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Neural Network Based Target User Recognition Model for Network Community

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Abstract. For multi-dimensional feature of user data in network community, available methods mainly use Rank scoring algorithm or user classification algorithm for target user recognition. However, Rank method has a low performance, and the classification algorithm needs high construction cost. Therefore, this paper uses a target user recognition model integrating the user content analysis and the user behavior analysis to improve performance and speed of the target user recognition by a neural network content analysis model with a single-layer neural network and N-gram features for discovering automatically the user feature. The proposed method outperforms the current Rank scoring and classification methods in terms of performance, in which the F value reaches 0.89 and the accuracy reaches 0.91. Moreover, avoiding the cost of manual design dependent on specific tasks shortens the training time. Ten thousand data can be modeled in one minute.

1. Introduction

With the development of social networks, people who express their views and comment on public social platforms such as online communities and micro-blogs can make a great influence. It is a challenging task to recognize the target user accurately according to the user data, and it is also a focus of research in related fields in recent years.

The current research methods of target user recognition are mainly through traditional statistical models or machine learning algorithms, such as Rank algorithm, SVM, etc. With the target is becoming more and more complex and some important features are difficult to quantify, feature-select-based machine learning systems need to pay a high price to select appropriate features, and the effect is poor. Conversely, neural network model does not require manual selection of features, which greatly reduces labor costs and improves certain effectiveness. This paper proposes a target user recognition model based on content feature and behavior feature analysis around neural network algorithm.

The neural network method can recognize the target user in a short time without artificial labeled negative dictionary, sensitive dictionary, etc. In the paper, the user behavior is firstly correlated with the content features after neural network analysis, and a new user recognition model is proposed. Experiments show that this model can significantly improve the performance and speed of target user recognition.

2. Related Work

At present, the main research directions of target user recognition can be divided into three categories: based on content characteristics analysis, based on social model of behavior analysis, and based on user statistics analysis. Among them, the analysis of the content characteristics is mainly through the neural network language model.

2.1. Neural Network Language Model

Language models are built to enable computers to understand natural language. In 2003, Bengio et al. [1] summarized a set of Neural Network Language Model (NNLM), and put forward the concept of word embedding, a distribution representation of words in vector space for the first time. Subsequently, in 2008, Collobert and Weston [2] constructed SENNA system, using word embedding method to complete various tasks in natural language processing, such as part-of-speech tagging, NOUN recognition, etc. Mnih and Hinton [3] proposed a hierarchic training language model in 2008. And during the period from 2013 to 2016, Mikolov et al. [4] successfully reduced the neural network model to acceptable levels using the Log-Bilinear model, and convert directly words into word embedding through neural network model (CBOW and Skip-gram). CBOW is learning to predict the word by the context and the skip-gram is designed to predict the context. However, both of them cannot directly recognition tags by word embedding. This paper optimizes CBOW model adding N-gram features and modifies SoftMax to make it more suitable for the task of content analysis.

### 2.2. Target user Recognition

Target user recognition has been widely needed and concerned since the birth of public media platform. In 2004, Hull et al. [5] have studied the interaction between users in social networks, and achieved the target user recognition in social networks. At the same year, Gyongyi et al. [6] proposes the concept of TrustRank based on PageRank, which starts with known normal users and propagates fractions at offset rates to recognition. In 2010, Gao et al. [7] based on the distribution and outbreak of target users in social networks and using statistical analysis to recognition. In 2013, Xue et al. [8] used random walk to detect and recognize accounts on social networks with graph structure composed of user interactions. With the development of research, researchers begin to combine the multi-directional features to recognize the target user. In 2010, Benevenuto et al. [9] analyzed a large number of data sets in Twitter, set up a tag set to divide the target user, and set up two sets of content attributes and user behavior attributes to recognize the target user by classification algorithm. In this paper, a feature analysis model based on content attributes and user behavior attributes is proposed.

3. Neural Network Based Target User Recognition Model for Network Community

In order to enhance the performance of the target user recognition model, this paper proposes a Neural Network Based Target User Recognition Model for Network Community, which consist of Neural Network Based Content Analysis Model with N-gram and Target User Recognition Model.

