Introduction to the Performance of My Strategies

***Claim** In this page, I only give introduction to the performance of my quant strategies. No any exposure to the tricky data mining method to different kinds of data, self designed network structures, specially self-defined loss function and the method to make a neural network totally interpretable.

Basic Setting

This basic setting is suitable for all the experiment results shown in this page. If I have used different settings on some experiments, I will give it a special description.

1.About the Market

All the experiments are done on the Chinese A-share market. In this market, I assume that I should strictly obey the trading principles, such as T+1 trading; can't short single stock; can't buy the stock which hits raising limit up; in a single fund product, contains more than 10 stocks and no single stock takes more than 10% weight and etc...

2.Rolling Forecast

All the experiments are done on the **rolling forecast, including the process of generating and combining alphas.** Many researchers, as far as I know, they will fit the history once, and then get the generated alphas. In this case, their gap between backtesting and paper trading will be much lager than expected. eg. today is T, [T-train_length-hoding-1, T-hoding-1] is the training set, [T, T+test length] is the testing set, normally, I set training set as 300 trading days, testing set as 21 trading days. And each neural network's loss functuon is predicting the next 3 trading days' rank return. **To sum up, for each 21 trading days, before trading, I will train several neural networks at T-1 day, and then use these modes for the next 21 trading days' trading. During the trading period, I will change the inventory every 3 days. As for the predicting the next 3 trading days' rank return, this is only the loss function of my model.** To simplify the descrption, I didn't mention validation set, actually I use it in my strategies, and it's very helpful and tricky. If you feel confused about this descrption, please feel free to read it again and again. This is the right and fair description, but most of people whom I talked to, all feel confused.

3.Backtesting

Normally, I apply 0.2% transaction fees on both side (Shown in the following experiment results). It's fair because the majority of institutional investors use it to do backtesting. It covers the sum of must paid fees and the assumption of market impact (if the turnover rate is much higher, the assumption will change). What's more, you can quickly calculate my performance in the suitation of 0.3% or 0.4% transcation fees on both side. Because my turnover rate is very low, thus, it bring impact but far from making my strategy doesn't work; For untradable stocks in each trading day, I will use it as a training sample, but in the testing set, I will clear it. Which means, I only trade tradable stocks in the real situation; For the trading price, I generate signals at T-1, and do trading at T day's moring. I use open price at T and T+3 day to do the trading. Also I try the close price, VWAP in the first 30 minutes, (open+high+low+close)/4 price to do the experiment, it doesn't bring significant change. (0-3% added alpha difference every year) **To sum up, this strategy is not sensitive to the obtained price and transaction fees.**

4.The Data Vendor

I use [Wind] to serve as my data source. Till now 15 Oct, 2021, I use its daily price and volume data (Daily), 3 accounting table's data (Seasonal), Wind financial indicators data (Seasonal), wind rolling consensus data (from Chinese sell side analyst) (Seasonal), the first 30 mins and the last 30 mins money flow data (Daily).

5.Performance Expectation

Here are two kinds of expectations I want to mention. **First is the expectation of trading performance in the Chinese A-share market.** This is a middle or low frequency strategy, only long stocks on CSI800, T+1 trading, and no any other short books. My final middle level expectation (currently, this strategy is not complete, doesn't finding alphas from all common data source) to this quant strategy is that it can trade more than 1 billion chinese yuan (without significant performance change), more than 10% added alpha every year (compared with CSI500), sharpe ratio should be between 1.5-2.5. (Maybe currently you are not a player in the Chinese A-share market, here is some info to better help you. For the hedge fund in the mainland, their CSI500 product is not selecting stocks from CSI800, they select from the 4000 stocks. For the mutual fund player, they must select stocks from CSI800, which is much harder but much safe. For these players, they can also enjoy pre-IPO benefits. pre-IPO will only need about 1-5% inventory, but bring 5%-10% income for the entire book every year! This description applies for the product's AUM less than 0.5 billion, but the majority of active quant investment mutual fund product, currently their AUM which is less than 0.5 billion.) So you can get more info, and measure my performance. **Second is the expectation of the gap between backtesting and real trading.** I think the history can not be fully repeated in the future, thus, there is some gap, more or less. However, in the process of feature construction and feature selection, whether we use rolling forecast is a big difference!!! A lot of people do rolling forecast on the strategy, but they fit all the history data onece, for the feature construction and selection. Thus, for this expectation, I hope you can go deep into the experiment setting and measure that whether my setting is decent.

6.Metrics

I have calculated the revenue before fee, after fee, daily turnover rate, max-drawdown, net sharpe ratio and etc. **More specifically, I want to stress out three metrics which are frequently used in this page! 1. The accumulated alpha curve is added net return curve, which means I add up T-2, T-1 and T day's return together, it's not multiply!** 2. **Accumulated Alpha (Long VS CSI500)** means that I long the top 20% stocks in each day, equal weighted, with 100% inventory. And then minus the index return of CSI 500 to show my access return. **Accumulated Alpha (Long VS Short)** is similar, I long the top 20% with 100% inventory and short the tail 20% with 100% inventory. 3.**Turnover Rate** refers to the daily turnover rate. In this page, I get used to calculate turnover rate on both side. eg. Turnover Rate 8% means that the I sell 4% and then I buy 4%.

