Chinese character style migration based on convolutional neural network

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Abstract

The number of Chinese characters is very large and their font styles are also very rich. It is very expensive to create a set of fonts with different styles for Chinese characters. In order to reduce the cost of Chinese character style migration, this paper uses a convolutional neural network to perform Chinese character style migration. Experiments show that the convolutional neural network with the help of backpropagation algorithm can perform the task of Chinese character style migration very well.

1 Introduction

There are about 2,000 to 3,000 Chinese characters that are often used, which is a lot more in numbers compared to the letters in English. And, for historical and cultural reasons, there are very many different writing styles for the same Chinese character. Creating the appropriate font for the Chinese character style is a very costly affair, not only in terms of money but also in terms of time. Due to their structural characteristics, Chinese characters can be easily processed as images, and convolutional neural networks are very advantageous in image processing. In this paper, an algorithm for Chinese character style migration is implemented based on convolutional neural networks. It can be used in conjunction with the back propagation algorithm to effectively perform the task of Chinese character style migration.

This paper first introduces the components of the backpropagation algorithm and the convolutional neural network, then explains the specific structure of the convolutional neural network that can perform Chinese character style migration, and finally demonstrates the effectiveness of the method using experiments.

The main three contributions of this paper are as follows.

1. An easy-to-train model for Chinese character font generation is proposed. The larger the model is, the more likely it is to achieve better generation results, but a larger model also means higher training costs. In this paper,

the proposed model has a small number of parameters and can be trained with few computational resources.

2. In this paper, some general conclusions are obtained about neural generation of Chinese characters through neural networks by trying to compare the effect of different sizes of convolutional kernels and different network depths. These conclusions are instructive for designing new Chinese character font generation networks.

3. The validity of the model is verified in the dataset constructed from the actual fonts.

2 Related work

The generation of new fonts for English or Latin alphabets has been studied in quite a few literatures. [2] found that neural networks can achieve letter font recognition and similar font generation using just 4 of the 26 English letters. [1] used conditional GAN in performing font style migration on letters.

However, the research on Chinese character generation is still relatively small. A possible GAN for generating calligraphic styles of specific Chinese characters is proposed in [8] with very realistic detail variations, but the main focus is on the generation of a small number of calligraphic characters and is not discussed in the context of a large number of Chinese character generation. [5] proposed a cross-language approach for font style migration between fonts that learn the same language. [6] decoupled the content and style of Chinese characters using Variational Autoencoder (VAE), which enabled the model to get one-shot generalization ability and get good results with only a small amount of data for training, but mainly considered to generate handwritten type fonts. [10] proposes a method to reduce the pattern collapse of GANs generated from Chinese characters. [3] proposed a method to generate handwritten style Chinese characters using CycleGAN. [7] proposed a meta-learning method based on recurrent neural networks that can mimic user handwritten fonts, but relying on the information of the stroke order when writing. [9] uses an unsupervised approach for font generation based on GAN.

Previous methods have made progress in Chinese character font generation, but each has shortcomings in training difficulty, model size, and usage scenarios. The method proposed in this paper has a simple training process, small resource consumption, and can generate common Chinese characters well.

3 Back propagation algorithm

A neural network is essentially a function $f_W(x)$ determined using the set of parameters W. The neural networks are trained to find a suitable value among all possible values of W so that the objective function $E = L(y, f_W(x))$ reaches a small value. Where x is the input to the neural network, $f_W(x)$ is the output obtained by the neural network, y is the ideal output corresponding to x, and E denotes the difference between the output of network and the target output.

In practical applications, it is very difficult to obtain the analytical solution of the parameter W mathematically because of the complexity of the network structure, so numerical methods are often used to obtain an approximate estimate of the optimal solution, which is often called the training of neural networks. With the increase in computing power of computers, the back propagation algorithm has become the mainstream method for network training. Back propagation is essentially calculating the gradients, and is called back propagation since in this method the gradients of the parameters close to the output are computed first, and the gradients of the parameters leaning forward are computed on top of that. The following is an example of the back propagation algorithm process used in a fully connected network.

A fully connected layer is a traditional multilayer perceptron that uses a softmax activation function in the output layer. "Fully connected" means that every neuron in the previous layer is connected to every neuron in the next layer. Let there are L layers in the fully connected network, x is the original input of the network, z_j is the output of the j layer of the network, a_j is the result of z_j after the activation function, and w_{ij} is the i parameter of the j layer of the network. The direction of updating w_{ij} can be obtained by calculating the partial derivative of E with respect to w_{ij}. In the calculation, the chain rule is used.

