Diversifying Information Needs in Results of Question Retrieval

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Abstract
Information need is an important factor in question retrieval. This paper proposes a method to diversify the results of question retrieval in term of types of information needs. CogQTaxo, a question hierarchy is leveraged to represent users’ information needs cognitively from three linguistic levels. Based on a prediction model of question types, three factors, i.e., scores of IR model, question type similarity and question type novelty are linearly combined to re-rank the retrieved questions. Preliminary experimental results show that the proposed method enhances the question retrieval performance in information coverage and diversity.

1 Introduction
Most current question retrieval system attempts to fetch questions semantically similar to the query question (Jeon et al, 2005), together with the accepted answers from a large question-answer pair archive. Previous works focus on reducing the lexicon gap between the query question and retrieved questions (Cao et al, 2010) or recognize the single question type, i.e., the type of information needs(infoNeeds) in the query, and confine the types of retrieved questions to be the same as the query (Lytinen and Tomuro, 2002). Normally, the retrieved questions are ranked according to the semantic similarity to the query question.

However, Taylor (1962) argues that the user may fail to express his infoNeeds fully in the question. Besides, given different contextual situations, users may have different intentions, which lead to different infoNeeds for the same question (Small and Strzalkowski, 2008).

For an example question $q_1$, “which bank provides the best credit card?”, if the user wants to confirm the bank he knows, the name of the bank is enough for an answer; while the user plans to open a credit card account, he may want to obtain detailed descriptions and comparisons between credit card services of different banks in addition to a single bank name. Furthermore, a play-it-safe user may expect the information source of the answer to be of authority or expertise, while a casual user may expect it to be commonsense that anyone can answer.

Considering these requirement, the following two questions $q_2$ and $q_3$ should be provided to the user under a certain context. Nevertheless, such infoNeeds are not given explicitly in the $q_1$.

$q_2$: Which bank should I choose for credit card, Citi Bank and Bank of America?
$q_3$: How to choose credit card?

As can be observed, the three questions have different types, which are entity, alternative and method, respectively (Diekema et al, 2003). Apparently, the single-dimensional question taxonomies employed at present are insufficient to model those aspects of users’ infoNeeds (Pomerantz, 2005). Thus, more comprehensive question taxonomy is needed. The question retrieval results should also be diversified accordingly to fulfill these implicit and context-dependent infoNeeds, thus making the results more comprehensive for average users.

Present works (Clark et al, 2009; Santos et al, 2010) mainly target on search result diversification for short queries instead of questions. Their focus is to mine the different interpretations of ambiguous queries or navigations for a broad-sense query. Achananuparp et al. (2010) attempted to diversify the aspects of the answer to complex questions, while they also focus on the short information nuggets returned by search engines.

Based on our knowledge, no previous work has been done on the results diversification for question retrieval. In this paper, we utilize CogQTaxo, a multi-dimensional question taxonomy to model both the explicit and implicit
infoNeeds of questions. Based on this, we propose an algorithm to diversify the results of question retrieval in terms of infoNeed types. The comparative experimental results show that the proposed algorithm enhances the information coverage and diversity of retrieved questions.

2 CogQTaxo - Three Dimensional Question Taxonomy

CogQTaxo is proposed by Zhang et al (2010). It is a framework of three-dimensional question taxonomy by using different levels of linguistic analysis (syntactic, semantic and pragmatic) as the classification criteria.

Let $T_i$ ($i=1,2,3$) denotes the $i$th dimension of CogQTaxo, then:

1. $T_1$ represents the surface information need ($surfaceIN$), which corresponds to the conventional definition of question types ($QuesTs$). A question can has one definite type in $surfaceIN$; 14 types are defined for $surfaceIN$, namely location, person, time, quantity, thing, alternative, definition, comparison, description, procedure, reason, yesNo, abstractEntity and other.

2. $T_2$ represents implicit information needs ($implicitIN$). $QuesTs$ in this dimension are the same as in $surfaceIN$. Nevertheless, it represents the infoNeeds which are not expressed explicitly in the question, yet are required to fill the user’s information gap. A question has at least one type in $implicitIN$.

3. $T_3$ represents users’ pragmatic expectations ($pragmaticE$) from the answer. Four binary-valued pragmatic aspects are currently considered: (1) Specification: whether the question contains detailed specific information as the context; (2) Knowledge source: whether the question requires commonsense or expertise to answer; (3) Temporal constraint: whether the answer is time sensitive, i.e., whether the answer should be constraint to a time-frame; (4) Subjectivity Orientation: whether the information in the expected answer is subjective-oriented or objective-oriented.

A prediction model is built by Zhang et al (2010) to recognize the types of a question in each dimension of CogQTaxo. In this study, CogQTaxo is employed to diversify the infoNeeds in the results of question retrieval.

