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TRADING STRATEGY: MONETIZING ELEVATED EARNINGS EXPECTATIONS

OVERVIEW



Earnings releases:
4x per year



Earnings above estimates usually result in stocks outperforming



Our target is cases where companies beat consensus estimates but see their stocks fall



A strategy that could identify these situations would create significant value



GOAL

SYSTEMATICALLY IDENTIFY THESE
SITUATIONS WELL ENOUGH TO
GENERATE CONSISTENT TRADING
PROFITS

STOCK SAMPLE

- SELECTION CRITERIA:
 - > \$100 MM in Sales over previous 4 quarters (total)
 - ≥ \$15 MM in Average Daily Traded Value over previous 3 months
- TIME FRAME:

Earnings reports from 1Q14 through 3Q18

STOCK RETURNS

- TIME HORIZON:

Measured price change from the day before earnings were announced ($t-1$) until three days after ($t+3$)

- RETURN TYPE:

Converted to a market relative return by adjusting for the return of the S&P 1500 over the same period

LABEL GENERATION

TARGET LABELS: BASED ON TWO RULES

- Announced earnings significantly[†] exceeded analyst consensus estimates
- &
- Relative returns over the period of measurement were $\leq -5\%$

[†] Significantly here is defined by exceeding the mean estimate by ≥ 0.25 of the total spread in the distribution of estimates

DATA SOURCES

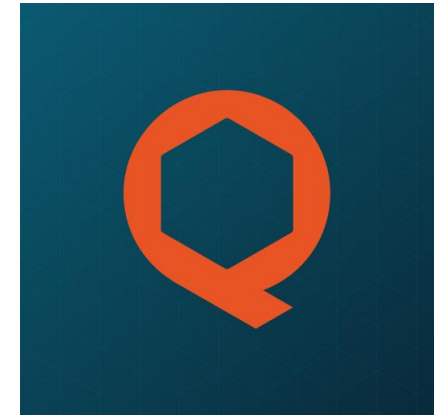
Factset Research Systems:

Financial data, downloaded as csv files,
through customized database queries



Quantcha data, via Quandl:

Historical and implied volatility data from
Quantcha, accessed via the Quandl
platform