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial a_j}\frac{\partial a_j}{\partial w_{ij}} = \frac{\partial E}{\partial a_j}\frac{\partial a_j}{\partial z_j}\frac{\partial z_j}{\partial w_{ij}} \tag{1}$$

In this formula above, only $\frac{\partial z_j}{\partial w_{ij}}$ is related to w_{ij}, the rest can be directly derived from the formula, and again from the procedure of z_j

$$\frac{\partial z_j}{\partial w_{ij}} = \frac{\partial}{\partial w_{ij}}\left(\sum_{k=1}^{n} w_{kj} \cdot a_{k,j-1}\right) = a_{i,j-1} \tag{2}$$

a_{j-1} has already been computed during the network forward computation, so the final result can be obtained.

By back propagation, the partial derivative of the cost function E with respect to the parameter w_{ij} can be obtained. The value of the function increases along the positive direction of the partial derivative, and the value of the cost function E can be reduced by simply following the negative direction of the partial derivative. The exact method of updating the parameter values using partial derivatives will be given in the next section.

4 Adam algorithm[4]

When updating new parameters, the simplest strategy can be used:

$$w_{ij}^{k} = w_{ij}^{k-1} - \lambda \Delta w_{ij}^{k} \tag{3}$$

where k denotes the number of iterations of the training process and Δw_{ij}^{k} is the partial derivative of E with respect to w_{ij}^{t} at the kth iteration. λ is the weight to modify the parameter values according to the partial derivatives, also called the learning rate.

But the parameters converge slowly when training the network using this method and it may take a longer time to get a usable network.Adam algorithm is proposed to speed up the training of the network. Adam algorithm uses the first and second order moments of the variables to update the parameters under the premise of computing the gradient. The main flow is shown in Algorithm 1.

Algorithm 1 Adam algorithm

Require: Learning rate λ
Require: ρ_1 and ρ_2 for exponential decay of moment estimation
Require: δ for numerical stability
  Initialize s and r to 0
  Initialize time step t to 0
  while No stopping guidelines met **do**
    Compute gradient: g
    Update biased first-order moment estimation: $s \leftarrow \rho_1 s + (1-\rho_1)g$
    Update biased second-order moment estimation: $r \leftarrow \rho_2 r + (1-\rho_2)g \odot g$
    Correct bias in first-order moment: $\hat{s} \leftarrow \frac{s}{1-\rho_1^t}$
    Correct bias in second-order moment: $\hat{r} \leftarrow \frac{r}{1-\rho_2^t}$
    Calculate update: $\Delta w \leftarrow -\epsilon \frac{\hat{s}}{\sqrt{\hat{r}}+\delta}$
    Update parameters: $w \leftarrow w + \Delta w$
  end while

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5 Other components of a convolutional network

5.1 Convolutional layer

Convolutional neural networks (ConvNets or CNNs) are a class of neural networks that have proven to be very effective in areas such as image recognition and classification. The convolution layer consists of a set of filters, which can be considered as a two-dimensional digital matrix. The main purpose of convolution is to extract features from the input image. The output image can be generated by convolving the filter with the input image. The convolution operation is performed as follows:

1. Overlaying a filter at a location on the image.

2. Multiplying the value in the filter with the value of the corresponding pixel in the image.
3. The sum of the products above is obtained by adding the values of the target pixels in the output image.

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Repeat this operation for all locations of the image. Usually, convolution helps to find specific local image features (e.g., edges) to be used in the network later. For a two-dimensional signal, the convolution layer is given by

$$Y[m,n] = x[m,n] * h[m,n] = \sum_j \sum_i x[i,j] \cdot h[m-i, n-j] \tag{4}$$

5.2 Fully connected layer

The output of the convolution and pooling layers represent high-level features of the input image. The purpose of the fully-connected layer is to use these features to classify the input image into various classes based on the training dataset. In addition to classification, adding a fully-connected layer is also an inexpensive way to learn non-linear combinations of image features.

Most features from the convolutional and pooling layers may be beneficial for classification task, but a combination of these features may be better. The core operation of the fully connected layer is formulated as

$$y = Wx \tag{5}$$

5.3 Batch normalization layer

the regularization is performed in terms of the mini-batch at the time of performing the study. Specifically, the regularization is performed so that the mean of the data distribution is 0 and the variance is 1. In mathematical terms, this is shown below.

