



# STOCK PRICE PREDICTON

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## INTRODUCTION

A stock market is a public market for the trading of company stock.

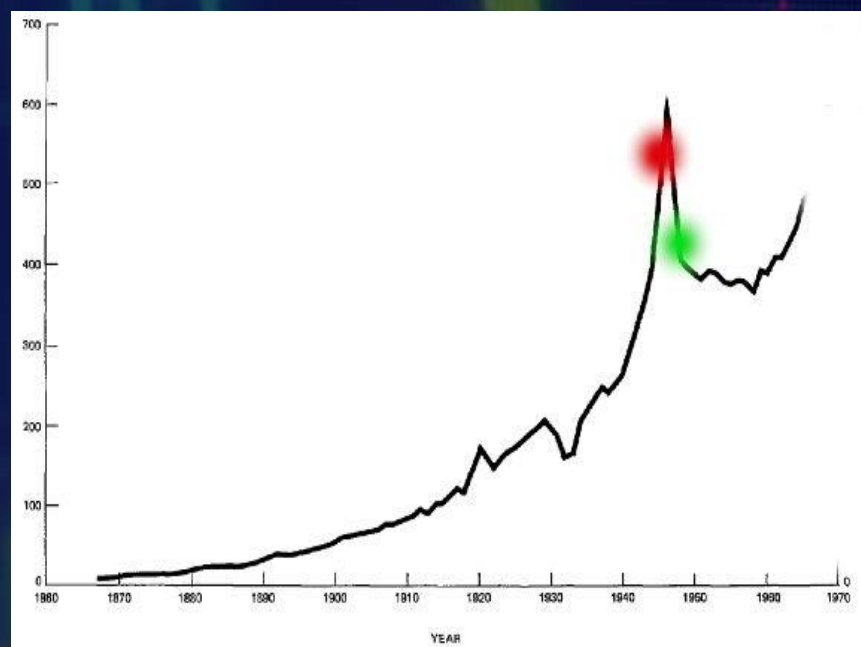
Stock market allows us to buy and sell units of stocks (ownership) of a company.

If the company's profits go up, then we own some of the profits and if they go down, then we lose profits with them.

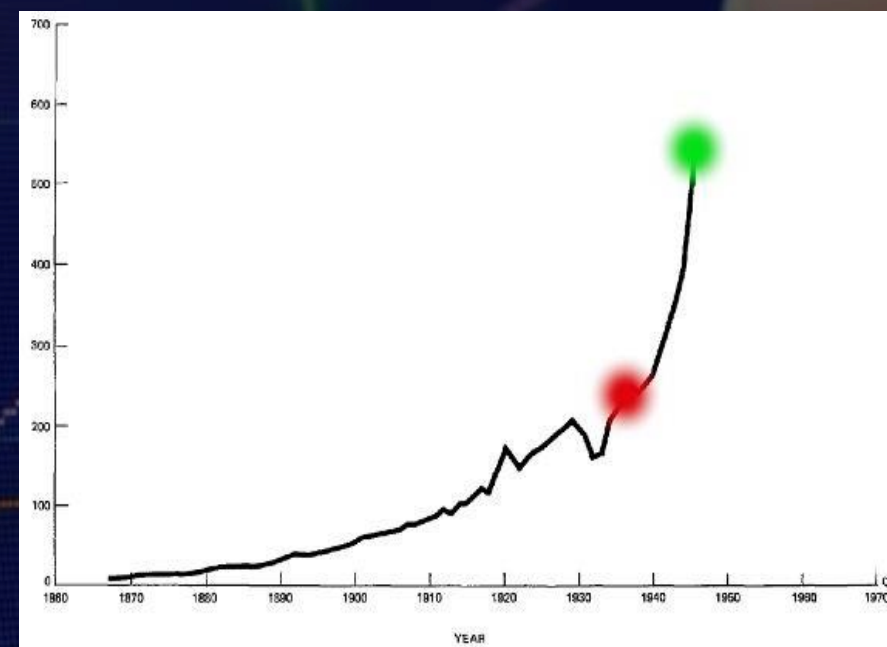
**If more seller than buyers, stock price tend to fall. Conversely, when more buyers than sellers, stock prices tend to rise.**



# INTRODUCTION



Loss



Profit

Red is purchased stock.  
Green is sold stock.



