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Research on Network Navy Behavior in the Field of Electronic Commerce

Xiaohan Xi[1, a], Yingding Zhao[2, 3, b]

[1]School of Computer and Information Engineering, Jiangxi Agricultural University, Nanchang 330045, China;

[2]School of Software, Jiangxi Agricultural University, Nanchang 330045, China;

[3]Key Laboratory of Agricultural Information Technology, Jiangxi Agricultural University, Nanchang 330045, China.

[a]948772240@qq.com, [b]915435518@qq.com

Abstract: With the development of web2.0, people's daily life is highly informationized, and the network navy has sprung up. It relies on huge amounts of garbage information to gain benefits and form a new industry chain. Among them, the identification of the E-commerce network Navy has become a prominent research issue in many network Navy problems. Compared with the normal users, the network navy has obvious differences. Starting from the behavior research of the E-commerce network Navy, analyzing the behavior pattern of the navy can achieve the purpose of identifying the abnormal users.

Keywords: E-commerce field, network navy, behavior research.

1. Introduction

In recent years, using the Internet to purchase merchandises has become the first choice for people to consume. When shopping online, people will give priority to the evaluation and praise rate of goods. Therefore, many businesses employ people to create and disseminate false information and conduct a unified evaluation of goods to publicize themselves or attack their competitors.

By analyzing the content of e-commerce users' comments and the common behavior patterns of naval reviews, this paper summarizes and the methods of identifying e-commerce users' comments and naval reviews from the aspect of behavior research.

2. Overview

E-commerce network Navy needs to complete a large number of complex comments as soon as possible, so the content of their comments is mostly similar or the same, they will also copy or evaluate other people's comments in large quantities, and their scores are extremely high or very low, always seriously deviating from the average score [1].In the image review area, QQ and WeChat Group are also promoted in the form of uploading pictures containing two-dimensional codes.

We model the behavioral patterns of the above users and adopt a scoring system. The higher the score, the more likely the users will be identified as navy. Literature [2-8] proves the feasibility of this experiment, including the classification of garbage reviews, various detection methods, supervised learning, manual labeling of data sets, etc.

3. Establishment of Detection Model for E-commerce Navy

3.1 Evaluation Function of Navy Comment Score for Individual Products

In the field of electronic commerce, Navy users can be inferred by observing the rating behavior of the same user in the product. Formula 1 is a rating model for u_i rating behavior of users:

$$C_e(u_i) = \frac{s_i}{Max_{u_i' \in U} s_i'} \tag{1}$$

We define U = {u_i} as the user set, O = {o_j} as the product set, and E = {e_k} as the score set. The expression of si is as follow:

$$s_i = \sum_{e_{ij} \in E_{ij}, |E_{ij}|>1} |E_{ij}| \cdot sim(E_{ij}) \tag{2}$$

E_{ij} = { e_k | $u(e_k) = u_i \wedge o(e_k) = o_j$ }, the user u_i score set under product o_j; sim () is a similar function used to compare ratings in a given set. It is defined as follow:

$$sim(E_{ij}) = 1 - \underset{e_k, e_{k'} \in E_{ij}, k<k'}{Avg} |e_k - e_{k'}| \tag{3}$$

Based on the above formula model, the higher the similarity of product o_j score given by users, the higher the score of sim () function.

3.2 Evaluation Function of Marine Review Content for Individual Products

According to the characteristics of the navy,it is very important to analyze the comment content. The user u_i's comment score model is defined as:

$$C_v(u_i) = \frac{s_i'}{Max_{u_i' \in U} s_{i'}'} \tag{4}$$

$$s'_i = \sum_{v_{ij} \in V_{ij}, |V_{ij}|>1} |V_{ij}| \cdot sim(V_{ij}) \tag{5}$$

V = { v_k } represents a collection of comments, each comment corresponds to a score e_k; V_{ij} = { v_k | $u(v_k) = u_i \wedge o(v_k) = o_j$ }, represents a set of comments from the user u_i under product o_j; sim (V_{ij}) has the same effect as sim (E_{ij}),used to compare content in a given set of comments, the expression is:

$$sim(V_{ij}) = \underset{v_k, v_{k'} \in V_{ij}, k<k'}{Avg} sim(v_k, v_{k'}) \tag{6}$$

sim (v_k, v_k') means to compare the similarity between v_k and v_k':

$$sim(v_k, v_{k'}) = cosine(v_k, v_{k'}) \tag{7}$$

Formula 7 shows that each comment is represented by cosine similarity of binary TF-IDF vectors containing v_k and v'_k. The greater the cosine similarity of the vectors, the more similar they are. So when sim (v_k, v_k') = 1, it is proved that the two comments are the same.

3.3 Marine Testing of Product Group

In this section, naval detection is carried out according to the multiple ratings of a product group. A product group includes all products in a store or in a product type or even a brand.

