HW5_Task2

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1 Applied Machine Learning Homework 5

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2 Task 2

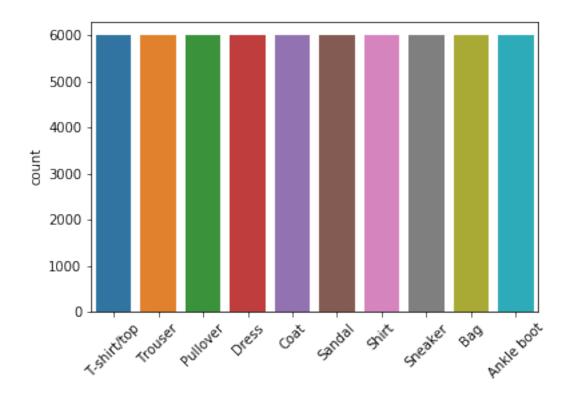
In [0]: import numpy as np

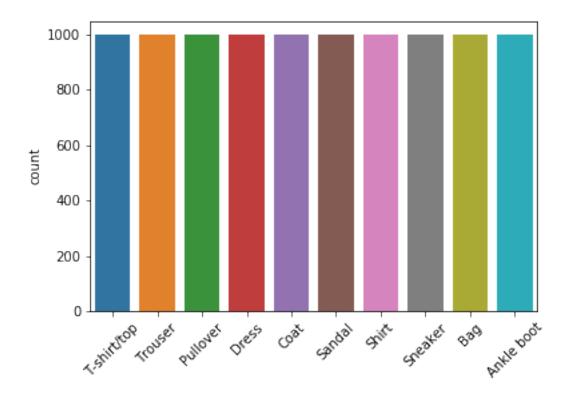
Train a multilayer perceptron (fully connected) on the Fashion MNIST dataset using the traditional train/test split as given by fashion_mnist.load_data in keras. Use a separate 10000 samples (from the training set) for model selection and to compute learning curves (accuracy vs epochs, not vs n_samples). Compare a "vanilla" model with a model using drop-out (potentially a bigger model), and to a model using batch normalization and residual connections (but not dropout). Visualize learning curves for all models.

Confirm that we have a balanced data set:

X_train = X_train/255
X_test = X_test/255

In [0]: # scale





Check GPU status

3 Base 'Vanilla' Model

```
In [0]: from keras import Sequential
    from keras.layers import Dense, Flatten, Dropout, BatchNormalization, Input, add, Activ
    from keras import regularizers
    from keras import Model

In [8]: # 1 layer model
    # initiate model
    model_vanilla1 = Sequential()

# flatten layer
    model_vanilla1.add(Flatten(input_shape = (28,28)))
```

```
# first layer
     model_vanilla1.add(Dense(128,
                input_dim = 784,
                activation='relu'))
     # output layer
     model_vanilla1.add(Dense(10, activation='softmax'))
     # compile
     model_vanilla1.compile(optimizer = 'adam',
               loss = 'sparse_categorical_crossentropy',
               metrics = ['accuracy'])
     model_vanilla1.summary()
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/framework/op_
Instructions for updating:
Colocations handled automatically by placer.
Layer (type) Output Shape Param #
______
flatten_1 (Flatten)
                   (None, 784)
-----
dense_1 (Dense)
                  (None, 128)
                                    100480
dense 2 (Dense)
                  (None, 10)
                                    1290
._____
Total params: 101,770
Trainable params: 101,770
Non-trainable params: 0
In [10]: vanilla1 = model_vanilla1.fit(X_train,
                          y_train,
                          epochs=50,
                          validation_split=10000/60000)
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/ops/math_ops.
Instructions for updating:
Use tf.cast instead.
Train on 50000 samples, validate on 10000 samples
Epoch 1/50
Epoch 2/50
Epoch 3/50
Epoch 4/50
```

```
Epoch 5/50
Epoch 6/50
Epoch 7/50
Epoch 8/50
Epoch 9/50
Epoch 10/50
Epoch 11/50
Epoch 12/50
Epoch 13/50
Epoch 14/50
Epoch 15/50
Epoch 16/50
Epoch 17/50
Epoch 18/50
Epoch 19/50
Epoch 20/50
50000/50000 [============== ] - 5s 97us/step - loss: 0.1776 - acc: 0.9336 - val
Epoch 21/50
50000/50000 [=============== ] - 5s 93us/step - loss: 0.1747 - acc: 0.9351 - val
Epoch 22/50
Epoch 23/50
Epoch 24/50
Epoch 25/50
Epoch 26/50
Epoch 27/50
Epoch 28/50
```

```
Epoch 29/50
50000/50000 [============== ] - 4s 88us/step - loss: 0.1419 - acc: 0.9471 - val
Epoch 30/50
Epoch 31/50
Epoch 32/50
50000/50000 [=============== ] - 4s 87us/step - loss: 0.1324 - acc: 0.9505 - val
Epoch 33/50
50000/50000 [============== ] - 5s 99us/step - loss: 0.1318 - acc: 0.9507 - val
Epoch 34/50
Epoch 35/50
Epoch 36/50
Epoch 37/50
50000/50000 [=============== ] - 4s 87us/step - loss: 0.1209 - acc: 0.9545 - val
Epoch 38/50
Epoch 39/50
Epoch 40/50
Epoch 41/50
Epoch 42/50
Epoch 43/50
Epoch 44/50
50000/50000 [=============== ] - 4s 87us/step - loss: 0.1066 - acc: 0.9597 - val
Epoch 45/50
Epoch 46/50
50000/50000 [=============== ] - 4s 88us/step - loss: 0.1010 - acc: 0.9630 - val
Epoch 47/50
Epoch 48/50
Epoch 49/50
Epoch 50/50
```

