Keras_assignment

February 20, 2019

1 Classify different data sets

1.0.1 Basic includes

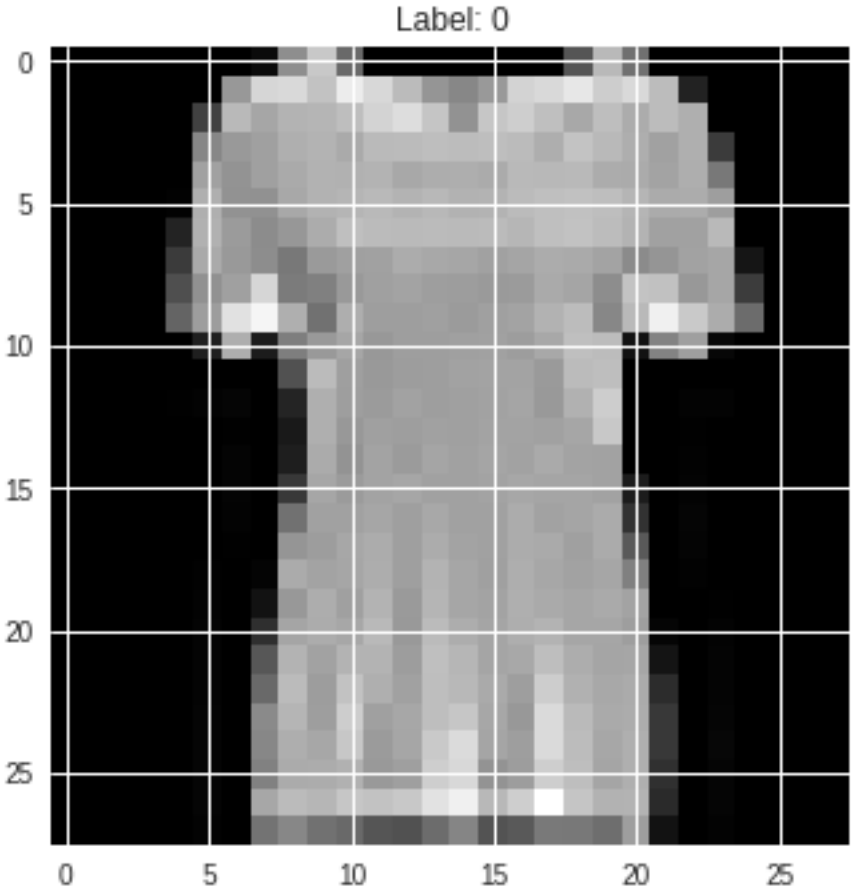
In [0]:
```
# Using pandas to load the csv file
import pandas as pd

import numpy as np
import matplotlib.pyplot as plt

from keras import models
from keras import layers
from keras import callbacks
from keras.utils import to_categorical

# reuters and fashin mnist data set from keras
from keras.datasets import reuters
from keras.datasets import fashion_mnist

# needed to preprocess text
from keras.preprocessing.text import Tokenizer
```

1.0.2 Classify the Fashion Mnist

In [98]:
```
(fashion_train_data, fashion_train_labels), (fashion_test_data, fashion_test_labels) =

print(fashion_train_data.shape)

test_index = 10

plt.title("Label: " + str(fashion_train_labels[test_index]))
plt.imshow(fashion_train_data[test_index], cmap="gray")
```

```
(60000, 28, 28)
```

```
Out[98]: <matplotlib.image.AxesImage at 0x7fa36006cc88>
```



TO DO: Preprocess the data

1. Normalize the input data set
2. Perform one hot encoding
3. Create a train, test, and validation set

```
In [0]: fashion_train_data = fashion_train_data.reshape((60000, 28 * 28))
        fashion_train_data = fashion_train_data.astype('float32') / 255

        fashion_test_data = fashion_test_data.reshape((10000, 28 * 28))
        fashion_test_data = fashion_test_data.astype('float32') / 255

        fashion_train_labels = to_categorical(fashion_train_labels)
        fashion_test_labels = to_categorical(fashion_test_labels)
```

TO DO: Define and train a network, then plot the accuracy of the training, validation, and testing

