

The background is a light beige color with a subtle, repeating pattern of faint dollar signs. Various decorative elements are scattered around the central text: a pink diamond in the top left, a yellow coin with a dollar sign at the top center, a yellow wavy line in the top right, a purple square in the middle right, a green curved shape on the left, a yellow coin at the bottom left, a blue wavy line at the bottom center, and a yellow coin at the bottom right. There are also several small, four-pointed star-like shapes in yellow, pink, and purple.

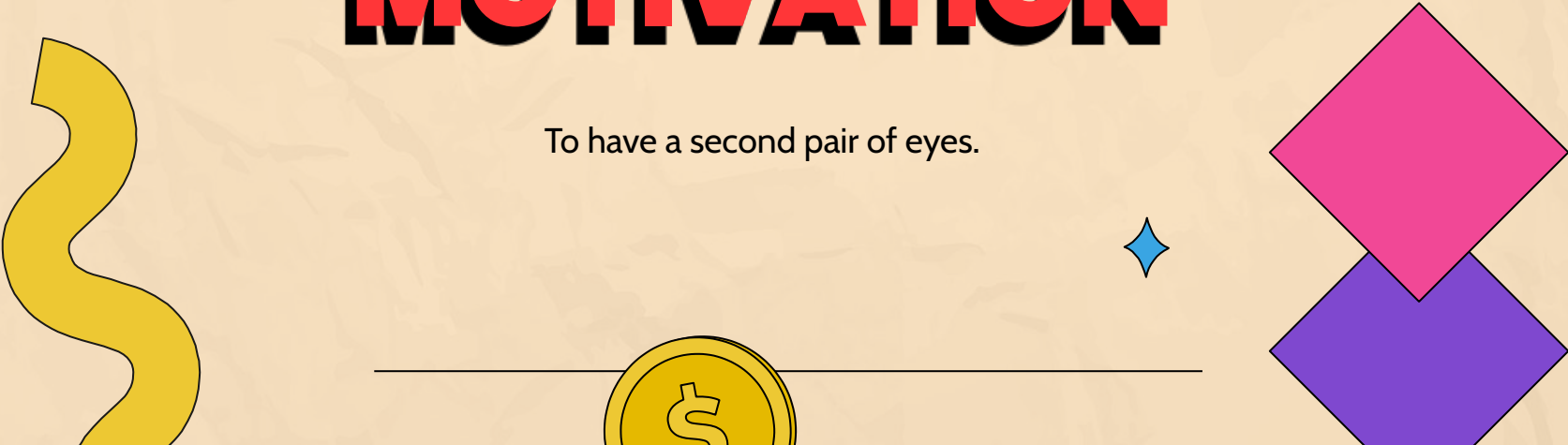
# **Stock Movement Prediction with LSTM**

Anapat Pararaman 6180280



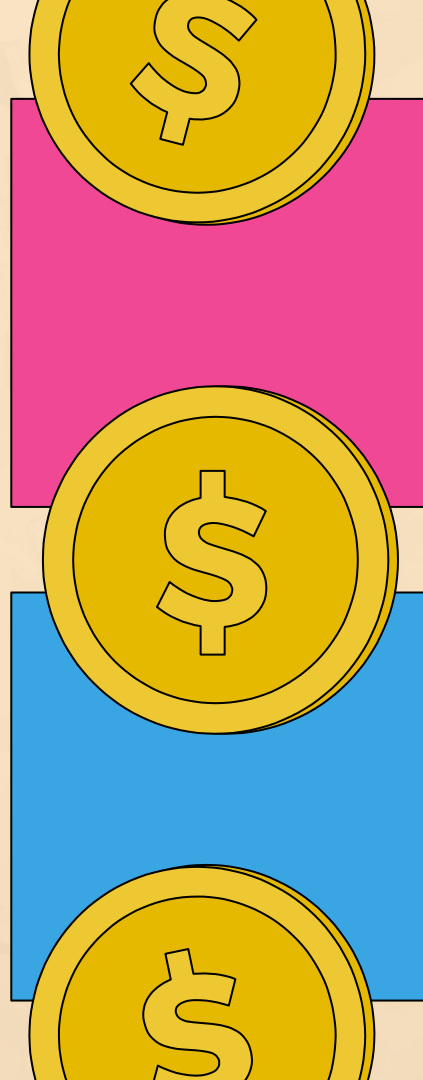
# PROJECT GOALS AND MOTIVATION

To have a second pair of eyes.

