General Article

Applying the document vector model to tour recommendation

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Abstract

Today many tourists read online tour reviews before planning their trips. However, it is stressful to thoroughly check online reviews because of a huge amount of information. In this paper, we propose a tour recommendation system based on online reviews. The system recommends tour reviews written by other tourists who have similar interests in tours to the user. The user's interest in tours is extracted from a review and it is modelled as a document vector based on the Word2Vec model. Interest matching between the user and other travellers is performed based on the vector space model. The proposed system is tested on a data set including 259,084 tour reviews and compared with a conventional recommendation system which is based on the BoW (bag-of-words) model. The experimental results show that the proposed system is effective and promising.

Keywords

recommendation systems, tour recommendation, online reviews, document vector model, Word2Vec

1. Introduction

The rapid growth of tourism industry contributes to the global economy. Tour companies customize sightseeing programs and release them as tour packages. Travel agencies provide online reservation sites for these packages. People can easily reserve tours via these web sites.

In online travel review sites such as TripAdvisor, many customer reviews are posted day by day. Since customer reviews contain honest opinions about tours, they are now one of the most useful information resources for people who are planning travel [Pang and Lee, 2008; Ye et al., 2011; Zehrer et al., 2011]. According to the surveys about the influence of customer reviews [Brown, 2012; Liu and Zhang, 2004, Nunes and Almeida, 2016], many tourists plan their trips using online reviews. However, it is stressful to thoroughly check online customer reviews because of a huge amount of information.

For helping tour planning, the use of a tour recommendation system is promising [Kawai et al., 2009; Huang et al., 2013; Santos et al., 2016]. In this paper, we propose a tour recommendation system based on customer reviews.

Figure 1 shows the outline of the proposed system. The proposed system receives a review which is written by a user. Analysing the input review, the system estimates user's interest about tours. The system searches for a database to recommend reviews written by others who have similar interests to the user. The user's interest is defined as a document vector based on the Word2Vec model. Using the document vectors, the system actualizes the interest matching.

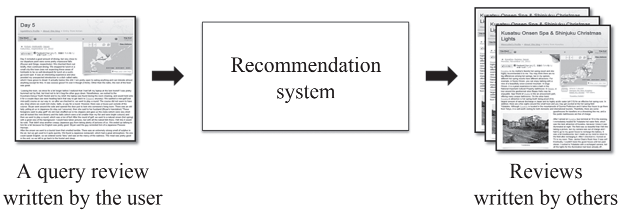

Figure 1: Outline of the proposed systems

The rest of the paper is organized as follows. In section 2, we describe a conventional recommendation system based on the BoW (bag-of-words) model and discuss the limitation of the conventional system. In section 3, we propose a recommendation system which combines the TF-IDF [Robertson and Sparck, 1976] and the Word2Vec model [Mikolov et al., 2013]. In section 4, to clarify the effectiveness of the proposed system, we show experimental results. Finally, we conclude the paper in section 5.

2. Related works

2.1 Overview

The problem of tour recommendation based on customer reviews can be modelled as a problem of similarity retrieval of text documents. As shown in Figure 2, in a similarity retrieval, a document is represented as a document vector. By evaluating the distance (dis-similarity) between document vectors of the query document and each document in a database, documents having similar content to the query document are recommended.

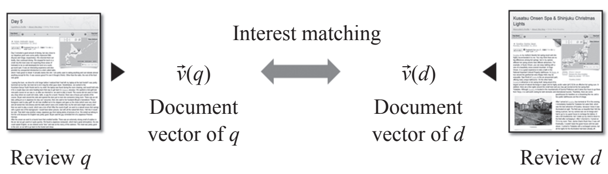

Figure 2: Interest matching based on document vectors

As a document vector, the BoW (bag-of-words) model has been widely used. In the BoW model, each element of a document vector is corresponded to the importance of each word. Generally, the importance of a word is defined by the TF-IDF metric [Robertson and Sparck, 1976] of the word in a document.

