

# **Stock Prediction Using RNN with Long Short-Term Memory**

**Jacky Wong & Renjun Cheng**

**W207 Fall 2020 Final Project**

# Motivation - An Introduction

## Stock Market?

- The place to trade company stock
- Sell/Buy certain units of company ownership
- If the price of a company goes up, a profit is made. And if the price of a company goes down, there will be a loss
- For a specific company stock, if the number of buyers exceeds that of seller, the stock price tends to rise, and vice versa.

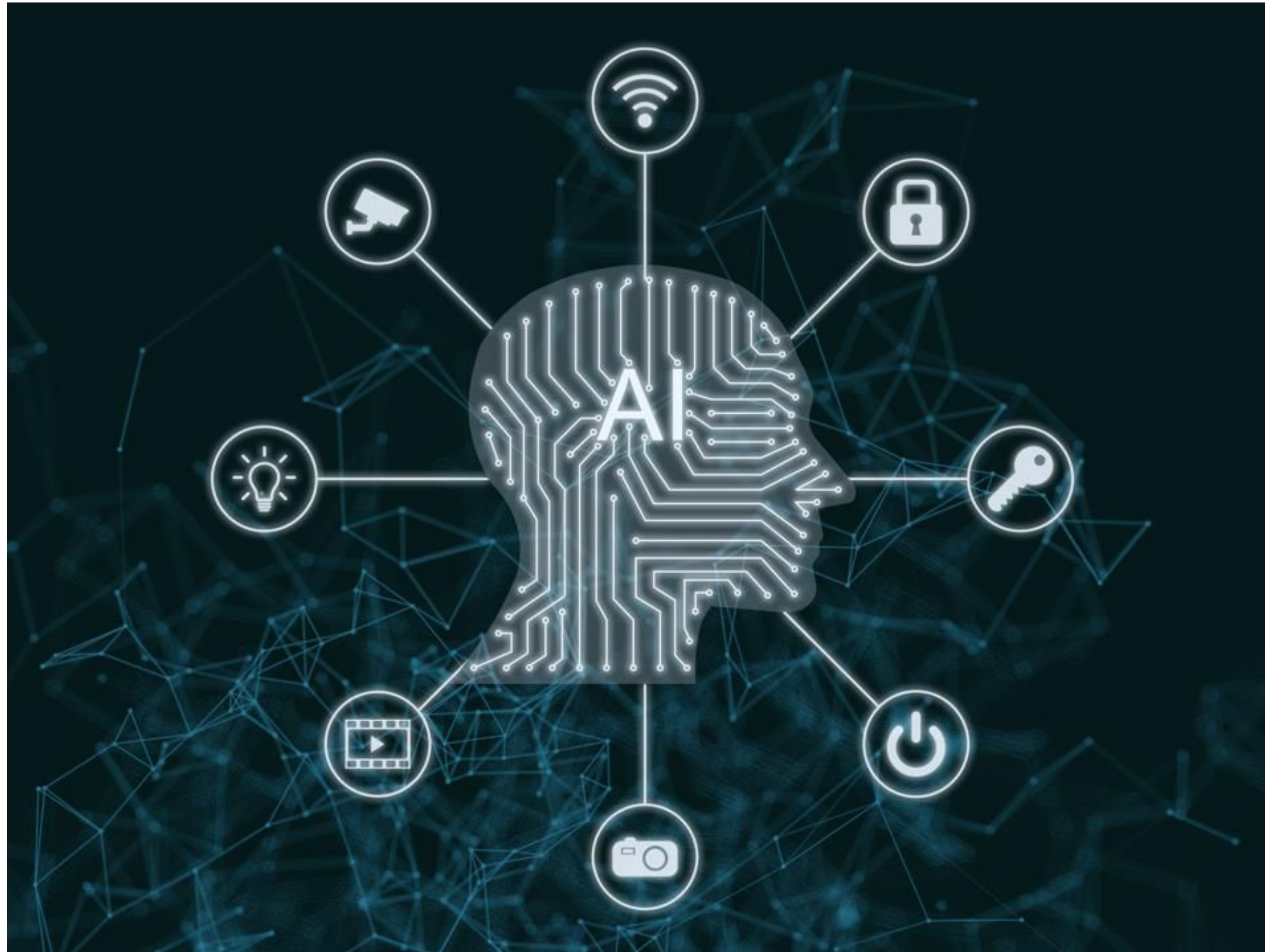


# Motivation - The Goal: Buy High, Sell Low (Short) vs. Buy Low, Sell High (Long)





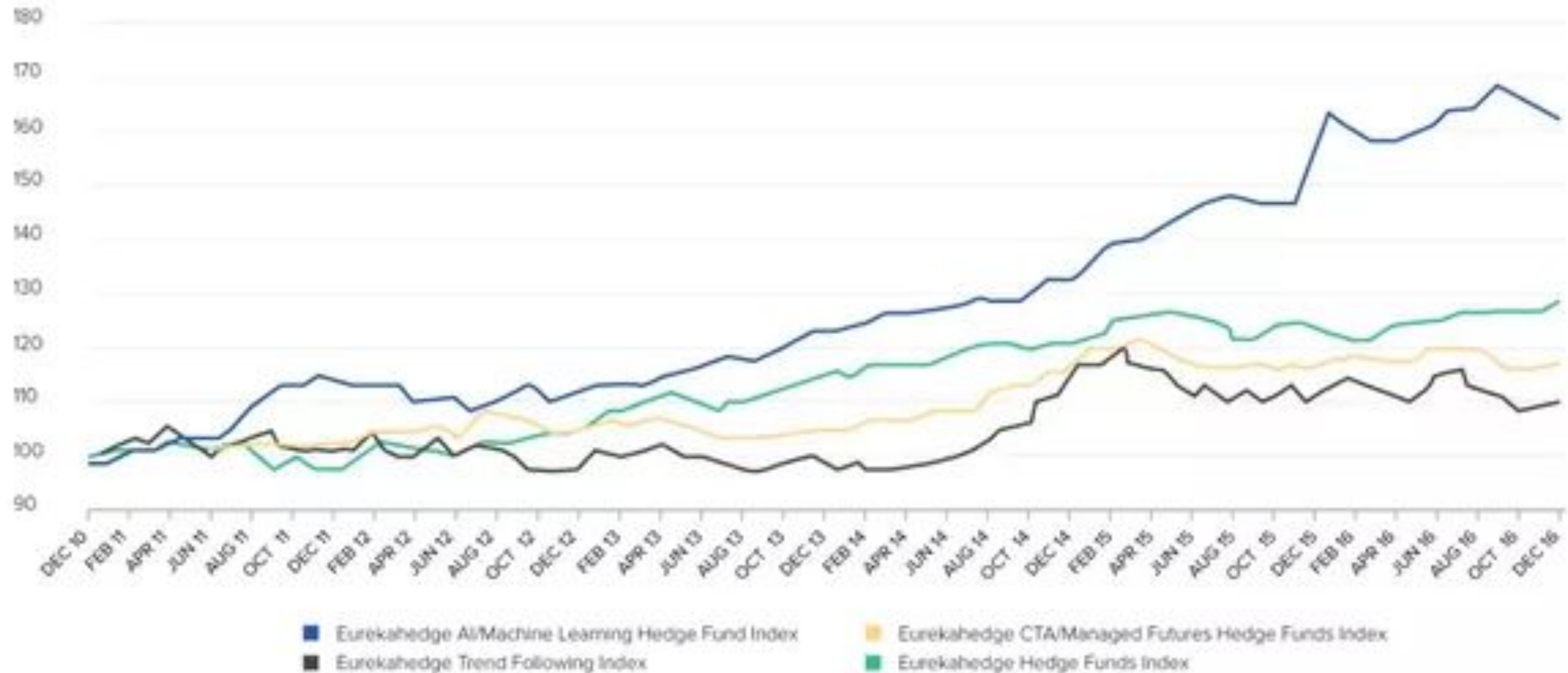
# Motivation - The AI World





# Motivation - AI in Stock Trading

**Chart 2:** AI/Machine Learning Hedge Funds Index vs. Quants and Traditional Hedge Funds



Source: EurekaHedge

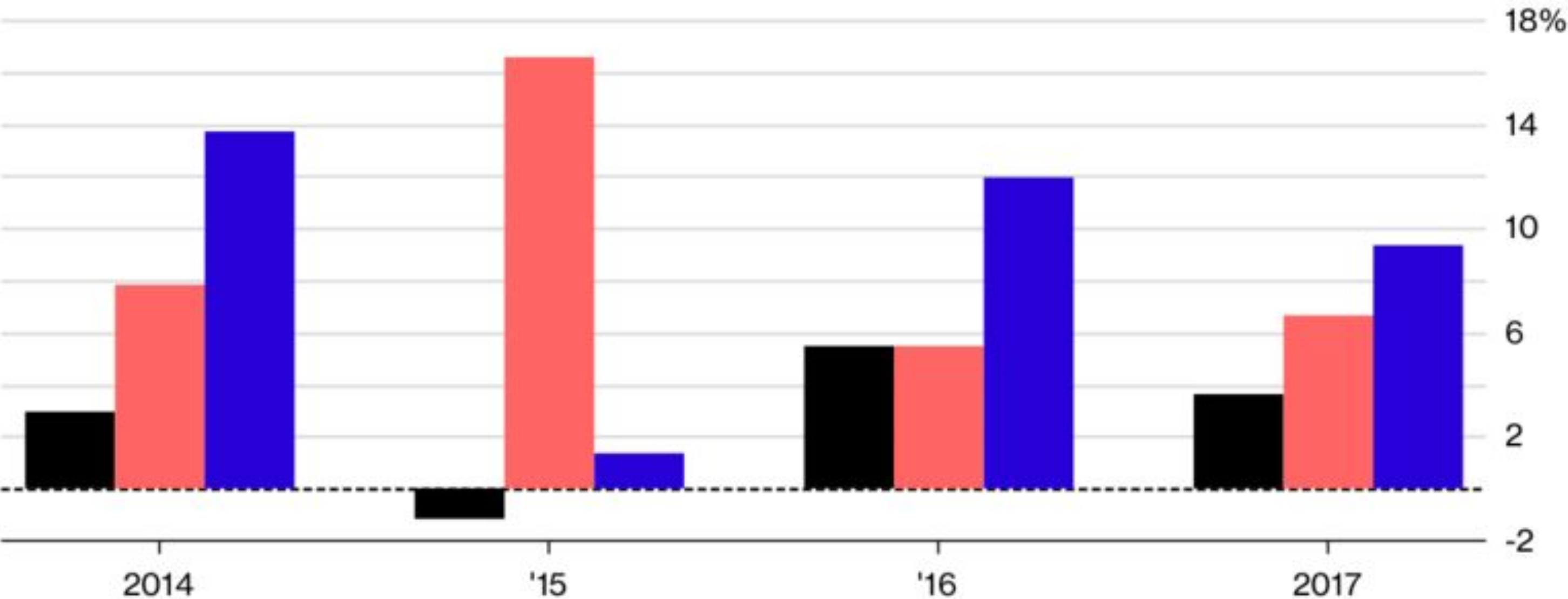
# Well-Known Company



## Machine Learning's Gains

Like hedge funds, AI strategies have struggled to beat the stock market

■ HFRI Fund Weighted Composite Index ■ EurekaHedge AI Hedge Fund Index ■ S&P 500



2017 returns YTD through June, S&P 500 Index returns are with dividend reinvested

Source: EurekaHedge, Hedge Fund Research, Inc., Bloomberg

**Bloomberg**



# Literature



## Why Artificial Intelligence Will Never Beat the Stock Market

By **Concoda** - March 3, 2020



Over the past decade, the belief that artificial intelligence could solve the complexities of the stock market has spread like a wildfire. The notion that humans lack the capacity and capability compared to machines, who will, without fail, consistently beat the market over time. By simply programming a machine, it will produce the ultimate formula making you filthy rich in the process. A radical change in society where anyone can make money, but not just a stable income: a modest fortune.

Unfortunately, though, this is a mere fantasy.

There’s a major flaw in algorithms built solely to predict future market moves: they don’t. They only respect the technical aspects of an asset by taking into account past price movements, avoiding any consideration for future fundamentals. Any veteran trader will tell you the market isn’t there to give away free money. Instead, it’s a competitive environment punishing anyone — or anything — who tries to make a quick buck by trading on reactionary information already priced in.