1. Use a validation set
2. Propose and train a network
3. Print the history of the training
4. Evaluate with a test set

```
In [100]: network = models.Sequential()

          network.add(layers.Dense(64, activation='sigmoid', input_shape=(28 * 28,)))
          network.add(layers.Dense(32, activation='sigmoid'))
          network.add(layers.Dense(10, activation='softmax'))

          network.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accu

          network.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_46 (Dense)             (None, 64)                50240
_________________________________________________________________
dense_47 (Dense)             (None, 32)                2080
_________________________________________________________________
dense_48 (Dense)             (None, 10)                330
=================================================================
Total params: 52,650
Trainable params: 52,650
Non-trainable params: 0
_________________________________________________________________
```

```
In [101]: early_stop = callbacks.EarlyStopping(monitor='val_loss', patience=5)
          network.compile(loss='categorical_crossentropy',
                        optimizer='rmsprop',
                        metrics=['accuracy'])

          history = network.fit(fashion_train_data, fashion_train_labels,
                    epochs=50,
                    validation_split=0.2,
                    callbacks=[early_stop],
                    verbose=2)

          test_loss, test_acc = network.evaluate(fashion_test_data, fashion_test_labels)

          print()
          print("test loss: ", test_loss, "test accuracy: ", test_acc)
```

```
Train on 48000 samples, validate on 12000 samples
Epoch 1/50
 - 4s - loss: 0.7833 - acc: 0.7617 - val_loss: 0.4673 - val_acc: 0.8359
```

```
Epoch 2/50
 - 3s - loss: 0.4315 - acc: 0.8464 - val_loss: 0.4236 - val_acc: 0.8458
Epoch 3/50
 - 3s - loss: 0.3901 - acc: 0.8592 - val_loss: 0.3808 - val_acc: 0.8612
Epoch 4/50
 - 3s - loss: 0.3649 - acc: 0.8682 - val_loss: 0.3882 - val_acc: 0.8558
Epoch 5/50
 - 3s - loss: 0.3495 - acc: 0.8745 - val_loss: 0.3659 - val_acc: 0.8672
Epoch 6/50
 - 3s - loss: 0.3358 - acc: 0.8792 - val_loss: 0.3507 - val_acc: 0.8718
Epoch 7/50
 - 3s - loss: 0.3230 - acc: 0.8843 - val_loss: 0.3519 - val_acc: 0.8741
Epoch 8/50
 - 3s - loss: 0.3133 - acc: 0.8874 - val_loss: 0.3401 - val_acc: 0.8777
Epoch 9/50
 - 3s - loss: 0.3054 - acc: 0.8893 - val_loss: 0.3529 - val_acc: 0.8789
Epoch 10/50
 - 3s - loss: 0.2971 - acc: 0.8929 - val_loss: 0.3304 - val_acc: 0.8850
Epoch 11/50
 - 3s - loss: 0.2892 - acc: 0.8951 - val_loss: 0.3385 - val_acc: 0.8829
Epoch 12/50
 - 3s - loss: 0.2837 - acc: 0.8979 - val_loss: 0.3295 - val_acc: 0.8819
Epoch 13/50
 - 3s - loss: 0.2769 - acc: 0.8993 - val_loss: 0.3296 - val_acc: 0.8803
Epoch 14/50
 - 3s - loss: 0.2714 - acc: 0.9025 - val_loss: 0.3226 - val_acc: 0.8859
Epoch 15/50
 - 3s - loss: 0.2657 - acc: 0.9028 - val_loss: 0.3253 - val_acc: 0.8845
Epoch 16/50
 - 3s - loss: 0.2618 - acc: 0.9037 - val_loss: 0.3260 - val_acc: 0.8848
Epoch 17/50
 - 3s - loss: 0.2569 - acc: 0.9071 - val_loss: 0.3300 - val_acc: 0.8844
Epoch 18/50
 - 3s - loss: 0.2520 - acc: 0.9090 - val_loss: 0.3373 - val_acc: 0.8824
Epoch 19/50
 - 3s - loss: 0.2480 - acc: 0.9107 - val_loss: 0.3364 - val_acc: 0.8833
10000/10000 [==============================] - 0s 28us/step

test loss:  0.3629855122923851 test accuracy:  0.8724
```

1.1 Classifying newswires

Build a network to classify Reuters newswires into 46 different mutually-exclusive topics.