2.2 The BoW model

In the BoW model, document d is represented as document vector $\vec{v}(d)$ defined as follows:

$$\vec{v}(d) = [w(t_1,d), w(t_2,d), \cdots, w(t_N,d)]^{\mathrm{T}}, \quad (1)$$

where $w(t_i,d)$ is the TF-IDF of word t_i in document d, and N is the number of unique words included in all the documents in a database.

$w(t_i,d)$ is defined by multiplying two weights $w_1\ (t_i,d)$ and $w_2\ (t_i)$ as follows:

$$w(t_i,d) = w_1\ (t_i,d)\ w_2\ (t_i), \quad (2)$$

where $w_1\ (t_i,d)$ evaluates the frequency of word t_i in document d, and $w_2\ (t_i)$ evaluates the specificity (document frequency) of word t_i in a document set [Jones, 1972]. These two weights can be calculated as follows:

$$w_1\ (t_i,d) = \frac{TF(t_i,d)}{n(d)}, \quad (3)$$

$$w_2\ (t_i) = log\ \frac{m}{DF(t_i)}, \quad (4)$$

where $TF(t_i,d)$ is the frequency of word t_i in document d, $n(d)$ is the number of words in document d, m is the number of documents in the database, and $DF(t_i)$ is the number of documents including word t_i in the database.

2.3 Similarity evaluation

Generally, the similarity between documents d_1 and d_2 is defined by the cosine measure as follows:

$$s(d_1,d_2) = \frac{\langle \vec{v}(d_1), \vec{v}(d_2) \rangle}{|\vec{v}(d_1)||\vec{v}(d_2)|}, \quad (5)$$

where $\vec{v}(d_i)$ is the document vector of document d_i and $\langle \cdot,\cdot \rangle$ denotes the inner product between two vectors. By the cosine measure, two documents whose document vectors having similar directions are regarded as similar. In the similarity retrieval, the documents are ranked based on their similarities.

2.4 Recommendation based on the BoW model

In the BoW model, document vectors have similar directions when these documents include same words. Therefore, the similarity between document vectors evaluates the commonality of words between documents.

For example, when a user submits a review about a Waikiki beach tour, the system also recommends Waikiki tours. This is because the same words are included in the input review and recommended reviews. However, since the user has already experienced a Waikiki tour, the content of the recommended reviews gives no new information to the user.

If the system was able to recommend reviews about other beach areas such as Phuket and Miami, the recommendation would be valuable for the user.

Unlike the conventional recommendation system, the proposed system explained in the next section focuses on the similarity of meta-level concepts such as genres of tours. Considering the similarity of concepts between reviews, the proposed system can broaden the recommendation range as shown in Figure 3. From the figure, we can notice that the proposed system can recommend similar types of tours in difference destinations.

3. Proposed system

3.1 Outline

Figure 4 shows the outline of the proposed tour recommendation system. The proposed system is composed of two subsystems: a sub-system for building a database and a sub-system for recommendation. These sub-systems are composed of the front-end module, the recommendation module, the review gathering module and a database.

As a pre-process for recommendation, the review gathering module collects customer reviews from online review sites such as TripAdvisor. The collected reviews are stored in the database.

The front-end module provides a user interface. With the interface, a user writes a review about a tour which the user

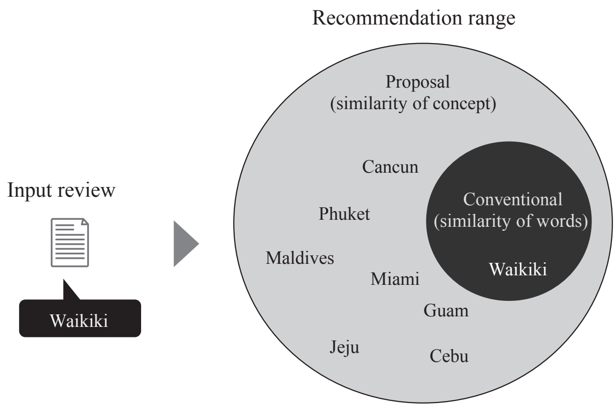

Figure 3: The difference of recommendation range in the proposed and conventional systems