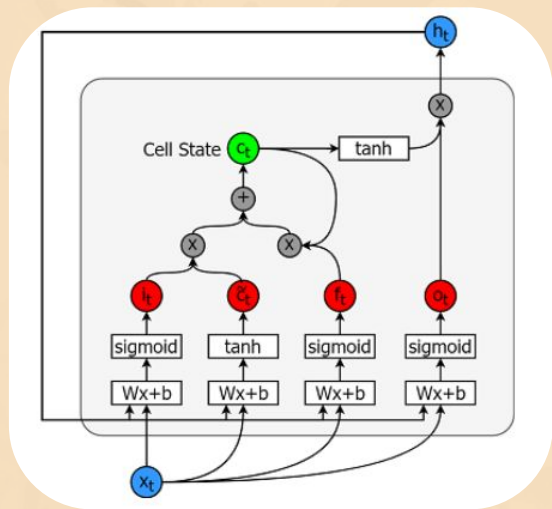


1

# What and Why LSTM?



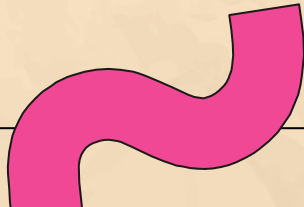
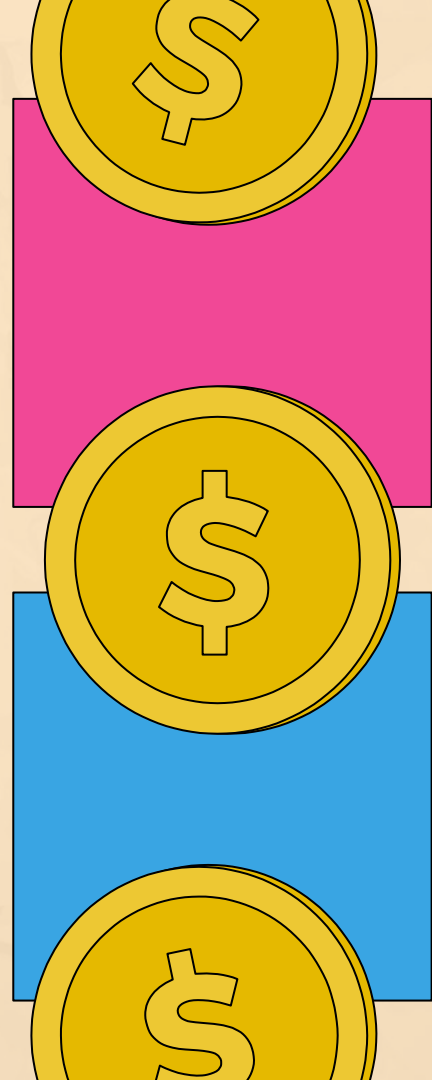
# What and Why LSTM



- **Cell state ( $c_t$ )** - This represents the internal memory of the cell which stores both short term memory and long-term memories
- **Hidden state ( $h_t$ )** - This is output state information calculated w.r.t. current input, previous hidden state and current cell input which you eventually use to predict the future stock market prices. Additionally, the hidden state can decide to only retrieve the short or long-term or both types of memory stored in the cell state to make the next prediction.
- **Input gate ( $i_t$ )** - Decides how much information from current input flows to the cell state
- **Forget gate ( $f_t$ )** - Decides how much information from the current input and the previous cell state flows into the current cell state
- **Output gate ( $o_t$ )** - Decides how much information from the current cell state flows into the hidden state, so that if needed LSTM can only pick the long-term memories or short-term memories and long-term memories

2

**Codes**



# 2.1.1: Importing Data



LSTM.py

```
import yfinance as yf

def getData(symbol, data):
    ticker = yf.Ticker(symbol)
    histData = ticker.history(period='5y')
    return histData[data][:-360]

price = getData("PTT.BK", "Close")
volume = getData("PTT.BK", "Volume")
```

Date	
2017-04-04	31.940359
2017-04-05	31.777393
2017-04-07	31.940359
2017-04-10	32.184795
2017-04-11	32.103321
...	
2020-10-01	30.750196
2020-10-02	30.051325
2020-10-05	30.051325
2020-10-06	30.750196
2020-10-07	30.750196

