Statistical Arbitrage on S&P 500 Components by Machine Learning Models

Springboard Data Science Career Track Capstone 1, April 27th 2020 Cohort
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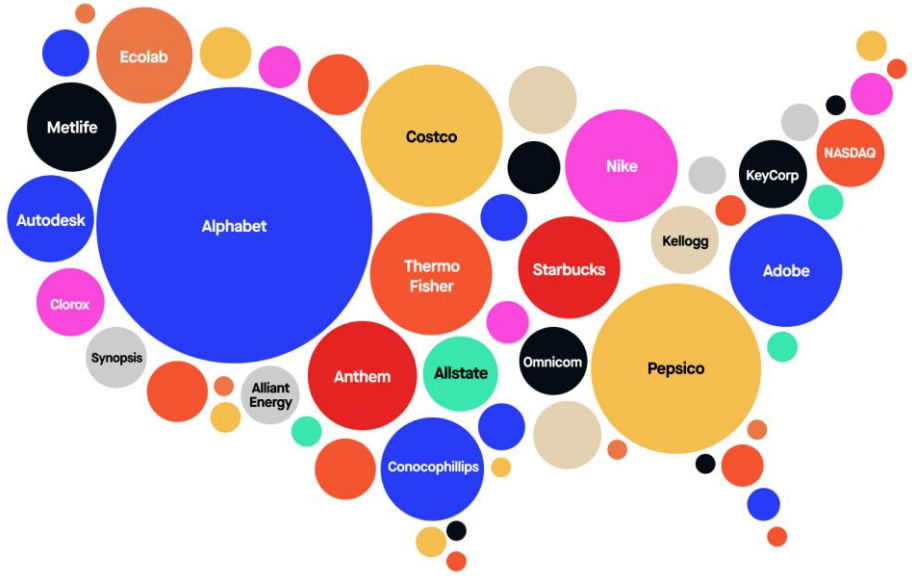
Thanks for Springboard mentor Kevin Glynn

The Next 20 minutes is dictated to

- Project Introduction
- Dataset Extract, Transform and Load (ETL)
- Exploration Data Analysis (EDA)
- Machine Learning Models, Parameters Tuning and Prediction Results
- Trading Results and Analysis
- Future Work

Why S&P 500 Components

- Attractive return - 9.8%/year, including dividends, since inception in 1926 (Wikipedia).
- Mr. Warren Buffet recommended to invest S&P 500 index (Berkshire Hathaway's annual meeting 2020).
- A hot topic to do statistical arbitrage trading on S&P 500 components.



Source: Robinhood Learn

Previous Related Work

- Jegadeesh and Titman (1993) - Early paper for momentum trading method. Select stocks based on their past 6-month returns and holds them for 6 months. Realize a compounded excess return of 12.01%/year from 1965-1989.

- Krauss et al. (2017) - A statistical arbitrage strategy based on deep neural networks (DNN), gradient-boosted trees (GBT), random forests (RAF) on S&P 500 constitutes from 1992 to 2015. Realized return 0.25%/day, Sharpe ratio 1.81/year without transaction cost.

- Fischer and Krauss (2018) - Long short-term memory (LSTM) networks on S&P 500 constitutes. Realized return 0.46%/day, Sharpe ratio 5.8/year without transaction cost.

- Fischer et al. (2019) - Logistic regression (LG) and RAF with 40 cryptocurrency coins on minute-binned data from 18 June 2018 to 17 September 2018. Realized excess return 0.038%/round-trip trade after transaction cost with 0.15%/half-turn.

Goal of This Project

- Find the optimal machine learning methods in one-step stock movement prediction with updated dataset (2005-01-01 to 2019-12-31) .

- Compare the results of my machine learning methods to the previous results, Krauss et al. (2017) and Fischer and Krauss (2018).

- Check the hypothesis that “profits are declining in recent years and there is a severe challenge to the semi-strong form of market efficiency”.

Dataset Extract, Transform and Load (ETL)

- List of historical S&P 500 components - Wharton Research Data Services (WRDS) and Wikipedia.
- Daily data of historical S&P 500 components - Python Yahoo finance module yahoo-finance-1.0.4.
- Missing Components – Delisted from Yahoo finance.

