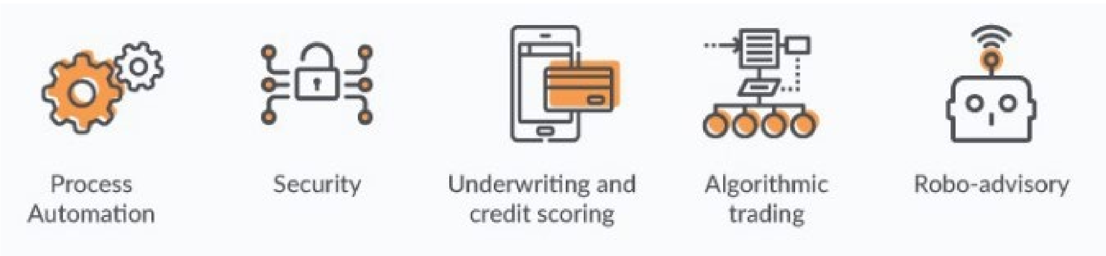
Application of Machine Learning / Deep Learning in Finance / Investment

Deep learning is a part of machine learning that learns data representations. Finance is money management. Deep learning in finance is the application of deep learning technologies in the finance field.

The application of machine learning / deep learning in the field of finance / investment is a hot topic in the fields of machine learning, neural networks and deep learning. There have been many relevant studies on how to correctly analyze past financial / investment activities and predict the future price / value of investment targets. This short story aims to introduce the application of machine learning / deep learning in finance / investment.

What?

* What financial application areas are of interest to DL community?



ML/DL Use Cases in finance

Financial / Invested Programmatic Trading and Decision Support Systems

There are many use cases in finance, but I will introduce the two main domain of the application of machine learning / deep learning in the field of finance / investment, and each of them corresponds to two major different schools of financial investment:

—1.1 Financial / invested programmatic trading

Financial / invested programmatic trading is based on the Trend Investment Methodology.They believe that *'Whatever has happened before will happen again. Whatever has been done before will be done again.'* They only care about prices and trends, not intrinsic values and current market valuations.

The trend investment methodology has also sometimes been named 'technology flow', which mainly focus on the research of the relation between past and future trend, the goal is the prediction of price. This investment genre believes that the price of financial products has fully reflected market expectations, and the use of past trends can effectively predict possible future trends. The most famous sentence we have ever heard is: ***'There's nothing new under the sun'***. This is mainly an investment / trading methodology based on trading psychology and analysis of various business trends.

The operation frequency of financial / investment program transactions is generally higher.

— 1.2 Decision Support Systems

Decision Support Systems is based on the Value Investment Methodology.

They believe that fundamental analysis can help to identify the value opportunities of stock in companies,such as trading at discounts to book value or tangible book value, those with high dividend yields, and those having low price-to-earning multiples, or low price-to-book ratios.They do not care about short-term prices and trends, and focus on the intrinsic value of the company, but buying and selling will also consider the current market valuation and other factors, aiming to buy when the market valuation is low (the safety margin is high), and When the market valuation is too high (too high to outrageously exceed its due value), they will sell and seek to buy the companies with lower valuations.

Value investing is an investment paradigm that involves buying securities that appear underpriced by some form of fundamental analysis. The various forms of value investing derive from the investment philosophy first taught by Benjamin Graham and David Dodd at Columbia Business School in 1928, and subsequently developed in their 1934 text Security Analysis.
High-profile proponents of value investing, including Berkshire

Hathaway chairman Warren Buffett, have argued that the essence of value investing is buying stocks at less than their intrinsic value.Hedge fund manager Seth Klarman has described value investing as rooted in a rejection of the efficient market hypothesis (EMH). While the EMH proposes that securities are accurately priced based on all available data, value investing proposes that some equities are not accurately priced.[1]

It does not directly operate transactions, but provides support for transaction decisions.

Why?

According to the author of the article “Deep Learning for Financial Applications: A Survey” (*source: https://arxiv.org/abs/2002.05786*):In the field of machine learning (ML), Numerous studies have been published resulting in various models.And deep learning (DL) has recently begun to receive Widely concerned, this is mainly due to its better performance than the classic model.[2]

The final output of a trading strategy should answer the following questions:

- DIRECTION:Identify is going rise of going down (or identify if an asset is cheap/expensive/fair value)
- ENTRY TRADE: Identify the timing of buy trade(or if an asset is cheap/expensive, should you buy/sell it)
- EXIT TRADE:Identify the timing of sell trade(or if an asset is fair priced and if we hold a position in that asset(bought or sold it earlier), should you exit that position)
- PRICE RANGE: Which price (or range) to make this trade at
- QUANTITY: Amount of capital to trade(example shares of a stock or percent of funding)

Machine Learning *or* Deep learning *can be* used to answer each of these questions---- both for **Financial / Invested Programmatic Trading** and **Decision Support Systems**.

In general, the more data you feed, the more accurate are the results in ML/DL. Coincidentally, there are huge datasets in the financial services industry,such as petabytes of data on transactions, customers, money transfers, news, reports.

How?

• Which ML/DL models are preferred (and more successful) in different applications?
• How do DL models pare against traditional soft computing / ML techniques?
• What is the future direction for DL research in Finance?
Our focus was on DL implementations for financial applications

- **Existing research on programmatic trading /Decision Support Systems and Machine Learning / Deep Learning**

In the Survey **"Deep Learning for Financial Applications: A Survey"**, they tried to provide a state-of-the-art snapshot of the developed DL models for financial applications, as of today. They not only categorized the works according to their intended subfield in finance but also analyzed them based on their DL models. In addition, they also aimed at identifying possible future implementations and highlighted the pathway for the ongoing research within the field.

And I will introduce other studies of the applications of ML/DL in the financial / investment field on similar topics, such as:

— Application of Deep Learning to Algorithmic Trading

— Stock market index prediction using artificial neural network

— Use of emerging technologies for investment in programmatic trading

— Machine Learning for day-trading

— Deep Learning-trading-hedge-funds

— The application of deep learning in foreign exchange trading

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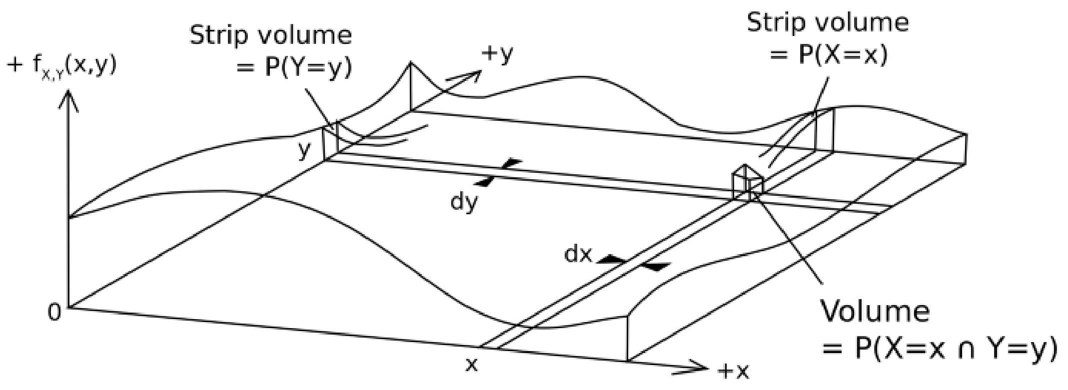
The basis of price prediction is probability theory and statistics,, one of the most important assumptions is the Bayers' theorem.

