Cryptocurrencies Price Prediction Using News and Social Networks Data

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Overview

1. Problem description
2. Data Collection
3. Feature Engineering
4. Model & Evaluation
5. Conclusion & Takeaways

Overview

Top 100 Cryptocurrencies by Market Capitalization

Cryptocurrencies | Exchanges | Watchlist | USD | Next 100 → | View All

#	Name	Market Cap	Price	Volume (24h)	Circulating Supply	Change (24h)	Price Graph (7d)
1	Bitcoin	$141,491,248,675	$7,976.12	$23,153,242,863	17,739,362 BTC	-7.40%	
2	Ethereum	$26,268,025,515	$247.00	$9,872,839,695	106,346,402 ETH	-7.68%	
3	XRP	$17,376,386,250	$0.411938	$2,553,674,556	42,181,995,112 XRP *	-8.36%	
4	Bitcoin Cash	$7,046,271,276	$395.44	$2,202,815,324	17,818,775 BCH	-9.79%	
5	Litecoin	$6,438,460,335	$103.73	$4,019,675,150	62,068,951 LTC	-9.20%	
6	EOS	$6,138,276,865	$6.69	$4,014,765,857	917,678,573 EOS *	-11.02%	
7	Binance Coin	$4,302,042,406	$30.47	$419,528,781	141,175,490 BNB *	-5.81%	
8	Bitcoin SV	$3,839,016,605	$215.47	$1,108,711,999	17,816,861 BSV	-1.95%	
9	Tether	$3,129,805,000	$0.997987	$24,228,629,558	3,136,118,221 USDT *	-0.55%	

Problem description

- Low barrier to entry for trading cryptocurrencies

- Large tradable market by dollar value
  - >2200 cryptocurrencies
  - 19000 markets trading crypto
  - $250bn market cap

- Is there a relationship between social network/news data and cryptocurrencies price?

Research Roadmap

Data Collection

- Market Data from Coinbase
- Google Trends search volume
- Twitter textual data

Exploratory Analysis

- Google Trend volume // BTC volume
- BTC keyword lagged // BTC volume
- Keyword volume // volatility

Directional prediction

- Sentiment Analysis
- Directional imbalances
- Condition on volatility

Model & Evaluation

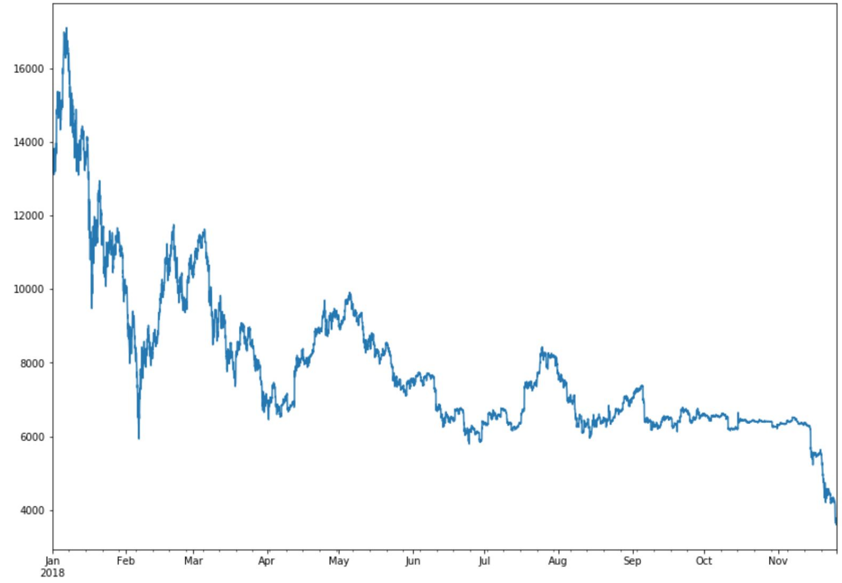
- Build a linear model
- Roll-forward Backtest

Data Collection

Market Data Collection

- L0 data from **Coinbase API** of currency pairs for 2018
- Different market behavior

