

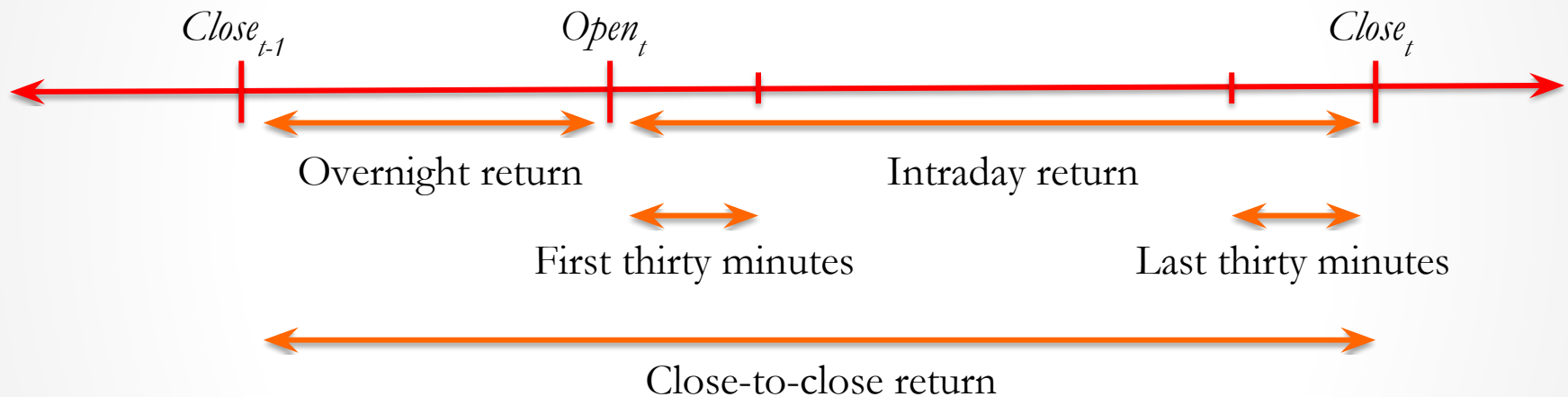
Alpha-Beta Soup: Mixing Anomalies for Maximum Effect

