This assignment focused on low rank model compression. In order to achieve compression singular value decomposition is used to isolate a lowrank model from the resulting matrices where the origin matrix is each set of weights from a previously trained model. The derived weights are used to initialize a new compressed model with reduced parameters which preserves the accuracy of the original model in decreasing amounts as the compression is increased.

Step 1: Design and Train the light-weight model: The model created is a dense feed forward neural network with 100, 50, and 10 neuron layers respectively. Here's the model summary. Layers are fully connected and contain a bias neuron initiated to 1. Relu activations are used.

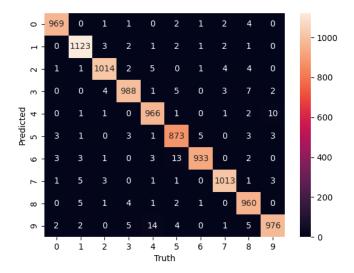
Model: "sequential"

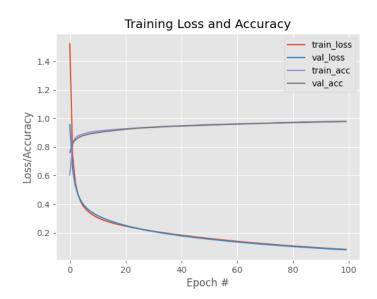
Layer (type)	Output Shape	Param #	
flatten (Flatten)	(None, 784)	0	
dense (Dense)	(None, 100)	78500	
dense_1 (Dense)	(None, 50)	5050	
dense_2 (Dense)	(None, 10)	510	

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Total params: 84,060 Trainable params: 84,060 Non-trainable params: 0

To train this network the mnist dataset was used. To preprocess the images they were shuffled, converted to floats, normalized to 0-1, translated in the x and y axis between -3 and +3, as well as rotated randomly between +35 and -35 degrees to increase the robustness of the model. Below you'll find the results of this model trained on the mnist dataset. Results were achieved using a .01 learning rate over 100 epochs.





## Step 2: Generate the low rank model:

To generate the low rank model I took advantage of the tensorflow linear algebra library to compute svd on each model layer. Following this the values were converted to numPy floats and scaled by the compression value set earlier in the program (for this section it was set to a default value of 1 for no compression). This resulted in u e vT, the singular alue decomposition of the weight matrix. For simplification u and e were multiplied into a single matrix and stored to be later used as weight layers in the new model. To create the new model I set each layer to the first shape dimension given a shape (x,y). From there I used the weights and bias from the previous steps. Some bias layers needed to be initiated randomly due to the change in shape, whereas for the U' layers the arrays could be sliced along with the matrix decomposition to match. This strategy seems a little hand wavey without running more testing.

Model: "sequential"

Layer (type)	Output Shape	Param #	
flatten (Flatten)	(None, 784)	0	
dense (Dense)	(None, 100)	78500	
dense_1 (Dense)	(None, 100)	10100	
dense_2 (Dense)	(None, 50)	5050	
dense_3 (Dense)	(None, 50)	2550	
dense_4 (Dense)	(None, 10)	510	
dense_5 (Dense)	(None, 10)	110	

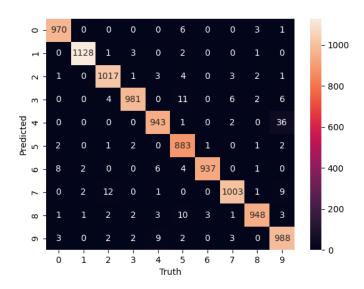
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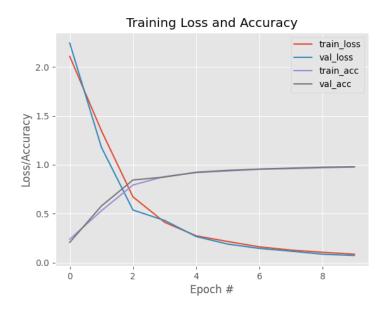
Total params: 96,820 Trainable params: 96,820 Non-trainable params: 0

Step 3: Apply refinement training to the low-rank model. For refinement training the model was trained on the dataset for 10 epochs and a trial and

error learning rate of .15 and no compression. Here are the results:

## Epoch 10/10 1/79 [......] - ETA: 0s - loss: 0.0758 - accuracy: 0.98433/79 [=======>.....] - ETA: 0s - loss: 0.0935 - accuracy: 0.97165/79





Step 4: Repeat steps 2 and 3 with 2x, 4x, and 8x compression. Report the same as the above results, and add in the model summary for each level of compression.

2x model compression: Learning rate: .1

The model performed close to the original with 2x compression.

## Epoch 10/10

1/79 [......] - ETA: 0s - loss: 0.101828/79 [=======>.....] - ETA: 0s -

[=============] - Os 4ms/step - loss: 0.1477 - accuracy: 0.9606 - val\_loss:

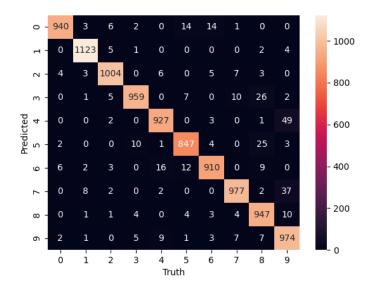
0.1330 - val accuracy: 0.9608

79/79 [=======] - 0s 1ms/step

Model: "sequential"

Layer (type)	Output Shape	Param #	
flatten (Flatten)	(None, 784)	0	
dense (Dense)	(None, 50)	39250	
dense_1 (Dense)	(None, 100)	5100	
dense_2 (Dense)	(None, 25)	2525	
dense_3 (Dense)	(None, 50)	1300	
dense_4 (Dense)	(None, 5)	255	
dense_5 (Dense)	(None, 10)	60	

Total params: 48,490 Trainable params: 48,490 Non-trainable params: 0





4x Compression: learning\_rate = .035 – the model lost a lot of steam being compressed 4x. The diagonal pattern of the confusion matrix is somewhat preserved, but is starting to fall away.

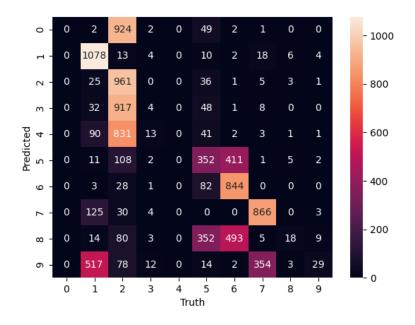
```
Epoch 10/10
```

Model: "sequential"

Layer (type)	Output Shape	Param #	
flatten (Flatten)	(None, 784)	0	
dense (Dense)	(None, 25)	19625	
dense_1 (Dense)	(None, 100)	2600	
dense_2 (Dense)	(None, 12)	1212	
dense_3 (Dense)	(None, 50)	650	
dense_4 (Dense)	(None, 2)	102	
dense_5 (Dense)	(None, 10)	30	

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Total params: 24,219 Trainable params: 24,219 Non-trainable params: 0





8x Compression: Learning rate: .015 – the model has lost most of its accuracy coming in at 18%. Tell tale signs of compression can be seen in the confusion matrix as the error is heightened.

## Model: "sequential"

Layer (type)	Output Shape	Param #
flatten (Flatten)	(None, 784)	0
dense (Dense)	(None, 12)	9420
dense_1 (Dense)	(None, 100)	1300
dense_2 (Dense)	(None, 6)	606
dense_3 (Dense)	(None, 50)	350
dense_4 (Dense)	(None, 1)	51
dense_5 (Dense)	(None, 10)	20

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Total params: 11,747 Trainable params: 11,747 Non-trainable params: 0