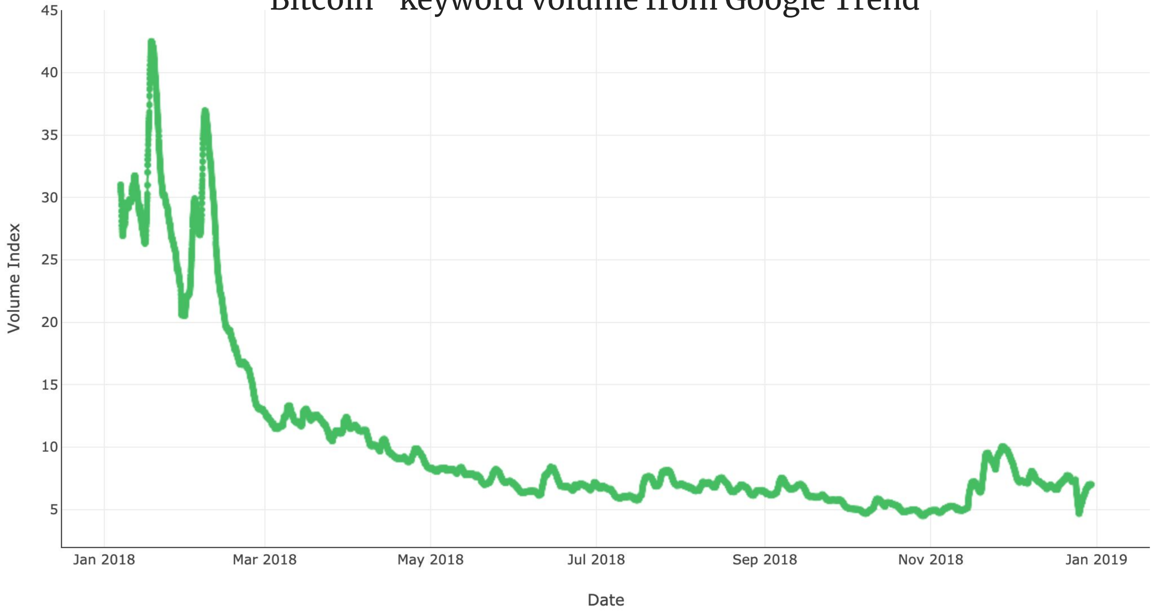
Price



Google Trends Data

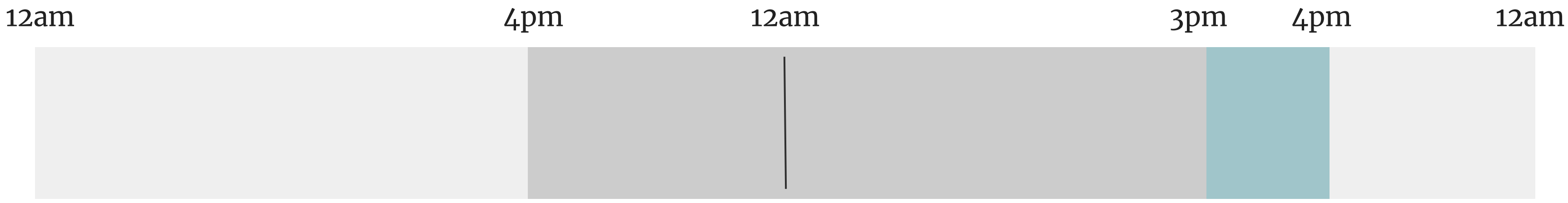
Example: Google Trend on “*bitcoin*”

“Bitcoin” keyword volume from Google Trend



Twitter Textual Data

- Used the “GetOldTweet” repository
- Returns all tweets in **chronological order** between 4pm to 4pm of the next day: **too much data**
- Selected only 1000 tweets between **3pm** and **4pm**

