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Research Article

New Media Public Relations Regulation Strategy Model Based on Generative Confrontation Network

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The rapid development of new media weakens the control of traditional news media on information. At the same time, under the impact of the rapid development of new media, it has brought new challenges to the regulation of public relations. In the new media environment, this paper constructs a text emotion generation model based on GAN to support the application of new media public relations regulation strategy. Aiming at the problem of insufficient constraint information of keywords in text generation, this paper uses the confrontation generation model based on reinforcement learning to supplement sentence components around keywords, so as to generate the text with the highest quality. At the same time, in order to extend GAN from continuous space to discrete space, the differentiable function based on Softmax transformation is adopted to approach the original nondifferentiable function. In this paper, LTP word segmentation system is used to select 356742 pieces of data with a length less than 20 for the experiment. Compared with Seqtoseq+attenion and Transform models, this model has higher similarity of real text distribution and higher text diversity. The retention degree of the main content of the input text is as high as 96.17%, which is higher than that of Seqtoseq+attenion model of 8.49% and Transform model of 6.11%. It provides effective support for the regulation of new media public relations.

1. Introduction

With the birth of digital technology, a new generation of emerging media with digital technology as its core has become the darling of the times [1]. In terms of speed and quality of communication, the media information has undergone earth-shaking changes. In the traditional media environment, the main body of news dissemination activities is professional news organizations [2]. The relatively unitary and highly organized subject of news communication leads to the relatively single information source in communication activities. The direction of news information communication often flows from "professional media organizations" to the audience, and the audience has little selectivity for information [3]. New media has completely got rid of the single limitation of traditional media, and it provides a very convenient communication space for people to transmit information [4]. New media communication breaks through the limitation of traditional media communication information and can timely and effectively transmit all the information that people need at the first time. The emergence of new media communication has brought us into a new communication era of "information explosion."

At the same time, public opinion and public opinion supervision under the new media environment show new features, which not only bring convenience to public opinion expression but also bring difficulties and problems to public opinion regulation and guidance [5]. Therefore, it is necessary to formulate and implement the public relations regulation strategy to adapt to the new media environment [6]. Generally speaking, the public's thoughts are hard to control, but the government and the media are always confident to guide the public to think. By setting the agenda, the government can set up hot topics of public opinion through the media and focus the public on some events that are beneficial to government management, so as to maintain benign public opinion and stable social development [7]. Under the new media environment, new media should be used to build a bridge between the disseminators and disseminators of public relations activities, so as to realize the mass dissemination and effective communication of information and establish a good image [8]. Only by recognizing the essence of new media public relations can information be widely disseminated, effective communication of information, and effective regulation of public relations be realized.

With the development of artificial intelligence and information technology, this paper builds a text emotion generation model based on GAN (generative adversarial networks) to support the application of new media public relations regulation strategy. In the field of natural language processing, text generation is an important research direction. How to automatically generate smooth and fluent text that meets the user's preferences has always been the research focus in this field, and at the same time, it has high application value [9]. At present, the manually labeled data can hardly meet the needs of deep learning. How to capture the high-order correlation of observed data or generate training samples by using the method of model generation without the information of target class labels has triggered the academic research on the unsupervised learning-based deep generation model [10]. At present, using the existing deep learning sequence model in the field of natural linguistics, usually using the method of maximum likelihood estimation, can easily lead to exposure deviation, semantic incoherence, and grammatical incoherence [11]. Compared with the deep learning sequence model, GAN has the advantages of simple construction, less computation, and high training efficiency and can obtain good generated samples through fewer iterations. Therefore, this paper proposes a text emotion generation model based on GAN. The innovations of this paper are as follows:

(1) On the basis of summarizing the communication and regulation of new media public relations, this paper studies the regulation strategy of new media public relations in detail by using the methods of literature research and content analysis so as to put forward a set of more practical control ideas and strategies

(2) Under the guiding ideology of exploring the regulation strategy of new media public relations, this paper proposes a text emotion generation model based on GAN. In order to solve the problem of insufficient keyword constraint information, a confrontation generation model based on reinforcement learning is used to supplement sentence components around keywords to generate the highest quality text. In addition, the keyword feedback mechanism is added to the confrontation learning block to strengthen the learning of keywords in the model and generate the text containing the specified keywords. Experiments show the rationality of this model in the field of text emotion generation and provide a reference for the next further work

This paper can be divided into five parts:

The first chapter is the introduction, which briefly introduces the research background of this paper and expounds the research objectives and significance of this paper. The second chapter is related work, which discusses the related literature at home and abroad, and puts forward the research work and methods of this paper. The third chapter is divided into three parts. Section 3.1 gives an overview of public relations communication under the background of new media. Section 3.2 discusses the regulation and control of new media public relations based on GAN. A text emotion generation model is proposed, and the detailed design and implementation process are given. In chapter four, the model proposed in this paper is analyzed experimentally. The fifth chapter is summary and prospect, which mainly summarizes the model proposed in this paper and looks forward to the next step.

2. Related Work

With the progress of science and technology and the rapid development of various emerging communication technologies, new media has attracted more and more attention. It drives the market of communication industry, causes the readjustment of the industrial structure of communication industry, and becomes a hot topic of discussion. The rapid development of new media is changing people's lives. It brings mass information and convenient access to information to the public; it also poses new challenges to the regulation of public relations. In the field of new media public relations, many scholars have done relevant research.