Name: Close, Length: 857, dtype: float64



## 2.1.2: Applying MinMax Scaler



LSTM.py

```
import numpy as np
from sklearn.preprocessing import MinMaxScaler

scaler=MinMaxScaler(feature_range=(0,1))
df1=scaler.fit_transform(np.array(price).reshape(-1,1))

scalerPrice = MinMaxScaler(feature_range= (0,1))
scalerVolume = MinMaxScaler(feature_range= (0,1))

df1 = scalerPrice.fit_transform(np.array(price).reshape(-1,1))
df2 = scalerVolume.fit_transform(np.array(volume).reshape(-1,1))
```





## 2.1.3: Splitting Datasets



LSTM.py

```
def splitData(df):  
    trainingSize = int(len(df)*0.65)  
    testSize = len(df)-trainingSize  
    trainData, testData = df[0:trainingSize,:], df[trainingSize:len(df),:1]  
    return trainData, testData  
  
df1TrainData, df1TestData = splitData(df1)  
df2TrainData, df2TestData = splitData(df2)
```





## 2.1.4: Data Pre-Processing

Training Dataset = [104, 129, 112, 102, 131, 141, 122, 152]

Timestep = 3

	X_Train			Y_Train
Price	104	129	112	102
	129	112	102	131



## 2.1.4: Data Pre-Processing



LSTM.py

```
def create_dataset(dataset, time_step):  
    dataX, dataY = [], []  
    for i in range(len(dataset)-time_step-1):  
        a = dataset[i:(i+time_step), 0]  
        dataX.append(a)  
        dataY.append(dataset[i + time_step, 0])  
    return np.array(dataX), np.array(dataY)  
  
df1XTrain, df1YTrain = create_dataset(df1TrainData, 100)  
df1XTest, df1YTest = create_dataset(df1TestData, 100)  
  
df2XTrain, df2YTrain = create_dataset(df2TrainData, 100)  
df2XTest, df2YTest = create_dataset(df2TestData, 100)
```



## 2.2: Initializing Model

```
LSTM.py

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import LSTM

priceModel=Sequential()
priceModel.add(LSTM(50,return_sequences=True,input_shape=(100,1)))
priceModel.add(LSTM(50,return_sequences=True))
priceModel.add(LSTM(50))
priceModel.add(Dense(1))
priceModel.compile(loss='mean_squared_error',optimizer='adam')

volumeModel=Sequential()
volumeModel.add(LSTM(50,return_sequences=True,input_shape=(100,1)))
volumeModel.add(LSTM(50,return_sequences=True))
volumeModel.add(LSTM(50))
volumeModel.add(Dense(1))
volumeModel.compile(loss='mean_squared_error',optimizer='adam')
```



## 2.2: Initializing Model

```
priceModel.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 100, 50)	10400
lstm_1 (LSTM)	(None, 100, 50)	20200
lstm_2 (LSTM)	(None, 50)	20200
dense (Dense)	(None, 1)	51

Total params: 50,851

Trainable params: 50,851

Non-trainable params: 0

```
volumeModel.summary()
```

Model: "sequential\_1"

Layer (type)	Output Shape	Param #
lstm_3 (LSTM)	(None, 100, 50)	10400
lstm_4 (LSTM)	(None, 100, 50)	20200
lstm_5 (LSTM)	(None, 50)	20200
dense_1 (Dense)	(None, 1)	51

Total params: 50,851

Trainable params: 50,851

Non-trainable params: 0

## 2.2: Initializing Model

LSTM.py

```
priceModel.fit(df1XTrain,df1YTrain,validation_data=(df1XTest,df1YTest),epochs=100,batch_size=64,verbose=1)  
volumeModel.fit(df2XTrain,df2YTrain,validation_data=(df2XTest,df2YTest),epochs=100,batch_size=64,verbose=1)
```



## 2.3.1: Predict Output

```
LSTM.py

import tensorflow as tf

df1TrainPredict=priceModel.predict(df1XTrain)
df1TestPredict=priceModel.predict(df1XTest)

df2TrainPredict=volumeModel.predict(df2XTrain)
df2TestPredict=volumeModel.predict(df2XTest)

##Transformback to original form
df1TrainPredict=scalerPrice.inverse_transform(df1TrainPredict)
df1TestPredict=scalerPrice.inverse_transform(df1TestPredict)

df2TrainPredict=scalerVolume.inverse_transform(df2TrainPredict)
df2TestPredict=scalerVolume.inverse_transform(df2TestPredict)
```





## 2.3.2: RMSE Performance