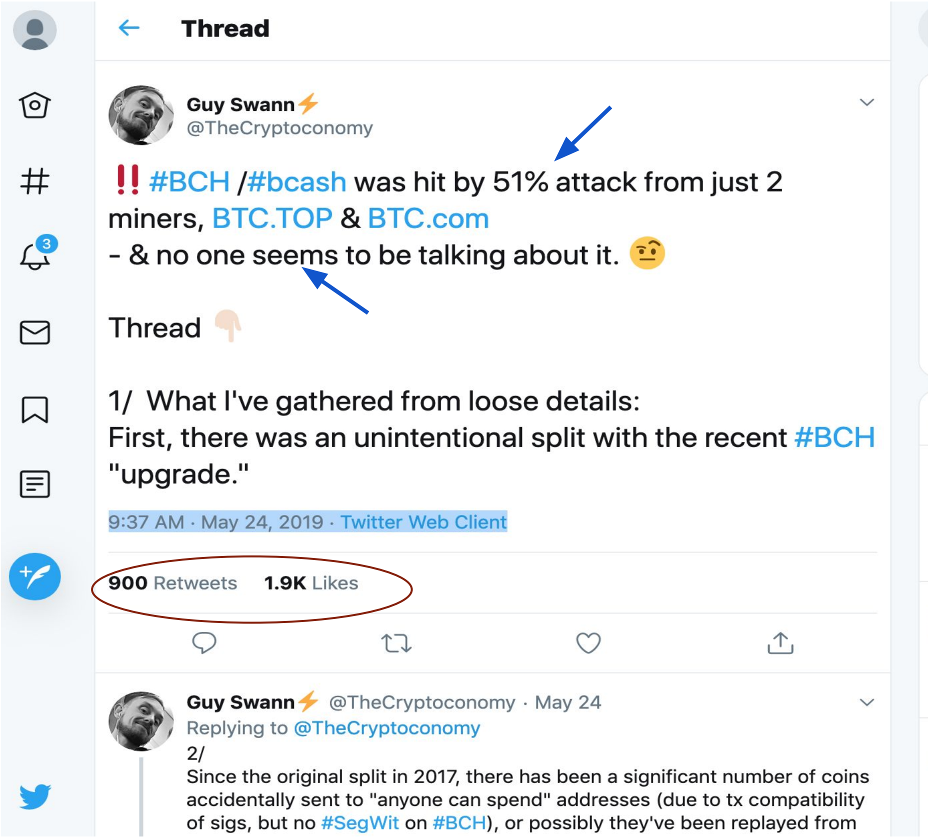


Feature Engineering

Tweets:

- Some very informative tweets but...

