User Behavior Prediction Based on DCGAN: The Case of Sina Weibo

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Abstract

E-commerce marketing forces are taking advantage of microblogs to deliver their advertisements to promote product information. The success of product information diffusion in microblog depends greatly on user behaviors -- browsing, commenting and reposting. In this paper, we divide user behaviors of Sina Weibo into four types corresponding to four different colors, and propose a method to predict user behavior based on DCGAN (Deep Convolutional Generative Adversarial Nets). By analyzing a real Sina Weibo dataset, the experimental results show that the prediction accuracy of the four types of user behaviors reaches more than 80%, which proves that our method is feasible and effective, and also can help companies succeed in their product advertisements.

Keywords: User behavior, DCGAN, E-commerce, Product advertisements

1 Introduction

In the past ten years, social media applications represented by Microblog, WeChat, Facebook, and Twitter have been widely used, making online social networks the main place for delivering advertisements to appropriate customers in the e-commerce [1-5]. More and more Companies tend to use microblogs to promote product information to help them succeed in their marketing activities [6-8]. However, a product information which rangs from an initial state that only a few people know to a large-scale propagation state that almost everyone knows, is inseparable from user participation behaviors, such as reposting and commenting. Thus, Predicting and analyzing user behaviors that influence the spread of advertising information are essential for companies to comprehend in the e-commerce [9-11]. At the same time, AI (Artificial Intelligence) technology has developed rapidly [12-14], among which GAN (Generative Adversarial Nets) [15] has attracted much attention for the achievements in image processing, sample image generation and other application fields.

Therefore, we design and propose a model to forecasting user behaviors of Sina Weibo based on DCGAN (Deep Convolutional Generative Adversarial Nets) [16]. Assuming that there are N^2 different users participating in the propagation of a topic microblog information, then these N^2 users will be mapped to a 2D (two-dimensional) image with N^2 areas. And, in the diffusion of a topic information, different users may have different behaviors. So, we divide user behaviors into different types, such as reposting, commenting, etc. One user behavior type corresponds to one color. In this way, the user behaviors in the diffusion of a topic information can be represented by a 2D color image. In addition, DCGAN is used for training the user behavior images of already-existing topics' information to predict a new user behavior image of emerging topics information, then the new image is converted into user behavior types, to achieve the purpose of predicting whether this user behavior is reposting or commenting, etc.

The organization of this paper is as follows: Section2 discusses some existing works related to our own. Section3 elaborates on our proposed approach, describes the architecture and preliminaries. Section4 conducts and analyses the experiments. Section5 concludes our work.

2 Related Works

This section contains a literature review on user behaviors analysis and prediction.

2.1 User Behavior Analysis

Over the past decade, many institutions and researchers have developed user behaviors analysis. In the applied field, for instance, Liu designed an system called UBER to enhance malware analysis sandboxes with emulated user behavior [17]. Liao examined the user behaviors of various of Facebook Live to develop social commerce and business models in Thailand [18]. Liu analyzed an improved model of user posting behavior co-driven by users' interests and interactions [19]. Tian attempted to address the waste of resources in cloud data integrity checking by utilizing user behavior prediction [20]. MEZAIR presented an Advanced Deep Learning framework for IoB (Internet of Behaviors) applied to connected vehicles and used CNN (Convolutional Neural Network), GCNN (Graph CNN), and LSTM (Long Short-Term Memory) [21], etc.

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2.2 User Behavior Prediction

In addition, user behavior prediction is also a focus of research. For example, Tseng proposed a SMAP (Sequential Mobile Access Pattern) data mining method to efficiently discover mobile users' sequential movement patterns associated with requested services [22]. Tian considered heterogeneous information and established a new user behavior prediction model, called HRSN (Heterogeneous Residual Self-Attention Shrinkage Network) [23]. Argade improved MCP (Mobile Commerce Predictor) prediction framework by introducing confidence parameter, for enhancing accuracy of user behavior prediction in M-commerce [24]. Dai proposed an improved SVM (Support Vector Machine) prediction method, for improving accuracy of user reposting behavior prediction [25]. Zhang presented an improved optimal weighted fusion method based on effectiveness factors that achieved accurate prediction of user service behaviors [26]. Belhadi explored convolution deep neural networks to collect abnormal human behaviors [27]. Gan presented a method to extract non-redundant correlated purchase behaviors considering the utility and correlation factors [28], etc.

