Adaptive Topic Tracking Research Based on Title Semantic Domain and Double-state Model

Qi Yincheng¹*, Zhang Suxiang² and Wu Junna¹

¹School of Electrical & Electronic Engineering, North China Electric Power University, Baoding, Hebei, 071003, P.R. China; ²Network Technology Institute Network Management Research Center, Beijing University of Posts and Telecommunications, Beijing, 100876, P.R. China

Abstract: Aiming at problems of sparse training corpora and topic excursion existing in topic detection and tracking, this paper examines twenty one most recent references and patents, proposes an adaptive topic tracking strategy based on title semantic domain topic model and double-state model. Title semantic domain topic model can enhance the title-centric semantic domain cohesion of reports, and reduce dimensions of reports’ feature space effectively. The double-state strategy is a tracking technology based on the combination of static model and dynamic model: static model uses a given number of training reports to construct topic model which is the basis of topic tracking; dynamic model uses the sliding text window mechanism to capture new contents of a topic, remove outdated ones and reflect the changes of topic’s focus in a timely manner. Experimental results show that the combination of double-state model tracking strategy and title semantic domain topic model can improve the performance of adaptive topic tracking system.

Keywords: Adaptive topic tracking, dynamic model, sliding text window, static model, title semantic domain.

1. INTRODUCTION

The main task of topic tracking (TT) is to get customer-satisfied information from a myriad of messages on the Internet. Topic tracking is a sub-evaluation task which belongs to Topic Detection and Tracking (TDT), its specific work is tracking follow-up reports of known topics. The known topic is not clearly described; it is given implicitly by certain related reports detected before. Basing on this, TT system judges the correlation of each report and topic in the follow-up reports one by one and collects relevant reports in order to play the tracking function [1]. Topic tracking can bring decentralized information related with a certain topic together, which let us know the topic completely. The basic idea of a topic tracking system is shown in Fig. (1).

Take a report on flood as an example, the Linguistic Data Consortium (LDC) defines topic correlation as follows: "reports that describe the flood and weather changes which directly influence this flood are all related to the topic; also, disasters caused by this flood, the direct result of disasters and so on are all on-topic" [2]. From the definition we can know, from "flooding reports" to "weather changes", "the number of casualties", "rescue work", and then "government’s response", it is a dynamic developing process, and the report’s focus of Internet news about the topic changes with the same trend. We call this "topic drift", which is one of the challenges for topic tracking study.

Patent US 6,104,989, titled “Real time detection of topical changes and topic identification via likelihood based methods” [3], proposes a method for detecting topical changes and topic identification in texts in real time using likelihood ratio based methods. Topic identification is achieved by evaluating text probabilities under each topic, and a new topic is selected when one of those probabilities becomes significantly larger than the others. Patent US 7,577,654, titled “Systems and methods for new event detection” [4], provides techniques for new event detection. For a new story and a corpus of stories, adjustments to the importance of terms are determined based on direct or indirect story characteristics associated with each story. Adjustments to the inter-story similarity metrics are determined based on story characteristics and/or a weighting function. New event scores and/or new event categorizations for stories are determined based on the inter-story similarity metrics. Patent US 8,386,240, titled “Domain dictionary creation by detection of new topic words using divergence value comparison” [5], discloses a method to identify topic words in a collection of documents that includes topic documents related to a topic. The candidate topic word is determined to be a topic word if the candidate topic word divergence value is greater than the reference topic word divergence value. The identification of such topics can improve the performance of a language model and/or a system using the language model for languages without boundaries in sentences.

The sparsity of training corpora is another problem to topic tracking study: according to the evaluation requirements, it is necessary to set up a topic model according to Nt (Nt is typically 1, 2, 4) reports, but a few reports neither could grasp the topic from the whole, nor could meet the requirements of topic tracking. To solve these two problems, many researchers point out that we should improve topic tracking's adaptive technology by unsupervised learning: on
The basic idea of the topic tracking system.

