QUANTITATIVE STRATEGY DESIGN

GROUP PROJECT OF MFE5100

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ABSTRACT

In this project, we consider asset allocation problem in American stock market. Using market data from 2001 to 2020, we develop investment strategy from different perspectives. Assume we were standing at the beginning of year 2018. Our task is to design investment strategy in the following 2 years. The general procedure is that: 1. impose a statistical model on the stock price, and get mean and variance estimators; 2. do mean-variance optimization 3. report the portfolio weights on each asset. It is very flexible to change the prior belief of data distribution, and rather common practice to choose various risk measures. As is suggested by the prompt of project, we would like to build models according to different divisions of future time horizons.

For the first part, we design 2-year fixed strategy. For the second part, we design monthly trading strategy. We use Markowitz Model as a benchmark, where we adopt moving average as predictor of the mean return next month. As the time goes on, we renew the prediction based on the recently observed data. To consider the randomness in the return of next month, we impose the distribution and do two-stage stochastic optimization. For the third part, we utilize heuristic strategies—Grid Trading Strategy, and test them carefully.

We do detailed comparison among different angles, and give insight on how to choose proper framework according to market features.

Keywords: fixed strategy, monthly trading strategy, Markowitz Model, grid trading strategy.

Contents

1. Introduction

A portfolio consists of various amounts held in different asset. Portfolio optimization is concerned with optimal allocation of limited capital to available financial assets to balance profit and risk. Investors try to maximize returns and also minimize the risk.

This report presents different portfolio optimization strategies, including fixed strategy, monthly-trade strategy and dynamic strategy.

The structure of the report is as follows: The fixed strategy is in section2. In section3, We will describe the Monthly-trading strategy. The dynamic strategy will be introduced in section4. And conclusion will be closed in section5.

2. Fixed Strategy

First, we only consider the return of the portfolio and ignore the variance. After we select stocks from historical data and estimate the mean return of the two years, we run the strategy on the sample data and compare these two results. Then we take variance into consideration and construct Markowitz models with covariance matrix we calculate and make a comparison between these two models. Calculation and modeling in the part are achieved using Python with Numpy, and Pandas.

2.1. Data Processing

We calculate the covariance of two stocks in their common time and build covariance matrix in this way. And in this report, we use the fixed risk aversion level λ=1.

2.2. Markowitz Model

Consider n assets.

With $R = [R_1, R_2, \dots, R_N]^T$, $\mu = [\mu_1, \mu_2, \dots, \eta_N]^T$, and $\sum = \begin{bmatrix} \sigma_1^2 & \cdots & \sigma_{1n} \\ \vdots & \ddots & \vdots \\ \sigma_{1n} & \cdots & \sigma_n^2 \end{bmatrix}$

If it is parametric-efficient for a fixed λ, then the strategy model follows:

$$\max_x \ \lambda \eta^T x - \frac{1}{2} x^T \sum x$$

$$s.t. \sum_{j=1}^{n} x_j = 1$$

$$x \geq 0$$

Indices & Sets

$j \in I$ set of stocks

Data

λ risk averse level

η the return of stocks

$\sum$ the covariance matrix of stocks

x the weight of stocks

2.3. Results and Discussion

Before applying Markowitz Model, first we build a linear program only concerned about the mean portfolio's return based on the historical data. To estimate the mean return, we use the median historical returns. It turns out that we can choose the stock NGH to invest in the next two years and the estimated net return is 0.1754. Then we run our strategy on the sample data. If the sample data were reality, the real net return by investing NGH is 1.1093, much greater than our estimated net return. The difference between the estimated net return and the real net return is 0.9339. However in the sample data, the best portfolio selection is to invest BQU, whose net return is 3.8800. The difference between best portfolio selection in the sample data and that we chose by training data is 2.7707.

Through such selection, we find that two-year return of stock can be uncertain and we can not predict the future. To take the uncertainty into consideration, we estimate the variance of each stock and covariance of every two stock. Then we assume the price are normally distributed. For the same 5000 scenarios, the percentile of our selected stocks' return is:

Percentile	Selected stocks' return
5%	-0.772077497
25%	-0.205601095

50%	0.172320961
75%	0.556495474
95%	1.125752483

Chart 2.1 The Selected Stock's Return Under Different Percentile

Finally, considering variance, we build Markowitz Model. The result shows that the net return is 0.1101. The strategy is that we invest 12.3% of our fund in NGH, 29.6% of our fund in GCV, and for the rest 48.1%, we should buy bond. The difference between Markowitz Model and the one obtained only considering the mean return is 0.9992. It is reasonable since Markowitz Model make a trade-off between profit and risk. The percentile of our selected stocks' return in Markowitz Model is:

Percentile	**Selected stocks' return**
5%	-0.264794622
25%	-0.038179302
50%	0.118744655
75%	0.275795455
95%	0.489830876

Chart 2.2 The Selected Stock's Return under Markowitz Model

The quantile in Markowitz Model is more robust and more concentrative than the former one.

