

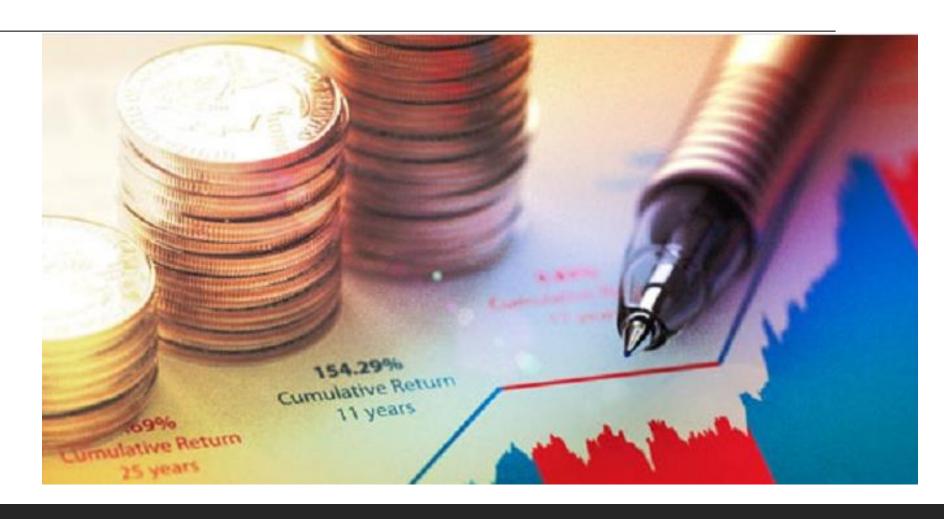
# How News affects stock prices

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DATA SCIENCE: CAPSTONE PROJECT

## Content

- ■Introduction
- □ Data Collection
- **EDA**
- Modeling
- Conclusion



## **Datasets Collection**

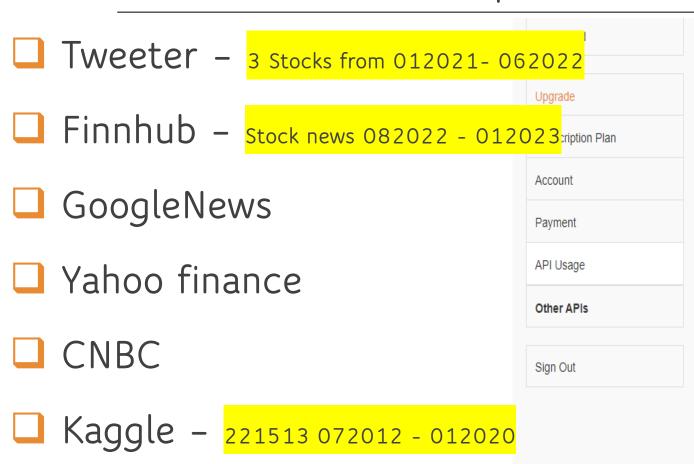
- Problem Statement

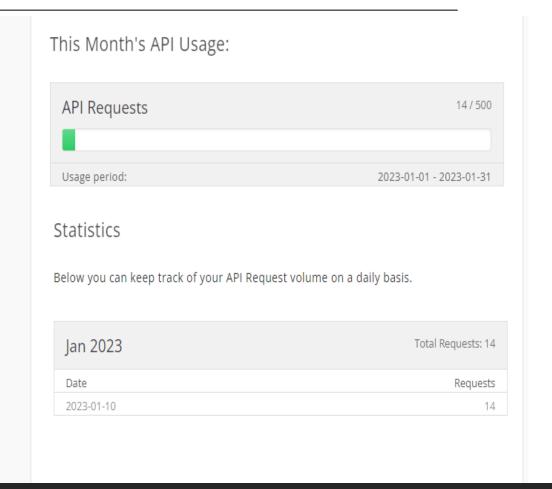
  To learn specific news, contents, and posts that affect a company's stock prices
  - posts that affect a company's stock prices and create a model to predict the closing price.
- ☐ Why: Interested in modeling as a result of my past experience.
- ☐ Future Development: Create a framework for future development of additional features.



