

# Stock Price Prediction Using LSTM



## Team **Random**

Yaming Cao

Jingzhen Hu

Qingzhong Liang

Arafatur Rahman

A K M Rokonzaman Sonet

**The Erdos Institute, Summer Boot Camp 2022**

## Data gathering and Preprocessing

- Historical data for the stocks AAPL, TSLA, AMD, SBUX, FB from Yahoo finance for the period **06/02/2012 – 06/02/2022**.
- Considered only the **daily opening prices**.
- **Testing data consists of last 90 days** (1/25/2022 - 06/02/2022)
- **Remaining** sample used for the **training** data (06/02/2012 – 1/24/2022)
- **Normalized** training and testing data using sklearn *StandardScaler* package.

# Modeling Approach: Long Short Term Memory (LSTM)

Today's stock price will be determined by:

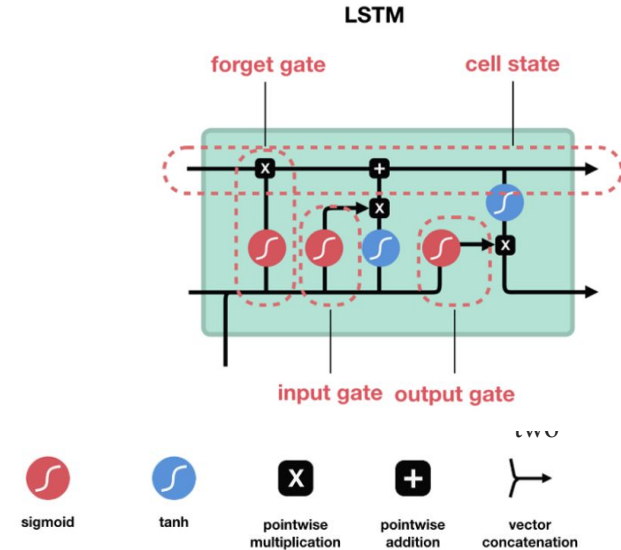
- The **pattern** the stock has been following in the **past days**, which could be **down or up**.
- The **price of the stock on the previous day**, because many traders compare the stock's previous day's price before buying it

These relationships can be generalized to any problem as:

- **The previous cell state:** information present in the memory after the previous time step
- **The previous hidden state:** output of the previous cell state,  $h_{t-1}$
- **The input at the current time step:** new information at that moment,  $x_t$

The Long Short Term Memory model has these features!

- LSTM is able to **store information** from the past which helps especially predict stock price based on past prices.
- LSTM has **gates capable of regulating** what information to **keep or forget**.
- LSTM cell contains a **forget state, input gate, output gate, and cell state**, along with **activation functions, Sigmoid and tanh**.



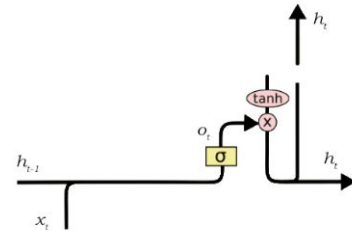
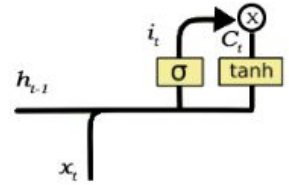
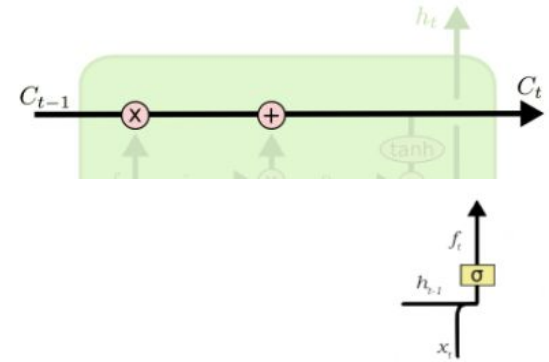
# LSTM Structure and Mechanism

**Cell State:** working like a memory and key to LSTMs. It carries informations and associated with some linear interactions. LSTM either remove information from this state or add information to this state to carry over.

**Forget Gate:** decides what information need to forget from the cell state. It takes inputs  $h_{t-1}$  and  $x_t$  and outputs a number from 0 to 1 for each number in the cell state  $C_{t-1}$ . 0 to forget and 1 to input.

**Input Gate:** add information to the cell state in three steps: (1) Like the forget gate act as a filter for all the information from  $h_{t-1}$  and  $x_t$ ; (2) Create a vector containing all possible values that can be added to the cell state by using tanh function; (3) multiply the created vector to the value of the regulatory filter and then add this information to the cell state.

**Output Gate:** outputs selected useful information from the current cell state in three steps: (1) apply tanh function to the cell state and create a vector; (2) make a filter using the values of  $h_{t-1}$  and  $x_t$  so that can regulate the values need to be output; (3) multiply the vector created in step 1 to the value of regulatory filter and send it as output and send it to the hidden state of next cell.



