Simple Housing Dataset

Create a regression model that predicts the price of boston house

In [145]:
```
!wget https://storage.googleapis.com/nicksdemobucket/housing-data.csv
```

```
--2019-03-26 01:02:40--  https://storage.googleapis.com/nicksdemobucket/housi
ng-data.csv
Resolving storage.googleapis.com (storage.googleapis.com)... 74.125.195.128,
2607:f8b0:400e:c08::80
Connecting to storage.googleapis.com (storage.googleapis.com)|74.125.195.128
|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 816 [application/octet-stream]
Saving to: ‘housing-data.csv.2’

housing-data.csv.2  100%[===================>]     816  --.-KB/s    in 0s

2019-03-26 01:02:40 (10.6 MB/s) - ‘housing-data.csv.2’ saved [816/816]
```

In [146]:
```
# Import necessary libraries and get the housing data
import pandas as pd
import numpy as np
df = pd.read_csv('housing-data.csv')
df.head()
```

Out[146]:

	sqft	bdrms	age	price
0	2104	3	70	399900
1	1600	3	28	329900
2	2400	3	44	369000
3	1416	2	49	232000
4	3000	4	75	539900

In [147]:
```
# Featurize and label the dataset
features = df.drop(['price'], axis=1).values
labels = df[['price']].values
print(features.shape, labels.shape)
```

```
(47, 3) (47, 1)
```

In [0]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
```

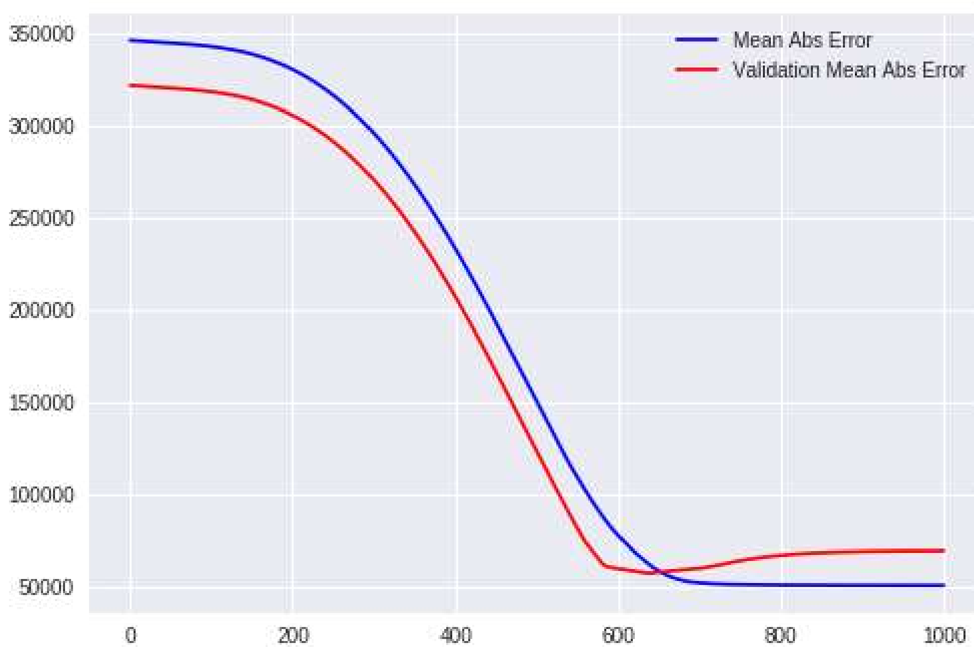
In [0]:
```
# Build the NN regression model
model = Sequential()
model.add(Dense(25, activation='relu', input_shape=(3,)))
model.add(Dense(25, activation='relu'))
model.add(Dense(1))

model.compile(optimizer='adam',
             loss='mean_squared_error',
             metrics=['mean_absolute_error'])

h = model.fit(features, labels, epochs=1000, validation_split=0.2,
              batch_size=130, verbose=0)
```

In [150]:
```
h.history.keys()
```

Out[150]:
```
dict_keys(['loss', 'mean_absolute_error', 'val_loss', 'val_mean_absolute_erro
r'])
```

In [151]:
```
# Plot the history
import matplotlib.pyplot as plt
plt.plot(h.history['mean_absolute_error'], color='b',
         label='Mean Abs Error')
plt.plot(h.history['val_mean_absolute_error'], color='r',
         label='Validation Mean Abs Error')
plt.legend()
```

Out[151]:
```
<matplotlib.legend.Legend at 0x7f108424ac18>
```



Binary Classification

Create a binary classifier for the titanic dataset, will person x survive?

In [152]:
```
!wget https://storage.googleapis.com/nicksdemobucket/titanic-train.csv
```