## Datasets Collection

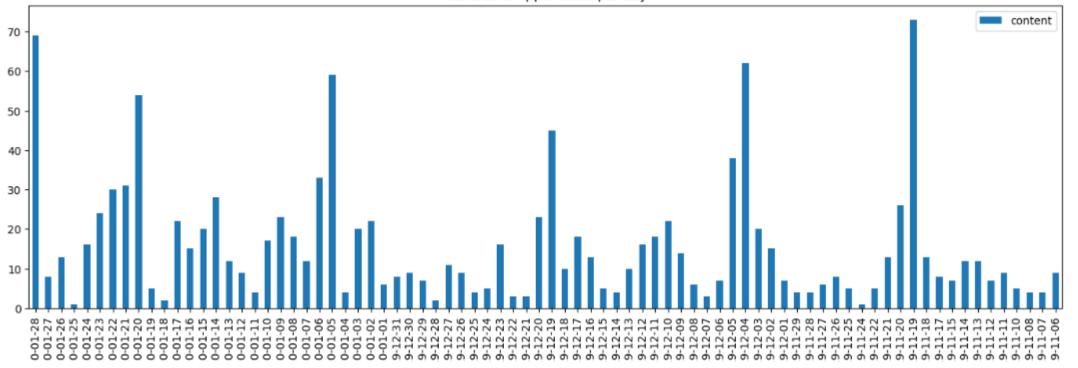
Financial data, News, Posts providers



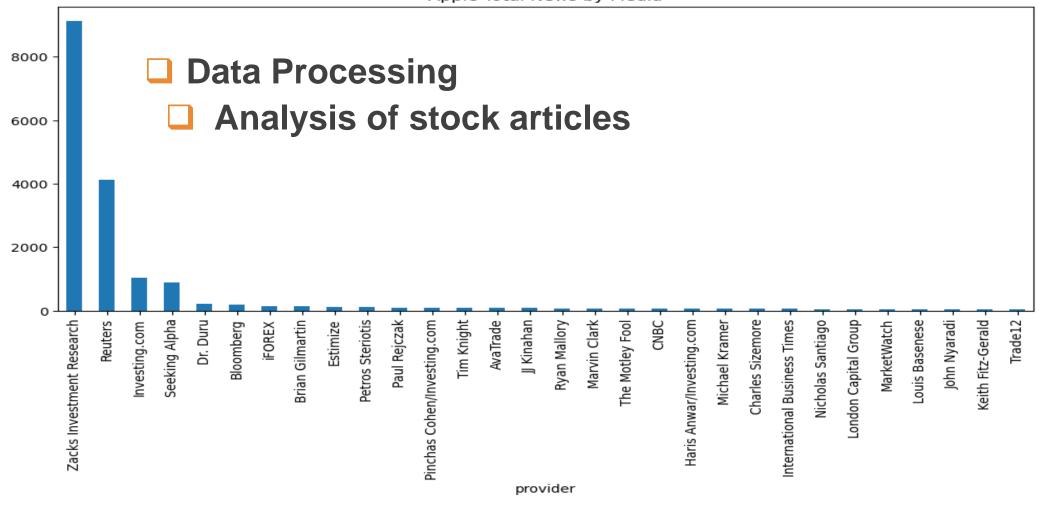


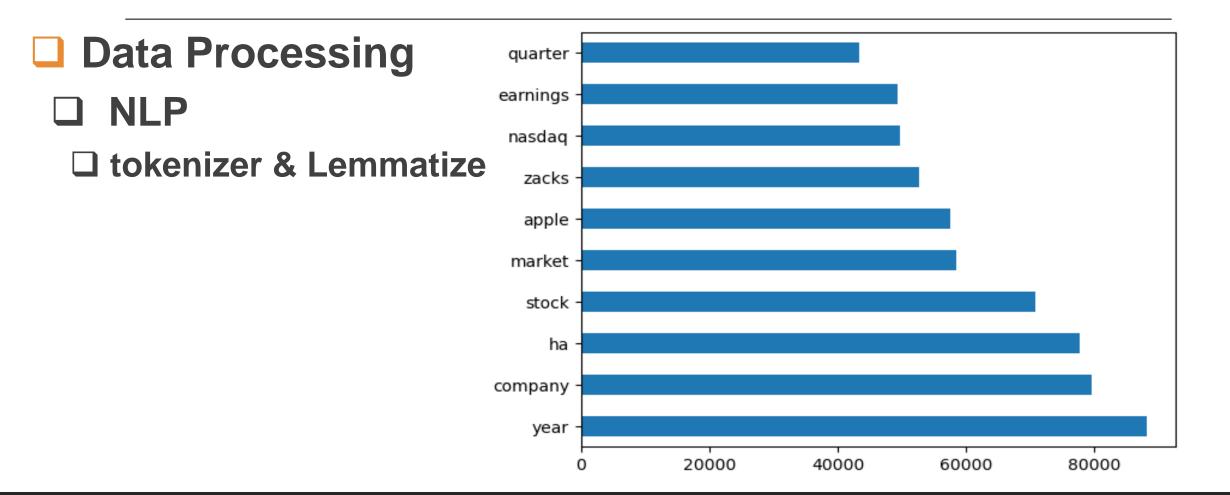
## Data Processing



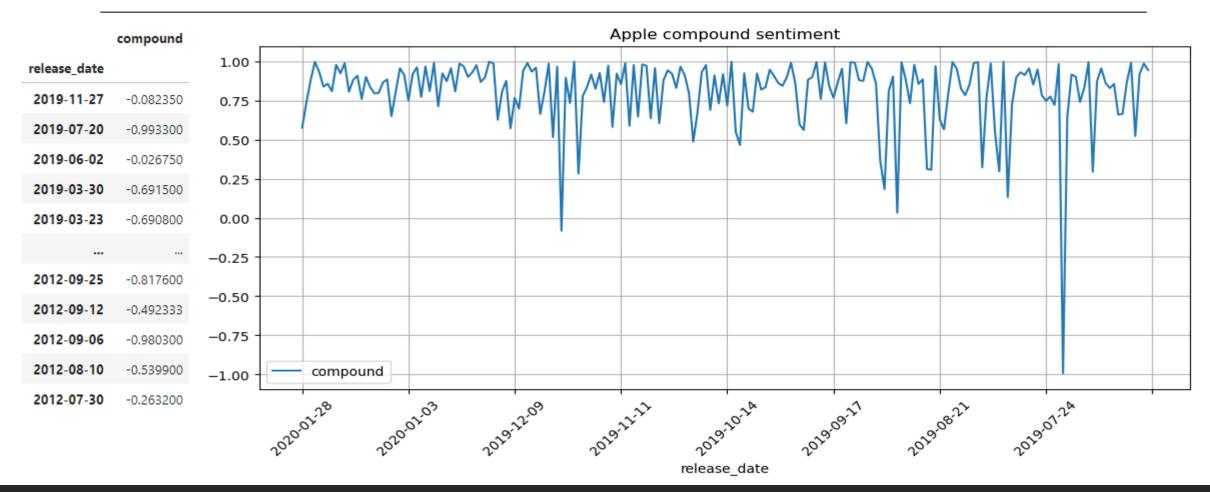


Apple Total News by Media





#### Sentiment score

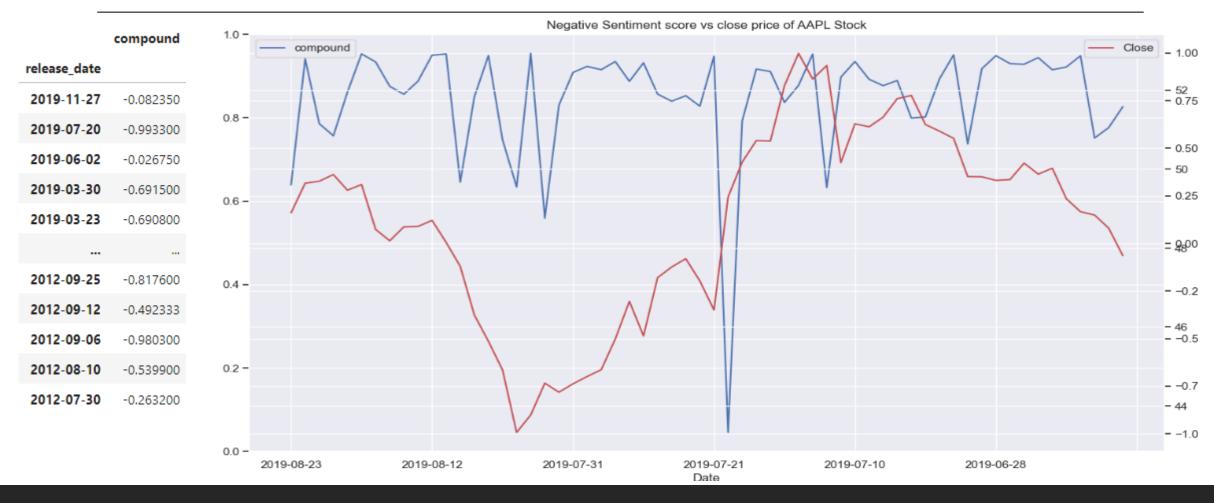


#### Sentiment

score	compound	
release_date		
2019-11-27	-0.082350	
2019-07-20	-0.993300	
2019-06-02	-0.026750	
2019-03-30	-0.691500	
2019-03-23	-0.690800	
2012-09-25	-0.817600	
2012-09-12	-0.492333	
2012-09-06	-0.980300	
2012-08-10	-0.539900	
2012-07-30	-0.263200	

'tim kelly sam nussey kyoto japan reuters many victim arson attack japanese animation studio young bright future joining april shaken company presid ent said saturday death toll climbed 34 thursday attack kyoto animation well known television series movie wa japan worst mass killing two decade was poignant youth victim country population among world oldest many victim attack ancient capital kyoto young woman company president hideaki hatta sai d joined u april eighth july gave small first bonus said people