Leverage Business Analytics and OWA to Recommend Appropriate Projects in Crowdfunding Platform

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Abstract

Nowadays, crowdfunding is becoming more and more popular. Many studies have been published on the crowdfunding platform from different perspectives. However, among all these studies, few are concerned about the recommendation methods, which, in effect, are highly beneficial to crowdfunding websites and the participants. Having considered the situation talked above, this paper works out the several features from the relative projects of user's current browsing project. Then we give different weights to each feature based on selective attention phenomenon, and adopt the method of OWA operator to calculate the final score of each relative project and accomplish our model by picking out the four projects with different outstanding characteristics. Finally, according to the statistics on China's famous crowdfunding website, we conducted a group of contrast experiments and eventually testified that our proposed model could, to some extent, help classify and give recommendation effectively. Furthermore, the results of this research can give guidance to the management of crowdfunding websites and they are also very significant advices for the future crowdfunding website development.

Keywords： Crowdfunding, project recommendation, selective attention phenomenon, TF-IDF, LDA, OWA operator

1. Introduction

Crowdfunding is a new way to gather financial resource. Since the first crowdfunding platform appeared in 2001, global fundraising has reached billions of dollars [7]. Crowdfunding is an very effective way to fundraise, so more and more people participate in crowdfunding and lots of crowdfunding websites are created worldwide. Crowdfunding is showing its magic power to the people all around the world. Crowdfunding is still a new and promising field, and many researchers show their great interest in it.

In recent years, many studies have been published in the field of crowdfunding on different perspectives. Etter, Grossglauser, and Thiran [6] used the method of combining the direct information of project and social information gathered from Tweet to predict whether the crowdfunding project will succeed or fail, and found that by using the information from social media, the accuracy of prediction can be obviously increased. While Hui, Gerber, and Greenberg [12, 13] did their research on the ethnographic perspective, which helped people to understand what the nature of crowdfunding is by gathering information from the people who just have created the project, and could inform the people how to build crowdfunding support tools and systems. But among those studies, few former researches concerned with the recommendation of crowdfunding projects. Nice recommendation is a good way to overcome the trouble of information overload, and enables the customers to figure out useful messages efficiently from large numbers of information. This is not only to improve the business efficiency of e-commerce websites, but also to avoid the heavy search task of users when faced with a wide variety of goods.

Hill, Stead, Rosenstein, and Furnas [10] recommended the movie to the users according to the ratings provided by other people. Lang [16] used the information of an item's description and some people's preference data to predict what kind of items people would like. With the development of technology, recommendation system has become an independent discipline. We present our recommendation model on the basic of fully studies of former researchers. Therefore, we propose our recommending model by combining the similarity, success rate, support degree, and positive rate of the comments. We utilize the method of TextRank to extract the keywords. Then we use the TF-IDF method combining with cosine similarity to find the relative projects and calculate the similarity rate of each project. Furthermore, we apply semantic-based LDA method to predict the success rate of projects respectively. We also adopt the normalization calculating way to deal with the support degree of the projects, and use the sentiment analysis method to deal with the comments information. At last, we take the similarity, success rate, support degree and positive rate of the comments as the inputs in OWA operator to get final recommendation proposal.

We organize the content of this paper as follows. In Section 2, we introduce the theoretical foundations. We present the proposal method in Section 3. In Section 4, we demonstrate the empirical analysis. Finally, in Section 5, we provide the conclusions and indicate suggestions for future work.

2. Theoretical Foundations

We set up recommendation model and adopt the recommendation indicators based on the existing theories. In this Section, we will briefly introduce the cueing effect theory, expectancy-value theory, social identity theory, and selective attention phenomenon.

2.1. Cueing Effect Theory

The effective cue the target formerly provided could help build reaction preparation or expectation, increase the reaction speed, reduce the uncertainty of reaction, and thus observe the expectation's influence on the task. Usually, Cueing Effect exists in object cue task, time background cue task, space background cue task. When the hint range appears, the target within this range could make more effective choices so as to more accurately classify the information [9, 19].

Cues could be divided into three types: respectively effective, ineffective and neutral. Effective cues could lead people giving more attention to the formation of the target and therefore are beneficial to the identification of the target. According to research, the advent of clues will make load of conscience, working memories as an attachment, therefore, the information provided by those clues will accelerate the whole process of people's reaction and also affect the selectiveness of attention. Therefore, the appearance of cues exerts impact on individual selection and handling of the targeted information [23, 15].

