Stock Prediction using LSTM Networks

Machine learning has found its application niche in many industries and fields, including Wall Street. Here, we will use an LSTM network to predict the trend and stock price for Apple. Long Short Term Memory (LSTM) networks are a subset of the overall Recurrent Neural Networks (RNN) neural network class. What is special about LSTM network elements is that they are capable of learning long-term dependencies and are explicitly designed to avoid the long-term dependency problem. Remembering information for long periods of time is practically their default behavior, not something they struggle to learn. A great source of information regarding LSTM's can be found at Andre karpathy’s blog (http://karpathy.github.io/2015/05/21/rnn-effectiveness/), which is considered one of the best resources on LSTM networks.

In [1]:
```
import pandas as pd
import numpy as np
from numpy import array
from numpy import array_equal
import random as rn
from tensorflow import set_random_seed
from math import sqrt
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
from keras.models import Model
from keras.layers import Input, LSTM, Dense, Dropout, Bidirectional, GRU
from keras.callbacks import ModelCheckpoint, TensorBoard
from keras import regularizers
from keras.optimizers import Adam, RMSprop
```

```
Using TensorFlow backend.
```

In [2]:
```
# set the random seed
sd = 777
np.random.seed(sd)
rn.seed(sd)
set_random_seed(sd)
```

In [3]:
```
# load & preview the dataset
df = pd.read_csv('data/AAPL.csv', engine='python')
df.head()
```

Out[3]:

	date	open	high	low	close	volume
0	1/9/14	71.6912	71.6991	70.1900	70.3432	69905199
1	1/10/14	70.7773	70.9045	69.6341	69.8740	76320664
2	1/13/14	69.4767	71.1274	69.4728	70.2398	94860843
3	1/14/14	70.5663	71.6820	70.4928	71.6374	83734371
4	1/15/14	72.5722	73.4481	72.3284	73.0757	98472619

