



Group 09

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OVERVIEW:

• Worked on tweets dataset which are linked with ticker symbols of the companies and performed sentiment analysis to check whether the tweets has an influence on the real-time stock price of the companies.

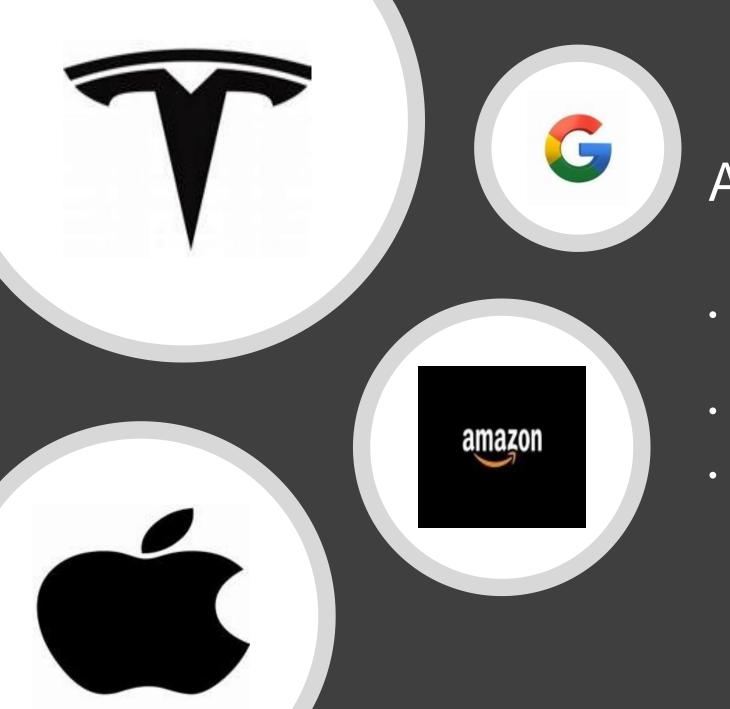
• The Real-Time stock market dataset of a company and forecasted the future trend for 30 days based on the past stock price using LSTM model.









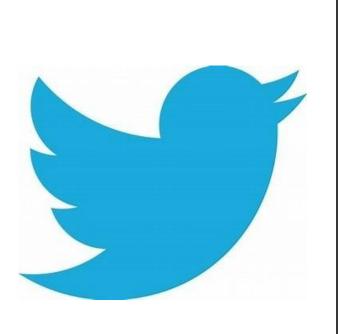


About the Dataset

- We have collected four datasets from Kaggle related to company, company ticker symbols, tweets, and stock prices.
- We have collected tweet data of top companies like Apple, Tesla, Google, Amazon
- Over 1.6 million tweets are collected for over 10 years period of time from 2011 to 2021.

Dataset

Tweets data loaded into DataFrames and displayed



+	++-	+			+	+
tweet id	writer	post date	body	comment num retwee	et num like	num
+	++-	· – :	, 		; 	+
550441509175443456	VisualStockRSRC 1	L420070457	lx21 made \$10,008	0	0	1
550441672312512512	KeralaGuy77 1	1420070496	Insanity of today	0	0	0
550441732014223360	DozenStocks 1	1420070510	S&P100 #Stocks Pe	0	0	0
550442977802207232	ShowDreamCar 1	1420070807	\$GM \$TSLA: Volksw	0	0	1
550443807834402816	i_Know_First 1	1420071005	Swing Trading: Up	0	0	1
550443808606126081	aaplstocknews 1	1420071005	Swing Trading: Up	0	0	1
550443809700851716	iknowfirst 1	1420071005	Swing Trading: Up	0	0	1
550443857142611968	Cprediction 1	1420071016	Swing Trading: Up	0	0	1
550443857595600896	iknowfirst_br 1	1420071017	Swing Trading: Up	0	0	1
550443857692078081	Gold_prediction 1	1420071017	Swing Trading: Up	0	0	1
550443858010861568	IKFResearch 1	1420071017	Swing Trading: Up	0	0	1
550444112328261632	GetAOM 1	L420071077	\$UNP \$ORCL \$QCOM	0	0	0
550444969924653056	AppleNewsAAPL 1	1420071282	\$AAPL Apple goes	0	0	1
550444970738335744	espositooooo 1	L420071282	"@WSJ: Apple is b	0	0	0
550445066444369921	Bidnessetc 1	L420071305	Apple filed for i	0	0	0
550445850170642432	JorelLaraKalel 1	L420071492	@CNBC 15 Top #tra	0	0	2
550447574285418497	btcgemini 1	L420071903	We searched throu	0	0	0
550447850857828352	JorelLaraKalel 1	1420071969	Top 10 searched #	0	0	2
550447998577426433	UPBOptionMil 1	1420072004	2014 The Year in	0	2	2
550448085789200384	MacHashNews 1	1420072025	Give your brain a	0	0	0
+	++-			·		+