At present, with the development of AI technology, many AI technologies including DCGAN are used for prediction or detection. For instance, Du proposed the HACNN (Hierarchical Attention Cooperative Neural Networks) model based on users' purchasing and reviewing behaviors [29]; Jiang proposed an end-to-end deep learning model to predict whether a user will check-in the searched place or not [30]. This kind of method mainly depends on DCGAN that has been built, such as, Peng proposed a model to predict reservoir dynamic pressure profile of fracture network based on DCGAN [31]. Viola proposed a methodology called FaultFace for failure detection on Ball-Bearing joints using DCGAN [32]. Cheng proposed data-driven modelling of nonlinear spatio-temporal fluid flows using DCGAN for the prediction of nonlinear fluid flows [33]. Liang proposed a MTS-DCGAN (multi-time scale deep convolutional generative adversarial network) framework to deal with anomaly detection of industrial time series [34], etc.

2.3 Discussion

From this literature review, it appears that these user behavior prediction technologies are widely used. In the business field, we can improve users' interest in purchasing goods and promote commodity sales through the prediction of user behaviors. In social networks, it is feasible to forecast the propagation of online public opinion based on user behavior prediction, such as forwarding behavior and commenting behavior. In the field of information security, anomaly warnings are issued in advance by predicting user behaviors, and so on. At present, the wide application of DCGAN and other AI technologies provide us with new research ideas in the field of user behavior prediction. On this basis, in order to better analyze user behaviors, a model is proposed based on DCGAN.

3 Model Description and Preliminaries

According to reference [16], The DCGAN is a variation of the GAN network, where the generator and discriminator multilayer perceptron neural networks are replaced by a convolutional neural network to exploit its image processing capabilities. Among them, the generator and the discriminator are two independent neural networks, which are involved in a competition. The generator (G) network creates a new probability distribution $P_G(x)$ based on a prior defined probability distribution $P(x)$, which can be considered as a black box. On the other hand, the discriminator (D) network determines the difference between the $P_G(x)$ and $P(x)$. Once the discriminator cannot distinguish between $P_G(x)$ and $P(x)$, it means that the generator learns the black-box behavior of $P(x)$. The CNN (Convolutional Neural Networks) networks employed on the DCGAN architecture, meanwhile, should have some specific features to ensure a stable training process of the generator and discriminator.

3.1 Architecture

The DCGAN has been given evidence to be more stable set of architectures for training generative adversarial networks and to be more generative modeling adversarial networks for learning good representations of images. Based on the DCGAN, the architecture of our model is shown in Figure 1.