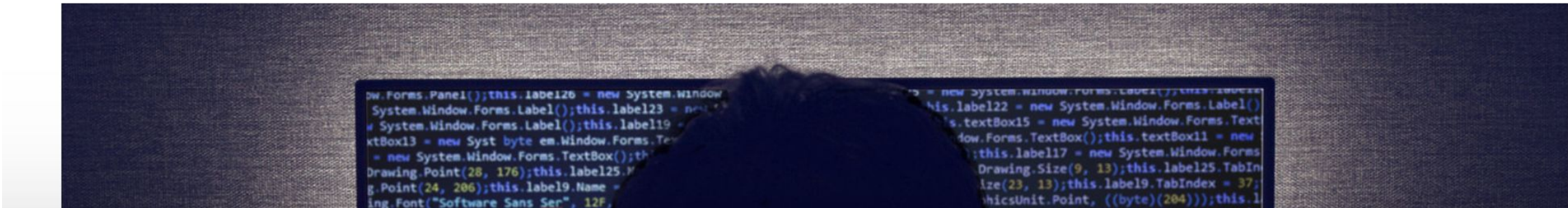
Outside the Box

## Opinion: Machine learning won’t crack the stock market — but here’s when investors should trust AI

Published: June 8, 2020 at 8:37 a.m. ET

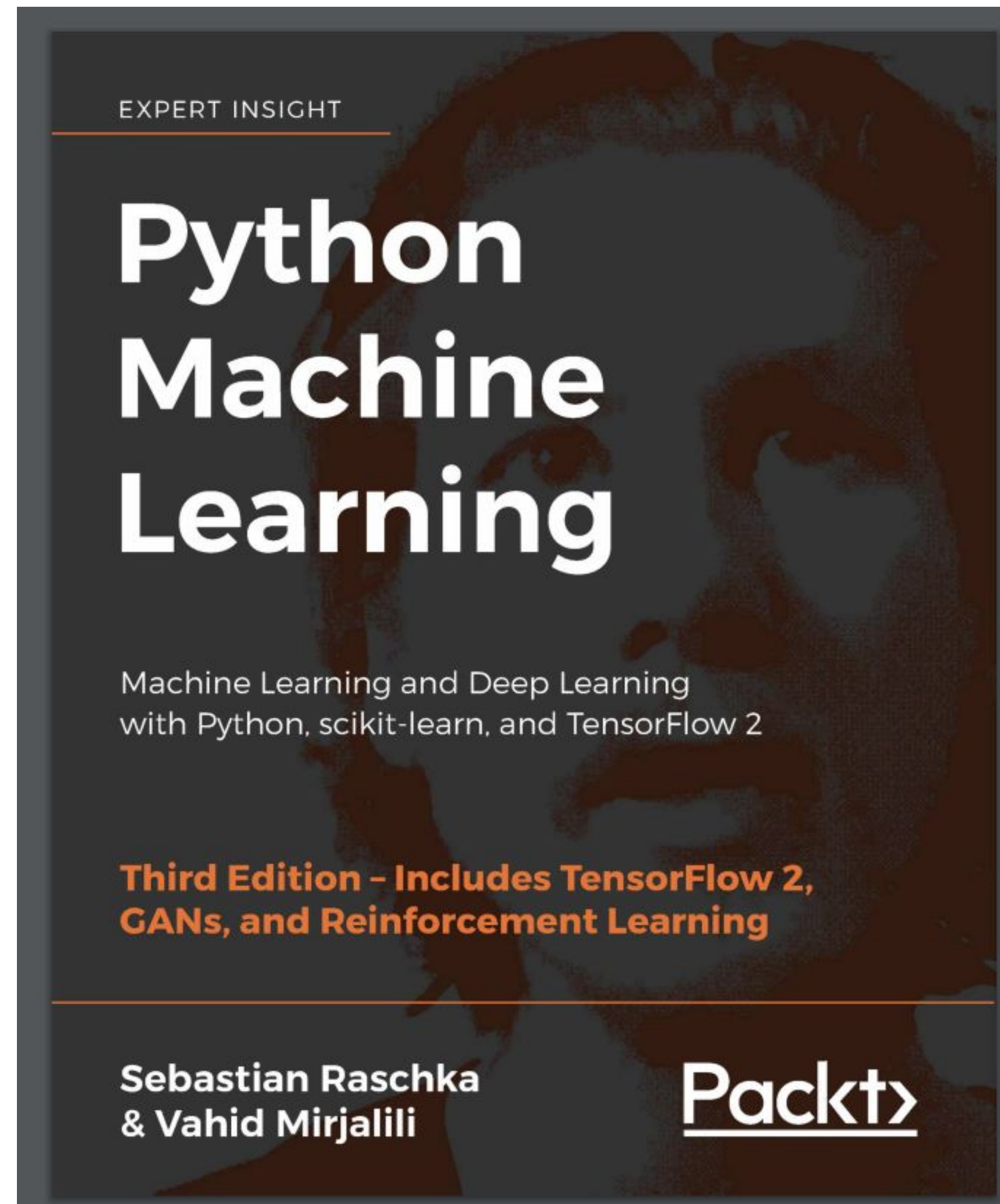
By Vasant Dhar

Ask these 5 questions before you invest with a machine-learning-based program





# Literature



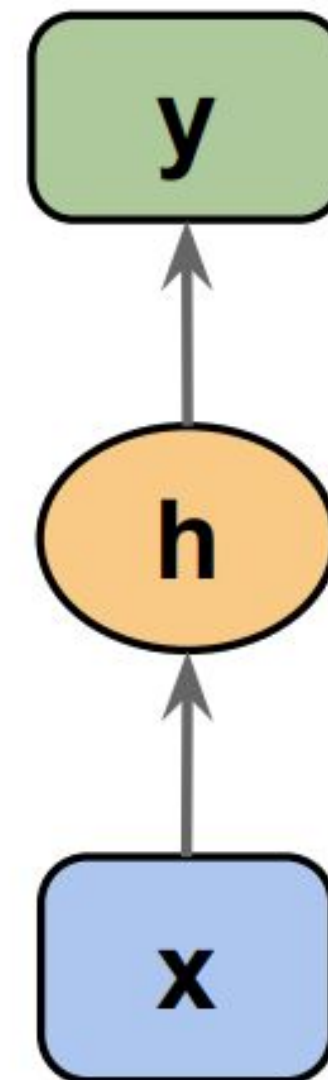
**By Sebastian Raschka & Vahid Mirjalili**



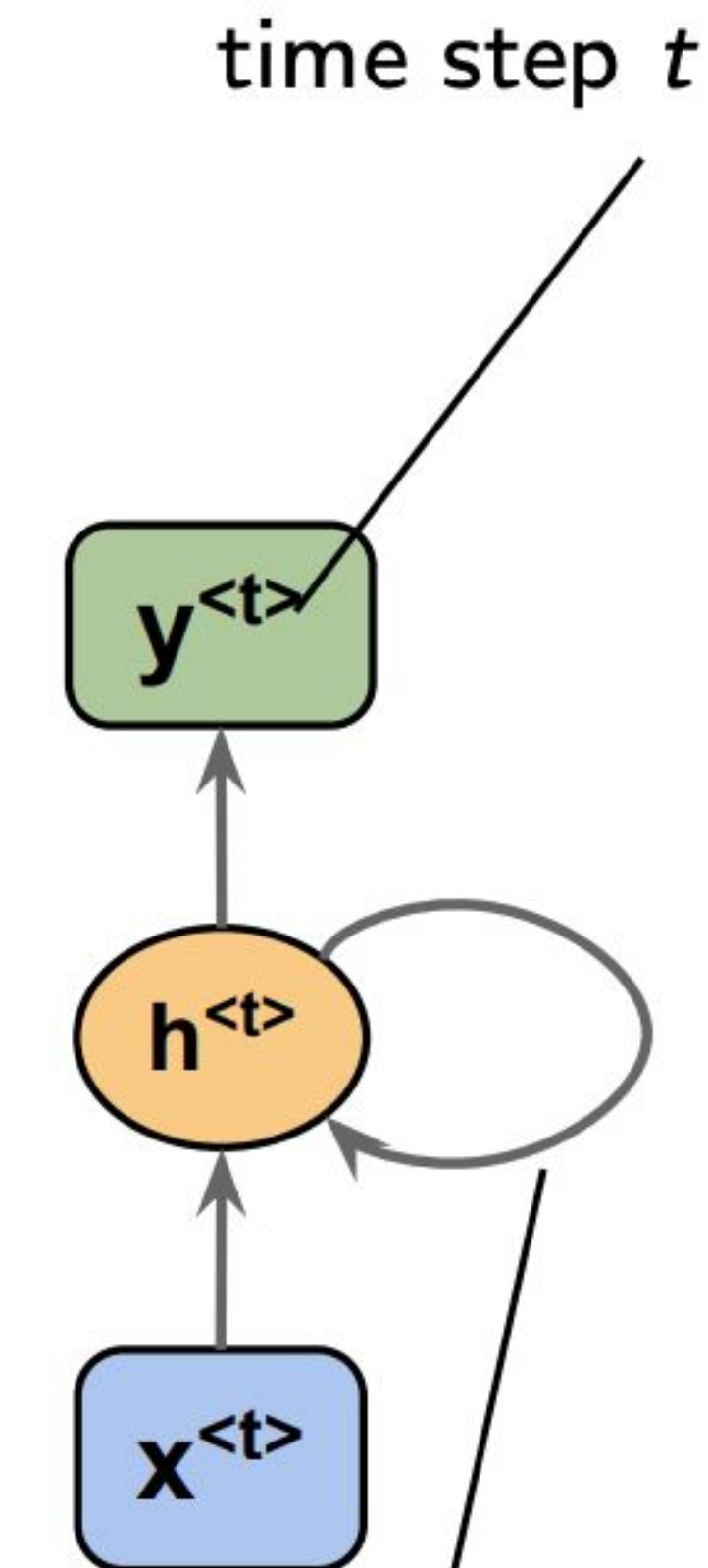
# Literature - Recurrent Neural Network (RNN)

## Overview

Networks we used previously: also called feedforward neural networks

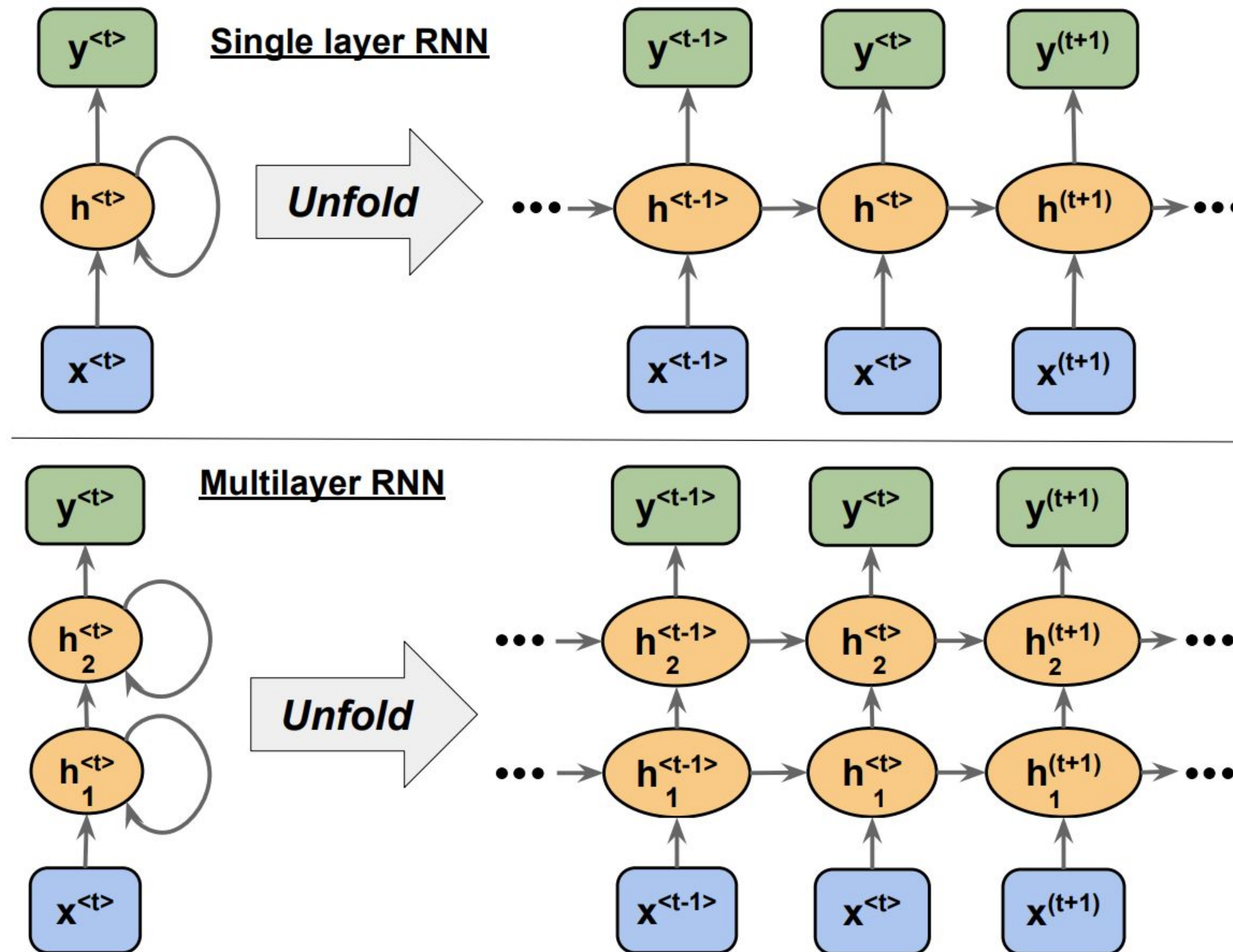


Recurrent Neural Network (RNN)



Recurrent edge

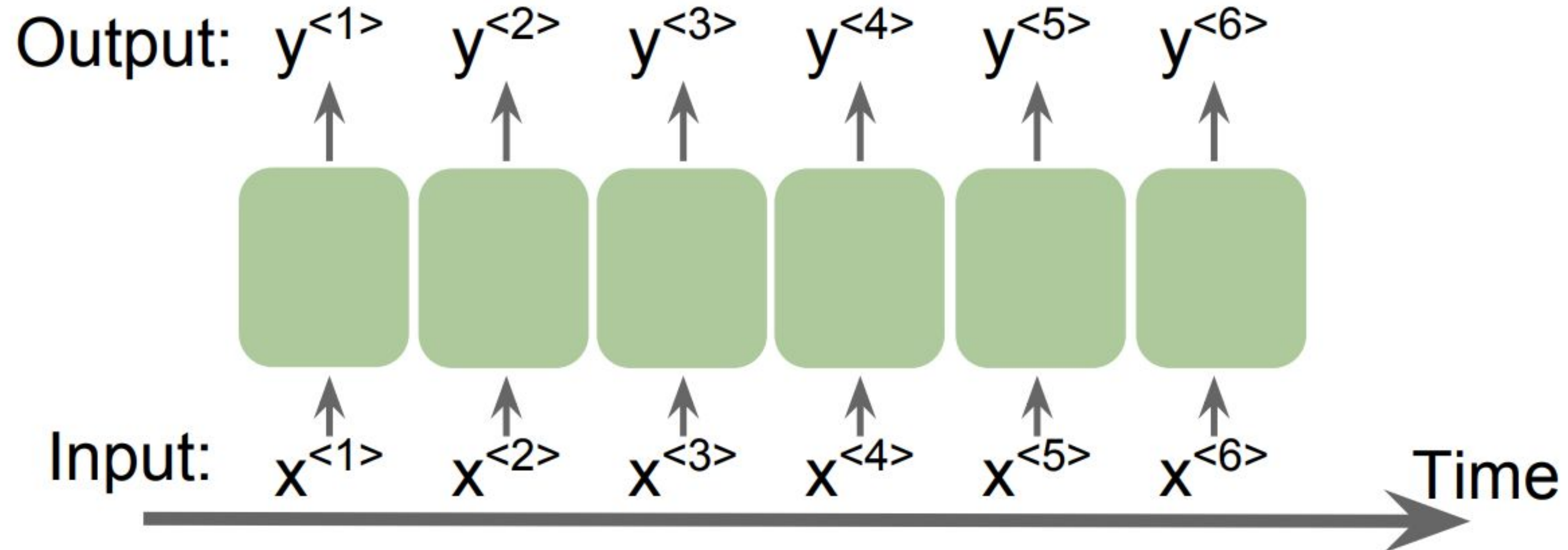
# Literature - Single Layer RNN vs. Multilayer RNN





