

# Bayesian Reordering Model with Feature Selection

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# Translation System Overview

Given a foreign sentence  $\mathbf{f}$ , the best translation  $\mathbf{e}$  is (Brown et al., 1993):

$$\begin{aligned} \mathbf{e}_{\text{best}} &= \arg \max_{\mathbf{e}} p(\mathbf{e}|\mathbf{f}) \\ &= \arg \max_{\mathbf{e}} \frac{p(\mathbf{f}|\mathbf{e})p(\mathbf{e})}{p(\mathbf{f})} \\ &= \arg \max_{\mathbf{e}} \text{Translation Model} \times \text{Language Model} \end{aligned}$$

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$$\begin{aligned}\mathbf{e}_{\text{best}} &= \arg \max_{\mathbf{e}} \{p_t(\mathbf{f}|\mathbf{e})^{\lambda_t} p_{lm}(\mathbf{e})^{\lambda_{lm}} p_{lex}(\mathbf{f}|\mathbf{e})^{\lambda_{lex}} p_{reo}(\mathbf{f}, \mathbf{e})^{\lambda_{reo}} w^{|\mathbf{e}|\lambda_w}\} \\ &= \arg \max_{\mathbf{e}} \sum_i \lambda_i \log p_i(\mathbf{f}, \mathbf{e})\end{aligned}$$

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In general, reordering model is defined as:

$$p_{reo}(\mathbf{f}, \mathbf{e}) = \prod_n p(o_n | \bar{f}_n, \bar{e}_n) = \prod_n \frac{h(\bar{f}_n, \bar{e}_n, o_n)}{\sum_k h(\bar{f}_n, \bar{e}_n, o_k)}$$

# Reordering Models

Foreign sentence  $\mathbf{f}$  :  $\bar{f}_1$   $\bar{f}_2$   $\bar{f}_3$  .

English sentence  $\mathbf{e}$  :  $\bar{e}_1$   $\bar{e}_3$   $\bar{e}_2$  .

$$p_{reo}(\mathbf{f}, \mathbf{e}) = p(o_1 = \text{mono} | \bar{f}_1, \bar{e}_1) \times p(o_2 = \text{swap} | \bar{f}_2, \bar{e}_2) \times p(o_3 = \text{other} | \bar{f}_3, \bar{e}_3)$$

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- Lexicalized Reordering Model (Tillmann, 2004; Kumar and Byrne, 2005; Koehn et al., 2005; Galley and Manning, 2008)

$$p(o_k | \bar{f}_n, \bar{e}_n) = \frac{\text{count}(\bar{f}_n, \bar{e}_n, o_k)}{\sum_{k'} \text{count}(\bar{f}_n, \bar{e}_n, o_{k'})}$$

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- Discriminative Reordering Model (Zens and Ney, 2006; Xiong et al., 2006; Nguyen et al., 2009; Xiang et al., 2011; Ni et al., 2011)

$$p(o_k | \bar{f}_n, \bar{e}_n) = \frac{\exp(\mathbf{w}_k^T \phi(\bar{f}_n, \bar{e}_n))}{\sum_{k'} \exp(\mathbf{w}_{k'}^T \phi(\bar{f}_n, \bar{e}_n))} \equiv \frac{\exp(\mathbf{w}^T \phi(\bar{f}_n, \bar{e}_n, o_k))}{\sum_{k'} \exp(\mathbf{w}^T \phi(\bar{f}_n, \bar{e}_n, o_{k'}))}$$

# Feature Extraction

Foreign sentence  $\mathbf{f}$  :  $f_1$   $f_2$   $f_3$   $f_4$   $f_5$   $f_6$  .  
English sentence  $\mathbf{e}$  :  $e_1$   $e_2$   $e_3$   $e_4$   $e_5$  .



# Feature Extraction

Foreign sentence  $\mathbf{f}$  :  $f_1 f_2$  <sub>1</sub>  $f_3 f_4 f_5$  <sub>2</sub>  $f_6$  <sub>3</sub> .  
 English sentence  $\mathbf{e}$  :  $e_1$  <sub>1</sub>  $e_2 e_3$  <sub>3</sub>  $e_4 e_5$  <sub>2</sub> .

## Extracted phrase pairs :

$\bar{f}_n$		$\bar{e}_n$		$o_n$		word alignment		context feature
$f_1 f_2$		$e_1$		mono		0-0 1-0		$+f_3$
$f_3 f_4 f_5$		$e_4 e_5$		swap		0-1 2-0		$-f_2 + f_6$
$f_6$		$e_2 e_3$		other		0-0 0-1		$-f_5$

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$f_6$		$e_2 e_3$		other		0-0 0-1		$-f_5$

## All linguistic features:

$(f_1 \& e_1)^1 (f_2 \& e_1)^2 (+f_3)^3 (f_3 \& e_5)^4 (f_5 \& e_4)^5 (-f_2)^6 (+f_6)^7 (f_6 \& e_2)^8 (f_6 \& e_3)^9 (-f_5)^{10}$

## Bag-of-words representation (0=not exist):

$\phi(\bar{f}_n, \bar{e}_n)$	1	2	3	4	5	6	7	8	9	10
$\phi(\bar{f}_1, \bar{e}_1) =$	1	1	1	0	0	0	0	0	0	0
$\phi(\bar{f}_2, \bar{e}_2) =$	0	0	0	1	1	1	1	0	0	0
$\phi(\bar{f}_3, \bar{e}_3) =$	0	0	0	0	0	0	0	1	1	1

# The Proposed Reordering Model

## Naive Bayes

$$p(o_k | \bar{f}_n, \bar{e}_n) = \frac{p(\bar{f}_n, \bar{e}_n | o_k) p(o_k)}{\sum_{k'} p(\bar{f}_n, \bar{e}_n | o_{k'}) p(o_{k'})}$$