```
import math
from sklearn.metrics import mean_squared_error
math.sqrt(mean_squared_error(df1YTrain,df1TrainPredict))
```

40.82547518029299

```
math.sqrt(mean_squared_error(df1YTest,df1TestPredict))
```

35.28085723288469

```
import math
from sklearn.metrics import mean_squared_error
math.sqrt(mean_squared_error(df2YTrain,df2TrainPredict))
```

77521299.5104038

```
math.sqrt(mean_squared_error(df2YTest,df2TestPredict))
```

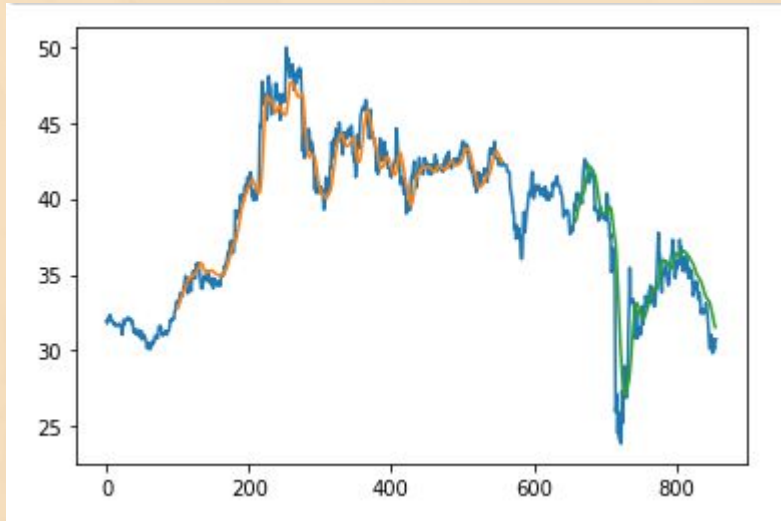
84757047.79172568



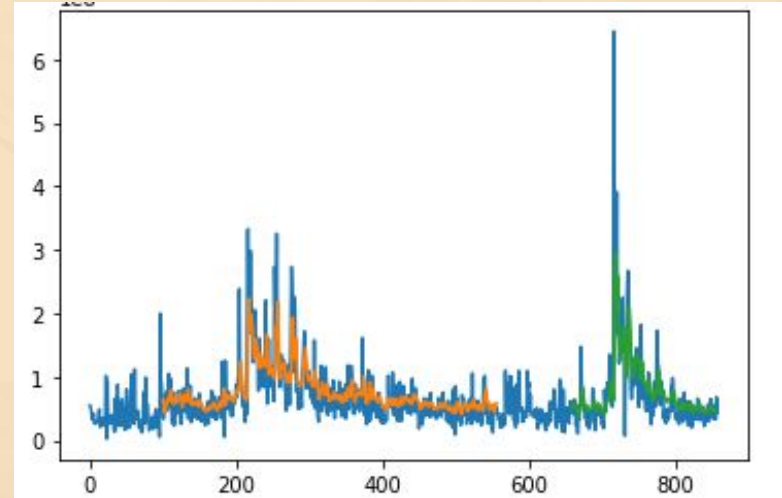


## 2.3.3: Plotting

PRICE



VOLUME



## 2.4.1: Predicting Future (30 Days)



LSTM.py

```
def tempInput(testData):  
    xInput=testData[200:].reshape(1,-1)  
    tempInput=list(xInput)  
    tempInput=tempInput[0].tolist()  
    return tempInput, xInput  
  
priceTempInput, priceInput = tempInput(df1TestData)  
volumeTempInput, volumeInput = tempInput(df2TestData)
```



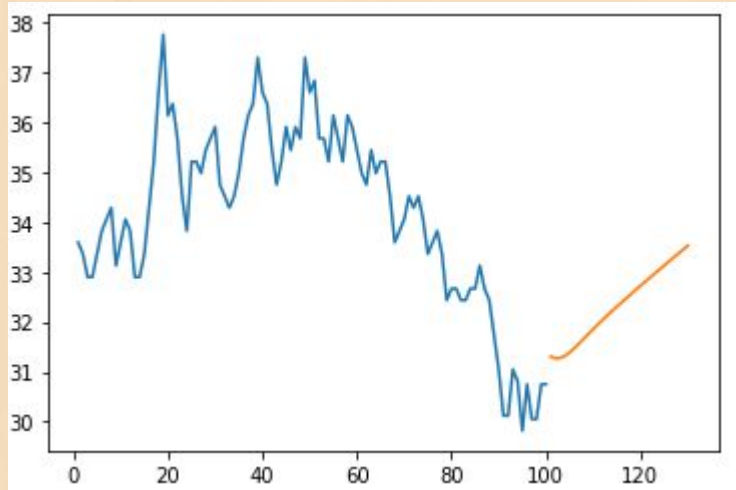
LSTM.py

