Customized Language Parsing for Sentence Retrieval[1]

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Abstract This paper reports on customized language parsing technique for information retrieval at sentence level. As linguistic preprocess, customized language parsing is more essential for sentence retrieval than documents. Starting from natural language, it aims to extract query intention from topics and analyze relevant information within sentences. Some sentence retrieval models and query expansion strategies have been applied on the basis of the linguistic parsing results. Experiments conducted on TREC novelty track test data show that sentence retrieval with customized language parsing rank top among previously published results. It indicates that customized language parsing is more effective for sentence retrieval.

Keywords language parsing, novelty detection, sentence retrieval

1 INTRODUCTION

Sentence retrieval aims to find on-topic sentences given a topic and document set. It is an essential step for question answering, text summarization and novelty detection. Sentence retrieval was first formally introduced as a required component in TREC novelty track [1] in the year of 2002. The track was designed to locate relevant sentences, and further filter reduplicate information from chronologically ordered relevant sentences. Any relevant sentence that does not contain new information should be discarded. This paper only emphasizes the first two stages: linguistic parsing technique and sentence retrieval.

With the development of TREC novelty track, sentence retrieval received increasingly attention. There have been 26 research groups participating in novelty track in the last three years. Previous works tend to apply some promising text-oriented techniques in sentences. M. Zhang et al. [2,3], Christof Monz et al. [4] and Leah S. et al. [5] extended document-based information retrieval approaches. Hong Qi et al. [6] detected relevant information using multi-document extractive summarizer. Srikanth K. et al. [7] and Ganesh R. et al. [8] also turn sentence retrieval into summarization. Ryosuke Ohgaya et al. [9] made use of information filtering framework. Jian Sun et al. [10] and Taoufiq D. et al. [11] treated relevant retrieval as text categorization, which categorized sentences into relevant or not. John M. et al. [12] tried hid-

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den Markov model, in which relevance and irrelevance are viewed as the possible state of a sentence. Due to the limitation of sentence level detection, almost all systems have to make query or term expansion. Some prior ontological knowledge, such as WordNet [3,8,10,13,14], synonym dictionary [2], conceptual fuzzy sets [9], term similarity tree [15] are very popular with expansion. In addition, term frequency, co-occurrence [3], document frequency and other statistical information proved to be more helpful. The hybrid of prior knowledge and local statistics are more informative. As for novelty detection measure, researchers often brought up self-defined novelty score based on various metrics, such as inverse document frequency [15], similarity comparison with previous sentences [15], maximum margin relevance [10, 16] and word overlapping [2,10].

Sentence retrieval is fine-tuned passage retrieval. It is more difficult than traditional document retrieval. A document contains dozens of terms and some keywords would occur frequently. However, the average number of substantial words in a sentence is less than five. In addition, the term frequency tends to be one within a single sentence. Hence, much work should be done to extract extensive linguistic knowledge from such few words. Meanwhile, the queries for retrieval should be generated from topics written in natural language. The linguistic parsing result is the basis of query generation, sentence retrieval and novelty detection. On one hand, natural language parsing becomes the indispensable preprocess, on the other hand, the complete and general processing on natural language is more complex, ineffective and time-consuming. In conclusion, an intermediate language parsing technique should be customized for sentence retrieval.

Natural language processing (NLP) technique, such as stemming, part-of-speech and query analysis was almost applied in all text-mining systems. To the best of our knowledge, however, researchers only make use of some basic tools for general languages and pay much attention on retrieval model. Less work has been done on language parsing customized for some applications with limited domain and special aims. The surprising result that we found is that language parsing customized for sentence retrieval is more effective than retrieval modeling. Specifically, a simple vector space model with customized language parsing could achieve the most competitive performance on all available data set.

