Topic-focused Dynamic Information Filtering in Social Media

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Abstract. With the quick development of online social media such as twitter or sina weibo in china, many users usually track hot topics to satisfy their desired information need. For a hot topic, new opinions or ideas will be continuously produced in the form of online data stream. In this scenario, how to effectively filter and display information for a certain topic dynamically, will be a critical problem. We call the problem as Topic-focused Dynamic Information Filtering (denoted as TDIF for short) in social media. In this paper, we start open discussions on such application problems. We first analyze the properties of the TDIF problem, which usually contains several typical requirements: relevance, diversity, recency and confidence. Recency means that users want to follow the recent opinions or news. Additionally, the confidence of information must be taken into consideration. How to balance these factors properly in online data stream is very important and challenging. We propose a dynamic preservation strategy on the basis of an existing feature-based utility function, to solve the TDIF problem. Additionally, we propose new dynamic diversity measures, to get a more reasonable evaluation for such application problems. Extensive exploratory experiments have been conducted on TREC public twitter dataset, and the experimental results validate the effectiveness of our approach.

Keywords: Data Stream, Utility Function, Dynamic Preservation Scheme, Evaluation

1 Introduction

The development of new social media such as twitter or sina weibo\footnote{http://weibo.com} accelerates the spread of online information. In the social media, new information will be continuously produced in the form of online data stream, and how to retrieval useful information effectively will be very challenging. Specially, for a hot topic, how to filter and display relevant information dynamically will be a critical problem, which can be called as Topic-focused Dynamic Information Filtering in social media.
The TDIF problem has three typical requirements: relevance, diversity and recency. The relevance requires the tweet information must be relevant to the topic. The diversity requires that corresponding tweet information can describe the topic from different aspects with little redundancy. Recency means that users want to follow the recent opinions or news quickly. Additionally, the human factor also affects the confidence of the tweet information. For example, the tweet information released by users with “V” authentication in sina weibo are usually with high confidence. Therefore, how to balance these critical factors becomes a new challenging problem.

In fact, little prior research work has been done to tackle the TDIF problem. Most existing work only focuses one or two factors in information retrieval, such as pure relevance [29][20], or pure diversity [30], or relevance combing with diversity [21][31]. Even in the industry field, such problem has also been not solved well. They usually only consider relevance, but can not capture diversity or recency, such as sina weibo in china.

In this paper, We utilize the relational learning-to-rank model (R-LTR for short) [31] as utility function, and combine with the dynamic preservation scheme based on time periodic windows, to solve the TDIF problem. R-LTR model is the state-of-the-art diverse ranking method, which models the diversity relations among documents in the ranking process, besides the content information of individual documents. It is a flexible feature-based ranking model with good adaptation to different application scenario. Although R-LTR model can tackle relevance and diversity well, it is limited in the static dataset. What’s more, R-LTR model is with time complexity of $O(n \times k)$, $n$ means the number of all the candidate objects, and $k$ indicates the number of desired results returned. Obviously, its efficiency can hardly satisfy the scenario of online data stream.

Therefore, we propose the dynamic preservation scheme based on the R-LTR model for proper solution. Specifically, we segment the data stream into disjoint periods with time length $T$ (segmentation granularity can be days or hours depending on detailed requirements). For each new time window, we preserve the top-$(k-m)$ most relevant results previously, then utilize the R-LTR ranking function to select new $m$ relevant results, and finally display all the $k$ results in chronological order. Here the parameter $m$ can flexibly control the “staleness” of the returned results depending on the requirements of scenario.

Additionally, due to the new properties of TDIF application problem, we also propose new dynamic diversity evaluation measures to get a more reasonable evaluation. In these new measures, we introduce the recency factor and confidence factor into existing popular diversity evaluation measures (i.e. $ERR-IA$[18], $\alpha$-$NDCG$[9] and $NRBP$[10]). Then we get a series of dynamic diversity evaluation measures: $d$-$ERR$, $d$-$NDCG$ and $d$-$NRBP$.

We conduct extensive evaluations on public TREC twitter dataset, and the experimental results show that our approach can achieve promising performance on both traditional diversity measures and new dynamic diversity measures. Meanwhile, our approach is also with high processing efficiency.
The rest of the paper is organized as follows. Section 2 introduces our proposed approach for TDIF problem. Section 3 introduces the new dynamic diversity evaluation measures. Section 4 presents the experimental results. Section 5 describes related work and Section 6 concludes the paper.

2 Our Approach

As described before, the TDIF problem in social media has several typical requirements: relevance, diversity, recency and confidence. Therefore, the basic motivation of our approach is how to effectively capture and balance these typical requirements. In this section, we will describe our strategy for dynamic information filtering, which mainly contains two parts. The first part is the chosen of basis utility function. The second part is the design of dynamic strategy that can take recency into consideration effectively.

2.1 Utility Function

The R-LTR model can effectively solve the diverse ranking problem in static dataset scenario, which models both relevance and diversity properly. As described in the literature [31], the score of a candidate document contains two parts: relevance score based on content information of individual documents, and diversity score based on the relationship between the current document and those previously selected. We use $X$ denotes all the candidate documents, $S$ denotes previously selected documents, and $X \setminus S$ denotes the remanent documents. The score function can be formalized as follows.

$$f_S(x_i, R_i) = \omega_r^T x_i + \omega_d^T h_S(R_i), \forall x_i \in X \setminus S$$

(1)

where $x_i$ denotes the relevance feature vector of the candidate document $x_i$, $R_i$ stands for the matrix of relationships between document $x_i$ and other selected documents, with each $R_{ij}$ stands for the diversity feature vector between document $x_i$ and $x_j$, represented by the feature vector of $(R_{ij1}, \cdots, R_{ijl}), x_j \in S$, and $R_{ijk}$ stands for the $k$-th diversity feature between documents $x_i$ and $x_j$, $h_S(R_i)$ stands for the relational function on $R_i$, $\omega_r^T$ and $\omega_d^T$ stands for the corresponding relevance and diversity weight vector.

The relational function $h_S(R_i)$ denotes the way of representing the diversity relationship between the current document $x_i$ and the previously selected documents in $S$. It can be defined in three ways: Minimal, Average and Maximal. Here we choose the Minimal way, defined as follows.

$$h_S(R_i) = \min_{x_j \in S} \{ R_{ij1}, \cdots, R_{ijl} \}$$

As described above, the R-LTR is a flexible feature-based ranking function, which has good adaptation to social media scenario and can be chosen as our basis utility function. Comparing with other heuristic definitions of utility function
such as “Max-Sum” or “Max-Min” \cite{17,14,23}, we can obtain a more reasonable basis utility function by supervised learning. When in real application, we need define and utilize specific relevance and diversity features close related to social media scenario.