Bayes' theorem

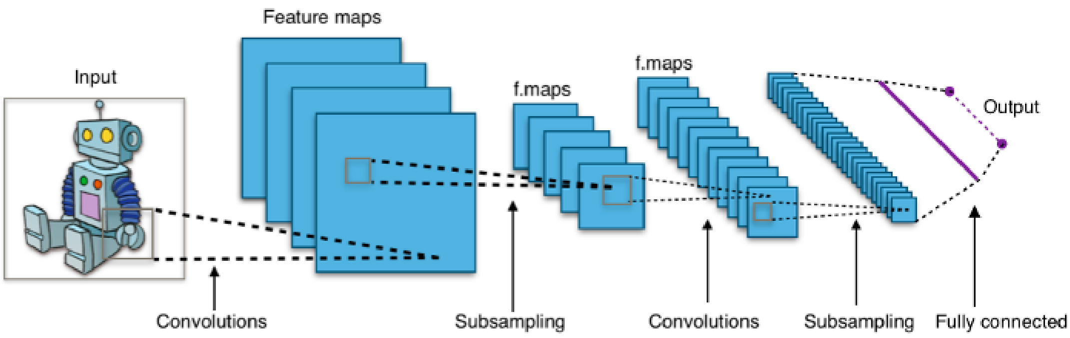
link: here



$$P(Y=y|X=x) = \frac{P(X=x \cap Y=y)}{P(X=x)} \qquad P(X=x|Y=y) = \frac{P(X=x \cap Y=y)}{P(Y=y)}$$

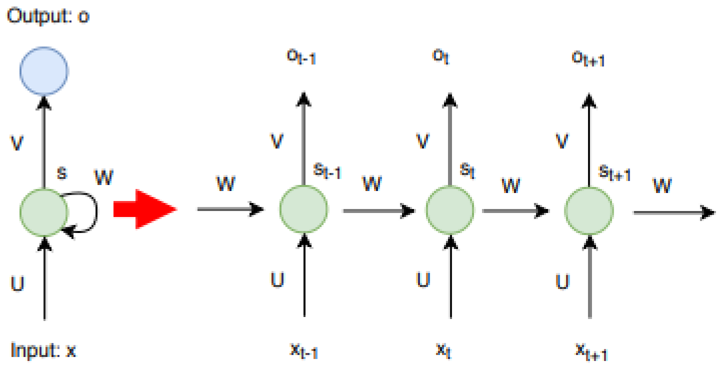
The proposed deep learning (DL) models that the source papers have used for their research.

- Convolutional neural network(CNN)



Typical CNN architecture

- Recurrent Neural Networks (RNN)

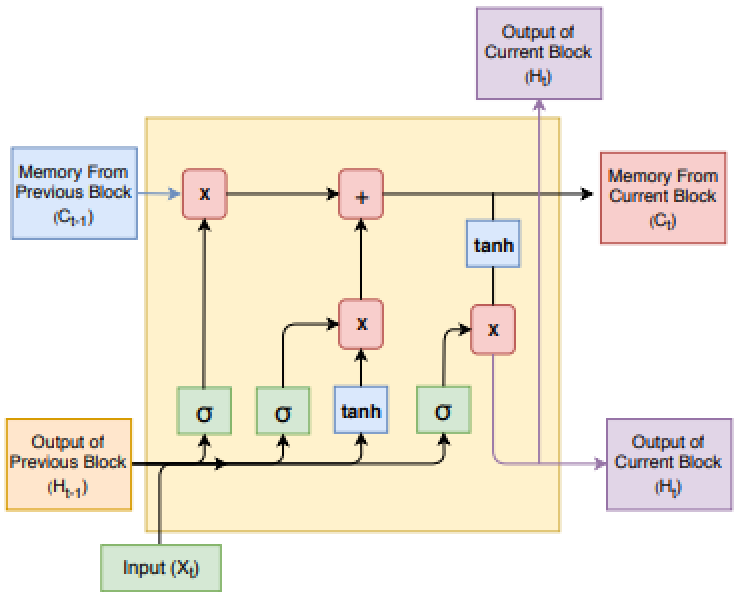


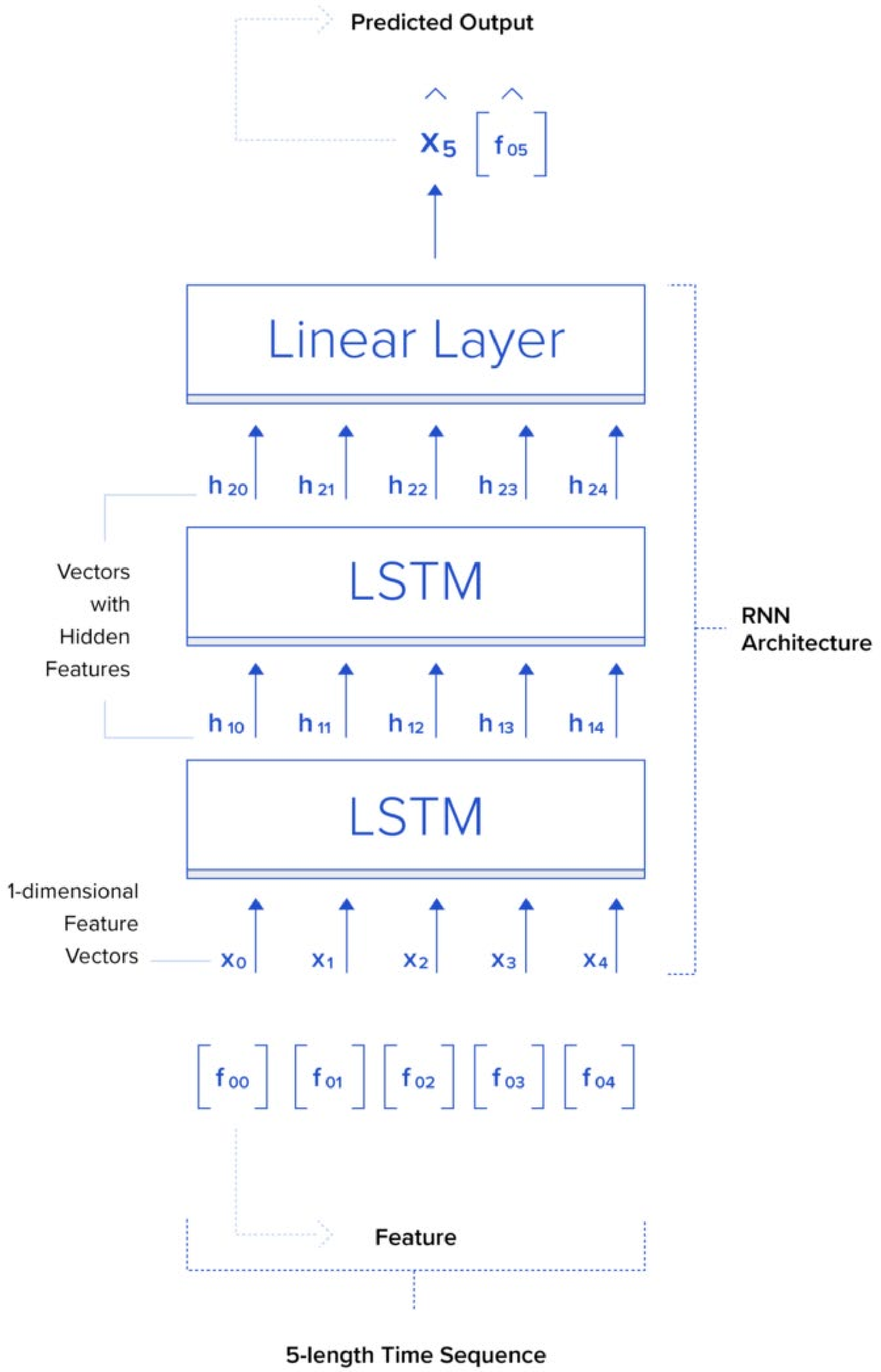
RNN

In contrast to feed-forward neural networks, in recurrent neural networks, data can flow in any direction. They can learn the time series dependency well.