3. Monthly Trading Strategy

The monthly-trading strategy is more flexible than the fixed strategy. At the beginning of each month, we solve an optimization problem using the historical data from the beginning to the end of the last month and adjust our portfolio accordingly. Because there is no transaction cost, our strategy is to sell all the stocks we hold at their close prices at the end of each month and the bond at its mature days if we hold. Then we get the cash and solve the optimization problem and buy at the open prices of the assets at the beginning of each month. Thus, there should be dynamic strategies that make more profits than fixed strategies.

We use Markowitz Model as the benchmark. The optimization problem is

$$\min_{w} \ \frac{1}{2} w^T C w - \lambda w^T \mu$$

$$s.t. \quad 1^T w \in [0,1], w \geq 0$$

where the risk-averse coefficient $\lambda = 1$ for our purpose. μ and C need to be estimated. The main difference with Q1 is that we solve this optimization problem every month, with different parameters.

3.1. Deterministic Rolling Horizon

Above all, we demonstrate the general workflow in this section.

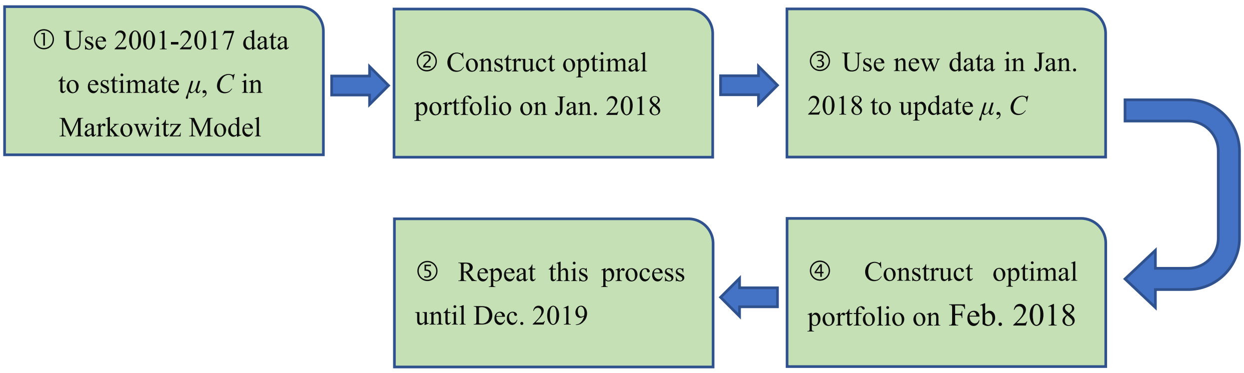

Chart 2.2 The Workflow of 3rd Section

Denote that stocks have monthly rate of return R_t (98×1 vector) in the period $[t-1, t]$. We consider R_t as independent and identically distributed (i.i.d) random variables when t varies. The estimation in part ①③ is done based on the data revealed till the current time point $t = T$. We do not have much knowledge about the estimation of covariance matrix C, thus, we always adopt the sample covariance as the truth. Denote $\mu_i = \frac{1}{T}\sum_{t=1}^{T} R_{t,\ i}$ to be the sample mean of the stock i, then

$$C_{ij} = \frac{1}{T-1}\sum_{t=1}^{T}(R_{t,\ i} - \mu_i)(R_{t,j} - \mu_j)$$

It is the mean μ that we pay special attention on. We start with the simplest idea: use sample mean as the true mean. In section 2.2, we discuss other estimation methods.

Having all the parameters ready, we solve the optimization problem to get the optimal weights on stocks. It should be clarified that, on the bond purchase date, we use $r_f = 3\% \div 12 = 0.25\%$ as the monthly risk-free rate. The parameter μ in Markowitz Model is actually the excess rate of return $\mu^e = \mu - r_f 1$. During the bond purchase date and the maturity date, we use risk-free rate $r_f = (1 + 0.005\%)^{30} - 1 \approx 0.15\%$, because holding the cash enjoys daily interest rate 0.005%.

