Predict stock prices with Long short-term memory (LSTM)

This simple example will show you how LSTM models predict time series data. Stock market data is a great choice for this because it's quite regular and widely available via the Internet.

Install requirements

We install Tensorflow 2.0 with GPU support first

```
!pip install tensorflow-gpu==2.0.0-alpha0
```

```
Requirement already satisfied: tensorflow-gpu==2.0.0-alpha0 in /usr/local/lib/python3.6/dist-packages (2.0.0a0)
Requirement already satisfied: absl-py>=0.7.0 in /usr/local/lib/python3.6/dist-packages (from tensorflow-gpu==2.0.0-alpha0) (0.7.1)
Requirement already satisfied: astor>=0.6.0 in /usr/local/lib/python3.6/dist-packages (from tensorflow-gpu==2.0.0-alpha0) (0.7.1)
Requirement already satisfied: google-pasta>=0.1.2 in /usr/local/lib/python3.6/dist-packages (from tensorflow-gpu==2.0.0-alpha0) (0.1.5)
Requirement already satisfied: gast>=0.2.0 in /usr/local/lib/python3.6/dist-packages (from tensorflow-gpu==2.0.0-alpha0) (0.2.2)
Requirement already satisfied: keras-preprocessing>=1.0.5 in /usr/local/lib/python3.6/dist-packages (from tensorflow-gpu==2.0.0-alpha0)
Requirement already satisfied: tb-nightly<1.14.0a20190302,>=1.14.0a20190301 in /usr/local/lib/python3.6/dist-packages (from tensorflow-g
Requirement already satisfied: tf-estimator-nightly<1.14.0.dev2019030116,>=1.14.0.dev2019030115 in /usr/local/lib/python3.6/dist-package
Requirement already satisfied: wheel>=0.26 in /usr/local/lib/python3.6/dist-packages (from tensorflow-gpu==2.0.0-alpha0) (0.33.1)
Requirement already satisfied: keras-applications>=1.0.6 in /usr/local/lib/python3.6/dist-packages (from tensorflow-gpu==2.0.0-alpha0) (
Requirement already satisfied: protobuf>=3.6.1 in /usr/local/lib/python3.6/dist-packages (from tensorflow-gpu==2.0.0-alpha0) (3.7.1)
Requirement already satisfied: six>=1.10.0 in /usr/local/lib/python3.6/dist-packages (from tensorflow-gpu==2.0.0-alpha0) (1.11.0)
Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.6/dist-packages (from tensorflow-gpu==2.0.0-alpha0) (1.1.0)
Requirement already satisfied: grpcio>=1.8.6 in /usr/local/lib/python3.6/dist-packages (from tensorflow-gpu==2.0.0-alpha0) (1.15.0)
Requirement already satisfied: numpy<2.0,>=1.14.5 in /usr/local/lib/python3.6/dist-packages (from tensorflow-gpu==2.0.0-alpha0) (1.16.2)
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.6/dist-packages (from tb-nightly<1.14.0a20190302,>=1.14.0a20190
Requirement already satisfied: werkzeug>=0.11.15 in /usr/local/lib/python3.6/dist-packages (from tb-nightly<1.14.0a20190302,>=1.14.0a201
Requirement already satisfied: h5py in /usr/local/lib/python3.6/dist-packages (from keras-applications>=1.0.6->tensorflow-gpu==2.0.0-alp
Requirement already satisfied: setuptools in /usr/local/lib/python3.6/dist-packages (from protobuf>=3.6.1->tensorflow-gpu==2.0.0-alpha0)
```

```
!pip install pandas-datareader
```

```
Requirement already satisfied: pandas-datareader in /usr/local/lib/python3.6/dist-packages (0.7.0)
Requirement already satisfied: pandas>=0.19.2 in /usr/local/lib/python3.6/dist-packages (from pandas-datareader) (0.23.4)
Requirement already satisfied: lxml in /usr/local/lib/python3.6/dist-packages (from pandas-datareader) (4.2.6)
Requirement already satisfied: wrapt in /usr/local/lib/python3.6/dist-packages (from pandas-datareader) (1.10.11)
Requirement already satisfied: requests>=2.3.0 in /usr/local/lib/python3.6/dist-packages (from pandas-datareader) (2.18.4)
Requirement already satisfied: numpy>=1.9.0 in /usr/local/lib/python3.6/dist-packages (from pandas>=0.19.2->pandas-datareader) (1.16.2)
Requirement already satisfied: python-dateutil>=2.5.0 in /usr/local/lib/python3.6/dist-packages (from pandas>=0.19.2->pandas-datareader)
Requirement already satisfied: pytz>=2011k in /usr/local/lib/python3.6/dist-packages (from pandas>=0.19.2->pandas-datareader) (2018.9)
Requirement already satisfied: urllib3<1.23,>=1.21.1 in /usr/local/lib/python3.6/dist-packages (from requests>=2.3.0->pandas-datareader)
Requirement already satisfied: idna<2.7,>=2.5 in /usr/local/lib/python3.6/dist-packages (from requests>=2.3.0->pandas-datareader) (2.6)
Requirement already satisfied: chardet<3.1.0,>=3.0.2 in /usr/local/lib/python3.6/dist-packages (from requests>=2.3.0->pandas-datareader)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.6/dist-packages (from requests>=2.3.0->pandas-datareader) (2
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.6/dist-packages (from python-dateutil>=2.5.0->pandas>=0.19.2->pandas-d
```

```
!apt install graphviz
```

```
Reading package lists... Done
Building dependency tree
Reading state information... Done
graphviz is already the newest version (2.40.1-2).
The following package was automatically installed and is no longer required:
  libnvidia-common-410
Use 'apt autoremove' to remove it.
0 upgraded, 0 newly installed, 0 to remove and 6 not upgraded.
```

```
!pip install pydot pydot-ng
```

```
Requirement already satisfied: pydot in /usr/local/lib/python3.6/dist-packages (1.3.0)
Requirement already satisfied: pydot-ng in /usr/local/lib/python3.6/dist-packages (2.0.0)
Requirement already satisfied: pyparsing>=2.1.4 in /usr/local/lib/python3.6/dist-packages (from pydot) (2.4.0)
```