3.3.1 Multiple High-score Evaluation Tests for Product Groups

In order to model the behavior of the same user who scored extremely high scores on the same attribute products in a short time, we divided the time period into fixed, same size and disjoint time windows w. Therefore, the user u_i defined the high score set of product group b_k in the time window w as follow:

$$E_{ik}^{H}(w) = \{e_{ij} \in E_{i*} | o_j \in b_k \wedge t(e_{ij}) \in w \wedge e_{ij} \in H\ RatingSet\} \tag{8}$$

$E_{i*} = \cup_j E_{ij}$ denotes all rating sets given by user u_i; H Rating Set is a higher rating set in product group. In Jingdong Mall, the original rating is up to 5, and the normalized rating is up to 1, so default H RatingSet = { 1 }; we need to capture the user's multiple ratings of the product in a short period of time and exclude the second purchase that is not in a period of time, so we set the time window w to one day.

When $E_{ik}^{H}(w)$ is large enough, we basically think that rating users exist in the e-commerce network Navy to improve the overall score. Therefore, we set the minimum standard $minisize^H$. Sets larger than this set will be stored in C_i^H to further evaluate users. According to [10] experimental analysis, set $minsize^H = 3$. The expression is defined as:

$$C_i^H = \cup_{k,w} \{ E_{ik}^{H}(w) \mid |E_{ik}^{H}(w)| \geq minsize^H \} \tag{9}$$

The model of naval inspection for high-score users of product group is as follow:

$$c_{g,H}(u_i) = \frac{C_i^H}{Max_{u'_i \in U} C_{i'}^H} \tag{10}$$

3.3.2 Multiple Low-score Evaluation Tests for Product Groups

Unlike high scores, low scores occur in order to hit competitors. As above, user u_i defines product group b_k score in time window w as follow:

$$E_{ik}^L(w) = \{ e_{ij} \in E_{i*} \mid o_j \in b_k \wedge t(e_{ij}) \in w \wedge e_{ij} \in L\ RatingSet \} \tag{11}$$

L RatingSet represents the lower score set in the product group. In Jingdong Mall, the original score of 1 and 2 is the lower score of the product group. Normalization is used to express the score of 0 and 0.25. Similarly, the minimum standard $minsize^L$ is set, and the set larger than this standard is stored in C_i^L to further evaluate the e-commerce network Navy. According to the experimental analysis of [10], the expression $minsize^L = 2$, C_i^L is defined as:

$$C_i^L = \cup_{k,w} \{ E_{ik}^L(w) \mid\mid E_{ik}^L(w) \mid \geq minsize^L \} \tag{12}$$

The model of low-level user detection for product group is as follow:

$$c_{g,L}(u_i) = \frac{C_i^L}{Max_{u'_i \in U} C_{i'}^L} \tag{13}$$

3.3.3 Testing Model for Product Groups

According to the above two models, the model of single product naval inspection is as follow:

$$C_g(u_i) = \frac{1}{2}(C_{g,H}(u_i) + C_{g,L}(u_i)) \tag{14}$$

3.4 Navy Detection Based on User's Scoring Deviation Behavior

From the analysis of the rating, we can see that there is a deviation between the Navy score and the average product score. Setting the e_{ij} as the difference between the average grades of the same product, then the user's deviation degree of product score d_{ij} is as follow:

$$d_{ij} = e_{ij} - \underset{e \in E_{*j}}{Avg}\, e \tag{15}$$

$E_{*j} = \cup_i E_{ij}$ represents all scoring sets under product o_j; Constructing a Navy Detection Model for scoring deviation:

$$c_d(u_i) = \underset{e \in E_{i*}}{Avg} \mid d_{ij} \mid \tag{16}$$

3.5 Detection of Irrelevant Comments

There will be some unrelated content in product reviews. Many users promote other things in the form of photo reviews, and upload public numbers and two-dimensional codes on discounted or low-priced items in the photo area of reviews. In view of such user behavior characteristics, we construct a naval model:

$$C_f(u_i) = \frac{f_i}{Max_{u'_i \in U} f'_i} \tag{17}$$

$$f_i = \frac{|Q|}{|F|} \tag{18}$$

Among them, $F = \{f_k\}$ denotes the collection of pictures in user reviews, and Q denotes pictures containing unrelated reviews.

4. Model Checking and Evaluating

Some of the five behaviors are not the main judgment characteristics. So we assign a weight to each model according to experience, and the weights of the behavior with weak influence are smaller. Finally, we get the scoring formula of e-commerce network Navy:

$$C(u_i) = \frac{1}{10}C_e(u_i) + \frac{3}{10}C_v(u_i) + \frac{3}{10}C_g(u_i) + \frac{1}{10}C_d(u_i) + \frac{2}{10}C_f(u_i) \tag{19}$$

4.1 Data Collection

We choose the latest listed vivo x21 mobile phone as the experimental object and Jingdong Mall as the experimental data source. There are seven sales pages in the mall, and a total of 3403 comments that can be derived. A total of 261 users evaluated the data several times and generated 637 comments.

