

April 13, 2024.

# A Journey Of Failures

A  
Presentation by  
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FAILURE # 1

# Our First paper



Ertuğrul, H. M., Güngör, B. O., & Soytaş, U. (2020). The Effect of the COVID-19 Outbreak on the Turkish Diesel Consumption Volatility Dynamics. *Energy RESEARCH LETTERS*, 1(3). <https://doi.org/10.46557/001c.17496>

COVID-19 and Energy

## The Effect of the COVID-19 Outbreak on the Turkish Diesel Consumption Volatility Dynamics

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Keywords: covid-19 pandemic, arch family models, arima models, diesel consumption

<https://doi.org/10.46557/001c.17496>

Energy RESEARCH LETTERS

Vol. 1, Issue 3, 2020

We analyze the effect of the COVID-19 outbreak on volatility dynamics of the Turkish diesel market. We observe that a high volatility pattern starts around mid-April, 2020 and reaches its peak on 24/05/2020. This is due to the government imposed weekend curfews and bans on intercity travels. Two policy suggestions are provided. First is a temporary rearrangement of profit margins of dealers and liquid fuel distributors; and, second is a temporary tax regulation to compensate lost tax revenue.

### 1. Introduction

Energy is a necessity for societies and its security and accessibility is a priority for policy makers. Since the 19<sup>th</sup> century, one of the main sources of energy has been oil and oil products, and the importance of energy has grown with time. Hence, movements in oil prices have been an important subject of research. All major oil price shocks, such as the rise in oil prices of the 1970s and 2000s and the oil price glut in the 1980s, have attracted research interests with the literature attempting to explain fluctuations (and hence volatility) in energy prices (Kocherlakota, 2009).

Energy consumption and production forecasts were

distributed lag based co-integration model in order to forecast gasoline and diesel demand for India. In a similar fashion, but with a simpler model, Bhutto et al. (2017) forecasted annual gasoline consumption for Pakistan. Given this literature, one research gap is that there are no studies that examine how energy consumption volatility changes in the face of a global pandemic. This study aims to fill this gap by studying the Turkish diesel market during the recent COVID-19 pandemic.<sup>1</sup> In addition, we also show how the pandemic distorts the forecasting performance of models.

The fluctuations in oil prices started at the beginning of 2020 with the spread of COVID-19. Volatility in energy markets increased. We add to the understanding of energy

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FAILURE # 2

# Our Second paper



Monge, M., & Infante, J. (2023). A Fractional ARIMA (ARFIMA) Model in the Analysis of Historical Crude Oil Prices. *Energy RESEARCH LETTERS*, 4(1).  
<https://doi.org/10.46557/001c.36578>

Peer-reviewed research

## A Fractional ARIMA (ARFIMA) Model in the Analysis of Historical Crude Oil Prices

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Keywords: Crude oil prices, Fractional integration, persistence, JEL C00 C22 E30 Q40

<https://doi.org/10.46557/001c.36578>

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We investigate historical data for crude oil prices using autoregressive fractionally integrated moving average (ARFIMA) models to determine whether shocks in the series have transitory or permanent effects. Our best specification is an ARFIMA(2,d,2) with an estimated value of  $d$  around 0.4, but its confidence interval is wide and does not allow us to either reject the  $I(0)$  or the  $I(1)$  hypotheses. This high level of uncertainty may be due to the presence of breaks or non-linear trends in the data.

### I. Introduction

The objective of this paper is to evaluate the market persistence properties for annual historical crude oil prices from 1861 to 2019, studying its evolution across time. In particular, we examine the order of integration of the series, allowing this number to be a fractional value. The fractional integration or  $I(d)$  approach consists of taking  $d$ -differences in a given time series to render it stationary  $I(0)$ , where  $d$  can be any real value, thus allowing for fractional degrees of differentiation. It permits us to distinguish between mean reversion and lack of it in a more flexible way than the standard methods that only use the values 0 (for stationary series) and 1 (for nonstationary ones). In the

(Registered Charity Number 1186433). Historical crude oil prices analyzed are from 1861 to 2019 with annual data. *Our World in Data* is produced as a collaborative effort between researchers at the University of Oxford, who are the scientific contributors of the website content, and the non-profit organization, Global Change Data Lab, which owns, publishes and maintains the website and the data tools. At the University of Oxford, the research team is affiliated with the Oxford Martin Programme on Global Development, whose mission is to produce academic research on the world's largest problems based on empirical analysis of global data.

Using this dataset, we first conduct standard unit root tests (Dickey & Fuller, 1979; Kwiatkowski et al., 1992; Phillips & Perron, 1988) on the crude oil prices. According

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# What Is an Autoregressive Integrated Moving Average (AR-I-MA)?

An autoregressive integrated moving average, or ARIMA, is a statistical analysis model that uses time series data to either better understand the data set or to predict future trends.



# AR-FI-MA?

In the ARIMA process to have the “d” value become a non-integer value, i.e., generalized the ARIMA model to make it have the differencing degree to be fractional values.

The main model’s purpose is to account for the persistence of memory that we find in economic and financial prices in levels while estimating an ARMA model on them.

$$\Phi(L)(1 - L)^d X_t = \Theta(L)u_t, \quad t = 1, 2, \dots,$$

# So What Happened?

**Table 1. Unit root test results**

	ADF			PP		KPSS	
	(i)	(ii)	(iii)	(ii)	(iii)	(ii)	(iii)
Oil prices	-0.9827	-1.4693	-2.5776	-1.1455	-2.2716	1.6264	0.4792

*Notes:* This table reports the unit root test results. (i) Refers to the model with no deterministic components; (ii) with an intercept, and (iii) with a linear time trend. I reflect t-statistic with test critical value at 5%.