We collected the ticker symbols and its associated companies along with the related tweet ids.



+ tweet_:	++ id ticker_symbol
55080361219745792 55080361082592870	
55080322511315763 55080295737015910 55080285512938293	04 AAPL
55080274573776896 55079749418814259 55079727578651852	50 AAPL 92 AAPL
5507972726869237 55079661744476569	76 AAPL 96 AAPL
55079551289996083 55079525410263859 55079516731870003	93 AAPL
55079508882188697 55079329835739136 5507932476692316	50 AAPL
55079310824219852 55079191981589299 55079123273859072	28 AAPL 92 AAPL
55079042388803584	200 N

PRE-PROCESSING:

- Joining the two dataframes using Tweet_id column.
- Converted the Post_date to required date format.
- Calculated the total_engagement column by adding the comments, retweets and likes.
- Dropped the unwanted columns.

	 writer	hody			+ liko numl	tickon cumboll	total engagements	++
tweet_id	writer	Douy	comment_num +	+	+ 		engagements	t_date
692169663577485315	ValaAfshar Apple has \$2	216 bi	42	984	677	AAPL	1703.0	2016-01-27
770310550991605760	cnntech Apple's next	iPho	11	729	918	AAPL	1658.0	2016-08-29
575014851363405824	RANsquawk Loving my Ap	ple W	66	882	654	AAPL		2015-03-09
816359802733555712	DavidSchawel Sometimes ha	ard to	14	646	900	AMZN		2017-01-03
854690001866686464	philstockworld Will We Hold			969		AMZN		2017-04-19
8546000010666064641	nhilatackunnldlwill We Hold			969		TSLA		2017-04-19
102 Total Engager	nent: sum of • - I'm b	eside	207	317		TSLA		2018-07-23
⁸⁷ tweet's comm	ienis, reiweels	stor		509		AMZN		2017-06-16
86 and likes	ergate We	dnesd		971		TSLA		2017-05-10
61 and likes.	d last of	our	153	671	533	AAPL		2015-06-24
1054/28662/86826240	CitronResearch \$TSLA droppi	ng ea	148	308	861	TSLA		2018-10-23
1018938697415315457	epichedge Live view of			366	927	AMZN	1300.0	2018-07-16
1020077355346169857	/incent13031925 "Tesla Spoke	espers	38	256	986	TSLA	1280.0	2018-07-19
1199424478536753155	AlexSibila ~Tesla featu	ıre re	563	48	662	TSLA	1273.0	2019-11-26
1135604016015060993 v	villchamberlain FACEBOOK, GC)OGLE	58	389	826	G00G	1273.0	2019-06-03
1045404879341137921	Reuters SEC files la	wsuit	56	630	585	TSLA	1271.0	2018-09-27
1167316598283071495	TeslaNY .@Tesla Mode	el 3 p∣	36	279	952	TSLA	1267.0	2019-08-30
1020036769629143040	Microsoft \$MSFT Q4 EAR	RNINGS	26	333	896	MSFT	1255.0	2018-07-19
1209424426904801280	YCalenge Last night,	\$TSLA	234	172	835	TSLA	1241.0	2019-12-24
1050135192109760525	charliebilello % Below 52-w	eek h	34	415	783	AMZN	1232.0	2018-10-10
+			+ + -	+	+			++

<u>Sentiment</u> <u>Analysis</u> is the process of classifying the text into positive, negative, or, neutral. Sentiment analysis is contextual mining of words which indicates the social sentiment of a brand and also helps the business to determine whether the product which they are manufacturing is going to make a demand in the market or not.

