Out of GIZA—Efficient Word Alignment Models for SMT

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NCLT Seminar Series

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Outline

1. Contexts
2. HMM and IBM Model 4
3. Improved HMM Alignment Models
4. Simultaneous Word Alignment and Phrase Extraction

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Word Alignment and SMT

All SMT systems rely on word alignment

- Word-Based SMT
- Phrase-Based SMT
- Hiero, hierarchical SMT
- Syntax-Based SMT, i.e, tree-to-string, string-to-tree, tree-to-tree

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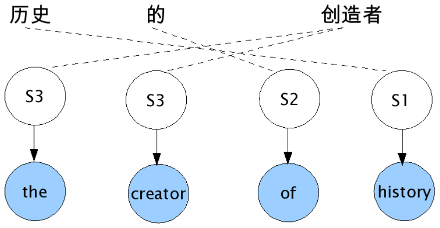
Giza implementation of IBM model 4 is dominant

“Viterbi” alignment from IBM model 4 is used

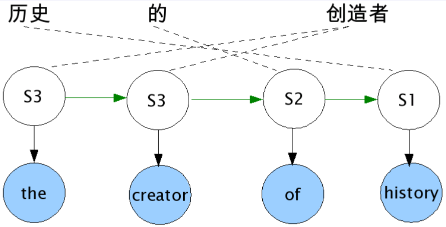
Outline

Efficient Model: HMM Model [Vogel et al., 1996]

HMM emission (translation) model $p(t_j|s_{a_j})$



HMM transition (alignment) model $p(a_j|a_j - a_{j-1})$



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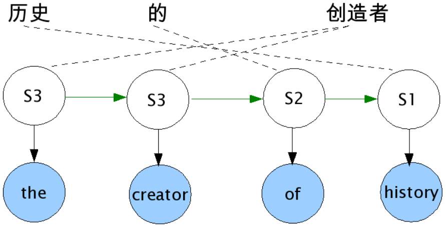
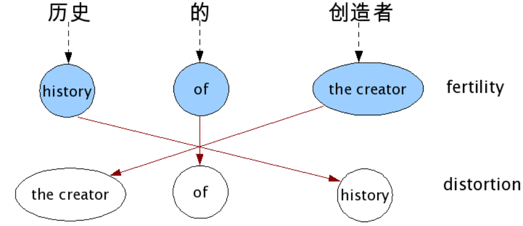


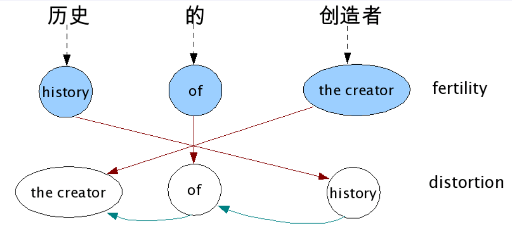
$$p(t, a|s) = \prod_j p(a_j|a_j - a_{j-1}) \cdot p(t_j|s_{a_j}) \tag{1}$$

Deficient Model: IBM Model 3 and 4

Model 3: zero-order distortion model



Model 4: first-order distortion model



Derivation

$$P(t_1^J, a_1^J | s_1^I) = P(t_1^J, B_0^I | s_1^I) \tag{2}$$

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$$P(t_1^J, a_1^J | s_1^I) = P(t_1^J, B_0^I | s_1^I) \quad (2)$$

$$= P(B_0 | B_1^I) \times \prod_{i=1}^{I} P(B_i | B_1^{i-1}, e_1^I) \times P(f_1^J | B_0^I, e_1^I) \quad (3)$$

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$$= P(B_0 | B_1^I) \times \prod_{i=1}^{I} \underbrace{p(B_i | B_{i-1}, e_i)}_{\text{fertility-distortion}} \tag{4}$$

Derivation

$$
\begin{aligned}
P(t_1^J, a_1^J | s_1^I) &= P(t_1^J, B_0^I | s_1^I) && (2)\\
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&= P(B_0|B_1^I) \times \prod_{i=1}^{I} \underbrace{p(B_i|B_{i-1}, e_i)}_{\text{fertility-distortion}} && (4)\\
&\quad \times \prod_{i=0}^{I} \prod_{j \in B_i} \underbrace{p(f_j|e_i)}_{\text{translation}} && (5)
\end{aligned}
$$

