Classify different data sets

Basic includes

```
In [164]: # 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

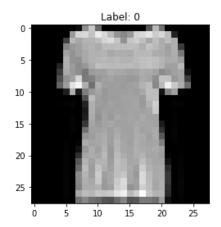
# reuters and fashin mnist data set from keras
from keras.datasets import reuters
from keras.datasets import fashion_mnist

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

Classify the Fashion Mnist

```
In [165]: (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[165]: <matplotlib.image.AxesImage at 0xb43422cf8>



TO DO: Preprocess the data

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

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

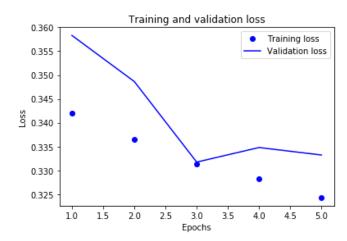
Trainable params: 109,386 Non-trainable params: 0

- 3. Print the history of the training
- 4. Evaluate with a test set

```
In [166]:
          fashion_train_data = fashion_train_data.reshape((60000, 28 * 28))# Normalizar datos
          fashion train data = fashion train data.astype('float32') / 255# Normalizar datos
          fashion_test_data = fashion_test_data.reshape((10000, 28 * 28))
          fashion_test_data = fashion_test_data.astype('float32') / 255
In [167]:
          fashion train labels = to categorical(fashion train labels) #hot encoding
          fashion_test_labels = to_categorical(fashion_test_labels)#hot encoding
In [168]:
          validation data = fashion train data[:30000] #Validación
          validation labels = fashion train labels[:30000] #Validación
          x data = fashion train data[30000:]
          y data = fashion train labels[30000:]
In [175]:
         network = models.Sequential()
          network.add(layers.Dense(128, activation='relu', input shape= (28 * 28,)))
          network.add(layers.Dropout(0.3))
          network.add(layers.Dense(64, activation='relu'))
          network.add(layers.Dropout(0.3))
          network.add(layers.Dense(10, activation='softmax'))
          network.summary()
          early stop = callbacks.EarlyStopping(monitor='val loss', patience=2)
          network.compile(loss='categorical crossentropy', optimizer='adam', metrics=['accurac
          Layer (type)
                                      Output Shape
                                                               Param #
          ______
          dense_59 (Dense)
                                      (None, 128)
                                                               100480
          dropout_41 (Dropout)
                                      (None, 128)
          dense_60 (Dense)
                                      (None, 64)
                                                               8256
          dropout 42 (Dropout)
                                      (None, 64)
          dense_61 (Dense)
                                      (None, 10)
                                                               650
          Total params: 109,386
```

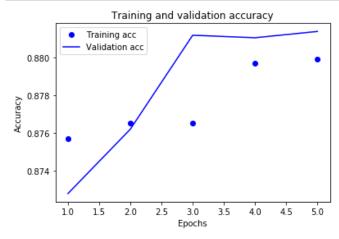
```
In [177]: history = network.fit(x_data, y_data, epochs=25, validation_data = (validation_data,
          Train on 30000 samples, validate on 30000 samples
          Epoch 1/25
           - 6s - loss: 0.3419 - acc: 0.8757 - val_loss: 0.3583 - val_acc: 0.8728
          Epoch 2/25
           - 5s - loss: 0.3365 - acc: 0.8765 - val loss: 0.3486 - val acc: 0.8762
          Epoch 3/25
           - 5s - loss: 0.3312 - acc: 0.8765 - val loss: 0.3317 - val acc: 0.8812
          Epoch 4/25
           - 4s - loss: 0.3283 - acc: 0.8797 - val loss: 0.3348 - val acc: 0.8810
          Epoch 5/25
           - 5s - loss: 0.3243 - acc: 0.8799 - val loss: 0.3332 - val acc: 0.8814
  In [ ]:
In [179]:
          test_loss, test_acc = network.evaluate(fashion_test_data, fashion_test_labels)
          print("test loss: ", test_loss, "test accuracy: ", test_acc) #imprimir evaluación
          history_dict = history.history
          acc = history_dict['acc']
          val_acc = history_dict['val_acc']
          loss = history dict['loss']
          val loss = history dict['val loss']
          epochs = range(1, len(acc) + 1)
          plt.plot(epochs, loss, 'bo', label='Training loss') #graficas
          plt.plot(epochs, val_loss, 'b', label='Validation loss')
          plt.title('Training and validation loss')
          plt.xlabel('Epochs')
          plt.ylabel('Loss')
          plt.legend()
          plt.show()
```

10000/10000 [=======] - 1s 63us/step test loss: 0.36716508737802506 test accuracy: 0.8691



```
In [181]:
    plt.clf()
    plt.plot(epochs, acc, 'bo', label='Training acc') #Grñafica de entrenamiento
    plt.plot(epochs, val_acc, 'b', label='Validation acc') #Gráfica de validación
    plt.title('Training and validation accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()

plt.show()
```



