Social networks sentiment analysis for cryptocurrencies

Using discriminative aggregation for price prediction

MS&E 448 Final Presentation

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Sentiment Analysis - Vanilla

- Define topic space T
- Define sentiment measure s(text) -> [-1, 1]
- Get all tweets for T
- Get sentiment for each tweet using s
- for each time period, average all sentiment in T
- use signal

-> A lot of structural information is lost (users, relations between users etc)

Sentiment Analysis - Discriminative

- Define topic space T, define context C
- Define sentiment measure s(text) -> [-1, 1]
- Get all tweets for T with context
- Get sentiment for each tweet using s
- Cluster users using context
- Define user importance using context
- for each time period, combine all sentiment in T in each cluster using user importance
- use multi-dimensional signal (regression, average...)

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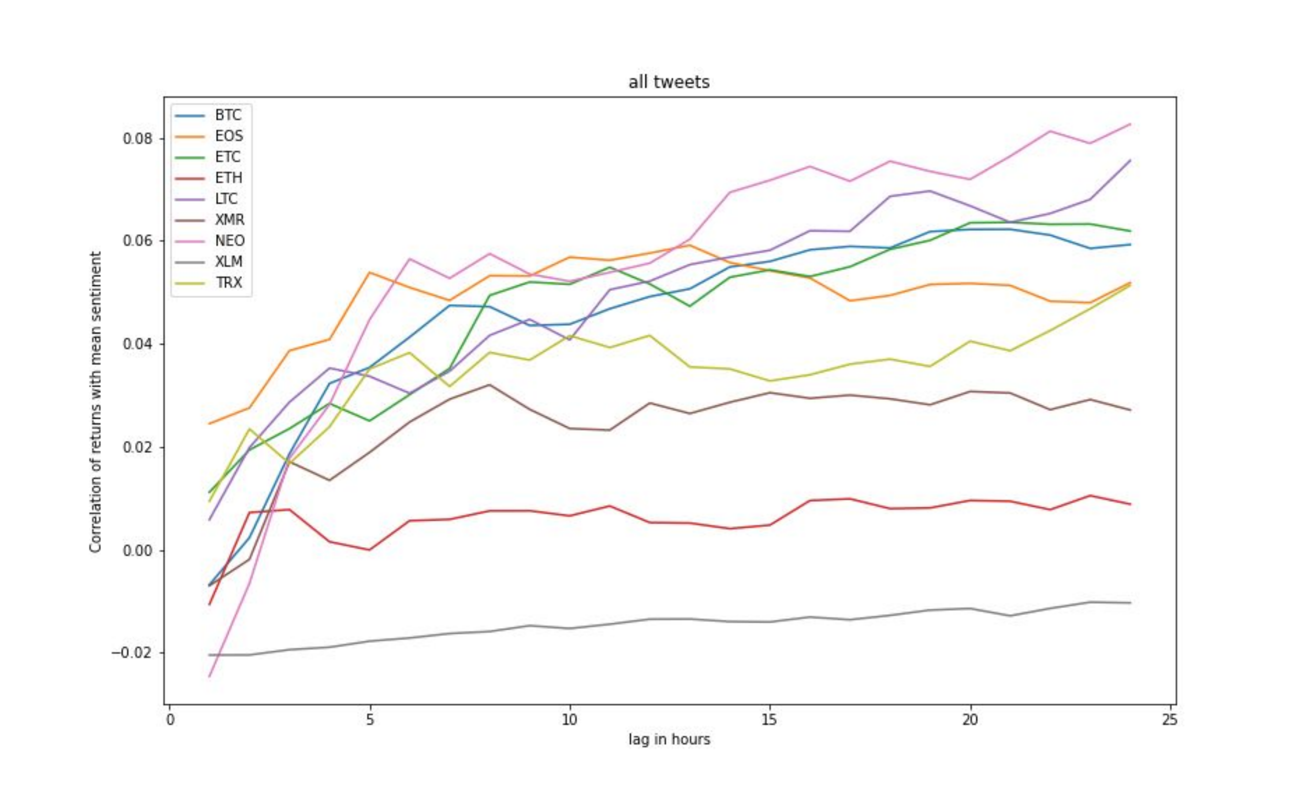
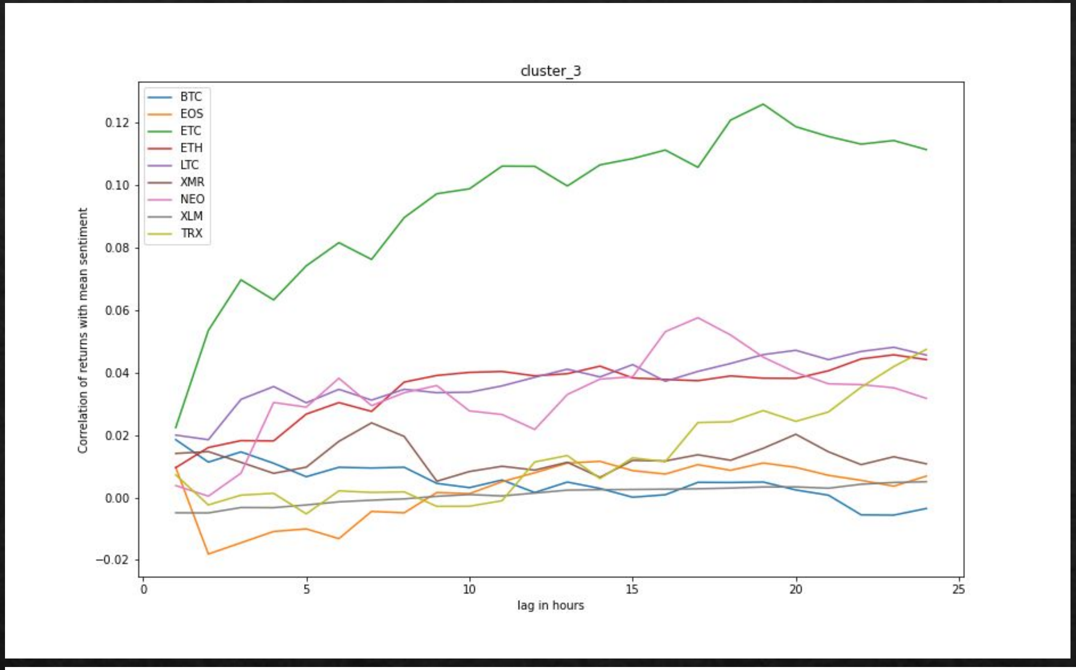
Our simple approach

