# Capstone project: Developing Multi Agent System for cryptocurrency trading at NUS Fintech Lab

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Naoya Ohara, CFA, CAIA
A0197178L, Candidate NUS Master of computing

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# Section 1: Fintech lab capstone internship roadmap.

# Checking, sharing, and confirming our goal and the positioning of this summer internship at Fintech lab.


- Vison of Fintech lab:
  - Make positive impact to the society by enabling everyone to touch, feel, and apply FinTech, and truly understand its potential at the tip of their fingers.
- Near term important milestone of Fintech lab:
  - Launch physical lab on Feb 2022.
  - Need showcases toward the launch of physical lab, to attract both financial institutes / Fintech companies and students who are interested in Fintech lab.
- Multi Agent System (MAS) of cryptocurrencies trading:
  - It will become one of the showcases mentioned above.
  - Ohara’s part in this summer internship.

Source: NUS Fintech lab, Naoya Ohara

# Ohara’s part of summer internship this time.

- Multi Agent Systems(Naoya): From Fintech lab needs, Mr. Shashank’s memo.
  - 1.Plan out the design of MAS for algotrading
  - 2.Inspiration from IS5006 class projects
  - 3.Integration of Python, Google sheets, Zapier, Hitbtc exchange and Dashboards
  - 4.To be deployed in inhouse exchange
  - 5.Real time visualization of portfolio performance by MAS

- Requirement from MComp General Track:
  - **4 months, fulltime:** 4 months of full-time internship as capstone project.
  - **Master course level:** It is the capstone internship that the NUS MComp requires students to complete for the graduation, such that the subject of internship should be enough high in its level, suitable as the master course. Ohara believes that the above project, i.e. the continuous work from IS5006, the elective course in MComp, must be eligible as MComp’s capstone project. But we need the approval from the MComp program director.
  - **Before project:** Submit pdf file of documentation that states the scope of the internship to MComp, and get approval from MComp program director, prof. Teo Yong Meng.
  - **At the end of internship:** Report the completion and outcome of the project.

Source: NUS Fintech Lab, Naoya Ohara

# Roadmap of summer internship at Fintech lab this time.

## Plan

❑ May 10-14:
- ➢ Understand Fintech lab.
- ➢ Set goal and scope of the project.
- ➢ Create overall plan for the 4 months of project.

## Analyze

❑ May 17-31:
- ➢ Create database of literatures / reference papers.
- ➢ Literature review.

## Implementation

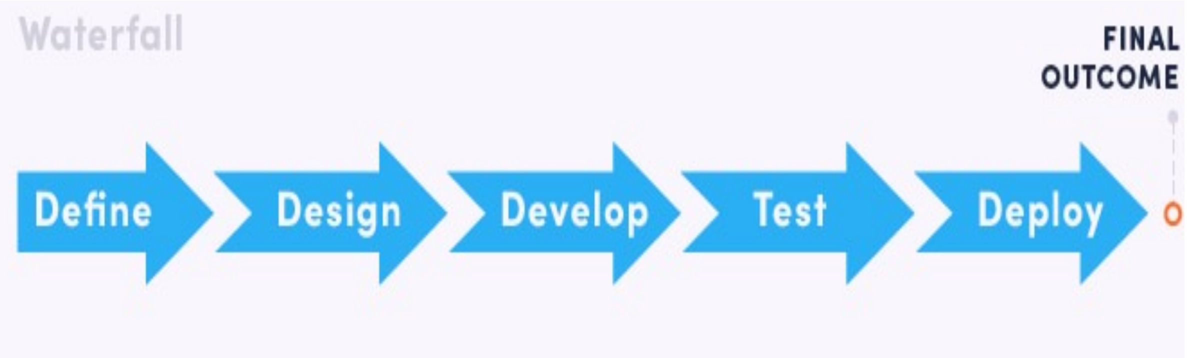
❑ June 1-Aug 20:
- ➢ Code review from the final project deliverables of IS5006 students.
- ➢ Define the requirement of system.
- ➢ Develop by agile approach. Implement from the simple functions with small scale, then make the system larger.
- ➢ Integrate SQL data library.
- ➢ (Implemented ad-hoc project such as Bank app development.)

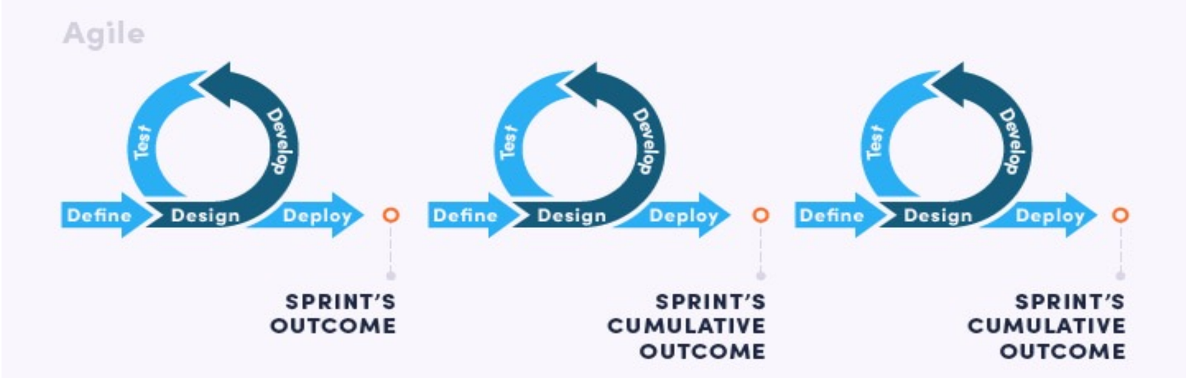
## Closing

❑ Aug 20 - Sept 13:
- ➢ Finalize the deliverable.
- ➢ Write final report and presentation.
- ➢ Other closing tasks.

Source: NUS Fintech Lab, Naoya Ohara

# Methodology of development: Agile development.



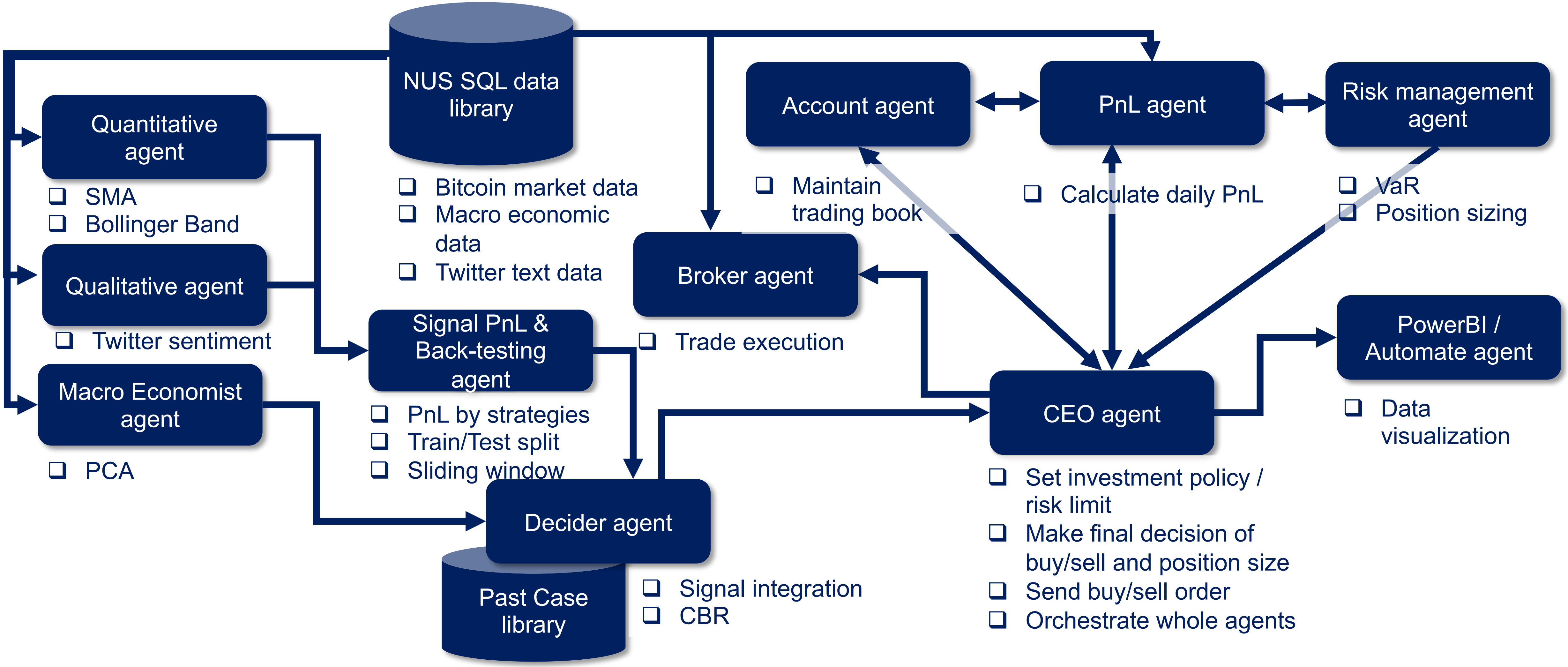

- Waterfall development:
  - Cascading from literature review -> planning -> design -> code review -> coding -> testing.
  - Good for large scale of projects.
  - Good for the project that we can finalize the system completely before the project.
  - But not efficient in small size of project which needs the flexibility and in which the time is limited.
  - The risk of stopping at uncompleted implementation when Ohara leaves on Sept.

- Agile development:
  - Starting from creating small prototype with simple functions.
  - Doing small baches of define, design, develop, test, deploy, iterating many cycles of those processes.
  - Good for flexible development by small team.
  - We can assure that at least we have some working codes, when Ohara leaves on Sept.

Source: https://selleo.com/blog/agile-software-development-process-everything-you-need-to-know, Naoya Ohara

# Section 2: System architecture of MAS.

# System architecture.




Source: NUS Fintech Lab, Naoya Ohara

# Brief explanation of each agent.

- Account agent:
  - Account agent launches and manages account book data i.e. buy/sell transaction data, PnL data, and Net Asset Value (NAV) data etc.

- Broker agent:
  - It establishes the connection with market data. Also, it enables the buy/sell trading execution..

- Quantitative signaling agent:
  - It recommends buy and sell decisions based on simple moving average (SMA) and bollinger band.

- Qualitative signaling agent:
  - It acquires and analyzes twitter text regarding bitcoin from major news sources and influential person's accounts (e.g. I picked Elon Musk who often mentions bitcoin), utilizing natural language processing (NLP). Then, the system converts the results from NLP into sentiment indicators then buy and sell recommendations using fuzzy logic.

Source: NUS Fintech Lab, Naoya Ohara

# (Contd.) Brief explanation of each agent.

- Macro Economist agent:
  - Also, to understand market circumstances at the time, the system utilizes data from macro economics and other asset classes, such as data from equity market, interest rate, commodity market, VIX index and so on. Macro economist agent receives those data and summarizes the market situation with 3 factors, using Principal Component Analysis (PCA).

- Signal PnL & Backtesting agent:
  - Those agents calculate the trading performance by each signaling agents, i.e. SMA, Bollinger band, and Twitter sentiment. Also, it implements back-testing utilizing train/test data split with sliding-window.

Source: NUS Fintech Lab, Naoya Ohara

# (Contd.) Brief explanation of each agent.

- **Decider agent:**
  - Then, the decider agent aggregates those recommendations and macro economic information and makes the final recommendation to the CEO agent.
  - In this process, the system utilizes case-based reasoning (CBR) to store and utilize historical prices, technical signals, and macro factor data with the resulting price direction on the following days. By referring to “same or similar combinations of quantitative and qualitative agent’s buy/sell signal under similar macro economic circumstance”, the CBR allows the trading system to generate better final recommendation.
  - For the implementation of CBR, I utilized k-nearest neighbours (kNN), which is a popular method in machine learning and for implementing CBR.

- **PnL Agent:**
  - This agent calculates daily PnL movement and returns it to the Account book and CEO agent.

- **PowerBI / Automate agent:**
  - It can establish the connection with PowerBI, which enables us the data visualization of daily Account book and market data. Also, it can enable the automation of sending monthly reports via email by using Power Automate.

Source: NUS Fintech Lab, Naoya Ohara

# (Contd.) Brief explanation of each agent.

- Risk management agent:
  - It implements Value at Risk (VaR), which is a popular method in market risk management. Also, it can support appropriate position sizing based on VaR metrics.

- CEO agent:
  - It receives final investment recommendation from decider agent and VaR risk metric report from risk management agent, and decides the final action (buy/sell/do nothing/terminate trading) and position size of trading, based on investment and risk management policy that we set up before the trading as CEO.

Source: NUS Fintech Lab, Naoya Ohara

# Section 3: Account agent.

# Account agent: Creates and maintains the account book.

- Account agent:
  - Account agent creates and maintains the account book shown above (Account.trade_info_df).
  - It records daily trading activity (buy/sell/no-trade), purchased/sold price, # of bitcoin holding, NAV (net asset value = cash amount + market value of holding bitcoin), daily PnL, and annualized Value at Risk (VaR), etc.
  - We can regard Account agent as the miniature of the back-office function in asset management companies.

```
Account.getTradeInfoDf().tail()
```

| | time | side | exec_price | last_price | cost_price | pnl_costprice | quantity | num_coins | coin_value | cash | nav | dailyPnL | dailyPnLPct | totalPnL | totalPnLPct | VaR_annualized |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **207** | 2021-07-27 | no-trade | 0.0 | 39406.941406 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 972308.639463 | 972308.639463 | 0.0 | 0.0 | -27691.360537 | -0.027691 | -0.0 |
| **208** | 2021-07-28 | no-trade | 0.0 | 39995.906250 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 972308.639463 | 972308.639463 | 0.0 | 0.0 | -27691.360537 | -0.027691 | -0.0 |
| **209** | 2021-07-29 | no-trade | 0.0 | 40008.421875 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 972308.639463 | 972308.639463 | 0.0 | 0.0 | -27691.360537 | -0.027691 | -0.0 |
| **210** | 2021-07-30 | no-trade | 0.0 | 42235.546875 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 972308.639463 | 972308.639463 | 0.0 | 0.0 | -27691.360537 | -0.027691 | -0.0 |
| **211** | 2021-07-31 | no-trade | 0.0 | 41626.195312 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 972308.639463 | 972308.639463 | 0.0 | 0.0 | -27691.360537 | -0.027691 | -0.0 |

Source: NUS Fintech Lab, Naoya Ohara

# Section 4: Broker agent.

# Broker agent: Handles market data acquisition and buy/sell trading execution.

- Market data acquisition:
  - Broker class has the ability to get both historical and real time cryptocurrency price and trade information.
  - The system obtains data from MySQL data library.
  - Broker agent maintains price data as Broker.longhist_price_df shown below. The system only uses closing prices, such that this dataframe just stores closing price data and daily volume. Then, the system adds day to day percent change and log-return too.

```
Broker.longhist_price_df.head()
```

| Date | close | volume | pct_change | log_return |
|---|---|---|---|---|
| **2014-09-17** | 457.334015 | 21056800.0 | NaN | NaN |
| **2014-09-18** | 424.440002 | 34483200.0 | -0.071926 | -0.074643 |
| **2014-09-19** | 394.795990 | 37919700.0 | -0.069843 | -0.072402 |
| **2014-09-20** | 408.903992 | 36863600.0 | 0.035735 | 0.035111 |
| **2014-09-21** | 398.821014 | 26580100.0 | -0.024659 | -0.024968 |

Source: NUS Fintech Lab, Naoya Ohara

# (Contd.) Broker agent: Handles market data acquisition and buy/sell trading execution.

- Trading execution
  - Broker agent has the ability to initialize the trade information stored in the Account Class, execute the trade according to the final decision made by the CEO agent, and update the account information.
  - The system assumed 0.1% of spread from closing price. i.e. we need to buy 0.1% higher than market close, while we need to sell 0.1% lower than market price.
  - In the future, if NUS Fintech Lab establishes simulated market exchange or directly trades real money at market exchange, a successor can modify Broker agent by which the system enables us to buy/sell at the simulated or real market exchange.

