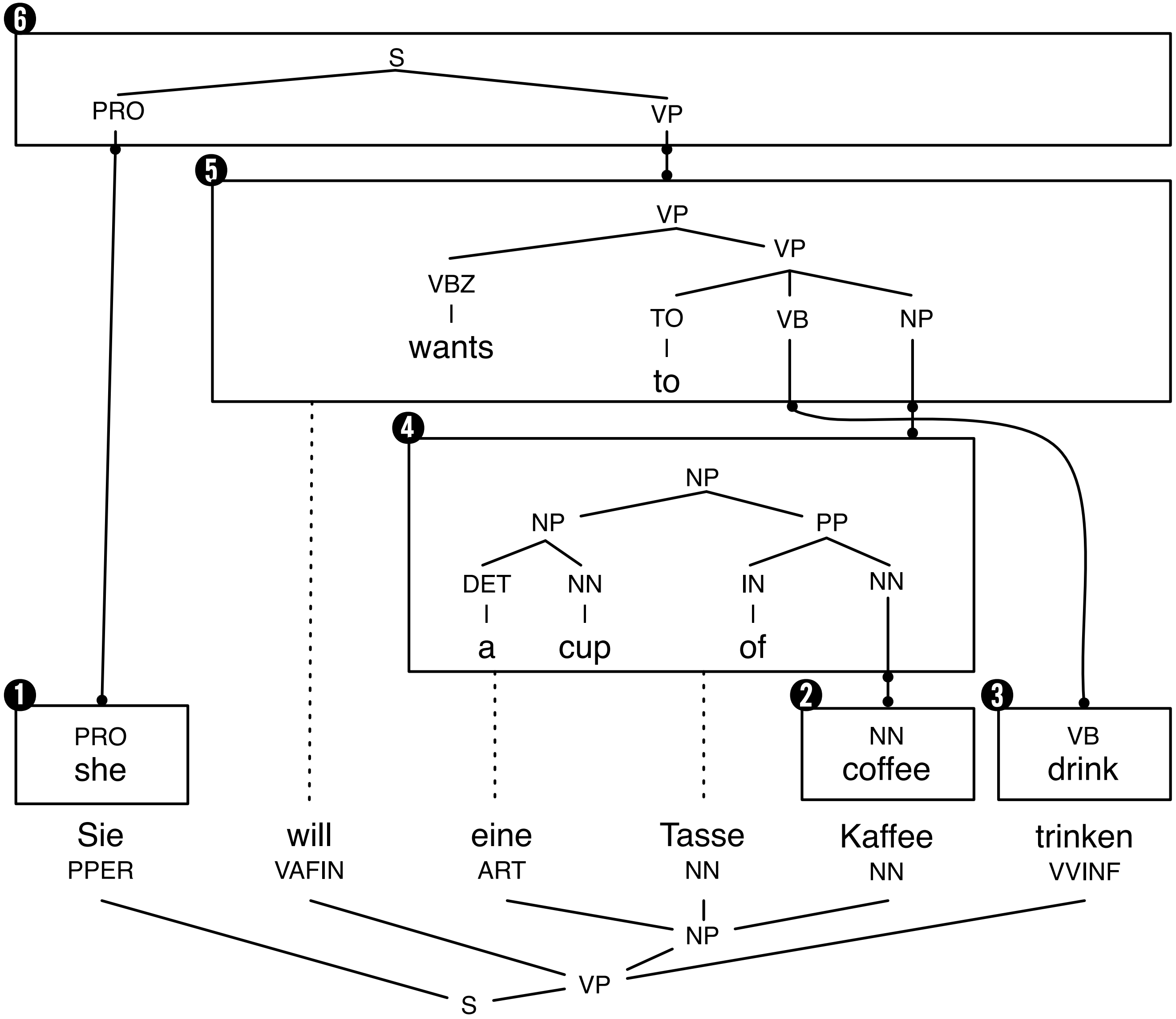


Syntax-based Decoding



Syntax-based Decoding





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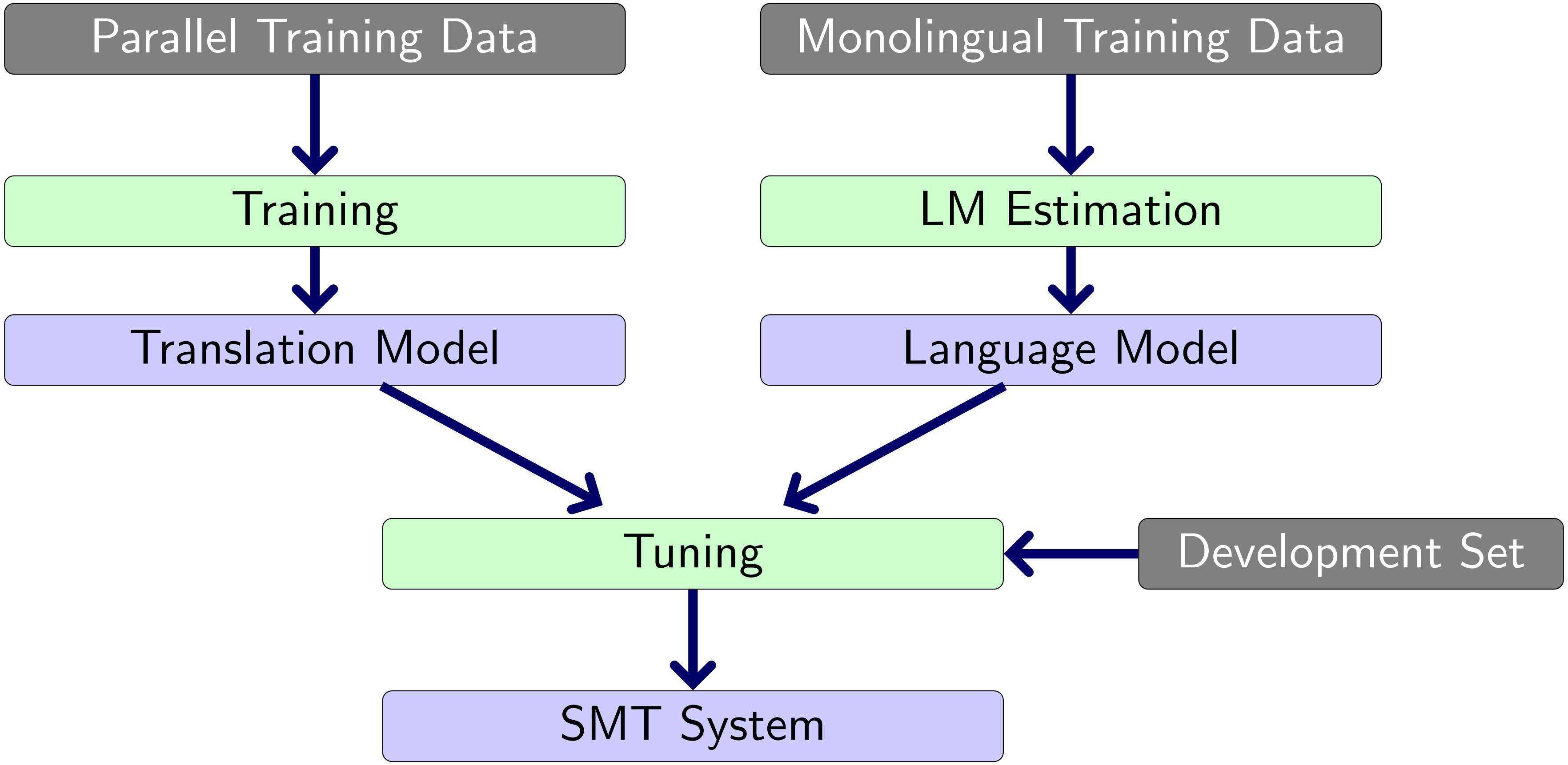
How do I get started?

- Collect your data
  - Parallel data
    - Freely available data, e.g. Europarl, MultiUN, WIT3, OPUS, . . .
    - TAUS, Linguistic Data Consortium (LDC), . . .
  - Monolingual data
    - CommonCrawl, WMT News Crawl corpus, . . .
- Set up Moses
  - Download source code for Moses, GIZA++, MGIZA
  - Compile, install
  - Or use precompiled Moses packages (Windows, Linux, Mac OS X)
  - More info: `http://www.statmt.org/moses/`
- Train system

Data-driven MT



Moses Pipeline

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 ...
```

Phrase-based Model Training with Moses

- Command line

```
train-model.perl ...
```

- Example phrase from model

```
Bndnisse ||| alliances ||| 1 1 1 1 2.718 ||| ||| 1 1
General Musharraf betrat am ||| general Musharraf appeared on ||| 1 1 1 1 2.718 ||| ||| 1 1
```

Phrase-based Decoding with Moses

- Command line

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

- Advantages
  - fast — under half a second per sentence for fast configuration
  - low memory requirements — ∼200MB RAM for lowest configuration
  - state-of-the-art translation quality on most tasks, especially for related language pairs
  - robust — does not rely on any syntactic annotation

- Disadvantages
  - poor modeling of linguistic knowledge and of long-distance dependencies

Hierarchical Model Training with Moses

- Hierarchical model:
  formally syntax-based, without linguistic annotation (string-to-string)

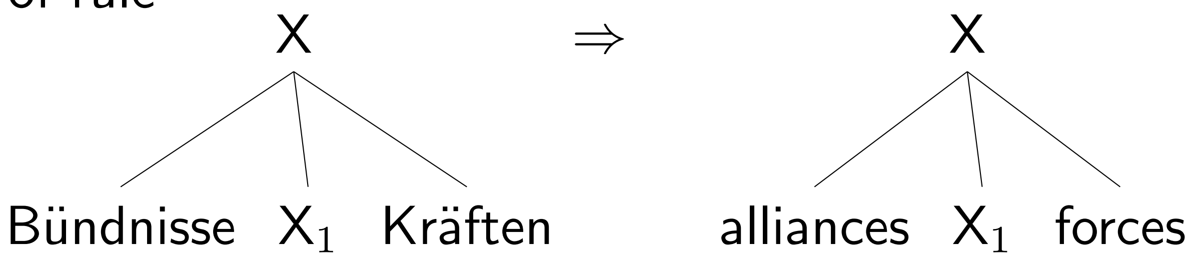
- Command line

```
train-model.perl -hierarchical ...
```

- 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
```

