Universitat Politècnica de València

Master in Artificial Intelligence, Pattern Recognition and Digital Imaging

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MACHINE TRANSLATION

2. Statistical Machine Translation

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General framework

- Every sentence y in one language is a translation of any sentence x in another language.

- For each possible pair of sentences, y and x, there is a probability $\Pr(y \mid x)$.

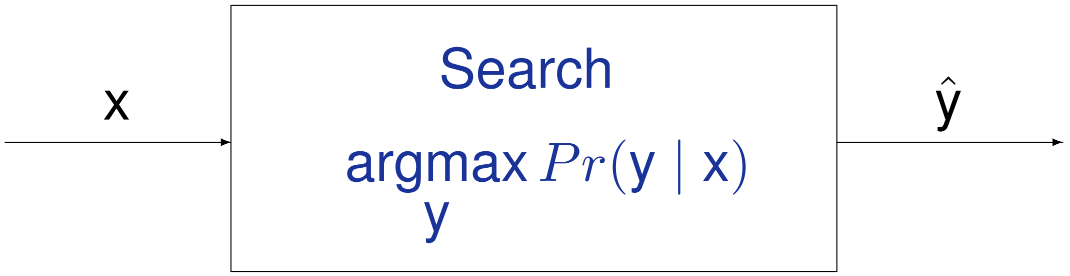
- $\Pr(y \mid x)$ should be low in the case of:

  y $=$ *quiero una habitación doble con vistas al mar*
  x $=$ *are all expenses included in the bill?*

- $\Pr(y \mid x)$ should be high in the case of:

  y $=$ *¿ hay alguna habitación tranquila libre ?*
  x $=$ *is there a quiet room available?*

Training and search



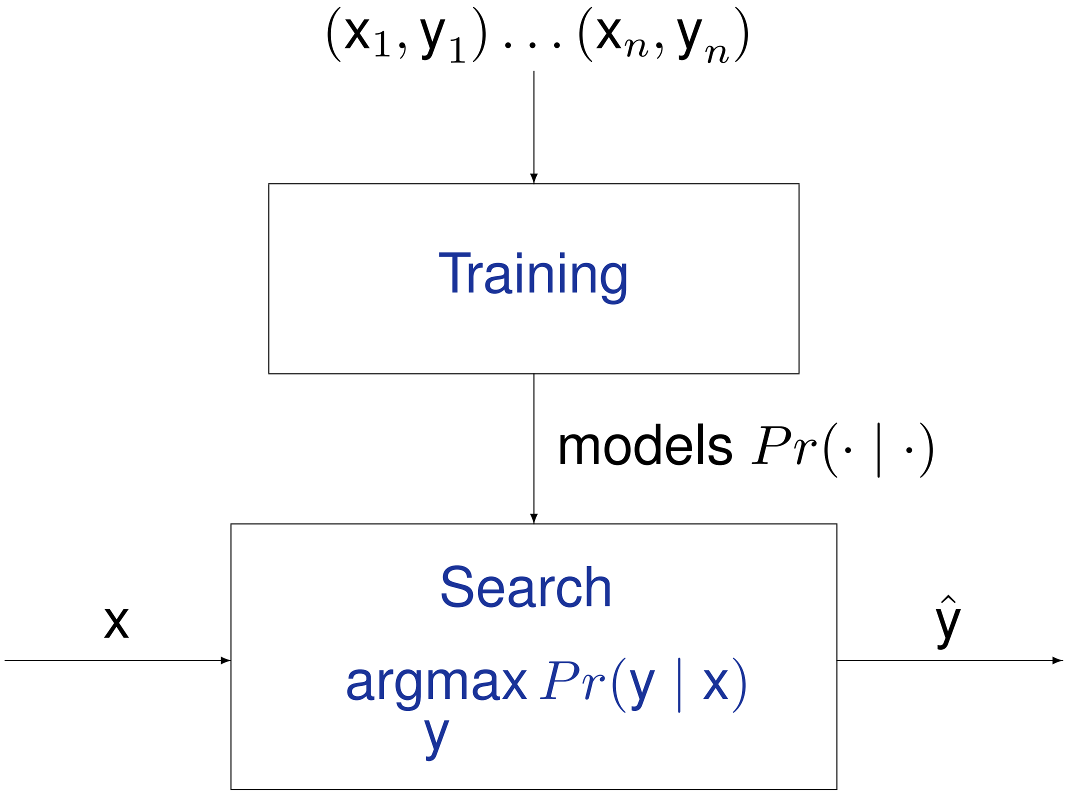
x

Search

$$\underset{\mathrm{y}}{\operatorname{argmax}}\, Pr(\mathrm{y} \mid \mathrm{x})$$

$\hat{\mathrm{y}}$

Training and search


$(x_1, y_1) \ldots (x_n, y_n)$
Training
models $Pr(\cdot \mid \cdot)$
x
Search
$\underset{y}{\text{argmax}}\, Pr(y \mid x)$
$\hat{y}$

Models

- Language models
- Word-based models
  - Alignment models
  - Stochastic dictionary
- Phrase-based models
  - Phrase tables
  - Lexicalized phrase models
  - Reordering model
  - ...

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Language models

In Computational Linguistics (MIARFID)

Word n-grams

$$\Pr(\mathsf{y}) = \prod_{i=1}^{|\mathsf{y}|} \Pr(\mathsf{y}_i \mid \mathsf{y}_1^{i-1}) \approx Pr(\mathsf{y}) = \prod_{i=1}^{|\mathsf{y}|} p_n(\mathsf{y}_i \mid \mathsf{y}_{i-n+1}^{i-1})$$

Regular or context-free grammars

$$\Pr(\mathsf{y}) \approx Pr(\mathsf{y}) = \sum_{d(\mathsf{y})} p_G(d(\mathsf{y})) \approx \max_{d(\mathsf{y})} p_G(d(\mathsf{y}))$$

Neural language models

$$\Pr(\mathsf{y}) = \prod_{i=1}^{|\mathsf{y}|} \Pr(\mathsf{y}_i \mid \mathsf{y}_1^{i-1}) \approx Pr(\mathsf{y}) = \prod_{i=1}^{|\mathsf{y}|} p(\mathsf{y}_i \mid \mathsf{y}_1^{i-1})$$

Learning language models

- Probabilistic estimation techniques: SMOOTHING.
- Grammatical inference techniques.
- Widely used statistical toolkits for n-grams:
  - KenLM Language Model Toolkit
    `http://kheafield.com/code/kenlm/`
  - The IRST Language Modeling Toolkit
    `http://sourceforge.net/projects/irstlm/`
  - SRILM - The SRI Language Modeling Toolkit
    `http://www.speech.sri.com/projects/srilm/`
  - The CMU Statistical Language Modeling (SLM) Toolkit
    `http://www.speech.cs.cmu.edu/SLM_info.html`
- Pre-trained neural language models: BERT (Google) , XLM (Meta), GPT-2 (OpenAI), GPT-3 (OpenAI), BART (Meta), T5 (Google), PaLM (Google), OPT (Meta), BLOOM (BigScience), ...

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Example of word alignments

	I	have	made	a	reservation	for	a	quiet	room	for	Rosario	Cabedo	.
.	.	.	.	.	.	.	.	.	.	.	.	.	■
Cabedo	.	.	.	.	.	.	.	.	.	.	.	■	.
Rosario	.	.	.	.	.	.	.	.	.	.	■	.	.
de	.	.	.	.	.	.	.	.	.	■	.	.	.
nombre	.	.	.	.	.	.	.	.	.	■	.	.	.
a	.	.	.	.	.	.	.	.	.	■	.	.	.
tranquila	.	.	.	.	.	.	.	■	.	.	.	.	.
habitación	.	.	.	.	.	.	.	.	■	.	.	.	.
una	.	.	.	.	.	.	■	.	.	.	.	.	.
de	.	.	.	.	.	■	.	.	.	.	.	.	.
reserva	.	.	.	.	■	.	.	.	.	.	.	.	.
la	.	.	.	■	.	.	.	.	.	.	.	.	.
hecho	.	.	■	.	.	.	.	.	.	.	.	.	.
he	.	■	.	.	.	.	.	.	.	.	.	.	.

Example of word alignments

	could	you	ask	for	a	taxi	,	please	?
taxi	.	.	.	.	.	■	.	.	.
un	.	.	.	.	■	.	.	.	.
pídame	■	■	■	■	.	.	.	.	.
,	.	.	.	.	.	.	■	.	.
favor	.	.	.	.	.	.	.	■	.
por	.	.	.	.	.	.	.	■	.

Example of word alignments

H. Ney, *Statistical Natural Language Processing*, 2003: Canadian Hansards

?	·	·	·	·	·	·	·	·	·	·	·	·	·	·	·	·	·	·	·	·	■
proposal	·	·	·	·	·	■	·	·	·	·	·	·	·	·	·	·	·	·	·	·	·
new	·	·	·	·	■	·	·	·	·	·	·	·	·	·	·	·	·	·	·	·	·
the	·	·	·	■	·	·	·	·	·	·	·	·	·	·	·	·	·	·	·	·	·
under	■	■	■	·	·	·	·	·	·	·	·	·	·	·	·	·	·	·	·	·	·
fees	·	·	·	·	·	·	·	·	·	·	·	·	·	·	·	·	·	■	■	■	·
collecting	·	·	·	·	·	·	·	·	·	·	·	·	·	·	·	■	■	·	·	·	·
and	·	·	·	·	·	·	·	·	·	·	·	·	·	·	■	·	·	·	·	·	·
administering	·	·	·	·	·	·	·	·	·	·	·	·	·	■	·	·	·	·	·	·	·
of	·	·	·	·	·	·	·	·	·	·	·	·	■	·	·	·	·	·	·	·	·
cost	·	·	·	·	·	·	·	·	·	·	■	·	·	·	·	·	·	·	·	·	·
anticipated	·	·	·	·	·	·	·	·	·	·	·	■	·	·	·	·	·	·	·	·	·
the	·	·	·	·	·	·	·	·	·	■	·	·	·	·	·	·	·	·	·	·	·
is	·	·	·	·	·	·	·	·	■	·	·	·	·	·	·	·	·	·	·	·	·
What	·	·	·	·	·	·	■	■	·	·	·	·	·	·	·	·	·	·	·	·	·
	En	vertu	de	les	nouvelles	propositions	,	quel	est	le	cout	prevu	de	administration	et	de	perception	de	les	droits	?

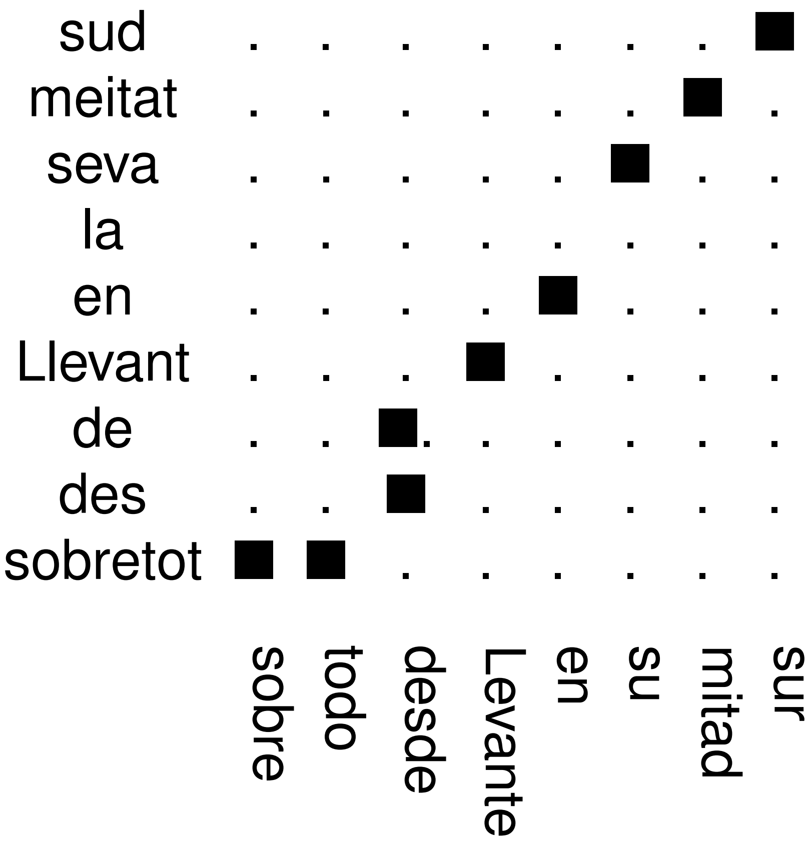
Example of word alignments

AMETRA corpus

1996	.	.	■	.	.
de	.	.	■	.	.
marzo	.	.	.	■	.
de	.	.	.	■	.
20	.	.	.	.	■
a	.	.	.	.	■
,	.	■	.	.	.
Lemoa	■	.	.	.	.
En	■	.	.	.	.
	Lemoan	,	1996ko	martxoaren	20an

Example of word alignments

METEO corpus



	sobre	todo	desde	Levante	en	su	mitad	sur
sud	.	.	.	.	.	.	.	■
meitat	.	.	.	.	.	.	■	.
seva	.	.	.	.	.	■	.	.
la	.	.	.	.	.	.	.	.
en	.	.	.	.	■	.	.	.
Llevant	.	.	.	■	.	.	.	.
de	.	.	■	.	.	.	.	.
des	.	.	■	.	.	.	.	.
sobretot	■	■	.	.	.	.	.	.

Alignments

- **Alignments:** (Brown et al. 90) $J = |\mathsf{x}|$ y $I = |\mathsf{y}|$

$$\mathsf{a} \subseteq \{1, ..., J\} \times \{1, ..., I\}$$

  - Number of connections: $I \; J$
  - Number of alignments: $2^{I \; J}$

- Constrain: $\mathsf{a} : \{1, ..., I\} \rightarrow \{0, ..., J\}$, ($\mathsf{a}_i = 0 \Rightarrow \; i$ in y is not aligned with any position in x).