Gardner and Lehnert analyzed the background of the public relations communication strategy in the new media environment, discussed the specific performance and problems of the public relations communication strategy in the new media environment, and finally proposed the realization method of the communication strategy [12]. Barnett believes that with the continuous improvement of the power of new media communication, it will inevitably affect the original media environment. Communication subjects will also increasingly believe in the communication power of new media, enabling it to be widely promoted and applied [13]. Reddy pointed out that in terms of speed and breadth, the spread of new media has broken all communication restrictions, has wide coverage, and has strong timeliness [14]. Stein pointed out that organizations adopt different types of public relations models due to different institutions and environments. The two-way peer-to-peer model is the preferred public relations model for most organizations, and the two-way peer-to-peer model has a positive correlation with the organization's understanding of public relations [15]. Liu and He studied the challenges posed by new social media to government regulation of media from both theoretical and practical levels and introduced a theoretical model of government regulation of new media [16]. Amorim et al. introduced public relations as a soft means into the regulation model by analyzing the "media access right" theory and the "media-source" relationship [17]. Matt et al. put forward a public relations strategy model for government regulation of new media. It mainly includes four types of public relations activities, four modes of public relations, and eight main means of public relations communication [18]. Ha et al. analyzed in detail four changes in the elements of science communication in the new media era [19]. Neijens summarized the social status and communication status of science communication in the new media era and summarized the communication methods and changes in the communication pattern in the new media era. In order to promote the sound development of science communication [20], Dong proposed countermeasures and solutions from four aspects: government, media, disseminator, and audience [21]. Ashwell pointed out that in the new media environment, the traditional public opinion-oriented model is facing new opportunities and challenges. First, the public opinion-oriented power base of the traditional mainstream media has been weakened. Second, the traditional top-down control-oriented public opinion-oriented model gradually fails in the new media environment. Third, the difficulty of supervising and guiding new media public opinion is increasing [22].

Based on the predecessors' research on new media public relations, this paper explores some new strategies for regulating new media public relations. And put forward a text emotion generation model based on GAN to support the application of new media public relations regulation strategy. In this paper, the self-encoder is used as the generation model, and on the basis of the above work, the distance between distributions provided by the discriminator based on the optimal transmission idea is used as the extra loss term of the generator. Emotion classifier is used to implicitly separate text content and text style, so that not only the text with the target emotion style can be obtained but also the content of the original text can be retained to the greatest extent. Aiming at the problem of insufficient keyword constraint information, a confrontation generation model based on reinforcement learning is used to generate high-quality text. In the confrontation learning, the keyword feedback mechanism is used to supplement sentence components around keywords, so as to strengthen the learning of keywords in the model and generate the text containing the specified keywords. Finally, the effectiveness and feasibility of this method are verified by experiments.

3. Methodology

3.1. Public Relations Communication under the Background of New Media. New media technology has brought rapid changes to human life, and the new media era has brought new communication modes, as well as more and more personalized communication and diversified integration and created a new communication pattern. In the communication activities under the new media environment, the communication subjects are more diversified than traditional media. The main body of new media communication activities can be websites run by traditional media, commercial portals, online game companies, and even ordinary new media users. At the same time, new media news can spread words, pictures, videos, audio, and other content at the same time, which other media cannot have [23]. The carrier of new media, such as the Internet, has also realized the democracy and equality of communication, which can make all information transparent. According to different groups and different media characteristics, the production content and dissemination mode of information will be different according to local conditions, and the initiative of editing and choosing information will be strengthened. At the same time, the information will be delivered to the audience in combination with different media, which is convenient, fast, and clear-cut and reduces redundant information. The formation of the new media environment is having a wide impact on the connotation of public relations, which is mainly reflected in the changes in the communication elements of public relations, for example, (1) the boundaries of the subjects and objects of public relations communication are blurred; (2) diversified modes of communication, paying more and more attention to interactivity; (3) the information spread is richer and richer, and the content involved is more and more extensive; and (4) personalized communication mode, rapid communication, and influence on globalization.

New media is more interactive and can get timely feedback. Compared with the traditional media such as newspapers, radio, and television in the past, the new media makes the spread of public opinion pervasive [24]. With the increasing scale of users of new media such as Internet and mobile phones, new media has become an important position of public opinion propaganda. The process of new media communication is open and unique. From the time point of view, the new media can keep track of the events and supplement the reports in time around the clock. From the space point of view, new media is open to all people, and anyone can participate in information dissemination anytime, anywhere. With the wide application of new media platforms, the awareness of broadening communication channels has penetrated into the field of public relations. When planning media events, public relations communicators can use powerful search engines and some new media platforms to build a huge relationship network, innovatively use various media forms, enrich public relations communication channels, and make public relations communication more dynamic.

The changes of communication behavior under the influence of new media are mainly reflected in the initiative of the audience to receive information, the interactivity of information dissemination, and the asynchrony of sending and receiving information. With the diversification of new media information sources, the audience is no longer passively receiving information under the unified communication caliber and can hear voices from various parties. New media communication has diversified information transmission channels, which can enable the audience to participate in information communication more quickly, thus gradually realizing "universal communication." Under the new media environment, the communication objects are around the Internet, forming a huge social network media, and each participant is of value to the branding and marketing communication of the communication subjects. The new media has extended the traditional public relations behavior of the communicators.