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MIRAJ Alpha

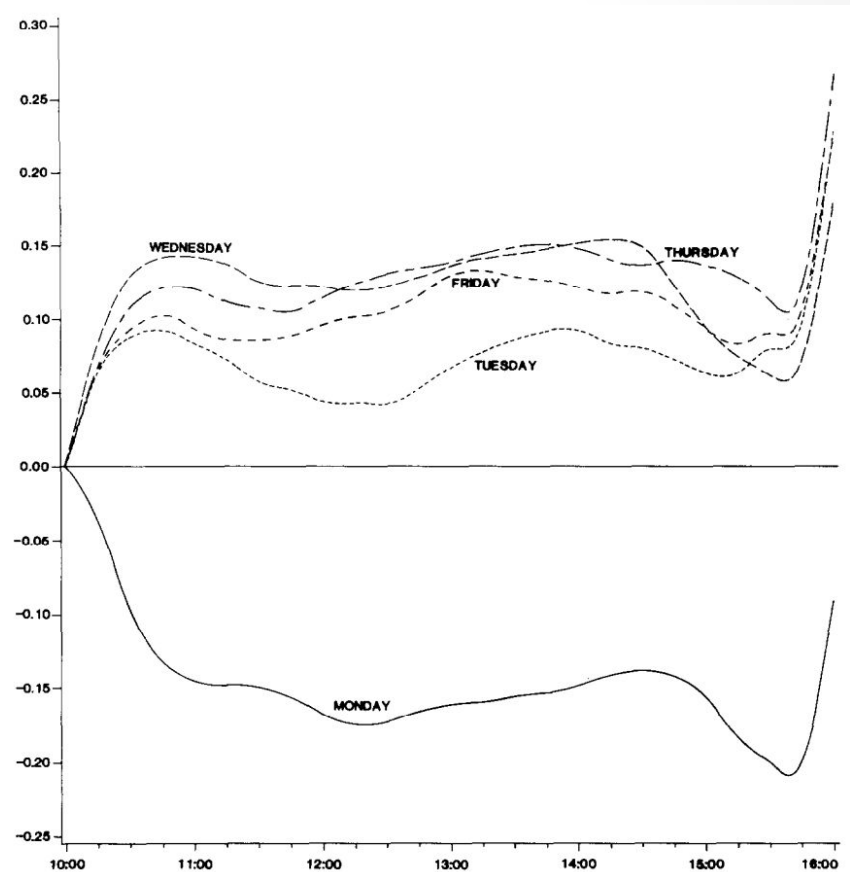
MS&E 448

Recap: Overnight and intraday returns



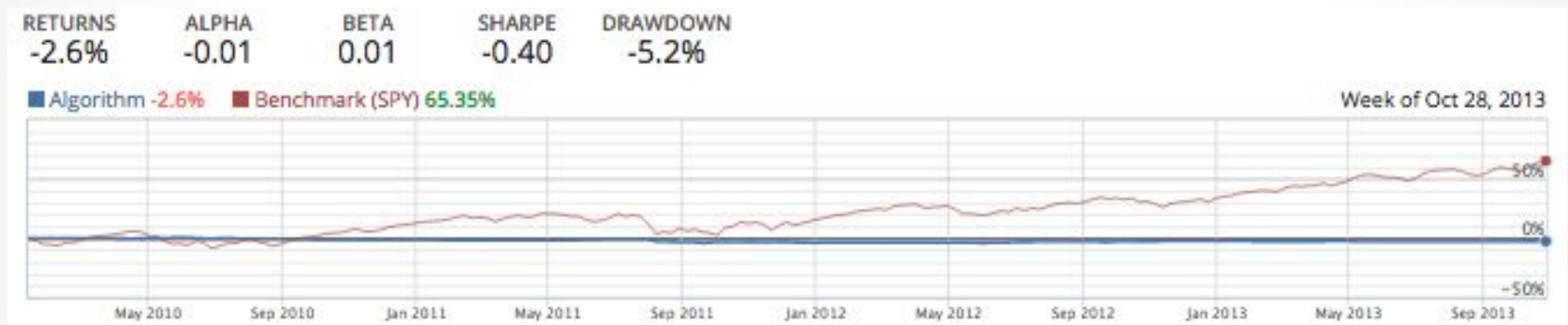
Intraday effects

- Intraday studies in the 1980s: Wood et al. (1985); Smirlock (1985)
 - Harris (1986): predictable patterns in returns through the day. Prices rise on all mornings but Monday
 - Potentially due to market-maker inventory control
 - Persistent despite expansive literature

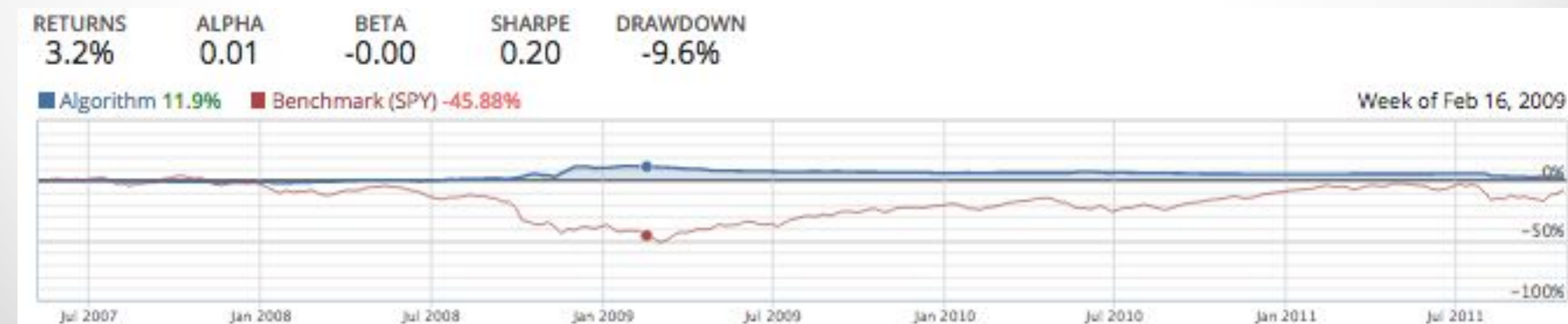


Previous findings

- Our first try at a Quantopian strategy with first 30/last 30 trading had consistent annual losses



- But, we managed to finagle better returns under high volatility



Previous analysis

- The signal did not appear to be very strong
 - Correlations were low
 - P-values were high
- Consistent with the results in Komarov (2017) that predictability does not imply profitability
- The way forward: look at other anomalies and see if they can be profitably traded in conjunction with first 30/last 30-type intraday effects, other momentum-type price dynamics, or news signals

New objectives

- Exploit the mean reversion of volatility: low vol/high vol
- Explore opportunities to combine low-vol strategies with the work we've already done in momentum trading
- Put Inferess data to use boosting signals by observing investor sentiment
 - Inferess dataset contains observations of news sentiment signals, as well as direction, strength, and novelty of these signals
 - We ran machine-learning algorithms to train a system to recognize profit opportunities based on sentiment signals and price changes

New objectives

- Smart beta strategy from Quantopian:



Challenges

- **Strategic:**
- As we learned, statistical predictability does not imply profitability.
- Do we model transaction costs? Can detract from strength of signals that can later be combined
- Interesting questions on the best metric and timeframe for volatility measure, how many stocks to buy
- “We foresee the reasonable probability of a smart beta crash as a consequence of...soaring popularity” – Research Affiliates white paper (2016), with specific references to low-vol

Challenges

- **Structural challenges with Inference:**
- We couldn't use intraday data because those are limited to the past 2 weeks on Google Finance and the past 6 months on Bloomberg; the data are not recent enough. (Quantopian lookups were too slow.)
- Limited us to looking at short timeframes but daily windows
 - Price changes from new information likely take a while to diffuse through the market (Hong et al., 1999) - will discuss this shortly
 - But we wouldn't be able to predict immediate shifts either due to lack of intraday data

Additional literature review

- Low-volatility anomaly is relatively well studied
- Excess returns to low-vol stocks because investors discount dividend returns: Ciliberti et al. (2015)
- Momentum strategies have been found to trade well in conjunction with volatility-dependent strategies (Polychronopoulos, 2014), so potential opportunities to combine with our previous work
- Also considered news events. Recent work supports the idea that news signals can be used to profitably predict price movements

Low volatility strategy

- Empirical support:



Source: NASDAQ

Low volatility strategy

- Trade Q1500 liquid stocks index
- Considers volatility over past 100 days, trades 10 highest and 10 lowest proportionally to rank: 100%, 90%, ...
- Long low-vol and hedge with high-vol shorts
- Typical long holdings: JNJ, CLX, MCD, MMC, SO
- Short only half value for the top 10
- Best results: rebalance short portfolio monthly and long portfolio weekly to take advantage of volatility effects