1.1.1 Load and review the data

```
In [102]: (reuters_train_data, reuters_train_labels), (reuters_test_data, reuters_test_labels)

          print(reuters_train_data.shape)
          print(reuters_train_labels.shape)
          print(reuters_train_data[0])
          print(reuters_train_labels[0])

          print(set(reuters_train_labels))
```

```
(8982,)
(8982,)
[1, 2, 2, 8, 43, 10, 447, 5, 25, 207, 270, 5, 3095, 111, 16, 369, 186, 90, 67, 7, 89, 5, 19, 10
3
{0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25,
```

Load the word index to decode the train data.

```
In [103]: word_index = reuters.get_word_index()

          reverse_index = dict([(value+3, key) for (key, value) in word_index.items()])

          reverse_index[0] = "<PAD>"
          reverse_index[1] = "<START>"
          reverse_index[2] = "<UNKNOWN>"  # unknown
          reverse_index[3] = "<UNUSED>"

          decoded_review = ' '.join([reverse_index.get(i,'?') for i in reuters_train_data[0]])

          print(decoded_review)
```

```
<START> <UNKNOWN> <UNKNOWN> said as a result of its december acquisition of space co it expects
```

TO DO: Preprocess the data

1. Normalize the input data set
2. Perform one hot encoding
3. Create a train, test, and validation set

```
In [0]: tokenizer = Tokenizer(num_words=5000)
        train_data_token = tokenizer.sequences_to_matrix(reuters_train_data, mode='binary')
        test_data_token = tokenizer.sequences_to_matrix(reuters_test_data, mode='binary')

        num_classes = 46
        one_hot_train_labels = to_categorical(reuters_train_labels, num_classes)
        one_hot_test_labels = to_categorical(reuters_test_labels, num_classes)
```

```
In [105]: model = models.Sequential()
          model.add(layers.Dense(128, activation='relu', input_dim=5000))
          model.add(layers.Dropout(0.3))
          model.add(layers.Dense(64, activation='relu'))
          model.add(layers.Dropout(0.3))
          model.add(layers.Dense(num_classes, activation='softmax'))
          model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_49 (Dense)             (None, 128)               640128
_________________________________________________________________
dropout_3 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_50 (Dense)             (None, 64)                8256
_________________________________________________________________
dropout_4 (Dropout)          (None, 64)                0
_________________________________________________________________
dense_51 (Dense)             (None, 46)                2990
=================================================================
Total params: 651,374
Trainable params: 651,374
Non-trainable params: 0
_________________________________________________________________
```

```
In [106]: early_stop = callbacks.EarlyStopping(monitor='val_loss', patience=5)
          model.compile(loss='categorical_crossentropy',
                        optimizer='rmsprop',
                        metrics=['accuracy'])

          history = model.fit(train_data_token, one_hot_train_labels,
                    batch_size=512,
                    epochs=40,
                    validation_split=0.2,
                    callbacks=[early_stop],
                    verbose=2)

          test_loss, test_acc = model.evaluate(test_data_token, one_hot_test_labels)

          print("test loss: ", test_loss, "test accuracy: ", test_acc)
```

```
Train on 7185 samples, validate on 1797 samples
Epoch 1/40
 - 2s - loss: 2.5707 - acc: 0.4466 - val_loss: 1.6775 - val_acc: 0.6383
Epoch 2/40
 - 1s - loss: 1.6056 - acc: 0.6468 - val_loss: 1.3646 - val_acc: 0.6939
```

```
Epoch 3/40
 - 1s - loss: 1.3118 - acc: 0.7076 - val_loss: 1.2169 - val_acc: 0.7318
Epoch 4/40
 - 1s - loss: 1.1140 - acc: 0.7520 - val_loss: 1.1405 - val_acc: 0.7468
Epoch 5/40
 - 1s - loss: 0.9727 - acc: 0.7825 - val_loss: 1.0472 - val_acc: 0.7730
Epoch 6/40
 - 1s - loss: 0.8599 - acc: 0.8043 - val_loss: 1.0144 - val_acc: 0.7780
Epoch 7/40
 - 1s - loss: 0.7629 - acc: 0.8263 - val_loss: 0.9838 - val_acc: 0.7880
Epoch 8/40
 - 1s - loss: 0.6774 - acc: 0.8438 - val_loss: 0.9579 - val_acc: 0.7941
Epoch 9/40
 - 1s - loss: 0.6214 - acc: 0.8571 - val_loss: 0.9825 - val_acc: 0.7874
Epoch 10/40
 - 1s - loss: 0.5662 - acc: 0.8685 - val_loss: 0.9389 - val_acc: 0.7974
Epoch 11/40
 - 1s - loss: 0.4964 - acc: 0.8841 - val_loss: 0.9359 - val_acc: 0.8002
Epoch 12/40
 - 1s - loss: 0.4589 - acc: 0.8953 - val_loss: 0.9358 - val_acc: 0.8047
Epoch 13/40
 - 1s - loss: 0.4080 - acc: 0.9041 - val_loss: 0.9721 - val_acc: 0.7986
Epoch 14/40
 - 1s - loss: 0.3800 - acc: 0.9081 - val_loss: 0.9477 - val_acc: 0.8041
Epoch 15/40
 - 1s - loss: 0.3404 - acc: 0.9176 - val_loss: 1.0055 - val_acc: 0.7924
Epoch 16/40
 - 1s - loss: 0.3214 - acc: 0.9267 - val_loss: 0.9751 - val_acc: 0.8047
Epoch 17/40
 - 1s - loss: 0.2821 - acc: 0.9346 - val_loss: 0.9920 - val_acc: 0.8047
2246/2246 [==============================] - 0s 83us/step
test loss:  1.0233403933653318 test accuracy:  0.790293855743544
```