In [30]: print('Vanilla modeltest score:',

```
model_vanilla1.evaluate(X_test, y_test))
10000/10000 [===========] - 0s 40us/step
Vanilla modeltest score: [0.5406438440233469, 0.8806]
In [27]: _ = pd.DataFrame(vanilla1.history).plot(
             title = 'Vanilla Model Learning Curve with Loss',
             xticks = range(0,51,5),
             yticks = [0.1* x for x in range(0,11)]
           = plt.legend(loc = 4)
           = plt.xlabel('epoch')
           = plt.ylabel('Accuracy/Loss')
                       Vanilla Model Learning Curve with Loss
          1.0
          0.9
          0.8
          0.7
       Accuracy/Loss
          0.6
          0.5
          0.4
          0.3
                                                                  val loss
                                                                  val acc
          0.2
                                                                  loss
          0.1
                                                                 acc
```

Quick observation Validation accuracy starts to flatten at around 5 epochs, while the validation loss bottoms out at about epoch 5, and thereafter steadily increases until the end.

25

epoch

30

35

40

45

50

Larger and Deeper Vanilla Model 6 layers with 512 cells

5

10

15

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0.0

```
# flatten layer
       model_vanilla2.add(Flatten(input_shape = (28,28)))
       # first layer
       model_vanilla2.add(Dense(512,
                     input_dim = 784,
                     activation='relu'))
       # second
       model_vanilla2.add(Dense(512,
                     activation='relu'))
       # third
       model_vanilla2.add(Dense(512,
                     activation='relu'))
       # fourth
       model_vanilla2.add(Dense(512,
                    activation='relu'))
       # fifth
       model_vanilla2.add(Dense(512,
                    activation='relu'))
       # sixth
       model_vanilla2.add(Dense(512,
                     activation='relu'))
       # output layer
       model_vanilla2.add(Dense(10, activation='softmax'))
       # compile
       model_vanilla2.compile(optimizer = 'adam',
                   loss = 'sparse_categorical_crossentropy',
                   metrics = ['accuracy'])
       model vanilla2.summary()
                Output Shape
Layer (type)
                                             Param #
______
                       (None, 784)
flatten 2 (Flatten)
_____
                      (None, 512)
dense_3 (Dense)
                                             401920
dense_4 (Dense)
               (None, 512)
                                            262656
               (None, 512)
dense_5 (Dense)
                                             262656
```

```
(None, 512)
dense 8 (Dense)
                   262656
dense_9 (Dense)
      (None, 10)
                   5130
Total params: 1,720,330
Trainable params: 1,720,330
Non-trainable params: 0
In [29]: vanilla2 = model_vanilla2.fit(X_train,
              y_train,
              epochs=50,
              validation_split= 10000/60000)
Train on 50000 samples, validate on 10000 samples
Epoch 1/50
Epoch 2/50
Epoch 3/50
Epoch 4/50
Epoch 5/50
50000/50000 [=============== ] - 8s 155us/step - loss: 0.3254 - acc: 0.8822 - va
Epoch 6/50
Epoch 7/50
50000/50000 [============== ] - 8s 157us/step - loss: 0.2969 - acc: 0.8938 - va
Epoch 8/50
Epoch 9/50
Epoch 10/50
Epoch 11/50
Epoch 12/50
Epoch 13/50
Epoch 14/50
```

(None, 512)

(None, 512)

262656

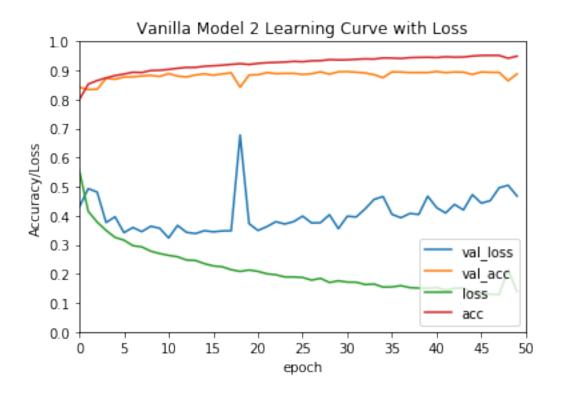
262656

dense_6 (Dense)

dense_7 (Dense)

```
Epoch 15/50
50000/50000 [============== ] - 7s 142us/step - loss: 0.2349 - acc: 0.9144 - va
Epoch 16/50
Epoch 17/50
50000/50000 [============== ] - 7s 149us/step - loss: 0.2243 - acc: 0.9180 - va
Epoch 18/50
50000/50000 [============== ] - 8s 154us/step - loss: 0.2142 - acc: 0.9209 - va
Epoch 19/50
50000/50000 [============== ] - 7s 142us/step - loss: 0.2083 - acc: 0.9232 - va
Epoch 20/50
Epoch 21/50
50000/50000 [============== ] - 7s 141us/step - loss: 0.2084 - acc: 0.9241 - va
Epoch 22/50
Epoch 23/50
Epoch 24/50
Epoch 25/50
Epoch 26/50
Epoch 27/50
50000/50000 [============== ] - 7s 141us/step - loss: 0.1783 - acc: 0.9330 - va
Epoch 28/50
Epoch 29/50
Epoch 30/50
Epoch 31/50
50000/50000 [============= ] - 7s 141us/step - loss: 0.1716 - acc: 0.9366 - va
Epoch 32/50
50000/50000 [============== ] - 7s 142us/step - loss: 0.1712 - acc: 0.9383 - va
Epoch 33/50
Epoch 34/50
Epoch 35/50
Epoch 36/50
Epoch 37/50
Epoch 38/50
```

```
Epoch 39/50
50000/50000 [============== ] - 7s 142us/step - loss: 0.1509 - acc: 0.9449 - va
Epoch 40/50
50000/50000 [============== ] - 8s 156us/step - loss: 0.1502 - acc: 0.9454 - va
Epoch 41/50
50000/50000 [============== ] - 7s 144us/step - loss: 0.1530 - acc: 0.9444 - va
Epoch 42/50
50000/50000 [============== ] - 7s 141us/step - loss: 0.1437 - acc: 0.9469 - va
Epoch 43/50
50000/50000 [============== ] - 7s 140us/step - loss: 0.1504 - acc: 0.9456 - va
Epoch 44/50
Epoch 45/50
Epoch 46/50
Epoch 47/50
Epoch 48/50
Epoch 49/50
Epoch 50/50
In [31]: print('Vanilla model 2 test score:',
        model_vanilla2.evaluate(X_test, y_test))
10000/10000 [=========== ] - 0s 46us/step
Vanilla model 2 test score: [0.49062124730870127, 0.8858]
In [32]: _ = pd.DataFrame(vanilla2.history).plot(
      title = 'Vanilla Model 2 Learning Curve with Loss',
      xticks = range(0,51,5),
      yticks = [0.1* x for x in range(0,11)]
    )
    _ = plt.legend(loc = 4)
    = plt.xlabel('epoch')
     _ = plt.ylabel('Accuracy/Loss')
```