Low volatility strategy results

- Short monthly portfolio

RETURNS	ALPHA	BETA	SHARPE	DRAWDOWN
-9.6%	0.06	-0.47	-0.14	-24.1%

■ Algorithm -3.46% ■ Benchmark (SPY) 69.5%

Week of Dec 21, 2015



- Long monthly portfolio

RETURNS	ALPHA	BETA	SHARPE	DRAWDOWN
50.5%	0.03	0.35	0.97	-12.3%

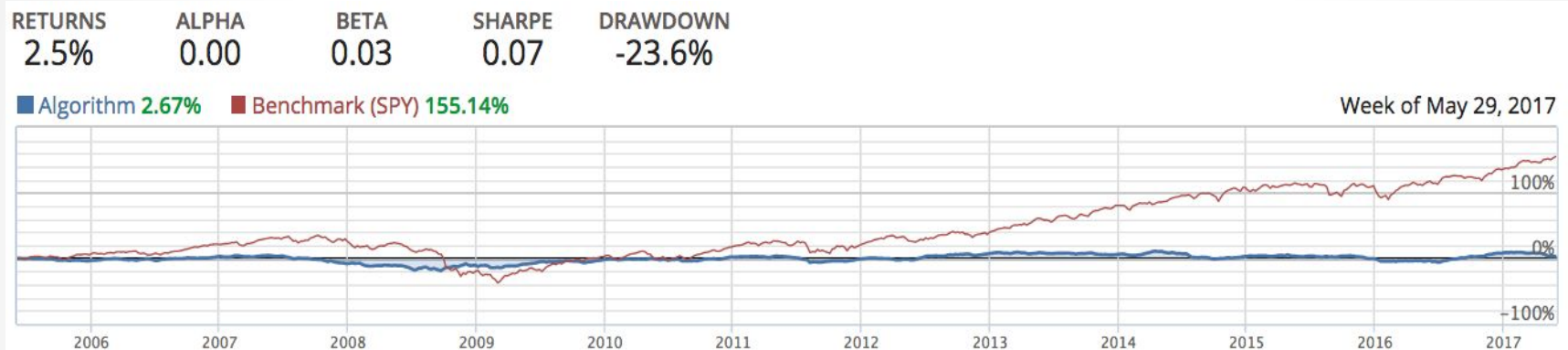
■ Algorithm 50.12% ■ Benchmark (SPY) 108.25%

Week of May 29, 2017



Low volatility strategy results

- Daily rebalancing – clearly, monthly is the way to go

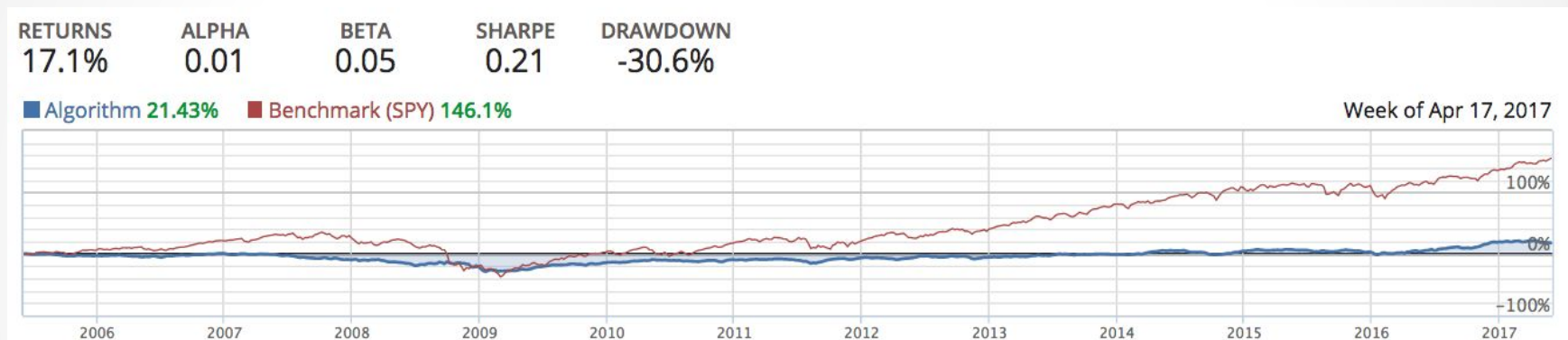


- Additionally, the strategy outperforms in the crisis:

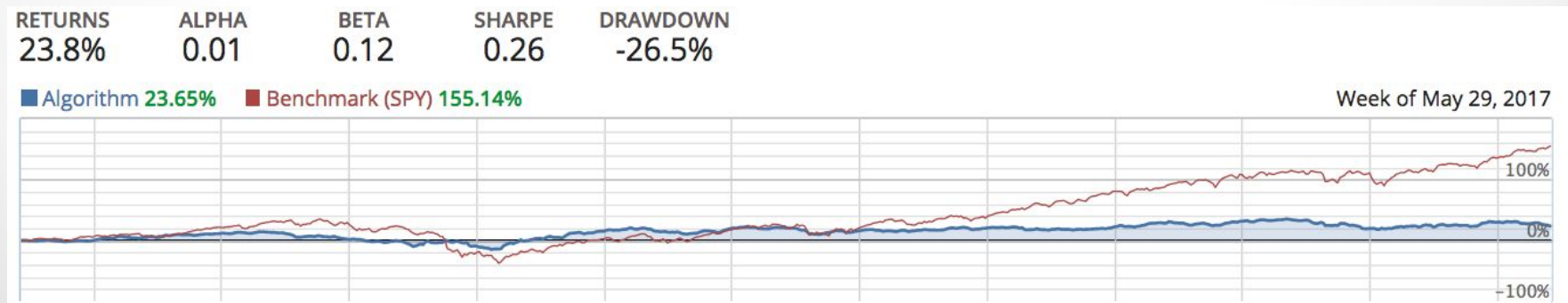


Low volatility strategy results

- Expanded portfolio with 100 long and 100 short (weekly)