**Relevance Feature Vector** $x_i$. For relevance feature vector, we first utilize traditional learning-to-rank relevance features, shown as follows.

- **Weighting Features.** The typical weighting models include TF-IDF, BM25 and language model. For language model, we use query-likelihood language model with Dirichlet prior.
- **Term Dependency Features.** We also employ the classic term dependency features such as MRF \cite{22}, to enhance relevance. The MRF has two types of values: ordered phrase and unordered phrase, so the total feature number is 2.

Additionally, we utilize some specific features in twitter, shown as follows.

- **Recency.** We take the time factor into consideration, and prefer more recent tweet information.
- **UserRank.** The importance of a certain user account, which can capture the confidence of information. It can be simply obtained via the followers of account.
- **Retweet Number.** If a tweet is retweet many times, it is usually with high importance.

This two types of features can be obtained via API \footnote{https://github.com/lintool/twitter-tools/wiki/TREC-2013-API-Specifications} provided by TREC.

**Diversity Feature Vector** $R_{ij}$ For diversity features, we utilize typical semantic diversity features shown as follows.

**Cosine Diversity.** The cosine diversity between two tweets is calculated based on their weighted term vector representations, and define the feature as follows.

$$R_{ij1} = 1 - \frac{s_i \cdot s_j}{\|s_i\| \|s_j\|}$$

where $s_i$, $s_j$ are the weighted term vectors of tweets based on $tf*idf$, and $tf$ denotes the term frequencies, $idf$ denotes inverse term frequencies.

**Jaccard Diversity.** The Jaccard diversity between two tweets measures the ratio of overlapped terms, and is defined as follows.

$$R_{ij2} = 1 - \frac{|S_i \cap S_j|}{|S_i \cup S_j|}$$

where $S_i$, $S_j$ are the term vectors of tweets.

**Subtopic Diversity.** Different tweets may associate with different aspects of the given topic. We use Probabilistic Latent Semantic Analysis (PLSA) \cite{18}
to model implicit subtopics distribution of candidate tweets. Then we can define a kind of subtopic diversity feature based on the KL distance, as follows.

$$R_{ij3} = \sum_{z_i \in Z} P(z_i|S_i) \log \frac{P(z_i|S_i)}{P(z_i|S_j)}$$

$$P(z_i|S_i) = \frac{1}{|S_i|} \sum_{w_j \in S_i} P(z_i|S_i, w_j)$$

where $P(z_i|S_i, w_j)$ is calculated and saved in the E-step of the EM procedure.

Based on these diversity features, we can obtain the diversity feature vector $R_{ij} = (R_{ij1}, R_{ij2}, R_{ij3})$. Please note that here we only list some representative diversity features used in our work, other useful diversity features can be easily adopted into the utility function.

### 2.2 Dynamic Preservation Scheme based on Periodic Windows

Recency requirement of TDIF application contains two aspects of demand. The first is that users want to follow the recent information about a certain topic. Secondly, for continuous data stream, the efficiency of information processing must be high.

Under the consideration of above two aspects, we propose a dynamic preservation scheme based on periodic time windows. Specifically, we segment the online data stream into disjoint periods in time units (or in number of items). Figure 1 is a simple example for illustration. The core idea of scheme contains several aspects as following:

1. periodic time windows are disjoint and non-overlapped;
2. utilizing the utility function as described in equation \ref{eq:utility_function};
3. utilizing reliant local preservation scheme. Specifically, for each new time window, we preserve the $top$-$(k-m)$ items in prior result set, then utilize the utility function to select $m$ new items reliant on the existing $k-m$ items. In this way, we can maintain diversity of the final result set.
Algorithm 1 Dynamic Preservation Scheme based on Periodic Windows

Input: $S_{K,t-1}$ - Result set with $K$ items until time $(t - 1)$
$X(t)$ - The number of items in the new periodic time window

Output: $S_{K,t}$ - Result set with $K$ items until time $t$

1: Initialize: $S_{K,t} \leftarrow \text{top-}(K-m)$ of $S_{K,t-1}$
2: for $i = 1, \ldots, m$ do
3: \hspace{1em} bestDoc $\leftarrow \arg\max_{x \in X_t} f_{S_{K,t}}(x, R)$
4: \hspace{1em} $S_{K,t} \leftarrow S_{K,t} \cup \text{bestDoc}$
5: end for
6: Sort $S_{K,t}$ by chronological order
7: return $S_{K,t}$

The overall algorithm is described as Algorithm 1. When merging the old top-$(k-m)$ items and new $m$ items into result set, we strictly display the results in chronological order, which is described in line 6 in Algorithm 1. It can be described as the freshness requirement of users in social media [15], where users are used to follow released information in chronological order.

The Algorithm 1 is with time complexity of $O(|X(t)| \ast m)$, $0 < m \leq K$, and $|X(t)| \ll \sum_{t=0}^{T} |X(t)| = N$. Therefore, comparing with the traditional all batch mode which is with time complexity of $O(N \ast K)$, the dynamic mechanism will have better processing efficiency. On the other hand, $m$ is a control parameter, which can flexibly control the “staleness” of the returned result set. For example, if $m = K$, the Algorithm 1 prefers to display the most recent information about the topic.

3 Dynamic Diversity Evaluation Measures

Topic-focused dynamic information filtering is a new application problem in current social media, which incorporates relevance, diversity, recency and confidence of information. Therefore, it is not easy to get a reasonable comprehensive evaluation for such a general task.

In the current Microblog task of TREC, the corresponding task evaluation only focuses on retrieval relevance [24, 27, 19], and the detailed evaluation metrics are just the traditional MAP and P@K [21]. While the diversity task of TREC Web track [7, 8, 11], the corresponding evaluation metrics take both relevance and diversity into consideration, which contain ERR-IA, $\alpha$-NDCG and NRBP. However, these existing measures can not take factors of recency and confidence into consideration, and also do not proper for the evaluation of TDIF application problem. Based on the above analysis, we will propose a series of new dynamic diversity evaluation measures to get a more reasonable evaluation for TDIF task.

