6_stock_price_prediction

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July 24, 2023

1 使用 LSTM 进行股票价格预测

[2]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
%matplotlib inline

from matplotlib.pylab import rcParams
rcParams['figure.figsize']=20,10

from keras.models import Sequential
from keras.layers import LSTM,Dropout,Dense

from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
```

```
2023-07-21 15:59:12.973041: I tensorflow/core/platform/cpu_feature_guard.cc:193]
This TensorFlow binary is optimized with oneAPI Deep Neural Network Library
(oneDNN) to use the following CPU instructions in performance-critical
operations:  SSE4.1 SSE4.2 AVX AVX2 FMA
To enable them in other operations, rebuild TensorFlow with the appropriate
compiler flags.
```

[3]:
```
df=pd.read_csv('../dataset/TATAGLOBAL.csv')
df.head()
```

[3]:
```
         Date    Open    High     Low    Last   Close  Total Trade Quantity  \
0  2019-01-04  210.60  214.90  210.00  213.50  213.80             1213181.0
1  2019-01-03  214.95  215.35  209.90  210.55  210.05             2096553.0
2  2019-01-02  219.00  220.35  213.60  214.20  214.60             1081778.0
3  2019-01-01  219.95  221.05  218.05  218.95  219.10              716275.0
4  2018-12-31  222.00  223.65  218.85  219.55  219.40              965858.0

   Turnover (Lacs)
0          2583.05
1          4433.50
2          2340.31
```

```
3           1571.63
4           2131.09
```

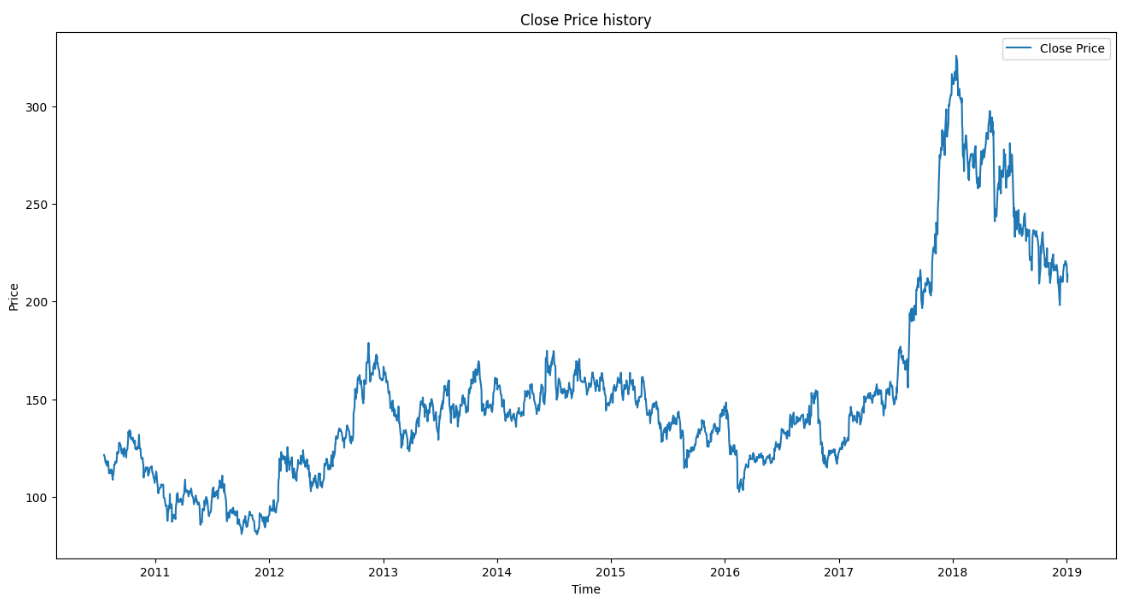
1.1 数据集说明

- 数据集中包含了日期, 开盘价格 (Open), 最高价 (High), 最低价 (Low), 最后一次交易价格 (Last), 收盘价格 (Close), 总交易量 (Total Trade Quantity), 周转金额 (Turnover, 单位 10 万)
- 接下来使用 LSTM 模型来预测收盘价, 首先可视化展示历史收盘股价

[4]:
```
# Display stock close price history
df['Date']=pd.to_datetime(df.Date,format='%Y-%m-%d')
df.index=df['Date']