Algorithm 2 Batch normalization

Compute mini-batch mean: $\mu \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i$
Compute mini-batch variance: $\delta^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu)^2$
Normalize: $\hat{x} \leftarrow \frac{x_i - \mu}{\sqrt{\delta^2 + \epsilon}}$
Scale and shift: $y_i \leftarrow \gamma \hat{x}_i + \beta$

The essence of neural network learning is the distribution of the learning data. Once the distribution of training data and test data are different, the generalization ability of the network is greatly reduced. On the other hand, once the distribution of each batch of training data is different (batch gradient descent), then the network must learn to adapt to a different distribution in each iteration, which will greatly reduce the training speed of the network. This is exactly the reason for doing normalized preprocessing on the data.

The uses of batch normalization layer include:

1. Speed up the training and convergence of the network.
2. Less dependent on initial values.
3. Prevent overfitting.

5.4 Activation function

The distribution of data is overwhelmingly nonlinear, while the general computation of neural networks is linear, the introduction of activation function is to introduce nonlinearity in the neural network and strengthen the learning ability of the network. The biggest feature of the activation function is nonlinearity.

ReLU (Rectified Linear Unit) is the corrected linear unit function. The form of the function can be expressed as

$$h(x) = \begin{cases} x & (x > 0) \\ 0 & (x \leq 0) \end{cases} \tag{6}$$

The effective derivative of ReLU is constant 1, which solves the problem of gradient disappearance that occurs in the deep network, and makes the deep network more trainable. At the same time, ReLU is a nonlinear function, which means that the first-order derivative is not constant. The derivative of ReLU is different for positive and negative input values, respectively. Therefore, ReLU is nonlinear.

6 Chinese character font conversion

6.1 Network Structure

The overall structure of the network used in this paper is shown in Fig 1, where Base extractor is mainly responsible for extracting sufficient features from the original image; Structure A and Structure B utilize the structure of residual and Inception fusion in Inception-ResNet v2, but unlike the original version, the number of channels of convolution is appropriately adjusted to improve the computational efficiency. Structure A and Structure B utilize the structure of residual and Inception fusion in Inception-ResNet v2, but unlike the original version, the number of channels of convolution is adjusted to improve the computational efficiency, making the overall computational scale smaller and more conducive to the application of Chinese character font generation, with m and n representing the number of repetitions of the corresponding modules, respectively. The specific structures of Stucture A, Structure B, and Reduce Block

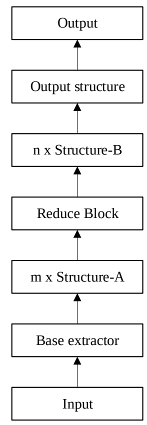
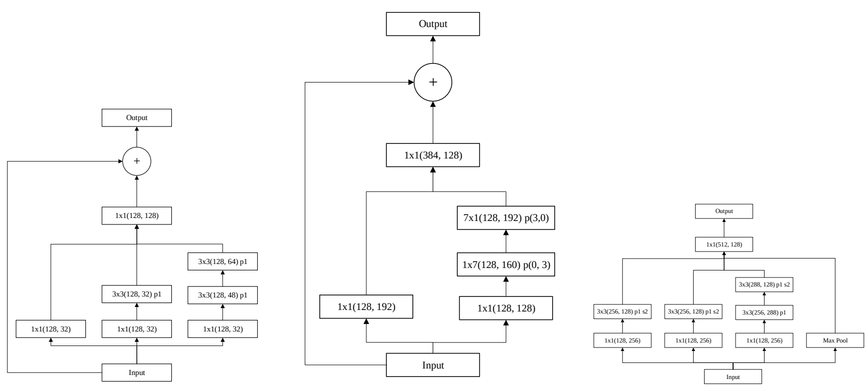


Figure 1: Network structure of the Chinese character font conversion network

are shown in Fig 2a, Fig 2b, and Fig 2c, while the structures of Base extractor and Output structure are different in different experiments. Therefore, they are listed in the experimental section.