In the process of browsing the project, the cues, which are produced during the process when people choose and go through the former product, help build reaction preparation or expectation. If the following-up product and the former one reach consensus, the former cues turn to effective cues and exert impact on attention's selection process and its speed.

H1: According to the cueing effect, we consider the similarity degree of the projects as one of the recommendation indicators.

2.2. Expectancy-value Theory

This theory states that motivation of accomplishing any task comes from two key factors, which are individuals' anticipation for success and how much people weigh the value of success. The higher the possibility of the visible success is, and the more encouraging the goal is, the higher individual's motivation will be [5, 24].

H2: According to the theory, the higher the success rate of a project is, the higher individuals' expectation of accomplishing the task is, the stronger the motivation will be. Therefore, we consider the success rate of each project as the recommendation indicator.

2.3. Social Identity Theory

Turner and Oakes [20] defined the social identity: the individual realizes that he belongs to a specific social group and recognizes the significance of emotion and value come from other members in group. According to social identity theory, one of the standards we use to judge right and wrong is to see what other people think about it, especially when we are going to decide the correct behavior. We conclude that something is reasonable if we find others have done the same thing before in certain occasion. No matter how to deal with the empty popcorn box in cinema, how fast we drive on the certain road, or how to eat chicken at the banquet, the actions by surrounding people play an important role in making decision about our own behavior. "Social identity" can trigger the direct effect upon the large amount of users when they make decisions. Therefore, at the same time the users read the comment of the product, they are inclined to make the same decision as those written on those comment, this phenomenon is called as the conformability effect.

H3: According to the theory, as for one project, its quality is effected by the users who have donated before and these comment will have effect on people's decision on whether choose this project or not. So we consider the comment as one of the indicators.

2.4. Selective Attention Phenomenon

Selective attention means that the effect on people's selective perception of objective things are numerous and diverse, and people cannot perceive everything clearly in the same moment; but according to some needs and purposes, people select few things (or a part of things) as the perception of the object initiatively and intentionally [2, 3, 18], or are attracted by something unconsciously, then use it as an object of perception. Selective attention is not only affected by the characteristics of the object, generally speaking, stimulants with large intensity, bright color, activity and variability are more possible to attract people's attention, which called bottom to up processing mechanism [14], including the automatically capture function by pop-out factor on visual attention [21, 27], but also selective attention is influenced by subjective factors of percipient such as interests, attitudes, hobbies, emotions, knowledge, experience, observation or analysis capability, which called top to down processing mechanism [4, 11]. In this way, we assume for a project that, on the one hand, from the angle of project itself, the recommending indicator with the maximum value is the pop-out factor mentioned above, and easily appeals to users, which led this project to be the object of perception. We also know that the higher value the indicators has, the higher possibility the indicators attract the attention. Therefore, when calculating the final score of the project, we give the highest weight to the recommending indicator with highest value. On the other hand, from the angle of user, according to top to down processing mechanism which affects people's attention, different people have different interests, attitudes, hobbies, emotions, knowledge, experiences, observation or even analysis capability, which led to the different characteristics of projects people interested in. As the result, it is better for us to offer more choices to users. Finally, we will recommend four projects with outstanding features.

3. The Proposed Method

As the crowdfunding websites are becoming more and more popular, websites also need to continuously improve their functions, allowing users to use more conveniently. In the crowdfunding area, the recommending mechanism is just at the beginning stage and far from maturity. So having considered this situation deeply, to help participants-sponsors finding their interested projects smoothly and reliably, we proposed a recommendation method based on the user's current browsing project. The overview of our proposed method is shown in Fig.1.