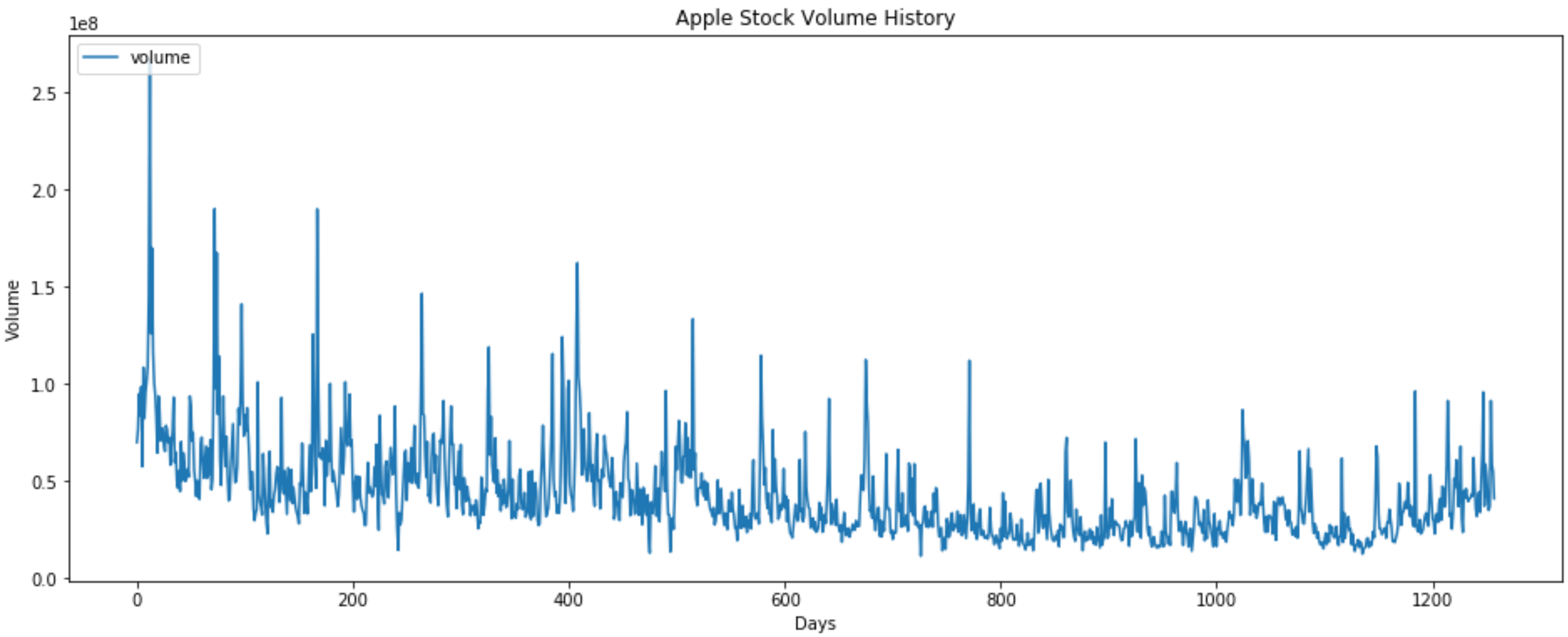
In [4]:
```
df.tail()
```

Out[4]:

	date	open	high	low	close	volume
1253	1/2/19	154.89	158.8500	154.23	157.92	37039737
1254	1/3/19	143.98	145.7200	142.00	142.19	91312195
1255	1/4/19	144.53	148.5499	143.80	148.26	58607070
1256	1/7/19	148.70	148.8300	145.90	147.93	54777764
1257	1/8/19	149.56	151.8200	148.52	150.75	41025314

In [5]:
```
# plot the price data
plt.figure(figsize=(16,6))
plt.plot(df["open"])
plt.plot(df["high"])
plt.plot(df["low"])
plt.plot(df["close"])
plt.title('Apple Stock Price History')
plt.ylabel('Price')
plt.xlabel('Days')
plt.legend(['open','high','low','close'], loc='upper left')
plt.show()
```

In [6]:
```
# plot the volume data
plt.figure(figsize=(16,6))
plt.plot(df["volume"])
plt.title('Apple Stock Volume History')
plt.ylabel('Volume')
plt.xlabel('Days')
plt.legend(['volume'], loc='upper left')
plt.show()
```



In [7]:
```
# plot just the closing price
plt.figure(figsize=(16,6))
plt.plot(df["close"])
plt.title('Apple Stock Closing Price History')
plt.ylabel('Price')
plt.xlabel('Days')
plt.legend(['close'], loc='upper left')
plt.show()
```

In [8]:
```
# check dataset for null values
print("Checking for null values:\n", df.isnull().sum())
```

```
Checking for null values:
 date      0
open      0
high      0
low       0
close     0
volume    0
dtype: int64
```

In [9]:
```
# split the dataset into training and testing sets
train, test = train_test_split(df, train_size=0.8, test_size=0.2, shuffle=False)
print("Training set size: %d, Test set size: %d" % (len(train), len(test)))
```

```
Training set size: 1006, Test set size: 252
```

In [10]:
```
# normalize the data
train_cols = ["open", "high", "low", "close", "volume"]
train = train.loc[:, train_cols].values
test = test.loc[:, train_cols].values
scaler = MinMaxScaler(feature_range=(0, 1))
train_scaled = scaler.fit_transform(train)
test_scaled = scaler.transform(test)
```

In [11]:
```
# transform dataset into supervised learning problem
def build_timeseries(data, time_steps, output_index):
    # output_index is the index of the column containing your desired output value
    # total number of time series samples is len(data) -  time_steps
    dim_0 = data.shape[0] - time_steps
    dim_1 = data.shape[1]
    x = np.zeros((dim_0, time_steps, dim_1))
    y = np.zeros((dim_0,))

    for i in range(dim_0):
        x[i] = data[i:time_steps+i]
        y[i] = data[time_steps+i, output_index]
    print("Input time series shape:", x.shape)
    print("Output time series shape:", y.shape)
    return x, y
```