3 Diversification Algorithm for Question Retrieval Result

According to the definition of CogQTaxo, the three dimensions have different functions in user infoNeeds fulfillment, in which $surfaceIN$ is fundamental and indispensable from the answer. $implicitIN$ provides supportive information and helps to make the answer coverage more comprehensive. Therefore, we use $surfaceIN$ and $implicitIN$ to diversify the types of infoNeeds in retrieval results. The predicted $QuesT$ sets in these two dimensions are merged into an extended one, in which the $QuesTs$ are equally weighted at present. Meanwhile, the third dimension in CogQTaxo, $pragmaticE$, adds pragmatic constraints to the former two.

As displayed in figure 1, our question diversification algorithm is given as follows:

For a input question $p$, the question retrieval system will:

Step 1: Question analysis: The content words (nouns, verbs and adjectives) are extracted from $p$ as the question content. Types of $p$ in line with CogQTaxo are recognized automatically by using the model proposed in (Zhang et al, 2010).

Step 2: Question retrieval: retrieve relevant questions with the information retrieval (IR) model by using question content as the query. The relevance score is denoted as $IRScore$, which is normalized by the highest score of retrieved questions for $p$.

Step 3: Question Reranking with $QuesT$ Similarity: Similar to (Lytinen and N. Tomuro, 2002) and (Cao et al, 2010), this step considers the relevance of $QuesT$ between $p$ and $q$ for result ranking. Nevertheless, the question taxonomy deployed here is multi-dimensional. For each question $q$ in the retrieved question set, $T_iScore$ is defined as the $QuesT$ set distance between $p$ and $q$ in the $i$th dimension of CogQTaxo, $i=1, 2, 3$. It is calculated by MASI (Passonneau, 2006). Since we
merge $T_1$ with $T_2$, the retrieved results are re-ranked by rerankScore, which is defined as:

$$
\text{rerankScore} = (1-l_{w,2} - l_1) \cdot IRScore + l_{w,2} \cdot T_1 \cdot Score + l_1 \cdot T_2 \cdot Score
$$

where $l_{w,2}, l_1 \in [0,1], l_{w,2} + l_1 \in [0,1]$.

Result questions with the rerankScore lower than a threshold $\lambda$ are filtered.

**Step 4: Question infoNeeds diversification:** This step employs a greedy algorithm to add one question with the largest infoNeeds novelty into the final returned question list in each iteration.

Suppose $m$ questions are left in the result set after step 3, we denote DiverseList as the list of $r$ questions re-ranked by diversity. For a question $q$ in the $m-r$ remaining result questions, its QuesTs novelty is defined as:

$$
\text{Novelty}(T) = \text{avg}(\sum \frac{1}{d_{type_j}^q}, \exists \text{type}_j \in T_{1+2}^q \cap T_{r+2}^q)
$$

where $d_{type_j}^q$ is the frequency of type$_j \in T_{1+2}^q \cap T_{r+2}^q$ in DiverseList.

Then diversScore is computed as follows:

$$
\text{diversScore} = (1-w) \cdot \text{rerankScore} + w \cdot \text{Novelty}(T), 0 \leq w \leq 1
$$

The question with the highest diversScore value is added to DiverseList$^1$.

Repeat Step 4 until the DiverseList with top $n$ ($m \geq n$) questions are returned to the user.

### 4 Experiment and Discussion

#### 4.1 Dataset and Experimental Setup

Questions with accepted answers are collected from the Yahoo! Knowledge portal and Baidu Zhida portal, respectively. After removing redundancy and invalid questions, more than 1,380,000 postings are obtained. The title of the posting is used as the question, while the accepted response is regarded as the answer.

100 questions are chosen randomly as the query questions, the other questions are indexed to build the question retrieval system. Only the content words of questions are indexed. In the experiment, we used three IR model, namely Okapi BM25 model, Vector space model and language model, respectively, in which BM25 outperforms. Therefore, only the performance achieved by BM25 is reported in the rest of this section.

**Relevance set:** The relevance set of the 100 query questions are built by judging the content relevance between the query and the results regardless of the infoNeeds. Poolings among the top 10 results by the evaluated methods are conducted. Finally, 2258 relevant questions are collected.

**Information need annotation:** Three annotators annotate the QuesTs of the 100 query questions individually, by following the same instruction as Zhang et al (2010). In this way, three different infoNeeds sets of the query questions are generated. The algorithm performance is evaluated on each infoNeeds set separately, while the average performance is reported.