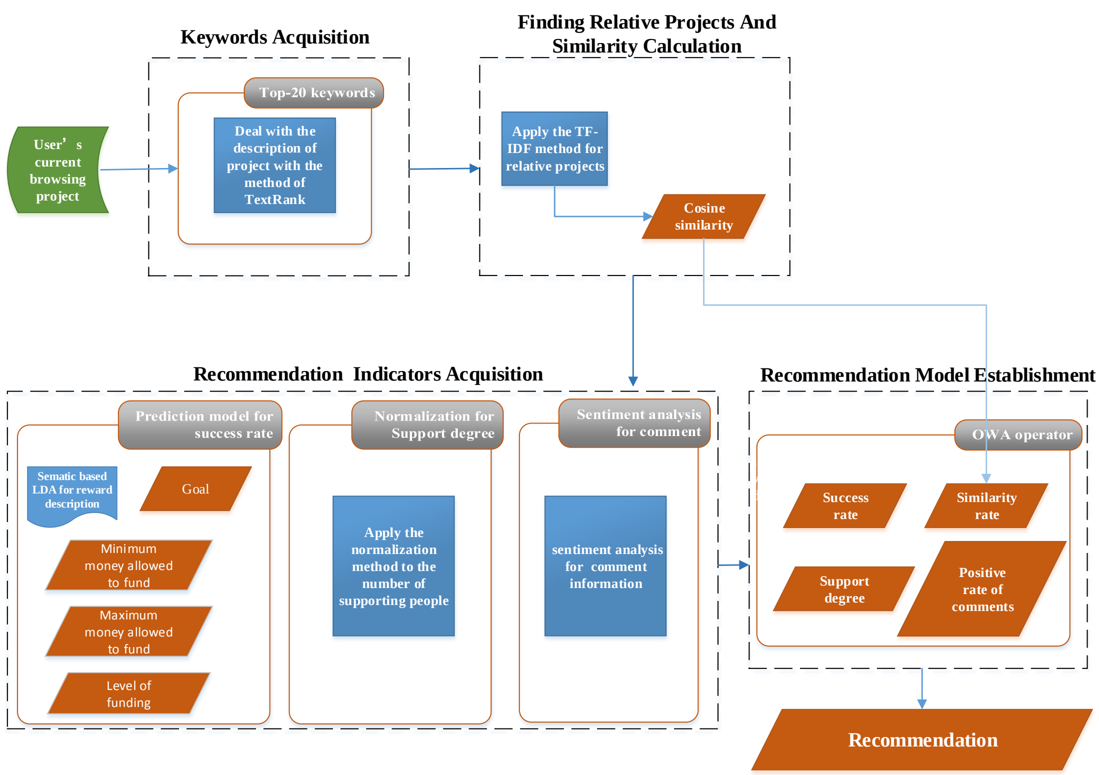

Fig. 1 The framework for our proposed model

As described in the Fig1 above, we divided our framework into four sections. Firstly, we extracted a set of keywords according to the current project being browsed. Secondly, via those keywords, we found several relative projects and further calculated to what extent they resembled. Thirdly, through the analysis of those relative projects, we worked out the success rate, support degree and positive rate of the comments separately. Fourthly, we used the recommending indicators obtained from the former steps, giving different weights to each recommending indicators based on selective attention phenomenon, and adopted the method of OWA operator to calculate the final synthetic score of each relative project and accomplish our model by picking out the four projects with different outstanding characteristics such as similarity rate, success rate, support degree, positive rate of the comments. Finally, by achieving the four steps mentioned above, we could build recommendation model effectively.

3.1. Keywords Acquisition

In this paper, we will use the method of TextRank [17] to extract keywords from the description of project.

TextRank is a graph-based ranking algorithm for computing vertex importance. It determines a vertex's importance by voting. One vertex's "vote" decided by the importance of all the links to this vertex, linked to a vertex equivalent to one vote on this vertex. The TextRank of a vertex is made up of all the importance of the vertex that links to it through a recursive algorithm. A vertex with more links will have a higher rank, instead if a vertex has no links to itself, it will not have a rank. The formula is shown as follows:

$$S(i) = (1-d) + d \times \sum_{j \in M(i)} \frac{1}{|L(i)|} S(j) \tag{1}$$

Let M (i) be the set of vertex that link to i, and L (i) be the set of vertexes that vertex i links to. The d is damping factor, which represents the probability of jumping from a specific vertex to another random vertex. In the context of web browsing, the damping factor d is a page that users reach a certain probability of continued access to its linked page. And 1-d is the probability on the user to jump to a new URL.

We can consider the process of using the TextRank to get keywords as it is to take every word as a vertex, and subsequent words are vertexes which link to the former one. When we started, arbitrary values will be assigned to each word in the text and the computation iterates until the value is below a given threshold. After running the algorithm, a value is associated with each word, which represents the “importance” of the word within the text. We put the top-20 highest value words as keywords.

So we applied this method to get the keywords from the description of a project. These keywords represent the main content of the description. To use this method, the first thing we had to do is preprocessing the description of the project, including the word segmentation and POS tagging with Fundan NLP tool.

3.2. Finding Relative Projects and Similarity Calculation

Through the previous step, we have obtainedthe keywords that represent the general description of a project. In this step, we used keywords to find relative projects of the current project. So we needed to complete this step by using TF-IDF method combining with cosine similarity [1] in this paper.

