Machine Translation

May 21/23, 2013

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Language Technology II
SS 2013

Machine Translation: Overview

- Relevance of MT, typical applications and requirements
- History of MT
- Basic approaches to MT
  - Rule-based
  - Example-based
  - **Statistical**
    - **word-based**
    - **tree-based**
  - **Hybrid, multi-engine**
- Evaluation techniques

Sources for Information

- MT in general, history:
  - http://www.MT-Archive.info: Electronic repository and bibliography of articles, books and papers on topics in machine translation and computer-based translation tools, regularly updated, contains over 3300 items
  - Hutchins, Somers: An introduction to machine translation. Academic Press, 1992, available under http://www.hutchinsweb.me.uk/IntroMT-TOC.htm
- MT systems:

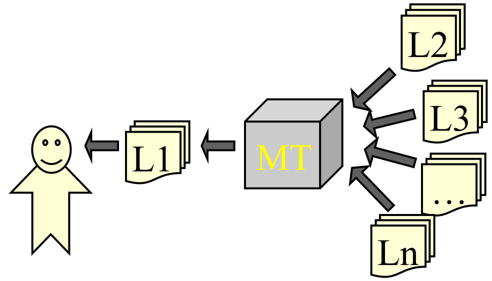
  Compendium of Translation Software, see http://www.hutchinsweb.me.uk/Compendium.htm
- Statistical Machine Translation:

  See www.statmt.org

  Book by Philipp Koehn is available in the coli-bib

Use cases and requirements for MT

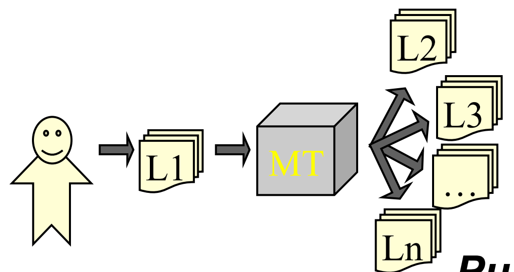
a) MT for assimilation
„inbound“



Robustness
Coverage

Daily throughput of online-MT-Systems > 500 M Words

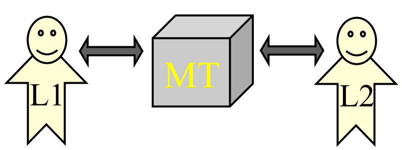
b) MT for dissemination
„outbound“



Textual quality

Publishable quality can only be authored by humans; Translation Memories & CAT-Tools mandatory for professional translators

c) MT for direct communication



Speech recognition, context dependence

Topic of many running and completed research projects (VerbMobil, TC Star, TransTac, …)
US-Military uses systems for spoken MT

On the Risks of Outbound MT

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Some recent examples

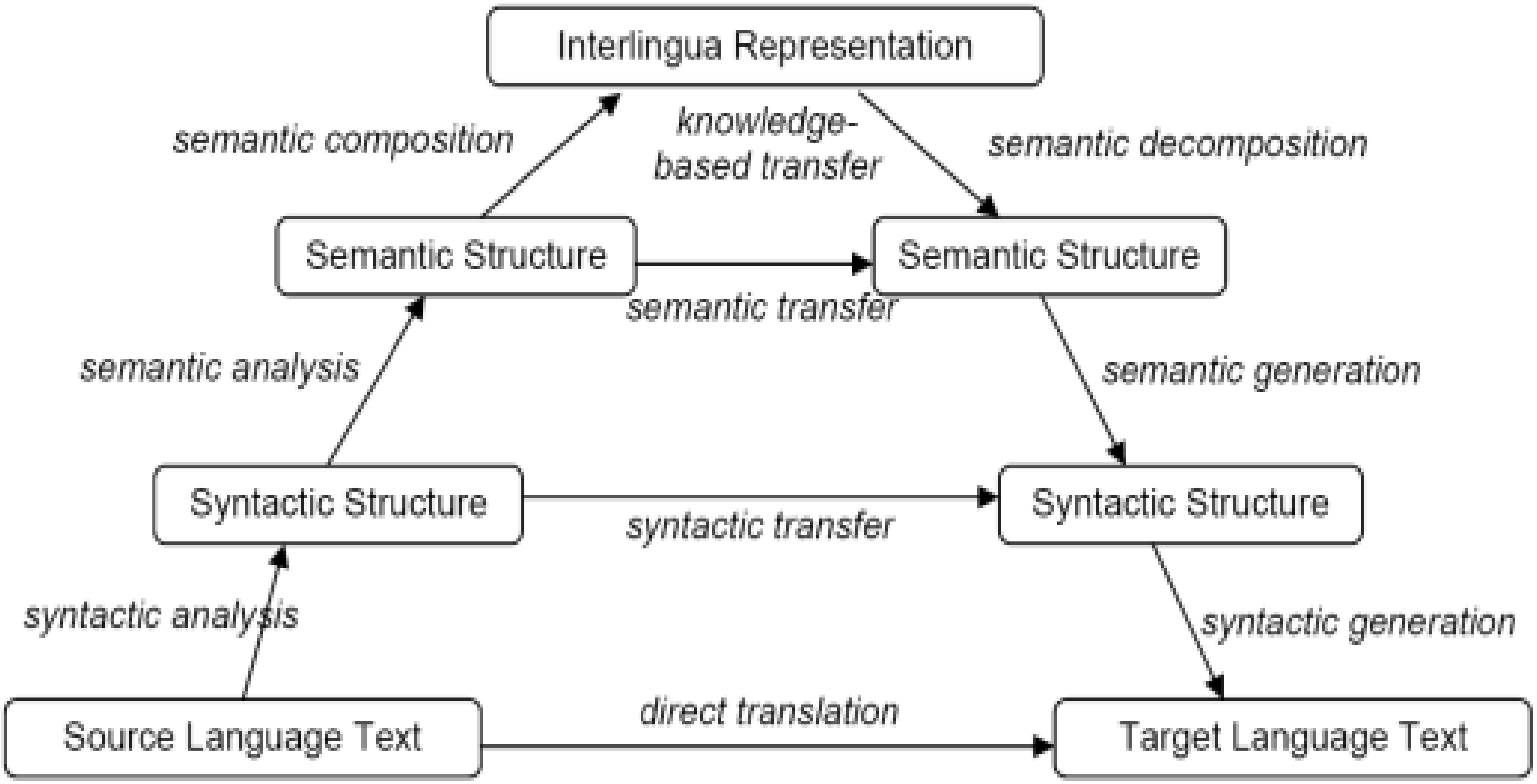
'I am not in the office at the moment. Please send any work to be translated'