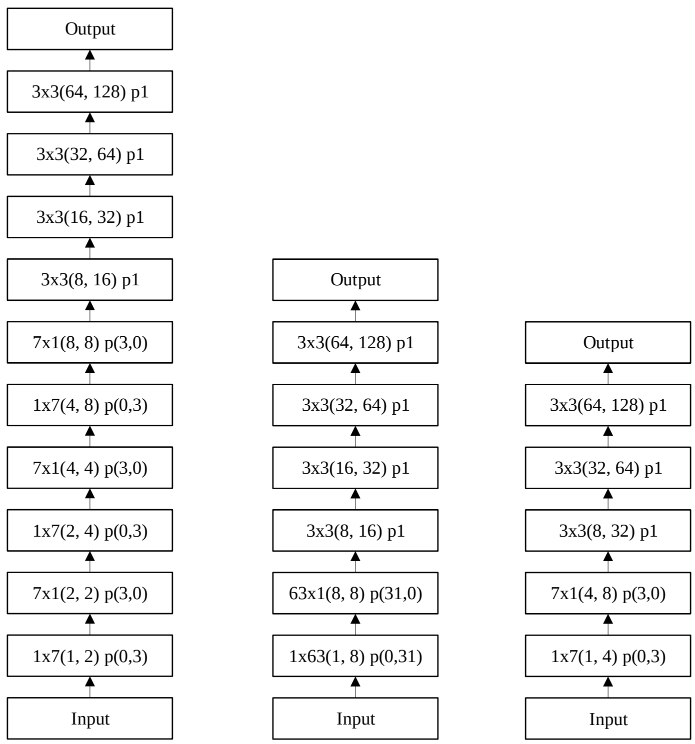


(a) Structure A (b) Structure B (c) Reduce Block

Figure 2: Structures of networks

In this paper, the input of the network is the source font image with a resolution of 160×160, and the output is the target font image with a resolution of 80×80. The resolution of the feature map is 160×160 in the Base extractor, which is the same as the input image; the resolution drops to 80×80 from the Reduce Block, which is the same as the output image.

The loss function used for network training is mean absolute error.



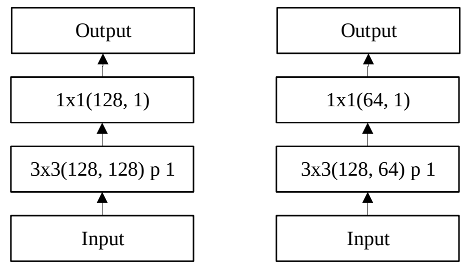
(a) Structure of B1 (b) Structure of B2 (c) Structure of B3

Figure 3: Base structures

7 Experiment

The different network structures used in the experiments are shown in Table 1, where B1, B2, and B3 are different structures of different Base extractors, and their specific compositions are shown in Fig. 3a, Fig. 3b, and Fig. 3c. O1 and O2 represent different Output structures, and their specific compositions are shown in Fig. 4a and Fig. 4b.

In the figure, 1x7 (1,2) p(0,3) means that the size of the convolution kernel of this layer is 1×7, the number of input channels is 1, the number of output channels is 2, and the size of the padding is (0 ,3). The size of the number after the letter s represents the size of the stride. The parameters of other convolutional layers can be explained accordingly.



