

# Equity Trading with Sentiment

A long-short equity quantitative trading strategy based on sentiment data

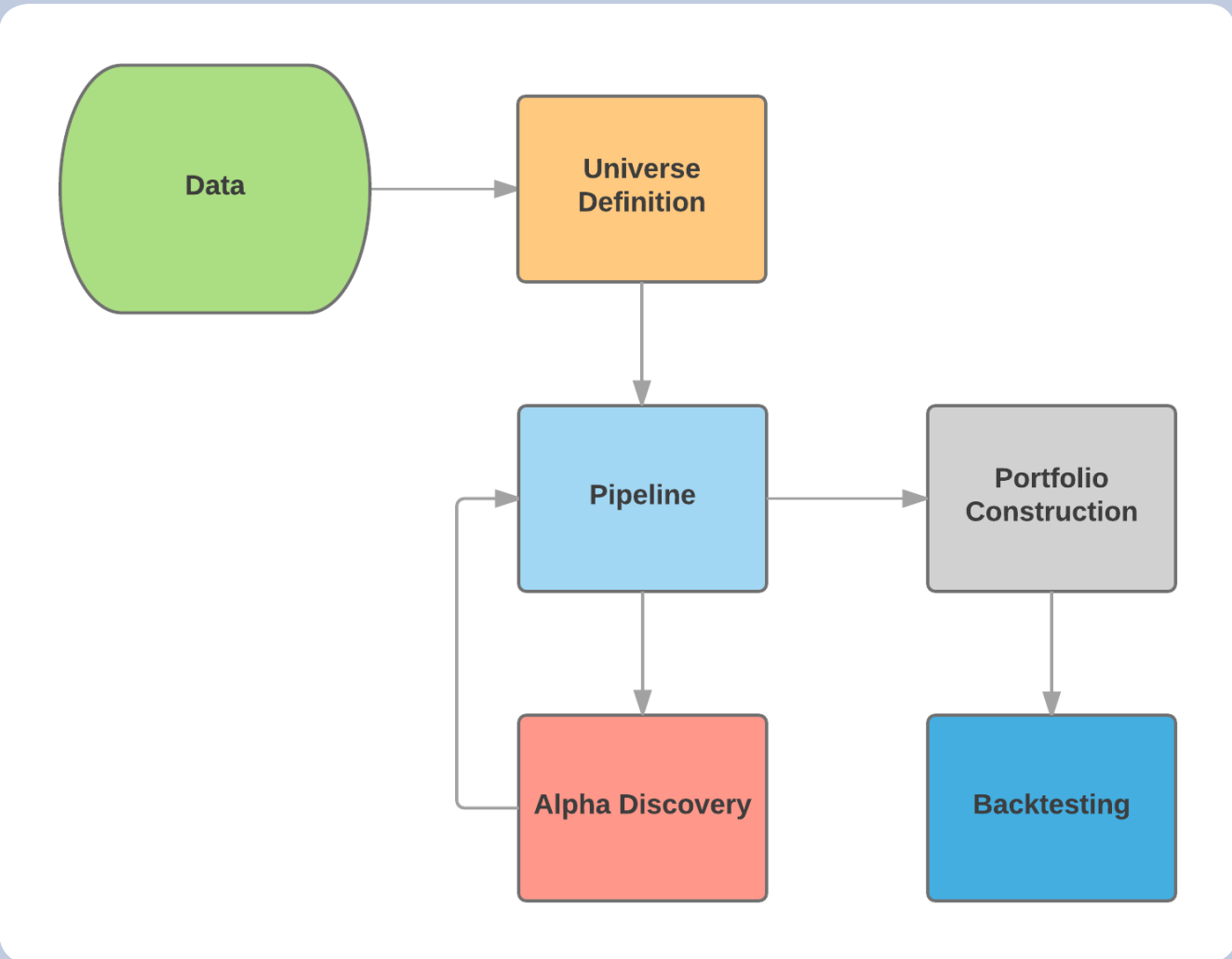
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## Overview

We sought to develop a profitable long-short equity strategy that uses sentiment analysis data as the ranking factor. To do so, many factors were analyzed using Quantopian’s Alphas tool which generates a tear-sheet of relevant statistics. An ideal factor has perfect predictive power of relative price movements. The averaged sentiment signal with a window length of 3 days was considered the most viable out 8 other candidates tested. Backtesting the strategy from early 2014 to late 2017 yielded a cumulative return of 42.5% and a Sharpe ratio of 1.33.

