Classify different data sets

Basic includes

In [1]:
```
# 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 import optimizers
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
```

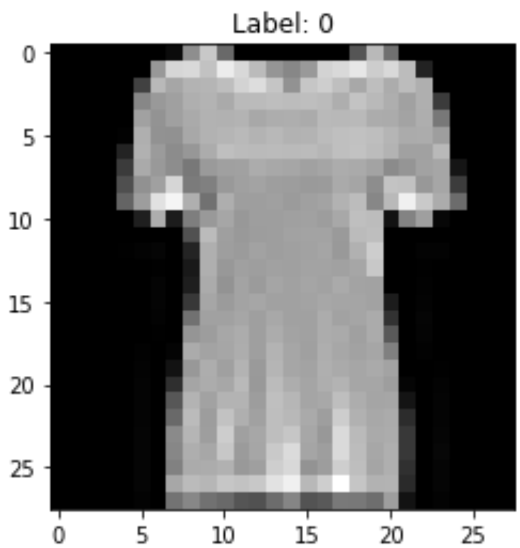
```
Using TensorFlow backend.
```

Classify the Fashion Mnist

In [2]:
```
(fashion_train_data, fashion_train_labels), (fashion_test_data, fashion_

print(fashion_train_data.shape)
print(fashion_test_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)
(10000, 28, 28)
```

Out[2]: <matplotlib.image.AxesImage at 0x132872438>



Standarizing images

standarizing data images and creating one hot labels

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 [3]:
```
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

# one hot encoding
fashion_one_hot_labels = to_categorical(fashion_train_labels)
fashion_test_one_hot_labels = to_categorical(fashion_test_labels)

#creating validation set for first 10000 elements
fashion_validation_data = fashion_train_data[:10000]
fashion_validation_labels = fashion_one_hot_labels[:10000]

#creating input set
x_data = fashion_train_data[10000:]
y_data = fashion_one_hot_labels[10000:]
print(x_data.shape)
print(y_data.shape)
```

```
(50000, 784)
(50000, 10)
```

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 [4]:
```
#building keras model
model = models.Sequential()
model.add(layers.Dense(256, activation='relu', input_dim=784))
model.add(layers.Dropout(0.4))
model.add(layers.Dense(128, activation='relu'))
model.add(layers.Dropout(0.4))
model.add(layers.Dense(len(fashion_one_hot_labels[0]), activation='softm
model.summary()

# included the early stopping which monitors the validation loss
early_stop = callbacks.EarlyStopping(monitor='val_loss', patience=4)
model.compile(loss='categorical_hinge',
              optimizer='rmsprop',
              metrics=['accuracy'])
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_1 (Dense)              (None, 256)               200960    
_________________________________________________________________
dropout_1 (Dropout)          (None, 256)               0         
_________________________________________________________________
dense_2 (Dense)              (None, 128)               32896     
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)               0         
_________________________________________________________________
dense_3 (Dense)              (None, 10)                1290      
=================================================================
Total params: 235,146
Trainable params: 235,146
Non-trainable params: 0
_________________________________________________________________
```

In [5]:
```
history = model.fit(x_data, y_data,
                    batch_size=512,
                    epochs=40,
                    validation_data=(fashion_validation_data, fashion_validation_l
                    callbacks=[early_stop],
                    verbose=2)
```

