ST790 Quantopian Final Project

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Introduction

We were tasked with constructing a cross-sectional, long-short US equity strategy on Quantopian that fulfilled the following constraints:

- Trade liquid stocks
- Have no more than 5% of capital invested in any one asset
- Have no more than 10% net dollar exposure
- Achieve mean daily turnover between 5% and 65% over a 63-trading-day rolling window
- Attain gross leverage between 0.8x and 1.1x
- Have low correlation to the market
- Have less than 20% exposed to each of the 11 sectors as defined on Quantopian
- Result in positive returns

Trading Strategy

1. Once a week, we choose a universe of liquid assets from `QTradeableStocksUS` that pass the following filters:
   - It is not trading within 2 days of any earnings announcements as assets are generally more volatile within these dates.
   - It has not been announced as an acquisition target. To further reduce any possible volatility, we avoid acquisition targets as they often pose huge risk to quant strategies.
   - We are able to calculate a 5 day moving average of the bull-minus-bear signal from the `StockTwits` API.

Trading Strategy

2. We build an alpha vector for the universe of liquid assets filtered. The alpha model we use is quite simple: we rank the assets by its bull-to-bear intensity, averaged over the past 5 days as evaluated from `StockTwits`, and find a set of new portfolio weights that maximizes the sum of each asset's weight times this alpha value. As a result, our routine effectively goes long on assets with high bullish signal and short on those with a high bearish signal.

Trading Strategy

3. Once a week, we calculate the portfolio that maximizes the alpha-weighted sum of our position sizes, subject to the following constraints:
   - Our portfolio maintains a gross leverage of, or less than, 1.0x.
   - Our portfolio has no more than 5% in any single asset.
   - Our portfolio does not pass mean daily turnover of 80%.

November Performance

Metric	Our Result	Overall
rank	105	-
score	0.338	0.35
max_beta_to_spy_126day	0.076	0.14
max_cumulative_common_returns	0.009	0.04
max_leverage	1.047	1.05
max_max_drawdown	0.000	-0.00
max_net_dollar_exposure	0.032	0.04
max_total_returns	0.025	0.14
min_total_returns	-0.007	-0.02
max_turnover	0.905	1.07
max_volatility_126day	0.044	0.06

Choice of the sentiment score

ASM Dec 3rd, 2:28 pm

Bullish

Its all about **$AAPL** baby and its RIPPING!!!!! So much for that fade!!!! LETS GOO!!!!! **$SPY $QQQ $AMZN**

1

4 Symbols **1** Like

AAPL Since Post ▲0.06 (0.03%) Then: 182.79 Now: 182.85

200pips Dec 3rd, 1:02 pm

Bearish

$QCOM so so weak, there's a catastrophe here somewhere any day now that will happen.. be careful

1 Symbol

QCOM Since Post ▼0.16 (0.27%) Then: 58.94 Now: 58.78

arizet Dec 2nd, 10:13 pm

Bullish

#1Year_Top_Gainers
#Backtested #Quant_Signals

#AI #Model #Patterns
$MRTX @ $38.59 | 125.01% => 2 LONG | 0 SHORT

More: **arizet.com/**

1 Symbol

MRTX Since Post ▲2.05 (5.31%) Then: 38.59 Now: 40.64

Related Work

- Cutler, Poterba, Summers 1989 First empirical study on the relationship between news coverage and stocks. Qualitative data did not help unaccompanied by macroeconomic indicators.
- Antweiler and Frank 2004 Messages flagged as buy, sell or hold have some predictive power in trading volume and stock volatility.
- Tetlock 2007 High pessimism expressed in WSJ predicts downward pressure on stock prices.
- Mitra and Bartolomeo 2008 Factor models do not update quickly enough, but with news risk estimates are improved.
- Leinweber and Sisk 2011 Further confirmation of the cliche “buy on the rumor, sell on the news”.
- Zhang, Fuehres, Gloor 2011 Emotional outbursts on Twitter is a good predictor for how the Dow performs the next day.
- Agrawal 2018 Extreme sentiment has an effect on liquidity.