Exploration Data Analysis (EDA)

- **Dataset**: S&P 500 composites from 2005/01/01 to 2020/01/01 (15 years data).

- **Subsets**: Split dataset into 12 subsets - each subset, 750 days/250 days as formation and trading window. All trading windows are non-overlapped. Each formation window, 80% training (5 folder cross validation), 20% testing.

Subset	form_start	form_start	trad_end	Subset	form_start	form_start	trad_end
0	1-1-2005	1-1-2008	1-1-2009	6	1-1-2011	1-1-2014	1-1-2015
1	1-1-2006	1-1-2009	1-1-2010	7	1-1-2012	1-1-2015	1-1-2016
2	1-1-2007	1-1-2010	1-1-2011	8	1-1-2013	1-1-2016	1-1-2017
3	1-1-2008	1-1-2011	1-1-2012	9	1-1-2014	1-1-2017	1-1-2018
4	1-1-2009	1-1-2012	1-1-2013	10	1-1-2015	1-1-2018	1-1-2019
5	1-1-2010	1-1-2013	1-1-2014	11	1-1-2016	1-1-2019	1-1-2020

Table 1: Formation and Trading periods for 12 non-overlapping trading batches

Exploration Data Analysis (EDA)

Feature generation:

- *Input:* Let $P^s = (P_t^s)_{t \in T}$ denote the price process of stock s or financial indicator, with $s \in \{1, \ldots, n\}$. Define the simple return $R_{t,m}^s$ for each stock or indicator over m periods as $R_{t,m}^s = \frac{P_t^s}{P_{t-m}^s} - 1$, Where $m \in \{\{1, \ldots, 20\} \cup \{40, 60, \ldots, 240\}\}$.

- *Output:* A binary response variable $Y_{t+j,j}^s \in \{0,1\}$ for each stock s. The response $Y_{t+j,j}^s$ equals to one (class 1), if the j-period return $R_{t+j,j}^s$ of stock s is larger than the corresponding cross-sectional median return computed over all stocks and zero otherwise (class 0). Here, set j=1.

Feature Description:

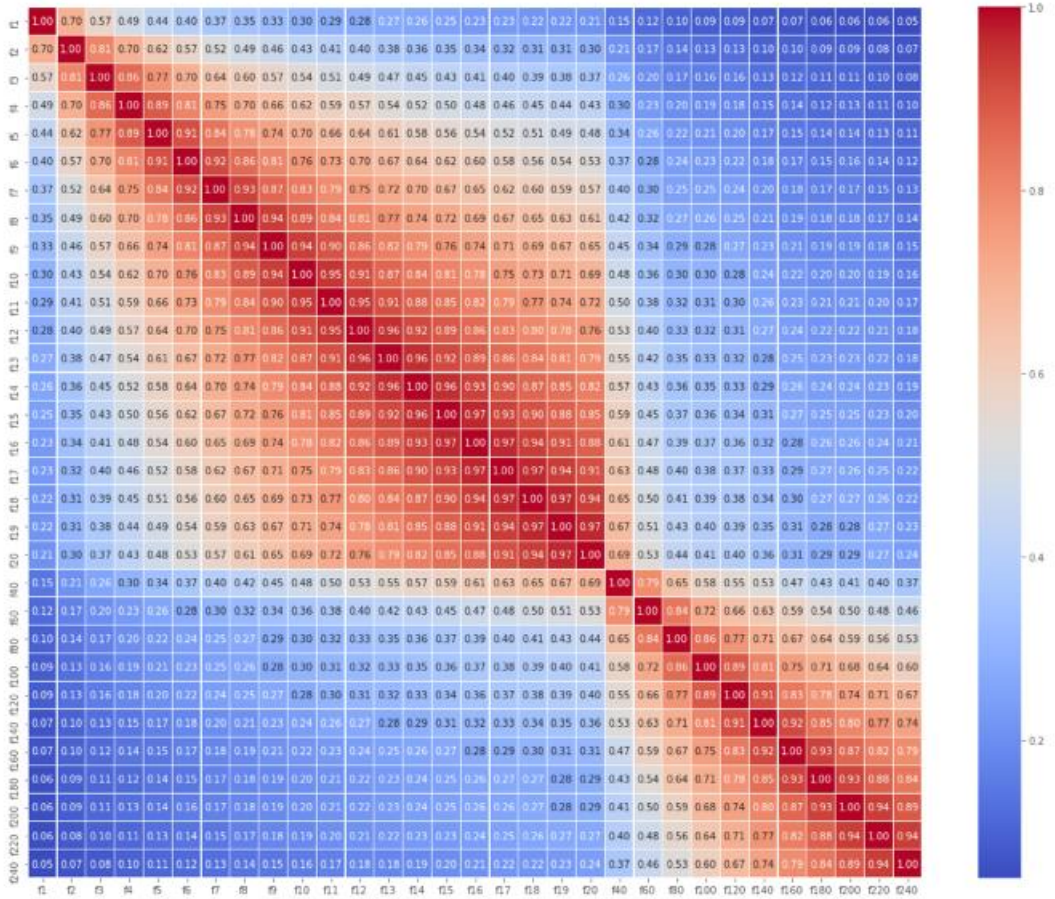


Figure 1. Feature Correlation Heatmap from Formation Subset 10

Machine Learning Methods, Grid-search parameters, Results

Methods	Paramters to be tuned	Be selected values	Optimal values for Dataset											
			0	1	2	3	4	5	6	7	8	9	10	11
knn	Number of neighbors	{3,5,7,11}	11							5	3		5	11
	Weight function used in prediction	{'uniform','distance'}	'uniform'	'distance'		'uniform'		'distance'						
	Metric	{'euclidean', 'manhattan'}	'manhattan'	'euclidean'		'manhattan'		'euclidean'		'euclidean'				
raf	The number of trees	{1500,2000,2500}	2500			2000	2500							
	The maximum depth of the tree	{20,25,30}	20		30		25		30	25	20			
	The number of features for the best split	{log2(n_features), sqrt(n_features)}	"sqrt"	"log2"		"sqrt"		"log2"						
	The number of samples to draw in boostrap	{500, 700, 1000}	700	1000		700	1000							
lg	Inverse of regularization strength	{10^-3, 10^-2,...,10^2,10^3}	0.01	0.1	0.001		1000	0.01	0.1	0.001			10	0.001
	Penalization (learning rate)	{'l2'}	l2'											
	Optimization solver	{'newton-cg','lbfgs','sag'}	"sag"	"newton-cg"	"lbfgs"	"newton-cg"	"lgfgs"	"newton-cg"	"sag"	"newton-cg"		"sag"	"lbfgs"	"newton-cg"
	Maximum iterations	{10000,20000}	1000											
xgboost	Maximum depth of a tree	{3,5,7}	7											
	Minimum sum of instance weight needed in a child	{5,10}	5								10		5	
	Number of trees	{500, 1000}	1000											
	Penalization (learning rate)	{0.01, 0.02, 0.05, 0.1}	0.01	0.02		0.05			0.02	0.01	0.02			
ensemble 1	Average of knn-xgboost	Average												
ensemble 2	Stacking of knn-xgboost	Meta-function												
mlp	structures, early stoping, activate function	31-10-5-1, 256-128-64-32-1	256-128-64-32-1											

Table 2: Grid-search parameters of machine learning methods with the optimal results