```
--2019-03-26 01:02:52--  https://storage.googleapis.com/nicksdemobucket/titan
ic-train.csv
Resolving storage.googleapis.com (storage.googleapis.com)... 74.125.195.128,
2607:f8b0:400e:c09::80
Connecting to storage.googleapis.com (storage.googleapis.com)|74.125.195.128
|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 61194 (60K) [application/octet-stream]
Saving to: ‘titanic-train.csv.2’

titanic-train.csv.2 100%[===================>]  59.76K  --.-KB/s    in 0.001s

2019-03-26 01:02:52 (88.3 MB/s) - ‘titanic-train.csv.2’ saved [61194/61194]
```

In [153]:
```
# Get the titanic data
df = pd.read_csv('titanic-train.csv')
df.head()
```

Out[153]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	F
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.25(
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.92
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1(
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.05(

In [0]:
```
# Remove features that seem unecessary off the bat
df = df.drop(['PassengerId', 'Name', 'Ticket'], axis=1)
```

In [155]:
```
df.head()
```

Out[155]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Cabin	Embarked
0	0	3	male	22.0	1	0	7.2500	NaN	S
1	1	1	female	38.0	1	0	71.2833	C85	C
2	1	3	female	26.0	0	0	7.9250	NaN	S
3	1	1	female	35.0	1	0	53.1000	C123	S
4	0	3	male	35.0	0	0	8.0500	NaN	S

In [156]:
```
# Visualize the null data in the dataset
import seaborn as sns
sns.heatmap(df.isnull(), cbar=False, yticklabels=False)
```

Out[156]: <matplotlib.axes._subplots.AxesSubplot at 0x7f10841aae80>

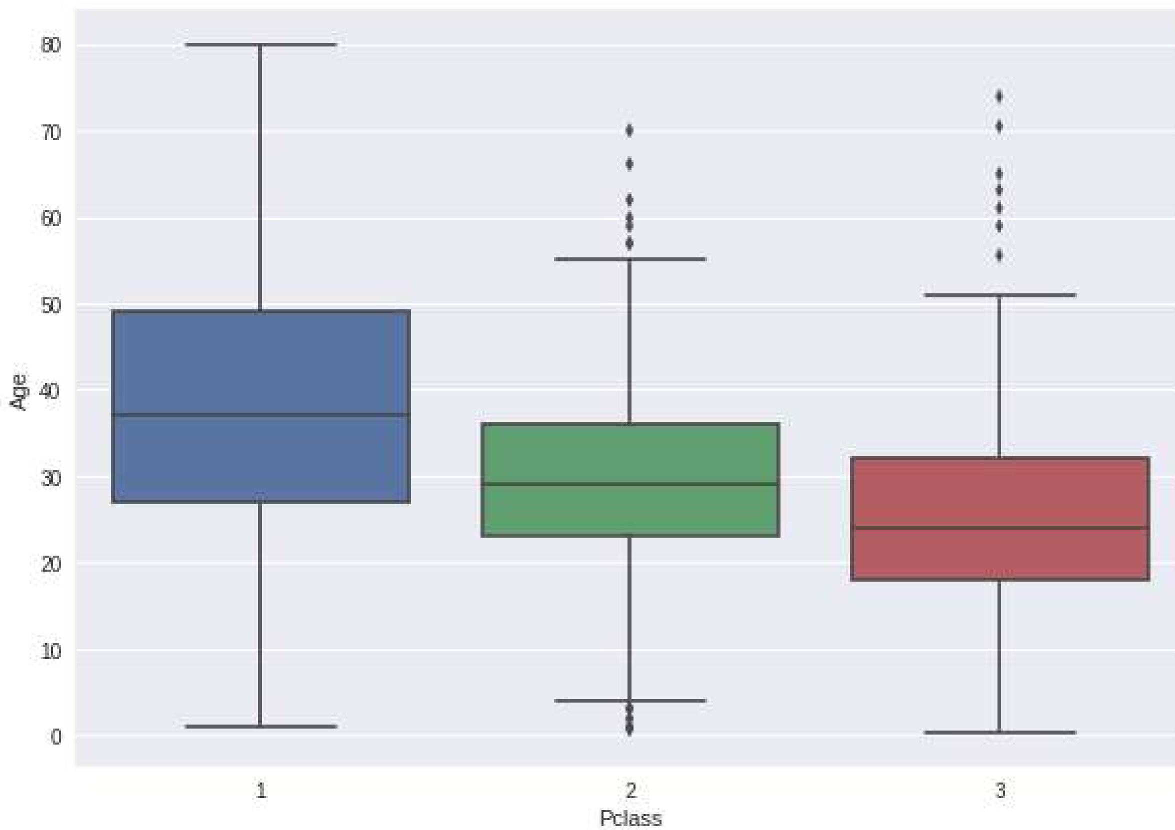
In [0]:
```
"""
Since there are only a few missing rows for Embarked we will
drop the missing rows entirely
"""
df = df.dropna(subset=['Embarked'])
```

In [0]:
```
"""
Remove the column "Cabin" from features as a lot of the data is missing and
we already have a proxy for socio-economic status (Pclass)
"""
df = df.drop(['Cabin'], axis=1)
```

In [159]:
```
# Investigate a good proxy for age - I suggest PClass
plt.figure(figsize=(10,7))
sns.boxplot(x='Pclass', y='Age', data=df)
```