We design the program to update our estimation based on rolling horizons. We sequentially solve optimization problems using spicy. The results are as follows:

Date	Investment	Date	Investment	Date	Investment	Date	Investment
2018/1/2	BMV 854.03 PSH 4374.85 TUP 8731.37	**2018/7/2**	XUD 6867.87	**2019/1/2**	BQU 2452.83 XUD 5544.76	**2019/7/1**	FWO 28051.29 GNH 6420.01
2018/2/1	BQU 6714.55 CQU 37105.19	**2018/8/1**	BQU 7344.68	**2019/2/1**	FWO 15183.24 TBS 27626.25	**2019/8/1**	NGH 410.67 ODN 1411.28 OTU 9580.39
2018/3/1	BQU 13615.59	**2018/9/3**	BQU 7352.79	**2019/3/1**	CQU 36697.67 GNH 7937.45	**2019/9/2**	B3N 12248.33 NGH 428.86
2018/4/3	B3N 8000.4	**2018/10/1**	UQN 15749.7	**2019/4/1**	BMV 1796.56 JFM 5050.28	**2019/10/1**	MMD 9743.6
2018/5/1	SNE 1144.54 TBS 40368.76	**2018/11/1**	OTU 12681.76 T43 985.96	**2019/5/1**	GNH 2454.55 XUD 5460.16	**2019/11/1**	BQU 4403.49 CME 4256.28 GCV 2837.36 GNH 2607.21
2018/6/1	CQU 62534.83	**2018/12/3**	TBS 42691.15	**2019/6/3**	NGH 3521.64	**2019/12/2**	JMV 20938.76

Chart 3.1: Number of Shares We Need to Buy at the Beginning of Each Month

This table is an instructive guideline for our trading practice. What we directly get from programming output is the optimal weights for stocks. Then, we compute the money allocated in each stock, and the number of shares follows as we buy stocks at the open price. We will keep such a portfolio for a month. On the last working day of this month, we calculate the current value of this portfolio. Hypothetically, we close out all positions in stock market. We solve a new optimization problem and buy in stocks on the first working day of the next month accordingly.

Since we have the test data in 2018-2019, the profit realized by our strategy is revealed in the next figure. We can see that our account has been almost doubled in two years.

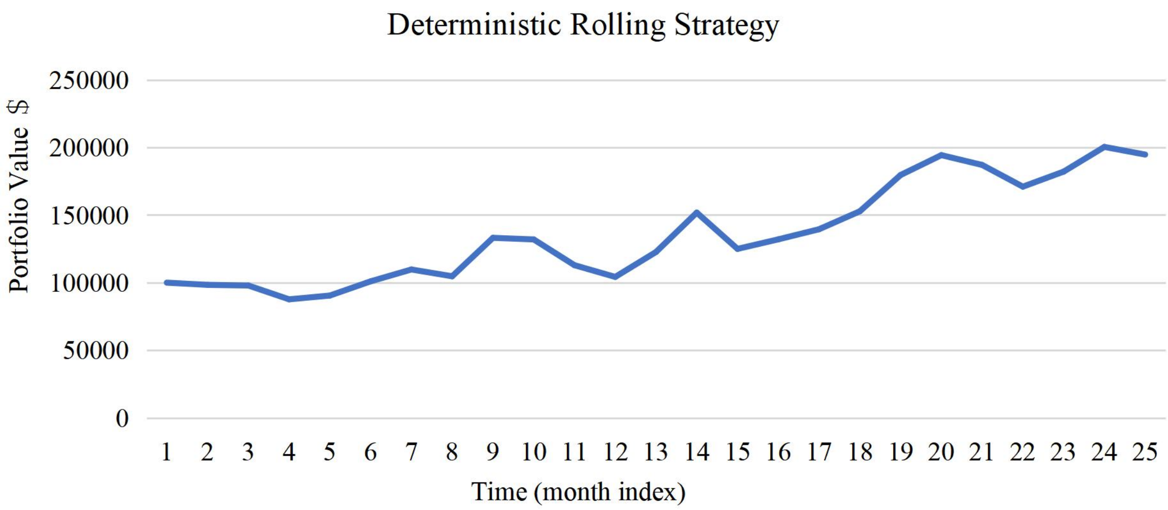

Chart 3.2: Profit Realized by the Strategy

3.2. Proposal for Other Estimation Methods

First, we propose a moving average estimation method as follows. Suppose the current time is $t = T$. Stock i's return $R_{t,\ i}$ are known for $t \leq T$. We will predict the return of next period by

$$\hat{\mu}_i = \frac{1}{N_i}\sum_{t=0}^{N_i} R_{T-t,\ i}$$

where N_i is an integer chosen properly stock i. We may use data in the past 18 years for training:

$$N_i \triangleq \underset{N\in\{1,2,\ldots,T\}}{argmin} \frac{1}{N}\sum_{t=N}^{T}\sum_{k=1}^{N} \left|R_{t-k,\ i} - R_{t,\ i}\right|$$

This is a more flexible approach to estimate μ than taking sample mean, which is to fix $N_i = T$ for all stocks $i = 1,2,\ldots,98$.