In [12]:
```
# create training & test sets for LSTM
time_steps = 60
X_train, y_train = build_timeseries(train_scaled, time_steps, 3)
X_temp, y_temp = build_timeseries(test_scaled, time_steps, 3)
```

```
Input time series shape: (946, 60, 5)
Output time series shape: (946,)
Input time series shape: (192, 60, 5)
Output time series shape: (192,)
```

In [13]:
```
# trim training & test sets to be divisible by the batch size
def trim_dataset(dataset, batch_size):
    no_of_rows_drop = dataset.shape[0] % batch_size
    if (no_of_rows_drop > 0):
        return dataset[: -no_of_rows_drop]
    else:
        return dataset
```

In [14]:
```
# trim datasets to fit batch size
batch_size = 10
X_val, X_test = np.split(X_temp, 2)
y_val, y_test = np.split(y_temp, 2)
X_train = trim_dataset(X_train, batch_size)
y_train = trim_dataset(y_train, batch_size)
X_val = trim_dataset(X_val, batch_size)
y_val = trim_dataset(y_val, batch_size)
X_test = trim_dataset(X_test, batch_size)
y_test = trim_dataset(y_test, batch_size)
```

In [15]:
```
# review dataset shapes
print("Training input shape:", X_train.shape)
print("Training output shape:", y_train.shape)
print("Test input shape:", X_test.shape)
print("Test output shape:", y_test.shape)
print("Validation input shape:", X_test.shape)
print("Validation output shape:", y_test.shape)
```

```
Training input shape: (940, 60, 5)
Training output shape: (940,)
Test input shape: (90, 60, 5)
Test output shape: (90,)
Validation input shape: (90, 60, 5)
Validation output shape: (90,)
```

In [16]:
```
# define the LSTM model
def lstm_model(X, batch_size):
    inputs = Input(batch_shape=(batch_size, X.shape[1], X.shape[2]))
    L1 = LSTM(192, stateful=True, kernel_initializer='random_uniform', activity_regularizer=regularizers.l2(10
e-6))(inputs)
    D1 = Dropout(0.5)(L1)
    L2 = Dense(32, activation='relu')(D1)
    output = Dense(1)(L2)
    model = Model(inputs=inputs, outputs=output)
    return model
```

In [17]:
```
# create the LSTM model
model = lstm_model(X_train, batch_size)
optimizer = RMSprop(lr=0.0001)
model.compile(optimizer=optimizer, loss='mse')
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (10, 60, 5)               0
_________________________________________________________________
lstm_1 (LSTM)                (10, 192)                 152064
_________________________________________________________________
dropout_1 (Dropout)          (10, 192)                 0
_________________________________________________________________
dense_1 (Dense)              (10, 32)                  6176
_________________________________________________________________
dense_2 (Dense)              (10, 1)                   33
=================================================================
Total params: 158,273
Trainable params: 158,273
Non-trainable params: 0
_________________________________________________________________
```

In [18]:
```
# define save weights checkpoint
filepath="Stock_Prediction_LSTM_weights-{val_loss:.4f}-{epoch: 02d}.hdf5"
checkpoint = ModelCheckpoint(filepath, monitor='val_loss', verbose=1, save_best_only=True, mode='min')
```