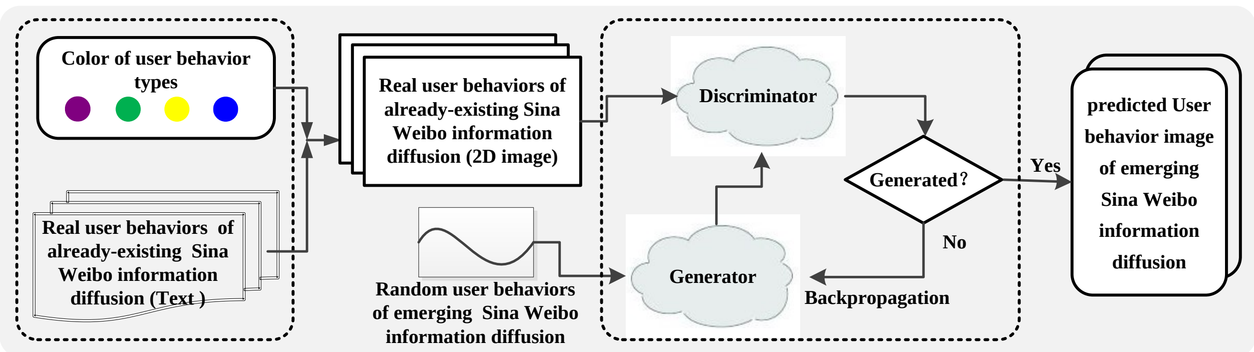


Figure 1. The architecture of the proposed model

First, user behavior types are set to be different colors. such as, reposting behavior is blue, commenting behavior is green, etc. Then, N^2 users is mapped to a 2D color image with N^2 areas, where one user corresponds to one area. These areas are filled with colors corresponding to the user behavior types. In this case, the images filled according to the real user behavior types of already-existing microblog information diffusion are used as the input of DCGAN discriminator. After that, random user behaviors of emerging microblog information diffusion are used as the input of the DCGAN generator. Finally, a new 2D color image of emerging microblog information diffusion is generated by DCGAN. The purpose of forecasting user behavior types is achieved through analyzing the new image.

3.2 User Behavior

According to the users' ID of Sina Weibo, we select *U* different users, and number them from 1 to *U*. Then, a 2D image is divided into *N***N* small areas, which corresponds the *u* user ($u \in [1\text{-}U]$) to a area [*i*, *j*] in the 2D image, where

$$\begin{aligned} i &= \mathrm{mod}(u / N) \\ j &= rem(u / N) \end{aligned} . \quad \textbf{(1)}$$

In addition, the user behaviors of microblog diffusion are divided into four types: commenting with reposting, commenting, reposting, browsing (i.e. no reposting and no commenting), and the four types of user behaviors are represented by four different colors. After the *u* user's area is filled with the corresponding color, one real user behavior 2D image of one already-existing microblog information diffusion is obtained. Repeat the steps above, until user behavior image datasets of already-existing topic microblog information diffusion are generated. Finally, each area in the predicted user behavior image by DCGAN is converted into user behavior type, according to the one-to-one match between each user behavior type and each color. And, the corresponding inverse operation of converting [*i*, *j*] to *u* is implemented, according to the following formula.

$$u = i * N + j \,. \quad \textbf{(2)}$$

3.3 Generator

In this paper, our generator consists of five-layer neural networks, and the pooling layer of traditional GAN is replaced by the deconvolutions. Furthermore, *BN* (Batch Normalization) [35] is used to make the generator learn stably. The structure of generator is shown in Figure 2.

In order to predict the user behavior of emerging microblog information diffusion, firstly, we randomly generate a uniformly distributed user behavior image as input of the generator. After a series of execution by the generator, a 64*64*3 RGB image is formed and used as the input of the discriminator. In the first layer of generator, *Dense*, *BN* and *LeakyRelu* are used to speed up the convergence process for converting the inputted image into a tensor of 8*8*256. Then, after the second, the third, the fourth and the fifth layer processing, the input image is gradually enlarged to 64*64*3 tensor, using *Deconvolution*, *BN* and *LeakyRelu*, etc.

3.4 Discriminator

The discriminator is an important part of our model. In this paper, the discriminator consists of six-layer neural networks. Among them, the convolution replaces the pooling layer of GAN. The structure of discriminator is shown in Figure 3.

In the first layer of the discriminator, the *Convolution*, *LeakyRelu* and *Dropout* are used to transform the 64*64*3 tensor from the generator into a 32*32*32 tensor. This 32*32*32 tensor is transformed into a tensor with 1024 length after the execution of the second, the third, the fourth and the fifth layer. In the sixth layer, Flatten is used to convert the tensor's length into 1.