If you find sth shown in this page is not a fair compare, or some important settings are not made clear in this page, or you want to make a double check on some important procedures, please feel free to write an e-mail to me. I will be grateful to you. E-mail: fangx18@tsinghua.org.cn

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@Finding Alpha from Daily Price and Volume

I design a neural network based framework to construct alphas. Each deep neural network represents a powerful alpha. It has been published on the top computer science conference [KDD 2020] and the well known financial journal [Quantitative Finance]. (You need to use scientific way to access the internet if you are in the Mainland of China...) If you want to get more info, you can read its original [arXiv version].

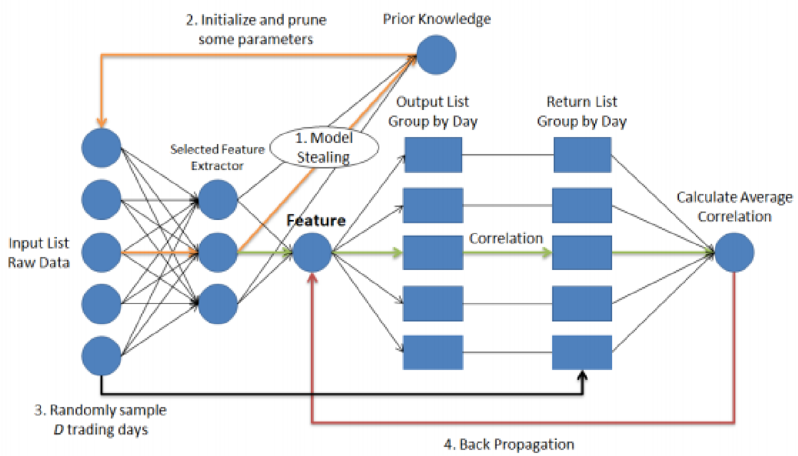

Figure 1.1 Use self-designed sampling rules, loss function and diversified method to automatically construct factors.

In my current framework, I propose a much better way to construct diversified factors. But for the loss function and basic sampling rules, I still used what I mentioned in the previous paper. Due to the NDA, I will not give more exposure about this diversified method. Deep neural network is no longer a black box, it inherits the pattern from diversified traditional factors, but for the detailed hyper-parameters and other uncertain settings, I let the neural network learn this things freely. To sum up, I settle down the pattern (computation logic), and let the neural network to learn sth uncertain but important freely. The freely learning part maybe the real meaning of aritifical intelligence. Each neural network is a single factor, and I can approximate its detailed formula.

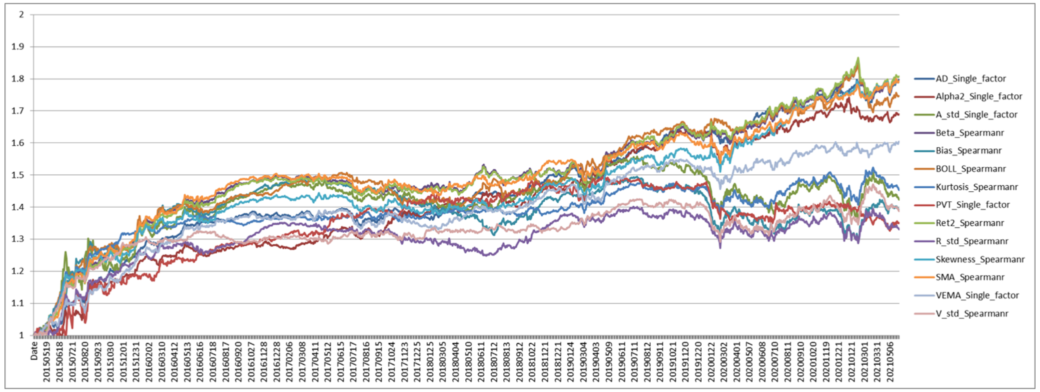

Figure 1.2 AlphaLib, alphas generated from daily price and volume, **Value is Accumulated Alpha (Long VS CSI500).** Notes: **xxx_Spearmanr** refers to the neural network factors, **xxx_Single_factor** refers to traditional factors.

Combine these technical indicators together, I can get the final alpha generated from daily price and volume. **Because currently I only specialized in alpha construction,have some experience in factor combination, no previous experience in factor selection and portfolio optimization. Thus, I simply adds up all these factors together to do the experiment. I think it can better show the contributions of this alpha construction system.**

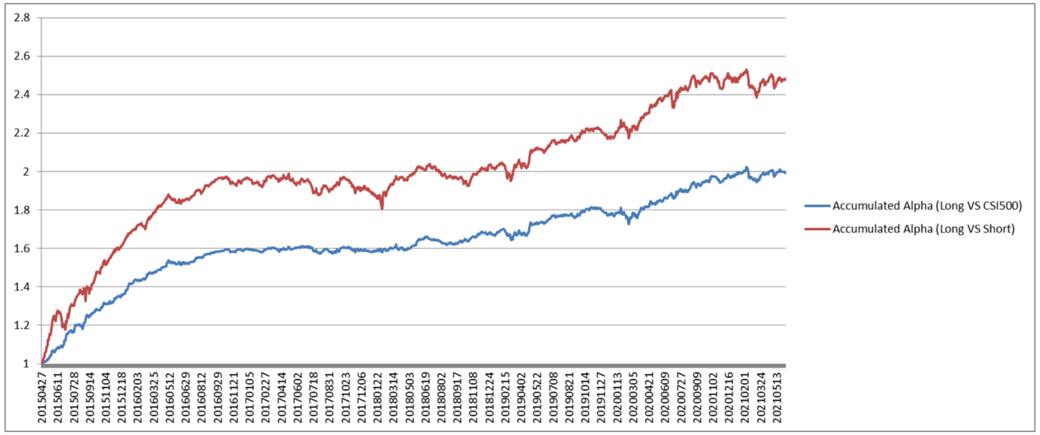

Figure 1.3 Combine all the price and volume related alphas together, into a big compounded alpha, avg daily turnover rate is 7%-12%. As for the metrics, please see Basic Setting - 6.Metrics.