Another idea is to use Bayesian method to infer μ. We consider return of each stock separately. Suppose the return of a stock is a random variable with likelihood function $f(r|\mu)$, where the parameter μ (mean of return) has a prior distribution $f(\mu)$. According to a popular modeling of stock market, the stock prices follow a Geometric Brownian Motion, and the rate of return follows normal distribution: $(r|\mu)\sim N(\mu,\sigma^2)$. To get an easy posterior, we take a conjugate pair with normal likelihood function, i.e., we adopt $\mu\sim N(a,b^2)$. Then, we directly get the posterior distribution after observing a batch of monthly return data $r=(r_1,r_2,\ldots,r_n)$: $(\mu|r)\sim N(a_n,b_n^2)$, where

$$a_n=\frac{\sigma^2 a}{\sigma^2+nb^2}+\frac{nb^2\,\bar{r}}{\sigma^2+nb^2}$$

$$b_n^2=\frac{\sigma^2 b^2}{\sigma^2+nb^2}$$

We only need to plug in a point estimate of μ into the optimization problem, meanwhile, we want to preserve the information of randomness given in posterior. Thus, we use sampling ideas. Suppose we set the number of samples to be M. For each stock, we get samples $\mu^1,\mu^2,\ldots,\mu^M$ from its posterior distribution $f(\mu|r)$, so we collectively get $\mu^1,\mu^2,\ldots,\mu^M$ for M different scenarios. Next, we plug them in Markowitz Model and get a sequence of optimal solutions $w_{(1)}^*,w_{(2)}^*,\ldots,w_{(M)}^*$ under these scenarios, respectively. Precisely speaking, $w_{(i)}^*$ is optimal solution to the i-th problem:

$$\min_{w_{(i)}}\ \frac{1}{2}w_{(i)}^T C w_{(i)}-w_{(i)}^T\mu^i$$

$$s.t.\quad 1^T w_{(i)}\in[0,1], w_{(i)}\geq 0$$

At a specific time, we do M optimization problems, and collectively use

$$w^*=\sum_{i=1}^{M}w_{(i)}^*$$

as the asset allocation weight to construct the portfolio.

We do not implement all the ideas in this section. They are promising in a sense that these methods are highly interpretable, and are very flexible.

3.3. Stochastic Rolling Horizon Method

In section 2.1, we do not consider the variability of parameter μ. It is not convincing, since we can never know precisely the mean of stock return, due to the well-known mean-blur effect. In Q2(c), we do stochastic programming to address the randomness of stock returns.

Suppose we are at time $t = T$. The monthly rate of return R_t is revealed for $t \leq T$, but R_{T+1} is random. We assume R_{T+1} follows multi-variate normal distribution with mean vector μ and covariance matrix C. The rate of return in period $[T,\ T+1]$ is $w^T R_t$, also random. We may adopt conditional value-at-risk as a risk measure, and we modify Markowitz Model as the following:

$$\min_{w} \ -w^T\mu + CVaR_\alpha(w^T R_{T+1})$$

$$s.t. \quad 1^T w \in [0,1], w \geq 0$$

Note that CVaR can be derived by solving an optimization problem:

$$CVaR_\alpha(w^T R_{T+1}) = \min_{b} \ \{b + \frac{1}{1-\alpha} E[\,max\,(-w^T R_{T+1} - b, 0)]\}$$

We use sampling to proceed derivation. $R^1_{T+1},\ R^2_{T+1},\ \ldots,\ R^M_{T+1}$ are M i.i.d samples from $MN(\mu, C)$. Then, we get an extensive formulation that is a linear programming:

$$\min_{w,\ v,\ \theta^i} \ -w^T\mu + v + \frac{1}{(1-\alpha)M}\sum_{i=1}^{M}\theta^i$$

$$s.t. \begin{cases} \theta^i \geq -w^T R^i_{T+1} - v \quad for\ i = 1,2,\ldots,M \\ \theta^i \geq 0 \qquad\qquad for\ i = 1,2,\ldots,M \\ 1^T w \in [0,1], w \geq 0 \end{cases}$$

In implementation, we use the same μ and C as section 2.1 and M=10000. Using COPT, we get the results which are shown in the appendix.

We see the number of stocks we hold in each month is considerably larger than that in Q2(b). This is reasonable because we involve more careful risk measure than Q2(b), so we tend to reduce volatility by diversification. We only earn 20117.27 dollars (20.12%) in two years using the strategy above.