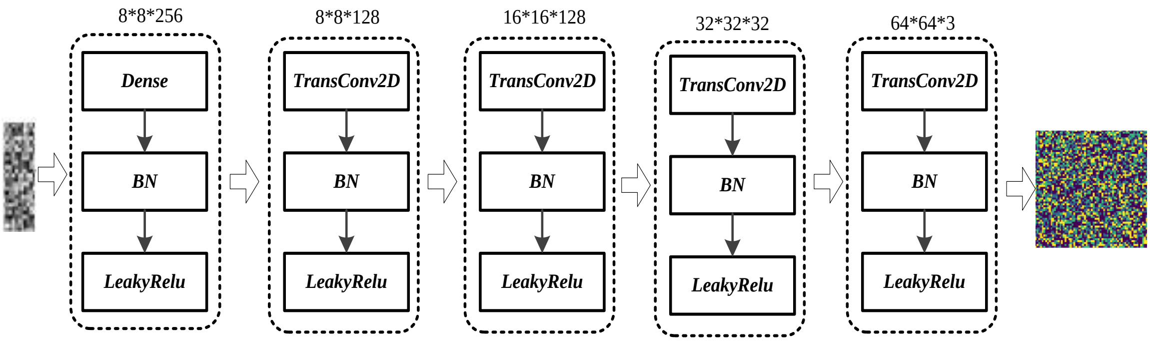


Figure 2. The structure of the generator

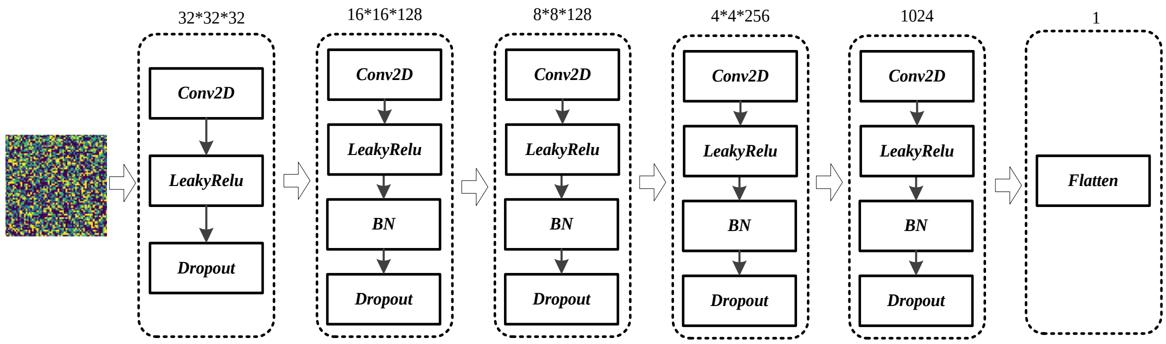


Figure 3. The structure of the discriminator

3.5 Algorithm or Function

The algorithms or functions are mainly composed of *LeakyRule*, *Loss*, *BN* (*Batch Normalization*), *Dropout*, *Adam*, etc.

3.5.1 Batch Normalization

In each layer of the generator and the discriminator, we use *BN* to adjust the values of training parameter timely during the model training process, along with maximizing the speed of model training and improving the generalization ability of neural network. The calculation formula is as follows:

$$\mu_B = \frac{1}{m}\sum_{i=1}^{m} x_i$$
$$\sigma_B^2 = \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_B)^2$$
$$\hat{x}_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 - \varepsilon}}$$
$$y_i = \gamma \hat{x}_i + \beta \equiv BN_{\gamma,\beta(x_i)} \quad (3)$$

Details are showed in reference [35].

3.5.2 Dropout

According to Hinton's theory [36-37], *Dropout* is used in each layer of the discriminator to prevent over-fitting due to small training dataset. The calculation formula is given by:

$$r_j^{(l)} \sim Bernoulli(p)$$
$$\tilde{y}^{(l)} = r^{(l)} * y^{(l)}$$
$$z_i^{(l+1)} = w_i^{(l+1)}\tilde{y}^{l} + b_i^{(l+1)}$$
$$y_i^{(l+1)} = f(z_i^{(l+1)}) \quad (4)$$

For detailed explanation of the formulas, see reference [36] and [37].