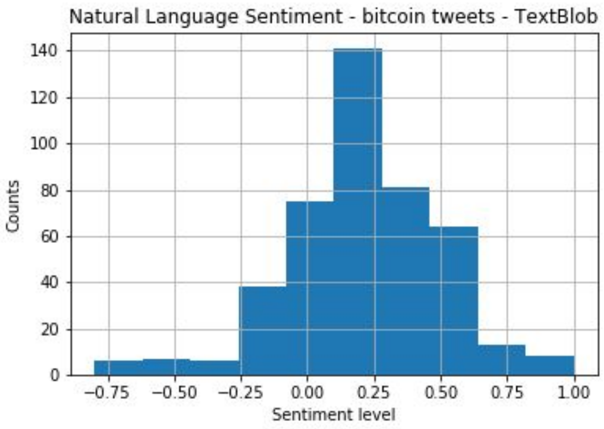
- Not structured
- Noisy

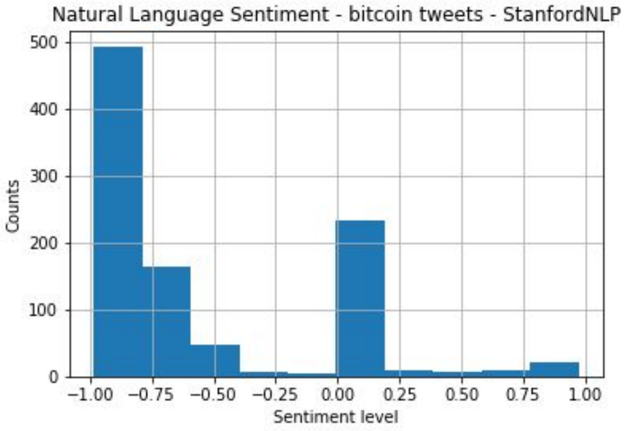


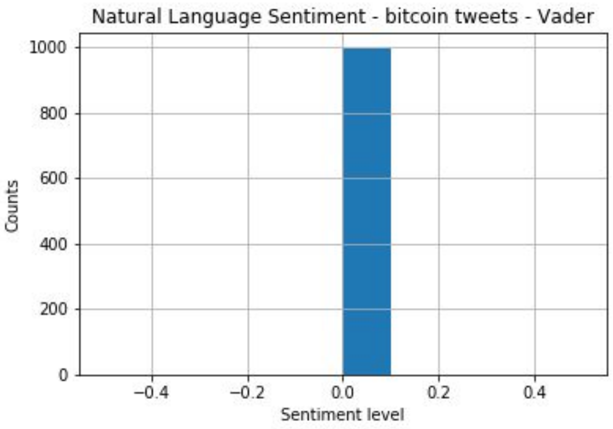
Sentiment Analysis for tweets

Compared 3 libraries on 1k tweets:

- *TextBlob* (naive Bayes classifier)
- *StanfordNLP*
- *Vader*







Keyword volume

- Counted positive and negative keywords volume in Tweets and Google Trends volume
- *Imbalance =*

  # positive words – # negative words

Positive Keywords:	**Negative Keywords:**
'conviction','bold','up', 'buy', 'bullish', 'bull', 'free money', 'long', 'rise', 'boom', 'bid', 'support', 'grow', 'get', 'make', 'earn', 'investment', 'invest', 'investing', 'invested', 'buying', 'bought', 'pump', 'like', 'skyrocket',	*'scam', 'capitulation', 'down', 'fork', 'sell', 'short', 'bear', 'bearish', 'bubble', 'stop', 'crash', 'clamp', 'shut', 'freeze', 'fall', 'bust', 'trash', 'forbid', 'oppose','dash', 'sold', 'selling', 'collapse', 'plummet', 'plunge'*

Predictor Construction for Twitter

	Positive Tone	Negative Tone
Positive Imbalance	Buy	Sell
Negative Imbalance	Sell	Buy

Keyword Score = *Imbalance* x *sign(sentiment score)*

Twitter Predictors

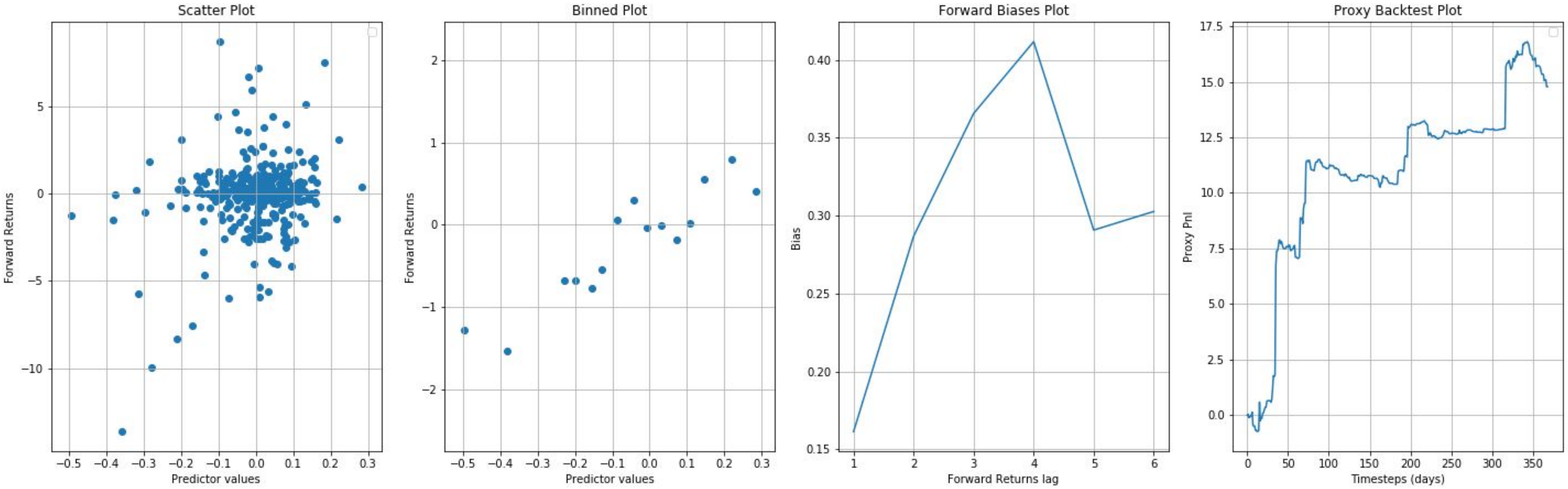
- Buy signal: Tweets with positive Sentiment Analysis score over the last hour.
- Sell signal: Tweets with negative Sentiment Analysis score over the last hour.
- Normalized signal: $$\frac{\text{Buy} - \text{Sell}}{\text{Buy} + \text{Sell}}$$