In this paper, we explore the technique that was employed in our novelty system NOOVEL, which was developed for TREC 2004 novelty track. The focus is the customized language parsing on the first required stage. The content is organized as follows: In Section 2, we review NOOVEL architecture. Section 3 details the processes of customized language parsing. The next section explores the approaches for sentence retrieval. Section 5 presents supervised and unsupervised experiments on data set of TREC2002, TREC2003 and TREC2004. Comparing with the previous best system, we investigate the contribution of customized language parsing to sentence retrieval. Query expansion is further surveyed in the retrieval experiments. We give our conclusions in Section 6 by summarizing our works.

2 NOOVEL ARCHITECTURE AND CUSTOMIZED LANGUAGE PARSING

NOOVEL system is the experimental platform for sentence retrieval and novelty detection. It includes four sequential processes: customized language parsing on documents and topics, document retrieval, sentence relevance and novelty detection. The architecture is given in Figure 1. Customized language parsing is a required component and independent of relevance retrieval and new detection. It extracts query from topics and parses the given sentences. The intermediate linguistic results are more valuable for the subsequent processes. Customized language parsing provides the input source for document and sentence retrieval, while relevant sentences are the scope for novelty detection.

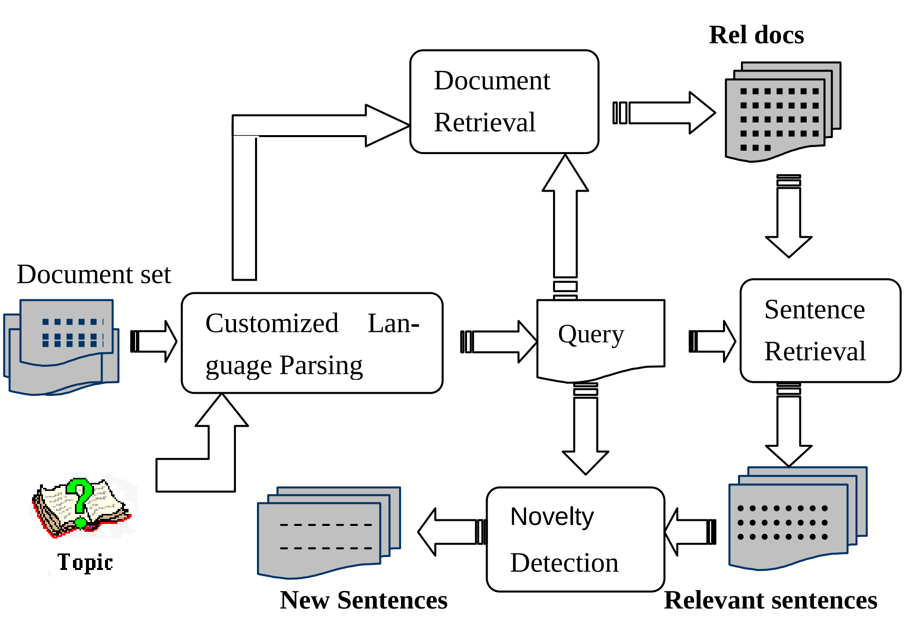

Fig. 1. Noovel System Architecture

3 CUSTOMIZED LANGUAGE PARSING TECHNIQUE

Customized language parsing includes the sequent processes: sentence boundary detection, tokenization, part-of-speech (POS) tagging, morphological analysis, stop list removal, query generation, and feature selection. This section only focused on the improvement and customization on previous works with the following issues.

3.1 Morphological Analysis

Document oriented application often make use of fine-grained stemming on different word forms. However, this is far from the requirement for sentence level analysis. For instance, "computers" and "computing" would be both stemmed as "comput" using Porter [17] stemming tool, which was popular with information processing. The result ignored the difference between two words. Although it is acceptable for document retrieval, it would affect sentence retrieval and greatly reduce the performance of novelty detection.

Hence, we apply morphological analysis instead of stemming. Based on WordNet codes, a powerful morphological analyzer was built on rules and exception list. It could extract the base of various word forms, such as noun plural, verb past tense and passive, adjective and adverb comparative.

3.2 Stop List Removal

Three strategies are introduced in stop list removal.

Firstly, any words in the topic title are reserved as possible keywords.