- Long Short Term Memory (LSTM)

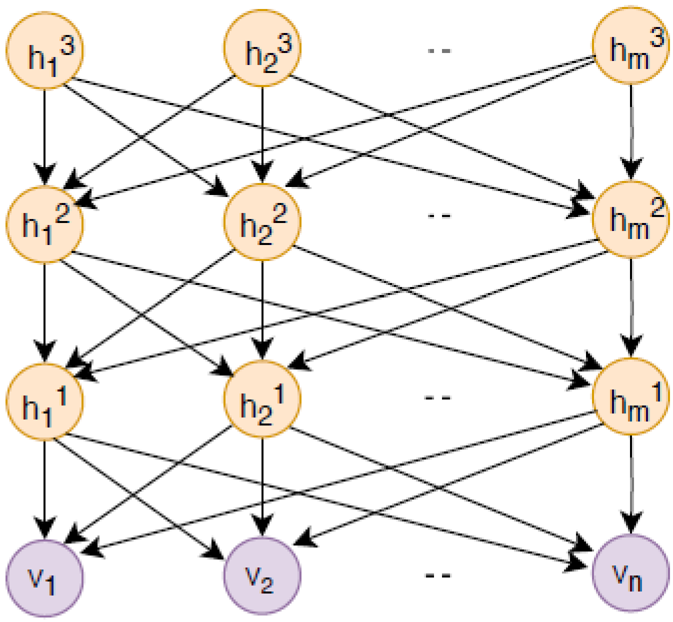
LSTM are also good at learning from sequential data, i.e. time series.




Predicted Output
$\hat{x}_5$ $[\hat{f}_{05}]$
Linear Layer
h_{20} h_{21} h_{22} h_{23} h_{24}
LSTM
Vectors with Hidden Features
RNN Architecture
h_{10} h_{11} h_{12} h_{13} h_{14}
LSTM
1-dimensional Feature Vectors
x_0 x_1 x_2 x_3 x_4
$[f_{00}]$ $[f_{01}]$ $[f_{02}]$ $[f_{03}]$ $[f_{04}]$
Feature
5-length Time Sequence

- Deep Belief Networks (DBNs)

DBN is a type of ANN that consists of a stack of RBM layers. DBN is a probabilistic generative model that consists of latent variables.



Deep Belief Networks (DBNs)

—**Algorithmic trading** is defined as buying and selling decisions made only by algorithms. These decisions can be based on simple rules, mathematical models, and the optimized process, or in the case of ML/DL. The most important role of algorithmic trading can overcome the aversion of human nature to loss (this will prevent traders from being difficult to operate when they should stop losses, and Algorithmic trading can avoid this) [1].

Table 1: Algo-trading Applications Embedded with Time Series Forecasting Models

Art.	Data Set	Period	Feature Set	Method	Performance Criteria	Environment
[35]	GarantiBank in BIST, Turkey	2016	OCHLV, Spread, Volatility, Turnover, etc.	PLR, Graves LSTM	MSE, RMSE, MAE, RSE, Correlation R-square	Spark
[36]	CSI300, Nifty50, HSI, Nikkei 225, S&P500, DJIA	2010-2016	OCHLV, Technical Indicators	WT, Stacked autoencoders, LSTM	MAPE, Correlation coefficient, THEIL-U	-
[37]	Chinese Stocks	2007-2017	OCHLV	CNN + LSTM	Annualized Return, Mxm Retracement	Python
[38]	50 stocks from NYSE	2007-2016	Price data	SFM	MSE	-
[39]	The LOB of 5 stocks of Finnish Stock Market	2010	FI-2010 dataset: bid/ask and volume	WMTR, MDA	Accuracy, Precision, Recall, F1-Score	-
[40]	300 stocks from SZSE, Commodity	2014-2015	Price data	FDDR, DNN+RL	Profit, return, SR, profit-loss curves	Keras
[41]	S&P500 Index	1989-2005	Price data, Volume	LSTM	Return, STD, SR, Accuracy	Python, TensorFlow, Keras, R, H2O
[42]	Stock of National Bank of Greece (ETE).	2009-2014	FTSE100, DJIA, GDAX, NIKKEI225, EUR/USD, Gold	GASVR, LSTM	Return, volatility, SR, Accuracy	Tensorflow
[43]	Chinese stock-IF-IH-IC contract	2016-2017	Decisions for price change	MODRL+LSTM	Profit and loss, SR	-
[44]	Singapore Stock Market Index	2010-2017	OCHL of last 10 days of Index	DNN	RMSE, MAPE, Profit, SR	-
[45]	GBP/USD	2017	Price data	Reinforcement Learning + LSTM + NES	SR, downside deviation ratio, total profit	Python, Keras, Tensorflow
[46]	Commodity, FX future, ETF	1991-2014	Price Data	DNN	SR, capability ratio, return	C++, Python
[47]	USD/GBP, S&P500, FTSE100, oil, gold	2016	Price data	AE + CNN	SR, % volatility, avg return/trans, rate of return	H2O
[48]	Bitcoin, Dash, Ripple, Monero, Litecoin, Dogecoin, Nxt, Namecoin	2014-2017	MA, BOLL, the CRIX returns, Euribor interest rates, OCHLV	LSTM, RNN, MLP	Accuracy, F1-measure	Python, Tensorflow
[49]	S&P500, KOSPI, HSI, and EuroStoxx50	1987-2017	200-days stock price	Deep Q-Learning, DNN	Total profit, Correlation	-
[50]	Stocks in the S&P500	1990-2015	Price data	DNN, GBT, RF	Mean return, MDD, Calmar ratio	H2O
[51]	Fundamental and Technical Data, Economic Data	-	Fundamental , technical and market information	CNN	-	-

Table 2: Classification (Buy-sell Signal, or Trend Detection) Based Algo-trading Models

Art.	Data Set	Period	Feature Set	Method	Performance Criteria	Environment
[52]	Stocks in Dow30	1997-2017	RSI	DMLP with genetic algorithm	Annualized return	Spark MLlib, Java
[53]	SPY ETF, 10 stocks from S&P500	2014-2016	Price data	FFNN	Cumulative gain	MatConvNet, Matlab
[54]	Dow30 stocks	2012-2016	Close data and several technical indicators	LSTM	Accuracy	Python, Keras, Tensorflow, TALIB
[55]	High-frequency record of all orders	2014-2017	Price data, record of all orders, transactions	LSTM	Accuracy	-
[56]	Nasdaq Nordic (Kesko Oyj, Outokumpu Oyj, Sampo, Rautaruukki, Wartsila Oyj)	2010	Price and volume data in LOB	LSTM	Precision, Recall, F1-score, Cohen's k	-
[57]	17 ETFs	2000-2016	Price data, technical indicators	CNN	Accuracy, MSE, Profit, AUROC	Keras, Tensorflow
[58]	Stocks in Dow30 and 9 Top Volume ETFs	1997-2017	Price data, technical indicators	CNN with feature imaging	Recall, precision, F1-score, annualized return	Python, Keras, Tensorflow, Java
[59]	FTSE100	2000-2017	Price data	CAE	TR, SR, MDD, mean return	-
[60]	Nasdaq Nordic (Kesko Oyj, Outokumpu Oyj, Sampo, Rautaruukki, Wartsila Oyj)	2010	Price, Volume data, 10 orders of the LOB	CNN	Precision, Recall, F1-score, Cohen's k	Theano, Scikit learn, Python
[61]	Borsa Istanbul 100 Stocks	2011-2015	75 technical indicators and OCHLV	CNN	Accuracy	Keras
[62]	ETFs and Dow30	1997-2007	Price data	CNN with feature imaging	Annualized return	Keras, Tensorflow
[63]	8 experimental assets from bond/derivative market	-	Asset prices data	RL, DNN, Genetic Algorithm	Learning and genetic algorithm error	-
[64]	10 stocks from S&P500	-	Stock Prices	TDNN, RNN, PNN	Missed opportunities, false alarms ratio	-
[65]	London Stock Exchange	2007-2008	Limit order book state, trades, buy/sell orders, order deletions	CNN	Accuracy, kappa	Caffe
[66]	Cryptocurrencies, Bitcoin	2014-2017	Price data	CNN, RNN, LSTM	Accumulative portfolio value, MDD, SR	-

Here some cases used text mining to extract information from the tweets and financial news and used LSTM, RNN, Gated-Recurrent Unit (GRU) for the generation of the trading signals.This could be part of **Decision Support Systems** too.