Quick observation For the deeper and larger vanilla model, the validation accuracy also starts to flatten at around the fifth epoch, while the validation loss seems to bottom out at around 15. It then has a very odd spike, but seems to correct itself and then steadily rise after that.

4 Dropout Model

```
# compile
     model_dropout1.compile(optimizer = 'adam',
             loss = 'sparse_categorical_crossentropy',
             metrics = ['accuracy'])
     model_dropout1.summary()
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backen
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep_prob`.
   -----
Layer (type)
               Output Shape
                              Param #
______
flatten_3 (Flatten)
               (None, 784)
   _____
dense_10 (Dense)
               (None, 128)
                              100480
______
dropout_1 (Dropout)
            (None, 128)
           (None, 10)
dense_11 (Dense)
                        1290
______
Total params: 101,770
Trainable params: 101,770
Non-trainable params: 0
._____
In [34]: dropout1 = model_dropout1.fit(X_train,
                      y_train,
                      epochs=50,
                      validation_split= 10000/60000)
Train on 50000 samples, validate on 10000 samples
Epoch 1/50
Epoch 2/50
50000/50000 [============== ] - 5s 92us/step - loss: 0.4833 - acc: 0.8257 - val
Epoch 3/50
Epoch 4/50
50000/50000 [=============== ] - 5s 92us/step - loss: 0.4260 - acc: 0.8448 - val
Epoch 5/50
Epoch 6/50
Epoch 7/50
```

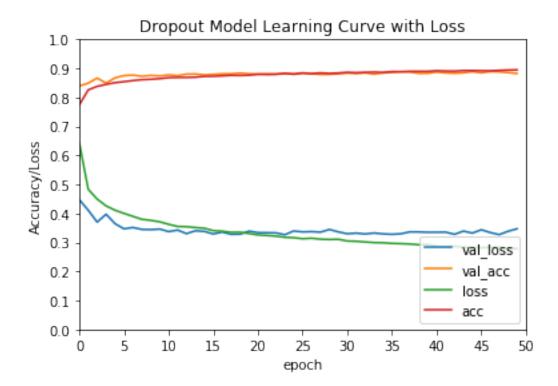
model_dropout1.add(Dense(10, activation='softmax'))

```
Epoch 8/50
50000/50000 [============== ] - 5s 92us/step - loss: 0.3797 - acc: 0.8610 - val
Epoch 9/50
50000/50000 [=============== ] - 5s 91us/step - loss: 0.3762 - acc: 0.8624 - val
Epoch 10/50
50000/50000 [=============== ] - 5s 92us/step - loss: 0.3712 - acc: 0.8644 - val
Epoch 11/50
Epoch 12/50
50000/50000 [=============== ] - 5s 98us/step - loss: 0.3551 - acc: 0.8687 - val
Epoch 13/50
Epoch 14/50
Epoch 15/50
Epoch 16/50
Epoch 17/50
Epoch 18/50
Epoch 19/50
Epoch 20/50
Epoch 21/50
Epoch 22/50
Epoch 23/50
50000/50000 [============== ] - 5s 92us/step - loss: 0.3219 - acc: 0.8795 - val
Epoch 24/50
Epoch 25/50
50000/50000 [=============== ] - 5s 93us/step - loss: 0.3163 - acc: 0.8798 - val
Epoch 26/50
Epoch 27/50
Epoch 28/50
Epoch 29/50
Epoch 30/50
Epoch 31/50
```

```
Epoch 32/50
50000/50000 [=============== ] - 5s 99us/step - loss: 0.3041 - acc: 0.8851 - val
Epoch 33/50
50000/50000 [============== ] - 5s 105us/step - loss: 0.3016 - acc: 0.8862 - va
Epoch 34/50
Epoch 35/50
Epoch 36/50
50000/50000 [============== ] - 5s 91us/step - loss: 0.2967 - acc: 0.8889 - val
Epoch 37/50
Epoch 38/50
Epoch 39/50
Epoch 40/50
50000/50000 [=============== ] - 5s 95us/step - loss: 0.2931 - acc: 0.8897 - val
Epoch 41/50
Epoch 42/50
Epoch 43/50
Epoch 44/50
Epoch 45/50
Epoch 46/50
Epoch 47/50
50000/50000 [============== ] - 5s 92us/step - loss: 0.2833 - acc: 0.8914 - val
Epoch 48/50
Epoch 49/50
50000/50000 [=============== ] - 5s 95us/step - loss: 0.2783 - acc: 0.8942 - val
Epoch 50/50
In [35]: print('Dropout model 1 test score:',
     model_dropout1.evaluate(X_test, y_test))
10000/10000 [=========== ] - Os 44us/step
Dropout model 1 test score: [0.36197602721452715, 0.883]
```