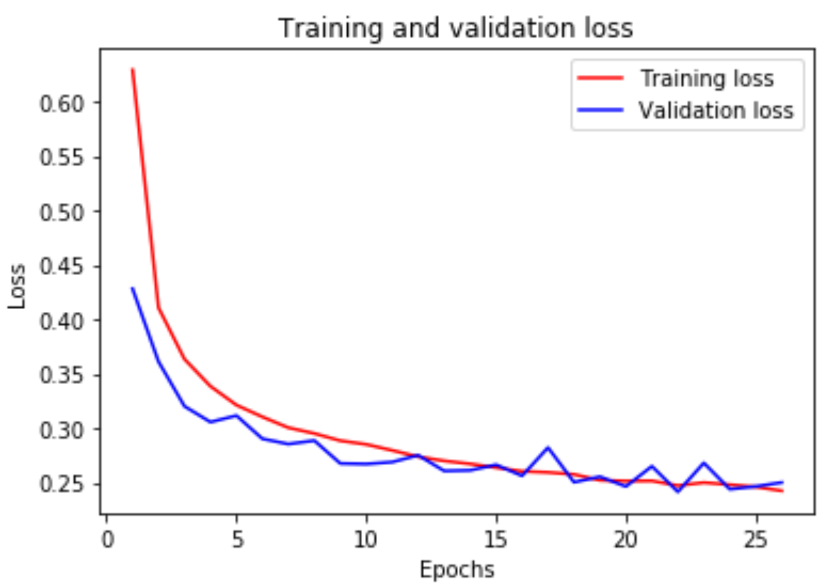
```
Train on 50000 samples, validate on 10000 samples
Epoch 1/40
 - 2s - loss: 0.6291 - acc: 0.6657 - val_loss: 0.4280 - val_acc: 0.782
5
Epoch 2/40
 - 2s - loss: 0.4106 - acc: 0.7980 - val_loss: 0.3610 - val_acc: 0.819
2
Epoch 3/40
 - 1s - loss: 0.3633 - acc: 0.8208 - val_loss: 0.3200 - val_acc: 0.838
```

```
3
Epoch 4/40
 - 2s - loss: 0.3384 - acc: 0.8318 - val_loss: 0.3055 - val_acc: 0.845
6
Epoch 5/40
 - 1s - loss: 0.3211 - acc: 0.8400 - val_loss: 0.3114 - val_acc: 0.844
4
Epoch 6/40
 - 2s - loss: 0.3102 - acc: 0.8457 - val_loss: 0.2901 - val_acc: 0.854
6
Epoch 7/40
 - 1s - loss: 0.3003 - acc: 0.8495 - val_loss: 0.2853 - val_acc: 0.856
5
Epoch 8/40
 - 2s - loss: 0.2950 - acc: 0.8525 - val_loss: 0.2885 - val_acc: 0.855
6
Epoch 9/40
 - 2s - loss: 0.2883 - acc: 0.8558 - val_loss: 0.2675 - val_acc: 0.866
0
Epoch 10/40
 - 2s - loss: 0.2850 - acc: 0.8579 - val_loss: 0.2670 - val_acc: 0.866
5
Epoch 11/40
 - 2s - loss: 0.2795 - acc: 0.8604 - val_loss: 0.2687 - val_acc: 0.864
5
Epoch 12/40
 - 1s - loss: 0.2736 - acc: 0.8631 - val_loss: 0.2750 - val_acc: 0.862
9
Epoch 13/40
 - 1s - loss: 0.2698 - acc: 0.8643 - val_loss: 0.2606 - val_acc: 0.868
7
Epoch 14/40
 - 1s - loss: 0.2671 - acc: 0.8667 - val_loss: 0.2611 - val_acc: 0.869
2
Epoch 15/40
 - 1s - loss: 0.2636 - acc: 0.8682 - val_loss: 0.2662 - val_acc: 0.866
1
Epoch 16/40
 - 1s - loss: 0.2602 - acc: 0.8700 - val_loss: 0.2561 - val_acc: 0.870
9
Epoch 17/40
 - 1s - loss: 0.2592 - acc: 0.8703 - val_loss: 0.2820 - val_acc: 0.858
0
Epoch 18/40
 - 2s - loss: 0.2574 - acc: 0.8713 - val_loss: 0.2502 - val_acc: 0.874
0
Epoch 19/40
 - 2s - loss: 0.2520 - acc: 0.8733 - val_loss: 0.2553 - val_acc: 0.869
8
Epoch 20/40
```

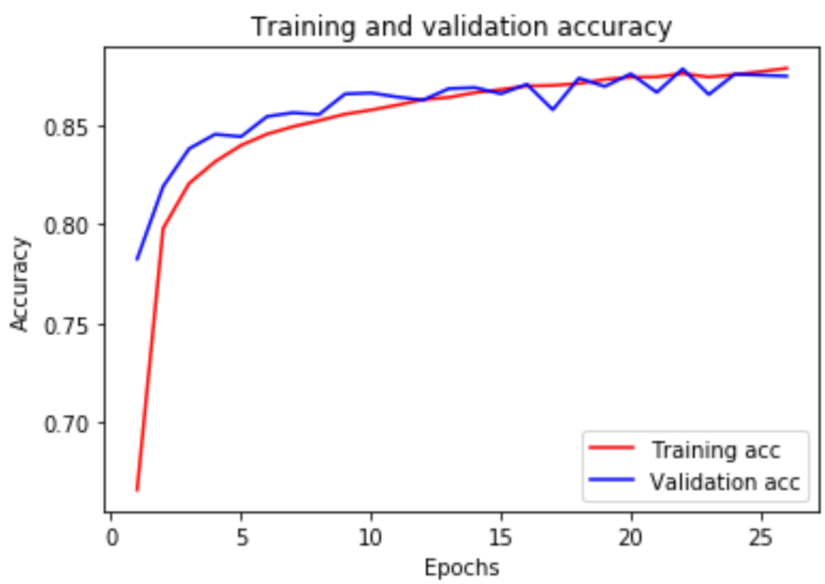
```
 - 2s - loss: 0.2513 - acc: 0.8744 - val_loss: 0.2463 - val_acc: 0.876
2
Epoch 21/40
 - 2s - loss: 0.2515 - acc: 0.8746 - val_loss: 0.2649 - val_acc: 0.866
8
Epoch 22/40
 - 2s - loss: 0.2471 - acc: 0.8763 - val_loss: 0.2414 - val_acc: 0.878
7
Epoch 23/40
 - 2s - loss: 0.2499 - acc: 0.8745 - val_loss: 0.2679 - val_acc: 0.865
7
Epoch 24/40
 - 2s - loss: 0.2479 - acc: 0.8758 - val_loss: 0.2438 - val_acc: 0.876
0
Epoch 25/40
 - 2s - loss: 0.2459 - acc: 0.8773 - val_loss: 0.2463 - val_acc: 0.875
5
Epoch 26/40
 - 1s - loss: 0.2423 - acc: 0.8790 - val_loss: 0.2499 - val_acc: 0.875
0
```