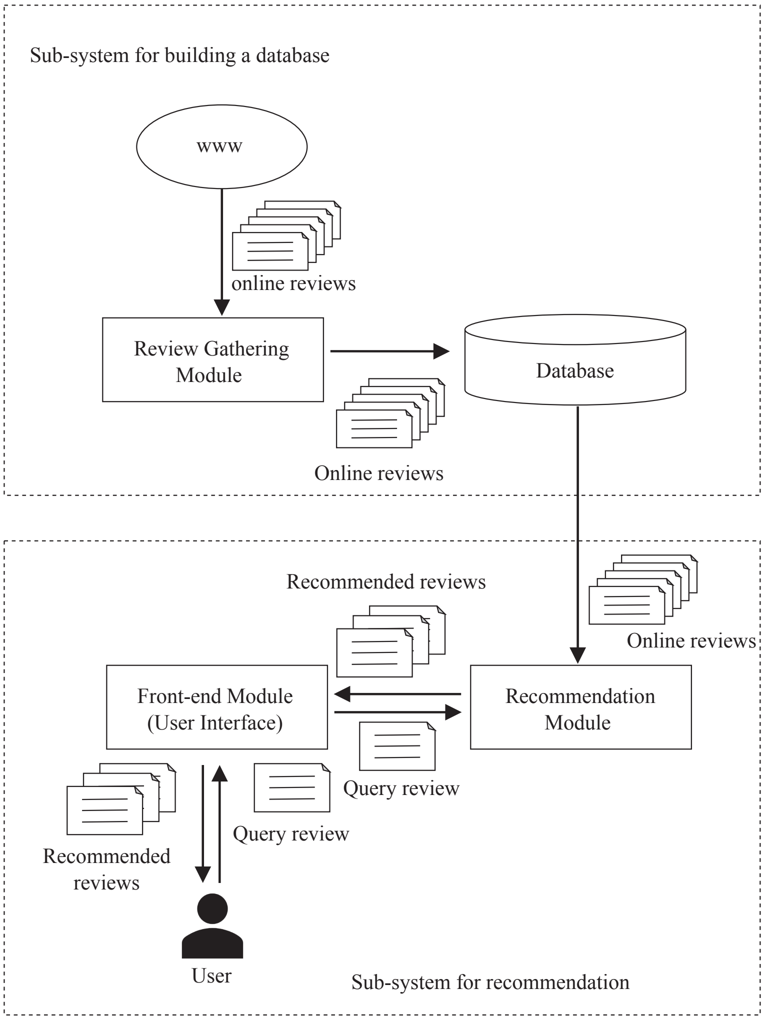

Figure 4: Outline of the proposed system

joined in a past trip. After the user submits the review, the system recommends some related reviews written by others to the user.

In the recommendation module, some reviews in the database are selected as recommendation results by evaluating the similarity of concepts between the input review and each review in the database.

3.2 Review recommendation with the Word2Vec model

In the proposed system, the meta-level concepts of a review are defined based on the Word2Vec model [Mikolov et al., 2013]. The effectiveness of the Word2Vec model has been reported in various natural language processing and information retrieval studies [Le and Mikolov, 2014; Kenter and Rijke 2015; Kusner et al., 2015; Xue et al., 2014].

The Word2Vec model is a model for generating a word vector. The orientation of a word vector is corresponded to the meaning of the word. When two different words have similar meaning, the word vectors of these words have similar directions.

For example, two words "Waikiki" and "Miami", can be represented with similar word vectors because the two words have a similar concept, namely these two words have the commonality that they are beach resort areas.

The Word2Vec model assumes that if two words have a similar meaning, co-occurrence words of these two words are also similar. By learning co-occurrence patterns of surrounding words for each word using a two-layer neural network, a proper representation of a word vector can be obtained (see Mikolov et al., 2013 for details).