In [37]: _ = pd.DataFrame(dropout1.history).plot(

```
title = 'Dropout Model Learning Curve with Loss',
    xticks = range(0,51,5),
    yticks = [0.1* x for x in range(0,11)]
)
_ = plt.legend(loc = 4)
_ = plt.xlabel('epoch')
_ = plt.ylabel('Accuracy/Loss')
```



Quick observation Both training and validation accuracy flatten at a level around 0.85~0.9. In comparison with the vanilla model, the training accuracy doesn't appear to be overfitted which reached 1, and also saw the validation loss steadily rise as it was approaching 1.

Larger and deeper dropout model

```
activation='relu'))
# drop out layer
model_dropout2.add(Dropout(rate = 0.5))
# second layer
model_dropout2.add(Dense(512,
                activation='relu'))
# drop out layer
model_dropout2.add(Dropout(rate = 0.5))
# third layer
model_dropout2.add(Dense(512,
                activation='relu'))
# drop out layer
model_dropout2.add(Dropout(rate = 0.5))
# fourth layer
model_dropout2.add(Dense(512,
                activation='relu'))
# drop out layer
model_dropout2.add(Dropout(rate = 0.5))
# fifth layer
model_dropout2.add(Dense(512,
                activation='relu'))
# drop out layer
model_dropout2.add(Dropout(rate = 0.5))
# sixth layer
model_dropout2.add(Dense(512,
                activation='relu'))
# drop out layer
model_dropout2.add(Dropout(rate = 0.5))
# output layer
model_dropout2.add(Dense(10, activation='softmax'))
# compile
model_dropout2.compile(optimizer = 'adam',
              loss = 'sparse_categorical_crossentropy',
              metrics = ['accuracy'])
```

model_dropout2.summary()

Layer (type)	Output	Shape	Param #
flatten_4 (Flatten)	(None,	784)	0
dense_12 (Dense)	(None,	512)	401920
dropout_2 (Dropout)	(None,	512)	0
dense_13 (Dense)	(None,	512)	262656
dropout_3 (Dropout)	(None,	512)	0
dense_14 (Dense)	(None,	512)	262656
dropout_4 (Dropout)	(None,	512)	0
dense_15 (Dense)	(None,	512)	262656
dropout_5 (Dropout)	(None,	512)	0
dense_16 (Dense)	(None,	512)	262656
dropout_6 (Dropout)	(None,	512)	0
dense_17 (Dense)	(None,	512)	262656
dropout_7 (Dropout)	(None,	512)	0
dense_18 (Dense)	(None,	10)	5130
Total params: 1,720,330 Trainable params: 1,720,330 Non-trainable params: 0			

```
In [39]: dropout2 = model_dropout2.fit(X_train,
                                       y_train,
                                       epochs=50,
                                       validation_split=10000/60000)
```

```
Train on 50000 samples, validate on 10000 samples
Epoch 1/50
Epoch 2/50
```

```
50000/50000 [=============== ] - 8s 166us/step - loss: 0.7129 - acc: 0.7362 - va
Epoch 3/50
50000/50000 [============== ] - 8s 158us/step - loss: 0.6647 - acc: 0.7648 - va
Epoch 4/50
50000/50000 [============== ] - 8s 157us/step - loss: 0.6460 - acc: 0.7766 - va
Epoch 5/50
50000/50000 [============== ] - 8s 157us/step - loss: 0.6257 - acc: 0.7862 - va
Epoch 6/50
50000/50000 [============== ] - 8s 158us/step - loss: 0.6193 - acc: 0.7891 - va
Epoch 7/50
Epoch 8/50
50000/50000 [============== ] - 8s 158us/step - loss: 0.6066 - acc: 0.7988 - va
Epoch 9/50
50000/50000 [============== ] - 8s 157us/step - loss: 0.5988 - acc: 0.7996 - va
Epoch 10/50
Epoch 11/50
Epoch 12/50
Epoch 13/50
Epoch 14/50
Epoch 15/50
50000/50000 [=============== ] - 8s 157us/step - loss: 0.6087 - acc: 0.8009 - va
Epoch 16/50
Epoch 17/50
50000/50000 [=============== ] - 8s 158us/step - loss: 0.5906 - acc: 0.8056 - va
Epoch 18/50
50000/50000 [============== ] - 8s 157us/step - loss: 0.5906 - acc: 0.8059 - va
Epoch 19/50
50000/50000 [============== ] - 8s 158us/step - loss: 0.5963 - acc: 0.8027 - va
Epoch 20/50
50000/50000 [============== ] - 8s 157us/step - loss: 0.5928 - acc: 0.8050 - va
Epoch 21/50
Epoch 22/50
Epoch 23/50
Epoch 24/50
Epoch 25/50
Epoch 26/50
```

```
50000/50000 [=============== ] - 8s 157us/step - loss: 0.6305 - acc: 0.7918 - va
Epoch 27/50
50000/50000 [============== ] - 8s 157us/step - loss: 0.5952 - acc: 0.8034 - va
Epoch 28/50
50000/50000 [============== ] - 8s 158us/step - loss: 0.6034 - acc: 0.8053 - va
Epoch 29/50
50000/50000 [============== ] - 8s 159us/step - loss: 0.6078 - acc: 0.8016 - va
Epoch 30/50
50000/50000 [============== ] - 8s 157us/step - loss: 0.6149 - acc: 0.8025 - va
Epoch 31/50
Epoch 32/50
Epoch 33/50
50000/50000 [============== ] - 8s 158us/step - loss: 0.6117 - acc: 0.7998 - va
Epoch 34/50
Epoch 35/50
Epoch 36/50
Epoch 37/50
Epoch 38/50
Epoch 39/50
50000/50000 [=============== ] - 8s 157us/step - loss: 0.6261 - acc: 0.7992 - va
Epoch 40/50
Epoch 41/50
Epoch 42/50
50000/50000 [============== ] - 8s 162us/step - loss: 0.6170 - acc: 0.8042 - va
Epoch 43/50
50000/50000 [============== ] - 8s 158us/step - loss: 0.6265 - acc: 0.8034 - va
Epoch 44/50
50000/50000 [============== ] - 8s 158us/step - loss: 0.6201 - acc: 0.8049 - va
Epoch 45/50
Epoch 46/50
Epoch 47/50
Epoch 48/50
Epoch 49/50
Epoch 50/50
```

```
In [40]: print('Dropout model 2 test score:',
             model_dropout2.evaluate(X_test, y_test))
10000/10000 [=======
                           ========= ] - Os 44us/step
Dropout model 2 test score: [0.6149588119506836, 0.8166]
In [42]: _ = pd.DataFrame(dropout2.history).plot(
           title = 'Dropout Model 2 Learning Curve with Loss',
           xticks = range(0,51,5),
           yticks = [0.1* x for x in range(0,11)]
         = plt.legend(loc = 4)
         = plt.xlabel('epoch')
         = plt.ylabel('Accuracy/Loss')
                  Dropout Model 2 Learning Curve with Loss
         1.0
         0.9
         0.8
         0.7
      Accuracy/Loss
         0.6
         0.5
         0.4
         0.3
                                                        val loss
```