Fig. (1). The basic idea of the topic tracking system.

topic model, vector space model, latent semantic indexing model [6], HMM model [7] and so on are all applied to the adaptive technology; on strategy, Rocchio method [8] and Pseudo-relevance feedback method [9] train the topic model again by reports relevant or irrelevant with the topic judged by TT system, which effectively improves the performance of TT system. A dynamic topic model is proposed based on the static model in reference [10]. It extends the initial topic model with the information from the incoming related stories and filters the noise using the latest unrelated story. Relevant model and irrelevant model are used to judge current reports and have good effects in noise reduction. In reference [11], several weak topics are combine into a strong topic, which also improves the performance of TT system. A double-centroid topic model is put forward in [12]. It dynamically chooses a division point and the topics are expressed as an initial centroid and a current centroid, and update them with follow-up reports to adapt to topics’ dynamic evolution. A dynamic network model for the evolution of online public opinion is proposed in [13], which focuses on the modeling theory of the dynamic network model such as its structure, evolution properties and description method, describes the dynamic process and microstructure of the evolution of online public opinion. Patent US 6,651,058, titled “System and method of automatic discovery of terms in a document that are relevant to a given target topic” [14], provides an automatic mining system to discover terms that are relevant to a given target topic from a large databases of unstructured information such as the World Wide Web. The operation is performed in three stages: new terms discovery, candidate terms discovery, and relevant terms discovery. Patent US 7,024,624, titled “Lexicon-based new idea detector” [15], discloses A method and apparatus for detecting the occurrence of new ideas in documents or communications. The method is comprised of three processes: lexicalizing all words or symbols in a set of documents, comparing all words in a second set of documents to the words in the lexicon, measuring the spatial and temporal spread of said fad and computing metrics based on additional occurrences of said fad. Patent US 7,739,261, titled “Identification of topics for online discussions based on language patterns” [16], provides a topic identification system identifies topics of online discussions by iteratively identifying topic words or keywords of the online discussions and identifying language patterns associated with those keywords. The relevance of a sentence is just based on whether the sentence contains a word relating to a topic of the discussion.

The double-judged method of relevance and irrelevance can filter out noise, but can also filter out useful information; topics’ combination and the double-centroid model both apply all the related reports to updating model and follow-up reports' judgment, this increases the amount of computation and may lead to accumulating errors. Once the judgment is wrong, erroneous reports will always have an impact on follow-up judgments. In view of these defects, this paper presents a novel double-state model tracking strategy.

The main idea of the strategy is that static model is used to reserve topic’s original contents, and dynamic model is used to capture new contents. They cooperate with each other to complete the task of tracking follow-up reports. In the process, static model plays an important role from start to finish. When dynamic model is updated, on one hand, it uses titles’ related factors as auxiliary feedback conditions to improve feedback’s accuracy; on the other hand, it removes old feedback reports and grasps the latest development of topic in time. The double-state tracking strategy takes full account of characteristics of topic evolution and makes up the deficiencies of existing adaptive methods.

Semantic domain is a collection of a set of language structures that their semantics are similar; the feature space that describes semantics is called semantic space [17]. The semantic-based Keyword Extraction Algorithm for Chinese Text (SKE) puts words’ semantic features into the process of keywords’ extraction, builds words’ semantics similarity network and uses intermediate density to measure the criticality of words’ semantics [18]. The semantic-based focused crawling approach maps theme's ontology semantics to the list of keywords. Inference services about assertion set expanding and domain-range relation are defined. The semantic relation among keywords can be inferred by inference services [19].

This paper applies title semantic domain to topic tracking study for the first time. The sentence is considered as a unit to segment the news report, considering the similarity between sentences, with the title as the core content of the report to condense sentence, thereby a large number of non-essential features are removed, and the core content of reports is Refined. Experimental results show that the combination of the double-state strategy and title semantic domain achieves a nice topic tracking effect.

2. TITLE SEMANTIC DOMAIN

Semantic domain maintains the consistency of semantics by sentences, and feature words constitute the comprehensiveness of semantic space. Semantic relation is an important part of natural language processing system. The combi-
nation of semantic relation emphasizes that non-adjacent sentences should build relations. These multi-sentence relations can be combined basally by two-connected mode.

Semantic domain is different from subtopic: semantic domain emphasizes on the meaning consistency of sentences; subtopic is a little “incident”, it can comprehensively describe this "incident", it focuses on integrity rather than consistency. By extracting sentences that have the same semantics with titles described by reports, it could agglutinate articles' significance and highlight the effect of center, weakening irrelevant characteristics' impact on topic description and reducing topic drifts.