```
/usr/local/lib/python3.6/dist-packages/seaborn/categorical.py:454: FutureWarn
ing: remove_na is deprecated and is a private function. Do not use.
  box_data = remove_na(group_data)
```

Out[159]: <matplotlib.axes._subplots.AxesSubplot at 0x7f10841dbd30>



In [0]:
```
"""
Create a function to impute the age based on the average age of each PClass
"""
def impute_age(cols):

  Age = cols[0]
  Pclass = cols[1]

  if pd.isnull(Age):
    if Pclass==1:
      return 37
    elif Pclass==2:
      return 29
    else:
      return 24
  else:
    return Age
```

In [0]:
```
# Apply impute_age to the dataset to fill in the missing age data
df['Age'] = df[['Age', 'Pclass']].apply(impute_age, axis=1)
```

In [162]:
```
# Show that all missing data is gone
sns.heatmap(df.isnull(), cbar=False, yticklabels=False)
```

Out[162]: <matplotlib.axes._subplots.AxesSubplot at 0x7f10840ec358>

In [0]:
```
# One-Hot-Encode the Sex and Embarked columns
df = pd.concat([df, pd.get_dummies(df['Sex'], prefix='Sex', drop_first=True)],
axis=1).drop(['Sex'],axis=1)
df = pd.concat([df, pd.get_dummies(df['Embarked'], prefix='Embarked', drop_fir
st=True)], axis=1).drop(['Embarked'],axis=1)
```

In [164]:
```
df.head()
```

Out[164]:

	Survived	Pclass	Age	SibSp	Parch	Fare	Sex_male	Embarked_Q	Embarked_S
0	0	3	22.0	1	0	7.2500	1	0	1
1	1	1	38.0	1	0	71.2833	0	0	0
2	1	3	26.0	0	0	7.9250	0	0	1
3	1	1	35.0	1	0	53.1000	0	0	1
4	0	3	35.0	0	0	8.0500	1	0	1

In [165]:
```
# Now split the data into features and labels
features = df.drop(['Survived'], axis=1)
labels = df[['Survived']].values
print(features.shape, labels.shape)
```