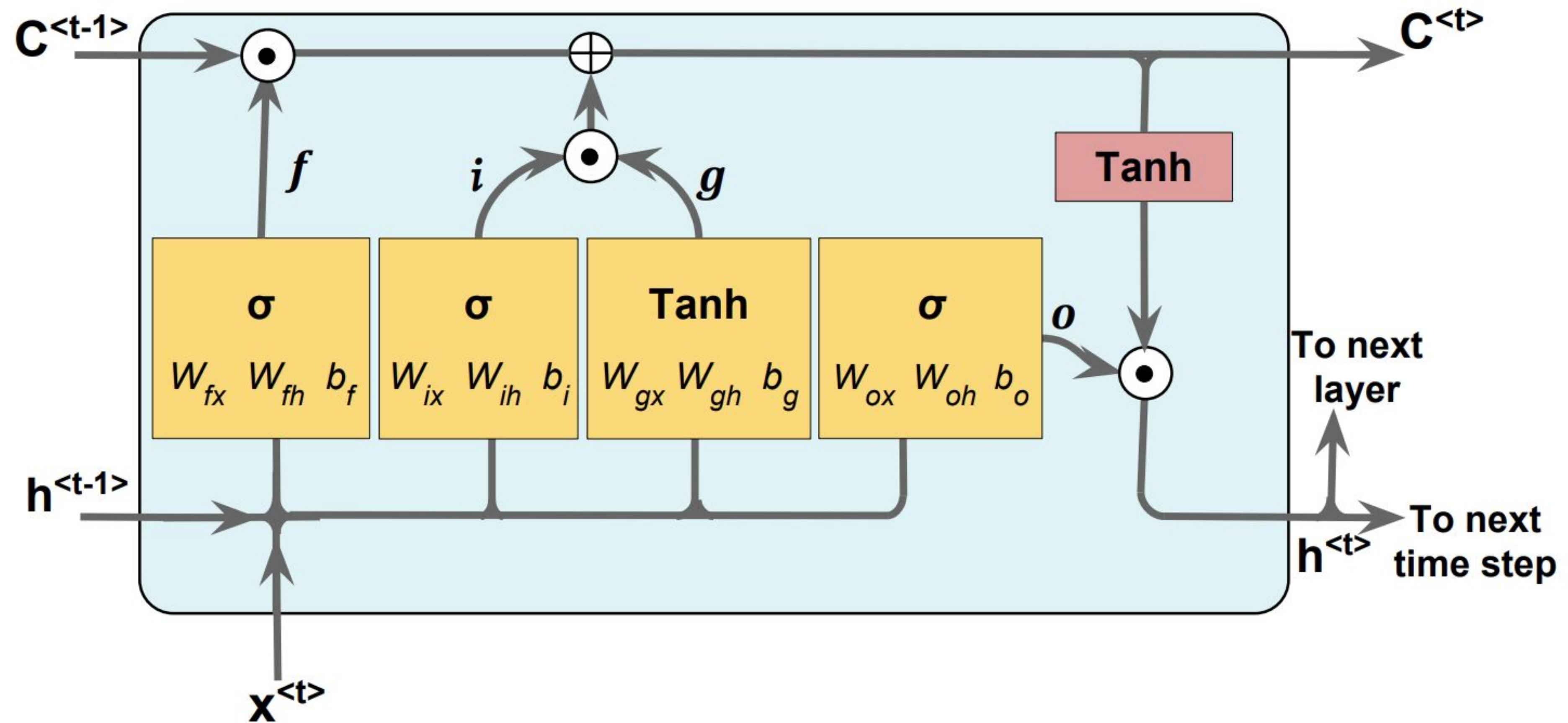
# Literature - RNN: Sequential Data

Sequential Data is NOT i.i.d.



# Literature - Long-Short Term Memory (LSTM)

LSTM cell:



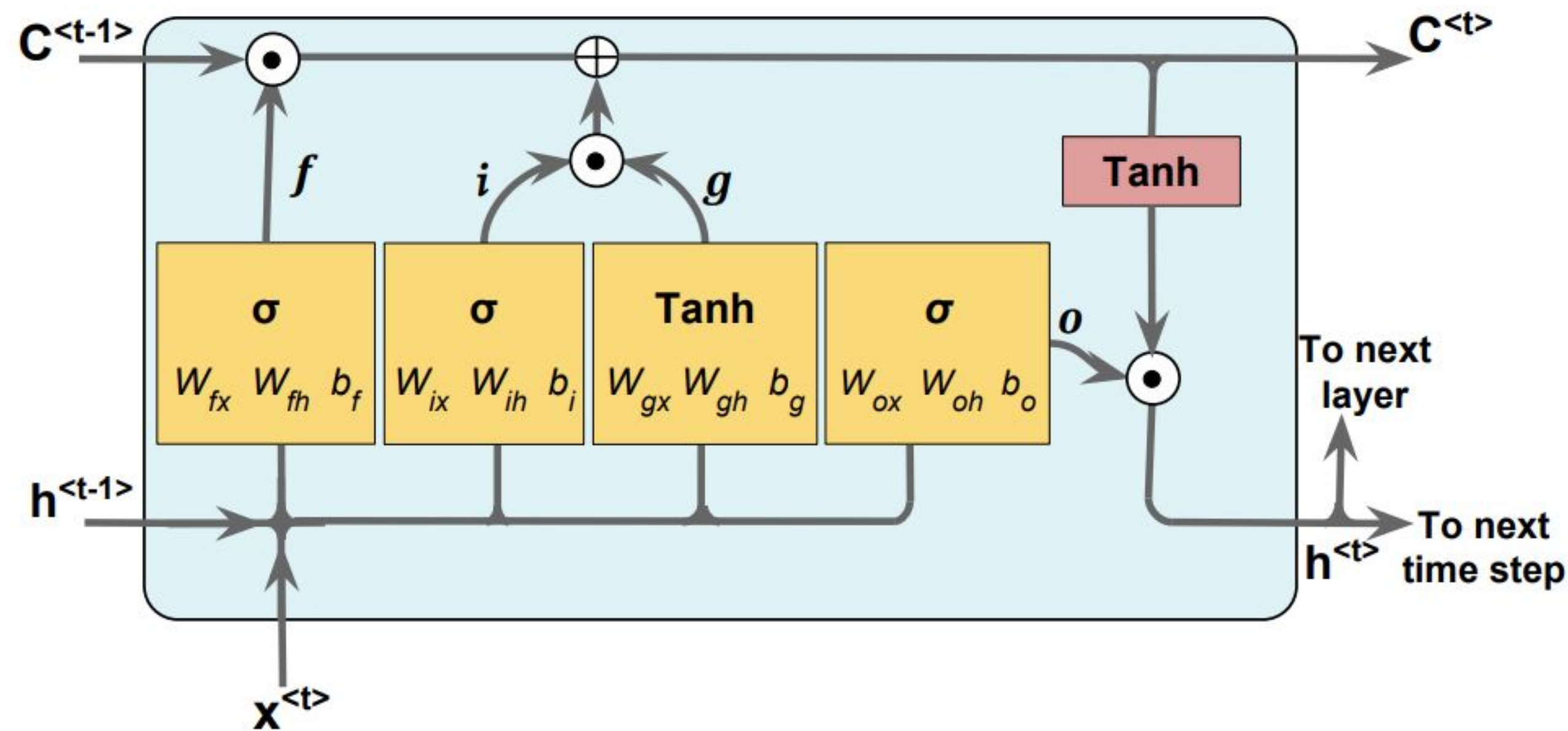


# Literature - Long-Short Term Memory (LSTM)

Forget Gate      Input Node      Input Gate

$$C^{<t>} = \left( C^{<t-1>} \odot f_t \right) \oplus \left( i_t \odot g_t \right)$$

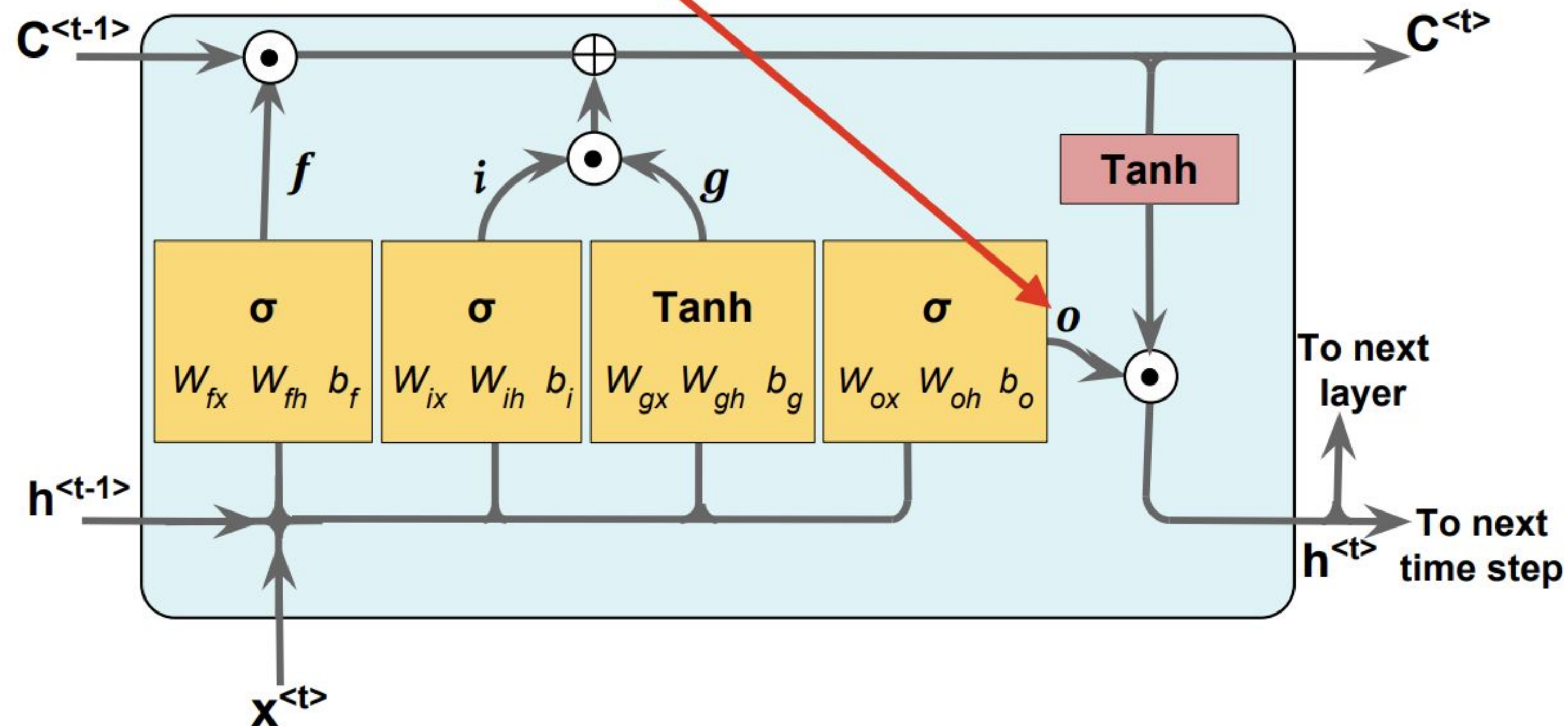
For updating the cell state



# Literature - Long-Short Term Memory (LSTM)

Output gate for updating the values of hidden units:

$$\mathbf{o}_t = \sigma \left( \mathbf{W}_{ox} \mathbf{x}^{(t)} + \mathbf{W}_{oh} \mathbf{h}^{(t-1)} + \mathbf{b}_o \right)$$

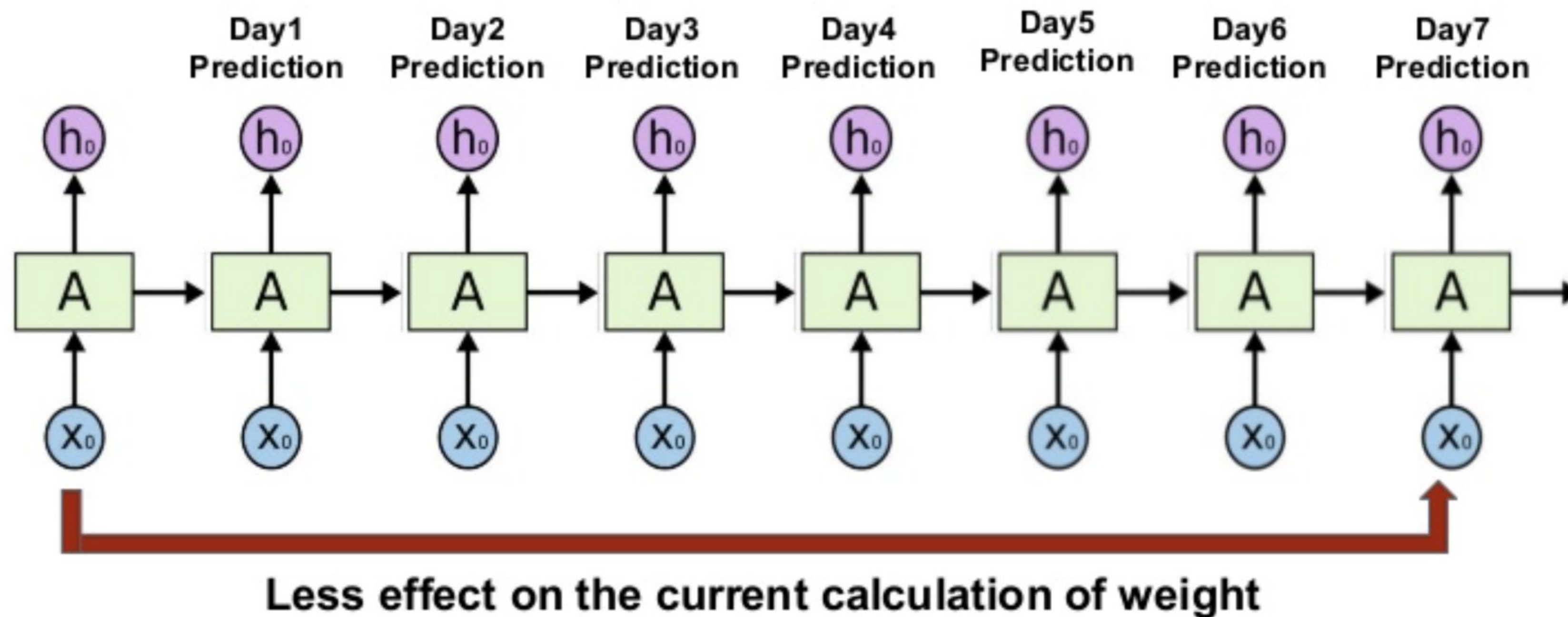




# Literature - Why LSTM?

- uses a memory cell for modeling long-range dependencies
- avoid vanishing gradient problems

## Vanishing Gradient Problem



So, it does not allow it to learn from past data as was expected.