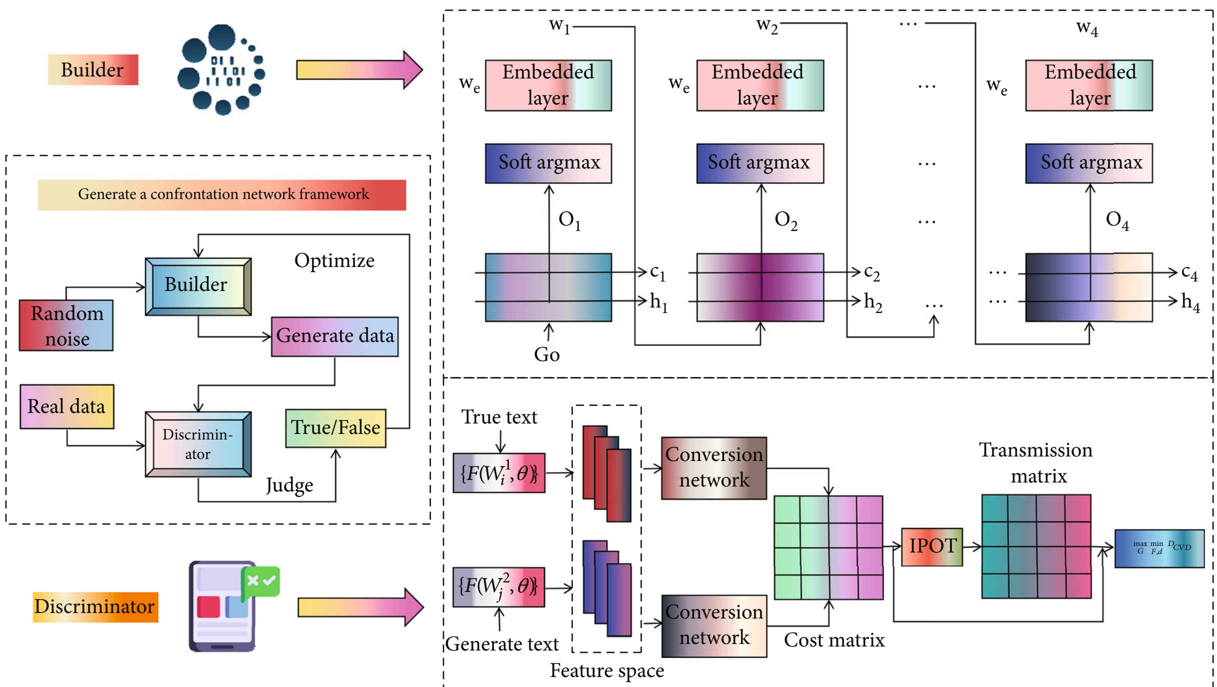

Figure 1: GAN model diagram.

3.2. GAN-Based Regulation of New Media Public Relations. Under the mode of news propaganda, the public relations department of the organization will take all possible measures to launch news propaganda in the media. News propaganda is one-way, and its purpose is not to change the organization's own behavior but only to change the public's understanding of the organization and public behavior. At the same time, the regulation of new media public relations can be effectively used in all aspects of political life, such as political propaganda, public opinion guidance, topic management, crisis management, reputation management, and image building. With the rapid development of artificial intelligence, text emotion generation has become a hot research topic at present. Various new media provide rich data for text generation and emotion analysis. Text generation can improve the experience of human-computer interaction, and it has broad prospects in the fields of comment generation, data augmentation, new media public relations regulation, etc. This paper builds a text emotion generation model based on GAN to support the application of new media public relations regulation strategy. GAN model is shown in Figure 1.

GAN consists of two parts: generation model and discrimination model. The core idea of model building is the confrontation between generation model and discrimination model: generation model is used to capture the distribution of target data, and samples conforming to the target distribution are generated as much as possible to confuse the judgment of discrimination model, while discrimination model needs to distinguish whether the input is real data or generated samples as much as possible, which is essentially a binary classifier that discriminates the real data as true and the generated data as false. The discriminant formula is as follows:

$$\begin{gathered} f = F(x\,;\varnothing_r), \\ D_\varnothing(s) = \operatorname{sigmoid}(\varnothing_1, F(s\,;\varnothing_r)) = \operatorname{sigmoid}(\varnothing_1, f). \end{gathered} \tag{1}$$

The generator formula is as follows:

$$\begin{gathered} g, h_t^M = M\left(f_t, h_{t-1}^M\,;\theta_m\right), \\ O_t, h_t^W = W(x_t, h_{t-1}^w\,;\theta_W). \end{gathered} \tag{2}$$

This paper uses minibatch training to set m and n equal, and due to the constraint of optimal transmission quality conservation, the transmission matrix T needs to meet the following conditions:

$$\begin{gathered} \sum_{j=1}^{n} T_{ij} = \frac{1}{m}, \\ \sum_{i=1}^{m} T_{ij} = \frac{1}{n}. \end{gathered} \tag{3}$$

This is because the elements in the transmission matrix T are a probability distribution of transmissions in which the sum of all elements is 1. And set the weights between all the generated text data feature vectors and the real text feature vectors to be equal.