- Visualization of rule



Hierarchical Decoding with Moses

- Command line

```
moses_chart -f moses.ini -i in.txt > out.txt
```

- Advantages
  - able to model non-contiguities like *ne ... pas* → *not*
  - better at medium-range reordering
  - outperforms phrase-based systems when translating between widely different languages, e.g. Chinese-English

- Disadvantages
  - more disk usage — translation model ×10 larger than phrase-based
  - slower — 0.5 - 2 sec/sent. for fastest configuration
  - higher memory requirements — more than 1GB RAM

Syntax-based Model Training with Moses

- Command line

```
train-model.perl -ghkm ...
```

- Example rule from model

```
[X][NP-SB] also wanted [X][ADJA] [X][NN] [X] ||| [X][NP-SB] wollten auch die [X][ADJA] [X][NN] [S-TOP] ||| ...
```

Syntax-based Decoding with Moses

- Command line

```
moses_chart -f moses.ini -i in.txt > out.txt
```

(like hierarchical)

- Advantage
  - can use outside linguistic information
  - promises to solve important problems in SMT, e.g. long-range reordering
- Disadvantages
  - training slow and difficult to get right
  - requires syntactic parse annotation
    - syntactic parsers available only for some languages
    - not designed for machine translation
    - unreliable

Experiment Management System

- EMS automates the entire pipeline
- One configuration file for all settings: record of all experimental details
- Scheduler of individual steps in pipeline
  - automatically keeps track of dependencies
  - parallel execution
  - crash detection
  - automatic re-use of prior results
- Fast to use
  - set up a new experiment in minutes
  - set up a variation of an experiment in seconds
- Disadvantage: not all Moses features are integrated

How does it work?

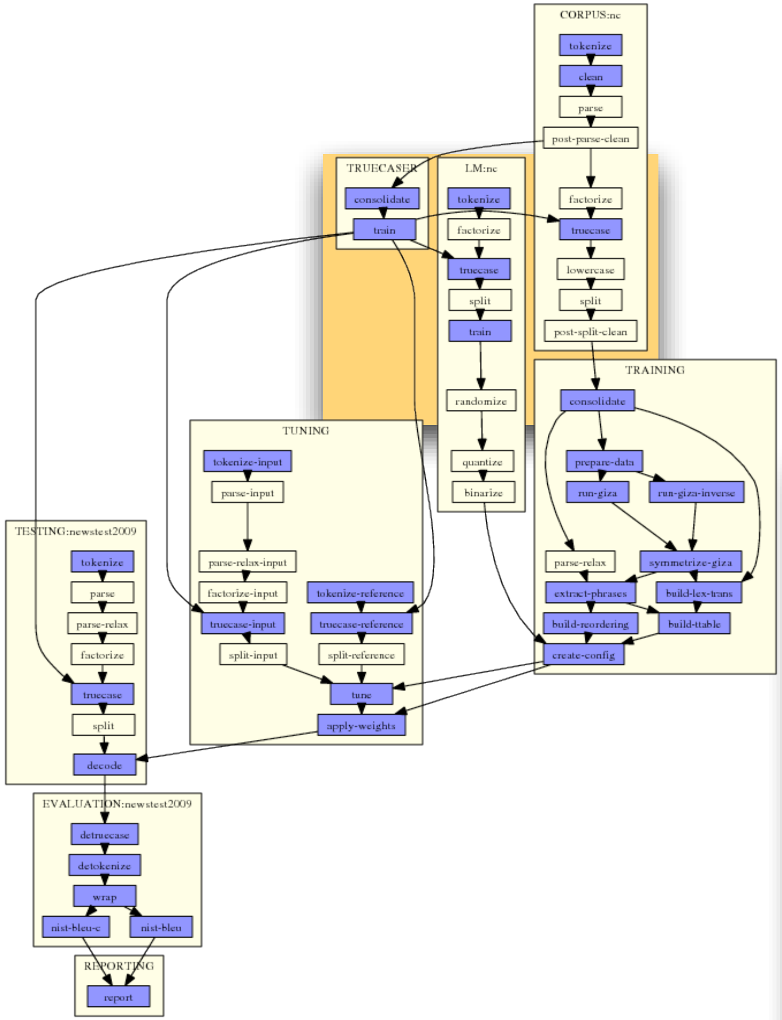
- Write a configuration file (typically by adapting an existing file)

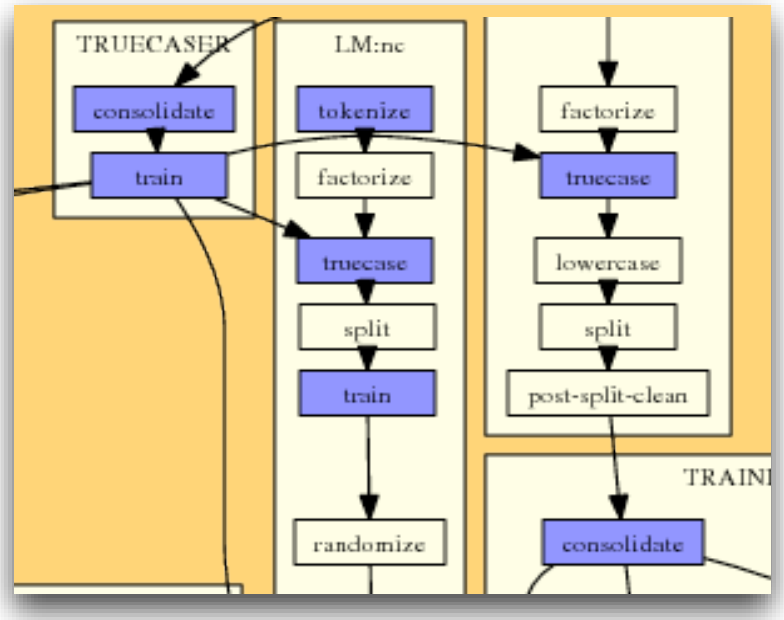
- Test:

```
experiment.perl -config config
```

- Execute:

```
experiment.perl -config config -exec
```





Workflow automatically generated by experiment.perl

Web Interface

All Experimental Setups

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

List of experiments

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	
cfg|par|img	[1042-16] 11+analysis	16 May	16 May	BLEU-c: 21.74 BLEU: 22.91	21.03 (1.002) 22.30 (1.002)	Ⓐ	22.45 (1.041) 23.51 (1.041)	Ⓐ
cfg|par|img	[1042-15] 11+Internal emplus test set	21 Apr	crashed	-	-		-	
cfg|par|img	[1042-14] 9+interpolated-tm.lm-weighted	21 Feb	21 Feb 9: 0.239258 -> 0.239296	-	20.81 (1.003) 22.06 (1.003)	Ⓐ	-	
cfg|par|img	[1042-13] 9+only-ep	21 Feb	21 Feb 13: 0.235046 -> 0.235053	-	20.42 (1.002) 21.69 (1.002)	Ⓐ	-	
cfg|par|img	[1042-12] 9+only-nc	21 Feb	21 Feb 7: 0.222237 ->	-	18.96 (1.002) 20.16	Ⓐ	-	

Analysis: Basic Statistics

Coverage		
	model	corpus
0	2047 (3.1%)	1708 (2.6%)
1	738 (1.1%)	518 (0.8%)
2-5	1483 (2.2%)	818 (1.2%)
6+	61745 (93.5%)	62969 (95.4%)

by token / by type / details

Phrase Segmentation				
	1	2	3	4+
1 to	26897 (40.7%)	2145 (3.2%)	278 (0.4%)	90 (0.1%)
2 to	4144 (6.3%)	14414 (21.8%)	2518 (3.8%)	432 (0.7%)
3 to	639 (1.0%)	3522 (5.3%)	4821 (7.3%)	1272 (1.9%)
4+ to	158 (0.2%)	855 (1.3%)	1693 (2.6%)	2135 (3.2%)

by word / by phrase

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

Analysis: Unknown Words

grouped by count in test set

unknown words

18	Eatonville
16	Hurston
12	Barrick
12	Hema
12	Stewards
11	Gebrselassie
10	Flamenco
10	Mango
9	Glitter
9	ÚOHS
9	ČTÚ
8	Coles
8	Deka
8	Garci
8	ITV

4: Eatonvilles, Együtt, Garver, Harmadik, Hurstons, Jobb, Jol, Jos, Jövőért, Kovalev, Krever, Lados, Mercandelli, Stehplätze, Tauro, Tórtola, Zenobia, fon, Évezredért, Ózd

3: Anmil, Atlasz, BR23C, BSA, Bayón, Biztos, Bt., Butch, Casado, Dal, Embraer, FT, Faymann, Fiatal, Gregg, Gélineau, HSV, Hanzelka, Illhäusern, Iván, Jansen, Jančura, Joanne, Kemrová, Kid, Llamazares, Loafs, Mangas, Medikamentes, Mobil.cz, Mutual,

2: Abfertigungen, Albums, Alondra, Andoh, Anm., Armiñon, Ashford, BZÖ, Baloldal, Bani, Baugesellschaften, Bedienkomfort, Bento, Bentos, Bingleys, Bojen, Bowens, Bowery, Boyd, Bringley, Browser, Bělohlávek, CBGB, Carci, Cera, Charts, Chemical, Chigi, Cineast, Comics, Commerzbank, Coppola, Corker, Cowon, DF, Dinkins, Download, Drehbewegung, Drzewiecki, Drápal, Düsseldorfer, Ella,

1: -Ach, -Minister, -Pakets, -weiss, .docx, .pptx, .xlsx, 1,45, 1.106,55, 1.983,73, 10.365,45, 10.579, 10.809,25, 106,85, 11,9, 11.743,61, 12.595.75, 14,2, 14,7, 145.29, 16,8, 17.9, 18,6, 18.286,90, 1802, 1834, 1880ern, 1920ern, 1925, 19252008, 199,61, 2,178, 2,37, 2.400, 26,3, 270.000, 29,2, 3,30, 3,632, 3,827, 3.0.0, 4,161, 4,357, 42,2, 43,4, 499, 49sten, 5.839, 506,43, 6,98, 684,81, 729,700, 75,5, 777,68, 8,25, 8,81, 9,14, 99.80, AAC, ADQ, ART, Aareal, Abbremsens, Abhöraktion, Absenzen, Abwesenheiten, Abwiegen, Abwärtssog, Achronot, Actor, AdSense, AdWords, Aday, Adobe, Adressverzeichnisses, Adwards, Adélard, Agazio, Akku, Akron, Aktuálně.cz, Alameda, Alatriste, Alcolock, Aleš, Alhambra, Alleinregierer, Amazonengebiet, Amil, Aminei, Amministrazione, Amway, Andalusierin, Andik, Android, Anděl, Angeklagtem, Ansa, Anthologie, Antiasthmatika, Apnoe, Aquel, Arabija, Arbeiternehmers, Arcandor, Arriaga, Asiana, Askale, Astronomen, Aufeislegen, Augäpfel, Ausdrückstärke, Ausführungs-, Ausgeruhter, Ausscheidungsspiele,