3.1. Neural Network Based Content Analysis Model

The Neural Network Based Content Analysis Model is designed single-layer neural network to simplify structure and speed up. In this model, a low-dimensional real vector is used to represent words to avoid the disaster of data dimension.
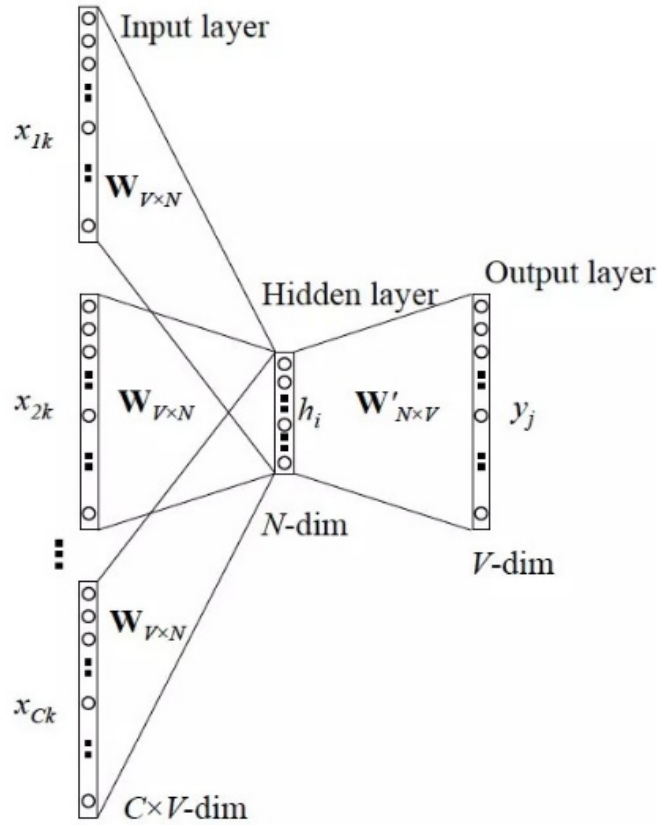
Figure 1. Neural network model architecture for single layer neural networks.

In Figure 1, each word is mapped to n-dimensional real vector space, i.e. $x \in R_n$, to form a word vector matrix $L \in R_{n \times V}$ based on the vocabulary V in the form of one-hot, which is the input to obtain word embedding. In input layer, dim of word vector space is V and the number of context words is C. All one-hots are multiplied by the shared input weight matrix W_{VxN} to initialize the weight matrix W. N is the preset number. Model add and average the one-hot vector as the hidden layer vector, length is 1N. The resulting vector multiplied by the output weight matrix W'_{VxN} to get the output layer results. The V-dim probability distribution is obtained by using the vector activation function. The word indicated by the maximum probability index is the predicted label and the true label to update matrix W and W' Therefore, it is necessary to define the cross entropy cost function as Formula (1) and gradient descent algorithm to update.

$$H(\hat{y}, y) = -\sum_{j=1}^{|V|} y_j \log(\hat{y}_j) \tag{1}$$

The final optimization function changed from Formula (1) is:

$$\min J = -\log P(w_c | w_{c-m}, \dots, w_c, \dots, w_{c+m})$$
$$\min J = -u_c^T \hat{v} + \log \sum_{j=1}^{|V|} \exp(u_j^T \hat{v}) \tag{2}$$

Formula (2) is used to update each related word vector u_c and v_j. After training, each vector of the input layer is multiplied by the matrix W to get the vector of label.

3.2. N-gram Feature

In order to enhance the feature analysis model of context relation, N-gram feature is added to the word vector representation. For N-gram, the string s id divided by length N. For example, "I like you" and "you like me" will be cut into "I like", "like you" and "you like", "like me". It can directly distinguish the front and rear relations. Segment the cut after n-gram as a word input.