promising future lost life know say rather feeling anger word hatta said fifteen vic tim 20 11 30 public broadcaster nhk said six 40 one wa least 60 age latest victim man died hospital wa known name victim disclosed yet wait definiti ve identification police confirmed identity suspect shinji aoba ex convict shop robbery formally arrested treated heavy burn unusual police release suspect name making arrest plagiarism claim aoba life modest two floor apartment building 500 km 310 mile kyoto rural suburb outside omiya commuter hub north tokyo 27 year old neighbor said aoba grabbed yelled noise dispute started yelling face shut grabbed collar started pulling hair wa terrify ing neighbor declined identified said aoba suspected carrying arson attack believed novel plagiarized local medium say hatta said idea plagiarism cl aim adding seen correspondence suspect people living near studio said saw man fitting aoba description park day attack police suspect may spent day area prepare resident rie bannai said nephew saw man sleeping bench park rui yamaguchi work factory nearby said saw suspect wa detained looked like mannequin hair blackened one pant leg gone around calf looked like burnt said beautiful warm near blackened studio building smell burning timber lir gered neighborhood animation fan many nationality local resident queued add growing pile flower drink offering bing xie 25 chinese student kyoto uni versity said could forgive arsonist criminal doe seems mentally disturbed forgive young people kyoto animation beautiful warm hard accept gone police e guarded site investigator roof near many died connecting stairwell examined torched three story building hatta said building needed torn wa badly damaged tribute victim lit social medium world leader apple inc aapl chief executive offering condolence hashtag prayforkyoani studio known among fa n ha become popular kyoto animation produce popular anime series sound euphonium also known violet evergarden ha shown netflix nasdaq nflx fumiko sh imizu 91 life close building watched fire balcony home said regularly greeted staff met street used see going convenience store group six buy lunch box lot young people twenty thirty died young would alright somebody like die anytime said'