Introduction

LSTMs are very powerful in sequence prediction problems. They can store past information.

Loading the dataset

I use pandas-datareader to get the historical stock prices from Yahoo! finance. For this example, I get only the historical data till the end of *training_end_data*.

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from pandas_datareader import data
```

```
tickers = 'AAPL'

start_date = '1980-12-01'
end_date = '2018-12-31'

stock_data = data.get_data_yahoo(tickers, start_date, end_date)
```

```
stock_data.head(10)
```

Date	High	Low	Open	Close	Volume	Adj Close
1980-12-12	0.515625	0.513393	0.513393	0.513393	117258400.0	0.023007
1980-12-15	0.488839	0.486607	0.488839	0.486607	43971200.0	0.021807
1980-12-16	0.453125	0.450893	0.453125	0.450893	26432000.0	0.020206
1980-12-17	0.464286	0.462054	0.462054	0.462054	21610400.0	0.020706
1980-12-18	0.477679	0.475446	0.475446	0.475446	18362400.0	0.021307
1980-12-19	0.506696	0.504464	0.504464	0.504464	12157600.0	0.022607
1980-12-22	0.531250	0.529018	0.529018	0.529018	9340800.0	0.023707
1980-12-23	0.553571	0.551339	0.551339	0.551339	11737600.0	0.024708
1980-12-24	0.582589	0.580357	0.580357	0.580357	12000800.0	0.026008
1980-12-26	0.636161	0.633929	0.633929	0.633929	13893600.0	0.028409

```
stock_data.describe()
```

	High	Low	Open	Close	Volume	Adj Close
count	9594.000000	9594.000000	9594.000000	9594.000000	9.594000e+03	9594.000000
mean	26.549240	26.026566	26.297032	26.292735	8.758682e+07	22.587725
std	47.280499	46.462657	46.880676	46.878276	8.676287e+07	44.664584
min	0.198661	0.196429	0.198661	0.196429	3.472000e+05	0.008803
25%	1.071429	1.031295	1.049464	1.051429	3.407435e+07	0.148196
50%	1.696429	1.633929	1.664286	1.665179	5.944890e+07	0.879176
75%	26.317500	25.404285	25.910000	25.841429	1.091926e+08	17.231145
max	233.470001	229.779999	230.779999	232.070007	1.855410e+09	230.275482

```
stock_data_len = stock_data['Close'].count()
print(stock_data_len)
```

```
9594
```

I'm only interested in *close* prices

```
close_prices = stock_data.iloc[:, 1:2].values
print(close_prices)
```

```
[[  0.51339287]
 [  0.48660713]
```

```
[  0.45089287]
 ...
[150.07000732]
[154.55000305]
[156.47999573]]
```

Of course, some of the weekdays might be public holidays in which case no price will be available. For this reason, we will fill the missing prices with the latest available prices