Source: NUS Fintech Lab, Naoya Ohara

# Section 5: PnL agent.

# PnL agent: Calculates and updates NAV and PnL information in the account book.

## ❑ PnL Agent:

- Based on the raw data collected and recorded by the Account and Broker agent, PNL agent is the one who calculates and updates NAV and PnL information in the account book which is created and maintained by Account agent.

Those calculation can be done by PnL agent.

```
Account.getTradeInfoDf().tail()
```

| | time | side | exec_price | last_price | cost_price | pnl_costprice | quantity | num_coins | coin_value | cash | nav | dailyPnL | dailyPnLPct | totalPnL | totalPnLPct | VaR_annualized |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **207** | 2021-07-27 | no-trade | 0.0 | 39406.941406 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 972308.639463 | 972308.639463 | 0.0 | 0.0 | -27691.360537 | -0.027691 | -0.0 |
| **208** | 2021-07-28 | no-trade | 0.0 | 39995.906250 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 972308.639463 | 972308.639463 | 0.0 | 0.0 | -27691.360537 | -0.027691 | -0.0 |
| **209** | 2021-07-29 | no-trade | 0.0 | 40008.421875 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 972308.639463 | 972308.639463 | 0.0 | 0.0 | -27691.360537 | -0.027691 | -0.0 |
| **210** | 2021-07-30 | no-trade | 0.0 | 42235.546875 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 972308.639463 | 972308.639463 | 0.0 | 0.0 | -27691.360537 | -0.027691 | -0.0 |
| **211** | 2021-07-31 | no-trade | 0.0 | 41626.195312 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 972308.639463 | 972308.639463 | 0.0 | 0.0 | -27691.360537 | -0.027691 | -0.0 |

Source: NUS Fintech Lab, Naoya Ohara

# Section 6: Quantitative signaling agent.

# Quantitative agent: SMA and Bollinger Bands.


- 1.Simple Moving Average (SMA):
  - One of the most popular and common technical indicators. SMA is the average price over a given number of time periods.
  - Golden cross and death cross:
    - ✓ The golden-cross occurs when the short-term moving average (short-term MA) price goes over long-term moving average (long-term MA) to the upside and is interpreted as buying opportunities.
    - ✓ Similarly downside moving average crossover constitutes the death-cross and is understood to signal a downturn in a market.
  - Trend-following strategy: Can perform well if the underlying asset class often shows strong and long-term upward and downward trends. On the other hand, can perform poorly if the market is within a narrow range i.e. consolidation.

Source: https://forextraininggroup.com/anatomy-of-popular-moving-averages-in-forex/ , NUS Fintech Lab, Naoya Ohara

# Quantitative agent: SMA and Bollinger Bands.


$$\mathrm{BOLU} = \mathrm{MA}(\mathrm{TP}, n) + m * \sigma[\mathrm{TP}, n]$$
$$\mathrm{BOLD} = \mathrm{MA}(\mathrm{TP}, n) - m * \sigma[\mathrm{TP}, n]$$

**where:**

BOLU = Upper Bollinger Band

BOLD = Lower Bollinger Band

MA = Moving average

TP (typical price) = (High + Low + Close) ÷ 3

$n$ = Number of days in smoothing period

$m$ = Number of standard deviations

$\sigma[\mathrm{TP}, n]$ = Standard Deviation over last $n$ periods of TP

- 2.Bollinger Bands:
  - Generating oversold or overbought signals. There are three lines that compose Bollinger Bands: A simple moving average (middle band) and an upper and lower band. The upper and lower bands are typically 2 standard deviations +/- from a 20-day simple moving average.
  - If the price goes up beyond the upper band, it is recognized as expensive such that it is a "sell" opportunity. As opposed, if the price goes down below the lower band, it is recognized as cheap such that it is a "buy" opportunity.
  - Mean-reversion strategy: This strategy can work well, when the market is in range bound i.e. in consolidation. On the other hand, when there exists a strong and long-term upward or downward trend, such a mean-reverting strategy cannot work well.

Source: https://www.tradingwithrayner.com/bollinger-bands-trading-strategy/, Reference [1], NUS Fintech Lab, Naoya Ohara

# (For reference) Other technical indicators.

## Category:Technical indicators

From Wikipedia, the free encyclopedia

### Pages in category "Technical indicators"

The following 44 pages are in this category, out of 44 total. This list may not reflect recent changes (learn more).

- Technical indicator

**A**
- Absolute currency strength
- Accumulation/distribution index
- Advance-Decline Data
- Average directional movement index
- Average true range

**B**
- Bollinger Bands

**C**
- Commodity channel index

**D**
- Detrended price oscillator
- Donchian channel
- Double exponential moving average

**E**
- Ease of movement

**F**
- Force index

**I**
- Ichimoku Kinkō Hyō

**K**
- Keltner channel

**M**
- MACD
- Mass index
- Momentum (technical analysis)
- Money flow index
- Moving average crossover
- Moving average envelope

**N**
- Negative volume index

**O**
- On-balance volume
- Oscillator (technical analysis)

**P**
- Parabolic SAR
- Put/call ratio

**R**
- Rahul Mohindar oscillator
- Range expansion index
- Relative currency strength
- Relative strength index
- Rising moving average

**S**
- Smart money index
- Stochastic oscillator

**T**
- KST oscillator
- Triple exponential moving average
- Trix (technical analysis)
- True strength index

**U**
- Ulcer index
- Ultimate oscillator

**V**
- Volume analysis
- Volume–price trend
- Vortex indicator

**W**
- Williams %R

**Z**
- Zero lag exponential moving average

- ❑ When searching for other indicators, we can note follows:
  - ➢ Does this indicator work as a trend-following, or mean-reversion algorithm?
  - ➢ Which kind of price movement this indicator tries to capture to make profit?
  - ➢ What does this indicator assume regarding price movement? (For example, price can keep going up or down with long-term trend, or price can revert to mean relatively in a short period of time, etc.)
- ❑ Other notes to be aware of:
  - ➢ One technical indicator rarely shows robust performance over a long period of time.
  - ➢ Also, parameter tuning and optimization based on historical data tend to fall into overfitting.

Source: Wikipedia, NUS Fintech Lab, Naoya Ohara

# (For reference) Normal class vs staticmethod.

- Normal class vs static method:
  - You may have noticed that **class quantsSignal()** is implemented by the usual class method, while previous Account, Broker, and PnL agents are implemented by so-called staticmethod with @staticmethod.

```
[11] class Car():

       def __init__(self, max_speed, gasoline_litter):
         self.max_speed = max_speed
         self.gasoline_litter = gasoline_litter

       def run(self):
         print("now running at {} km/h".format(self.max_speed))

       def gasolineSupply(self):
         print("gasoline is now full with {} litter".format(self.gasoline_litter))

carToyota = Car(100,30)
carToyota.run()
carToyota.gasolineSupply()

now running at 100 km/h
gasoline is now full with 30 litter

[13] carPorsche = Car(200,60)
     carPorsche.run()
     carPorsche.gasolineSupply()

now running at 200 km/h
gasoline is now full with 60 litter
```

```
[16] class Car(object):

       @staticmethod
       def initialization(max_speed, gasoline_litter):
         Car.max_speed = max_speed
         Car.gasoline_litter = gasoline_litter

       @staticmethod
       def run():
         print("now running at {} km/h".format(Car.max_speed))

       @staticmethod
       def gasolineSupply():
         print("gasoline is now full with {} litter".format(Car.gasoline_litter))

[18] Car.initialization(100, 30)
     Car.run()
     Car.gasolineSupply()

now running at 100 km/h
gasoline is now full with 30 litter

Car.initialization(200, 60)
Car.run()
Car.gasolineSupply()

now running at 200 km/h
gasoline is now full with 60 litter
```

Usual class implementation (left) and staticmethod (right)

Source: NUS Fintech Lab, Naoya Ohara

# (For reference) Normal class vs staticmethod.

## Normal class

- **Pros**
  - It's normal. In many cases, codes are implemented as such.
  - When we would like to create multiple instances based on the class, a normal class method with a constructor can be useful.
- **Cons**
  - We need instantiation to utilize the class.

## staticmethod

- **Pros**
  - We do not need instantiation to utilize the class. We can call it directly.
  - We can improve readability in some cases. For example, the reader can understand that **def run():** is used only under class **Car(object):** in the example.
  - Especially, when we just keep one whole object as one class, it's easy to handle and maintain.
- **Cons**
  - It may not be a normal implementation. Some people may not know staticmethod.

- If multiple instances should be created and maintained based on the class, the class is implemented as a usual class method. (This is the reason that quantitative agent is implemented by a normal class.)
- If only one object is required and we do not need to produce multiple instances by instantiation, the class is implemented as staticmethod. (This is why Account, Broker, and PnL agents are implemented by staticmethod.)

Source: NUS Fintech Lab, Naoya Ohara

# Section 7: Qualitative signaling agent.

# Qualitative signaling agent (Twitter agent): Buy/sell recommendation based on twitter text data.

- ❑ Qualitative signaling agent:
  - ➢ Qualitative anget is the agent which formulates buy/sell signals based on qualitative data such as text. In our implementation, we try to formulate buy/sell signals by analyzing twitter text sentiment and converting those into trading buy/sell signals, by implementing Twitter agent.

- ❑ 4 steps:
  - ➢ Data acquisition.
  - ➢ Data preprocessing
  - ➢ Data transformation
  - ➢ Fuzzy logic

```
testTwitter.tweets_df
```

| | index | crypto | url | date | id | username | content | text_length | content_processed | polarity | subjectivity | label | text_processed_length |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1799 | bitcoin | https://twitter.com/business/status/1340922472... | 2020-12-21 07:30:05 | 1340922472351330307 | business | JPMorgan says the odds of a Bitcoin correction... | 161 | jpmorgan says odds bitcoin correction would in... | 0.037500 | 0.637500 | 4 | 112 |
| 1 | 7472 | btc | https://twitter.com/Investingcom/status/134099... | 2020-12-21 12:11:41 | 1340993341916393472 | Investingcom | Here are https://t.co/HMaYPuSux7's #Top5Things... | 272 | monday deal agreed new strain found uk st... | 0.136364 | 0.454545 | 4 | 114 |
| 2 | 7471 | btc | https://twitter.com/Investingcom/status/134102... | 2020-12-21 14:06:15 | 1341022172014325761 | Investingcom | "Bitcoin slumps 6% as new COVID-19 strain upse... | 119 | bitcoin slumps new covid strain upsets wider ... | 0.136364 | 0.454545 | 4 | 59 |
| 3 | 5508 | bitcoin | https://twitter.com/Investingcom/status/134102... | 2020-12-21 14:06:15 | 1341022172014325761 | Investingcom | "Bitcoin slumps 6% as new COVID-19 strain upse... | 119 | bitcoin slumps new covid strain upsets wider ... | 0.136364 | 0.454545 | 4 | 59 |
| 4 | 164 | bitcoin | https://twitter.com/WSJ/status/134159061918200... | 2020-12-23 03:45:03 | 1341590619182002177 | WSJ | Ripple said it will defend itself against a la... | 199 | ripple said defend lawsuit sec claims company ... | -0.050000 | 0.300000 | 2 | 121 |

| score | magnitude | google_language | google_entities | google_categories |
|---|---|---|---|---|
| -0.2 | 0.2 | en | OTHER,LOCATION,ORGANIZATION | /Finance/Investing/Currencies & Foreign Exchange |
| 0.0 | 1.0 | en | ORGANIZATION,OTHER,LOCATION,PERSON | |
| 0.0 | 0.4 | en | OTHER,NUMBER,LOCATION | None |
| 0.0 | 0.4 | en | OTHER,NUMBER,LOCATION | None |
| -0.5 | 0.5 | en | OTHER,ORGANIZATION | /Finance/Investing |

Source: NUS Fintech Lab, Naoya Ohara

# Step 1: Data acquisition.

❑ Tool, scope and process of data acquisition:

- Snscrape: This time, the system applied the “snscrape” library to obtain tweet data several years ago.
- Scope:
  - Wall Street Journal (WSJ)
  - Bloomberg
  - Investing.com
  - CNN
  - NYTimes
  - Financial Times (FT)
  - Elon Musk.
- Collected data from 2014 with 7612 tweets, but many of the tweets are recent one after 2018, when bitcoin price showed a bubble and burst with large price movement.
- Then, we added those data into SQL data library.

Source: Reference [2-4], NUS Fintech Lab, Naoya Ohara

# Step 2: Data preprocessing.

- Process of data preprocessing: Those preprocessing can remove noise in text data, such that it affects the quality of sentiment analysis significantly.
  - Clean-up twitter text:
    - For example, we remove strings starting with “@”, “#”, “$”. Also, we remove hyperlinks and URL, video, and “RT”, etc, the words which are not important to evaluate the sentiment.
  - Eliminating stop-words:
    - Stop-words means meaningless words such as “a”, “the”, “of”, and so on.
    - Using nltk: When we deal with stopwords, nltk (Natural Language ToolKit) library is popularly used, so I introduced it in the system implementation.

Source: NUS Fintech Lab, Naoya Ohara

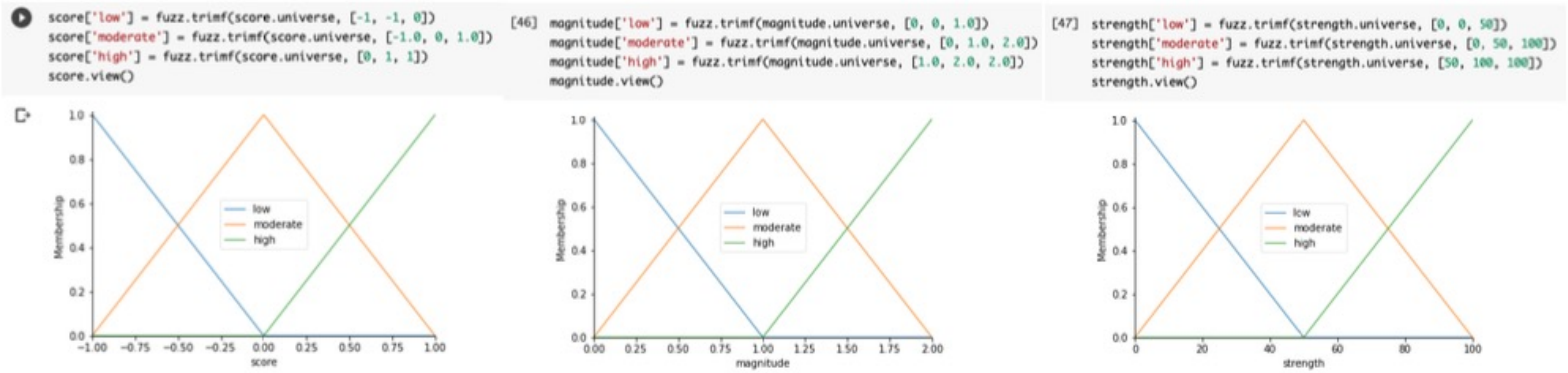
# Step 3: Data transformation.