**Table 2. Results of long memory tests**

Data Analyzed	ARFIMA model	d	Std. Error	Interval	I(d)
Oil prices	ARFIMA (0, d, 0)	0.9506	0.0757	[0.83, 1.07]	I(1)
	ARFIMA (1, d, 0)	0.6858	0.1556	[0.43, 0.94]	I(d)
	ARFIMA (2, d, 0)	0.7777	0.1658	[0.50, 1.05]	I(1)
	ARFIMA (0, d, 1)	0.7325	0.0872	[0.59, 0.88]	I(d)
	ARFIMA (0, d, 2)	0.7790	0.1323	[0.56, 1.00]	I(1)
	ARFIMA (1, d, 1)	0.7817	0.1065	[0.61, 0.96]	I(d)
	ARFIMA (2, d, 1)	0.7604	0.1543	[0.51, 1.01]	I(1)
	ARFIMA (1, d, 2)	0.7754	0.1167	[0.58, 0.97]	I(d)
	<b>ARFIMA (2, d, 2)</b>	<b>0.4085</b>	<b>0.6464</b>	<b>[-0.65, 1.47]</b>	<b>I(0), I(d), I(1)</b>

*Notes:* The table reports the long memory test results. In bold we have selected the ARFIMA (2, d, 2) model following the criteria (greater value) of AIC and BIC.



FAILURE # 3?  
(Not Really!)

# Finally Our Paper!



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Computer Science

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International Conference on Computational Intelligence and Data Science (ICCIDS 2019)

## Stock Closing Price Prediction using Machine Learning Techniques

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### Abstract

Accurate prediction of stock market returns is a very challenging task due to volatile and non-linear nature of the financial stock markets. With the introduction of artificial intelligence and increased computational capabilities, programmed methods of prediction have proved to be more efficient in predicting stock prices. In this work, Artificial Neural Network and Random Forest techniques have been utilized for predicting the next day closing price for five companies belonging to different sectors of operation. The financial data: Open, High, Low and Close prices of stock are used for creating new variables which are used as inputs to the model. The models are evaluated using standard strategic indicators: RMSE and MAPE. The low values of these two indicators show that the models are efficient in predicting stock closing price.

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Peer-review under responsibility of the scientific committee of the International Conference on Computational Intelligence and Data Science (ICCIDS 2019).

**Keywords:** Random Forest Regression; Artificial Neural Network; Stock market prediction

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### 1. Introduction

Stock market is characterized as dynamic, unpredictable and non-linear in nature. Predicting stock prices is a challenging task as it depends on various factors including but not limited to political conditions, global economy, company's financial reports and performance etc. Thus, to maximize the profit and minimize the losses, techniques to

Vijh, M., Chandola, D., Tikkiwal, V. A., Kumar, A., (2020). Stock Closing Price Prediction using Machine Learning Techniques. Procedia Computer Science, 167, pp. 599–606.  
<https://doi.org/10.1016/j.procs.2020.03.326>

# The first step to any ML model

1

Training Data:

2009-05-05 to 2017-04-03

2

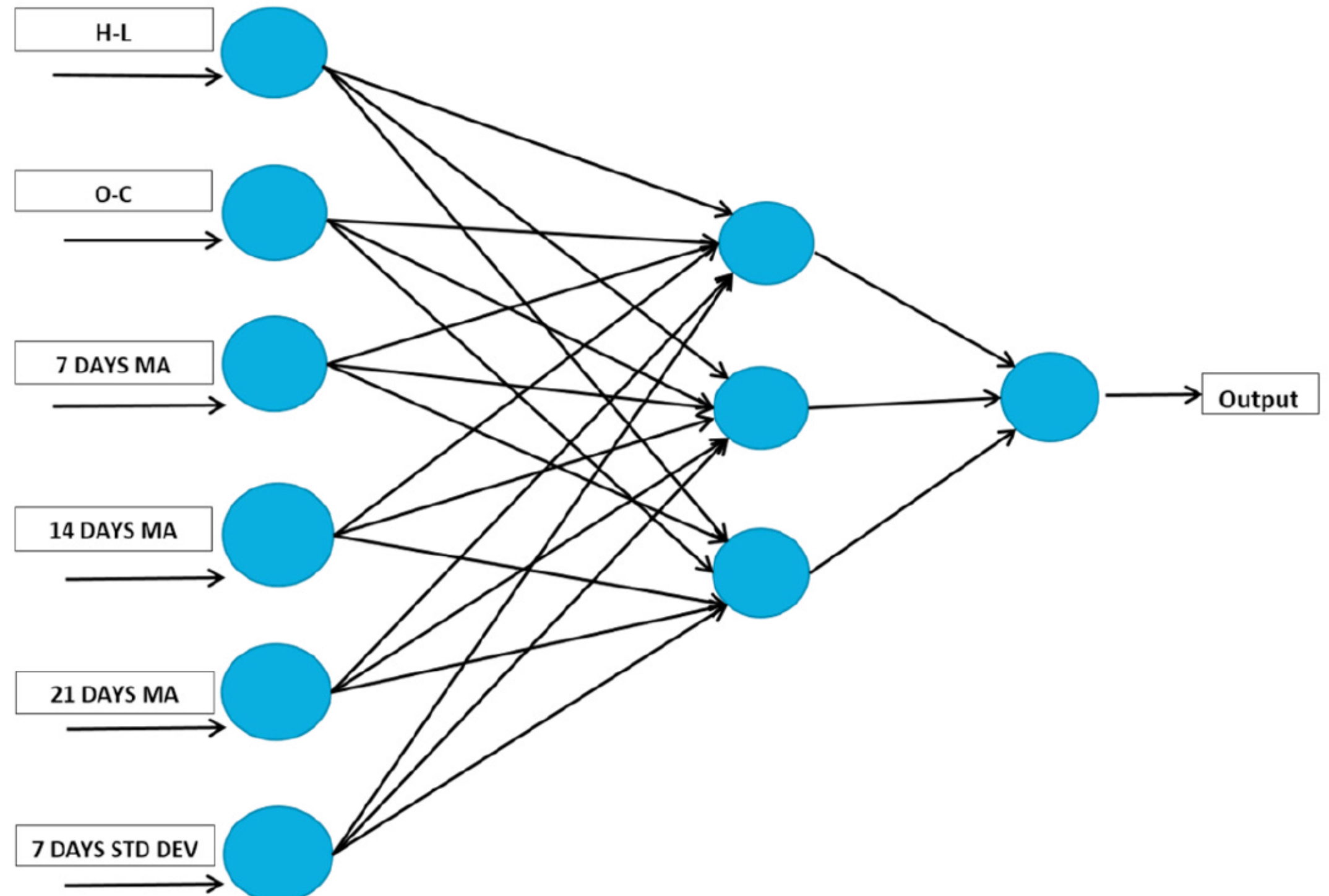
Test Data:

2017-04-04 to 2019-04-05

# Features

- 1 High minus Low Price
- 2 Close minus Open Price
- 3 7 days Moving Average
- 4 14 days Moving Average
- 5 21 days Moving Average
- 6 7 days Standard Deviation days

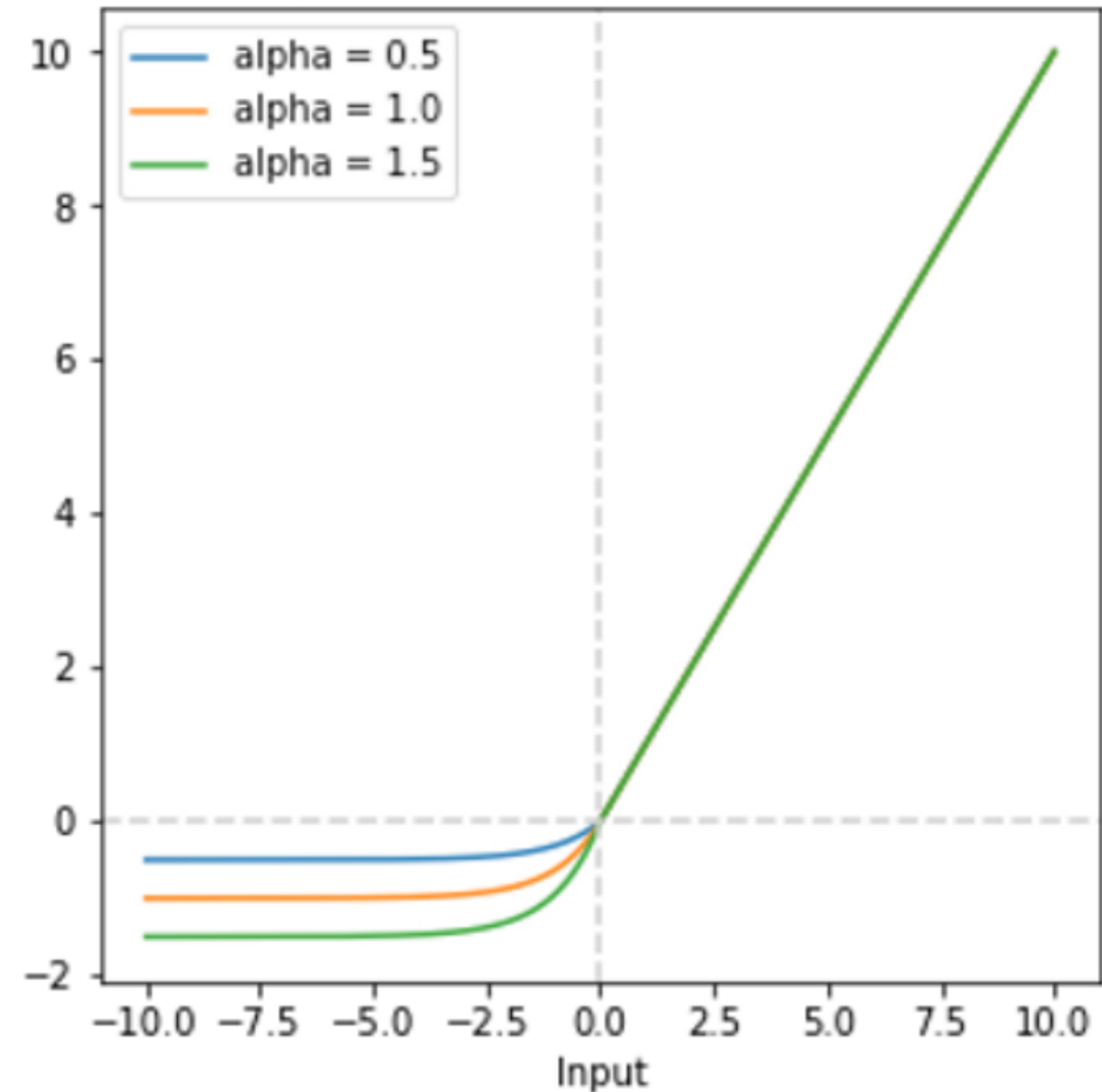