- Monthly rebalancing



Low volatility strategy analysis

- We think high-vol stocks may have been outperforming recently vis-à-vis baseline considered in studies
- Tech stocks like FANG have a high beta, as discussed in the guest lecture:
- JNJ:

Current		1 WK AGO	1 MO AGO	52 wk Hi/Date
HISTORICAL VOLATILITY ?				
10 days	6.95%	14.92%	6.05%	20.57% - 22-Nov
20 days	11.50%	11.05%	13.16%	18.01% - 14-Nov
30 days	9.91%	13.58%	11.19%	16.87% - 15-Dec

- NFLX:

Current		1 WK AGO	1 MO AGO	52 wk Hi/Date
HISTORICAL VOLATILITY ?				
10 days	17.22%	29.34%	35.04%	93.48% - 18-Oct
20 days	22.65%	23.57%	30.33%	69.34% - 11-Nov
30 days	25.89%	29.69%	26.47%	59.52% - 10-Nov

Source: IVolatility.com (accessed 6/5/2017)

Additional literature review: momentum

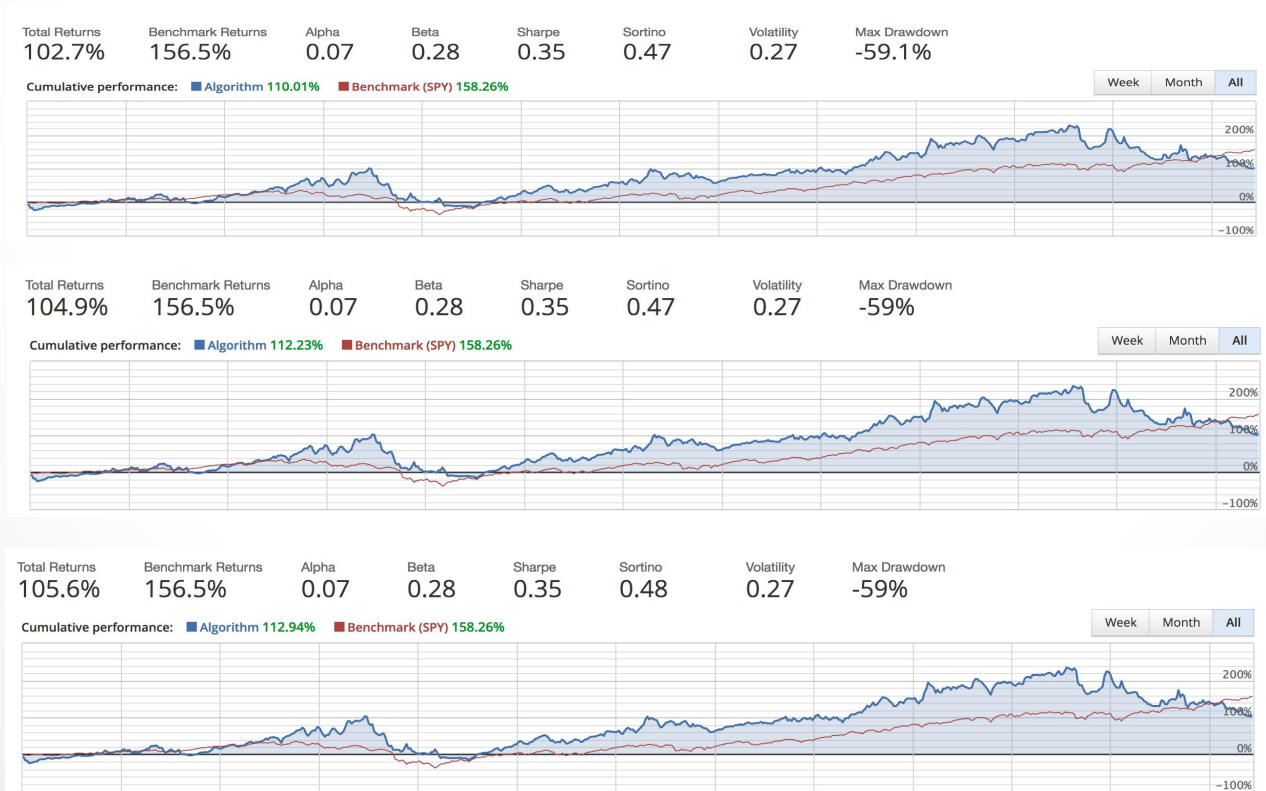
- Wanted to consider longer-term momentum as in Jegadeesh and Titman (1993)
- JT pioneered first momentum strategy: sort into deciles on returns, buy the top decile and short the bottom. Lag of six months
- Antithetical to low-vol in some sense: typically ends up being higher-volatility
- Modeled on information diffusion: Hong et al. (1999)
 - Negative information diffuses gradually, so momentum is the result of more and more investors updating their beliefs
 - Confirmed in Hong and Stein (2000)