- Process of data transformation: we can transform text data to convert those into quantified sentiment data.
  - **Using textblob:** a very simple, but powerful way to start text sentiment analysis.
    - Polarity: a float within the range [-1.0, 1.0], where 1 means positive statement and -1 means a negative statement.
    - Subjectivity: a float within the range [0.0, 1.0] where 0 is objective and 1.0 is subjective. Subjective sentences generally refer to personal opinion, emotion or judgment whereas objective refers to factual information.
  - **Google Text Analytics:** To move one step ahead for the text sentiment analysis, the system utilized Google Text Analytics.
    - Score: It ranges between -1.0 (negative) and 1.0 (positive) and corresponds to the overall emotional leaning of the text.
    - Magnitude: It indicates the overall strength of emotion (both positive and negative) within the given text, between 0.0 and +inf. Each expression of emotion within the text (both positive and negative) contributes to the text's magnitude (so longer text blocks may have greater magnitudes).

Source: Reference [5,6], NUS Fintech Lab, Naoya Ohara

# Step 4: Fuzzy logic.

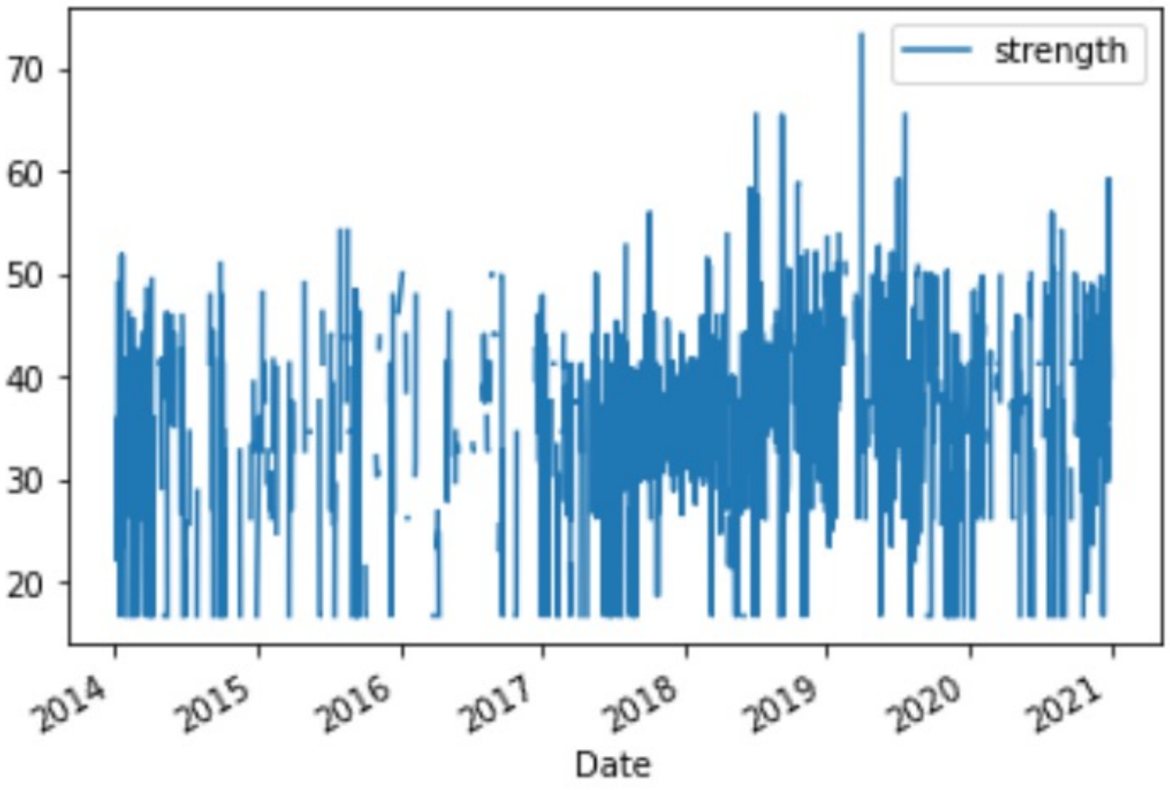
- Fuzzy logic: Convert “score” and “magnitude” into one integrated sentiment indicator of “strength”.
  - Set membership functions for score, magnitude, and strength.
    - For example, by setting membership functions for score and magnitude, we can define “how much of the score is regarded as low score i.e. negative, how much is mediocre i.e. neutral, and how much is positive” in a “fuzzy” manner.




    - Then, the fuzzy logic can output the final integrated sentiment outcome as “strength” by combining “score” and “magnitude”.

Source: Reference [7], NUS Fintech Lab, Naoya Ohara

# Final output of qualitative signaling agent.




- Final output: Sentiment strength indicator from 0 to 100.
  - Finally, we can obtain a “strength” sentiment indicator between 0-100, shown below in the graph.
  - By utilizing this indicator, we can make buy and sell decisions.

    Example:
    - If the 5 days moving average of strength falls below 20, it shows negative sentiment such that we sell bitcoin.
    - When the 5 days moving average of strength goes above 40, it indicates positive sentiment such that we buy bitcoin.
  - The Twitter agent passes those decisions to the Decider agent.

Source: NUS Fintech Lab, Naoya Ohara

# Section 8: Macro Economist agent.

Confidential & Proprietary

# Macro Economist Agent: Utilize macroeconomic data for trading.

- Macro economist agent:
  - From the past, many industry practitioners have combined technical indicators and macroeconomic data for better understanding of financial market circumstances and better trading decisions.
  - In this section, I introduce how we can utilize macroeconomic data for trading with the combination of technical indicators and twitter sentiment.
- 3 steps:
  - 1.Macro economic data
  - 2.Data transformation
  - 3.Principal Component Analysis (PCA)

Source: Reference [8], NUS Fintech Lab, Naoya Ohara

# Step 1: Macro economic data.

- Data acquisition:
  - Extracted macro economic data from FRED (https://fred.stlouisfed.org/).
  - Chose popular macro and market indices that many industry professionals check market conditions of "risk-on" and "risk-off" sentiment.

| | NASDAQCOM | DGS10 | TEDRATE | T10Y2Y | BAA10Y | DCOILWTICO | GOLDAMGBD228NLBM | VIXCLS |
|---|---|---|---|---|---|---|---|---|
| Date | | | | | | | | |
| **2019-01-01** | 6635.277 | 2.69 | 0.41 | 0.21 | 2.45 | 45.15 | 1281.65 | 25.42 |
| **2019-01-02** | 6665.938 | 2.66 | 0.42 | 0.16 | 2.45 | 46.31 | 1287.20 | 23.22 |
| **2019-01-03** | 6463.504 | 2.56 | 0.44 | 0.17 | 2.48 | 46.92 | 1287.95 | 25.45 |
| **2019-01-04** | 6738.855 | 2.67 | 0.43 | 0.17 | 2.45 | 47.76 | 1290.35 | 21.38 |
| **2019-01-05** | 6738.855 | 2.67 | 0.43 | 0.17 | 2.45 | 47.76 | 1290.35 | 21.38 |

Source: FRED, NUS Fintech Lab, Naoya Ohara

# (Contd.) Step 1: Introduction of each macroeconomic data.

- NASDAQCOM:
  - NASDAQ Composite Index, which is a major USA technology equity market index.
- DGS10:
  - 10-Year Treasury Constant Maturity Rate. Interest rate of US government bonds with 10 years of maturity is often referenced as a major reference rate as risk free rate.
- TEDRATE:
  - TED Spread, the spread between 3-month LIBOR and Treasury bills, which indicates perceived credit risk. LIBOR is the benchmark interest rate of London's inter-bank lending/borrowing.
  - When credit crunch happens in the financial sector, LIBOR can increase rapidly, compared with the interest of 3 month US Treasury bills.

  (Note: While US dollar LIBOR is disclosed until 2023, it will not be used after that. We need to find an alternative index to check the credit situation in the banking sector.)
- T10Y2Y:
  - The 10-year minus 2-year Treasury (constant maturity) yields: Positive values may imply future growth, negative values may imply economic downturns.
  - Especially, if this figure becomes negative, it is called "inverse yield". In many cases, within 2 years after inverse yield, economic downturns and equity market crashes happened in the past.

Source: FRED, NUS Fintech Lab, Naoya Ohara

# (Contd.) Step 1: Introduction of each macroeconomic data.

- BAA10Y:
  - Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity. It shows the corporate sector's funding and credit circumstances.
  - In the "risk-on" market, it decreases i.e. companies can easily issue corporate bonds with low interest rates, while in the "risk-off" market, it expands i.e. companies can feel difficulty in funding by issuing corporate bonds even with high interest rates.
- DCOILWTICO:
  - Crude Oil Prices, West Texas Intermediate (WTI) - Cushing, Oklahoma. It is a major index of oil price. And oil price represents overall commodity price movements and global inflation.
  - When the inflation rate goes up, oil prices tend to go up synthetically.
- GOLDPMGBD228NLBM:
  - Gold price. Gold also constitutes an important portion in commodity asset classes. Gold price represents the "value of physical currency", compared with the US dollar which represents the "value of paper currency".
  - When the risk of an emergency (such as war) rises, the gold price tends to rise. Also, when people expect high inflation, i.e. the depreciation of paper money's value, people tend to buy gold such that the gold price tends to rise.

Source: FRED, NUS Fintech Lab, Naoya Ohara

# (Contd.) Step 1: Introduction of each macroeconomic data.

- VIXCLS:
  - CBOE Volatility Index: VIX. VIX measures market expectation of near term volatility conveyed by stock index option prices. It shows overall market sentiment of equity market participants.
  - When many market participants expect that the equity market can be stable in the near future, VIX stays at low range. When many market participants expect that the equity market can become unstable in the near future, VIX can go up.

Source: FRED, NUS Fintech Lab, Naoya Ohara

# Step 2: Data transformation – Preprocessing, adding % changes, MinMax scalar, and PCA.

- Data transformation:
  - After gathering the above data, the system does preprocessing and then implements data transformation by Principal Component Analysis (PCA).
- Data filling:
  - Macro economic data is usually priced and disclosed on Monday-Friday and holiday is closed i.e., around 250 trading days annually. On the other hand, bitcoin is traded every day i.e. 365 trading days annually.
  - To fit both data comparable, the system converts annual 250 days of trading data into annual 365 days trading data, then executes fillna to fill by previous days data if the macroeconomic data is not available.
- Rolling % change:
  - Calculates 30 days rolling % changes of macroeconomic data.
  - The reason for taking 30 days % change and not taking daily % change is that the daily % changes of macroeconomics data is too noisy. By taking 1 month % change of macroeconomic data, the system can capture macroeconomic sentiment in a reasonable manner for practitioners as well.

Source: NUS Fintech Lab, Naoya Ohara

# (Contd.) Step 2: Data transformation – Preprocessing, adding % changes, MinMax scalar, and PCA.

- MinMax scalar:
  - Next, the system executes PCA by the function of pcaDimReduction(day, macro_pct_df). But before executing PCA, the system implements another data transformation, data normalization of MinMax scalar shown on the formula below.

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

  - Data normalization intends that normalized values allow the comparison of corresponding normalized values for different datasets in a way that eliminates the effects of certain gross influences.

Source: Wikipedia, NUS Fintech Lab, Naoya Ohara

# (Reference) Other data normalization: MinMax or z-normalization, which one to use?

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \qquad z = \frac{x - \mu}{\sigma}$$

$\mu =$ Mean

$\sigma =$ Standard Deviation

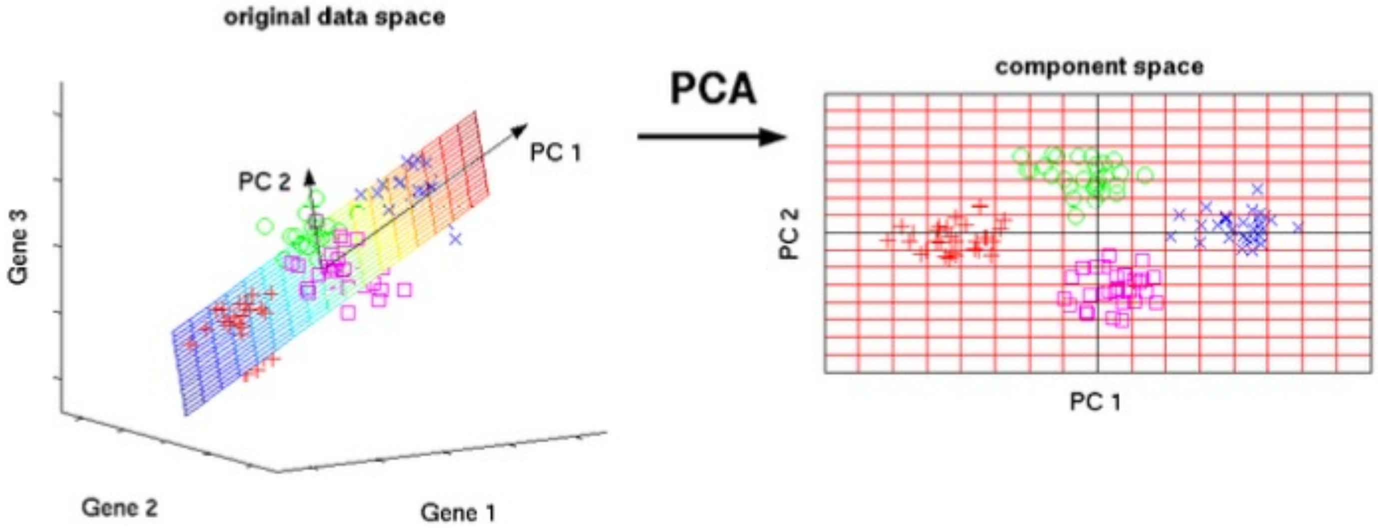
0-1 (Min-Max) normalization (left) and z-normalization (right)

- Two major normalization:
  - **0-1 (or Min-Max) normalization:** It can normalize a certain data set within the range between 0 -1, by using minimum value and maximum value in the dataset. By this normalization, the minimum data takes 0, while the maximum data takes 1.
  - **Z-normalization:** It takes mean and standard deviation of the dataset, then converts raw data x into standardized data z in the above right hand side of the formula. In this case, most data can range between -3 to +3, by assuming normal distribution of the dataset. Often, more than +3 and less than -3 are truncated into +3 and -3 to eliminate outlier data, in the community of financial practitioners.
- Which one to use?: Depending on a situation.
  - It looks that the machine learning community likes 0-1 normalization, while financial practitioners like z-normalization.
  - When we can assume a bell-curve of the dataset's distribution and we would like to eliminate outliers from analysis, z-normalization can work nicely.
  - If the data may not follow the normal distribution and the information of outliers can be important in the analysis, we can use MinMax normalization.

Source: Wikipedia, NUS Fintech Lab, Naoya Ohara

# Step 3: Principal Component Analysis (PCA).

- Principal Component Analysis (PCA):
  - PCA is used to decompose a multivariate dataset in a set of successive orthogonal components that explain a maximum amount of the variance. It is popularly used to reduce the dimensionality of the dataset.
- Importance of data normalization:
  - As PCA is interested in the components that maximize the variance, if one component varies less than another because of their respective scales, PCA can work wrongly, such that data normalization is executed beforehand, as mentioned above.