In [19]:
```
# train the model
nb_epochs = 500
history = model.fit(X_train, y_train, epochs=nb_epochs, batch_size=batch_size, shuffle=False, validation_dat
a=(X_val, y_val), callbacks=[checkpoint]).history
```

```
Train on 940 samples, validate on 90 samples
Epoch 1/500
920/940 [============================>.] - ETA: 0s - loss: 0.0145Epoch 00001: val_loss improved from inf to
0.00459, saving model to Stock_Prediction_LSTM_weights-0.0046- 1.hdf5
940/940 [==============================] - 5s 6ms/step - loss: 0.0145 - val_loss: 0.0046
Epoch 2/500
930/940 [============================>.] - ETA: 0s - loss: 0.0057Epoch 00002: val_loss improved from 0.00459
to 0.00407, saving model to Stock_Prediction_LSTM_weights-0.0041- 2.hdf5
940/940 [==============================] - 5s 6ms/step - loss: 0.0058 - val_loss: 0.0041
Epoch 3/500
930/940 [============================>.] - ETA: 0s - loss: 0.0055Epoch 00003: val_loss did not improve
940/940 [==============================] - 5s 6ms/step - loss: 0.0056 - val_loss: 0.0054
Epoch 4/500
930/940 [============================>.] - ETA: 0s - loss: 0.0043Epoch 00004: val_loss did not improve
940/940 [==============================] - 6s 6ms/step - loss: 0.0044 - val_loss: 0.0047
Epoch 5/500
930/940 [============================>.] - ETA: 0s - loss: 0.0041Epoch 00005: val_loss did not improve
940/940 [==============================] - 5s 5ms/step - loss: 0.0042 - val_loss: 0.0069
Epoch 6/500
920/940 [============================>.] - ETA: 0s - loss: 0.0033Epoch 00006: val_loss did not improve
940/940 [==============================] - 4s 4ms/step - loss: 0.0035 - val_loss: 0.0071
Epoch 7/500
930/940 [============================>.] - ETA: 0s - loss: 0.0035Epoch 00007: val_loss improved from 0.00407
to 0.00395, saving model to Stock_Prediction_LSTM_weights-0.0040- 7.hdf5
940/940 [==============================] - 4s 4ms/step - loss: 0.0035 - val_loss: 0.0040
Epoch 8/500
920/940 [============================>.] - ETA: 0s - loss: 0.0031Epoch 00008: val_loss improved from 0.00395
to 0.00336, saving model to Stock_Prediction_LSTM_weights-0.0034- 8.hdf5
940/940 [==============================] - 4s 4ms/step - loss: 0.0032 - val_loss: 0.0034
Epoch 9/500
930/940 [============================>.] - ETA: 0s - loss: 0.0031Epoch 00009: val_loss improved from 0.00336
to 0.00288, saving model to Stock_Prediction_LSTM_weights-0.0029- 9.hdf5
940/940 [==============================] - 4s 4ms/step - loss: 0.0031 - val_loss: 0.0029
Epoch 10/500
920/940 [============================>.] - ETA: 0s - loss: 0.0026Epoch 00010: val_loss improved from 0.00288
to 0.00282, saving model to Stock_Prediction_LSTM_weights-0.0028- 10.hdf5
940/940 [==============================] - 4s 4ms/step - loss: 0.0027 - val_loss: 0.0028
Epoch 11/500
920/940 [============================>.] - ETA: 0s - loss: 0.0028Epoch 00011: val_loss did not improve
940/940 [==============================] - 4s 4ms/step - loss: 0.0028 - val_loss: 0.0067
Epoch 12/500
930/940 [============================>.] - ETA: 0s - loss: 0.0028Epoch 00012: val_loss did not improve
940/940 [==============================] - 4s 4ms/step - loss: 0.0028 - val_loss: 0.0032
Epoch 13/500
930/940 [============================>.] - ETA: 0s - loss: 0.0027Epoch 00013: val_loss did not improve
940/940 [==============================] - 4s 5ms/step - loss: 0.0028 - val_loss: 0.0029
```