In [9]:
```
#evaluating the model with the test data
results = model.evaluate(fashion_test_data, fashion_test_one_hot_labels)
print(results)

history_dict = history.history
print(history_dict.keys())

#creating list variables for plotting validation
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)



#plotting validation and training loss

plt.plot(epochs, loss, 'r', label='Training loss')
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 [==============================] - 0s 33us/step
[0.2633243887126446, 0.8671]
dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
```



In [8]:
```
#plotting validation and train accuracy

plt.clf()

plt.plot(epochs, acc, 'r', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
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 [3]:
```
(reuters_train_data, reuters_train_labels),(reuters_test_data, reuters_t

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, 1
5, 7, 48, 9, 4579, 1005, 504, 6, 258, 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]
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, 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 [4]:
```
word_index = reuters.get_word_index()

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

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_tra

print(decoded_review)
```

```
<START> <UNKNOWN> <UNKNOWN> said as a result of its december acquisiti
on of space co it expects earnings per share in 1987 of 1 15 to 1 30 d
lrs per share up from 70 cts in 1986 the company said pretax net shoul
d rise to nine to 10 mln dlrs from six mln dlrs in 1986 and rental ope
ration revenues to 19 to 22 mln dlrs from 12 5 mln dlrs it said cash f
low per share this year should be 2 50 to three dlrs reuter 3
```

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 [5]:
```
tokenizer = Tokenizer(reuters_train_data.shape[0])
reuters_train_data_token = tokenizer.sequences_to_matrix(reuters_train_d
reuters_test_data_token = tokenizer.sequences_to_matrix(reuters_test_dat
print(reuters_train_data_token.shape)
print(reuters_test_data_token.shape)

# One-hot encoding the output
reuters_one_hot_train_labels = to_categorical(reuters_train_labels)
reuters_one_hot_test_labels = to_categorical(reuters_test_labels)
print(reuters_one_hot_train_labels.shape)
print(reuters_one_hot_test_labels.shape)

# Creating a validation set with the first 10000 reviews
reuters_validation_data = reuters_train_data_token[:3000]
reuters_validation_labels = reuters_one_hot_train_labels[:3000]
print(reuters_validation_data.shape)
print(reuters_validation_labels.shape)
# Creating the input set for the
x_data = reuters_train_data_token[3000:]
y_data = reuters_one_hot_train_labels[3000:]
print("x:",x_data.shape)
print("y:",y_data.shape)
```

```
(8982, 8982)
(2246, 8982)
(8982, 46)
(2246, 46)
(3000, 8982)
(3000, 46)
x: (5982, 8982)
y: (5982, 46)
```

In [6]:
```
#building keras model
model1 = models.Sequential()
model1.add(layers.Dense(256, activation='relu', input_dim=len(reuters_tr
model1.add(layers.Dropout(0.5))
# model1.add(layers.Dropout(0.3))
model1.add(layers.Dense(len(reuters_one_hot_test_labels[0]), activation=
model1.summary()

# included the early stopping which monitors the validation loss
early_stop = callbacks.EarlyStopping(monitor='val_loss', patience=8)
model1.compile(loss='categorical_hinge',
              optimizer='adadelta',
              metrics=['accuracy'])
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 256)               2299648
_________________________________________________________________
dropout_1 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_2 (Dense)              (None, 46)                11822
=================================================================
Total params: 2,311,470
Trainable params: 2,311,470
Non-trainable params: 0
_________________________________________________________________
```