Model 3 fertility and distortion

$$p(B_i|B_{i-1}, e_i) = \underbrace{p(\phi_i|e_i)}_{\text{fertility}} \phi_i! \prod_{j \in B_i} \underbrace{p(j|i, J)}_{\text{distortion}} \tag{6}$$

Model 3 fertility and distortion

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Model 4 fertility and distortion

$$p(B_i|B_{i-1}, e_i) = \underbrace{p(\phi_i|e_i)}_{\text{fertility}} \underbrace{p_{=1}(B_{i1} - \overline{B_{\rho(i)}}|\cdots)}_{\text{first word}} \underbrace{\prod_{k=2}^{\phi_i} p_{>1}(B_{ik} - B_{i,k-1}|\cdots)}_{\text{remaining words}} \tag{7}$$

Decoding

HMM

- Viterbi decoding: $\hat{a} = \underset{a}{\text{argmax}} p(a|s,t)$
- Posterior decoding: Align point $a_j \rightarrow i$ iff. $p(a_j \rightarrow i|s,t) \geq \delta$

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IBM model 3 and 4

- No efficient algorithm available

Advantages of HMM models

Efficient parameter estimation algorithm: forward-backward algorithm (Baum-Welch algorithm)

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Figure: Eric B. Baum (son of Leonard E. Baum, who was the inventor of the algorithm) and Lloyd R. Welch

Advantages of HMM models

Efficient parameter estimation algorithm: forward-backward algorithm (Baum-Welch algorithm)

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The resulting posterior probabilities are useful

Disadvantages of standard HMM models

Objective is maximising the likelihood

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- There is no garantee that the optimised parameters correspond to more accurate alignments
- To complicate things (sometimes!) does help, e.g. IBM model 4

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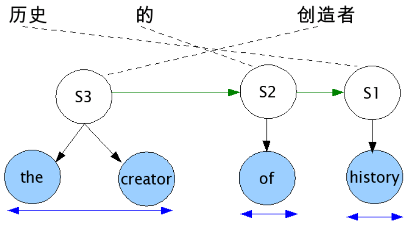
Improved HMM models

Two more sophisticated HMM models

- Segmental HMM model, word-to-phrase alignment model
- Constrained HMM model, agreement-guided alignment model

HMM Word-to-Phrase Alignment [Deng and Byrne, 2008]

Introducing a segmentation model: segmental HMM



$$P(t, a|s) = P(v_1^K, K, a_1^K, h_1^K, \phi_1^K|s) \tag{8}$$

$$
\begin{aligned}
P(t, a|s) &= P(v_1^K, K, a_1^K, h_1^K, \phi_1^K | s) && (8) \\
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&\quad \times \underbrace{P(a_1^K, \phi_1^K, h_1^K | K, J, s)}_{\text{alignment-fertility}} && (10)\\
&\quad \times \underbrace{P(v_1^K | a_1^K, \phi_1^K, h_1^K, K, J, s)}_{\text{translation}} && (11)
\end{aligned}
$$

HMM Word-to-Phrase Alignment

$$P(a_1^K, \phi_1^K, h_1^K | K, J, s) = \prod_{k=1}^{K} P(a_k, h_k, \phi_k | a_{k-1}, \phi_{k-1}, h_{k-1}, K, J, s) \quad (12)$$

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$$= \prod_{k=1}^{K} \underbrace{p(a_k, | a_{k-1}, h_k; I)}_{\text{alignment}} \cdot \underbrace{d(h_k)}_{\text{null alignment}} \cdot \underbrace{n(\phi_k; s_{a_k})}_{\text{fertility}} \quad (13)$$

Performance of HMM Word-to-Phrase Alignment

MTTK implementation

Performance of HMM Word-to-Phrase Alignment

MTTK implementation

Used by Cambridge University Engineering Department

- Arabic–English NIST 2008 (6th out of 16, third best university participant, behind LIUM and ISI)
- Consistent performance for Chinese–English for differently sized collections of corpus
- Parallelised to handle large amount of data (e.g. 10M sentence pairs)

Agreement Constrained HMM Alignment [Ganchev et al., 2008]

Objective

$$\underset{q(a)\in(Q)}{\operatorname{argmin}}\{KL(q(a)||p_\theta(a|s,t))\} \text{ s.t. } E_q[f(s,t,a)] \leq b \tag{14}$$