TF (term frequency) represents the frequency of a term appearing in the document d. In general, higher frequency represents the higher relativity between the term and the document, and this term should be given higher weighting. For the term that is in a particular file, its importance can be expressed as:

$$tf_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}} \tag{2}$$

In the equation above, $n_{i,j}$ is the total number a term occurrences in file d_j, and the denominator is the total number of occurrences of all words in file d_j.

IDF (inverse document frequency) is a universal measure of the importance of words. The main idea of the IDF: If the documents contain term T less, that is, the greater the IDF is, the stronger the terms T's classification capability is. The IDF formula is as follows:

$$idf_i = log\frac{|D|}{|\{j : t_i \in d_j\}|} \tag{3}$$

In the equation above, |D| is the total number of files in the corpus, $|\{j{:}t_i \in d_j\}|$ is the number of documents containing the word t_i(that is, file number $n_{i,j} \neq 0$), if the word is not in the corpus, it will leads to the situation that denominator is zero, so the general case uses $1+|\{j{:}t_i \in d_j\}|$.Then:

$$tf\text{-}idf_{i,j} = tf_{i,j} \times idf_i \tag{4}$$

By the equation above, the TF-IDF tends to filter out common words to keep keywords.

We apply the method described above combining with cosine similarity, using keywords that already have, find the relative projects and calculate the similarity. During this course, we need some pre-processing, including Word segmentation and POS tagging with ICTCLAS tool.

3.3. Recommendation Indicators Acquisition

Through the two steps mentioned above, we have gained a set of relative projects. In this step, by dealing with these projects, we got the recommendation factors with the method described in subsections.

The LDA method for success rate

LDA (Latent Dirichlet Allocation) is an unsupervised machine learning technology. It can be used to identify the theme information lurking in the large scale of document collection or the corpus. It uses method of bag of words to treat each document as a vector of word frequency. Thus it can convert the text information into digital information which is easy for modeling, and each document represents a probability distribution of some of the topics posed, and each topic also represents a probability distribution consisting of many words. Formula is shown as follows:

$$\mathrm{p}(w|d) = \sum_{topics} p(w|t) \times p(t|d) \tag{5}$$

In the formula above, the p (w/d) represents the probability of word w appears in document d. It can be obtained by p (w/t) and p (t/d). p (w/t) means the probability of word w appears in the topic t and p(t/d) indicates the probability of topic t appear in the document d.

In our paper, we through a combination of Latent Dirichlet Allocation and Gibbs Sampling [8] based on the semantic of text information to help us establish our prediction model. Gibbs Sampling is a special case of the Markov-Chain Monte Carlo algorithm. We used this algorithm to get the LDA parameter. Here, we had to deal with the rewarding information by the method described above, then the feature selection based on the theory, using the machine learning techniques to build our prediction model, we can get the success rate of each project through this model. To build the prediction model, the rewarding information must be preprocessed including word segmentation, POS tagging and noun-term selection.

The normalization tool for support degree

In this paper, we use the Min-Max Normalization method, which is a linear transformation of the original data, so that the resulting value is mapped to [0-1]. Conversion function is shown as follows:

$$X_i^* = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{6}$$

In the function above, x_{max} is the maximum value of sample data, x_{min} is the minimum value of the sample data. And, x_i is the value before conversion and x_i* is the value after conversion.

In the paper, we apply the normalization method to deal with the number of supporting people of each relative project so that we can get the support degree of each project.

The sentiment analysis for comments

Crowdfunding website, as a form of social media, comments of each project is an important reference information for user who browsing the project. So, in this paper, we apply the semantic analysis method to analyze the emotional trend of comments of relative projects based on the HowNet emotion dictionary.

Turney [22] introduced a method for classifying sentiment polarity of reviews at the document level. So the main idea of sentiment analysis in our paper is that we use HowNet vocabulary as a basis, we need to give each comments a semantically orientation values whose size is determined by how tightly the words in comments associated with seed words. Seed word means that the words that its judgments attitude is very clear, strong, representative words. If contact positive seed words more closely, the comment tend to be more positive. Instead, contact the negative seed words more closely, the more negative the tendency will be. We calculate the each comment's sentimental orientation value.

During this course, we need some pre-processing, first of all, comments information are conducted to word segmentation with ICTCLAS tool.