From the point of view of feedback mechanism, the discrimination model only gives true or false two-dimensional feedback after the generation model completely generates a whole sentence. Obviously, the information given by the discrimination model in guiding and restricting the generation model to fit the distribution of real text is not comprehensive. The generator hopes that the distribution of generated sentences can be the same as that of real sentences, and in order to deceive the discriminator, it hopes that the distance obtained by the final distribution measurement is as small as possible. However, the network in the discriminator hopes to distinguish the generated distribution from the real distribution as much as possible; that is, the distance obtained by distribution measurement is as large as possible, which forms a typical max-min problem.

Add sentiment label information t, $t \in \{\text{Positive}, \text{Negative}, \text{Neutral}\}$, to the input of the generator and discriminator. Let $P_{\text{data}}(\text{x})$ denote the target distribution, Z denote random noise data, and $z \in P_{\text{noise}}(z)$. The generative model takes z as the input, specifies the emotion as t, and obtains the generated sample $G_\theta(z|t)$. θ is the parameter set of the generative model, and $D_\varphi(x)$ is used to represent the probability of judging that the x belongs to the target distribution $P(x|t)$. $D_j(G_q(x|t))$ represents the probability that $G_q(x|t)$ belongs to the target distribution, and φ is the parameter set of the discriminant model:

$$\begin{gathered} X_g = G_\theta(z|t), \\ D_\varphi(x) = P(x \in p_{\text{data}}(x|t)) = \text{sigmoid}(\theta, x|t). \end{gathered} \tag{4}$$

Correspondingly, the loss functions of the generative model and the discriminant model are shown in equations (5) and (6), and the game process of the entire network is shown in

$$\min_\theta E_{z\sim p_{\text{noise}}(z)}\left[\log\left(1 - D_\varphi(G_\theta(z|t))\right)\right] \tag{5}$$

$$\begin{aligned} &\max_\varphi E_{x\sim p_{\text{darta}}(x)}\left[\log\left(D_\varphi(x|t)\right)\right] \\ &\quad + E_{z\sim p_{\text{noise}}(z)}\left[\log\left(1 - D_\varphi(G_\theta(z|t))\right)\right] \end{aligned} \tag{6}$$

$$\begin{aligned} \min_G \max_D V(D, G) = {} & E_{x\sim p_{\text{darta}}(x)}\left[\log\left(D_\varphi(x|t)\right)\right] \\ & + E_{z\sim p_{\text{noise}}(z)}\left[\log\left(1 - D_\varphi(G_\theta(z|t))\right)\right] \end{aligned} \tag{7}$$

Since the reward of reinforcement confrontation learning is related to the discriminant model, it is meaningless to use the discriminant result obtained by randomly initialized discriminant model as reward feedback directly at the beginning of model training, and it cannot play a guiding role in generating model learning. Discontinuous discrete objects, such as texts, need to generate models to fit in real space. In the process of alternating training, it is difficult to adjust the parametric high-dimensional text information through the back propagation of the network from the noise data, and the deviation between them is step-like. When the generator is trained in confrontation training and the generator is not well trained at this time, the sentences generated by the generator will be very random, and the discriminator, which serves as an output reward and guides the training of the generator, will be very easy to distinguish whether the input text comes from the generator or the real data at this time, which cannot guide the generator towards a good improvement direction, thus leading to an invalid training process. Therefore, before the discriminator is pretrained, it is meaningless to use the discrimination result obtained by the discriminator with initialization parameters as reward and punishment feedback. In order to reduce the influence of this deviation, pretraining process should be carried out before intensifying confrontation training. Make the discriminator have a certain discrimination ability before alternate training. This paper modifies the activation function and uses bounded activation function to speed up the training of the model. The activation functions of all layers of the generation model except the output layer are changed to ReLU functions, the activation functions of the output layer adopt Tanh functions, and all activation functions in the discrimination model are changed to LeakyReLU functions. The trend analysis of new media based on feature fusion is shown in Figure 2.

In the whole process of standard GAN, the goal of model generation is to generate data that can be faked. When these data and real data are sent to the discriminator, the discriminator cannot distinguish them. In the reinforcement learning part of confrontation generation network, we adopt the algorithm of reinforcement learning strategy gradient. The smaller the cosine distance, the larger the cosine value, which indicates that the sentences generated by the generator are more similar to the real sentences. Then, the larger the reward value obtained by the generator, the more the generator will be guided to generate sentences with a distribution similar to that of the real sentences. In this paper, the tagging of emotional tags is done by expression, and the role of adding emotional tags is to give constraints in the training and generation of the model, so that the model can pay special attention to the emotional factors in the text when learning the law of text distribution. When keywords are used as input, the input order of each keyword is irrelevant; that is, there is no grammatical and semantic relationship between keywords, and they are independent. Therefore, the encoder changes the current hidden layer state by adjusting different keyword input order, and the decoder generates the next word according to the current state and the previous word. In this way, we can also get diversified sentences, expand the reward space, and ensure that the keywords contained in the generated sentences are not lost.