- To accurately predict the future closing value of a given stock across a given period of time in the future.
- Use different machine learning and deep learning models available and compare them in terms of graphical analysis.

## PROBLEM STATEMENT



# HOW TO READ A STOCK TABLE?

**Date-** day on which the stock is traded



**High-** **high** is the **highest** price at which a **stock** traded during the course of the day



**Close-** refers to the last **price** at which a **stock** trades during a regular trading session



1.	Date	Open	High	Low	Close	Volume
2.	20-Jul-17	997.00	998.68	984.62	992.19	1418385
3.	19-Jul-17	990.01	995.60	987.01	992.77	1412148

**Open-** price of the first trade for any listed **stock** is its daily **opening** price.



**Low-** lowest price at which a **stock** trades over the course of a **trading** day.



**Volume-** the number of **shares** or contracts traded in a security or an entire **market** during a given period of time





```
1 import pandas as pd
2 import numpy as np
3 import matplotlib.pyplot as plt
4 df=pd.read_csv("NSE-TATA.csv")
5
6 print(df.head())
7 ...
```

# DATASET

To build the stock price prediction model, we will use the **NSETATA GLOBAL** dataset. This is a dataset of Tata Beverages from Tata Global Beverages Limited, National Stock Exchange of India.

Windows PowerShell  
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Try the new cross-platform PowerShell <https://aka.ms/pscore6>

PS E:\AL-code\Stock\_Prediction> **python** demo.py

	Date	Open	High	Low	Last	Close	Total Trade Quantity	Turnover (Lacs)
0	2018-10-08	208.00	222.25	206.85	216.00	215.15	4642146.0	10062.83
1	2018-10-05	217.00	218.60	205.90	210.25	209.20	3519515.0	7407.06
2	2018-10-04	223.50	227.80	216.15	217.25	218.20	1728786.0	3815.79
3	2018-10-03	230.00	237.50	225.75	226.45	227.60	1708590.0	3960.27
4	2018-10-01	234.55	234.60	221.05	230.30	230.90	1534749.0	3486.05

PS E:\AL-code\Stock\_Prediction>

The background of the slide is a blurred financial chart. It features a candlestick chart with green and red bars, overlaid with several colored trend lines (pink, orange, blue) and numerical data points like "18407", "18514", and "18357".

# PREPARING THE DATA



## DEALING WITH MISSING DATA

As there we are having no missing value in your data .We can move forward.

```
test2.py  stock_pred.py
1  import pandas as pd
2  import numpy as np
3  import matplotlib.pyplot as plt
4  df=pd.read_csv("NSE-TATA.csv")
5
6  df["Date"]=pd.to_datetime(df.Date,format="%Y-%m-%d")
7  df.index=df['Date']
8  print(df.isnull().sum())
9  ...

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Try the new cross-platform PowerShell https://aka.ms/pscore6

PS E:\AL-code\Stock_Prediction> python demo.py
Date                                0
Open                                0
High                                0
Low                                 0
Last                                0
Close                               0
Total Trade Quantity                0
Turnover (Lacs)                     0
dtype: int64
PS E:\AL-code\Stock_Prediction>
```