Firstly we will review the existing diversity evaluation measures that are summarized in table 1. These measures have the same nature, and are different in some tiny components such as the way of position discounting. We find that there are 2 key points in these measures: diversity and the gain. The diversity means
Table 1. Summary of typical diversity measures

| diversity | novelty | gain | discount | measure |
|-----------|---------|------|----------|---------|
| $S = \frac{\sum_{i=1}^{M} p_i S_i}{N}$ | $S_i = \sum_{k=1}^{K} q_{it}^k$ | $Q_i^k = q_i^k \prod_{j=1}^{k-1} (1 - q_j^i)$ | $Q_i^k = q_i^k(1 - \alpha)^{c_i^k}$ | $\alpha$-NDCG |
| or simplified to | or simplified to | or simplified to | $D_k = \log(k + 1)$ | $D_k = k$ |
| $D_k = \log(1/\beta)^{k-1}$ | $D_k = (1/\beta)^{k-1}$ | $D_k = k/\alpha$ | $ER-IA$ | $NRBP$ |

Subtopic (or aspect) coverage, which is based on explicit subtopic information of a query. Specific to a certain subtopic, the gain describes redundancy penalizing and position discounting when accumulating the relevance in every rank. We take $\alpha$-NDCG for example, $\alpha$-NDCG is formulated as follows:

$$\alpha\text{-NDCG} = \frac{1}{N} \sum_{i=1}^{M} \sum_{k=1}^{K} p_i \frac{q_i^k(1 - \alpha)^{c_i^k}}{\log_2(k + 1)}$$

where $q_i^k$ is a binary relevance value for document at position $k$ with respect to subtopic $i$, $\alpha$ is a constant belong to $(0, 1]$, $c_i^k = \sum_{j=1}^{k-1} g_{ij}$, which is the number of documents ranked before position $k$ that are judged relevant to subtopic $i$, $K$ is the number of documents in a ranking list, $M$ is the number of subtopics, $p_i$ is the probability of each subtopic, and $N$ is a normalization factor.

We incorporate recency and confidence factors into existing diversity evaluation measures such as $\alpha$-NDCG, and then propose a new dynamic diversity evaluation measure $d$-NDCG as follows:

$$d\text{-NDCG} = \frac{1}{N} \sum_{i=1}^{M} \sum_{k=1}^{K} g_i^k \frac{q_i^k(1 - \alpha)^{c_i^k} * u_r}{\log_2(k + 1)}$$

and

$$t_{recy} = \text{topic.timestamp} - \text{tweet.timestamp}$$

where $\text{topic.timestamp}$ means the current time of topic tracking, $\text{tweet.timestamp}$ means the released time of tweet information. $\gamma$ is the corresponding trade-off parameter, $0 < \gamma \leq 1$. We set $\gamma = 0.5$ in our following experiment. $\gamma_{recy}$ part measures the recency of information. $u_r$ measures the confidence of information via the way of user account weight [154].

Based on the definition of $d$-NDCG, we find that the final evaluation score of each item is depended on several factors: recency, relevance, diversity and confidence. When in real application, we usually need to rescale the value of $t_{recy}$ and $u_r$ upon the scale of relevance label $g_i^k$. For example, the public twitter dataset in TREC Microblog task has three grade label: 2 (relevant), 1 (partly relevant) and 0 (not relevant). When in following experimental evaluation, we can simply rescale $t_{recy}$ into three grade label: 2 (i.e. history), 1 (i.e. recent) and 0 (i.e. latest) based on a certain threshold, and rescale $u_r$ into three grade label: 3 (i.e. significant user account), 2 (i.e. important user account) and 1 (i.e. normal user account).
Similarly, we can give the corresponding definition of $d$-ERR and $d$-NRBP, and simply replace the "gain" component in table 1 with $\gamma_{rcy}^k g_i^k (1 - \alpha)^{c_j^k} u_r$, formalized as follows.

$$d\text{-ERR} = \frac{1}{N} \sum_{i=1}^{M} p_i \sum_{k=1}^{K} \gamma_{rcy}^k g_i^k (1 - \alpha)^{c_j^k} u_r$$

$$d\text{-NRBP} = \frac{1}{N} \sum_{i=1}^{M} p_i \sum_{k=1}^{K} \frac{\gamma_{rcy}^k g_i^k (1 - \alpha)^{c_j^k} u_r}{(1/\beta)^{k-1}}$$

4 Experiments

In this section, we will evaluate the TDIF task from different aspects. We first describe the experimental setup that includes dataset, evaluation metrics and baseline methods. Then we conduct extensive automatic evaluation for our approach and baseline strategies. Finally, we conduct manual evaluation for further analysis.

4.1 Experimental Setup

Here we give some introductions on the experimental setup, including data collections, evaluation metrics and baseline methods.

Data Collections We use the public Twitter dataset in Microblog task of TREC 2011 and TREC 2012, which has approximately a sample of 16M tweets, ranging over a period of 16 days. TREC 2011 provides 50 test topics, and TREC 2012 provides 60 test topics.

In our experiments, we only preserve English tweet data, and apply porter stemmer for tweet information and test topics. Based on the consideration of "short text" of Microblog, we do not apply stopwords removing to avoid information loss. We use Indri toolkit (version 5.2\[^3\]) as the basic retrieval platform. We also utilize the Twitter API\[^4\] provided by TREC2013 to retrieval several features such as the number of followers and retweet number. We conduct query expansion by pseudo relevance feedback and external expansion via Google search engine\[^5\], which aims to obtain more aspects of test topic for covering more information.

Evaluation Metrics We will evaluate all the methods from two aspects of effectiveness and efficiency. For effectiveness, we first utilize representative diversity measure $\alpha$-NDCG\[^9\], and then utilize the proposed dynamic diversity measure $d$-NDCG. For $\alpha$-NDCG and $d$-NDCG, the cutoff is set as $K = 20.$

\[^3\] http://lemurproject.org/indri
\[^4\] https://github.com/lintool/twitter-tools
\[^5\] http://google.com
No matter $\alpha$-NDCG or $d$-NDCG, they all need relevance label at subtopic level, while the current public dataset has not provided such information. Therefore, we do further manual relevance labeling at subtopic level, on the basis of existing all the relevant tweets. The labeling method is simple, for each relevant tweet, we judge whether it cover different subtopics comparing with prior relevant tweets. If yes, we will think it is relevant with a new subtopic. We label 2955 relevant tweets for 49 test topics in total for TREC 2011, and label 6286 relevant tweets for 60 test topics in total for TREC 2012. On average there are 3.6 subtopics per test topic.