We expect signals to work best when using their discrete derivative, so we substract them from their moving average.

Plots & Metrics

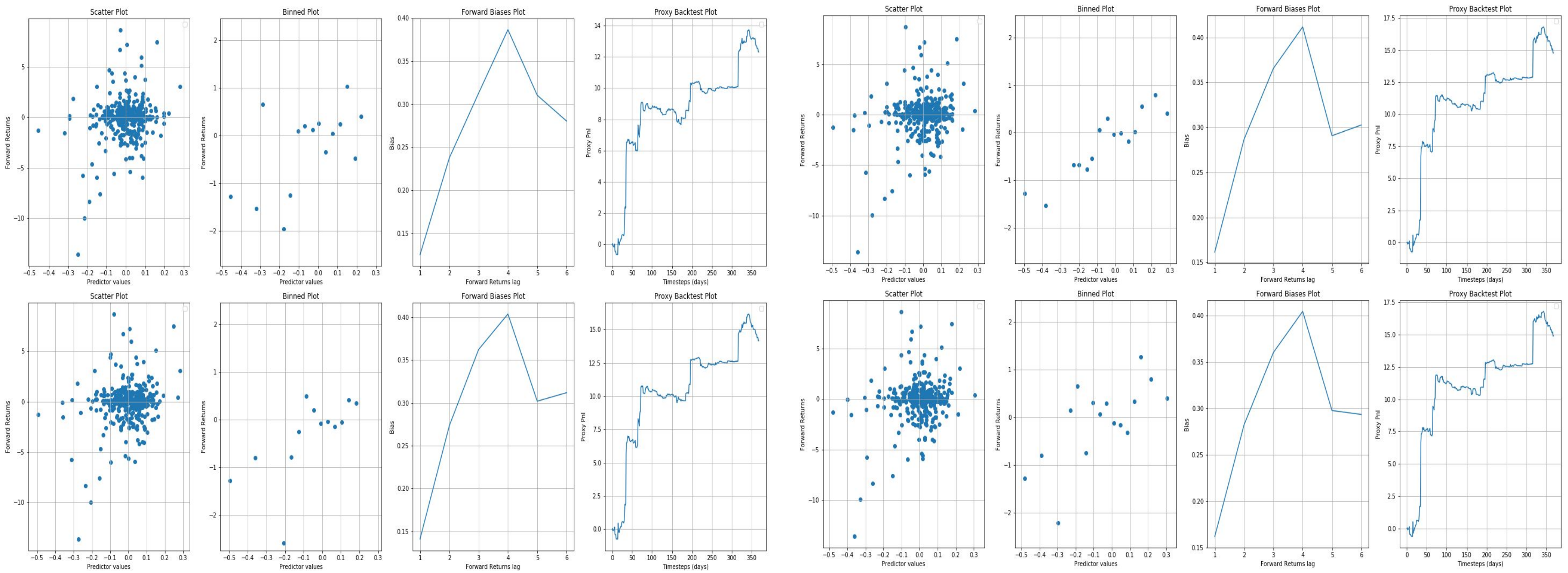
$$bias(lag) = \mathrm{corr}\left[return(t+lag),\, predictor(t)\right] \cdot \sigma(t+lag)$$