Sentiment analysis tries to gain is to analyze people's opinion in a way that it can help the businesses expand. It focuses not only on polarity (positive, negative & neutral) but also on emotions (happy, sad, angry, etc.). It uses various Natural Language Processing algorithms such as Rulebased, Automatic, and Hybrid.

we shall now make a function that takes in text and returns the sentiment of that text.

```
[16] def getSentiment(body):
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
analyzer = SentimentIntensityAnalyzer()
assert body is not None
vs = analyzer.polarity_scores(body)
score = vs['compound']
if (score >= 0.05):
    return "Positive"
elif (score < 0.05 and score > -0.05):
    return "Neutral"
elif (score <= -0.05):
    return "Negative"
print(score)
```

- Vader Sentiment is used to determine sentiment of each post.
- Tweets are classified into three types: Positive, Negative, Neutral.

• We categorized the tweets into positive, negative and neutral.

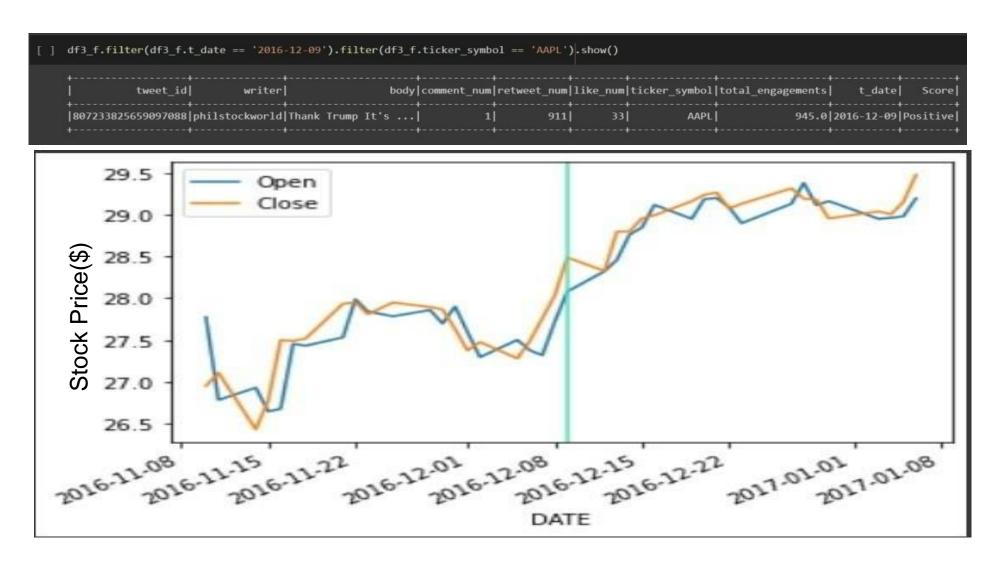


tweet_id	writer	+ body	comment_num	retweet_nu	-+ n like_num	ticker_symbol t	cotal_engagements t_date Sco
		- 			- 		
3577485315		Apple has \$216 bi					1703.0 2016-01-27 Neutr
0991605760		Apple's next iPho					1658.0 2016-08-2 <mark>9 N</mark> eutr
1363405824	la transfer de la contraction	Loving my Apple W		88	2 654	AAPL	1602.0 2015-03- <mark>09 </mark> Positi
2733555712	DavidSchawel	Sometimes hard to	14	64	6 900	AMZN	1560.0 2017-01- <mark>03 </mark> Negati
1866686464	philstockworld	Will We Hold It W	0	96	9 520	AMZN	1489.0 2017-04- <mark>19</mark> Neutr
1866686464	philstockworld	Will We Hold It W	0	96	9 520	TSLA	1489.0 2017-04- <mark>19 </mark> Neutr
8403382272	QTRResearch	Guys - I'm beside	207	31	7 899	TSLA	1423.0 2018-07-2 <mark>3 N</mark> egati
7003791362	SJosephBurns	\$AMZN has no stor	40	50	9 837	AMZN	1386.0 2017-06-1 <mark>6 Ne</mark> gati
3010203648	philstockworld	Watergate Wednesd	1	97	1 400	TSLA	1372.0 2017-05-10 Neutr
7219076096	Carl C Icahn	Sold last of our	153	67	1 533	AAPL	1357.0 2015-06-24 Positi
2786826240	CitronResearch	\$TSLA dropping ea	148	30	8 861	TSLA	1317.0 2018-10-23 Negati
7415315457	epichedge	Live view of \$AMZ	7	36	6 927	AMZN	1300.0 2018-07-16 Neutr
5346169857	vincent13031925	"Tesla Spokespers	38	25	6 986	TSLA	1280.0 2018-07-19 Negati
6015060993	willchamberlain	FACEBOOK, GOOGLE	58	38	9 826	GOOG	1273.0 2019-06-03 Negati
8536753155	AlexSibila	∿Tesla feature re	563	4	8 662	TSLA	1273.0 2019-11-26 Positi
9341137921		SEC files lawsuit		63			1271.0 2018-09-27 Negati
8283071495		.@Tesla Model 3 p					1267.0 2019-08-30 Neutr
9629143040		\$MSFT Q4 EARNINGS		33	•		1255.0 2018-07-19 Negati
6904801280		Last night, \$TSLA	:			:	1241.0 2019-12-24 Positi
2109760525	, , ,	% Below 52-week h		41		•	1232.0 2018-10-10 Neutr
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			l				