  - Number of alignments: $(J + 1)^I$

- Inverted alignments: $\mathsf{b} : \{1, ..., J\} \rightarrow \{0, ..., I\}$,

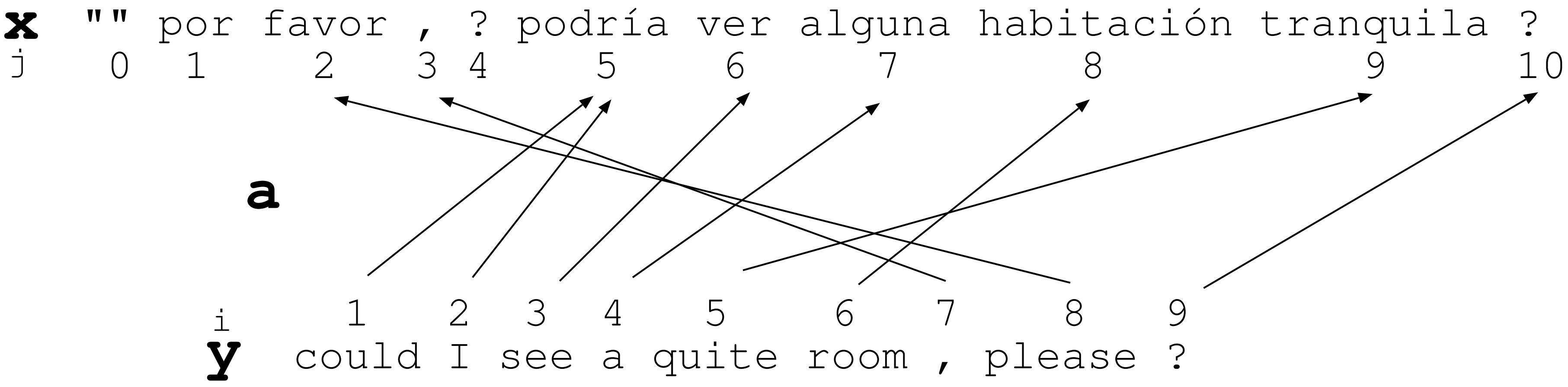
- Notation:

$$\mathsf{x} \equiv \mathsf{x}_1, \ldots, \mathsf{x}_J \equiv \mathsf{x}_1^J$$

$$\mathsf{y} \equiv \mathsf{y}_1, \ldots, \mathsf{y}_I \equiv \mathsf{y}_1^I$$

$$\mathsf{a} \equiv \mathsf{a}_1, \ldots, \mathsf{a}_I \equiv \mathsf{a}_1^I$$

Alignments



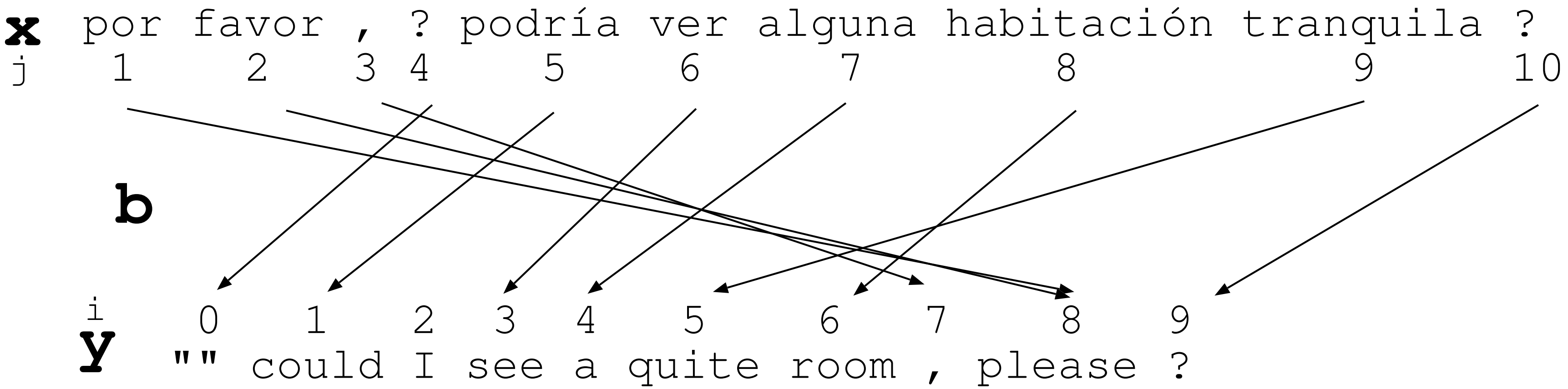
x "" por favor , ? podría ver alguna habitación tranquila ?

j 0 1 2 3 4 5 6 7 8 9 10

a

i 1 2 3 4 5 6 7 8 9

y could I see a quite room , please ?



x por favor , ? podría ver alguna habitación tranquila ?

j 1 2 3 4 5 6 7 8 9 10

b

i 0 1 2 3 4 5 6 7 8 9

y "" could I see a quite room , please ?

Alignments

- Set of possible alignments: $\mathcal{A}(\mathsf{x},\mathsf{y}) = \{\mathsf{a} : \{1, ..., I\} \rightarrow \{0, ..., J\}\}$

- The probability of translation x to y through an alignment a is $\Pr(\mathsf{y}, \mathsf{a} \mid \mathsf{x})$

$$
\begin{aligned}
\Pr(\mathsf{y} \mid \mathsf{x}) &= \Pr(\mathsf{y}, I \mid \mathsf{x}) \\
&= \Pr(I \mid \mathsf{x}) \ \Pr(\mathsf{y} \mid I, \mathsf{x}) \\
&= \Pr(I \mid \mathsf{x}) \sum_{\mathsf{a} \in \mathcal{A}(\mathsf{x},\mathsf{y})} \Pr(\mathsf{y}, \mathsf{a} \mid I, \mathsf{x}) \\
&= \Pr(I \mid \mathsf{x}) \sum_{\mathsf{a} \in \mathcal{A}(\mathsf{x},\mathsf{y})} \Pr(\mathsf{a} \mid I, \mathsf{x}) \ \Pr(\mathsf{y} \mid \mathsf{a}, I, \mathsf{x})
\end{aligned}
$$

- Length probability: $\Pr(I \mid \mathsf{x}) \approx \mathcal{N}(I \mid J)$

Alignments

$$\Pr(\mathsf{y}, \mathsf{a} \mid I, \mathsf{x}) = \Pr(\mathsf{a} \mid I, \mathsf{x}) \; \Pr(\mathsf{y} \mid \mathsf{a}, I, \mathsf{x})$$

$$\Pr(\mathsf{a} \mid I, \mathsf{x}) = \prod_{i=1}^{I} \Pr(\mathsf{a}_i \mid \mathsf{a}_1^{i-1}, I, \mathsf{x}) \qquad \Pr(\mathsf{y} \mid \mathsf{a}, I, \mathsf{x}) = \prod_{i=1}^{I} \Pr(\mathsf{y}_i \mid \mathsf{y}_1^{i-1}, \mathsf{a}, I, \mathsf{x})$$

$$\Pr(\mathsf{y}, \mathsf{a} \mid I, \mathsf{x}) = \prod_{i=1}^{I} \Pr(\mathsf{a}_i \mid \mathsf{a}_1^{i-1}, I, \mathsf{x}) \; \Pr(\mathsf{y}_i \mid \mathsf{y}_1^{i-1}, \mathsf{a}, I, \mathsf{x})$$

$$\Pr(\mathsf{y} \mid \mathsf{x}) = \Pr(I \mid \mathsf{x}) \sum_{\mathsf{a} \in \mathcal{A}(\mathsf{x}, \mathsf{y})} \prod_{i=1}^{I} \Pr(\mathsf{a}_i \mid \mathsf{a}_1^{i-1}, I, \mathsf{x}) \; \Pr(\mathsf{y}_i \mid \mathsf{y}_1^{i-1}, \mathsf{a}, I, \mathsf{x})$$

Alignments

$$\Pr(\mathsf{y}, \mathsf{a} \mid I, \mathsf{x}) = \prod_{i=1}^{I} \Pr(\mathsf{a}_i \mid \mathsf{a}_1^{i-1}, I, \mathsf{x}) \; \Pr(\mathsf{y}_i \mid \mathsf{y}_1^{i-1}, \mathsf{a}, I, \mathsf{x})$$

- Alignment probability: $\Pr(\mathsf{a}_i \mid \mathsf{a}_1^{i-1}, I, \mathsf{x})$
- Lexicon probability: $\Pr(\mathsf{y}_i \mid \mathsf{y}_1^{i-1}, \mathsf{a}, I, \mathsf{x})$

- Zero-order translation models
  - Model 1
  - Model 2
  - Fertility: Model 3
- First-order translation models
  - Hidden Markov models
  - Model 4
  - Model 5
  - Model 6

Model 1

$$\Pr(\mathsf{y}, \mathsf{a} \mid I, \mathsf{x}) = \prod_{i=1}^{I} \Pr(\mathsf{a}_i \mid \mathsf{a}_1^{i-1}, I, \mathsf{x}) \ \Pr(\mathsf{y}_i \mid \mathsf{y}_1^{i-1}, \mathsf{a}, I, \mathsf{x})$$

- $\Pr(\mathsf{a}_i \mid \mathsf{a}_1^{i-1}, I, \mathsf{x}) \approx \frac{1}{(J+1)}$
- $\Pr(\mathsf{y}_i \mid \mathsf{y}_1^{i-1}, \mathsf{a}, I, \mathsf{x}) \approx l(\mathsf{y}_i \mid \mathsf{x}_{\mathsf{a}_i})$

- $l(\mathsf{y}_i \mid \mathsf{x}_j)$ defines a **statistical lexicon**

$$\Pr(\mathsf{y} \mid \mathsf{x}) = \Pr(I \mid \mathsf{x}) \sum_{\mathsf{a}} \Pr(\mathsf{y}, \mathsf{a} \mid I, \mathsf{x}) \approx P_{M1}(\mathsf{y} \mid \mathsf{x}) = \frac{\mathcal{N}(I \mid J)}{(J+1)^I} \prod_{i=1}^{I} \sum_{j=0}^{J} l(\mathsf{y}_i \mid \mathsf{x}_j)$$

Model 1

$$
\begin{aligned}
\Pr(\mathsf{y} \mid \mathsf{x}) &= \Pr(I \mid \mathsf{x}) \sum_{\mathsf{a}} \Pr(\mathsf{y}, \mathsf{a} \mid I, \mathsf{x}) \\
&\approx \mathcal{N}(I \mid J) \sum_{\mathsf{a}} \prod_{i=1}^{I} \left[\frac{1}{(J+1)} \, l(\mathsf{y}_i \mid \mathsf{x}_{\mathsf{a}_i}) \right] \\
&= \frac{\mathcal{N}(I \mid J)}{(J+1)^I} \sum_{\mathsf{a}_1=0}^{J} \cdots \sum_{\mathsf{a}_I=0}^{J} \prod_{i=1}^{I} l(\mathsf{y}_i \mid \mathsf{x}_{\mathsf{a}_i}) \\
&= \frac{\mathcal{N}(I \mid J)}{(J+1)^I} \prod_{i=1}^{I} \sum_{\mathsf{a}_i=0}^{J} l(\mathsf{y}_i \mid \mathsf{x}_{\mathsf{a}_i}) \\
&= \frac{\mathcal{N}(I \mid J)}{(J+1)^I} \prod_{i=1}^{I} \sum_{j=0}^{J} l(\mathsf{y}_i \mid \mathsf{x}_j) = P_{M1}(\mathsf{y} \mid \mathsf{x})
\end{aligned}
$$

Model 1: parameter estimation

- Training sample: $A = \{(\mathsf{x}^{(1)}, \mathsf{y}^{(1)}), (\mathsf{x}^{(2)}, \mathsf{y}^{(2)}), \ldots, (\mathsf{x}^{(N)}, \mathsf{y}^{(N)})\}$
- Goal: maximize the likelihood (or log-likelihood)

$$\operatorname*{argmax}_{l} \mathcal{L}_A(l) = \operatorname*{argmax}_{l} \log \prod_{n=1}^{N} P_{M1}(\mathsf{y}^{(n)} \mid \mathsf{x}^{(n)}) = \operatorname*{argmax}_{l} \sum_{n=1}^{N} \log P_{M1}(\mathsf{y}^{(n)} \mid \mathsf{x}^{(n)})$$

- Procedure: Expectation-maximization or growth transformations:

```
Initialize $l$ and counts $c(y,x)$ for all source and target words $y$ and $x$
Iterate
    For all training sample $(\mathsf{x}^{(n)}, \mathsf{y}^{(n)}) \in A$
        For all source word $x \in \mathsf{x}^{(n)}$ and target word $y \in \mathsf{y}^{(n)}$
            *Counting step:* $c(y,x) = c(y,x) + \frac{l(y \mid x)\ \#(x, \mathsf{x}^{(n)})\ \#(y, \mathsf{y}^{(n)})}{\sum_{j=0}^{J^{(n)}} l(y \mid \mathsf{x}_j^{(n)})}$
    For all source word $x \in L_X$ and target word $y \in L_Y$
        *Normalization step:* $l(y \mid x) = \frac{c(y,x)}{\sum_{y'} c(y',x)}$
until convergence
```

Parameter estimation in Model 1

- PROPERTY: the increase of the likelihood of the training set in each iteration:

$$\prod_{n=1}^{N} P_{M1(k)}(\mathsf{y}^{(n)} \mid \mathsf{x}^{(n)}) \leq \prod_{n=1}^{N} P_{M1(k+1)}(\mathsf{y}^{(n)} \mid \mathsf{x}^{(n)})$$

- PROPERTY: eventually an absolute maximum is achieved!

- COMPUTATIONAL COST : if $I_M = \max_n I^{(n)}$ y $J_M = \max_n J^{(n)}$

  - time: $O(N \times (I_M + J_M))$
  - space: $O(|L_X| \times |L_Y|)$

- Public software for training Model 1: `https://github.com/moses-smt/mgiza`

Model 2

$$\Pr(\mathsf{y}, \mathsf{a} \mid I, \mathsf{x}) = \prod_{i=1}^{I} \Pr(\mathsf{a}_i \mid \mathsf{a}_1^{i-1}, I, \mathsf{x}) \; \Pr(\mathsf{y}_i \mid \mathsf{y}_1^{i-1}, \mathsf{a}, I, \mathsf{x})$$

- $\Pr(\mathsf{a}_i \mid \mathsf{a}_1^{i-1}, I, \mathsf{x}) \approx a(\mathsf{a}_i \mid i, I, J)$
- $\Pr(\mathsf{y}_i \mid \mathsf{y}_1^{i-1}, \mathsf{a}, I, \mathsf{x}) \approx l(\mathsf{y}_i \mid \mathsf{x}_{\mathsf{a}_i})$

- $l(\mathsf{y}_i \mid \mathsf{x}_j)$ defines a **statistical lexicon**
- $a(j \mid i, I, J)$ defines **statistical alignments**

$$\Pr(\mathsf{y} \mid \mathsf{x}) \approx P_{M2}(\mathsf{y} \mid \mathsf{x}) = \mathcal{N}(I \mid J) \prod_{i=1}^{I} \sum_{j=0}^{J} a(j \mid i, I, J) \; l(\mathsf{y}_i \mid \mathsf{x}_j) \qquad \text{(Exercise)}$$

Parameter estimation (l and a):
Public software for training Model 2: `https://github.com/moses-smt/mgiza`

Optimal alignment with Model 2

Search for the “best” alignment from $\mathcal{A}(\mathsf{x},\mathsf{y})$

$$\begin{aligned}
\Pr(\mathsf{y} \mid \mathsf{x}) &= \Pr(I \mid \mathsf{x}) \sum_{\mathsf{a}\in\mathcal{A}(\mathsf{y},\mathsf{x})} \Pr(\mathsf{y},\mathsf{a} \mid I, \mathsf{x}) \\
&\approx \Pr(I \mid \mathsf{x}) \max_{\mathsf{a}\in\mathcal{A}(\mathsf{y},\mathsf{x})} \Pr(\mathsf{y},\mathsf{a} \mid I, \mathsf{x}) = \widehat{\Pr}(\mathsf{y} \mid \mathsf{x})
\end{aligned}$$

Using Model 2,

$$\begin{aligned}
\widehat{\Pr}(\mathsf{y} \mid \mathsf{x}) &= \Pr(I \mid \mathsf{x}) \max_{\mathsf{a}} \Pr(\mathsf{y},\mathsf{a} \mid I, \mathsf{x}) \\
&\approx \mathcal{N}(I \mid J) \max_{\mathsf{a}} \prod_{i=1}^{I} [a(\mathsf{a}_i \mid i, I, J)\; l(\mathsf{y}_i \mid \mathsf{x}_{\mathsf{a}_i})] \\
&= \mathcal{N}(I \mid J) \prod_{i=1}^{I} \max_{0\leq j\leq J} [a(j \mid i, I, J)\; l(\mathsf{y}_i \mid \mathsf{x}_j)] = \widehat{P}_{M2}(\mathsf{y} \mid \mathsf{x})
\end{aligned}$$

Optimal alignment with Model 2

```
Algorithm Viterbi (x, y, $l$, $a$)
Input: A pair x, y and the parameters $l$ and $a$ of Model 2
Output: An optimal alignment $A$ between x and y.

For $i = 1$ until $I$
    $A[i] := \operatorname{argmax}_{0 \leq j \leq J} [a(j \mid i, I, J)\ l(\mathrm{y}_i \mid \mathrm{x}_j)]$
End-for
Return: $A$
```

- The computational cost of this algorithm is $O(J \times I)$.
- Public software for training Models 1 and 2 and for computing the optimal alignments: `https://github.com/moses-smt/mgiza`
- Optimal alignments can be used in an alternative training procedure: Viterbi estimation (exercise)

Fast_align: An alternative to alignment with Model 2 [Dyer NAACL 2013]

$a(j \mid i, I, J)$ is not a table[1]

$$h(i,j,I,J) = -\left|\frac{i}{I} - \frac{j}{J}\right|$$

$$a(j \mid i, I, J) = \begin{cases} p_0 & j = 0 \\ (1-p_0)\,\frac{\exp(\lambda\ h(i,j,I,J))}{Z_\lambda(i,I,J)} & 0 < j \leq J \\ 0 & \text{otherwise} \end{cases}$$

$$Z_\lambda(i,I,J) = \sum_{j=1}^{J} \exp(\lambda\, h(i,j,I,J))$$

$Z_\lambda(i, I, J)$ can be computed in $O(1)$[1]

[1] http://github.com/clab/fast_align

Examples of alignments

EuTrans-I corpus: Spanish-English

- Vocabulary: 680 Spanish words, and 513 English words.
- Training: 10,000 pairs (97,000/99,000 words).

