WORD ALIGNMENT MODELS

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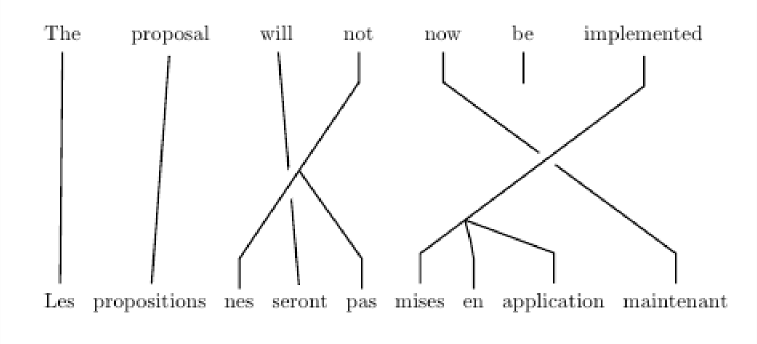
an alignment



'The Mathematics of Machine Translation: Parameter Estimation', Brown et al. (1993).

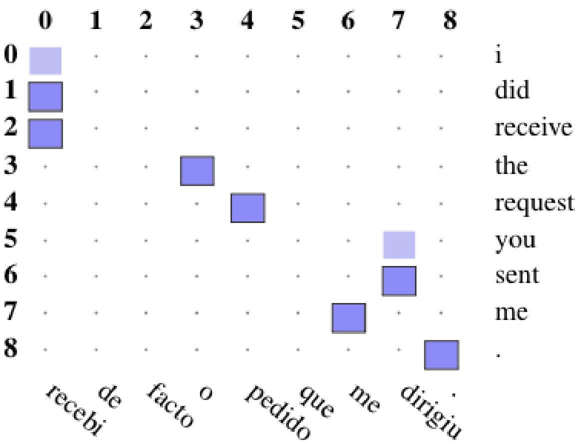
ibm papers (1990-1993)

- Formulated a generative model of parallel sentence pairs

$$\Pr(F = \mathbf{f} | E = \mathbf{e}) = \sum_{\mathbf{a} \in \mathcal{A}} \Pr(A = \mathbf{a}, F = \mathbf{f} | E = \mathbf{e})$$

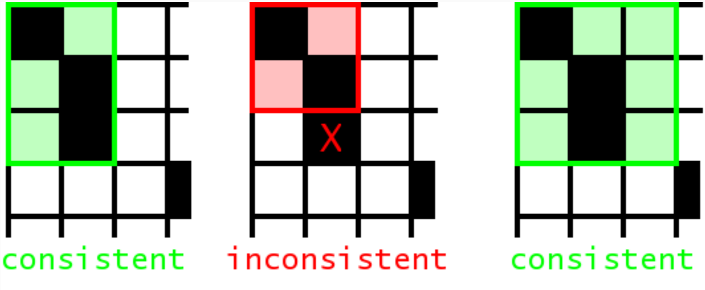
  where F is a French sentence, E is an English sentence and $\mathcal{A}$ is the set of all possible alignments for the sentence pair.
- Proposed using the EM algorithm to learn the parameters and infer word alignment matrix.

word alignment matrix



Natural way to visualize an alignment.

used in phrase-based mt



Word alignments constrain the set of possible phrase pairs.

We're given corpus of translated sentence pairs $D = \{(\mathsf{e}, \mathsf{f})_1, (\mathsf{e}, \mathsf{f})_2, (\mathsf{e}, \mathsf{f})_3, ...\}$.

We assume these sentence pairs are distributed *i.i.d.* given the parameters θ,

$$\begin{aligned}
\Pr(D|\theta) &= \prod_{k \in D} \Pr(\mathsf{f}_k|\mathsf{e}_k, \theta) \\
&= \prod_{k \in D} \sum_{\mathsf{a}_k \in \mathcal{A}} \Pr(\mathsf{a}_k, \mathsf{f}_k|\mathsf{e}_k, \theta) \\
&= \prod_{k \in D} \sum_{\mathsf{a}_k \in \mathcal{A}} \underbrace{\Pr(\mathsf{a}_k|\mathsf{e}_k, \theta)}_{\text{Prior}} \underbrace{\Pr(\mathsf{f}_k|\mathsf{e}_k, \mathsf{a}_k, \theta)}_{\text{Translation model}}
\end{aligned}$$

choosing a model: observed data

Bias-variance trade-off

Simple models (few parameters) generalize better to new data, but may not capture the structure of the data (e.g. unigram n-gram model).

Complex models (many parameters) capture the structure of the training data, but generalize less well to new data (e.g. unsmoothed 5-gram model).

How do hidden variables complicate the choice of model structure?

choosing a model: hidden data

How does the structure of A (the alignments) affect the computation?

How big is A for a single sentence pair $|\mathbf{e}| = I$ and $|\mathbf{f}| = J$?