```
all_bussinessdays = pd.date_range(start=start_date, end=end_date, freq='B')
print(all_bussinessdays)
```

```
DatetimeIndex(['1980-12-01', '1980-12-02', '1980-12-03', '1980-12-04',
               '1980-12-05', '1980-12-08', '1980-12-09', '1980-12-10',
               '1980-12-11', '1980-12-12',
               ...
               '2018-12-18', '2018-12-19', '2018-12-20', '2018-12-21',
               '2018-12-24', '2018-12-25', '2018-12-26', '2018-12-27',
               '2018-12-28', '2018-12-31'],
              dtype='datetime64[ns]', length=9936, freq='B')
```

```
close_prices = stock_data.reindex(all_bussinessdays)
close_prices = stock_data.fillna(method='ffill')
```

```
close_prices.head(10)
```

	High	Low	Open	Close	Volume	Adj Close
Date						
1980-12-12	0.515625	0.513393	0.513393	0.513393	117258400.0	0.023007
1980-12-15	0.488839	0.486607	0.488839	0.486607	43971200.0	0.021807
1980-12-16	0.453125	0.450893	0.453125	0.450893	26432000.0	0.020206
1980-12-17	0.464286	0.462054	0.462054	0.462054	21610400.0	0.020706
1980-12-18	0.477679	0.475446	0.475446	0.475446	18362400.0	0.021307
1980-12-19	0.506696	0.504464	0.504464	0.504464	12157600.0	0.022607
1980-12-22	0.531250	0.529018	0.529018	0.529018	9340800.0	0.023707
1980-12-23	0.553571	0.551339	0.551339	0.551339	11737600.0	0.024708
1980-12-24	0.582589	0.580357	0.580357	0.580357	12000800.0	0.026008
1980-12-26	0.636161	0.633929	0.633929	0.633929	13893600.0	0.028409

The dataset is now complete and free of missing values. Let's have a look to the data frame summary:

Feature scaling

```
training_set = close_prices.iloc[:, 1:2].values
```

```
print(training_set)
```

```
[[  0.51339287]
 [  0.48660713]
 [  0.45089287]
 ...
 [150.07000732]
 [154.55000305]
 [156.47999573]]
```

```
from sklearn.preprocessing import MinMaxScaler
sc = MinMaxScaler(feature_range = (0, 1))
training_set_scaled = sc.fit_transform(training_set)
print(training_set_scaled.shape)
```

```
(9594, 1)
```

LSTMs expect the data in a specific format, usually a 3D tensor. I start by creating data with 60 days and converting it into an array using NumPy. Next, I convert the data into a 3D dimension array with feature_set samples, 60 days and one feature at each step.

```
features = []
labels = []
for i in range(60, stock_data_len):
    features.append(training_set_scaled[i-60:i, 0])
    labels.append(training_set_scaled[i, 0])

features = np.array(features)
labels = np.array(labels)

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

```
print(labels)
```

```
[0.00082642 0.00089448 0.00087503 ... 0.6528062  0.67231978 0.68072627]
```

```
print(features)
```

```
[[[1.38060532e-03]
  [1.26393438e-03]
  [1.10837330e-03]
  ...
  [1.13754103e-03]
  [9.81979819e-04]
  [8.94476613e-04]]

 [[1.26393438e-03]
  [1.10837330e-03]
  [1.15698610e-03]
  ...
  [9.81979819e-04]
  [8.94476613e-04]
  [8.26418607e-04]]

 [[1.10837330e-03]
  [1.15698610e-03]
  [1.21532157e-03]
  ...
  [8.94476613e-04]
  [8.26418607e-04]
  [8.94476613e-04]]

 ...

 [[9.85059938e-01]
  [9.86279533e-01]
  [1.00000000e+00]
  ...
  [6.50889679e-01]
  [6.37648276e-01]
  [6.38214540e-01]]

 [[9.86279533e-01]
  [1.00000000e+00]
  [9.86715064e-01]
  ...
  [6.37648276e-01]
  [6.38214540e-01]
  [6.52806203e-01]]

 [[1.00000000e+00]
  [9.86715064e-01]
  [9.59927459e-01]
  ...
  [6.38214540e-01]
  [6.52806203e-01]
  [6.72319776e-01]]]
```

Feature tensor with three dimension: features[0] contains the ..., features[1] contains the last 60 days of values and features [2] contains the ...

```
print(features.shape)
```

```
(9534, 60, 1)
```