Classifying newswires

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

Load and review the data

```
In [182]: (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, 102, 6, 19, 124, 15, 90, 67, 84, 22, 482, 26, 7, 48, 4, 49, 8, 864, 39,
          209, 154, 6, 151, 6, 83, 11, 15, 22, 155, 11, 15, 7, 48, 9, 4579, 1005, 504, 6, 25
          8, 6, 272, 11, 15, 22, 134, 44, 11, 15, 16, 8, 197, 1245, 90, 67, 52, 29, 209, 30,
          32, 132, 6, 109, 15, 17, 12]
          {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, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43
          , 44, 45}
```

Load the word index to decode the train data.

```
In [183]: 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 earnings per share in 1987 of 1 15 to 1 30 dlrs per share up from 70 cts in 1986 the company said pretax net should rise to nine to 10 mln dlrs from si x mln dlrs in 1986 and rental operation revenues to 19 to 22 mln dlrs from 12 5 ml n dlrs it said cash flow per share this year should be 2 50 to three dlrs reuter 3

TO DO: Preprocess the data

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- 3. Print the history of the training
- 4. Evaluate with a test set

```
In [186]: tokenizer = Tokenizer(num_words=8982)
    train_data_token = tokenizer.sequences_to_matrix(reuters_train_data, mode='binary')
    test_data_token = tokenizer.sequences_to_matrix(reuters_test_data, mode='binary')
    one_hot_train_labels = to_categorical(reuters_train_labels) #hot encoding
    one_hot_test_labels = to_categorical(reuters_test_labels)
```

```
In [187]: validation_data = train_data_token[:3000] #validación
validation_labels = one_hot_train_labels[:3000]
x_data = train_data_token[3000:]
y_data = one_hot_train_labels[3000:]
```

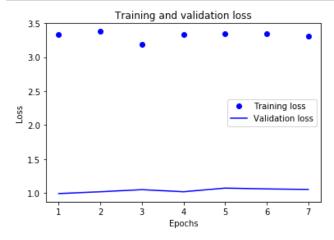
```
In [191]:
         network = models.Sequential()
         network.add(layers.Dense(92, activation='relu', input_shape= (8982,)))
         network.add(layers.Dropout(0.3))
         network.add(layers.Dense(46, activation='softmax'))
         network.add(layers.Dropout(0.2))
         network.summary()
         Layer (type)
                                    Output Shape
                                                           Param #
         _____
         dense 68 (Dense)
                                    (None, 92)
                                                           826436
         dropout 49 (Dropout)
                                    (None, 92)
         dense_69 (Dense)
                                    (None, 46)
                                                           4278
         dropout 50 (Dropout)
                                                           Λ
                                    (None, 46)
         _____
         Total params: 830,714
         Trainable params: 830,714
         Non-trainable params: 0
In [192]:
         early stop = callbacks.EarlyStopping(monitor='val loss', patience=6)
         network.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accurac
 In [ ]:
In [194]: history = network.fit(x_data, y_data, epochs=15, validation_data = (validation_data,
         Train on 5982 samples, validate on 3000 samples
         Epoch 1/15
          - 4s - loss: 3.3350 - acc: 0.7775 - val loss: 0.9927 - val acc: 0.8030
         Epoch 2/15
          - 4s - loss: 3.3791 - acc: 0.7732 - val loss: 1.0194 - val acc: 0.8033
         Epoch 3/15
          - 4s - loss: 3.1882 - acc: 0.7850 - val loss: 1.0500 - val acc: 0.8033
         Epoch 4/15
          - 4s - loss: 3.3338 - acc: 0.7767 - val_loss: 1.0196 - val_acc: 0.8043
         Epoch 5/15
          - 4s - loss: 3.3476 - acc: 0.7743 - val_loss: 1.0730 - val_acc: 0.8017
         Epoch 6/15
          - 4s - loss: 3.3471 - acc: 0.7763 - val_loss: 1.0612 - val_acc: 0.8023
         Epoch 7/15
          - 4s - loss: 3.3135 - acc: 0.7780 - val loss: 1.0533 - val acc: 0.8040
In [195]: test_loss, test_acc = network.evaluate(test_data_token, one_hot_test_labels) #evalua
         print("test loss: ", test_loss, "test accuracy: ", test_acc)
         test loss: 1.12112430473151 test accuracy: 0.7911843277202157
```

```
In [196]: history_dict = history.history
    acc = history_dict['acc']
    val_acc = history_dict['val_acc']
    loss = history_dict['loss']
    val_loss = history_dict['val_loss']
    epochs = range(1, len(acc) + 1)
```