3.5.3 LeakyRule

In order to reduce errors of generator and speed up the convergence process, *LeakyRule* is used as the activation function. The calculation formula is defined by:

$$a = \begin{cases} 0, z = 0 \\ leak * z, z < 0 \\ z, z > 0 \end{cases} \quad (5)$$

3.5.4 Loss Function

During the execution of the generator/discriminator, errors may occur and cause the failures. Therefore, it is necessary to correct parameters by calculating the *loss* value. We use cross-entropy to calculate the errors of generator/discriminator as follows:

$$E = -\sum_k t_k \log y_k \quad (6)$$

Among them, t_k represents the true probability distribution about the correct label, and y_k represents the distribution of the output of the neural network, that is, the prediction probability distribution.

3.5.5 Optimization

Our model is optimized by error gradient calculation and Adam. Firstly, the error gradient is calculated by the gradient descent function. Then Adam optimization is used to find the minimum gradient quickly.

4 Experiment and Results

In this part, we introduce the experimental setting and dataset, and then report empirical results.

4.1 Experimental Settings

Our proposed model is realized by Tensorflow framework and the execution algorithm is shown in Table 1.

Specifically, we set *epochs* =1000, *batch_Size*=128, *Adam_step*=0.0001, and the following methods are adopted for better data processing:

(1) The *Data* in tensorflow is used to read in image dataset;
(2) The *decode_png* and *RGB* channels are used to parse image dataset and save the neural network pixels;
(3) The *shuffle* is used to shuffle and prevent the hidden similarity in the dataset;
(4) The *prefetch* is used to speed up the calculation;
(5) The *model.save()* is used to save data generated by the generator/discriminator;
(6) The *model.load()* is used to load data;
(7) The *model.summary()* is used to output parameters.

In our model, the parameters of the generator and the discriminator are shown in Table 2 and Table 3 respectively. The first column "Layer(type)" represents the components of the generator/discriminator, the second column "Output Shape" represents the shape of outgoing image, and the third column "Param#" represents the number of parameters that need to be trained for each layer in the generator/discriminator. According to statistics, the generator has 2,781,432 parameters, including 2,729,216 training parameters. The discriminator has 1,348,161 parameters, including 1,345,217 training parameters.

4.2 Dataset

We evaluate the effectiveness of our proposed model on Sina Weibo. We select 4096 users, and crawl the behavior data (i.e., reposting, commenting.) of these users in the specified microblog information diffusion. The user name with reposting and commenting behaviors are stored separately in ZF_List.txt and PL_List.txt. In this experiment, the user behavior of 2,000 already-existing topics information in Sina Weibo are crawled, and the examples of user names with reposting/commenting behaviors in information diffusion are shown in Table 4.

The user behaviors are divided into four types: commenting with reposting, commenting, reposting and browsing. The user name exists in both ZF_List.txt and PL_List.txt, indicating that this user's behavior is commenting with reposting, such as '战争史研究WHS' in Table 4. The user name only exists in PL_List.txt, but does not appear in ZF_List.txt, meaning that this user's behavior is commenting. On the contrary, it is reposting. If the user name does not exist in ZF_List.txt and PL_List.txt, it is browsing.

Table 1. The execution algorithm in this paper

Input:
e: epochs
real_images: the real user behavior image of already-existing microblog information diffusion
rand_image: the user behavior image by randomly generated
Output:
Predicted_image: the user behavior image of emerging microblog information diffusion

```
m=0, n=0;
gen_loss=[], dis_loss=[];
for i=1:e do
  if gen_loss==0.5 then m⇐m+1
  if dis_loss==0.5 then n⇐n+1
  generator ⇐ rand_image;
  if (m>=20) and (n>=20)
  then
      break
  else
      execute generator;
          // Dense, BatchNormalization, Conv2Dtranspose, Dropout, ete.
      generate the predicted user behavior image;
      calculate gen_loss;
      discriminator ⇐ the predicted user behavior image;
      discriminator ⇐ real_images;
      execute discriminator;
          //Conv2D, LeakyReLU, Dropout, BatchNormalization, Flatten, ete.
      calculate dis_loss;
  end
  Predicted_image ⇐ the predicted user behavior image;
End
Output ⇐ Predicted_image
```

