Maximum Sharpe Ratio by Non-Negative Least Square and Bayesian Optimization

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Problem Statement

Choosing the portfolio contains K over N stocks that maximize the Sharpe Ratio:

Sharpe Ratio

Sharpe Ratio =
$$\sqrt{n} * \frac{\mathbb{E}[R - R_f]}{\sqrt{\text{var}[R - R_f]}} = \sqrt{252} * \frac{\mathbb{E}[R]}{\sqrt{\text{var}[R]}}$$

where:

- $R_f = 0$
- n = 252
- R is the returns of portfolio
- R is equally distributed by the returns of K stocks: $R = \frac{1}{K} \sum_{i=1}^{K} R_i$

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Approach Ideas

- Optimization Methods
- Best subset selection

Project Baseline

- Preprocessing Data
- Using Non-Negative Least Square to remove Short Position
- Using Simple Moving Average to filter downtrend stocks
- Using Bayesian Optimization to searching the best stock combination

Data

• The data has 520432 rows and four attributes of 443 tickers.

	ticker	date	close	volume
0	VN30	2013-01-02	490.82	22641550.0
1	VN30	2013-01-03	491.34	35219262.0
2	VN30	2013-01-04	498.31	21387780.0
3	VN30	2013-01-07	509.18	26031020.0
4	VN30	2013-01-08	525.36	65840432.0

Figure 1: Data

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Transforming Data

• The data are transformed into the $T \times N$ data frame with the row's index is the T trading dates and columns index is N ticker ids.

ticker	AAA	AAM	ABT	ACC	ACL	ADS	AGD	AGF	AGM	AGR
date										
2013- 01-02	NaN	11.25	22.54	13.44	10.17	NaN	61.0	10.48	13.81	5.21
2013- 01-03	NaN	10.98	22.54	13.44	9.84	NaN	64.0	10.96	13.12	5.30
2013- 01-04	NaN	10.98	22.44	13.39	9.92	NaN	64.0	10.96	13.18	5.40
2013- 01-07	NaN	11.07	22.44	13.34	10.25	NaN	64.0	10.44	13.18	5.49
2013- 01-08	NaN	11.44	22.28	13.60	10.57	NaN	61.0	9.96	12.87	5.49

Figure 2: Transform Data

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Sample Stock Prices



Figure 3: Sample Stocks Price and its Simple Moving Average

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Cleaning Data

- \bullet Remove all stocks which had missing value in long interval till the end of 31/07/2019.
- Left the stock which had missing from the beginning. This means that the company still not join the stock market until the days that data was available.
- Fill data missing in middle by **Linear Interpolation**.

Selecting Data

- The market could be segment to vary era.
- The further data in past, the lesser affect on current behavior.
- Selecting the Data back to 1 years, which the data using for model is from 31/07/2018 to 31/07/2019.
- The stock which does not join market before 31/07/2018 will be remove from data.

Markowitz's Mean Variances Problems

• Finding the Minimum Variance Portfolio subject to Expected Return.

$$\begin{aligned} & \min_{\mathbf{w}} & & \frac{1}{2}\mathbf{w}^T \mathbf{\Sigma} \mathbf{w} \\ \text{subject to} & & & \mathbf{w}^T \hat{\mu} = p \end{aligned}$$

 Solution to Maximize Sharpe Ratio is also the solution of Minimum Variances problems with normalize weight.

$$\mathbf{w}^* = rac{\sum^{-1} \hat{\mu}}{1_N^T \Sigma^{-1} \hat{\mu}}$$

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Markowitz's Mean Variances Problems

• The problem could be rewrite as follow:

$$\min_{\mathbf{w}} \quad \|p\mathbf{1}_{T} - R\mathbf{w}\|_{2}^{2}$$
 subject to
$$\mathbf{w}^{T}\hat{\mu} = p$$
 and
$$\mathbf{w}^{T}\mathbf{1}_{N} = 1$$

- The Entropy problems is the Markowitz' Mean Variances Problems with:
 - Selecting stocks
 - Equally weight
 - No short Position
- Solving by Shrinkage Methods with Non Negative Weight

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Non Negative Least Square Methods

$$\min_{\mathbf{w}\succeq 0}\|\tilde{\mu}-R\mathbf{w}\|_2^2$$

where:

• $\tilde{\mu}$ is the expected value of daily return market which each row t^{th} of $\tilde{\mu}$ is calculate by simple average all asset at time t-1

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Filtering Downtrend Stock

- The stock that behavior well in training data could drop down in the futures
- Filtering the stock with Simple Moving Average Technical Indicator.
 The stock with have price path below the SMA is have the uptrend on future.