3.4. Recommendation Model Establishment

Through the methods presented above, we already have acquired four recommending indicators including similarity rate, success rate, support degree and positive rate of the comments of these projects. In this step, we need to give each recommending indicator reasonable weight according to the theory mentioned in the theories foundation part to get the final recommending proposal. According to pop out effect in bottom to up processing mechanism which introduced in selective attention phenomenon, the maximum recommending indicator in each project may lead to pop out effect, and attract people's attention to this object. That is to say, the higher value the indicators has, the higher possibility the indicators attract the attention. So, when we calculate the final scores of each project, the higher indicator gets the higher weight and the highest weight needs to be provided to the maximum recommending indicator. To implement the theory, we apply the Ordered Weighted Averaging (OWA) operator to calculate the weight of each indicator.

The conception of ordered weighted averaging (OWA) operator defined by the Yager [25] is as follows: OWA is a mapping of dimension of n, OWA: $R^n \to R$.

$$OWA(a_1, a_2 \ldots\ldots\ldots\ldots a_n) = \sum_{j=1}^{n} w_j \times a_{\sigma(j)} \tag{7}$$

Among the function above w=(w_1,w_2,w_3...) is weight vector associated with OWA operator and $\sum_{j=1}^{n} w_j$=1. $a_{\sigma(j)}$is J-th largest elementin the a set of data ($a_1, a_2 \ldots\ldots a_n$), that is to say ($a_{\sigma(1)}$,$a_{\sigma(2)}$,$a_{\sigma(3)}$...) is the result of ($a_1, a_2 \ldots\ldots a_n$) arranging by descending order.

According to the Yager [26], he introduce the idea of dependent OWA Operators, it allows the weight to be the function of polymerization parameter, as follows:

$$OWA(a_1, a_2 \ldots\ldots\ldots\ldots a_n) = \sum_{j=1}^{n} f_j\left(a_{\sigma(1)}, a_{\sigma(2)}, a_{\sigma(3)} \ldots a_{\sigma(n)}\right) \times a_{\sigma(j)} \tag{8}$$

In Yager's families of OWA operators, a kind of the aggregate dependent weight is shown as follows:

$$w_j = \frac{{a_{\sigma(j)}}^{a}}{\sum_{j=1}^{n} {a_{\sigma(j)}}^{a}} \tag{9}$$

In this case, the higher value the parameter has, the higher weight the parameter gets, that is to say, the element with highest value is given the highest weight. This is consistent with the theory presented above.

After we have got four recommending indicators, which are the value from 0 to 1, for each relative project, we can recognize that the projects have different maximum recommending indicator. As the result, the projects can be divided into four groups according to their maximum recommending indicator, and the maximum recommending indicator for every project in each group is: similarity rate, success rate, support degree, positive rate of comments. We calculate projects in each group by OWA operator and get the project with highest synthetic score in each group. According to top to down processing mechanism mentioned in selective attention phenomenon in theoretical foundation part, because of the different interests of users', we offer the projects which have different outstanding characteristics to users in order to achieve higher successful recommending rate. Therefore, we choose the project with highest synthetic score in each four groups as the recommending proposal.

4. Empirical Analysis

4.1. Data Description and Evaluation Criteria

In this paper, the date crawled from the Chinese crowdfunding website: www.dreamore.com, which is served as the experiment date in our research. We used a program written in python to crawl 725 projects, among them 385 projects complete the crowdfunding successfully, while other 340 projects are failed. We filtered the projects whose deadline is October 10th, 2014. Then, we used our own designed program to extract the experimental required features.

Furthermore, We used the common evaluation strategy in the field of information retrieval, calculated P@N (precision of first N result) and R@N (recall of first N result) to compare the recommendation results by the proposed method with the standard recommendation results, here are the formulas to calculate the precision and recall rates, respectively, as shown in equation 10 and equation 11.

$$P@N = \frac{the\ number\ \ of\ the\ correct\ \ solutions\ \ among\ \ the\ first\ -N\ recommending\ \ \ result}{N} \tag{10}$$

$$R@N = \frac{the\ number\ \ of\ the\ correct\ \ solutions\ \ among\ \ the\ first\ -N\ recommending\ \ \ result}{the\ number\ \ of\ the\ standard\ \ recommended\ \ \ results} \tag{11}$$

4.2. Experimental Results

The performance of recommendation system is generally evaluated by the scores of recommendation results made by users, this paper also uses this kind of evaluation approach. We consulted a teacher whose profession is the information management，several master graduate students of computer science and another two people who engage in IT field artificially to mark out the standard recommendation answer of 10 projects.