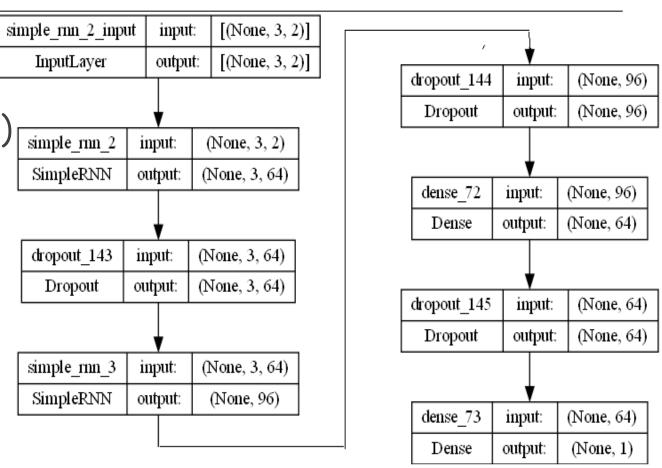
#### Sentiment score



## Build Models

#### Model Used

- Linear Regression
- □ GRU (Gated Recurrent Unit)<sub>I</sub>
- RNN (Recursive Neural Network)
- ☐ LSTM (Long Short-Term Memory)

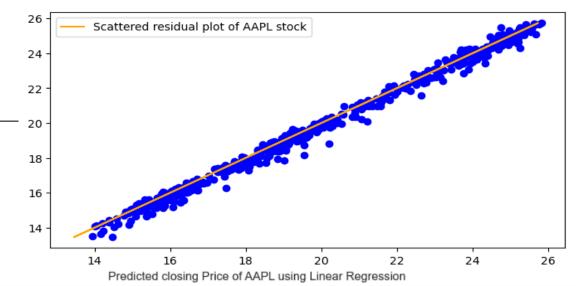


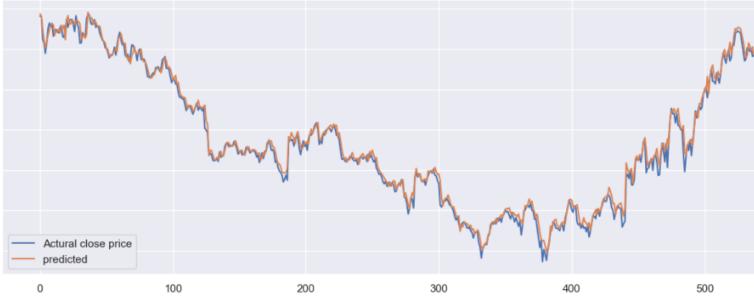
## Linear Regression

Line	ear Regression:
Train score	0.998467
Test score	0.990316
rmse	0.31766

#### Linear Regression

Actual	Predicted
25.74749947	25.62897801
25.61750031	25.60230001
24.94000053	24.46949041
24.41749954	24.28663658
24.06500053	23.7838852
24.38500023	24.30603232
24.6875	25.02405547
24.95249939	25.29328952
25.18250084	25.10461924
25.25499916	25.27499134