Let's look at the blue curve at Figure 1.3, it perform well in the 2015 and 2016, very bad at 2017, not bad at 2018, 2019, very good at 2020. 2021 is not fully tested.

I want to talk more about this part. In 2017, this is a very tough time for Chinese A share market's price and volume data. You can earn the money easily if you use fundamental data. But look at the technical indicator, there are still some can make revenue at 2017. You may say that I am foolish, why I don't pick out them. Actually, 2017 is a big change. The technical indicators works well in 2017, which is very very weak before and after 2017. Some of them can't make money, let alone to get enough weight if I do factor selection according to the momentum. Thus, to be honest, if you don't look at the future and fully use quant method, it's hard to make daily technical alpha in 2017. To further improve this part, absolutely, using the fundamental. But if I want to stick to the daily price and volume, maybe some factor timing (more than momentum) will be a good direction. For the early 2021, MingHong (one of the biggest hedge fund in China) also faces big max-drawdown. For me, not only in price and volume, but also in my final big singal, it's the point which causes max-drawdown. But luckily, my drawdown is not as big as MingHong. I think it's mainly because I chose stocks from CSI800, but they chose from the entire market.

To sum up, the performance may looks far from perfect if I only use daily price and volume data. I think it's good enough, although there is still much and much can be done. If you interested and think your's are better, please contact, we can let all the experiment settings be the same and fairly compare.

	AD_Single_factor	Alpha2_Single_factor	Beta_Spearmanr	Bias_Spearmanr	BOLL_Spearmanr	Ret2_Spearmanr	R_std_Spearmanr	SMA_Spearmanr	V_std_Spearmanr
AD_Single_factor	1.00000	0.42426	0.74091	0.20249	0.58602	0.76625	0.16967	0.73980	0.32269
Alpha2_Single_factor	0.42426	1.00000	0.48381	0.17207	0.43652	0.47356	0.19833	0.47322	0.19686
Beta_Spearmanr	0.74091	0.48381	1.00000	0.24169	0.84001	0.95925	0.17074	0.71224	0.19774
Bias_Spearmanr	0.20249	0.17207	0.24169	1.00000	0.19111	0.20381	0.63228	0.59936	0.69997
BOLL_Spearmanr	0.58602	0.43652	0.84001	0.19111	1.00000	0.84864	0.06723	0.52240	0.10282
Ret2_Spearmanr	0.76625	0.47356	0.95925	0.20381	0.84864	1.00000	0.14775	0.72435	0.20050
R_std_Spearmanr	0.16967	0.19833	0.17074	0.63228	0.06723	0.14775	1.00000	0.53092	0.67828
SMA_Spearmanr	0.73980	0.47322	0.71224	0.59936	0.52240	0.72435	0.53092	1.00000	0.59338
V_std_Spearmanr	0.32269	0.19686	0.19774	0.69997	0.10282	0.20050	0.67828	0.59338	1.00000

	AD_Single_factor	Alpha2_Single_factor	Beta_Spearmanr	Bias_Spearmanr	BOLL_Spearmanr	Ret2_Spearmanr	R_std_Spearmanr	SMA_Spearmanr	V_std_Spearmanr
AD_Single_factor	1.00000	0.07203	0.30154	0.15500	0.47296	0.57531	0.02051	0.45836	0.28335
Alpha2_Single_factor	0.07203	1.00000	0.23267	0.05696	0.21943	0.24450	0.01791	0.18367	-0.06312
Beta_Spearmanr	0.30154	0.23267	1.00000	0.24493	0.89138	0.80375	0.01134	0.90693	-0.57179
Bias_Spearmanr	0.15500	0.05696	0.24493	1.00000	0.37113	0.33753	0.05627	0.30782	0.05524
BOLL_Spearmanr	0.47296	0.21943	0.89138	0.37113	1.00000	0.78193	0.02196	0.97083	-0.40345
Ret2_Spearmanr	0.57531	0.24450	0.80375	0.33753	0.78193	1.00000	0.02023	0.76594	-0.03420
R_std_Spearmanr	0.02051	0.01791	0.01134	0.05627	0.02196	0.02023	1.00000	0.01765	0.00972
SMA_Spearmanr	0.45836	0.18367	0.90693	0.30782	0.97083	0.76594	0.01765	1.00000	-0.43196
V_std_Spearmanr	0.28335	-0.06312	-0.57179	0.05524	-0.40345	-0.03420	0.00972	-0.43196	1.00000

Figure 1.4 The spearmanr correlation of different factor value (up), and the spearmanr correlation of same day's long short return (down), measured as average value of the testing sets.

As we can see from Figure 1.2 and Figure 1.3, simply add up all the technical indicators can make its overall performance better. Because I have calcualte the covariance metrics of these factors, both the factor value and daily long short return's covariance matrix. Their correlation ranges from 0.5-0.9, shown in Figure 1.4. Now, we have got a big compounded alpha generated from daily price and volume.(I want to make a difference between daily price and intraday price, because their function and conclusion is very different). Because I have very little experience in risk control and portfolio optimization. Thus, I do some simple experiment. First, I did a industry balance, let the portfolio's industry exposure 100% same at the CSI500's industry exposure. Second, I did the marke value balance, use market value to do linear regression with my signal, and keep the residual. Third, due to some contracts' strict requirement, I let 90% of inventorr put into CSI500, and the other 10% inventory goes into CSI300, which is index balance.