An example

1	2	3	4	5	6	7	8	9	10
por	favor	,	¿	podría	ver	alguna	habitación	tranquila	?

- Model 1, Iteration 5
  could (5) I (6) see (6) a (7) quiet (9) room (8) , (3) please (2) ? (4)
- Model 2, Iteration 2
  could (5) I (6) see (6) a (7) quiet (9) room (8) , (3) please (3) ? (10)

Homogeneous HMM alignment

$$\Pr(\mathsf{y}, \mathsf{a} \mid I, \mathsf{x}) = \prod_{i=1}^{I} \Pr(\mathsf{a}_i \mid \mathsf{a}_1^{i-1}, \mathsf{y}_1^{i-1}, I, \mathsf{x}) \; \Pr(\mathsf{y}_i \mid \mathsf{a}_1^{i}, \mathsf{y}_1^{i-1}, I, \mathsf{x})$$

- $\Pr(\mathsf{a}_i \mid \mathsf{a}_1^{i-1}, \mathsf{y}_1^{i-1}, I, \mathsf{x}) \approx h(\mathsf{a}_i \mid \mathsf{a}_{i-1}, I, J)$
- $\Pr(\mathsf{y}_i \mid \mathsf{a}_1^{i}, \mathsf{y}_1^{i-1}, I, \mathsf{x}) \approx l(\mathsf{y}_i \mid \mathsf{x}_{\mathsf{a}_i})$

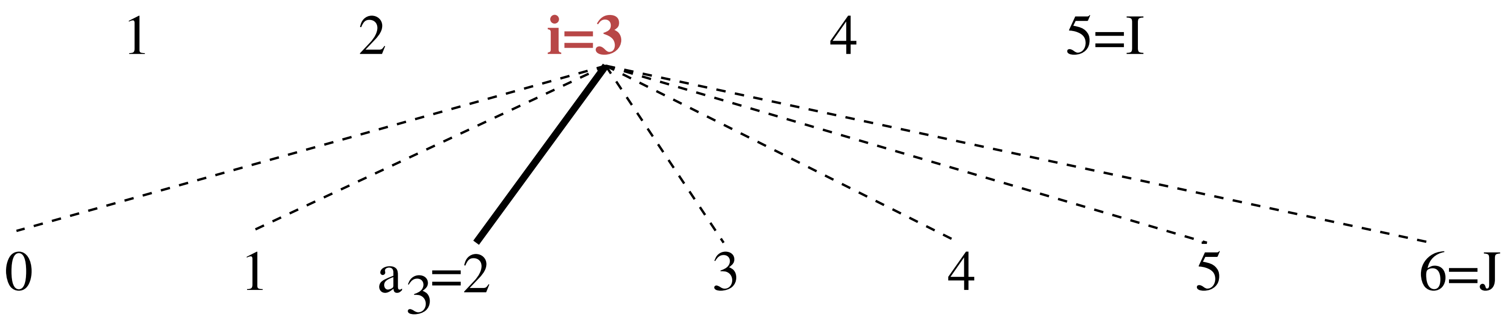
$h(\mathsf{a}_i \mid \mathsf{a}_{i-1}, I, J)$ defines statistical alignment with first-order dependencies

$$h(j \mid j', I, J) = \frac{q(j - j')}{\sum_{j''=1}^{J} q(j'' - j')}$$

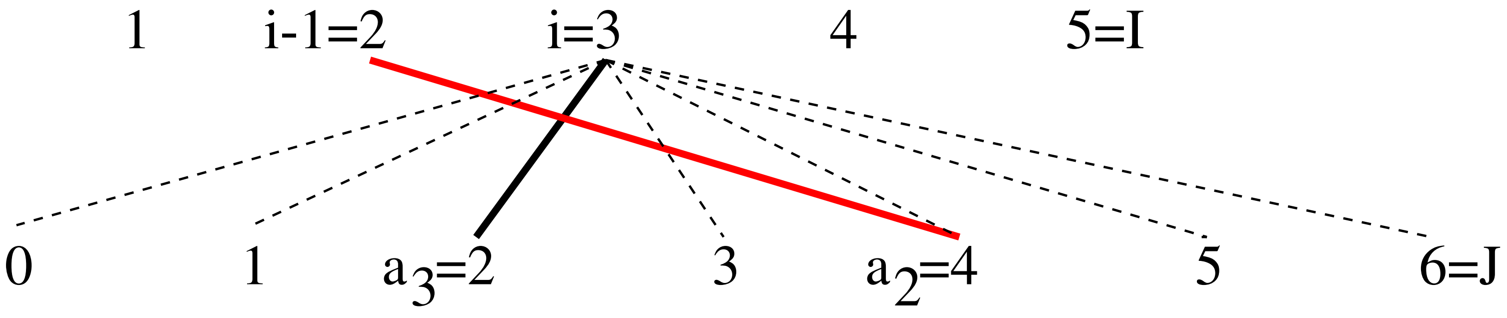
A set of non-negative parameters $q(j - j')$

Homogeneous HMM alignment

A comparison between alignments in M2 and HMM



$\mathtt{a}(a_3=2 \mid i=3, I=5, J=6)$



$h(a_3=2 \mid a_2=4, I=5, J=6)$

Homogeneous HMM alignment

$$P_{HMM}(\mathsf{y} \mid \mathsf{x}) = \mathcal{N}(I \mid J) \sum_{\mathsf{a}} \prod_{i=1}^{I} h(\mathsf{a}_i \mid \mathsf{a}_{i-1}, I, J)\; l(\mathsf{y}_i \mid \mathsf{x}_{\mathsf{a}_i})$$

- Forward computation of $P_{HMM}(\mathsf{y} \mid \mathsf{x})$: $P_{HMM}(\mathsf{y} \mid \mathsf{x}) = \mathcal{N}(I \mid J)\; Q(I, J)$ with

$$Q(i, j) = l(\mathsf{y}_i \mid \mathsf{x}_j) \sum_{j'} h(j \mid j', I, J)\; Q(i-1, j')$$

- Using a maximum approach:

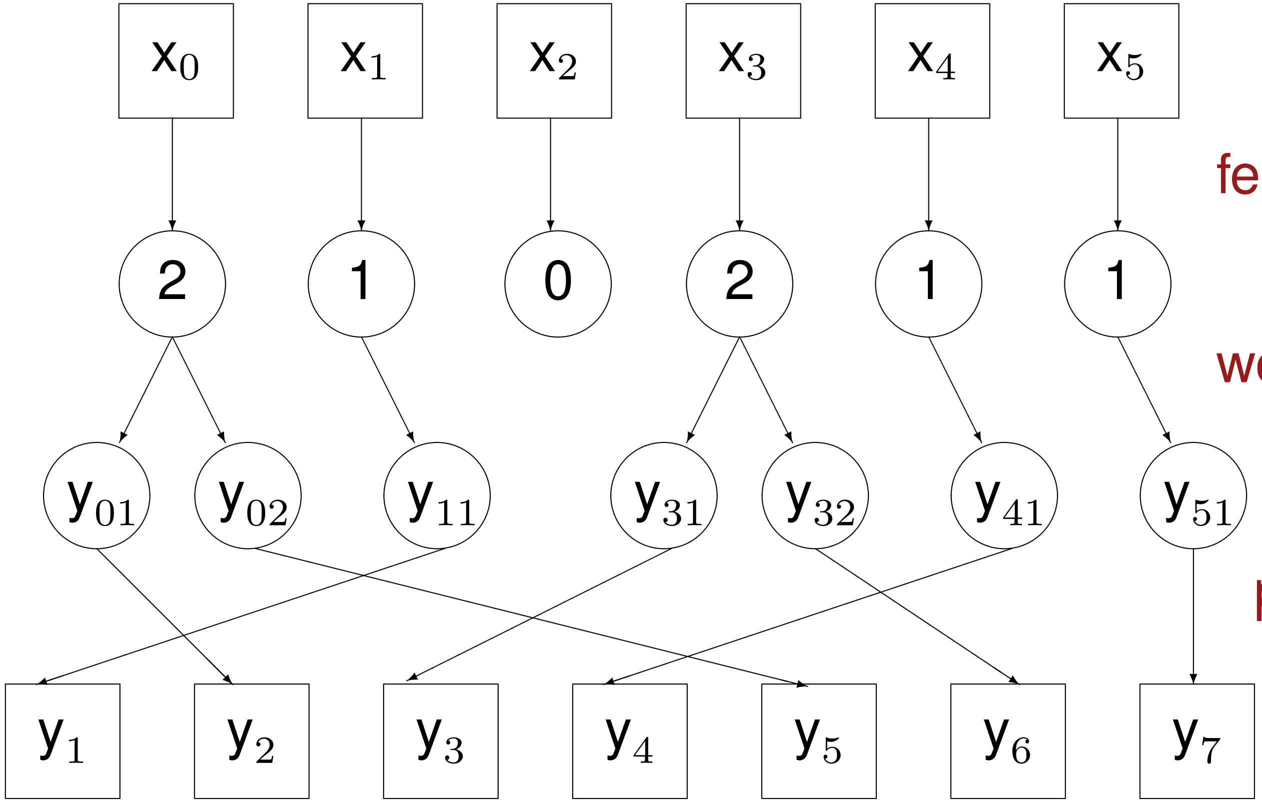
$$\widehat{P}_{HMM}(\mathsf{y} \mid \mathsf{x}) = \mathcal{N}(I \mid J)\; \max_{\mathsf{a}} \prod_{i=1}^{I} h(\mathsf{a}_i \mid \mathsf{a}_{i-1}, I, J)\; l(\mathsf{y}_i \mid \mathsf{x}_{\mathsf{a}_i}) = \mathcal{N}(I \mid J)\; \widehat{Q}(I, J)$$

$$\widehat{Q}(i, j) = l(\mathsf{y}_i \mid \mathsf{x}_j)\; \max_{j'} \Big(h(j \mid j', I, J)\; \widehat{Q}(i-1, j') \Big)$$

- Training with the maximum approach
  - Position alignment by computing $\widehat{Q}(i, j)$
  - Parameter estimation (relative frequencies)

Fertility

source sentence



fertility generation

word generation

permutation generation

target sentence

Fertility

Fertility ϕ of x$_j \in L_X$: number of the target words connected to a source word x$_j$.

1. Choose how many target words are connected to a source word x$_j$: *fertility* of x$_j$: $\phi_j = \phi(\mathrm{x}_j)$
2. Choose a set of the target words, a *tablet* τ_j, that is connected to j-th target word $\tau_{j,k} \in L_X$ for $1 \leq k \leq \phi(\mathrm{x}_j)$
3. Choose the *position* $\pi_{j,k}$ in the target source sentence of the k-th word $\tau_{j,k}$ that is connected to the j-th source word, $1 \leq \pi_{j,k} \leq I$

Model 3

$$\Pr(\mathsf{y} \mid \mathsf{x}) = \sum_{\mathsf{a}} \Pr(\mathsf{y}, \mathsf{a} \mid \mathsf{x}) = \sum_{\mathsf{a}} \sum_{(\tau,\pi)\in\mathcal{F}(\phi,\mathsf{y},\mathsf{a})} \Pr(\phi, \tau, \pi \mid \mathsf{x})$$

The probability for a tablet τ and a permutation π is:

$$\Pr(\phi, \tau, \pi \mid \mathsf{x}) = \Pr(\phi \mid \mathsf{x}) \; \Pr(\tau \mid \phi, \mathsf{x}) \; \Pr(\pi \mid \tau, \phi, \mathsf{x})$$

- $\Pr(\phi_j \mid \phi_1^{j-1}, \mathsf{x}) \approx f(\phi_j \mid \mathsf{x}_j)$ *fertility probability*
- $\Pr(\tau_{jk} = y \mid \tau_{j,1}^{k-1}, \tau_0^{j-1}, \phi_0^J, \mathsf{x}) \approx l(y \mid \mathsf{x}_j)$ *lexicon probability*
- $\Pr(\pi_{jk} = i \mid \pi_{j,1}^{k-1}, \pi_1^{j-1}, \tau_0^J, \phi_0^J, \mathsf{x}) \approx d(i \mid j, I, J)$ *distortion probability*

$$P_{M3}(\mathsf{y} \mid \mathsf{x}) = \sum_{\mathsf{a}} \sum_{(\tau,\pi)\in\mathcal{F}(\phi,\mathsf{y},\mathsf{a})} P_{M3}(\phi, \tau, \pi \mid \mathsf{x}) =$$

$$\sum_{a_1=0}^{J} \cdots \sum_{a_I=0}^{J} \binom{I-\phi_0}{\phi_0} p_0^{I-2\phi_0} \, p_1^{\phi_0} \prod_{j=1}^{J} \phi_j! \; f(\phi_j \mid \mathsf{x}_j) \; \prod_{i=1}^{I} l(\mathsf{y}_i \mid \mathsf{x}_{\mathsf{a}_i}) \; d(i \mid \mathsf{a}_i, I, J)$$

Examples of alignments

Corpus EuTrans-I: Spanish-English

1	2	3	4	5	6	7	8	9	10
por	favor	,	¿	podría	ver	alguna	habitación	tranquila	?