```
(889, 8) (889, 1)
```

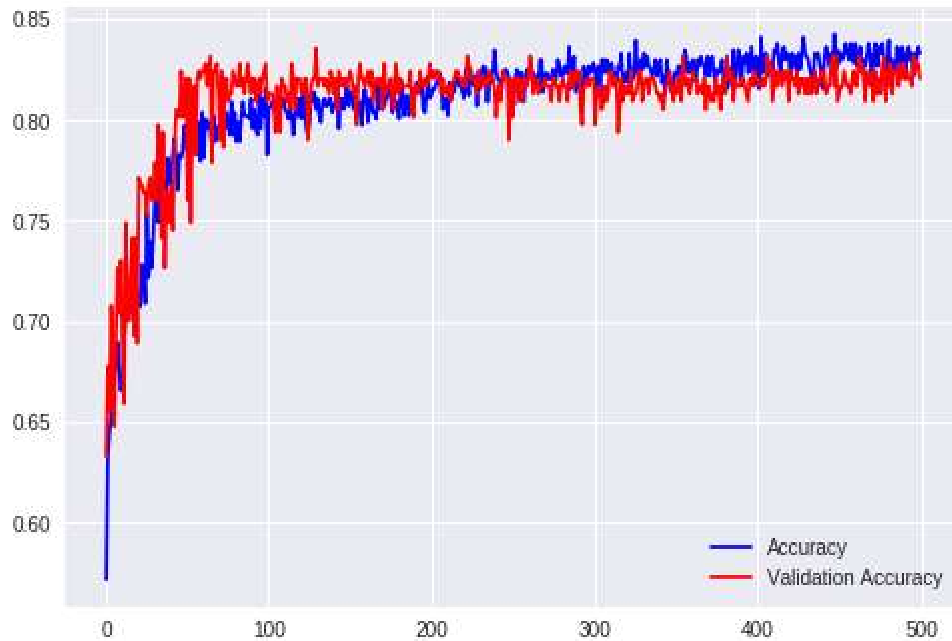
In [0]:
```
# Now that the features are cleaned up - we can train the binary classifier:

model = Sequential()

model.add(Dense(20, activation='relu', input_shape=(8,)))
model.add(Dense(20, activation='relu'))
model.add(Dense(1, activation='sigmoid'))

model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy'])