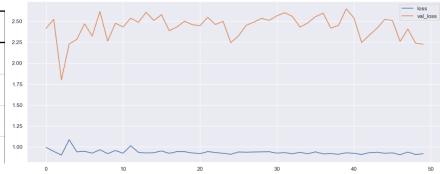




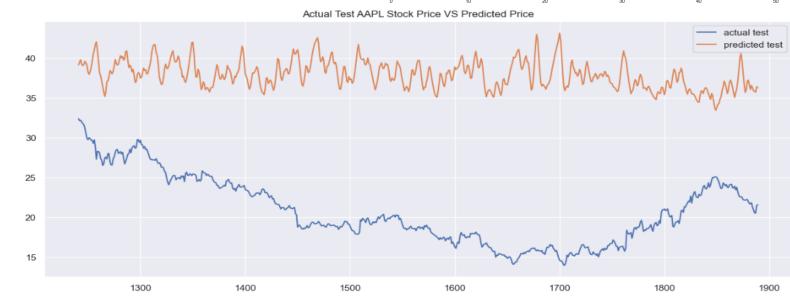
## **GRU** with tweets sentiment only

Parameters used:		
Length [3,11,50]		
batch	[16,32, 64]	
ecpoch [50,100, 200]		

Best parameters			
optimizer rmsprop			
Test score	2.2254		
length	11		
epochs	50		



	actual test	predicted test
1241	32.375000	39.141136
1242	32.112499	39.511097
1243	32.180000	39.787495
1244	31.957500	39.212704
1245	31.770000	39.043598



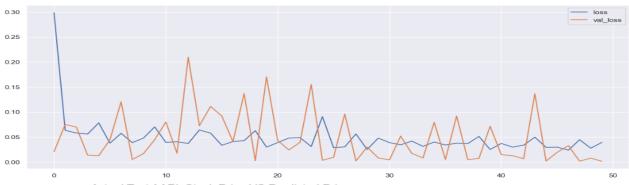
## GRU with tweets/open price of stock

32.006588

Parameters used:		
Length	ngth [3,11,50]	
batch	[16,32, 64]	
ecpoch	[50,100, 200]	

actual test predicted test

_				
	Best parameters			
	optimizer	rmsprop		
	Test score	0.00156		
	length	11		
	epochs	50		



1241	32.375000	32.486126
1242	32.112499	32.396526
1243	32.180000	32.255733
1244	31.957500	32.112583

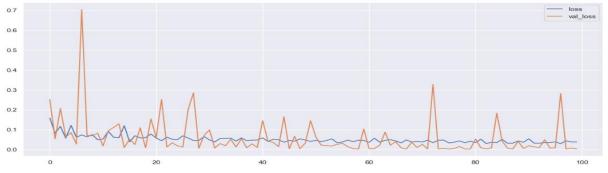
31.770000

1245



## LSTM with tweets/open price of stock

Pa	rameters used:	Best pa	arameters
Length	[3,11,50]	optimizer	rmsprop
batch	[16,32, 64]	Test score	0.003704
•		length	11
ecpoch	[50,100, 200]	—epochs	100

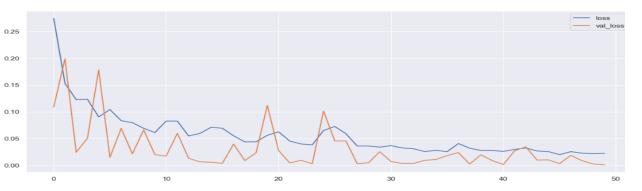


	actual test	predicted test
1241	32.375000	32.621872
1242	32.112499	32.533440
1243	32.180000	32.404701
1244	31.957500	32.267345
1245	31.770000	32.122486



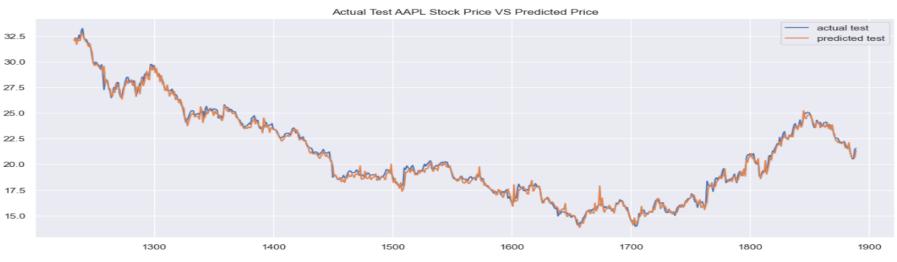
#### RNN with tweets/open price of stock