Result from Formation (Train/Test) Window

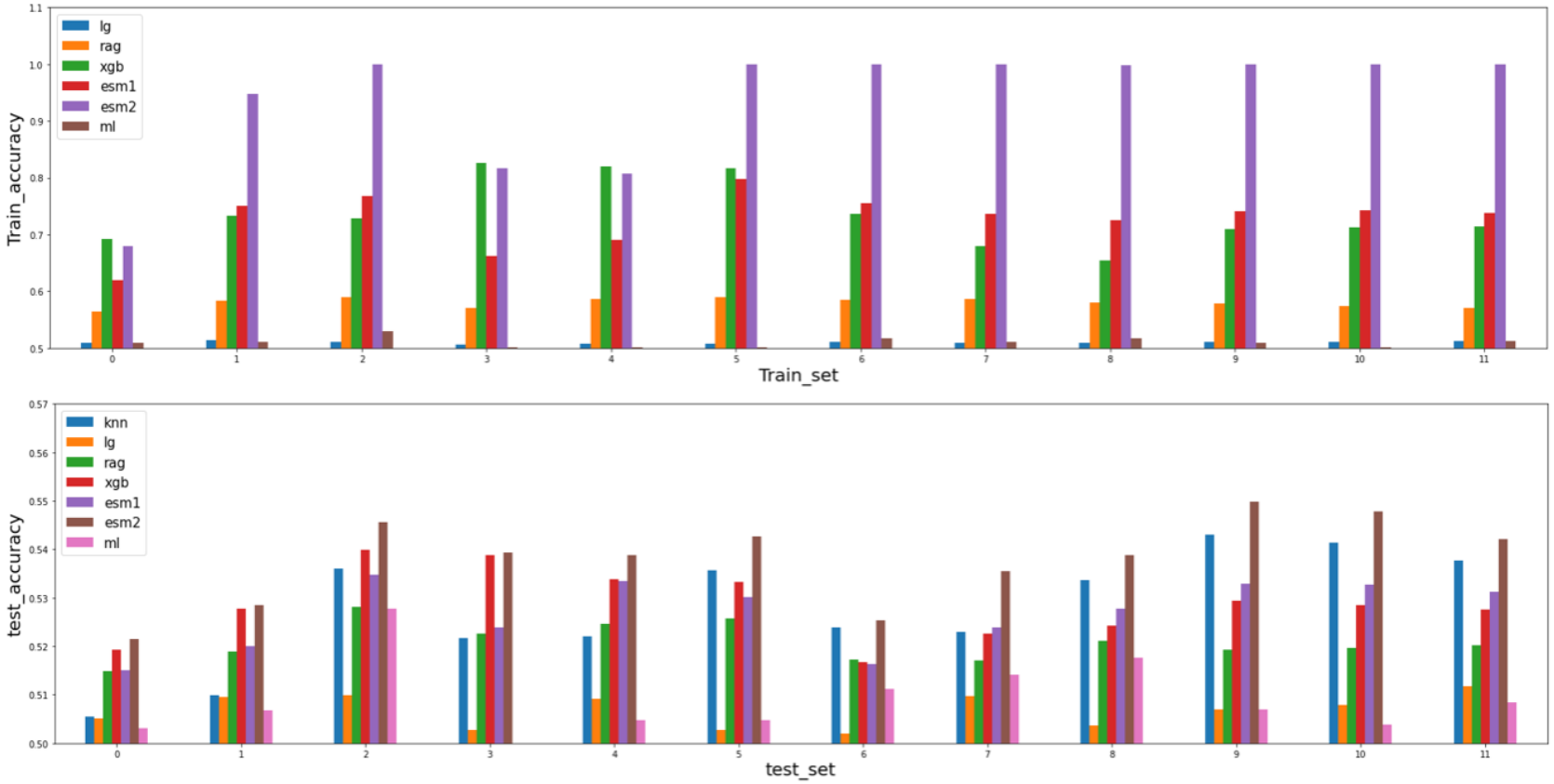


Figure 2. Train and Test Accuracy for machine learning methods with optimal parameters in all subsets

- For train subsets

- Stacking ensemble performs best.
- Besides stacking ensemble, for subset 0, 1, 3, 4 and 5, xgboost performs best, for the remaining subsets, average ensemble performs best.

- For test subsets

- Stacking ensemble performs best.
- Besides stacking ensemble, for subset 0, 1, 2, 3 and 4, xgboost performs best, for subset 7, average ensemble performs best, for the remaining subsets, knn performs best.

Trading window with Momentum

For each of trading dataset

- Sorting all stocks over the cross-section in descending order with the prediction probabilities which are reached by stacking ensemble method with the optimal parameters in table2.

- Long the highest (“expected winner”) k probabilities and short the lowest (“expected loser”) k probabilities simultaneously.