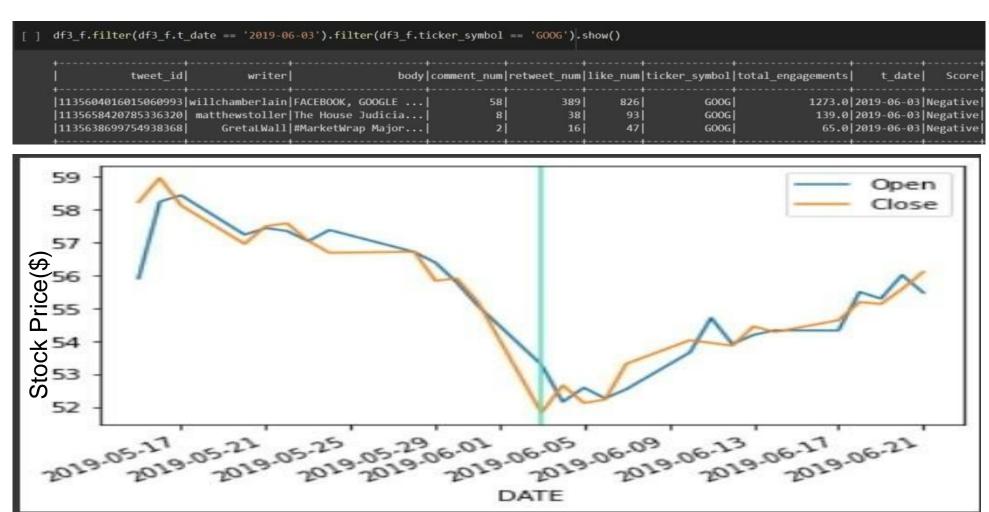
Real-Time Stock Market Data

+		+ ·	+		+	+	+	+		+
ticker_s	ymbol	Date	₽	0pen	High	Low	Close	Adj	Close	Volume
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ļ					152.169998		145.029999	•		•
ļ				10		149.130005		•		**
Į.				100	-25	151.919998		•		**
Ţ			•	100	• E	147.820007		•		•
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Ţ						148.039993	40	•		
I	AAPL	10/25/202	2 150.	.089996	152.490005	149.360001	152.339996	152.	087708	74732300
1	AAPL	10/24/202	2 147 .	.190002	150.229996	146	149.449997	149.	202484	75981900
I	AAPL	10/21/202	2 142 .	.869995	147.850006	142.649994	147.270004	147.0	026108	86464700
Ĩ	AAPL	10/20/202	2 143.	.020004	145.889999	142.649994	143.389999	143.	152527	64522000
Ĩ	AAPL	10/19/202	2 141 .	.690002	144.949997	141.5	143.860001	143	.62175	61758300
Ĩ	AAPL	10/18/202	2 145	.490005	146.699997	140.610001	143.75	143.	511932	99136600
Î	AAPL	10/17/202	2 141 .	.070007	142.899994	140.270004	142.410004	142.	174164	85250900
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Ť					E ()	134.369995	GP 9	7		70 (7.1
Ť					± 3	138.160004		•		50
i					±3.	138.220001		•		50
Ť .					± 3	138.570007		•		50
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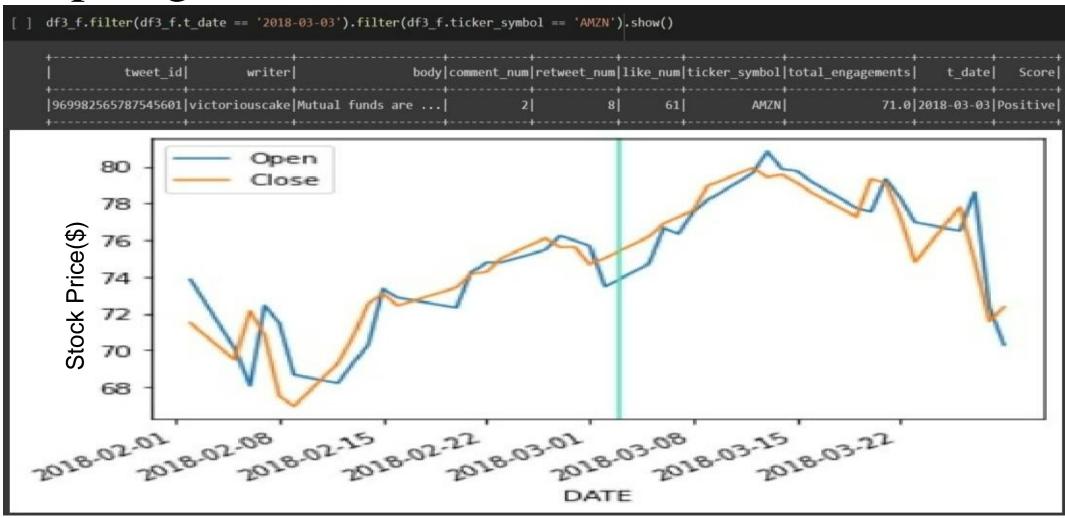
Graphing the trend