```
from numpy import array  
  
priceOutput=[]  
n_steps=100  
i=0  
while(i<30):  
  
    if(len(priceTempInput)>100):  
        priceInput=np.array(priceTempInput[1:])  
        priceInput=priceInput.reshape(1,-1)  
        priceInput = priceInput.reshape((1, n_steps, 1))  
        yhat = priceModel.predict(priceInput, verbose=0)  
        priceTempInput.extend(yhat[0].tolist())  
        priceTempInput=priceTempInput[1:]  
        priceOutput.extend(yhat.tolist())  
        i=i+1  
    else:  
        priceInput = priceInput.reshape((1, n_steps,1))  
        yhat = priceModel.predict(priceInput, verbose=0)  
        print(yhat[0])  
        priceTempInput.extend(yhat[0].tolist())  
        print(len(priceTempInput))  
        priceOutput.extend(yhat.tolist())  
        i=i+1  
  
print(priceOutput)
```

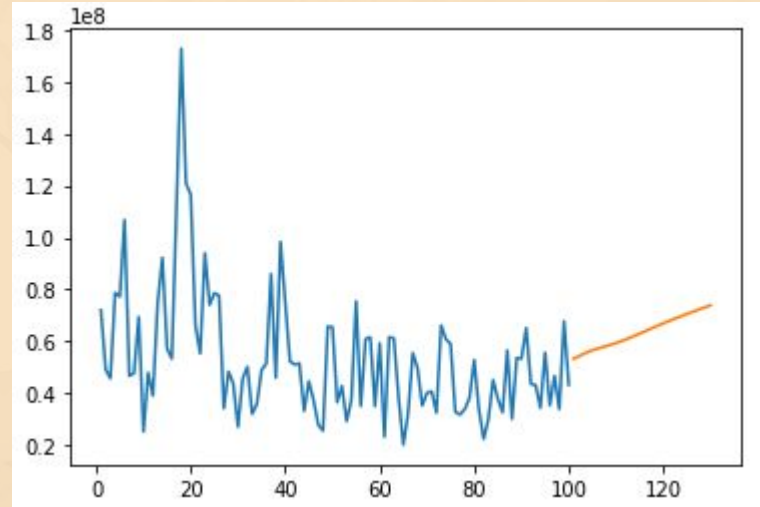


## 2.4.2: Plotting

PRICE

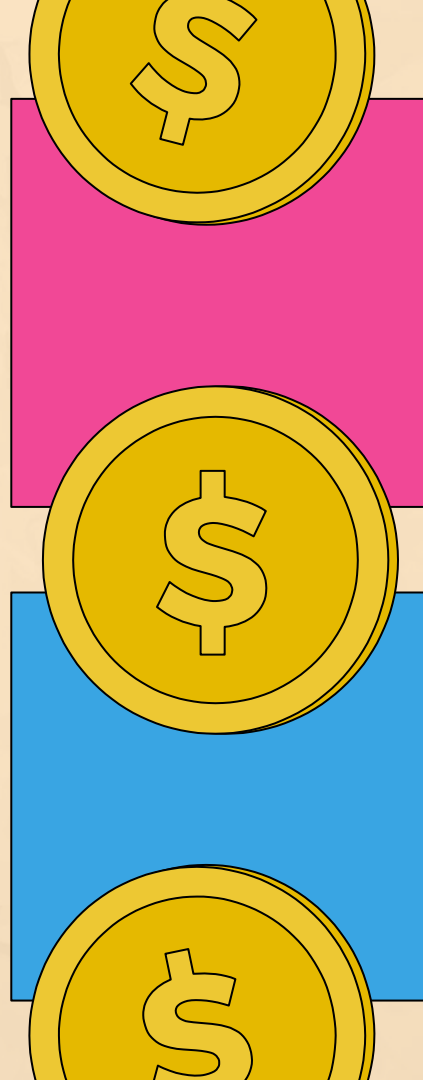


VOLUME



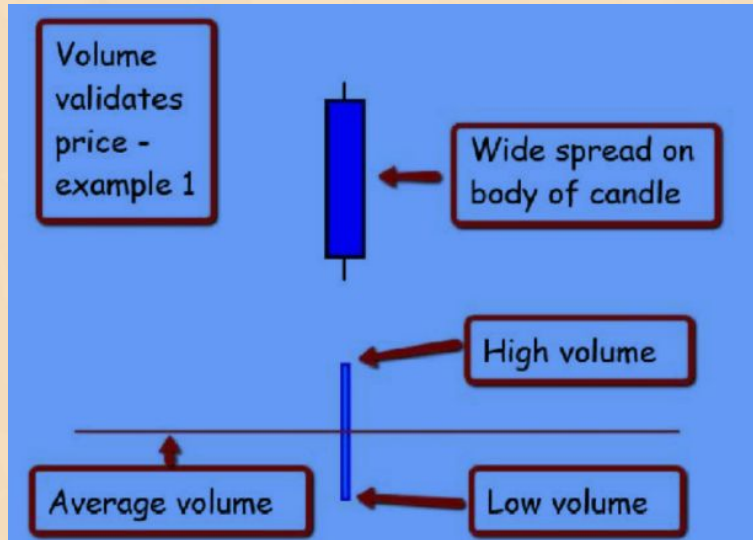
3

# Analyzing Results

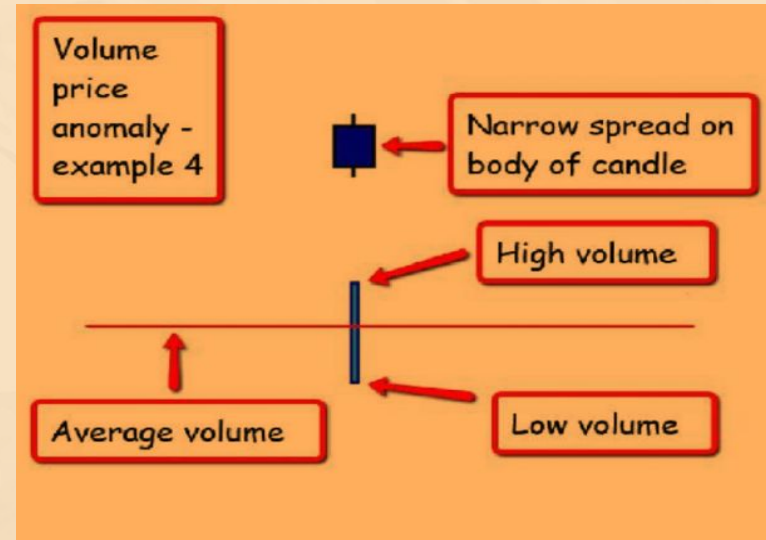


# 3.1: Why Both?

## VALIDATION

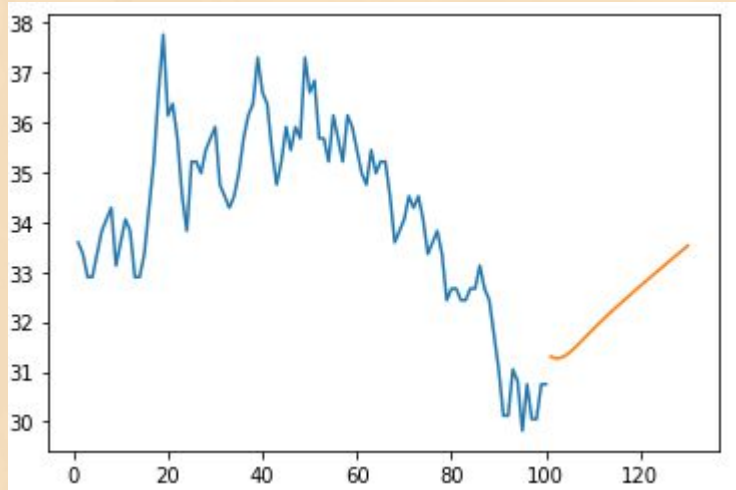


## ANOMALY

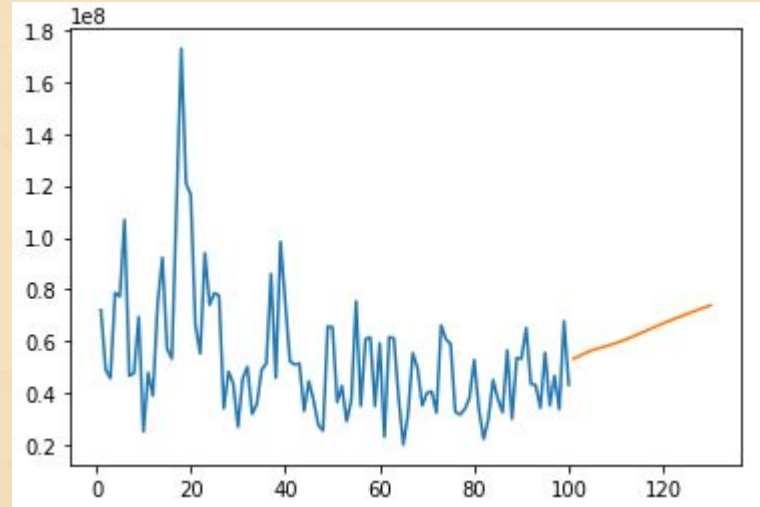


## 3.2: Analyzing

PRICE