Source: :https://www.analyticsvidhya.com/blog/2016/03/pca-practical-guide-principal-component-analysis-python/, NUS Fintech Lab, Naoya Ohara

# Final outcome of Macroeconomist agent.

- Final outcome of Macroeconomist agent:
  - Finally, 8 macroeconomic data can be summarized by 3 factors, shown in the following picture.
  - Macroeconomic agent pass those data to the Decider agent, such that the Decider agent can utilize those macroeconomic data to capture the market circumstance for the day and reflect this insight when the system implements case based reasoning (CBR).

| | macro_factor1 | macro_factor2 | macro_factor3 |
|---|---|---|---|
| Date | | | |
| **2019-01-01** | -0.891191 | 0.096499 | 0.378480 |
| **2019-01-02** | -0.858942 | 0.064011 | -0.299344 |
| **2019-01-03** | -0.523940 | 0.178067 | 0.417479 |
| **2019-01-04** | -0.141390 | -0.660551 | 0.554137 |
| **2019-01-05** | -0.179610 | 1.024015 | 0.176716 |

Source: NUS Fintech Lab, Naoya Ohara

# Section 9: Signal PnL and Backtesting agents.

# Signal PnL agent: PnL Recording function for each signal agent.

```
CEO.movingAvg_strat.df.head()
```

| Date | close | long_signal | short_signal | log_return | long | short | long_costprice | short_costprice | long_dailypnl_pct |
|---|---|---|---|---|---|---|---|---|---|
| 2021-01-01 | 29374.152344 | 1.0 | 0.0 | NaN | 1.0 | 0.0 | 29403.526496 | 0.0 | -0.001000 |
| 2021-01-02 | 32127.267578 | 1.0 | 0.0 | 0.089590 | 1.0 | 0.0 | 29403.526496 | 0.0 | 0.089590 |
| 2021-01-03 | 32782.023438 | 1.0 | 0.0 | 0.020175 | 1.0 | 0.0 | 29403.526496 | 0.0 | 0.020175 |
| 2021-01-04 | 31971.914062 | 1.0 | 0.0 | -0.025022 | 1.0 | 0.0 | 29403.526496 | 0.0 | -0.025022 |
| 2021-01-05 | 33992.429688 | 1.0 | 0.0 | 0.061280 | 1.0 | 0.0 | 29403.526496 | 0.0 | 0.061280 |

| short_dailypnl_pct | total_dailypnl_pct | long_dailypnl_pct_posi | long_dailypnl_pct_nega | short_dailypnl_pct_posi |
|---|---|---|---|---|
| 0.0 | -0.001000 | 6.325383 | -4.063342 | 3.105151 |
| 0.0 | 0.089590 | 0.089590 | 0.000000 | 0.000000 |
| 0.0 | 0.020175 | 0.020175 | 0.000000 | 0.000000 |
| 0.0 | -0.025022 | 0.000000 | -0.025022 | 0.000000 |
| 0.0 | 0.061280 | 0.061280 | 0.000000 | 0.000000 |

| short_dailypnl_pct_nega | total_dailypnl_pct_posi | total_dailypnl_pct_nega | long_sumprofit | long_sumloss | short_sumprofit |
|---|---|---|---|---|---|
| -3.029772 | 9.430534 | -7.093114 | 6.325383 | -4.063342 | 3.105151 |
| 0.000000 | 0.089590 | 0.000000 | 6.414973 | -4.063342 | 3.105151 |
| 0.000000 | 0.020175 | 0.000000 | 6.435148 | -4.063342 | 3.105151 |
| 0.000000 | 0.000000 | -0.025022 | 6.435148 | -4.088365 | 3.105151 |
| 0.000000 | 0.061280 | 0.000000 | 6.496428 | -4.088365 | 3.105151 |

| short_sumloss | total_sumprofit | total_sumloss | long_PF | short_PF | total_PF | long_cumpnl_pct_pertrade | short_cumpnl_pct_pertrade |
|---|---|---|---|---|---|---|---|
| -3.029772 | 9.430534 | -7.093114 | 1.556695 | 1.02488 | 1.329534 | -0.001000 | 0.0 |
| -3.029772 | 9.520124 | -7.093114 | 1.578743 | 1.02488 | 1.342164 | 0.088591 | 0.0 |
| -3.029772 | 9.540300 | -7.093114 | 1.583708 | 1.02488 | 1.345009 | 0.108766 | 0.0 |
| -3.029772 | 9.540300 | -7.118137 | 1.574015 | 1.02488 | 1.340280 | 0.083743 | 0.0 |
| -3.029772 | 9.601580 | -7.118137 | 1.589004 | 1.02488 | 1.348889 | 0.145023 | 0.0 |

| long_cumsignal_pertrade | short_cumsignal_pertrade | long_cumpnl_pct | short_cumpnl_pct | long_recovperiod | short_recovperiod |
|---|---|---|---|---|---|
| 0.0 | 0.0 | -0.001000 | 0.0 | 0.0 | 0.0 |
| 1.0 | 0.0 | 0.088591 | 0.0 | 0.0 | 0.0 |
| 2.0 | 0.0 | 0.108766 | 0.0 | 0.0 | 0.0 |
| 3.0 | 0.0 | 0.083743 | 0.0 | 1.0 | 0.0 |
| 4.0 | 0.0 | 0.145023 | 0.0 | 0.0 | 0.0 |

| total_recovperiod | total_cumpnl_pct | long_cumpnl_max | short_cumpnl_max | total_cumpnl_max | long_drawdown |
|---|---|---|---|---|---|
| 0.0 | -0.001000 | -0.001000 | 0.0 | -0.001000 | 0.000000 |
| 0.0 | 0.088591 | 0.088591 | 0.0 | 0.088591 | 0.000000 |
| 0.0 | 0.108766 | 0.108766 | 0.0 | 0.108766 | 0.000000 |
| 1.0 | 0.083743 | 0.108766 | 0.0 | 0.108766 | -0.025022 |
| 0.0 | 0.145023 | 0.145023 | 0.0 | 0.145023 | 0.000000 |

| short_drawdown | total_drawdown | long_recovery_flag | short_recovery_flag | total_recovery_flag | long_position | short_position |
|---|---|---|---|---|---|---|
| 0.0 | 0.000000 | 0 | 0 | 0 | NaN | NaN |
| 0.0 | 0.000000 | 0 | 0 | 0 | 0.0 | 0.0 |
| 0.0 | 0.000000 | 0 | 0 | 0 | 0.0 | 0.0 |
| 0.0 | -0.025022 | 1 | 0 | 1 | 0.0 | 0.0 |
| 0.0 | 0.000000 | 0 | 0 | 0 | 0.0 | 0.0 |

- Signal PnL agent:
  - Signal PnL agent (in the system, class stratPnL()) is the agent to calculate profit and loss for each trading signal (i.e. SMA, Bollinger Bands, and Twitter sentiment) under certain levels of profit-taking and stop loss.
  - For example, by receiving daily trading signals of Simple Moving Average strategy from quantitative agent, this agent calculates the PnL of a certain training and test period in the back test and daily trading activity.

Source: NUS Fintech Lab, Naoya Ohara

# Signal PnL agent: Calculation process.

- Calculation process of Signal PnL agent:
  - First, this agent receives buy/sell signals from quantitative or qualitative agent (column long_signal and short_signal).
  - When the long (short) signal turns from 0 to 1, trade starts.
  - When any of the following criteria is met, trade is exited.
    - The long (short) signal moves back to 0.
    - Opposite signal arises i.e., when buying, short_signal turns from 0 to 1 and vice versa.
    - The price reaches a certain profit taking or loss cut point. (For example, if the system sets (profit_taking, loss_cut) = (0.2, 0.1), the trade is closed when the price increases by 20% from cost price or the price decreases by -10% from cost price.)
  - This agent records cumulative profit of profitable trades and cumulative losses from loss-making trades. Then, this agent calculates “Profit Factor” for long position, short position, and long/short total.
  - Also, this agent records “Drawdown”, the loss from its peak performance.
  - Transaction cost of buying/selling is assumed as 0.1% of the price for each trade.

Source: NUS Fintech Lab, Naoya Ohara

# Signal PnL agent: What is "Profit Factor"?

$$Overall\ PF = \frac{\sum pips\ won}{\sum pips\ lost} - 1$$

$$Long\ PF = \frac{\sum pips\ won\ when\ predicting\ up}{\sum pips\ lost\ when\ predicting\ up} - 1$$

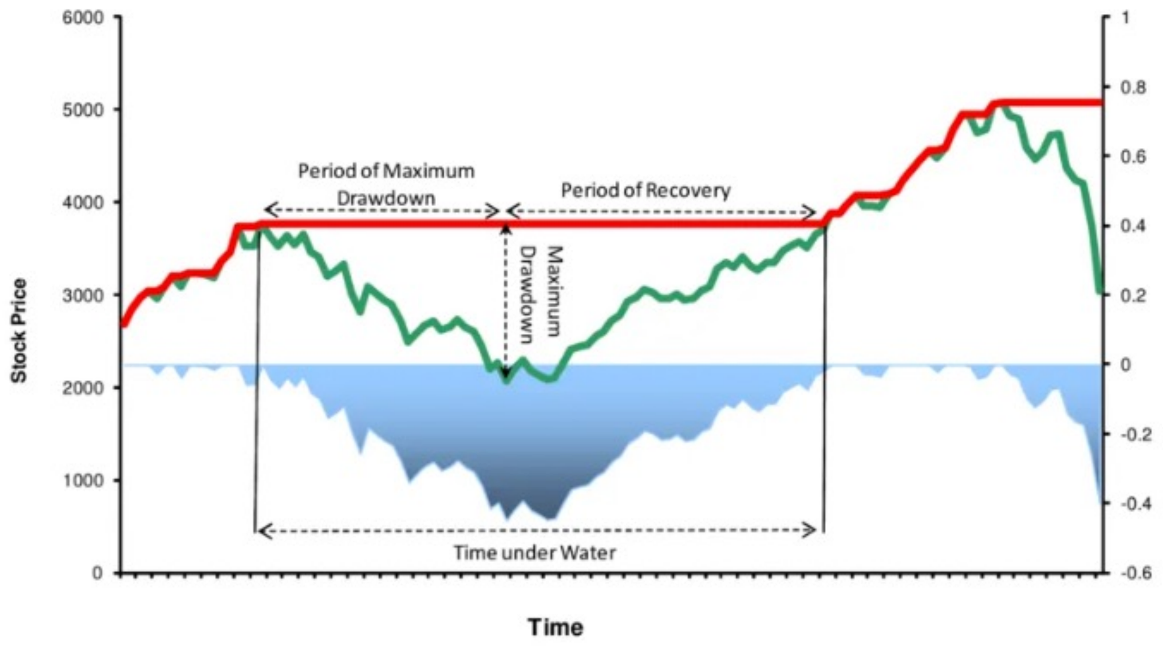
$$Short\ PF = \frac{\sum pips\ won\ when\ predicting\ down}{\sum pips\ lost\ when\ predicting\ down} - 1$$

## ❑ Profit Factor:

- ➢ Above is the formula. Numerator is the sum of past profit, while denominator is the sum of past loss.
- ➢ However, in the actual workplace, PF is often calculated just with the gross profit divided by the gross loss (including commissions) for the entire trading period i.e. "-1" in the formula can be omitted and PF can take positive value (if profit is zero and only loss, PF=0. If there are tons of profit with very small loss, PF = very large number).
- ➢ To prevent PF taking extremely large values, the system capped PF <= 5.0.
- ➢ PF measures the profit per unit of risk, with PF >= 1.0 indicating a profitable trading strategy.
- ➢ The system utilize PF as the profitability measurement of each trading strategy (i.e. SMA, Bollinger Bands, and Twitter Sentiment), such that the system determine the weightage of how much we rely on each strategy's recommendation at Case Based Reasoning in the Decider agent.

Source: Reference [9, 10], NUS Fintech Lab, Naoya Ohara

# Signal PnL agent: What is “Drawdown”?




- Drawdown:
  - In the system, stratPnL() class also calculates the “drawdown” of each strategy.
  - “Drawdown” means the amount of loss from its peak performance.
  - “Time under water” a.k.a. “Recovery period” shows total period of time from the day when the fund/strategy began to make a loss from peak, to the day when the fund/strategy could recover its loss (i.e. “going back above water”). Of course, a shallow drawdown with fewer days of Time Under Water is better for investors, such that industry practitioners in fund industry often check those figures when they evaluate the performance of funds/trading strategies.
  - The stratPnL() class calculates those figures to visualize them into a graph.

Source: https://corporatefinanceinstitute.com/resources/knowledge/trading-investing/maximum-drawdown/, NUS Fintech Lab, Naoya Ohara

# Signal PnL agent: Definition of “Transaction cost”.

$$Tcost = x + y + MI + OC$$

$$Tcost = a + c \cdot \sigma \cdot \sqrt{\frac{V_{trade}}{V_{daily}}} + OC$$

(Where:

Tcost = total transaction cost,

x = exchange fee,

y = bid-ask spread/price,

MI = Market Impact Cost=c*σ*√Vtrade/Vdaily,

OC = Opportunity Cost, in transaction cost estimate, usually 0.0 is used because we assume all trade can be executed in the transaction cost estimation.

a = x+y (i.e. observable cost),

c = market impact metrics (usually, 1.0 is used),

σ = Daily market volatility,

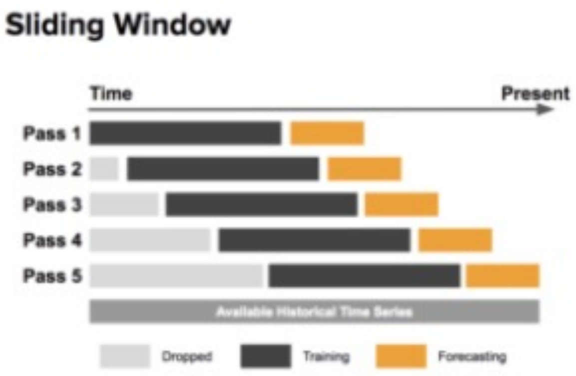
Vtrade = Volume of this fund’s/strategy’s trade in a day,

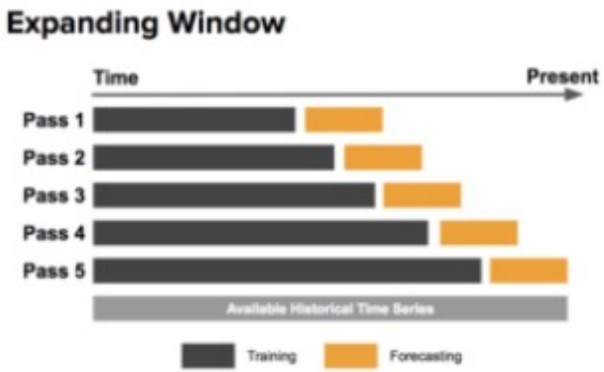
Vdaily = daily market volume.)

- Transaction cost:
  - Formally, the “transaction cost” can be decomposed shown as left formula. The key point is as follows:
    - Total transaction cost can be decomposed into **observable cost** i.e. exchange fee x + bid-ask spread/price y, and **unobservable cost** i.e. Market Impact cost and Opportunity Cost.
    - In unobservable cost, while we assume Opportunity Cost as zero in the transaction cost estimation, market impact cost cannot be zero in the real world.
    - Market Impact cost can rise by 1.volatility of the market increases, and 2.the fund size becomes larger and transaction volume i.e. Vtrade increases, compared with market liquidity Vdaily.
  - As a starting point of learning algorithmic trading, just simplified the transaction cost as a fixed number of 0.1% (Market Impact cost is very close to zero for small investors).