Momentum play: New and improved

- Overlay long-horizon (one month) long-only momentum strategy with long-short intraday strategy
- Intuition: Capture momentum risk premia, while increasing baseline alpha on an intraday scale
- Strategy:
 - Long-Horizon: sort asset universe on returns over a 200 day lookback, for the top x stocks if the overnight return is greater than the 200 day moving average, buy a rank-weighted percentage of the stock. Rebalance monthly
 - Intra-day: For each stock in our current positions, calculate the 30-day historic return, volume, and volatility data for each 30 minute period throughout the day. If the current day's volume and volatility in the first period and penultimate period are greater than a specified quantile AND the returns in those period are greater (less) than a specified quantile buy (short) a percentage of your position at the opening of the period and close that position at the end of the day.
 - Hyperparameters: leverage of long-only horizon, number of assets to include in portfolio, volatility and volume quantiles, return quantiles

Overlaid momentum results

- Hyperparameters can be further optimized; current choices:
 - Volume/Vol Quantile Thresholds: .9
 - Return Quantiles (.75, .15)
- Results Below: half, 1/5th, 1/10th of current position



Intuition and improvements

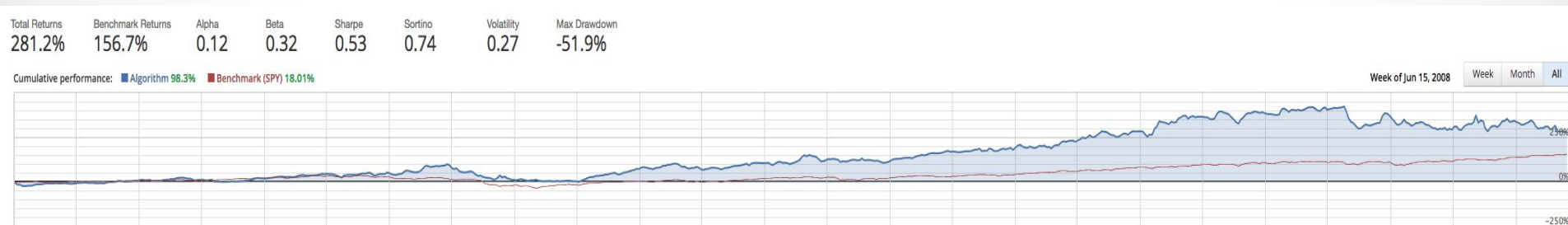
- Adding the overlaid intraday momentum strategy significantly reduced the skewed distribution of returns typically exhibited in momentum strategies. This is because we are capturing intraday profit that is uncorrelated with the overarching momentum trend
- Nevertheless, drawdowns are high and the intraday strategy increases transaction costs
- Further optimization of hyperparameters

Combine the signals

- Goal: combine our three signals to create a stronger strategy
 - Combine the volatility reversion play with the long-only momentum play - intuitively, these should be fairly uncorrelated, especially when acting on separate stocks
 - Overlay the intraday momentum strategy on all assets within both strategy
 - Volatility specifics: Rebalance monthly, act on top/bottom 50 stocks
 - Hyperparameters: Since the vol-reversion strategy is self-financing, how much of our portfolio should we allocate to it, how much should we allocate to the long-only momentum?

Combined strategy results

- Hyperparameters:
 - 95% in long-only momentum, 95% vol weighting, 50% of position in intraday. Top 10 stocks for momentum, top/bottom 50 for vol play.
 - These are not chosen based on optimization, and the results are promising, beating the benchmark by over 100%.



- In volatile periods with no large swings, we tend to lose. How can we improve our Sharpe?

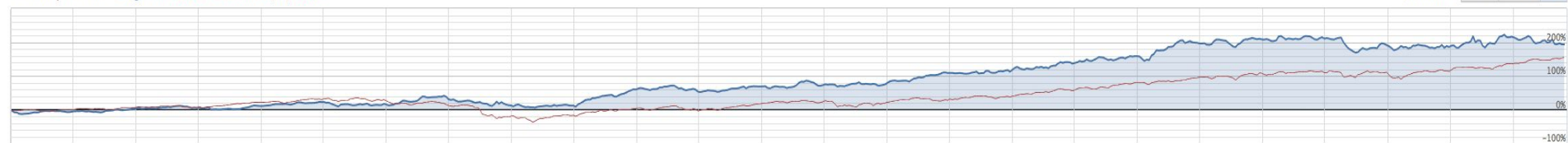
Combined strategy results

- If we increase the asset universe of the momentum strategy to 30, and give only 50% of our portfolio to the long-only momentum play...
 - Large improvement in Sharpe and Sortino Ratio. Very little drawdown as compared to the previous strategy. Promising results!

Total Returns	Benchmark Returns	Alpha	Beta	Sharpe	Sortino	Volatility	Max Drawdown
194.2%	156.7%	0.08	0.17	0.64	0.90	0.15	-27.2%

Cumulative performance: ■ Algorithm 196.72% ■ Benchmark (SPY) 156.88%

Jun 1, 2017 Week Month All



Combined strategy analysis

- We found alpha!
- Combining the three strategies is starting to yield promising results, beating the market consistently - independent of optimization of the hyperparameters
- Nevertheless, the choice of hyperparameters is crucial to improvements in the Sharpe ratio
- Next steps: Use historic data to dynamically adjust weighting of long-only and vol strategies. If there is a small momentum gap, overweight momentum; if entering a hovering volatility period, overweight low-vol.