StockTwits Data

Excerpt from Bergman (2017) on sentiment data points on Apple:

Date	Open	High	Low	Close	Delta	Volume
2017-03-02	140.0	140.28	138.76	138.96	-0.83	26210984
2017-03-01	137.89	140.15	137.6	139.79	2.80	36414585
2017-02-28	137.08	137.44	136.7	136.99	0.06	23482860
2017-02-27	137.14	137.44	136.28	136.93	0.27	20257426
2017-02-24	135.91	136.66	135.28	136.66	0.13	21776585
2017-02-23	137.38	137.48	136.3	136.53	-0.58	20788186
2017-02-22	136.43	137.12	136.11	137.11	0.41	20836932
2017-02-21	136.23	136.75	135.98	136.7	0.98	24507156
2017-02-17	135.1	135.83	135.1	135.72	0.38	22198197
2017-02-16	135.67	135.9	134.84	135.34	-0.17	22584555

Date	Positivity	Activity	Bullish Intensity	Bearish Intensity
2017-03-02	0.62	45.80	1.82	1.87
2017-03-01	0.68	637.20	1.75	1.73
2017-02-28	0.63	-247.60	1.80	1.79
2017-02-27	0.69	120.20	1.90	1.85
2017-02-24	0.62	55.80	1.73	1.66
2017-02-23	0.61	-146.80	1.95	1.64
2017-02-22	0.64	-228.00	1.87	1.82
2017-02-21	0.69	-270.40	1.83	1.75
2017-02-17	0.62	-438.20	1.71	1.78
2017-02-16	0.68	-295.20	1.85	1.49

StockTwits Data

	mean	std	min	max
Total scanned messages	1072.41	966.04	26.00	8387.00
Bull scored messages	257.51	230.27	3.00	1995.00
Bear scored messages	157.33	155.76	0.00	1380.00
Bullish intensity	1.71	0.11	1.16	2.18
Bearish intensity	1.76	0.18	0.00	2.80

- Positivity: ratio of bullish tweets from all messages that have been classified.
- Activity: total scanned messages over a 5-day average
- Bullish/Bearish Intensity: Score on a 0-4 scale for bullishness/bearishness.
- Bull/Bear Scored: Total count of bullish/bearish sentiment messages scored.

Trading Strategy Analysis

Given that sentiment might be an early indicator for changes in financial assets and has low correlation to traditional alpha factors, we decide the weights of our portfolio by:

$$\max_{\boldsymbol{w} \in \mathbb{R}^n} \alpha^T \boldsymbol{w} \quad \text{subject to} \quad w_i \leq 0.05, \ \sum_i |w_i| \leq 1.00, \ \sum_i |w_i - w_{i-1}| \leq 0.80$$

The weights must also sum to 1.

Backtest Results

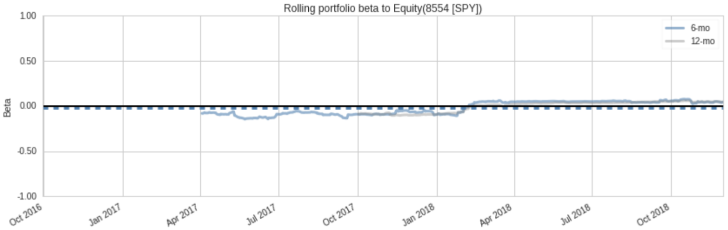
Key metrics from our final backtest between 2016-09-30 and 2018-12-03:

Annual Return	1.7%
Cumulative Return	3.6%
Annual Volatility	4.0%
Sharpe Ratio	0.43
Max Drawdown	-3.1%

Skew	0.18
Gross Leverage	0.99
Daily Turnover	18.6%
Alpha	0.01
Beta	0.02

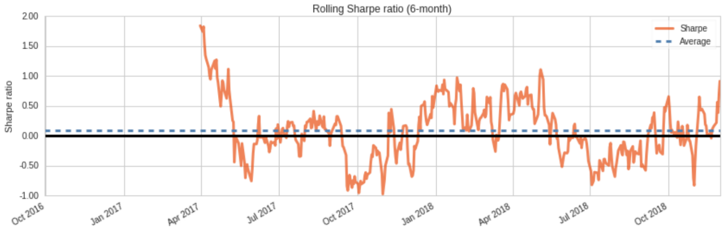
Backtest Results

Rolling beta suggests our strategy is market neutral.