$$lag^* = \mathrm{argmax}_{lag}(bias) = 4\mathrm{hours}$$



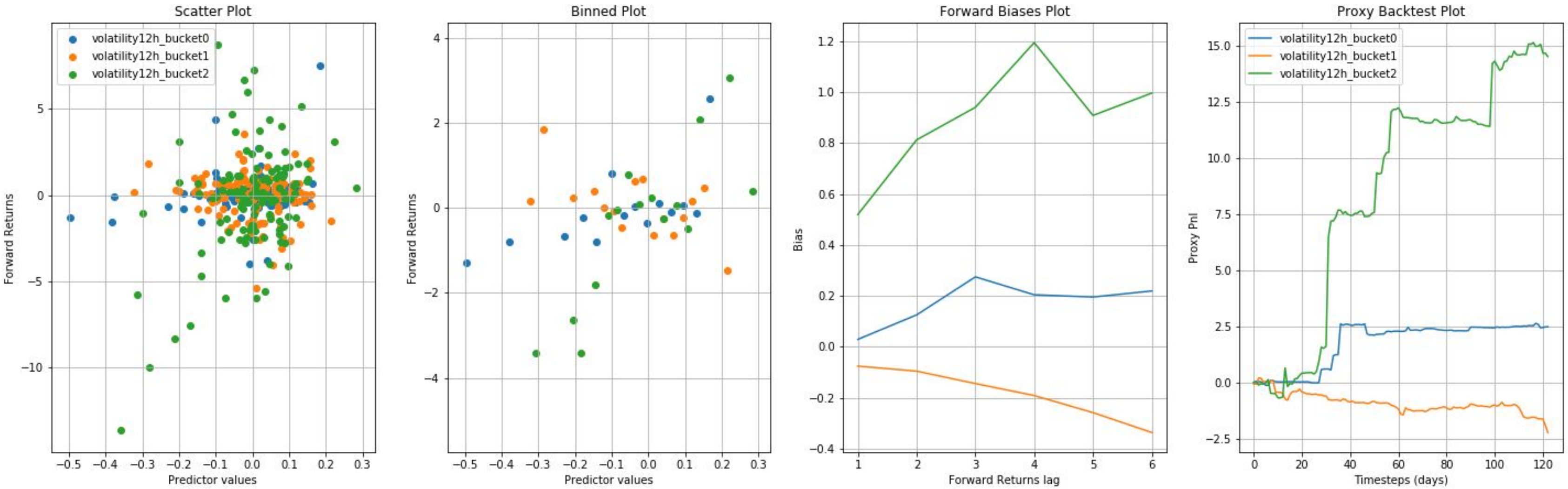
Parameters selection

- Moving average: 3, 5, 7 & 9 days
- Returns horizon



Final predictor

Normalized predictor + Conditioning on volatility regime



High

Medium

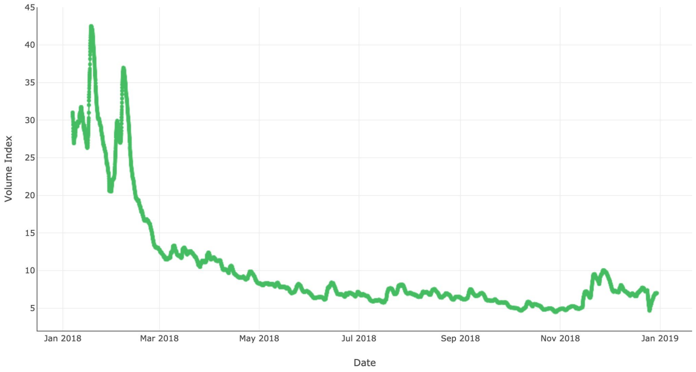
Low

Predictor Construction for Google Trends

Signal for Google Trends:

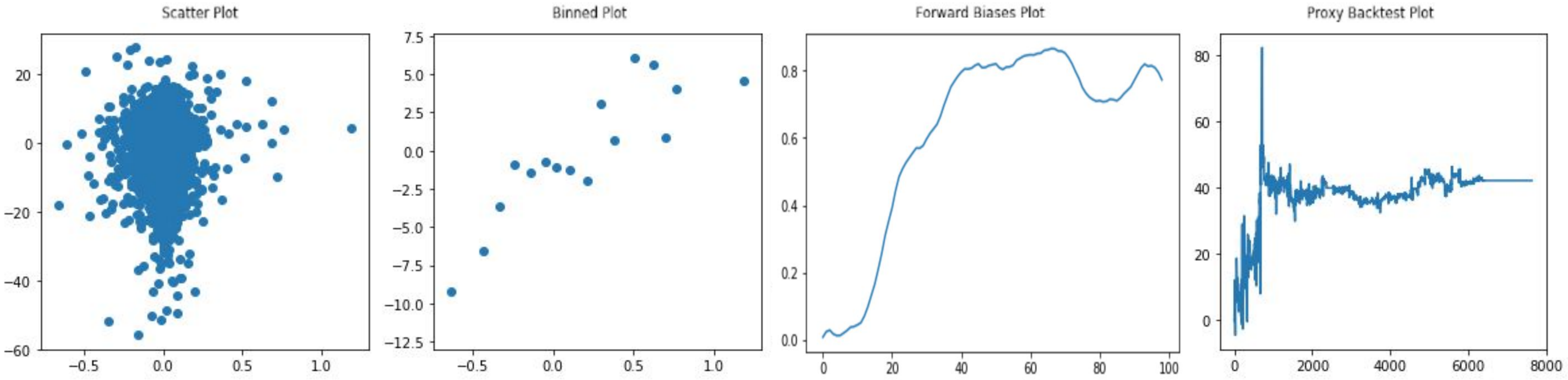
$$\frac{\text{Positive Volume} - \text{Negative Volume}}{\text{Total Volume}}$$

Centered with the ewm



Google Trends Predictors

- Positive correlation
- Longer horizon (2 days)
- Limited prediction power after the beginning of the year



Model & Evaluation

Model

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3$$

- No intercept
- Y = BTC-USD return 4 hours ahead of 4pm
- X_i = sentiment feature conditioned on past 12 hour volatility regime: low/median/high
- Moving average of 7 days
- In-sample $R^2 = 0.041$

Evaluation

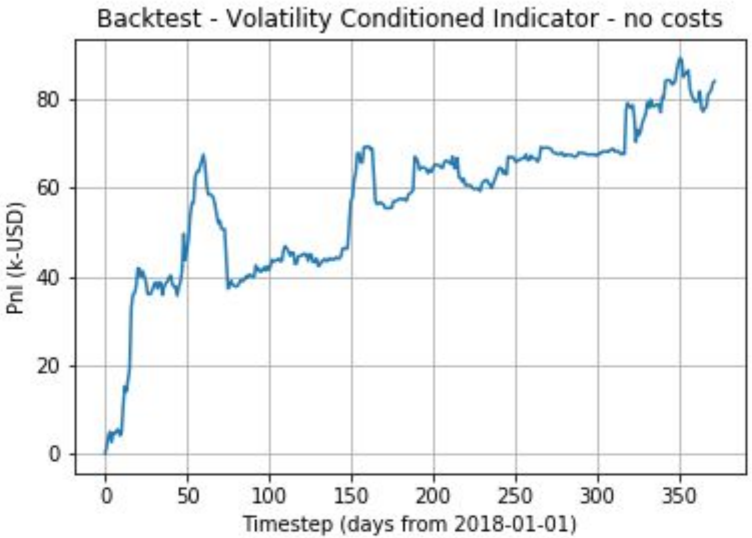
Roll-forward backtest of two weeks span

Week 1	Week 2	Week 3	Week 4				
Week 1	Week 2	Week 3	Week 4	Week 5	Week 6		
Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8

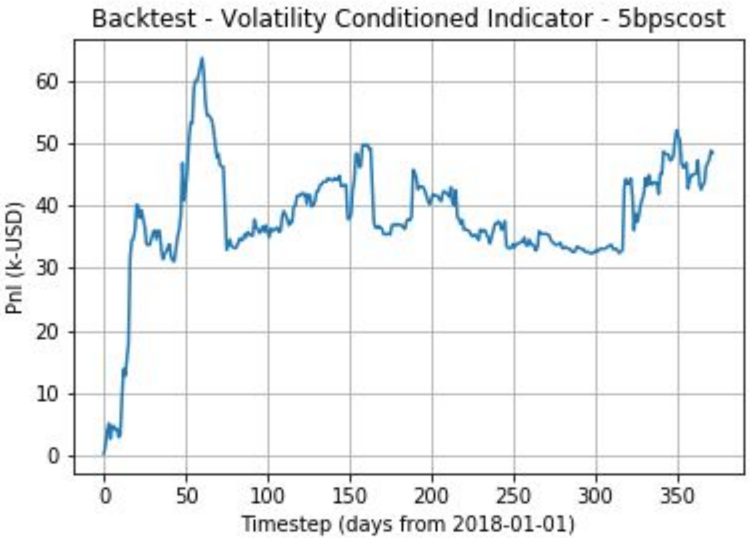
- Threshold based trading strategy
- Threshold Γ= trading cost
- Linear trading costs