Create the LSTM network

Let's create a sequenced LSTM network with 50 units. Also the net includes some dropout layers with 0.2 which means that 20% of the neurons will be dropped.

```
import tensorflow as tf


model = tf.keras.models.Sequential([
    tf.keras.layers.LSTM(units = 50, return_sequences = True, input_shape = (features.shape[1], 1)),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.LSTM(units = 50, return_sequences = True),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.LSTM(units = 50, return_sequences = True),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.LSTM(units = 50),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(units = 1)
])
```

```
WARNING: Logging before flag parsing goes to stderr.
W0414 15:18:15.979501 139980101556096 tf_logging.py:161] <tensorflow.python.keras.layers.recurrent.UnifiedLSTM object at 0x7f4f34285860>
W0414 15:18:16.001110 139980101556096 tf_logging.py:161] <tensorflow.python.keras.layers.recurrent.UnifiedLSTM object at 0x7f4f34285ef0>
W0414 15:18:16.006853 139980101556096 tf_logging.py:161] <tensorflow.python.keras.layers.recurrent.UnifiedLSTM object at 0x7f4f342a6748>
W0414 15:18:16.013553 139980101556096 tf_logging.py:161] <tensorflow.python.keras.layers.recurrent.UnifiedLSTM object at 0x7f4f342a6e48>
```

```
print(model.summary())
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
unified_lstm (UnifiedLSTM)   (None, 60, 50)            10400
_________________________________________________________________
dropout (Dropout)            (None, 60, 50)            0
_________________________________________________________________
unified_lstm_1 (UnifiedLSTM) (None, 60, 50)            20200
_________________________________________________________________
dropout_1 (Dropout)          (None, 60, 50)            0
_________________________________________________________________
unified_lstm_2 (UnifiedLSTM) (None, 60, 50)            20200
_________________________________________________________________
dropout_2 (Dropout)          (None, 60, 50)            0
_________________________________________________________________
unified_lstm_3 (UnifiedLSTM) (None, 50)                20200
_________________________________________________________________
dropout_3 (Dropout)          (None, 50)                0
_________________________________________________________________
dense (Dense)                (None, 1)                 51
=================================================================
Total params: 71,051
Trainable params: 71,051
Non-trainable params: 0
_________________________________________________________________
None
```

The model will be compiled and optimize by the adam optimizer and set the loss function as mean_squarred_error

```
model.compile(optimizer = 'adam', loss = 'mean_squared_error')
```

```
from time import time
start = time()
history = model.fit(features, labels, epochs = 20, batch_size = 32, verbose = 1)
end = time()
```

```
Epoch 1/20
9534/9534 [==============================] - 19s 2ms/sample - loss: 0.0017
Epoch 2/20
9534/9534 [==============================] - 17s 2ms/sample - loss: 8.3861e-04
Epoch 3/20
9534/9534 [==============================] - 17s 2ms/sample - loss: 8.4889e-04
Epoch 4/20
9534/9534 [==============================] - 17s 2ms/sample - loss: 6.7823e-04
Epoch 5/20
9534/9534 [==============================] - 17s 2ms/sample - loss: 6.0230e-04
```

```
Epoch 6/20
9534/9534 [==============================] - 17s 2ms/sample - loss: 5.9530e-04
Epoch 7/20
9534/9534 [==============================] - 17s 2ms/sample - loss: 5.6053e-04
Epoch 8/20
9534/9534 [==============================] - 18s 2ms/sample - loss: 5.6923e-04
Epoch 9/20
9534/9534 [==============================] - 17s 2ms/sample - loss: 4.9843e-04
Epoch 10/20
9534/9534 [==============================] - 17s 2ms/sample - loss: 5.7040e-04
Epoch 11/20
9534/9534 [==============================] - 17s 2ms/sample - loss: 4.5142e-04
Epoch 12/20
9534/9534 [==============================] - 17s 2ms/sample - loss: 5.1318e-04
Epoch 13/20
9534/9534 [==============================] - 17s 2ms/sample - loss: 4.6513e-04
Epoch 14/20
9534/9534 [==============================] - 17s 2ms/sample - loss: 4.5369e-04
Epoch 15/20
9534/9534 [==============================] - 17s 2ms/sample - loss: 4.3363e-04
Epoch 16/20
9534/9534 [==============================] - 17s 2ms/sample - loss: 4.8583e-04
Epoch 17/20
9534/9534 [==============================] - 17s 2ms/sample - loss: 5.3111e-04
Epoch 18/20
9534/9534 [==============================] - 17s 2ms/sample - loss: 4.6322e-04
Epoch 19/20
9534/9534 [==============================] - 17s 2ms/sample - loss: 4.5440e-04
Epoch 20/20
9534/9534 [==============================] - 17s 2ms/sample - loss: 4.6059e-04
```

```
print('Total training time {} seconds'.format(end - start))
```

```
Total training time 349.84911346435547 seconds
```

```
#  [samples, days, features]
print(features.shape)
```

```
(9534, 60, 1)
```

```
testing_start_date = '2019-01-01'
testing_end_date = '2019-04-10'

test_stock_data = data.get_data_yahoo(tickers, testing_start_date, testing_end_date)
```

```
test_stock_data.tail()
```