—**Risk Assessment:** Another study area that has been of interest to DL researchers is Risk Assessment which identifies the “riskiness” of any given asset, firm, person, product, bank, etc. Such as financial distress prediction to avoid choose the problem companies.This is part of **Decision Support Systems.**

Table 4: Credit Scoring or Classification Studies

Art.	Data Set	Period	Feature Set	Method	Performance Criteria	Env.
[77]	The XR 14 CDS contracts	2016	Recovery rate, spreads, sector and region	DBN+RBM	AUROC, FN, FP, Accuracy	WEKA
[78]	German, Japanese credit datasets	-	Personal financial variables	SVM + DBN	Weighted-accuracy, TP, TN	-
[79]	Credit data from Kaggle	-	Personal financial variables	DNN	Accuracy, TP, TN, G-mean	-
[80]	Australian, German credit data	-	Personal financial variables	GP + AE as Boosted DNN	FP	Python, Scikit-learn
[81]	German, Australian credit dataset	-	Personal financial variables	DCNN, MLP	Accuracy, False/Missed alarm	-
[82]	Consumer credit data from Chinese finance company	-	Relief algorithm chose the 50 most important features	CNN + Relief	AUROC, K-s statistic, Accuracy	Keras
[83]	Credit approval dataset by UCI Machine Learning repo	-	UCI credit approval dataset	Rectifier, Tanh, Maxout DL	-	AWS EC2, H2O, R

Risk Assessment

— **Portfolio Management** is the process of choosing various assets within the portfolio for a predetermined period.This could be part of **Financial / Invested Programmatic Trading** or **Decision Support Systems.**

Table 7: Portfolio Management Studies

Art.	Data Set	Period	Feature Set	Method	Performance Criteria	Env.
[66]	Cryptocurrencies, Bitcoin	2014-2017	Price data	CNN, RNN, LSTM	Accumulative portfolio value, MDD, SR	-
[127]	Stocks from NYSE, AMEX, NASDAQ	1965-2009	Price data	Autoencoder + RBM	Accuracy, confusion matrix	-
[128]	20 stocks from S&P500	2012-2015	Technical indicators	MLP	Accuracy	Python, Scikit Learn, Keras, Theano
[129]	Chinese stock data	2012-2013	Technical, fundamental data	Logistic Regression, RF, DNN	AUC, accuracy, precision, recall, f1, tpr, fpr	Keras, Tensorflow, Python, Scikit learn
[130]	Top 5 companies in S&P500	-	Price data and Financial ratios	LSTM, Auto-encoding, Smart indexing	CAGR	-
[131]	IBB biotechnology index, stocks	2012-2016	Price data	Auto-encoding, Calibrating, Validating, Verifying	Returns	-
[132]	Taiwans stock market	-	Price data	Elman RNN	MSE, return	-
[133]	FOREX (EUR/USD, etc), Gold	2013	Price data	Evolino RNN	Return	Python
[134]	Stocks in NYSE, AMEX, NASDAQ, TAQ intraday trade	1993-2017	Price, 15 firm characteristics	LSTM+MLP	Monthly return, SR	Python,Keras, Tensorflow in AWS
[135]	S&P500	1985-2006	monthly and daily log-returns	DBN+MLP	Validation, Test Error	Theano, Python, Matlab
[136]	10 stocks in S&P500	1997-2016	OCHLV, Price data	RNN, LSTM, GRU	Accuracy, Monthly return	Keras, Tensorflow
[137]	Analyst reports on the TSE and Osaka Exchange	2016-2018	Text	LSTM, CNN, Bi-LSTM	Accuracy, R^2	R, Python, MeCab
[138]	Stocks from Chinese/American stock market	2015-2018	OCHLV, Fundamental data	DDPG, PPO	SR, MDD	-
[139]	Hedge fund monthly return data	1996-2015	Return, SR, STD, Skewness, Kurtosis, Omega ratio, Fund alpha	DNN	Sharpe ratio, Annual return, Cum. return	-
[140]	12 most-volumed cryptocurrency	2015-2016	Price data	CNN + RL	SR, portfolio value, MDD	-

Portfolio selection and smart indexing were the main focuses of and using AE and LSTM networks.[2]

Asset Pricing and Derivatives Market (options, futures, forward contracts) could be a part of **Portfolio Management.**

Table 8: Asset Pricing and Derivatives Market Studies

Art.	Der.Type	Data Set	Period	Feature Set	Method	Performance Criteria	Env.
[137]	Stock exchange	Analyst reports on the TSE and Osaka Exchange	2016-2018	Text	LSTM, CNN, Bi-LSTM	Accuracy, R^2	R, Python, MeCab
[142]	Options	Simulated a range of call option prices	-	Price data, option strike/maturity, dividend/risk free rates, volatility	DNN	RMSE, the average percentage pricing error	Tensorflow
[143]	Futures, Options	TAIEX Options	2017	OCHLV, fundamental analysis, option price	MLP, MLP with Black scholes	RMSE, MAE, MAPE	-
[144]	Equity returns	Returns in NYSE, AMEX, NASDAQ	1975-2017	57 firm characteristics	Fama-French n-factor model DL	R^2,RMSE	Tensorflow

— **Cryptocurrency and Block chain Studies:**In recent years, there has also been some research on using deep learning to study the behavior of the Cryptocurrency market.As an early participant in the Cryptocurrency market, in my opinion, this market is very immature, the volatility is extremely large and the manipulation behavior is very serious. Participating in this transaction is actually no different from a casino. I' d suggest that only use a very small proportion of funds (such as 3% to 5%) to participate, perhaps this market may reach a very high price, or it may return to zero, it is not worth using deep learning algorithms to research.In this part, my opinion is far different from the opinion of the *Survey*.

— Other Studies:**Financial Sentiment Analysis and Behavioral Finance,Financial Text Mining,Theoretical or Conceptual Studies…**

This could be part of any of **Financial / Invested Programmatic Trading** or **Decision Support Systems** .

Table 10: Financial Sentiment Studies coupled with Text Mining for Forecasting

Art.	Data Set	Period	Feature Set	Method	Performance Criteria	Env.
[137]	Analyst reports on the TSE and Osaka Exchange	2016-2018	Text	LSTM, CNN, Bi-LSTM	Accuracy, R^2	R, Python, MeCab
[150]	Sina Weibo, Stock market records	2012-2015	Technical indicators, sentences	DRSE	F1-score, precision, recall, accuracy, AUROC	Python
[151]	News from Reuters and Bloomberg for S&P500 stocks	2006-2015	Financial news, price data	DeepClue	Accuracy	Dynet software
[152]	News from Reuters and Bloomberg, Historical stock security data	2006-2013	News, price data	DNN	Accuracy	-
[153]	SCI prices	2008-2015	OCHL of change rate, price	Emotional Analysis + LSTM	MSE	-
[154]	SCI prices	2013-2016	Text data and Price data	LSTM	Accuracy, F1-Measure	Python, Keras
[155]	Stocks of Google, Microsoft and Apple	2016-2017	Twitter sentiment and stock prices	RNN	-	Spark, Flume,Twitter API,
[156]	30 DJIA stocks, S&P500, DJI, news from Reuters	2002-2016	Price data and features from news articles	LSTM, NN, CNN and word2vec	Accuracy	VADER