# Neural Network Architecture



# Activation Function- ELU

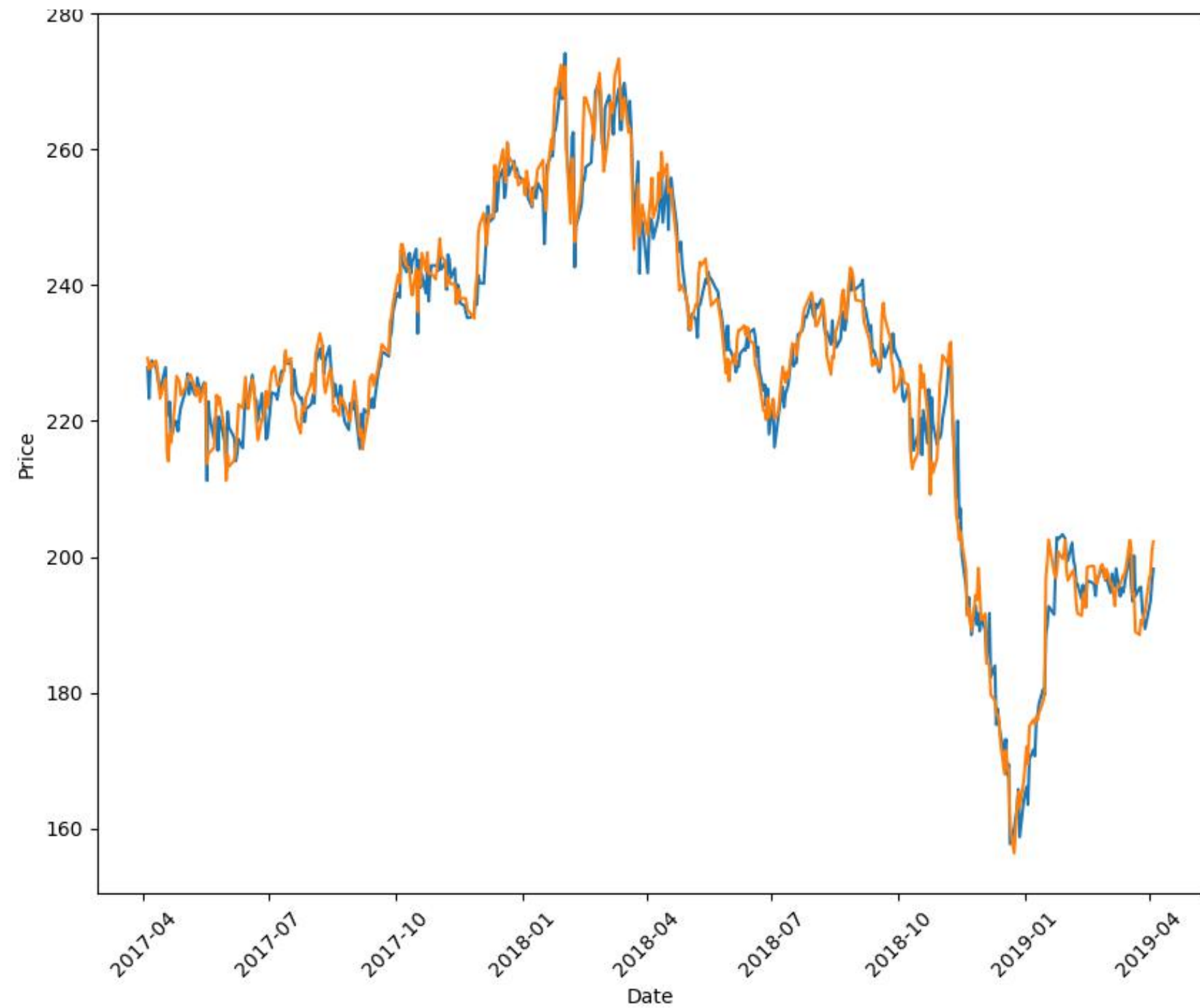
$$f(x) = x \text{ if } x > 0$$

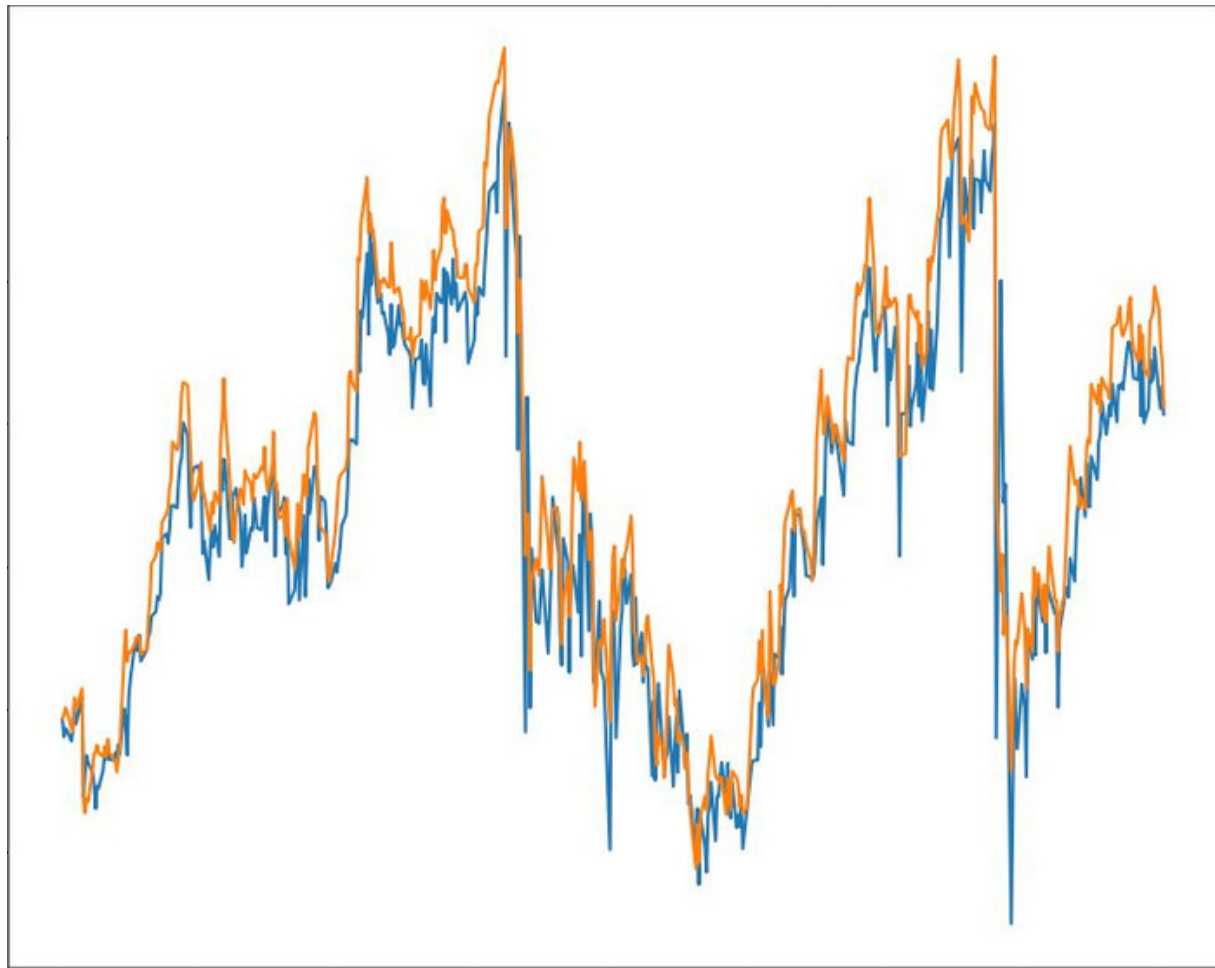
$$\alpha(\exp(x) - 1) \text{ if } x \leq 0$$