Date	High	Low	Open	Close	Volume	Adj Close
2019-04-04	196.369995	193.139999	194.789993	195.690002	19114300.0	195.690002
2019-04-05	197.100006	195.929993	196.449997	197.000000	18526600.0	197.000000
2019-04-08	200.229996	196.339996	196.419998	200.100006	25881700.0	200.100006
2019-04-09	202.850006	199.229996	200.320007	199.500000	35768200.0	199.500000
2019-04-10	200.740005	198.179993	198.679993	200.619995	21695300.0	200.619995

```
test_stock_data_processed = test_stock_data.iloc[:, 1:2].values
```

```
print(test_stock_data_processed.shape)
```

```
(69, 1)
```

```
all_stock_data = pd.concat((stock_data['Close'], test_stock_data['Close']), axis = 0)
```

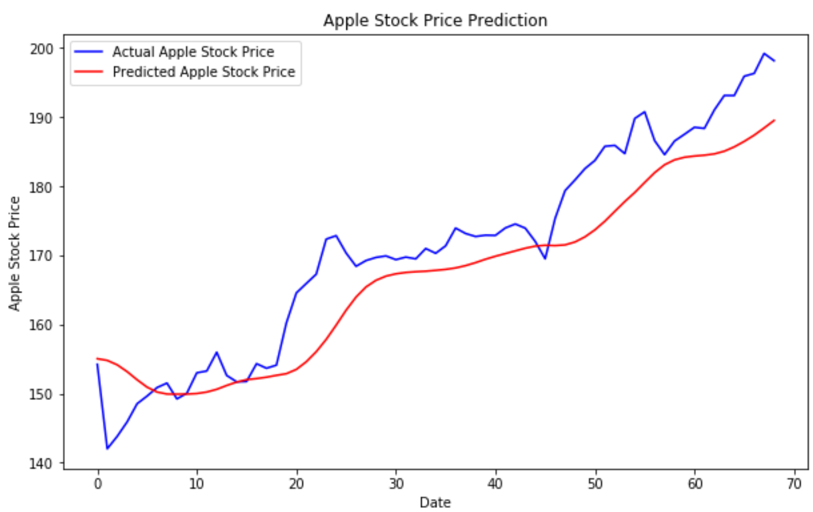
```
inputs = all_stock_data[len(all_stock_data) - len(test_stock_data) - 60:].values
inputs = inputs.reshape(-1,1)
inputs = sc.transform(inputs)
```

```
X_test = []
for i in range(60, 129):
```

```
    X_test.append(inputs[i-60:i, 0])


X_test = np.array(X_test)
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
predicted_stock_price = model.predict(X_test)
predicted_stock_price = sc.inverse_transform(predicted_stock_price)


plt.figure(figsize=(10,6))
plt.plot(test_stock_data_processed, color='blue', label='Actual Apple Stock Price')
plt.plot(predicted_stock_price , color='red', label='Predicted Apple Stock Price')
plt.title('Apple Stock Price Prediction')
plt.xlabel('Date')
plt.ylabel('Apple Stock Price')
plt.legend()
plt.show()
```




```
test_inputs = test_stock_data_processed.reshape(-1,1)
test_inputs = sc.transform(test_inputs)


print(test_inputs.shape)


test_features = []
for i in range(60, 291):
    test_features.append(test_inputs[i-60:i, 0])

test_features = np.array(test_features)


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


predicted_stock_price = model.predict(test_features)


predicted_stock_price = sc.inverse_transform(predicted_stock_price)
print(predicted_stock_price.shape)


print(test_stock_data_processed.shape)


plt.figure(figsize=(10,6))
plt.plot(test_stock_data_processed, color='blue', label='Actual Apple Stock Price')
plt.plot(predicted_stock_price , color='red', label='Predicted Apple Stock Price')
plt.title('Apple Stock Price Prediction')
plt.xlabel('Date')
plt.ylabel('Apple Stock Price')
plt.legend()
plt.show()
```