For efficiency, we mainly utilize the average processing time of different methods for each test topic.

Baseline Methods The R-LTR has been proved to be state-of-the-art diverse ranking methods. Therefore, in topic-focused information filtering task, we mainly focus on strategy comparison but not the detailed ranking models (or utility function). The typical baseline methods are shown as follows:

- **All_old.** All_old strategy means the original R-LTR method optimized for traditional diversity measures such as $\alpha$-NDCG, and then in each new time point, it will rank all the candidate items in a batch way.

- **All_new.** All_new strategy denotes the R-LTR method optimized for new dynamic diversity measure such as $d$-NDCG, and rank all the candidate items in each time point.

- **TopRel.** This method will select $K$ most relevant items in each new periodic time window. Specifically, it will use ListMLE method [29] as utility function, and display result in chronological order. This method does not consider the requirement of diversity, which is similar to the way used in industry.

Our proposed “Dynamic reliant local Preservation scheme” is denoted as “DP”, which is based on the R-LTR utility function optimizing for $\alpha$-NDCG. If no special statement, the default value of parameter $m$ will be set as 10.

For proper evaluation, we choose ‘2 days’ as a time unit, due to that there are not enough relevant tweets for each test topic in our dataset if we choose smaller time window size less than 2 days. Here we must state clearly that we can choose any proper window size based on the real application scenario.

We utilize the tweet data in first two days as training data, for utility function ListMLE and R-LTR, the detailed training process can be referred to the corresponding literature [29,31].

4.2 Evaluation on Traditional Diversity Measure

We first utilize traditional diversity measure $\alpha$-NDCG for evaluation, and the detailed result is shown as figure [2]. The horizontal axis means different time points in chronological order, and vertical axis denotes corresponding $\alpha$-NDCG score.
From the figure, we can observe that All_old performs best, which is in accordance with our intuition. All_new also performs worse than All_old due to optimizing for new diversity measure. All_Batch strategies (i.e., All_old and All_new) will rank all the candidate items in each time points. Therefore, they perform better than two other approaches. Our DP approach shows less but approximate performance comparing with All_Batch strategy. In fact, DP method can be viewed as an approximation of All_old under online data stream scenario. It can capture more recency factors with the sacrifice of little performance on $\alpha$-NDCG. TopRel performs worse because it only consider relevance requirement. It can be applied easily, and used normally in industry filed.

4.3 Evaluation on Dynamic Diversity Measure

The $d$-NDCG is a new dynamic diversity measure, which also takes recency and confidence factors into consideration besides traditional relevance and diversity factors. Then we utilize $d$-NDCG for further evaluation. The evaluation result is shown as figure 3.

We can see that the proposed DP performs best among all baseline methods. Although optimizing directly for $d$-NDCG measure, All_new still performs worse than DP strategy, which enforces capturing more recency factor based on time periodic window scheme. Combing with the results in figure 2, All_old and All_new perform better under each optimizing diversity measure. TopRel performs worst in all baselines, which is also consistent with the evaluation results in figure 2.

Overall, our proposed DP strategy shows better performance on $d$-NDCG measure, which means our approach is more suitable for topic-focused dynamic information filtering task.
4.4 Efficiency Evaluation

An important requirement of the TDIF task is the processing efficiency for online data stream. Therefore, we will conduct efficiency evaluation with average processing time of each test topic.

The evaluation results are shown as figure 4. Here we use ‘All’ denotes both All-old and All-new strategy since they are nearly with same efficiency. We can see that All-Batch strategy has lowest efficiency, because it will process all the
Candidate items at each time point. The DP strategy shows much higher efficiency than AllBatch way, which is also consistent with the theoretical analysis in section 2.2. It will choose $m$ items in a candidate set with relatively small size at each time point.

TopRel shows lower efficiency than DP, but higher than AllBatch. Because it will choose 20 items in each time window, and performs slower than Periodic approach (default $m = 10$). In fact, TopRel method drops the consideration of diversity relations, so it will perform faster than DP approach when $m = 20$, which will be proved in the following evaluation of parameter $m$ sensitivity.

**4.5 Parameter Sensitivity**

In our DP approach, the parameter $m$ ($0 < m \leq K$) control the “staleness” of the result set. In this subsection, we will evaluate its effect from two aspects of d-NDCG and efficiency.

We choose three situations of $m = 5$, $m = 10$ and $m = 20$. The evaluation result is shown as figure 5. From the performance of d-NDCG (i.e. subfigure (a)), we can find that the case of $m = 10$ performs best, and then followed with $m = 20$ and $m = 5$. Form the aspect of efficiency (i.e. subfigure (b)), the case of $m = 5$ performs best, and then followed with $m = 10$ and $m = 20$. Therefore, based on the analysis of two aspects, $m = 10$ will have better comprehensive performance, which is also set as default parameter value.

Additionally, when $m = 20$, its processing time is during 20-25 milliseconds, which is slower than TopRel method (its average processing time is about 20 milliseconds, from figure 4), due to the consideration of diversity relations.

**5 Related Work**

Most existing research work all treats the problem of diverse ranking as a ‘static subset problem’ [11,17,28,26,25,12]. Specifically, they will try to find optimal or suboptimal subset on a static data set. With the development of new social media such as twitter or sina weibo in china, the ranking scenario has changed.
In this new scenario, new information will be continuously released online as a data stream, and how to process stream information effectively has become a new challenging problem.

The research work on the scenario of data stream is little, and several representative research work is \[14,23,15\]. Drosou et al. [14] do some heuristic attempt on “publish/subscribe” scenario. Specifically, they give the definition of ‘diversity on sliding window’, then utilize the classical “Max-Sum” object [17] as utility function, to conduct heuristic greedy strategy. The idea of this work also inspires their following research work [15], which further focuses on the high efficient computing of dynamic diversity via an indexing scheme of “cover tree”. It can support high efficient update operation such as inserting and deleting. Mninack et al. give the definition of “incremental diversity”. In their work, they can maintain a near optimal diverse set at any point in the data stream. The authors also utilize classical “Max-Sum” or “Max-Min” object as their utility function, to conduct heuristic interchange scheme. For each new items, it will make decision of discard or insert, to improve the diversity of the result set.