VOLUME

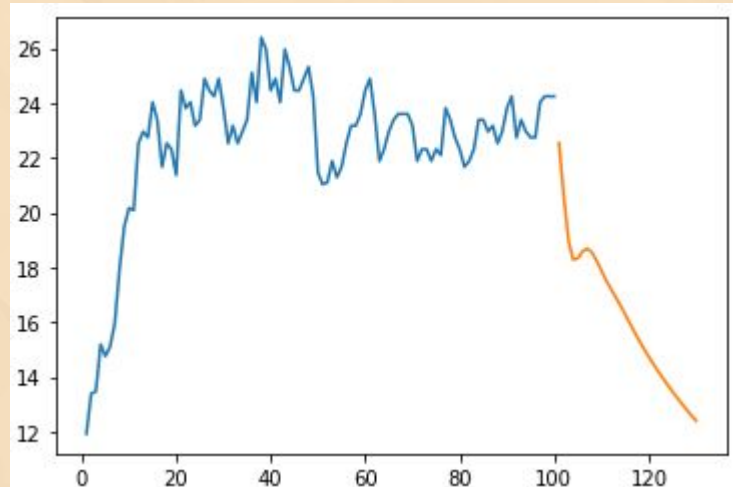




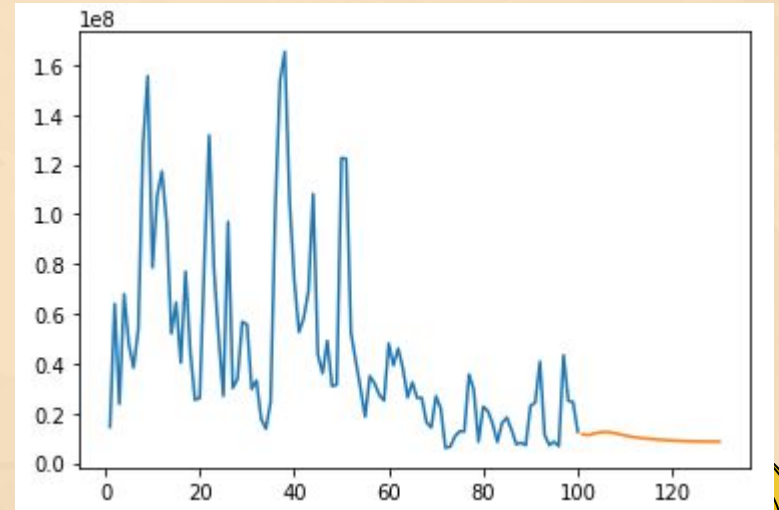


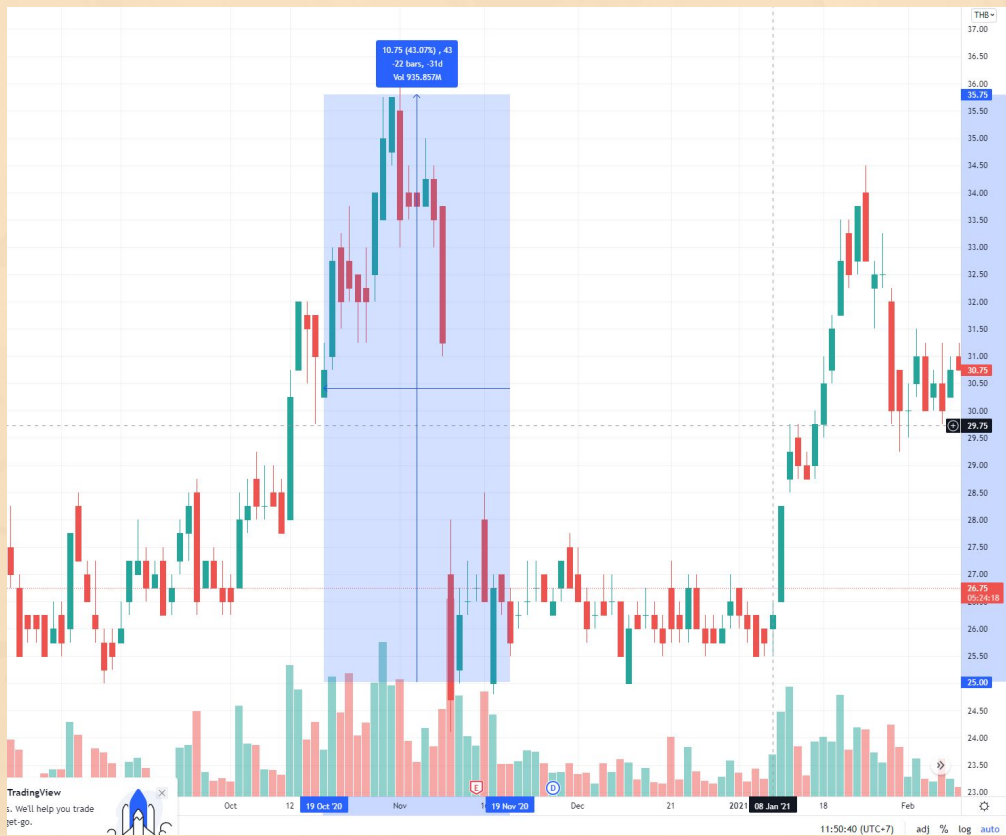
## 3.2: Analyzing

PRICE



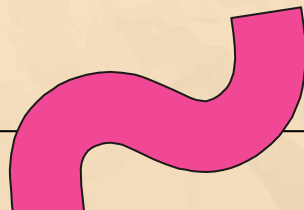
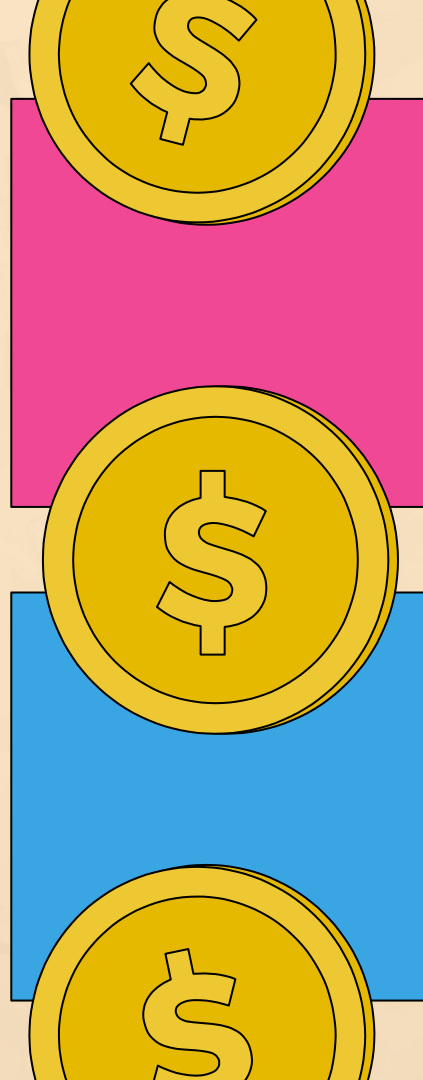
VOLUME





3

**Final**  
**Remark**



ANNA COULLING

A  
Complete Guide  
to  
Volume Price  
Analysis

Read the book  
then read the  
market