Motivation for rule-based MT

- Good translation requires knowledge of linguistic rules
  - …for understanding the source text
  - …for generating well-formed target text
- Rule-based accounts for certain linguistic levels exist and should be used, especially for
  - Morphology
  - Syntax
- Writing one rule is better than finding hundreds of examples, as the rule will apply for new, unseen cases
- Following a set of rules can be more efficient than search for the most probable translation in a large statistical model

Possible (rule-based) MT architectures

The „Vauquois Triangle“



Motivation for statistical MT

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- Good translation requires knowledge and decisions on many levels
  - syntactic disambiguation (POS, attachments)
  - semantic disambiguation (collocations, scope, word sense)
  - reference resolution
  - lexical choice in target language
  - application-specific terminology, register, connotations, good style …
- Rule-based models of all these levels are very expensive to build, maintain, and adapt to new domains
- Statistical approaches have been quite successful in many areas of NLP, once data has been annotated
- Learning from existing translation will focus on distinctions that matter (not on the linguist's favorite subject)
- Translation corpora are available in rapidly growing amounts
- SMT *can* integrate rule-based modules (morphologies, lexicons)
- SMT *can* use feed-back for on-line adaptation to domain and user preferences

History of SMT and Important Players I

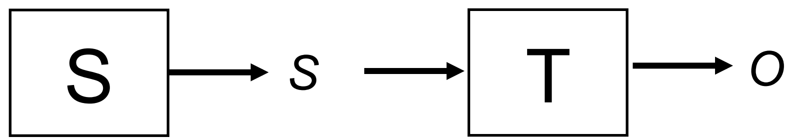
- 1949: Warren Weaver: *the translation problem can be largely solved by "statistical semantic studies"*
- 1950s..1970s: Predominance of rule-based approaches
- 1966: ALPAC report: general discouragement for MT (in the US)
- 1980s: example-based MT proposed in Japan (Nagao), statistical approaches to speech recognition (Jelinek e.a. at IBM)
- Late 80s: Statistical POS taggers, SMT models at IBM, work on translation alignment at Xerox (M. Kay)
- Early 90s: many statistical approaches to NLP in general, IBM's Candide claimed to be as good as Systran
- Late 90s: Statistical MT successful as a fallback approach within Verbmobil System (Ney, Och). Wide distribution of translation memory technology (Trados) indicates big commercial potential of SMT
- 1999 Johns Hopkins workshop: open source re-implementation of IBM's SMT methods (GIZA)

History of SMT and Important Players II

- Since 2001: DARPA/NIST evaluation campaign (XYZ → English), uses BLEU score for automatic evaluation
- Various companies start marketing/exploring SMT:
  language weaver, aixplain GmbH, Linear B Ltd., esteam, Google Labs
- 2002: Philipp Koehn (ISI) makes EuroParl corpus available
- 2003: Koehn, Och & Marcu propose *Statistical Phrase-Based MT*
- 2004: ISI publishes Philipp Koehn's SMT decoder *Pharaoh*
- 2005: First SMT workshop with shared task
- 2006: Johns Hopkins workshop on OS factored SMT decoder Moses, Start of EuroMatrix project for MT between all EU languages, Acquis Communautaire (EU laws in 20+ languages) made available
- 2007: Google abandons Systran and switches to own SMT technology
- 2009: Start of EuroMatrixPlus *"bringing MT to the user"*
- 2010: Start of many additional MT-related EU projects (Let's MT, ACCURAT, …)

Statistical Machine Translation

- Based on *„distorted channel"* paradigm
- Assume a signal that has to be transmitted through a channel that may add distortion/noise/etc.