Table 11: Text Mining Studies without Sentiment Analysis for Forecasting

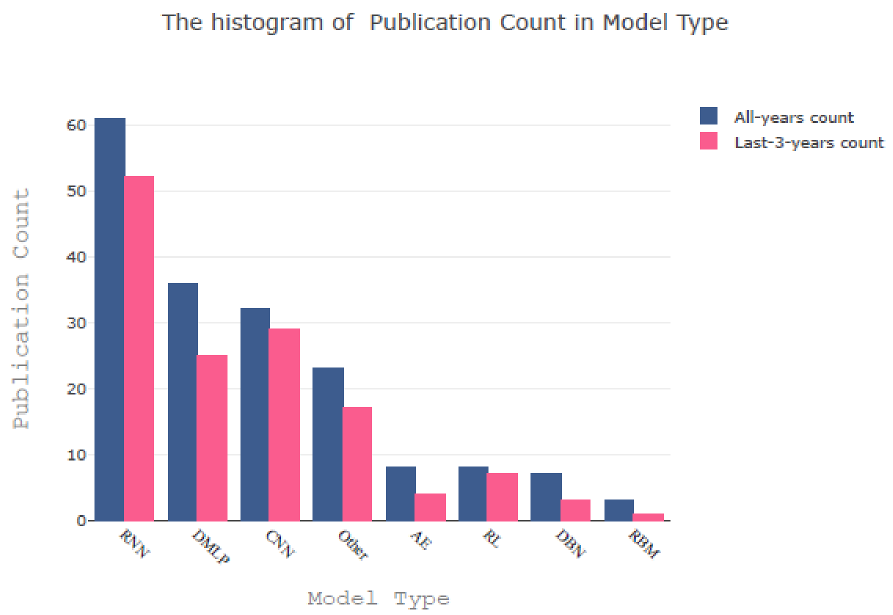
Art.	Data Set	Period	Feature Set	Method	Performance Criteria	Env.
[69]	Energy-Sector/ Company-Centric Tweets in S&P500	2015-2016	Text and Price data		Return, SR, precision, recall, accuracy	Python, Tweepy API
[165]	News from Reuters, Bloomberg	2006-2013	Financial news, price data	Bi-GRU	Accuracy	Python, Keras
[166]	News from Sina.com, ACE2005 Chinese corpus	2012-2016	A set of news text	Their unique algorithm	Precision, Recall, F1-score	-
[167]	CDAX stock market data	2010-2013	Financial news, stock market data	LSTM	MSE, RMSE, MAE, Accuracy, AUC	TensorFlow, Theano, Python, Scikit-Learn
[168]	Apple, Airbus, Amazon news from Reuters, Bloomberg, S&P500 stock prices	2006-2013	Price data, news, technical indicators	TGRU, stock2vec	Accuracy, precision, AUROC	Keras, Python
[169]	S&P500 Index, 15 stocks in S&P500	2006-2013	News from Reuters and Bloomberg	CNN	Accuracy, MCC	-
[170]	S&P500 index news from Reuters	2006-2013	Financial news titles, Technical indicators	SI-RCNN (LSTM + CNN)	Accuracy	-
[171]	10 stocks in Nikkei 225 and news	2001-2008	Textual information and Stock prices	Paragraph Vector + LSTM	Profit	-
[172]	NIFTY50 Index, NIFTY Bank/Auto/IT/Energy Index, News	2013-2017	Index data, news	LSTM	MCC, Accuracy	-
[173]	Price data, index data, news, social media data	2015	Price data, news from articles and social media	Coupled matrix and tensor	Accuracy, MCC	Jieba
[174]	HS300	2015-2017	Social media news, price data	RNN-Boost with LDA	Accuracy, MAE, MAPE, RMSE	Python, Scikit-learn
[175]	News and Chinese stock data	2014-2017	Selected words in a news	HAN	Accuracy, Annual return	-
[176]	News, stock prices from Hong Kong Stock Exchange	2001	Price data and TF-IDF from news	ELM, DLR, PCA, BELM, KELM, NN	Accuracy	Matlab

Table 15: Other Financial Applications

Art.	Subtopic	Data Set	Period	Feature Set	Method	Performance Criteria	Env.
[49]	Improving trading decisions	S&P500, KOSPI, HSI, and EuroStoxx50	1987-2017	200-days stock price	Deep Q-Learning and DNN	Total profit, Correlation	-
[193]	Identifying Top Sellers In Underground Economy	Forums data	2004-2013	Sentences and keywords	Recursive neural tensor networks	Precision, recall, f-measure	-
[195]	Predicting Social Ins. Payment Behavior	Taiwan's National Pension Insurance	2008-2014	Insured's id, area-code, gender, etc.	RNN	Accuracy, total error	Python
[199]	Speedup	45 CME listed commodity and FX futures	1991-2014	Price data	DNN	-	-

RNN(LSTM),CNN should be the main methods.

Also, it is worth to mention that the few papers that were published before 2013 all used RNN based models.



As shown above, we can see that the advantages of RNN, DMLP and CNN on the remaining models, because these models are the most commonly used models in general DL implementation. At the same time, RNN is a universal umbrella model with multiple versions Including LSTM, GRU, etc. In RNN selection, most models actually belong to LSTM, which is very popular in time series prediction or regression problems. Also It is often used in algorithmic trading. Over 70% of RNN papers include LSTM model.

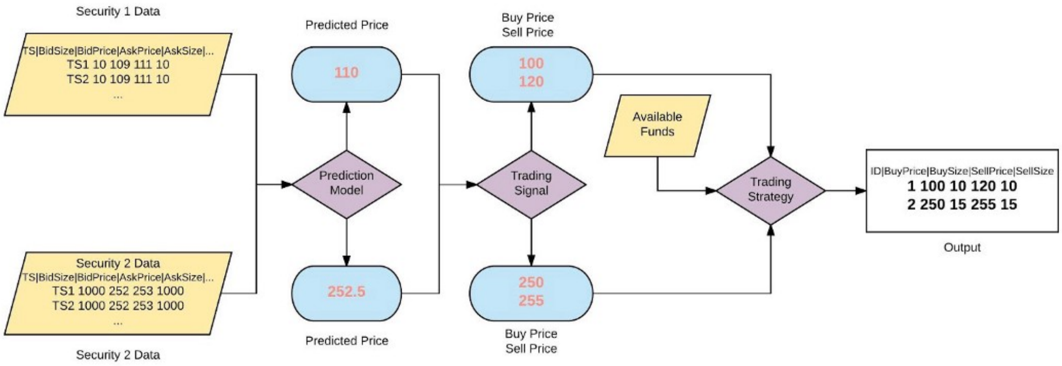
When developing DL solutions, we should use Occam’s razor principle, which means that it is not too complicated. In fact, most companies targeting ML / DL need to focus on data / features engineering and apply statistical data to the original data.[6]

The **hybrid model** is preferred to go beyond the native model for better achievements. Many researchers configure topology and network parameters to achieve higher performance.

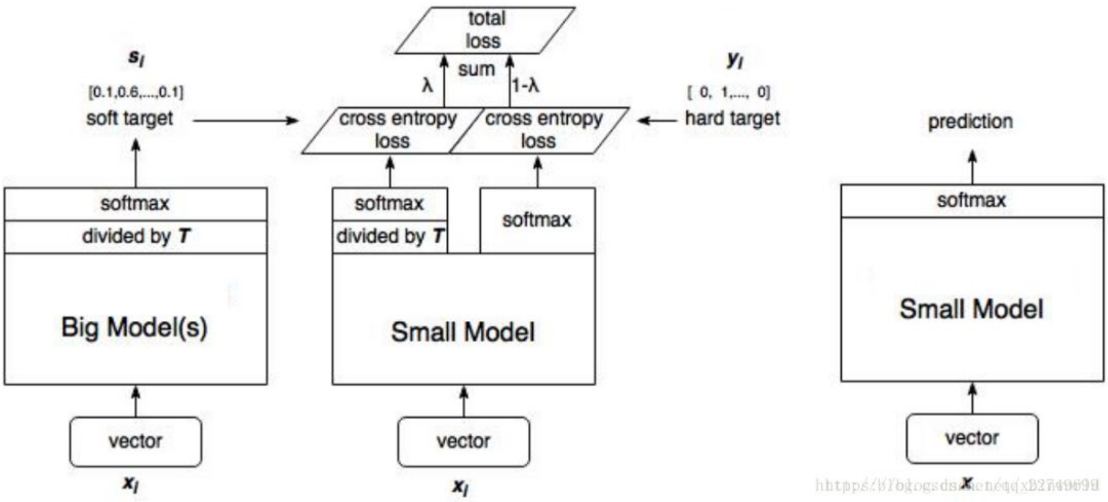
* [How to develop a trading strategy?]