3. DOUBLE-STATE MODEL TRACKING STRATEGY

By analyzing the contents of topic tags in massive training corpora, characteristics we find are as follows:

1) Some feature items appeared in topic's initial \( N_t \) reports will appear in the whole evolution process of topic, they are shared by different focuses of topic, we call them "relatively static contents" in the development of topic.

2) Some feature items appear in the dynamic process of topic, they come from new focuses and development of topic, we call them "dynamic contents" of topic.

In order to reduce accumulating errors, in this paper, a fixed-length sliding text detector structure is used to calculate the similarity of feedback reports and current test reports within window.

Based on the above, the double-state tracking strategy's specific steps are as follows:

1) Building static model: building topic static model on the base of \( N_t \) reports, these \( N_t \) reports are all early reports about topic, many important feature items (entity nouns like person's name, place's name, constitution's name and so on) and even short terms for the topic all appear in the \( N_t \) reports. Therefore, the topic model based on \( N_t \) reports is not changed or updated in the process of topic tracking, this paper call it static model(SM).

2) Judging relevance: judging relevant reports according to relevant threshold \( Tr \) and extracting feedback reports from relevant reports according to feedback conditions.

3) Building dynamic model: it begins to train topic dynamic model (DM) when reports meet feedback conditions. With the increment of feedback reports \( d_i \), feature items of DM are re-counted continuously and their weights are calculated, which update DM continuously.

4) Adjusting dynamic model: when the number of feedback reports \( l \) in the dynamic model reaches to the pre-set text window length \( L \), dynamic model is bi-directionally dealt. As a new feedback report \( d_i \) is added, the earliest report \( d_l \) is removed immediately, so \( L \) keeps unchangeable, \( L = \{d_0, d_1, \ldots, d_{l-1}\}, 0 \leq l \leq L-1 \), and slides forward along with feedback reports.

Basing on cooperation of the double-state model, this method determines follow-up reports whether belong to a topic or not. Its advantages are as follows:

1) It solves, to some extent, the sparsity of training corpora by expanding training corpora.

2) Dynamic model can grasp topic's new contents in time, which could solve the problem of topic drift effectively.

3) If wrong feedback gets into dynamic model, static model will also play a balancing role and reduce accumulated errors.

Specific analysis can be seen in section 6.

4. BUILDING SYSTEM

4.1. Reports Segmenting

In fact, it appears messy if a single feature word is taken as the basic analyzing unit, and at the same time, there are many of less important feature words. Then we need to find larger unit in higher level as basic unit of text analysis. Practice has proved that analyzing text in unit of sentence is feasible and efficient.

Segmenting report is the method that segments a complete news report into collections of sentence groups based on sentences and builds report model according to collections of sentence groups. This paper takes periods, question marks, exclamation points and so on as the sign of the end of sentences. Then, this paper segments training corpora and test corpora into collections of sentences relatively and sorts them by title, forming reports' sentences space model:

\[
\Psi(D) = \{S_1, S_2, ..., S_t\}
\]

(1) where \( D \) denotes a certain report; \( S \) denotes every sentence in \( D \); \( i \) denotes the number of sentences in \( D \), and \( i \) is different as reports are different.

In this step, the title does not need to be segmented by punctuations, but it must be the first sentence of reports' sentence space model.

The current ceramic enterprises in ceramic product design process and production process of detailed study, the design process of ceramic products for further analysis and decomposition, Exploring the project design of ceramic needs human interaction steps in the 3d CAD system, and needs to be done by the system automatically in order to better improve enterprise's key steps in the efficiency of product design and in the decomposition on the basis of the design process to classify modeling of ceramic products, and finished components decomposition of complex products. Ceramic products decomposition is different from the mechanical parts and components industry and other industry products, ceramic products decomposition lies mainly in the design of the components in the process of decomposition, and the final product in general is not an integral whole, for example, in the design process for more complex products such as “pot” will be broken down parts into the pot body, the pot, a spout, the lid and lid knob, a girder of the pot, an ear piece [10]. And set up all kinds of parts in the three-dimensional model of the material library.