Secondly, noun, verb, adjective and adverb are reserved, and others are viewed as removal list. Besides, the numeric expression occurred in the topic field was also important. Take exemplification with the topic N56 in TREC 2004 novelty track, the number in “Woodstock 99 music festival reunion in Rome, NY” emphasized the festival year. Such numbers could not be filtered out.

Finally, reserved words would be excluded if they were included in the stop word list.

3.3 Query Generation

Query is generated from the topics that expressed the user’s requirement with natural languages. Query generated decides whether returned results are appropriate to the users. It affects the performance of sentence retrieval and novelty detection. As for novelty track, the query content is generated from TREC topic fields such as title, description and narrative.

In query generation, tokens in topic after stop list removal could be categorized into query words and supplementary words. Query words express the user’s inherent query, while supplementary words have no any explicit relationship with query. As demonstrated in Figure 2, supplementary words are in italic font and other words are normal. In the process of generating query, supplementary words are discarded and only query words are reserved. In NOOVEL system, hundreds of supplementary words are collected from all TREC topics.

The generated queries are further divided into positive and negative by its tendency. Here, negative query is assumed to be a sentence including negative words like “irrelevant” and “not”. Otherwise, it is positive. In the figure 2, the underlined sentence is negative query. It is assumed that a single sentence only has one tendency. In other word, both positive and negative query would not be expressed within one sentence.

To be *relevant*, a *document contains* any *opinion* of the family, the public, the police, the judicial or even those of the news reporter as to the reason for the dragging. Also *relevant* is the ongoing investigation into the crime, the suspects, the juror selection, and the trial results regarding the dragging death of James Byrd, Jr. <u>*Documents* that *reflect* only on the incident without elaboration are not *relevant*.</u>

Fig. 2. Segment in TREC topic N53

Therefore, the topic in Fig.2 generates the positive query including word set {family, public, police, judicial, drag, investigation, crime, suspect, juror, selection, trial, results, death, James Byrd Jr.} and the negative query including the set {incident, elaboration}.

3.4 Feature Selection

In order to reduce noise, we further take feature selection on all reserved terms after stop list removal.

Feature selection is performed with $\chi 2$ (Chi) statistics, mutual information (MI) and hybrid. Given a topic, the corresponding documents are considered as relevance while documents in all other topics are irrelevant. Empirically threshold in $\chi 2$ statistics is set with 3.841 and MI threshold is 0.1. The results of hybrid are intersection between feature set of $\chi 2$ statistics and that of MI.

NOOVEL takes the hybrid approach in feature selection.

After customized language parsing, sentences in topics and documents are converted to sequences of term ID. The intermediate data in XML format is shown in the following figure. It could be directly used for document retrieval, sentence retrieval and novelty detection.

```
<SENTENCE>He/PRP will/MD also/RB seek/VB
the/DT general/NN 's/POS extradition/NN to/TO
Spain/NNP ./.    </SENTENCE>
<SENTENCE_Query>seek/VB general/NN extradi-
tion/NN spain/NNP </SENTENCE_Query>
<SENTENCE_QueryID>24358/NN 28581/NN
63288/VB 66983/NNP</SENTENCE_QueryID>
```

Fig. 3. Segment in the intermediate data set

4 SENTENCE RETRIEVAL MODELS

Sentences are treated as a mini-document in NOOVEL. Besides the traditional document retrieval algorithm, some extra technique was applied in retrieving relevant sentences. Based on the linguistic results from customized language parsing, we have tried three sentence retrieval models: vector space model (VSM), probabilistic model and statistical language model.

4.1 VSM and Query Expansion (QE)

In the standard VSM, query and sentences are represented with a vector. Each term is weighted with log(tf+1)* log(N/df+1.0), where tf is term frequency in a sentence and df is the sentence frequency. Traditionally, relevance or similarity is estimated with the inner product:

$$sim(q,d) = \sum_{t \in q \wedge d} w_{d,t} * w_{q,t} \tag{1}$$

As for vector normalization, we have tried cosine, length, and pivoted document length normalization [18].