There are Various difficulties

- Scaling data to train the deep network.
- Deciding on appropriate network architecture.
- Tuning the hyperparameters of the network and optimization algorithm.
- Dozens hyperparameters that affect the model.
- Cost function.
- Market data tends to be non-stationary
- Little signal in historical market data with respect to the future direction of the market.



How to develop a trading strategy?

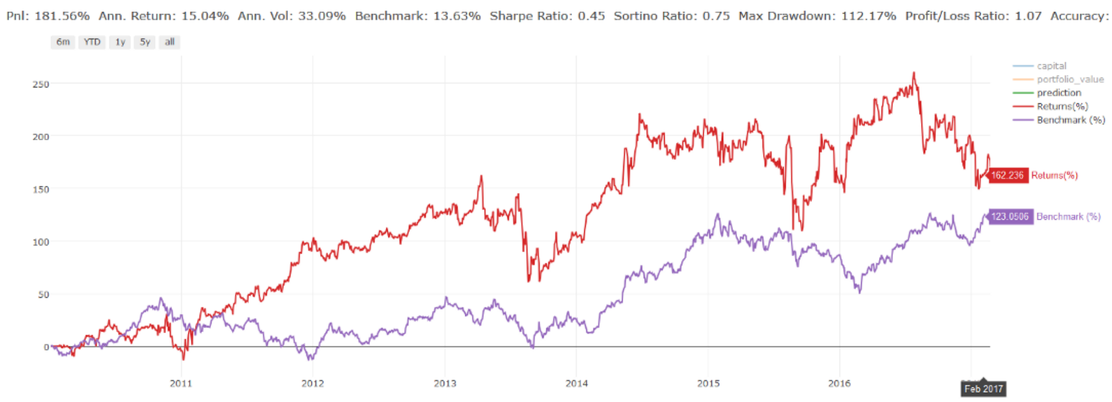


Distilling the Knowledge in a Neural Network

How do you compare different systems? Some back-tester provides you with the following metrics to quantify your system’ s performance. These set of metrics are not exhaustive, but they’ re a good place to start:

1. Total Return
2. Annualized Return
3. Annualized Volatility
4. Sharpe Ratio
5. Sortino Ratio
6. Maximum Drawdown
7. % Profitability
8. Profit Factor

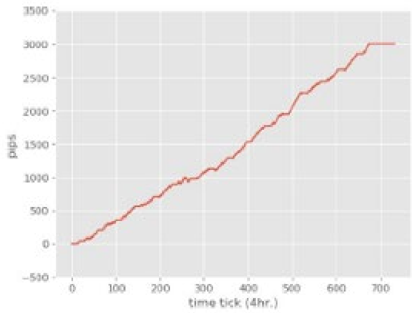
You can read in detail about them [here](#).



Sample of Backtesting Resul

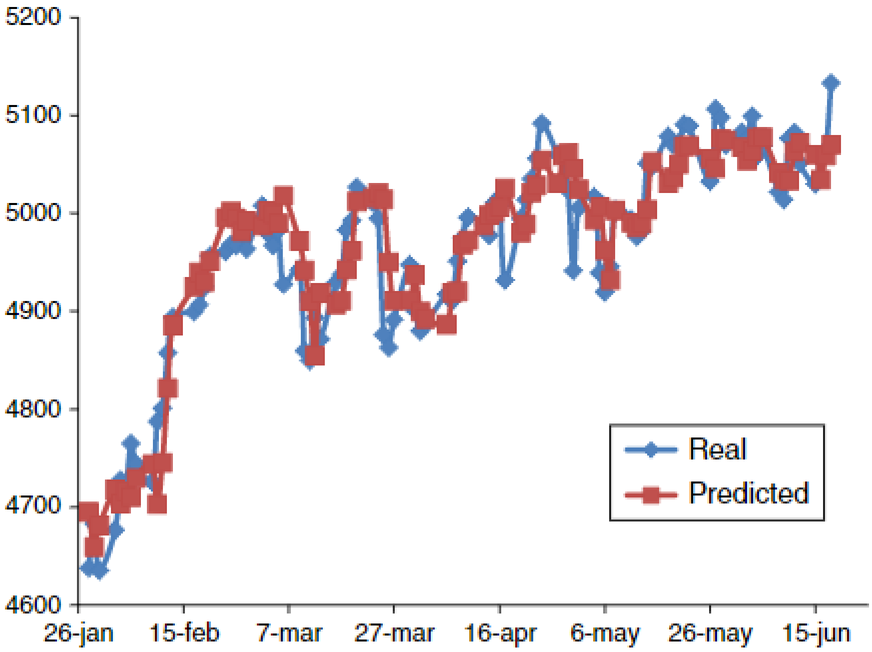
- **Performance of DL in finance:**

The improvements are most notable in trend prediction based algo-trading implementations and text-mining studies due to deeper and/or more versatile networks and new innovative model developments. This is also reflected through the increasing number of published papers year over year.



Total Trades	Win Trades	Lose Trades
916	786	130
Net Profit	Profit Factor	Max Drawdown
3006	2.91	-2.00%

[Deep Reinforcement Learning for Foreign Exchange Trading](#) performance table



simple

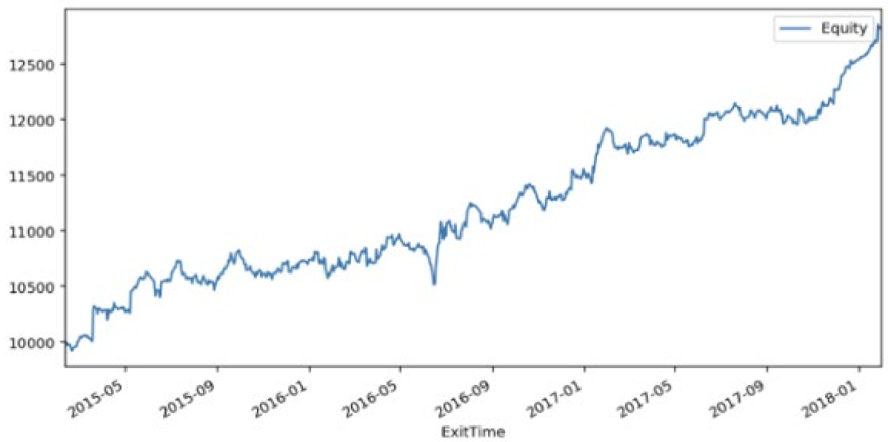
Fig. 6: Cumulative daily return of the Buy-and-Hold (blue line), the LSTM-based (green), and the LWR-based (red line) strategies.