(a) Structure of O1 (b) Structure of O2

Figure 4: Output blocks

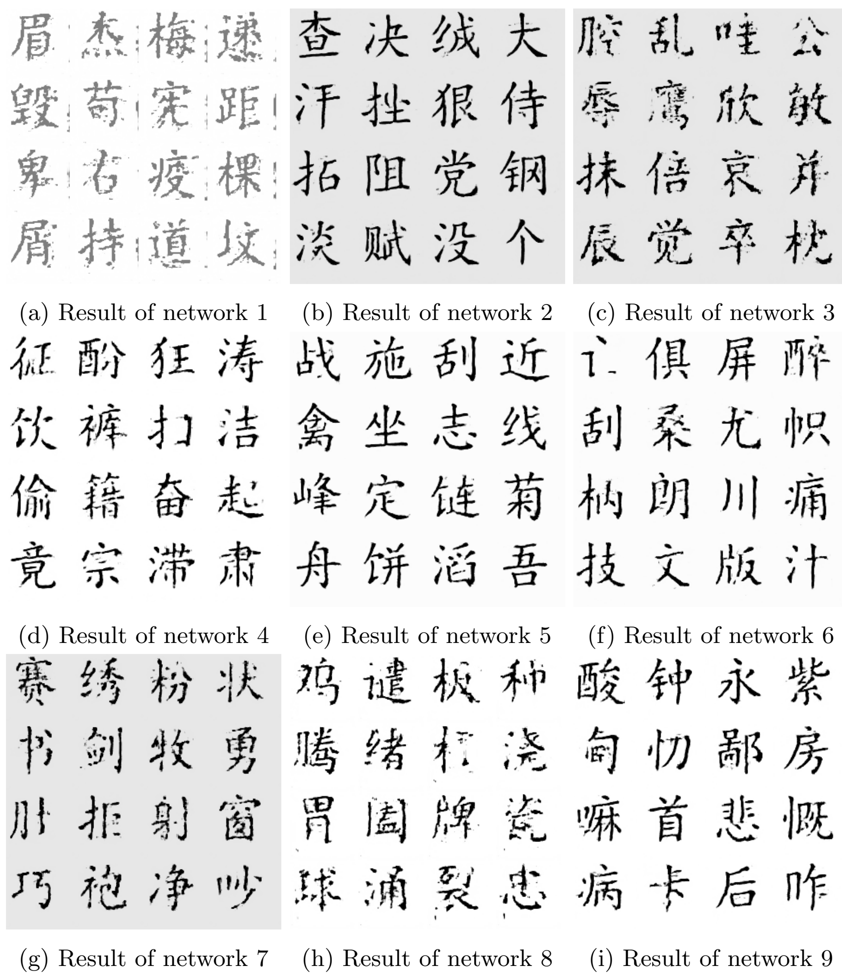
Table 1: Configurations of networks

Configuration	Base extractor	m	n	Output structure	dropout	Sigmod
1	B1	5	5	O1	0.9	Yes
2	B2	5	5	O1	0.9	-
3	B3	3	3	O2	0.9	-
4	B1	5	5	O1	-	-
5	B2	5	5	O1	-	-
6	B2	3	3	O1	-	-
7	B3	3	3	O2	-	-
8	B3	3	3	O2	-	-
9	B2	3	3	O2	-	-

Because larger convolution kernels will take up more computational resources, and the excessive number of parameters will also make the network training difficult, two corresponding one-dimensional convolutions are used for convolution kernels larger than 3×3 in the experiments of this paper.

By pairing the experiments, the following points can be found.

1. using Dropout at the end of the kanji generation network will use the presence of noise in the final generated result of the network. The dropout layers are used in net1, net2, net3, and net4, and with a small probability of 0 of 0.1, all the 4 networks show noise in the generated results, and the strokes of the Chinese characters are missing to some extent. This is probably due to the fact that the dropout layer is located at the end of the network and the network has no chance to correct the defects in the feature maps afterwards. It also shows that it is better not to use dropout at the end of the Chinese character font generation network.
2. The larger convolutional energy in the first stage gives better results. In



(a) Result of network 1 (b) Result of network 2 (c) Result of network 3

(d) Result of network 4 (e) Result of network 5 (f) Result of network 6

(g) Result of network 7 (h) Result of network 8 (i) Result of network 9

Figure 5: Results of different networks

net2, net5, net6, and net9, the largest convolution kernels are used, and the results of these networks are significantly better than those of the other networks. This illustrates that using larger convolutional kernels in shallower layers can yield better results in Chinese character font generation networks.

3. more intermediate layers can get better results. In net1, net2, net4, and net5, a relatively large number of intermediate layers are used, and it is observed that all three networks except net1 have better results than the version with fewer derivatives.

4. The use of Sigmod at the end of the network impairs the performance of the Chinese character generation network. Of the 9 networks trained in the experiment, only net1 uses sigmod. even though more derivatives are used in net1, it still performs worse than all other versions. In summary, when using convolutional neural networks for Chinese character font generation, not using dropout and sigmod at the end of the network and using larger convolutional kernels with more convolutional layers can give better results.

There are more examples in Fig.6 for the result. On the left is the standard Chinese character image in the computer, and on the right is the corresponding changed style of Chinese characters generated by the neural network. You can see that the characters have not changed, but the style has changed significantly

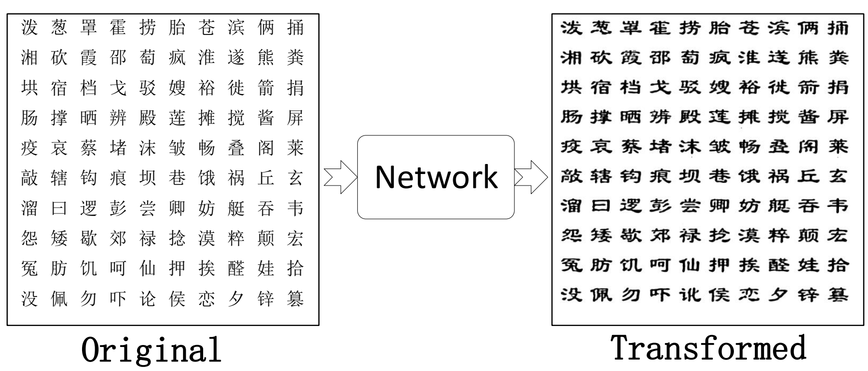


Figure 6: Network Output Illustration

8 Conclusion

In order to achieve efficient and low-cost Chinese character font generation, this paper conducts a series of explorations. Using 9 sets of comparative experiments, we propose several design principles for Chinese character generation networks:

using larger convolutional kernels, using deeper networks, and not using dropout and sigmod at the end. It is also shown that using only convolutional neural networks without other complex network structures can achieve good results in Chinese character font generation.

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