Analysis: Output Annotation

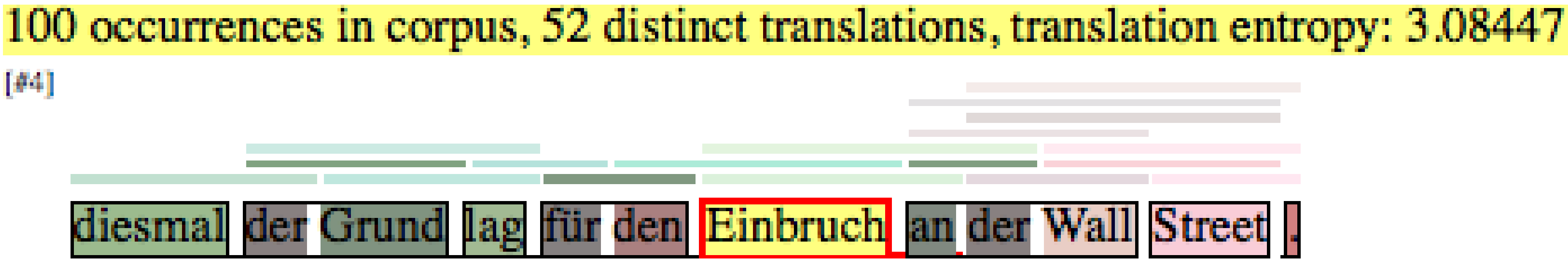
[0.2152] This time was the reason for the collapse on Wall Street .

[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



- 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)

Analysis: Bilingual Concordancer

entre autres(560/1554)

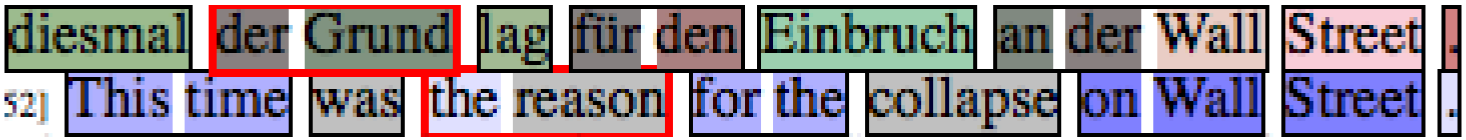
...d and made recommendations , " **inter alia** " , with respect to the follow...	...� des recommandations concernant , **entre autres** , les questions spécifiques suiva...
...on (EC) No 1995 / 2000 imposing , **inter alia** , a definitive anti @-@ dumping dut...	...995 / 2000 du Conseil instituant , **entre autres** , un droit antidumping définitif ...
...ervices . this increase , arising , **inter alia** , as a result of economic growth , ...	...nsports . cette augmentation , due **entre autres** facteurs à la croissance économi...
...of paragraph 1 the Commission may , **inter alia** , bring forward :	...aragraphe 1 , la Commission peut , **entre autres** , présenter :
... of stocks of obsolete pesticides , **inter alia** , by supporting projects aimed at s...	...r les stocks de vieux pesticides , **entre autres** en soutenant des projets à cet ef...
...wn rules of procedure which shall , **inter alia** , contain provisions for convening ...	...lement intérieur , qui contient , **entre autres** dispositions , les modalités de c...
...uch specific agreements may cover , **inter alia** , financing provisions , assignment...	...ords spécifiques peuvent porter , **entre autres** , sur les mécanismes financiers s...
...he internal market and concerning , **inter alia** , health and environmental protecti...	...hé intérieur et qui concernent , **entre autres** , la santé et la protection de l&...
...e product concerned) originating , **inter alia** , in Belarus and Russia (the count...	...it concerné ") originaire , **entre autres** , du Belarus et de Russie (ci @-@ ...
...e product concerned) originating , **inter alia** , in India .	...t concerné ") originaires , **entre autres** , de l ' Inde .

notamment(447/1554)

... the EU budget by addressing " **inter alia** " the problems of accountabili...	...get de l' Union , ce qui passe **notamment** par la résolution du problème de r...
...ates , the Commission has adopted , **inter alia** , Decision 2003 / 526 / EC (3) wh...	...es États membres , la Commission a **notamment** arrêté la décision 2003 / 526 / C...
...d equitable development involving , **inter alia** , access to productive resources , ...	... durable et équitable , impliquant **notamment** l' accès aux ressources produc...
...ertain products which could be used **inter alia** , as equipment on board ships but w...	...usceptibles d' être utilisés **notamment** comme équipements mis à bord , mai...
...nexes , taking into consideration , **inter alia** , available scientific , technical ...	...ion et à ses annexes , compte tenu **notamment** des informations scientifiques , tec...
...w that it is absolutely necessary , **inter alia** , because of enlargement , to find ...	...os; il est absolument nécessaire , **notamment** en raison de l' élargissement ...
...paragraphs 1 and 2 as appropriate , **inter alia** , by conducting studies and compili...	...ragraphes 1 et 2 le cas échéant , **notamment** en menant des études et en compilan...
...liability and efficiency , caused , **inter alia** , by insufficient technical and adm...	... et d' efficacité en raison , **notamment** , d' une interopérabilité tec...
...in the Programme shall be pursued , **inter alia** , by the following means :	...nis dans le programme , il convient **notamment** de mettre en oeuvre les moyens ci @-...

translation of input phrase in training data context

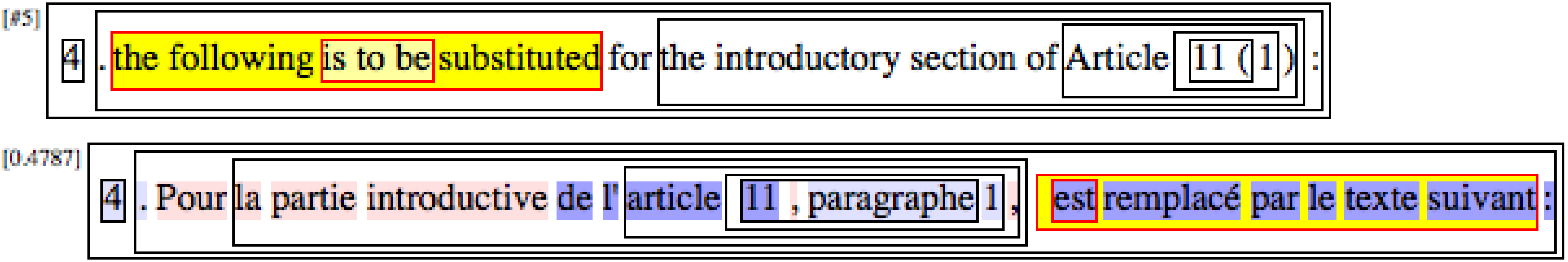
Analysis: Alignment



Phrase alignment of the decoding process

(red border, interactive)

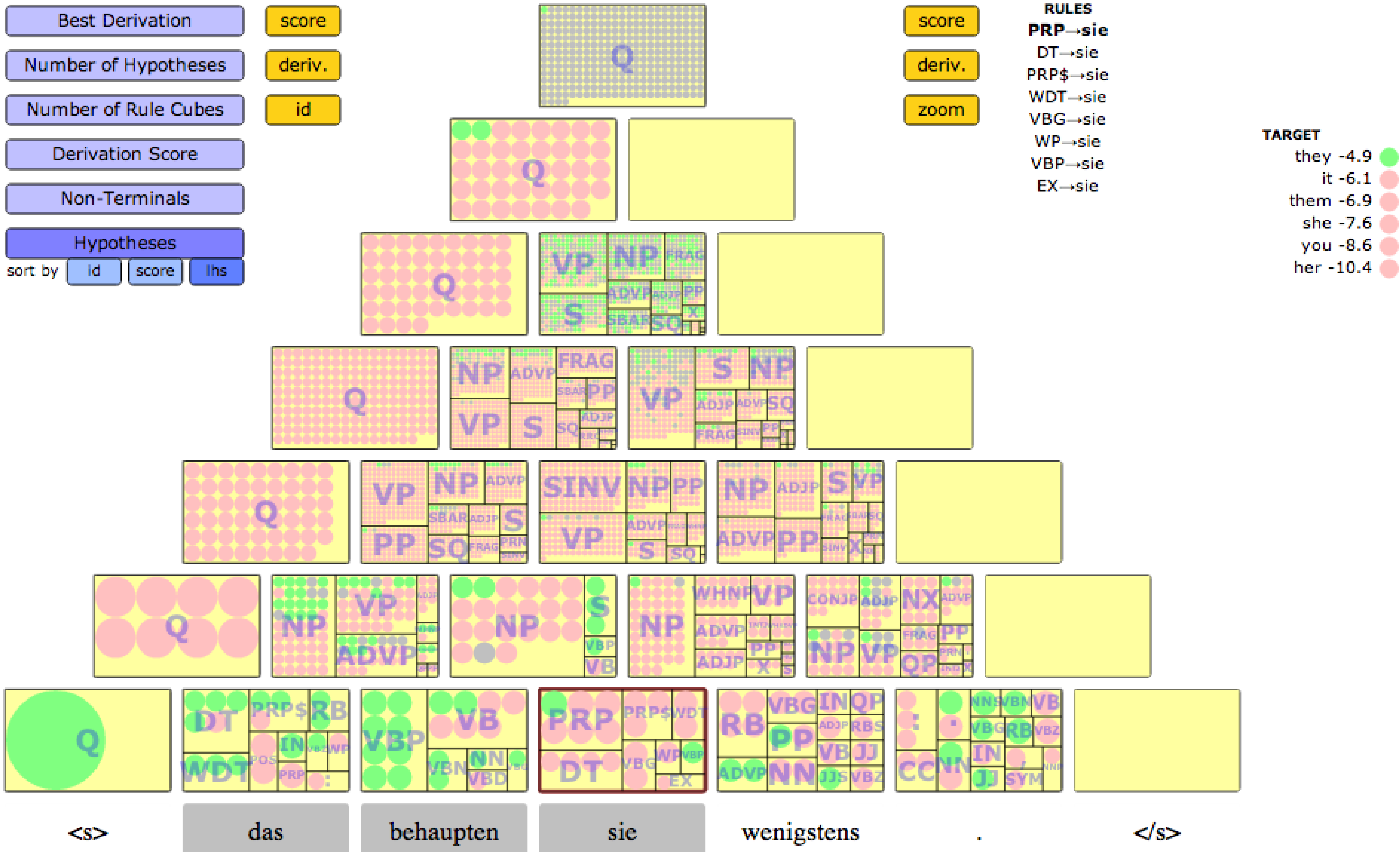
Analysis: Tree Alignment



Uses nested boxes to indicate tree structure

(red border, yellow shaded spans in focus, interactive)