As marking method, all labeling man were given 10 target projects respectively and the target projects that are given to each labeling man are same. We obtained 20 projects as candidates recommended for each goal project, then let labeling men giving score to the each candidate project and summarize the rating result. We used the high scoring projects which marked by all labeling man as a standard recommendation result. Using artificial recommendation result as a standard set, we designed the following models, and compared the recommendation performance of each model.

Our proposed model

Here, as our research is based on the user's current browsing project, we picked out 10 projects randomly, assuming that we are browsing these projects now, and want to recommend several projects based on these projects. We found relative projects and extracted four recommending indicators with the method described above. Every project was grouped according to its maximum indicator. In this way, we would have four groups and each group has different maximum indicators: similarity rate, success rate, support degree and positive rate of comments. The maximum indicator of projects in group one is similarity rate, and success rate in group two, support degree in group three, positive rate of comments in group four. Then we gave diverse weights to every indicator by OWA method in consideration of selective attention phenomenon. Our recommendation model consists of the projects with highest synthetic scores in each group, that is to say, we picked out the four projects with different outstanding characteristics such as similarity rate, success rate, support degree, positive rate of comments as our recommending result, which is shown in Table 1 below(e.g. assuming current browsing project ID:15509):

Table 1 The recommendation result generated by our proposed model

Group	Project ID	Page URL
Similarity	14948	http://www.dreamore.com/projects/14948.html
Success rate	13763	http://www.dreamore.com/projects/13763.html
Support degree	13177	http://www.dreamore.com/projects/13177.html
Positive rate of comments	11146	http://www.dreamore.com/projects/11146.html

Equal-weight model

In this model, the former steps are same as our proposed model above. What different is that we gave the same weight to each recommendation indicator, and recommended the project with highest composite scores in each group. As the result, we finally got recommendation proposal consisted by four projects. The result is shown in Table 2(e.g. assuming current browsing project ID:15509).

Table 2 The recommendation result generated by equal-weight model

Group	project ID	Page URL
Similarity	10793	http://www.dreamore.com/projects/10793.html
Success rate	13763	http://www.dreamore.com/projects/13763.html
Support degree	14558	http://www.dreamore.com/projects/14558.html
Positive rate of comments	12225	http://www.dreamore.com/projects/12225.html

Single indicator model

Here, we set similarity-only model, success rate-only model, support degree-only model and positive comments only-model to test the hypothesis we get in former part. Assuming that we are browsing the same project chosen in former model, we sort the relative projects according to the only one indicator. Then choose the top 4 projects as recommending results, that are shown below :(e.g. assuming current browsing project ID:15509):

Table 3 The recommendation result generated by similarity-only model

Serial number	project ID	Page URL
1	14948	http://www.dreamore.com/projects/14948.html
2	10793	http://www.dreamore.com/projects/10793.html
3	12225	http://www.dreamore.com/projects/12225.html

4	415	http://www.dreamore.com/projects/415.html

Table 4 The recommendation result generated by success rate-only model

Serial number	**project ID**	**Page URL**
1	13763	http://www.dreamore.com/projects/13763.html
2	13177	http://www.dreamore.com/projects/13177.html
3	13154	http://www.dreamore.com/projects/13154.html
4	415	http://www.dreamore.com/projects/415.html

Table 5 The recommendation result generated by support degree-only model

Serial number	**project ID**	**Page URL**
1	13177	http://www.dreamore.com/projects/13177.html
2	13154	http://www.dreamore.com/projects/13154.html
3	14558	http://www.dreamore.com/projects/14558.html
4	415	http://www.dreamore.com/projects/415.html

Table 6 The recommendation result generated by positive comment-only model

Serial number	**project ID**	**Page URL**
1	13154	http://www.dreamore.com/projects/13154.html
2	11146	http://www.dreamore.com/projects/11146.html
3	12225	http://www.dreamore.com/projects/12225.html
4	12633	http://www.dreamore.com/projects/12633.html

4.3. Comparison

In this subsection, our proposed recommending model is compared with single indicator model and equal-weight model. The experimental result is shown in Fig2.