**Evaluation criteria:** We use MAP$\_IA$, MRR$\_IA$ and P@K$\_IA$ designed by Agrawal et al (2009) as the evaluation metrics. These metrics are originally defined as the weighted arithmetic mean of performance of each subtopic of a query. In this paper, we substitute the subtopics of a query into the potential types of a question. At present we consider all of QuesTs as equally weighted. For example, the formula of MAP$\_IA$ is as follows:

$$
\text{MAP$\_IA$} = \frac{\sum_{QuesT \in \text{Query}} W \cdot \text{MAP}(QuesT)}{|T| + |P|}
$$

Furthermore, the relevance judgment in those metrics between question $p$ and $q$ is not simply bi-
Table 2 Question retrieval results are listed for the query “Which stock is good to buy?”, using BM25 as the retrieval model.

| BM25 model | BM25 model with question type diversity |
|------------|----------------------------------------|
| Which stock is good to buy? | Which stock is good to buy? |
| Which stock is good recently? | Which stock is good recently? |
| Which stock should I buy recently? | What characteristics good stocks have? |
| Recommend some good stocks to me. | How to identify a good stock? |
| Is there any good stock to buy? | Which stocks should I buy; good recommendations will be highly rewarded. |

Table 3 Information needs diversification performance of the evaluated methods.

|                           | Retrive_M | Pop_Div | SurfaceIN_M | implicitIN_M | PragmaticE_M | LinearC | Bow_Div | Predict_Div |
|---------------------------|-----------|---------|--------------|--------------|--------------|---------|---------|-------------|
| MRR IA                    | 0.343     | 0.526   | 0.375        | 0.371        | 0.347        | 0.390   | 0.527   | 0.529       |
| MAP IA                    | 0.114     | 0.140   | 0.138        | 0.134        | 0.120        | 0.149   | 0.164   |             |
| P IA @1                   | 0.181     | 0.211   | 0.239        | 0.237        | 0.213        | 0.245   | 0.245   | 0.262       |
| P IA@5                    | 0.192     | 0.197   | 0.218        | 0.215        | 0.205        | 0.230   | 0.106   | 0.244       |

The infoNeed_relevance(q) is binary valued, as either relevant or not; it is replaced by the similarity between p and q in pragmaticE. As mentioned before, pragmaticE adds pragmatic constraints to the other two dimensions of infoNeeds.

\[
\text{infoNeed}\_\text{relevance}(q) = \begin{cases} 
T\text{Score}, & \text{if relevance}(q) = 1 \\
0, & \text{if relevance}(q) = 0 
\end{cases}
\]

**Evaluated question diversification methods:**
1. **Retrive_M**: only using the IR model; 2. **Pop_Div**: Instead of using the QuesT prediction model built by (Zhang et al, 2000), the QuesTs with the highest relative frequency (larger than 10%), i.e., the most popular QuesTs in the top 200 retrieved results by Retrive_M are used as the potential type of infoNeeds of the query question; 3. **SurfaceIN_M, implicitIN_M, PragmaticE_M**: using each of the three dimensions of CogQTaxo in the diversification algorithm, individually; 4. **LinearC**: The first three steps of the diversification algorithm, i.e., without the diversification iteration step; 5. **Bow_Div**: treating the question as bag-of-words, follows the same procedure without Step 3 in section 3, and only considers the novelty of content words in result questions in Step 4; 6. **Predict_Div**: the complete proposed diversification algorithm.

**4.2 Experimental Results**
Table 2 illustrates the top 5 search results of query “Which stock is good to buy?” using Retrive_M and Predict_Div, respectively. As can be seen, the infoNeeds in questions retrieved by Predict_Div are more diverse than those retrieved by Retrive_M.

Table 3 lists the infoNeeds diversification performance achieved by each method, respectively. It is observed that Predict_Div outperforms. It is also shown that performance of Bow_Div is comparable with Predict_Div in MRR IA and P IA @1; however, it is even inferior to Retrive M in MAP IA and P IA @5. This indicates that the naive bag-of-word baseline is unable to recall diverse infoNeeds of the query, and even deteriorates the performance. Pop_Div and Predict_Div are comparable in MRR IA. However, in terms of other metrics, LinearC and Predict_Div are consistently at the top 2 ranks. The reason is that since the predicted types of a question are already diversified by CogQTaxo, incorporating it into question re-ranking already enables us to diversify the infoNeeds in the results implicitly. Therefore, the explicit diversification step enhances the performance further.

One deficit of the evaluation framework is that the infoNeeds of questions in the relevance set are predicted automatically instead of manually annotated; this may result in a bias towards our proposed algorithm. However, since the training set of the question classifier is manually annotated. Thus, it reflects the real user infoNeeds distribution. It is assumed that the automatic prediction can also reflect real user infoNeeds to some extent. More detailed analysis will be conducted later to examine this problem.

**5 Conclusion**
This paper proposes a method to diversify the results of question retrieval in term of types of information needs. Comparison results show that the proposed method improves the information need coverage and diversity in retrieved questions.
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