for syntax model, non-terminals are also shown


Best Derivation
Number of Hypotheses
Number of Rule Cubes
Derivation Score
Non-Terminals
Hypotheses
sort by id score lhs
score
deriv.
id
score
deriv.
zoom
RULES
PRP→sie
DT→sie
PRP$→sie
WDT→sie
VBG→sie
WP→sie
VBP→sie
EX→sie
TARGET
they -4.9
it -6.1
them -6.9
she -7.6
you -8.6
her -10.4
<s>
das
behaupten
sie
wenigstens
.
</s>

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

Hands-On Session

Advanced Features

- **Faster Training**
- Faster Decoding
- Moses Server
- Data and domain adaptation
- Instructions to decoder
- Input formats
- Output formats
- Incremental Training

Advanced Features

- **Faster Training**
  - Tokenization
  - Tuning
  - Alignment
  - Phrase-Table Extraction
  - Train language model

...

Faster Training

- Run steps in parallel (that do not depend on each other)

- Multicore Parallelization

```
.../train-model.perl -parallel
```

- EMS:

```
[TRAINING]
parallel = yes
```

Advanced Features

- Faster Training
  - **Tokenization**
  - Tuning
  - Alignment
  - Phrase-Table Extraction
  - Train language model

...

Faster Training

- Multi-threaded tokenization

- Specify number of threads

```
.../tokenizer.perl -threads NUM
```

- EMS:

```
input-tokenizer = "$moses-script-dir/tokenizer/tokenizer.perl
                   -threads NUM "
```

Advanced Features

- Faster Training
  - Tokenization
  - **Tuning**
  - Alignment
  - Phrase-Table Extraction
  - Train language model

...

Faster Training

- Multi-threaded tokenization

- Specify number of threads

```
.../mert -threads NUM
```

- EMS:

```
tuning-settings = "-threads NUM"
```

Advanced Features

- Faster Training
  - Tokenization
  - Tuning
  - **Alignment**
  - Phrase-Table Extraction
  - Train language model

...

Faster Training

- Word Alignment
- Multi-threaded
  - Use MGIZA, not GIZA++

```
.../train-model.perl -mgiza -mgiza-cpus NUM
```

EMS:

```
training-options = " -mgiza -mgiza-cpus NUM "
```

- On: memory-limited machines
  - snt2cooc program requires 6GB+ memory
  - Reimplementation uses 10MB, but take longer to run

```
.../train-model.perl -snt2cooc snt2cooc.pl
```

EMS:

```
training-options = "-snt2cooc snt2cooc.pl"
```

Advanced Features

- Faster Training
  - Tokenization
  - Tuning
  - Alignment
  - **Phrase-Table Extraction**
  - Train language model

...

Faster Training

- Phrase-Table Extraction
  - Split training data into NUM equal parts
  - Extract concurrently

```
.../train-model.perl -cores NUM
```

Faster Training

- Sorting
  - Rely heavily on Unix 'sort' command
  - may take 50%+ of translation model build time
  - Need to optimize for
    - speed
    - disk usage
  - Dependent on
    - sort version
    - Unix version
    - available memory

Faster Training

- Plain sorted

```
sort < extract.txt > extract.sorted.txt
```

- Optimized for large server

```
sort --buffer-size 10G --parallel 5
     --batch-size 253 --compress-program [gzip/pigz] ...
```

  – Use 10GB of RAM — the more the better
  – 5 CPUs — the more the better
  – mergesort at most 253 files
  – compress intermediate files — less disk i/o

- In Moses:

```
.../train-model.perl -sort-buffer-size 10G -sort-parallel 5
     -sort-batch-size 253 -sort-compress pigz
```

Advanced Features

- Faster Training
  - Tokenization
  - Tuning
  - Alignment
  - Phrase-Table Extraction
  - **Train language model**

...

IRSTLM: Training

- Developed by FBK-irst, Trento, Italy
- Specialized training for large corpora
  - parallelization
  - reduce memory usage
- Quantization of probabilities
  - reduces memory but lose accuracy
  - probability stored in 1 byte instead of 4 bytes

IRSTLM: Training

- Training:

```
build-lm.sh -i "gunzip -c corpus.gz" -n 3
      -o train.irstlm.gz -k 10
```

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

- EMS:

```
irst-dir = [IRST path]
lm-training = "$moses-script-dir/generic/trainlm-irst.perl
                -cores NUM -irst-dir $irst-dir"
```

New: KENLM Training

- Can train very large language models with limited RAM (on disk streaming)

```
lmplz -o [order] -S [memory] < text > text.lm
```

- `-o order` = n-gram order

- `-S memory` = How much memory to use.
  - `NUM%` = percentage of physical memory
  - `NUM[b/K/M/G/T]` = specified amount in bytes, kilo bytes, etc.

Advanced Features

- Faster Training
- **Faster Decoding**
- Moses Server
- Data and domain adaptation
- Instructions to decoder
- Input formats
- Output formats
- Incremental Training

Advanced Features

- Faster Training
- **Faster Decoding**
  - Multi-threading
  - Speed vs. Memory
  - Speed vs. Quality

...

Advanced Features

- Faster Training
- Faster Decoding
  - **Multi-threading**
  - Speed vs. Memory
  - Speed vs. Quality

...

Faster Decoding

- Multi-threaded decoding

```
.../moses --threads NUM
```

- Easy speed-up

Advanced Features

- Faster Training
- Faster Decoding
  - Multi-threading
  - **Speed vs. Memory**
  - Speed vs. Quality

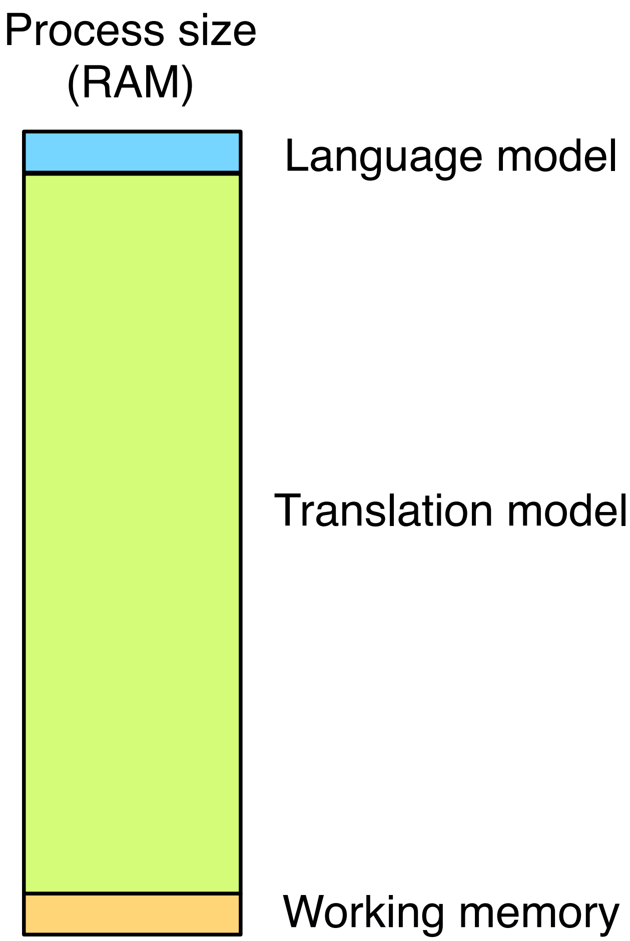
...

Speed vs. Memory Use

Typical Europarl file sizes:

- Language model
  - 170 MB (trigram)
  - 412 MB (5-gram)
- Phrase table
  - 11GB
- Lexicalized reordering
  - 9.4GB

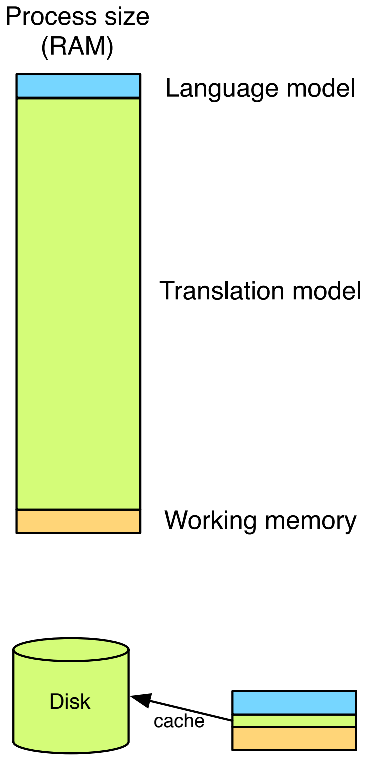
→ total = 20.8 GB



Speed vs. Memory Use

- Load into memory
  - long load time
  - large memory usage
  - fast decoding

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



Create Binary Tables

Phrase Table:

Phrase-based

```
export LC_ALL=C
cat pt.txt | sort | ./processPhraseTable -ttable 0 0 -  \
    -nscores 4 -out out.file
```

```
export LC_ALL=C   ./CreateOnDiskPt 1 1 4 100 2 pt.txt out.folder
```

Hierarchical / Syntax

```
export LC_ALL=C ./CreateOnDiskPt 1 1 4 100 2 pt.txt out.folder
```