Source: Reference [11], NUS Fintech Lab, Naoya Ohara

# Backtesting agent: Train/Test split, using sliding window.

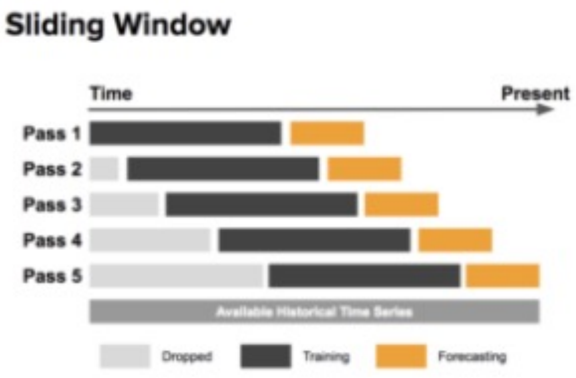


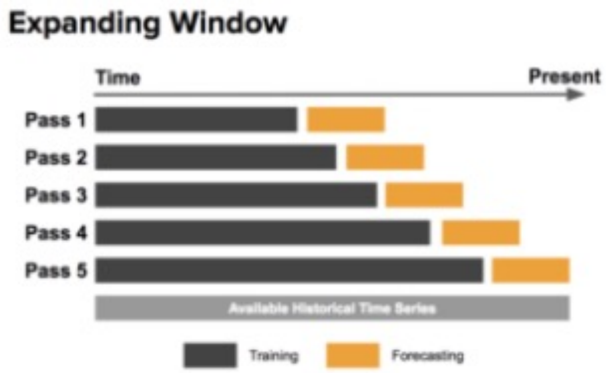




- Train/test splits using sliding window:
  - Then, need to implement the "Sliding Window" (aka "Work Forward") shown in the above picture. By doing so, we can avoid overfitting to past data and can check whether this strategy can work in the future. Train/test split using sliding windows is important to do back-test and build machine learning models for time-series data.

Source: https://stackoverflow.com/questions/56601488/is-there-a-way-to-get-a-sliding-nested-cross-validation-using-sklearn ,NUS Fintech Lab, Naoya Ohara

# (Contd.) Backtesting agent: Train/Test split, using sliding window.

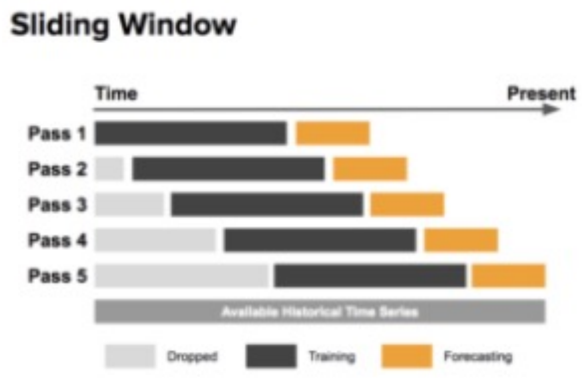


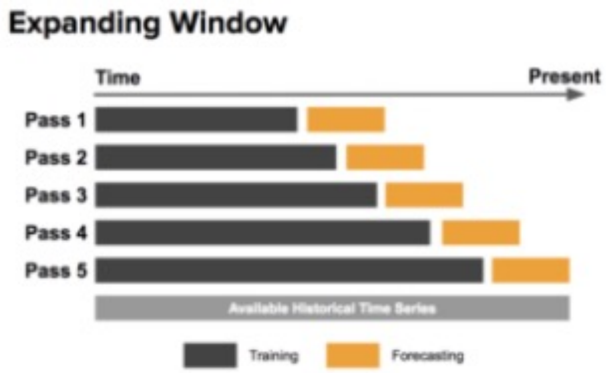




- Train/test splits:
  - **Training data:** By training data, we optimize the parameters of strategy (For example, in SMA, day combination of short-term moving average and long-term moving average) to obtain best return.
  - **Test data:** Then, in the test or forecasting period, we check whether an optimized strategy can work in an out-of-sample period.

Source: https://stackoverflow.com/questions/56601488/is-there-a-way-to-get-a-sliding-nested-cross-validation-using-sklearn ,NUS Fintech Lab, Naoya Ohara

# (Contd.) Backtesting agent: Train/Test split, using sliding window.




- Sliding window:
  - **Sliding window:** One is the sliding window, shown on the left hand side of the picture below. In this case, both training periods are fixed (i.e. training period: 2 years, test period: 1 year, for example). Then, we slide train/test period.
  - **Expanding window:** The other is the expanding window, shown on the right hand side of the picture below. In this case, the training period spans from the starting time until immediate before the test period. It means that the period of training data becomes longer and longer, as we test recent data.
  - While some quants' finance books suggest the expanding window, many industry practitioners and quantitative finance literature apply the sliding window as industry standard. We followed industry standards by applying the sliding window in the system.

Source: https://stackoverflow.com/questions/56601488/is-there-a-way-to-get-a-sliding-nested-cross-validation-using-sklearn , Reference [12,13], NUS Fintech Lab, Naoya Ohara

# Backtesting agent: Parameter optimization by Sharpe Ratio.

- Parameter optimization: we should determine the criteria for the parameter optimization.
  - **Maximize return?:** One way is just to maximize the return in the training period. For example, we can choose the combination of short-term moving average days and long-term moving average days (like short-term MA = 10 day, long-term MA = 20 days), the combination by which we can maximize the return in the training period and apply those parameters into the test period.
  - **Taking account risk -> Sharpe Ratio:** However, it is not the industry standard. When we consider the return, we also take into account how much we take the risk to obtain this return. In this context, Sharpe Ratio is popularly used in the financial industry to evaluate the performance of certain trading strategies or funds, shown as follows.

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p}$$

**where:**

$R_p$ = return of portfolio

$R_f$ = risk-free rate

$\sigma_p$ = standard deviation of the portfolio's excess return

Source: https://www.investopedia.com/terms/s/sharperatio.asp,NUS Fintech Lab, Naoya Ohara

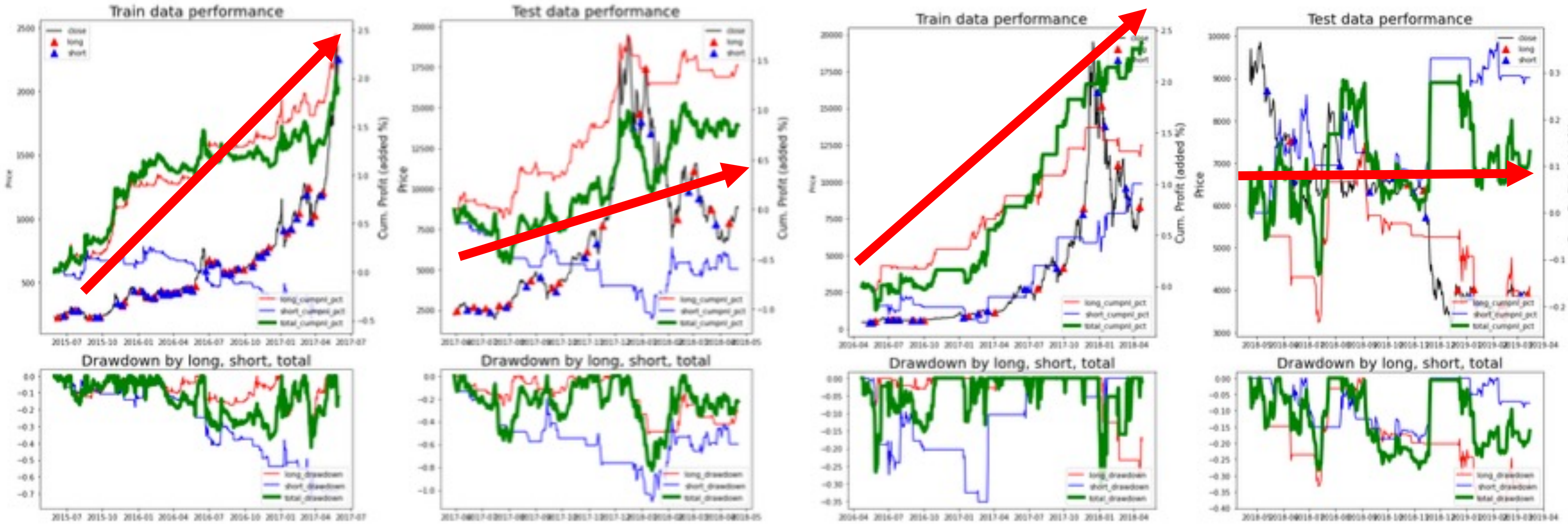
# (Contd.) Backtesting agent: Parameter optimization by Sharpe Ratio.

- Sharpe Ratio: Tips and details.
  - **Annual return:** Usually, Rp is stated as an annual return. Just summing up the daily log returns for 1 years, it can become the annual return.
  - **Annual volatility:** Also, σp is stated as an annual volatility. By converting daily volatility based on daily % changes into annual volatility, the formula is σ_annual = σ_day**sqrt(trading days for 1 year i.e. 365 in bitcoin's case). When it comes to equity which we do not trade Saturday/Sunday and national holiday, usually 250 days are used i.e. σ_annual = σ_day**sqrt(250).
  - **Treatment of Rf:** Risk-free rate can be often omitted and σp can be just calculated as the portfolio's volatility (not the volatility of the portfolio's excess return, i.e. σ(Rp - Rf)) in industry custom, because nowadays the risk free rate tends to be low and because the calculation of Rp / σp can be just simpler. By following such industry custom, the system calculates the Sharpe Ratio of trading strategy as Rp / σp, by omitting Rf.
  - The system optimizes parameters of each strategy to maximize the annualized Sharpe Ratio by greedy search. For example, in SMA strategy, the system tries (short-term MA, long-term MA) = (5,10),(5,20),(10,20) and calculates the sharpe ratio by using each (short-term MA, long-term MA) under training data period. Then, the system applies the parameter with best performance at train data into test data.

Source: https://www.investopedia.com/terms/s/sharperatio.asp, Reference [14], NUS Fintech Lab, Naoya Ohara

# Backtesting agent: Performance example of train/test split with sliding windows…Traders' dilemma of overfitting.

- Example of train/test split with sliding windows: SMA strategy. Train >> Test for performance.




Source: NUS Fintech Lab, Naoya Ohara

# (Contd.) Backtesting agent: Performance example of train/test split with sliding windows…Traders' dilemma of overfitting.

- Details and points: The performance by train/test split with sliding window.
  - Previous page was the examples of performance in the training period and test period with 4 sets of sliding windows for the SMA strategy. (Note: 2 set on the picture are shown as an example.)
  - **Train/test split:** Former 2 years of data is used as a training period to optimize parameters of short term moving average and long term moving average. Also, with the optimized parameters, the last 1 year is traded as a test period.
  - **Sliding window:** Then, the system slides a dataset of 2 years of training data and 1 year of test data, by 1 year ahead.

Source: NUS Fintech Lab, Naoya Ohara

# (Contd.) Backtesting agent: Performance example of train/test split with sliding windows…Traders' dilemma of overfitting.

- Details and points: The performance by train/test split with sliding window.
  - **Result:** As you can see, in the training data period on the left hand side of the graph, the performance is great i.e. total cumulative profit of the green line goes upward in a constant manner because it is the performance with the optimized parameters after try-and-errors by greedy search. However, in the test data period on the right hand side, the performance is not as great as was in the training data period.
  - **Traders' dilemma...Overfitting:** Such result shows typical reality in algorithmic trading. Many traders optimize the parameter by past data such that the back-testing performance i.e. training data's performance looks great. However, in reality, when we apply the optimized parameter into future data for real trading, the performance cannot be as good as was in the test data. It is a popular phenomena called "overfitting" toward training data. Many trading systems just show great performance in the training data period, but most of them cannot be reproducible in the real trading for the future coming data.
  - **Where is holy grail?:** Searching for the robust trading model which shows constant performance in the both training and test period can be the important theme for the quantitative researchers, while it is very challenging.

Source: NUS Fintech Lab, Naoya Ohara

# Backtesting agent: Multi threading.

- Multi threading:
  - While it is a technical matter, I introduced multi-threading at the implementation of **def backtestWithSlidingWindow(start,end)** in **class backTest(object).**
  - By multithreading, the system is able to process multiple threads of codes or functions concurrently.
  - In algorithmic trading, there can be the situation when we need to run multiple agents together, especially if the data time-horizon becomes shorter than a day, i.e. trading with 5 minutes of price tick data. In such a situation, we can utilize multithreading.
- Note:
  - Under the Python environment, the system operates each thread just with a single core CPU by switching between threads.
  - So, multithreading by Python may not contribute to the faster operation. Rather, it can become slower due to the additional tasks of switching operations among the working threads.
  - If we would like to implement very short term trading by using minute ticks or shorter, such operational speed can become the issue and we may need to implement the algorithm by Java (faster than Python, but slower than C++) or C++ (faster than Python and Java.
  - In the area of HFT (High Frequency Trading) in which the algorithmic system trades equities just by microseconds, mainly C++ or FPGA are used.

Source: NUS Fintech Lab, Naoya Ohara

# (Contd.) Backtesting agent: Multi threading…Example with “boiling noodle”.

(Functions to run)

```
def boil_noodle(seconds):
  print('Boiling noodle for {} secondes\n'.format(seconds))
  time.sleep(seconds)
  print('Noodle is boiled \n')

def prepare_soup(seconds):
  print('Preparing soup for the noodle for {} seconds \n'.format(seconds))
  time.sleep(seconds)
  print('Soup is prepared \n')
```

Noodle boiling and soup prep are concurrently done! Tasty!

(No multi-thread vs multi-thread)

```
print('Start cooking noodle')
boil_noodle(3)
prepare_soup(2)
print('Put noodle and soup together in the bowl')
print('Ramen is done!')
```

```
Start cooking noodle
Boiling noodle for 3 secondes

Noodle is boiled

Preparing soup for the noodle for 2 seconds

Soup is prepared

Put noodle and soup together in the bowl
Ramen is done!
```

```
print('Start cooking noodle')
#Creating threads
thread1 = threading.Thread(target=boil_noodle, args=(3,))
thread2 = threading.Thread(target=prepare_soup, args=(2,))
#Starting thread 1
thread1.start()
#Starting thread 2
thread2.start()
#Wait until the execution of thread 1 is done
thread1.join()
#Wait until the execution of thread 2 is done
thread2.join()
#Both thread 1, 2 are done
print('Put noodle and soup together in the bowl')
print('Ramen is done!')
```

```
Start cooking noodle
Boiling noodle for 3 secondes

Preparing soup for the noodle for 2 seconds

Soup is prepared

Noodle is boiled

Put noodle and soup together in the bowl
Ramen is done!
```

After noodle is boiled, soup is prepared…Noodle gets soggy and not tasty!

Pictures: WITHOUT multithreading (left hand side) and WITH multithreading (right hand side)

Source: NUS Fintech Lab, Naoya Ohara

# Section 10: Decider agent.

# Decider agent: Overall function.

- Overall function of the Decider agent:
  - The decider agent receives daily buy/sell trading signals from quantitative agent (SMA and Bollinger Bands) and qualitative agent (Twitter sentiment strategy).
  - Also, the decider agent receives daily 3 macroeconomic factor data calculated by the macro economist agent. Then, the decider creates the final recommendation based on signaling agents, macro economic factors, and CBR's case retrieval.
  - Finally, the CEO agent will receive the final recommendation from the decider agent to take final action.

