Automatically Mining Question Reformulation Patterns from Search Log Data

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Abstract
Natural language questions have become popular in web search. However, various questions can be formulated to convey the same information need, which poses a great challenge to search systems. In this paper, we automatically mined 5w1h question reformulation patterns from large scale search log data. The question reformulations generated from these patterns are further incorporated into the retrieval model. Experiments show that using question reformulation patterns can significantly improve the search performance of natural language questions.

1 Introduction
More and more web users tend to use natural language questions as queries for web search. Some commercial natural language search engines such as InQuira and Ask have also been developed to answer this type of queries. One major challenge is that various questions can be formulated for the same information need. Table 1 shows some alternative expressions for the question “how far is it from Boston to Seattle”. It is difficult for search systems to achieve satisfactory retrieval performance without considering these alternative expressions.

In this paper, we propose a method of automatically mining 5w1h question reformulation patterns to improve the search relevance of 5w1h questions. Question reformulations represent the alternative expressions for 5w1h questions. A question reformulation pattern generalizes a set of similar question reformulations that share the same structure. For example, users may ask similar questions “how far is it from $X_1$ to $X_2$” where $X_1$ and $X_2$ represent some other cities besides Boston and Seattle. Then, similar question reformulations as in Table 1 will be generated with the city names changed. These patterns increase the coverage of the system by handling the queries that did not appear before but share similar structures as previous queries.

Using reformulation patterns as the key concept, we propose a question reformulation framework. First, we mine the question reformulation patterns from search logs that record users’ reformulation behavior. Second, given a new question, we use the most relevant reformulation patterns to generate question reformulations and each of the reformulations is associated with its probability. Third, the original question and these question reformulations are then combined together for retrieval.

The contributions of this paper are summarized as two folds. First, we propose a simple yet effective approach to automatically mine 5w1h question reformulation patterns. Second, we conduct comprehensive studies in improving the search performance of 5w1h questions using the mined patterns.
Figure 1: The framework of reformulating questions.

2 Related Work

In the Natural Language Processing (NLP) area, different expressions that convey the same meaning are referred as paraphrases (Lin and Pantel, 2001; Barzilay and McKeown, 2001; Pang et al., 2003; Pasca and Dienes, 2005; Bannard and Callison-Burch, 2005; Bhagat and Ravichandran, 2008; Callison-Burch, 2008; Zhao et al., 2008). Paraphrases have been studied in a variety of NLP applications such as machine translation (Kauchak and Barzilay, 2006; Callison-Burch et al., 2006), question answering (Ravichandran and Hovy, 2002) and document summarization (McKeown et al., 2002). Yet, little research has considered improving web search performance using paraphrases.

Query logs have become an important resource for many NLP applications such as class and attribute extraction (Pasca and Van Durme, 2008), paraphrasing (Zhao et al., 2010) and language modeling (Huang et al., 2010). Little research has been conducted to automatically mine w1h question reformulation patterns from query logs.

Recently, query reformulation (Boldi et al., 2009; Jansen et al., 2009) has been studied in web search. Different techniques have been developed for query segmentation (Bergsma and Wang, 2007; Tan and Peng, 2008) and query substitution (Jones et al., 2006; Wang and Zhai, 2008). Yet, most previous research focused on keyword queries without considering w1h questions.

3 Mining Question Reformulation Patterns for Web Search

Our framework consists of three major components, which is illustrated in Fig. 1.

Table 2: Question reformulation patterns generated for the query pair (“how far is it from Boston to Seattle” , “distance from Boston to Seattle”).

| Pattern Base | Retrieved Documents |
|-------------|---------------------|
| Set = { (q, q)} | P = { (p, p)} |
| S_1 = {Boston}: (“how far is it from X_1 to Seattle” , “distance from X_1 to Seattle”) | |
| S_2 = {Seattle}: (“how far is it from Boston to X_1” , “distance from Boston to X_1”) | |
| S_3 = {Boston, Seattle}: (“how far is it from X_1 to X_2” , “distance from X_1 to X_2”) | |

3.1 Generating Reformulation Patterns

From the search log, we extract all successive query pairs issued by the same user within a certain time period where the first query is a w1h question. In such query pair, the second query is considered as a question reformulation. Our method takes these query pairs, i.e. Set = { (q, q)}, as the input and outputs a pattern base consisting of w1h question reformulation patterns, i.e. P = { (p, p)}. Specifically, for each query pair (q, q), we first collect all common words between q and q, except for stopwords ST2, where CW = {w|w ∈ q, w ∈ q, w ∈ ST}. For any non-empty subset S of CW, the words in S are replaced as slots in q and q to construct a reformulation pattern. Table 2 shows examples of question reformulation patterns. Finally, the patterns observed in many different query pairs are kept. In other words, we rely on the frequency of a pattern to filter noisy patterns. Generating patterns using more NLP features such as the parsing information will be studied in the future work.