- Model 1, Iteration 5
  could (5) I (6) see (6) a (7) quiet (9) room (8) , (3) please (2) ? (4)

- Model 2, Iteration 2
  could (5) I (6) see (6) a (7) quiet (9) room (8) , (3) please (3) ? (10)

- Model 3, Iteration 2
  could (5) I (5) see (6) a (7) quiet (9) room (8) , (3) please (2) ? (10)

Model 4 & 5

- $\Pr(\phi_j \mid \phi_1^{j-1}, \mathsf{x}) \approx f(\phi_j \mid \mathsf{x}_j)$ *fertility probability*
- $\Pr(\pi_{jk} = y \mid \tau_{j,1}^{k-1}, \tau_0^{j-1}, \phi_0^J, \mathsf{x}) \approx l(y \mid \mathsf{x}_j)$ *lexicon probability*
- $\Pr(\pi_{jk} = i \mid \pi_{j,1}^{k-1}, \pi_1^{j-1}, \tau_0^J, \phi_0^J, \mathsf{x}) \approx$ two first-order models *distortion probability*
  - *distortion probability for the first position in a tablet*
  - *distortion probability for the rest of positions in a tablet*

The training process

- Every model has a specific set of free parameters. For example for IBM Model 4: $\theta = \left\{ \{l(y \mid x)\}, \{p_{=1}(\Delta_i)\}, \{p_{>1}(\Delta_i)\}, \{p(\phi \mid x)\}, p_1 \right\}$
- To train the model parameters θ: A maximum likelihood criterium, using a parallel training corpus consisting of S sentence pairs $\{(\mathsf{x}^{(n)}, \mathsf{y}^{(n)}) : n = 1, \ldots, N\}$:

$$\hat{\theta} = \underset{\theta}{\text{argmax}} \prod_{n=1}^{N} \sum_{\mathsf{a}} p_\theta(\mathsf{y}^{(n)}, \mathsf{a} \mid \mathsf{x}^{(n)})$$

- The training is carried out using the Expectation-Maximization (EM) algorithm.
- The estimated counts are approximate by:
  - Computing the (approximate) most probable alignment (Model 2 or HMM)
  - Apply modifications: moves and swaps
  - Sum the estimated counts for all alignments whose probability is larger than the probability of the probable alignment times a given constant.
- Initialization: random, model 1 (5 iterations), model 2 or HMM (0-2 iterations), model 3 (3 iterations), model 4 (3 iterations).

Brown et al. *The mathematics of statistical machine translation: parameter estimation.* Comput. Ling., 19(2):263–310, 1993.

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Categorization

- Too many parameters to be estimated

- Many words play the same role: names, dates, etc.

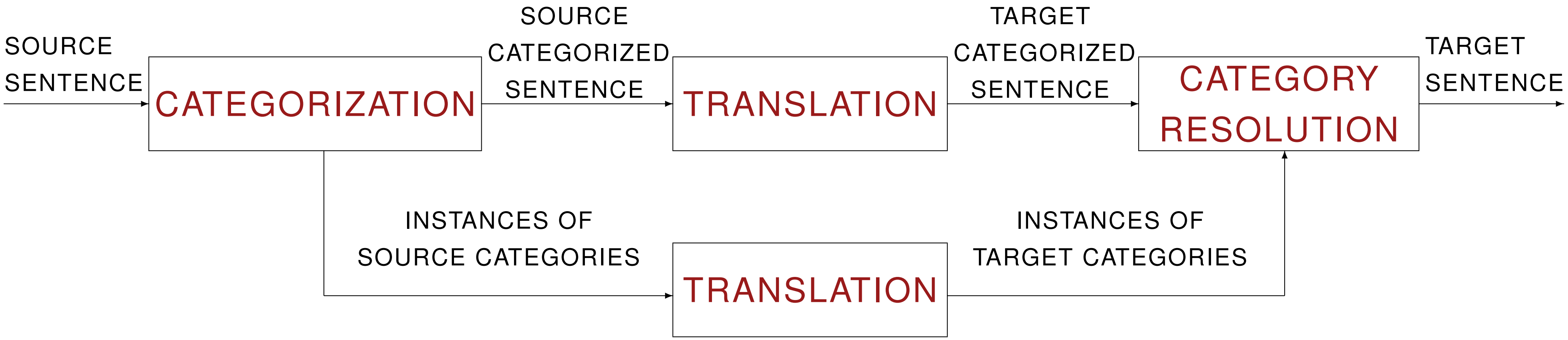
- Substitution of words by categories:
  - The vocabulary size decreases.
  - Easy word addition to the vocabulary.

- Examples:
  - `mi nombre es $NAME.masc $SURNAME . # my name is $NAME.masc $SURNAME .`
  - `nos vamos a ir el  $DATE a $HOUR . # we are leaving on $DATE at $HOUR .`

- Given a bilingual corpus:
  - Automatic extraction of bilingual categories.
  - Manual extraction of bilingual categories.

An approach

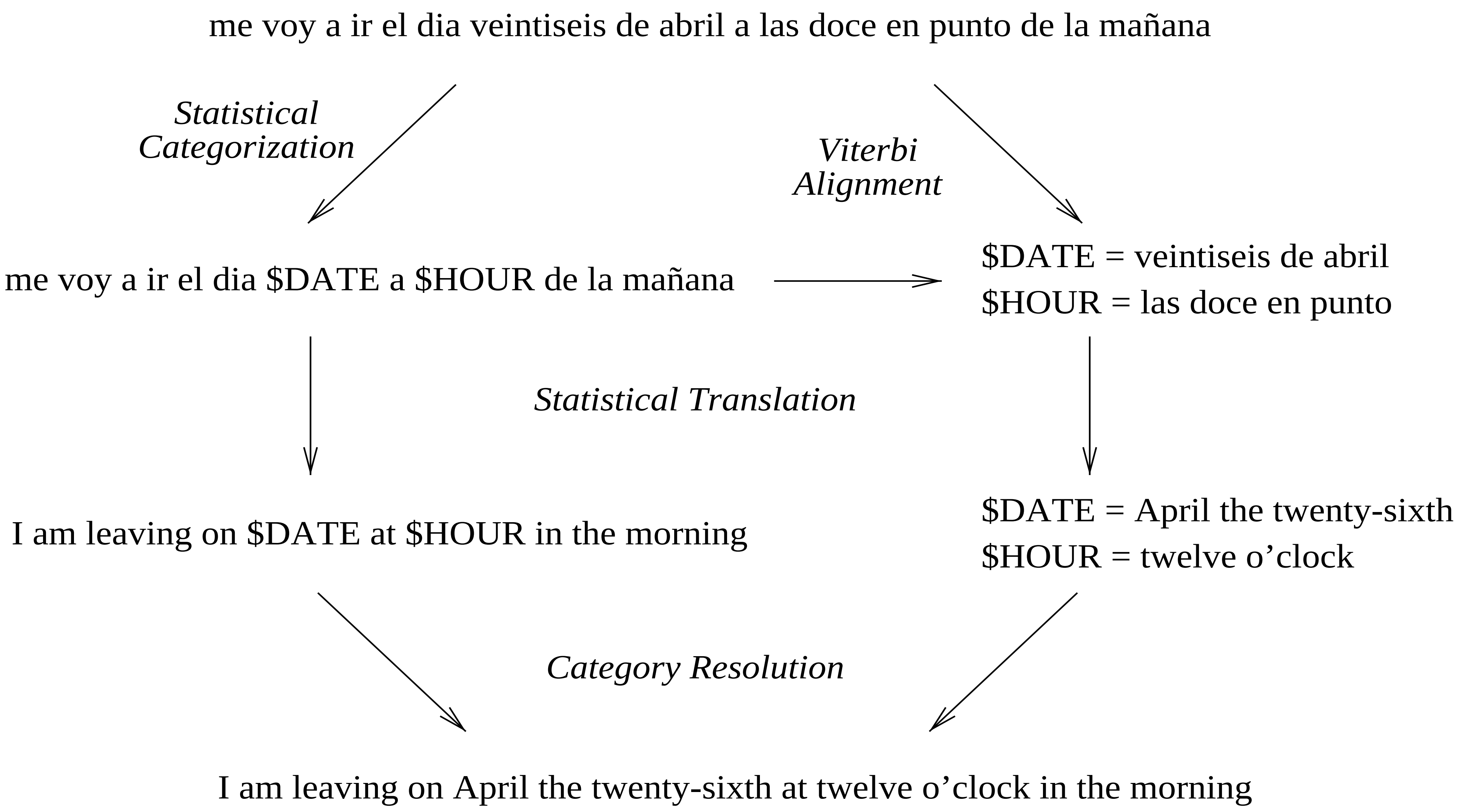
(I.Garcia-Varea, F.Casacuberta. *An iterative, DP-based search algorithm for statistical machine translation.* ICSLP. 1998.)


SOURCE SENTENCE
CATEGORIZATION
SOURCE CATEGORIZED SENTENCE
TRANSLATION
TARGET CATEGORIZED SENTENCE
CATEGORY RESOLUTION
TARGET SENTENCE
INSTANCES OF SOURCE CATEGORIES
TRANSLATION
INSTANCES OF TARGET CATEGORIES

1. CATEGORIZATION: Translating the source sentence into an source categorized sentence and obtaining the source instances of each category.
2. CATEGORIZED TRANSLATION: Translating the source categorized sentence into a target categorized sentence.
3. TRANSLATION OF EACH CATEGORY: Translating the source instances of each category detected.
4. CATEGORY RESOLUTION: Substitution of each target category by the corresponding instance translation.

An example

(I.Garcia-Varea, F.Casacuberta. *An iterative, DP-based search algorithm for statistical machine translation.* ICSLP. 1998.)



me voy a ir el dia veintiseis de abril a las doce en punto de la mañana

Statistical Categorization

Viterbi Alignment

me voy a ir el dia $DATE a $HOUR de la mañana

$DATE = veintiseis de abril

$HOUR = las doce en punto

Statistical Translation

I am leaving on $DATE at $HOUR in the morning

$DATE = April the twenty-sixth

$HOUR = twelve o'clock

Category Resolution

I am leaving on April the twenty-sixth at twelve o'clock in the morning

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Phrase-based models

- Modelling the correspondences between word segments (phrases)
- Log-linear models: combining different models.
- Moses: a widely used free software, statistical machine translation engine that can be used to train statistical models.

Exemple of word alignments

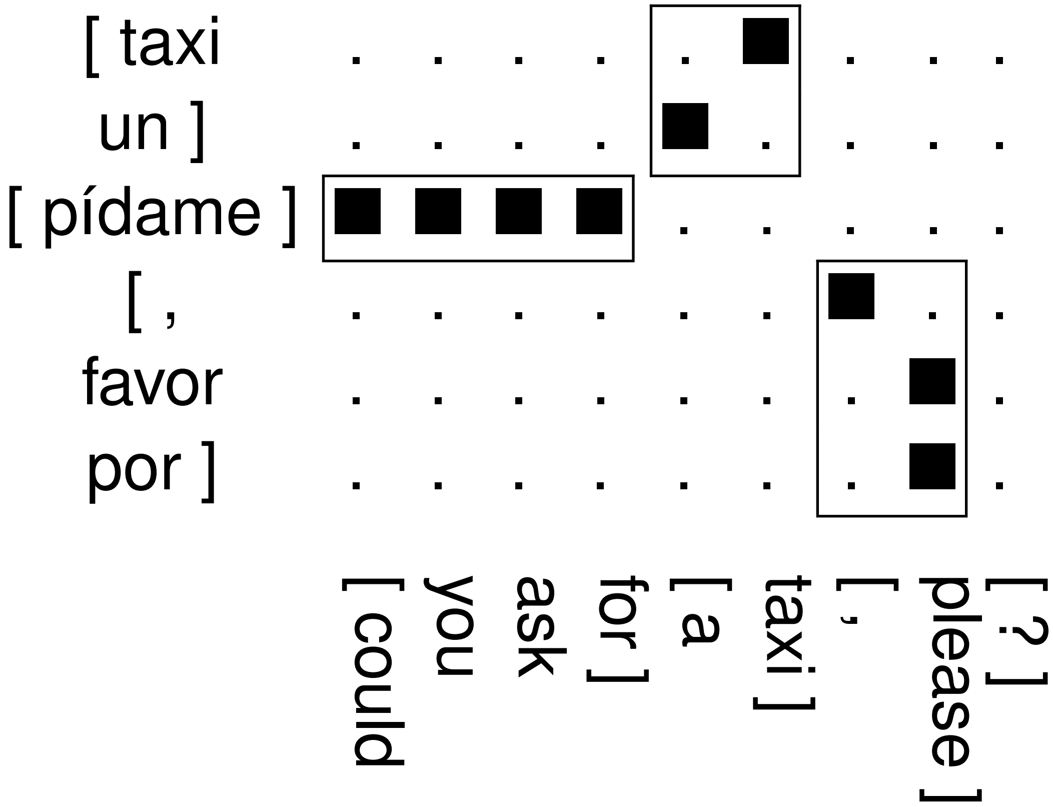
taxi	.	.	.	.	.	■	.	.	.
un	.	.	.	.	■	.	.	.	.
pídame	■	■	■	■	.	.	.	.	.
,	.	.	.	.	.	.	■	.	.
favor	.	.	.	.	.	.	.	■	.
por	.	.	.	.	.	.	.	■	.
	could	you	ask	for	a	taxi	,	please	?

Segment alignment

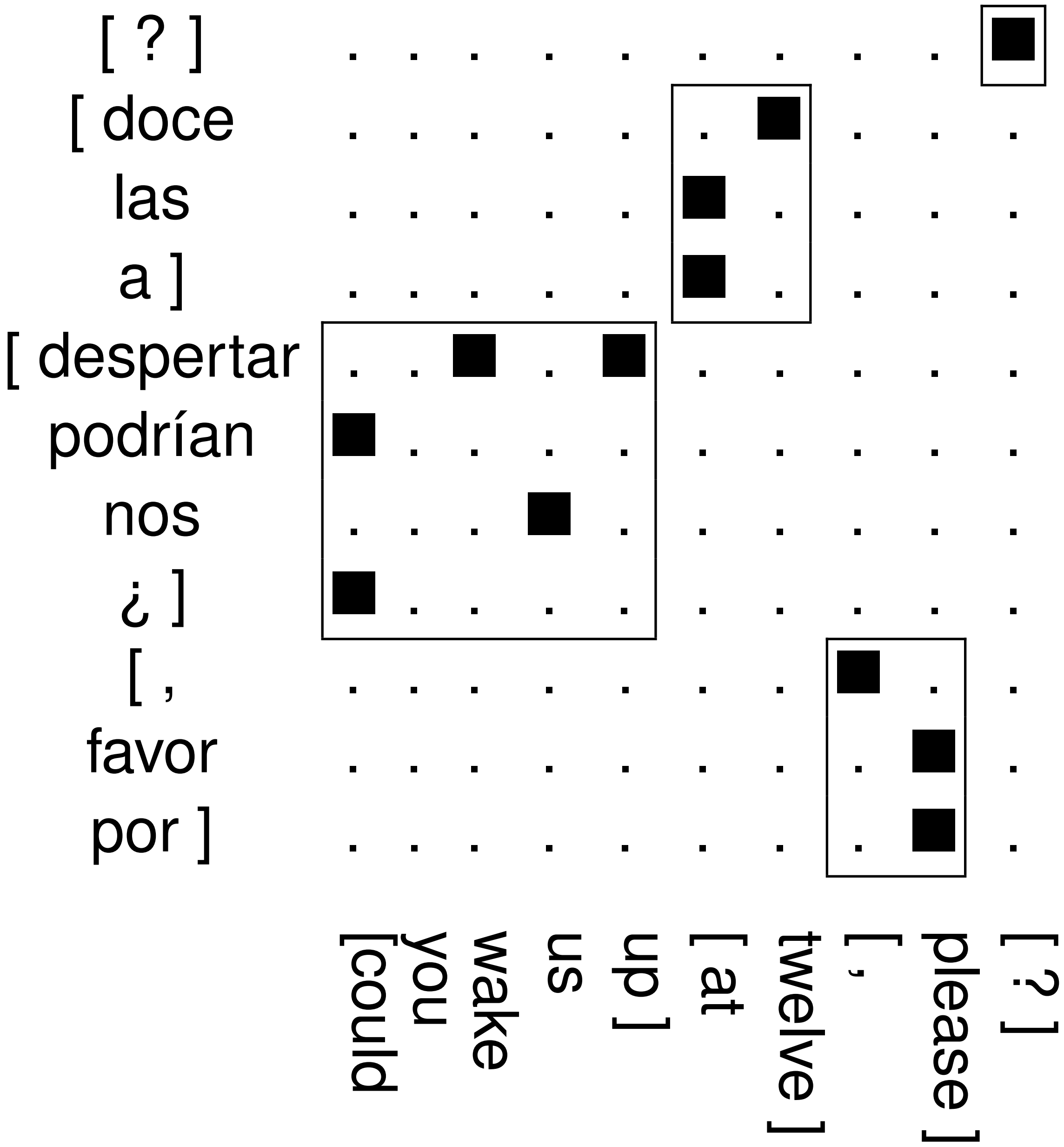
SINGLE-WORD ALIGNMENTS: only model the correspondence between words.

