

Outline





Problem Statement

How to predict the stock price?

How to apply deep learning to stock research to get more accurate prediction results?



Can stock prices be predicted?

Stock prices change according to time series. Does this mean that stock prices change regularly over time?

What can we learn from this project?

From the predicted results and the exploration of the market, can we get some guiding opinions on investment?



Start with Apple Inc.



Pre-processing

Loading the data

- Stock of Apple Inc. from Feb. 2013 to Feb. 2018
- Source: Super DataScience
- Daily close price
- Predicted Apple's stock price 7 days in advance

Cutting time series into sequences

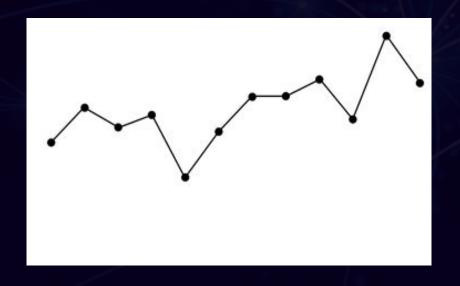
Splitting training and testing sets

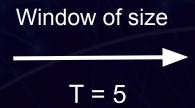
- 80% training data
 - o 1000 records
 - o Feb. 2013 Feb. 2017
- 20% testing data
 - o 251 records
 - o Feb. 2017 Feb. 2018

Pre-processing —— Cutting time series in sequences



where sp is the numerical value of the time series at time period p and where P is the total length of the series.



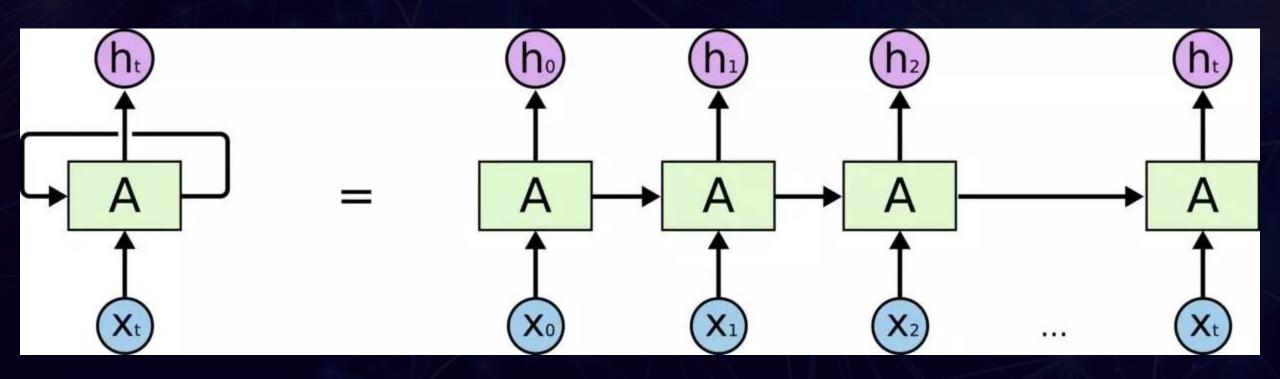


Input	Output
$\langle s_1, s_2, s_3, s_4, s_5 \rangle$	<i>s</i> ₆
$\langle s_2, s_3, s_4, s_5, s_6 \rangle$	<i>S</i> 7
$\langle s_{P-5}, s_{P-4}, s_{P-3}, s_{P-2}, s_{P-1} \rangle$	SP

Start with Apple Inc.