h = model.fit(features, labels, epochs=500, validation_split=0.3, verbose=0)
```

In [167]:
```
h.history.keys()
```

Out[167]:
```
dict_keys(['loss', 'acc', 'val_loss', 'val_acc'])
```

In [168]:
```
# Plot the accuracy during training
plt.plot(h.history['acc'], color='b', label='Accuracy')
plt.plot(h.history['val_acc'], color='r', label='Validation Accuracy')
plt.legend()
```

Out[168]: <matplotlib.legend.Legend at 0x7f1083a39eb8>



MNIST

See how well a fully connected Neural Network performs on MNSIT

In [0]:
```
# Import MNIST dataset
from keras.datasets import mnist
(x_train, y_train), (x_test, y_test) = mnist.load_data()
```

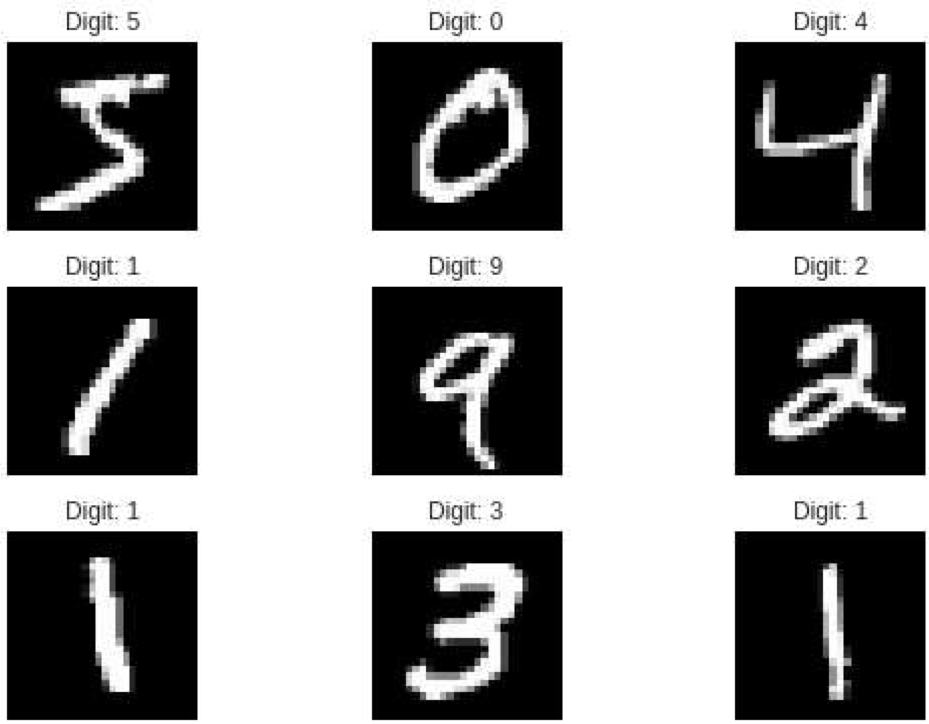
In [170]:
```
print(x_train.shape, y_train.shape)
```

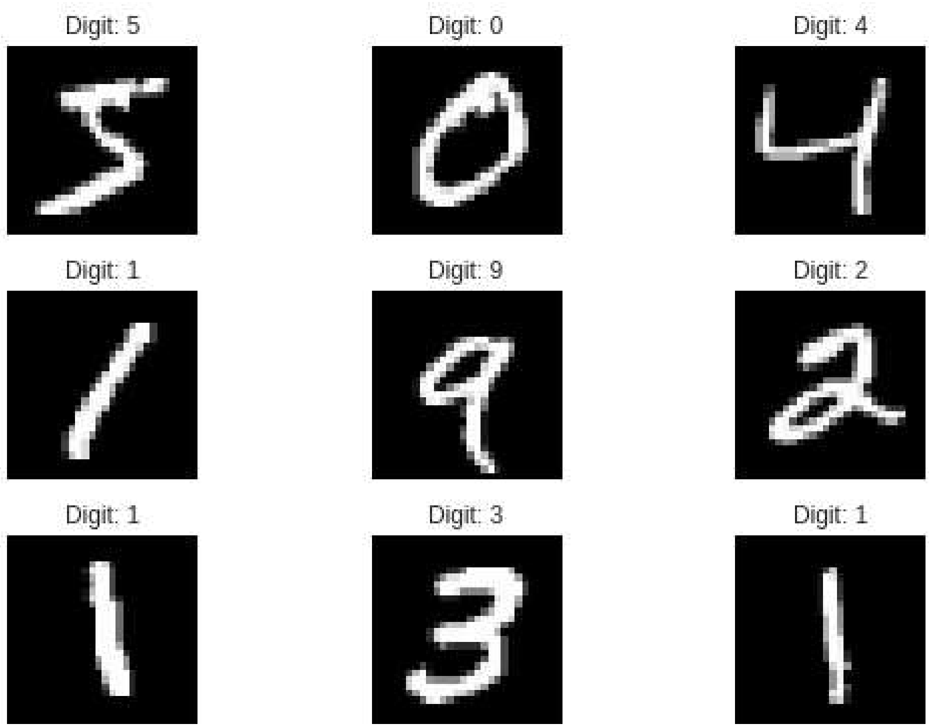
```
(60000, 28, 28) (60000,)
```

In [171]:

```
# Visualize the data
fig = plt.figure()
for i in range(9):
  plt.subplot(3,3,i+1)
  plt.tight_layout()
  plt.imshow(x_train[i], cmap='gray', interpolation='none')
  plt.title("Digit: {}".format(y_train[i]))
  plt.xticks([])
  plt.yticks([])
fig
```

Out[171]:





In [0]:
```
# Flatten the input vectors
x_train = x_train.reshape(60000, 784)
x_test = x_test.reshape(10000, 784)
x_train = x_train.astype('float32')
x_test = x_test.astype('float32')