4.2. Sentences Modeling

According to the theory of anthropological linguistics, language sentence consists of key ingredients like subject,
Sentence processing consists of segmentation and removing unused words. After processing, sentences are expressed as the collection of feature items:

\[ L(S) = \{ t_1, t_2, ..., t_n \} \]  

where \( t_i \) is the feature items in sentences; \( n \) denotes the number of words in processed sentences \( S \), namely the number of feature items.

Then we can build feature vector space of every sentence:

\[ V(S) = \{ t_1, w_1; t_2, w_2; ..., t_n, w_n \} \]  

where \( w_n \) denotes the weight of every feature item in sentence's collection, and it can be calculated according to the proportion of a word's frequency in all words' frequencies.

### 4.3. Semantic Domain's Cohesion

The concrete steps of semantic domain cohesion strategy on a to-be-texted report \( D \) are as follows:

1. Calculating the similarity \( P(s_i, s_j) \) of all sentence pairs in \( S \{ (s_i, s_j) | s_i, s_j \in S \} \) according to the language model:

\[ P(S_i, S_j) = \frac{ \sum_{k=1}^{n} w_{ik} \times w_{jk} } { \sqrt{ (\sum_{k=1}^{n} w_{ik}^2) \times (\sum_{k=1}^{n} w_{jk}^2) } } \]  

where \( s_i, s_j \) are sentences that their similarities are to be calculated; \( n \) is the dimension consisting of all features of two sentences.

2. Taking every report's title as cohesion kernel sentence, and taking report's sentences that their correlation with the sentence is above the given threshold value \( T_b \) as candidate semantic domain and embed them into the collection \( L = \{ s_1, s_2, ..., s_k \} \), \( k \) is the number of sentences. The collection is report's semantic domain. Then we can calculate the weight of every feature item of the collection and form the semantic domain feature vector space of reports.

Semantic domain cohesion strategy is an important part of building topic semantic domain model. There are two advantages of this treatment: the first is simplifying reports, removing a large number of irrelevant sentences and redundant feature words; the second is condensing the core, taking key contents from the report according to the important position of title in news report, highlighting the report's main content and providing a simple and effective model for following topic tracking.

### 4.4. Static Topic Model Building

We will build static topic model according to the semantic domain feature vector space of \( N_t \) pieces of training corpora. The training report \( d_i \) is treated as a normalized feature eigenvector: \( V(d_i) = (\text{term}_{1i}, w_1(d_i); \ldots; \text{term}_{ni}, w_n(d_i)) \). \( w_k(d_i) \) is the weight of \( \text{term}_k \) in \( d_i \), its abbreviation is \( w_{ik} \). This paper uses TF-IDF (term frequency-inverse document frequency) to calculate the weight of every feature item:

\[ w_{ik} = \frac{ tf_{ik} \times \log(N / n_k + 0.01)}{ \sqrt{ \sum_{k=1}^{m} [tf_{ik} \times \log(N / n_k + 0.01)]^2 } } \]  

where \( N \) is the number of verified news reports, \( n_k \) is the number of news reports that have feature item \( \text{term}_k \) in verified news reports, \( tf_{ik} \) is the frequency of feature item \( \text{term}_k \) in news reports \( d_i \).

### 4.5. System Dynamic Topic Model Building

In the double-state model tracking strategy, two thresholds are set: relevant threshold \( T_r \) is used to judge whether the following reports are related with the topic or not; feedback threshold \( T_f \) is used to judge whether the topic should update the dynamic model or not. Usually, we take \( T_f > T_r \).

The specific procedure is shown in Fig. (2).

Selection rules for threshold value \( T_f \) and \( T_r \) are:

1. The value of \( T_f \) and \( T_r \) is concern with the performance index of the system and the performance index precision \( P \) and recall \( R \) are contradictory. In the process of determining the value of \( T_f \) and \( T_r \), consideration should be given to both precision and recall. Try to make the two performance index in balance. That should not only consider the higher precision or recall.

2. Generally speaking, \( T_r \) Controls the preliminary selection of the report text, and \( T_f \) is used to choose the text of feedback report carefully. Therefore, we demand \( T_r \) is greater than \( T_f \).

Actual values of \( T_f \) and \( T_r \) are shown in section 6.3, and the analysis of feedback condition is shown in section 4.7.
4.6. Process of Dynamic Tracking

This paper builds the double-state model tracking strategy by combining static model and dynamic model and finishes tracking task of topic adaptive in the strategy.