In [7]:
```
history = model1.fit(x_data, y_data,
          batch_size=256,
          epochs=50,
          validation_data=(reuters_validation_data, reuters_validation_l
          callbacks=[early_stop],
          verbose=2)
```

```
Train on 5982 samples, validate on 3000 samples
Epoch 1/50
 - 3s - loss: 1.0027 - acc: 0.3009 - val_loss: 0.9933 - val_acc: 0.493
0
Epoch 2/50
 - 3s - loss: 0.8711 - acc: 0.4689 - val_loss: 0.7503 - val_acc: 0.518
0
Epoch 3/50
 - 3s - loss: 0.6960 - acc: 0.5401 - val_loss: 0.6380 - val_acc: 0.577
0
Epoch 4/50
 - 3s - loss: 0.5893 - acc: 0.5834 - val_loss: 0.5755 - val_acc: 0.630
7
Epoch 5/50
```

```
 - 3s - loss: 0.5547 - acc: 0.6133 - val_loss: 0.5611 - val_acc: 0.659
3
Epoch 6/50
 - 3s - loss: 0.5399 - acc: 0.6456 - val_loss: 0.5531 - val_acc: 0.665
7
Epoch 7/50
 - 2s - loss: 0.5283 - acc: 0.6603 - val_loss: 0.5491 - val_acc: 0.678
0
Epoch 8/50
 - 2s - loss: 0.5190 - acc: 0.6854 - val_loss: 0.5431 - val_acc: 0.687
0
Epoch 9/50
 - 2s - loss: 0.5104 - acc: 0.6954 - val_loss: 0.5345 - val_acc: 0.696
7
Epoch 10/50
 - 2s - loss: 0.4962 - acc: 0.7098 - val_loss: 0.5242 - val_acc: 0.696
3
Epoch 11/50
 - 2s - loss: 0.4735 - acc: 0.7150 - val_loss: 0.5063 - val_acc: 0.696
0
Epoch 12/50
 - 3s - loss: 0.4532 - acc: 0.7245 - val_loss: 0.4900 - val_acc: 0.704
3
Epoch 13/50
 - 2s - loss: 0.4314 - acc: 0.7379 - val_loss: 0.4811 - val_acc: 0.718
3
Epoch 14/50
 - 2s - loss: 0.4175 - acc: 0.7441 - val_loss: 0.4720 - val_acc: 0.720
0
Epoch 15/50
 - 2s - loss: 0.4000 - acc: 0.7546 - val_loss: 0.4666 - val_acc: 0.727
0
Epoch 16/50
 - 2s - loss: 0.3871 - acc: 0.7646 - val_loss: 0.4596 - val_acc: 0.733
3
Epoch 17/50
 - 2s - loss: 0.3763 - acc: 0.7753 - val_loss: 0.4561 - val_acc: 0.734
3
Epoch 18/50
 - 2s - loss: 0.3657 - acc: 0.7823 - val_loss: 0.4540 - val_acc: 0.738
3
Epoch 19/50
 - 2s - loss: 0.3546 - acc: 0.7909 - val_loss: 0.4488 - val_acc: 0.744
3
Epoch 20/50
 - 2s - loss: 0.3450 - acc: 0.7991 - val_loss: 0.4450 - val_acc: 0.745
0
Epoch 21/50
 - 2s - loss: 0.3354 - acc: 0.8061 - val_loss: 0.4407 - val_acc: 0.750
3
```

```
Epoch 22/50
 - 3s - loss: 0.3269 - acc: 0.8104 - val_loss: 0.4363 - val_acc: 0.757
3
Epoch 23/50
 - 2s - loss: 0.3177 - acc: 0.8183 - val_loss: 0.4318 - val_acc: 0.760
3
Epoch 24/50
 - 2s - loss: 0.3098 - acc: 0.8206 - val_loss: 0.4293 - val_acc: 0.759
0
Epoch 25/50
 - 2s - loss: 0.3005 - acc: 0.8255 - val_loss: 0.4270 - val_acc: 0.765
3
Epoch 26/50
 - 2s - loss: 0.2925 - acc: 0.8290 - val_loss: 0.4233 - val_acc: 0.767
3
Epoch 27/50
 - 3s - loss: 0.2850 - acc: 0.8307 - val_loss: 0.4198 - val_acc: 0.767
7
Epoch 28/50
 - 2s - loss: 0.2796 - acc: 0.8368 - val_loss: 0.4203 - val_acc: 0.768
3
Epoch 29/50
 - 2s - loss: 0.2741 - acc: 0.8372 - val_loss: 0.4157 - val_acc: 0.770
0
Epoch 30/50
 - 2s - loss: 0.2679 - acc: 0.8397 - val_loss: 0.4153 - val_acc: 0.771
3
Epoch 31/50
 - 2s - loss: 0.2615 - acc: 0.8432 - val_loss: 0.4110 - val_acc: 0.774
7
Epoch 32/50
 - 3s - loss: 0.2554 - acc: 0.8460 - val_loss: 0.4105 - val_acc: 0.778
0
Epoch 33/50
 - 2s - loss: 0.2517 - acc: 0.8482 - val_loss: 0.4077 - val_acc: 0.778
0
Epoch 34/50
 - 3s - loss: 0.2489 - acc: 0.8501 - val_loss: 0.4063 - val_acc: 0.779
3
Epoch 35/50
 - 2s - loss: 0.2415 - acc: 0.8526 - val_loss: 0.4032 - val_acc: 0.782
3
Epoch 36/50
 - 2s - loss: 0.2373 - acc: 0.8547 - val_loss: 0.4041 - val_acc: 0.779
7
Epoch 37/50
 - 3s - loss: 0.2341 - acc: 0.8571 - val_loss: 0.4054 - val_acc: 0.780
0
Epoch 38/50
 - 2s - loss: 0.2315 - acc: 0.8587 - val_loss: 0.4046 - val_acc: 0.780
```