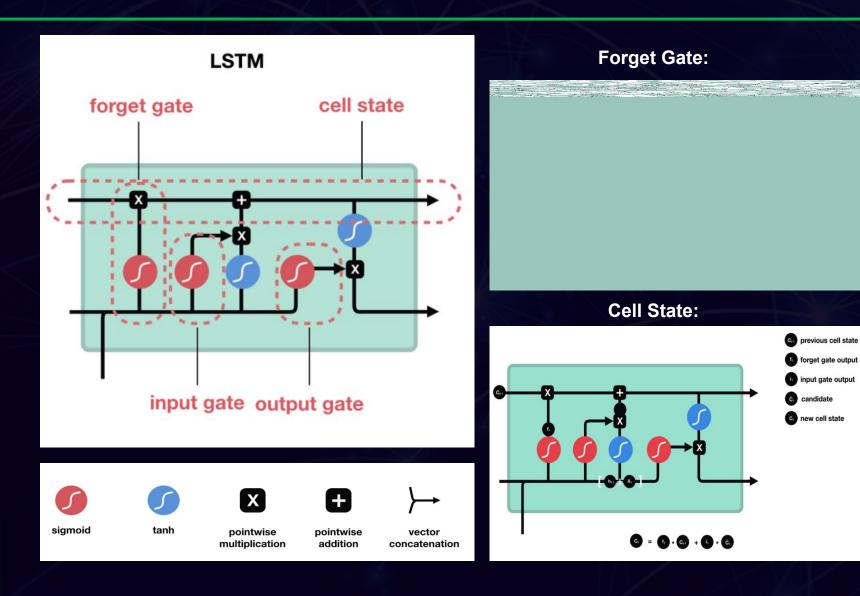


Basic Structure of RNN

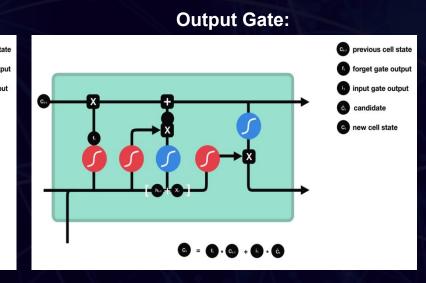


- Problem that RNN solve: sequence problem
- Elements are not independent of each other. They have dependencies.

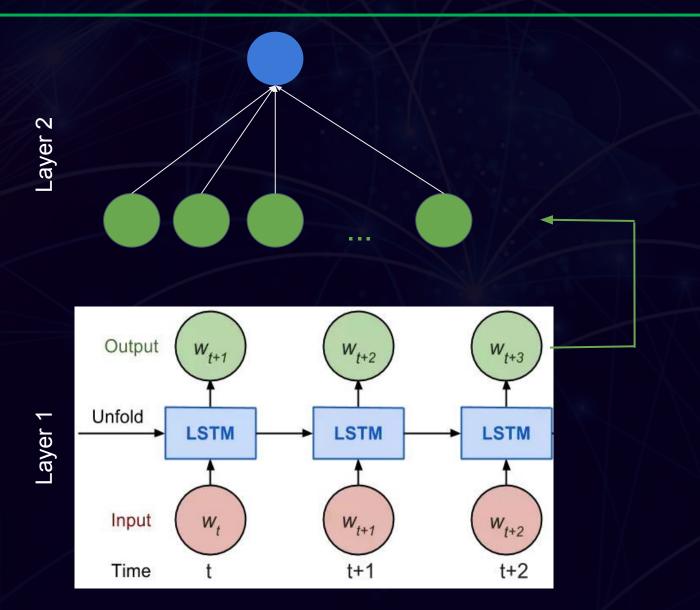
Basic Structure of LSTM



Input Gate: Co. previous cell state (i) forget gate output (ii) input gate output (ic) candidate



Basic Structure of LSTM



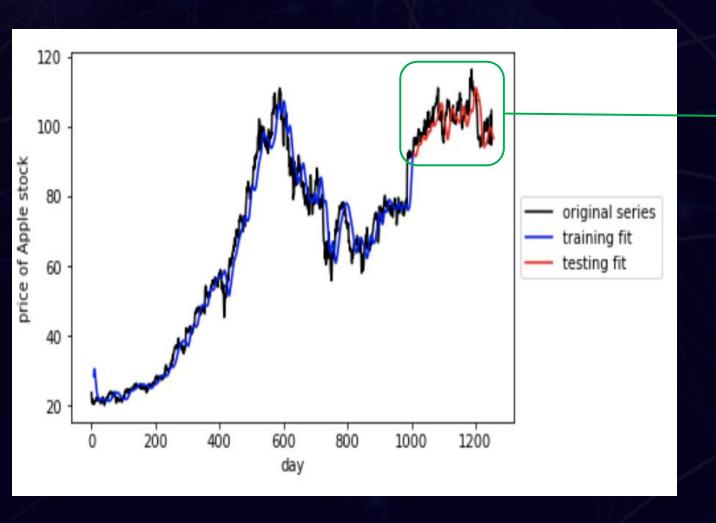
Two hidden layer RNN of the following specifications:

