STEVENS INSTITUTE OF TECHNOLOGY

DEPARTMENT OF ELECTRICAL ENGINEERING

EE628: DATA ACQUISITION/PROC II

Homework Assignment 5

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1 Part 1:

1.1 What are the advantages of a CNN over a fully connected deep neural network for image classification?

A convolutional neural network (CNN) has the following properties:

- Local receptive fields
- Shared weights (weight replication)
- Spatial or temporal sub-sampling

CNNs exploit the local structure in the input vector by connecting each neuron with a small set of neighboring variables (or pixels) (local receptive field). This allows to extract elementary visual features in an image by using neighboring pixels that are closely correlated. Instead of having different weights for each connection, the parameters are replicated over these connections for a given filter (weight replication). Moreover, pooling layers reduce the resolution of the images by making the network invariant of scale, shift or distortion [1]

1.2 Why would you want to add a max pooling layer rather than a convolutional layer with the same stride?

Max pooling sub-samples the input image by replacing a small neighborhood of pixels with the maximum value in that neighborhood, thereby reducing the resolution whereas convolutional layer involves taking the weighted sum of inputs and involves more computations and parameters.

1.3 When would you want to add a local response normalization layer?

Normalization helps solve the problem of vanishing or exploding values of input. It is normally done at the start of a deep network so that in the successive layers the inputs don't vanish (reduce to zero) or explode (increase exponentially). This is commonly done in inception networks that use multiple filters of different sizes in parallel and later concatenate their output by stacking. In order to maintain consistency in the input values after stacking, the values are normalized.

1.4 Test below CNN codes with MNIST data set and show the model accuracy.

Total params: 594,922 Trainable params: 594,922 Non-trainable params: 0 Epoch 2/5 937/937 0.9931 Epoch 3/5 937/937 [= ======] - 147s 157ms/step - loss: 0.0481 - acc: 0.9851 - val_loss: 0.0208 - val_acc: 0.9927 Epoch 4/5 937/937 [=======] - 146s 156ms/step - loss: 0.0401 - acc: 0.9877 - val_loss: 0.0217 - val_acc: Epoch 5/5 937/937 [: =======] - 146s 156ms/step - loss: 0.0360 - acc: 0.9891 - val loss: 0.0185 - val acc: 10000/10000 [====== =====] - 6s 631us/step Test accuracy: 0.9945

1.5 Make comments on your results in step 4.

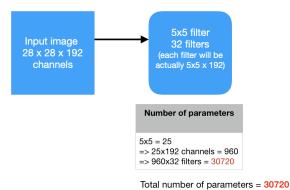
In Homework 3 we saw that a conventional, fully-connected, sequential neural network gave 98.38% accuracy on MNIST dataset whereas CNN gives an accuracy of 99.45% thereby giving a 1.1% increase in test set accuracy. Hence, CNN performs better than traditional fully-connected neural network on the same dataset.

1.6 Repeat step 4 with Fashion-MNIST dataset and remark your results.

In Homework 3 we saw that a conventional, fully-connected, sequential neural network gave 89.50% accuracy on FASHION-MNIST dataset whereas CNN gives an accuracy of 90.35%. Although the accuracy still hasn't improved much but CNN performs better than traditional fully-connected neural network for the same dataset.

2 Part 2:

We will choose Option 2 because it has half the number of parameters than Option 1.



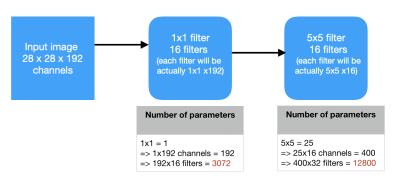


Figure 1: Option 1

Total number of parameters = 3072 + 12800 = 15872

Figure 2: Option 2

References

[1] Y. LeCun, L. Bottou, Y. Bengio, P. Haffner, et al. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998.