Source: NUS Fintech Lab, Naoya Ohara

# Logic of combining buy/sell decisions from 3 different agents.

- Logic of combining buy/sell decisions from 3 different agents:
  - First, the Decider agent receives buy/sell recommendations of SMA, Bollinger Bands, and Twitter sentiment from quantitative and qualitative agents. To merge different trading signals into one final recommendation, I defined the following formula.

$$finalrecommendation = \sum_{i=1}^{n} \mathrm{w_i} * (SignalLong_i - SignalShort_i)$$

Where:

$$n = number\ of\ signals. In\ the\ system, n = 3.$$
$$i = each\ signal. SMA = 1, Bollinger\ Bands = 2, Twitter\ sentiment = 3$$
$$SignalLong_i = 1\ if\ long\ signal\ triggered, else\ 0$$
$$SignalShort_i = 1\ if\ short\ signal\ triggered, else\ 0$$

$$w_i = \frac{PF(total)_i}{\sum_{i=1}^{n} PF(total)_i}$$

$$PF(total)_i$$
$$= signaling\ agent\ i's\ total\ (i.e. including\ both\ long\ and\ short)\ Profit\ Factor$$
$$\sum_{i=1}^{n} PF(total)_i = sum\ of\ PF(total)_i, such\ that \sum_{i=1}^{n} w_i = 1$$

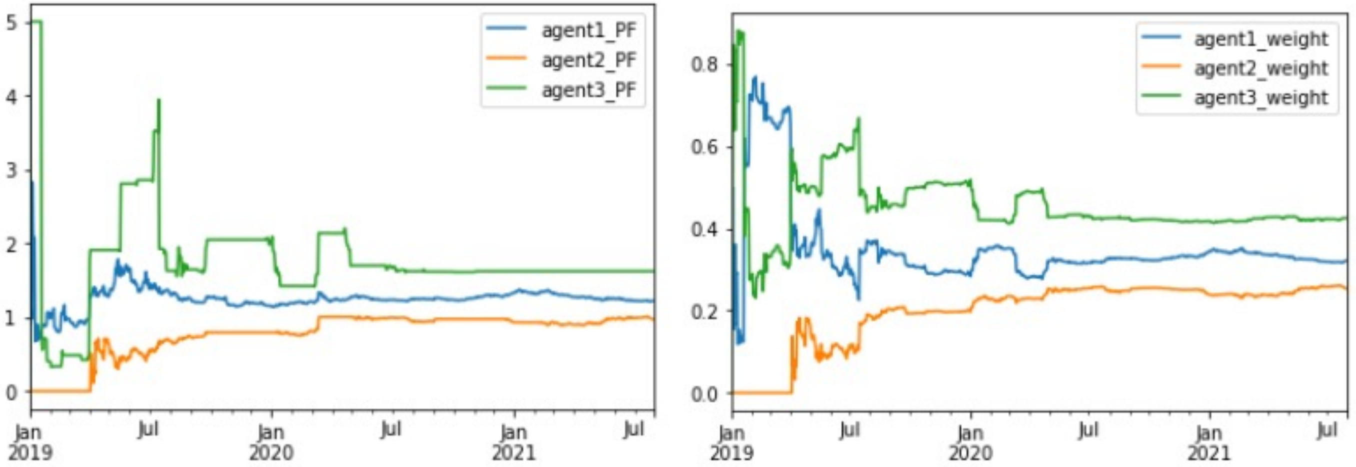
Source: NUS Fintech Lab, Naoya Ohara

# (Contd.) Logic of combining buy/sell decisions from 3 different agents.

- Example:
  - Final recommendation is the weighted average of (SignalLong - SignalShort), in terms of the weight w calculated by the Profit Factor, which is calculated at the section of Signal PnL and Backtesting agents.
  - Above equation looks scary, but it just means that, if the Profit Factor from a certain agent is high, the weightage of this trading strategy becomes high.
  - Below charts shows the example of the movements for PF and weights regarding each agent (agent1=SMA, agent2=Bollinger Bands, agent3=Twitter sentiment).

SMA agent has PF=2.0 (very profitable)
Bollinger Bands has PF=1.0 (zero profit or loss)
Twitter sentiment has PF=0.5 (loss is larger than profit)

Weightage of SMA = 2.0 / (2.0+1.0+0.5) = 0.5714
Weightage of Bollinger Bands = 1.0 / (2.0+1.0+0.5) = 0.2857
Weightage of Twitter sentiment = 0.5 / (2.0+1.0+0.5) = 0.1428




(Lhs: Example of PF movement for each agent, Rhs: Example of weights movement for each agent)

Source: NUS Fintech Lab, Naoya Ohara

# (Contd.) Logic of combining buy/sell decisions from 3 different agents.

- (Contd.) Example:
  - And today, for example, if SMA shows buy, Bollinger Band shows neutral (both buy/sell signals are 0), and Twitter sentiment shows sell, then the finalrecommendation will become as follows.

$$\text{finalrecommendation} = 0.5714 * (1 - 0) + 0.2857 * (0 - 0) + 0.1428 ( 0 - 1)$$
$$= 0.5714 + 0 - 0.1428 = 0.4286$$

  - When all trading signals show buy recommendation, finalrecommendation is equal to 1.0, while when all trading signals show sell recommendation, finalrecommendation is equal to -1.0. Also, when all signals are neutral, finalrecommendation = 0.0.
  - Then, the system convert "finalrecommendation" into 5 (strong buy), 4 (buy), 3 (neutral), 2 (sell), and 1 (strong sell) with following criteria. In above example of 0.4286, it becomes Buy (4) rating.

finalrecommendation > 0.5: Strong buy 5

0.1 < finalrecommendation <= 0.5: Buy 4

0.1 < finalrecommendation <= 0.1: Neutral 3

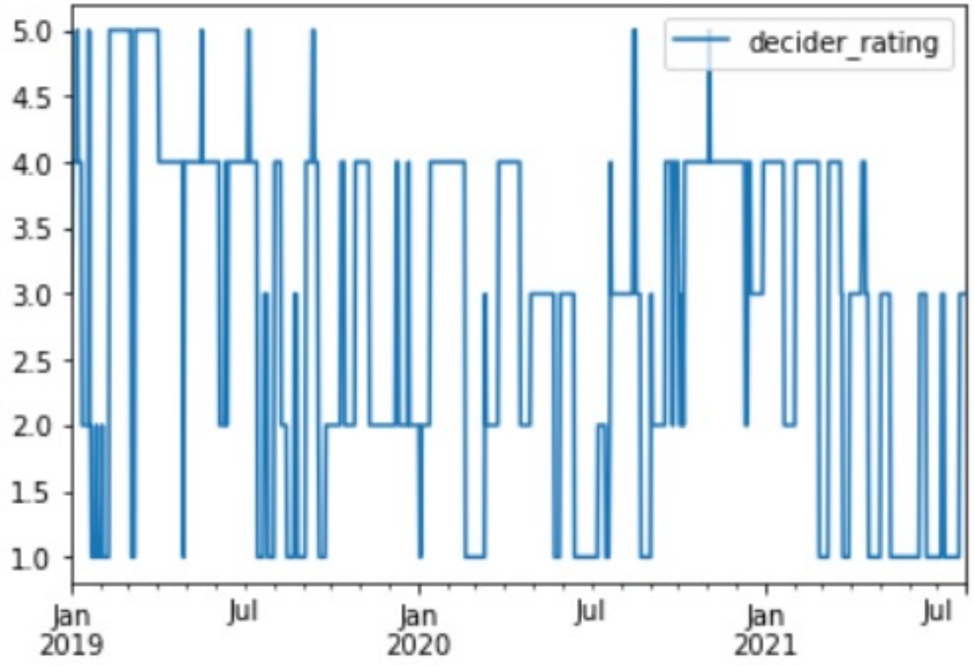
-0.5 < finalrecommendation <= -0.1: Sell 2

finalrecommendation <= -0.5: Strong sell 1

Source: NUS Fintech Lab, Naoya Ohara

# (Contd.) Logic of combining buy/sell decisions from 3 different agents.

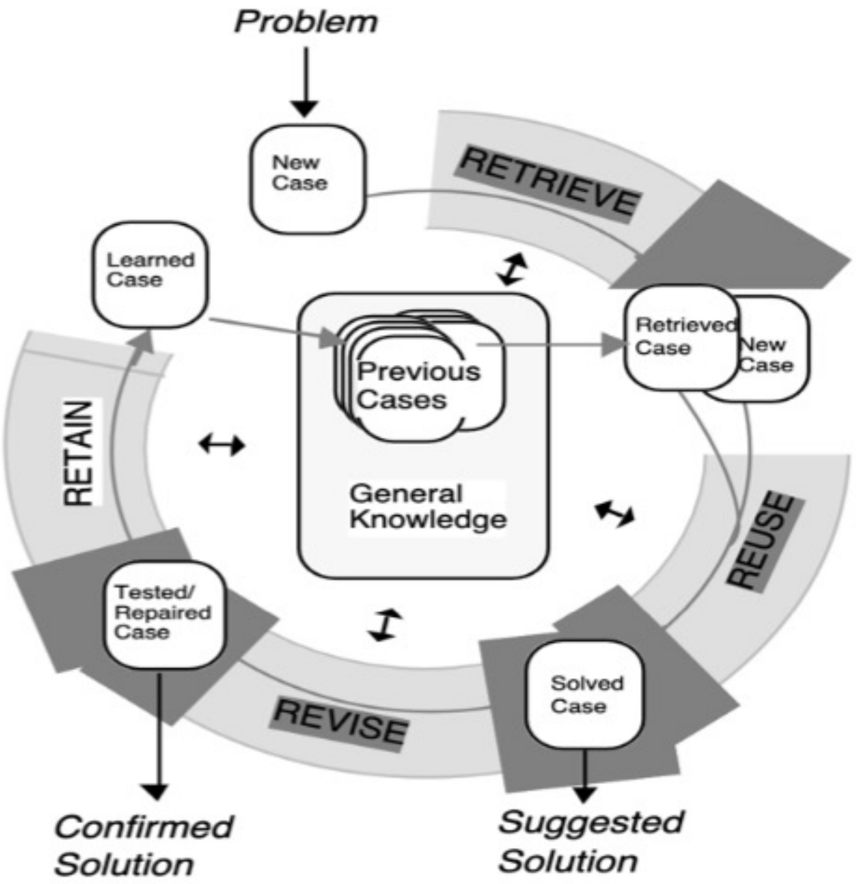
- (Contd.) Example:
  - Below chart shows the trading decisions made by the Decider, which reflects PF and weights for each agent shown in previous charts.




(Example of 1-5 rating)

Source: NUS Fintech Lab, Naoya Ohara

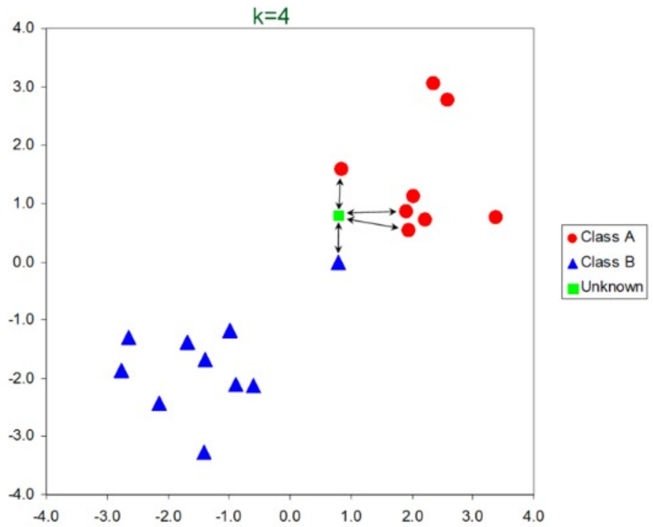
# Case Based Reasoning (CBR).




- CBR:
  - Central tasks of CBR are to deal with identifying the current problem situation, finding past cases similar to the new one (Retrieve), using those similar cases to suggest a solution to the current problem (Reuse), evaluating the proposed solution (Revise), and updating the system by learning from this experience (Retain).
  - In the financial market, searching for "past similar market circumstances with today" to find some insights for the future is a natural way of thinking for many market practitioners. The purpose of CBR application toward algorithmic trading is to mimic such market practitioners' methodology.

Source: Reference [15], NUS Fintech Lab, Naoya Ohara

# k-Nearest Neighbors (kNN).




$$d(X, Y) = \sqrt[q]{\sum_{i=1}^{n} |x_i - y_i|^q},$$

Where:

X, Y: two different feature vectors i.e. dataset, X=(x1, x2,...xn), Y=(y1, y2,...yn)

n: # of features in X and Y

q: if q=1, d(X, Y) is called the Manhattan distance. If q=2, d(X, Y) is called the Euclidean distance.

- kNN:
  - To implement the case retrieval in CBR system, k-nearest neighbour (kNN) algorithm is widely used.
  - K Nearest Neighbours (kNN) is the algorithm to take the distance among certain feature vectors and extract top kth nearest vectors in terms of distances.
  - With regard to taking distance, the Minkowski distance below is popular. Especially, when we take q=2, it becomes Euclidean distance and popularly used in the kNN algorithm.
  - **Curse of dimensionality:** kNN performs better with a lower number of features. If the number of features increases, it requires more data to perform kNN appropriately. Increase in dimension of the feature vector can also lead to the problem of overfitting.
  - **Reason to use PCA before kNN:** To avoid the curse of dimensionality, we often use PCA to reduce the dimensionality of data, as shown in Macro Economist agent.

Source: Reference [16-22], NUS Fintech Lab, Naoya Ohara

# Implementation of Case Retrieval in CBR by kNN.

## ❑ Case Retrieval by kNN:

- In our system, data shown below picture is stored in the past case data storage (i.e. dataframe of cbrDecider.case_data_df), and we can extract the top 30 (i.e. k=30) of the most similar datasets compared with the certain day, by using kNN.

```
cbrDecider.case_data_df
```

| | agent1_long | agent1_short | agent2_long | agent2_short | agent3_long | agent3_short | macro_factor1 | macro_factor2 | macro_factor3 |
|---|---|---|---|---|---|---|---|---|---|
| 2019-01-01 | 1.0 | 0.0 | 0.0 | 0.0 | 1.0 | 0.0 | -0.891191 | 0.096499 | 0.378480 |
| 2019-01-02 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | -0.858942 | 0.064011 | -0.299344 |
| 2019-01-03 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | -0.523940 | 0.178067 | 0.417479 |
| 2019-01-04 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | -0.141390 | -0.660551 | 0.554137 |
| 2019-01-05 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | -0.179610 | 1.024015 | 0.176716 |

- As a result, the CBR system can obtain the data of "the most similar past market condition" in terms of the buy/sell recommendation from 3 signaling agents and the macroeconomic environment summarized by 3 macroeconomic factors.
- To avoid the curse of dimensionality mentioned above, macroeconomic data is summarized into 3 factors, using PCA in the previous section.
- Usually, the performance of kNN can improve by the dimensionality reduction using PCA (or other methodologies of dimensionality reduction of data), such that you can utilize the combination of PCA => kNN as one of your tools.

Source: NUS Fintech Lab, Naoya Ohara

# Case Reuse: It can serve as “double-checking” of recommendation, by referring to the past performance of similar cases.

| r1 | macro_factor2 | macro_factor3 | t+1_ret | t+2_ret | t+3_ret | t+4_ret | t+5_ret | t+6_ret | t+7_ret | t+8_ret | t+9_ret | t+10_ret |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 91 | 0.096499 | 0.378480 | 0.0[illegible]5989 | -0.001[illegible]64 | 0.003694 | 0.000436 | 0.060651 | 0.047282 | 0.048739 | 0.049896 | -0.042824 | -0.0[illegible]0628 |
| 42 | 0.064011 | -0.299344 | -0.0[illegible]7050 | -0.021[illegible]30 | -0.[illegible]24[illegible]06 | 0.033784 | 0.020753 | 0.022173 | 0.023301 | -0.067070 | -0.064930 | -0.0[illegible]1539 |
| 40 | 0.178067 | 0.417479 | 0.0[illegible]5467 | 0.002[illegible]03 | 0.062[illegible] | [illegible] | [illegible] | [illegible] | [illegible]133 | -0.038933 | -0.045726 | -0.0[illegible]3966 |
| 90 | -0.660551 | 0.554137 | -0.0[illegible]3246 | 0.056[illegible]47 | 0.[illegible] | [illegible] | [illegible] | [illegible] | [illegible]159 | -0.050915 | -0.079001 | -0.0[illegible]9315 |
| 10 | 1.024015 | 0.176716 | 0.0[illegible]0189 | 0.046[illegible]26 | 0.048282 | [illegible] | [illegible] | -0.0[illegible]046 | -0.047824 | -0.076002 | -0.036186 | -0.0[illegible]5789 |

Calculate mean and σ vertically on t+1…t+10 days for top k=30 of similar past days.