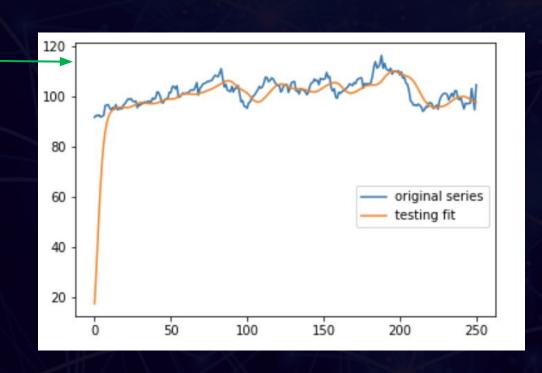
- layer 1 uses 3 LSTM module with 64 hidden units, input size is 7.
- layer 2 uses a fully connected module with one unit
- Loss function: MSE

Start with Apple Inc.



Prediction Result





Apply Same Modle to Four Main Sectors

	Loading the data			
	Sou	roo: Vahoo Einanoo		
		Source: Yahoo Finance		
•	4 Se	ectors:		
	0	XLK: Technology		
	0	XLV: Hearlth Care		
	0	XLF: Finicial		
	0	XTN:		

Transportation

Dec. 2010 - Dec. 2020

Daily close price

Cutting time series into sequences

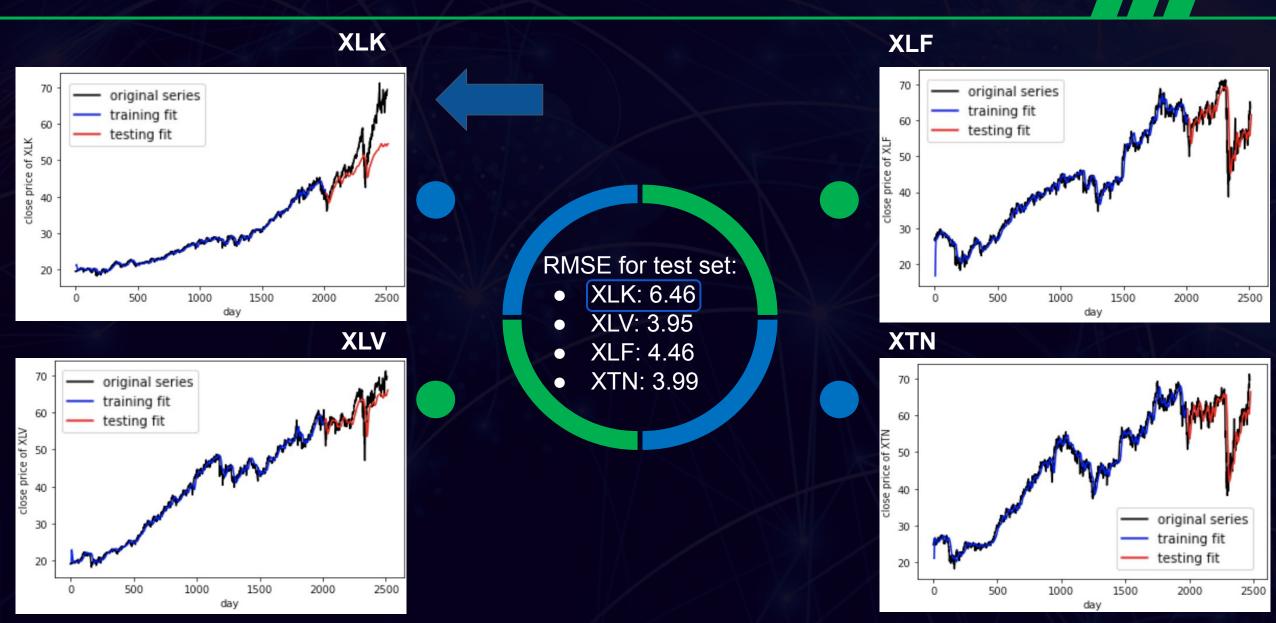
Spliting training and testing sets

Building RNN model Check model performance