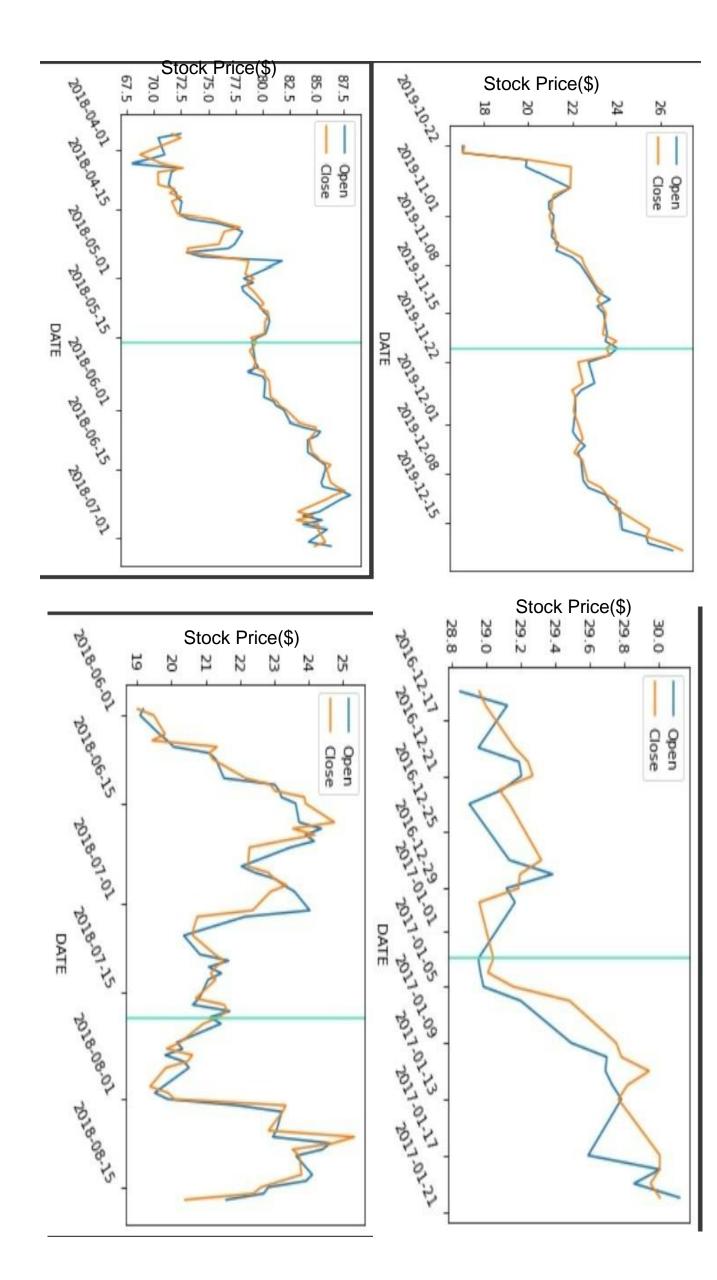


Graphing the trend



Graphing the trend





AAPL STOCK DATA

27		Date	Low	Open	Volume	High	Close	Adjusted Close	1.
	0	12-12-1980	0.128348	0.128348	469033600.0	0.128906	0.128348	0.100922	
	1	15-12-1980	0.121652	0.122210	175884800.0	0.122210	0.121652	0.095657	
	2	16-12-1980	0.112723	0.113281	105728000.0	0.113281	0.112723	0.088636	
	3	17-12-1980	0.115513	0.115513	86441600.0	0.116071	0.115513	0.090830	
	4	18-12-1980	0.118862	0.118862	73449600.0	0.119420	0.118862	0.093463	
	10167	12-04-2021	130.630005	132.520004	91420000.0	132.850006	131.240005	131.240005	
	10168	13-04-2021	131.929993	132.440002	91266500.0	134.660004	134.429993	134.429993	
	10169	14-04-2021	131.660004	134.940002	87222800.0	135.000000	132.029999	132.029999	
	10170	15-04-2021	133.639999	133.820007	89347100.0	135.000000	134.500000	134.500000	
	10171	16-04-2021	133.279999	134.300003	84818500.0	134.669998	134.160004	134.160004	