With the rise of social media, there are many related research work on social media. Chen et al. \[5,6\] discuss and analyze content recommendation in twitter from several feature dimensionality. Hong et al. focus on how to build effective systems for ranking social updates from a unique perspective of LinkedIn. They leverage ideas from information retrieval and recommender systems, which has shown promising performance. Choudhury et al. \[13\] focus on the research of topic retrieval in twitter, to obtain the most relevant results. However, their work is still limited to search scenario, which is almost same as traditional Web search.

Overall, comparing with prior research work, our work has shown several differences as follows: (1) the research problem is different, our work aims to tackle the topic-focused dynamic information filtering in social media, which is a new application problem; (2) our detailed approach also shows many differences. We utilize different utility function - R-LTR ranking model, which is a supervised feature-based ranking model with good adaptation to different application scenario. Our dynamic preservation scheme also shows difference with prior work.

6 Conclusions

In this paper, we investigate the problem of topic-focused dynamic information filtering in social media. Firstly we analyze the properties of the application problem, which has several typical requirements: relevance, diversity, recency and confidence. In this scenario, how to balance these factors properly is very important. Then we propose to utilize the relational learning-to-rank model, and combine with dynamic preservation scheme based on periodic time windows, to solve the TDIF problem. In this way, we can capture these ranking factors effectively. Due to the new requirements of TDIF problem, we propose new dynamic diversity evaluation measures to get a more reasonable evaluation for such ap-
plication problem, which can take recency and confidence factors into consideration on the basis of relevance and diversity. We conduct extensive automatic and manual evaluation on public TREC twitter dataset, and the experimental results prove the effectiveness of our approach.

Overall, we present a completed investigation of a typical application problem in social media, which contains the analysis, solution and evaluation of the problem. Our work shed some light on the TDIF problem, which is significant for future research work.

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Topic-focused Dynamic Information Filtering in Social Media

No Institute Given

Abstract. With the development of online social media such as twitter, many users usually track hot topics to satisfy their desired information need. For a hot topic, new opinions or ideas will be continuously produced in the form of online data stream. In this scenario, how to effectively filter and display information dynamically will be a critical problem. We call the problem as Topic-focused Dynamic Information Filtering (denoted as TDIF for short) in social media. In this paper, we start open discussions on such application problems. We first analyze the properties of the TDIF problem, which usually contains several typical requirements: relevance, diversity, recency and confidence. Recency means that users want to follow the recent opinions or news, and the confidence of information must be also taken into consideration. How to balance these factors properly is very important and challenging. We propose a dynamic preservation strategy on the basis of an existing feature-based utility function, to solve the TDIF problem. Additionally, we propose new dynamic diversity measures, to get a more reasonable evaluation for such application problems. Extensive exploratory experiments have been conducted on TREC public twitter dataset, and the experimental results validate the effectiveness of our approach.

Keywords: Data Stream, Utility Function, Dynamic Preservation Scheme

1 Introduction

The development of new social media such as twitter accelerates the spread of online information. In the social media, new information will be continuously produced in the form of online data stream. For a hot topic, how to filter and display relevant information dynamically will be a critical problem, which can be called as Topic-focused Dynamic Information Filtering in social media.

The TDIF problem has three typical requirements: relevance, diversity and recency. The relevance requires the tweet information must be relevant to the topic. The diversity requires result set can describe the topic from different aspects with little redundancy. Recency means that users want to follow the recent opinions or news quickly. Additionally, the human factor also affects the confidence of the tweet information. Therefore, how to balance these critical factors becomes a new challenging problem.

In fact, little prior research work has been done to tackle the TDIF problem. Most existing work only focuses one or two factors in information retrieval,
such as pure relevance [24,19], or pure diversity [25], or relevance combing with diversity [21,26]. Even in the industry field, such problem has also been not solved well. They usually only consider relevance and ignore diversity or recency.

In this paper, We utilize the relational learning-to-rank model (R-LTR for short) [26] as utility function, and combine with the dynamic preservation scheme based on periodic time windows, to solve the TDIF problem. R-LTR model is the state-of-the-art diverse ranking method, which models the diversity relations among documents in the ranking process, besides the content information of individual documents. It is a flexible feature-based ranking model with good adaptation to different application scenario. Although R-LTR model can tackle relevance and diversity well, yet it is limited in the static dataset, and its efficiency can hardly satisfy the scenario of online data stream.

Therefore, we propose the dynamic preservation scheme based on the R-LTR model for proper solution. Specifically, we segment the data stream into disjoint periods with time length $T$ (segmentation granularity can be days or hours depending on detailed requirements). For each new time window, we preserve the top-$(k-m)$ most relevant results previously, then utilize the R-LTR ranking function to select new $m$ relevant results, and finally display all the $k$ results in chronological order. Here the parameter $m$ can flexibly control the “staleness” of the returned results.

Due to the requirements of TDIF application problem, we also propose new dynamic diversity measures to get a more reasonable evaluation. We introduce the recency factor and confidence factor into existing popular diversity evaluation measures (i.e. ERR-IA [13], $\alpha$-NDCG [8] and NRBP [9]). Then we get a series of dynamic diversity evaluation measures: $d$-ERR, $d$-NDCG and $d$-NRBP.

We conduct extensive evaluations on public TREC twitter dataset, and the experimental results show that our approach can achieve promising performance on both traditional diversity measures and new dynamic diversity measures. Meanwhile, our approach is also with high processing efficiency.

The rest of the paper is organized as follows. Section 2 introduces our approach for TDIF problem. Section 3 introduces the new dynamic diversity measures. Section 4 presents the experimental results. Section 5 describes related work and Section 6 concludes the paper.

2 Our Approach

The TDIF problem in social media has several typical requirements: relevance, diversity, recency and confidence. Therefore, the basic motivation of our approach is how to effectively capture and balance these requirements. In this section, we will describe our strategy detailedly, which mainly contains two parts: the basis utility function and the dynamic strategy.

2.1 Utility Function

The R-LTR model can effectively solve the diverse ranking problem in static dataset scenario, which models both relevance and diversity properly. As de-
scribed in the literature [26], the score of a candidate document contains two parts: relevance score based on content information of individual documents, and diversity score based on the relationship between the current document and those previously selected. We use $X$ denotes all the candidate documents, $S$ denotes previously selected documents, and $X\setminus S$ denotes the remanent documents. The score function can be formalized as follows.

$$f_S(x_i, R_i) = \omega_T^T x_i + \omega_D^T h_S(R_i), \forall x_i \in X\setminus S$$

where $x_i$ denotes the relevance feature vector of the candidate document $x_i$, $R_i$ stands for the matrix of relationships between document $x_i$ and other selected documents, with each $R_{ij}$ stands for the diversity feature vector between document $x_i$ and $x_j$, represented by the feature vector of $(R_{ij1}, \ldots, R_{ijl})$, $x_j \in S$, and $R_{ijk}$ stands for the $k$-th diversity feature between documents $x_i$ and $x_j$, $h_S(R_i)$ stands for the relational function on $R_i$, $\omega_T^T$ and $\omega_D^T$ stands for the corresponding relevance and diversity weight vector.