UNDERSTANDING THE DATA SET

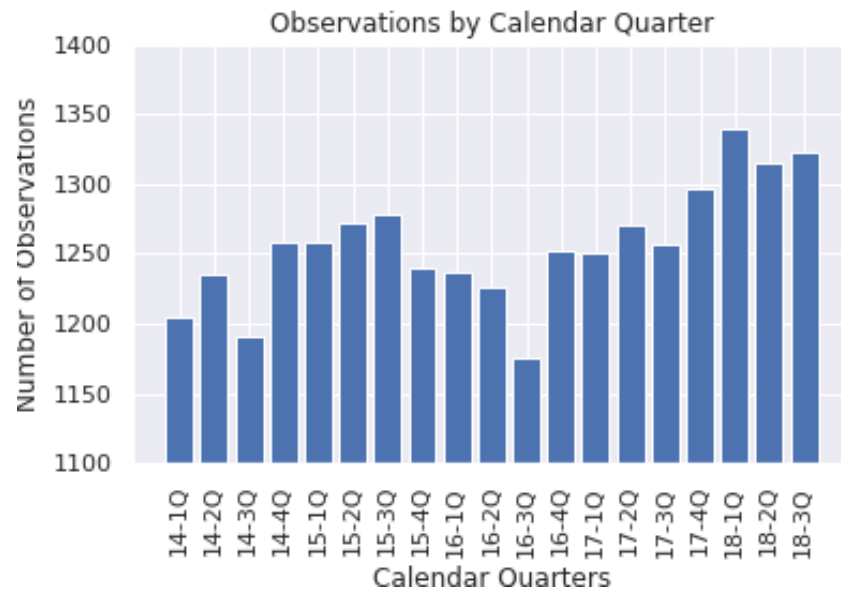


EXPLORATORY DATA
ANALYSIS

OBSERVATIONS & TARGETS OVER TIME

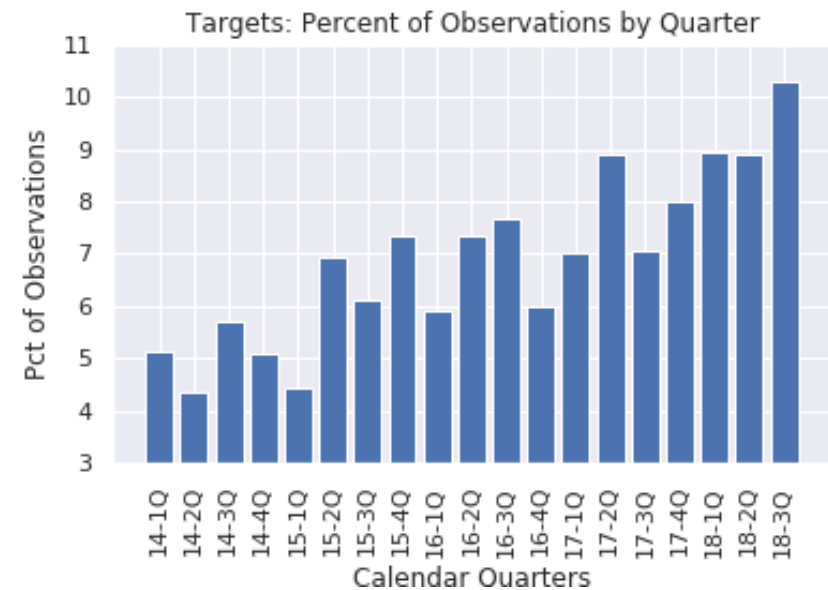