ANN predicted

Performance Report

	All	Long	Short
Net P&L	2,830.20	2,230.50	599.70
Gross Profit	11,093.50	7,011.20	4,082.30
Gross Loss	-8,263.30	-4,780.70	-3,482.60
Profit Factor	1.34	1.47	1.17
Total # of Trades	771.00	459.00	312.00
Number Winning Trades	425.00	252.00	173.00
Number Losing Trades	346.00	207.00	139.00
Percent Profitable	0.55	0.55	0.55
Avg Trade Win Loss	3.67	4.86	1.92
Avg Winning Trade	26.10	27.82	23.60
Avg Losing Trade	-23.88	-23.10	-25.05
Ratio Avg Win Loss	1.09	1.20	0.94
Largest Winning Trade	275.50	275.50	165.30
Largest Losing Trade	-156.10	-156.10	-151.10
Opened P&L	0.00	0.00	0.00

Equity Curve

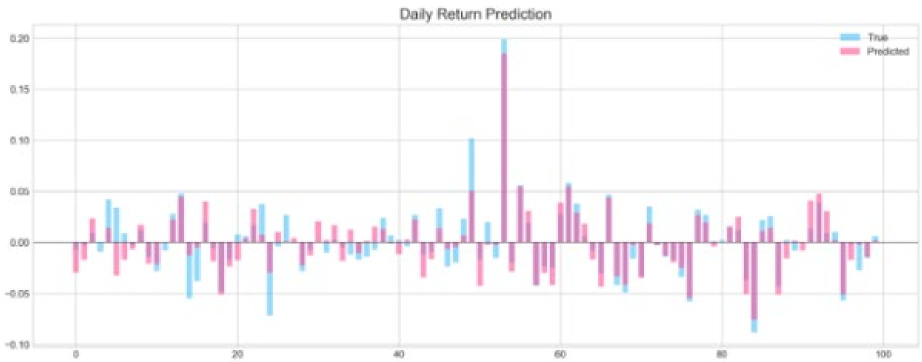


Deep Learning for Forex Trading

It seems very exciting from the above introduction.

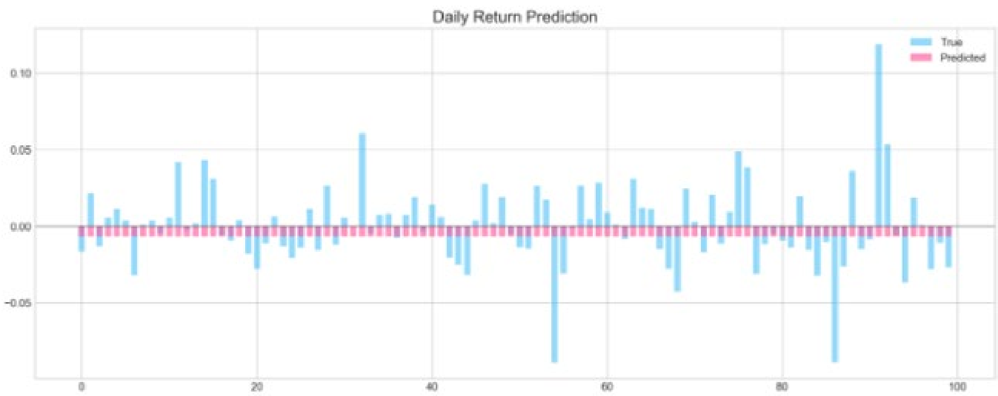
But...

Sometimes, [DL network was prone to overfitting in short-time], meaning it learned patterns in the train data very well but failed to make any meaningful predictions on test data. Accuracy was as good as a random guess.



Overfitting (Accuracy: 80%)

DL network was prone to overfitting in predicting the next day/week price



And…

YOU NEVER KNOWN!

Over the years, the Black Swan incident has occurred from time to time.

In March and April 2020, we witnessed an extreme market that has never appeared in the history of investment, even Warren Buffett, who is already 90 years old never saw that.

It' s really as long as you live long enough to continue to witness history, such as ***Three times a week Fuse and Negative oil prices***.

Therefore, none of the above algorithms and models can handle such small probability events. If the position is not properly controlled, it will bring disastrous consequences, but if you keep the position at a low level, it is likely that you will not be able to obtain sufficient returns in the long run.

Negative crude oil futures prices that have never happened in history@April 20th 2020

Market summary >

SPDR S&P 500 ETF Trust

NYSEARCA: SPY

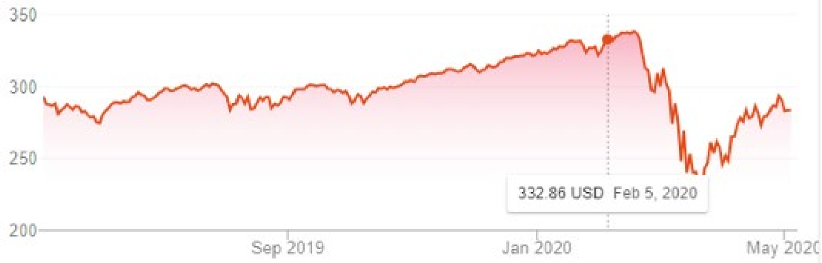
Following

Overview Compare

283.57 USD +0.78 (0.28%) ↑

May 4, 8:00 PM EDT · Disclaimer

1 day | 5 days | 1 month | 6 months | YTD | **1 year** | 5 years | Max



Open	280.46	Div yield	2.04%
High	283.90	Prev close	282.79
Low	279.14	52-wk high	339.08
Mkt cap	255.42B	52-wk low	218.26
P/E ratio	-		

Market summary >

Dow Jones Industrial Average

INDEXDJX: .DJI

+ Follow

Overview News Compare

23,749.76 +26.07 (0.11%) ↑

May 4, 5:22 PM EDT · Disclaimer

1 day 5 days 1 month 6 months YTD 1 year 5 years Max

Open	23,581.55	Low	23,361.16
High	23,769.56		

Market summary >

Nasdaq Composite

INDEXNASDAQ: .IXIC

+ Follow

Overview News Compare

8,710.72 +105.77 (1.23%)

May 4, 5:15 PM EDT · Disclaimer

1 day 5 days 1 month 6 months YTD 1 year 5 years Max

Open	8,555.32	Low	8,537.83
High	8,715.82		

Market summary >

S&P 500 Index

INDEXSP: .INX

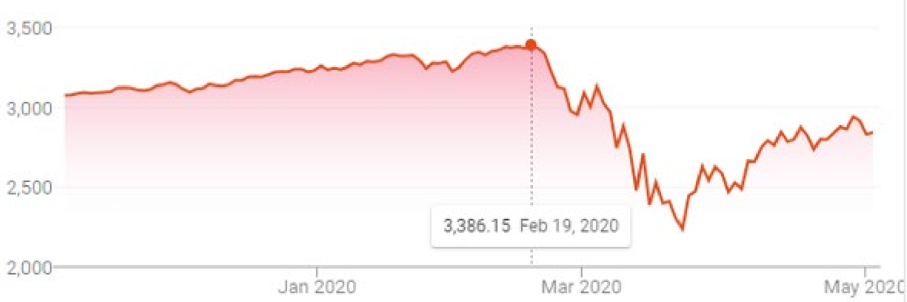
+ Follow

Overview News Compare

2,842.74 +12.03 (0.42%) ↑

May 4, 5:22 PM EDT · Disclaimer

1 day 5 days 1 month 6 months YTD 1 year 5 years Max



Open	2,815.01	Low	2,797.85
High	2,844.24		

Market summary >

Nasdaq Composite

INDEXNASDAQ: .IXIC

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Overview News Compare

8,710.72 +105.77 (1.23%) ↑

May 4, 5:15 PM EDT · Disclaimer

1 day 5 days 1 month 6 months YTD 1 year 5 years Max

Open	8,555.32	Low	8,537.83
High	8,715.82		

The existence of irrational traders makes price bubbles inevitable, and sometimes causes various tramples due to excessive panic in the market.

“In the capital market, anything bizarre can happen. All you have to do is handle your own affairs, and strive to survive when the most bizarre events happen.

—The time the market remains irrational may continue until you go bankrupt.’

Conclusion

- Financial text mining, Algo-trading, risk assessments, sentiment analysis, portfolio management and fraud detection are the most studied areas of finance research.
-Behavioral finance and derivatives market have promising potentials for research.
- RNN based models (in particular LSTM), CNN and DMLP have been used extensively in implementations. LSTM is more successful and preferred in time-series forecasting, while DMLP and CNN are better suited to applications requiring classification.