plt.figure(figsize=(16,8))
plt.xlabel('Time')
plt.ylabel('Price')
plt.plot(df['Close'],label='Close Price')
plt.legend(loc='best')
plt.title('Close Price history')
```

[4]:
```
Text(0.5, 1.0, 'Close Price history')
```



使用历史收盘股价预测未来股价, 预处理中删除其他列

[5]:
```
# sort the dataset on date time, and filter 'Date' and 'Close' columns
data=df.sort_index(ascending=True,axis=0)
new_dataset=pd.DataFrame(index=range(0,len(df)),columns=['Date','Close'])
print(len(df))
```

```
for i in range(0,len(data)):
    new_dataset['Date'][i]=data['Date'][i]
    new_dataset['Close'][i]=data['Close'][i]
```

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1.2 数据预处理

- **数据索引和清除**: 设置 Date 列为索引列, 因为他提供了股票价格的逻辑顺序. 由于该列不需要传入模型, 故将其删除;
- **数据规范化 (Normalization)**: 将数据集中的数据规范化变换到范围 [0,1] 中. 这可以加速训练, 并且避免过大数值在训练过程中支配其他特征;
- **数据划分**: 数据集被划分为训练集和验证集. 前 987 个数据被用于训练, 其余用来验证. 该划分确保了模型在训练集上进行训练, 但在没有见到过的验证集序列上进行验证, 帮助确保了模型可以在新数据上泛化良好;
- **特征和标签创建**: 对股票收市价格预测这个任务, 使用过去 60 天的数据来预测下一天的收市价格. 为了实现该目的, 创建连续 60 天的价格序列作为特征 (X_train), 下一天的收市价格作为标签 (y_train). 对整个训练集都如此处理;
- **数据变形**: 根据 LSTM 模型的需要, 将 X_train 从 2D 转为 3D 形式. 格式为 [samples, time steps, features]. 其中 `samples` 是训练序列总数, `time steps` 是每个序列的长度 (60 days), `features` 是序列中每天的特征 (1 特征, 即正规化的收市价).

[6]:
```
train_size = 987
print(f"train_size[{train_size}]")

# set Date as index, and drop Date column
new_dataset.index = new_dataset.Date
new_dataset.drop("Date", axis=1, inplace=True)
print(new_dataset.head())

final_dataset = new_dataset.values

# normalize the new filtered dataset to range (0, 1)
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_data = scaler.fit_transform(final_dataset)

# split train and valid data
train_data, valid_data = (
    final_dataset[:train_size,:],
    final_dataset[train_size:,:],
)

# Construct train arrays
X_train, y_train = [], []

for i in range(60, len(train_data)):
    X_train.append(scaled_data[i - 60 : i, 0])
```

```
    y_train.append(scaled_data[i, 0])

X_train, y_train = np.array(X_train), np.array(y_train)

print(X_train.shape)
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))
print(X_train.shape)
```

```
train_size[987]
             Close
Date
2010-07-21  121.55
2010-07-22   120.9
2010-07-23  120.65
2010-07-26   117.6
2010-07-27  118.65
(927, 60)
(927, 60, 1)
```

1.3 模型架构和训练

- **模型架构**: 借助 Keras 库中的 Sequential 模型来搭建 LSTM 模型. 包含输入层具有 50 个单元的 LSTM 层, `return_sequences` 设置为 `True`, 意味着下一层也是 LSTM 层. 第二个 LSTM 层有 50 个单元, 但是没有 return sequences. 最终, 有一个具有一个 unit 的 Dense layer, 输出预测的股票收市价.
- **模型编译**: 在训练钱, 使用 `adam` 优化器和 `mean_squared_error` 损失函数来编译模型. 平均平方差是回归问题常见的损失函数, 计算预测值和实际值之间的平均平方差.
- **模型训练**: 使用 `fit` 函数对模型进行训练. 训练 100 轮 (对数据集训练 100 次), 批次大小为 1;
- **还原预测大小**: 由于模型训练在正规化数据上, 预测值也是被正规化的, 因此, 借助 `inverse_transform` 函数来还原预测收市价格到原本范围.

[7]:
```
from keras.callbacks import EarlyStopping