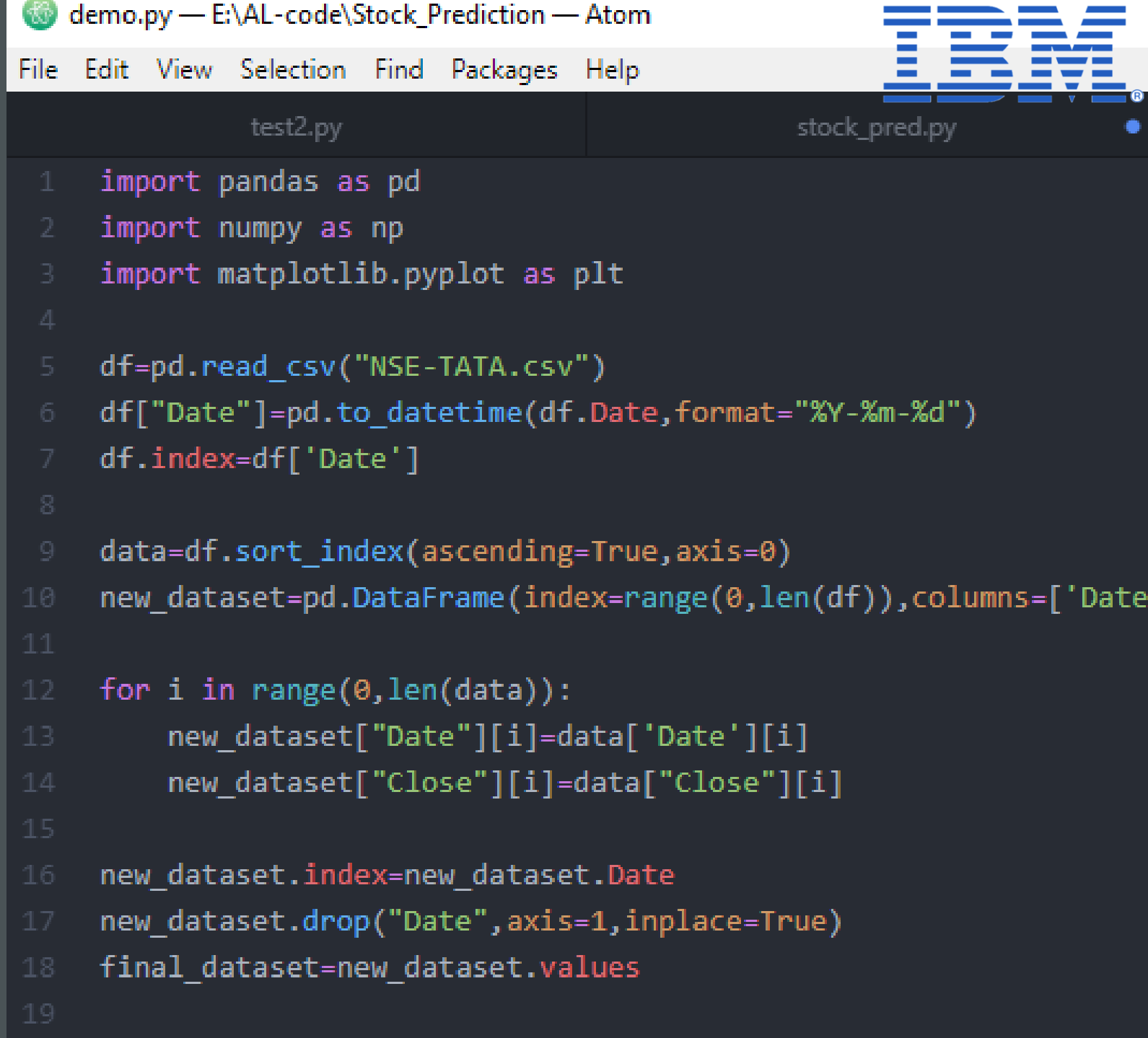


# VISUALIZE THE CLOSING PRICE HISTORY



## SORT THE DATASET ON DATE TIME AND FILTER “DATE” AND “CLOSE” COLUMNS

We have sort your data into ascending order and make a new dataframe for your target variable.



The screenshot shows the Atom code editor interface. The title bar at the top reads "demo.py — E:\AL-code\Stock\_Prediction — Atom". The menu bar includes "File", "Edit", "View", "Selection", "Find", "Packages", and "Help". The editor has two tabs: "test2.py" (active) and "stock\_pred.py". The code in "test2.py" is as follows:

```
1 import pandas as pd
2 import numpy as np
3 import matplotlib.pyplot as plt
4
5 df=pd.read_csv("NSE-TATA.csv")
6 df["Date"]=pd.to_datetime(df.Date,format="%Y-%m-%d")
7 df.index=df['Date']
8
9 data=df.sort_index(ascending=True,axis=0)
10 new_dataset=pd.DataFrame(index=range(0,len(df)),columns=['Date
11
12 for i in range(0,len(data)):
13     new_dataset["Date"][i]=data['Date'][i]
14     new_dataset["Close"][i]=data["Close"][i]
15
16 new_dataset.index=new_dataset.Date
17 new_dataset.drop("Date",axis=1,inplace=True)
18 final_dataset=new_dataset.values
19
```