Observations:

n \approx 23,900
 \approx 1,250 per qtr



Targets:

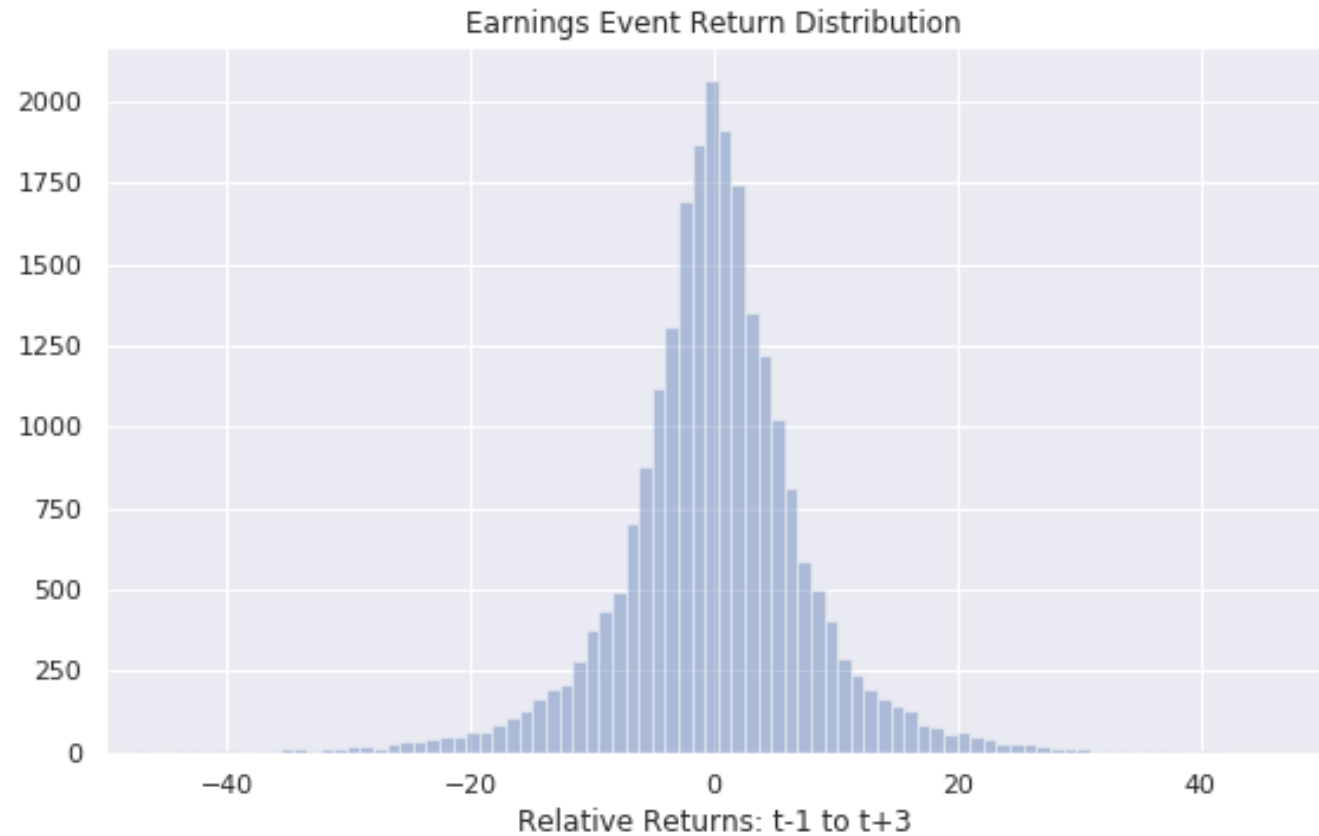
Avg 6.8% of obs / qtr
Range from 4.4% to 10.3%