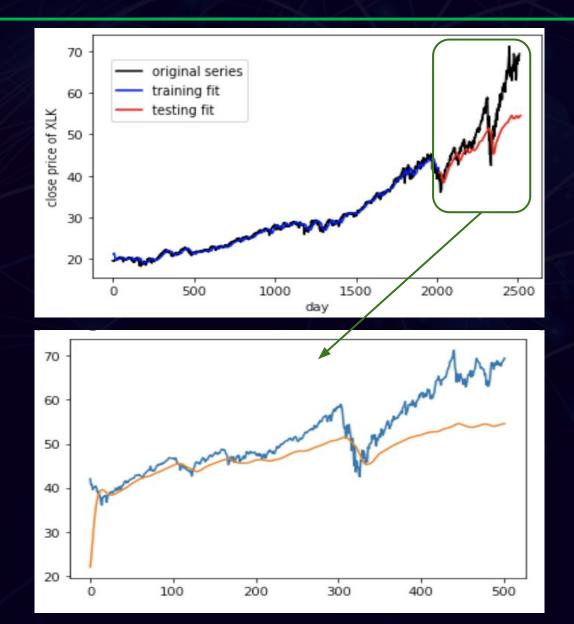
- Window size = 7
- Predicted 7 days in advance
- 80% training data
 - o 2008 records
 - Dec. 2010 -Dec. 2018
- 20% testing data
 - 502 records
 - o Dec. 2018 Dec. 2020

- RNN + LSTM
- 2 layers:
 - o LSTM
 - FullyConnection

Model Performance for 4 Sectors



Refine the LSTM Model for XLK

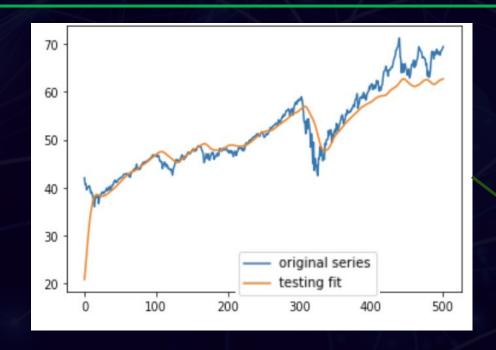


Performance well in training set but not well in testing set

Overfitting

- L1 and L2 Regression
- Dropout +
- Early Stopping
- Simplier model structure +
- Increase data
- ...

Refine the LSTM Model for XLK

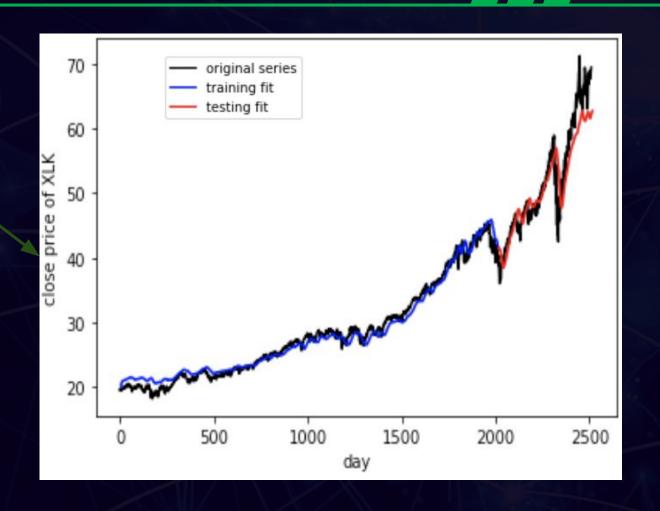


Method:

- Decrease the layers number (layer_number = 2)
- Increase the dropout rate (dropout = 0.2)
- Adjust the learning rate (learning_rate = 0.001)

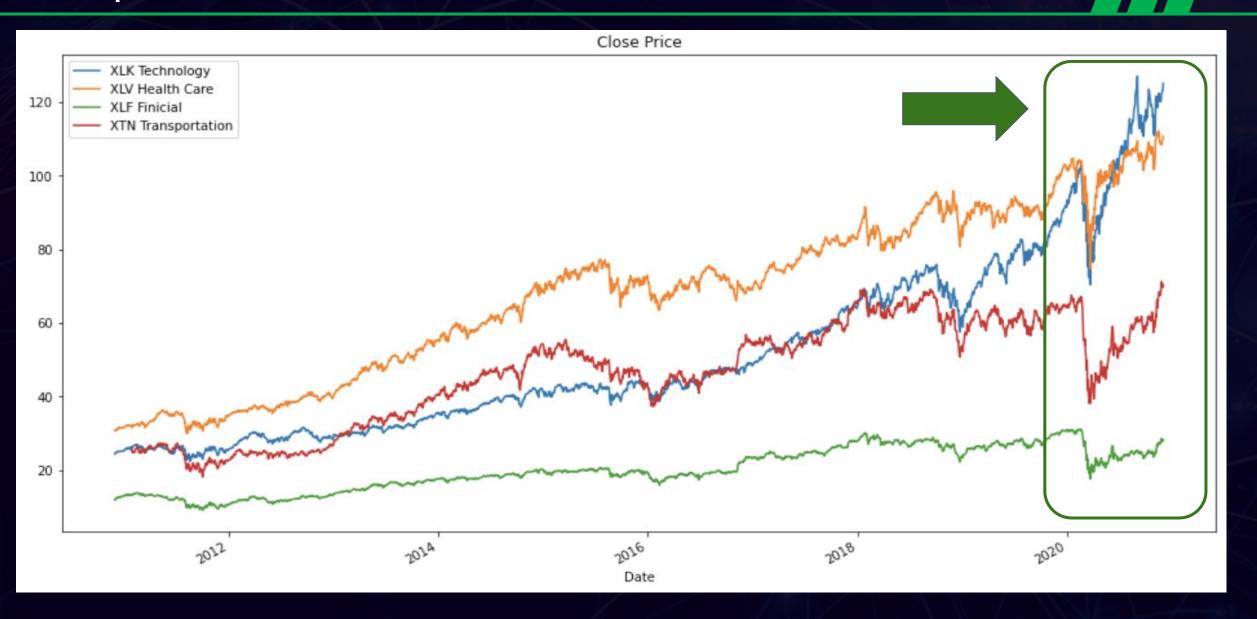


RMSE for testing set = 3.33

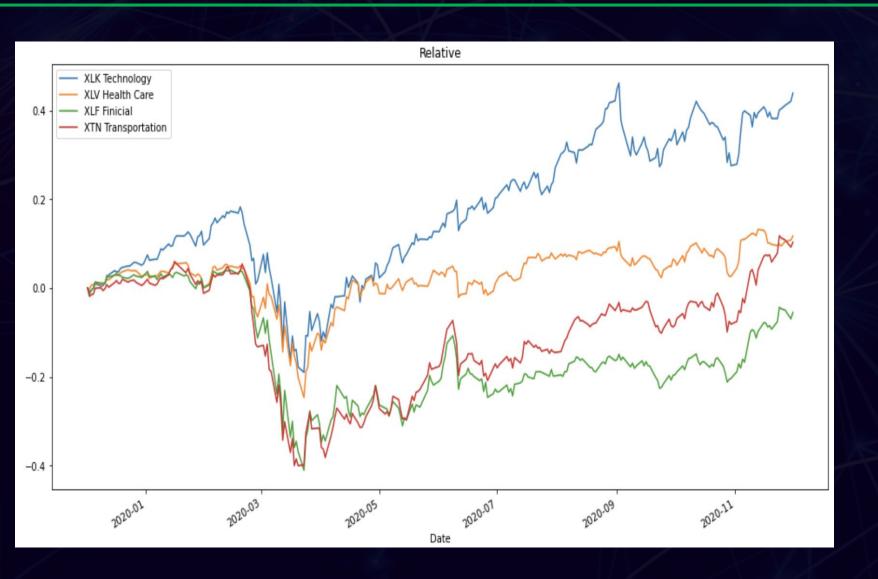




Sepecial Time Period: Covid-19 Period

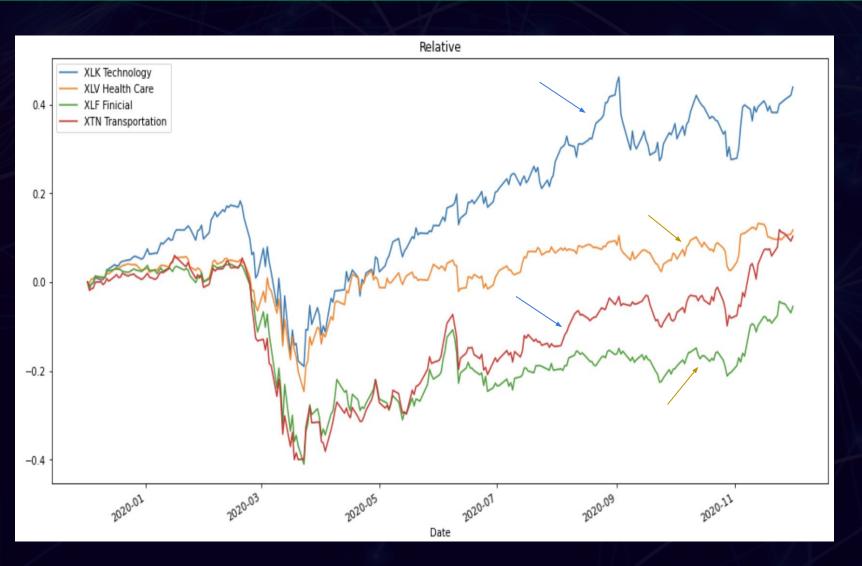


Relative Change in Covid-19 Period



- All sectors experienced precipitous declines in April, then gradually recovering.