0.2

0.1

0.0 +

5

10

15

Quick observation The larger and deeper net with dropout can effectively control the overfitting, as can be seen in this chart. The training and validation scores are much closer together, while the validation loss does not exhibit the steady increase in the later epochs, as was noticed earlier. This generalizability came at a cost in terms of accuracy, though, as the ended around 0.8.

20

25

epoch

30

35

val acc

loss

acc

45

50

40

5 Batch Normalization and Residual Connection Model

```
In [43]: # 1 layer model, which can't adopt res connect in this
       # initiate model
      model_batch1 = Sequential()
       # flatten layer
      model_batch1.add(Flatten(input_shape = (28,28)))
      # first layer
      model_batch1.add(Dense(128,
                   input dim = 784,
                   activation='relu'))
      # batchnormalize layer
      model_batch1.add(BatchNormalization())
      # output layer
      model_batch1.add(Dense(10, activation='softmax'))
       # compile
      model_batch1.compile(optimizer = 'adam',
                 loss = 'sparse_categorical_crossentropy',
                 metrics = ['accuracy'])
      model_batch1.summary()
             Output Shape Param #
Layer (type)
  -----
flatten_5 (Flatten)
                     (None, 784)
_____
dense_19 (Dense)
                (None, 128)
                                         100480
batch_normalization_1 (Batch (None, 128)
                                         512
              (None, 10)
dense 20 (Dense)
_____
Total params: 102,282
Trainable params: 102,026
Non-trainable params: 256
______
In [44]: batch1 = model_batch1.fit(X_train,
                          y_train,
                          epochs=50,
                          validation_split=10000/60000)
```

```
Train on 50000 samples, validate on 10000 samples
Epoch 1/50
50000/50000 [============== ] - 7s 140us/step - loss: 0.4980 - acc: 0.8264 - va
Epoch 2/50
Epoch 3/50
Epoch 4/50
50000/50000 [============== ] - 7s 136us/step - loss: 0.3536 - acc: 0.8733 - va
Epoch 5/50
Epoch 6/50
Epoch 7/50
50000/50000 [============== ] - 6s 123us/step - loss: 0.3181 - acc: 0.8822 - va
Epoch 8/50
Epoch 9/50
Epoch 10/50
Epoch 11/50
Epoch 12/50
Epoch 13/50
Epoch 14/50
Epoch 15/50
Epoch 16/50
50000/50000 [============== ] - 7s 142us/step - loss: 0.2637 - acc: 0.9019 - va
Epoch 17/50
50000/50000 [============= ] - 6s 127us/step - loss: 0.2604 - acc: 0.9042 - va
Epoch 18/50
Epoch 19/50
Epoch 20/50
Epoch 21/50
Epoch 22/50
Epoch 23/50
Epoch 24/50
```

```
Epoch 25/50
Epoch 26/50
50000/50000 [============== ] - 7s 130us/step - loss: 0.2233 - acc: 0.9170 - va
Epoch 27/50
Epoch 28/50
50000/50000 [============== ] - 7s 138us/step - loss: 0.2147 - acc: 0.9193 - va
Epoch 29/50
Epoch 30/50
Epoch 31/50
50000/50000 [============== ] - 6s 123us/step - loss: 0.2083 - acc: 0.9232 - va
Epoch 32/50
Epoch 33/50
Epoch 34/50
Epoch 35/50
Epoch 36/50
Epoch 37/50
Epoch 38/50
Epoch 39/50
Epoch 40/50
50000/50000 [============== ] - 6s 124us/step - loss: 0.1912 - acc: 0.9279 - va
Epoch 41/50
50000/50000 [============= ] - 7s 141us/step - loss: 0.1898 - acc: 0.9303 - va
Epoch 42/50
50000/50000 [============== ] - 7s 133us/step - loss: 0.1853 - acc: 0.9308 - va
Epoch 43/50
Epoch 44/50
Epoch 45/50
Epoch 46/50
Epoch 47/50
Epoch 48/50
```

```
Epoch 49/50
Epoch 50/50
                         =======] - 6s 124us/step - loss: 0.1723 - acc: 0.9359 - va
50000/50000 [====
In [45]: print('Batch normalized model 1 test score:',
           model_batch1.evaluate(X_test, y_test))
10000/10000 [========= ] - 0s 45us/step
Batch normalized model 1 test score: [0.3997763850092888, 0.8806]
In [46]: _ = pd.DataFrame(batch1.history).plot(
          title = 'Batchnorm Model Learning Curve with Loss',
          xticks = range(0,51,5),
          yticks = [0.1* x for x in range(0,11)]
       )
        = plt.legend(loc = 4)
       _ = plt.xlabel('epoch')
       _ = plt.ylabel('Accuracy/Loss')
                Batchnorm Model Learning Curve with Loss
        1.0
        0.9
        0.8
        0.7
     Accuracy/Loss
        0.6
        0.5
        0.4
        0.3
                                                   val loss
        0.2
                                                   val acc
                                                   loss
        0.1
                                                   acc
        0.0
           0
               5
                   10
                        15
                             20
                                  25
                                      30
                                           35
                                                40
                                                     45
                                                         50
                                epoch
```

