



#### PARAPHRASING ADAPTATION FOR WEB SEARCH RANKING

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### MOTIVATION

Mismatch between queries and documents is a key issue for the web search task

- Caused by expressing the same meaning in different natural language ways
  - E.g.

X is the author of Y Y was written by X



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Y was written by X

Paraphrasing engine produces alternative expressions to convey the same meaning of the input text

- Improve paraphrasing from different perspectives
  - E.g.

Paraphrase extraction Paraphrase generation Model optimization

## **MOTIVATION (CONT.)**

**Q1:** Could paraphrasing engine alleviate the mismatches of query and its relevant documents?

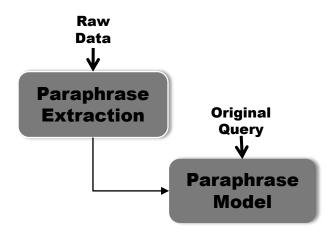
Q2: How to adapt the paraphrasing engine for web search ranking task specifically?





#### **Paraphrase Extraction**

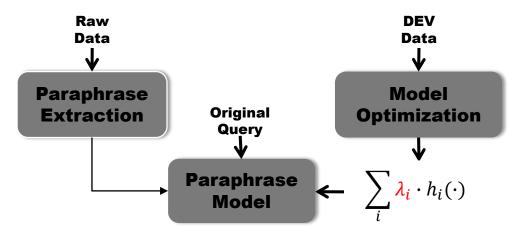
 Extract paraphrase pairs from various data sources



#### **Paraphrase Extraction**

Extract paraphrase pairs from various data sources •

Paraphrase Model • A search-oriented model generates candidates for each original query



#### **Paraphrase Extraction**

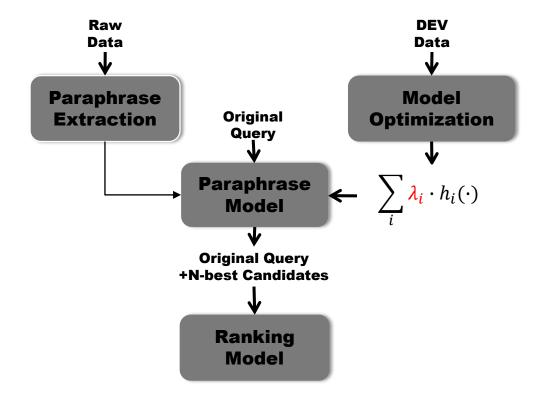
 Extract paraphrase pairs from various data sources

#### **Paraphrase Model**

 A search-oriented model generates candidates for each original query

#### **Parameter Optimization**

 Optimize the weights of the features used in paraphrasing model on development data



#### **Paraphrase Extraction**

 Extract paraphrase pairs from various data sources

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 A search-oriented model generates candidates for each original query

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 Optimize the weights of the features used in paraphrasing model on development data

#### **Ranking Model**

 An enhanced ranking model by using augmented features computed on paraphrases of original queries

#### **PARAPHRASE EXTRACTION**

#### **Monolingual-based**

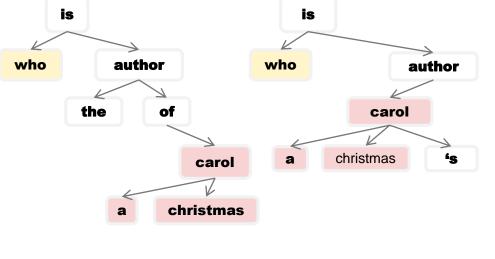
 Hypothesis: Words/Phrases that share the same context tend to have similar meanings

(Lin and Pantel (2001))

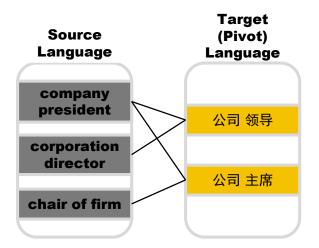


 Hypothesis: Phrases that align with identical pivot phrases tend to have similar meanings