# Literature - LSTM: A summary of gates...

**Input gate** — discover which value from input should be used to modify the memory.

**Sigmoid** function decides which values to let through **0,1**. and **tanh** function gives weightage to the values which are passed deciding their level of importance ranging from **-1** to **1**.

$$i_t = \sigma (W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

**Forget gate** — discover what details to be discarded from the block. It is decided by the **sigmoid function**. it looks at the previous state(**ht-1**) and the content input(**Xt**) and outputs a number between **0(omit this)** and **1(keep this)** for each number in the cell state **Ct-1**.

$$f_t = \sigma (W_f \cdot [h_{t-1}, x_t] + b_f)$$

**Output gate** — the input and the memory of the block is used to decide the output. **Sigmoid** function decides which values to let through **0,1**. and **tanh** function gives weightage to the values which are passed deciding their level of importance ranging from **-1** to **1** and multiplied with output of **Sigmoid**.

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

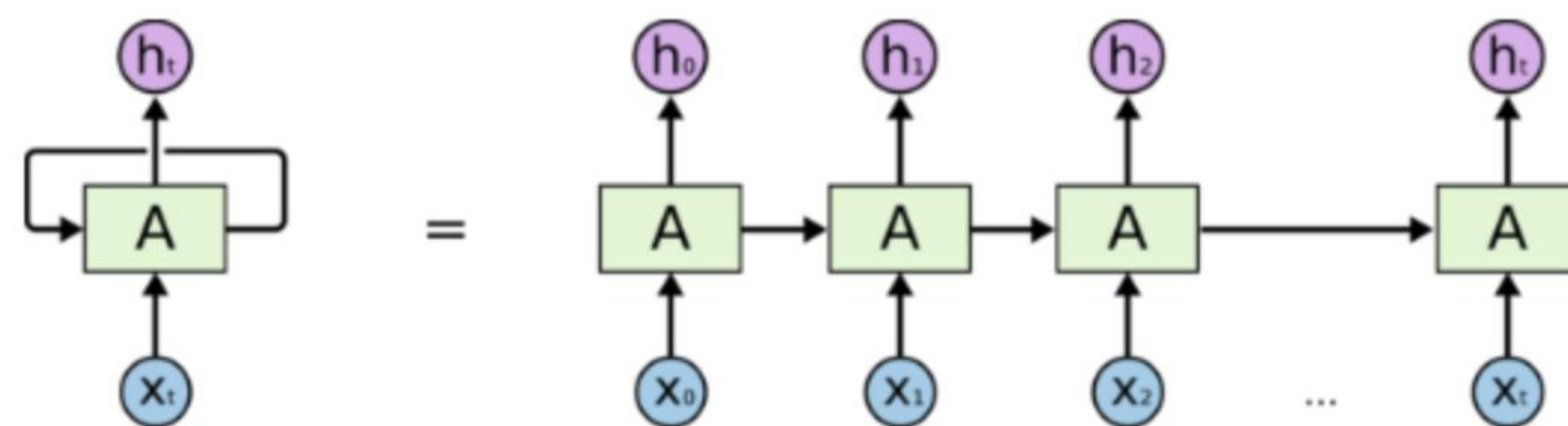
$$h_t = o_t * \tanh (C_t)$$



# Our approach: RNN with LSTM

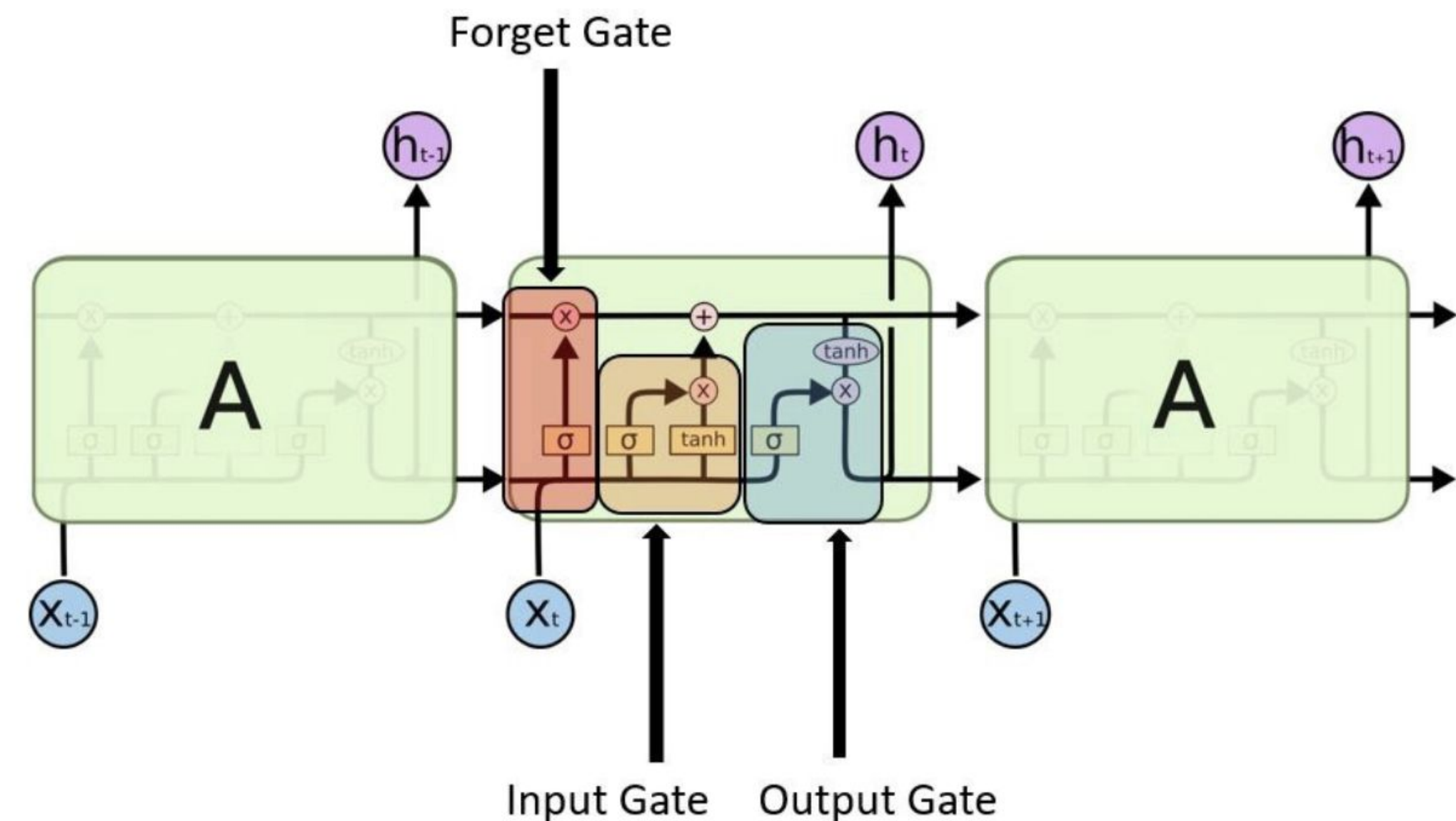
Recurrent Neural Network is a generalization of feedforward neural network that has an internal memory. RNN is recurrent in nature as it performs the same function for every input of data while the output of the current input depends on the past one computation. After producing the output, it is copied and sent back into the recurrent network. For making a decision, it considers the current input and the output that it has learned from the previous input.

Unlike feedforward neural networks, RNNs can use their internal state (memory) to process sequences of inputs. This makes them applicable to tasks such as unsegmented, connected handwriting recognition or speech recognition. In other neural networks, all the inputs are independent of each other. But in RNN, all the inputs are related to each other.



An unrolled recurrent neural network.

Long Short-Term Memory (LSTM) networks are a modified version of recurrent neural networks, which makes it easier to remember past data in memory. The vanishing gradient problem of RNN is resolved here. LSTM is well-suited to classify, process and predict time series given time lags of unknown duration. It trains the model by using back-propagation. In an LSTM network, three gates are present:



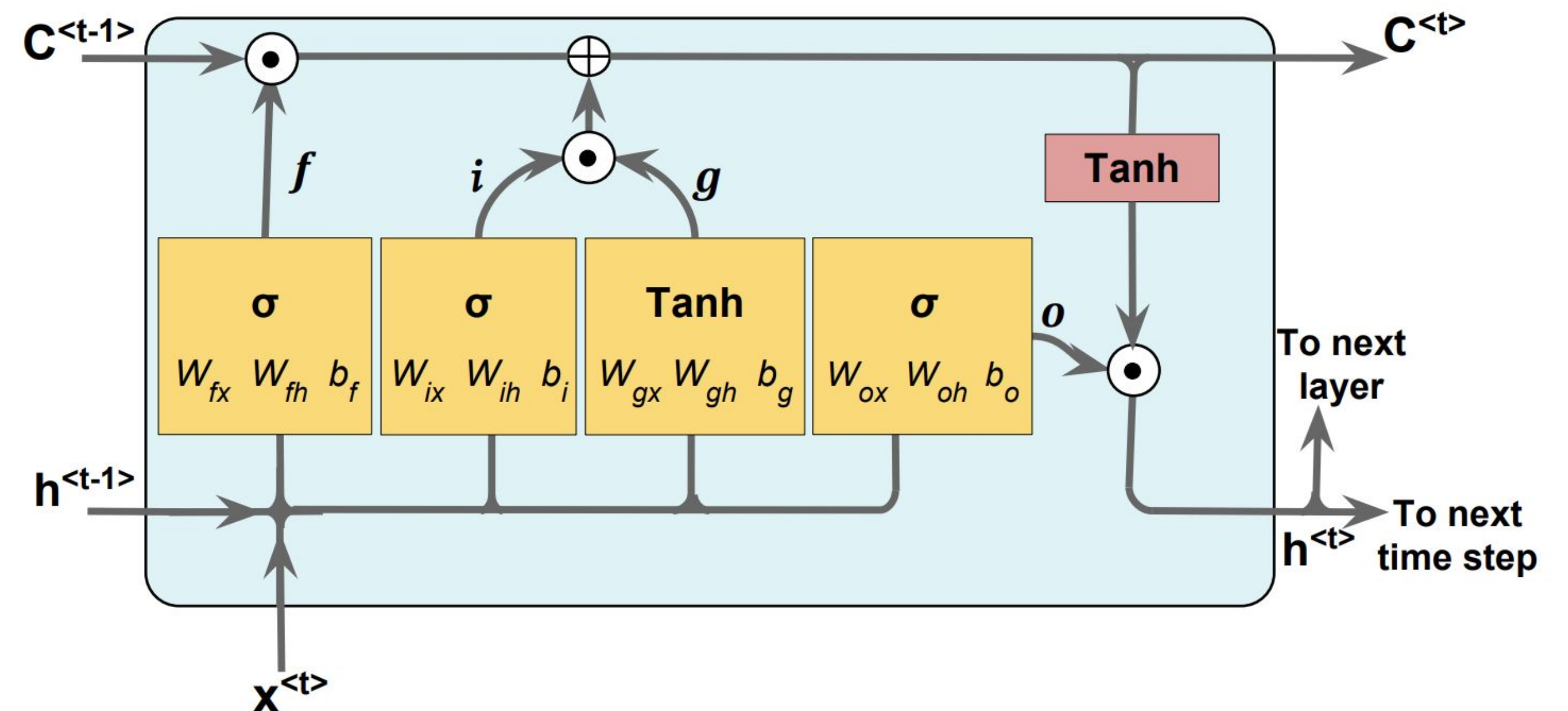
# Our approach: RNN with LSTM - How does it work?

Step 1: Forget gate outputs a number between 0 and 1.  
(1 represents “keep the information” and 0 represents “remove the information”)

Step 2: Input gate decides which values will be updated, thereby creating an update to the state

Step 3: Update the old cell  $C(t-1)$  to  $C(t)$

Step 4: Output (based on the cell state)





# Data - Stocks Selection

**Index: Nasdaq Index**(NASDAQ: QQQ), **S&P 500**(NYSEARCA: SPY)

**QQQ:** QQQ is an ETF that includes 100 of the largest international and domestic companies listed on the Nasdaq stock exchange, just like the Nasdaq 100 Index that it tracks. 1 The index excludes financial companies, and it is based on market capitalization.

**SPY:** The SPDR® S&P 500® ETF Trust seeks to provide investment results that, before expenses, correspond generally to the price and yield performance of the S&P 500® Index (the "Index")

**Single Stock: Tesla Inc** (NASDAQ: TSLA), **Exxon Mobil Corporation**(NYSE: XOM)

**TSLA:** Tesla is accelerating the world's transition to sustainable energy with electric cars, solar and integrated renewable energy solutions for homes and businesses.

**XOM:** Exxon Mobil Corporation, doing business as ExxonMobil, is an American multinational oil and gas corporation headquartered in Irving, Texas. It is the largest direct descendant of John D. Rockefeller's Standard Oil, and was formed on November 30, 1999 by the merger of Exxon and Mobil.