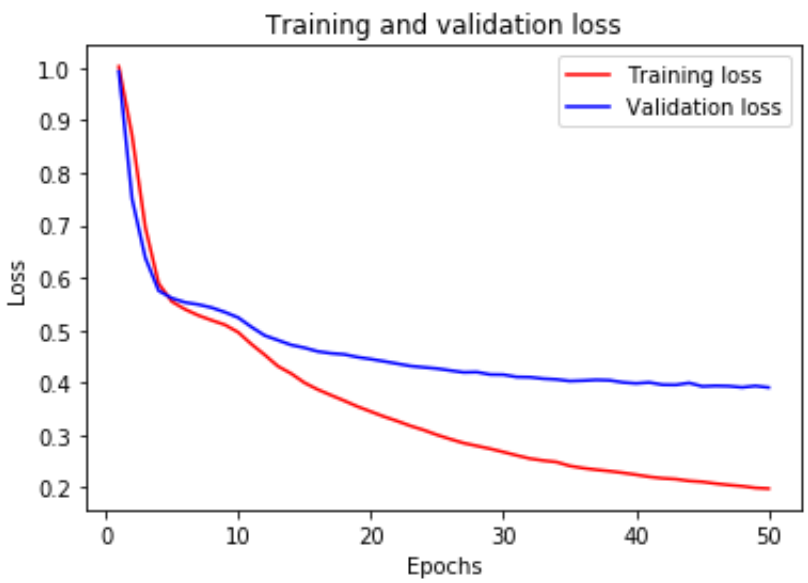
```
7
Epoch 39/50
 - 2s - loss: 0.2283 - acc: 0.8616 - val_loss: 0.4007 - val_acc: 0.783
3
Epoch 40/50
 - 2s - loss: 0.2247 - acc: 0.8639 - val_loss: 0.3988 - val_acc: 0.783
7
Epoch 41/50
 - 2s - loss: 0.2206 - acc: 0.8641 - val_loss: 0.4006 - val_acc: 0.783
7
Epoch 42/50
 - 3s - loss: 0.2178 - acc: 0.8699 - val_loss: 0.3962 - val_acc: 0.786
3
Epoch 43/50
 - 2s - loss: 0.2163 - acc: 0.8701 - val_loss: 0.3959 - val_acc: 0.787
3
Epoch 44/50
 - 2s - loss: 0.2128 - acc: 0.8719 - val_loss: 0.3997 - val_acc: 0.786
3
Epoch 45/50
 - 2s - loss: 0.2111 - acc: 0.8723 - val_loss: 0.3931 - val_acc: 0.788
0
Epoch 46/50
 - 2s - loss: 0.2078 - acc: 0.8801 - val_loss: 0.3941 - val_acc: 0.791
0
Epoch 47/50
 - 2s - loss: 0.2050 - acc: 0.8801 - val_loss: 0.3935 - val_acc: 0.789
0
Epoch 48/50
 - 2s - loss: 0.2028 - acc: 0.8828 - val_loss: 0.3912 - val_acc: 0.791
0
Epoch 49/50
 - 2s - loss: 0.1995 - acc: 0.8838 - val_loss: 0.3939 - val_acc: 0.792
7
Epoch 50/50
 - 2s - loss: 0.1982 - acc: 0.8858 - val_loss: 0.3910 - val_acc: 0.794
3
```

In [8]:

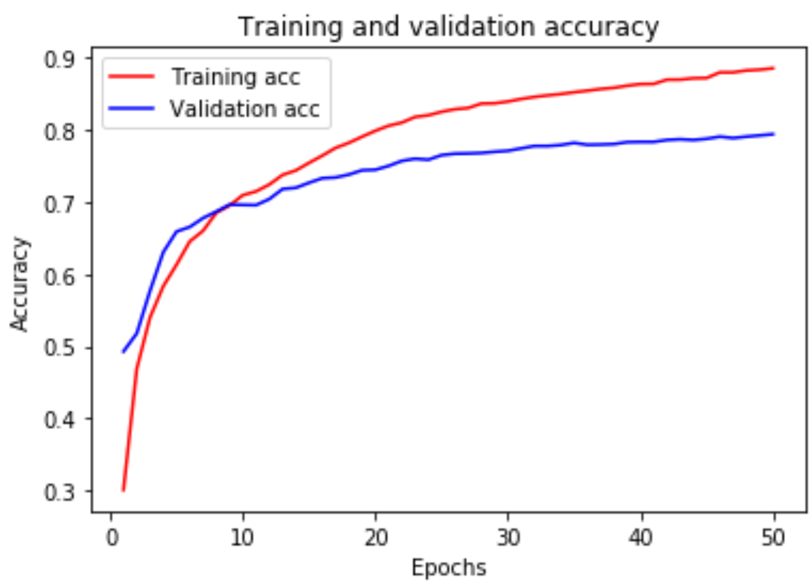
```
#evaluating the model with the test data
print(reuters_test_data.shape)
print(reuters_one_hot_test_labels.shape)
results = model1.evaluate(reuters_test_data_token, reuters_one_hot_test_
print(results)

history_dict = history.history
print(history_dict.keys())

#creating list variables for plotting validation
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)



#plotting validation and training loss

plt.plot(epochs, loss, 'r', label='Training loss')
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()
```

```
(2246,)
(2246, 46)
2246/2246 [==============================] - 0s 185us/step
[0.39702498440432527, 0.7800534283700843]
dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
```



In [9]:
```
#plotting validation and train accuracy

plt.clf()

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

plt.show()
```



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

Predicting Student Admissions

Predict student admissions based on three pieces of data:

- GRE Scores
- GPA Scores
- Class rank

Load and visualize the data

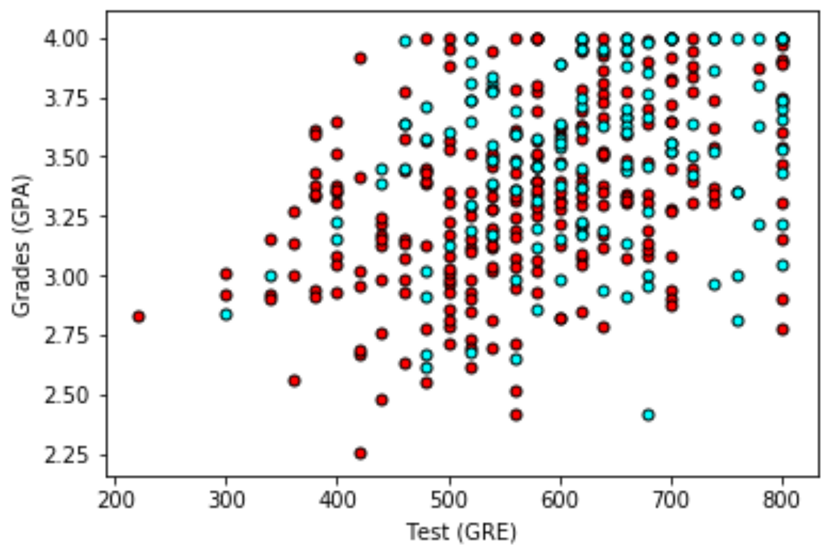
In [2]:
```
student_data = pd.read_csv("student_data.csv")
print(student_data)
```

```
    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]
```