As described above, the information in a single sentence is very limited. Therefore, three query expansion strategies are introduced: pseudo-relevance feedback, WordNet and local co-occurrence.

In pseudo-relevance feedback QE, sentences whose similarity with query ranked top 5% were treated as “relevance”. They are added to extend the original query as positive feedback.

WordNet is used to extend a term with those words that co-occurs both in its synset/synonym and the given documents. For example, given “leg” in the query, the hyponym word “body” would be added if “body” is also appeared in the relevant documents. We have tried sentence similarity computation using WordNet in TREC 2003 [19].

Local co-occurrence expansion extends a query term with those highly co-occurred words in the same sentences. From 25 documents relevant to the topic “partial birth abortion ban”, we could get some local co-occurrence terms in the Table 1.

Table 1. Sample list with local co-occurrence expansion

W_i	W_j	Co-occurrence Prob. $p(W_i \mid W_j)$
partial	court	0.166667
partial	supreme	0.119048
supreme	court	0.107143
birth	procedure	0.083333

4.2 Probabilistic Model

We extend the probabilistic model used in OKAPI [20] system to sentence retrieval. It estimates the similarity between query q and sentence d with the following formulas:

$$sim(q,d) = \sum_{t \in q \wedge d} w_{d,t} * W_{q,t}$$

$$w_{d,t} = \frac{(k_1+1) * f_{d,t}}{k_1 * [(1-b) + b * \frac{W_d}{avr\_W_d}] + f_{d,t}}$$

$$W_{q,t} = \frac{(k_3+1) * f_{q,t}}{k_3 + f_{q,t}} * \log \frac{N - f_t + 0.5}{0.5} \qquad (2)$$

avr_W_d is the average sentence length; f_t is the number of sentences which term t occurs, and $f_{x,t}$=term t frequency in either query q or sentence d.

And in NOOVEL system, the parameters are set as:

k_1=1.2 , k_2=1000, b=0.75

4.3 Statistical Language Model

In statistical language model [21], similarity between a sentence S and topic T is computed by the logarithm of conditional probability within language distribution model. The formula is:

$$Sim(Q,S) = \ln P(Q|S) = \sum_{w \in Q} \ln[\lambda p(w|S) + (1-\lambda) p(w|D)] \qquad (3)$$

where D is the document what S belongs to; λ is the smoothing argument between sentence and document.

However, SLM is not applicable at sentence level since the corpus size is too small to get a reliable language probability. We eventually discarded the approach in the official runs.

5 EXPERIMENTS AND DISCUSSION

Three groups of experiments were conducted on NOOVEL. The first group was designed to compare with previous works. It aims to testify the contribution of customized language parsing to sentence retrieval. The second further investigated query expansion strategies on the basis of standard VSM. The last discussed supervised sentence retrieval.

5.1 Metrics

Both sentence retrieval and new detection are evaluated with standard precision, recall and F measure. It is well accepted in TREC novelty track.

The performance on a given topic are estimated with:

$$\text{Recall} = \frac{\#\,\text{results matched}}{\#\,\text{answers}}$$

$$\text{Precision} = \frac{\#\text{results matched}}{\#\,\text{results submitted}} \qquad (4)$$

$$F = \frac{\text{Recall} \times \text{Precision} \times (1+\beta^2)}{\text{Recall} + \text{Precision} \times \beta^2}$$

where weighting parameter β value is set with 1.

For all given topics, the synthetic performance is given with average performance. Specifically, they are formulated with:

$$AverR = \frac{\sum_{i=1}^{N} \text{Recall(i)}}{N}$$

$$AverP = \frac{\sum_{i=1}^{N} \text{Precision(i)}}{N} \qquad (5)$$

$$AverF = \frac{\sum_{i=1}^{N} \text{F(i)}}{N}$$

Where N = # topics

As for TREC novelty track, the final performance of sentence retrieval is evaluated with average relevant F measure on 50 topics.