Larger and deeper dropout batch norm. and residual connection model

```
In [47]: # 6 layer model
        num_class = 10
         # define input layer
         inputs = Input(shape=(28,28,1))
         # flatten
         flat = Flatten()(inputs)
         # 1st Dense layer
         L1_1 = Dense(512, activation='relu')(flat)
         L1_2 = BatchNormalization()(L1_1)
         # 2nd layer
         L2_1 = Dense(512, activation='relu')(L1_2)
         L2_2 = BatchNormalization()(L2_1)
         # 3rd layer
         L3_1 = Dense(512, activation='relu')(L2_2)
         L3_2 = BatchNormalization()(L3_1)
         # skip1
         skip1 = add([L1_2, L3_2])
         # 4th layer
         L4_1 = Dense(512, activation='relu')(skip1)
         L4_2 = BatchNormalization()(L4_1)
         # 5th layer
         L5_1 = Dense(512, activation='relu')(L4_2)
         L5_2 = BatchNormalization()(L5_1)
         #skip2
         skip2 = add([skip1, L5_2])
         # 6th layer
         L6_1 = Dense(512, activation='relu')(skip2)
         L6_2 = BatchNormalization()(L6_1)
         # output layer
         dense = Dense(num_class, activation='softmax')(L6_2)
         # compile
         model_batch2 = Model(inputs = inputs, outputs = dense)
         model_batch2.compile(optimizer = 'adam',
                       loss = 'sparse_categorical_crossentropy',
```

metrics = ['accuracy'])
model_batch2.summary()

Layer (type)	Output	Shape	 Param #	Connected to
input_1 (InputLayer)	(None,	28, 28, 1)	0	
flatten_6 (Flatten)	(None,	784)	0	input_1[0][0]
dense_21 (Dense)	(None,	512)	401920	flatten_6[0][0]
batch_normalization_2 (BatchNor	(None,	512)	2048	dense_21[0][0]
dense_22 (Dense)	(None,	512)	262656	batch_normalization_2[0][0]
batch_normalization_3 (BatchNor	(None,	512)	2048	dense_22[0][0]
dense_23 (Dense)	(None,	512)	262656	batch_normalization_3[0][0]
batch_normalization_4 (BatchNor	(None,	512)	2048	dense_23[0][0]
add_1 (Add)	(None,	512)	0	batch_normalization_2[0][0] batch_normalization_4[0][0]
dense_24 (Dense)	(None,	512)	262656	add_1[0][0]
batch_normalization_5 (BatchNor	(None,	512)	2048	dense_24[0][0]
dense_25 (Dense)	(None,	512)	262656	batch_normalization_5[0][0]
batch_normalization_6 (BatchNor	(None,	512)	2048	dense_25[0][0]
add_2 (Add)	(None,	512)	0	add_1[0][0] batch_normalization_6[0][0]
dense_26 (Dense)	(None,	512)	262656	add_2[0][0]
batch_normalization_7 (BatchNor	(None,	512)	2048	dense_26[0][0]
dense_27 (Dense)	(None,	10)	5130 =======	batch_normalization_7[0][0]

Total params: 1,732,618
Trainable params: 1,726,474
Non-trainable params: 6,144

In [49]: X_train_ = X_train.reshape(X_train.shape[0], 28, 28, 1)