- The source of the signal and the transmission channel can be characterized as probability distributions:
  - P(s): propability that signal s is generated
  - P(o|s): probability that observation o is made, *given* s
  - P(o,s) = P(s)*P(o|s): probability that s is sent *and* o is observed
- In typical applications, the most likely cause s' for a given observation o is sought, i.e.

  $s' = \mathrm{argmax}_s P(s|o) = \mathrm{argmax}_s P(s,o) = \mathrm{argmax}_s P(s)*P(o|s)$

Applications of Distorted Channel Paradigm

- Communications Engineering:
  - S may be an input device
  - T a transmission line (modem line, audio/video transmission)
- Speech recognition:
  - S is the speaker's brain, generating a string of words
  - T is the chain consisting of speakers articulatory device, sound transmission, microphone, signal processing up to morpheme hypotheses. The task is to reconstruct from a string of decoded sound events the intended chain of words.
- Machine translation:
  - S is text in one language
  - T is translation to another
  - applying this model means to translate from the target language of the assumed "distortion" to the source
- Error correction
  - S is the intended (correct) text
  - T is the modification by introducing typing, spelling and other errors
- OCR, …

Statistical Machine Translation

- How does that work in SMT?

$$\boxed{P(E)} \rightarrow E \rightarrow \boxed{P(F|E)} \rightarrow F$$

- Decoding: Given observation **F**, find most likely cause **E***

$$E^* = \mathrm{argmax}_E\, P(E|F) = \mathrm{argmax}_E\, P(E,F) = \mathrm{argmax}_E\, P(E) * P(F|E)$$

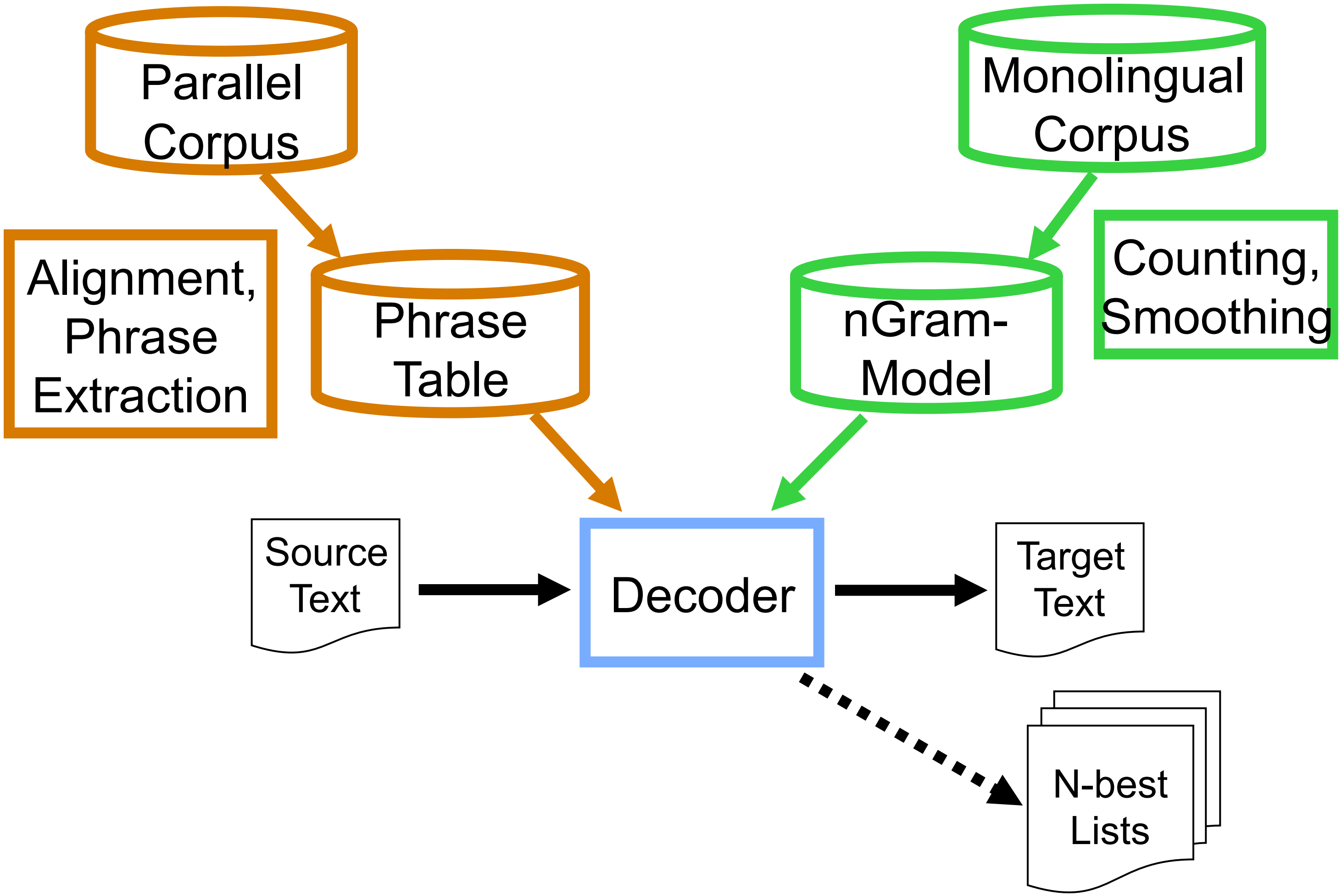
→ Three subproblems
Model of **P(E)**
Model of **P(F|E)**
Search for **E***

each has approximative solutions:
→ n-gram-Models $P(e_1 \ldots e_n) = \Pi P(e_i | e_{i-2}\ e_{i-1})$
→ Transfer of „phrases“ $P(F|E) = \Pi P(\mathbf{f}_i | \mathbf{e}_i) * P(d_i)$
→ Heuristic *(beam)* search