3.3. New Media Public Relations Regulation Strategy. With the development of information technology, new media presents various new media features. When the network credit system has not yet been established, it not only brings great convenience to people but also brings a lot of worries. This puts high demands on the government's supervision of new media. The essence of new media public relations is to combine the Internet thinking and public relations in the new media environment, keep an insight into social trends, enhance public relations awareness, and carry out public

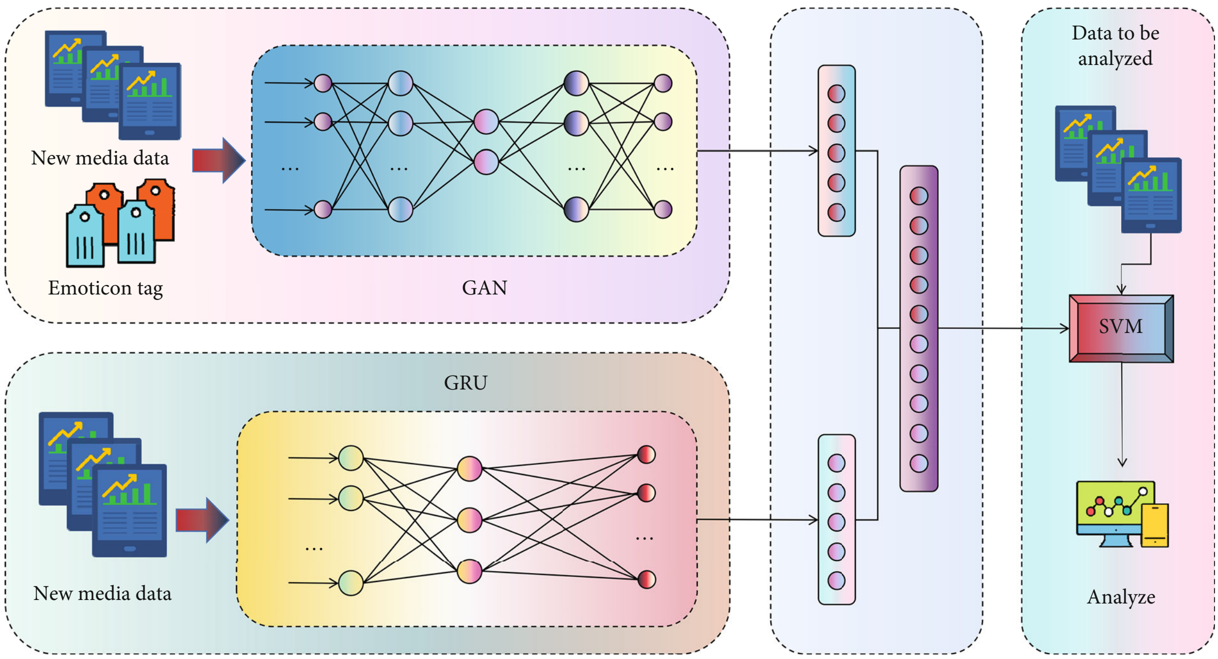

Figure 2: New media tendency analysis based on feature fusion.

Table 1: Training stage parameter setting table.

Parameter category	Value
Embed_ size	64
N_ cnn_ layer	4
N_ lstm_ hid	120
Batch_size	65
Iteration	60000

relations planning and activities for enterprises, organizations, or individuals from a strategic perspective. New media communication integrates words, sounds, and pictures. Under the background of new media, the audience is more inclined to diversified and rich communication, which is the same for public relations communication. Rich content, novelty, uniqueness, and exclusiveness have become the focus of public relations communication competition. Moreover, the regulation of public relations should also classify the content of communication according to the needs and interests of the audience, so as to attract the attention of the audience more and achieve the purpose of effective regulation.

Public relations communication in the new media environment requires the communication subject to grasp it from both content and form, which is challenging to some extent. This challenge mainly comes from the powerful influence of new media: as long as the information spread through the new media platform is sure to get a quick response from the audience, it is highly subjective. New media information is released quickly, and the speed of negative information dissemination is also very fast. Because the new media is not under the control of the public relations subject, and the competitors of enterprises may make use of the new media to create negative public opinion; it has brought great uncontrollability to the communication and regulation of public relations. The expression of public opinion in the new media environment is characterized by emotionalization and irrationality. There are three main reasons. First, the uneven quality of communication subjects makes the quality of public opinion uneven. Second, the information release threshold is low, and the convenience makes the content of public opinion random. Third, under the new media environment, the role of "strict control" has been weakened. The trend of diversified public opinion has caused many obstacles for people to make reasonable judgments, but it also provides more information for reasonable judgments. Therefore, we should strictly control the objective environment of such a scientific communication system, not relax our vigilance, and attach importance to the control and reasonable guidance of public opinion pluralism in the process of scientific communication.

The monitoring of new media by government technical means is the most mandatory, and the media technicians and the personnel of relevant government management departments set up some technical settings, that is, supervise, prohibit, control, adjust, or guide the spread of new media in certain content and channels. New media has new features. It is not its sole purpose to convey information to the target audience. It pays more attention to improving the utilization rate of information by effective means, thus bringing benefits to the target audience. At the same time, under the new media environment, if the rulers do not set up the idea of "governing for the people," avoid problems, and do nothing in providing information for the sake of superficial "achievements"; it may cause major problems. People can obtain information through many channels, including the Internet, mobile phones, interpersonal communication, and other channels, and this information may be uncertain. After the crisis, the government's inaction may lead to wild rumors, which may eventually lead to social chaos.