The relational function $h_S(R_i)$ denotes the way of representing the diversity relationship between the current document $x_i$ and the previously selected documents in $S$. It can be defined in three ways: Minimal, Average and Maximal. Here we choose the Minimal way, defined as follows.

$$h_S(R_i) = \left(\min_{x_j \in S} R_{ij1}, \ldots, \min_{x_j \in S} R_{ijl}\right).$$

The R-LTR is a flexible feature-based ranking function, which has good adaptation to social media scenario and can be chosen as our basis utility function. Comparing with other heuristic definitions of utility function such as “Max-Sum” or “Max-Min” [16,13,20], we can obtain a more reasonable basis utility function by supervised learning. When in real application, we need define and utilize specific relevance and diversity features close related to social media scenario.

**Relevance Feature Vector $x_i$.** For relevance feature vector, we can utilize traditional learning-to-rank relevance features, such as Weighting Models including typical TF-IDF, BM25 and language model.

Additionally, we also utilize some specific features in twitter, shown as follows.

- Recency. We take the tweet released time into consideration, and prefer more recent information.
- UserRank. The importance of a user account can measure the confidence of information, which can be simply obtained via the followers of user.
- Retweet Number. If a tweet is retweet many times, it is usually with high importance.

**Diversity Feature Vector $R_{ij}$** For diversity features, we utilize typical semantic diversity features such as Cosine Diversity ($R_{ij1}$), Jaccard Diversity ($R_{ij2}$) features, and Subtopic Diversity ($R_{ij3}$). For subtopic diversity, we use Probabilistic Latent Semantic Analysis (PLSA) [17] to model implicit subtopics distribution of candidate tweets. Then we can define a kind of subtopic diversity
feature based on the KL distance, as follows.

\[ R_{ij} = \sum_{z_i \in Z} P(z_i | S_i) \log \frac{P(z_i | S_i)}{P(z_i | S_j)} \]

\[ P(z_i | S_i) = \frac{1}{|S_i|} \sum_{w_j \in S_i} P(z_i | S_i, w_j) \]

where \( P(z_i | S_i, w_j) \) is calculated and saved in the E-step of the EM procedure.

Based on these diversity features, we can obtain the diversity feature vector \( R_{ij} = (R_{ij1}, R_{ij2}, R_{ij3}) \). Please note that here we only list some representative diversity features used in our work, other useful diversity features can be easily adopted into the utility function.

### 2.2 Dynamic Preservation Scheme based on Periodic Windows

![Dynamic Preservation Strategy](image)

For TDIF application problem, social users want to follow the recent information on a certain topic. Meanwhile for continuous online data stream, the efficiency of information processing must be high. Therefore, we propose a dynamic preservation scheme based on periodic time windows. Specifically, we segment the online data stream into disjoint time units. Figure 1 is a simple illustration.

The strategy contains two key points as follows:

1. Periodic time windows are **disjoint** and **non-overlapped**.
2. Utilize **reliant local preservation scheme**. For each new time window, we preserve the top-\((k-m)\) items in prior result set, and then utilize the utility function to select \(m\) new items **reliant** on the existing \(k-m\) items. In this way, we can maintain **diversity** of the final result set.

The approach can be described as Algorithm 1. When merging the old top-\((k-m)\) items and new \(m\) items into the final result set, we strictly display the results in chronological order, which is described as line 6 in Algorithm 1 since social users are used to follow released information in chronological order [14].

The Algorithm 1 is with time complexity of \(O(|X(t)| \ast m), 0 < m \leq K\), and \(|X(t)| \ll \sum_{t=0}^T |X(t)| = N\). Comparing with the traditional all batch mode which is with time complexity of \(O(N \ast K)\), the dynamic preservation strategy will have much higher processing efficiency. \(m\) is a control parameter, which can flexibly control the “staleness” of the result set. For example, if \(m = K\), the Algorithm 1 prefers to display the most recent information about the topic.
Dynamic Information Filtering

Algorithm 1 dynamic preservation scheme based on periodic windows

**Input:** $S_{K,t-1}$ - Result set with $K$ items until time $(t-1)$

$X^{(t)}$ - The items set in the new periodic time window

**Output:** $S_{K,t}$ - Result set with $K$ items until time $t$

1: Initialize: $S_{K,t} \leftarrow \text{top-}(K-m)$ of $S_{K,t-1}$
2: for $i = 1, \ldots, m$ do
3: bestDoc $\leftarrow \arg\max_{x \in X^{(t)}} f_{S_{K,t}}(x, R)$
4: $S_{K,t} \leftarrow S_{K,t} \cup \text{bestDoc}$
5: end for
6: Sort $S_{K,t}$ by chronological order
7: return $S_{K,t}$

---

Table 1. Summary of typical diversity measures [7]

| diversity | novelty | gain | discount | measure |
|-----------|---------|------|----------|---------|
| $S = \sum_{i=1}^{M} p_i S_i$ | $S_i = \sum_{k=1}^{K} Q_i^k$ | $Q_i^k = q_i^k \prod_{j=1}^{k-1} (1 - q_j^i)$ or simplified to $Q_i^k = g_i^k (1 - \alpha)^j$ | $D_k = \log(k+1)$ | $\alpha$-NDCG |
| | | | $D_k = k$ | ERR-IA |
| | | | $D_k = (1/\beta)^{k-1}$ | NRBP |

3 Dynamic Diversity Evaluation Measures

Topic-focused dynamic information filtering is a new application problem in social media, which incorporates relevance, diversity, recency and confidence of information. Therefore, it is not easy to get a reasonable comprehensive evaluation for such a general task.

In the current Microblog task of TREC, the corresponding task evaluation only focuses on retrieval relevance [21,23,18], and the detailed evaluation metrics are just the traditional MAP and P@K. While the diversity task of TREC Web track [10], the corresponding evaluation metrics take both relevance and diversity into consideration, which contain ERR-IA, $\alpha$-NDCG and NRBP. However, these existing measures do not take recency and confidence into consideration, and are not proper for the evaluation of TDIF application problem. Based on the above analysis, we will attempt to propose a series of new dynamic diversity evaluation measures to get a more reasonable evaluation for TDIF task.