# Data - Sources: Yahoo! Finance

QQQ Historical Price:

Currency in USD

[Download](#)

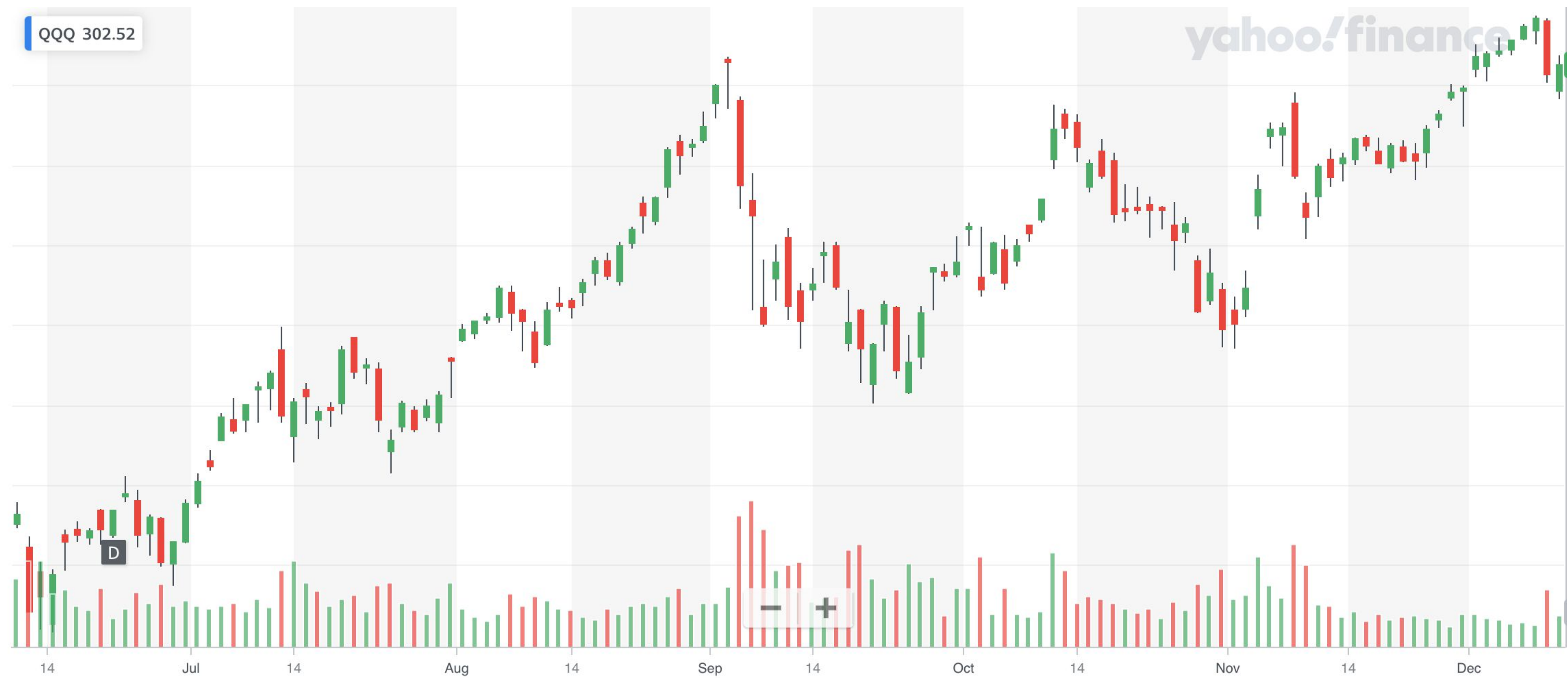
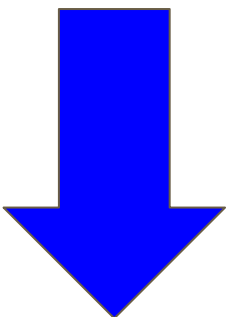
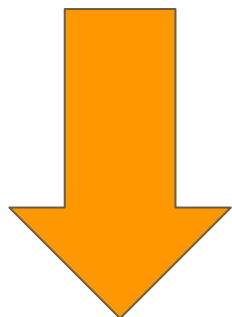
Date	Open	High	Low	Close*	Adj Close**	Volume
Dec 10, 2020	299.21	303.68	298.09	301.80	301.80	22,958,763
Dec 09, 2020	308.07	308.36	300.21	301.31	301.31	48,758,800
Dec 08, 2020	306.76	308.60	304.95	308.29	308.29	18,341,500
Dec 07, 2020	305.71	307.63	305.52	307.25	307.25	20,851,000
Dec 04, 2020	304.33	305.67	303.63	305.52	305.52	19,332,100

\*Close price adjusted for splits.

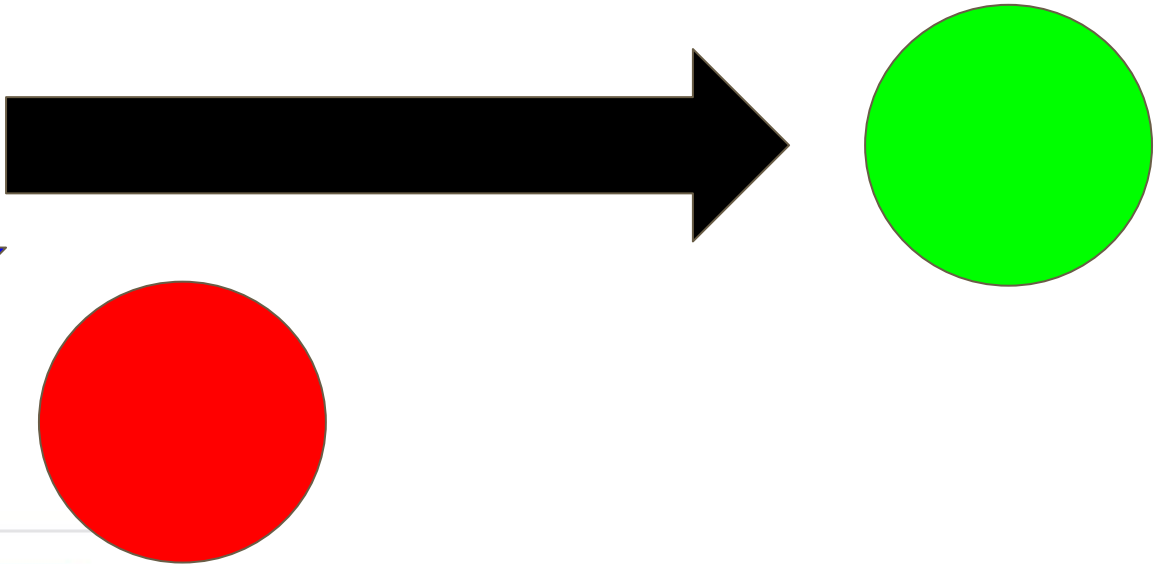
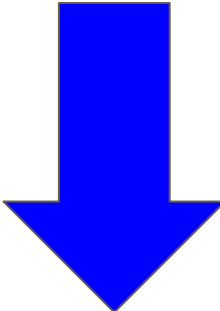
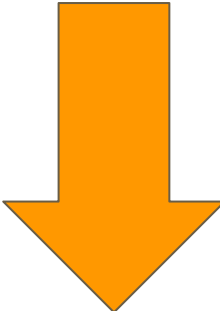
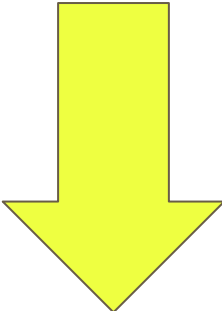
\*\*Adjusted close price adjusted for both dividends and splits.



# Data



# Data





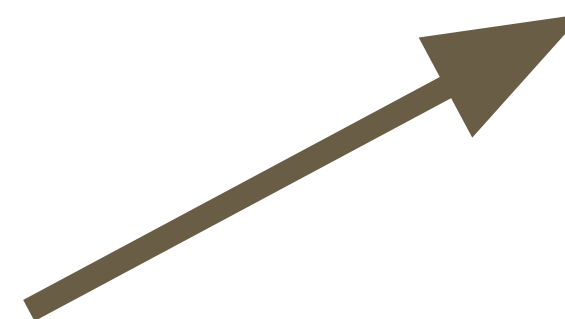
# Result Methodology

1. Accuracy: The correct prediction rate
2. Return Backtest: Invest 1 dollar in our strategy. What will be the return after a time period

## Result Methodology: Accuracy

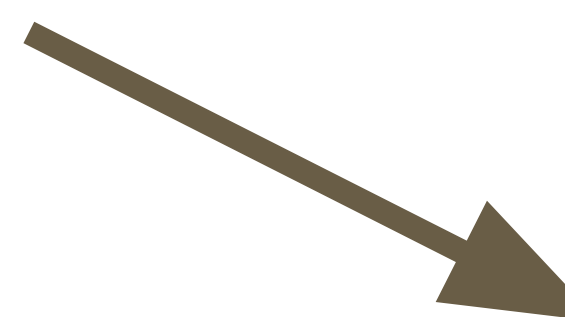
My Prediction for tomorrow: \$121

Apple Stock Price Closed Today: \$120



Apple Stock Price : \$122

**Correct Prediction**



Apple Stock Price : \$119

**Wrong Prediction**

**Accuracy = % of our Correct Prediction**



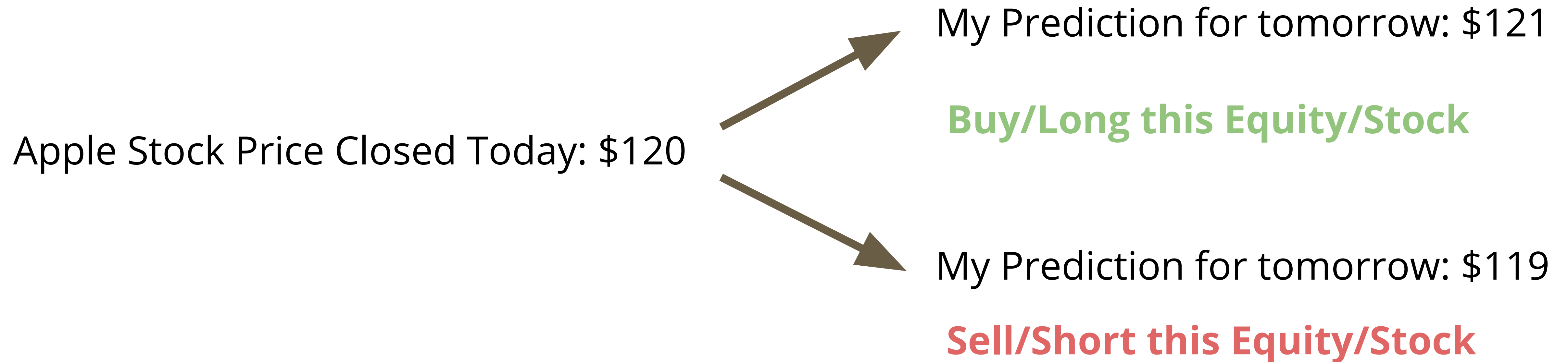
# Result Methodology: Return Backtest



Buy/Long: We make money if stock goes up

Sell/Short: We make money if stock goes down

## Result Methodology: Return Backtest



Return = If I Invest 1 dollar in this Stock in the past  
Using our Strategy, how much will that 1 dollar become today.

**Then, We will compare our return to the market return**

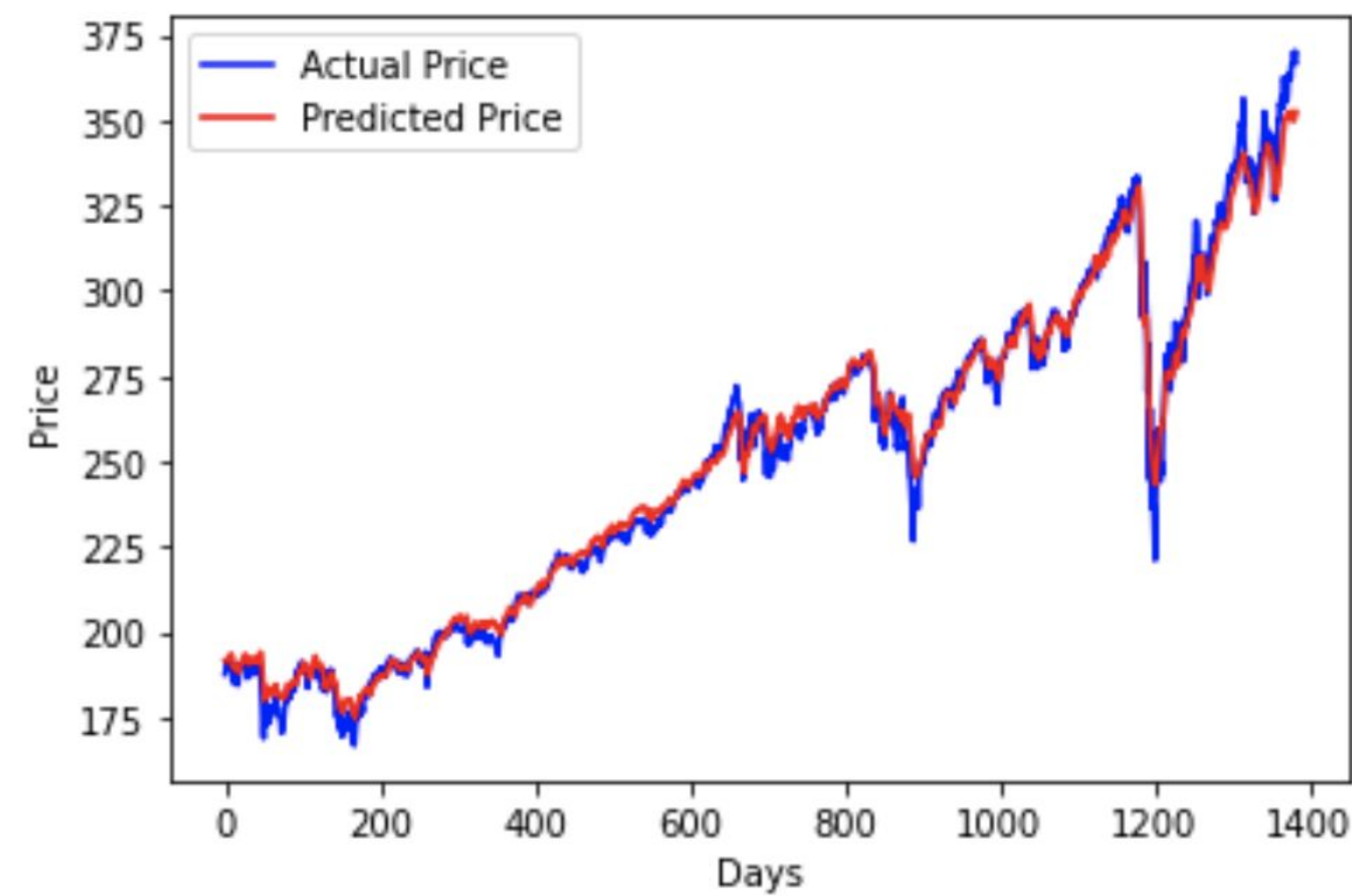


# Result Methodology: Return Backtest

Our Strategy: \$1	➡	\$2	Bad Performance
Invest in Market: \$1	➡	\$3	
Our Strategy: \$1	➡	\$0.8	Bad Performance
Invest in Market: \$1	➡	\$1.2	
Our Strategy: \$1	➡	\$3	Good Performance
Invest in Market: \$1	➡	\$2	