Multinomial distribution:

$$p(\bar{f}_n, \bar{e}_n | \mathbf{q}_k) = C \prod_m^M q_{km}^{\phi_m(\bar{f}_n, \bar{e}_n)}$$

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Maximum-likelihood estimation:

$$q_{km}^* = \arg \max_{\mathbf{q}_k} \prod_n^{N_k} p(\bar{f}_n, \bar{e}_n | \mathbf{q}_k) = \frac{\sum_n^{N_k} \phi_m(\bar{f}_n, \bar{e}_n)}{\sum_{m'}^M \sum_n^{N_k} \phi_{m'}(\bar{f}_n, \bar{e}_n)}$$

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Maximum a posteriori (MAP) estimation:

$$q_{km}^* = \arg \max_{\mathbf{q}_k} \prod_n^{N_k} p(\bar{f}_n, \bar{e}_n | \mathbf{q}_k) p(\mathbf{q}_k | \alpha) = \frac{\alpha - 1 + \sum_n^{N_k} \phi_m(\bar{f}_n, \bar{e}_n)}{M(\alpha - 1) + \sum_{m'}^M \sum_n^{N_k} \phi_{m'}(\bar{f}_n, \bar{e}_n)}$$

# The Proposed Reordering Model

## Bayesian Naive Bayes (Barber, 2012)

$$p(o_k | \bar{f}_n, \bar{e}_n) = \frac{p(\bar{f}_n, \bar{e}_n | o_k) p(o_k)}{\sum_{k'} p(\bar{f}_n, \bar{e}_n | o_{k'}) p(o_{k'})}$$

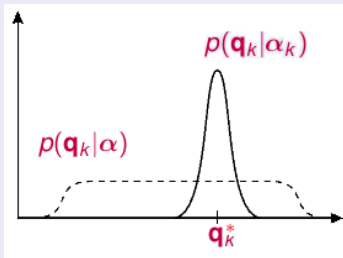
### Full Bayesian Inference

#### Multinomial-Dirichlet

$$\begin{aligned} p(\bar{f}_n, \bar{e}_n | o_k) &= \int p(\bar{f}_n, \bar{e}_n | \mathbf{q}_k) p(\mathbf{q}_k | \alpha_k) d\mathbf{q}_k \\ &= C \frac{\Gamma(\sum_m \alpha_{km}) \prod_m \Gamma(\alpha_{km} + \phi_m(\bar{f}_n, \bar{e}_n))}{\prod_m \Gamma(\alpha_{km}) \Gamma(\sum_m \alpha_{km} + \phi_m(\bar{f}_n, \bar{e}_n))} \end{aligned}$$

$$p(\mathbf{q}_k | \alpha_k) = \frac{p(\mathbf{q}_k | \alpha) \prod_n^{N_k} p(\bar{f}_n, \bar{e}_n | \mathbf{q}_k)}{\int p(\mathbf{q}_k | \alpha) \prod_n^{N_k} p(\bar{f}_n, \bar{e}_n | \mathbf{q}_k) d\mathbf{q}_k}$$

### Prior and Posterior



$$\alpha_k = \alpha + \sum_n^{N_k} \phi(\bar{f}_n, \bar{e}_n)$$

# Classification Results

## 3-class problem: mono , swap , other

Table: Arabic-English MultiUN corpus ([Eisele and Chen, 2010](#))

Statistics	Arabic	English
Sentence Pairs	9.7 M	
Running Words	255.5 M	285.7 M
Word/Line	22	25
Vocabulary Size	677 K	410 K

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Table: Error rate based on 3-fold cross-validation

Classifier	Error Rate
Lexicalized model	25.2%
Bayes-MAP estimate	<b>19.53%</b>
Bayes-Bayesian inference	20.13%



# Feature Selection

Normalized mutual information (Estevez et al., 2009):

$$I_{norm}(X; Y) = \frac{I(X; Y)}{\min(H(X), H(Y))}.$$

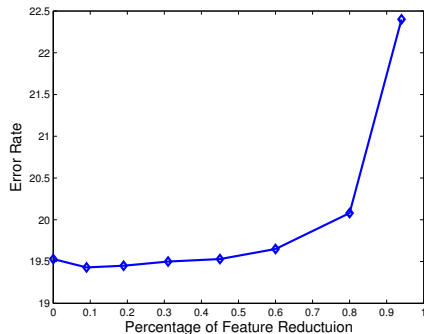
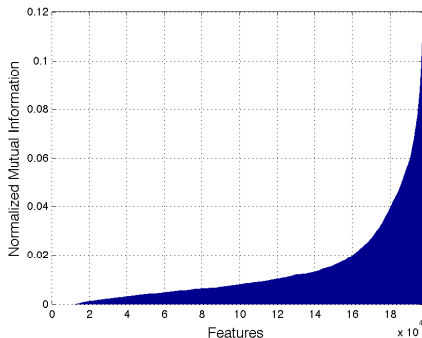


Table: NIST test sets (4 references for each Arabic sentence)

Evaluation Set		Arabic	English
NIST MT06	sentences	1797	7188
	words	49 K	223 K
NIST MT08	sentences	813	3252
	words	25 K	117 K

# Translation Results

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Table: BLEU Score (Papineni et al., 2002)

Translation System	ReoM Size	Speed	MT06	MT08
Baseline	-	-	28.92	32.13
BL + Lexicalized ReoM	604 MB	2.2 sec/s	30.86	34.22
BL + Bayes-MAP ReoM	18 MB	2.6 sec/s	<b>31.21</b>	<b>34.72</b>
BL + Bayes-Baysien ReoM	18 MB	2.6 sec/s	<b>31.20</b>	<b>34.69</b>

Thank you for your attention.