The calculation of similarity between topic reports can use the cosine formula, namely is:

\[
sim(m_i, m_j) = \frac{\sum_{k=1}^{M} w_{ik} \times w_{jk}}{\sqrt{\left( \sum_{k=1}^{M} w_{ik}^2 \right) \times \left( \sum_{k=1}^{M} w_{jk}^2 \right)}}
\]

(6)

where \(m_i\) is the feature vector of the to be tested news reports \(d_i\), \(m_j\) is the feature vector of the \(j\)th tested news report \(d_j\). \(M\) is the dimension of feature vector, \(w_{ik}\) and \(w_{jk}\) are the kth dimension of feature vector in news report \(d_i\) and \(d_j\), respectively.

Dynamic model can grasp the development of topic in time, but it can also introduce wrong feedbacks. To reduce the impact of possible wrong feedbacks, the strategy endows static model and dynamic model with equal weights. The calculating method of weight is as follows:

(1) Prior to the establishment of the dynamic model, the number of feedback reports \(l\) is zero, i.e. \(l=0\). The calculation of the comprehensive similarity is:

\[
Sim = 1.0 \times Sim_{SM} + 0 \times Sim_{DM}
\]

(7)

where \(Sim\) is the comprehensive similarity value; \(Sim_{SM}\) is the similarity between current report and the static model; \(Sim_{DM}\) is the similarity between current report and the dynamic model.

(2) In the process of the establishment of the dynamic model, the number of feedback reports \(l\) is less than the window length \(L\), i.e. \(l< L\). The calculation of the comprehensive similarity is:

\[
Sim = (1 - \frac{l}{N_l + L})Sim_{SM} + \frac{l}{N_l + L}Sim_{DM}
\]

(8)

where \(N_l\) is the number of feedback reports.

The window length \(L\) is determined by experiments.

(3) After dynamic model has been established, the number of feedback reports \(l\) equals to the window length \(L\), i.e. \(l= L\). The calculation of the comprehensive similarity is:

\[
Sim = \frac{N_l}{N_l + L}Sim_{SM} + \frac{L}{N_l + L}Sim_{DM}
\]

(9)

4.7. Feedback Conditions

In existing studies, feedback condition may be the number of related documents \([8]\); it may also be the uncertainty of the samples \([2]\) or some characteristics’ selection rules \([7]\). In this paper, feedback conditions are set by feedback’s threshold \(T_f\).

It's hardly to avoid misjudgment if only rely on feedback threshold to choose feedback reports. Adding some judgment rules appropriately can improve the accuracy. Internet news title usually contains some important information related with the topic, it play a very important role in topic detection. So this paper uses Title Related Factor (TRF) to set feedback rules:

\[
TRF = m \times |title_{model} \cap title_i|
\]

(10)

where \(title_{model}\) is the collection of title feature items of the double-state model; \(title_i\) is the collection of report \(D_i\)'s title feature items; \(|\cdot|\) is the number of feature items; \(m\) is the adjustment factor.

One topic has different reports, and the contents of titles are also different. So it’s hard to make sure TRF's specific value. This paper takes "Diaooyu Island Event" as an example to do experiment. This topic model feature space has 34 features and 263 titles to be tested. We count the number of 34 topic model features appearing in 263 titles. Statistical result is shown in Fig. (3).

From the results we can see that the number of common features shared by feature space of the title in the topic model and the title of the follow up reports has peak at 0,1and 2. So, we set feedback condition as TRF≥1.

In summary, only when the tested report meets the requirement of \((Sim≥Tf) \cup (TRF≥1)\), can it be considered as feedback reports and update the dynamic model. When grasping new topic contents, it could reduce the accumulation of errors effectively.

5. SYSTEM FRAMEWORK

According to earlier parts' description, the flow chart of proposed adaptive topic tracking system is shown in Fig. (4).

The following factors are taken into consideration in calculating of similarity between topic reports. Static content of topic concern to the semantic domain feature vector space of Nt pieces of training corpora, dynamic contents coming from new focuses and development of topic, and the tracking strategy by combining static and dynamic model.