# Build and train the LSTM model
lstm_model = Sequential()
lstm_model.add(
    LSTM(units=50, return_sequences=True, input_shape=(X_train.shape[1], 1))
)
lstm_model.add(Dropout(0.2))
lstm_model.add(LSTM(units=50))
lstm_model.add(Dropout(0.2))
lstm_model.add(Dense(1))

inputs = new_dataset[len(new_dataset) - len(valid_data) - 60 :].values
inputs = inputs.reshape(-1, 1)
inputs = scaler.transform(inputs)
print(inputs.shape)
```

```python
lstm_model.compile(loss="mean_squared_error", optimizer="adam")

# patience is the number of epochs to check for improvement
early_stop=EarlyStopping(monitor='val_loss', patience=10, verbose=1)

lstm_model.fit(X_train, y_train, epochs=100, batch_size=1, verbose=2,␣
 ↪validation_split=0.2, callbacks=[early_stop])
```

```
2023-07-21 15:59:14.582620: I
tensorflow/compiler/xla/stream_executor/cuda/cuda_gpu_executor.cc:981]
successful NUMA node read from SysFS had negative value (-1), but there must be
at least one NUMA node, so returning NUMA node zero
2023-07-21 15:59:14.596146: I
tensorflow/compiler/xla/stream_executor/cuda/cuda_gpu_executor.cc:981]
successful NUMA node read from SysFS had negative value (-1), but there must be
at least one NUMA node, so returning NUMA node zero
2023-07-21 15:59:14.596323: I
tensorflow/compiler/xla/stream_executor/cuda/cuda_gpu_executor.cc:981]
successful NUMA node read from SysFS had negative value (-1), but there must be
at least one NUMA node, so returning NUMA node zero
2023-07-21 15:59:14.596755: I tensorflow/core/platform/cpu_feature_guard.cc:193]
This TensorFlow binary is optimized with oneAPI Deep Neural Network Library
(oneDNN) to use the following CPU instructions in performance-critical
operations:  SSE4.1 SSE4.2 AVX AVX2 FMA
To enable them in other operations, rebuild TensorFlow with the appropriate
compiler flags.
2023-07-21 15:59:14.597340: I
tensorflow/compiler/xla/stream_executor/cuda/cuda_gpu_executor.cc:981]
successful NUMA node read from SysFS had negative value (-1), but there must be
at least one NUMA node, so returning NUMA node zero
2023-07-21 15:59:14.597473: I
tensorflow/compiler/xla/stream_executor/cuda/cuda_gpu_executor.cc:981]
successful NUMA node read from SysFS had negative value (-1), but there must be
at least one NUMA node, so returning NUMA node zero
2023-07-21 15:59:14.597599: I
tensorflow/compiler/xla/stream_executor/cuda/cuda_gpu_executor.cc:981]
successful NUMA node read from SysFS had negative value (-1), but there must be
at least one NUMA node, so returning NUMA node zero
2023-07-21 15:59:14.645029: I
tensorflow/compiler/xla/stream_executor/cuda/cuda_gpu_executor.cc:981]
successful NUMA node read from SysFS had negative value (-1), but there must be
at least one NUMA node, so returning NUMA node zero
2023-07-21 15:59:14.645178: I
tensorflow/compiler/xla/stream_executor/cuda/cuda_gpu_executor.cc:981]
successful NUMA node read from SysFS had negative value (-1), but there must be
at least one NUMA node, so returning NUMA node zero
2023-07-21 15:59:14.645296: I
```