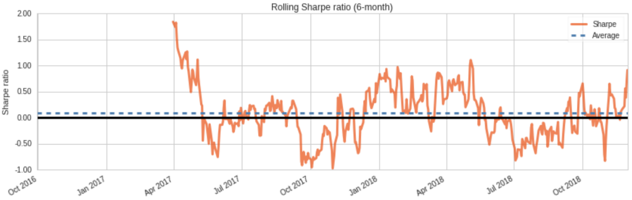
Backtest Results

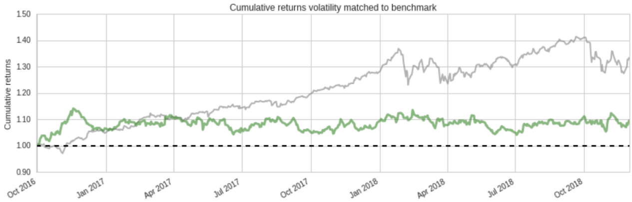
While our average Sharpe suggests low risk-adjusted return, we see that it is not consistent:



Backtest Results

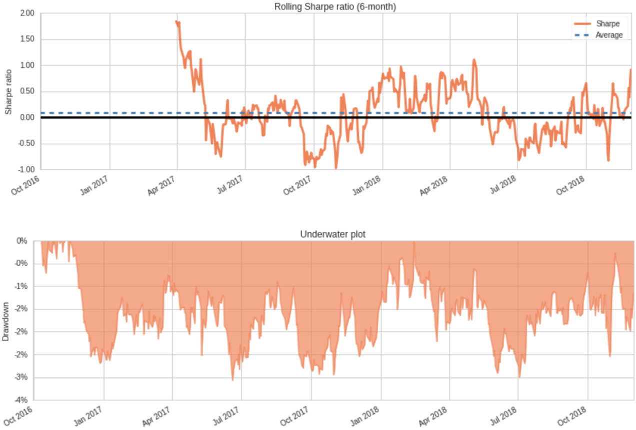
We can see the Jun 2017 to Jan 2018 period in which our Sharpe ratio underperforms takes place when the market is particularly volatile:





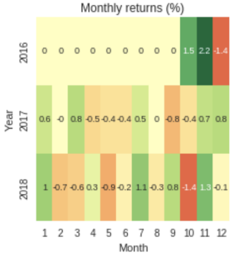
Backtest Results

We can also compare it against our underwater plot to pinpoint where our strategy performed worse:



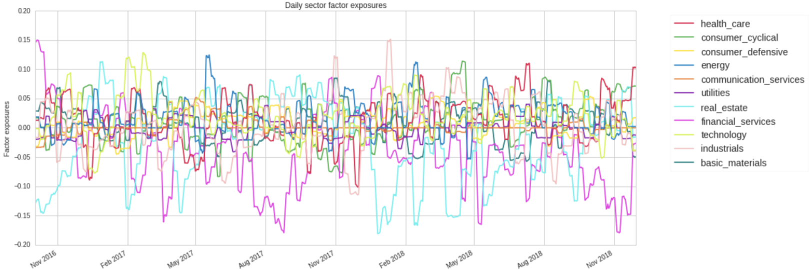
Backtest Results

While our drawdowns are minimal, there might be a seasonal component to when our drawdowns occur:



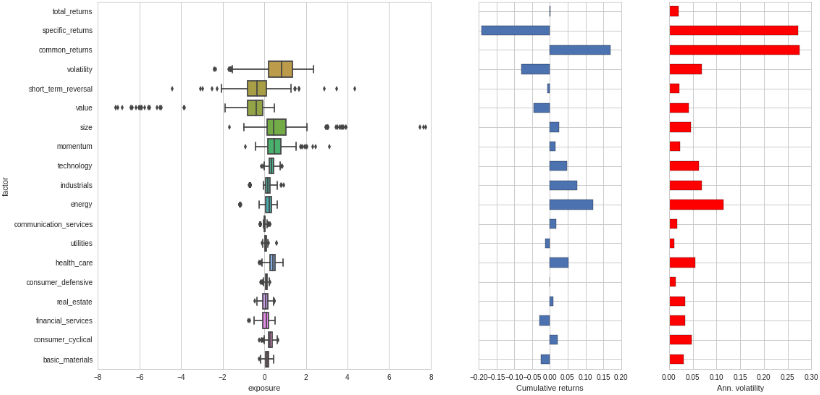
Backtest Results

We also benefit from the fact that we have relatively low exposures to each industry:



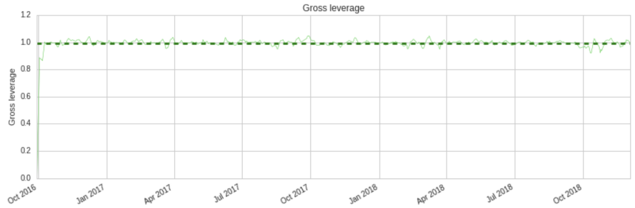
Pyfolio

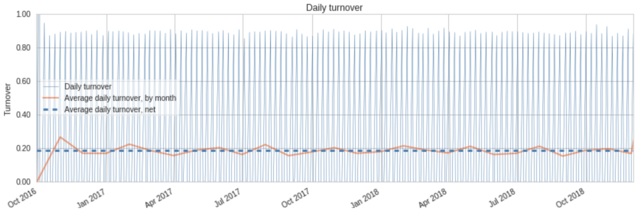
We can also observe this behavior via the `perf_attrib` function. Most of our returns appear to be explained by volatility risk.



Backtest Results

Lastly, we can see that our constraints are satisfied:





Backtest Results

With no individual security having a significant impact on the portfolio:

Top 10 long positions of all time	max	Top 10 short positions of all time	max
SAGE-47332	2.53%	CMPR-27674	-2.48%
SGEN-22563	2.44%	SYNH-48027	-2.46%
ESPR-44989	2.41%	MCY-5017	-2.45%
RGEN-6449	2.39%	MRTX-45080	-2.41%
DLTH-49615	2.36%	SSD-11386	-2.40%
TREX-20028	2.35%	FSM-41915	-2.39%
LOGI-16649	2.34%	BZH-10728	-2.37%
FFIN-10148	2.33%	FORM-25182	-2.34%
NGHC-44929	2.30%	AVNS-47929	-2.31%
EIGI-45735	2.30%	PARR-43375	-2.29%

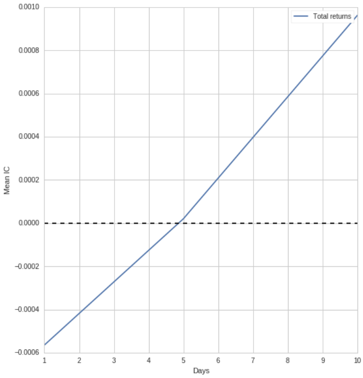
Trading Strategy Analysis

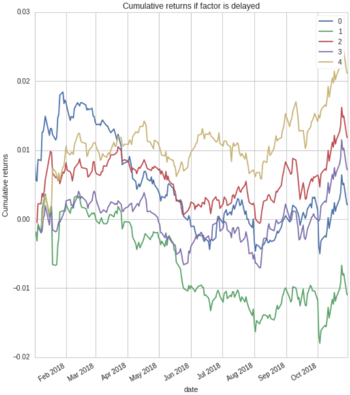
The problem with our approach is that we used backtesting as a tuning mechanism for our input parameters. Our strategy might have bad out-of-sample performance due to overfitting. We can also see this in our information coefficient, which is robust to extreme values.

$$IC = 1 - \frac{6\sum_i d_i^2}{n(n^2-1)}$$

Trading Strategy Analysis

Lack of predictive alpha:





Performance Analysis

Metric	Our Result	Overall
rank	105	-
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max_beta_to_spy_126day	0.076	0.14
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max_turnover	0.905	1.07
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Discussion

1. Narrow the universe of equities where sentiment is utilized by the factors in the Fama-French, or the Carhart four factor model (market risk, market cap, book-to-price, and momentum)
2. Take a hedge out by buying VIX/VXV to cancel out the risk from the volatility factor.
3. Design our own sentiment index that removes classification from robo cashtag users.

References

Argarwal, Shreyash, et al. “Momentum, Mean-Reversion and Social Media: Evidence from StockTwits and Twitter.” (2018).

Antweiler, Werner, and Murray Z. Frank. “Is all that talk just noise? The information content of internet stock message boards.” (2004).

Cutler, David M., James M. Poterba, and Lawrence H. Summers. “What moves stock prices?.” (1988).

Leinweber, David and Sisk, Jacob, “Event Driven Trading and the ‘New News’.” (2011).

Mitra, Leela R. and Mitra, Gautam and di Bartolomeo, Dan, “Equity Portfolio Risk Estimation Using Market Information and Sentiment.” (2008).

Tetlock, Paul C. “Giving content to investor sentiment: The role of media in the stock market.” (2007).

Quantopian. https://www.quantopian.com/lectures.

Zhang, Xue, Hauke Fuehres, and Peter A. Gloor. “Predicting stock market indicators through twitter ‘I hope it is not as bad as I fear’.” (2011).