Table 2. Parameters in the generator

Layer (type)	Output shape	Param #
dense (*Dense*)	(*None*, *16384*)	1638400
batch_normalization (*BatchNo*)	(*None*, *16384*)	65536
leaky_re_lu (*LeakyReLU*)	(*None*, *16384*)	0
reshape (*Reshape*)	(*None*, *8*, *8*, *256*)	0
conv2d_transpose (*Conv2DTrain*)	(*None*, *None*, *None*, *128*)	819200
batch_normalization_1 (*Batch*)	(*None*, *None*, *None*, *128*)	512
leaky_re_lu_1 (*LeakyReLU*)	(*None*, *None*, *None*, *128*)	0
conv2d_transpose_1 (*Conv2DTrain*)	(*None*, *None*, *None*, *64*)	204800
batch_normalization_2 (*Batch*)	(*None*, *None*, *None*, *64*)	256
leaky_re_lu_2 (*LeakyReLU*)	(*None*, *None*, *None*, *64*)	0
conv2d_transpose_2 (*Conv2DTrain*)	(*None*, *None*, *None*, *32*)	51200
batch_normalization_3 (*Batch*)	(*None*, *None*, *None*, *32*)	128
leaky_re_lu_3 (*LeakyReLU*)	(*None*, *None*, *None*, *32*)	0
conv2d_transpose_3 (*Conv2DTrain*)	(*None*, *None*, *None*, *3*)	2400

Table 3. Parameters in the discriminator

Layer (type)	Output shape	Param #
conv2d (*Conv2D*)	(*None*, *32*, *32*, *32*)	2432
leaky_re_lu_4 (*LeakyReLU*)	(*None*, *32*, *32*, *32*)	0
dropout (*Dropout*)	(*None*, *32*, *32*, *32*)	0
conv2d_1 (*Conv2D*)	(*None*, *16*, *16*, *64*)	51264
batch_normalization_4 (*Batch*)	(*None*, *16*, *16*, *64*)	256
leaky_re_lu_5 (*LeakyReLU*)	(*None*, *16*, *16*, *64*)	0
dropout_1 (*Dropout*)	(*None*, *16*, *16*, *64*)	0
conv2d_2 (*Conv2D*)	(*None*, *8*, *8*, *128*)	204928
batch_normalization_5 (*Batch*)	(*None*, *8*, *8*, *128*)	512
leaky_re_lu_6 (*LeakyReLU*)	(*None*, *8*, *8*, *128*)	0
dropout_2 (*Dropout*)	(*None*, *8*, *8*, *128*)	0
conv2d_3 (*Conv2D*)	(*None*, *4*, *4*, *256*)	819456
batch_normalization_6 (*Batch*)	(*None*, *4*, *4*, *256*)	1024
leaky_re_lu_7 (*LeakyReLU*)	(*None*, *4*, *4*, *256*)	0
global_average_pooling2d (*Gl*)	(*None*, *256*)	0
dense_1 (*Dense*)	(*None*, *1024*)	263168
batch_normalization_7 (*Batch*)	(*None*, *1024*)	4096
leaky_re_lu_8 (*LeakyReLU*)	(*None*, *1024*)	0
flatten (*Flatten*)	(*None*, *1024*)	0
dense_2 (*Dense*)	(*None*, *1*)	1025

Table 4. The user names for reposting/commenting

User names of reposting	User names of commenting
‘战争史研究WHS’	‘豆豆今天也在努力’
‘迷惑行为大赏’	‘猫猫annscat’
‘维稳先锋卡菊轮’	‘冰蛇陛下’
‘临冬女爵珊莎史塔克’	‘简木生--撰稿者’
‘KISAMA’	‘唤阿离’
‘茶月洵’	‘战争史研究WHS’
‘猫与四叶草’	‘纸板箱上的喵’
‘水翼的窝’	‘樱红Cheung’
‘小金金Love’	‘时常错过风景不自知’
‘纸板箱上的喵’	‘今年也要加油鸭荞荞’
‘军需官二姨太’	‘叫我小太阳嘿哟’
‘卖鱼倩二号摊’	‘我就是小短耶’
‘失眠6559’	‘SH-Sissi1012四代’
…………….	…………….