# Result - SPY

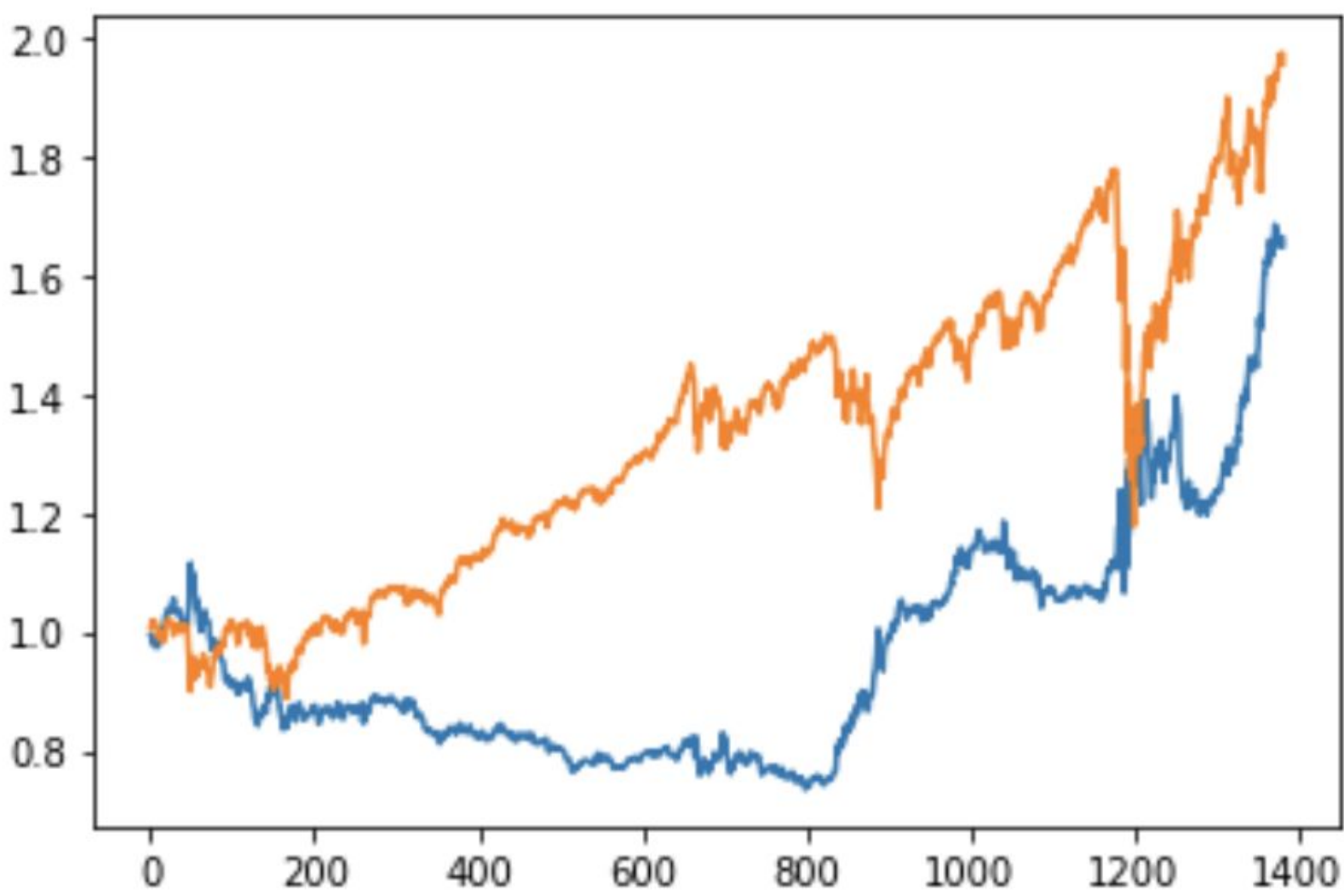
Predicted vs Actual



Accuracy

0.5430

Return



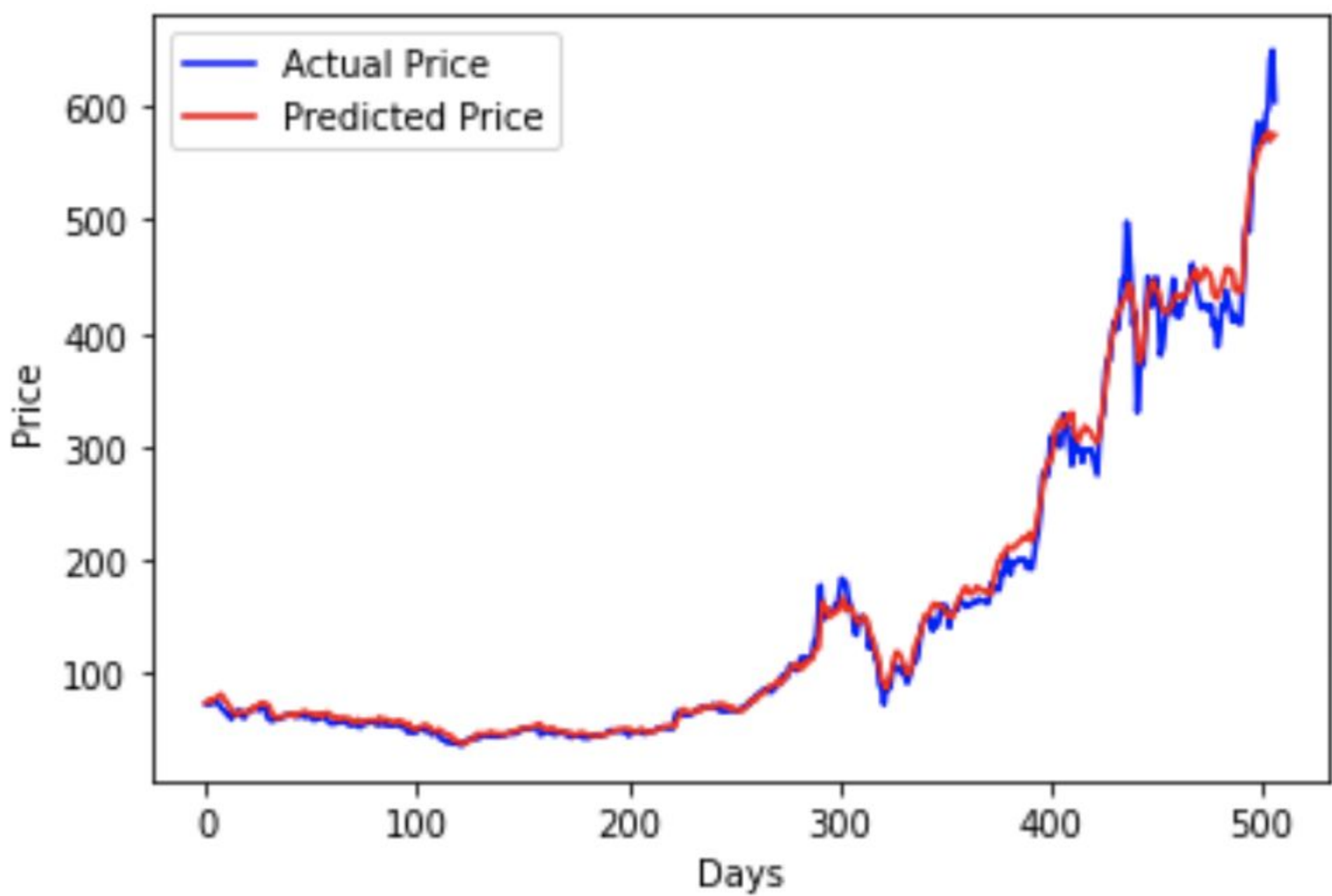
Our Strategy: 1.6490

Market Return: 1.9550



# Result - TSLA

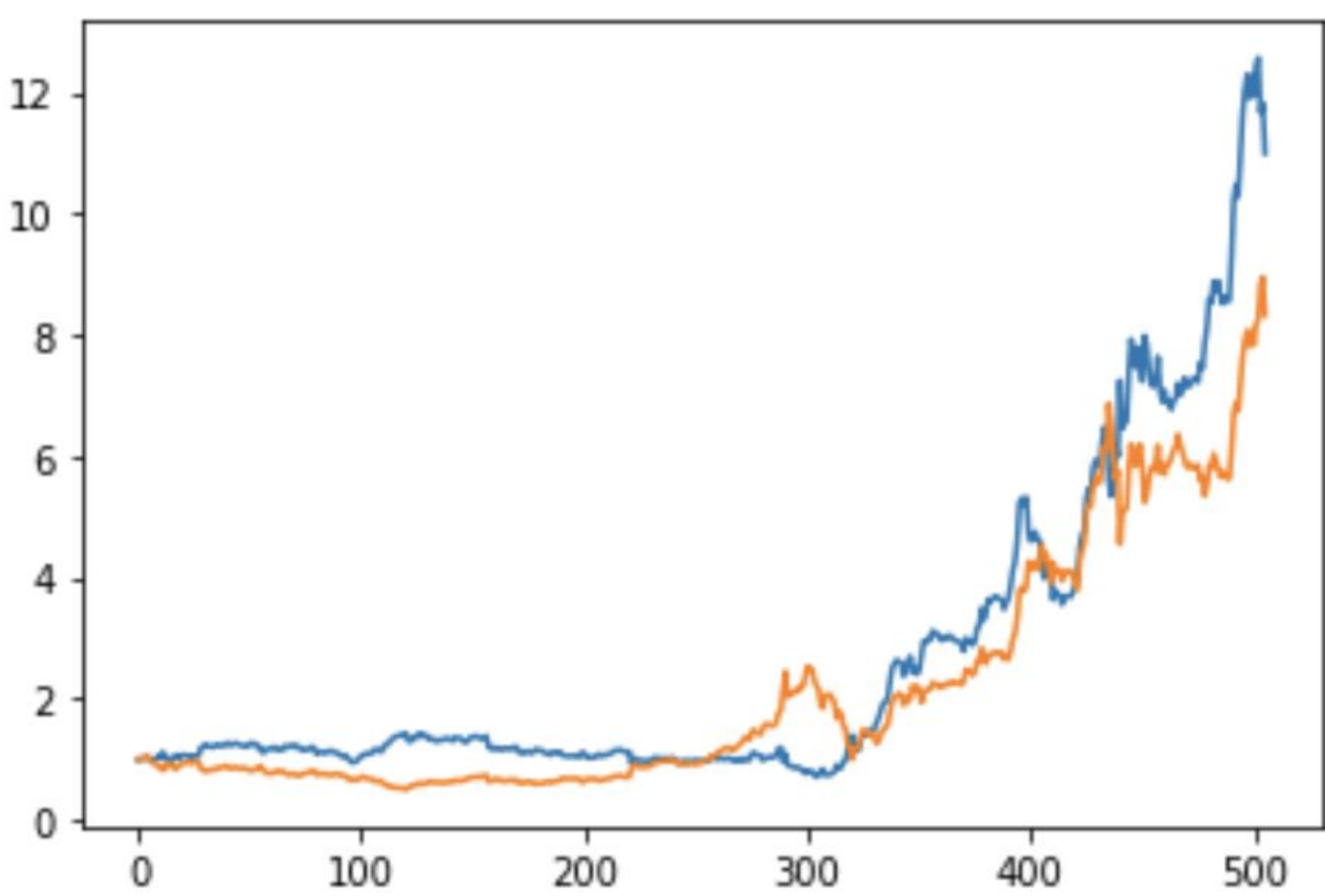
Predicted vs Actual



Accuracy

0.5474

Return



Our Strategy

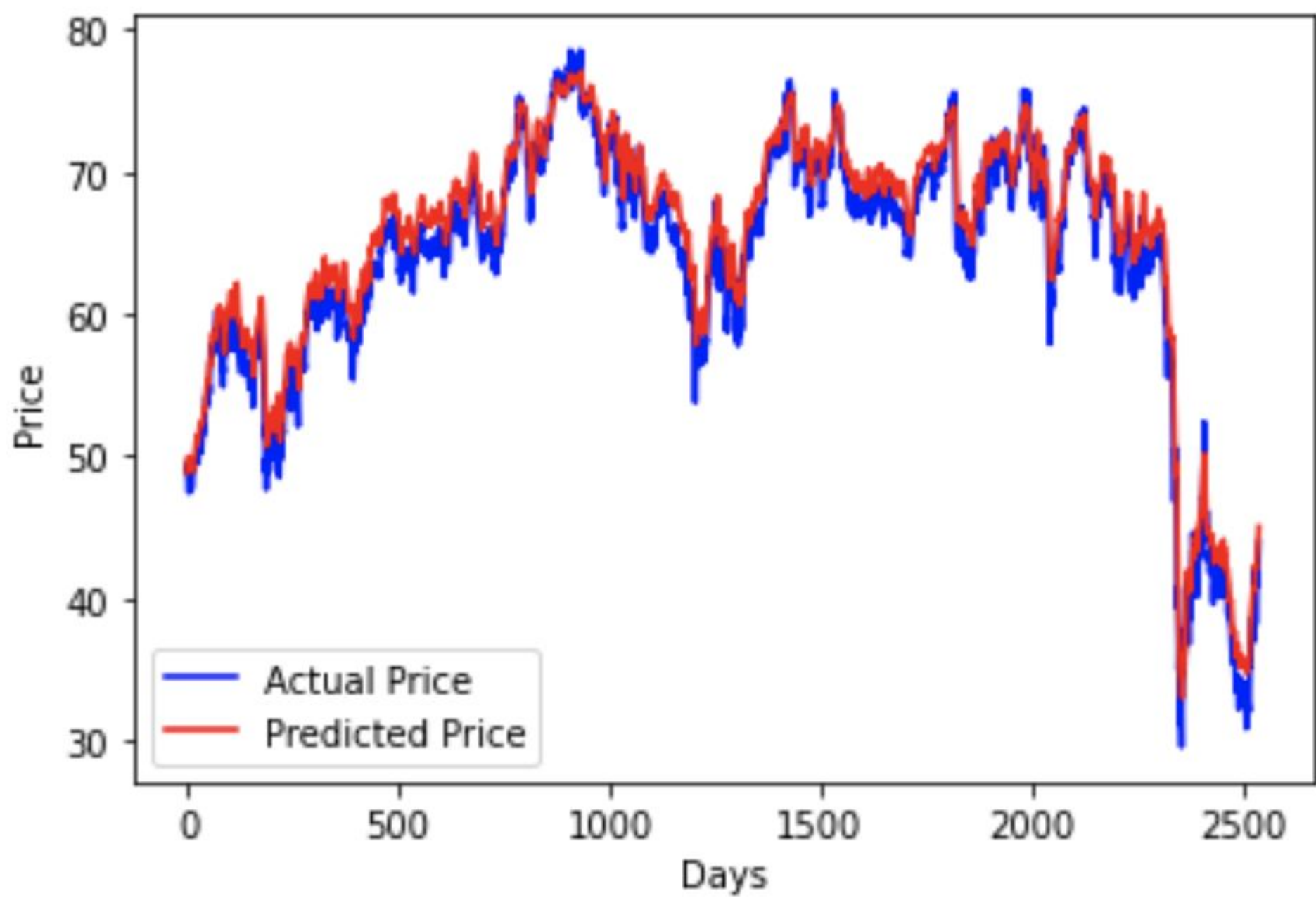
Market Return

Our Strategy: 10.9957

Market Return: 8.3248

# Result - XOM

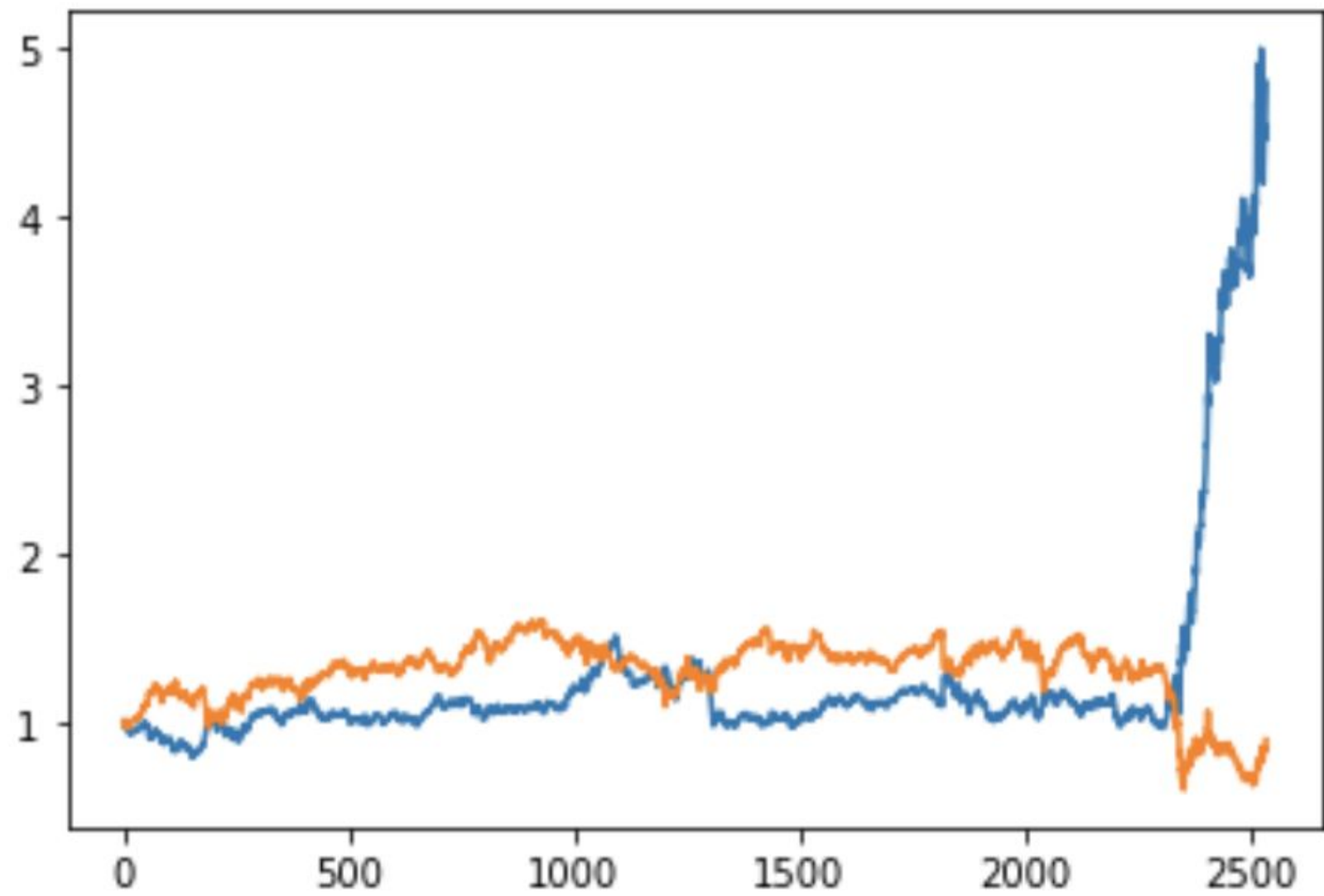
Predicted vs Actual



Accuracy

0.5126