6. EXPERIMENT AND RESULTS ANALYSIS

6.1. Evaluation Mechanism

This paper uses traditional precision \((P)\), recall \((R)\) and overall classification rate \((F_r)\) to evaluate the experimental results, the formula is as follows:

\[
P = \frac{x}{x + y}
\]

(11)
The specific design of experiments is described as follows:

Experiment 1: measuring the influence of the slide text window's length $L$ in dynamic model on tracking effect.

Experiment 2: using the basic topic tracking model built by experiment 1 in reference 20 as Baseline system. The system judges whether following reports are related with the topic or not according to the relevant threshold $T_r$, it doesn’t use self-learning technology. We use Baseline-Track to denote the system and the experimental results. In order to analyze the adaptive technology’s influence on the performance of topic tracking system, the double-state topic's adaptive method is compared with the traditional increment's adaptive method in reference 21. In the topic tracking system of traditional increment's adaptive method, we use two thresholds $(T_r$ and $T_f)$ to judge whether following reports are related with the topic or not, reports that their similarity is above $T_f$ are all used to update the old topic model, it is denoted by Increment-Track. In addition, the double-state tracking strategy and title semantic domain get experimental verification respectively: Double-state-ATT is the topic tracking system of double-state adaptive tracking strategy, this system doesn’t use the title semantic domain technology to deal with training corpus and test corpus, it uses Title-domain-Track to stand for TT system of title semantic domain language model, namely, it uses title semantic domain space model to replace TT system of traditional vector space model in experiment 1 of [20]. In the end, combine semantic domain language model with the double-state tracking strategy and put forward double-state strategy ATT system basing on title semantic domain, which is denoted by Title-Doublestate-ATT.
Table 1. Sample events.

<table>
<thead>
<tr>
<th>Topic Number</th>
<th>Topic Description</th>
<th>Number of Related Reports</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>The US mid-term elections</td>
<td>217</td>
</tr>
<tr>
<td>2</td>
<td>Indonesia tsunami</td>
<td>148</td>
</tr>
<tr>
<td>3</td>
<td>Somali pirates event</td>
<td>31</td>
</tr>
<tr>
<td>4</td>
<td>President visit countries</td>
<td>29</td>
</tr>
<tr>
<td>5</td>
<td>Libyan military attacks</td>
<td>296</td>
</tr>
<tr>
<td>6</td>
<td>Bank exchange rate adjustment</td>
<td>244</td>
</tr>
<tr>
<td>7</td>
<td>Inter-Korean conflict</td>
<td>505</td>
</tr>
<tr>
<td>8</td>
<td>Diaoyu island incident</td>
<td>134</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>1608</td>
</tr>
</tbody>
</table>

6.3. Experimental Results Analysis

In all experiments, \( N_t = 4 \), and the focuses of study are semantic domain topic model and the double-state tracking strategy. Firstly, to determine the best value of \( L \), we do double-state topic tracking experiment with different values of \( L \), the results are shown in Table 2.

Table 2. Results of experiment 1 \( (T_r=0.44, T_f=0.3) \).

<table>
<thead>
<tr>
<th>( L )</th>
<th>( P(%) )</th>
<th>( R(%) )</th>
<th>( F_1(%) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>71.94</td>
<td>91.21</td>
<td>80.44</td>
</tr>
<tr>
<td>3</td>
<td>72.07</td>
<td>92.74</td>
<td>81.11</td>
</tr>
<tr>
<td>4</td>
<td>71.79</td>
<td>96.52</td>
<td>82.34</td>
</tr>
<tr>
<td>5</td>
<td>67.58</td>
<td>95.52</td>
<td>79.16</td>
</tr>
<tr>
<td>6</td>
<td>65.99</td>
<td>96.02</td>
<td>78.22</td>
</tr>
</tbody>
</table>

From the results of experiment 1 in Table 2 we know: the precision and recall of double-state topic model's ATT system increase gradually when the length of the text window increases gradually from 2, the value of comprehensive measure \( F_1 \) is becoming better and better. But when the length is larger than 4, the precision and recall both begin to decrease, the value of \( F_1 \) is also worse and worse. Experimental results show that it will get good tracking effect when static model's text length gets close to dynamic model's text length. So, \( L \) is selected as 4.

The results of experiment 2 are shown in Table 3.