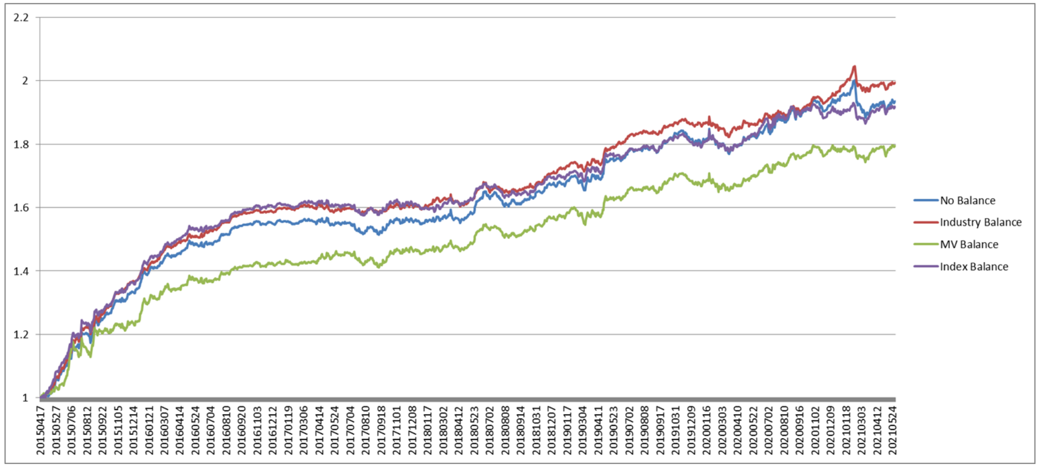

Figure 1.5 Control some risks in the big compounded alpha.

I have realized the importance of this part. First it can help me to conrtol some risks. Second, after get rid of some risk, I can measure whether my alpha is pure or not. For future improvement, I will learn the Chinese Barra risk model, CNE5.

Here is a short end for my daily price and volume factors. In the following part, I will give brief introduction to the performance of other factors.

@Finding Alpha from Seasonal Fundamental Data

The seasonal fundamental data can be divided into three groups, which are growth, quality and value. I didn't just use the raw data, but construct some financial indicators, according to some reprensentative sell side equity report.

For some of these factors, I direclty combine them by using neural network. For some of them, I get rid of the size and industry, and then keep the residual. And more importantly, factor timing is very important in fundamental data. To sum up, the data minning in fundamental data is limited. But it doesn't mean that we can do nothing. **So far, there are three types of operators, I think, which is useful for fundamental data. 1. Linear adds up. 2.Do regression, get the residual. 3.Timing different fundamental factors, and then combine it. I am still looking for more reasonable operators, I think the current AI can't live without the domain knowledge.** Here is the result, I don't want to exposre more details according to the NDA.

One kind of factors can be looked like this:

	x	y	Weight	Return（过去六年滚动预测，6年费前总超额收益，累加）	Turnover（每天的总换手率，含买卖）	Return（过去六年滚动预测，6年费后总超额收益，累加）
0	Current, Operate_imcone_revenue, NCFP, YOY_profit_raw, Sales_G_t, Gross_profit_margin_raw, Net_profit_raw, Price_dps_raw, Debt_assets_raw, EP	EP	-0.004, -0.004, -0.005, -0.021, 0.04, 0.046, -0.05, -0.091, -0.167, 0.184	0.409365049	0.033434901	0.309060347
1	OCF_sales, Profit_G_t, Q_yoysales_raw, OCFTOOR_raw, NCFP, FCFF_raw, Asset_turn_raw, PB_raw, Gross_profit_margin_raw, Operate_imcone_revenue	Operate_imcone_revenue	-0.005, -0.012, 0.02, -0.043, 0.045, 0.076, 0.088, -0.092, 0.093, 0.263	0.539139713	0.039200475	0.421538287
2	T_yoysales_raw, PEG, OCF_sales, Total_assets_raw, Total_debt_raw, Operate_imcone_revenue, Profit_G_q, PE_raw, EP_cut, ROA	ROA_raw	-0.002, 0.003, -0.005, -0.007, -0.007, -0.022, -0.061, -0.069, 0.187, 0.342	0.446041821	0.036974285	0.335118967
3	Market_value_raw, Net_assets_raw, YOY_profit_raw, PEG, PB_raw, PE_raw, Profit_revenue_raw, FCFF_raw, Net_profit_raw, ROE_G_t	T_yoyprofit_raw	-0.013, 0.015, -0.02, 0.029, -0.042, -0.056, 0.059, 0.059, 0.08, 0.083	0.747666907	0.033888944	0.646000075
4	PEG, OCFTOOR1_raw, Deducted_profit_raw, ROE_G_t, Total_debt_raw, SP, PE_raw, EP, ROA_raw, ROIC	ROIC	0.0, -0.002, -0.008, -0.012, -0.036, 0.038, -0.049, 0.15, 0.184, 0.275	0.446609794	0.03712532	0.335233835
5	Sales_G_t, Deducted_profit_raw, PEG, Gross_profit_margin, ROE_raw, ROE, Operate_income_profit_raw, Q_yoyprofit_raw, ROA_raw, Debt_assets_raw	EP_cut	0.001, 0.003, -0.005, 0.032, -0.05, -0.05, -0.074, -0.087, 0.103, -0.139	0.441613654	0.039365179	0.323518117
6	DP_p, OCF_sales, OCFTOOR1_raw, Net_assets_raw, Deducted_profit_raw, Current, NCFTTM_raw, NCFP, YOY_profit_raw, ROA_raw	Operate_income_profit_raw	-0.012, -0.013, -0.019, 0.028, 0.033, -0.04, -0.042, 0.073, -0.082, 0.217	0.332787698	0.03450096	0.229284818
7	Current_raw, Q_yoysales_raw, Sales_G_q, T_yoysales_raw, OCFTTM_raw, Profit_revenue_raw, FCFF_raw, Current_debt_debt, Price_dps_raw, Deducted_profit_raw	Deducted_profit_raw	0.002, 0.014, 0.014, 0.017, -0.042, 0.065, 0.072, 0.1, -0.199, 0.268	0.488940059	0.032530906	0.391347343
8	OCFTOOR1_raw, Market_value_raw, T_yoysales_raw, Gross_profit_margin, Current_debt_debt, OCFTTM_raw, Asset_turn_raw, FCFF_raw, PB_raw, Price_dps_raw	Net_profit_raw	0.001, -0.001, 0.031, 0.034, 0.038, -0.046, 0.053, 0.058, -0.062, -0.132	0.665541338	0.038624535	0.549667734
9	Gross_profit_margin, Net_profit_raw, T_yoysales_raw, ROE_G_t, T_yoyroe_raw, FCFF_raw, ROIC, ROA, EP_cut, ROE	ROE	0.005, -0.01, 0.011, -0.018, -0.018, 0.024, 0.029, 0.144, 0.181, 0.378	0.500322148	0.040404471	0.379108734
10	NCFTTM_raw, Gross_profit_margin_raw, NCFP, Profit_G_t, Market_value_raw, SP, ROA_raw, ROE_raw, Debt_assets_raw, PB_raw	DP_p	-0.021, 0.034, 0.041, -0.055, 0.064, 0.076, 0.077, 0.077, -0.096, -0.098	0.576806669	0.037318627	0.464850789
11	OCF_ratio, T_yoyprofit_raw, Profit_G_t, ROE_G_t, Sales_G_q, FCFP, PE_raw, Debt_assets_raw, Asset_turn_raw, FCFF_raw	OCFTOOR_raw	0.014, -0.017, -0.017, 0.036, 0.041, 0.065, -0.098, -0.104, 0.122, 0.128	0.186945582	0.040363208	0.065855958
12	OCF_ratio, PEG, Operate_imcone_revenue, ROIC_raw, Profit_G_t, Current_debt_debt, PE_raw, ROA, EP, Total_assets_raw	Total_assets_raw	-0.007, -0.009, -0.013, -0.018, -0.027, 0.035, -0.053, 0.089, 0.188, 0.31	0.512755808	0.034801883	0.408350159
13	OCFTOOR1_raw, PEG, NCFTTM_raw, Gross_profit_margin, T_yoysales_raw, ROE, SP, Debt_assets_raw, EP, T_yoyprofit_raw	T_yoyprofit_raw	0.003, 0.006, -0.011, 0.019, 0.02, 0.047, 0.065, -0.123, 0.16, 0.311	0.439824959	0.036527296	0.330243071
14	Current_debt_debt, ROE_G_t, Profit_revenue_raw, Asset_turn, Asset_multiply_raw, FCFF_raw, Debt_assets_raw, Price_dps_raw, SP, ROA_raw	Gross_profit_margin	0.002, -0.009, 0.026, -0.035, 0.046, 0.059, -0.11, -0.144, 0.147, 0.166	0.285042306	0.03991191	0.165306574
15	Deducted_profit_raw, Asset_turn, OCFTOOR1_raw, Net_assets_raw, FCFP, NCFP, Current_debt_debt_raw, ROIC, Price_dps_raw, EP	ROE_G_t	-0.0, 0.006, -0.006, -0.007, -0.022, -0.029, 0.043, 0.072, -0.13, 0.23	0.637327443	0.034127746	0.534944205
16	Current, NCFP, Asset_turn, Gross_profit_margin_raw, ROE_G_t, OCFTTM_raw, FCFF_raw, Asset_multiply_raw, Price_dps_raw, EP_cut	ROE	-0.001, 0.006, 0.023, 0.031, -0.051, -0.058, 0.069, -0.08, -0.159, 0.232	0.408777355	0.040051129	0.288623967
17	Current, Asset_turn_raw, NCFP, Profit_G_t, NCFTTM_raw, Total_assets_raw, ROE, ROA_raw, ROA, EP	OCFTOOR_raw	-0.013, -0.016, -0.031, -0.032, -0.035, -0.037, -0.047, 0.088, 0.088, 0.235	0.572113494	0.034404136	0.468901085
18	PEG, Current_debt_debt_raw, Q_yoysales_raw, Operate_income_profit_raw, DP_p, Revenue_raw, OCFTOOR_raw, Deducted_profit_raw, SP, ROE_raw	FCFP	0.002, 0.007, -0.011, -0.011, -0.023, -0.051, -0.07, 0.074, 0.114, 0.153	0.277961566	0.040603884	0.156149914

Figure 2.1 One kind of fundamental data's alpha lib.

Here are 3 types of big compounded fundamental alphas, each one consists of 20-300 small factors.