- Models are trained with (parallel) corpora, correspondences (alignments) between languages are estimated via EM-Algorithm (GIZA++, F.J.Och)

Statistical Machine Translation

schematic architecture



IBM Translation Models

- Brown et al. 1993 propose 5 different ways to define P(F|E) and to train the parameters from a bilingual corpus
- There is a chicken-and-egg situation between translation models and alignments: given one, we can estimate the other. The standard approach to bootstrap reasonable models from partially hidden data is the Expectation-Maximization (EM) Algorithm (as also used e.g. for HMMs)
- Model 1 assumes a one-to-one relation between individual words and a uniform distribution over all possible permutations
- Model 2 is similar, but prefers alignments that roughly preserve the original order

Word Alignment Example from Europarl

	Frau	Ludford	,	möchten	Sie	auch	wirklich	eine	Anmerkung	zum	Protokoll	machen	?
NULL	.	.	.	.	.	####	.	####	.	.	.	####	.
Mrs	###	.	.	.	.	.	.	.	.	.	.	.	.
Ludford	.	####	.	.	.	.	.	.	.	.	.	.	.
,	.	.	####	.	.	.	.	.	.	.	.	.	.
are	.	.	.	####	.	.	.	.	.	.	.	.	.
you	.	.	.	.	####	.	.	.	.	.	.	.	.
sure	.	.	.	.	.	.	####	.	.	.	.	.	.
your	.	.	.	.	.	.	.	.	.	.	.	.	.
point	.	.	.	.	.	.	.	.	####	.	.	.	.
of	.	.	.	.	.	.	.	.	.	.	.	.	.
order	.	.	.	.	.	.	.	.	.	.	.	.	.
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related	.	.	.	.	.	.	.	.	.	.	.	.	.
to	.	.	.	.	.	.	.	.	.	.	.	.	.
the	.	.	.	.	.	.	.	.	.	####	.	.	.
Minutes	.	.	.	.	.	.	.	.	.	.	####	.	.
?	.	.	.	.	.	.	.	.	.	.	.	.	*

IBM Translation Models

- Model 3 assumes that one English word can give rise to multiple French words by introducing "fertilities", i.e. distributions over the number of words in the translation of a given word. Exact calculation of EM-estimates becomes infeasible and is replaced with approximations restricted to plausible subsets of all possible alignments.
- Model 4 introduces a distinction between groups of words (derived from one source word) that tend to stay together (like: *implemented* → *mis en application*) and groups that tend to get separated (like: not → ne … pas).
- Model 5 is similar to Model 4, but avoids to distribute probability mass over impossible word sequences, e.g. sequences where words are missing or positions are simultaneously occupied with more than one word.
- Formulas in the CL'93 paper look heavy, but there are many tutorials and even an open-source implementation available.

IBM Translation Models

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- Bootstrapping also works across models of increasing complexity (i.e. alignment from Model *i* is used to estimate parameters for Model *i+1*)

- Development of the IBM models was based on about 1.8 million sentence pairs from the Canadian parliament debates (Hansards)

- Decoding (i.e. search for $\text{argmax}_s\ P(s) * P(o|s)$) was computationally challenging for long sentences, hence various heuristics for sentence splitting were used

- All models assume that correspondences are triggered by single words on the source level side, i.e. there is no support for phrase-to-phrase alignments

SMT: A Walkthrough

- Parallel text
  - Sentence segmentation and tokenization
  - Sentence alignment
  - Make sure you will have unseen test data
  - Word alignment
  - Phrasetable construction