Lexical Reordering Table:

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

Language Models (later)

Specify Binary Tables

Change ini file

Phrase Table

```
[feature]
PhraseDictionaryBinary name=TranslationModel0 table-limit=20 \
   num-features=4 path=/.../phrase-table
```

Hierarchical / Syntax

```
[feature]
PhraseDictionaryOnDisk name=TranslationModel0 table-limit=20 \
   num-features=4 path=/.../phrase-table
```

Lexical Reordering Table

automatically detected

Compact Phrase Table

- Memory-efficient data structure
  - phrase table 6–7 times smaller than on-disk binary table
  - lexical reordering table 12–15 times smaller than on-disk binary table
- Stored in RAM
- May be memory mapped
- Train with `processPhraseTableMin`
- Specify with `PhraseDictionaryCompact`

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
- Not multithreaded

IRSTLM in Moses

- Compile the decoder with IRSTLM library

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

- Create binary format:

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

- Load-on-demand:

```
rename file .mm
```

- Change ini file to use IRSTLM implementation

```
[feature]
IRSTLM name=LM0 factor=0 path=/.../lm order=5
```

KENLM

- Developed by Kenneth Heafield (CMU / Edinburgh / Stanford)
- Fastest and smallest language model implementation
- Compile from LM trained with SRILM

```
build_binary model.lm model.binlm
```

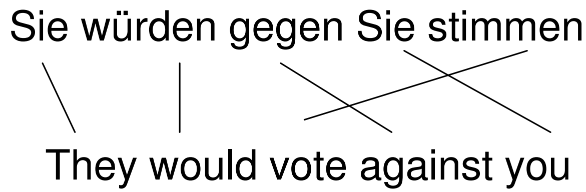
- Specify in decoder

```
[feature]
KENLM name=LM0 factor=0 path=/.../model.binlm order=5
```

New: OSM (Operations Sequence Model)

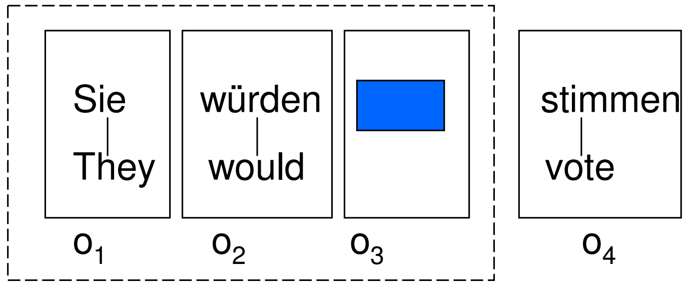
- A model that
  - considers source and target contextual information across phrases
  - integrates translation and reordering into a single model
- Convert a bilingual sentence to a sequence of operations
  - Translate (Generate a minimal translation unit)
  - Reordering (Insert a gap or Jump)
- P(e,f,a) = N-gram model over resulting operation sequences
- Overcomes phrasal independence assumption
  - Considers source and target contextual information across phrases
- Better reordering model
  - Translation and reordering decisions influence each
  - Handles local and long distance reorderings in a unified manner
- No spurious phrasal segmentation problem
- Average gain of +0.40 on news-test2013 across 10 pairs

New: OSM (Operations Sequence Model)



Operations

- o_1 Generate (Sie, They)
- o_2 Generate (würden, would)
- o_3 Insert Gap
- o_4 Generate (stimmen, vote)
- o_5 Jump Back (1)
- o_6 Generate (gegen, against)
- o_7 Generate (Sie, you)



Context Window

Model:

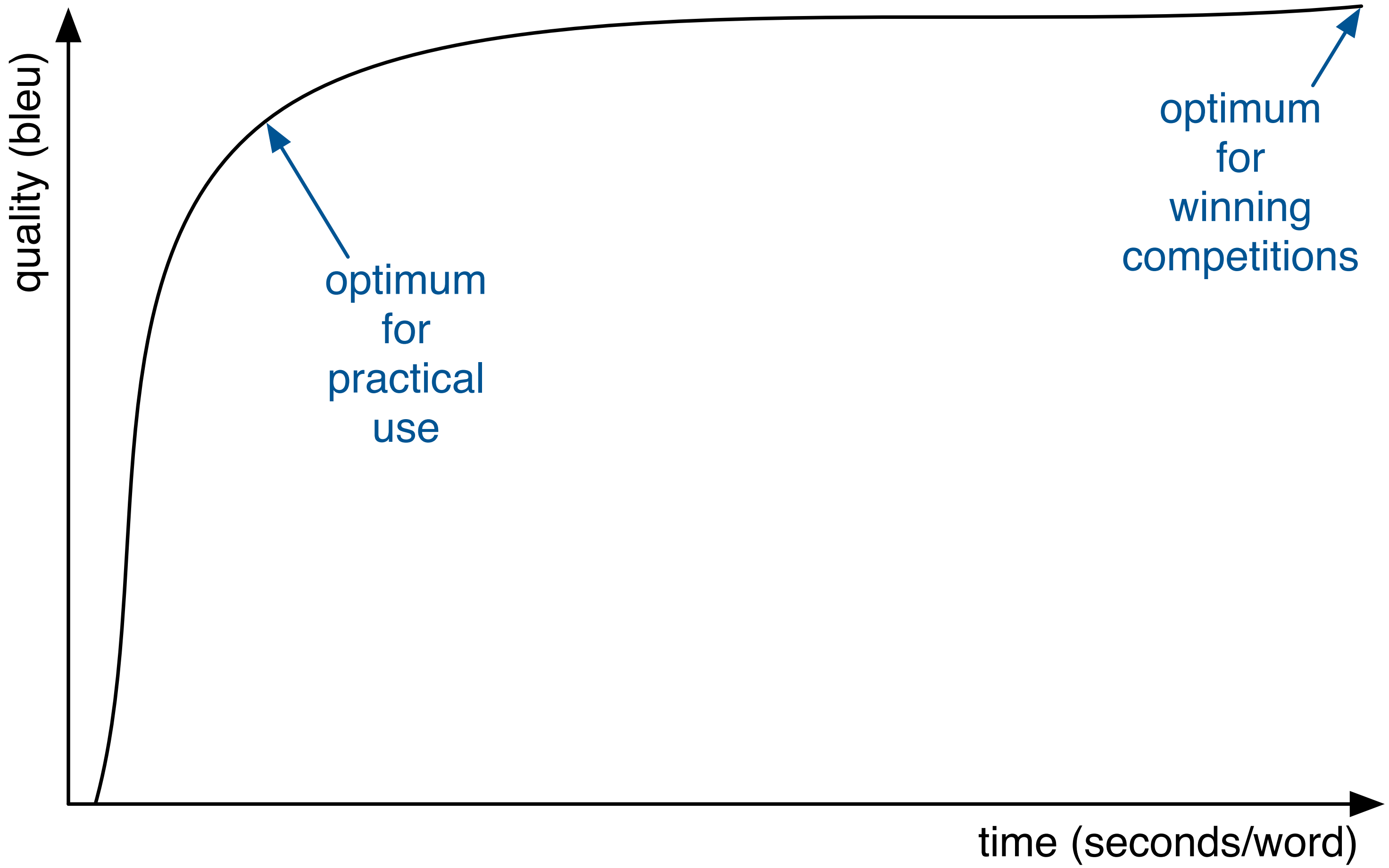
$$p_{osm}(F,E,A) = p(o_1,\ldots,o_N) = \prod_i p(o_i|o_{i-n+1}\ldots o_{i-1})$$

Advanced Features

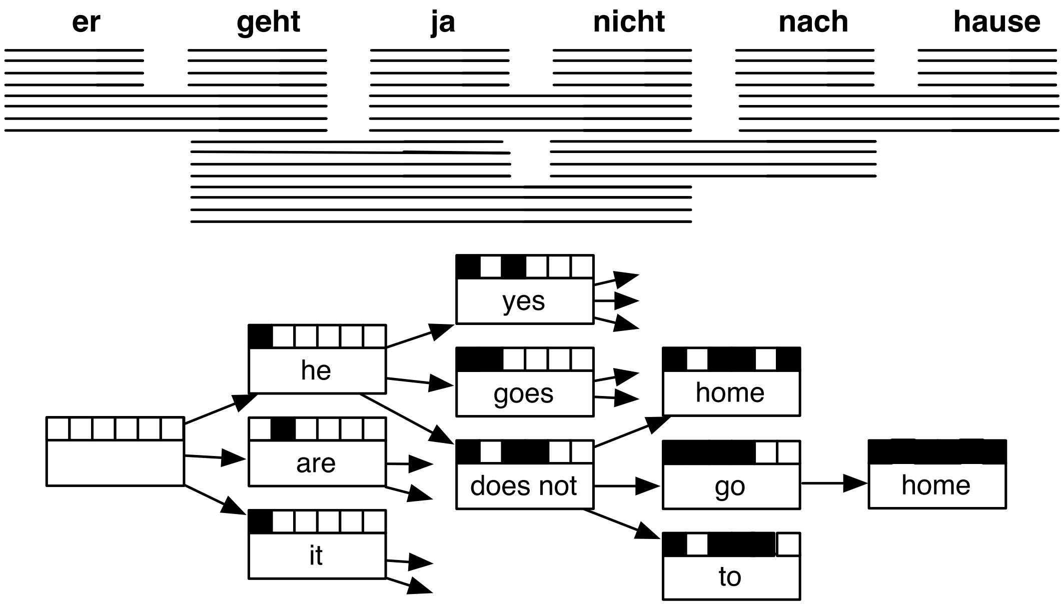
- Faster Training
- Faster Decoding
  - Multi-threading
  - Speed vs. Memory
  - **Speed vs. Quality**

...