Alternative:

SEGMENT ALIGNMENTS: modelling the correspondences between word segments.



Segment alignment



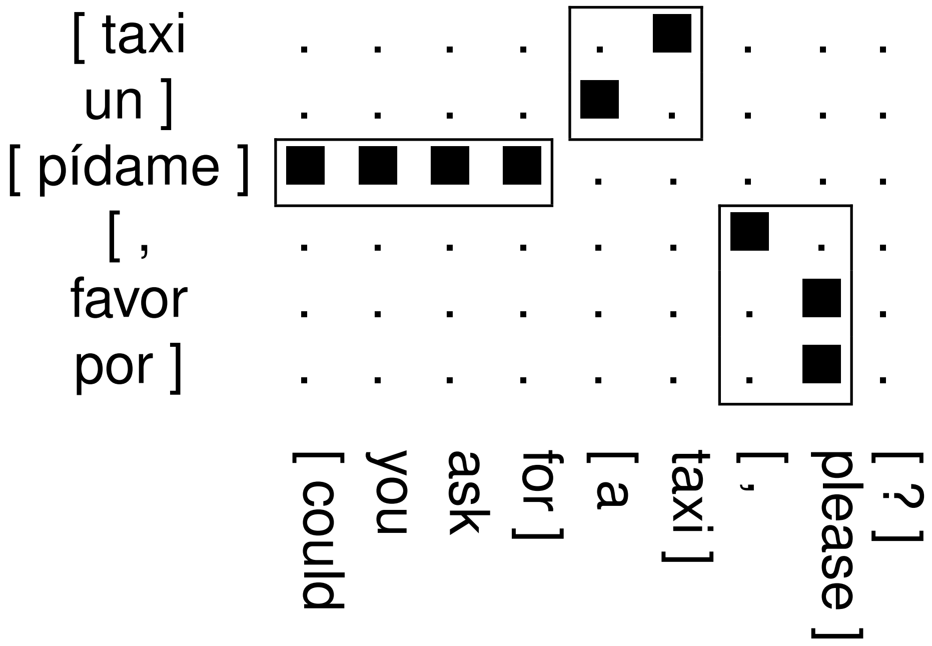
	[could	you	wake	us	up]	[at	twelve]	[,	please]	[?]
[?]	.	.	.	.	.	.	.	.	.	■
[doce	.	.	.	.	.	.	■	.	.	.
las	.	.	.	.	.	■	.	.	.	.
a]	.	.	.	.	.	■	.	.	.	.
[despertar	.	.	■	.	■	.	.	.	.	.
podrían	■	.	.	.	.	.	.	.	.	.
nos	.	.	.	■	.	.	.	.	.	.
¿]	■	.	.	.	.	.	.	.	.	.
[,	.	.	.	.	.	.	.	■	.	.
favor	.	.	.	.	.	.	.	.	■	.
por]	.	.	.	.	.	.	.	.	■	.

Beyond word-based models

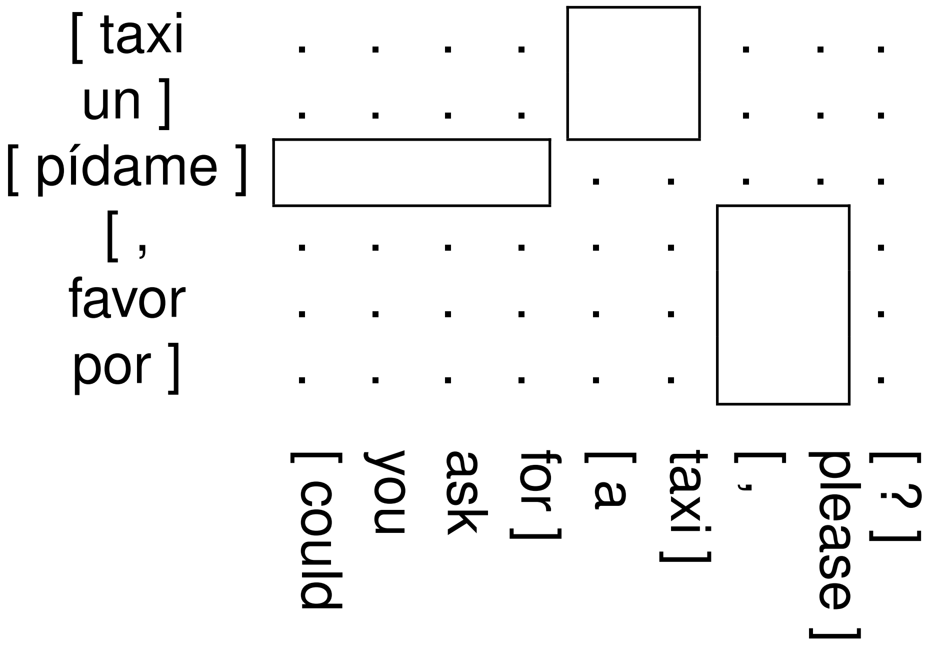
- The basic assumption in the word-based models: Each source word is generated by only one target word.
- This assumption does not correspond to the nature of natural language. In some cases, it is necessary to know the context.
- Solutions:
  - *Context-dependent dictionaries*. The basic unit is the word.
  - *Word sequences*:
    - *Alignment templates*: A sequence of source (classes of) words is aligned with a sequence of target (classes of) words. Inside the templates there are word-to-word correspondences. The basic unit is the word. (Och & Ney, CL, 2006)
    - *Phrase-based models*: [1] A sequence of source words is aligned with a sequence of target words. The basic unit is the phrase. (Koehn, 2010)
    - *Hierarchical phrase-based models*: Phrases that contain subphrases. The model is formally a synchronous context-free grammar. (Koehn, 2010)

[1] By “phrase” we will mean a possible word sequence.

Word sequences



Alignment templates



Bilingual phrases

Phrase-based models

- The *bilingual phrases* are pairs of word sequences.
- Bilingual phrases are related with a bilingual segmentation.
- The statistical dictionaries of single word pairs are substituted by statistical dictionaries of bilingual phrases.
- Problems:
  - The generalisation capability, since only word sequences that appear in a segmentation of the training corpus are accepted.
  - The selection of adequate bilingual phrases.

An example

x: could you ask for a taxi , please ?

	x	could you ask for	a taxi	, please ?
	j	1 2 3 4	5 6	7 8 9=J
Segmentation	μ	μ_1	μ_2	μ_3
Translation	y	[pídame]	[un taxi .]	[por favor ,]
Permutation	α	$\alpha_1 = 2$	$\alpha_2 = 3$	$\alpha_3 = 1$
		por favor ,	pídame	un taxi .
	i	1 2 3	4	5 6 7=I
Segmentation	γ	γ_1	γ_2	γ_3

y: por favor , pídame un taxi .

General framework

- Given a source sentence x and a target sentence y.
- Assumption: Let K be the number of segments in x and in y,
- Process:
  - Segmentation of the source sentence

$$\mu : \{1, \dots, K\} \rightarrow \{1, \dots, J\} : \mu_k \geq \mu_{k-1} \;\; 1 < k \leq K \;\; \& \;\; \mu_K = J$$

  - Source phrases: $\bar{\mathsf{x}}_k = \mathsf{x}_{\mu_{k-1}+1}, \dots, \mathsf{x}_{\mu_k} \equiv \mathsf{x}_{\mu_{k-1}+1}^{\mu_k}$ for $1 \leq k \leq K$
  - Target phrases: $\bar{\mathsf{y}}_k$ translation of $\bar{\mathsf{x}}_k$
  - Segment alignment (Permutation): $\alpha : \{1, \dots, K\} \rightarrow \{1, \dots, K\} : \alpha_k = \alpha_{k'}$ iff $k = k'$
  - Target sentence: $\bar{\mathsf{y}}_{\alpha_1}, \dots, \bar{\mathsf{y}}_{\alpha_K}$

General framework

- The most used models are inspired in HMM word-models:
  - Statistical dictionaries: $l(\mathrm{y}_i \mid \mathrm{x}_j)$
  - Statistical alignment with first-order dependencies: $h(\mathrm{a}_i \mid \mathrm{a}_{i-1}, J)$

  For a given source sentence x and a given target length I:

$$P_{HMM}(\mathrm{y} \mid \mathrm{x}) = \sum_{\mathrm{a}} \prod_{i=1}^{I} h(\mathrm{a}_i \mid \mathrm{a}_{i-1}, J)\, l(\mathrm{y}_i \mid \mathrm{x}_{\mathrm{a}_i})$$

- For phrase-based models
  - Phrase tables: $p(\bar{\mathrm{y}} \mid \bar{\mathrm{x}})$
  - First-order alignments between phrases or segments: $q(\alpha_k \mid \alpha_{k-1}, K)$

  For a given source sentence x and a given target length I:

$$P_{PB}(\mathrm{y} \mid \mathrm{x}) = \sum_{K} \sum_{\mu_1^K} \sum_{\alpha_1^K} \sum_{\gamma_1^K} \prod_{k=1}^{K} q(\alpha_k \mid \alpha_{k-1}, K)\, p(\mathrm{y}_{\gamma_{\alpha_k-1}+1}^{\gamma_{\alpha_k}} \mid \mathrm{x}_{\mu_{k-1}+1}^{\mu_k})$$

Monotone vs. no monotone alignments

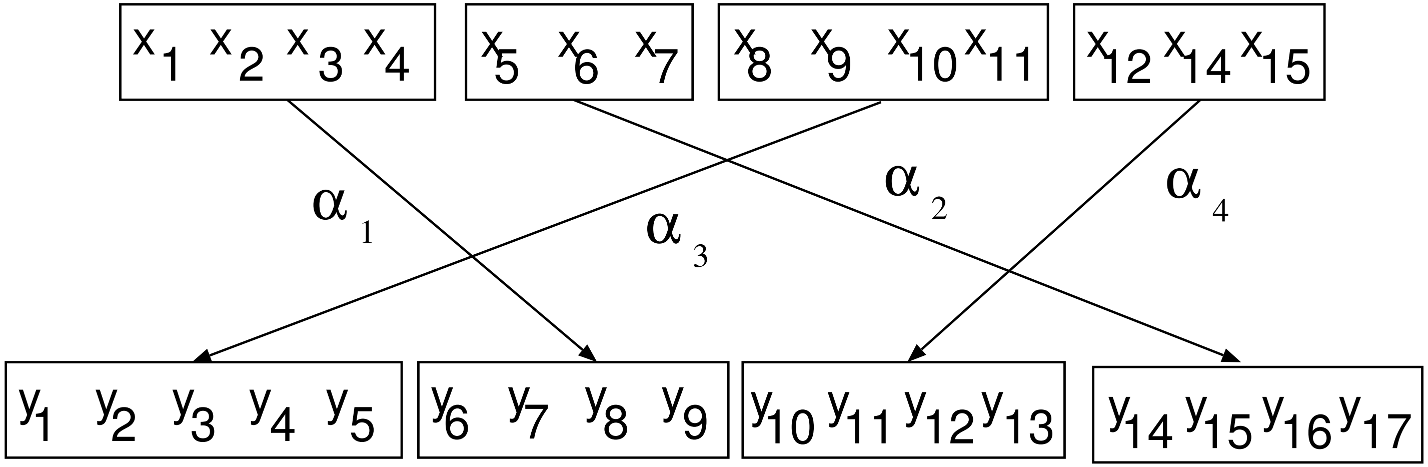
No monotone alignment

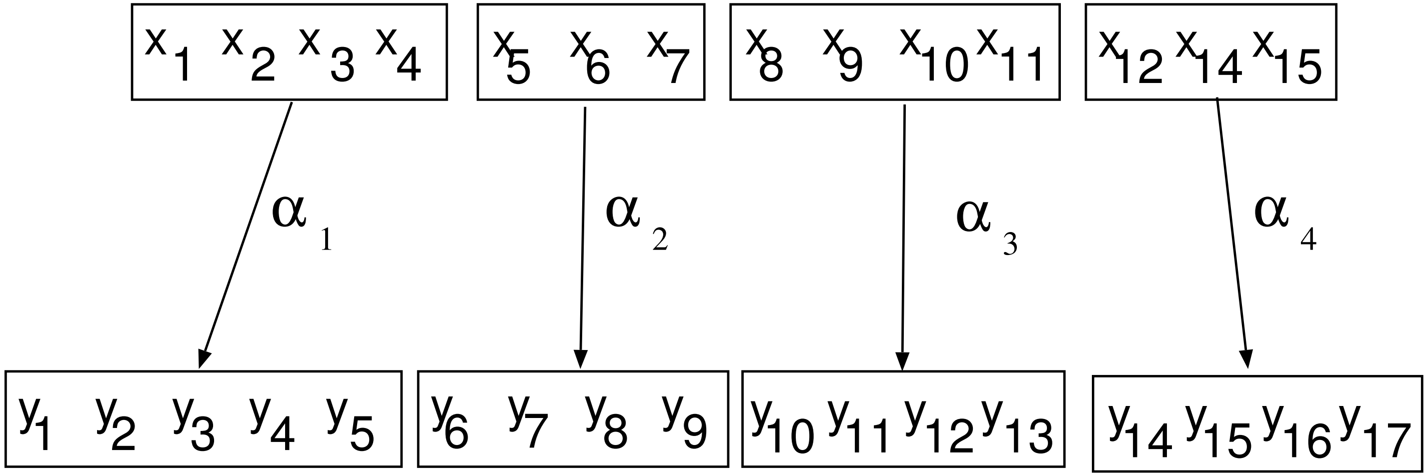
$$\Pr(\mathsf{y} \mid \mathsf{x}) \approx P(\mathsf{y} \mid \mathsf{x}) = \mathcal{N}(I \mid J) \sum_{K} \sum_{\mu_1^K} \sum_{\alpha_1^K} \sum_{\gamma_1^K} \prod_{k=1}^{K} q(\alpha_k \mid \alpha_{k-1})\, p(\mathsf{y}_{\gamma_{\alpha_k -1}+1}^{\gamma_{\alpha_k}} \mid \mathsf{x}_{\mu_{k-1}+1}^{\mu_k})$$

Monotone alignment ⇒ $\alpha_k = k$

$$\Pr(\mathsf{y} \mid \mathsf{x}) \approx P(\mathsf{y} \mid \mathsf{x}) = \mathcal{N}(I \mid J) \sum_{K} \sum_{\mu_1^K} \sum_{\gamma_1^K} \prod_{k=1}^{K} p(\mathsf{y}_{\gamma_{k-1}+1}^{\gamma_k} \mid \mathsf{x}_{\mu_{k-1}+1}^{\mu_k})$$