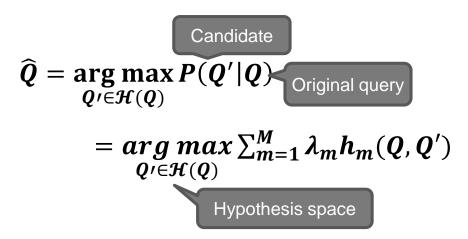
(Bannard and Callison-Burch (2005))



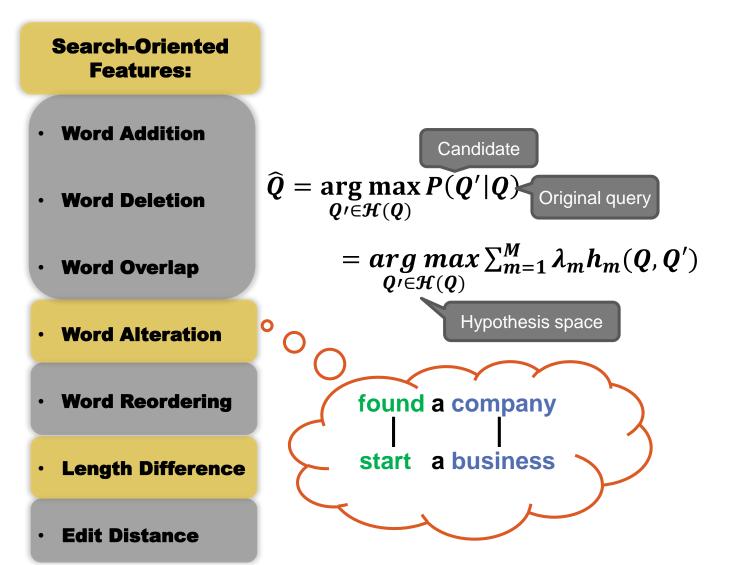
#1 is the author of #2 #1 is #2 's author



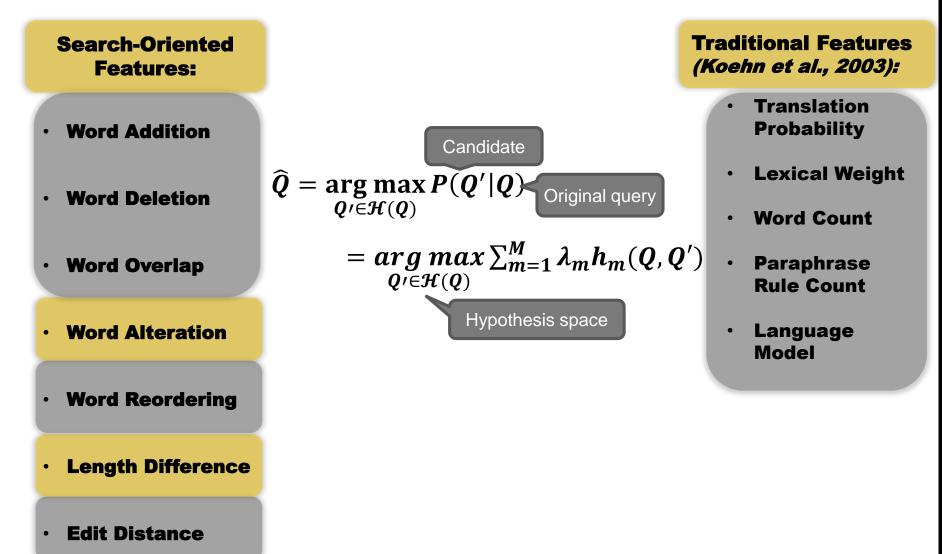
### SEARCH-ORIENTED PARAPHRASING MODEL



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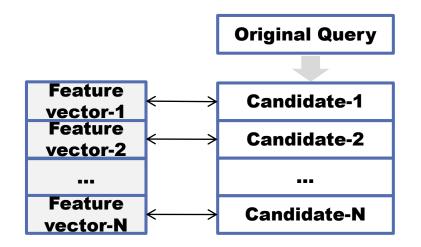