- More text from target language
  - Stochastic (target) language model

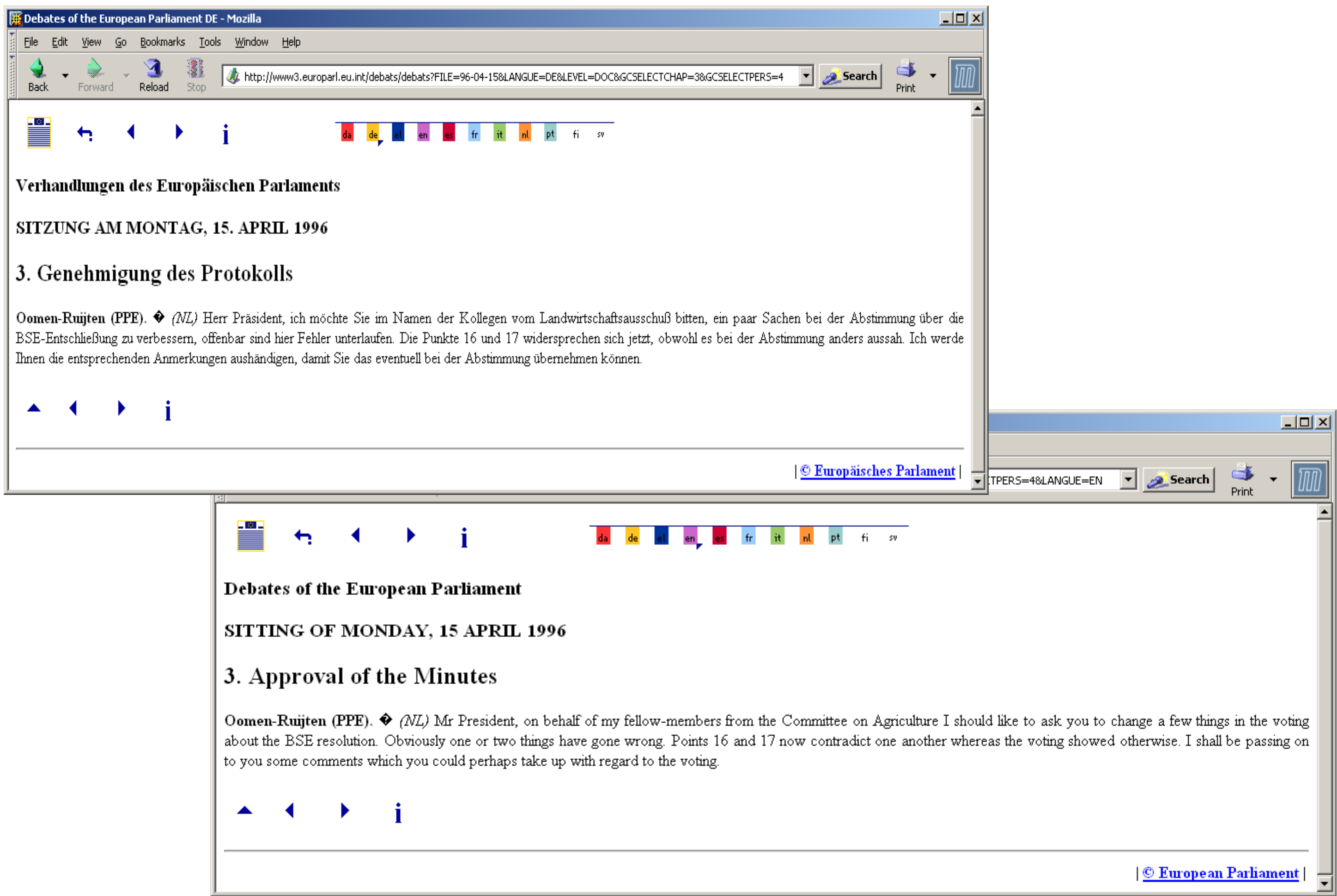
- Decoding
- Inspect/evaluate results

Parallel text

- **De-facto standard: EUROPARL corpus**
  - "Successor" of Canadian Hansards used by IBM
  - free, no legal constraints
  - current version includes 21 official EU languages
- **But:**
  - does not cover the most difficult/interesting languages (Chinese, Arabic, Japanese, Walpiri, Inuktitut, …)
  - not very technical
  - dependencies on context as in typical written text
- **In the meantime:**
  - EU has been extended to 27 states with 23 official languages
  - official law has been translated to all these languages

  ➔ "**Acquis Communautaire**" corpus

Parallel text: EUROPARL



Tokenization and sentence segmentation

- Both can be tricky if you want to get all the details right
  - "That is not true!" he said.
    → 1 or 2 sentences?
  - doesn't
    → [doesn + ' + t] **vs.** [does + n't] ?
- Distinguishing end-of-sentence marks from sentence-internal punctuation requires recognition of abbreviations, which are language-specific.

Sentence alignment

- Problem: During translation, sentences may have been split, merged, dropped or re-ordered.

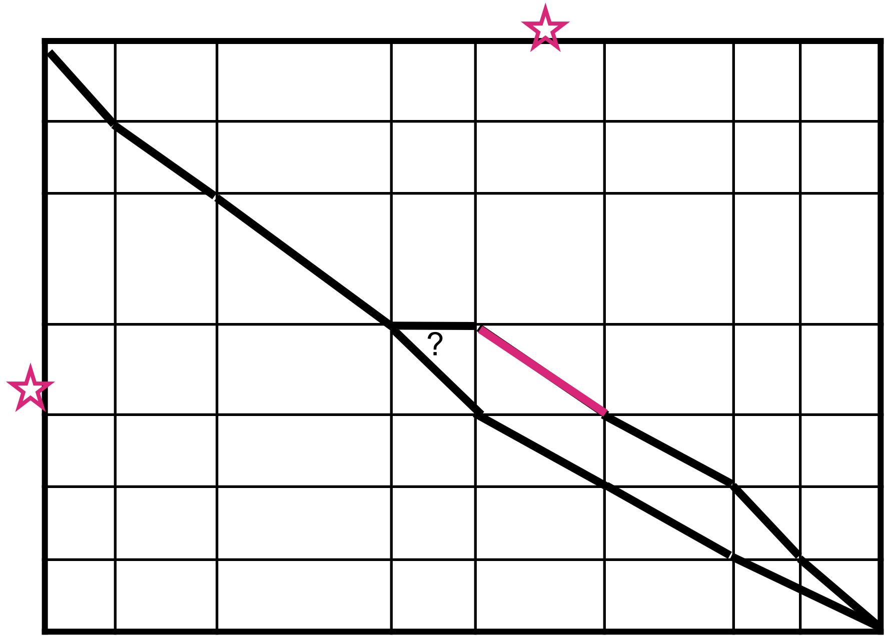
- If data is clean and some errors are acceptable: Simple length-based heuristic does the job