Since a review consists of multiple words, by adding all the word vectors of the words in a document with proper weights, the document vector of the review can be calculated as follows:

$$\vec{v}(d) = \sum_{t \in T(d)} w(t,d)\ \vec{u}(t), \quad (6)$$

where $T(d)$ is the set of words in review d, weight $w(t,d)$ is the TF-IDF of word t in review d, $\vec{u}(t)$ is the word vector of word t generated by the Word2Vec model.

Once document vectors of the reviews in the database and the document vector of the input review are calculated, the similarity between the input review and each review in the database can be defined by the cosine measure like the conventional system.

4. Experimental results

4.1 Method

As an experiment, we compared two recommendation systems: (1) the proposed system and (2) the conventional BoW-based recommendation system explained in Sec. 2.

In the experiment 12 subjects participated. The subjects wrote total 27 reviews (2-3 review par one user) about tours they experienced in their past trips. These reviews were used as input reviews. Using the input reviews, the systems recommended related tours and their reviews to the subjects.

To build a database for the two systems, 259,084 online reviews were collected from VELTRA[(1)], an online tour reservation and review site.

For each input review, 10 tours and their customer reviews were recommended to the user. Namely, to the 27 input reviews, total 540 (270 + 270) tours and their customer reviews are recommended by the proposed system and the conventional system.

We conducted questionnaire surveys for each recommended tour. Figure 5 shows the questionnaires used in the experiment. The first question (Q1) asks whether the subject has joined to the recommended tour or not. The second question (Q2) asks to what extent user's interest were aroused by the recommended tour. To the question, the subject rated on a 5-point scale. The third question (Q3) asks the strength of relevance between the input review and recommended reviews. In this question, the subject rated on a 5-point scale.

We require you to answer the following questions:

Q1. **Have you ever joined to the recommended tour ?**

1. yes
2. no

Q2. **Do you agree or disagree with the following statement:**
"I am interested in the customer review and want to participate in the recommended tour."

1. strongly disagree
2. disagree
3. neither disagree nor agree
4. agree
5. strongly agree

Q3. **Do you agree or disagree with the following statement:**
"The topic of the customer review is relevant to your review."

1. strongly disagree
2. disagree
3. neither disagree nor agree
4. agree
5. strongly agree

Figure 5: Questionnaires used in the experiment

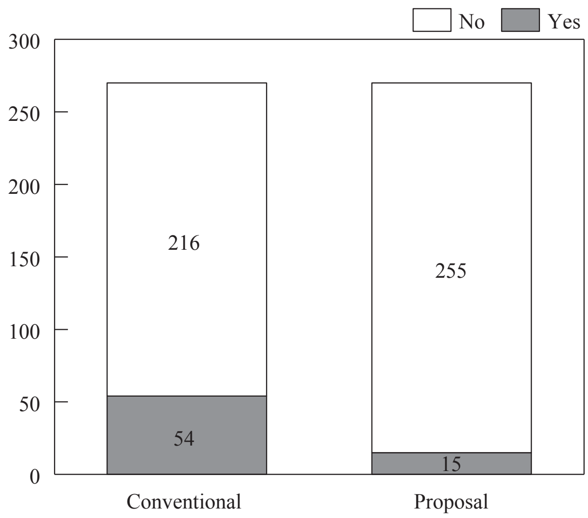

Figure 6: The results of question Q1

4.2 Results

Figure 6 shows the results of question Q1. As shown in the figure, 20.0 % (54 / 270) of the tours recommended by the conventional system are the tours the subjects have already experienced in their past trips. These recommendations give no new information for the users. On the other hand, by the proposed system, this ratio can be reduced to 5.6 % (15 / 270). These results indicate worthless recommendation can be reduced by the proposed system.