3.2 Generating Question Reformulations

We describe how to generate a set of question reformulations {q^new} for an unseen question q^new.

First, we search P = { (p, p)} to find all question reformulation patterns where p matches q^new. Then, we pick the best question pattern p* according to the number of prefix words and the total number of words in a pattern. We select the pattern that has the most prefix words, since this pattern is more likely to have the same information as q^new. If several patterns have the same number of prefix words, we use the total number of words to break the tie.

After picking the best question pattern p*, we further rank all question reformulation patterns containing p*, i.e. (p*, p), according to Eq. 1.

2Stopwords refer to the function words that have little meaning by themselves, such as “the”, “a”, “an”, “that” and “those”.

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Table 3: Examples of the question reformulations and their corresponding reformulation patterns

| $q_{new}$: how good is the Eden Pure Air System | $p^\star$: how market a restaurant | $q_{new}$: how to market a restaurant | $p^\star$: how to market a X |
|-----------------|---------------------------------|-------------------------------|------------------|
| Eden Pure Air System | $X$ | marketing a restaurant | $X$ |
| Eden Pure Air System Review | $X$ Review | how to promote a restaurant | $X$ Review |
| Rate the Eden Pure Air System | rate the $X$ | how to sell a restaurant | reviews on the X |
| Reviews on the Eden Pure Air System | | how to advertise a restaurant | |

$$P(p_r|p^\star) = \frac{f(p^\star, p_r)}{\sum_{p_r'} f(p^\star, p_r')} \quad (1)$$

Finally, we generate $k$ question reformulations $q_{new}^r$ by applying the top $k$ question reformulation patterns containing $p^\star$. The probability $P(p_r|p^\star)$ associated with the pattern $(p^\star, p_r)$ is assigned to the corresponding question reformulation $q_{new}^r$.

3.3 Retrieval Model

Given the original question $q_{new}$ and $k$ question reformulations $\{q_{new}^r\}$, the query distribution model (Xue and Croft, 2010) (denoted as QDist) is adopted to combine $q_{new}$ and $\{q_{new}^r\}$ using their associated probabilities. The retrieval score of the document $D$, i.e. $score(q_{new}, D)$, is calculated as follows:

$$score(q_{new}, D) = \lambda \log P(q_{new}|D) + (1-\lambda) \sum_{i=1}^{k} P(p_{ri}|p^\star) \log P(q_{new}^r|D) \quad (2)$$

In Eq. 2, $\lambda$ is a parameter that indicates the probability assigned to the original query. $P(p_{ri}|p^\star)$ is the probability assigned to $q_{new}^r$. $P(q_{new}^r|D)$ and $P(q_{new}|D)$ are calculated using the language model (Ponte and Croft, 1998; Zhai and Lafferty, 2001).

4 Experiments

A large scale search log from a commercial search engine (2011.1-2011.6) is used in experiments. From the search log, we extract all successive query pairs issued by the same user within 30 minutes (Boldi et al., 2008) where the first query is a 5w1h question. Finally, we extracted 6,680,278 question reformulation patterns.

For the retrieval experiments, we randomly sample 10,000 natural language questions as queries from the search log before 2011. For each question, we generate the top ten questions reformulations. The Indri toolkit is used to implement the language model. A web collection from a commercial search engine is used for retrieval experiments. For each question, the relevance judgments are provided by human annotators. The standard NDCG@$k$ is used to measure performance.

4.1 Examples and Performance

Table 3 shows examples of the generated question reformulations. Several interesting expressions are generated to reformulate the original question.

We compare the retrieval performance of using the question reformulations (QDist) with the performance of using the original question (Orig) in Table 4. The parameter $\lambda$ of QDist is decided using ten-fold cross validation. Two sided t-test are conducted to measure significance.

Table 4 shows that using the question reformulations can significantly improve the retrieval performance of natural language questions. Note that, considering the scale of experiments (10,000 queries), around 3% improvement with respect to NDCG is a very interesting result for web search.