3.3. Target User Recognition Model

Combining user content attributes and user behavior attributes can get higher performance has been proved. Therefore, Neural Network Based Content Analysis Model combined with behavior distribution analysis constitutes the target user recognition model to improve the recognition ability. The analysis of behavior attributes is accomplished by analyzing Gauss distribution. EM algorithm is used to obtain the approximate distribution $\theta^{(i+1)}$ of Gauss model. EM algorithm has two step. E-step, the expected value Z can be calculated by the current parameter $\theta^{(i)}$:

$$Q(\theta, \theta^{(i)}) = \mathbb{E}_Z[logP(Y, X|\theta)|Y, \theta^{(i)}] \tag{3}$$

In the formula (3), X is judgment result from content analysis and Y is the observed data, such as plate information and time data. M-step, finding θ maximizing Q (θ, $\theta^{(i)}$), and determining the estimated value of the parameter $\theta^{(i+1)}$:

$$\theta^{(i+1)} = arg\max_{\theta} Q(\theta, \theta^{(i)}) \tag{4}$$

(The analysis of user content computes the value of discriminant probability as C. The final model analysis combine the user content attributes and behavior attributes, using standardized Euclidean distance to calculate the similarity with the standard user.

$$\text{distance} = \sqrt{\left(\frac{\bar{c} - c}{s_c}\right)^2 + \left(\frac{\bar{\theta} - \theta^{yj}}{s_\theta}\right)^2} \tag{5}$$

In the formula (5), distance can be used as the measured value of discriminating the target user, and the final decision threshold of the target user can be determined according to the training set. The target user value above the threshold value μ is the result of the recognition model.

4. Validation and Results

In order to compare the performance of Neural Network Based Target User Recognition Model for Network Community with other models, an experimental scheme is designed to verify the performance of the target user recognition model. In this paper, according to the design of the experimental scheme, the model is displayed and compared with other models through the preset process of the experiment.

4.1. Experiment Scheme Design

Because the target user of the model is the user of the network community, in order to ensure the reliability of the experimental results, experiment not only use the ordinary content data, but also some common user data involved. Two data sets are selected to verify the validity of the Neural Network Based Target User Recognition Model for Network Community. (1) In the network community data set of colleges and universities, 5000 pieces of data which have been detected in the system have been extracted by semi-manual annotation as training set, another 5000 pieces of data as validation data set. (2) The domestic and foreign public network community data sets, also a total of 10,000 data, 5,000 data as a training set, and other 5,000 data as an experimental verification set.

In addition, for each data set, the experiment extracts user behavior data, including publishing content time, publishing content plate, reply object and other data. These user behavior data are used

to analyze user behavior in the target user recognition model. Because of the problem of user discrimination, the experiment uses the user who disseminates malicious information as the target user. For the training set, 2000 pieces of data are malicious, and another 3000 pieces of data are normal forum data.

Table 1. Positive and negative example of network community content data set of colleges and the domestic and foreign data Table.

Positive	Negative
Is the telnet link of the forum page hung up?	China entered the system of independence?
To you, my sunshine.	Tell the truth, how terrible it is to be a hero!
Recruitment Shenzhen -BAT company.	Treat the students with the same pig feeling
It should be OK today, but not a few days ago.	Is fbb really running away?
If you like EDM, Club Roma is the place to be.	Saya assaulting pregnant women.

Experiments include: parameter settings to determine the impact of adjustable parameters on the algorithm and to select a set of optimal parameters; some mainstream recognition models and Neural Network Based Target User Recognition Model for Network Community are trained with the above training sets, and the performance differences are compared with the test sets; compare the performance differences between content-and-behavior analysis models and direct user classification models.

4.2. Experiment Process
In order to determine the optimal parameters (including word embedding dimension and iteration times), the influence of each parameter on the performance of the algorithm is tested.
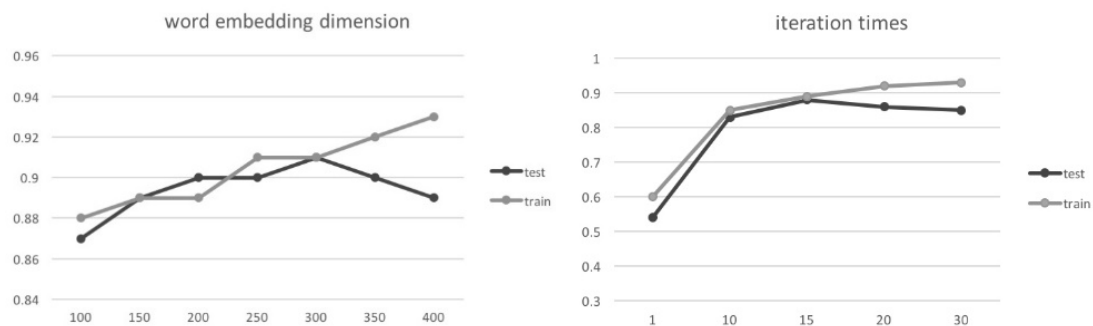

Figure 2. Influence of different word embedding dimension and iteration on F value.