Firstly we will review the existing diversity evaluation measures that are summarized in Table 1. These measures are different only in some tiny components such as the way of position discounting. We find that there are 2 key points in these measures: diversity and the gain. The diversity means subtopic (or aspect) coverage, which is based on explicit subtopic information of a query. Specific to a certain subtopic, the gain describes redundancy penalizing and position discounting when accumulating the relevance in every rank. We take $\alpha$-NDCG for example, and it is formulated as follows:

$$\alpha\text{-NDCG} = \frac{1}{N} \sum_{i=1}^{M} p_i \sum_{k=1}^{K} \frac{g_i^k (1 - \alpha)^j}{\log_2(k+1)}$$
where \( g_k^i \) is a binary relevance value for document at position \( k \) with respect to subtopic \( i \), \( \alpha \) is a constant belong to \((0, 1]\), \( c_j^k = \sum_{j=1}^{k-1} g_j^i \), which is the number of documents ranked before position \( k \) that are judged relevant to subtopic \( i \), \( K \) is the number of documents in a ranking list, \( M \) is the number of subtopics, \( p_i \) is the probability of each subtopic, and \( N \) is a normalization factor.

We incorporate recency and confidence factors into existing diversity evaluation measures such as \( \alpha \)-NDCG, and then propose a new dynamic diversity evaluation measure \( d\text{-NDCG} \) as follows:

\[
d\text{-NDCG} = \frac{1}{N} \sum_{i=1}^{M} p_i \sum_{k=1}^{K} \frac{\gamma^{t_{rcy}} \cdot g_k^i (1 - \alpha)^{c_k^j} \cdot u_r}{\log_2(k + 1)}
\]

and

\[
t_{rcy} = \text{topic.timestamp} - \text{tweet.timestamp}
\]

where \( \text{topic.timestamp} \) means the current time of topic tracking, \( \text{tweet.timestamp} \) means the released time of tweet information. \( \gamma \) is the corresponding trade-off parameter, \( 0 < \gamma \leq 1 \). we set \( \gamma = 0.5 \) in our following experiment. \( \gamma^{t_{rcy}} \) part measures the recency of information. \( u_r \) measures the confidence of information via the weight of user account [15,4].

When in real application, we usually need to rescale the value of \( t_{rcy} \) and \( u_r \) upon the scale of relevance label \( g_k^i \). For example, the public twitter dataset in TREC Microblog task has three grade labels: 2 (relevant), 1 (partly relevant) and 0 (not relevant). When in following experimental evaluation, we simply rescale \( t_{rcy} \) into three grade labels: 2 (i.e. history), 1 (i.e. recent) and 0 (i.e. latest) based on a certain threshold, and rescale \( u_r \) into three grade labels: 3 (i.e. significant user), 2 (i.e. important user) and 1 (i.e. normal user).

Similarly, we can give the corresponding definitions of \( d\text{-ERR} \) and \( d\text{-NRBP} \), and simply replace the “gain” component in Table 1 with \( \gamma^{t_{rcy}} \cdot g_k^i (1 - \alpha)^{c_k^j} \cdot u_r \).

4 Experiments

In this section, we will evaluate the TDIF task from different aspects. We first describe the experimental setup that includes dataset, evaluation metrics and baseline methods. Then we conduct extensive automatic evaluation for our approach and baseline strategies.

4.1 Experimental Setup

Data Collections We use the public twitter dataset in Microblog task of TREC 2011 and TREC 2012, which has approximately a sample of 16M tweets, ranging over a period of 16 days. TREC 2011 provides 50 test topics, and TREC 2012 provides 60 test topics.

In our experiments, we only preserve English tweet data, and apply porter stemmer for tweet information and test topics. Based on the consideration of
“short text” of Microblog, we do not apply stopwords removing to avoid information loss. We use Indri toolkit (version 5.2) as the basic retrieval platform. We also utilize the twitter API provided by TREC2013 to retrieval several features such as the follower number and retweet number.

**Evaluation Metrics** We will evaluate all the methods from two aspects of effectiveness and efficiency. For effectiveness, we first utilize representative diversity measure $\alpha$-NDCG\cite{8}, and then utilize the proposed dynamic diversity measure $d$-NDCG. For $\alpha$-NDCG and $d$-NDCG, the cutoff is set as $K = 20$.

No matter $\alpha$-NDCG or $d$-NDCG, they all need relevance label at subtopic level, while the current public dataset has not provided such information. Therefore, we do further manual relevance labeling at subtopic level, on the basis of existing all the relevant tweets. The labeling method is very simple, for each relevant tweet, we judge whether it cover different subtopics comparing with prior relevant tweets. If yes, we will think it is relevant with a new subtopic. We label 2955 relevant tweets for 49 test topics in total for TREC 2011, and label 6286 relevant tweets for 60 test topics in total for TREC 2012. On average, there are 3.6 subtopics under each test topic.

For efficiency, we measure the average processing time for each test topic.

**Baseline Methods** The R-LTR has been proved to be state-of-the-art diverse ranking method. Therefore, in TDIF task, we mainly focus on strategy comparison but not the detailed ranking models (or utility functions). The typical baseline methods are shown as follows:

- **All_old**. All_old strategy means the original R-LTR method optimized for traditional diversity measure $\alpha$-NDCG, and it will rank all the candidate items in each new time point.
- **All_new**. All_new strategy is similar to All_old, and it utilizes the R-LTR method optimized for new dynamic diversity measure $d$-NDCG.
- **TopRel**. This method will select $K$ most relevant items in each new periodic time window. Specifically, it will use ListMLE method \cite{24} as utility function, and display result in chronological order. This method does not consider the requirement of diversity, which is similar to the way used in industry.

Our proposed “Dynamic Preservation scheme” is denoted as “DP”, which is based on the R-LTR utility function optimizing for $\alpha$-NDCG. If no special statement, the default value of parameter $m$ will be set as 10.

For proper evaluation, we choose ‘2 days’ as a time unit. If we choose smaller window size less than 2 days, there will be not enough relevant tweets for each test topic in our dataset. In fact, we can choose any proper window size when in real application scenario.

\[^1\] http://lemurproject.org/indri
\[^2\] https://github.com/lintool/twitter-tools
We utilize the tweet data in first two days as training data for utility functions ListMLE and R-LTR, the detailed training process can be referred to the corresponding literature \[23,26\].