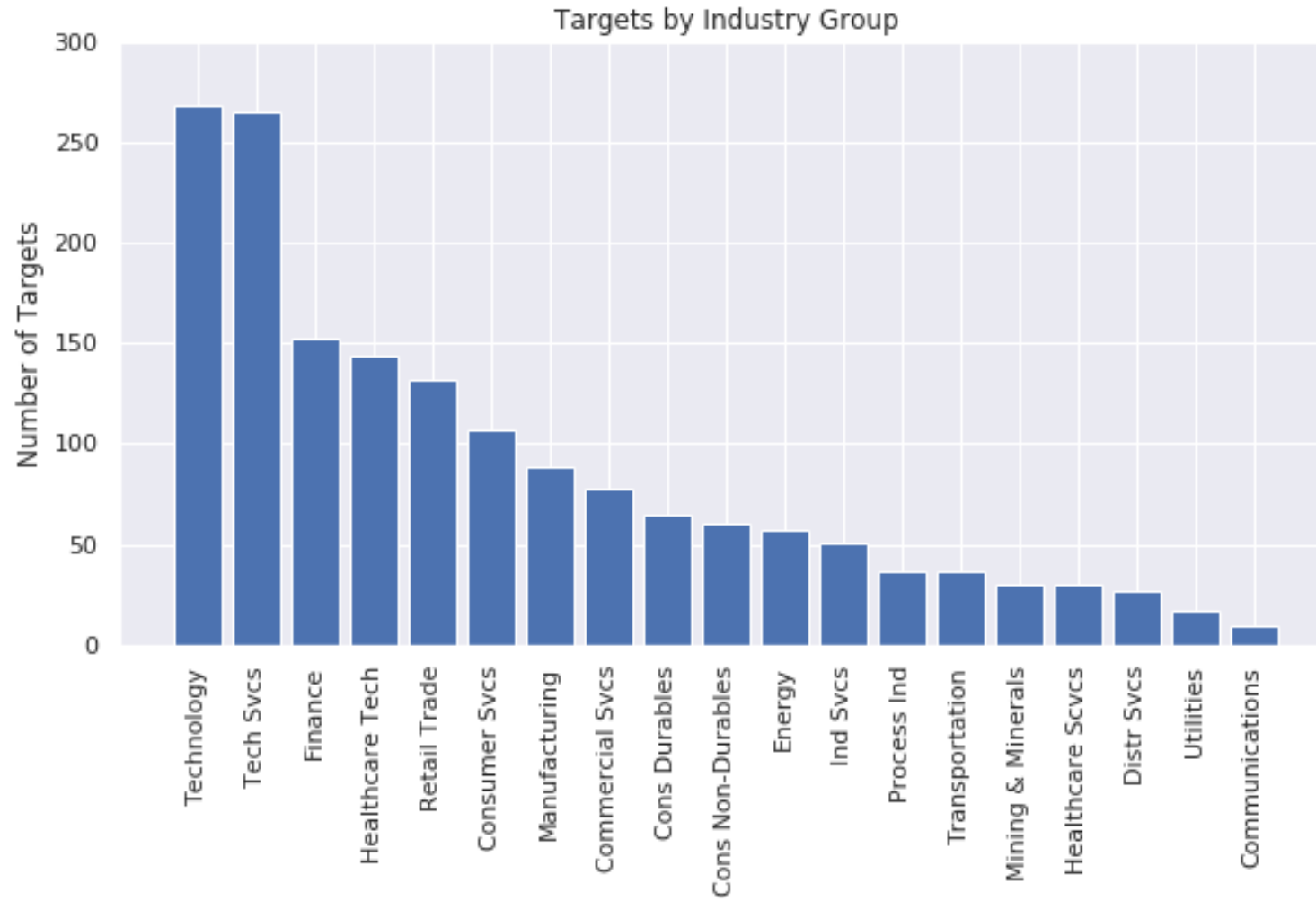


EARNINGS EVENT RETURN DISTRIBUTION

Approximately Normally
Distributed Around Zero

$$\sigma \approx 8\%$$





TARGETS BY INDUSTRY GROUP

FEATURE TYPES & TRANSFORMATIONS

FEATURE TYPES:

- Stock valuation
- Stock performance
- Earnings estimate revisions
- Analyst ratings
- Historical company financial performance
- Stock volatility data (historical & options implied)
- Industry group classification

TRANSFORMATIONS:

- Absolute (un-transformed)
- Relative to all stocks in sample (by qtr)
- Relative to industry group peers (by qtr)

MACHINE LEARNING



MODEL SELECTION &
TESTING
METHODOLOGY

MODEL SELECTION

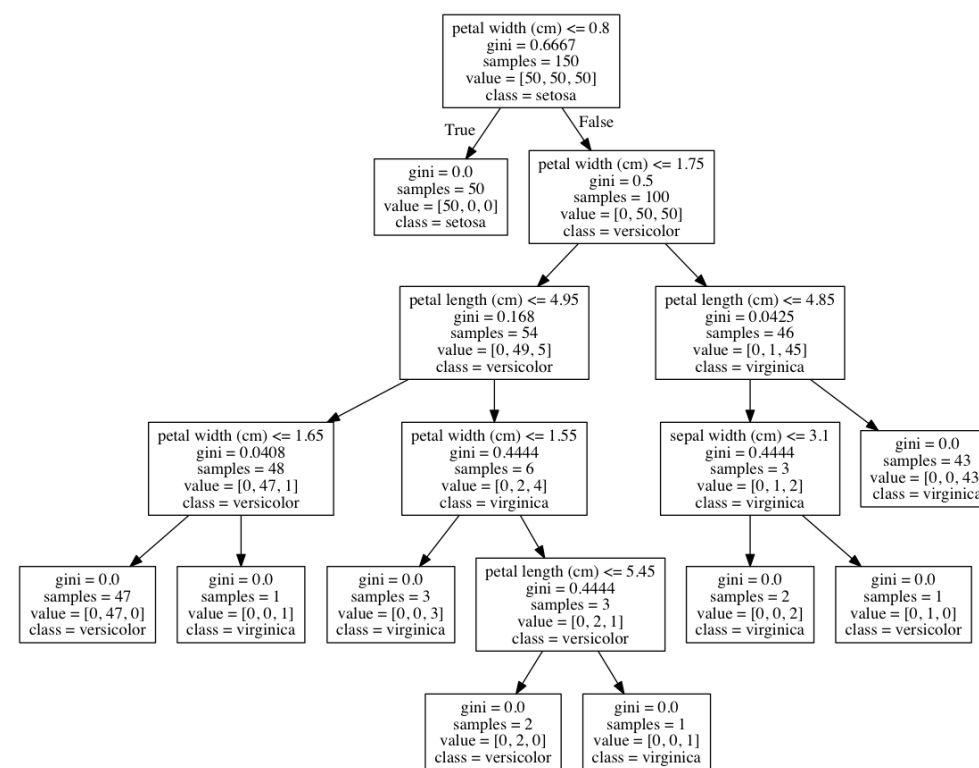
KEY CONSIDERATIONS:

- Significantly imbalanced classes
- Soft classification desired
- Mix of numerical and categorical data
- Standardization problematic due to mix of temporal spaces in data
- Significant complex interactions between features likely

CONCLUSION:

Tree-based models (Random Forest & Gradient Boosting) most appropriate

Example Decision Tree



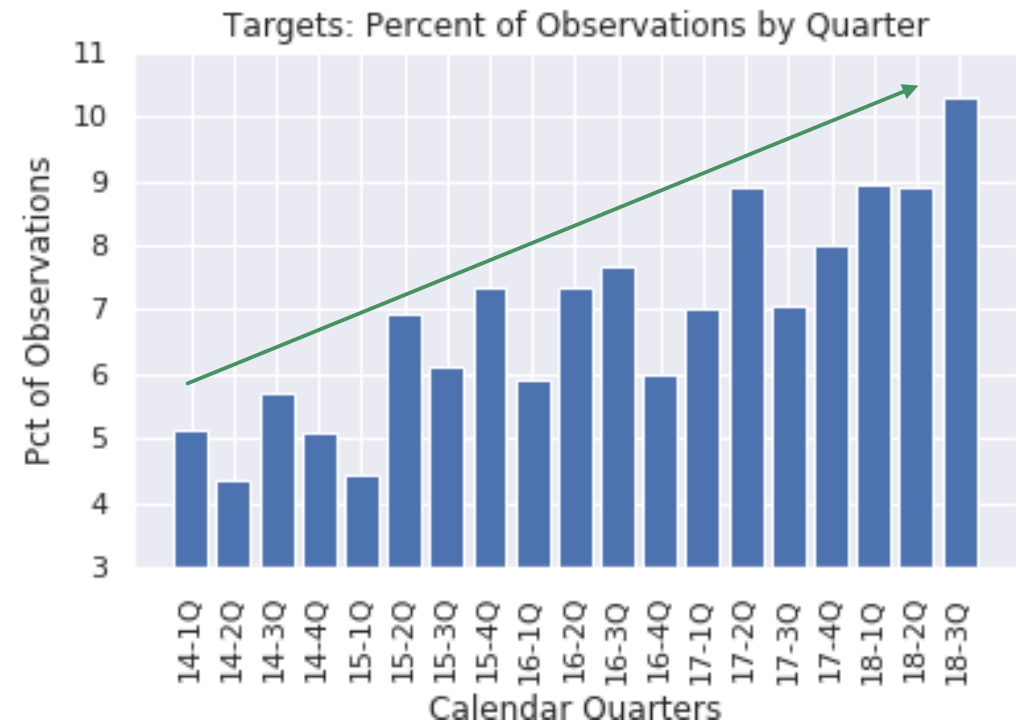
METHODOLOGY CHALLENGE

CHALLENGE:

- The proportion of observations in the target class shows a rising trend over time.
- Typical random train/test splitting and cross-validation methods showed some random instability, as a result.