Table 5. The corresponding relationship between colors and types

ID	Colors	User behaviors
0	Purple	Browsing
1	Blue	Reposting
2	Green	Commenting
3	Yellow	Commenting with reposting

Moreover, we set four types of user behaviors corresponding to four different colors. The corresponding relationship between user behavior types and colors is shown in Table 5.

So, the user behavior in one topic microblog information diffusion can be represented by one 2D color image. The Figure 4 shows a 2D colored image according to different types of user behaviors in a topic microblog information diffusion.

The image dataset of user behaviors is formed based on many already-existing topics of Sina Weibo information diffusion.

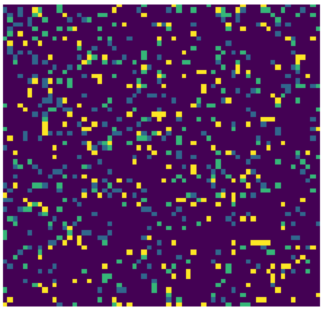


Figure 4. The 2D color image of user behavior

4.3 Results

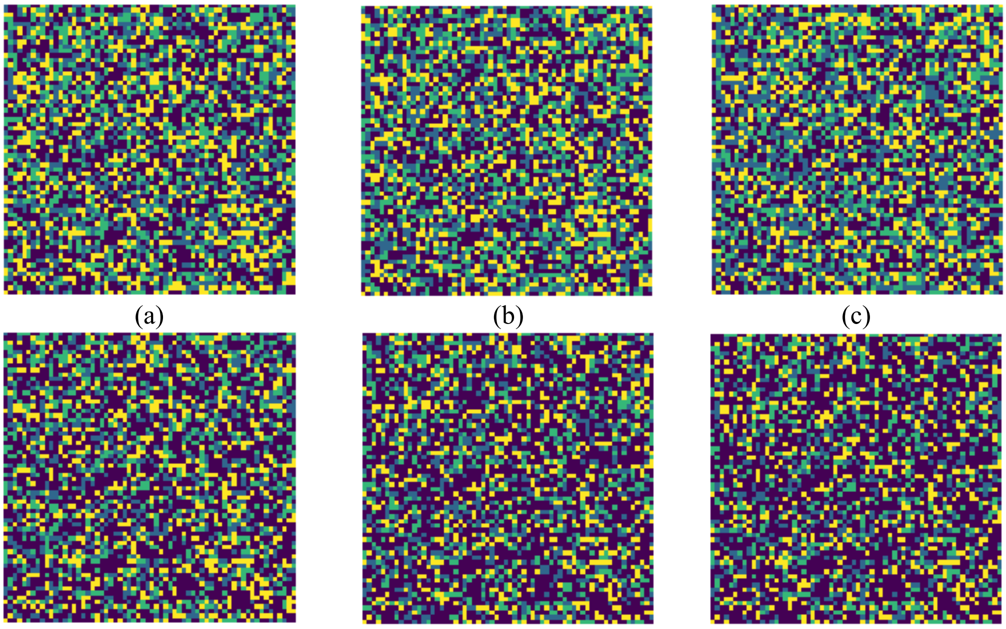
We randomly select 30 topics user behavior images of crawled 2000 topics microblog information diffusion as test dataset, and the rest as training data. The experiment is carried out according to the steps described in 3.1 and 4.1 section. Some images generated during training, as shown in Figure 5.