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$$\Pr(f_1, ..., f_J | e_1, ..., e_I, \theta) = \sum_{a_1=1}^{I} ... \sum_{a_J=1}^{I} \Pr(a_1, ..., a_J, f_1, ..., f_J | e_1, ..., e_I, \theta)$$

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Exact E-step is only tractable for a very limited set of models.

simplifying assumptions

Assumption 1

Each French word f_j is generated independently given the English word to which it is aligned e_{a_j}

$$\mathrm{Pr}(\mathbf{f}|\mathbf{e}) \approx \prod_{j=1}^{J} \sum_{\mathbf{a} \in \mathcal{A}} \mathrm{Pr}(\mathbf{a}|\mathbf{e}, \theta) \mathrm{Pr}(f_j | e_{a_j}, \theta)$$

What's an obvious problem with this assumption?

simplifying assumptions

Assumption 2

We'll parameterize the translation model $\Pr(f_j | e_{a_j}, \theta)$ with a table of conditional probabilities $t(f|e)$.

E.g. for Russian to English translation the table $t(\text{f}|dog)$ could be defined as

$$t(\text{собака}|\text{dog}) = 0.5$$

$$t(\text{собаку}|\text{dog}) = 0.3$$

$$t(\text{кошка}|\text{dog}) = 0.2.$$

What's an obvious problem with this?

simplifying assumptions

Assumption 3

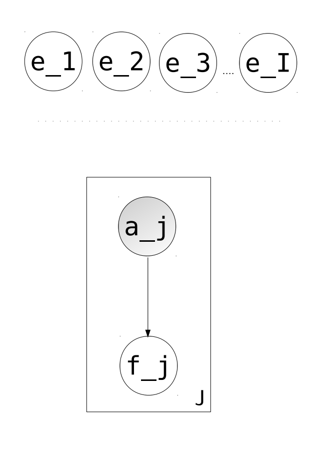
We'll simplify the 'prior' $\mathsf{Pr}(a|\mathsf{e},\theta)$ significantly.

At first we'll assume a uniform prior, i.e. that all alignments are *a priori* equally likely (i.e. they don't depend on the English words or any other alignments).

$$\forall \mathsf{a} \in A, \mathsf{Pr}(\mathsf{a}|\mathsf{e},\theta) = \epsilon.$$

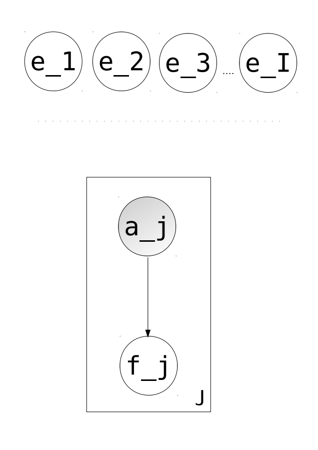
Why is this not a great assumption?

ibm model 1



$$\Pr(\mathsf{f}, \mathsf{a} | \mathsf{e}, \theta) \approx \prod_{j=1}^{J} \Pr(f_j, a_j | \mathsf{e}, \theta)$$

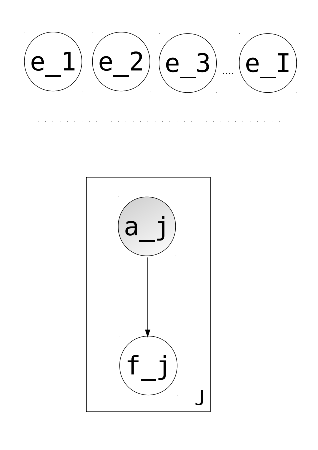
ibm model 1



$$\Pr(\mathsf{f}, \mathsf{a}|\mathsf{e}, \theta) \approx \prod_{j=1}^{J} \Pr(f_j, a_j|\mathsf{e}, \theta)$$

$$= \prod_{j=1}^{J} \Pr(a_j|\mathsf{e}) \Pr(f_j|\mathsf{e}, a_j, \theta)$$

ibm model 1



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\Pr(\mathrm{f}, \mathrm{a} | \mathrm{e}, \theta) &\approx \prod_{j=1}^{J} \Pr(f_j, a_j | \mathrm{e}, \theta) \\
&= \prod_{j=1}^{J} \Pr(a_j | \mathrm{e}) \Pr(f_j | \mathrm{e}, a_j, \theta) \\
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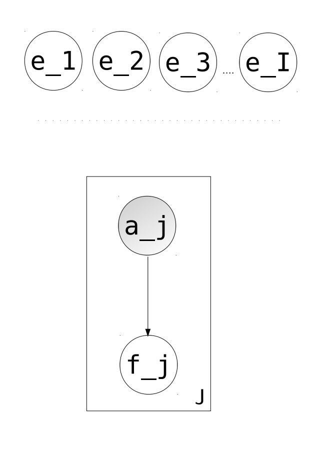

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&\approx \prod_{j=1}^{J} \epsilon \mathrm{Pr}(f_j|e_{a_j}, \theta) \\
&\propto \prod_{j=1}^{J} t(f_j|e_{a_j})
\end{aligned}
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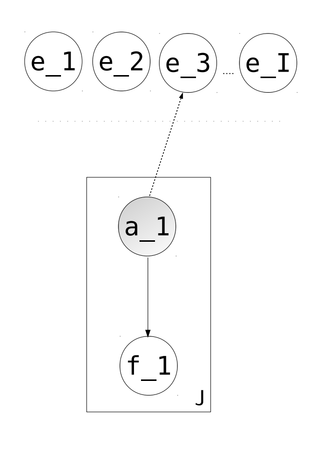