Monotone vs. no monotone alignments





Log-linear models

Search for a target sentence with maximum *posterior* probability:

$$\underset{\mathsf{y}}{\text{argmax}}\,\Pr(\mathsf{y} \mid \mathsf{x}) = \underset{\mathsf{y}}{\text{argmax}} \frac{\exp\left(\sum_{m=1}^{M} \lambda_m h_m(\mathsf{x},\mathsf{y})\right)}{\sum_{\mathsf{y}'} \exp\left(\sum_{m=1}^{M} \lambda_m h_m(\mathsf{x},\mathsf{y}')\right)} = \underset{\mathsf{y}}{\text{argmax}} \sum_{m=1}^{M} \lambda_m h_m(\mathsf{x},\mathsf{y})$$

- Target language model: $h_1(\mathsf{x},\mathsf{y}) = \log Pr(\mathsf{y})$ (from a n-gram model)
- Phrase-based model: $h_2(\mathsf{x},\mathsf{y}) = \log Pr_{PB}(\mathsf{y} \mid \mathsf{x})$, (from the phrase table $p(\tilde{\mathsf{y}} \mid \tilde{\mathsf{x}})$)
- Phrase-based inverse model: $h_3(\mathsf{x},\mathsf{y}) = \log Pr_{PB}(\mathsf{x} \mid \mathsf{y})$, (from the inverse phrase table $p(\tilde{\mathsf{x}} \mid \tilde{\mathsf{y}})$)
- Reordering model: $h_4(\mathsf{x},\mathsf{y}) = q(\alpha_k \mid \alpha_{k-1}) = \frac{\gamma^{|\alpha_k - \alpha_{k-1}|}}{\mathcal{Q}_{\mathcal{N}}}$ ($\mathcal{Q}_{\mathcal{N}}$ is a normalization factor)
- More features

Log-linear models: More features

- Lexicalized model: $h_4(\mathsf{x}, \mathsf{y}) = \log Pr_{LEX}(\mathsf{x} \mid \mathsf{y})$ computed from $p_{lex}(\tilde{\mathsf{y}} \mid \tilde{\mathsf{x}}, \tilde{\mathsf{a}})$, where $\tilde{\mathsf{a}}$ is a word alignement from $\tilde{\mathsf{x}}$ to $\tilde{\mathsf{y}}$.

$$p_{lex}(\tilde{\mathsf{y}} \mid \tilde{\mathsf{x}}, \tilde{\mathsf{a}}) = \prod_{i=1}^{|\tilde{\mathsf{y}}|} \frac{1}{|\{j \mid (i,j) \in \tilde{\mathsf{a}}\}|} \sum_{(i,j)\in\tilde{\mathsf{a}}} l(\mathsf{y}_i \mid \mathsf{x}_j)$$

- Inverse lexicalized model: $h_5(\mathsf{x}, \mathsf{y}) = \log Pr_{LEX}(\mathsf{y} \mid \mathsf{x})$ computed from $p_{lex}(\tilde{\mathsf{x}} \mid \tilde{\mathsf{y}}, \tilde{\mathsf{b}})$, where $\tilde{\mathsf{b}}$ is a word alignement from $\tilde{\mathsf{y}}$ to $\tilde{\mathsf{x}}$.

$$p_{lex}(\tilde{\mathsf{x}} \mid \tilde{\mathsf{y}}, \tilde{\mathsf{b}}) = \prod_{j=1}^{|\tilde{\mathsf{x}}|} \frac{1}{|\{i \mid (i,j) \in \tilde{\mathsf{b}}\}|} \sum_{(i,j)\in\tilde{\mathsf{b}}} l(\mathsf{x}_j \mid \mathsf{y}_i)$$

- Target word penalty: $\log I$

- Phrase penalty: $\log K$

- More ...

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Learning phrase-based models

- Training with a sentence-aligned corpus.
  - Using the EM algorithm
    (Marcu & Wong, EMNLP, 2002, Andrés-Ferrer et al., AAI, 2008)
- Training with a word-aligned corpus.
  - Symmetrization alignments and counting
    (Koehn, Statistical Machine Translation, 2010)
- Complementary techniques.
  - Phrase-table pruning (Sanchis et al., EAMT, 2011)
  - Incremental learning (Ortiz et al, NAACL, 2010)

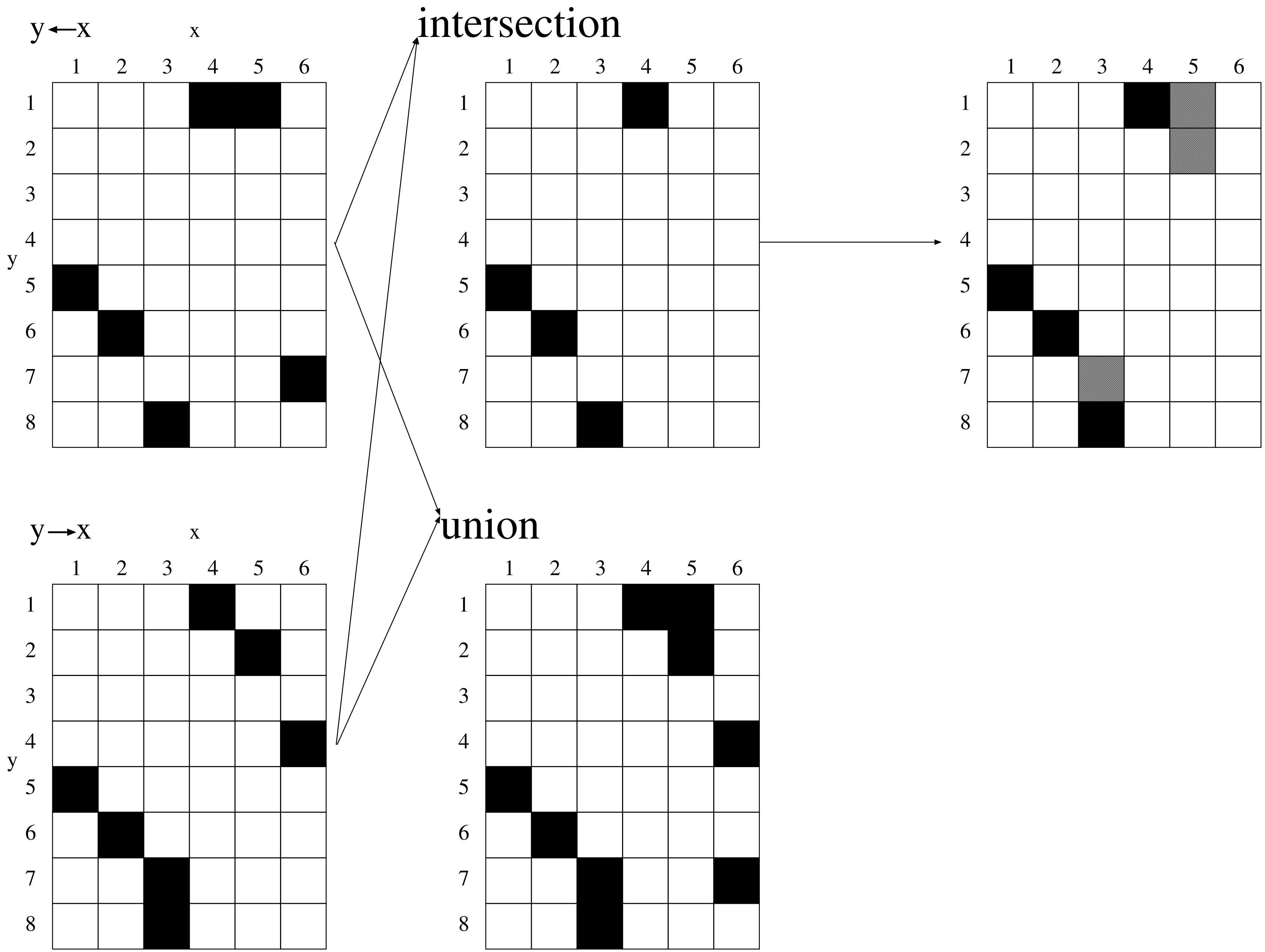
Symmetrized aligments

[M. Federico 2008]

Given a sentence-aligned corpus $\mathcal{T} = \{(\mathrm{x}_1, \mathrm{y}_1), \ldots, (\mathrm{x}_N, \mathrm{y}_N)\}$:

- For a pair $(\mathrm{x}_n, \mathrm{y}_n)$, of length J_n and I_n, alignments are computed using mgiza:
  - Alignment from target to source: $\mathrm{a} : \{1, ..., I_n\} \rightarrow \{0, ..., J_n\}$
  - Alignment from source to target: $\mathrm{b} : \{1, ..., J_n\} \rightarrow \{0, ..., I_n\}$
- The symmetrized aligments can be obtained:
  - Union: $\mathrm{u} = \{(i, j) \mid 1 \leq i \leq I_n, 1 \leq j \leq J_n, \mathrm{a}_i = j \text{ OR } \mathrm{b}_j = i\}$
  - Intersection $\mathrm{i} = \{(i, j) \mid 1 \leq i \leq I_n, 1 \leq j \leq J_n, \mathrm{a}_i = j \text{ AND } \mathrm{b}_j = i\}$
  - Grow-diagonal: intersection plus selected links from a and b
- A set of bilingual word sequences from a word simmetrized aligned corpus
- The parameters of the phrase-model are estimated.

Symmetrized aligments



y←x

y \ x	1	2	3	4	5	6
1				■	■	
2						
3						
4						
5	■					
6		■				
7						■
8			■			

y→x

y \ x	1	2	3	4	5	6
1				■		
2					■	
3						
4						■
5	■					
6		■				
7			■			
8			■			

intersection

	1	2	3	4	5	6
1				■		
2						
3						
4						
5	■					
6		■				
7						
8			■			

union

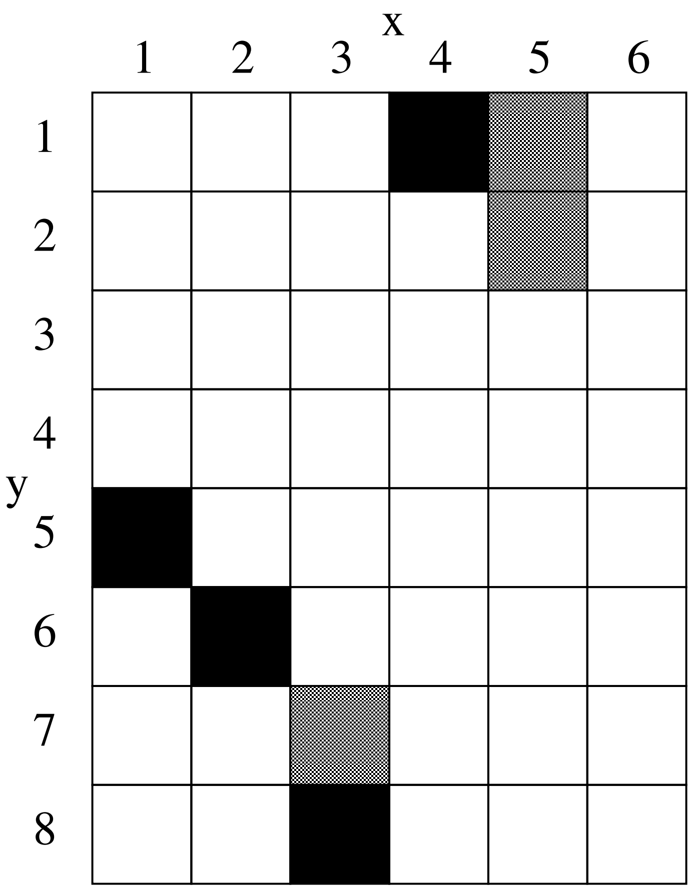
	1	2	3	4	5	6
1				■	■	
2					■	
3						
4						■
5	■					
6		■				
7			■			■
8			■			

	1	2	3	4	5	6
1				■	▨	
2					▨	
3						
4						
5	■					
6		■				
7			▨			
8			■			

Extracting bilingual phrases

[M. Federico 2008]

$(\widetilde{x}, \widetilde{y})$ is a phrase-pair $(\mathrm{x}_{j_1}^{j_2}, \mathrm{y}_{i_1}^{i_2})$ from a pair (x, y) by a symmetrized aligment if the set of target positions linked to source positions in $[j_1, \ldots, j_2]$ by the alignment is included in $[i_1, \ldots, i_2]$ and viceversa



y \ x	1	2	3	4	5	6
1				■	▨	
2					▨	
3						
4						
5	■					
6		■				
7			▨			
8			■			

$(\mathrm{x}_4, \mathrm{y}_1),\ (\mathrm{x}_4\mathrm{x}_5, \mathrm{y}_1),\ (\mathrm{x}_4\mathrm{x}_5, \mathrm{y}_1\mathrm{y}_2),$

$(\mathrm{x}_5, \mathrm{y}_1),\ (\mathrm{x}_5, \mathrm{y}_1\mathrm{y}_2),\ (\mathrm{x}_5, \mathrm{y}_2)$

$(\mathrm{x}_1, \mathrm{y}_5),\ (\mathrm{x}_1\mathrm{x}_2, \mathrm{y}_5\mathrm{y}_6),\ \ldots$

$(\mathrm{x}_2\mathrm{x}_3, \mathrm{y}_6\mathrm{y}_7\mathrm{y}_8),\ \ldots$

Estimating the phrase table and the distortion model

- Phrase probabilities by relative frequencies: for each pair of segments $(\widetilde{x}, \widetilde{y})$:

$$p(\widetilde{y} \mid \widetilde{x}) = \frac{N(\widetilde{y}, \widetilde{x})}{N(\widetilde{x})} \qquad p(\widetilde{x} \mid \widetilde{y}) = \frac{N(\widetilde{y}, \widetilde{x})}{N(\widetilde{y})}$$

where $N(\widetilde{y})$ denotes the number of times that phrase $\widetilde{y}$ has appeared, and $N(\widetilde{x}, \widetilde{y})$ is the number of times that the bilingual phrase $(\widetilde{x}, \widetilde{y})$ has appeared.

- Distortion model $p(\alpha_k \mid \alpha_{k-1})$:

$$p(\alpha_k \mid \alpha_{k-1}) = p_0^{|\gamma_{\alpha_k} - \gamma_{\alpha_{k-1}}|}$$

where p_0 is a parameter to be ajusted using a validation set.