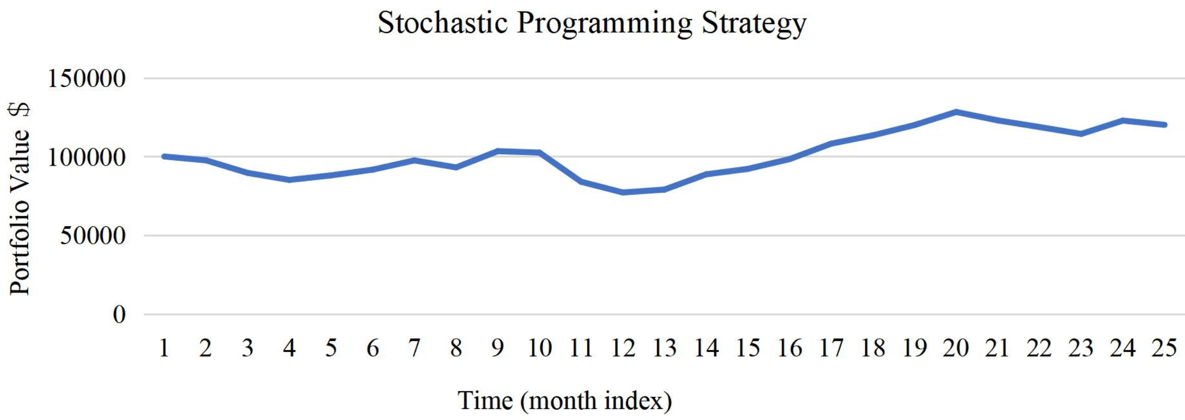

Chart 3.3: Portfolio Value of Stochastic Programming Strategy

The rate of return of this strategy is not as good as Q2(b). The fact that we have taken thousands of scenarios into account greatly diminishes the potential to earn profits. The good news is that we have a good control of retracement. We have established fruitful results from stochastic point of view. More discussion on stochastic programming is needed beyond this project.

4. Dynamic Strategy

The mean variance model used above requires that variance minimization is risk minimization to obtain the maximum rate of return. In this part, we change the original concept and explore the benefits brought by risk, that is, starting from the perspective of maximizing variance, supplementing the shortcomings brought by the absoluteness of the previous research.

4.1. Introduction to Grid Trading Strategy

Grid trading revolves around the benchmark price, and whenever the price falls, a buy operation is performed at the trigger point; Whenever it rises, a sell operation is performed at the trigger point. The core idea of grid trading is that if a security is in a swing, it can seek to attract chips at a low level and release chips at a high level, so as to repeat the cycle in order to obtain excess returns.

The grid trading method essentially uses the strategy of low absorption and high selling. That is, first choose the target to buy a certain bottom position, set a price fluctuation range (lowest price - highest price), and divide the fluctuation range into N equal parts (difference), buy one for every difference in the price falls, sell one for every difference in price rise, and sell one for low absorption and high selling to earn the band difference.

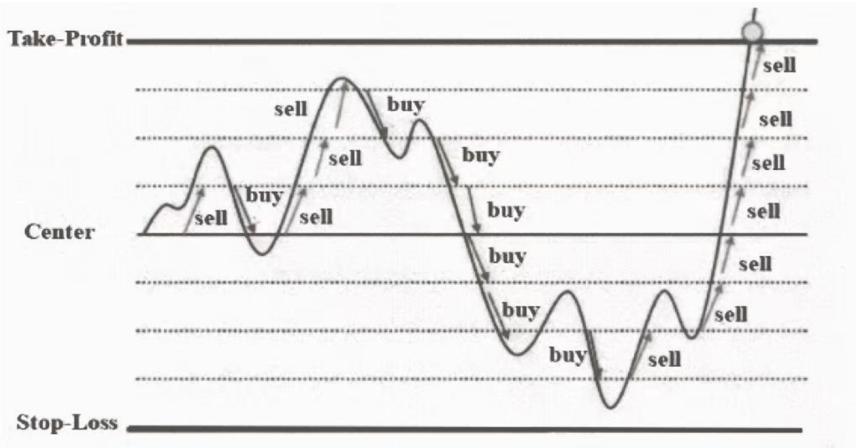

Chart 4.1: The Diagram of Grid Trading Strategy

4.2. Features of Grid Trading Strategy

4.2.1 Advantages of Grid Trading Strategy

Buy in batches, improve the error tolerance rate, reduce the impact of one-time investment, and greatly reduce the requirements for buying points.

Increase positions in declines and reduce holding costs. In the set grid, constantly buying at a low level, even in a state of continuous loss, but the overall cost of holding is constantly decreasing, once the market rebounds, the accumulated lower cost can easily generate profits. Moreover, the shares of the transactions in the grid correspond one to one, as long as there is a rebound, it meets the requirements of the grid and immediately sells to get the spread profit of the corresponding share.