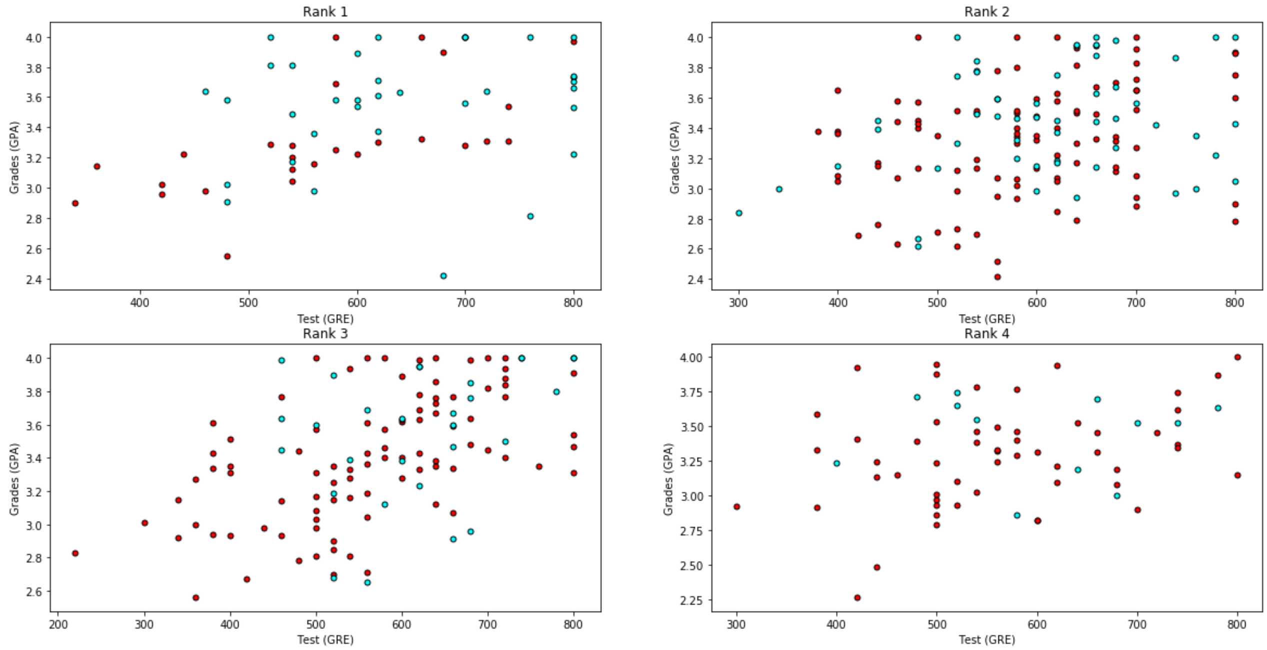
Plot of the GRE and the GPA from the data.

In [3]:
```
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
plt.scatter([s[0][0] for s in admitted], [s[0][1] for s in admitted], s
plt.xlabel('Test (GRE)')
plt.ylabel('Grades (GPA)')

plt.show()
```



Plot of the data by class rank.

In [4]:
```
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
    plot.scatter([s[0][0] for s in admitted], [s[0][1] for s in admitted
    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 [5]:
```
# admit    gre   gpa  rank
student_data.fillna(value= 0, inplace= True)
gpa = np.array(student_data["gpa"])
gpa = (gpa - np.nanmean(gpa))/np.nanstd(gpa)
gre = np.array(student_data["gre"])
gre = (gre - np.nanmean(gre))/np.nanstd(gre)
rank = np.array(student_data["rank"])
rank = to_categorical(rank)
standarizedStudentData = np.zeros((len(gre), 2))
standarizedStudentData[:,0] = gre
standarizedStudentData[:,1] = gpa
studentDataFinal = np.zeros((len(gre), 7))
for i, (studentData, cat) in enumerate(zip(standarizedStudentData, rank)
    studentDataFinal[i] = np.concatenate((studentData, cat))


admit = np.array(student_data["admit"])
studentOneHotLabels = to_categorical(admit)

print(studentDataFinal.shape)
print(studentOneHotLabels.shape)

studentTrainData = studentDataFinal[:300]
studentTrainLabels = studentOneHotLabels[:300]
studentTestData = studentDataFinal[300:]
studentTestLabels = studentOneHotLabels[300:]
```

```
(400, 7)
(400, 2)
```

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In [6]:
```
#building keras model
model2 = models.Sequential()
model2.add(layers.Dense(32, activation='relu', input_dim=7))
# model1.add(layers.Dropout(0.4))
model2.add(layers.Dense(32, activation='relu'))
# model1.add(layers.Dropout(0.3))
model2.add(layers.Dense(2, activation='sigmoid'))
model2.summary()

