

CS 273: Machine Learning Final Project

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1 Introduction

2 Dataset

3 Neural Network Models

To analyse the capacity of neural network models on the fashion-mnist data, we chose to use a feedforward and convolutional neural network. While holding all other parameters constant, the number of hidden layers, k was varied for values 1, 2, 4, 8. Results of this analysis are presented below with a summary of the architectures of both models.

3.1 FeedForward model

3.1.1 Architecture

Using tensorflow with keras, we built a feedforward network that takes fashion mnist data as input read through the mnist-reader.py script. The network has k hidden layers where k is varied for an analysis of capacity, that is a comparison of deep vs shallow networks on the fashion-mnist dataset. The data is split into training and validation data as shown in the model parameters below and the model is trained for 50 epochs where each epoch has 40000 iterations. In addition we use dropout factors less than 1 for regularization and cross entropy as loss function with the adadelata optimizer as a learning rate method for our gradient descent. The hidden layers use relu for an activation function while the output layer uses softmax. All inputs are normalized. Below are parameters and results for each k in the set 1, 2, 4, 8

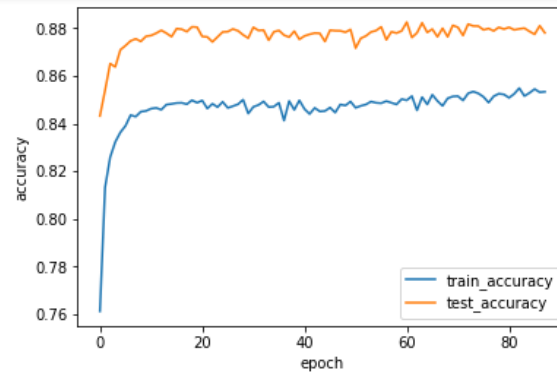
1. $K = 1$

x_train shape: (60000, 784) y_train shape: (60000,)

Layer (type)	Output Shape	Param #
input_3 (InputLayer)	(None, 784)	0
batch_normalization_2 (Batch Normalization)	(None, 784)	3136
dropout_4 (Dropout)	(None, 784)	0
dense_4 (Dense)	(None, 128)	100480
dropout_5 (Dropout)	(None, 128)	0
dense_5 (Dense)	(None, 10)	1290

Total params: 104,906
Trainable params: 103,338
Non-trainable params: 1,568

Train on 40199 samples, validate on 19801 samples



10000/10000 [=====] - 0s 37us/step

Out[2]: [0.40412045266628266, 0.8688]

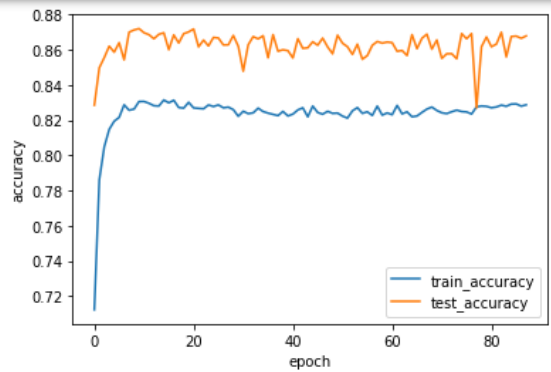
2. $K = 2$

x_train shape: (60000, 784) y_train shape: (60000,)

Layer (type)	Output Shape	Param #
input_4 (InputLayer)	(None, 784)	0
batch_normalization_3 (Batch Normalization)	(None, 784)	3136
dropout_6 (Dropout)	(None, 784)	0
dense_6 (Dense)	(None, 128)	100480
dropout_7 (Dropout)	(None, 128)	0
dense_7 (Dense)	(None, 256)	33024
dropout_8 (Dropout)	(None, 256)	0
dense_8 (Dense)	(None, 10)	2570

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Total params: 139,210
Trainable params: 137,642
Non-trainable params: 1,568

Train on 40199 samples, validate on 19801 samples



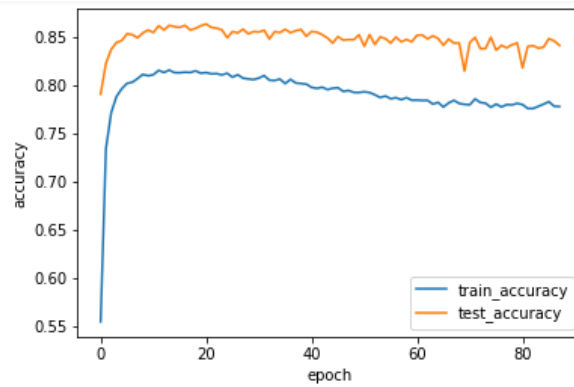
10000/10000 [=====] - 0s 35us/step

Out[4]: [0.46054650063514707, 0.8587]

3. $K = 4$

x_train shape: (60000, 784) y_train shape: (60000,)