The operation is simple and easy to execute, reducing the emotional impact. As long as the grid and parameters are set, the system automatically buys and sells, and does not need to pay attention to the market trend for a long time.

4.2.2 Disadvantages of Grid Trading Strategy

The unilateral market returns in the bull market are not high. Because the position is often short after breaking through the highest price, you should change the trading strategy or enlarge the grid space in time when facing a unilateral market.

Falling below the minimum price is prone to losses. The grid trading method works best in the bottom oscillating area and is more secure. However, the market is unpredictable, often contrary to investors' judgment, when it falls, it may accelerate its decline, and when it falls below the lowest price, it is recommended to stop the market in time.

The use of funds is not efficient. Grid trading itself is a trading strategy of gradual buying and gradual selling, which will lead to the utilization rate of the overall funds at about 60%~70%, and the final profit is limited.

4.3. Construct Stock Portfolio

We hope to make a bigger profit by adjusting the strategy every day, which means we would maximize the expected profit in the future.

$$\max_{x} \ E(\eta^T x)$$

$$s.t. \quad \sum_{j=1}^{n} x_{ij} = 1 \quad \forall i \in T$$

where x_{ij} represents the investment strategy on day i, T represents the time when sample_test data set is located, and η represents the expected return of each stock within time T. With this model, we need to optimize and iterate once a day, which leads to a surge in computation and excessive computational costs.

The grid trading strategy actually uses price volatility to make a profit, therefore, bond and cash would be not considered in this strategy. First we need to build a portfolio of stocks that are likely to have the greatest volatility in the future. Measure volatility by stock variance, and calculate the variance of each stock on a rolling basis within the time interval where the sample_test data set is located: take all stock information before the day as the input to calculate the variance of the day, and then get the output result: the variance of the stock of the day.

We use the five stocks with the highest daily price fluctuations as the stock portfolio FIVE of the day, and believe that the different stock variances of each day contain all the information about the stock price changes, so we can use the volatility ratio of each of the five most volatile stocks as the investment ratio of the day, so as to construct the stock portfolio with the greatest volatility in the future:

$$x_{ij} = \frac{x_{ij}}{\sum_j xij} \quad \forall i \in T, \forall j \in \{1,2,3,4,5\}$$

Considering this combination as a fund format, we can get the price of FIVE from 2018-1-2 to 2019-12-31.

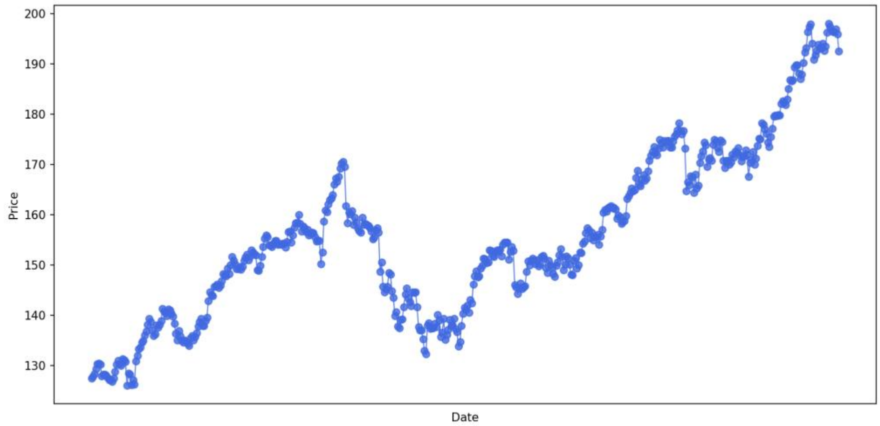

Chart 4.2 The Price of FIVE from 2018-1-2 to 2019-12-31

4.4. Parameter Setting and Trading Process

4.4.1 Select the Target and Determine the Initial Amount or Share

The initial amount is 100,000, the initial price is calculated at the price of January 2, 2018, and subsequent transactions are carried out in shares. Record daily trading shares, current holdings, current holdings, and daily returns when touching the network.

Parameter	Tag	Remark
Initial holding amount	money_begin	Investor setting, this report is set to 100000
Initial shareholding	volumn_begin	volumn_begin=money_begin/all[0]
Daily trading shares	k	k=round((c-a)/distance)*buy
Currently holding shares	volumn	volumn-=k
Amount currently held	money	money+=k*b
Daily rate of return	profit	profit=(money-money_begin)/money_begin*100

Chart 4.3 The Tag and Remark of Parameters

4.4.2 Set the Grid Size and Number

This report sets the grid stop loss yield to 50% and the take profit yield to 150%, but unlike usual trading, this report assumes that when the price touches the take profit and stop loss gridlines, sell 1/2 and 1/3 of the shares, respectively, instead of selling all of them, and the remaining securities remain in the pool for the next day's grid trading.