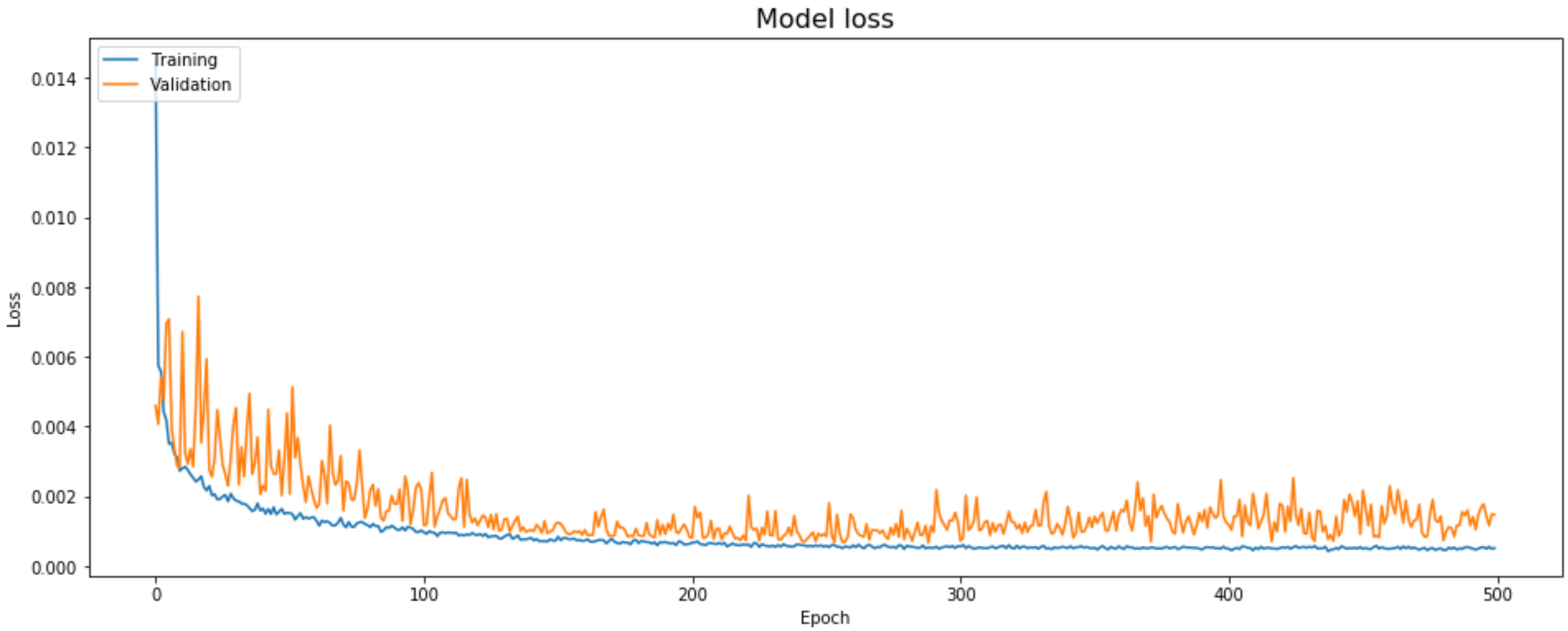
In [20]:

```
# evaluate the training set
test_val = model.evaluate(X_test, y_test, batch_size=batch_size)
print("Test Model Stats: ")
print("Loss: %.6f" % (test_val))
```

```
90/90 [==============================] - 0s 2ms/step
Test Model Stats:
Loss: 0.001845
```

In [21]:

```
# plot the model loss
plt.figure(figsize=(16,6))
plt.plot(history['loss'], label='Train')
plt.plot(history['val_loss'], label='Validation')
plt.title('Model loss', fontsize=16)
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Training', 'Validation'], loc='upper left')
plt.show()
```