TO DO: Define and train a network, then plot the accuracy of the training, validation, and testing

1. Use a validation set
2. Propose and train a network
3. Print the history of the training
4. Evaluate with a test set

1.2 Predicting Student Admissions

Predict student admissions based on three pieces of data:

- GRE Scores

- GPA Scores
- Class rank

1.2.1 Load and visualize the data

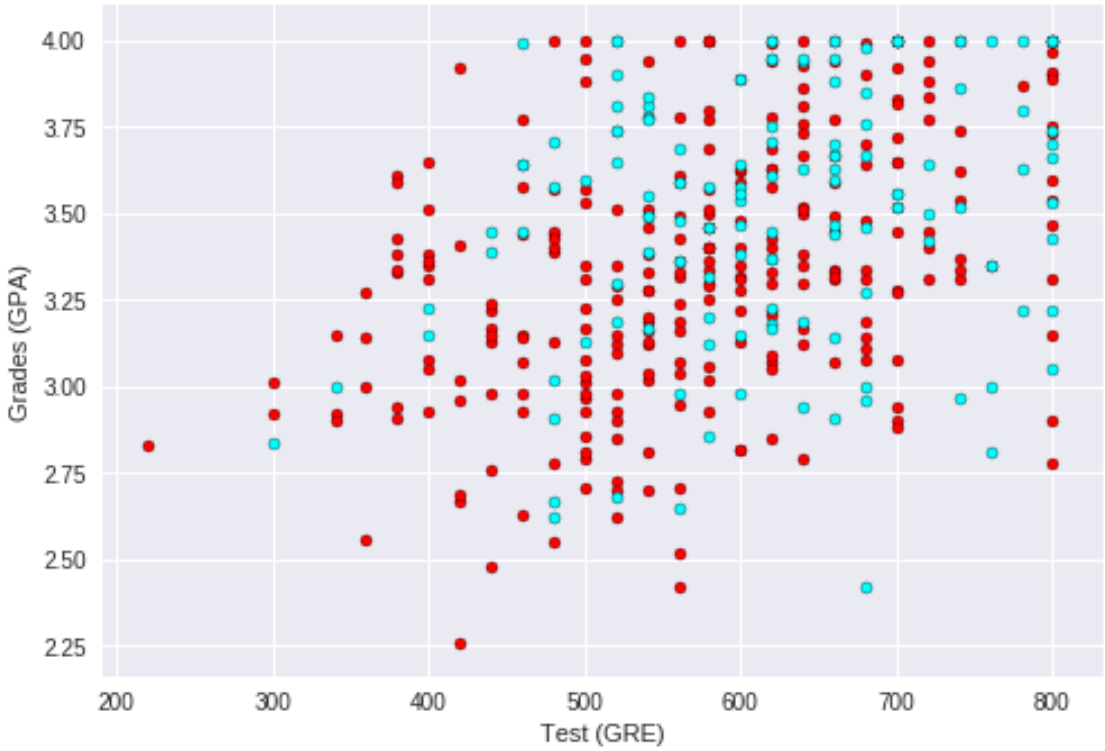
```
In [107]: # student_data = pd.read_csv("students_data.csv")
          student_data = pd.read_csv("https://raw.githubusercontent.com/DeepLearningVision-201
          print(student_data)
```

```
     admit    gre   gpa  rank
0        0  380.0  3.61   3.0
1        1  660.0  3.67   3.0
2        1  800.0  4.00   1.0
3        1  640.0  3.19   4.0
4        0  520.0  2.93   4.0
5        1  760.0  3.00   2.0
6        1  560.0  2.98   1.0
7        0  400.0  3.08   2.0
8        1  540.0  3.39   3.0
9        0  700.0  3.92   2.0
10       0  800.0  4.00   4.0
11       0  440.0  3.22   1.0
12       1  760.0  4.00   1.0
13       0  700.0  3.08   2.0
14       1  700.0  4.00   1.0
15       0  480.0  3.44   3.0
16       0  780.0  3.87   4.0
17       0  360.0  2.56   3.0
18       0  800.0  3.75   2.0
19       1  540.0  3.81   1.0
20       0  500.0  3.17   3.0
21       1  660.0  3.63   2.0
22       0  600.0  2.82   4.0
23       0  680.0  3.19   4.0
24       1  760.0  3.35   2.0
25       1  800.0  3.66   1.0
26       1  620.0  3.61   1.0
27       1  520.0  3.74   4.0
28       1  780.0  3.22   2.0
29       0  520.0  3.29   1.0
..     ...    ...   ...   ...
370      1  540.0  3.77   2.0
371      1  680.0  3.76   3.0
372      1  680.0  2.42   1.0
373      1  620.0  3.37   1.0
374      0  560.0  3.78   2.0
375      0  560.0  3.49   4.0
376      0  620.0  3.63   2.0
```

```
377      1  800.0  4.00   2.0
378      0  640.0  3.12   3.0
379      0  540.0  2.70   2.0
380      0  700.0  3.65   2.0
381      1  540.0  3.49   2.0
382      0  540.0  3.51   2.0
383      0  660.0  4.00   1.0
384      1  480.0  2.62   2.0
385      0  420.0  3.02   1.0
386      1  740.0  3.86   2.0
387      0  580.0  3.36   2.0
388      0  640.0  3.17   2.0
389      0  640.0  3.51   2.0
390      1  800.0  3.05   2.0
391      1  660.0  3.88   2.0
392      1  600.0  3.38   3.0
393      1  620.0  3.75   2.0
394      1  460.0  3.99   3.0
395      0  620.0  4.00   2.0
396      0  560.0  3.04   3.0
397      0  460.0  2.63   2.0
398      0  700.0  3.65   2.0
399      0  600.0  3.89   3.0

[400 rows x 4 columns]
```