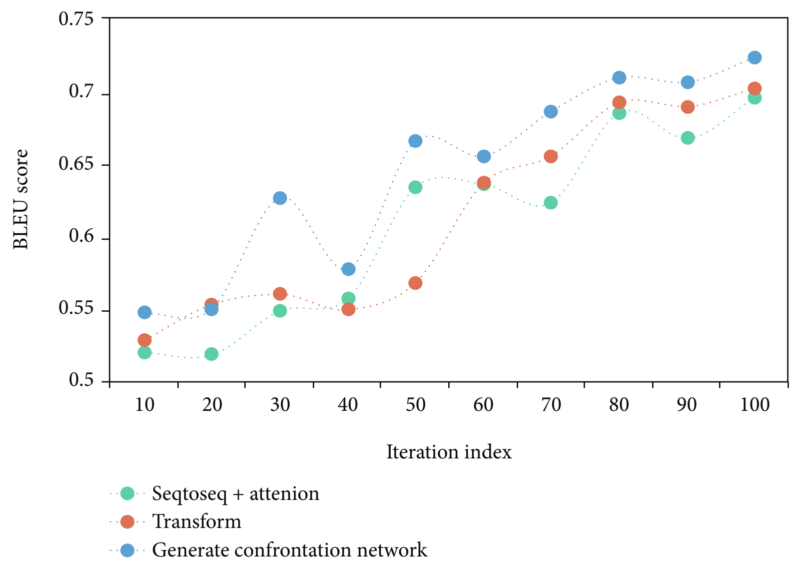

Figure 3: BLEU scores of different models.

Table 2: Evaluation index scores of different models.

Model	Diversity	Bleu score	Keyword addition degree
BLSTM	23.1%	0.714	56.78%
FixLSTM	26.5%	0.612	59.14%
Seqtoseq+attenion	66.78%	0.697	62.46%
Transform	70.25%	0.704	72.58%
Generate confrontation network	85.36%	0.725	82.75%

The emergence of new media has led to the shift of energy in communication activities. Shift the center of gravity to the audience. Media communicators are no longer the authoritative controllers of information, and the audience has more participation and more right to speak in communication activities. The audience can actively lead a communication activity. It can be said that the "audience" is no longer a simple "information receiver" but a dual identity of "receiver" and "communicator." Under the influence of new media such as Weibo and WeChat, more and more public relations communicators tend to share their experiences and feelings with other communicators. In a word, high communication efficiency is a major feature of public relations communicators in the new media environment. The crisis of public opinion under the background of new media has brought new challenges to government public relations. Every new technology has extended the carrier of public opinion and will also expand the communication form of public opinion. With the diversification of information sources, when the facts happen, the government must make a statement at the first time and release the most authoritative information in time to appease the people. At the same time, it is necessary to guarantee the right of public participation and supervision of the government in power, change from the idea of "all-powerful government" to the idea of "limited government," and fully mobilize all kinds of social forces to participate in solving public crises.

4. Result Analysis and Discussion

Word is the smallest unit in Chinese morpheme, because Chinese words and words are connected together. Compared with English corpus, to process Chinese Weibo corpus, word segmentation tools should be used first. The word segmentation system used in this paper is LTP system. The data set used in this paper is collected from a new media platform. This experiment mainly includes data processing stage, input stage, and training stage. Firstly, preprocess the data, cleaning the dataset, segmenting words, and extracting keywords. Filtering out sentences with inappropriate length and sentences that failed to extract keywords, a total of 356,742 pieces of data were obtained. In this task, we pay more attention to the generation of short sentences, so we only selected the data of sentences less than 20 in length. In this paper, it is divided into training set and test set according to a certain proportion. Finally, a total of 306,942 data training sets and 49,800 data test sets are obtained. In the input stage, the text to be converted, the emotional style of the text, and the target emotional style need to be input. In the training stage, the text to be converted is sent to the GRU encoder, and the emotional style of the input text will be combined with the zero vector after the projection of the style embedding matrix and sent to the GRU encoder as the initial state. The target emotion style is combined with the hidden content vector output by the encoder after projection as the initial state of the decoder. In this paper, neutral emotion sentences are omitted in the training data set, and only sentences with positive and negative tendencies are used. Avoid that neutral emotional sentences make the model confused in learning and judging emotional tendency during training.

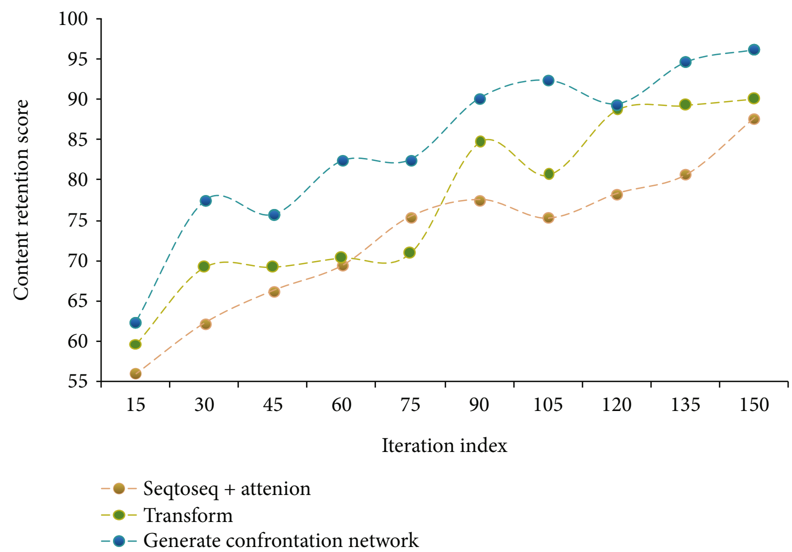

Figure 4: Retention of the main content of input and output text.