```
tensorflow/compiler/xla/stream_executor/cuda/cuda_gpu_executor.cc:981]
successful NUMA node read from SysFS had negative value (-1), but there must be
at least one NUMA node, so returning NUMA node zero
2023-07-21 15:59:14.645381: I
tensorflow/core/common_runtime/gpu/gpu_device.cc:1613] Created device
/job:localhost/replica:0/task:0/device:GPU:0 with 4279 MB memory:  -> device: 0,
name: NVIDIA GeForce RTX 3060 Laptop GPU, pci bus id: 0000:01:00.0, compute
capability: 8.6
```

```
(1173, 1)
Epoch 1/100
```

```
2023-07-21 15:59:16.349128: I
tensorflow/compiler/xla/stream_executor/cuda/cuda_dnn.cc:428] Loaded cuDNN
version 8800
2023-07-21 15:59:16.393478: I
tensorflow/compiler/xla/stream_executor/cuda/cuda_blas.cc:630] TensorFloat-32
will be used for the matrix multiplication. This will only be logged once.
2023-07-21 15:59:16.394141: I tensorflow/compiler/xla/service/service.cc:173]
XLA service 0x7f027d723780 initialized for platform CUDA (this does not
guarantee that XLA will be used). Devices:
2023-07-21 15:59:16.394184: I tensorflow/compiler/xla/service/service.cc:181]
StreamExecutor device (0): NVIDIA GeForce RTX 3060 Laptop GPU, Compute
Capability 8.6
2023-07-21 15:59:16.398826: I
tensorflow/compiler/mlir/tensorflow/utils/dump_mlir_util.cc:268] disabling MLIR
crash reproducer, set env var `MLIR_CRASH_REPRODUCER_DIRECTORY` to enable.
2023-07-21 15:59:16.475479: I
tensorflow/compiler/jit/xla_compilation_cache.cc:477] Compiled cluster using
XLA!  This line is logged at most once for the lifetime of the process.
```

```
741/741 - 7s - loss: 0.0015 - val_loss: 7.1432e-04 - 7s/epoch - 10ms/step
Epoch 2/100
741/741 - 5s - loss: 7.6713e-04 - val_loss: 9.8199e-04 - 5s/epoch - 7ms/step
Epoch 3/100
741/741 - 3s - loss: 7.3787e-04 - val_loss: 8.0880e-04 - 3s/epoch - 5ms/step
Epoch 4/100
741/741 - 5s - loss: 5.5893e-04 - val_loss: 3.3829e-04 - 5s/epoch - 6ms/step
Epoch 5/100
741/741 - 4s - loss: 5.6176e-04 - val_loss: 8.9266e-04 - 4s/epoch - 6ms/step
Epoch 6/100
741/741 - 4s - loss: 4.9984e-04 - val_loss: 2.5765e-04 - 4s/epoch - 6ms/step
Epoch 7/100
741/741 - 5s - loss: 4.4709e-04 - val_loss: 4.4149e-04 - 5s/epoch - 6ms/step
Epoch 8/100
741/741 - 5s - loss: 3.9459e-04 - val_loss: 1.9746e-04 - 5s/epoch - 7ms/step
Epoch 9/100
741/741 - 5s - loss: 4.3092e-04 - val_loss: 2.6681e-04 - 5s/epoch - 7ms/step
Epoch 10/100
```