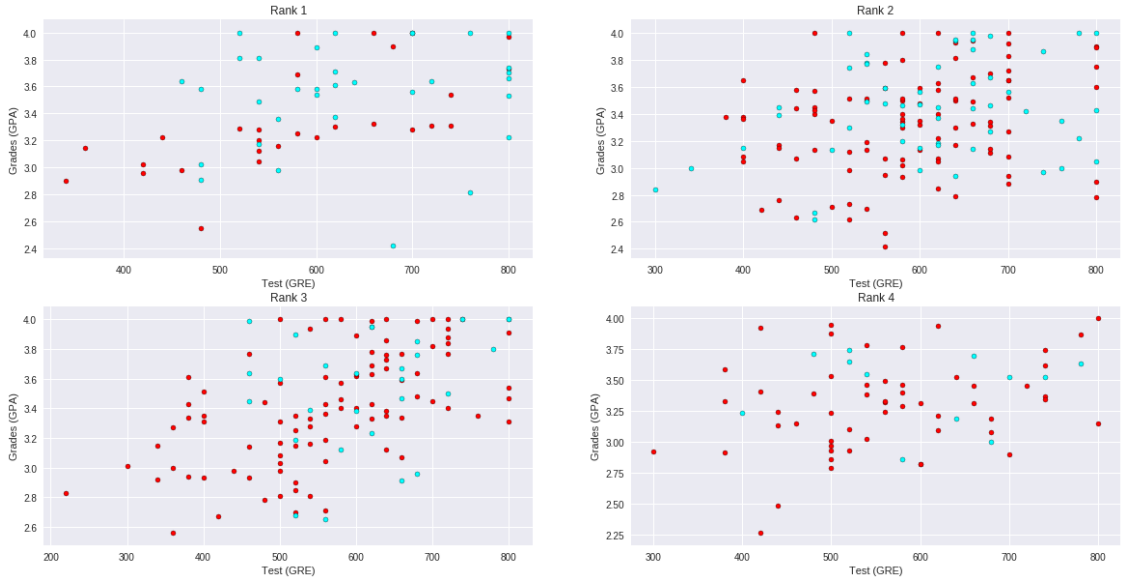
Plot of the GRE and the GPA from the data.

```
In [108]: X = np.array(student_data[["gre","gpa"]])
          y = np.array(student_data["admit"])
          admitted = X[np.argwhere(y==1)]
          rejected = X[np.argwhere(y==0)]
          plt.scatter([s[0][0] for s in rejected], [s[0][1] for s in rejected], s = 25, color =
          plt.scatter([s[0][0] for s in admitted], [s[0][1] for s in admitted], s = 25, color =
          plt.xlabel('Test (GRE)')
          plt.ylabel('Grades (GPA)')

          plt.show()
```