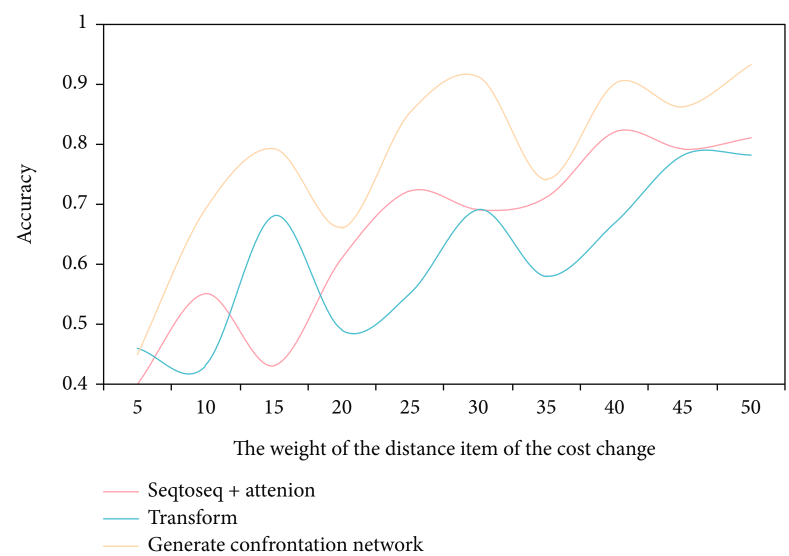

Figure 5: The curve of the proportion of the distance loss term in the accuracy with the change of cost.

In the training stage, the real text with noise added is input into the encoder to generate the hidden code Z. And the hidden code is input into two neural networks with different parameters to obtain the mean and variance to construct a normal distribution. The code sampled from the distribution is combined with the real text and input into the decoder, and the model is trained according to the similarity between the text output by the decoder and the input text. The main parameters of this stage include word vector dimension, convolution layer number, unit hidden vector dimension, batch size, and training times. The parameter settings are shown in Table 1.

In this paper, the keywords of each sentence are extracted from the preprocessed sentences as input, and the keywords are composed of nouns in the syntax analysis tree. At present, the mainstream technology of syntactic analysis is based on statistics. In this paper, Stanford's syntax analyzer is used to extract words with specific noun attributes like PN, NR, and NN. Considering the operability of the experiment, the extracted words are duplicated, and sentences without extracted keywords are deleted, and the number of keywords extracted in each sentence is about 2. At present, there is no unified evaluation standard for the generated text. This paper evaluates the quality of text generation from two aspects: grammar and emotion. Among them, grammar mainly pays attention to the similarity between the generated text and Weibo text and uses BLEU, a widely used evaluation method in natural language processing machine translation. The larger the BLEU value, the higher the similarity between the two sentences. The BLEU scores of different models are shown in Figure 3.

Emotionally, we pay attention to whether the emotion of the generated text is consistent with the target emotion and the emotional intensity. We use the emotional tendency

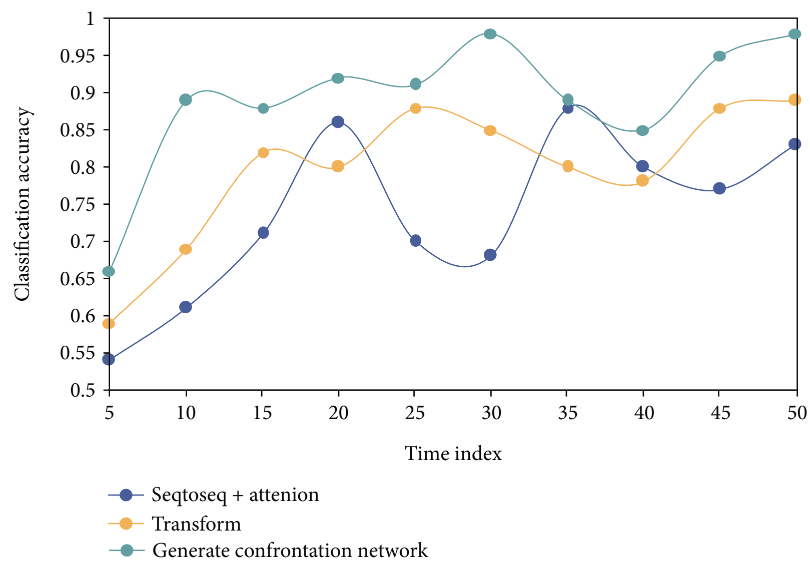

Figure 6: Classification accuracy results.