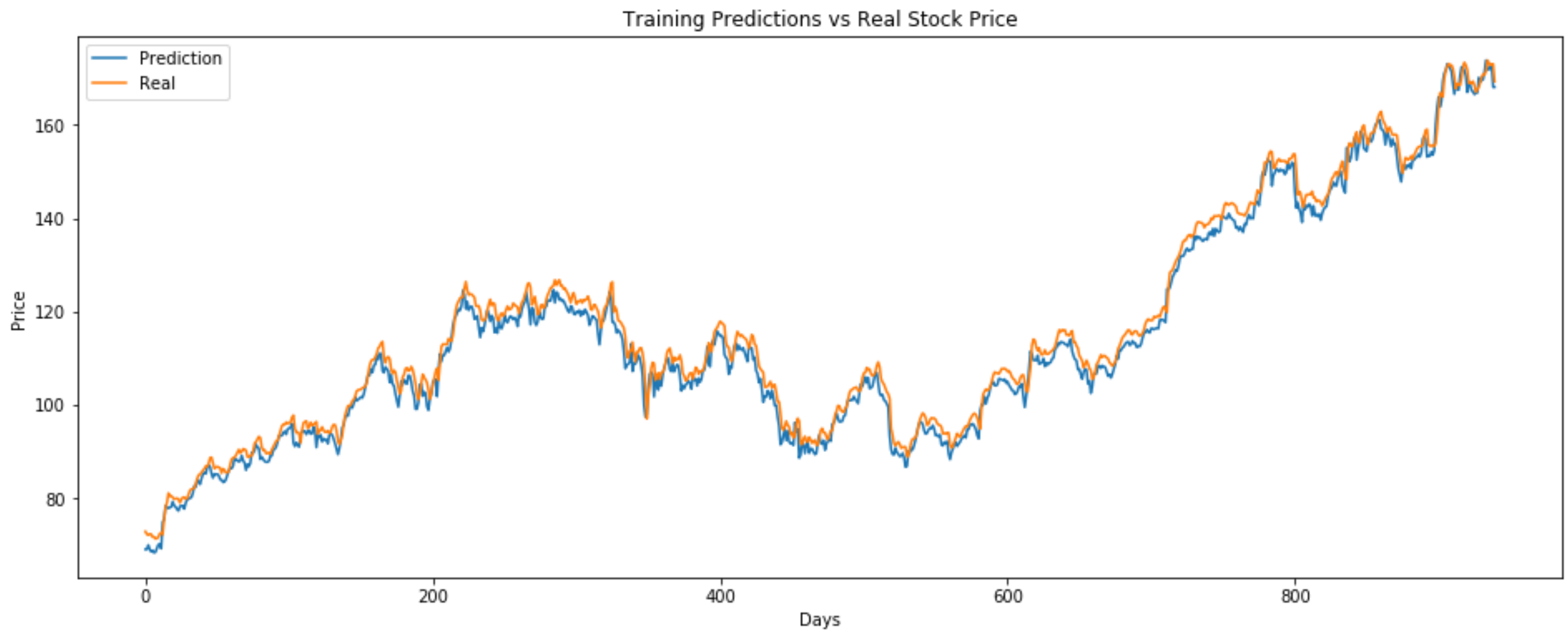


In [22]:
```
# load the best network weights
filename = "Stock_Prediction_LSTM_weights-0.0007- 257.hdf5"
model.load_weights(filename)
model.compile(optimizer=optimizer, loss='mse')
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (10, 60, 5)               0
_________________________________________________________________
lstm_1 (LSTM)                (10, 192)                 152064
_________________________________________________________________
dropout_1 (Dropout)          (10, 192)                 0
_________________________________________________________________
dense_1 (Dense)              (10, 32)                  6176
_________________________________________________________________
dense_2 (Dense)              (10, 1)                   33
=================================================================
Total params: 158,273
Trainable params: 158,273
Non-trainable params: 0
_________________________________________________________________
```