Speed vs. Quality

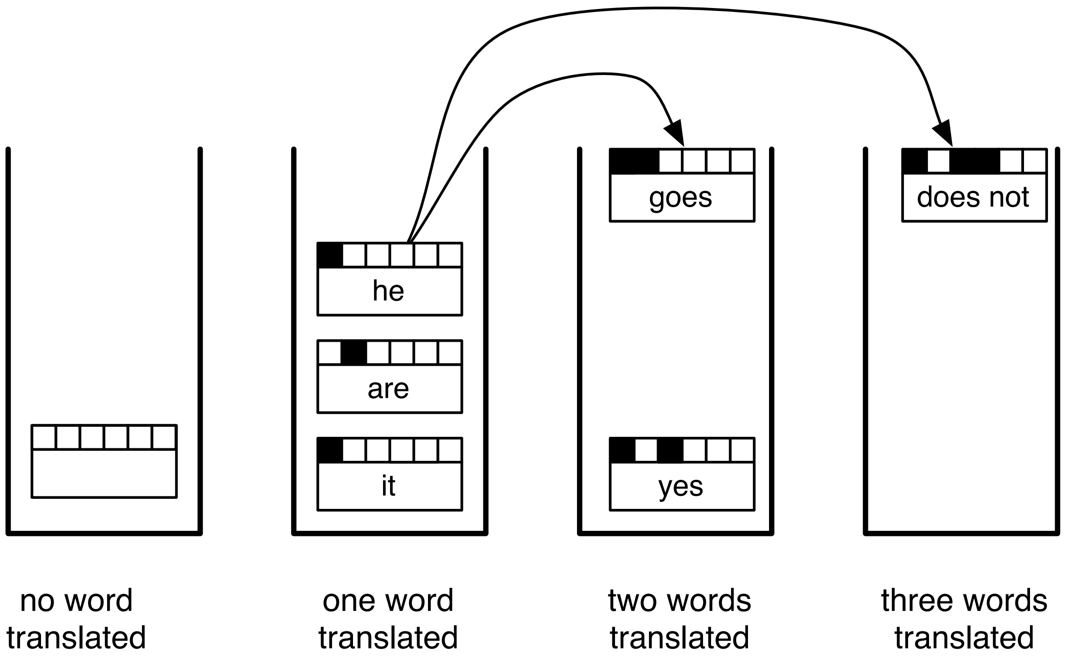


Speed vs. Quality



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

Hypothesis Stacks

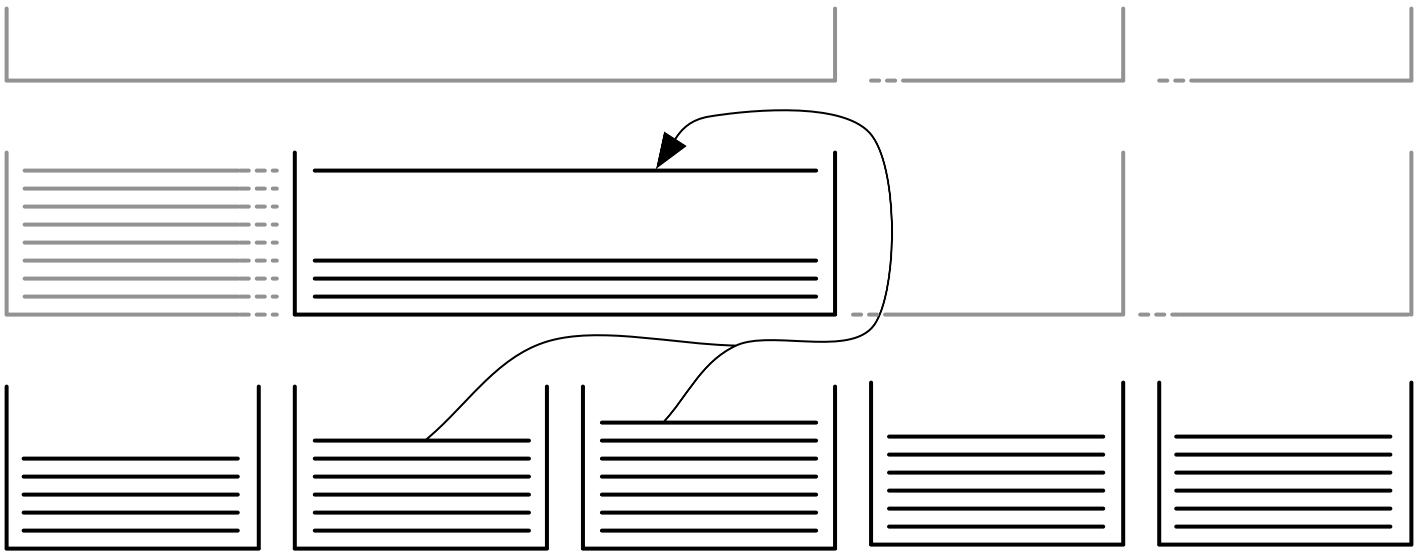


- Phrase-based: One stack per number of input words covered
- Number of hypothesis created =
  sentence length $\times$ stack size $\times$ applicable translation options

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

Syntax Hypothesis Stacks



- One stack per input word span
- Number of hypothesis created =
  sentence length^2 $\times$ number of hypotheses added to each stack

`--cube-pruning-pop-limit NUM`	number of hypotheses added to each stack

Advanced Features

- Faster Training
- Faster Decoding
- **Moses Server**
- Data and domain adaptation
- Instructions to decoder
- Input formats
- Output formats
- Incremental Training

Moses Server

- Moses command line:

```
.../moses -f [ini] < [input file] > [output file]
```

  - Not practical for commercial use
- Moses Server:

```
.../mosesserver -f [ini] --server-port [PORT] --server-log [LOG]
```

  - Accept HTTP input. XML SOAP format
- Client:
  - Communicate via http
  - Example clients in Java and Perl
  - Write your own client
  - Integrate into your own application

Advanced Features

- Faster Training
- Faster Decoding
- Moses Server
- **Data and domain adaptation**
  - Train everything together
  - Secondary phrase table
  - Domain indicator features
  - Interpolated language models

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)
- Always tune towards target domain

Advanced Features

- Faster Training
- Faster Decoding
- Moses Server
- Data and domain adaptation
  - **Train everything together**
  - Secondary phrase table
  - Domain indicator features
  - Interpolated language models

Default: Train Everything Together

- Easy to implement
  - Concatenate new data with existing data
  - Retrain

- Disadvantages:
  - Slower training for large amount of data
  - Cannot weight old and new data separately

Default: Train Everything Together

Specification in EMS:

- Phrase-table

```
[CORPUS]
[CORPUS:in-domain]
raw-stem = ....
[CORPUS:background]
raw-stem = ....
```

- LM

```
[LM]
[LM:in-domain]
raw-corpus = ....
[LM:background]
raw-corpus = ....
```

Advanced Features

- Faster Training
- Faster Decoding
- Moses Server
- Data and domain adaptation
  - Train everything together
  - **Secondary phrase table**
  - Domain indicator features
  - Interpolated language models

Secondary Phrase Table

- Train initial phrase table and LM on baseline data
- Train secondary phrase table and LM new/in-domain data
- Use both in Moses
  - Secondary phrase table

```
[feature]
PhraseDictionaryMemory path=.../path.1
PhraseDictionaryMemory path=.../path.2

[mapping]
0 T 0
1 T 1
```

Secondary Phrase Table

- – Secondary LM

```
[feature]
KENLM path=.../path.1
KENLM path=.../path.2
```

- Can give different weights for primary and secondary tables
- Not integrated into the EMS

Secondary Phrase Table

- Terminology/Glossary database
  - fixed translation
  - per client, project, etc
- Primary phrase table
  - backoff to 'normal' phrase-table if no glossary term

```
[feature]
PhraseDictionaryMemory path=.../glossary
PhraseDictionaryMemory path=.../normal.phrase.table

[mapping]
0 T 0
1 T 1

[decoding-graph-backoff]
0
1
```

Advanced Features

- Faster Training
- Faster Decoding
- Moses Server
- Data and domain adaptation
  - Train everything together
  - Secondary phrase table
  - **Domain indicator features**
  - Interpolated language models

Domain Indicator Features

- One translation model
- Flag each phrase pair's origin
  - indicator: binary flag if it occurs in specific domain
  - ratio: how often it occurs in specific domain relative to all
  - subset: similar to indicator, but if in multiple domains, marked with multiple-domain feature
- In EMS:

```
[TRAINING]
domain-features = "indicator"
```

Advanced Features

- Faster Training
- Faster Decoding
- Moses Server
- Data and domain adaptation
  - Train everything together
  - Secondary phrase table
  - Domain indicator features
  - **Interpolated language models**

Interpolated Language Models

- Train one language model per corpus
- Combine them by weighting each according to its importance
  - weights obtained by optimizing perplexity
    of resulting language model on tuning set
    (not the same as machine translation quality)
  - models are linearly combined
- EMS provides a section `[INTERPOLATED-LM]` that needs to be commented out
- Alternative: use multiple language models
  (disadvantage: larger process, slower)

Advanced Features

- Faster Training
- Faster Decoding
- Moses Server
- Data and domain adaptation
- **Instructions to decoder**
- Input formats
- Output formats
- Incremental Training

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 .

Specifying Translations with XML

```
./moses -xml-input [exclusive | inclusive | constraint ]
```

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

Three types of XML input:

- Exclusive
  Only possible translation is given in XML
- Inclusive
  Translation is given in XML is in addition to phrase-table
- Constraint
  Only use translations from phrase-table if it match XML specification

Constraint XML

- Specifically for translating terminology
  - consistently translate particular phrase in a document
  - may have learned larger phrase pairs that contain terminology term
- Example:

```
Microsoft <option translation="Windows"> Windows </option> 8 ...
```

- Allows use of phrase pair only if maps Windows to Windows

Placeholders

- Translate:
  - You owe me 100 dollars !
  - You owe me 200 dollars !
  - You owe me 9.56 dollars !
- Problem: need translations for
  - 100
  - 200
  - 9.56
- Some things are better off being handled by simple rules:
  - Numbers
  - Dates
  - Currency
  - Named entities

Placeholders

- Input
  You owe me 100 dollars !

- Replace numbers with `@num@`

  You owe me `@num@` dollars !

- Specification

  You owe me `<ne translation="@num@" entity="100">@num@</ne>` dollars !

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

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 .

Preserving Markup

- How do you translate this:

<h1>My Home Page</h1>
I really like to eat chicken!

- 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	eat	chicken	!
1	2	3	4	5	6	7
-	-	-	-		-	-

  - translate without markup

I really like to eat chicken !

  - keep word alignment to source

Ich	esse	wirklich	gerne	Hühnchen	!
1	5	2	3-4	6	7

  - re-insert markup

Ich esse wirklich gerne Hühnchen!