### Goals

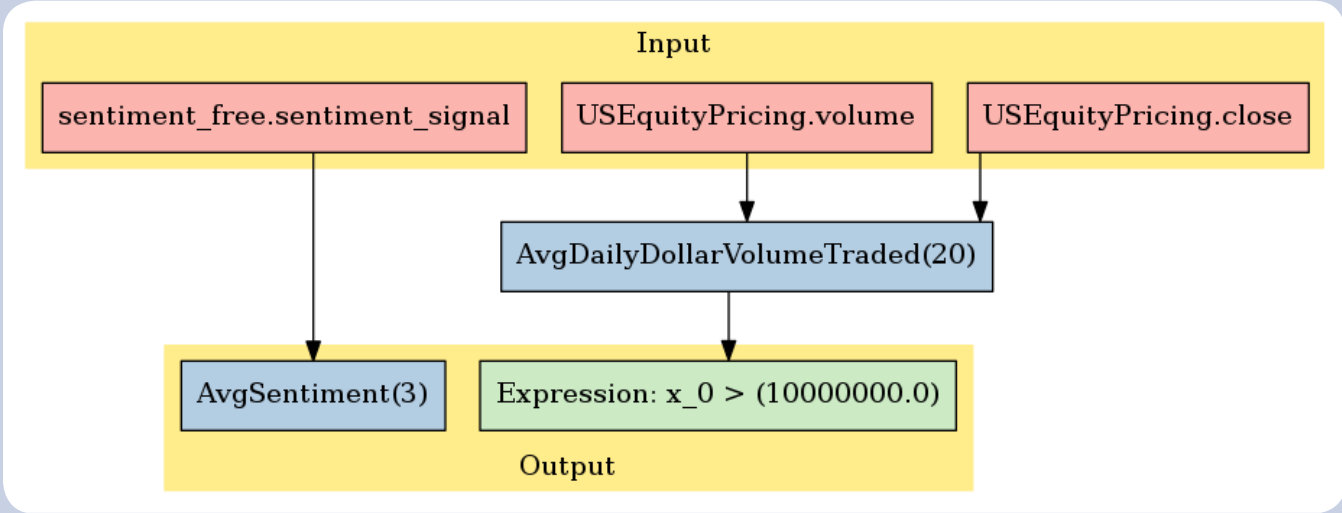
- Sharpe ratio greater than 1
- Close to neutral Beta
- Cumulative returns on par with the S&P 500 benchmark



**Figure 1: Research Workflow**  
Illustration of our research workflow, starting with sentiment data provided by Sentdex and PsychSignal and equity data from Quantopian. We used the Q1500US universe filtered by average daily dollar volume traded. Pipeline is Quantopian’s way of dynamically selecting equities from a universe, which was used in the alpha discovery process and in the trading algorithm.