Inferess model

Features were a subset of:

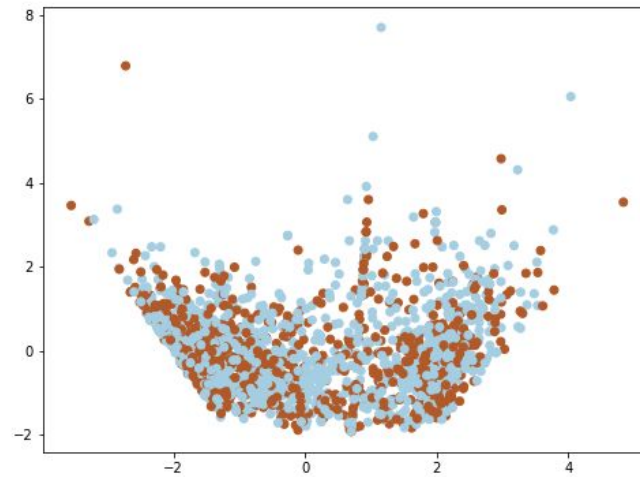
- Positive and negative sentiments
- Percentage of positive and negative words
- Percentage of positive and negative sentences

Labels:

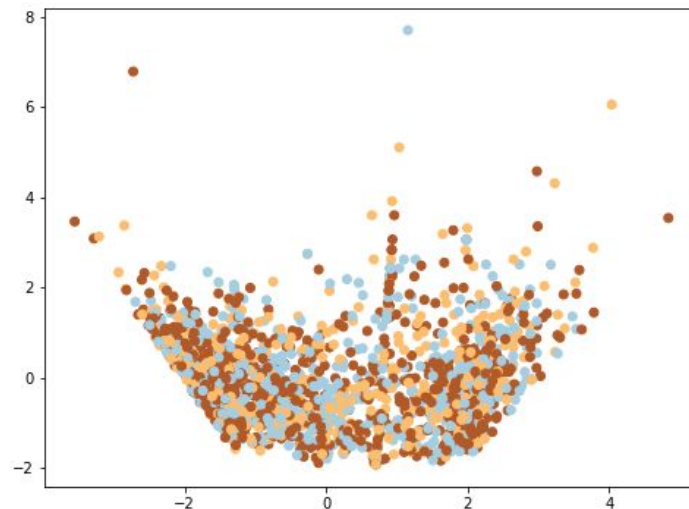
- Binary labels indicating a 0.5% daily return
- Tertiary labels indicating a 0.5% daily positive or negative return
- Same as above with weekly returns at a 2% threshold

Preliminary analysis of Inferess data tractability

- Performed PCA
- Binary classification:

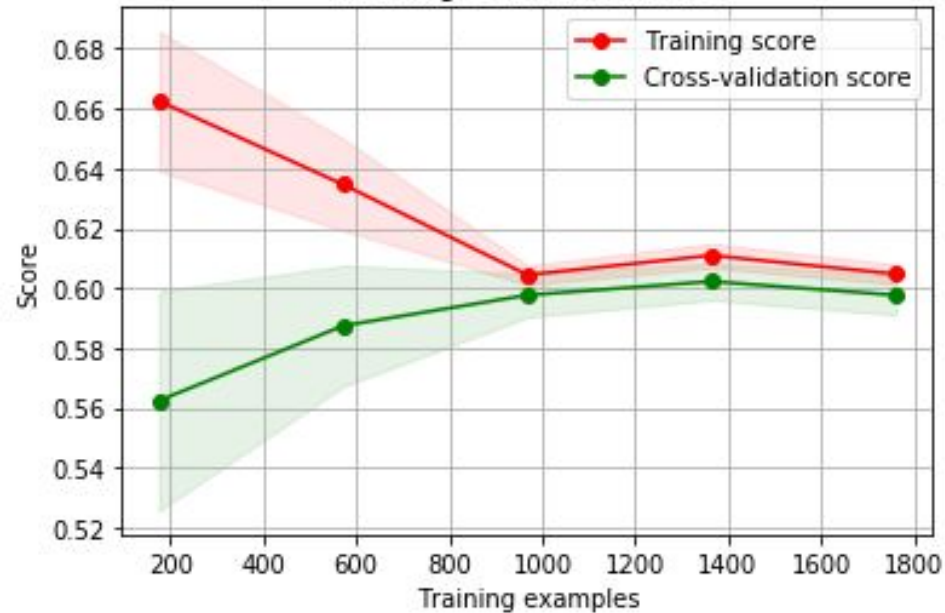


- Tertiary:

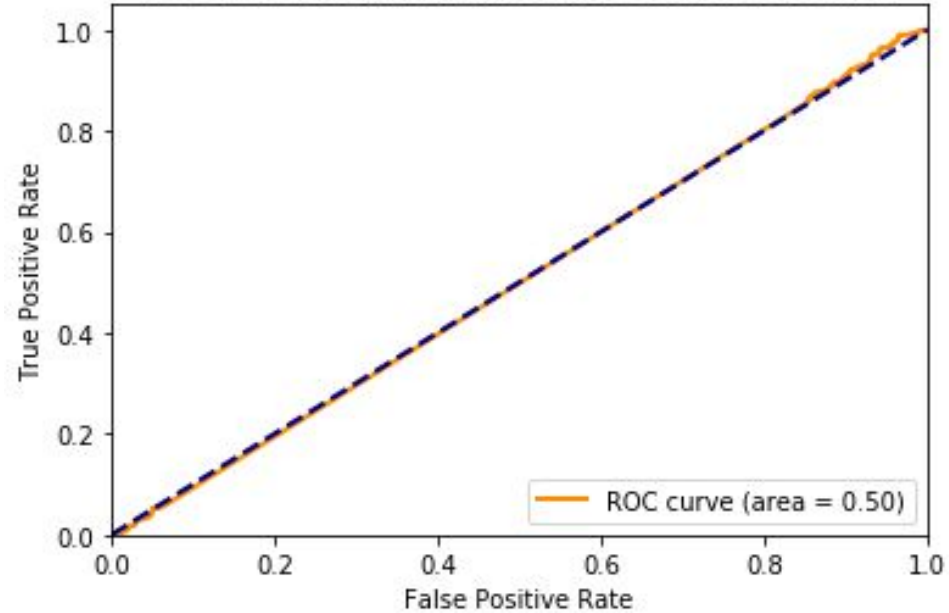


Results: Neural Net

Learning Curve: Neural Net

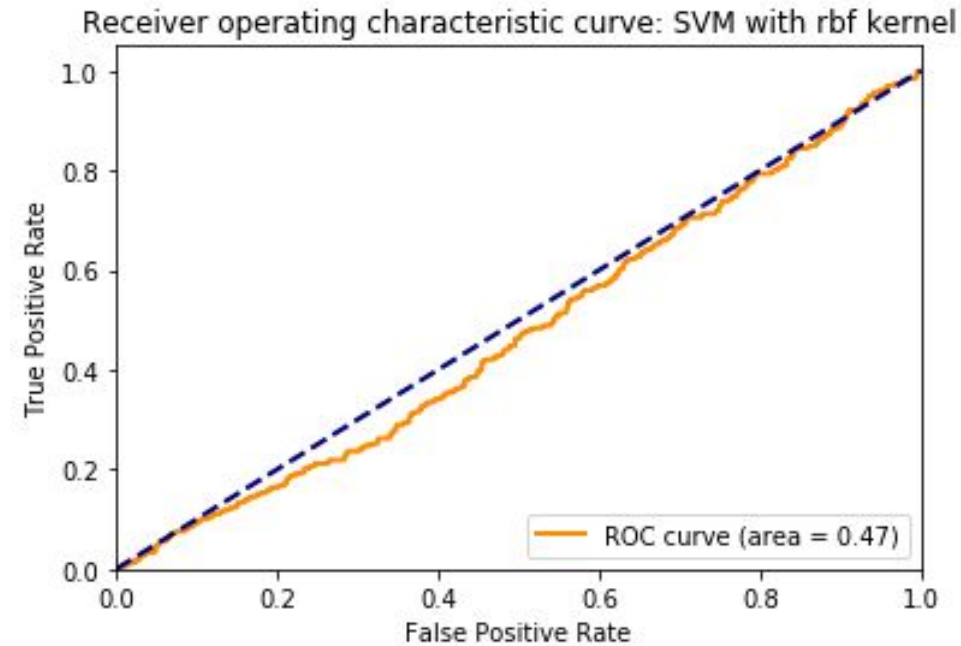
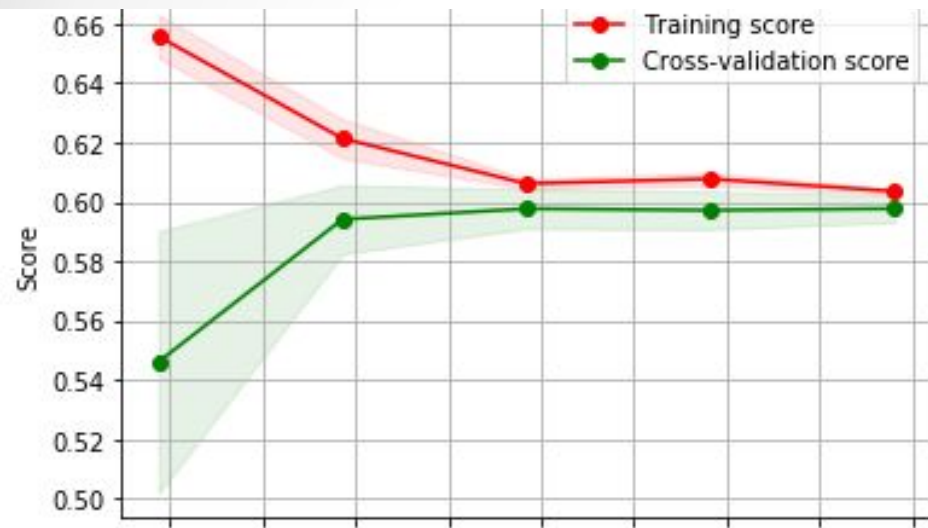


Receiver operating characteristic curve: Neural Net



	precision	recall	f1-score	support
0.0	0.60	0.95	0.74	578
1.0	0.33	0.04	0.07	378
avg / total	0.50	0.59	0.47	956