❑ Methodology:

- ➢ Calculate mean and σ of return on t+1…t+10 days for the top k=30 of similar past cases.
- ➢ Calculate t-values on t+1…t+10, based on mean and σ.
- ➢ Take average of t-values and obtain p-value.
- ➢ If mean return of t+1…t+10>0, the p-value < 0.05, and finalrecommendation = 4 or 5, send 4 or 5 of buy recommendation to CEO.
- ➢ If mean return of t+1…t+10<0, the p-value < 0.05, and finalrecommendation = 1 or 2, send 1 or 2 of sell recommendation to CEO.

Source: NUS Fintech Lab, Naoya Ohara

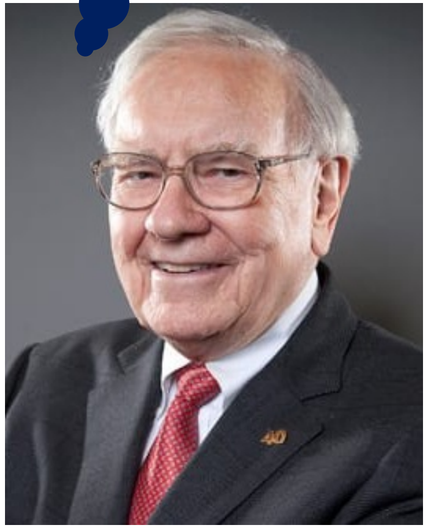
# Section 11: Risk management agent.

# Risk management agent.

“Survival first, then make profit!”.

"Rule 1: Never Lose Money. Rule 2: Never Forget Rule 1"

George Soros

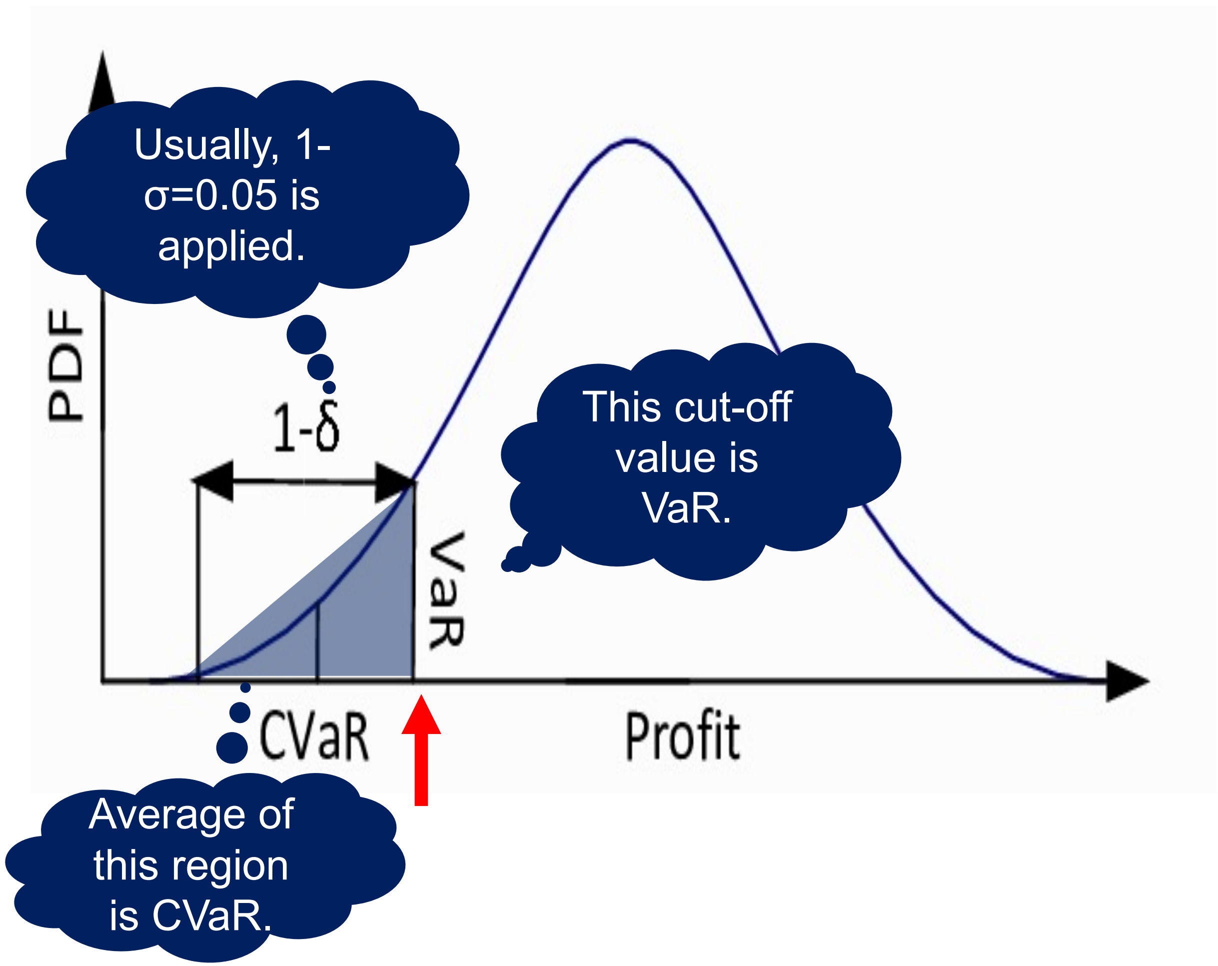


Warren Buffett

- Why risk management is important?:
  - I implemented an independent risk management agent, based on Value at Risk (VaR).
  - Basically, institutional investors (i.e. such as hedge-fund) determine the position size based on "how much we can make loss". The legendary hedge-fund manager George Soros also mentioned this point as “Survival first, then make profit”.
  - This chapter introduces the concept of VaR. The CEO agent will set the maximum limit of annualized 5% VaR, i.e. possible annual loss with 5% of probability as initial risk management policy. Then, the position size is determined based on this annualized VaR limit.

Source: Several websites, NUS Fintech Lab, Naoya Ohara

# What is Value at Risk?




- ❑ VaR (Value at Risk): To measure “how much can we expect to lose”.
  - ➢ VaR tries to provide a reasonable estimate of the maximum probable loss in value of an investment portfolio over a particular time period.
  - ➢ Three parameters: a portfolio, a time period, and a probability. 5% VaR is normal.
  - ➢ We estimated 5% probability VaR in 1 year time period.
- ❑ (For reference...CVaR (Conditional VaR, or Expected shortfall):
  - ➢ Basel Committee on Banking Supervision has recently proposed as a better and more conservative risk measure than VaR.
  - ➢ CVaR considers the expected loss instead of the cutoff value.
  - ➢ It is out of the scope for the project.

Source: Reference [23], NUS Fintech Lab, Naoya Ohara

# Methods for Calculating VaR.

We apply it this time!

- Variance-Covariance:
  - Variance-covariance is by far the simplest and least computationally intensive method. Its model assumes that the return of each instrument is normally distributed, which allows deriving an estimate analytically.

- Historical simulation:
  - Historical simulation extrapolates risk from historical data by using its distribution directly instead of relying on summary statistics. For example, to determine a 95% VaR for a portfolio, we might look at that portfolio's performance for the last 100 days and estimate the statistic as its value on the fifth-worst day.
  - A drawback of this method is that historical data can be limited and fails to include all market scenario such as market collapse.

- Monte Carlo Simulation:
  - Monte Carlo simulation tries to weaken the assumptions in the previous methods by simulating the portfolio under random conditions.

Source: Reference [23], NUS Fintech Lab, Naoya Ohara

# How to calculate portfolio volatility.

## ❑ How to calculate portfolio volatility:

- When we apply the variance-covariance method, we need to calculate the portfolio volatility i.e. standard deviation of $\sigma$ (Note: variance is the square of standard deviation). The portfolio volatility for 2 securities is shown as follows.

$$\sigma_{portfolio} = \sqrt{w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + 2w_1w_2\rho_{1,2}\sigma_1\sigma_2}$$

Where:

| | | |
|---|---|---|
| $W_1$ | = | Proportion of the portfolio invested in Asset 1 |
| $W_2$ | = | Proportion of the portfolio invested in Asset 2 |
| $\sigma_1$ | = | Asset 1 standard deviation of returns |
| $\sigma_2$ | = | Asset 2 standard deviation of returns |
| $\rho_{1,2}$ | = | Correlation coefficient between the returns of Asset 1 and Asset 2 |

- In our case, w1=cash, w2=bitcoin. Also, cash has zero volatility i.e. $\sigma_1 = 0$. Therefore, above equation can be simplified as follows.

$$\sigma\_portfolio = \sqrt{{w_2}^2{\sigma_2}^2} = w_2\,\sigma_2$$

Source: https://medium.com/python-data/assessing-the-riskiness-of-a-portfolio-with-python-6444c727c474, Reference [23], NUS Fintech Lab, Naoya Ohara

# (Note:How to calculate portfolio volatility.)

- If the portfolio can consist of multiple securities, portfolio volatility is calculated by matrix algebra shown as follows:

The formula for portfolio volatility is:

$$\sigma_{Portfolio} = \sqrt{w_T \cdot \Sigma \cdot w}$$

- $\sigma_{Portfolio}$: Portfolio volatility
- $\Sigma$: Covariance matrix of returns
- w: Portfolio weights ($w_T$ is transposed portfolio weights)
- $\cdot$ The dot-multiplication operator

- For example, above portfolio volatility of 2 securities can be shown in context of matrix algebra, as follows:

$$\sigma_p^2 = \begin{bmatrix} w_1 & w_2 \end{bmatrix} \begin{bmatrix} \sigma_1^2 & \sigma_{1,2} \\ \sigma_{2,1} & \sigma_2^2 \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} = \begin{bmatrix} w_1 \sigma_1^2 + w_2 \sigma_{2,1} & w_1 \sigma_{1,2} + w_2 \sigma_2^2 \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \end{bmatrix}$$
$$= w_1^2 \sigma_1^2 + w_1 w_2 \sigma_{2,1} + w_1 w_2 \sigma_{1,2} + w_2^2 \sigma_2^2$$
$$= w_1^2 \sigma_1^2 + 2 w_1 w_2 \sigma_{1,2} + w_2^2 \sigma_2^2$$

Source::https://stackoverflow.com/questions/59462628/is-there-a-way-to-vectorize-the-portfolio-standard-deviation-in-python-pandas, https://medium.com/python-data/assessing-the-riskiness-of-a-portfolio-with-python-6444c727c474, Reference [23], NUS Fintech Lab, Naoya Ohara

# Position sizing using VaR.

- Position sizing using VaR:
  - After we can calculate the portfolio of VaR, we can decide the position size using VaR. For example, the CEO agent sets the maximum VaR limit = 0.2 (20% of loss in 1 year with 5% of probability), we can take the position as such, by calculating follows: σ_portfolio = weight of bitcoin in total NAV*σ_bitcoin, s.t.
    the weight of bitcoin in total NAV = σ_portfolio / σ_bitcoin.
  - The system implements such a function at **def targetPositionFromVaR(day, VaRLimit, var_pct=0.05)** in in **class riskManagement(object)**. In this function, using above logic, the target bitcoin's position size is calculated by Target Coin Value = NAV*VaR_limit / VaR_bitcoin.
  - As you can infer, the bitcoin volatility σ_bitcoin can change over time as the degree of market fluctuation of bitcoin changes, such that our portfolio volatility σ_portfolio can change over time.
  - The CEO function can decide the position sizing using this function, and can rebalance the portfolio using this function, i.e. if the VaR becomes too large at the current position size in terms of VaR limit, the system can slush the position size, and vice versa.
  - It is the operation that many institutional investors actually do in daily portfolio management, such that I implemented such a function to introduce such basic portfolio management activities in the financial and investment management industries.

Source: Reference [23], NUS Fintech Lab, Naoya Ohara

# Section 12: Data visualization and RPA agent.

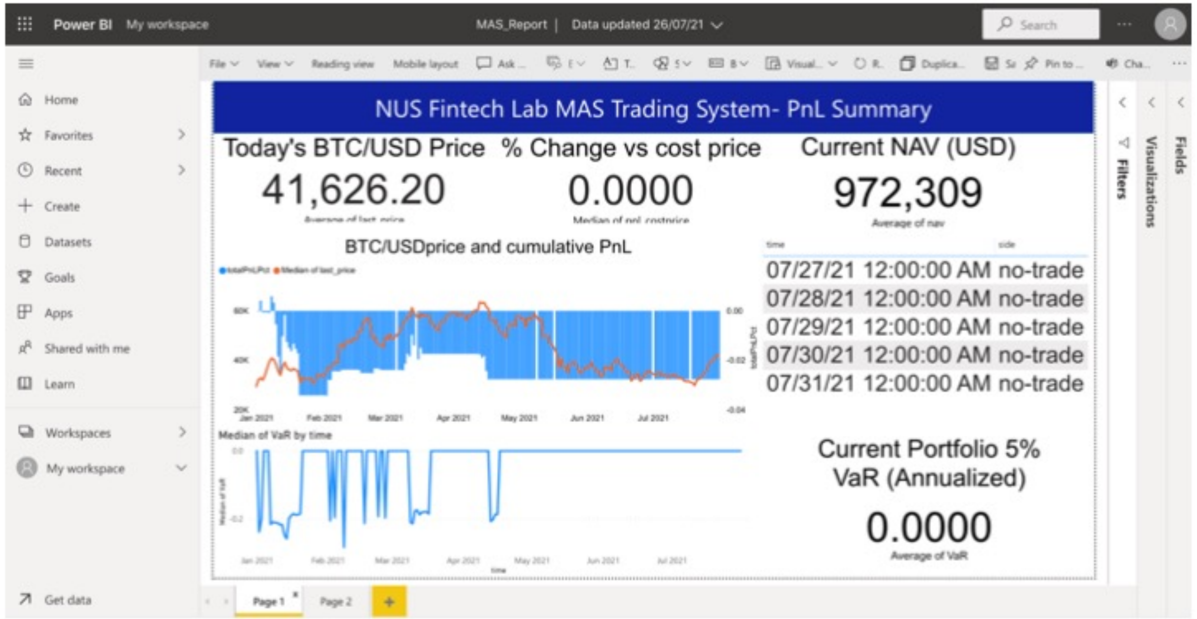
# Data visualization and RPA agent.

❑ General guide for data visualization and RPA.

- Data visualization and RPA (Robotic Process Automation) are also important parts in business operational flow.
- **Data Visualization:** By data visualization with several graphs and charts, we can recognize what's going on in the market and our portfolio easily and can make decisions toward the market timely (such as the human decision making of whether we should stop working the trading system etc).
- **RPA:** Also, we can improve efficiency of daily operation by automating repetitive operations such as sending monthly reports by email and storing attached files in email to specific data storage (such as One Drive).
- **PowerBI and Power Automate:** This agent takes those tasks such as data visualization and RPA. I introduced PowerBI for data visualization and Power Automate for RPA. Those Microsoft products are widely used, such that we can utilize those in our workplace to improve operational efficiency.