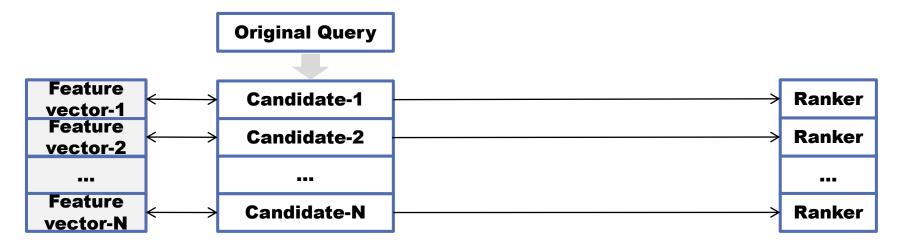
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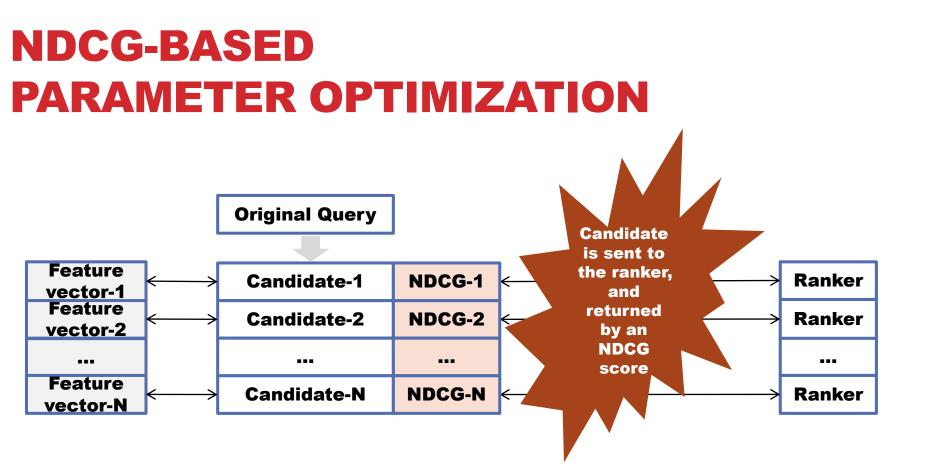