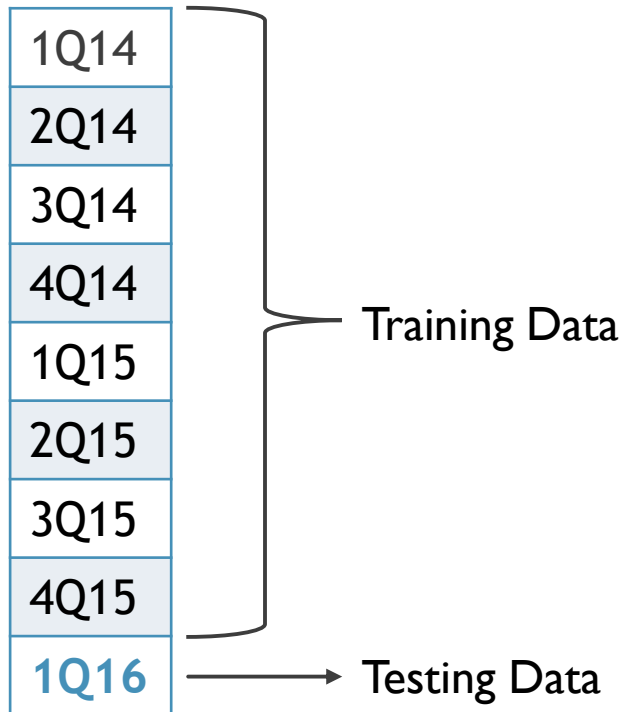
SOLUTION:

- Sequential simulations based on look-back windows of both 4 and 8 quarters of data, in order to generate probability predictions for the following quarter



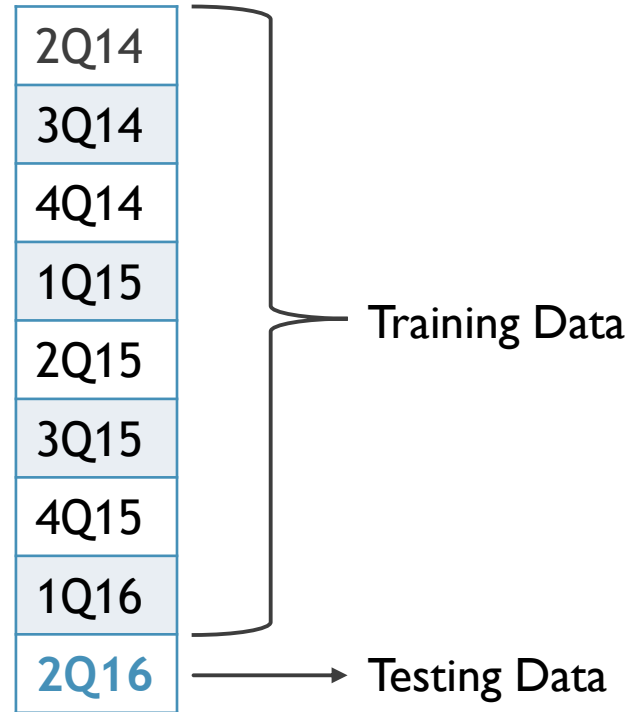
METHODOLOGY ILLUSTRATION

Iteration 1



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Iteration 2



...

Iteration k

Et cetera

MODELING OBSERVATIONS

- Random Forest models consistently generate AUC of ROC ≈ 0.65
 - Performance is relative insensitive to tuning parameters
 - Initial tests of Gradient Boosting models performed slightly better, but tuning them proved inordinately time consuming, given the multiple simulations
- False positives are a significant issue
 - Positive Predictive Value (aka Precision) rarely exceeds 0.20 and never does so consistently
- Estimated profits based on average values for correct vs. incorrect classification often severely overestimate profitability compared to simulation using actual returns