5.2 Contribution of Customized Language Parsing

Novelty detection is a complicated system. Generally, what may affect the results are linguistic analysis, sentence retrieval, document retrieval, novelty detection modeling and even some other trivial tricks. As described above, customized language parsing is an essential linguistic preprocessing mechanism in NOOVEL architecture. However, how to estimate its contribution to the final performance among so many diverse factors?

Relevant retrieved sentences are more related to retrieval model and linguistic parsing, while the performance of novelty detection depends more on relevant results. Therefore, we only take sentence retrieval into account to investigate the contribution of customized language parsing.

As for sentence retrieval model, we use a standard vector space model without any more process. A sentence is judged as relevance if its cosine value with topic vector is over than a certain threshold θ. For simplicity, θ is set to be 0.0. Two experiments were conducted on TREC 2002 and 2003 data set. At the same time, we took the best run published in the corresponding track as comparison. Table 1 and Table 2 give the performance comparison with the best run respectively. The Run ID column indicates the run id, where NOOVEL indicates the run submitted by NOOVEL system based on customized language parsing.

Table 2. Performance Comparison of sentence retrieval on TREC 2002

RunID	**AverP**	**AverR**	**AverF**
NOOVEL	0.19	0.68	0.257
Thunv1	0.23	0.34	0.235

Thunv1 [2] ranks top in Novelty 2002 track. It focused expansion-based technologies. It incorporated dynamic results selection and tried four weighting strategies into the official result.

Table 3. Performance Comparison of sentence retrieval on TREC 2003

RunID	**AverP**	**AverR**	**AverF**
NOOVEL	0.59	0.79	0.614
THUIRnv0315	0.62	0.67	0.564

THUIRnv0315 integrated pseudo feedback, short and long query, and topic-oriented clustering approach. It achieved the best performance among submitted runs.

Compared with the best runs, NOOVEL have not taken any expansion or other further technique except standard VSM with customized language parsing on given topics and sentences. The sentence retrieval model is very preliminary and far from previous fine-tuned systems. However, the simplest retrieval model with customized language parsing achieved better than all previous systems. It indicated that customized language parsing greatly improved the performance of sentence retrieval.

With the similar strategies, NOOVEL system further participated in TREC 2004 novelty track. Table 3 gives our official run ICTOKAPIOVLP using probability retrieval model. It ranks 5th, and it is slightly less than the best run UIowa04Nov11, which involved named entity, word sense, and statistical similarity schemes [22].

Table 4. Performance Comparison of sentence retrieval on TREC 2004

RunID	**AverP**	**AverR**	**AverF**
ICTOKAPIOVLP	0.32	0.73	0.415
UIowa04Nov11	0.31	0.82	0.420

Based on the relevant sentences returned in ICTOKAPIOVLP, new sentences are detected with word overlapping measure. The performance on novelty detection is given in Table 5. The novelty average F-measure of ICTOKAPIOVLP ranks top among all submitted runs.

Table 5. Performance of novelty detection on TREC 2004

RunID	AverP	AverR	AverF
ICTOKAPIOVLP	0.17	0.57	0.239

From the experiments on the last three years of novelty track, it can be concluded that customized language parsing is more effective for sentence retrieval than retrieval modeling. At sentence level, linguistic preprocessing becomes the bottleneck of retrieval and novelty.

5.3 Survey on Query Expansion

On TREC 2003 test data, NOOVEL have tried three query expansion strategies described in section 4. 1. The average F measure of sentence retrieval is shown in Figure 4.

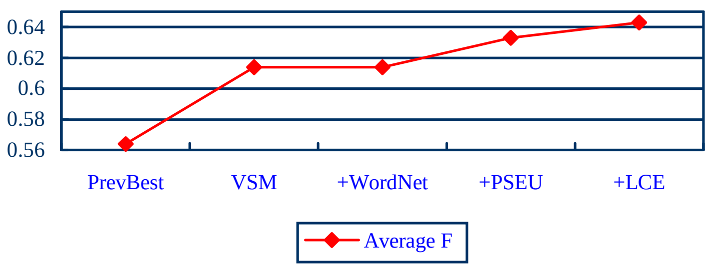

Fig. 4. Performance Comparison with Various Query Expansion (Here, PrevBest: previous best result. VSM: standard VSM; +WordNet: VSM with WordNet expansion; +PSEU: VSM with pseudo-relevance feedback expansion; +LCE: VSM with local co-occurrence expansion)

From the figure, it was found that WordNet expansion could be nearly ignored. It does not perform well in sentence retrieval. However, pseudo-relevance feedback expansion could improve F-measure by 0.19. Significantly, VSM with local co-occurrence expansion could achieve 0.643 on F measure. It proves that LCE is most promising in sentence retrieval.