## NORMALIZE THE NEW FILTERED DATASET:

Now scale the data set to be values between 0 and 1 inclusive, I do this because it is generally good practice to scale your data before giving it to the neural network.

**Denormalized Dataset**

Open	Close	Volume
997.00	992.19	1418385
990.01	992.77	1412148
973.36	986.95	1413335
976.32	975.96	1660464

**Normalized Dataset**

Open	Close	Volume
0.012051212203759196	0.015141267590269444	0.37724770218929105
0.01419776627621902	0.010657794262026843	0.3256440180584465
0.009893761917733584	0.010112359550561806	0.1898197785299343
0.010874421138654333	0.007407003381695226	0.24270137132323968
0.008368292018523571	0.010297807352459915	0.22490508770060744

$$X_{changed} = \frac{X - X_{min}}{X_{max} - X_{min}}$$





# DATA SPLITTING

## X\_TRAIN, Y\_TRAIN AND RESHAPE

Reshape the data to be 3-dimensional in the form [number of **samples**, number of **time steps**, and number of **features**]. This needs to be done, because the LSTM model is expecting a 3-dimensional data set.

```

56
57 new_dataset.index=new_dataset.Date
58 new_dataset.drop("Date",axis=1,inplace=True)
59
60 final_dataset=new_dataset.values
61
62 train_data=final_dataset[0:987,:]
63 valid_data=final_dataset[987:,:]
64
65 scaler=MinMaxScaler(feature_range=(0,1))
66 scaled_data=scaler.fit_transform(final_dataset)
67
68 x_train_data,y_train_data=[],[]
69
70 for i in range(60,len(train_data)):
71     x_train_data.append(scaled_data[i-60:i,0])
72     y_train_data.append(scaled_data[i,0])
73
74 x_train_data,y_train_data=np.array(x_train_data),np.array(y_train_data)
75
76 x_train_data=np.reshape(x_train_data,(x_train_data.shape[0],x_train_data.shape[1],x_train_data.shape[2]))
77
78
79

```

## BUILD THE LSTM MODEL

Build the LSTM model to have two LSTM layers with 50 neurons and two Dense layers, one with 25 neurons and the other with 1 neuron.

```
77
78
79
80 lstm_model=Sequential()
81 lstm_model.add(LSTM(units=50,return_sequences=True,input_shape=(x_train_data.shape[1],1)))
82 lstm_model.add(LSTM(units=50))
83 lstm_model.add(Dense(1))
84
85 lstm_model.compile(loss='mean_squared_error',optimizer='adam')
86 lstm_model.fit(x_train_data,y_train_data,epochs=1,batch_size=1,verbose=2)
87
88 inputs_data=new_dataset[len(new_dataset)-len(valid_data)-60:].values
89 inputs_data=inputs_data.reshape(-1,1)
90 inputs_data=scaler.transform(inputs_data)
91
92
```



TAKE A SAMPLE OF A  
DATASET TO MAKE  
STOCK PRICE  
PREDICTIONS USING  
THE LSTM MODEL:

So the first column in the '**x\_train**' data set will contain values from the data set from index 0 to index 59 (60 values total) and the second column will contain values from the data set from index 1 to index 60 (60 values) and so on and so forth.