Plot of the data by class rank.

```
In [109]: f, plots = plt.subplots(2, 2, figsize=(20,10))
          plots = [plot for sublist in plots for plot in sublist]

          for idx, plot in enumerate(plots):
              data_rank = student_data[student_data["rank"]==idx+1]
              plot.set_title("Rank " + str(idx+1))
              X = np.array(data_rank[["gre","gpa"]])
              y = np.array(data_rank["admit"])
              admitted = X[np.argwhere(y==1)]
              rejected = X[np.argwhere(y==0)]
              plot.scatter([s[0][0] for s in rejected], [s[0][1] for s in rejected], s = 25, c
              plot.scatter([s[0][0] for s in admitted], [s[0][1] for s in admitted], s = 25, c
              plot.set_xlabel('Test (GRE)')
              plot.set_ylabel('Grades (GPA)')
```



TO DO: Preprocess the data

1. Normalize the input data set
2. Perform one hot encoding
3. Create a train, test, and validation set

```
In [110]: student_data.fillna(0)

          mean_gre = student_data['gre'].mean(axis = 0)
          std_gre = student_data['gre'].std(axis = 0)

          mean_gpa = student_data['gpa'].mean(axis = 0)
          std_gpa = student_data['gpa'].std(axis = 0)

          rank = np.array(student_data[["rank"]])

          student_data['gre'] -= mean_gre
          student_data['gre'] /= std_gre

          student_data['gpa'] -= mean_gpa
          student_data['gpa'] /= std_gpa

          data = np.array(student_data[["gre","gpa","rank"]])
          labels = np.array(student_data["admit"])

          train_data = data[320:]
          train_labels = labels[320:]
```

```
          validate_data = data[:80]
          validate_labels = labels[:80]

          print(data.shape)
          print(labels.shape)
```

```
(400, 3)
(400,)
```

```
In [0]: def build_model():
          model = models.Sequential()
          model.add(layers.Dense(256, activation='relu', input_dim=3))
          model.add(layers.Dense(256, activation='relu'))

          model.add(layers.Dense(1))

          # mean squared error
          model.compile(optimizer='rmsprop', loss='mse', metrics=['mae'])

          return model
```

```
In [112]: k = 4

          num_val_samples = len(train_data) // k

          all_mae_histories = []
          num_epochs = 500

          for i in range(k):
            print("Fold:", i)
            val_data = train_data[i * num_val_samples : (i+1) * num_val_samples]
            val_labels = train_labels[i * num_val_samples : (i+1) * num_val_samples]

            partial_train_data = np.concatenate([train_data[:i * num_val_samples],
                                                 train_data[(i+1) * num_val_samples:]], axis =

            partial_train_labels = np.concatenate([train_labels[:i * num_val_samples],
                                                   train_labels[(i+1) * num_val_samples:]], axis

            model = build_model()

            history = model.fit(partial_train_data, partial_train_labels, epochs = num_epochs,
                                validation_data = (val_data, val_labels), batch_size = 20, verb

            all_mae_histories.append(history.history['val_mean_absolute_error'])

          test_loss, test_acc = model.evaluate(validate_data, validate_labels)
          print("test loss: ", test_loss, "test accuracy: ", test_acc)
```

```
Fold: 0
Fold: 1
Fold: 2
Fold: 3
80/80 [==============================] - 0s 112us/step
test loss:  0.3409411430358887 test accuracy:  0.521298861503601
```