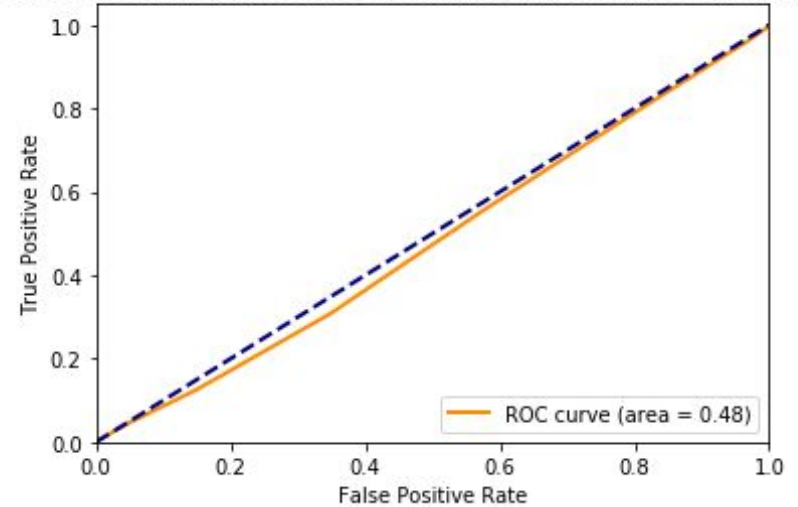
Results: SVM with RBF kernel



Results: *K*-Nearest Neighbors

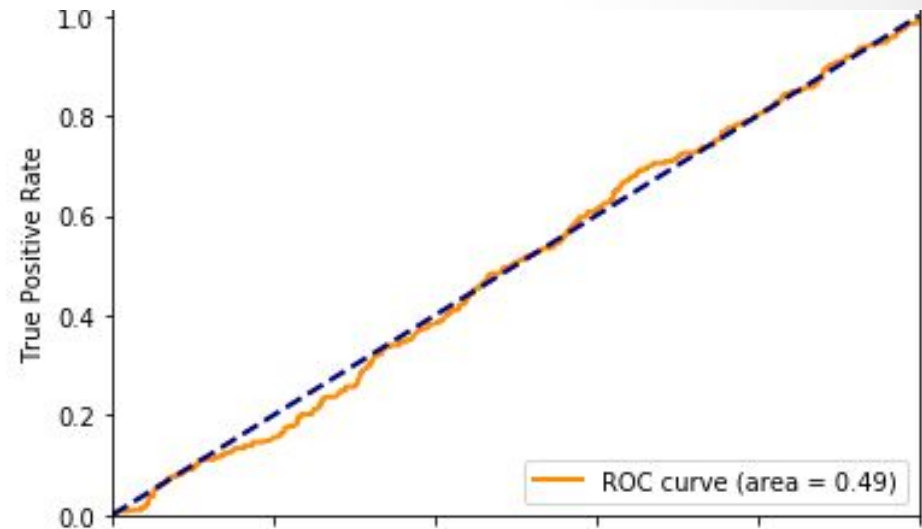
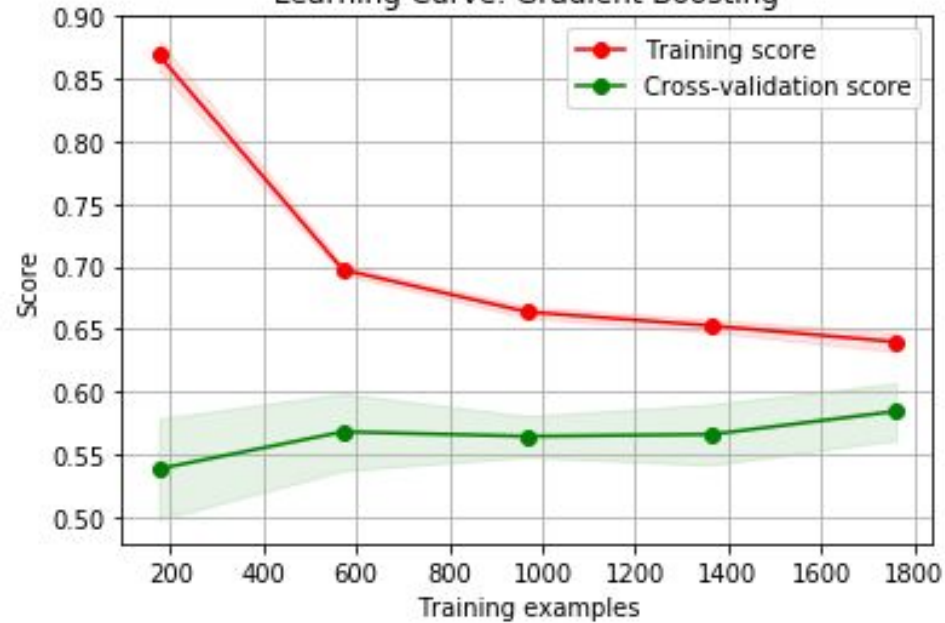


Receiver operating characteristic curve: K-nn with 10 neighbors and 30 leafs



Results: Gradient Boosting

Learning Curve: Gradient Boosting



Inferess analysis

- Data did not provide opportunity for substantial differentiation between direction of effects of signals
- Needed minute data to train system properly
- Bit of a double bind; either
 - Articles dealt with widely traded stocks which probably had limited opportunities for arbitrage, or
 - Limits to available stock price data for illiquid stocks prevent effective training of machine-learning algorithms

Next steps

- The best way to deal with our limited training dataset for the Inferess data would be to acquire thorough intraday data, possibly from a supplier like Bloomberg at cost
- For our smart beta algorithms need to fine-tune hyperparameters; we've done a preliminary analysis
 - Dynamic adjustment of portfolio weights
 - Trading times
 - Leverage
- Perform more expansive cross-validation
- Lots more anomalies to investigate –
 - Value/carry
 - P/E ratio