The '**y\_train**' data set will contain the 61st value located at index 60 for it's first column and the 62nd value located at index 61 of the data set for it's second value and so on and so forth.

```
X_test=[]  
for i in range(60,inputs_data.shape[0]):  
    X_test.append(inputs_data[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))  
closing_price=lstm_model.predict(X_test)  
closing_price=scaler.inverse_transform(closing_price)
```

VISUALIZE THE  
PREDICTED STOCK  
COSTS WITH ACTUAL  
STOCK COSTS:

```
train_data=new_dataset[:987]
valid_data=new_dataset[987:]
valid_data['Predictions']=closing_price

model_F_score(valid_data['Predictions'],valid_data['Close'])

plt.plot(train_data["Close"])
plt.plot(valid_data[['Close',"Predictions"]])
plt.legend()
plt.show()
```



Model

Close Price USD (\$)

300  
250  
200  
150  
100

2014

2015

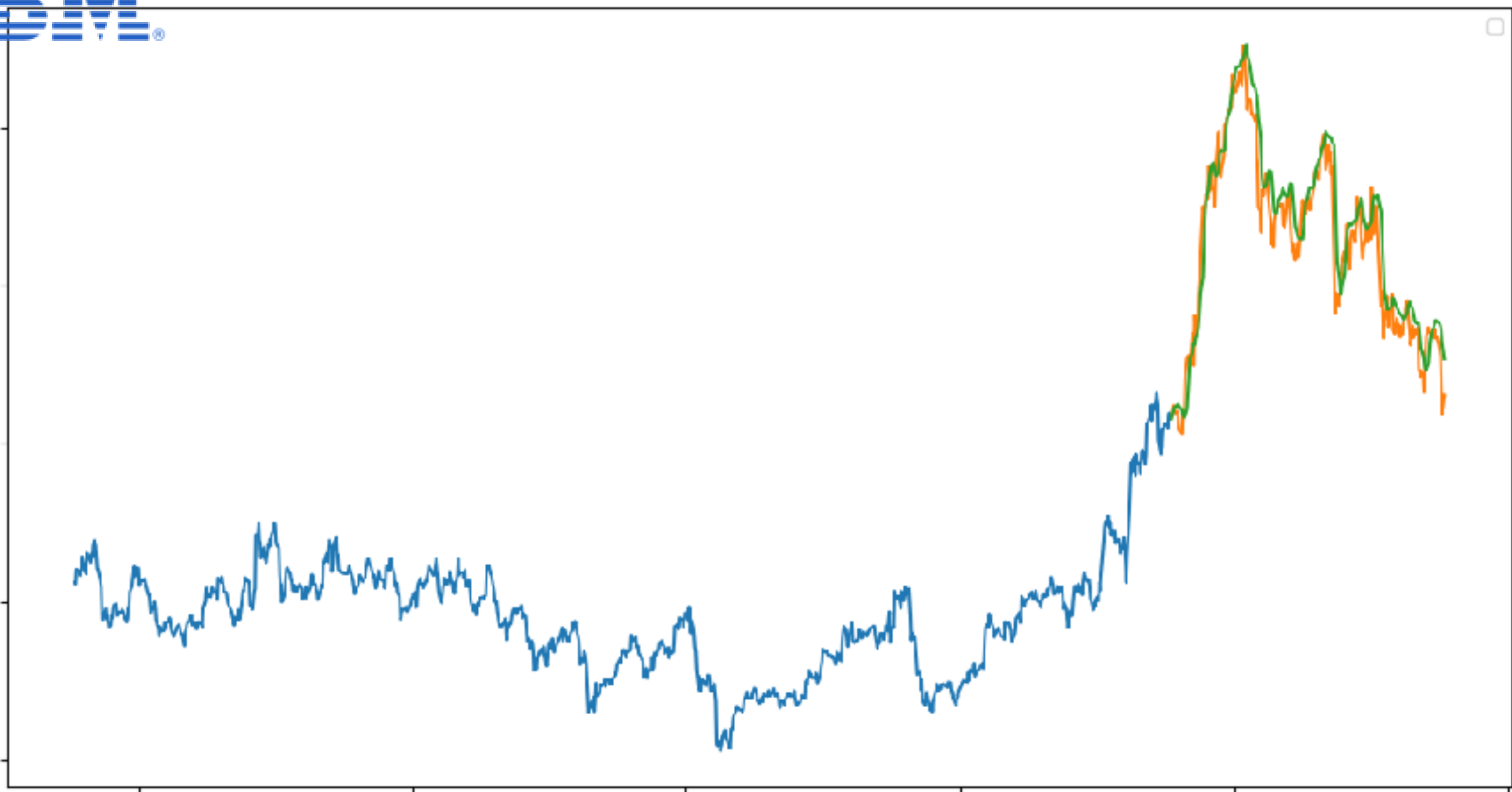
2016

2017

2018

2019

Date



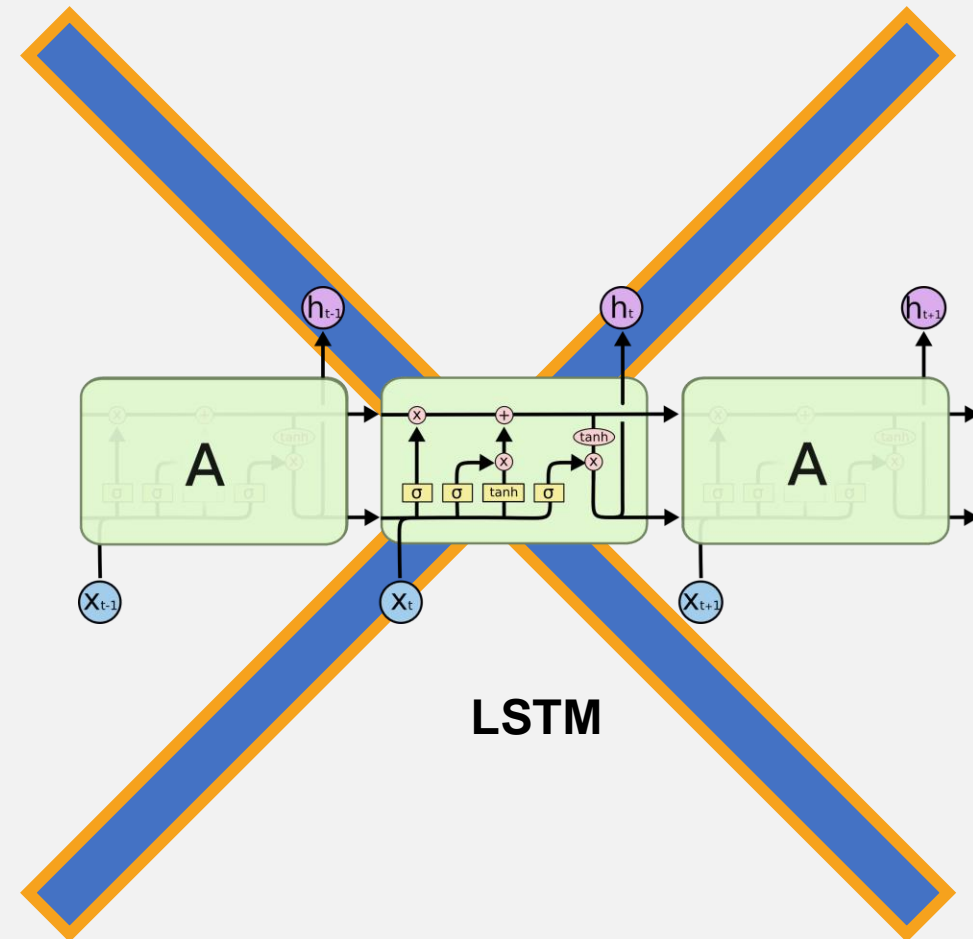


# HOW LSTM WORKS ?

# LSTM

## LSTM (Long Short Term Memory)

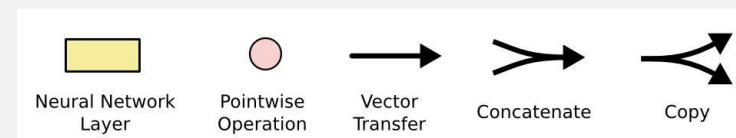
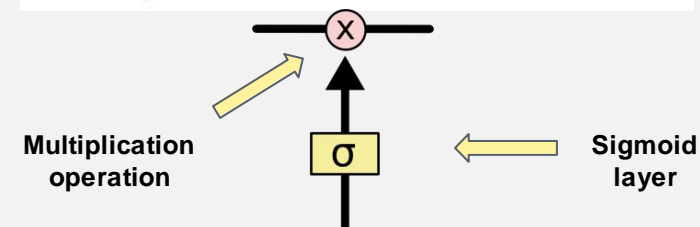
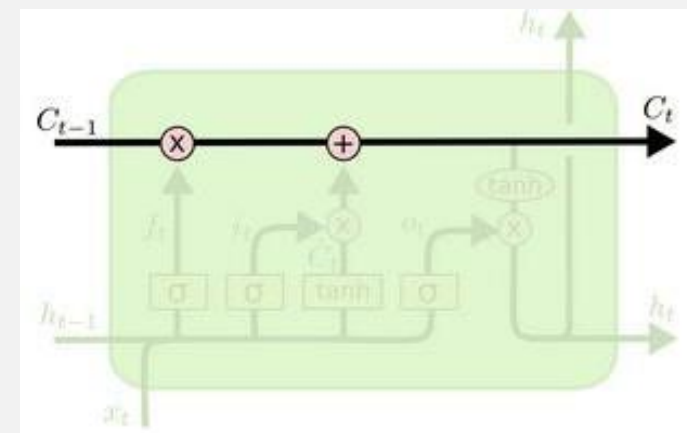
LSTMs are explicitly designed to avoid the long-term dependency problem. Remembering information for **long periods of time** is practically their default behavior, not something they