```
741/741 - 5s - loss: 4.0207e-04 - val_loss: 3.5336e-04 - 5s/epoch - 7ms/step
Epoch 11/100
741/741 - 5s - loss: 3.5193e-04 - val_loss: 0.0016 - 5s/epoch - 6ms/step
Epoch 12/100
741/741 - 5s - loss: 4.0975e-04 - val_loss: 3.7392e-04 - 5s/epoch - 7ms/step
Epoch 13/100
741/741 - 5s - loss: 3.1512e-04 - val_loss: 2.3135e-04 - 5s/epoch - 7ms/step
Epoch 14/100
741/741 - 5s - loss: 3.2785e-04 - val_loss: 1.5030e-04 - 5s/epoch - 7ms/step
Epoch 15/100
741/741 - 5s - loss: 3.4912e-04 - val_loss: 1.4673e-04 - 5s/epoch - 7ms/step
Epoch 16/100
741/741 - 5s - loss: 3.1780e-04 - val_loss: 5.3904e-04 - 5s/epoch - 6ms/step
Epoch 17/100
741/741 - 5s - loss: 3.4584e-04 - val_loss: 1.7035e-04 - 5s/epoch - 7ms/step
Epoch 18/100
741/741 - 5s - loss: 3.0819e-04 - val_loss: 2.1680e-04 - 5s/epoch - 7ms/step
Epoch 19/100
741/741 - 5s - loss: 3.0371e-04 - val_loss: 1.5961e-04 - 5s/epoch - 6ms/step
Epoch 20/100
741/741 - 5s - loss: 2.9713e-04 - val_loss: 1.4569e-04 - 5s/epoch - 7ms/step
Epoch 21/100
741/741 - 5s - loss: 3.2084e-04 - val_loss: 6.5265e-04 - 5s/epoch - 6ms/step
Epoch 22/100
741/741 - 5s - loss: 3.3395e-04 - val_loss: 1.3690e-04 - 5s/epoch - 7ms/step
Epoch 23/100
741/741 - 5s - loss: 2.9665e-04 - val_loss: 3.6110e-04 - 5s/epoch - 7ms/step
Epoch 24/100
741/741 - 5s - loss: 3.2465e-04 - val_loss: 1.4439e-04 - 5s/epoch - 7ms/step
Epoch 25/100
741/741 - 5s - loss: 3.0953e-04 - val_loss: 1.4555e-04 - 5s/epoch - 7ms/step
Epoch 26/100
741/741 - 5s - loss: 3.2337e-04 - val_loss: 2.7187e-04 - 5s/epoch - 7ms/step
Epoch 27/100
741/741 - 5s - loss: 3.0384e-04 - val_loss: 2.2130e-04 - 5s/epoch - 7ms/step
Epoch 28/100
741/741 - 5s - loss: 3.3285e-04 - val_loss: 3.9861e-04 - 5s/epoch - 7ms/step
Epoch 29/100
741/741 - 5s - loss: 2.9305e-04 - val_loss: 0.0011 - 5s/epoch - 6ms/step
Epoch 30/100
741/741 - 5s - loss: 2.9173e-04 - val_loss: 1.3465e-04 - 5s/epoch - 7ms/step
Epoch 31/100
741/741 - 5s - loss: 2.7395e-04 - val_loss: 1.8179e-04 - 5s/epoch - 7ms/step
Epoch 32/100
741/741 - 5s - loss: 3.0898e-04 - val_loss: 1.3793e-04 - 5s/epoch - 6ms/step
Epoch 33/100
741/741 - 5s - loss: 2.9024e-04 - val_loss: 1.4782e-04 - 5s/epoch - 7ms/step
Epoch 34/100
```

```
741/741 - 5s - loss: 2.6524e-04 - val_loss: 1.3738e-04 - 5s/epoch - 6ms/step
Epoch 35/100
741/741 - 5s - loss: 2.7002e-04 - val_loss: 1.6552e-04 - 5s/epoch - 7ms/step
Epoch 36/100
741/741 - 6s - loss: 2.6745e-04 - val_loss: 1.5639e-04 - 6s/epoch - 8ms/step
Epoch 37/100
741/741 - 5s - loss: 2.6204e-04 - val_loss: 1.3704e-04 - 5s/epoch - 7ms/step
Epoch 38/100
741/741 - 5s - loss: 2.4901e-04 - val_loss: 1.6514e-04 - 5s/epoch - 7ms/step
Epoch 39/100
741/741 - 5s - loss: 2.8131e-04 - val_loss: 1.6380e-04 - 5s/epoch - 7ms/step
Epoch 40/100
741/741 - 5s - loss: 3.0784e-04 - val_loss: 1.4729e-04 - 5s/epoch - 6ms/step
Epoch 40: early stopping
```

[7]:
```
<keras.callbacks.History at 0x7f03a0702800>
```

[8]:
```python
# take a sample of a dataset to make stock price predictions using the LSTM
# model
X_test = []
for i in range(60, inputs.shape[0]):
    X_test.append(inputs[i-60:i,0])
X_test=np.array(X_test)

print(X_test.shape)
X_test=np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
print(X_test.shape)

predicted_closing_price=lstm_model.predict(X_test)
# Restore origin data from normalized output
predicted_closing_price=scaler.inverse_transform(predicted_closing_price)
```