Layer (type)	Output Shape	Param #
input_5 (InputLayer)	(None, 784)	0
batch_normalization_4 (Batch Normalization)	(None, 784)	3136
dropout_9 (Dropout)	(None, 784)	0
dense_9 (Dense)	(None, 128)	100480
dropout_10 (Dropout)	(None, 128)	0
dense_10 (Dense)	(None, 256)	33024
dropout_11 (Dropout)	(None, 256)	0
dense_11 (Dense)	(None, 128)	32896
dropout_12 (Dropout)	(None, 128)	0
dense_12 (Dense)	(None, 128)	16512
dropout_13 (Dropout)	(None, 128)	0
dense_13 (Dense)	(None, 10)	1290
Total params: 187,338		
Trainable params: 185,770		
Non-trainable params: 1,568		
Train on 40199 samples, validate on 19801 samples		



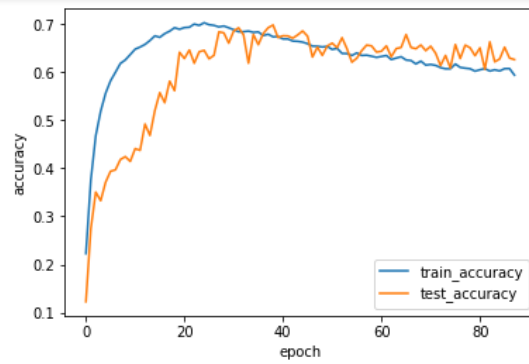
10000/10000 [=====] - 1s 54us/step

Out[5]: [0.549263471364975, 0.8291]

4. $K = 8$

x_train shape: (60000, 784) y_train shape: (60000,)

Layer (type)	Output Shape	Param #
input_6 (InputLayer)	(None, 784)	0
batch_normalization_5 (Batch Normalization)	(None, 784)	3136
dropout_14 (Dropout)	(None, 784)	0
dense_14 (Dense)	(None, 128)	100480
dropout_15 (Dropout)	(None, 128)	0
dense_15 (Dense)	(None, 256)	33024
dropout_16 (Dropout)	(None, 256)	0
dense_16 (Dense)	(None, 128)	32896
dropout_17 (Dropout)	(None, 128)	0
dense_17 (Dense)	(None, 128)	16512
dropout_18 (Dropout)	(None, 128)	0
dense_18 (Dense)	(None, 128)	16512
dropout_19 (Dropout)	(None, 128)	0
dense_19 (Dense)	(None, 128)	16512
dropout_20 (Dropout)	(None, 128)	0
dense_20 (Dense)	(None, 128)	16512
dropout_21 (Dropout)	(None, 128)	0
dense_21 (Dense)	(None, 128)	16512
dropout_22 (Dropout)	(None, 128)	0
dense_22 (Dense)	(None, 10)	1290
Total params: 253,386		
Trainable params: 251,818		
Non-trainable params: 1,568		
Train on 40199 samples, validate on 19801 samples		



10000/10000 [=====] - 1s 67us/step

Out[6]: [1.0562932844161987, 0.6197]

3.2 Convolutional model

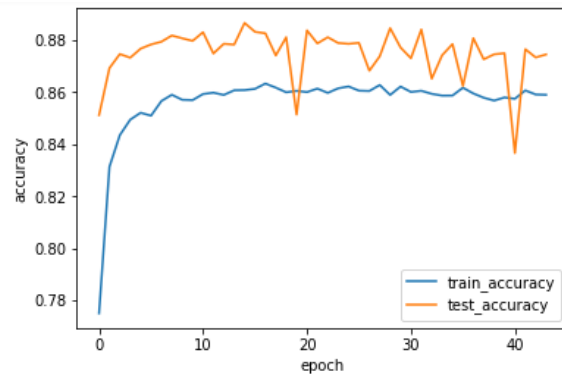
3.2.1 Architecture

The convolutional model(cnn) is similar to the feedforward model in number of hidden layers, optimizer, regularization, activation functions, and validation. However, the cnn also has 2 3x3 convolutional filters and a 2x2 max pooling layer for downsampling the convolution layers. Results follow below.

1. $K = 1$

x_train shape: (60000, 784) y_train shape: (60000,)

Layer (type)	Output Shape	Param #
input_5 (InputLayer)	(None, 784)	0
batch_normalization_4 (Batch Normalization)	(None, 784)	3136
dropout_15 (Dropout)	(None, 784)	0
reshape_4 (Reshape)	(None, 28, 28, 1)	0
conv2d_8 (Conv2D)	(None, 26, 26, 32)	320
dropout_16 (Dropout)	(None, 26, 26, 32)	0
max_pooling2d_4 (MaxPooling2D)	(None, 13, 13, 32)	0
flatten_4 (Flatten)	(None, 5408)	0
dense_7 (Dense)	(None, 128)	692352
dropout_17 (Dropout)	(None, 128)	0
dense_8 (Dense)	(None, 10)	1290
Total params: 697,098		
Trainable params: 695,530		
Non-trainable params: 1,568		
Train on 40199 samples, validate on 19801 samples		