# HOW IT WORKS?

## LSTM (How it works?)

- The key to LSTM is the **Memory cell state** which stores the information. It runs straight down the **entire chain**.
- LSTM has the ability to **remove or add** information to these cell state, regulated by structures called **gates**.

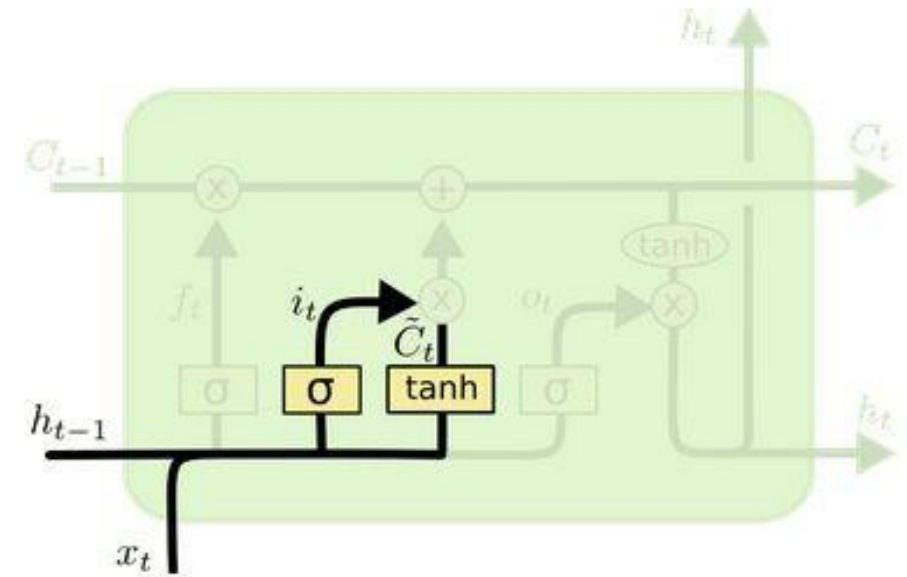




# HOW IT WORKS?

## LSTM (How it works?)

- **First**, forget gate looks at  $h_{t-1}$  and  $x_t$  and outputs a number between 0 and 1.
- 1 represents “**keep the information**” and 0 represents “**remove the information**”.
- **Second**, input gate decides which values will be updated, in order to do that a  $\tanh$  layer creates a vector of  $\tilde{C}_t$  (**bar**).
- Combining these two, create an update to the state.