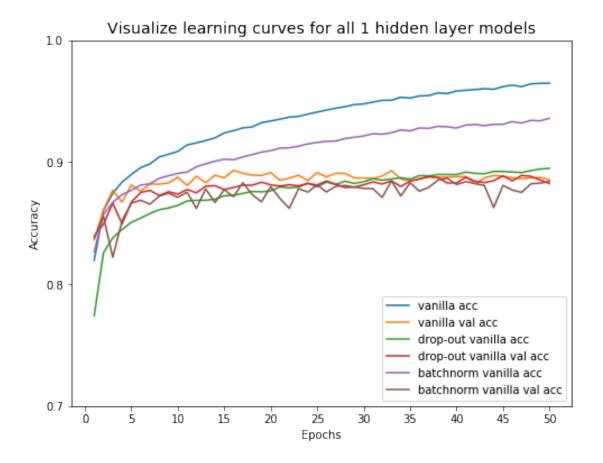
```
Train on 50000 samples, validate on 10000 samples
Epoch 1/50
Epoch 2/50
Epoch 3/50
50000/50000 [=============== ] - 19s 379us/step - loss: 0.3911 - acc: 0.8565 - va
Epoch 4/50
Epoch 5/50
50000/50000 [============== ] - 19s 371us/step - loss: 0.3401 - acc: 0.8759 - variables
Epoch 6/50
50000/50000 [============== ] - 18s 364us/step - loss: 0.3203 - acc: 0.8821 - va
Epoch 7/50
50000/50000 [============== ] - 18s 364us/step - loss: 0.3081 - acc: 0.8872 - variables - variables - loss: 0.3081 - acc: 0.8872 - variables - loss: 0.8722 - variables - loss:
Epoch 8/50
Epoch 9/50
Epoch 10/50
Epoch 11/50
Epoch 12/50
50000/50000 [============== ] - 18s 365us/step - loss: 0.2472 - acc: 0.9075 - value - 
Epoch 13/50
Epoch 14/50
Epoch 15/50
Epoch 16/50
Epoch 17/50
Epoch 18/50
Epoch 19/50
50000/50000 [============== ] - 19s 379us/step - loss: 0.1995 - acc: 0.9225 - variables - 10ss: 0.1995 - acc: 0.9225 - variables - 0.9225 - variables 
Epoch 20/50
Epoch 21/50
```

```
Epoch 22/50
Epoch 23/50
Epoch 24/50
Epoch 25/50
Epoch 26/50
Epoch 27/50
50000/50000 [============== ] - 18s 368us/step - loss: 0.1568 - acc: 0.9396 - value = 18s 368us/step - loss: 0.1568 - acc: 0.9396 - value = 18s 368us/step - loss: 0.1568 - acc: 0.9396 - value = 18s 368us/step - loss: 0.1568 - acc: 0.9396 - value = 18s 368us/step - loss: 0.1568 - acc: 0.9396 - value = 18s 368us/step - loss: 0.1568 - acc: 0.9396 - value = 18s 368us/step - loss: 0.1568 - acc: 0.9396 - value = 18s 368us/step - loss: 0.1568 - acc: 0.9396 - value = 18s 368us/step - loss: 0.1568 - acc: 0.9396 - value = 18s 368us/step - loss: 0.1568 - acc: 0.9396 - value = 18s 368us/step - loss: 0.1568 - acc: 0.9396 - value = 18s 368us/step - loss: 0.1568 - acc: 0.9396 - value = 18s 368us/step - loss: 0.1568 - acc: 0.9396 - value = 18s 368us/step - loss: 0.1568 - acc: 0.9396 - value = 18s 368us/step - loss: 0.1568 - acc: 0.9396 - value = 18s 368us/step - loss: 0.1568 - acc: 0.9396 - value = 18s 368us/step - loss: 0.1568 - acc: 0.9396 - value = 18s 368us/step - loss: 0.1568 - acc: 0.9396 - value = 18s 368us/step - acc: 0.9396 - acc: 0.9
Epoch 28/50
Epoch 29/50
Epoch 30/50
Epoch 31/50
Epoch 32/50
Epoch 33/50
Epoch 34/50
50000/50000 [============== ] - 19s 378us/step - loss: 0.1272 - acc: 0.9510 - variables
Epoch 35/50
50000/50000 [============== ] - 19s 388us/step - loss: 0.1251 - acc: 0.9523 - value | 19s 388us/step - loss: 0.1251 - acc: 0.9523 - value | 19s 388us/step - loss: 0.1251 - acc: 0.9523 - value | 19s 388us/step - loss: 0.1251 - acc: 0.9523 - value | 19s 388us/step - loss: 0.1251 - acc: 0.9523 - value | 19s 388us/step - loss: 0.1251 - acc: 0.9523 - value | 19s 388us/step - loss: 0.1251 - acc: 0.9523 - value | 19s 388us/step - loss: 0.1251 - acc: 0.9523 - value | 19s 388us/step - loss: 0.1251 - acc: 0.9523 - value | 19s 388us/step - loss: 0.1251 - acc: 0.9523 - value | 19s 388us/step - loss: 0.1251 - acc: 0.9523 - value | 19s 388us/step - loss: 0.1251 - acc: 0.9523 - value | 19s 388us/step - loss: 0.1251 - acc: 0.9523 - value | 19s 388us/step - loss: 0.1251 - acc: 0.9523 - value | 19s 388us/step - loss: 0.1251 - acc: 0.9523 - value | 19s 388us/step - loss: 0.1251 - acc: 0.9523 - value | 19s 388us/step - loss: 0.1251 - acc: 0.9523 - value | 19s 388us/step - loss: 0.1251 - acc: 0.9523 - value | 19s 388us/step - acc: 0.9525 - value | 19s 388us/step - acc: 0.9525
Epoch 36/50
Epoch 37/50
Epoch 38/50
Epoch 39/50
Epoch 40/50
Epoch 41/50
Epoch 42/50
Epoch 43/50
Epoch 44/50
Epoch 45/50
50000/50000 [============== ] - 18s 366us/step - loss: 0.0975 - acc: 0.9622 - value | 18s 366us/step - loss: 0.0975 - acc: 0.9622 - value | 18s 366us/step - loss: 0.0975 - acc: 0.9622 - value | 18s 366us/step - loss: 0.0975 - acc: 0.9622 - value | 18s 366us/step - loss: 0.0975 - acc: 0.9622 - value | 18s 366us/step - loss: 0.0975 - acc: 0.9622 - value | 18s 366us/step - loss: 0.0975 - acc: 0.9622 - value | 18s 366us/step - loss: 0.0975 - acc: 0.9622 - value | 18s 366us/step - loss: 0.0975 - acc: 0.9622 - value | 18s 366us/step - loss: 0.0975 - acc: 0.9622 - value | 18s 366us/step - loss: 0.0975 - acc: 0.9622 - value | 18s 366us/step - loss: 0.0975 - acc: 0.9622 - value | 18s 366us/step - loss: 0.0975 - acc: 0.9622 - value | 18s 366us/step - loss: 0.0975 - acc: 0.9622 - value | 18s 366us/step - loss: 0.0975 - acc: 0.9622 - value | 18s 366us/step - loss: 0.0975 - acc: 0.9622 - value | 18s 366us/step - loss: 0.0975 - acc: 0.9622 - value | 18s 366us/step - loss: 0.0975 - acc: 0.9622 - value | 18s 366us/step - acc: 0.9622
```