Source: Microsoft, NUS Fintech Lab, Naoya Ohara

# Data visualization by Power BI.




## ❑ Data visualization by Power BI.

- ➢ In the data visualization tool, Tableau and PowerBI are popularly used in business corporations, and the PowerBI is the one which is released by Microsoft.
- ➢ With regard to the basic usage and how-to, we can refer to Microsoft's website as follows. You can learn how to create and manage Report and Account in Power BI to visualize our data with graphs and charts.

Get started using Power BI
https://docs.microsoft.com/en-us/users/microsoftpowerplatform-5978/collections/k8xidwwnzk1em

- ➢ By utilizing API (Application Programming Interface) of Power BI, we can send our data, which are generated by Python's dataframe in google Colab notebook, into Power BI.

Source: Microsoft, NUS Fintech Lab, Naoya Ohara

# RPA by Power Automate.

## ❑ RPA by Power Automate.

- Robotic process automation (RPA) is a technology that mimics and automates the way humans interact with software to perform high-volume, repeatable tasks.
- While there are many RPA software and services available, Microsoft Power Automate is a convenient solution for RPA, especially as we would like to automate operations around softwares and services of Microsoft family (i.e. Office 365, One Drive etc).
- With regard to the basics of how-to and what we can do by Power Automate, we can refer to the following tutorials from Microsoft.

Get started with Power Automate
https://docs.microsoft.com/en-us/power-automate/getting-started

- On the other hand, unfortunately, Power Automate cannot set Google Drive and google Colab as the trigger of doing automated action.
- Also, with regard to the frequently used function such as sending email automatically, we can write code to send email automatically.

Source: Microsoft, NUS Fintech Lab, Naoya Ohara

# RPA procedure: Send email with attaching monthly performance report and store the attached file in email into One Drive automatically.

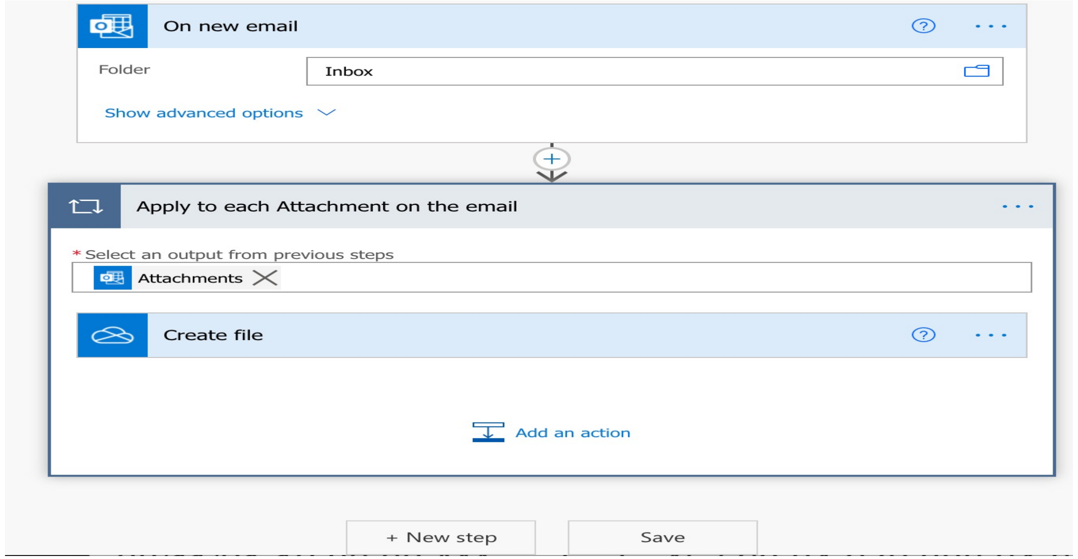
## ❑ What tasks we automated

Send monthly report via email with the file attachment automatically by Python code

Receiving email, then automatically save attached monthly report file into One Drive

## ❑ How we automated

```
@staticmethod
def outlookSend(file_name):
```




Source: Microsoft, NUS Fintech Lab, Naoya Ohara

# Section 13: CEO agent.

# CEO agent.

- CEO agent.
  - **Investment and risk management policy:** First, the CEO agent establishes investment and risk management policy at ceoInitialSetUp() function. CEO sets up initial fund amount, starting day, risk management policy such as annualized VaR limit, and profit target/maximum loss tolerance when the fund terminates trading if it reaches to that point. Such investment and risk policy are set before we start daily trading and fund management activities in the real world of fund management too.
  - **Orchestration of daily activity:** Then, the CEO agent orchestrates the buy/sell recommendation from the Decider agent, Account recording by Account agent, risk management from Risk management agent, and makes final trading decisions and asks trade execution to the Broker agent.

Source: NUS Fintech Lab, Naoya Ohara

# Section 14: Simulated trading performance and its insight.

# Backtest performance of 3 each strategies (SMA, Bollinger Band, and Twitter sentiment).

❑ Methodology:

- Below data is the connected performance data of 4 test data periods, based on the 4 training data and its parameter optimization.
- The parameter optimizations were executed in training periods, and those parameters were applied in the test period.
- Below charts consist only of test data, such that we could avoid the overfitting issue by train/test split and sliding window approach.

❑ SMA strategy.


❑ Bollinger Bands strategy.


❑ Twitter sentiment strategy.


Source: NUS Fintech Lab, Naoya Ohara

# Key takeaways from backtest performance of 3 each strategies.

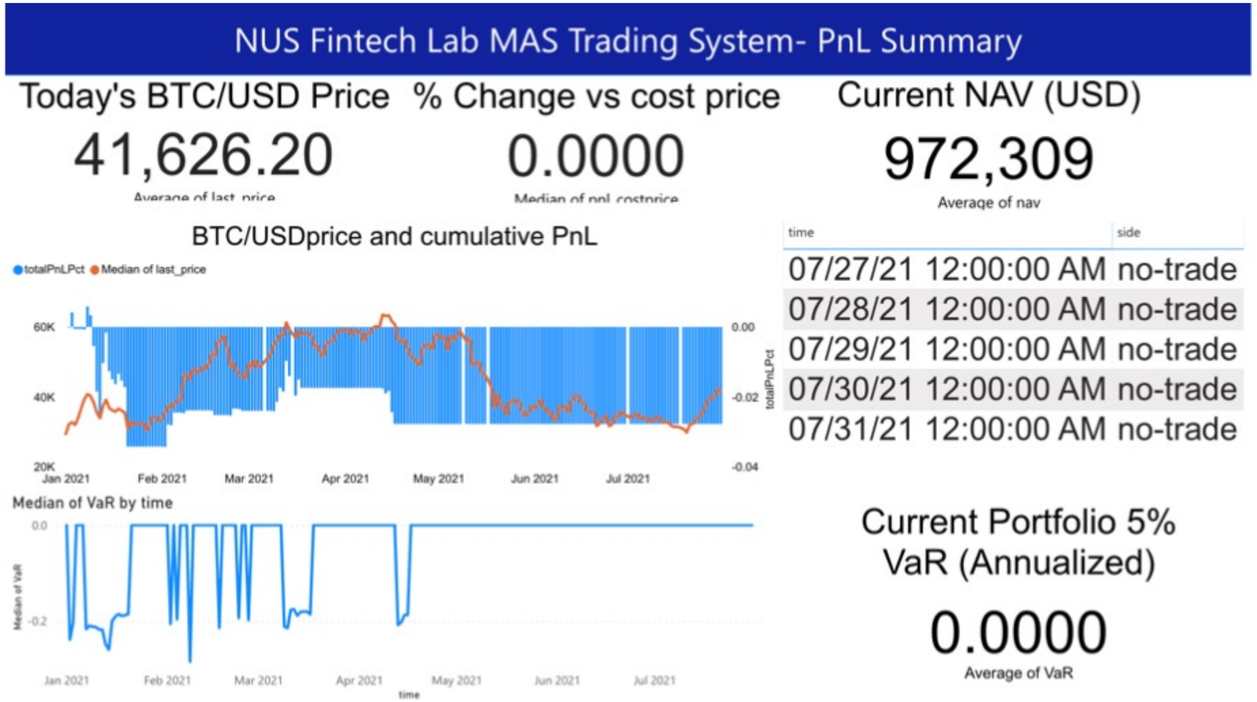
- Key takeaways:
  - **SMA works well:**
    - This result implies that there exists a long-lasting price trend in the bitcoin market, and the trend-following strategy can work relatively well.
  - **Bollinger Bands did not work well:**
    - In particular, the recommendation of short-selling suffered a lot, i.e. the price went up further after the system recommended to sell.
    - The failure of this strategy can show the same implication as the SMA strategy: The bitcoin price tends to have a long-lasting price trend.
  - **Twitter sentiment moderately works:**
    - This result suggests there can be rooms for improvement in text sentiment analysis.
    - For example, while we picked up twitter data mainly from popular news media such as Bloomberg, NYT, CNN, FT etc, those news media can be "lagged" indicators.
    - Also, we can improve the methodology of obtaining text sentiment scores from texts, by developing our own NLP algorithms too.

Source: NUS Fintech Lab, Naoya Ohara

# Performance of simulated trading in 2021 (Jan-July), by integrating 3 signals using CBR and VaR risk management.

## ❑ Methodology:

➢ Next, the below shows the performance of simulated trading in 2021 from Jan to July, by integrating 3 signals using CBR implemented in the Decider agent, and by enhancing risk management with VaR in the Risk Management agent, those which were orchestrated by the CEO agent.




Source: NUS Fintech Lab, Naoya Ohara

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# Key takeaways from Performance of simulated trading in 2021 (Jan-July).

- Key takeaways:
  - As a result, while at the time of the bitcoin price plunge the system could safeguard the performance with CBR function and VaR risk management system, still the performance was -2.8% YTD (Year-To-Date), slightly negative performance which reduced 1 mio USD of NAV to 972,309 USD.
  - To improve the performance, first, we need to find more profitable buy/sell signals as in particular the Bollinger Bands was not profitable.
  - Then, we can think about how we can improve the Decider function and risk management as well.

Source: NUS Fintech Lab, Naoya Ohara

# Section 15: Future improvement.

# 1.Time horizon of data: From day to minutes, second or less than that.

- This time, I implemented the whole system with day OHLCV data for several reasons, such as follows:
  - **Data availability.** Day OHLCV data can be available since around 2014 easily by yahoo finance.
  - **Nice data to understand long-term historical movement** in bitcoin. By checking daily price data of bitcoin more than 5 years, we can understand the basic history and characteristics of bitcoin price movement appropriately.
  - **Appropriate complexity** in system development as the showcase at NUS Fintech lab.

- However, in the real world of trading, short-term trading within some minutes using minute tick data is not so special.
  - In equity and currency markets with thick liquidity, second or even less than mili-second of trading is also popular.
  - But we need to implement Java, C++ or FPGA to implement such a very fast trading, and such implementation is out of the scope for this project.

Source: NUS Fintech Lab, Naoya Ohara

# 2.Searching and picking up more profitable technical indicators at quantitative agents.

- Searching and picking up more profitable indicators:
  - I picked the SMA and Bollinger band, because SMA is the basic technical indicator for trend-following and the bollinger band is also very popular in using the basic mean-reverting indicator.
  - However, we can search for more profitable technical indicators in the future.
  - Also, we can pursue more advanced statistical analysis to generate better buy/sell recommendations.

Source: NUS Fintech Lab, Naoya Ohara

# 3.The rooms for improvement in qualitative agent, NLP of twitter text.

- There are additional topics for the improvement in twitter text analysis shown as follows:
  - **Using data such as likes and retweets:** This time, we did not use twitter information such as the number of likes and retweets, due to the constraints of data availability within free and easy data acquisition.
  - **Analyzing context of reply and retweets:** We did not include analysis of reply and retweet of tweets. In the twitter context, each tweet does not stand alone. In reality, to understand the context of conversation and its tone, we should analyse whole communication flows of reply and retweet.
  - **Data sources:** We can increase or change data sources too. This time, I just obtained twitter from popular news' twitter accounts such as Bloomberg, FT, NewYork Times and Elon Musk. While limiting data source into such major accounts assures relatively low noise and high quality in data, especially official news accounts may just mention the past and may not predict about the future.
  - **Developing advanced NLP model by machine learning:** We can utilize advanced machine learning techniques or originally developed NLP tools. This time, we mainly utilized google sentiment analysis tool for natural language processing. However, if we'd like to differentiate the quality of twitter sentiment by the improvement of the NLP algorithm, we may need to develop it by ourselves, utilizing advanced machine learning techniques such as BERT, by diving deeper into NLP itself.

Source: NUS Fintech Lab, Naoya Ohara

# 4. Utilizing more advanced concepts in finance domain.

- This time, to make the system tractable for the students including the people without finance background, I implemented some finance concepts in a simple way shown as follows:
  - **Fixed market impact cost:** I omitted the calculation of market impact estimate such that the transaction cost is just fixed as 0.1% per one buy/sell trade.
  - **Using simple VaR model:** Also, I just implemented VaR by the simplest method i.e. mean-variance approach. However, we can also develop it in more advanced ways such as monte-carlo method. Also, VaR has more advanced relatives such as CVaR (Conditional VaR), which can be more conservative and a better way for risk management. In the future, the sophistication of VaR implementation can become one of the important topics to improve the performance of a system.
  - **Cash or bitcoin portfolio:** In addition, this time, I just implemented a “cash or bitcoin” portfolio, to simplify the portfolio management process. However, we can introduce multi currency portfolio or multi asset class portfolio including equity and fixed income in the future, the implementation which can become more realistic in the actual institutional portfolio management.

By improving the above points, the system can become closer to the institutional, professional investor level.

Source: NUS Fintech Lab, Naoya Ohara

# 5. Utilizing advanced machine learning.

- This time, just introduced PCA and kNN with scikit learn as the body-of-knowledge.
  - However, with regard to CBR, some literature offer more advanced methodologies to improve the quality of CBR. Also, many market practitioners are now trying to apply more advanced machine learning (such as deep learning and reinforcement learning) into the algorithmic trading arena.
  - With regard to the application of advanced machine learning into financial trading and portfolio management, I recommend referring and studying books written by Marcos Lopez De Prado shown as follows. Those books contain advanced topics, but you can follow many of the topics covered by those books, after learning topics covered in this paper.
    - Marcos Lopez De Prado. Advances in Financial Machine Learning. John Wiley & Sons, 2018
    - Marcos Lopez De Prado. Machine Learning for Asset Managers. Cambridge University Press, 2020

Source: Reference [12, 16-21, 26-27], NUS Fintech Lab, Naoya Ohara

# 6. Connection with simulated exchange or real money trading.

- From simulation to more realistic environment.
  - **Main purpose this time:** The main purpose of creating the system this time is to show the body-of-knowledge in algorithmic trading and real-world application of machine learning, such that I implemented the system as the simulated environment without the real trading in market exchange.
  - **Simulated market exchange:** However, in the future, if the NUS Fintech lab could launch the simulated market exchange, we can connect the system with its simulated market exchange.
  - **Real money trading if possible:** Also, after the trial at simulated market exchange and feasibility study for real money trading, we may proceed to the real money trading to make profit in the future, while it requires more stringent standards regarding the system robustness, several risk management, and other safeguards not to lose money by several risks including system failure risk.

Source: NUS Fintech Lab, Naoya Ohara

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