5.4 Supervised Sentence Retrieval

Compared with unsupervised retrieval, supervised sentence retrieval is given a part of relevant results. NOOVEL employed known results to make further feature selection, train the weighting parameters and adjust the selected results count. In Task 3 of TREC novelty track, the participants are provided with results in the first five documents. Table 6 presents our two official runs using OKAPI and VSM.

Table 6. Supervised Sentence Retrieval on TREC 2004 Task 3

RunID	AverP	AverR	AverF
ICT3OKAPIOLP	0.37	0.76	0.464
ICT3VSMOLP	0.37	0.76	0.464

Both of them ranked top among all of 40 runs with 0.464 on average F-measure. Individually, they achieved the best performance among 22% topics. Compared with unsupervised sentence retrieval, the performance of supervised retrieval improves by 11.81%. It shows that supervised learning on some effective feedback do much well to sentence retrieval.

CONCLUSION

We have presented our work of language parsing technique customized for sentence retrieval. Linguistic parsing on topics and documents is an essential preprocessing in the whole architecture of novelty detection. It becomes the bottleneck for sentence retrieval and the final performance. Although few efforts have been made on modeling to find relevant and new information, using customized language parsing we achieved the best performance among all systems on the last three years of TREC novelty track. This may be the case because customized language parsing is more decisive than retrieval modeling at sentence level.

We also introduce some query expansion strategies in sentence retrieval. Pseudo-relevance feedback and local co-occurrence expansion is proved to be more effective.

References

[1] I. Soboroff. Overview of the TREC 2004 Novelty Track. In Proceedings of the 13th Text Retrieval Conference (TREC ’04) , Gaithersburg, MD USA, November 16-19, 2004, 57-60.

[2] M. Zhang, C. Lin, Y. Liu, L. Zhao, L. Ma, S. Ma. THUIR at TREC 2003: Novelty, Robust and Web.In *Proceeding of the Twelfth Text Retrieval Conference*, Gaithersburg, MD USA, November 18-21, 2003, pp.556

[3] M. Zhang, R. Song, C. Lin, S. Ma, Z. Jiang, Y. Jin, Y. Liu, L. Zhao and S. Ma. Expansion-Based Technologies in Finding Relevant and New Information: THU TREC2002 novelty track experiments.In *Proceeding of the Eleventh Text Retrieval Conference*, Gaithersburg, MD USA, November 19-22, 2002, pp.591

[4] Christof Monz,Jaap Kamps, and Maarten de Rijke. The University of Amsterdam at TREC 2002. In *Proceeding of the Eleventh Text Retrieval Conference*, Gaithersburg, Maryland, November 19-22, 2002, pp.603

[5] Leah S..James Allen, Magaret. E.,Alvaro B. and Courtey. W., UMass at TREC 2002: Cross Language and Novelty Tracks, In *Proceeding of the Eleventh Text Retrieval Conference*, Gaithersburg, Maryland, November 19-22, 2002, pp.721

[6] Hong Qi. Jahna O.,and Dragomir R. The University of Michigan at TREC 2002: Question Answering and Novelty Tracks. In *Proceeding of the Eleventh Text Retrieval Conference*, Gaithersburg, Maryland, November 19-22, 2002, pp 733

[7] Srikanth K., Yongmei S., R. Scott Cost, Charles N., Akshay J., Christopher J., Sowjanya R., Vishal S., Sachin B., and Drew O.. UMBC at TREC 12. In *Proceeding of the Twelfth Text Retrieval Conference*, Gaithersburg, Maryland, November 18-21, 2003, pp.699