Transform Problems Objective Functions

$$\begin{array}{ll} \text{maximize} & \sqrt{n} \frac{\mathbb{E}[R]}{\sqrt{\text{var}[R]}} \\ \Leftrightarrow & \text{maximize} & \frac{\mathbf{w}^T \mu}{(\mathbf{w}^T \mathbf{\Sigma} \mathbf{w})^{\frac{1}{2}}} \end{array} \qquad (n \text{ is annuallization constant factors}) \end{array}$$

Transform Problems Objective Functions

• Because the expect return are compute by the mean of all return of K stock (which K < N) we select, then we could rewrite the weight as form:

$$\mathbf{w}^T = \frac{1}{|K|} \mathbf{w'}^T$$

- where
 - $\mathbf{w'}^T = [w_1, w_2, ... w_i]$ $w_i = 0 \text{ or } 1, i \in [0, N]$
 - $|K| = \mathbf{w'}^T \mathbf{1}_N$ (|K| is the number of selected assets)

Transform Problems Objective Functions

$$\mathbf{w}' = \arg \max_{\mathbf{w}'} \quad \frac{\frac{1}{|K|} \mathbf{w}'^T \mu}{\left(\frac{1}{|K|} \mathbf{w}'^T \mathbf{\Sigma} \frac{1}{|K|} \mathbf{w}'\right)^{\frac{1}{2}}}$$
$$= \arg \max_{\mathbf{w}'} \quad \frac{\mathbf{w}'^T \mu}{\left(\mathbf{w}'^T \mathbf{\Sigma} \mathbf{w}'\right)^{\frac{1}{2}}}$$

Bayesian Optimization

- Bayesian Optimization is a class of iterative optimization methods using Bayesian Rules to updating knowledge about target function.
- Bayesian Optimization has two feature: Surrogate Model and Acquisition Function
- Surrogate Model try to approximate target function by consider it has the Gaussian Process trajectory.
- Acquisition Function based on the Surrogate Model to choosing the next point to observe.

Bayesian Optimization

Gaussian Process and Utility Function After 4 Steps

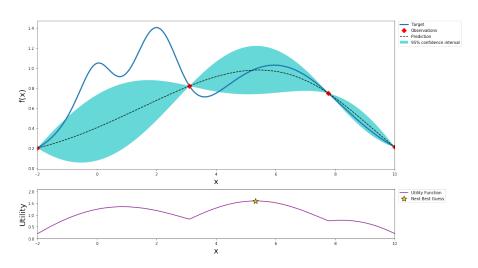


Figure 4: Example of Bayesian Optimization

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Surrogate Model

$$f(x) = \frac{\mathbf{g}(x)^T \mu}{(\mathbf{g}(x)^T \Sigma \mathbf{g}(x))^{\frac{1}{2}}} , \quad x \in [0, 2^{|N|} - 1]$$

where:

•

$$g(x)^T = [w_N, w_{N-1}, \dots, w_1]$$

•

$$x = 2^{|N|-1} \times w_N + 2^{|N|-2} \times w_{N-1} + \dots + 2^1 \times w_2 + 2^0 \times w_1$$

Acquisition Function

• Upper confidence bound:

$$\mathbf{x}_{t+1} = \arg\max_{\mathbf{x}} \left(\mu_t(\mathbf{x}) + \kappa \sigma_t(\mathbf{x}) \right)$$

- where
 - $\mu_t(\mathbf{x})$ is the mean of Surrogate model at x point
 - $\sigma_t(\mathbf{x})$ is the variance of Surrogate model at x point
 - ullet κ is the hyperparameter
- Setting $\kappa = 5$ for exploration.

Result

- Acquire the combination of 20 stocks: ABT, AST, BCE, HII, JVC, KMR, L10, LIX, PGD, ROS, SBV, SFC, SJF, TCL, TDC, TMS, TNT, VCF, VIS, VNE
- The Sharpe Ratio test result in API at 03/09/2019 is 11.132025544144525.

Thank you for listening!