Return

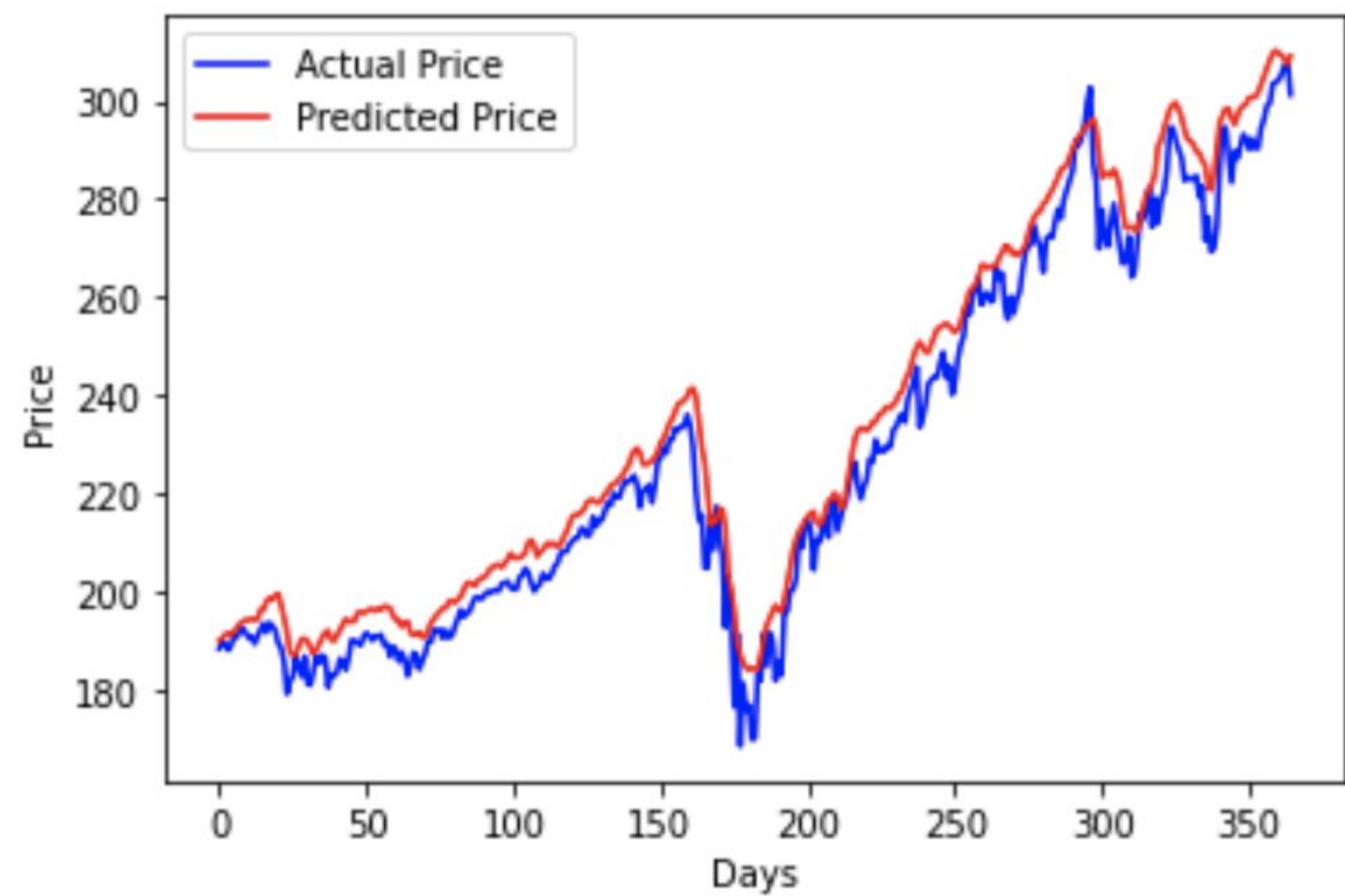


Our Strategy: 3.7783

Market Return: 0.8988

# Result - QQQ

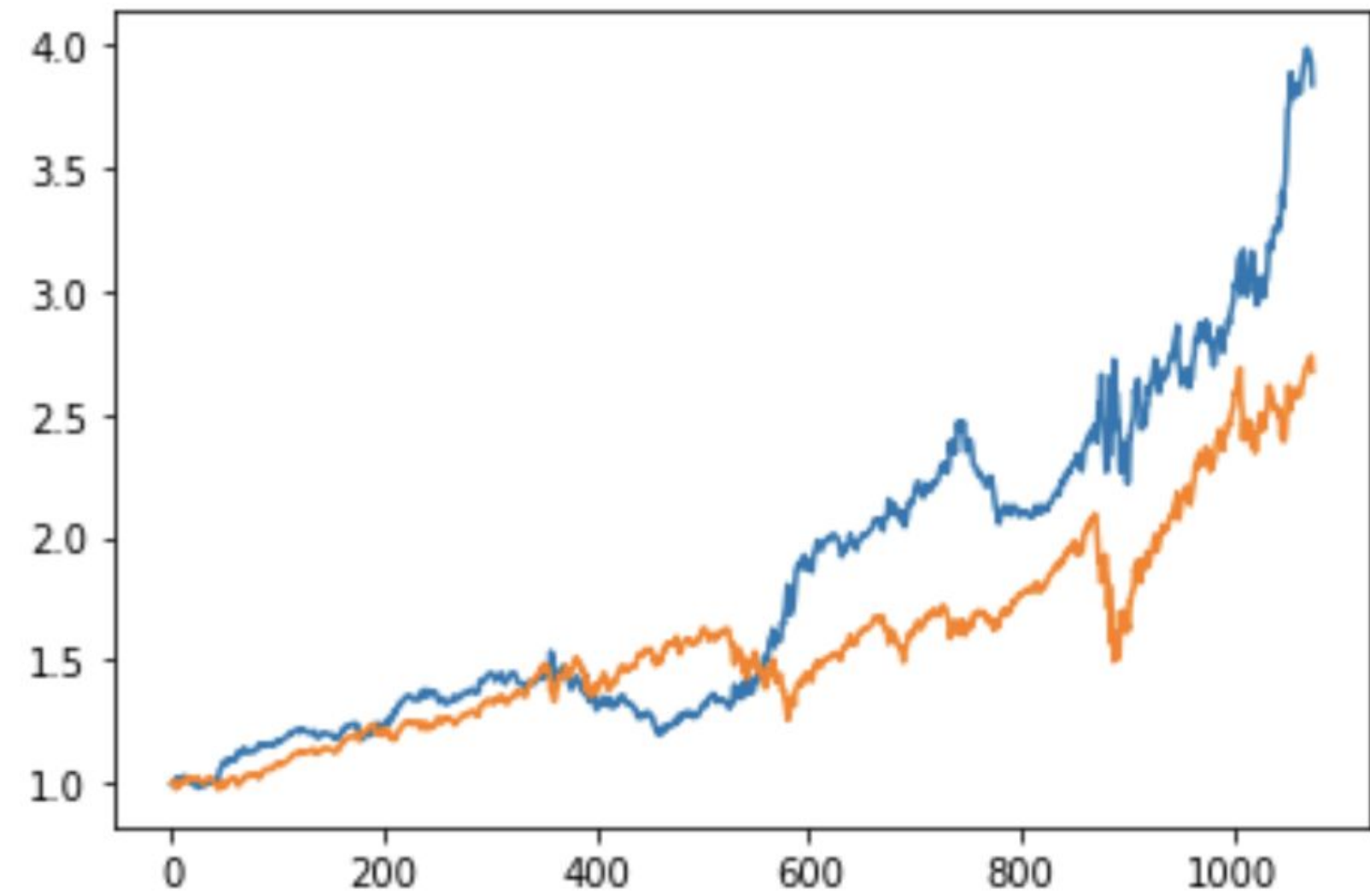
Predicted vs Actual



Accuracy

0.5637

Return



Our Strategy

Market Return

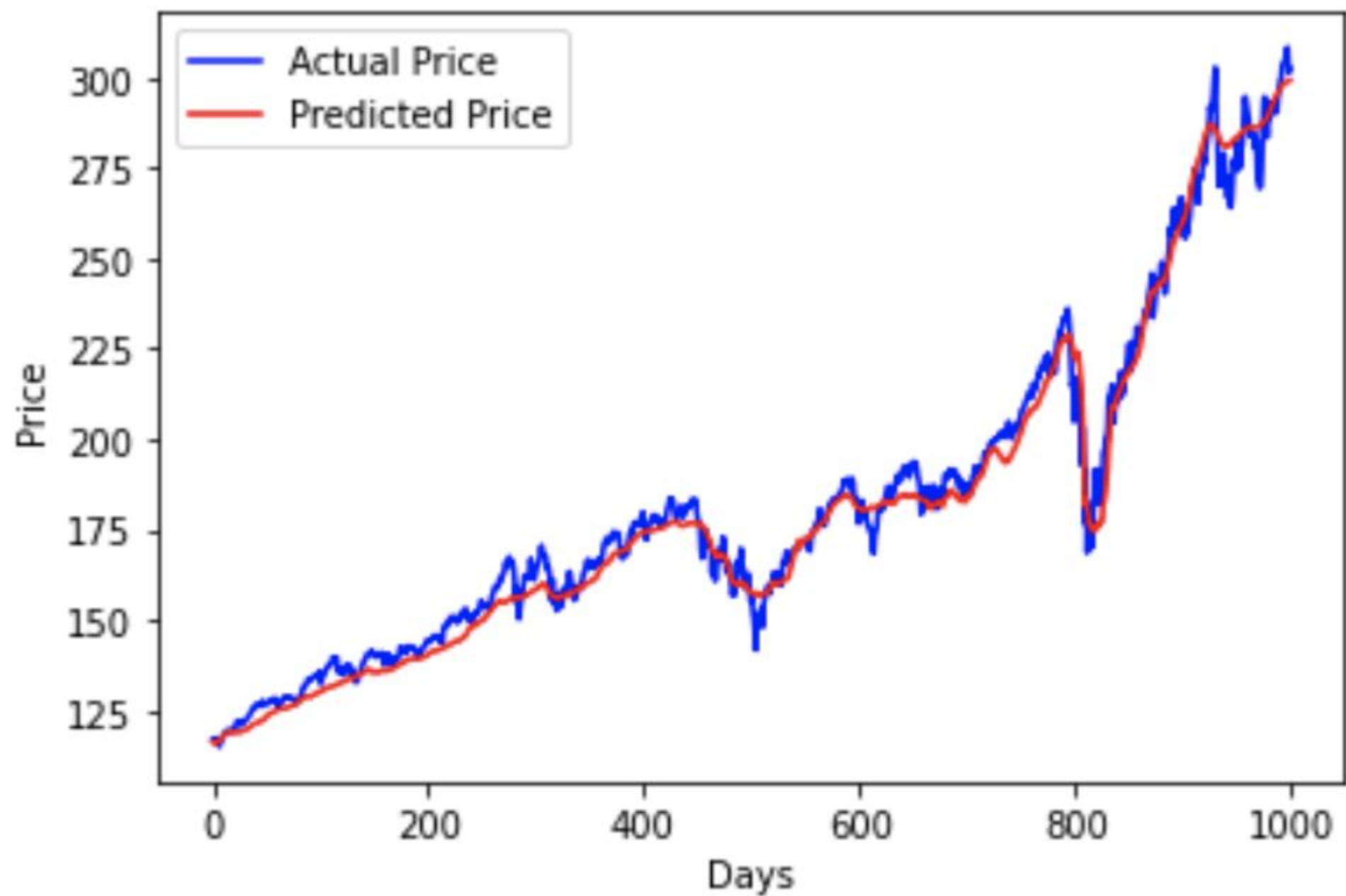
Our Strategy: 3.8363

Market Return: 2.6686



# Result - QQQ (300 day to predict next 30 days)

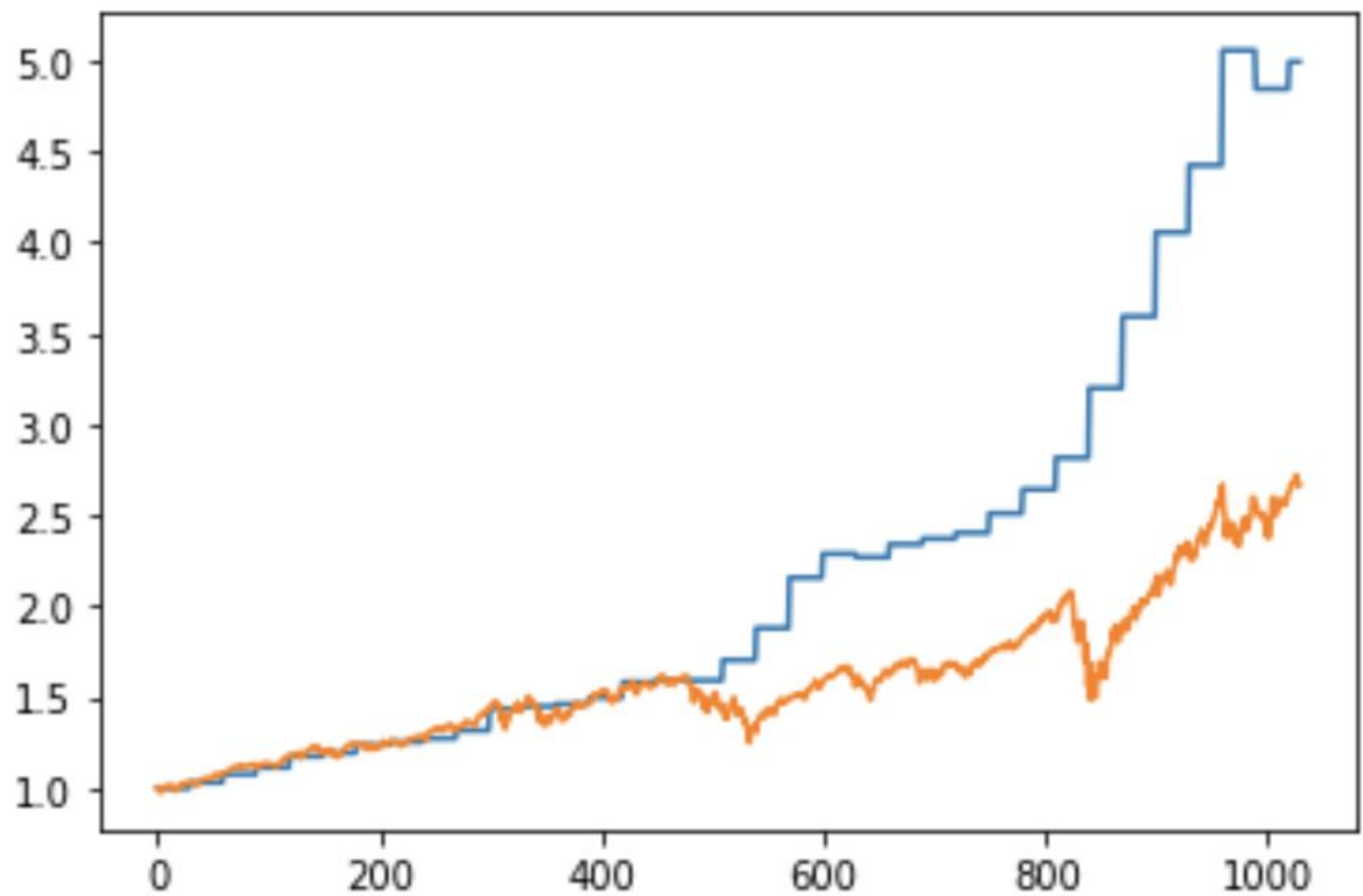
Predicted vs Actual



Accuracy

0.834

Return



Our Strategy

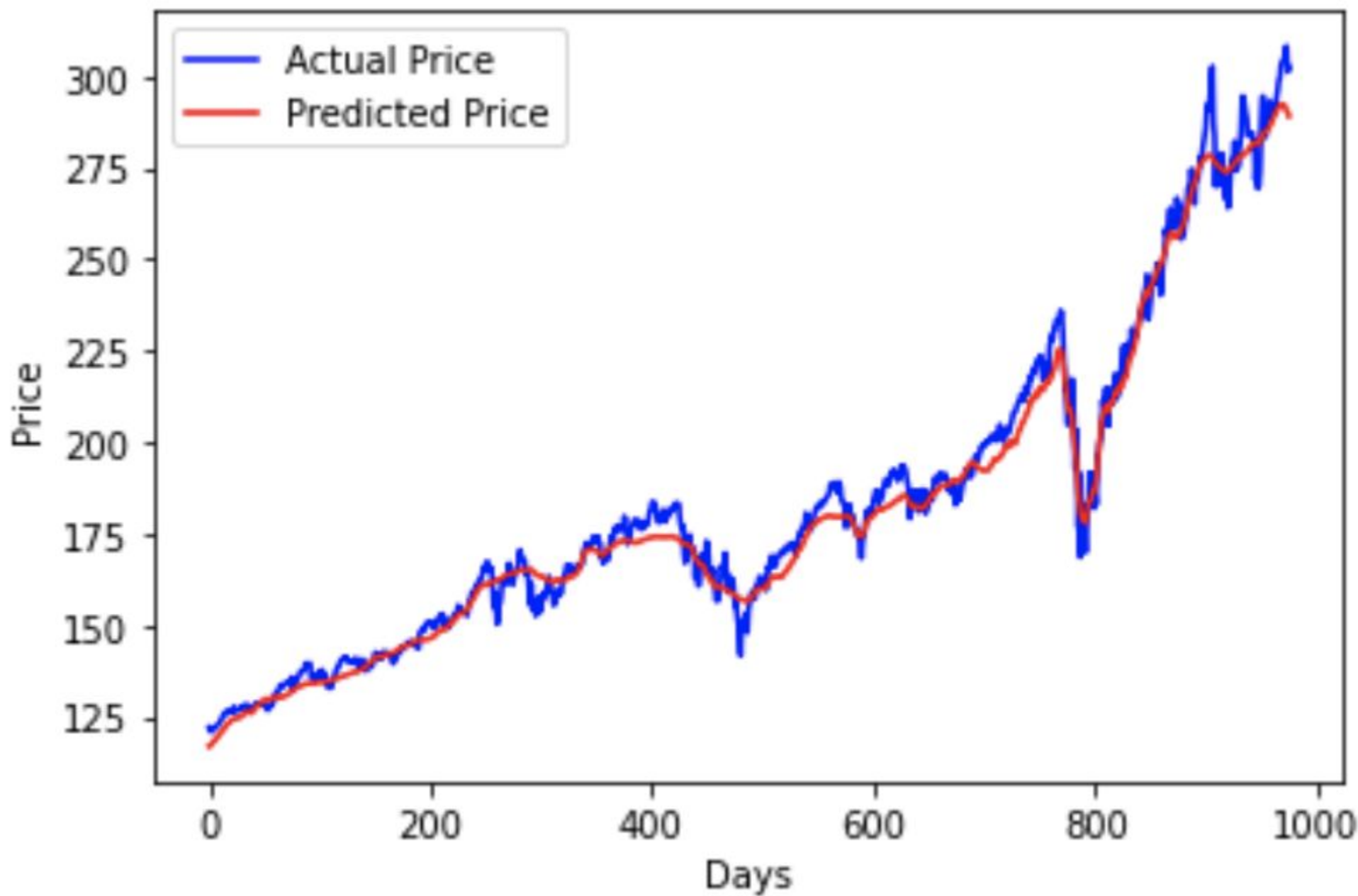