4.2 Evaluation on Traditional Diversity Measure

![Graph showing performance comparison on $\alpha$-NDCG measure](image)

**Fig. 2.** Performance comparison on $\alpha$-NDCG measure

We first utilize traditional diversity measure $\alpha$-NDCG for evaluation, and the detailed result is shown as figure 2. The horizontal axis means different time points in chronological order, and vertical axis denotes $\alpha$-NDCG score.

From the figure, we can observe that All\_old performs best, which is in accordance with our intuition. All\_new performs worse than All\_old due to optimizing for new diversity measure. All\_Batch strategies (i.e., All\_old and All\_new) will rank all the candidate items in each time points. Therefore, they perform better than two other approaches. Our DP approach shows less but approximate performance comparing with All\_Batch strategy. In fact, DP method can be viewed as an approximation of All\_old in online data stream scenario. It can capture recency better with the sacrifice of a little performance on $\alpha$-NDCG. TopRel performs worst because it only consider relevance requirement, while it can be applied easily and used normally in industry filed.

4.3 Evaluation on Dynamic Diversity Measure

The $d$-NDCG takes recency and confidence into consideration besides relevance and diversity. The evaluation result on $d$-NDCG is shown as figure 3.

We can see that the proposed DP approach performs best among all baseline methods. Although optimizing directly for $d$-NDCG measure, All\_new still performs worse than DP. Because DP strategy enforce capturing more recency based on periodic time window. Combing with the results in figure 2, All\_old and All\_new all perform better under their corresponding optimizing diversity measures. TopRel performs worst in all baselines, which is also consistent with the evaluation results in figure 3.
4.4 Efficiency Evaluation

An important requirement of the TDIF task is the processing efficiency for online data stream. Therefore, we will conduct efficiency evaluation with average processing time of each test topic.

The evaluation results are shown as figure 3. Here we use ‘All’ denotes both All_old and All_new strategies since they are with nearly same efficiency. We can see that All_Batch strategy is with the lowest efficiency, because it processes all the candidate items at each time point. The DP strategy shows much higher efficiency than All_Batch way, which is also consistent with the theoretical analysis in section 2.2. It will choose $m$ items in a candidate set with relatively small size at each time point.

TopRel shows lower efficiency than DP, but higher than All_Batch. Because it will choose 20 items in each time window, and perform slower than DP approach (default $m = 10$). In fact, TopRel method drops the consideration of diversity relations, so it will perform faster than DP approach when $m = 20$, which will be proved in the following evaluation of parameter $m$ sensitivity.
4.5 Parameter Sensitivity

In our DP approach, the parameter $m$ ($0 < m \leq K$) controls the “staleness” of the result set. In this subsection, we will evaluate its effect from two aspects of $d$-$NDCG$ and efficiency.

We choose three situations of $m = 5$, $m = 10$ and $m = 20$. The evaluation result is shown as figure 5. From the performance of $d$-$NDCG$ (i.e. subfigure (a)), we can find that the case of $m = 10$ performs best, and then followed with $m = 20$ and $m = 5$. Form the aspect of efficiency (i.e. subfigure (b)), the case of $m = 5$ performs best, and then followed with $m = 10$ and $m = 20$. Therefore, based on the analysis of two aspects, $m = 10$ will have better comprehensive performance, which is also set as default parameter value in our work.

Additionally, when $m = 20$, its processing time is during 20-25 milliseconds, which is slower than TopRel method (its average processing time is about 20 milliseconds described in figure 4), due to the consideration of diversity relations.

5 Related Work

Most existing research work studies the problem of diverse ranking in a static dataset scenario [16,22,11]. They try to find optimal or suboptimal subset of a static data set. With the development of new social media such as twitter, the ranking scenario has changed. In this new scenario, new information will be continuously released online as a data stream, and how to process stream information effectively has become a new challenging problem.

The research work on the scenario of dynamic data stream is little, and several representative research work is [13,20,14]. Drosou et al. [13] do some heuristic attempt on “publish/subscribe” scenario. Specifically, they give the definition of ‘diversity on sliding window’, and utilize the classical “Max-Sum” object [16] as utility function to conduct heuristic greedy strategy. The idea of this work also inspires their following research work [14], which further focuses on the high efficient computing of dynamic diversity via an indexing scheme of “cover tree”. It can support high efficient update operation such as inserting and deleting.

Mninack et al. give the definition of “incremental diversity”. In their work, they maintain a near optimal diverse set at any point in the data stream. The authors utilize classical “Max-Sum” and “Max-Min” objects as their utility functions, to
conduct heuristic interchange scheme. For each new coming item, it will make decision of discard or insert, to maintain diversity of the result set.

With the rise of social media, there are many research work on social media. Chen et al. [5,6] discuss and analyze content recommendation in twitter from several feature dimensionalities. Hong et al. focus on how to build effective systems for ranking social updates of LinkedIn. They leverage ideas from information retrieval and recommender system, which has shown promising performance. Choudhury et al. [12] focus on the research of topic retrieval in twitter, to obtain the most relevant results. However, their work is still limited to search scenario, which is almost same as traditional Web search.

Overall, comparing with prior research work, our work has shown several differences as follows: (1) The research problem is different. Our work aims to tackle the topic-focused dynamic information filtering in social media, which is a new application problem; (2) Our detailed approach also shows many differences. We utilize different utility function (i.e. R-LTR), which is a supervised feature-based ranking model with good adaptation to different application problems. Our dynamic preservation scheme also shows differences with prior work.

6 Conclusions

In this paper, we investigate the problem of topic-focused dynamic information filtering in social media. Firstly we analyze the properties of the application problem, which has several typical requirements: relevance, diversity, recency and confidence. In this scenario, how to balance these factors properly is very important. Then we propose to utilize the R-LTR model, and combine with dynamic preservation scheme based on periodic time windows, to solve the TDIF problem. In this way, we can capture these factors effectively. Due to the new requirements of TDIF problem, we propose new dynamic diversity measures to get a more reasonable evaluation for such application problems, which can take recency and confidence into consideration besides relevance and diversity. We conduct extensive evaluations on public TREC twitter dataset, and the experimental results prove the effectiveness of our approach.

Overall, we present a completed investigation of a typical application problem in social media, which contains the problem analysis, solution and evaluation. Our work shed some light on such application problem, which is significative for future research work.

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