Transliteration

- Languages are written in different scripts
  - Russian, Bulgarian and Serbian - written in Cyrillic script
  - Urdu, Farsi and Pashto - written in Arabic script
  - Hindi, Marathi and Nepalese - written in Devanagri
- Transliteration can be used to translate OOVs and Named Entities
- Problem: Transliteration corpus is not always available
- Naive Solution:
  - Crawl training data from Wikipedia titles
  - Build character-based transliteration model
  - Replace OOV words with 1-best transliteration

Transliteration

- 2 methods to integrate into MT
- Post-decoding method
  - Use language model to pick best transliteration
  - Transliteration features
- In-decoding method
  - Integrate transliteration inside decoder
  - Words can be translated OR transliterated

Transliteration

- EMS:

```
[TRAINING]
transliteration-module = "yes"
```

- Post-processing method

```
post-decoding-transliteration = "yes"
```

- In-decoding method

```
in-decoding-transliteration = "yes"
transliteration-file = /list of words to be transliterated/
```

Advanced Features

- Faster Training
- Faster Decoding
- Moses Server
- Data and domain adaptation
- Instructions to decoder
- **Input formats**
- Output formats
- Incremental Training

Example: Misspelt Words

- Misspelt sentence:

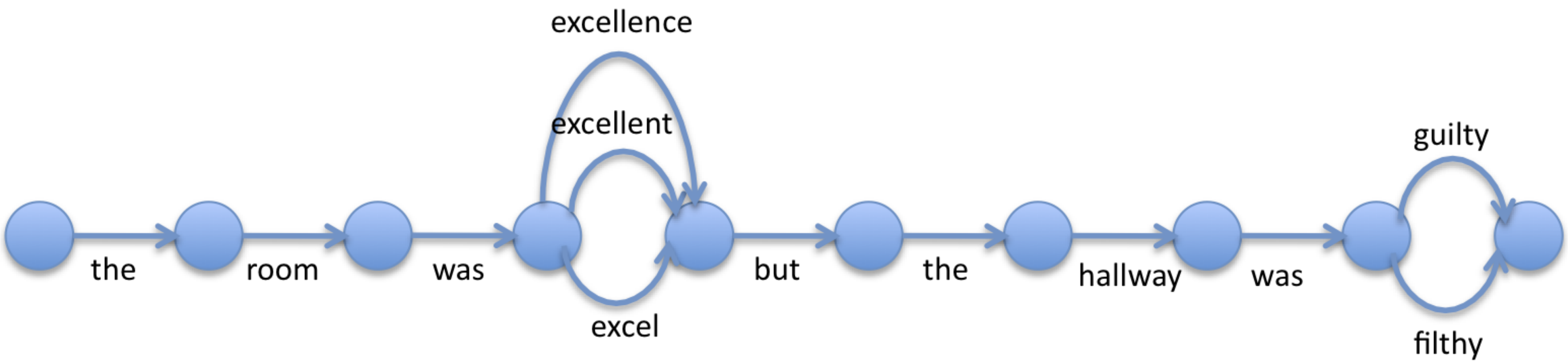
  The room was *exellent but the hallway was *filty .

- 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

Example: Diacritics

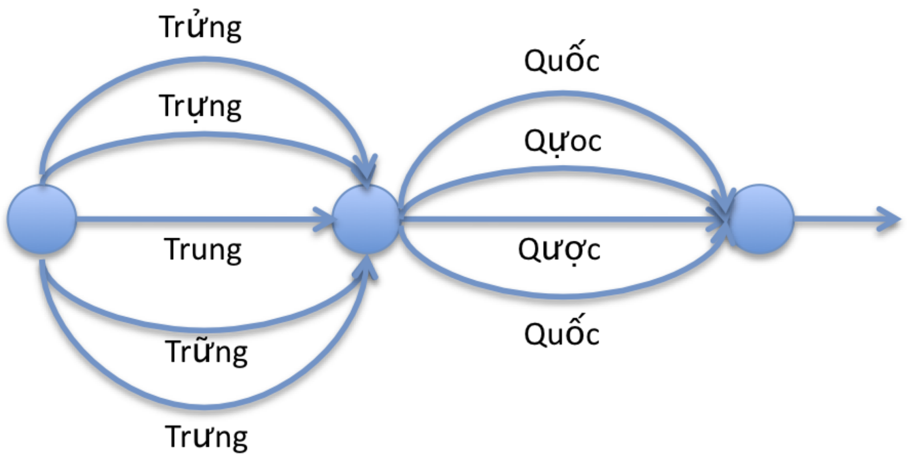
- Correct sentence

  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
```

Lattice

Example: Chinese Word Segmentation

- Unsegmented sentence

硬质合金号称"工业牙齿"

- Incorrect segmention

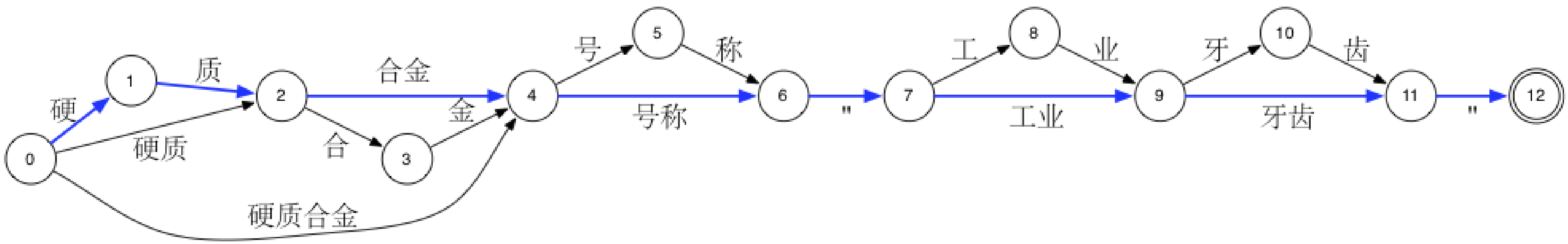
硬质 合 金 号称 " 工 业牙 齿 "

- Correct segmention

硬 质 合金 号称 " 工业 牙齿 "

Lattice

Input to decoder:



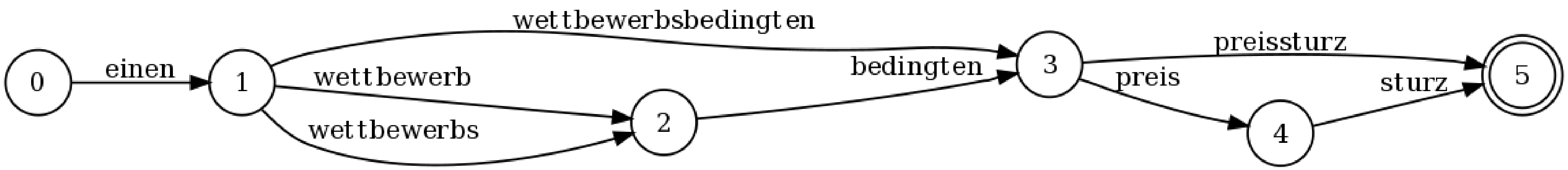
Let the decoder decide

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

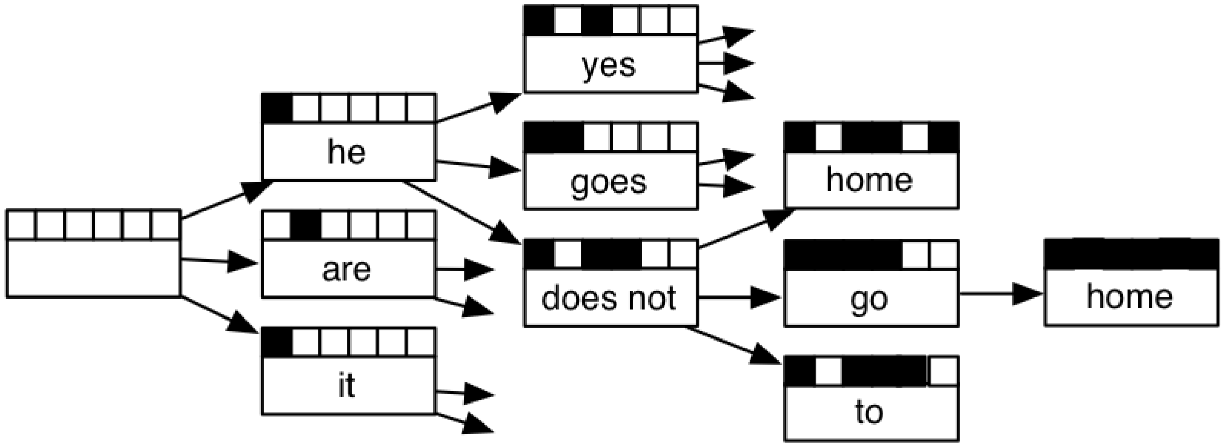
```
0 ||| there are various different opinions .  ||| d: 0 lm: -21.6664 w: -6 ...  ||| -113.734
0 ||| there are various other opinions .  ||| d: 0 lm: -25.3276 w: -6 ... ||| -114.004
0 ||| there are different different opinions .  ||| d: 0 lm: -27.8429 w: -6 ...  ||| -117.738
0 ||| there are other different 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