- Task can be seen as finding an optimal path through rectangular grid (see next slide)

- Europarl v.1: 10 sentence alignments XY ⇔ EN
- Europarl v.2ff: sentences + generic alignment tool

Sentence alignment

- Can be solved by dynamic programming



- Complexity is O(n*m)
- Additional evidence (e.g. from invariant or cognate words) can be helpful

Word alignment

- The problem: We need to know alignments between texts and translations on word or phrase level

- This is more difficult as for sentences, as the order on both sides does not agree

- There is no a priory notion of similarity, possible correspondences need to be learned from data

Word alignment

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- Words may (dis-)appear during translation, they get reordered, words replace constructions …

  → almost impossible to reach full agreement on valid correspondences

- Simple stochastic models will automatically get the typical cases right, but will miss the tricky (=interesting) cases

- For SMT, the typical cases are most important; we may have to live with 10% error rate

Word alignment

- A typical solution:
  - Assume a probabilistic model for co-occurrences between words/phrases
  - Train parameters from data

- But we have a chicken-and-egg situation:
  - given alignments, we can learn the parameters
  - given parameters, we can estimate alignments
  - we don't know how to start

Expectation Maximization (EM)

- Similar situations are ubiquitous in learning stochastic models from raw data lacking annotation
  - There is a generic scheme for how to deal with this problem, called EM algorithm

- Basic idea:
  - Start with a simple model (e.g. a uniform probability distribution)
  - Estimate a probabilistic annotation
  - Train a model from this estimate
  - Iterate re-estimation until result is good enough

- Properties of EM:
  - Likelihood of model is guaranteed to increase in each iteration
  - EM hence converges towards a maximum likelihood estimate (MLE)
  - But this maximum is only local
  - (Even global) MLE need not be useful for unseen data, less iterations may give better models

IBM Model I

- Each word of the foreign sentence is generated/ explained by some English word
- There is no limitation on the number of foreign words a given English word may generate, these influences are seen as independent
- Word order is completely ignored (bag of word)
- These slightly unrealistic assumptions simplify the mathematical analysis tremendously: Given a model and a sentence pair (f,e), estimated counts for the events can be obtained in closed form.

IBM Model I

Joint Probability of alignment and translation:

$$\Pr(\mathbf{f}, \mathbf{a}|\mathbf{e}) = \frac{\epsilon}{(l+1)^m} \prod_{j=1}^{m} t(f_j|e_{a_j}). \quad (5)$$

Probability of translation:

$$\Pr(\mathbf{f}|\mathbf{e}) = \frac{\epsilon}{(l+1)^m} \sum_{a_1=0}^{l} \cdots \sum_{a_m=0}^{l} \prod_{j=1}^{m} t(f_j|e_{a_j}). \quad (6)$$

Can be reorganized into:

$$\sum_{a_1=0}^{l} \cdots \sum_{a_m=0}^{l} \prod_{j=1}^{m} t(f_j|e_{a_j}) = \prod_{j=1}^{m} \sum_{i=0}^{l} t(f_j|e_i). \quad (15)$$

Counts for word-pair events can now be collected for foreign words, given bag of English words, but independent of foreign context

Simplified model for word alignment

- We will use a simplified version of IBM Model 1 (called Model 0), assuming that each word in a foreign language text f is the translation of (generated by) some word in the English version e

- Probability that the i-th foreign word f_i is generated, given an English sentence e, is modeled as:

$$P(f_i|e) = \sum_j P(f_i \mid e_j)$$

- Probability that the complete foreign sentence is generated (omitting some boring details):

$$P(f|e) = \prod_i P(f_i|e) = \prod_i \sum_j P(f_i \mid e_j)$$

EM algorithm for word alignment

- From a set of annotated data (i.e. sentence pairs with word alignments), we can obtain a new translation model:

$$P(f_i|e_j) = freq(f_i,e_j) / freq(e_j)$$

- From a model P, a foreign word f_i, and a sequence $e = e_1 \ldots e_n$ of possible “causes”, we can estimate frequencies as

$$freq(f_i|e_j) = P(f_i|e_j) / \sum_{k=1}^{n} P(f_i|e_k)$$

The training corpus and models

- Corpus:
  chien méchant ←→ dangerous dog
  petit chien ←→ small dog

- Initial model:
  - $p_0(f_i|e_j)$ = constant

- Update steps:
  - $P(f_i|e_j) = freq(f_i,e_j) / freq(e_j)$
  - $freq(f_i|e_j) = P(f_i|e_j) / \sum_{k=1}^{n} P(f_i|e_k)$