$$o_t = \sigma(W_o [h_{t-1}, x_t] + b_o)$$

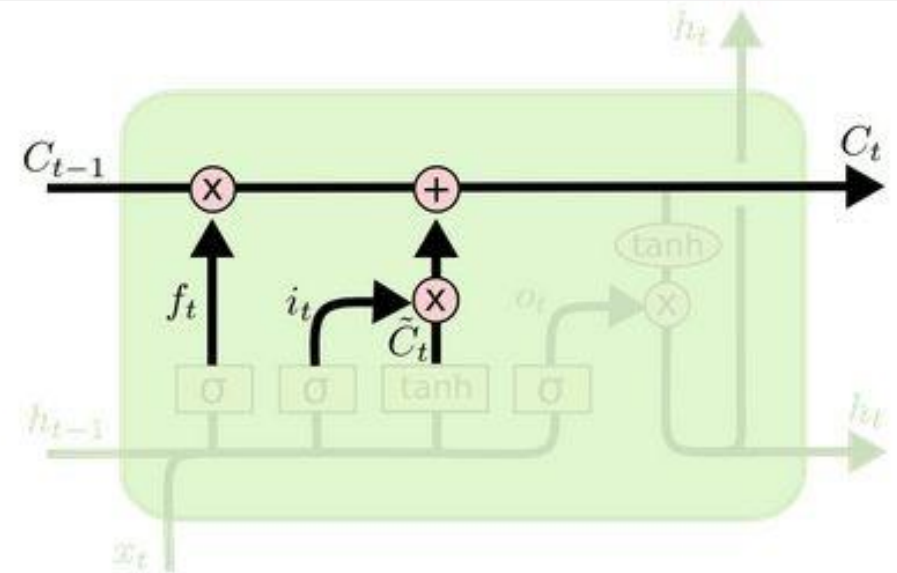
$$h_t = o_t * \tanh(C_t)$$

↑  
required for  
updating the  
weight

# HOW IT WORKS?

## LSTM (How it works?)

- **Third**, It's time to update the old cell  $C_{t-1}$  to  $C_t$ .



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

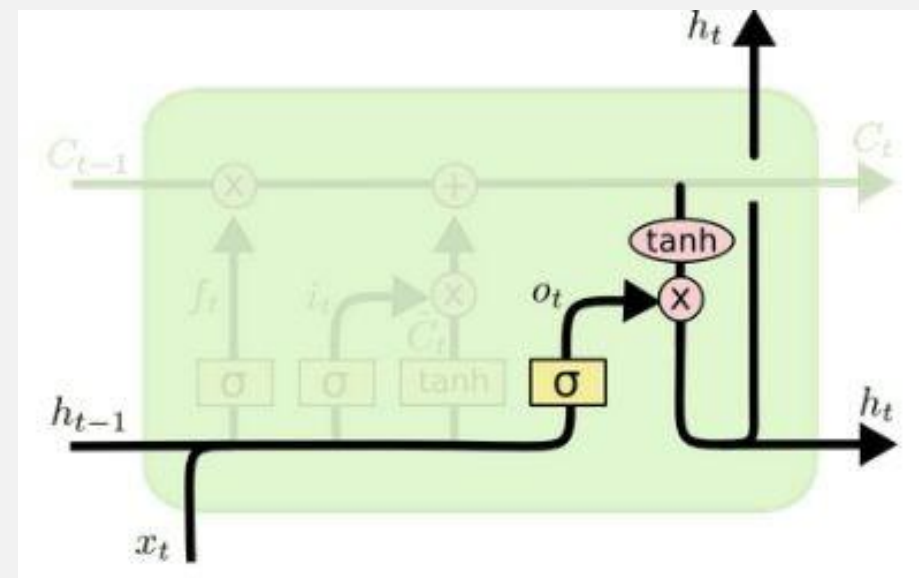
↗  
New Cell state

# HOW IT WORKS?

## LSTM (How it works?)

**Fourth** output will be based on our cell.

A sigmoid layer will decide what parts of the cell state we're going to output.



Output  
Layer

$$o_t = \sigma (W_o [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t * \tanh (C_t)$$

Current hidden  
layer information

THANK YOU