Evaluation

Roll-forward backtest of two weeks span



no trading cost

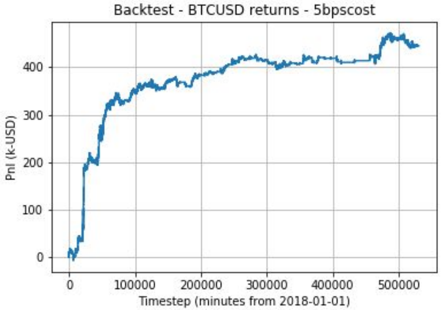


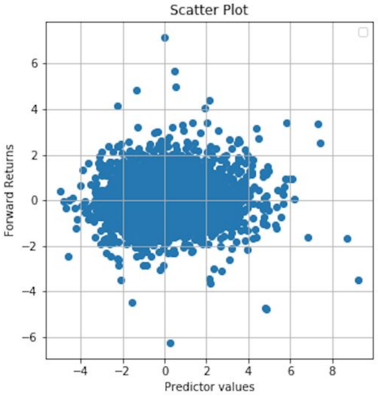
trading cost = 5 bps

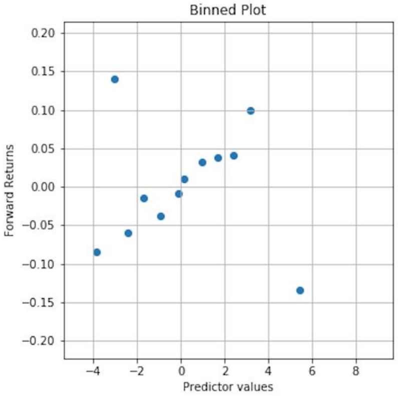
Sharpe ratio with no trading cost: $S = 2.44$

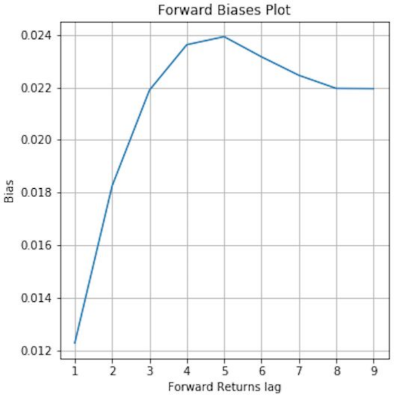
Market Data based model

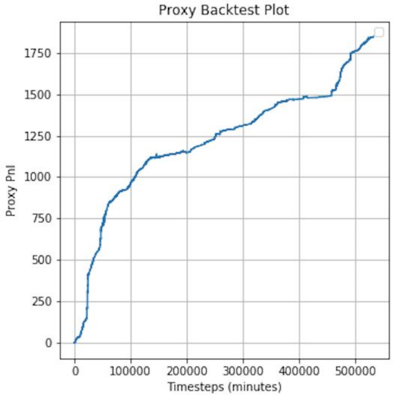
- <u>Extension</u>: Market data for higher frequency strategies
- Lead lag Bitcoin ➡ LiteCoin 5 min
- Sharpe ratio of 38.5











Conclusion & Takeaways

- Choice of sentiment analysis package is important
- Engineering challenges: quality of sentiment data, feature construction
- Filtering methods (e.g. volatility conditioning) produces more reliable results and align with the fundamentals observed in finance
- Portfolio construction: accounting for trading cost, introducing alpha threshold to determine position turnover, imitating real trading environment
- Extension: combining our signals to produce lower risk reliable strategies

Questions