## Pipeline

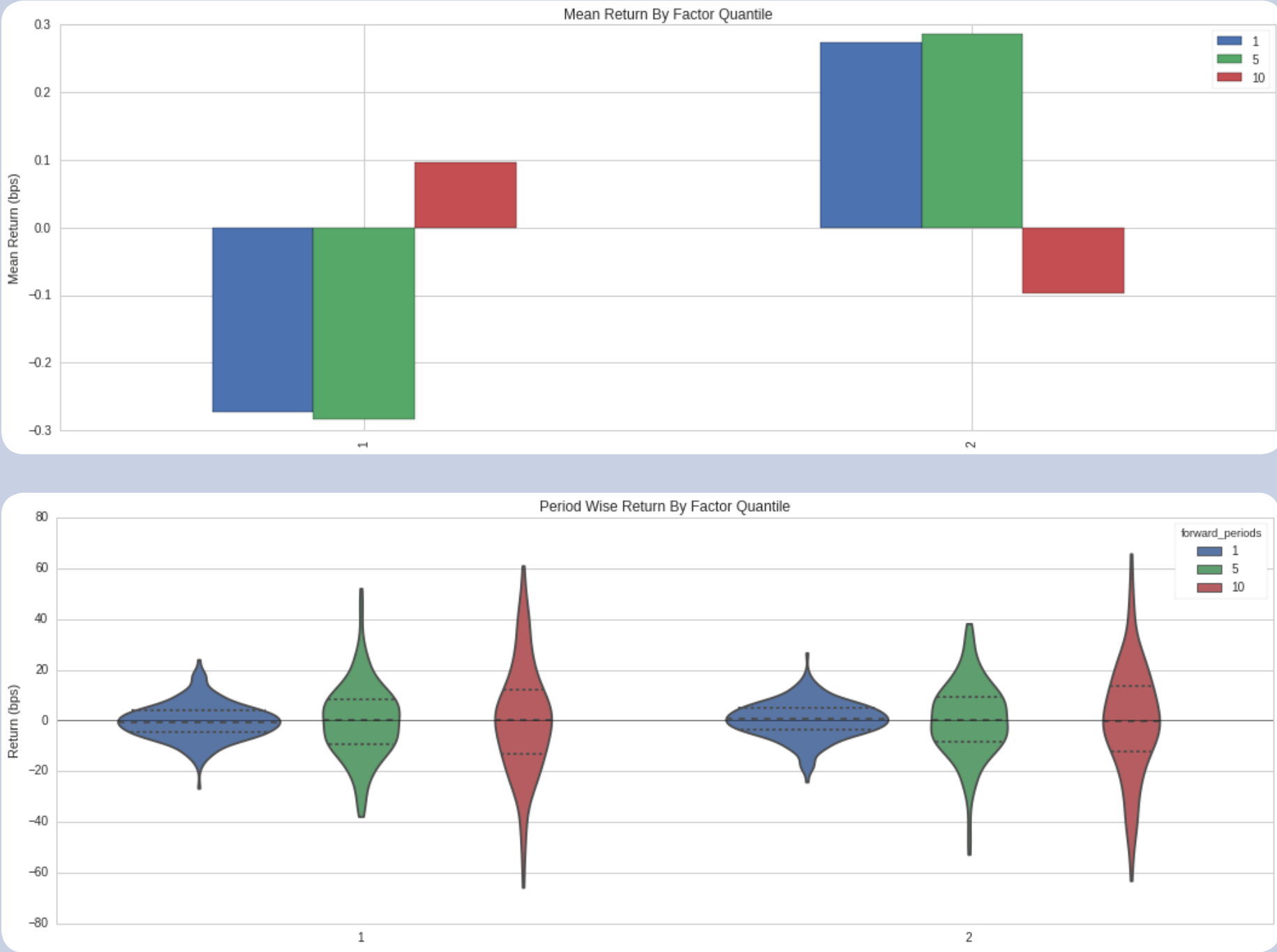
Pipeline is Quantopian’s way of dynamical-ly selecting equities from the Q1500US uni-verse. It is used in both the alpha discovery stage and in the trading algorithm. The alpha factor that had the best performance was the average sentiment over a 3 day window.



**Figure 2: Pipeline Analysis**  
The sentiment data is used by the custom factor, AvgSenti-ment. The equity data from Quantopian is filtered by a custom factor, AvgDailyDollarVolumeTraded. The trading algorithm rebalances its long and short positions every day 1 hour after the market opens.

## Alpha Discovery

Alpha discovery is necessary to de-terminate whether an alpha factor is acceptable for the given strate-gy. We used the Pipeline and in-terpolated the NaN values from its output. Quantopian’s package, Al-phas, was used to evaluate 8 dif-ferent potential alpha factors. From the PsychSignal data, we looked at bullish and bearish intensity. From the Sentdex data, we evaluated the sentiment signal, and a simple mov-ing average of the sentiment signal as a lagging indicator over window lengths of 3, 10, 20, 30, 50, and 80.