Figure 7 shows the distributions of scores in question Q2. As shown in the figure, the ratios of recommended tours which gained good ratings (score ≥ 4) in the conventional and proposed systems are 60.7 % (164 / 270) and 72.2 % (195 / 255),

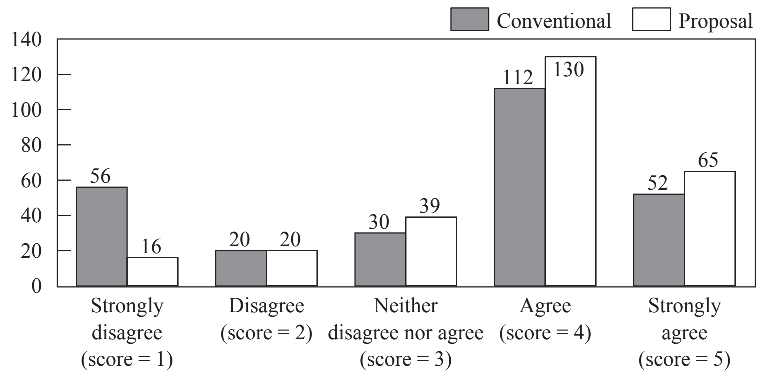

Figure 7: The results of question Q2

respectively. The average scores in the conventional and proposed system are 3.31 and 3.77, respectively. These results show that recommendation by the proposed system is superior to the conventional system.

Figure 8 shows the results of question Q3. The average scores in the conventional and proposed systems are 3.95 and 3.79, respectively. These results indicate that the conventional system tends to recommend tour reviews having higher relevance to the input review. However, as shown in the Fig. 6 and Fig. 7, the ratio of useful recommendation is larger in the proposed system than the one in the conventional system. Considering these results, we can confirm that too strong relevancy in review content is not always mandatory for effective recommendation.

4.3 Discussion

Table 1 shows examples of recommended tours by the two systems used in the experiment. The figure shows the top 3 tours recommendation results obtained when using an input review which describes a Borobudur temple tour in Indonesia. As shown in the table, the recommendation by the conventional system have no variation. The destinations of the three recommended tours are the same. Therefore, these recommendations give no value to the user. On the other hand, various tours were recommended by the proposed system. While the travel destinations in these tours are different, these tours have a commonality that they visit to religious heritage sites. In other words, similar types of tours visiting different destinations can be recommended by the proposed system. These results show that considering similarity of meta-level concepts in recommendation works effectively for broadening the recommendation range and providing valuable information to the user.

Table 1: Examples of recommended tours

Recommendation order	Conventional	Proposal
1	Borobudur temple (Indonesia)	My Son Sanctuary (Vietnam)
2	Borobudur temple (Indonesia)	Sri Srinivasa Perumal Temple (Singapore)
3	Borobudur temple (Indonesia)	Phnom Kulen (Sri Lanka)

5. Conclusions

In this paper, we proposed a system for recommending tours and their customer reviews. The proposed system focuses on the meta-level concepts in reviews such as tour genres. For effective recommendation, a document vector is defined based on the Word2Vec model. From experimental results, we confirmed that the proposed system can provide more valuable information to users than the conventional system.

The framework of the review-based recommendation can be applied to various tourism related services such as hotel recommendation and restaurant recommendation. As a future work, we are planning to develop various recommendation systems and integrate them for providing a tour coordinator service.

Note

(1) VELTRA: https://www.veltra.com/.

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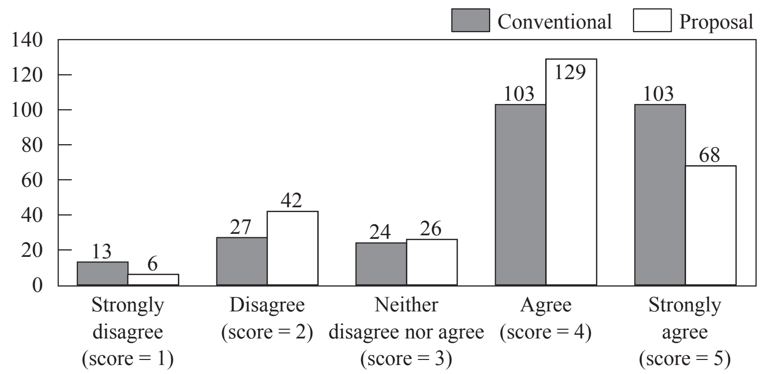

Figure 8: The results of question Q3

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