This report sets January 2, 2018 as the initial trading day, the fund price on that day is the midpoint of the grid line, and the number of one-sided grids is 100 (including the take profit and stop loss grids), that is, the total number of grids is 200. Set the grid size to 7, that is, every $7 down you buy the set share and sell the set share every $7 up.

Parameter	Tag	Remark
Number of single-sided meshes	number	Investor setting, this report is set to 100
Take profit yield	up_stop	Investor setting, this report is set to 0.5
Stop loss yield	down_stop	Investor setting, this report is set to 0.5
The percentage of shares sold that hit the take profit line	up_rate	Investor setting, this report is set to 0.5
The proportion of shares sold when the stop loss line is reached	down_rate	Investor setting, this report is set to 0.5
Grid size	distance	Investor setting, this report is set to 7

Chart 4.4 The Tag and Remark of Parameters

4.4.3 Set the Share per Cell

According to the total amount of investment and the subjective opinion of investors, the trading share when touching the net is set, with the lot as the trading unit, not the amount as the trading unit, and this report assumes that the trading share is infinitely divisible.

Parameter	Tag	Remark
The proportion of the share of the online transaction	buy_rate	Investor setting, this report is set to 0.05

Chart 4.5 The Tag and Remark of Parameter

4.5. Result and Discussion

Applying the grid strategy, we get a yield of 140.15%.

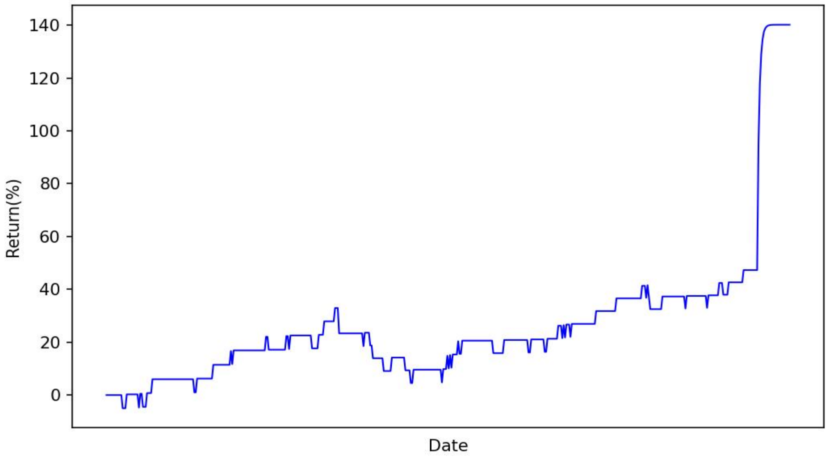

Chart 4.5 The Return Rate of Grid Trading Strategy

Compared with the previous two strategies, the net return of grid trading strategy is better than the fixed strategy and stochastic programming strategy, which is reasonable because daily transaction are updated with information and more information would be included when making trading decisions.

Strategy	Net Return
Fixed Strategy Applying Markowitz Model	11.01%
Deterministic Rolling Strategy	94.73%
Stochastic Programming Strategy	20.12%
Dynamic Strategy Applying Grid Trading Strategy	40.15%

Chart 4.6 The Net Return of Different Strategies

Risk and return have always been directly proportional, and stocks with less volatility are more guaranteed returns, but there are also theories that risk is also positively correlated with the return, and grid strategies can be used as a supplement to the above.

5. Conclusion

This report focuses on applying optimization strategies in financial investment. Firstly, we design 2-year fixed strategy and compare the expected return under the Markowitz Model, which takes volatility into account, and the case which does not take volatility into account. Secondly, we design monthly trading strategy where we do two-stage stochastic optimization to estimate the randomness in the return of next month. For the third part, we utilize heuristic strategies—Grid Trading Strategy to obtain a daily strategy.

Although we have achieved positive returns in all three strategies, there are more factors to consider when applying the strategy to real world, like economic trend, company financial situation and so on.