Parameters used:		sentiment sco	ore & stock opening price
		_	RNN
Length	[3,11,50]	optimizer	adam
batch	[16,32, 64]	Test score	0.0008744
		length	11
ecpoch	[50,100, 200]	epochs	200

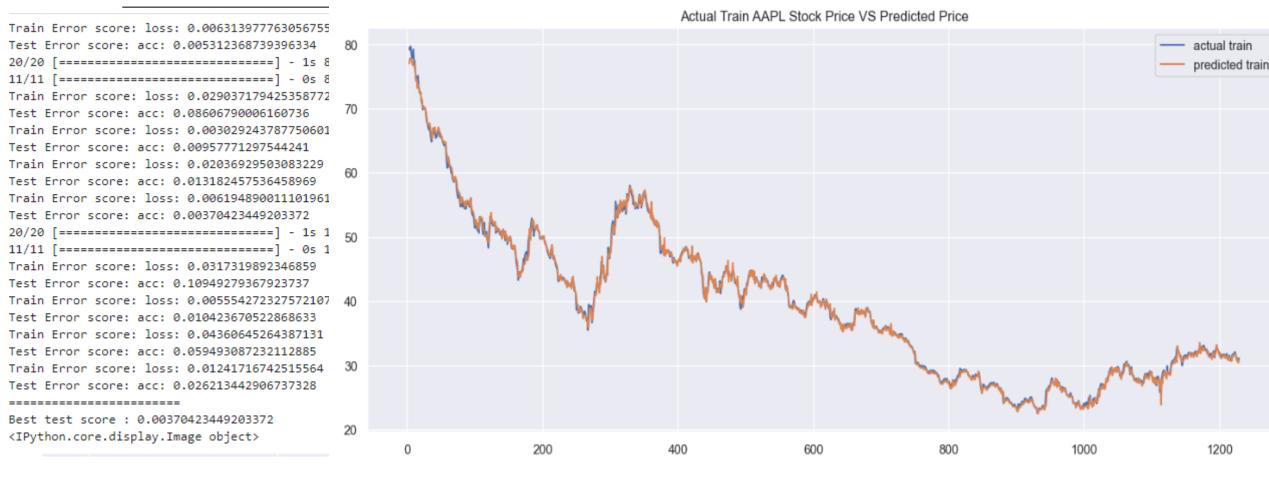


#### actual test predicted test

	-	
1233	32.134998	32.050903
1234	32.340000	32.329674
1235	32.272499	31.681116
1236	32.115002	32.260738
1237	32.605000	32.038532



#### GRU with tweets/open price of stock - Loss /val-loss



## Conclusion

- RNN model predicted better than others
- ☐ Very difficult to predict with only sentiment score.
- ☐ Attempt to execute all models with combination of news, tweets, and other social media.

Just stock opening price		sentiment score & stock opening price	
		LSTM	
optimizer	rmsprop	optimizer	rmsprop
Test score	0.00139811	Test score	0.0037043
length	50	length	11
epochs	50	epochs	100
sentiment score & stock opening price		sentiment score & stock opening price	
GRU		RNN	
optimizer	rmsprop	optimizer	adam
Test score	0.000984	Test score	0.0008744
length	50	length	11
epochs	50	epochs	200
sentiment score only		sentiment score & stock opening price	
GRU		RNN	
optimizer	rmsprop	optimizer	rmsprop
Test score	2.22546	Test score	0.000898
length	11	length	11
epochs	50	epochs	200

# Questions?

Suggestion