```
(1113, 60)
(1113, 60, 1)
35/35 [==============================] - 0s 2ms/step
```

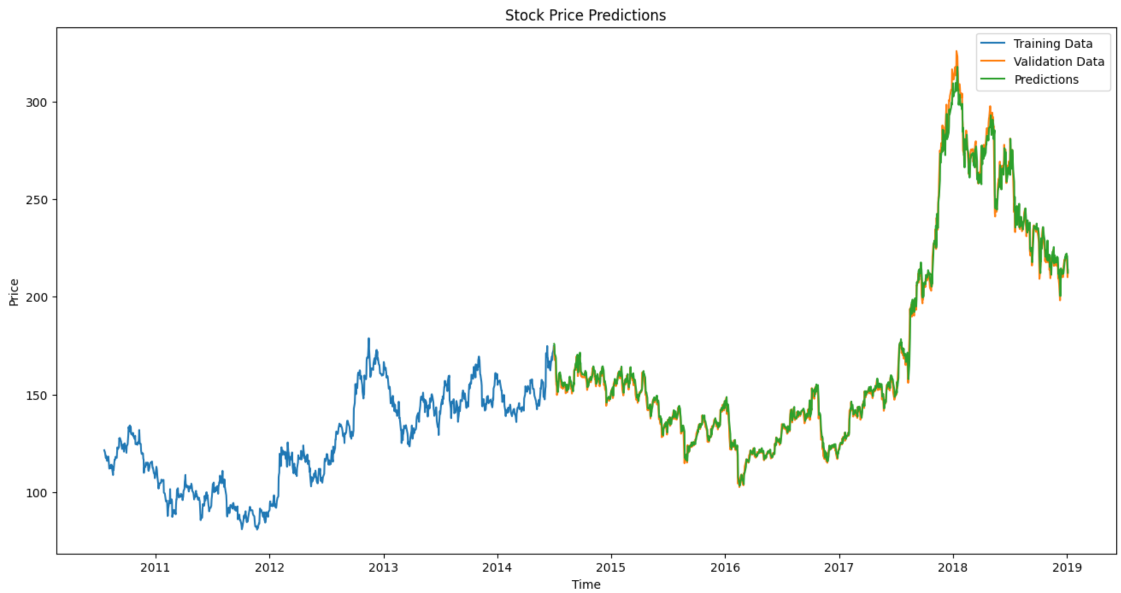
[9]:
```python
# save the lstm model
lstm_model.save('model.h5')
```

1.4 可视化结果并评估模型性能

将预测股票价格和实际股票价格进行可视化, 可以看到预测价格较准确.

[10]:
```python
# visualize the predicted stock costs with actual stock costs
train_data = new_dataset[:train_size].copy()
valid_data = new_dataset[train_size:].copy()
valid_data.loc[:, "Predictions"] = predicted_closing_price
```

