

Convolutional neural network

Peng Tan (pengtan3@vt.edu)

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1 Introduction

1.1 Background

Convolutional Neural Network (CNN, or ConvNet) is a class of deep neural networks, most commonly applied to analyzing visual imagery. CNNs are regularized versions of multilayer perceptrons. Multilayer perceptrons usually mean fully connected networks, that is, each neuron in one layer is connected to all neurons in the next layer. [1]

CNNs use relatively little pre-processing compared to other image classification algorithms. This means that the network learns to optimize the filters or convolution kernels that in traditional algorithms are hand-engineered. This independence from prior knowledge and human intervention in feature extraction is a major advantage. [1]

2 Experiment

2.1 Datasets

In this Experiment, we just use cifar10 and cifar100 as our dataset to train and test our model. Cifar10 and Cifar100 are subsets of the 80 million tiny images dataset.

The CIFAR-10 dataset consists of 60000 32x32 colour images in 10 classes, with 6000 images per class. There are 50000 training images and 10000 test images.

The CIFAR-100 dataset consists of 60000 32x32 colour images in 100 classes, with 600 images per class. There are 50000 training images and 10000 test images.

2.2 Experiment design

We will use keras Sequential Model API to build the whole model, which include Convolution2D layer, BatchNormalization layer, Dropout layer, MaxPool layer, Flatten layer, Dense layer.

First, building an Convolution layer to clarify the shape of Input data and set initial filter number. In this project, The shape of Input data is [32, 32, 3]. After passing convolution layer, the dimension of data will transfer from [32, 32, 3] to [32, 32, 32]. And then build BatchNormalization layer to enhance the learning of each node. Building dropout layers to avoid model overfitting.

Secondly, building Maxpool layer on the layer. The purpose of Maxpool is to reduce or downsample the dimensionality of the input image. After passing Maxpool layer, the dimension of data will transfer from [32, 32, 32] to [16, 16, 32].

Third, Repeat the above layer building process to obtain several blocks of convolution layer in order to training model and then flatten the output from above layer and connected to full connected layer. In this step, the dimension of data will transfer from [4, 4, 128] to [256,]

Finally, the last layer will be used to classify. So, In this dense layer, the activation function will be softmax. When the data set is applied to cifar10 or cifar100, the number of output nodes will be 10 or 100 respectively.

Finally, When compiling our model, we will use categorical-crossentropy as loss function, SGD or Adam as optimizer.

```

Model: "sequential"
=====
Layer (type)                Output Shape                Param #
-----
conv2d (Conv2D)              (None, 32, 32, 32)         896
batch_normalization (Batch Normalization) (None, 32, 32, 32)         128
dropout (Dropout)            (None, 32, 32, 32)         0
max_pooling2d (MaxPooling2D) (None, 16, 16, 32)         0
conv2d_1 (Conv2D)            (None, 16, 16, 64)         18496
batch_normalization_1 (Batch Normalization) (None, 16, 16, 64)         256
max_pooling2d_1 (MaxPooling2D) (None, 8, 8, 64)          0
conv2d_2 (Conv2D)            (None, 8, 8, 128)          73856
batch_normalization_2 (Batch Normalization) (None, 8, 8, 128)         512
max_pooling2d_2 (MaxPooling2D) (None, 4, 4, 128)         0
flatten (Flatten)            (None, 2048)               0
dropout_3 (Dropout)          (None, 2048)               0
dense (Dense)                (None, 256)                524544
re_lu (ReLU)                 (None, 256)                0
dense_1 (Dense)              (None, 10)                 2570
=====
Total params: 621,258
Trainable params: 620,810
Non-trainable params: 448

```

Figure 1: The Summary of model layers for cifar10

```

Model: "sequential_1"
=====
Layer (type)                Output Shape                Param #
-----
conv2d_3 (Conv2D)              (None, 32, 32, 32)         896
batch_normalization_3 (Batch Normalization) (None, 32, 32, 32)         128
dropout_4 (Dropout)            (None, 32, 32, 32)         0
max_pooling2d_3 (MaxPooling2D) (None, 16, 16, 32)         0
conv2d_4 (Conv2D)            (None, 16, 16, 64)         18496
batch_normalization_4 (Batch Normalization) (None, 16, 16, 64)         256
max_pooling2d_4 (MaxPooling2D) (None, 8, 8, 64)          0
conv2d_5 (Conv2D)            (None, 8, 8, 128)          73856
batch_normalization_5 (Batch Normalization) (None, 8, 8, 128)         512
max_pooling2d_5 (MaxPooling2D) (None, 4, 4, 128)         0
flatten_1 (Flatten)           (None, 2048)               0
dropout_7 (Dropout)          (None, 2048)               0
dense_2 (Dense)              (None, 256)                524544
re_lu_1 (ReLU)               (None, 256)                0
dense_3 (Dense)              (None, 100)                25700
=====
Total params: 644,388
Trainable params: 643,940
Non-trainable params: 448

```

Figure 2: The Summary of model layers for cifar100

3 Discussion

3.1 Training Performance and Validation Performance

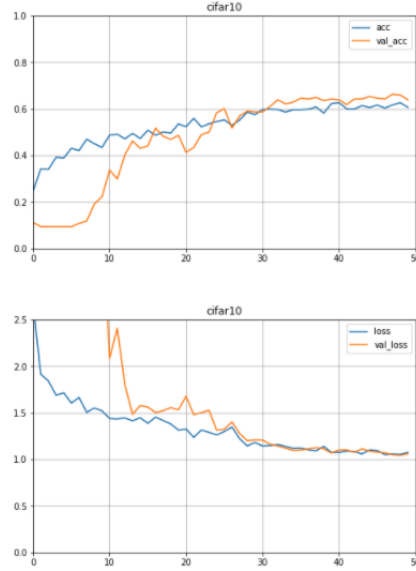


Figure 3: The Performance of CNN in cifar10 dataset

In the Training Performance and Validation Performance in cifar10 dataset(Figure3), we can find that the accuracy increased a lot at first 20 epoch and converge after epoch 30.