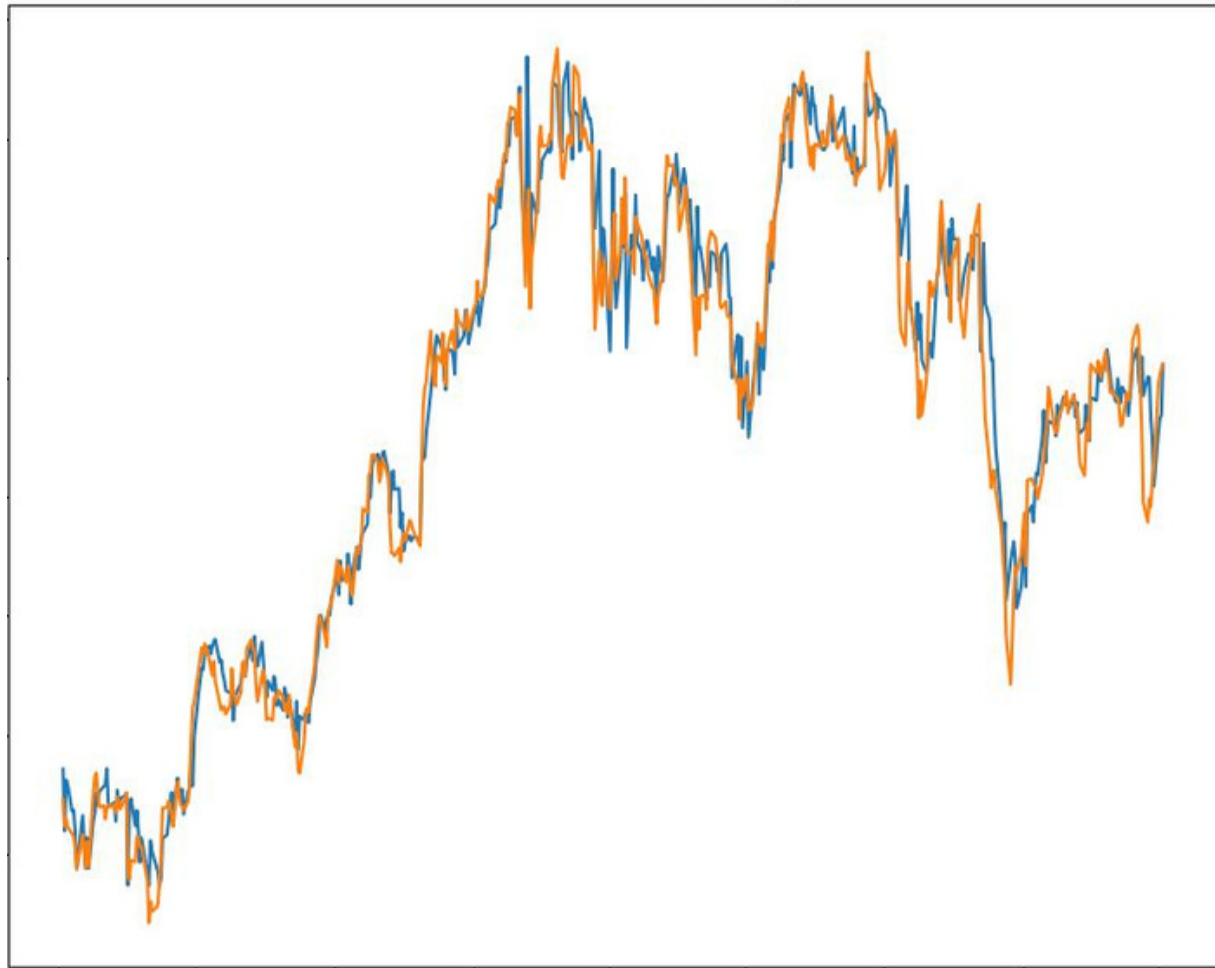
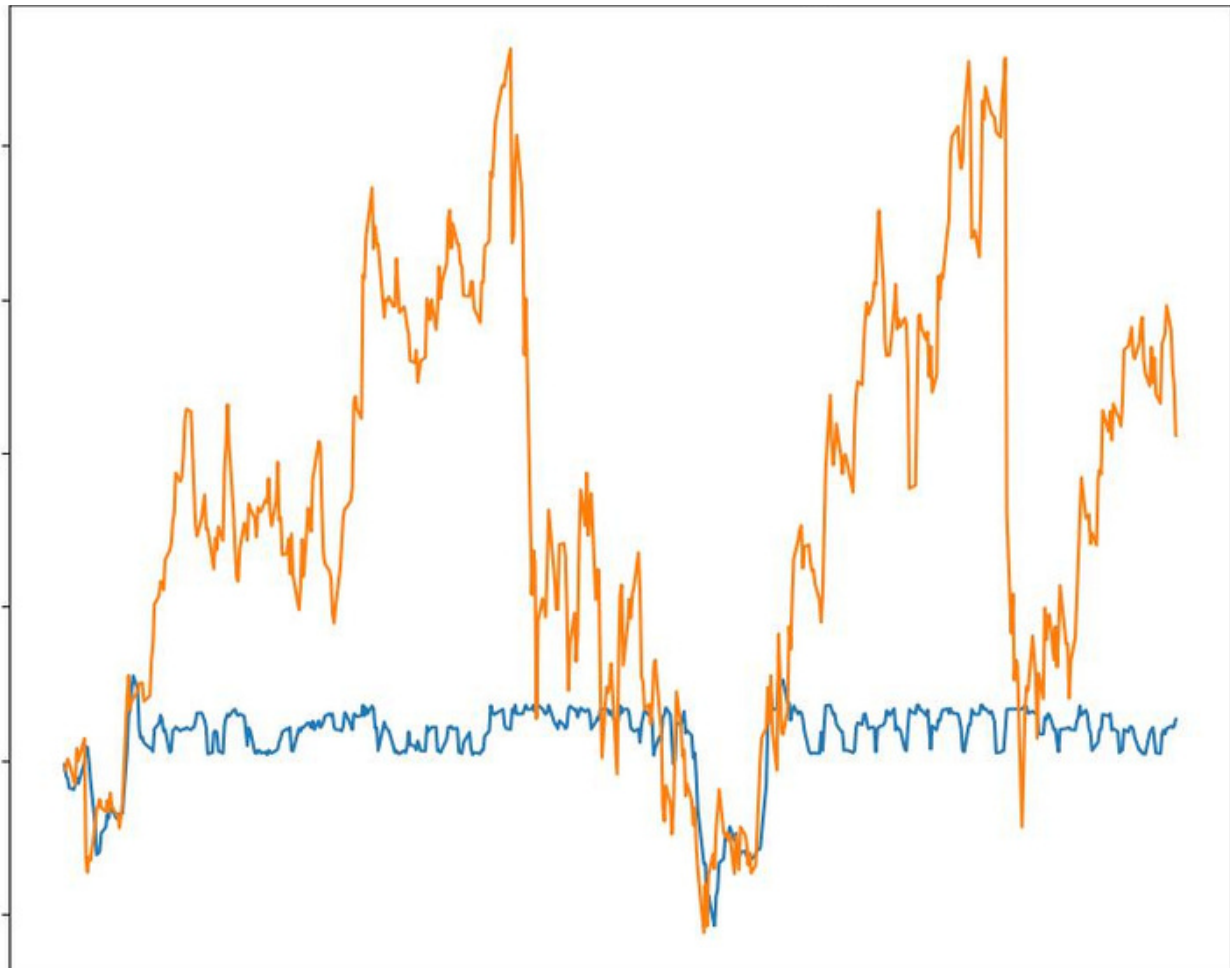