10172 rows × 7 columns									

- Long Term Short Memory, says that it not only processes single data points but also entire sequences of data(such as speech, images and video).
- Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture used in the field of deep learning which is proposed in 1997.
- Unlike standard feed-forward neural networks, LSTM has feedback connections.
- "Long Short- Term Memory (LSTM) networks are a modified version of recurrent neural networks, which makes it easier to remember past data in memory".

WHY LSTM?



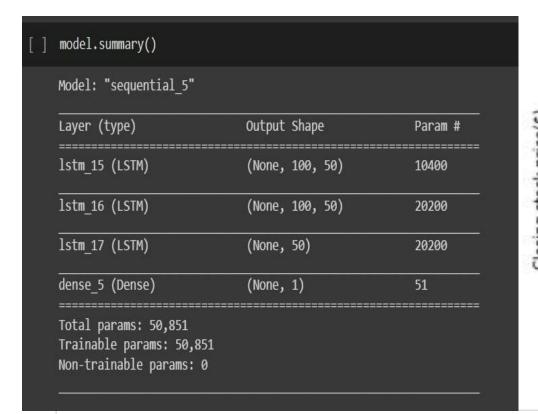
LONG SHORT TERM MEMEORY

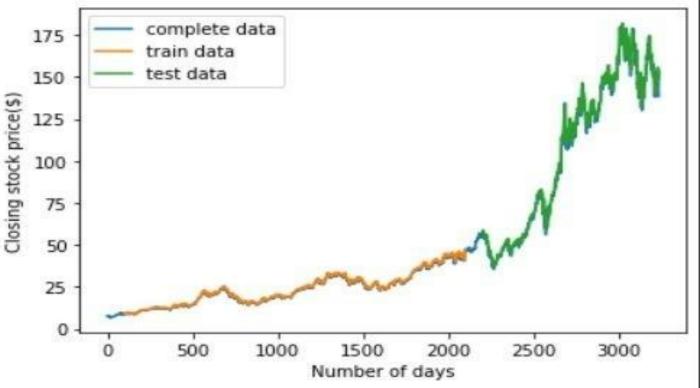


LSTM could not process a single data point. it needs a sequence of data for processing and able to store historical information. LSTM is an appropriate algorithm to make prediction and process based-on time-series data.