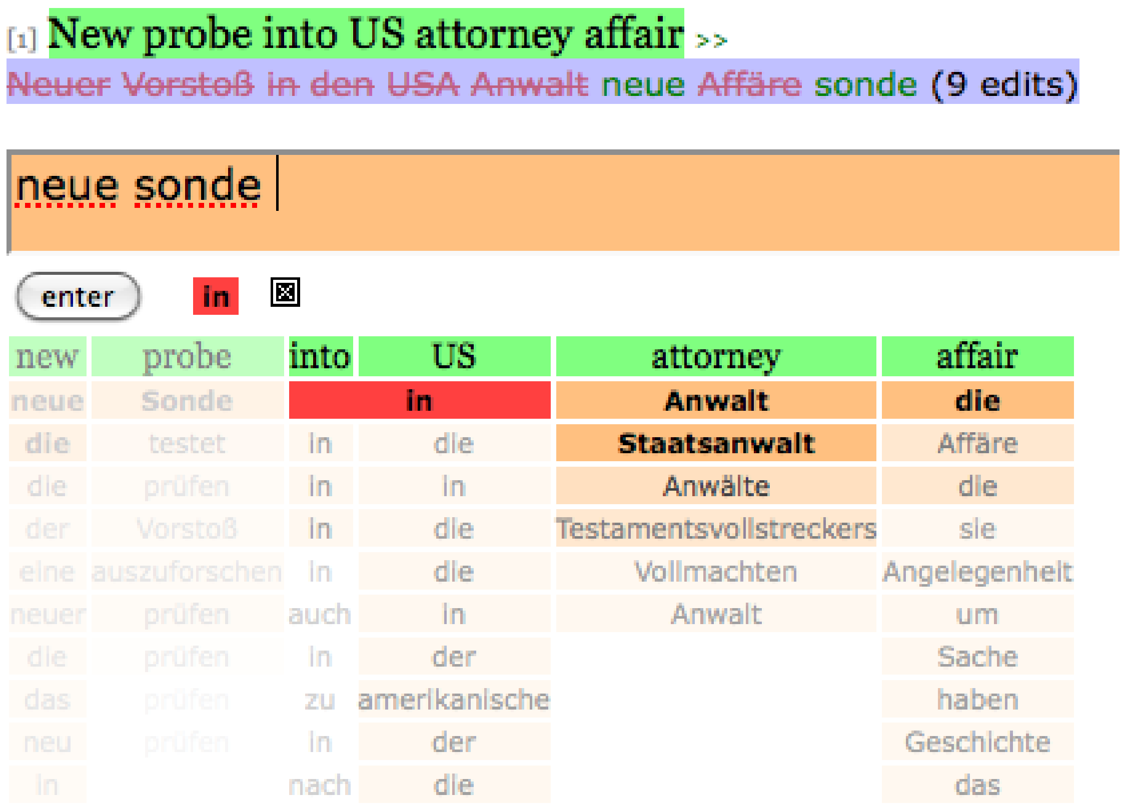
- Return internal structure from the decoder



- 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



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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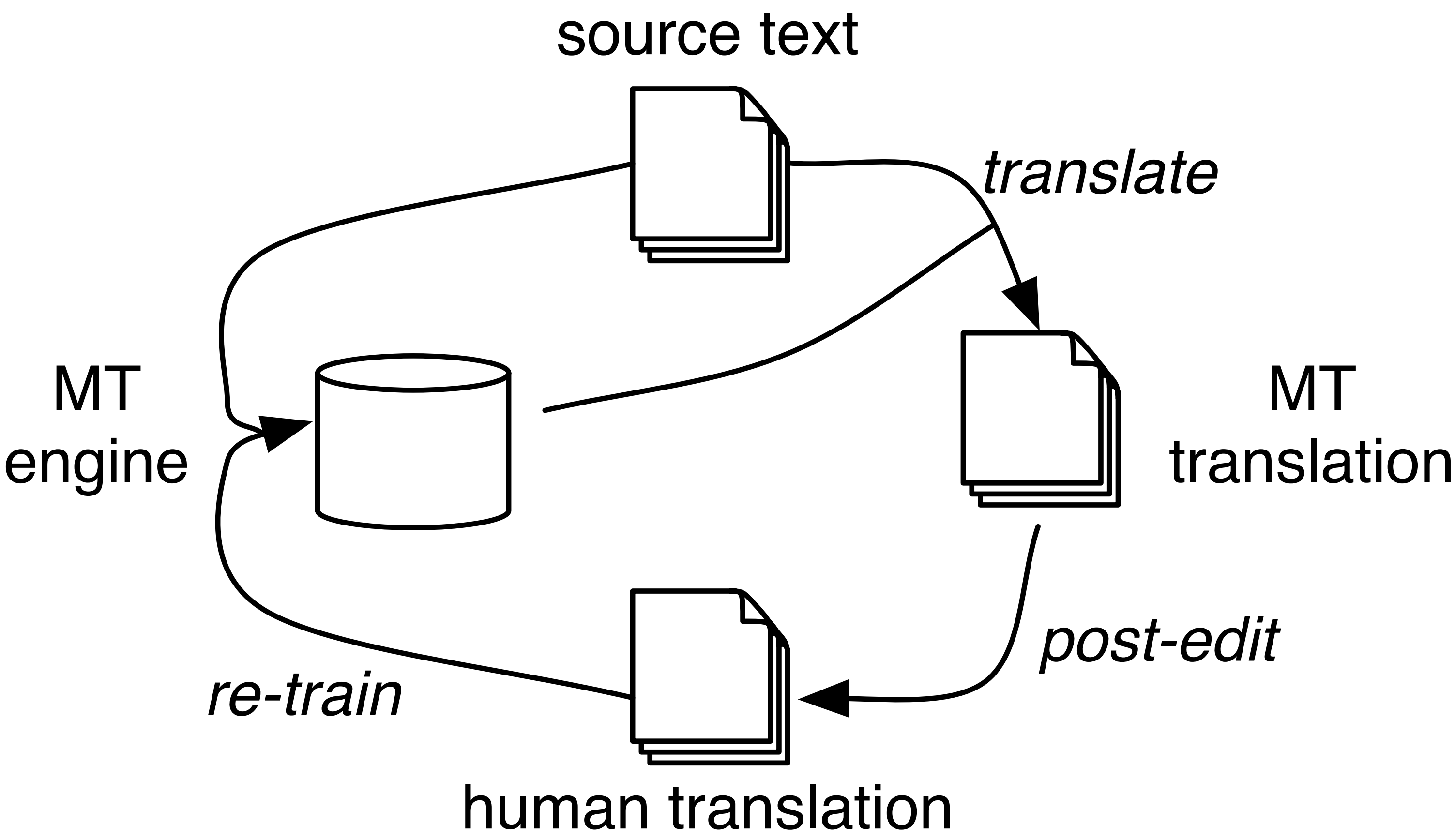
Incremental Training



Incremental Training

- Incremental word alignment
  - requires modified version of GIZA++
    (available at http://code.google.com/p/inc-giza-pp/)
  - only works for HMM alignment (not the common IBM Model 4)

- Translation model is defined by parallel corpus

```
PhraseDictionaryBitextSampling \
    path=/path/to/corpus \
    L1=source language extension \
    L2=target language extension
```

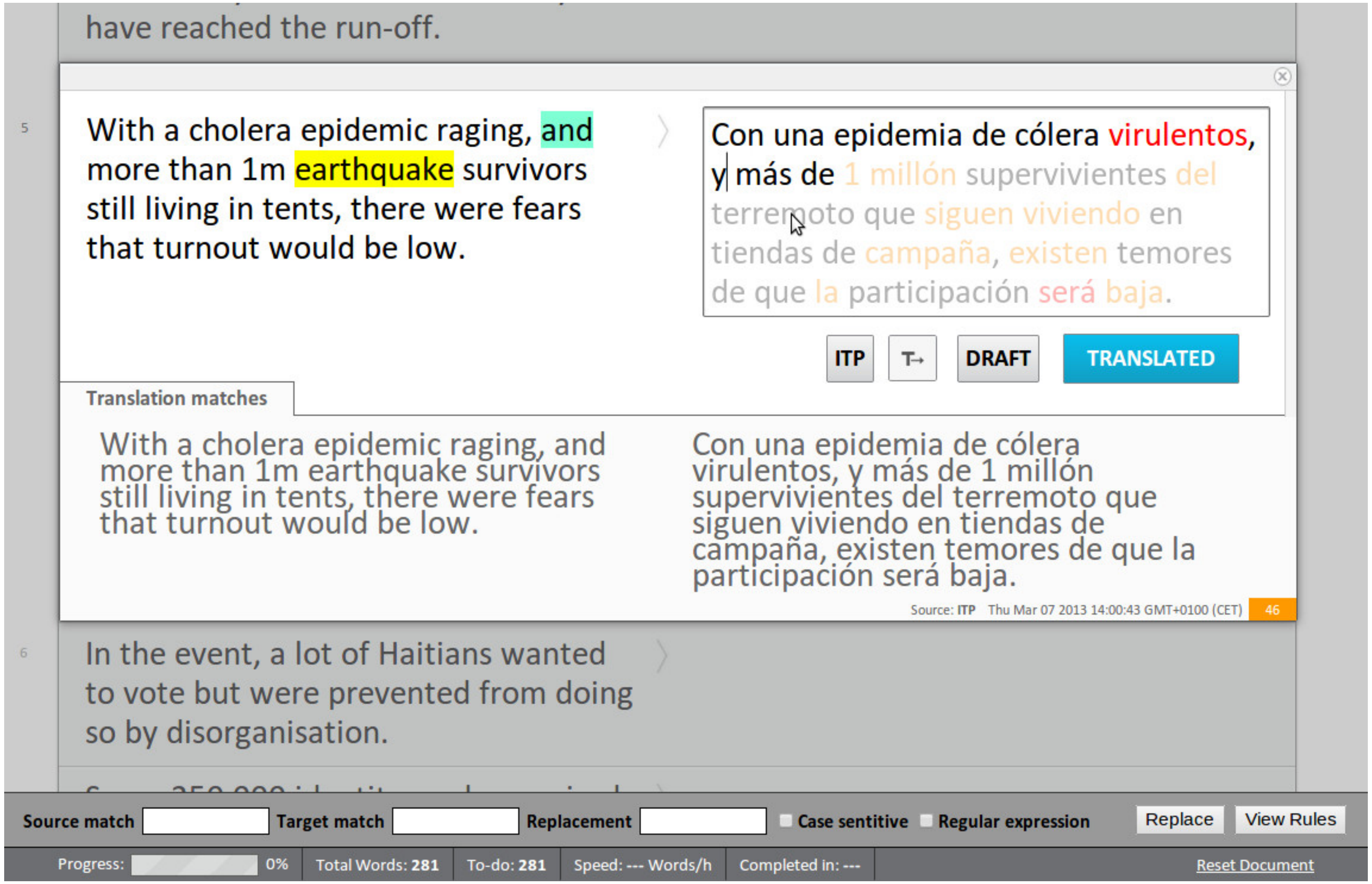
Update Word Alignment

- Uses original word alignment models
  (with additional model files stored after training)
- Incremental GIZA++ loads model
- New sentence pairs is aligned on the fly
- Typically, GIZA++ processes are run in both directions, symmetrized

Update Translation Model

- Translation table is stored as word-aligned parallel corpus
- Update = add word aligned sentence pair
- Updating a running Moses instance via XML RPC

Beyond Moses: CASMACAT Workbench



Acknowledgements

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