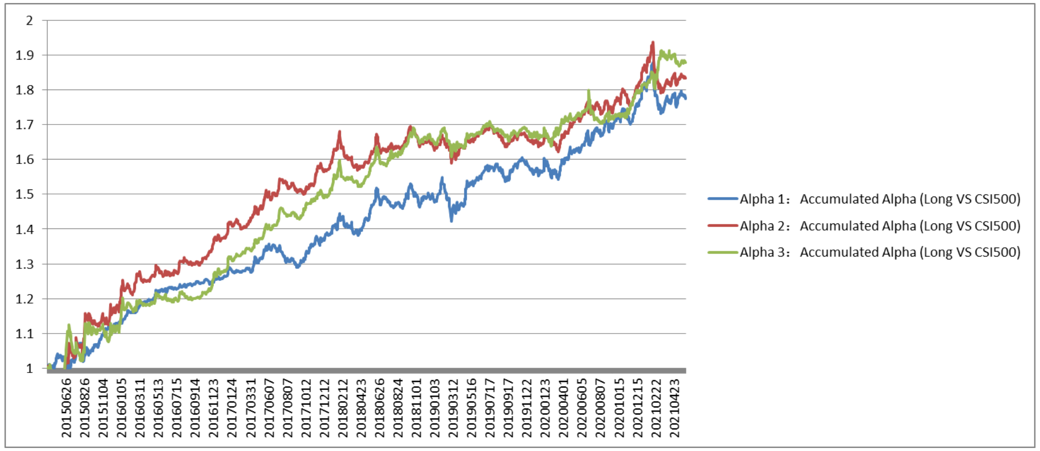

Figure 2.2 Seasonal_fundamental_data.

The correlation of technical indicator and fundamental factors is very low. They ranges from -0.1 to 0.3, in my experiment. Fundamental data is very important to middle and low frequency strategies, because they are very helpful for enlarging the size of our portfolio and provide extra info to my current alpha lib. However, its drawback is also clear. The alpha from fundamental data has larger volatility, maxdrawdown, and their immediate booming performance is not as big as technical indicators.

This is a short end for the structured fundamental data from Wind. For further research, I will use the trained NLP model like BERT and GPT-3, combined with few shot learning, semi-supervised learning, unsupervised learning, to find alphas in unstructured data. What's more, currently I do factor timing operation for this fundamental data, but the input of this sub algorithm is still not fully researched. I think I can make it better.

@Finding Alpha from Daily Money Flow Data

Money Flow is one kind of intraday price and volume data. It tells how much money and orders come in and come out during certain period of time. Wind gives the first 30 mins and last 30 mins money flow data, and big order, middle order, small order's flow data. They are very helpful, however, the data missing problem is a little annoying. Btw, this is not level2 data, they only give a total value in the first 30 mins but not give each mins' data. I think things can be much improved with level 2 data, especially the order book data. Previously, I have experience in high frequency market making strategies.

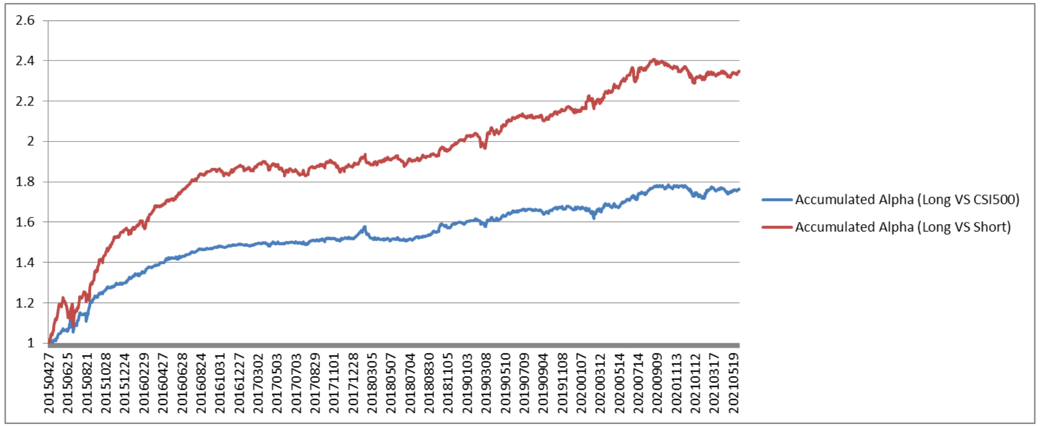

Figure 3.1 Big compounded alpha generated from money flow data, avg daily turnover rate is 15%-25%.

As we can see above, the money flow is intraday data, it can bring in a lot of new alpha but with high turnover rate. If I directly use it, is turnover can be as high as 25%, if I penalized the inventory change, it can be lowered down without significantly hurting the revenue. I keep open mind to this kind of high frequency, high turnover alpha source. Because after certain threshold, the revenue must come from trading's turnover. It's okay to let this kind of factors to join in, and at the end, the overall turnover rate is not that high. Because there are much low frequency factors, and even if two factors have same turnover rate, their combination's volatility and turnover will decrease with high possibility.

For further research, the level 2 data can make it better.

@Final Signal (No portfolio optimization and risk control yet)

Okay, here let's put all the factors together. Each factors is a big compounded alpha, which consists of 15-300 small factors.