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\Pr(\mathrm{f}, \mathrm{a} | \mathrm{e}, \theta) &\approx \prod_{j=1}^{J} \Pr(f_j, a_j | e_{a_j}, \theta) \\
&= \Pr(f_1, a_1 = 3 | e_3, \theta) \ldots
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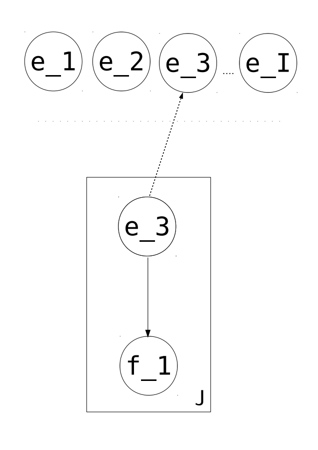

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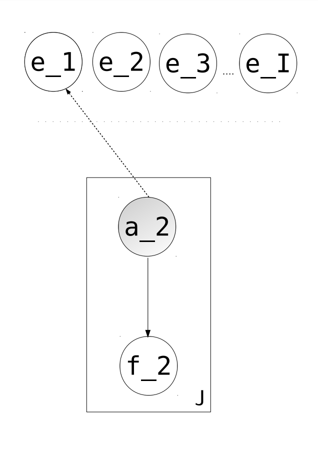

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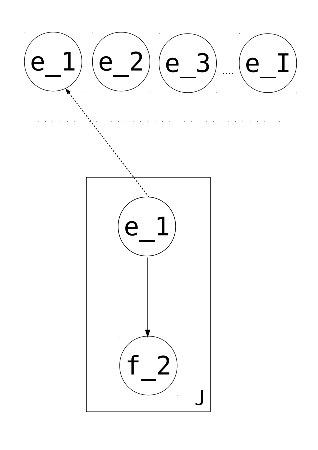

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&= \Pr(f_1, a_1 = 3 | e_3, \theta) \ldots \\
&\approx t(f_1, | e_3) \ldots \\
&\approx t(f_1, | e_3) t(f_2 | e_1) \ldots
\end{aligned}
$$

em for ibm model 1

The expected log-likelihood for $\mathbf{f}$ given $\mathbf{e}$ under IBM Model 1 is

$$\begin{aligned}\mathbb{E}[log(\mathbf{f}|\mathbf{e},\theta)] &= \sum_{j=1}^{J}\sum_{i=1}^{I} \Pr(a_j = i|\mathbf{f},\mathbf{e},\theta) \log \Pr(f_j, a_j = i|e_i,\theta) \\ &\propto \sum_{j=1}^{J}\sum_{i=1}^{I} \Pr(a_j = i|\mathbf{f},\mathbf{e},\theta) \log t(f_j|e_i).\end{aligned}$$

To apply EM we need to compute $\Pr(a_j = i|\mathbf{f},\mathbf{e},\theta)$ for each source and target pair and then maximize this term w.r.t. our parameters $\theta = t(f|e)$.

em for ibm model 1 cont.

The posterior alignment probabilities, $\Pr(a_j = i|\mathbf{f}, \mathbf{e}, \theta)$ can be computed as follows

$$\begin{aligned}
\Pr(a_j = i|\mathbf{f}, \mathbf{e}, \theta) &= \frac{\Pr(f_j, a_j = i|\mathbf{e}, \theta)}{\Pr(f_j|\mathbf{e}, \theta)} \\
&= \frac{\Pr(a_j = i|\mathbf{e}, \theta)\Pr(f_j|a_j = i, \mathbf{e}, \theta)}{\sum_{k=1}^{l} \Pr(a_j = k|\mathbf{e}, \theta)\Pr(f_j|a_j = k, \mathbf{e}, \theta)} \\
&= \frac{\epsilon t(f_j|e_i)}{\sum_{k=1}^{l} \epsilon t(f_j|e_k)} \\
&= \frac{t(f_j|e_i)}{\sum_{k=1}^{l} t(f_j|e_k)}.
\end{aligned}$$

measuring alignment quality

Given a golden set of manually created M consisting of probable P and sure S alignments. We can measure the error rate of an automatic alignment A:

$$Precision(A; P) = \frac{|P \cap A|}{|A|}$$

$$Recall(A; S) = \frac{|S \cap A|}{|S|}$$

$$AlignmentErrorRate(A; S, P) = 1 - \frac{|P \cap A| + |S \cap A|}{|S| + |A|}.$$

improving on model 1

Suggestions:

- Parameter tying
- Better use of positional information in prior (e.g. words align with words close by)
- Using prior information, e.g. character level model
- Using linguistic annotations (see other files)

Who can get the lowest *alignment error rate* by tomorrow?