Trading Results of Momentum (3 stocks/pair)

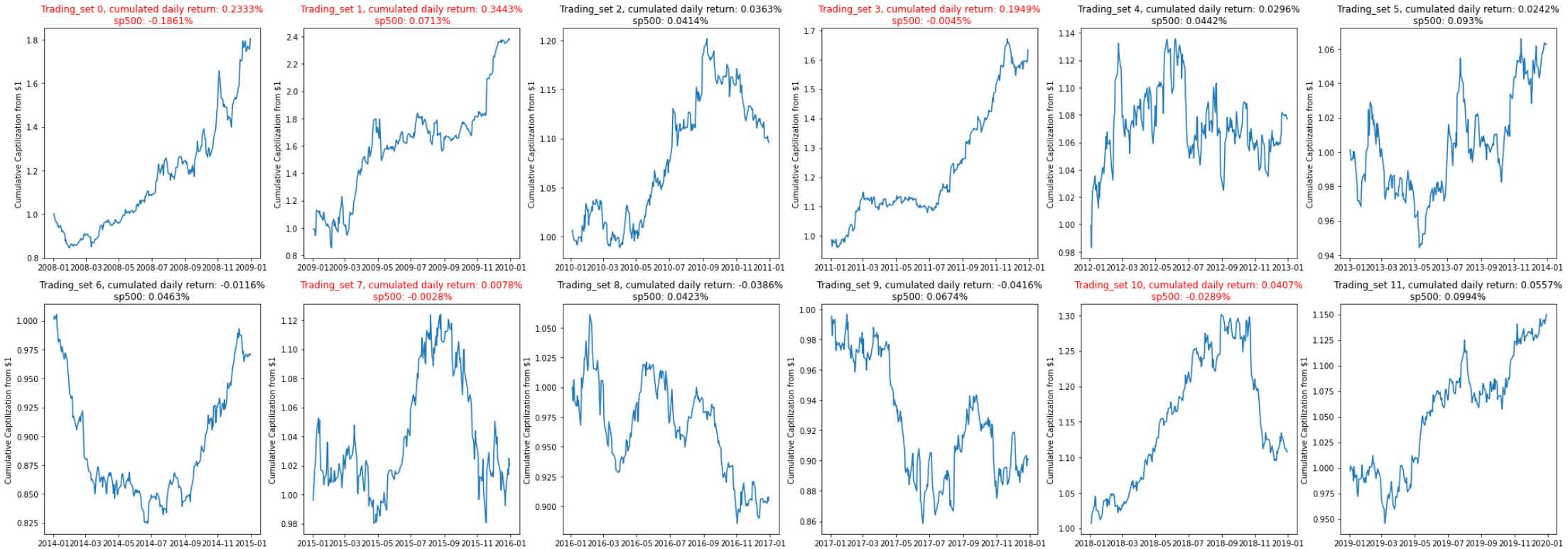


Figure 3: Results of Momentum with 3 stock/pairs

Stocks K=3, 5, 10, 15, 20/pair vs S&P 500

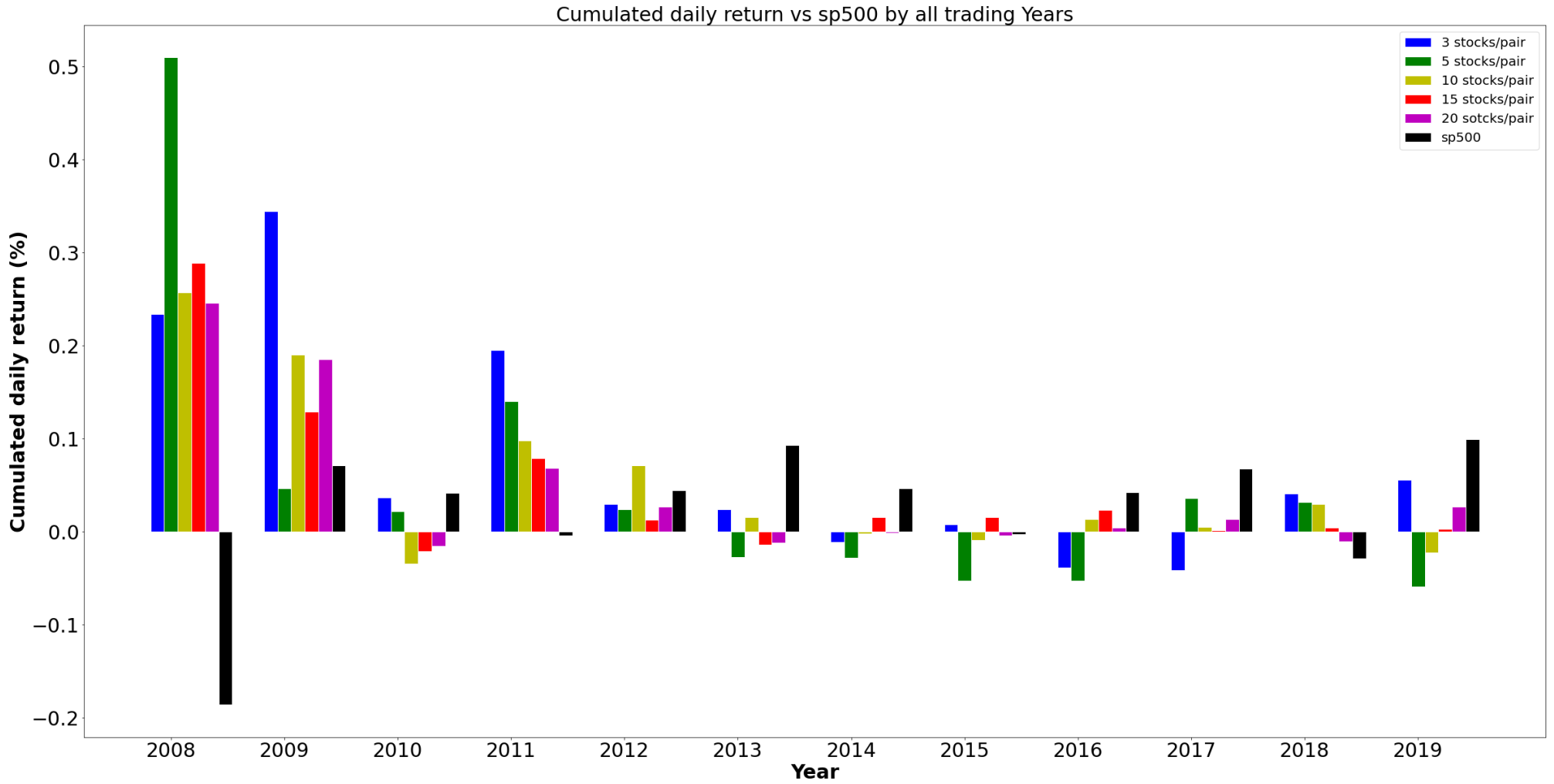


Figure 4: Results of Momentum with 3,5,10,15,20 stock/pair

Conclusion

- In years 2008, 2009 and 2011, most of my method with different stocks in each pair performed better than S&P 500.
- In years 2013, 2014, 2016, 2017 and 2019, even the best performance of my method got less return than S&P 500.
- Comparing to Krauss et al. (2017), although they got 0.25% daily return, most of their returns are realized before year 2008 (especially from year 1993 to 2000). In year 2010 to Oct 2015, loss of their capitalization was over 50% after taking the transaction cost while positive daily returns still can be achieved by my method (although I didn't take transaction cost).
- My result also confirms our hypothesis that "profits are declining in recent years and there is a severe challenge to the semi-strong form of market efficiency."

Future Work

- Check the data quality. The data stored in Yahoo Finance may not be 100% accurate and we may try purchase the high-quality data (daily or minute).
- Try other models such as recurrent neural network (RNN) and long short-term memory (LSTM).
- Try multi-classification to predict stock's movement.
- Use different datasets such the Financial Times Stock Exchange (FTSE) 100 or Asian market data.
- Analysis detailly with more criteria such as maximum drawdown and reasons why in the years 2013, 2014, 2016, 2017 and 2019, my method doesn't perform well.
- Continue to tune and find the "optimal" parameters to replace table 3 and do the momentum trading again.

Reference

- Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. The Journal of finance, 48(1), 65-91.

- Krauss, C., Do, X. A., & Huck, N. (2017). Deep neural networks, gradient-boosted trees, random forests: Statistical arbitrage on the S&P 500. European Journal of Operational Research, 259(2), 689-702.

- Fischer, T., & Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. European Journal of Operational Research, 270(2), 654-669.

- Fischer, T. G., Krauss, C., & Deinert, A. (2019). Statistical arbitrage in cryptocurrency markets. Journal of Risk and Financial Management, 12(1), 31.

Thank You!

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Project report: https://github.com/jiaqixu/Springboard/blob/master/Capstone/Capstone1/Capstone1_Final_report.pdf