Market Return

Our Strategy: 4.9940

Market Return: 2.6686

# Result - QQQ (Using previous 500 days to predict next 100 days)

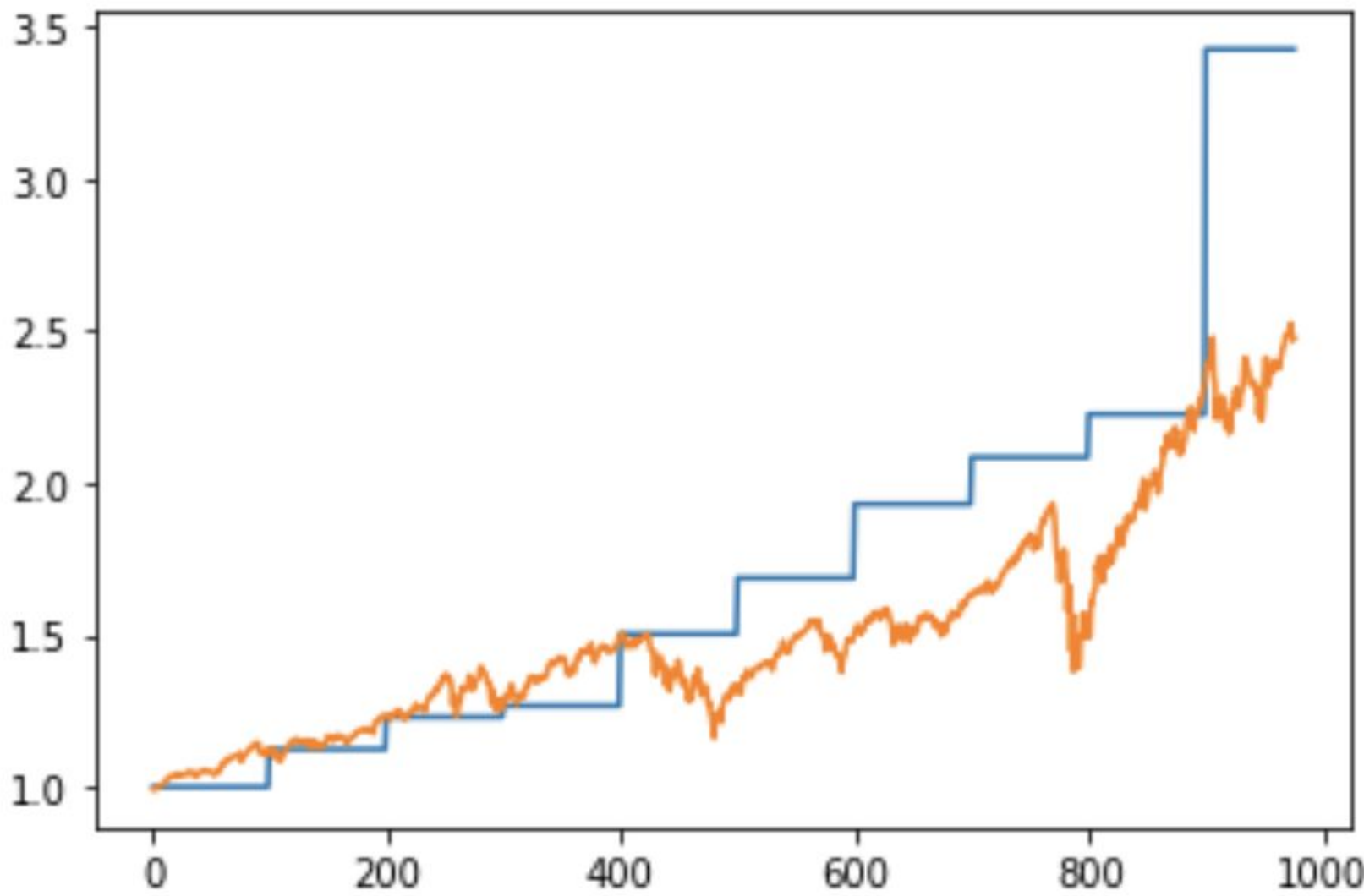
Predicted vs Actual



Accuracy

0.9863

Return



Our Strategy

Market Return

Our Strategy: 3.4269

Market Return: 2.6686

# Conclusion

## Goal:

Using machine learning to gain stock return.

## At the moment:

Some Our model has decent return comparing to market return

## Next Steps:

As our next steps, we could try more risk-relevant model.