10000/10000 [=====] - 2s 218us/step

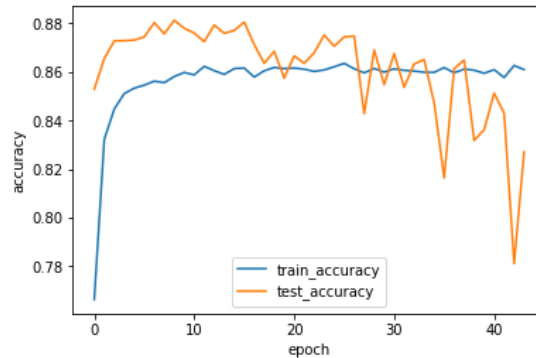
Out[5]: [0.40157343983650207, 0.8689]

2. $K = 2$

x_train shape: (60000, 784) y_train shape: (60000,)

Layer (type)	Output Shape	Param #
input_3 (InputLayer)	(None, 784)	0
batch_normalization_2 (Batch Normalization)	(None, 784)	3136
dropout_6 (Dropout)	(None, 784)	0
reshape_2 (Reshape)	(None, 28, 28, 1)	0
conv2d_4 (Conv2D)	(None, 26, 26, 32)	320
dropout_7 (Dropout)	(None, 26, 26, 32)	0
conv2d_5 (Conv2D)	(None, 24, 24, 32)	9248
dropout_8 (Dropout)	(None, 24, 24, 32)	0
max_pooling2d_2 (MaxPooling2D)	(None, 12, 12, 32)	0
flatten_2 (Flatten)	(None, 4608)	0
dense_2 (Dense)	(None, 128)	589952
dropout_9 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 10)	1290
Total params: 603,946		
Trainable params: 602,378		
Non-trainable params: 1,568		

Train on 40199 samples, validate on 19801 samples



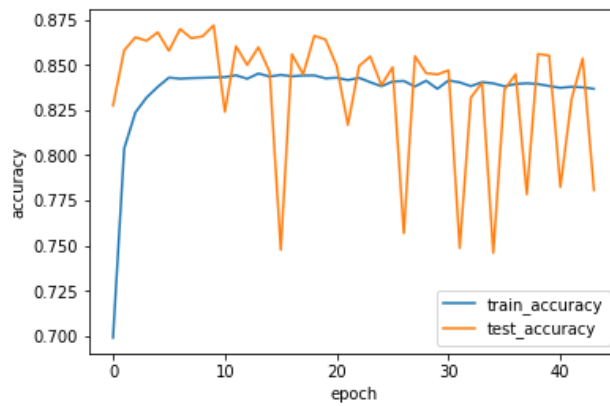
10000/10000 [=====] - 4s 440us/step

Out[3]: [0.5941237535476684, 0.8212]

3. $K = 4$

x_train shape: (60000, 784) y_train shape: (60000,)

Layer (type)	Output Shape	Param #
input_4 (InputLayer)	(None, 784)	0
batch_normalization_3 (Batch Normalization)	(None, 784)	3136
dropout_10 (Dropout)	(None, 784)	0
reshape_3 (Reshape)	(None, 28, 28, 1)	0
conv2d_6 (Conv2D)	(None, 26, 26, 32)	320
dropout_11 (Dropout)	(None, 26, 26, 32)	0
conv2d_7 (Conv2D)	(None, 24, 24, 32)	9248
dropout_12 (Dropout)	(None, 24, 24, 32)	0
max_pooling2d_3 (MaxPooling2D)	(None, 12, 12, 32)	0
flatten_3 (Flatten)	(None, 4608)	0
dense_4 (Dense)	(None, 128)	589952
dropout_13 (Dropout)	(None, 128)	0
dense_5 (Dense)	(None, 128)	16512
dropout_14 (Dropout)	(None, 128)	0
dense_6 (Dense)	(None, 10)	1290
Total params: 620,458		
Trainable params: 618,890		
Non-trainable params: 1,568		
Train on 40199 samples, validate on 19801 samples		



10000/10000 [=====] - 5s 460us/step

4]: [0.7686937316894531, 0.7717]

3.3 Discussion of results

The feedforward model gave more consistent predictions with a smoother curve while the cnn gave us higher accuracy with a peak of about 90%. For both architectures, the rate of overfitting increased with increase in the number of hidden layers. More so for the cnn where by $k = 4$ we see an overwhelming amount of overfitting. We also see that the peak accuracy never increased with increase in number of hidden layers. Further proving the known fact that capacity of a neural network doesnot increase with deeper networks but only the type of functions that can be estimated improves. A good next step in the capacity study would be to look at how the network performance changes with wider hidden layer, that is hidden layers with more neurons.