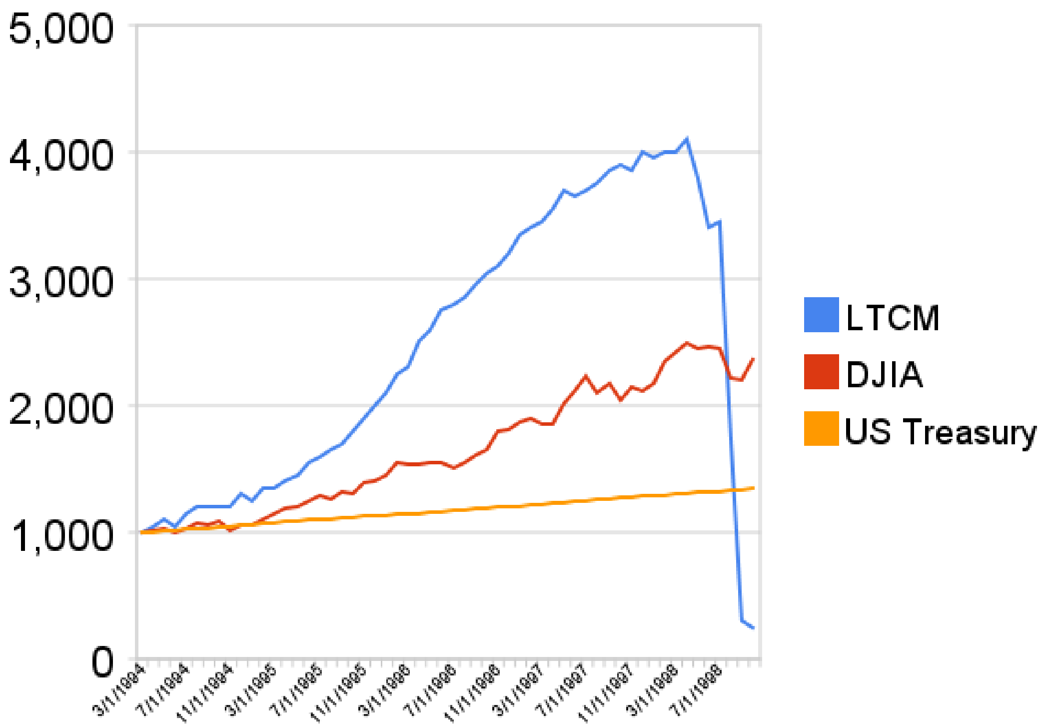
A**part from god and scammers, no one can predict the short-term trend of the stock, even with the help of high-tech technologies such as machine learning and deep learning.**

Of course, some investors and some trading strategies will perform better in a short period of time, such as those on the Las Vegas roulette table, some gamblers can win. But we believes that past performance is not indicative of future results, simple forecasters still cannot beat the market in the long run.

A crucial issue in investment activities: **Certainty.**

The lower the certainty, the less money can be used to participate. Once this principle is violated, it may be eliminated in a small probability event.

The fact is that the stock market is a very complex system, and historical data alone is not enough to explain its behavior. Machine learning and deep learning algorithms sometimes treat short-term historical data as random walks or white noise, but they are indeed important and sometimes produce terrible results (see Resources, *the story of long-term capital Management company*). Fundamental analysis, Twitter analysis, news analysis, local / global economic analysis-things like this have the potential to improve forecasts.



The value of $1,000 invested in LTCM, the Dow Jones Industrial Average and invested monthly in U.S. Treasuries at constant maturity. LTCM was founded in 1994 by John Meriwether, the former vice-chairman and head of bond trading at Salomon Brothers. Members of LTCM's board of directors included Myron S. Scholes and Robert C. Merton, who shared the 1997 Nobel Memorial Prize in Economic Sciences for a "new method to determine the value of derivatives".

Initially successful with annualized return of over 21% (after fees) in its first year, 43% in the second year and 41% in the third year, in 1998 it lost $4.6 billion in less than four months due to a combination of high leverage and exposure to the 1997 Asian financial crisis and 1998 Russian financial crisis.[12]

Only long-term research and the use of technology to better understand the company can make your financial activities /

investments obtain long-term and effective returns. **After all, in the long run, the stock market will always be slightly higher than inflation.**

Market summary >

S&P 500 Index

INDEXSP: .INX

+ Follow

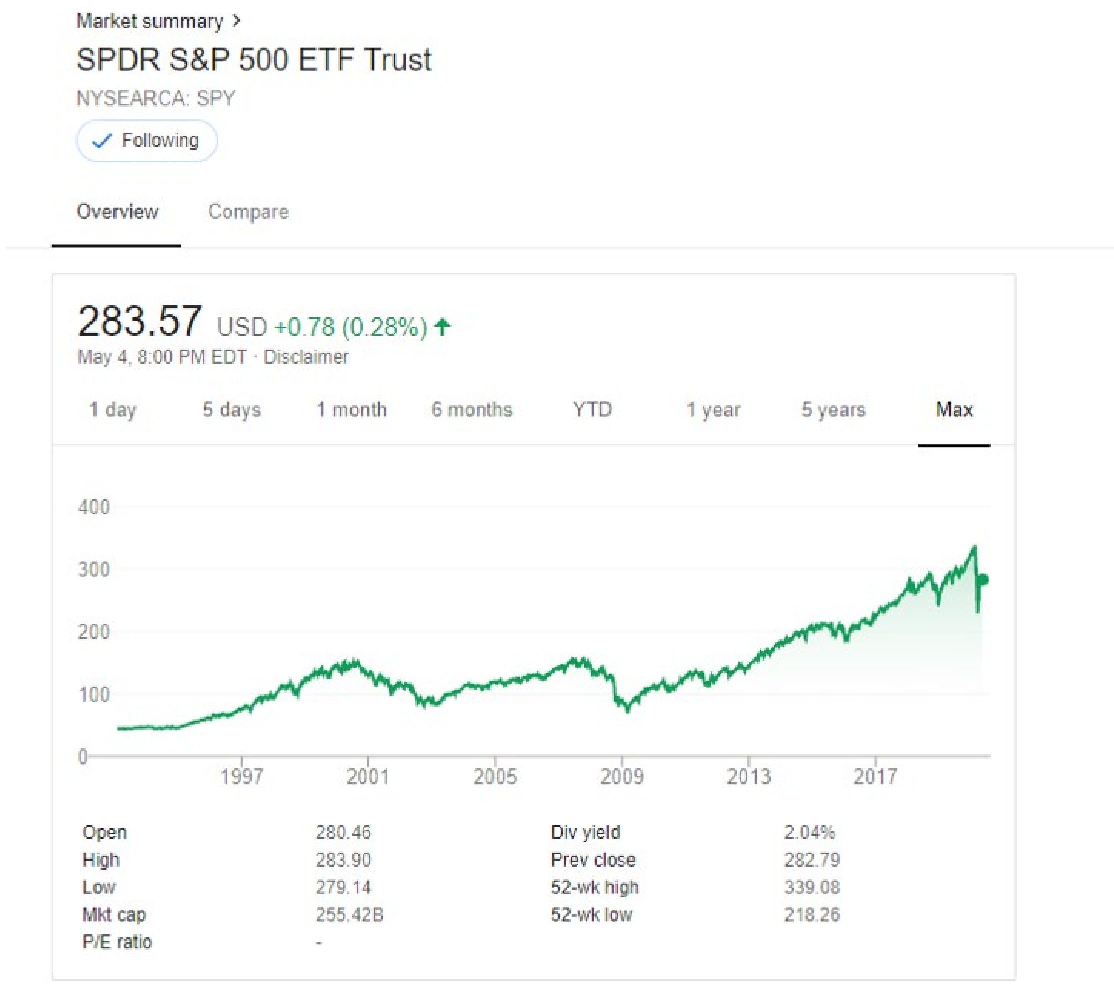
Overview News Compare

2,842.74 +12.03 (0.42%)

May 4, 5:22 PM EDT · Disclaimer

1 day 5 days 1 month 6 months YTD 1 year 5 years Max

Open	2,815.01	Low	2,797.85
High	2,844.24		



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