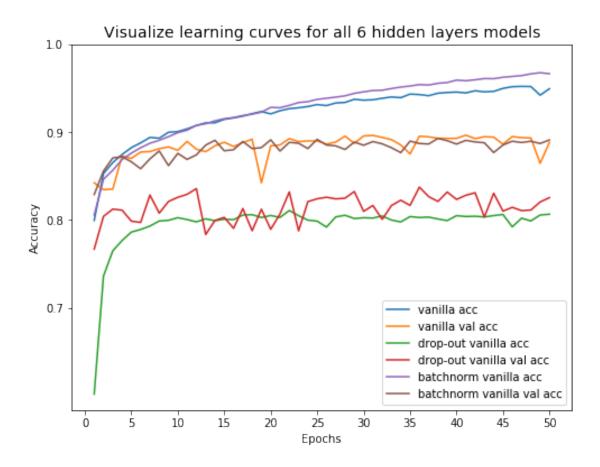
```
Epoch 46/50
Epoch 47/50
50000/50000 [=====
                   =========] - 21s 414us/step - loss: 0.0935 - acc: 0.9641 - v
Epoch 48/50
50000/50000 [==
                   Epoch 49/50
Epoch 50/50
50000/50000 [===
                     In [50]: X_test_ = X_test.reshape(X_test.shape[0], 28, 28, 1)
      print('Batch normalized model 2 test score:',
           model_batch2.evaluate(X_test_, y_test))
10000/10000 [============ ] - 1s 76us/step
Batch normalized model 2 test score: [0.4340573483712971, 0.8855]
In [51]: _ = pd.DataFrame(batch2.history).plot(
         title = 'ResNet Batchnorm Model Learning Curve with Loss',
         xticks = range(0,51,5),
         yticks = [0.1* x for x in range(0,11)]
      )
      _ = plt.legend(loc = 4)
       _ = plt.xlabel('epoch')
      _ = plt.ylabel('Accuracy/Loss')
            ResNet Batchnorm Model Learning Curve with Loss
       1.0
       0.9
       0.8
       0.7
     Accuracy/Loss
       0.6
       0.5
       0.4
       0.3
                                               val loss
                                               val acc
       0.2
                                               loss
       0.1
                                               acc
       0.0
              5
                  10
                      15
                           20
                               25
                                   30
                                        35
                                            40
                                                45
                                                     50
                              epoch
```

6 Visualization

```
In [61]: plt.figure(figsize=(8, 6))
         _ = sns.lineplot(y = vanilla1.history['acc'],
                      x = range(1,51), label='vanilla acc')
         _ = sns.lineplot(y = vanilla1.history['val_acc'],
                      x = range(1,51),label='vanilla val acc')
         _ = sns.lineplot(y = dropout1.history['acc'],
                      x = range(1,51),label='drop-out vanilla acc')
         = sns.lineplot(y = dropout1.history['val_acc'],
                      x = range(1,51),label='drop-out vanilla val acc')
         _ = sns.lineplot(y = batch1.history['acc'],
                      x = range(1,51),label='batchnorm vanilla acc')
         _ = sns.lineplot(y = batch1.history['val_acc'],
                      x = range(1,51),label='batchnorm vanilla val acc')
         _ = plt.title('Visualize learning curves for all 1 hidden layer models', size=14)
         _ = plt.xlabel('Epochs')
         = plt.ylabel('Accuracy')
         _= plt.yticks([x/10 for x in range(7,11)])
         _{-} = plt.xticks(range(0,51,5))
```



```
In [64]: plt.figure(figsize=(8, 6))
           = sns.lineplot(y = vanilla2.history['acc'],
                      x = range(1,51), label='vanilla acc')
             sns.lineplot(y = vanilla2.history['val_acc'],
                      x = range(1,51),label='vanilla val acc')
             sns.lineplot(y = dropout2.history['acc'],
                      x = range(1,51),label='drop-out vanilla acc')
             sns.lineplot(y = dropout2.history['val_acc'],
                      x = range(1,51),label='drop-out vanilla val acc')
             sns.lineplot(y = batch2.history['acc'],
                      x = range(1,51),label='batchnorm vanilla acc')
             sns.lineplot(y = batch2.history['val_acc'],
                      x = range(1,51),label='batchnorm vanilla val acc')
           = plt.title('Visualize learning curves for all 6 hidden layers models', size=14)
           = plt.xlabel('Epochs')
           = plt.ylabel('Accuracy')
           = plt.yticks([x/10 \text{ for } x \text{ in } range(7,11)])
           = plt.xticks(range(0,51,5))
```



7 Summary

In this task, we tested six models: a shallow (1 hidden layer) and a deeper (6 hidden layers) model for three model types:

- 1. Base model
- 2. Model with dropout
- 3. Model with batch normalization and residual connections (without dropout)

Our most successful model, in terms of validation set accuracy, was not surprisingly the deeper model with six hidden layers and batch normalization (without dropout). It approached the mid-to-upper 80s in accuracy. The vanilla model was nearly identical in validation set accuracy, and slightly below the training set accuracy of the batch normalization model.

Drop out did not seem to be an effetcive strategy, as accuracy scores were considerably below those of the base model and the batch normalization model. It should be noted, however, that it was very effective at reducing the degree of overfitting, as the training and validation scores were nearly identical.