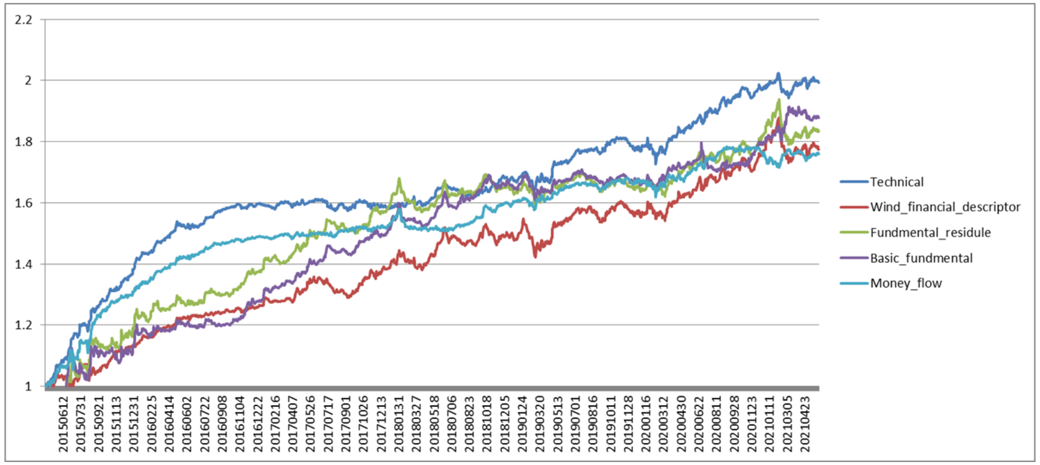

Figure 4.1 Final alpha curve, the value shown in this picture is **Accumulated Alpha (Long VS CSI500)**, avg daily turnover rate is 10%-13%.

Shown in Figure 4.1, during different peirod of time, there is a main actor. In the Chinese A share market, 2017 is hard to technical indicators, but fundamental factors can take care of it. In the late 2018 and beginning of 2019, fundamental data is suffering, maybe the Trade War lauched by Trump. But at this time, the technical indicator can pay back. In 2020, they all the shinning star, but in my lib, technical indicator is more powerful and easy to attract money's attention.

Combine all these compounded alphas together into the final signal. I simply adds up all the factors together, equally weighted. Here are two things I tried. First, the factor timing neural network I designed for fundamental data doesn't bring significant improve. I need do more experiment. I suspect that the input data is the key. The thing can timing the fundamental data may far from enough to timing the technical data, due the frequency and info flow. Second, I have tried use simle neural network to ocmbine them together. For this method, its can improve but still not impress me. If the performance can not impress me, I think the linear regression is much better, in this case. Still, I need more experience in combination and portfolio optimization.

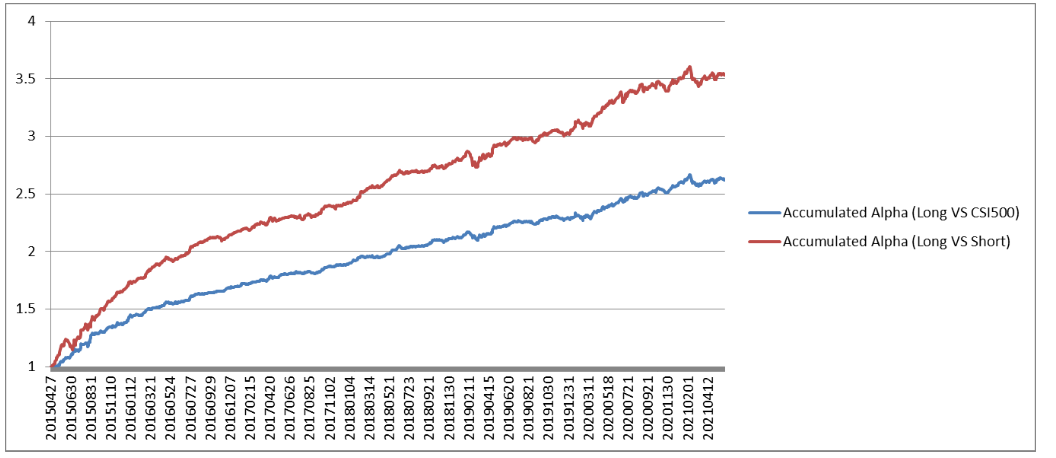

Figure 4.2 The added alpha curve. (+)

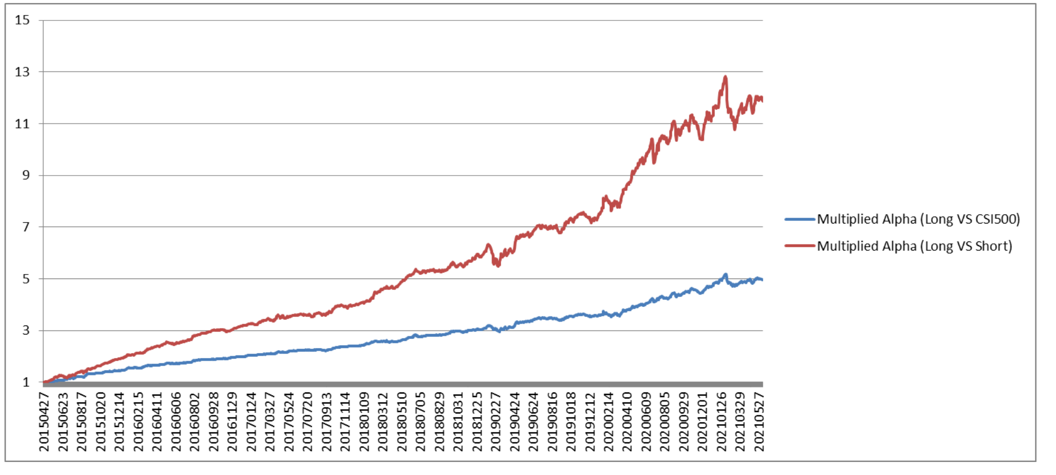

Figure 4.3 The multiply alpha curve. (*)