In Figure 2, with the range of word vector dimension approaching 300, the fitting of training data is getting better and better, and the F value can reach 0.9. The following problem is the over-fitting, which leads to the decline of the ability to distinguish between words and their relations. From the influence of iteration times on the model, it can be seen that when the iteration times are 15, the training data and test data can achieve better results. F value can reach 0.88. Similarly, with the increase of penalty coefficient, the over-fitting happens (the accuracy of test data decreases).

Experiment prepare some mainstream user recognition models for experimental comparison, mainly RANK and SVM. In order to adapt to the network community, we optimize the model. RANK model uses the same training set to generate model seeds, attenuation and allocation use 0.2 as transfer coefficient. SVM model selects user content attributes (Chi) and user behavior attributes related content (plate, time and other data). The kernel function selects a general RBF with a C value of 1, which is trained by the same training set. And test them compare with the model proposed.

4.3. Experiment Results

The experimental results are shown in terms of accuracy, recall, and F values, and the results are shown in diagrams. The following figure shows the comparison of the results of Neural Network Based Target User Recognition Model for Network Community, Rank model and SVM classification model, mainly comparing the performance differences between the mainstream scheme and the experimental scheme.
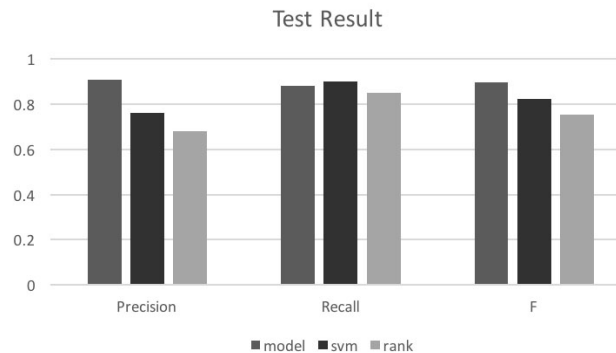
Figure 3. Compare the performance of different models on data sets.

The data in the Figure 3 shows that the accuracy of the target user recognition model is 15% higher than other models, reaching 0.91. In terms of recall rate, it is close to other systems, reaching 0.88. In terms of F value, the F value of the model is higher than 10% of other models, reaching 0.89.

In order to show the effect of the user content and behavior analysis recognition model, the experiment compares the results of the model with that of the direct user classification model.

Table 2. Comparison between Content-behavior-analysis Model and User-Classify Model Table.

Model	Accuracy	Recall	F-value	Speed of modelling
Content-behavior-analysis Model	0.91	0.88	0.89	<1min
User-Classify Model	0.81	0.84	0.82	>15min

Through the Table 2, it shows that the model has been significantly improved after using this model to do the neural-network analysis of user content attributes. The accuracy rate increased from 0.81 to 0.91, the recovery rate increased from 0.84 to 0.88, and the F value increased from 0.82 to 0.89. Compared with the direct user classification pattern, the model uses neural network can find more hidden content and behavior features, while using N-gram features makes the user content attributes increase the context of the relationship, which is very common for the context of the target user association. The performance of the model has been improved. Because the model can be classified by a single-layer neural network without any artificial design patterns, the training time required is greatly reduced, and the time of modelling for the 10,000 pieces of data are reduced from 10 minutes to 1 minute. It has been applied to applications.

5. Concluding Remark

In this paper, we propose Neural Network Based Target User Recognition Model for Network Community. Without the use of non-source data information, the model improves the accuracy of target user recognition in network community. The performance of the model exceeds some mainstream user recognition algorithms (RANK, SVM) and the efficiency of model surpasses direct user classification model. There are still many problems need to be further explored in the study of user content and behavior analysis. From the above experimental results, it can be seen that the neural network model is easy to over-fit the training model, and the adaptability of the special target needs to

be studied. The next step is to study how to reduce the structural risk of the model, so as to find a more suitable user recognition scheme for the network community.

6. Acknowledgements

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