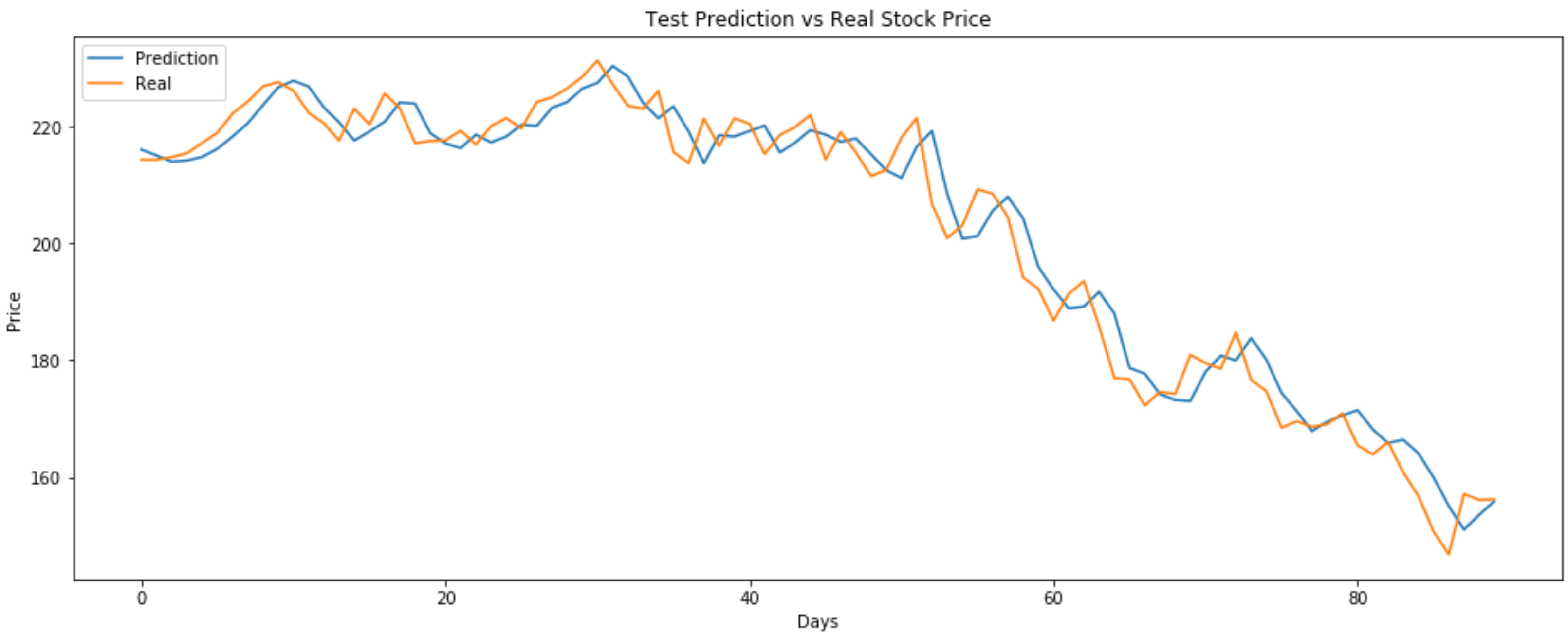
In [23]:
```
train_pred = model.predict(X_train, batch_size)
train_pred_org = (train_pred * scaler.data_range_[3]) + scaler.data_min_[3]
y_train_org = (y_train * scaler.data_range_[3]) + scaler.data_min_[3]
```

In [24]:
```
# Visualize the training predictions
plt.figure(figsize=(16,6))
plt.plot(y_train_org)
plt.plot(train_pred_org)
plt.title('Training Predictions vs Real Stock Price')
plt.ylabel('Price')
plt.xlabel('Days')
plt.legend(['Prediction', 'Real'], loc='upper left')
plt.show()
```



In [25]:
```
# predict model results on test set and reverse scale outputs
y_pred = model.predict(X_test, batch_size)
y_pred_org = (y_pred * scaler.data_range_[3]) + scaler.data_min_[3]
y_test_org = (y_test * scaler.data_range_[3]) + scaler.data_min_[3]
```

In [26]:
```
# Visualize the test set predictions
plt.figure(figsize=(16,6))
plt.plot(y_pred_org, label='Prediction')
plt.plot(y_test_org, label='Real')
plt.title('Test Prediction vs Real Stock Price')
plt.ylabel('Price')
plt.xlabel('Days')
plt.legend(['Prediction', 'Real'], loc='upper left')
plt.show()
```



In [27]:
```
# make a prediction of the next stock price
X = X_test[-10:]
yhat = model.predict(X, batch_size=batch_size)
prediction = (yhat[0,0] * scaler.data_range_[3]) + scaler.data_min_[3]
print("The prediction for the next stock price is $%.2f" % round(prediction, 2))
```

```
The prediction for the next stock price is $171.49
```