[8] Ganesh R., Kedar. B, Chirag Shah., Deepa P.. Generic Text Summarization Using WordNet for Novelty and Hard. In *Proceeding of the Twelfth Text Retrieval Conference*, Gaithersburg, Maryland, November 18-21, 2003, pp.303

[9] Ryosuke Ohgaya, Akiyoshi Shimmura and Tomohiro Takagi. Meiji University Web and Novelty Track Experiments at TREC 2003, In *Proceeding of the Twelfth Text Retrieval Conference*, Gaithersburg, Maryland, November 18-21, 2003, pp.399

[10] Jian Sun, Wenfeng Pan, Hua-ping Zhang. TREC 2003 Novelty and Web Track at ICT, In *Proceeding of the Twelfth Text Retrieval Conference*, Gaithersburg, Maryland, November 18-21, 2003, pp.138

[11] Taoufiq D., Josiane M..TREC NOVELTY TRACK AT IRIT – SIG. In *Proceeding of the Twelfth Text Retrieval Conference*, Gaithersburg, Maryland, November 18-21, 2003, pp.337

[12] John M., Daniel M., Dianne P.. From TREC to DUC to TREC Again In *Proceeding of the Twelfth Text Retrieval Conference*, Gaithersburg, Maryland, November 18-21, 2003, pp.293

[13] Fellbaum, C., ed. *"WordNet: An Electronic Lexical Database"* . MIT Press, Cambridge, MA. 1998

[14] Ming-Feng Tsai, Wen-Juan Hou, Chun-Yuan Teng, Ming-Hung Hsu, Chih Lee and Hsin-Hsi Chen, Similarity Computation in Novelty Detection and GeneRIF Annotation. In *Proceeding of the Twelfth Text Retrieval Conference*, Gaithersburg, Maryland, November 18-21, 2003, pp.474

[15] Qianli Jin, Jun Zhao, Bo Xu. NLPR at TREC 2003: Novelty and Robust . In *Proceeding of*

the Twelfth Text Retrieval Conference, Gaithersburg, Maryland, November 18-21, 2003, pp.126

[16] J. Carbonell and J. Goldstein. The use of MMR, diversity-based reranking for reordering documents and producing summaries. In *Proceedings of SIGIR*, pages 335–336, 1998.

[17] Porter, M.F., *An Algorithm For Suffix Stripping*, Program 14 (3), July 1980, pp. 130-137.

[18] Singhal A., C. Buckley, and M. Mitra. *Pivoted Document Length Normalization*. In H. Frei, D.Harman, P. Schauble, and R. Wilkinson, editors, Proceedings of the Nineteenth Annual International A CM SIGIR Conference on Research and Development in Information Retrieval, 1996.

[19] Hua-Ping ZHANG, Jian SUN, Bing WANG, Shuo BAI. *Computation on Sentence Semantic Distance for Novelty Detection*, Journal of Computer and Science Technology, 2005. Vol.20(3):331-337

[20] Robertson, S.E., Walker, S., Beaulieu, M.M., Gatford, M., Payne, A. Okapi at TREC-4, The *Fourth Text REtrieval Conference (TREC-4)*, NIST Special Publication 500-236, National Institute of Standards and Technology, Gaithersburg, MD, pp. 73-86, October 1996.

[21] C. Zhai and J. Lafferty. Two-stage language models for information retrieval. In *Proceedings of the 25th annual international ACM SIGIR conference on Research and development in information retrieval*, pages 49–56. ACM Press, 2002.

[22] D. Eichmann, Y. Zhang, S. Bradshaw, X. Ying Qiu, L. Zhou, P. Srinivasan, A. Kumar Sehgal, H. Wong. Novelty, Question Answering and Genomics: The University of Iowa Response. In *Proceedings of the 13th Text Retrieval Conference* (TREC ’04) , Gaithersburg, MD USA, November 16-19, 2004, 71

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