```python
plt.figure(figsize=(16, 8))
plt.plot(train_data["Close"], label="Training Data")
plt.plot(valid_data["Close"], label="Validation Data")
plt.plot(valid_data["Predictions"], label="Predictions")
plt.title("Stock Price Predictions")
plt.xlabel("Time")
plt.ylabel("Price")
plt.legend(loc="best")
plt.show()
```

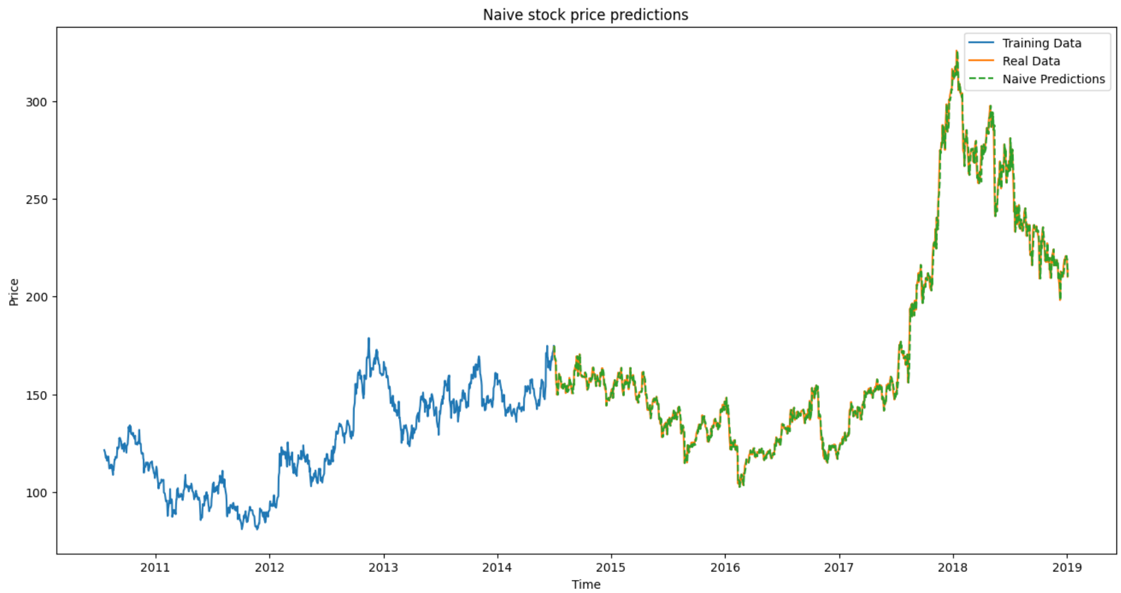


但是实际上使用 LSTM 将股价作为 label 进行预测的结果是没有价值的. 可以看到下面的代码中, 使用昨天的股价作为第二天的预测价相比 LSTM 的拟合程度更好. 这是因为股价是非稳定序列, 且相邻两天之间的变动很小.

[31]:
```python
# Use yesterday's close price as today's predicted close price
train_data = new_dataset[:train_size].copy()
naive_data = new_dataset[train_size:].copy()
naive_data.loc[:, "Naive Predictions"] = new_dataset[train_size - 1 : -1][
    "Close"
].values

plt.figure(figsize=(16, 8))
plt.plot(train_data["Close"], label="Training Data")
plt.plot(naive_data["Close"], label="Real Data",linestyle='-')
plt.plot(
    naive_data.index,
    naive_data["Naive Predictions"],
    label="Naive Predictions",
```

```
    linestyle="--",
)
plt.title("Naive stock price predictions")
plt.xlabel("Time")
plt.ylabel("Price")
plt.legend(loc="best")
plt.show()
```



2 使用预测差值图来评价两个模型的预测效果

预测股票的收益率, 或者涨跌是更好的方式. 将股票昨天和今天真实价格的差作为 x 轴, 预测价格的差作为 y 轴画散点图进行观察.

可以看到, 两个模型的预测结果都是与 x 轴没有什么相关性的散点图. 因此本实验仅作为对 LSTM 的了解和练习, 并不能帮助获取股票收益.

[33]:
```
diff_data = pd.DataFrame(index=valid_data.index)

# calculate the true diff
diff_data['True_Difference']=valid_data['Close'].diff()

# calculate the prediction difference for LSTM and naive model
diff_data['LSTM_Predicted_Difference']=valid_data['Predictions'].diff()
diff_data['Naive_Predicted_Difference']=naive_data['Naive Predictions'].diff()

# create scatter figure
plt.figure(figsize=(16,8))
```

```python
plt.scatter(diff_data['True_Difference'],␣
    ↪diff_data['LSTM_Predicted_Difference'], label='LSTM Predicted Difference',␣
    ↪alpha=0.5)
plt.scatter(diff_data['True_Difference'],␣
    ↪diff_data['Naive_Predicted_Difference'], label='Naive Predicted Difference',␣
    ↪alpha=0.5)
plt.title('True Difference vs Predicted Difference')
plt.xlabel('True Difference')
plt.ylabel('Predicted Difference')
plt.legend(loc='best')
plt.show()
```