# ANN vs RF: Goldman Sachs

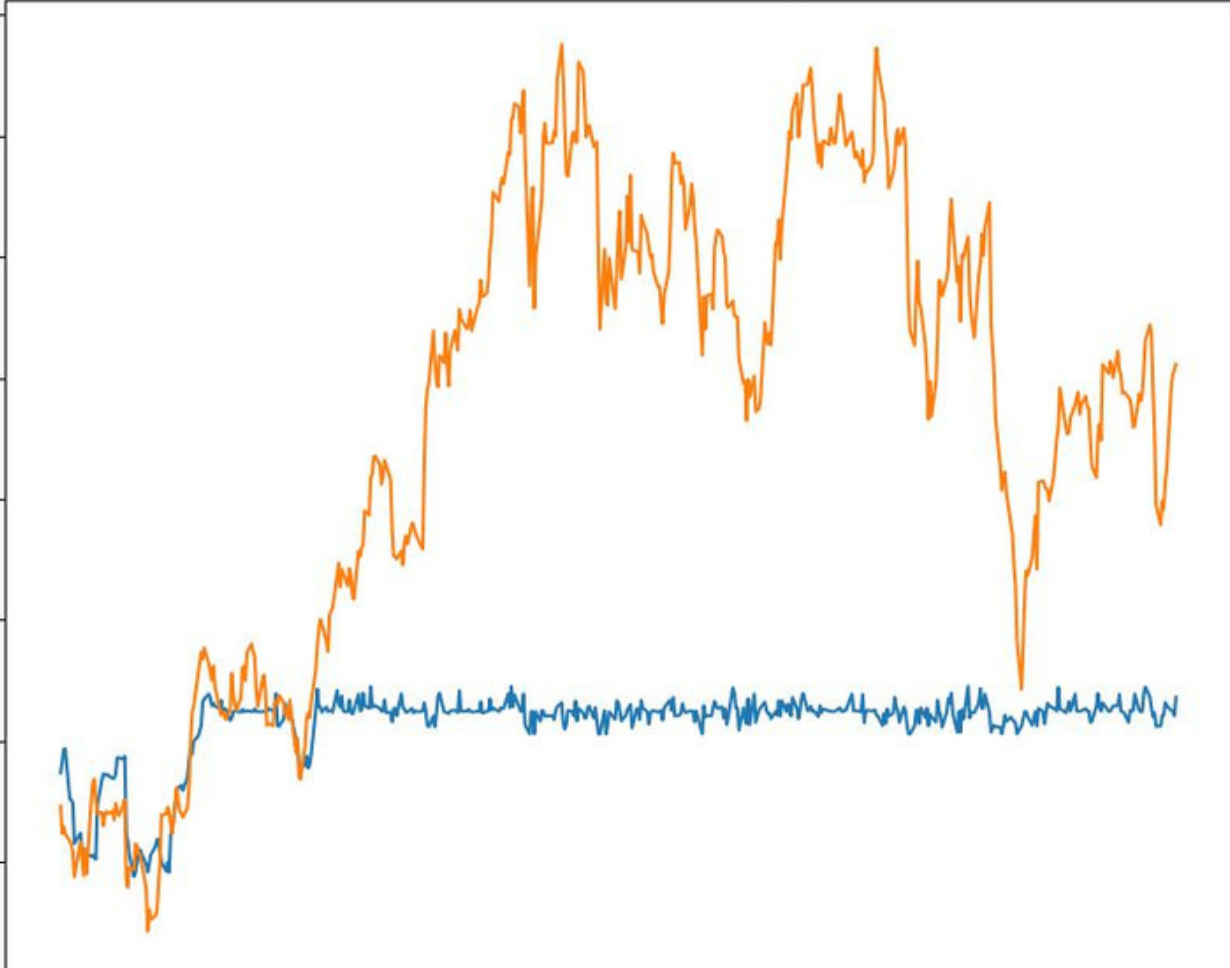




**Johnson &  
Johnson**



**J P Morgan**



What  
makes a  
model  
better?

- 1  $RMS E = \sqrt{\frac{\sum_{i=1}^n (O_i - F_i)^2}{n}}$
- 2  $MAPE = \frac{1}{n} \sum_{i=1}^n \frac{(O_i - F_i)}{O_i} * 100$
- 3  $MBE = \frac{1}{n} \sum_{i=1}^n (O_i - F_i)$

Comparative analysis of RMSE, MAPE and MBE values for ANN of authors (A) vs ours (O)						
Company	ANN (Authors)			ANN (Ours)		
	RMSE	MAPE	MBE	RMSE	MAPE	MBE
Nike	1.1	1.07%	−0.0522	1.13	1.15%	−0.0101
Goldman Sachs	3.3	1.09%	0.0762	3.44	1.19%	0.5252
J.P. Morgan and Co.	1.28	0.89%	−0.031	1.5	1.02%	−0.318
Johnson & Johnson	1.54	0.70%	−0.0138	2.09	1.23%	1.3427
Pfizer Inc.	0.42	0.77%	−0.0156	0.42	0.81%	0.0577

Comparative analysis of RMSE, MAPE and MBE values for RF of authors (A) vs ours (O)						
Company	RF (Authors)			RF (Ours)		
	RMSE	MAPE	MBE	RMSE	MAPE	MBE
Nike	1.29	1.14%	-0.0521	9.44	8.28%	6.1836
Goldman Sachs	3.4	1.01%	0.0761	9.42	3.24%	-2.4351
J.P. Morgan and Co.	1.41	0.93%	-0.0313	15.35	11.81%	12.5863
Johnson & Johnson	1.53	0.75%	-0.0138	9.73	5.66%	7.5587
Pfizer Inc.	0.43	0.80%	-0.0155	3.58	5.62%	2.1082