4.2 Analysis

In this subsection, we analyze the results to better understand the effect of question reformulations.

First, we report the performance of always picking the best question reformulation for each query (denoted as Upper) in Table 5, which provides an

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Table 4: Retrieval Performance of using question reformulations. * denotes significantly different with Orig.

|         | NDCG@1 | NDCG@3 | NDCG@5 |
|---------|--------|--------|--------|
| Orig    | 0.2946 | 0.2923 | 0.2991 |
| QDist   | 0.3032*| 0.2991*| 0.3067*|

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3In web search, queries issued within 30 minutes are usually considered having the same information need.

4www.lemurproject.org/
Table 5: Performance of the upper bound.

|            | NDCG@1 | NDCG@3 | NDCG@5 |
|------------|--------|--------|--------|
| Orig       | 0.2946 | 0.2923 | 0.2991 |
| QDist      | 0.3032 | 0.2991 | 0.3067 |
| Upper      | 0.3826 | 0.3588 | 0.3584 |

Table 6: Best reformulation within different positions.

|            | top 1  | within top 2 | within top 3 |
|------------|--------|--------------|--------------|
|            | 49.2%  | 64.7%        | 75.4%        |

Table 7: Analysis of different types of reformulations.

| Type                  | increase | decrease | same |
|-----------------------|----------|----------|------|
| Morphological change  | 11%      | 10%      | 79%  |
| Equivalent meaning    | 32%      | 30%      | 38%  |
| More specific/Add words | 45%    | 39%      | 16%  |
| More general/Remove words | 38%    | 48%      | 14%  |
| Not relevant          | 14%      | 72%      | 14%  |

Table 8: Retrieval Performance of other query processing techniques.

|            | NDCG@1 | NDCG@3 | NDCG@5 |
|------------|--------|--------|--------|
| ORIG       | 0.2720 | 0.2937 | 0.3151 |
| NoStop     | 0.2697 | 0.2893 | 0.3112 |
| DropOne    | 0.2630 | 0.2888 | 0.3102 |
| QDist      | 0.2978 | 0.3052 | 0.3250 |

upper bound for the performance of the question reformulation. Table 5 shows that if we were able to always picking the best question reformulation, the performance of Orig could be improved by around 30% (from 0.2926 to 0.3826 with respect to NDCG@1). It indicates that we do generate some high quality question reformulations.

Table 6 further reports the percent of those 10,000 queries where the best question reformulation can be observed in the top 1 position, within the top 2 positions and within the top 3 positions, respectively.

Table 6 shows that for most queries, our method successfully ranks the best reformulation within the top 3 positions.

Second, we study the effect of different types of question reformulations. We roughly divide the question reformulations generated by our method into five categories as shown in Table 7. For each category, we report the percent of reformulations which performance is bigger/smaller/equal with respect to the original question.

Table 7 shows that the “more specific” reformulations and the “equivalent” reformulations are more likely to improve the original question. Reformulations that make “morphological change” do not have much effect on improving the original question. “More general” and “not relevant” reformulations usually decrease the performance.

Third, we conduct the error analysis on the question reformulations that decrease the performance of the original question. Three typical types of errors are observed. First, some important words are removed from the original question. For example, “what is the role of corporate executives” is reformulated as “corporate executives”. Second, the reformulation is too specific. For example, “how to effectively organize your classroom” is reformulated as “how to effectively organize your elementary classroom”. Third, some reformulations entirely change the meaning of the original question. For example, “what is the adjective of anxiously” is reformulated as “what is the noun of anxiously”.

Fourth, we compare our question reformulation method with two long query processing techniques, i.e. NoStop (Huston and Croft, 2010) and DropOne (Balasubramanian et al., 2010). NoStop removes all stopwords in the query and DropOne learns to drop a single word from the query. The same query set as Balasubramanian et al. (2010) is used. Table 8 reports the retrieval performance of different methods.

Table 8 shows that both NoStop and DropOne perform worse than using the original question, which indicates that the general techniques developed for long queries are not appropriate for natural language questions. On the other hand, our proposed method outperforms all the baselines.

5 Conclusion

Improving the search relevance of natural language questions poses a great challenge for search systems. We propose to automatically mine 5w1h question reformulation patterns from search log data. The effectiveness of the extracted patterns has been shown on web search. These patterns are potentially useful for many other applications, which will be studied in the future work. How to automatically classify the extracted patterns is also an interesting future issue.

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