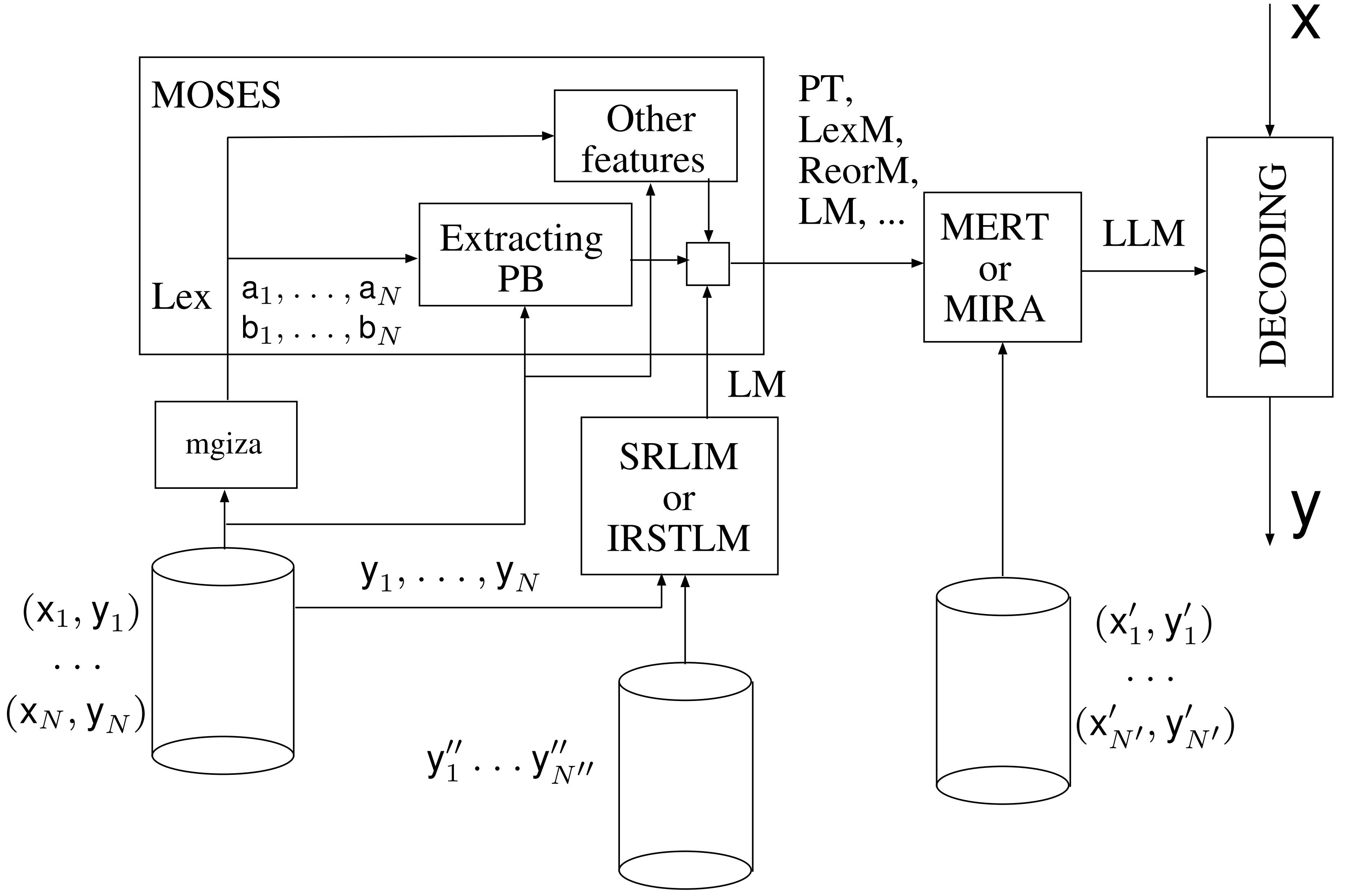
Learning log-linear models

- Learning the features $h_m(\text{x}, \text{y})$ for $1 \leq m \leq M$. Target language model, phrase-based models, phrase-based inverse models, reordering model, lexicalized model, inverse lexicalized model, target word penalty, phrase penalty, ...
- Estimate the weights λ_i of the log-linear model using a developpment set and the Minimum Error Rate Training (MERT) or Margin Infused Relaxed Algorithm (MIRA) procedures

Learning features of the log-linear models

- Given a sentence-aligned corpus $\mathcal{T} = \{(\mathsf{x}_1, \mathsf{y}_1), \ldots, (\mathsf{x}_N, \mathsf{y}_N)\}$
- Training target language models ($Pr(\mathsf{y})$) using the target sentences of the bilingual training corpus $\{\mathsf{y}_1, \ldots, \mathsf{y}_N\}$ (maybe with the addition of other target data)
- Use mgiza with the bilingual corpus $\mathcal{T}$ to build:
  - a symetrized word-aligned corpus from word-alignement in both directions;
  - a stochastic dictionary
- Build the set of bilingual phrases and estimate $p(\widetilde{x} \mid \widetilde{y})$ and $p(\widetilde{y} \mid \widetilde{x})$ (inverse phrase translation probability and direct phrase translation probability)
- Build the set of lexical bilingual weighting lex $p_{lex}(\widetilde{x} \mid \widetilde{y})$ and $p_{lex}(\widetilde{y} \mid \widetilde{x})$ (inverse lexical weighting and direct lexical weighting)
- Build the rest of the models: phrase penalty, distance-based reordering model, word penalty and others

Learning log-linear models



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The search problem in statistical machine translation

$$\hat{\text{y}} = \underset{\text{y}}{\text{argmax}} \Pr(\text{y} \mid \text{x}) = \underset{\text{y}}{\text{argmax}} \sum_{k=1}^{K} \lambda_k h_k(\text{x}, \text{y})$$

- $h_1(\text{x}, \text{y}) = \log Pr(\text{y})$, a language model
- $h_2(\text{x}, \text{y}) = \log Pr(\text{y} \mid \text{x})$, a translation model model
- $h_3(\text{x}, \text{y}) = \log Pr(\text{x} \mid \text{y})$, an inverse translation model model
- $\ldots$

- Search is a **NP**-Hard problem. (Knight, 1999) (Udupa and Maji, 2006)

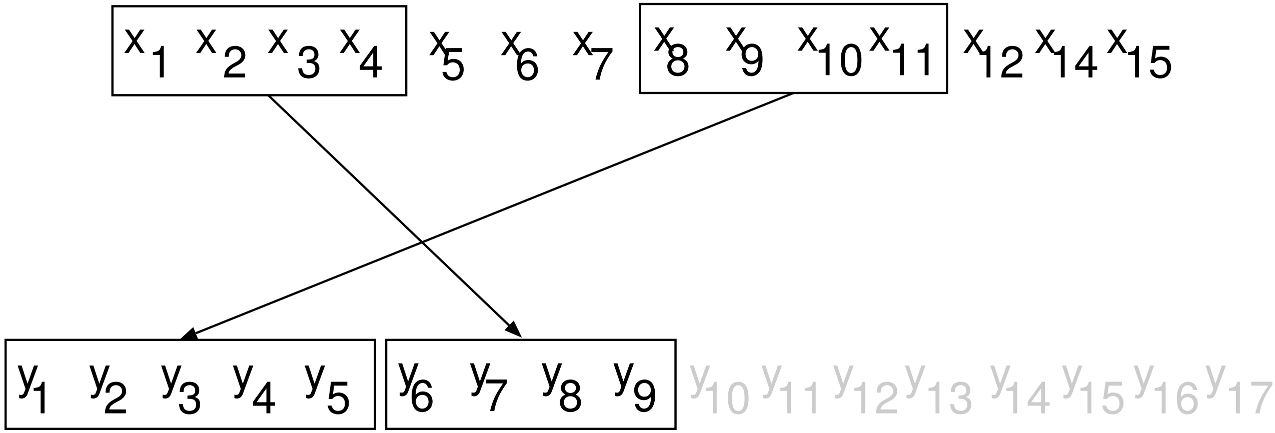
- Algorithmic solutions: (+ heuristics for efficient suboptimal solutions)
  - *Stack-decoding* (*A** *or Branch & Bound*) (Ortiz, 2003) (Koehn, 2010)
  - *Dynamic Programming* (Ney 2003) (Tillmann & Ney 2003)

Basic stack-decoding strategy

- Origin of the *stack decoding* or $A^{\star}$: ASR (Jelinek, 1976)
- Optimal solution to the search problem.
- Applied to translation with word-based models: Candide systems [Berger et al. 96], [Wang and Waibel 98], [Ueffing et al. 01] [Och and Ney 03]
- Incremental development of partial hyphotesis.
- The hypotheses are stored in a stack (a type of 'prioritary queue')
- Selection and expansion of the top of the stack(s)
- Prunning the search space:
  - Beam-search or threshold prunnig
  - Histogram prunning

Basic multiple stack decoding (I)

- A hypothesis in a stack:
  - A prefix of the target sentence (y_1^i)
  - A coverage subset of source positions ($\mathcal{C}$)
  - A score (S).


x_1 x_2 x_3 x_4 x_5 x_6 x_7 x_8 x_9 x_{10} x_{11} x_{12} x_{14} x_{15}
y_1 y_2 y_3 y_4 y_5 y_6 y_7 y_8 y_9 y_{10} y_{11} y_{12} y_{13} y_{14} y_{15} y_{16} y_{17}

- y_1^9
- $\mathcal{C} = \{1, 2, 3, 4, 8, 9, 10, 11\}$
- S = a function of $p_{LM}(y_1^9)$, $p(x_1^4 \mid y_6^9)$, $p(x_8^{11} \mid y_1^9)$, $p(y_6^9 \mid x_1^4)$, $p(y_1^9 \mid x_8^{11})$, $p_{lex}(x_1^4 \mid y_6^9)$, $p_{lex}(x_8^{11} \mid y_1^9)$, $p_{lex}(y_6^9 \mid x_1^4)$, $p_{lex}(y_1^9 \mid x_8^{11})$, . . .

- There is one stack for each possible subset of source positions which words has already been translated.

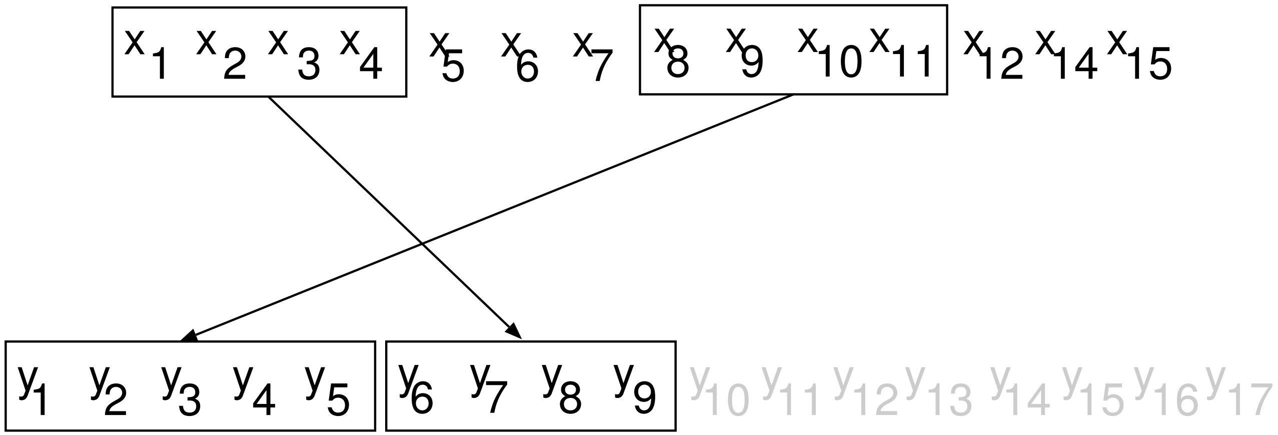
- The possible number of stacks can be very high ($\leq 2^J$)

- In practice, there is one stack for each size of subset of source positions which words has already been translated.

Basic multiple stack decoding (II)

- In each iteration, the best hypothesis from each available stack is selected to generate new extended hypothesis.
- Selection of phrases that match a subset of free source positions (from the complementary set of $\mathcal{C}$ (assuming some constraints))
- The new target prefix is the concatenation of the target prefix of the selected hypothesis and the target words of the selected phrase.
- The new score is computed using the new n-gram and the new source positions.
- A new $\mathcal{C}$ is produced.
- The new hypothesis is stored in the corresponding stack.

Basic multiple stack decoding (III)

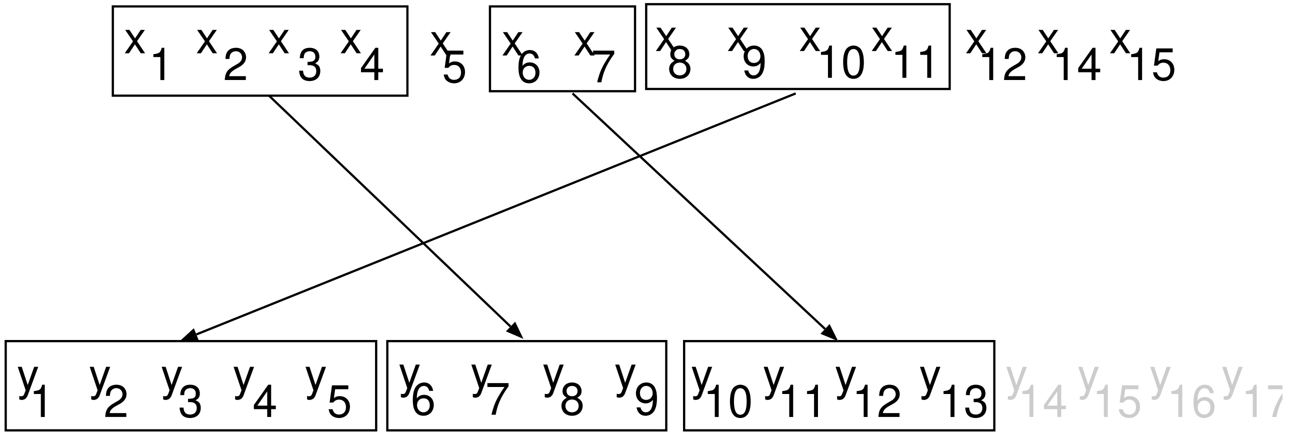


$x_1\ x_2\ x_3\ x_4$ x_5 x_6 x_7 $x_8\ x_9\ x_{10}\ x_{11}$ $x_{12}\ x_{14}\ x_{15}$

$y_1\ y_2\ y_3\ y_4\ y_5$ $y_6\ y_7\ y_8\ y_9$ $y_{10}\ y_{11}\ y_{12}\ y_{13}\ y_{14}\ y_{15}\ y_{16}\ y_{17}$

- y_1^9
- $\mathcal{C} = \{1, 2, 3, 4, 8, 9, 10, 11\}$
- $S =$ a function of $p_{LM}(y_1^9)$, $p(x_1^4 \mid y_6^9)$, $p(x_8^1 \mid y_1^9)$, $p(y_6^9 \mid x_1^4)$, $p(y_1^9 \mid x_8^1)$, $p_{lex}(x_1^4 \mid y_6^9)$, $p_{lex}(x_8^1 \mid y_1^9)$, $p_{lex}(y_6^9 \mid x_1^4)$, $p_{lex}(y_1^9 \mid x_8^1)$, $\ldots$

If there is bililngual phrase $(x_6 x_7, y_{10} y_{11} y_{12} y_{13})$ in the phrase table:



$x_1\ x_2\ x_3\ x_4$ x_5 $x_6\ x_7$ $x_8\ x_9\ x_{10}\ x_{11}$ $x_{12}\ x_{14}\ x_{15}$

$y_1\ y_2\ y_3\ y_4\ y_5$ $y_6\ y_7\ y_8\ y_9$ $y_{10}\ y_{11}\ y_{12}\ y_{13}$ $y_{14}\ y_{15}\ y_{16}\ y_{17}$