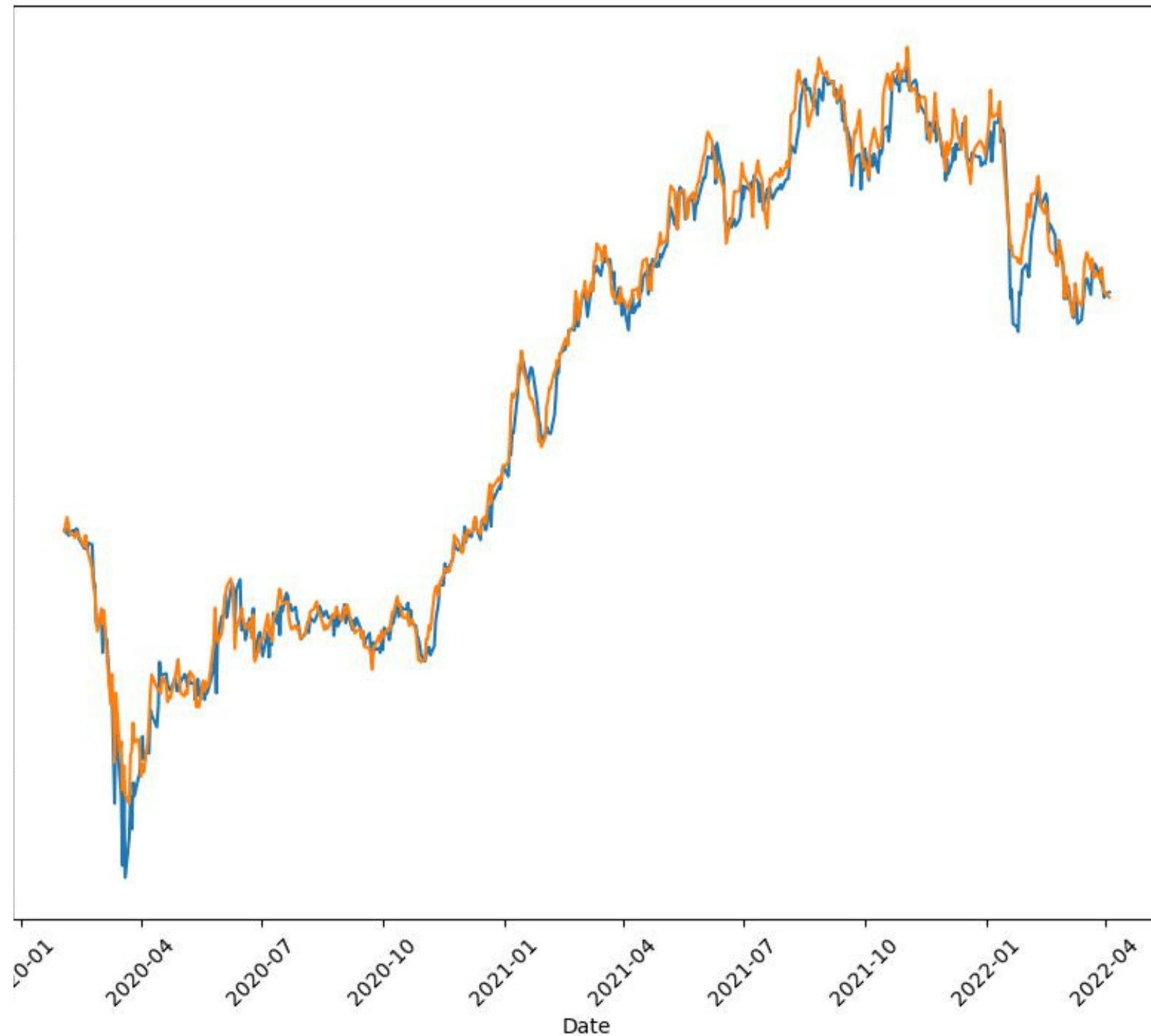


# Extension 1

1

Training Data:

2009-05-05 to 2020-01-31

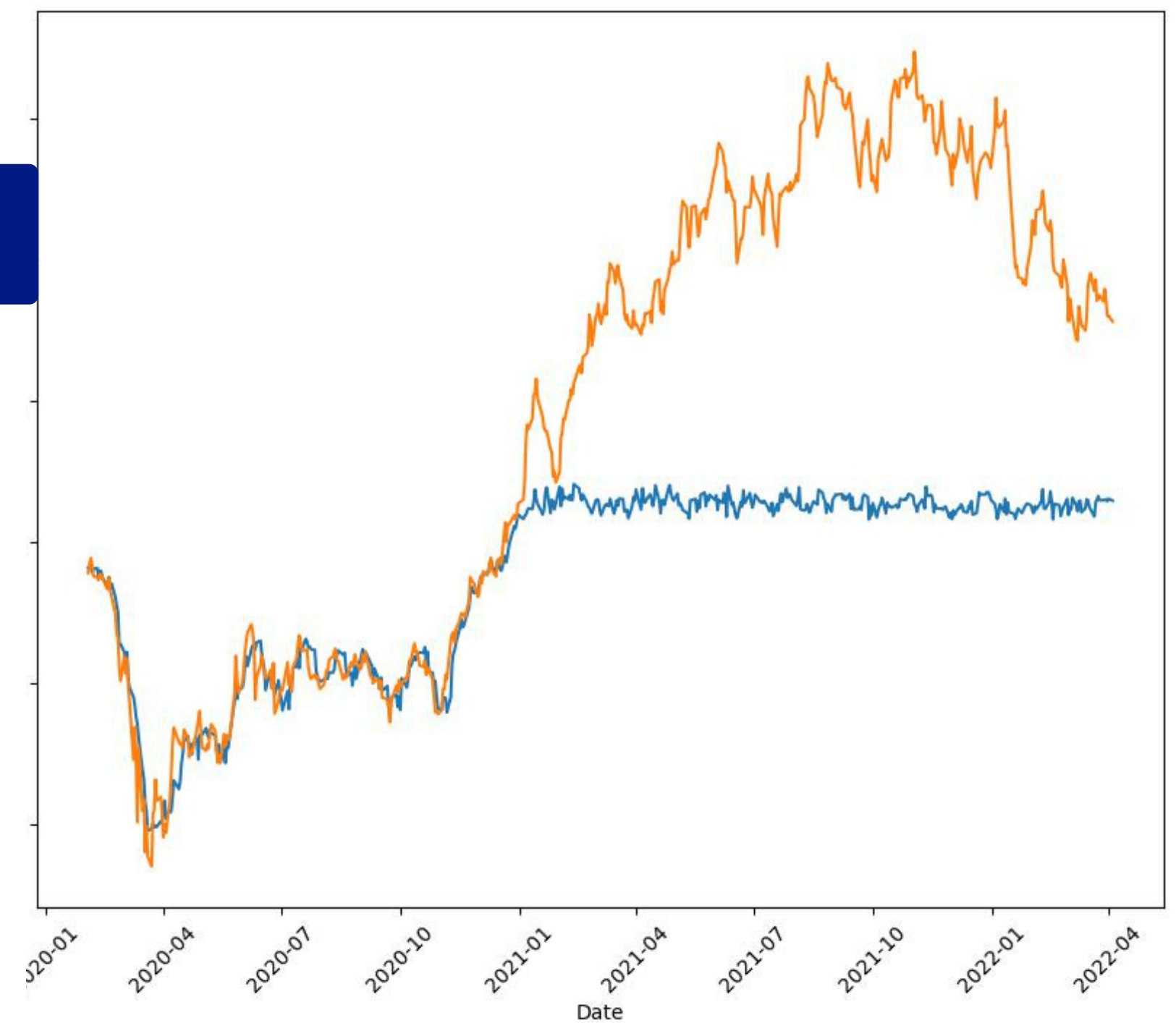


Goldman  
Sachs

2

Test Data:

2020-02-03 to 2022-04-05





**Why would  
anyone want  
to predict  
stock  
prices?**

# Extension 2

- Buy if stock increases for 4 consecutive days
- Sell if stock decreases days (and we've made a profit)

**Starting Amount:  
\$1000**

<u>Company</u>	<u>ANN (\$)</u>	<u>RF (\$)</u>
Nike	<b>1270</b>	940
Goldman Sachs	780	<b>860</b>
J.P. Morgan and Co.	<b>1100</b>	940
Johnson & Johnson	<b>990</b>	910
Pfizer Inc.	<b>950</b>	870

**Thank  
you!**

Have a great  
day ahead.