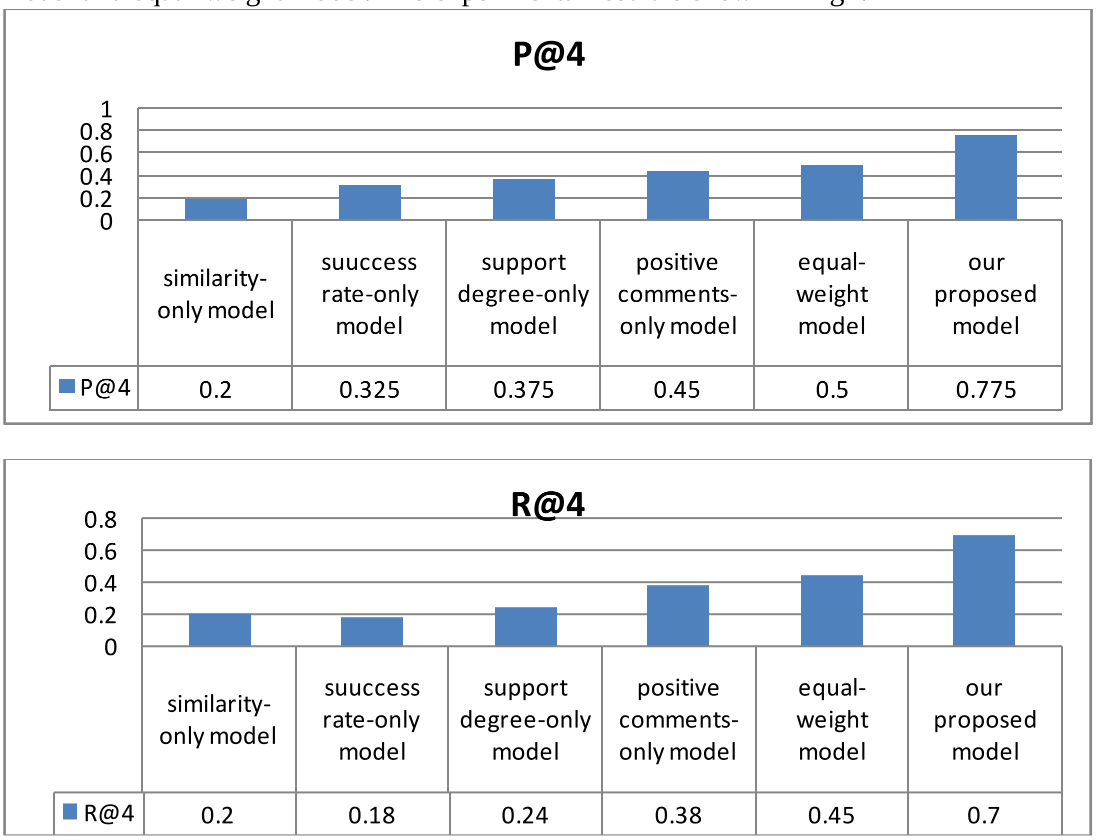

Fig. 2 the comparison aboutP@4 and R@4 index for different model

As can be seen from Fig. 2, the performance of our recommending model is best. The equal-weight model is followed. This result illustrated the validity of selective attention phenomenon in our proposal. However the results obtained by single indicator models are low. This phenomenon fully explains the function of related theories. So, at any way, our proposed recommendation model is a promising and exercisable one for crowdfunding website's project recommendation.

5. Conclusions and Future Work

This paper illustrates an idea of crowdfunding project recommendation based on current suffering. More specifically, we extracted several keywords by utilizing the method of TextRank which performs very effectively in our experiment. Afterwards, these keywords were used to find relative projects. Experiment proved that such method could remove the noise words effectively and very helpful for finding relative projects. In the prediction part, we used the semantic-based LDA method combining with several features selected based on theories to calculate the success rate. Then we adopted four recommending indicators: the success rate, the similarity rate, the support degree and the positive rate of comments, and applied the OWA operator based on selective attention phenomenon to fix the recommending model which emphasizes the most outstanding characteristic of projects and increases the users' options. Compared with other recommending models, this method improves the recommendation performance significantly.

In addition, there are some questions need further researches. First of all, in process of finding relative projects, we use the method of TF-IDF combining with cosine similarity, while in future research we can explore the Latent Dirichlet Allocation (LDA) instead. Secondly, the prediction model utilized in our experiment performances relatively well. So the optimized prediction model will be helpful to improve the recommending result. Finally, the weight of each recommending indicator calculated according to the dependent OWA operator might be more reasonable depending on further studies.

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References

[1] Adomavicius, G., and Tuzhilin, A. 2005. "Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions, " Knowledge and Data Engineering, IEEE Transactions on, 17(6), pp. 734-749.

[2] Broadbent, D. E. 1958. Perception and communication (in London). Pergamon.