EM iteration 1

Local frequency estimates

$freq(f_i\|e_j)$	chien	méchant
dangerous	0.5	0.5
dog	0.5	0.5

$freq(f_i\|e_j)$	petit	chien
small	0.5	0.5
dog	0.5	0.5

Global frequencies and probabilities

$freq(f_i\|e_j)$	petit	chien	méchant
small	0.5	0.5	
dangerous		0.5	0.5
dog	0.5	1.0	0.5

$p(f_i\|e_j)$	petit	chien	méchant
small	0.5	0.5	
dangerous		0.5	0.5
dog	0.25	0.5	0.25

EM iteration 2

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Probabilities from iteration 1

$p(f_i \mid e_j)$	petit	chien	méchant
small	0.5	0.5	
dangerous		0.5	0.5
dog	0.25	0.5	0.25

New frequency estimates

$freq(f_i \mid e_j)$	chien	méchant
dangerous	0.5	0.67
dog	0.5	0.33

$freq(f_i \mid e_j)$	petit	chien
small	0.67	0.5
dog	0.33	0.5

EM iteration 2

Local frequency estimates

$freq(f_i\|e_j)$	chien	méchant
dangerous	0.5	0.67
dog	0.5	0.33

$freq(f_i\|e_j)$	petit	chien
small	0.67	0.5
dog	0.33	0.5

Global frequencies and probabilities

$freq(f_i\|e_j)$	petit	chien	méchant
small	0.67	0.5	
dangerous		0.5	0.67
dog	0.33	1.0	0.33

$p(f_i\|e_j)$	petit	chien	méchant
small	0.57	0.43	
dangerous		0.43	0.57
dog	0.2	0.6	0.2

Word alignment

Sample from the DE⇔EN alignment:

Die$_0$ Punkte$_1$ 16$_2$ und$_3$ 17$_4$ widersprechen$_5$ sich$_6$ jetzt$_7$,$_8$ obwohl$_9$ es$_{10}$ bei$_{11}$ der$_{12}$ Abstimmung$_{13}$ anders$_{14}$ aussah$_{15}$.$_{16}$

Points$_0$ 16$_1$ and$_2$ 17$_3$ now$_4$ contradict$_5$ one$_6$ another$_7$ whereas$_8$ the$_9$ voting$_{10}$ showed$_{11}$ otherwise$_{12}$.$_{13}$

0-9 1-0 2-1 3-2 4-3 5-5 6-5 7-4 9-8 10-9 11-8 12-9 13-10 14-12 15-6 15-7 15-11 15-12 16-13

Word alignment

Same sample represented graphically:

```
                            Die
                          .   Punkte
                        .  <#>  16
                      .   .   .   und
                    .   .  <#>  .   17
                  .   .   .   .   .   widersprechen
                .   .   .  <#>  .   .   sich
              .   .   .   .   .   .   .   jetzt
            .   .   .   .  <#>  .   .   .   ,
          .   .   .   .   .   .   .   .   .   obwohl
       <#>  .   .   .   .   .   .   .   .   .   es
      .   .   .   .   .  <#>  .   .   .   .   .   bei
    .   .   .   .   .   .  <#> <#>  .   .   .   .   der
  .   .   .   .   .   .   .   .   .   .   .   .   .   Abstimmung
.   .   .   .   .   .   .   .   .   .   .   .   .   .   anders
  .   .   .   .   .   .   .   .   .   .   .   .   .   .   aussah
    .   .   .   .   .   .   .   .   .   .   .   .   .   .   .
      .   .   .   .   .   .   .   .   .   .   .   .   .   .
        .   .   .   .   .  <#>  .   .   .   .   .   .   .   Points
          .   .   .   .   .   .   .   .   .   .   .   .   16
            .   .   .   .  <#> <#>  .   .   .   .   .   and
              .   .   .   .   .   .   .   .   .   .   17
                .   .   .   .  <#>  .   .  <#>  .   now
                  .   .   .   .   .   .  <#>  .   contradict
                    .   .   .  <#>  .   .   .   one
                      .   .   .   .   .   .   another
                        .   .   .   .   .   whereas
                          .  <#> <#>  .   the
                            .  <#>  .   voting
                              .   .   showed
                               <#>  otherwise
                                  .
```

Word alignment

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- Typical approach: use IBM models as implemented in GIZA++ system
  - Apply it in both directions
  - Take intersection of results (increasing precision at the cost of recall)
  - Extend using various heuristics

- Partial word alignments for 4 language pairs DE/ES/FI/FR⇔EN available from `http://www.statmt.org/wpt05/mt-shared-task/`

Phrase-table construction

- Idea: collect pairs of substrings that are compatible with word alignment
- Phrasetable is annotated with scores that will be used during decoding
- Alternatively: in tree-based models we try to learn a grammar:
  - hierarchical: not based on any syntactic theory
  - syntax-based: needs annotated (=parsed) data