# Normalize the input data
x_train /= 255
x_test /= 255
```

In [173]:
```
print(x_train.shape, y_train.shape)
```

```
(60000, 784) (60000,)
```

In [0]:
```
# Now one-hot encode the labels
from keras.utils import np_utils
y_train = np_utils.to_categorical(y_train, 10)
y_test = np_utils.to_categorical(y_test, 10)
```

In [175]:
```
print(x_train.shape, y_train.shape)
```

```
(60000, 784) (60000, 10)
```

In [176]:
```
# Build the NN and train it

model = Sequential()

model.add(Dense(512, activation='relu', input_shape=(784,)))
model.add(Dense(512, activation='relu'))
model.add(Dense(10, activation='softmax'))

model.compile(optimizer='adam',
             loss='categorical_crossentropy',
             metrics=['accuracy'])

h = model.fit(x_train, y_train,
          batch_size=128, epochs=20,
          verbose=2,
          validation_data=(x_test, y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
 - 10s - loss: 0.2203 - acc: 0.9349 - val_loss: 0.0998 - val_acc: 0.9699
Epoch 2/20
 - 9s - loss: 0.0789 - acc: 0.9756 - val_loss: 0.0892 - val_acc: 0.9699
Epoch 3/20
 - 9s - loss: 0.0508 - acc: 0.9836 - val_loss: 0.0705 - val_acc: 0.9778
Epoch 4/20
 - 9s - loss: 0.0369 - acc: 0.9880 - val_loss: 0.0704 - val_acc: 0.9792
Epoch 5/20
 - 9s - loss: 0.0277 - acc: 0.9909 - val_loss: 0.0746 - val_acc: 0.9770
Epoch 6/20
 - 9s - loss: 0.0215 - acc: 0.9926 - val_loss: 0.0861 - val_acc: 0.9759
Epoch 7/20
 - 9s - loss: 0.0188 - acc: 0.9941 - val_loss: 0.0773 - val_acc: 0.9817
Epoch 8/20
 - 9s - loss: 0.0148 - acc: 0.9950 - val_loss: 0.0813 - val_acc: 0.9796
Epoch 9/20
 - 9s - loss: 0.0129 - acc: 0.9958 - val_loss: 0.0874 - val_acc: 0.9799
Epoch 10/20
 - 9s - loss: 0.0170 - acc: 0.9945 - val_loss: 0.0919 - val_acc: 0.9773
Epoch 11/20
 - 9s - loss: 0.0110 - acc: 0.9966 - val_loss: 0.0877 - val_acc: 0.9778
Epoch 12/20
 - 9s - loss: 0.0144 - acc: 0.9953 - val_loss: 0.0858 - val_acc: 0.9813
Epoch 13/20
 - 9s - loss: 0.0102 - acc: 0.9966 - val_loss: 0.0861 - val_acc: 0.9806
Epoch 14/20
 - 9s - loss: 0.0094 - acc: 0.9967 - val_loss: 0.0926 - val_acc: 0.9790
Epoch 15/20
 - 9s - loss: 0.0074 - acc: 0.9974 - val_loss: 0.0908 - val_acc: 0.9815
Epoch 16/20
 - 9s - loss: 0.0090 - acc: 0.9972 - val_loss: 0.0962 - val_acc: 0.9807
Epoch 17/20
 - 9s - loss: 0.0103 - acc: 0.9966 - val_loss: 0.0900 - val_acc: 0.9811
Epoch 18/20
 - 9s - loss: 0.0060 - acc: 0.9977 - val_loss: 0.0949 - val_acc: 0.9818
Epoch 19/20
 - 9s - loss: 0.0094 - acc: 0.9970 - val_loss: 0.0900 - val_acc: 0.9839
Epoch 20/20
 - 9s - loss: 0.0073 - acc: 0.9979 - val_loss: 0.0925 - val_acc: 0.9809
```

In [177]:
```
h.history.keys()
```

Out[177]:
```
dict_keys(['loss', 'acc', 'val_loss', 'val_acc'])
```

In [179]:
```
# Plot the accuracy during training
plt.plot(h.history['acc'], color='b', label='Accuracy')
plt.plot(h.history['val_acc'], color='r', label='Validation Accuracy')
plt.legend()
```

Out[179]:
```
<matplotlib.legend.Legend at 0x7f108310c710>
```