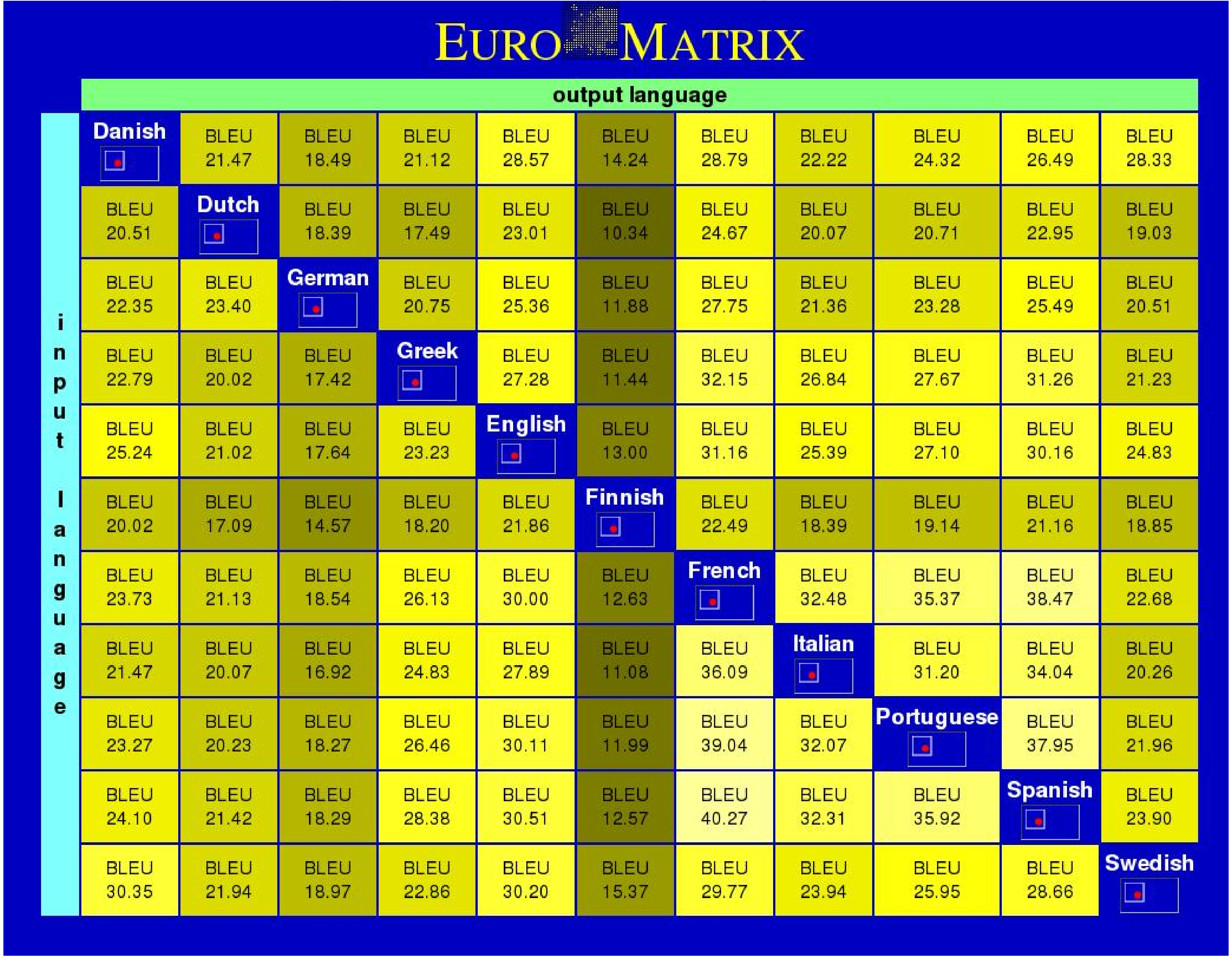
- y_1^{13}
- $\mathcal{C} = \{1, 2, 3, 4, 6, 7, 8, 9, 10, 11\}$
- $S =$ a function of $p_{LM}(y_1^{13})$, $p(x_1^4 \mid y_6^9)$, $p(x_8^1 \mid y_1^9)$, $p(y_6^9 \mid x_1^4)$, $p(y_1^9 \mid x_8^1)$, $p(y_{10}^{13} \mid x_6^7)$, $p(x_6^7 \mid y_{10}^{13})$, $p_{lex}(x_1^4 \mid y_6^9)$, $p_{lex}(x_8^1 \mid y_1^9)$, $p_{lex}(y_6^9 \mid x_1^4)$, $p_{lex}(y_1^9 \mid x_8^1)$, $p_{lex}(y_{10}^{13} \mid x_6^7)$, $p_{lex}(x_6^7 \mid y_{10}^{13})$, $\ldots$

Assessment

- Word error rate (WER): The minimum number of substitution, insertion and deletion operations needed to convert the word string hypothesized by the translation system into a given single reference word string.
- Multi reference WER (mWER): Similar to WER, but for each source test sentence there are more than one target sentences as references.
- BiLingual Evaluation Understudy (BLEU): it is based on the n-grams of the hypothesized translation that occur in the reference translations (geometric mean). The BLEU metric ranges from 0.0 (worst score) to 1.0 (best score).
- Translation error rate (TER): Similar to WER, but swaps are allowed without penalty. http://www.cs.umd.edu/~snover/tercom/
- NIST: similar to BLEU but arithmetic mean is used
- METEOR: Metric for evaluation of translation with explicit ordering and no exact matching.
- BEER: A trained system of a linear combination of features.

EuroMatrix (2006-2009)

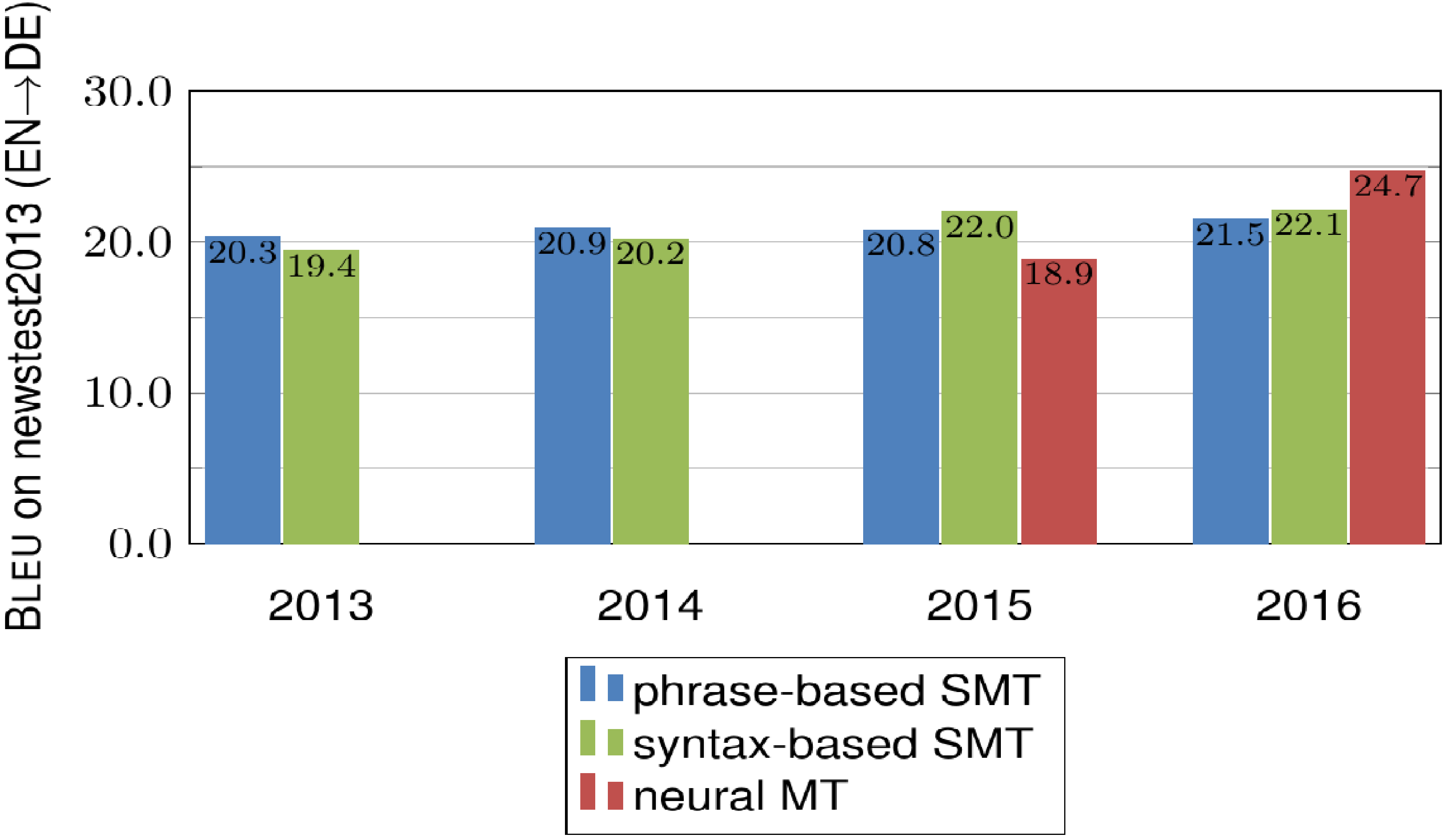
http://www.statmt.org/matrix/



EURO MATRIX

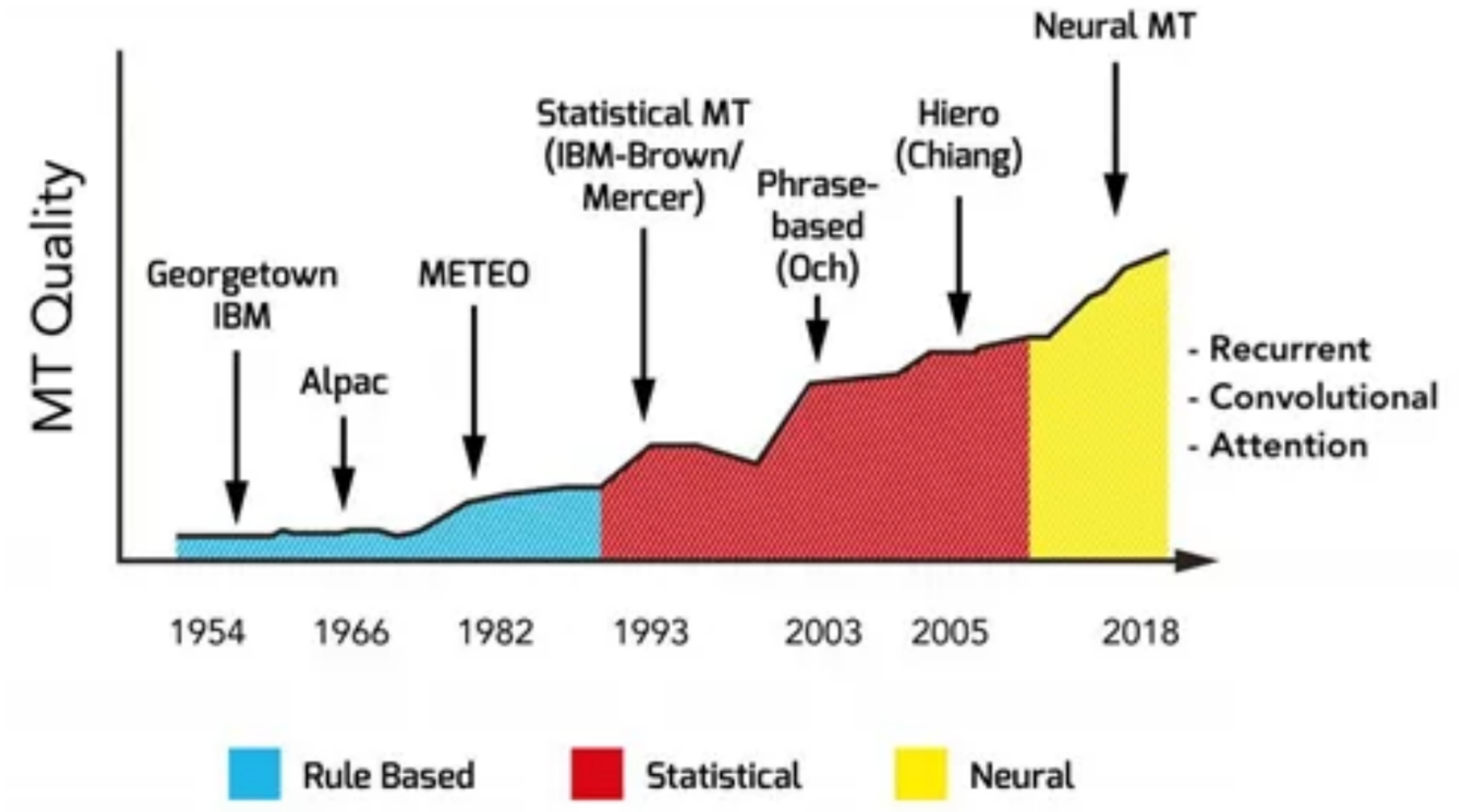
	output language										
input language	Danish	BLEU 21.47	BLEU 18.49	BLEU 21.12	BLEU 28.57	BLEU 14.24	BLEU 28.79	BLEU 22.22	BLEU 24.32	BLEU 26.49	BLEU 28.33
	BLEU 20.51	Dutch	BLEU 18.39	BLEU 17.49	BLEU 23.01	BLEU 10.34	BLEU 24.67	BLEU 20.07	BLEU 20.71	BLEU 22.95	BLEU 19.03
	BLEU 22.35	BLEU 23.40	German	BLEU 20.75	BLEU 25.36	BLEU 11.88	BLEU 27.75	BLEU 21.36	BLEU 23.28	BLEU 25.49	BLEU 20.51
	BLEU 22.79	BLEU 20.02	BLEU 17.42	Greek	BLEU 27.28	BLEU 11.44	BLEU 32.15	BLEU 26.84	BLEU 27.67	BLEU 31.26	BLEU 21.23
	BLEU 25.24	BLEU 21.02	BLEU 17.64	BLEU 23.23	English	BLEU 13.00	BLEU 31.16	BLEU 25.39	BLEU 27.10	BLEU 30.16	BLEU 24.83
	BLEU 20.02	BLEU 17.09	BLEU 14.57	BLEU 18.20	BLEU 21.86	Finnish	BLEU 22.49	BLEU 18.39	BLEU 19.14	BLEU 21.16	BLEU 18.85
	BLEU 23.73	BLEU 21.13	BLEU 18.54	BLEU 26.13	BLEU 30.00	BLEU 12.63	French	BLEU 32.48	BLEU 35.37	BLEU 38.47	BLEU 22.68
	BLEU 21.47	BLEU 20.07	BLEU 16.92	BLEU 24.83	BLEU 27.89	BLEU 11.08	BLEU 36.09	Italian	BLEU 31.20	BLEU 34.04	BLEU 20.26
	BLEU 23.27	BLEU 20.23	BLEU 18.27	BLEU 26.46	BLEU 30.11	BLEU 11.99	BLEU 39.04	BLEU 32.07	Portuguese	BLEU 37.95	BLEU 21.96
	BLEU 24.10	BLEU 21.42	BLEU 18.29	BLEU 28.38	BLEU 30.51	BLEU 12.57	BLEU 40.27	BLEU 32.31	BLEU 35.92	Spanish	BLEU 23.90
	BLEU 30.35	BLEU 21.94	BLEU 18.97	BLEU 22.86	BLEU 30.20	BLEU 15.37	BLEU 29.77	BLEU 23.94	BLEU 25.95	BLEU 28.66	Swedish

Edinburgh's WMT results over the years[1]



[1] Sennrich et al. Advances in Neural Machine Translation. AMTA. 2016.

MT quality over the years[1]



[1] https://syncedreview.com/2020/05/20/neural-network-ai-is-the-future-of-the-translation-industry/

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