## Network Architecture

- Model type: **Keras sequential API**
- Two LSTM network with outer spaces **dimension 64 and 32** respectively.
- **Dropout 20%**
- Activation Function: **Relu**; Optimizer: **Adam** ; Loss : **mse**
- **Input space: A 3D tensor** [no of sample, time step, no of features]
- No of **epoch: 3**; batch size: **1**

# Empirical Results

Stock Prediction with 14 time steps:

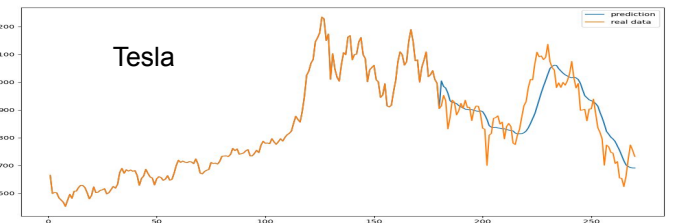
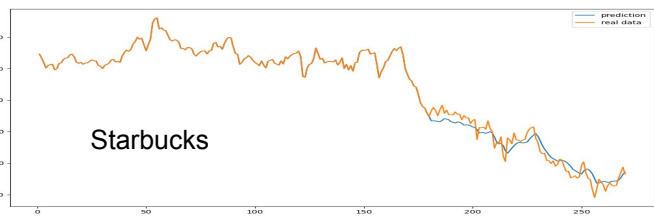
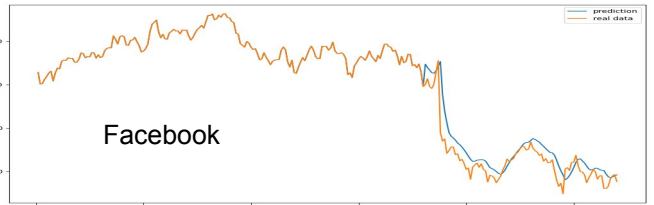
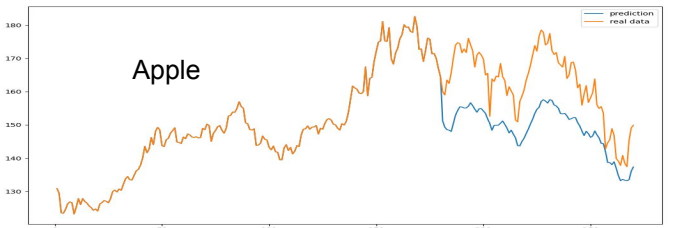
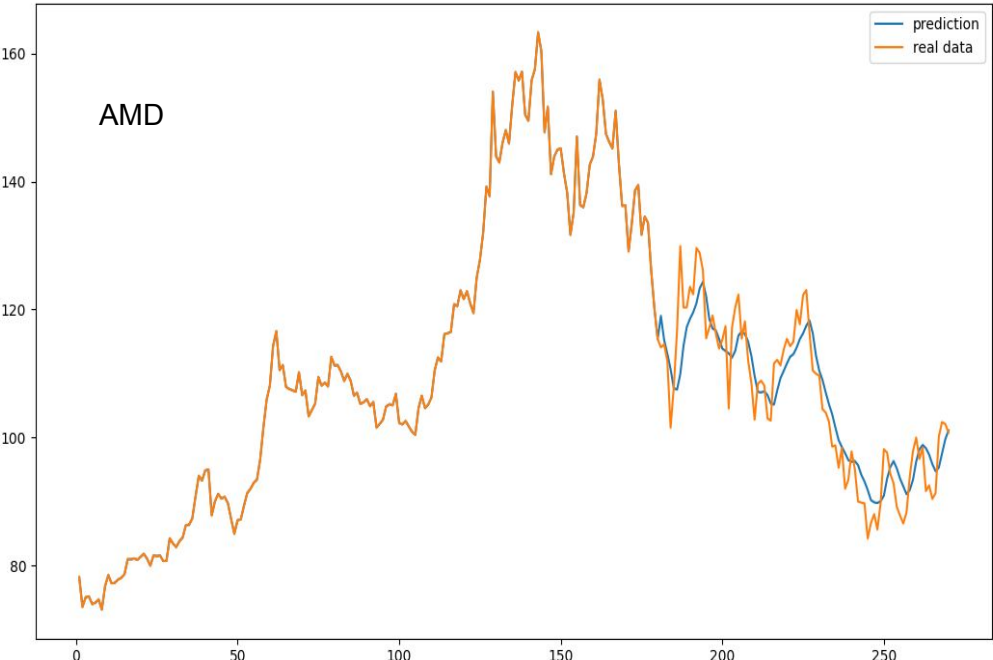


Figure: Actual (Orange) and Predicted (Blue) Stock Price

# Empirical Results

Stock Prediction with 60 time steps:

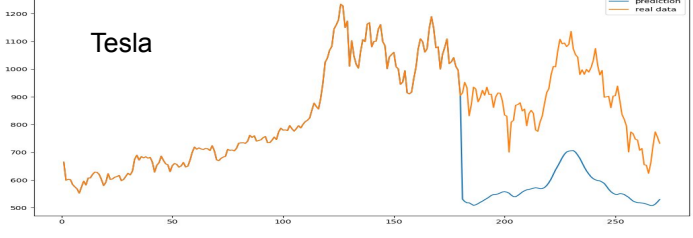
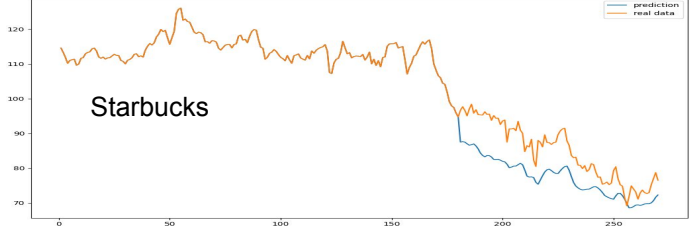
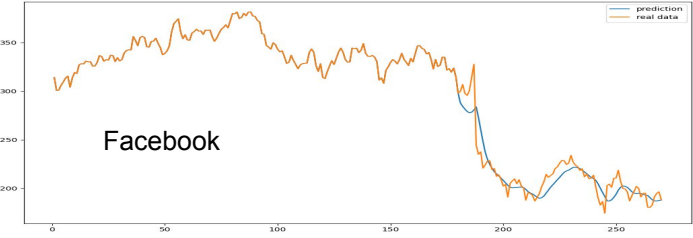
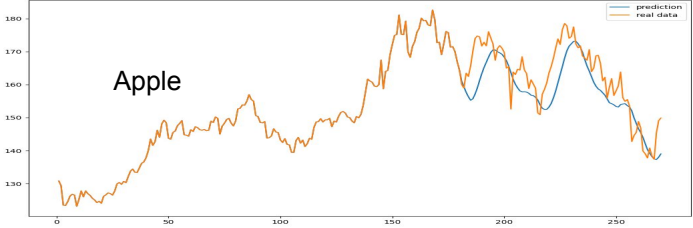
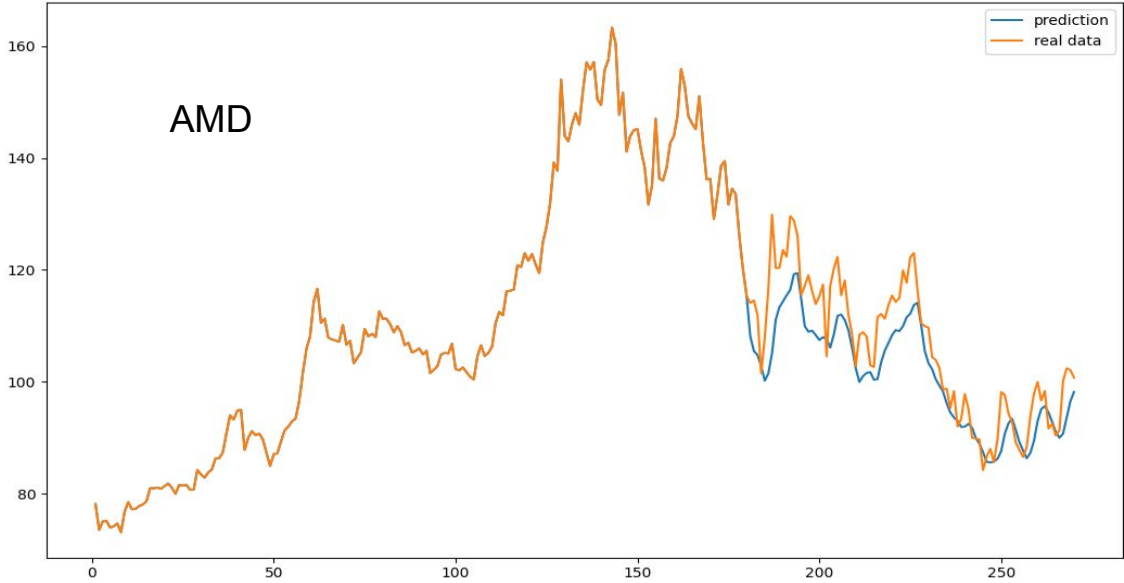


Figure: Actual (Orange) and Predicted (Blue) Stock Price

## Results Discussion

- The predicted value was not very accurate compared to the real price, but it could **capture the direction** of price movement most of the times.
- Among all the stocks, prediction for **AMD** looked more promising and more inaccurate for Tesla.
- **Time steps 14** provided slightly **better** prediction than time **step 60**.



## Future Direction

- Can play with **different model architecture**, hyperparameter tuning to see if that increases the performance
- Can do more **exploratory data analysis** to figure out some relation between the model prediction and the properties of data.
- Can do **time series cross validation** to improve the generalization power of our model.
- The predicted results can be used for **portfolio optimization problems**.

# References

- **Data:** [Yahoo Finance](#)
- [Using LSTMs to Predict Future Stock Price](#)
- [LSTM Network](#)
- [Introduction to LSTM](#)
- [Data science approach to stock prices forecasting in Indonesia during Covid-19 using Long Short-Term Memory \(LSTM\)](#)
- [Machine Learning to Predict Stock Price](#)