# included the early stopping which monitors the validation loss
early_stop = callbacks.EarlyStopping(monitor='val_loss', patience=8)
model2.compile(loss='kullback_leibler_divergence',
              optimizer='nadam',
              metrics=['accuracy'])
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_1 (Dense)              (None, 32)                256       
_________________________________________________________________
dense_2 (Dense)              (None, 32)                1056      
_________________________________________________________________
dense_3 (Dense)              (None, 2)                 66        
=================================================================
Total params: 1,378
Trainable params: 1,378
Non-trainable params: 0
_________________________________________________________________
```

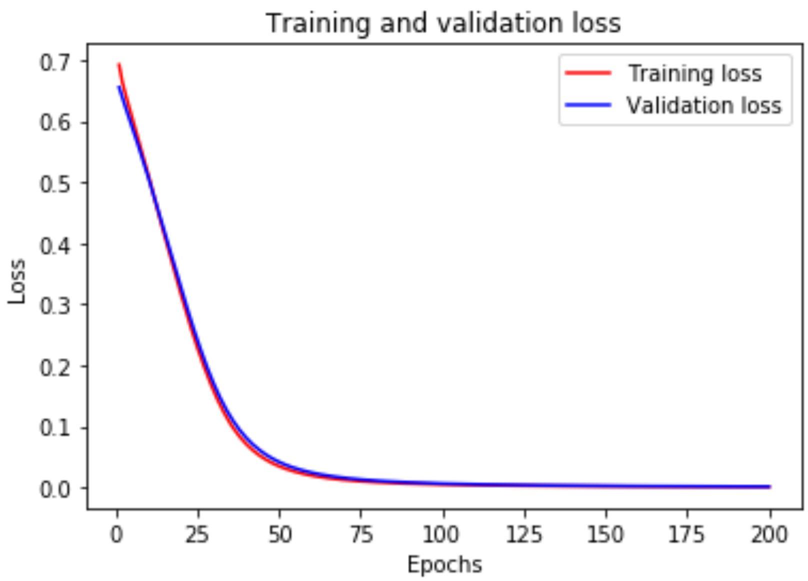
In [7]:
```
history = model2.fit(studentTrainData, studentTrainLabels,
          batch_size=512,
          epochs=200,
          validation_split=0.2,
          verbose=2)
```

```
Train on 240 samples, validate on 60 samples
Epoch 1/200
 - 0s - loss: 0.6918 - acc: 0.3958 - val_loss: 0.6550 - val_acc: 0.583
3
Epoch 2/200
 - 0s - loss: 0.6635 - acc: 0.4917 - val_loss: 0.6377 - val_acc: 0.633
3
Epoch 3/200
 - 0s - loss: 0.6432 - acc: 0.5625 - val_loss: 0.6217 - val_acc: 0.666
7
Epoch 4/200
 - 0s - loss: 0.6244 - acc: 0.6208 - val_loss: 0.6058 - val_acc: 0.716
7
Epoch 5/200
 - 0s - loss: 0.6059 - acc: 0.6542 - val_loss: 0.5900 - val_acc: 0.700
0
Epoch 6/200
 - 0s - loss: 0.5873 - acc: 0.6792 - val_loss: 0.5739 - val_acc: 0.650
0
```

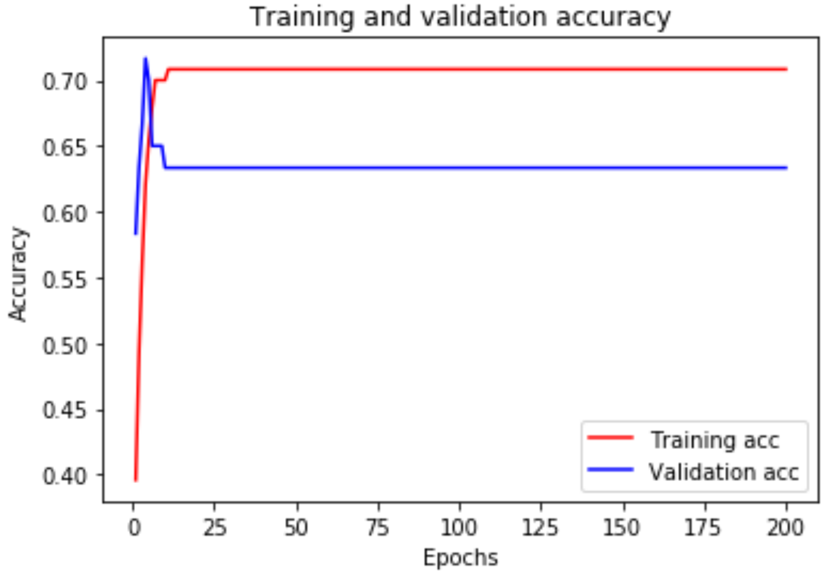
In [8]:
```
#evaluating the model with the test data
print(studentTestData.shape)
print(studentTestLabels.shape)
results = model2.evaluate(studentTestData, studentTestLabels)
print(results)

history_dict = history.history
print(history_dict.keys())

#creating list variables for plotting validation
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)



#plotting validation and training loss

plt.plot(epochs, loss, 'r', label='Training loss')
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()
```

```
(100, 7)
(100, 2)
100/100 [==============================] - 0s 41us/step
[0.0012386897555552424, 0.65]
dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
```



In [9]:
```
#plotting validation and train accuracy

plt.clf()

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

plt.show()
```



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