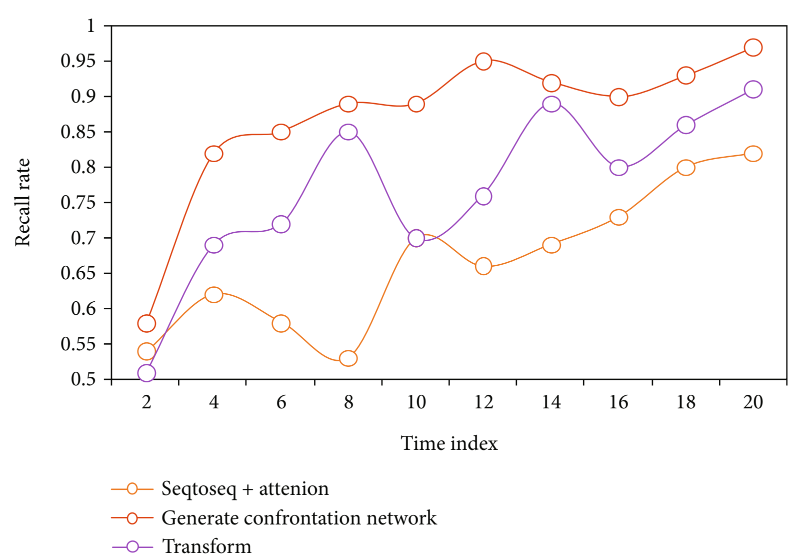

Figure 7: Algorithm recall results.

analysis tool provided by Baidu cloud computing. In this paper, the quality of the model is evaluated from two dimensions, namely, accuracy and diversity, in which accuracy indicates whether the sentences generated by the trained model can be false or not, and diversity indicates that the content of the generated text is diverse and not monotonous, and the model mode will not collapse.

In this chapter, we use the test set to compare the BLSTM method, FixLSTM method, Seqtoseq+attenion method, Transform method, and this method, respectively. The experiment was designed with three evaluation indexes: diversity, Bleu, keyword addition degree, and so on. According to the keywords, the evaluation indexes of different models are shown in Table 2.

It can be seen from the data in the table that the model proposed in this paper is obviously superior to other models in diversity generation. Compared with the model without keyword constraint, this model adds keyword information without losing a small part of semantic information, which is optimal compared with other models. At the same time, the sequence-to-sequence model can learn keyword information better by strengthening the feedback mechanism of learning keywords in the generation of alternating confrontation. Therefore, this model has the highest degree of keyword addition. The main content retention degree of the input text is shown in Figure 4.

As can be seen from the figure, the model in this paper gets a good score for content retention. The retention degree of the main contents of the input and output text in this paper is as high as 96.17%, which is higher than 8.49% of the Seqtoseq+attenion model and 6.11% of the Transform model.

GAN uses emotion tag information in training and needs to provide emotion tag when generating. Therefore, in this paper, a feature is generated by positive, negative, and neutral emotions, and then, the average of the three emotional features is obtained as the final feature of GAN. In this paper, emotional consistency adopts the classification function of emotional tendency analysis tool, and the accuracy of emotion generation is taken as the judging standard. Emotion intensity refers to the probability value of emotion discrimination by the emotional tendency analysis tool. The larger the probability value, the more positive the model's judgment on this sentence, that is, the more obvious the emotional tendency contained in this sentence. Because of the uncertainty and complexity of unsupervised text generation, these two methods still cannot quantitatively evaluate the quality of generated text. Therefore, in the experiment process, in order to ensure the effectiveness and stability of model training, manual observation will still be added to evaluate the quality of text. The accuracy of different models varies with the cost. The curve of the proportion of distance loss term is shown in Figure 5.

The purpose of this experiment is to test whether feature fusion can enhance the classification ability of GRU features in new media tendency analysis. The final emotion classification results are evaluated by classification accuracy and recall rate. The classification accuracy is shown in Figure 6. The recall rate is shown in Figure 7.

The results show that the features of this model are much better than those of Seqtoseq+attenion and Transform models in emotion classification. The reason may be that this model focuses on textual features and emotional discrimination features, while the other two models focus on the distribution of fitting words and sentences. Therefore, the method using this model is superior to the other two models.

5. Conclusions

The regulation of public relations under the new media background brings both opportunities and challenges. The media reform is to meet the needs of the audience, and enterprises based on the society also need to improve for this purpose. Public relations communication under the new media environment pays more attention to the two-way interaction of subject and object elements. Under the new media environment, public opinion and public opinion supervision show new features, which not only bring convenience to public opinion expression but also bring difficulties and problems to public opinion regulation and guidance. Therefore, it is necessary to formulate and implement public relations regulation strategies to adapt to the new media environment. This paper discusses the change and brand-new influence of public relations regulation strategy from the communication and regulation level of new media public relations. And in the new media environment, a text emotion generation model based on GAN is built to support the application of new media public relations regulation strategy. The effectiveness and feasibility of this method are verified by experiments. The retention degree of the main content of the input and output text of this model is as high as 96.17%, which is higher than that of Seqtoseq+attenion model of 8.49% and Transform model of 6.11%. And compared with Seqtoseq+attenion and Transform models, the real text distribution similarity of this model is higher, and it has higher text diversity. The research in this paper is of great practical significance to the regulation and control of public relations in the new media environment. Although the work in this paper has achieved remarkable results in effect, there are still some spaces for improvement and optimization and directions worth studying. In the next step, we can consider adding the punishment mechanism of short texts to the training of generators and consider adding the attention mechanism.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

No competing interests exist concerning this study.

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