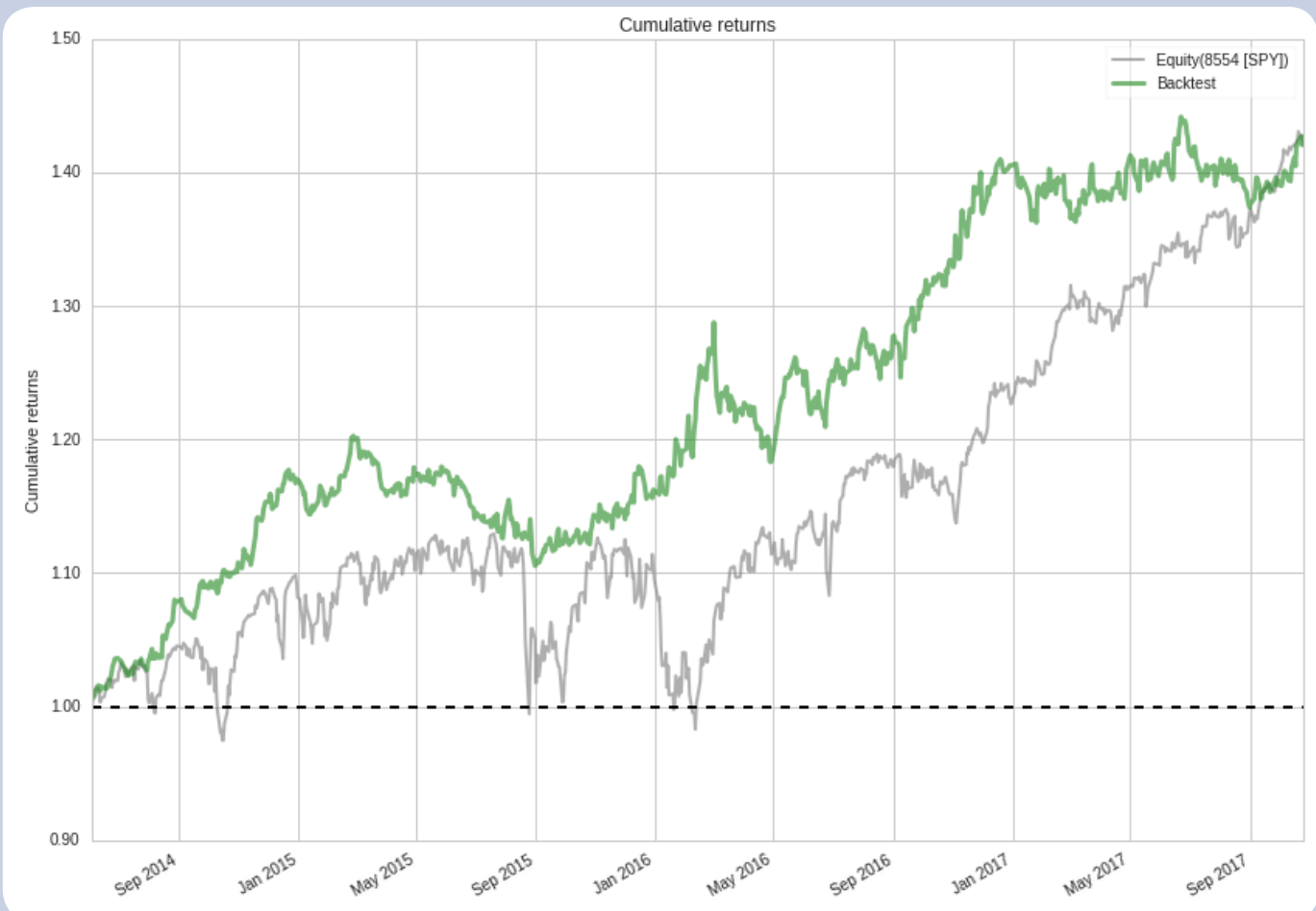
**Figure 3: Mean Return by Factor Quantile**  
The plot describes the optimal window length for which the alpha factor, average sentiment, is most predictive. It breaks it down by 1, 5, and 10 days. The visualization shows that average sentiment operates best as a short term predictor, and that 1 and 5 days are very similar, with a steep drop off by 10 days. Quantile 1 and 2 represent the short and long positions, respectively.

**Figure 4: Period Wise Return by Factor Quantile**  
The violin plot of our timeseries of quantile 1 and 2 (short and long positions, respectively) shows that a 1 day period had the highest density of returns and values relatively close to the mean.

## Strategy

We worked with a long-short equity strategy, which involves maintaining a long position on equities that are supposed to increase in price and maintaining a short position on equities that are supposed to decrease in price. The equities are ranked by the average sentiment factor that we created. If the average sentiment value associated with the corre-sponding equity was greater than 0 put it on the long bastket, and if it was less than 0, put it in the short basket. The strategy then or-ders all the equities in the long and short bas-kets one hour after the market opens each day, and is rebalanced every day. This strate-gy works best with a very high starting capital and is market neutral so it could theoretically perform well in any economic climate. The goal is to minimize exposure to the market.

## Results



**Figure 6: Backtest Cumulative Returns**  
The plot shows the cumulative returns of the trading strategy versus the S&P 500 from June 3, 2014 to October 25, 2017.

**Figure 7: Rolling Volatility**  
The plot shows the rolling volatility (6 months) of the trading algorithm ver-sus the benchmark, S&P 500, as well as the average volatility of the trading algorithm. The trading strategy has a lower volatility than the benchmark, and greater returns up to the last few months of 2017.