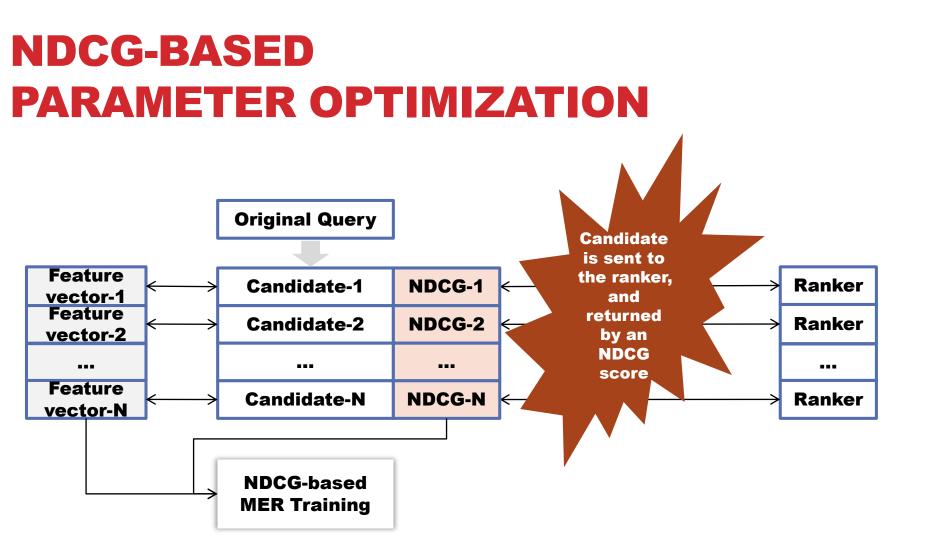
**Original Query** 

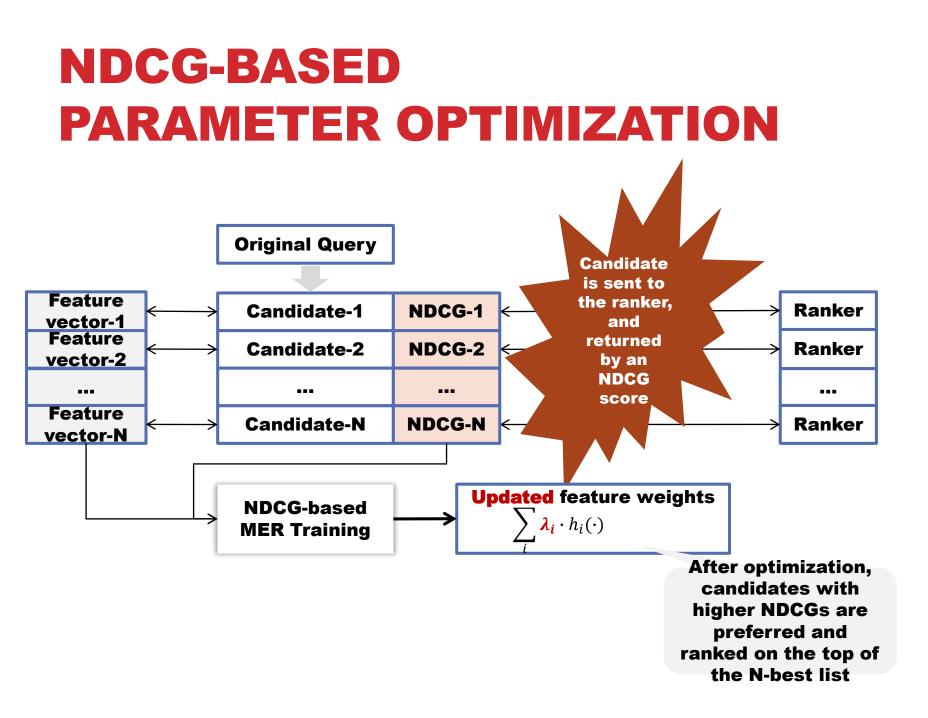
Original Query		
Candidate-1		
Candidate-2		
Candidate-N		











### NDCG-BASED PARAMETER OPTIMIZATION (CONT.)

#### Minimum error rate training (MERT) (Och, 2003)

 To find the optimal feature weight vector that minimizes the error criterion *Err* according to the NDCG scores of top-1 paraphrase candidates

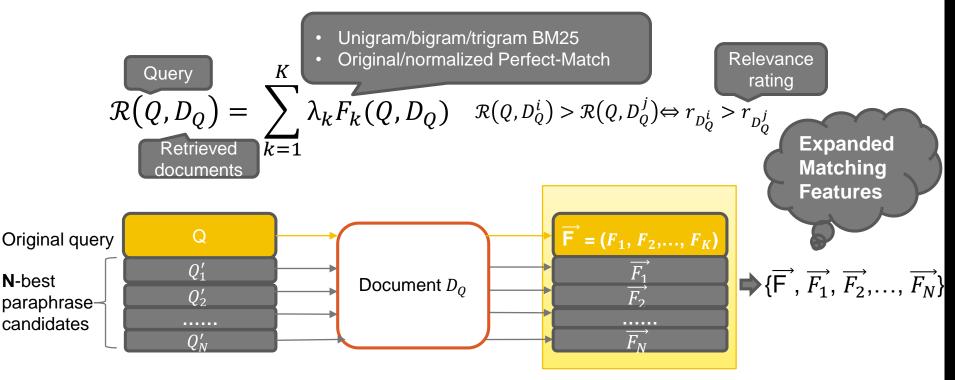
$$\hat{\lambda}_{1}^{M} = \arg\min_{\lambda_{1}^{M}} \{\sum_{i=1}^{S} \frac{Err(D_{i}^{Label}, \hat{Q}_{i}; \lambda_{1}^{M}, \mathcal{R})}{Best \text{ paraphrase}} \{\sum_{i=1}^{NDCG \text{ score}} NDCG \text{ score} \}$$

$$Err(D_{i}^{Label}, \hat{Q}_{i}; \lambda_{1}^{M}, \mathcal{R}) = 1 - N(D_{i}^{Label}, \hat{Q}_{i}, \mathcal{R})$$