- XLK:
 - One of the fastest to recover.
 - Returned to normal levels in July
 - Continuing to rise rapidly.
- XLV:
 - Fastest to return to the level before covid-19
 - Stay horizontal
- XLF:
 - o Recovery, but not much
- XTN:
 - Increase rapidly after July
 - Another quickly growth after November

Relationship Among Four Sectors

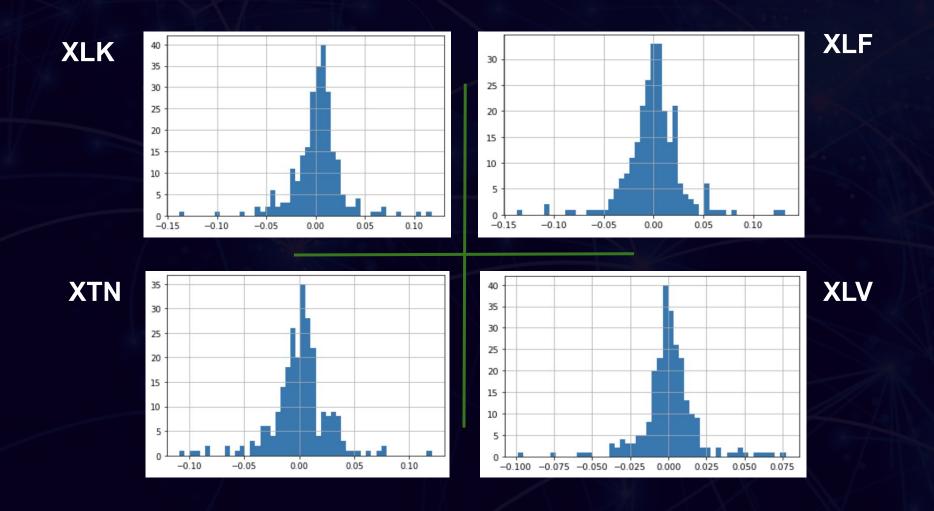


Pearson Correlation:

- XLK and XTN: 0.897
- XLV and XLF: 0.798

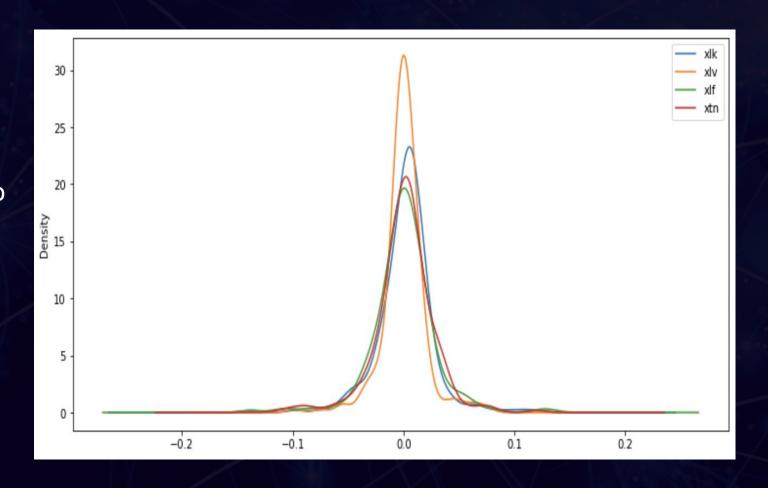
The relative change of XLK and XTN have strong correlation, so as XLV and XLF.

Daily Percentage Change in Covid-19 Period

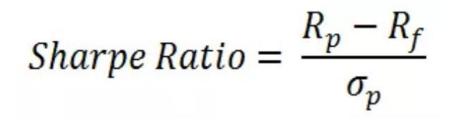


Daily Percentage Change in Covid-19 Period

- Most close price are unchanged
- The change percentage of XLV is the most concentrated
- XLF and XLK are really close to normal distribution
- XTN has more days with price decreasing
- XLV more days with price increasing.



Sharpe Ratio in Covid-19 Period



 R_p = Return of portfolio

R_f = Risk-Free rate

 σ_p = Standard deviation of portfolio's excess return

	Sharpe Ratio before Covid-19	Sharpe Ratio in Covid-19 Period
XLK	2.685	1.108
XLV	2.001	0.515
XLF	1.388	0.103
XTN	1.296	0.444

For every extra unit of risk, the premium that investor can get in covid-19 period is lower than previous years. However, the technology sector still managed to make a decent return this year.



Conclusion

- The mothod to predict stocks: LSTM
 - Basic structure of RNN
 - Basic structure of LSTM
 - Combine together and apply in data
 - Apple Inc
 - 4 sectors in S&P500: XLK, XLV, XLF, XTN
- Special time period: Covid-19
 - Relative change:
 - XLK increased fast after April. The stock price even higher than before.
 - XTN had an extremly rapid increase
 - The relative change of XLK and XTN have strong correlation, so as XLV and XLF
 - Correlation:
 - The relative change of XLK and XTN have strong correlation
 - The relative change of XLV and XLF have strong correlation
 - Daily percentage change:
 - Most investment are unchanged
 - XTN has more days with price decreasing
 - XLV more days with price increasing
 - Sharpe ratio:
 - The sharpe ratio in covid-19 is lower than normal
 - XLK is still the best choice

Conclusion

Suggestions for investors based on the project



- Technology sector is always the best choice.
- Health Care is the best choice for investors who want to invest in the lowest risk.
- Transcription has a rapid increase recently.
- Financial is slowly recovering.
- Stock prices can be predicted by LSTM algorithm.

Directions for the future work



- For each sector, detect which company is the best choice to invest.
- Studying stock market changes in recent years as all pandemics occur. It may contains some regularities.