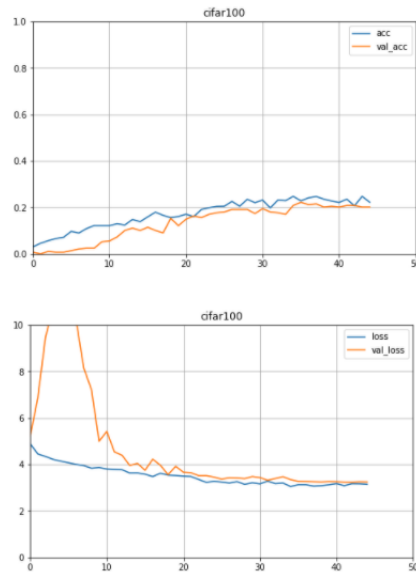


Figure 4: The Performance of CNN in cifar100 dataset

In the Training Performance and Validation Performance in cifar100 dataset(Figure4), we can find that the accuracy only 20 percent after training the model.

3.2 Study the performance of Y-networks with Optimize

From Figure5, we can find that the model with 3 layers, [64, 128, 256] filter-number, 0.25 dropout rate, 'adam' optimizer is the best model for cifar10 dataset.

We can find that the model with 3 layers, [32, 64, 128] filter-number, 0.25 dropout rate, 'adam' optimizer is the best model for cifar100 dataset.

	dataset	layers	filter_number	dropout	optimizer	test_accuracy
0	cifar10	2	32	0.25	adam	0.6465
1	cifar10	2	64	0.25	adam	0.5972
2	cifar10	3	64	0.25	adam	0.6522
3	cifar10	3	32	0.35	adam	0.6211
4	cifar10	2	32	0.25	SGD	0.5799
5	cifar100	2	32	0.25	adam	0.2279
6	cifar100	3	32	0.25	adam	0.2431
7	cifar100	3	64	0.25	adam	0.2128
8	cifar100	3	32	0.35	adam	0.2272
9	cifar100	3	32	0.25	SGD	0.1880

Figure 5: The performance of Y-networks with Optimize

3.2.1 Visualize feature maps

Feature maps are generated by applying Filters to the input image or the feature map output of the prior layers. Feature map visualization will provide insight into the internal representations for specific input for each of the Convolutional layers in the model.

Each convolutional layer will reduce the number of features in a dataset by creating new features from the existing ones. For example, In the first convolutional layer, the original img [32, 32,3] will be transferred to [32, 32, 32]. These new 32 pictures will be able to summarize most of the information contained in the original set of features.

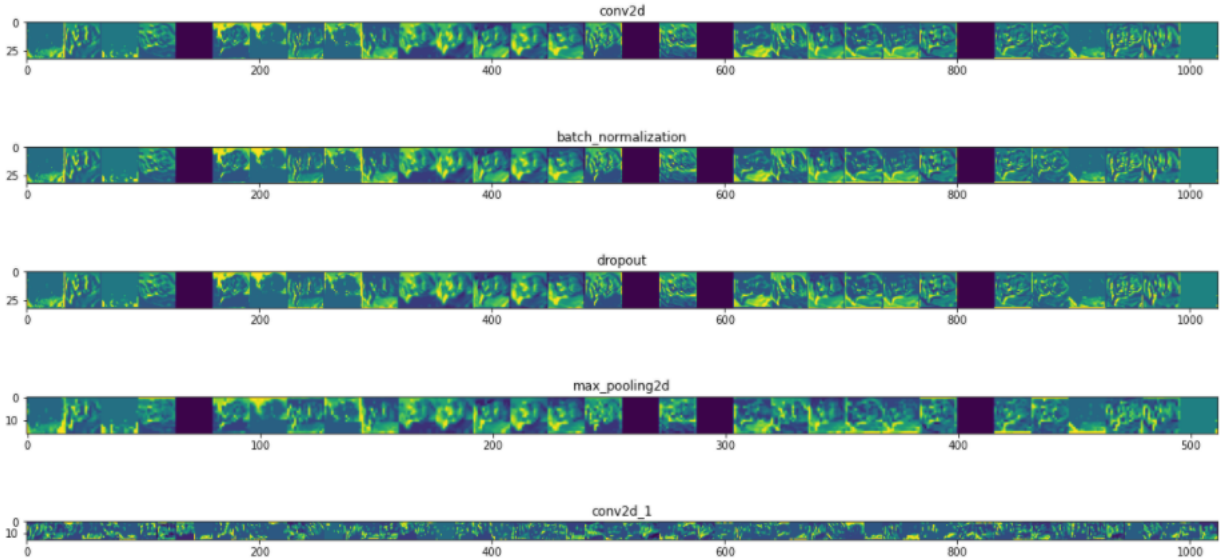


Figure 6: Feature Map

References

- [1] Wikipedia, *Convolutional neural network*, Oct. 13, 2020. https://en.wikipedia.org/wiki/Convolutional_neural_network.