We can get such conclusions from experiment 2:

(1) Comparing with Baseline-Track, Increment-Track's precision increases by 2.73%, the recall increases by 1.98%, and \( F_1 \) increases by 2.42%. The results show that comparing with the baseline-Track system in experiment 1, double-state topic tracking model can improve the performance of adaptive topic tracking system. The experiment is done for many times and the thresholds are different, the precision and recall are both improved. Among the three systems, Doublestate-ATT has the best effect, which indicates that the double-state tracking strategy could get a good effect in topic tracking.

(2) Comparing with Baseline-Track, Doublestate-ATT's precision increases by 2.73%, the recall increases by 1.98%, and \( F_1 \) increases by 2.42%. The results show that comparing with the baseline-Track system in experiment 1, double-state topic tracking model can improve the performance of adaptive topic tracking system. The experiment is done for many times and the thresholds are different, the precision and recall are both improved. Among the three systems, Doublestate-ATT has the best effect, which indicates that the double-state tracking strategy could get a good effect in topic tracking.

(3) Comparing with Baseline-Track, Title-Domain-Track's precision increases by 13.74%, the recall increases by 2.52%, \( F_1 \) increases by 8.4%. By analyzing every topic model feature space, feature dimensions of Title-Domain-Track decrease significantly. Taking "Indonesia's tsunami event" for example, the topic model's dimensions of Baseline-Track are 408, but Title-Domain-Track's are only 149. Features reserved can well reflect important contents of topics. Comparing with traditional TT system used in experiment 1 according to reference 20, topic title semantic domain model has the advantage of better expressing the topic and improving the performance of adaptive topic tracking.

(4) Comparing with Title-Domain-Track, TitleDoublestate-ATT's precision increases by 0.96%, the recall increases by 4.40%, \( F_1 \) increases by 2.64%. The double-state strategy is combined with semantic domain's topic model; they play a role together and improve ATT's performance. By analyzing experimental data, we can find that the feature dimensions of topic model are few, but the features are all relevant and important; in collections of tracked news reports, irrelevant reports are few and dispersed in time and contents, no serial wrong judgment reports. This tells us that the double-state tracking strategy can deal with topic drift effectively, even if wrong feedbacks get into dynamic model, static model will inhibit the following reports' similarity and decrease frequency of misjudgment. The fixed-length sliding

<table>
<thead>
<tr>
<th>Experimental System</th>
<th>( P(%) )</th>
<th>( R(%) )</th>
<th>( F_1(%) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline-Track</td>
<td>76.48</td>
<td>87.89</td>
<td>81.78</td>
</tr>
<tr>
<td>Increment-Track</td>
<td>54.86</td>
<td>99.31</td>
<td>70.68</td>
</tr>
<tr>
<td>Doublestate-ATT</td>
<td>79.21</td>
<td>89.87</td>
<td>84.20</td>
</tr>
<tr>
<td>Title-Domain-Track</td>
<td>89.95</td>
<td>90.41</td>
<td>90.18</td>
</tr>
<tr>
<td>Title-Doublestate-ATT</td>
<td>90.91</td>
<td>94.81</td>
<td>92.82</td>
</tr>
</tbody>
</table>
window mechanism of dynamic model can also remove earlier feedback reports in time, reducing errors' accumulation and realizing dynamic tracking. Experimental results show that Title-Doublestate-ATT system proposed by this paper is the best. It can substantially improve the performance of ATT system.

CONCLUSION

According to problems of sparse training data and topic drift existing in adaptive topic tracking, this paper puts forward adaptive tracking algorithm basing on the combination of title semantic domain and double-state model. This algorithm takes topic's two features into consideration: some topic contents exist throughout the topic's whole evolution, they are topic's static contents; some are new contents, they are topic's dynamic contents. In double-state strategy, topic model remains topic's static contents, grasps topic's changes in time and also uses sliding text window mechanism to prevent errors' accumulation. Title semantic domain can effectively reduce feature dimensions of reports vector space. The experimental results show that either the double-state tracking strategy or title semantic domain or even the combination of them can improve the performance of adaptive topic tracking system.

Adaptive topic tracking technology is an interdisciplinary key research of natural language processing, data mining and intelligent information processing. What more, it’s an important means to provide convenient access to information in real life and has broad prospects.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

ACKNOWLEDGEMENTS

This research has been partially supported by Grants from Fund of National Natural Science Foundation of China (Grant No: 61202248).

REFERENCES