Phrase-table construction

```
widersprechen ||| contradict ||| 0.5 0.174039 0.227273 0.119306 2.718
widersprechen , ||| to contradict ||| 0.333333 0.046708 0.2 0.0134216 2.718
Kommissar Bolkestein ausdrücklich widersprechen ||| expressly contradict Commissioner Bolkestein ||| 1
    0.0417032 1 0.0147184 2.718
widersprechen ||| contravening ||| 0.333333 0.0320171 0.0113636 0.0032612 2.718
nicht widersprechen ||| not contradictory ||| 0.125 0.0291049 0.111111 0.017083 2.718
nicht widersprechen ||| does not contravene ||| 0.5 0.0288053 0.111111 0.000371669 2.718
widersprechen oder ||| contradictory or ||| 0.333333 0.0251621 1 0.0207105 2.718
widersprechen ||| run counter ||| 0.4 0.017062 0.0681818 0.00114863 2.718
widersprechen ||| disagree ||| 0.0106383 0.0167791 0.0113636 0.0714746 2.718
Wir widersprechen ||| We disagree ||| 0.0666667 0.00997179 1 0.0503599 2.718
teilweise widersprechen ||| partly contradictory ||| 1 0.00637625 1 0.00291665 2.718
widersprechen ||| inconsistent ||| 0.0169492 0.00598197 0.0113636 0.0032612 2.718
widersprechen uns ||| contradicts us ||| 1 0.00561145 1 0.00174914 2.718
nur dann widersprechen ||| only overrule ||| 1 0.00216227 1 0.000444817 2.718
auch der Konferenz der Präsidenten widersprechen ||| contradict both the Conference of Presidents ||| 1
    0.001813 1 5.17342e-05 2.718
Herr Bolkestein widersprechen ||| Mr Bolkestein disagrees with ||| 1 0.00175593 1 0.00041956 2.718
könnte dem widersprechen ||| could gainsay that ||| 1 0.00174458 1 4.90747e-06 2.718
widersprechen muß ||| have to contradict ||| 0.333333 0.00163608 0.5 0.000911924 2.718
widersprechen , wird ||| contradictory , is ||| 1 0.00161673 1 0.00362608 2.718
Änderungsanträge widersprechen dem ||| amendments contravene the ||| 1 0.00160169 1 0.0101469 2.718
17 widersprechen sich jetzt ||| 17 now contradict ||| 1 0.00143452 1 0.0283876 2.718
und 17 widersprechen sich jetzt ||| and 17 now contradict ||| 1 0.00120543 1 0.0256701 2.718
widersprechen zu müssen ||| to have to contradict ||| 1 0.00111525 0.333333 0.00167714 2.718
Herrn Brinkhorst nicht widersprechen ||| not disagree with Mr Brinkhorst ||| 1 0.00103174 1 0.00613701 2.718
einander widersprechen ||| contradict ||| 0.025 0.00101814 1 0.0609116 2.718
sich nicht widersprechen ||| are not contradictory ||| 0.25 0.000998935 1 0.00137116 2.718
widersprechen ||| any case contrary ||| 1 0.000890016 0.0113636 4.16211e-07 2.718
16 und 17 widersprechen sich jetzt ||| 16 and 17 now contradict ||| 1 0.000830368 1 0.0236414 2.718
widersprechen ||| conflict with ||| 0.0465116 0.000750812 0.0454545 0.00236106 2.718
James Elles widersprechen ||| what James Elles said ||| 1 0.00071772 1 0.00011574 2.718
nicht widersprechen ||| not conflict with ||| 0.4 0.00060168 0.222222 0.00164904 2.718
Rassismus , Fremdenfeindlichkeit und Antisemitismus widersprechen ||| racism , xenophobia and antisemitism
    are completely incompatible with ||| 1 0.00055052 1 1.87174e-08 2.718
```

Stochastic language model

- Motivation: Translations should satisfy 2 requirements:
  - equivalence with source sentence P(f|e)
  - well-formedness P(e)

- So far, we have only dealt with equivalence

- Well-formedness can be approximated via even simpler stochastic models, based on n-gram probabilities.

- We know (since Chomsky '57…) that n-gram models cannot capture essential long-distance effects, but in practice, 5-grams seem to be good enough.

Stochastic language model

- Toolkits for counting word co-occurrences and estimating sentence probabilities have been developed for speech recognition.
- Some are freely available:
  - SRILM (Stolcke)
  - CMU/Cambridge (Clarkson&Rosenfeld)
  - IRST-LM (FBK)

- Philipp Koehn's Moses decoder can make use of several different models; it comes with KenLM (Heafield)

- Dilemma: More text of slightly different type may help or hurt, one needs to try it out.

Decoding

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- The decoder…
  - uses source sentence *f* and phrase table to estimate *P(e|f)*
  - uses LM to estimate *P(e)*
  - searches for target sentence *e* that maximizes *P(e)*P(f|e)*
  - uses beam-search approximation, as complete search for optimal solution is not feasible
  - has some additional bells and whistles (factored models, tree-based) that will improve the quality