

Convolutional Neural Network for Image Classification of the CIFAR-10 dataset

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1 Introduction

In this project we perform the training of a convolutional neural network for image classification using the [CIFAR-10 dataset](#). The reason behind deep convolutional networks is that they have been applied recently specially for object recognition. The convolution name comes from the "convolution" operator which are matrix filters that perform smoothing, detect edges, get gradient features, etc., that put all together help train the network for image recognition.

The neural network design and training was made using [TFLearn](#), which is a high-level API built on top of TensorFlow. Using TFLearn, the network design and training is made in just a few lines, that is why we decided to use it for fast experimentation.

2 Network Design

The network design involves a series of steps. The main steps are convolution, downsampling and making the prediction. This process is better described in Figure 1.

The first step is doing the convolution itself. As stated before, convolution is useful for detecting certain patterns through a series of masks applied all over the image. That is showed in the second column of Figure 1. After applying convolution, we will be given a smaller set of values that represent the areas of the image that might be interesting to analyze for recognition.

The second step is to downsample the resulting values of the convolution. It means that we will only keep the most representative values of our set. This process is achieved applying the *max_pooling* function.

Finally the whole number of values of the input image is reduced and now we have a smaller set of values. This values can enter a final bigger neural network for the classification itself.

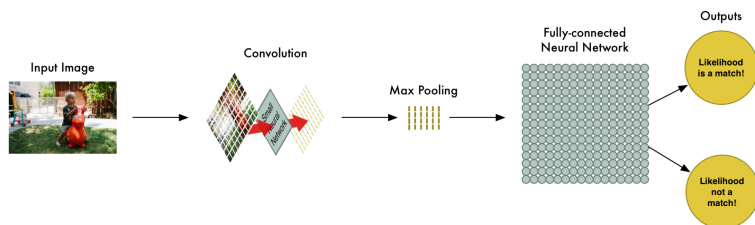


Figure 1: Convolutional Network for image classification. Image extracted from [\[Gei16\]](#).

3 Results

We run a model similar to the one found in [\[Gei16\]](#). We performed a total of 70 iterations on the data, using a *batch_size* of 96 and a *learning_rate* of 0.001. Also we made a preprocessing of the

images using the tools provided by TFLearn.

After the 40th iterations it can be observed that the accuracy rate does not improve nor decrease considerably.

Finally the accuracy obtained is of approximately 0.8588.

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Training Step: 29697 | total loss: 0.49076 | time: 130.294s
| Adam | epoch: 057 | loss: 0.49076 - acc: 0.8379 | val_loss: 0.59079 - val_acc: 0.8070 -- iter: 5000
0/50000
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Training Step: 30218 | total loss: 0.47891 | time: 130.610s
| Adam | epoch: 058 | loss: 0.47891 - acc: 0.8351 | val_loss: 0.58880 - val_acc: 0.8067 -- iter: 5000
0/50000
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Training Step: 30739 | total loss: 0.46708 | time: 127.543s
| Adam | epoch: 059 | loss: 0.46708 - acc: 0.8300 | val_loss: 0.59080 - val_acc: 0.8043 -- iter: 5000
0/50000
--
Training Step: 31260 | total loss: 0.45190 | time: 128.192s
| Adam | epoch: 060 | loss: 0.45190 - acc: 0.8368 | val_loss: 0.57213 - val_acc: 0.8110 -- iter: 5000
0/50000
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Training Step: 31781 | total loss: 0.48440 | time: 127.859s
| Adam | epoch: 061 | loss: 0.48440 - acc: 0.8320 | val_loss: 0.59026 - val_acc: 0.8076 -- iter: 5000
0/50000
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Training Step: 32302 | total loss: 0.50060 | time: 127.735s
| Adam | epoch: 062 | loss: 0.50060 - acc: 0.8253 | val_loss: 0.59484 - val_acc: 0.8064 -- iter: 5000
0/50000
--
Training Step: 32823 | total loss: 0.44248 | time: 129.295s
| Adam | epoch: 063 | loss: 0.44248 - acc: 0.8485 | val_loss: 0.59090 - val_acc: 0.8096 -- iter: 5000
0/50000
--
Training Step: 33344 | total loss: 0.42287 | time: 129.557s
| Adam | epoch: 064 | loss: 0.42287 - acc: 0.8439 | val_loss: 0.56150 - val_acc: 0.8175 -- iter: 5000
0/50000
--
Training Step: 33865 | total loss: 0.44179 | time: 127.885s
| Adam | epoch: 065 | loss: 0.44179 - acc: 0.8437 | val_loss: 0.57298 - val_acc: 0.8145 -- iter: 5000
0/50000
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Training Step: 34386 | total loss: 0.41071 | time: 130.235s
| Adam | epoch: 066 | loss: 0.41071 - acc: 0.8508 | val_loss: 0.58996 - val_acc: 0.8076 -- iter: 5000
0/50000
--
Training Step: 34907 | total loss: 0.43419 | time: 131.953s
| Adam | epoch: 067 | loss: 0.43419 - acc: 0.8428 | val_loss: 0.56881 - val_acc: 0.8157 -- iter: 5000
0/50000
--
Training Step: 35428 | total loss: 0.44736 | time: 125.423s
| Adam | epoch: 068 | loss: 0.44736 - acc: 0.8439 | val_loss: 0.57239 - val_acc: 0.8129 -- iter: 5000
0/50000
--
Training Step: 35949 | total loss: 0.47329 | time: 125.473s
| Adam | epoch: 069 | loss: 0.47329 - acc: 0.8353 | val_loss: 0.57881 - val_acc: 0.8093 -- iter: 5000
0/50000
--
Training Step: 36470 | total loss: 0.44886 | time: 131.177s
| Adam | epoch: 070 | loss: 0.44886 - acc: 0.8439 | val_loss: 0.57713 - val_acc: 0.8120 -- iter: 5000
0/50000
--

```

Figure 2: Training results

4 Conclusions

This is the basic modeling for a convolutional neural network for the classification of images in the CIFAR-10 dataset, but this same idea can be applied for the recognition of other types of objects. Also, depending on the kind of the dataset we are trying to classify, many more layers of convolution and downsampling can be added to the network in order to improve its performance.

References

- [Gei16] Adam Geitgey. Machine Learning is Fun! Part 3: deep learning and convolutional neural networks. 2016.