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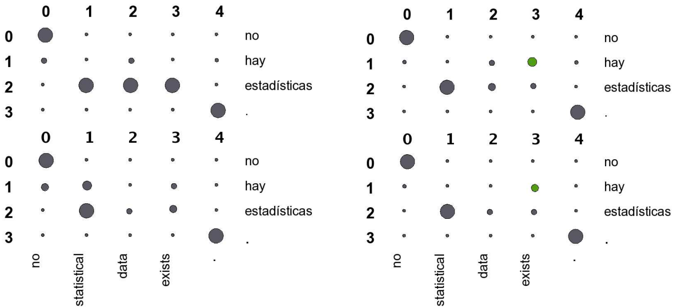
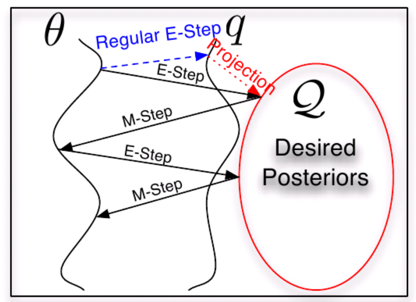


Figure: $\overrightarrow{p}_\theta(a|s,t)$, $\overleftarrow{p}_\theta(a|s,t)$ and $\overrightarrow{q}(a)$, $\overleftarrow{q}_{(}a)$

Agreement Constrained HMM Alignment [Ganchev et al., 2008]

Constrained E(M)



Performance of Agreement Constrained HMM

PostCAT implementation

Evaluation

- Six language pairs, from 100,000 to 1M sentence pairs
- Outperform IBM Model 4 (16 out 18 times)
- However... getting slightly worse when the training data is over 1M

Algorithm 1 Agreement Constrained HMM Alignment

$\lambda_{ij} \leftarrow \forall i, j$
for T interations **do**
  $\overrightarrow{\theta}'_t(t_j|s_i) \leftarrow \overrightarrow{\theta}_t(t_j|s_i)e^{\lambda_{ij}} \forall i, j$
  $\overleftarrow{\theta}'_t(s_i|t_j) \leftarrow \overleftarrow{\theta}_t(s_i|t_j)e^{-\lambda_{ij}} \forall i, j$
  $\overrightarrow{q} \leftarrow \text{forwardBackward}(\overrightarrow{\theta}'_t, \overrightarrow{\theta}_a)$
  $\overleftarrow{q} \leftarrow \text{forwardBackward}(\overleftarrow{\theta}'_t, \overleftarrow{\theta}_a)$
end for
return $(\overrightarrow{q}, \overleftarrow{q})$

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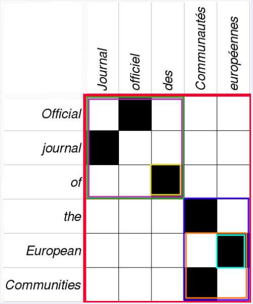
Phrase Pair Extraction

State-of-the-art: using viterbi alignment only



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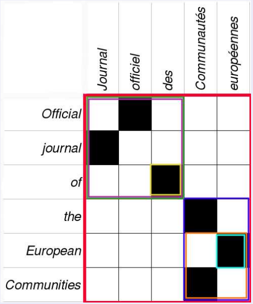

Using all possible alignments

$$A(i_1, i_2; j_1, j_2) = \{a = a_1^J : a_j \in [i_1, i_2] \text{ iff. } j \in [j_1, j_2]\} \tag{15}$$

Phrase Pair Extraction via Model-Based Posteriors

Derivation

$$P(t, A(i_1, i_2; j_1, j_2)|s; \theta) = \sum_{a \in A(i_1,i_2;j_1,j_2)} P(t, a|s; \theta) \tag{16}$$

Phrase Pair Extraction via Model-Based Posteriors

Derivation

$$P(t, A(i_1, i_2; j_1, j_2)|s; \theta) = \sum_{a \in A(i_1, i_2; j_1, j_2)} P(t, a|s; \theta) \quad (16)$$

$$P(A(i_1, i_2; j_1, j_2)|s, t; \theta) = \frac{P(t, A(i_1, i_2; j_1, j_2)|s; \theta)}{P(t, a|s; \theta)} \quad (17)$$

Evaluation

- Significant gains when used as an augmentation to the original phrase extraction strategy

References

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