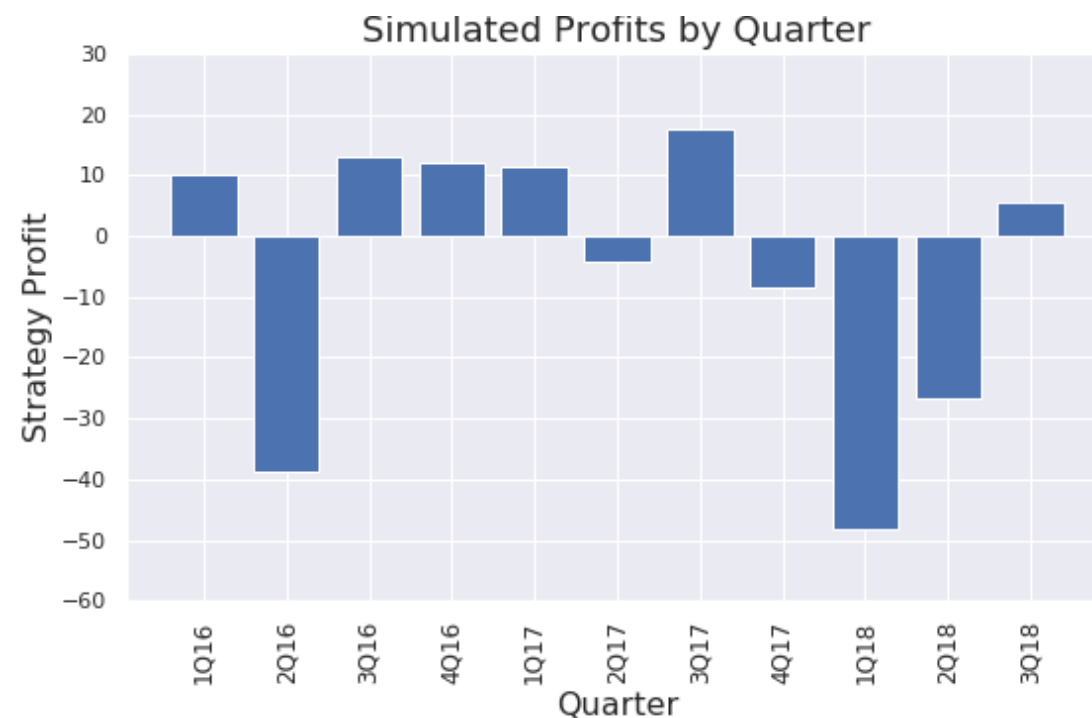
Detailed Results Example

Prob Threshold	Positive Signals			PPV	Naïve Profit Est.	Simulated Profits	
	True	False	Total			8Q Model	4Q Model
0.05	121	983	1,104	0.11	11.4	10.1	7.7
0.06	114	900	1,014	0.11	12.0	10.1	8.6
0.07	110	822	932	0.12	13.9	12.2	12.5
0.08	104	733	837	0.12	15.4	12.4	10.9
0.09	97	646	743	0.13	16.2	11.2	12.8
0.10	89	563	652	0.14	16.3	5.6	16.0
0.11	79	463	542	0.15	16.3	4.7	14.0
0.12	72	397	469	0.15	16.2	5.5	15.2
0.13	61	334	395	0.15	13.8	-0.3	16.8
0.14	57	276	333	0.17	14.7	1.7	11.9
0.15	52	230	282	0.18	14.5	4.1	13.2
0.16	44	187	231	0.19	12.7	5.5	8.9
0.17	34	156	190	0.18	9.2	3.9	6.8
0.18	30	135	165	0.18	8.3	4.7	5.2
0.19	26	110	136	0.19	7.5	4.3	3.1
0.20	20	92	112	0.18	5.4	2.6	3.0
0.21	14	73	87	0.16	3.4	4.7	5.0
0.22	11	54	65	0.17	2.8	1.1	3.1

**3Q18
RESULTS –
SUCCESS**

SIMULATION OVER MULTIPLE QUARTERS TELLS ANOTHER STORY

- Results shown to the right are based on a threshold probability level of 0.10
- Simulation assumes investment of 5 units for every instance of a signal (probability of target ≥ 0.10)
- Large down quarters in 2Q16, 1Q18, and 2Q18 overwhelm the fairly consistent results seen in other quarters
- Adverse Selection: While the model does a good job identifying favorable situations for betting against stocks, it also seems to identify some of the most risky bets.





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graph TD; A[Research] --> B[Explore]; B --> C[Test];
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Research

Research and add additional features

Explore

Explore whether different models for industry-based subsets of the data set improve results

Test

Test whether model predicts increases in stock volatility better than it does direction of stock moves; this would also be quite valuable.

NEXT STEPS