### **ENHANCED RANKING MODEL**

#### **Ranking model**

• The paraphrase candidates act as hidden variables and expanded matching features between queries and documents



### EXPERIMENTS: DATASETS

#### **Paraphrase Extraction**

- Training data
  - Bilingual corpus (NIST 2008 constrained track): 5.1M sentence pairs
  - Monolingual corpus (Bing's query log): 16.7M queries
  - Human annotated data (WordNet dictionary): 0.3M synonym pairs
- # of paraphrase pairs: 58M

#### **Evaluation Set**

Bing's query log	# of queries
Development	1,419
Test	1,419

### **SYSTEMS**

#### Paraphrasing

Denotation	Features	Optimization Metric
BL-Para (baseline)	Traditional features	BLEU
BL-Para+SF	Traditional features + Search-oriented features	BLEU
BL-Para+SF+Opt	Traditional features + Search-oriented features	NDCG

#### **Ranking Model**

Denotion	Features
BL-Rank (baseline: Liu et al., 2007)	Query-documents matching features (unigram/bigram/trigram BM25 and original/normalized Perfect-Match)
BL-Rank+Para (Enhanced ranking model)	Query+Paraphrase-documents matching features

\*The ranking model is learned based on SVMrank toolkit (Joachims, 2006) with default parameter setting.

### IMPACTS OF SEARCH-ORIENTED FEATURES

	Test Set		
	BL-Para	BL-Para+SF	Top-1
<b>Original Query</b>	Cand@1	Cand@1	Paraphrase Candidate
27.28%	26.44%	26.53%	Candidate

BL-Para: Paraphrase Baseline with Features: Traditional features

**Optimization Metric:** BLEU

BL-Para+SF: Paraphrase Baseline with Features: Traditional features + Search-oriented features Optimization Metric: BLEU

### IMPACTS OF OPTIMIZATION ALGORITHM

	Test Set		
	BL-Para+SF	BL-Para+SF+Opt	
<b>Original Query</b>	Cand@1	Cand@1	Paraphrase Candidate
27.28%	26.53%	27.06% <mark>(+0.53%)</mark>	

BL-Para+SF: Paraphrase Baseline with Features: Traditional features + Search-oriented features Optimization Metric: BLEU BL-Para+SF+Opt: Paraphrase Baseline with Features: Traditional features + Search-oriented features Optimization Metric: NDCG

### IMPACTS OF ENHANCED RANKING MODEL

)		
	Dev Set	
	NDCG@1	NDCG@5
BL-Rank	25.31%	33.76%
BL-Rank+Para	28.59% <mark>(+3.28%)</mark>	34.25% <b>(+0.49%)</b>
Test set		
	NDCG@1	NDCG@5
BL-Rank	27.28%	34.79%
BL-Rank+Para	28.42% <mark>(+1.14%)</mark>	35.68% <b>(+0.89%)</b>
	BL-Rank+Para BL-Rank	NDCG@1           BL-Rank         25.31%           BL-Rank+Para         28.59%(+3.28%)           Test set           NDCG@1           BL-Rank         27.28%

BL-Rank: *Query-documents* matching features (unigram/bigram/trigram BM25 and original/normalized Perfect-Match)

#### **BL-Rank+Para:**

Query+Top 1 Paraphrasedocuments matching features (unigram/bigram/trigram BM25 and original/normalized Perfect-Match)

### CONCLUSION

We present an in-depth study on adapting paraphrasing for web search

- Paraphrasing model with search-oriented features
- NDCG-based optimization method

#### **Future directions:**

- Compare and combine paraphrasing with other query reformulation techniques to further improve the search quality
  - E.g., pseudo-relevance feedback, and conditional random field-based approach

# THANK YOU!

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