The 16 subgraphs in Figure 5 are arranged according to generation sequence. It is clear that most areas are yellow in Figure 5(a), but in Figure 5(l) the purple areas are the majority. This means that at the beginning of our model, the outgoing image is that the number of commenting with reposting behaviors is large, which is not consistent with the facts. But with the constant adjustment of our model parameters, the number of yellow areas is becoming less and less, and the number of purple areas is gradually increasing, which represents that the most user behaviors in microblog information diffusion is browsing. That is in line with the real situation.

Finally, the number of the four types of user behaviors in outgoing image is calculated, and compared with the test data. We mainly use *Accuracy* as the measurement parameter, the calculation formula is shown below:

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN}, \quad \textbf{(6)}$$

where *TP* is true positive, *FP* is false positive, *TN* is true negative, *FN* is false negative. That is, the *Accuracy* is the proportion of true results (both true positives and true negatives) in the population. The average *Accuracy* of the four types of user behaviors after 100 repeated experiment is listed in Table 6.



(a) (b) (c)

(d) (e) (f)

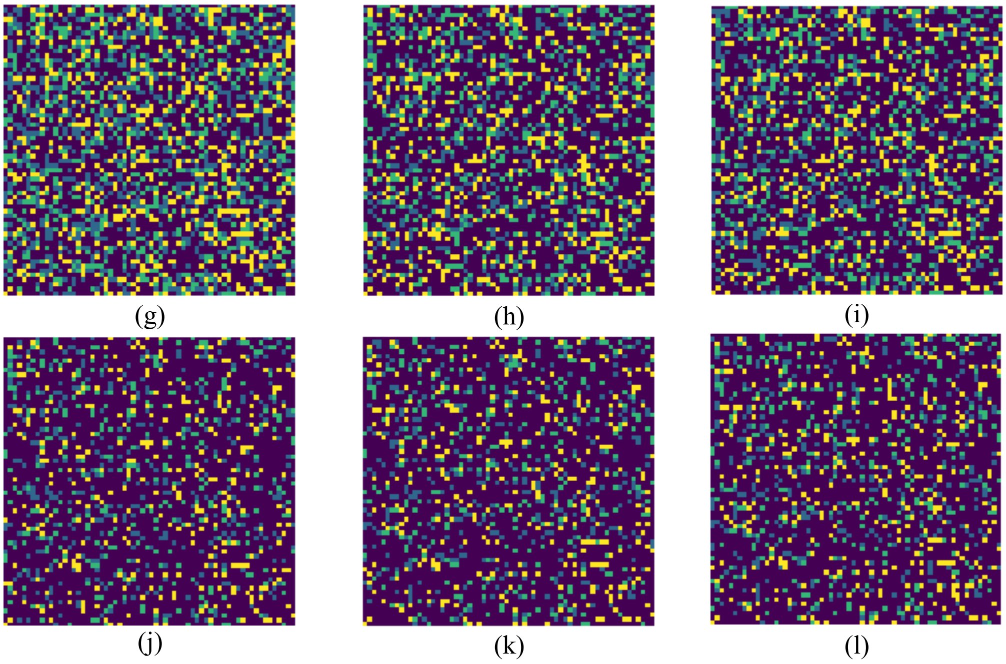


Figure 5. The images during the training process

Table 6. The average accuracy of the four types of user behaviors

User behavior	Browsing	Reposting	Commenting	Commenting with reposting
Accuracy	0.91	0.81	0.87	0.83

As can be seen from Table 6, the *Accuracy* of the four types of user behaviors all exceed 80%, and the browsing even reaches more than 90%, which proves the feasibility and effectiveness of the proposed method.

5 Conclusion

Forecasting user behavior is an important aspect of monitoring the development and change of information diffusion in social media, which is beneficial for enterprises in e-commerce to monitor and predict the advertising information diffusion. This paper proposes a new model for user behavior prediction, with DCGAN as a basic architecture. The experiment results demonstrate the efficiency of the model in Sina Weibo Dataset. This work suggests interesting directions for future research. In the future, we also are going to explore other social media datasets and artificial intelligence technologies in the research of user behavior prediction.

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