References

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Appendix

The results of stochastic programming strategy is as follows:

	1	2	3	4	5	6
2018/1/2	BMV 120	BMY 168	BQB 71	BTU4176	CTM 259	CYC 141
	TDH1020	TUP 4281	UBI 646	UQN 746	WDY2621	XUD 181
2018/2/1	BMM 76	BQU 2491	CQU9297	CTM 689	FWO 193	GQI 97
2018/3/1	B3N 552	BMV 395	BQU3136	CQU 935	FWO 347	GMU 295
2018/4/3	B3N6129	BMV 920				
2018/5/1	BMR 352	BMY 704	BXD1441	CYC 671	ENQ 113	EYT 49
	TLJ1728	TPM 401	TQL2740	TZE 194	YSP 275	TDH 577
2018/6/1	BMM 146	CQU12019	DXZ 387	SNE 42	T433466	TUP5078
2018/7/2	XUD6102					
2018/8/1	BMV 75	BQB 2104	BQU1159	CQU 773	DUY 37	FWO 759
	XUD 164	YSP 238	XQM 102			
2018/9/3	BQU5709					
2018/10/1	UQN8549	XUD 1412				
2018/11/1	BMY 47	CQU 4193	HP11522	JMV 792	JQM 394	OTU1400
2018/12/3	BTU1986	FWO 2436	ODN 7	OTU 25	TBS7479	TPM1808
2019/1/2	B3N 1	BMV 43	BO1 243	BQU1036	EYT 14	FWO 868
2019/2/1	BHM 775	CIQ 153	DID1177	EPX 251	FWO1865	HNH 602
2019/3/1	BQU1947	CQU16082	GNH1681	NGH 79	XPS 508	XUD 101
2019/4/1	BMV 564	JFM 3308	NGH 561	TWX 633		
2019/5/1	BQU 540	DID 3001	EYT 279	GNH 557	IWO2324	KCI 321
2019/6/3	B3N1063	BMV 1	BQU 862	DXO 570	IWO 75	JFM 268
2019/7/1	BMM 98	CME 299	FWO3477	GNH 523	JFM 26	JMV 522
2019/8/1	BMY 499	CTM 652	FWO 940	GNH 78	HNH1421	JMV 518
2019/9/2	B3N2222	FWO 504	KCI 108	NGH 683	ODN 131	TBS 400
2019/10/1	BQU 428	CQU 2883	DID 522	ENQ 96	KCI 153	KIY 220
2019/11/1	BNQ1518	BQU 611	BXD 348	CME2862	DHG1375	DUY 110
2019/12/2	CTM 860	DHG 1048	DTM 30	ENQ 151	GQI 206	JFM1207

	7	8	9	10	11	12
2018/1/2	DBS 82	DID 1905	DXO 247	EYT 263	HP1 633	JBH 1151
	SFB 8	OTU 571				
2018/2/1	KCI 82	PTI 754	UBI 4696	UQN 238	XUD1245	

2018/3/1	IWO 669	KCI 241	UXF 205	XUD1151	YSP 262	
2018/4/3						
2018/5/1	FWO 772	HNH 717	HP1 1576	JFM 939	JMV 177	KCI 22
	TBS 944					
2018/6/1	UXF 456	XPS 326	YSP 287			
2018/7/2						
2018/8/1	GQI 243	HNH 197	JFM 849	NRH 23	OTU 769	PTI 697
2018/9/3						
2018/10/1						
2018/11/1	RVC 169	SJP 43	SNE 36	T43 4441	TPM 916	TWX 83
2018/12/3						
2019/1/2	GMU 20	GNH 50	KCI 67	ODN 107	RBO 1547	RVC3252
2019/2/1	HP1 1337	JFM 598	NQM 890	ODN 95	OTU 750	SNE 196
2019/3/1						
2019/4/1						
2019/5/1	ODN 68	TBS 96	THQ 327	XUD1608		
2019/6/3	NGH 801	TWX 48	UXF1278	YSP 176		
2019/7/1	KCI 11	NQM2824	OTU 882	TBS 250	TFL 612	THQ13238
2019/8/1	NGH 420	ODN 312	OTU1493	RVC 462	TBS 1101	XPS 457
2019/9/2	UXF1402	XUD 535				
2019/10/1	MMD3148	XUD 556				
2019/11/1	ENQ 69	GCV 4337	GNH 406	JMV1502	KCI 69	KIY 78
2019/12/2	JMV 3064	KCI 63	SNE 51	TBS 169	TFL 10	THS 793

	13	14	15	16	17	18
2018/1/2	JFM 225	KCI 65	NQM 554			
2018/2/1						
2018/3/1						
2018/4/3						
2018/5/1	OTU 265	SFB 18	T43 203			
2018/6/1						
2018/7/2						
2018/8/1	TFL 17	TUP 361	XFT 71			

2018/9/3				
2018/10/1				
2018/11/1	XUD 134			
2018/12/3				
2019/1/2	TQL 2251	XUD 1484		
2019/2/1	T43 1140	TBS 1415	UXF 173	YSP 77
2019/3/1				
2019/4/1				
2019/5/1				
2019/6/3				
2019/7/1				
2019/8/1	XUD 515			
2019/9/2				
2019/10/1				
2019/11/1	OBC 34	PTI 2085	THS 1139	
2019/12/2	TWX 199	TZE 373	YSP 170	