

Added Objective Guided Optimization of Adversarial Text Generation Method

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Abstract: The problem of error accumulation is caused by the supervision of deep neural network text generation model. In order to solve this problem, a text generation model based on the reinforcement of antagonistic thought training is proposed. The adversarial network can be generated by the proposed model, and then the adversarial network can be used for identification, the learning reward function can be optimized, and the generated model can be optimized to reduce the probability of error accumulation. More text structure knowledge can be added into the generated text model by integrating the target guidance feature into the actual generation process to make the generated text model have higher authenticity. In this paper, the author optimizes the adversarial text generation method on the basis of target-guided optimization, which can be used for reference by practitioners. **Keywords:** Generative Adversarial Networks (GAN); Objective Guided Optimization; Antagonistic Text; Generate

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1. Related Work

In order to ensure the smooth completion of the text generation, the relevant staff should maximize the training data based on the maximum likelihood four-line training recurrent neural network model, so as to improve the authenticity of the text generated by the guidance mode^[1]. Bengio et al. stated that because of the difference in data used for training and testing, there was an accumulation of errors, which made it possible for them to achieve satisfactory maximum likelihood estimates. To solve this problem, they proposed a strategy of regular sampling. However, through actual verification, it is found that these methods cannot directly complete the formulation of neural network output loss function model, cannot guarantee the quality of sample sampling, and cannot improve the authenticity of the generated text.

Generative adversarial networks (GAN) based on adversarial thought training generation model will be based on real data layout^[2]. In order to weaken the influence of discrete text data on GAN, Gumbel GAN and Wasserstein GAN optimize the internal calculation method of GAN^[3]. Two methods of Gumbel-Softmax distribution and Wasserstein divergence are introduced in order to redistribute discrete labels and obtain the continuous approximation of Softmax function^[4]. It provides more possibilities for employees to carry out generative model optimization and discriminant model optimization.

2. Text generation technology based on the idea of strengthened confrontation

2.1 Basic Process

In this paper, the text sequence generation model used by the author mainly consists of three modules, namely generator, discriminator and target guidance module. At the same time, the text sequence generation problem is defined again in combination with the model structure: based on the sequence data set in the real text structure, a generator C_θ based on the training parameter θ is used to generate the sequence. In this paper, the text sequence generation model used by the author mainly consists of three modules, namely generator, discriminator and target guidance module. At the same time, the text sequence generation problem is defined again in combination with the model structure: based on the sequence data set in the real text structure, a generator C_θ based on the training parameter θ is used to generate the sequence. $x: T = (x_1, x_2, \dots, x_t, \dots, x_T)$, $t \in (1, T)$, $x \in Y$, In this sequence, the full sequence length is represented by T , the dictionary is represented by Y , the time is represented by T , s_t is the definition of the generated sequence, $s_t = (x_1, x_2, \dots, x_t)$, S_t represents the complete sequence completed using Monte Carlo search, that is $s_t' = (x_1, x_2, \dots, x_{t+1}, x_{t+2}, \dots, x_T)$, The choice of word X_{t+1} is completed under the definition of action a_t , and the training parameter of ϕ is used to identify its D_ϕ , so that the discriminator can simultaneously obtain the real sentence and the sentence s_t ^[9] generated by MC Search completion generator. The discriminator module has two main functions, one is to act as a reward function to evaluate the quality of the sentences generated by the generator, the other is to remember the feature extraction layer to complete the feature vector FT extraction, and then pass it to the target guidance module R_μ . Through training, R_μ can help the high-dimensional feature vector to complete the change operation and obtain the target embedding vector ω_t , which provides help for guiding the generator to optimize. Based on ω_t , generator C_θ is generated in the corresponding environment to complete the acquisition of x_{T+1} of the next generated word. The specific process is shown in Figure 1:

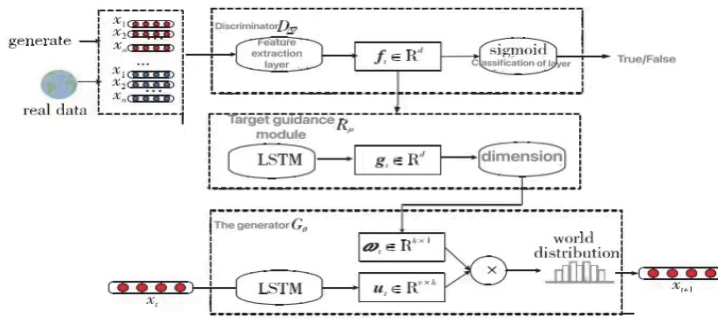


Figure 1: Enhanced adversarial text generation with fused goal guidance

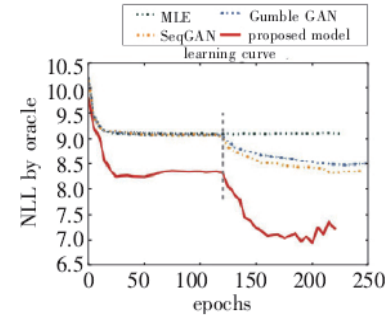


Table 2: NLL performance of each method in synthetic data

2.2 Generation Process

Discriminator D_ϕ information extraction in the middle of the fit nature belongs to the high dimensional feature vector, if pass it directly to the generator module, the generator used by training reference will show exponential growth situation, so that the actual calculation steps increasing and used to store data, will increase the difficulty of practical training, so that the dimension disaster.

3. Experimental Analysis

In order to analyze the effectiveness of the model used in this paper, the author compares the synthetic data with the real data. The specific environment and configuration are shown in Table 1:

Table 1: Experimental environment configuration

The test environment	Environment configuration
The operating system	Windows7
The processor	Intel® Core™i7-6700
GPU	CUDA8.0
A programming language	Python 3.6
Deep learning framework	TensorFlow1.2.1

Table 3: NLL convergence of the number of iterations

indicators	MLE	Gumble GAN	Seq GAN	Proposed model
NLL	9.017	8.883	8.587	7.036

3.1 Experiment of synthetic data

In order to further analyze the specific performance of the model used in this paper and strengthen my understanding of the model, the author used some synthetic data to carry out simulation tests in the experiment. In order to fit the real structured sequence, the author uses the language model to understand the relationship between words, and takes the random initial LSTM as the real model to obtain the data needed for the experiment [5]. There are two benefits to this approach: the first is the ability to provide real training data, and the second is the ability to provide a specific evaluation of the performance of the generated model.

3.2 Experimental Methods

In this paper, the author used the following three methods in the actual testing process: (1) LSTM based on MLE training: Text model generation is completed by LSTM, and model parameters are adjusted by MLE maximum likelihood thought training model. (2) GumbleGAN: Obtain the continuous approximation of polynomial distribution based on SoftMax function with Gumble-SoftMax, optimize the traditional GAN back propagation, improve the application probability of model parameters, and improve the authenticity of text generation. (3) SeqGAN: Based on the antagonistic network structure and integrating the reinforcement learning idea, the parameters of the formal model of the reward function are optimized. Comparing the above three methods with the model in this paper, the experimental results of synthetic data are shown in Table 2 and Figure 3:

4. Conclusion

According to the study in this paper, the use of the enhanced confrontation training method can improve the generation of model text, and in the actual process, more intermediate information can be generated for the reference of researchers, which can effectively improve the effectiveness of the model.

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