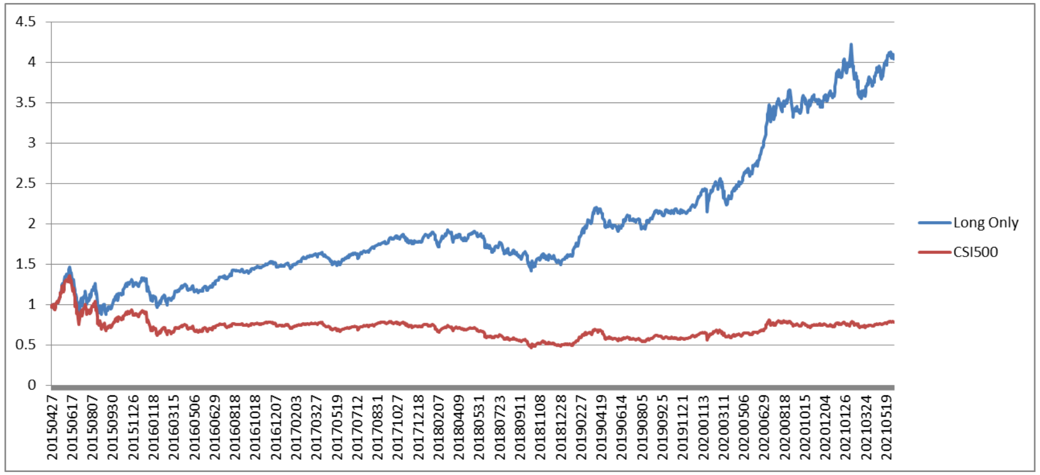

Figure 4.4 The multiply net value curve. (*)

Here is the backtest table:

Table 4.1 Backtest Result Table.

	A	B	C	D	E	F	G	H
1		Total Return (Added)	Net Return (Added)	Volatility	Net Sharpe	Net Maxdrawdown	Daily Total Turnover rate	Net Calmer
2	2015	0.402097307	0.353665049	0.100252292	3.527750255	-0.036815928	0.142447818	9.606305365
3	2016	0.296072226	0.222906345	0.060240315	3.700285195	-0.021874154	0.149930084	10.19039829
4	2017	0.193472745	0.122299668	0.054197902	2.256538785	-0.023882862	0.145846469	5.120812804
5	2018	0.233849953	0.165324884	0.059786788	2.765241084	-0.027108563	0.140998085	6.09862211
6	2019	0.166227315	0.104566657	0.083193396	1.256910555	-0.074421763	0.126353807	1.405054826
7	2020	0.282642207	0.232925226	0.106388952	2.189374192	-0.061011904	0.102298315	3.8177013
8	2021(1-6)	0.046730036	0.024491042	0.073489159	0.333260613	-0.097349048	0.10795628	0.251579677
9	Total	1.621091789	1.226178871	0.210288234	5.830943783	-0.097349048	0.132432233	12.59569449

In the past 6 years, the max-drawdown happenes in Feb 2021 which is same as MingHong (a leading hedge fund in China). Thus, I did bad in the 2021 Q1, but at 2021 Q2, I earn all the loss back and win new money. So far, I know that 2021 Q3 is easy for finding alpha. Later I will find a time to update my data.

To deal with this max-drawdown, I have several ideas. Listed according to the priority.

1. I have designed experiment (this idea is from a very senior colleague specialized in trading), what if I construct a single factor by using the data of 2021 Q1 and Q2, and then add this factor into the rolling forecast system. I found that before 2020, add this new factor can bring significant imrpove, in 2020 don't add this factor is a wise decision. Thus, I suspect that the training set 300 trading days is the main cause of this maxdrawdown. 2021 and 2018,2019 maybe similar, but 2021 is very different from 2020! Maybe, I should repeat and enlarge my alpha libs, use 150/300/600 as training length! But for this moment I am crying for decent infrastructure support...64G CPU, 20G GPU (the more the better), 32 Cores will be temporarily enough...

2. Shown in Table 4.1, this maxdrawdown is very distinct, compared with the max-drawdown in the other years. Thus, I can calculate the value at risk, and design a stop lossing strategy. If the loss is bigger than VaR, then I follow the index for N days. Of course, N and VaR are important hyper-parameters, I need do sensitivity analysis, if they are not robust on some para-space, this method will be regarded as failure.

3. Common barra risk control may be helpful, but I am not sure whether it will hurt the revenue, and how much?

This method is so far I can think, if possible, I hope to get more idea. But I bet that this problem can be solved by point 1.

@Last Update, 19 Oct 2021.

All these work's algorithm and knowledge comes from my 3 years' academic master program at Tsinghua. Near the graduation, I look at my Linux Server, and found that I have more than 1000 day's experience in quant research and deep learning algo. I use these knowledge and experience to do these new experiments from July 2021 to Oct 2021, as a full time quant analyst at a Top2 investment banks in China. So please measure all the things by yourself, take less into account, about the full time experience I sit on an industry quant desk. Thanks for your great attention to read here, sincerely.