4.2 Marking Method of Navy

At present, there is no data set clearly identifying naval users on the network, so manual marking is needed. Firstly, sort out the data and separately arrange the scores of five evaluation models. Then, select ten most likely to be Navy users and ten most likely to be ordinary shoppers (top ten and bottom ten).Construct a new data set. Because of the overlapping parts, a data set composed of 75 shoppers is finally obtained. After that, the new data sets are sorted by the naval evaluation. Finally, the top 25 and the bottom 25 users are extracted to form a new small data set.

After the data is sorted out, three Navy markers are selected to label the small data sets manually. The three markers work independently and do not interfere with each other. Information flow is prohibited before the end of the labeling.

4.3 Methodological Assessment

nDCG is used to evaluate the experiment, which is often used as the evaluation index of ranking. The accuracy of ranking is evaluated by this method.

$$\text{DCG} = \sum_{i=1}^{50} \frac{2^{rel_i} - 1}{\log_2(1+i)} \tag{20}$$

$$\text{nDCG} = \frac{DCG}{iDCG} \tag{21}$$

In the above formulas, rel_i the score of the first result, which refers to the number of votes of Navy markers obtained by user u_i; iDCG is an ideal DCG. Through nDCG, it can be concluded which evaluation model is more consistent with the ideal ranking.

5. Analysis of Experimental Results

5.1 Artificial Marking Results

Tables 1 and 2 show the results of manual marking. The number of Navy and common users marked with diagonal line is the number of overlapping labels of the two markers, while the number of non-diagonal line is the number of overlapping labels of the two markers. The number of naval markers shared by the three persons was 19, and the number of normal user markers was 22.

Table 1 Network Navy manual marking results

	Mark Man 1	Mark Man 2	Mark Man 3
Mark Man 1	28	21	20
Mark Man 2	\	24	25
Mark Man 3	\	\	25

Table 2 General user manual markup results

	Mark Man 1	Mark Man 2	Mark Man 3
Mark Man 1	22	22	22
Mark Man 2	\	26	23
Mark Man 3	\	\	25

Two or three persons at the same time will prove that the user is a Navy user. The final 27 users will be marked as navy users (8 users are two tickets, 19 users are three tickets), and 23 users will be marked as normal users (1 user is two tickets, 22 users are three tickets).

Choose the top ten and the bottom ten of Navy users and normal users, and count whether the scores of the five detection models in Section 2 are consistent with the final total ranking, if they are consistent, write into Table 3.

Table 3 Number of users ranked in the top ten and bottom ten

	Score similarity	Comment Similarity	Product group	Scoring bias	Irrelevant comments	comprehensive
Navy user	9	9	7	4	3	10
Normal user	7	8	6	3	10	10

The ranking of marked users is regarded as the most ideal state of ranking. According to this ranking, calculate iDCG, five kinds of ranking DCG and nDCG, and then display them in the form of graphs, like Fig. 3:

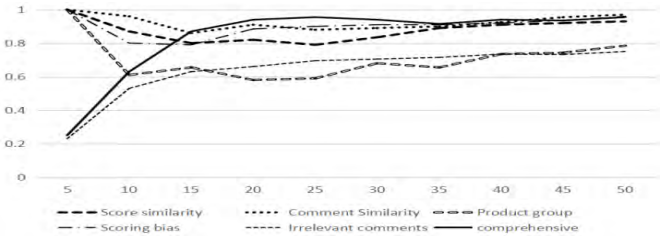

Fig. 1 nDCG normalization score

From the chart, it can be seen that product rating and product reviews can well represent the behavior of e-commerce, while the model of score deviation and related reviews is quite different.

5.2 Linear Regression Model

Based on the marking results of the final naval users, we can train a linear regression model to predict the possibility of a given user being a commercial navy. To ensure accuracy, we use the number of votes as the optimal solution of the linear regression model.

Let the linear regression model trained in 50 users be as follows:

$$C(u_i) = w_1 C_e(u_i) + w_2 C_v(u_i) + w_3 C_g(u_i) + w_4 C_d(u_i) + w_5 C_f(u_i) \quad (22)$$

The final results are w_1=-1.3694, w_2=4.2055, w_3=0.8194, w_4=1.0593, w_5=-1.9511.

The linear regression equation is applied to 3403 data collected. The user score is obtained according to the linear function and normalized to get the comment user score. According to the results, 387 reviews scored more than 0.6, accounting for 11.37% of the total.

6. Summary

By analyzing the behavior characteristics of reviewers in e-commerce websites, constructs the detection model of network Navy according to various behavior patterns, and finally finds out their account hidden in the reviewers by calculating the score.This experiment also adds the function of recognizing picture comments on the basis of the previous ones. At the same time, there are obvious shortcomings in the experiment for lack of accurate data of Navy user reviews. Our experimental analysis is carried out by relying on individual partition, which has a tendency and needs to be improved urgently.

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