[3] Broadbent, D. E. 1982. "Task combination and selective intake of information," Acta psychologica,50(3), pp. 253-290.

[4] Duncan, J., and Humphreys, G. W. 1989. "Visual search and stimulus similarity," Psychological review,96(3), pp.433.

[5] Eccles, J. S. 1983. "Expectancies values and academic behaviors, "

[6] Etter, V., Grossglauser, M., and Thiran, P. 2013. "Launch hard or go home!: predicting the success of kickstarter campaigns," In Proceedings of the first ACM conference on Online social networks: ACM , pp. 177-182.

[7] Giudici, G., Nava, R., Rossi Lamastra, C., and Verecondo, C. 2012. "Crowdfunding: The new frontier for financing entrepreneurship?," Available at SSRN 2157429.

[8] Griffiths, T. L., and Steyvers, M. 2004. "Finding scientific topics," Proceedings of the National Academy of Sciences,101(suppl 1), pp. 5228-5235.

[9] Henderson, J. M. 1991. "Stimulus discrimination following covert attentional orienting to an exogenous cue," Journal of Experimental Psychology: Human Perception and Performance,17(1),pp. 91.

[10] Hill, W., Stead, L., Rosenstein, M., and Furnas, G. 1995. "Recommending and evaluating choices in a virtual community of use," In Proceedings of the SIGCHI

conference on Human factors in computing systems. ACM Press/Addison-Wesley Publishing Co., pp. 194-201.

[11] Hodsoll, J., and Humphreys, G. W. 2001. "Driving attention with the top down: The relative contribution of target templates to the linear separability effect in the size dimension," Perception & psychophysics, 63(5), pp. 918-926.

[12] Hui, J. S., Greenberg, M. D., & Gerber, E. M. 2014. "Understanding the role of community in crowdfunding work," In Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing: ACM, pp. 62-74

[13] Hui, J. S., Gerber, E., and Greenberg, M. 2012. "Easy money? The demands of crowdfunding work. Proceedings of the Segal Technical Report: 12,4, 2012.

[14] Itti, L., and Koch, C. 2001. "Feature combination strategies for saliency-based visual attention systems," Journal of Electronic Imaging, 10(1), pp.161-169.

[15] Lai, G., and Mangels, J. A. 2007. "Cueing effects on semantic and perceptual categorization: ERPs reveal differential effects of validity as a function of processing stage, " Neuropsychologia,45(9), pp. 2038-2050.

[16] Lang, K. 1995. "Newsweeder: Learning to filter netnews," In Proceedings of the 12th international conference on machine learning, pp. 331-339.

[17] Mihalcea, R., and Tarau, P. 2004. "TextRank: Bringing order into texts," Association for Computational Linguistics.

[18] Neisser, U. 1967.Cognitive psychology (in New York). Appleton-Century-Crofts.

[19] Pestilli, F., and Carrasco, M. 2005. "Attention enhances contrast sensitivity at cued and impairs it at uncued locations, " Vision research,45(14), pp. 1867-1875.

[20] Turner, J. C., & Oakes, P. J. 1986. "The significance of the social identity concept for social psychology with reference to individualism, interactionism and social influence," British Journal of Social Psychology, 25(3), pp.237-252.

[21] Theeuwes, J. 1992. "Perceptual selectivity for color and form," Perception & Psychophysics,51(6), pp.599-606.

[22] Turney, P. D. 2002. "Thumbs up or thumbs down?: semantic orientation applied to unsupervised classification of reviews," In Proceedings of the 40th annual meeting on association for computational linguistics, Association for Computational Linguistics, pp. 417-424.

[23] Valdes-Sosa, M., Bobes, M. A., Rodriguez, V., and Pinilla, T. 1998. "Switching attention without shifting the spotlight: Object-based attentional modulation of brain potentials, " Journal of Cognitive Neuroscience, 10(1), pp.137-151.

[24] Wigfield, A., and Eccles, J. S. 2000. "Expectancy–value theory of achievement motivation," Contemporary educational psychology, 25(1), pp. 68-81.

[25] Yager, R. R. 1988. "On ordered weighted averaging aggregation operators in multicriteria decisionmaking," Systems, Man and Cybernetics, IEEE Transactions on,18(1), pp.183-190.

[26] Yager, R. R. (1993). "Families of OWA operators," Fuzzy sets and systems,59(2), pp,125-148.

[27] Yantis, S. 1993. "Stimulus-driven attentional capture," Current Directions in Psychological Science, pp.156-161.