The stock market has enormously historical data that varies with trade date, which is time-series data, but the LSTM model predicts future price of stock within a short-time period with higher accuracy when the dataset has a huge amount of data.

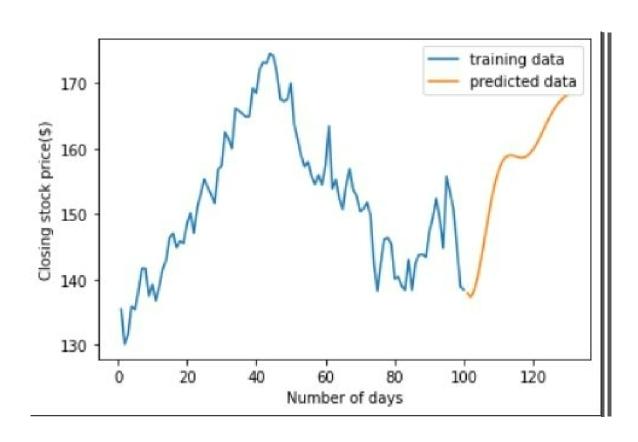




We are using a sequential model and adding the layers of the LSTM

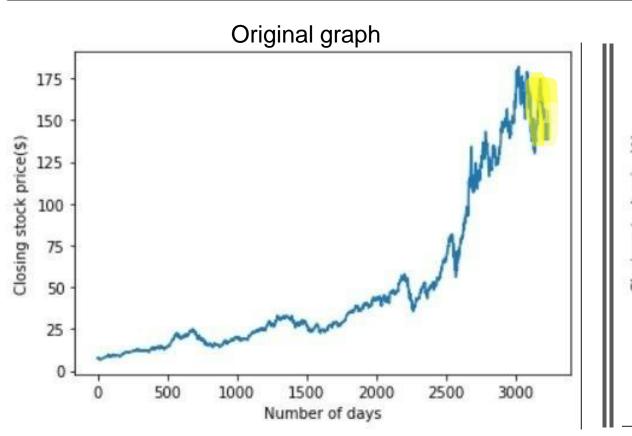
- Green indicates the Test Data
- Blue indicates the Complete Data
- Orange indicates the Train Data

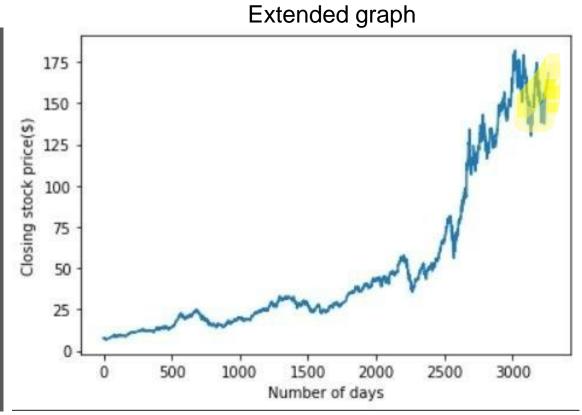
PREDICTION FOR THE NEXT 30 DAYS



The orange color line in the plot represents the value of stock price for the next 30 days.

Before and After Modelling





CONCLUSION:

SENTIMENT ANALYSIS:

- Out of 8 random tweets only 4 (50%) influenced the stock prices when compared with the opening and closing values.
- So, in conclusion, Yes, twitter does have an effect on the stock market, but it is not necessary that if your tweet does go viral, based on emotion behind tweet it will influence the stock prices of company.

LSTM MODELLING TIME FORECASTING:

• While the exact price points from our predicted price weren't always close to the actual price, our model did still indicate overall trends such as going up or down. This project teaches us how the LSTMs can be effective in times series forecasting.

Thank You