```
In [197]:
    plt.plot(epochs, loss, 'bo', label='Training loss') #gráfica

    plt.plot(epochs, val_loss, 'b', label='Validation loss')
    plt.title('Training and validation loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()

plt.show()
```

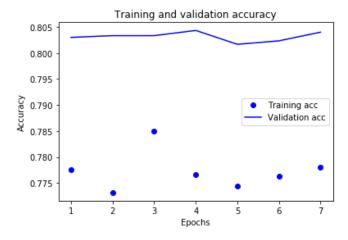


```
In [ ]:
```

```
In [199]:
    plt.clf()

plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy') #gráfica de validación
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.show()
```



In []:

Predicting Student Admissions

Predict student admissions based on three pieces of data:

- GRE Scores
- GPA Scores
- Class rank

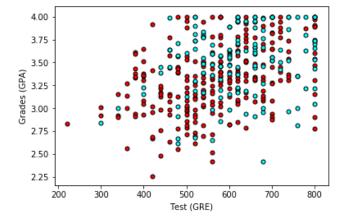
Load and visualize the data

In [232]: student_data = pd.read_csv("data/student_data.csv") #se creo carpeta data
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 3.88		
391	1	660.0	3.88	2.0	
392	1	600.0		3.0 2.0	
393	1	620.0	3.75		
394	1	460.0	3.99	3.0	
395	0	620.0	4.00	2.0	
396 397	0	560.0	3.04	3.0	
397	U	460.0	2.63	2.0	

Plot of the GRE and the GPA from the data.

```
In [253]: 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.

Test (GRE)

```
In [254]:
           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)')
             3.8
                                                             3.8
             3.6
                                                             3.6
            (B) 3.4
                                                            (B) 3.4
             3.2
                                                             3.2
                                                             3.0
                                                             2.8
             2.6
                                                             2.6
                                                                                                    800
                                                            4.00
             3.8
                                                             3.75
             3.6
                                                             3.50
            (F) 3.4
                                                           8 3.25
```

TO DO: Preprocess the data

3.2

2.8

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

Test (GRE)

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

9 3.00 2.75

2.50

- 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 [258]: student_data = student_data.fillna(0)
    normalized_student_data = pd.get_dummies(student_data, columns=['rank']) #normalizan
    normalized_student_data["gre"] = normalized_student_data["gre"] / 800
    normalized_student_data["gpa"] = normalized_student_data["gpa"] / 4
    np.random.shuffle(normalized_student_data.values)

student_x = np.array(normalized_student_data)[:,1:]
    student_x = student_x.astype('float32')
    student_y = to_categorical(student_data["admit"])

In [259]:

student_validation_data = student_x[:100] #validando
    student_validation_labels = student_y[:100]
    student_x data = student_x[100:]
    student_y_data = student_y[100:]
```

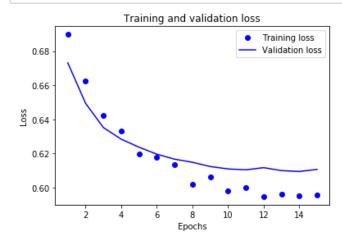
Param #

Layer (type)

Output Shape

=======================================		=======================================							
dense_83 (Dense)	(None, 128)	1024							
dropout_59 (Dropout)	(None, 128)	0							
dense_84 (Dense)	(None, 64)	8256							
dropout_60 (Dropout)	(None, 64)	0							
dense_85 (Dense)	(None, 32)	2080							
dense_86 (Dense)	(None, 2)	66							
Total params: 11,426 Trainable params: 11,426 Non-trainable params: 0									
Train on 300 samples, validate on 100 samples Epoch 1/15 300/300 [===================================									
300/300 [===================================	_	204us/step - loss: 0.66	25 - acc: 0.6						
300/300 [===================================	•	147us/step - loss: 0.64	25 - acc: 0.6						
300/300 [===================================		359us/step - loss: 0.63	32 - acc: 0.6						
300/300 [===================================	_	340us/step - loss: 0.61	95 - acc: 0.6						
300/300 [==========] - 0s	190us/step - loss: 0.61	77 - acc: 0.6						

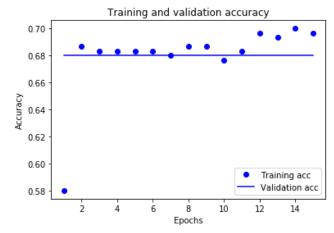
```
In [272]:
          student_history_dict = student_history.history
          print(student_history_dict.keys())
          student acc = student history dict['acc']
          student val acc = student history dict['val acc']
          student loss = student history dict['loss']
          student val loss = student history dict['val loss']
          student_epochs = range(1, len(student_acc) + 1)
          dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
In [274]:
          plt.plot(student_epochs, student_loss, 'bo', label='Training loss')
          plt.plot(student_epochs, student_val_loss, 'b', label='Validation loss')
          plt.title('Training and validation loss')
          plt.xlabel('Epochs')
          plt.ylabel('Loss')
          plt.legend()
          plt.show()
```



```
In [275]:
    plt.clf()

    plt.plot(student_epochs, student_acc, 'bo', label='Training acc')
    plt.plot(student_epochs, student_val_acc, 'b', label='Validation acc')
    plt.title('Training and validation accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()

plt.show()
```



```
In [ ]:

In [ ]:
```