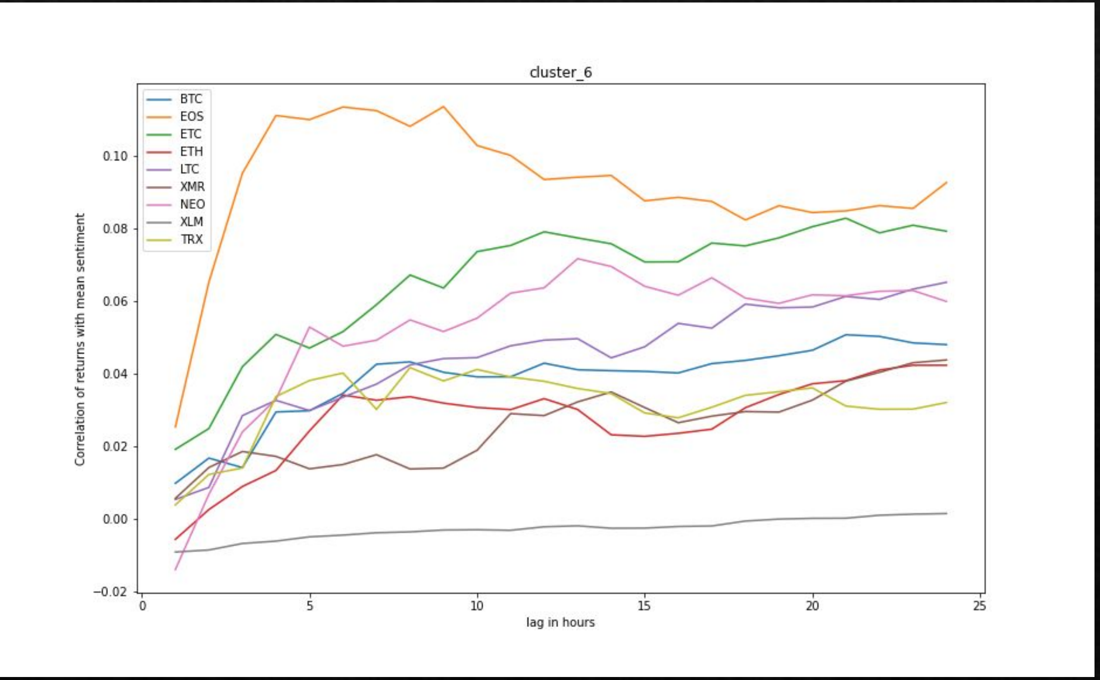
- Social data : tweets on 20 different cryptocurrencies (dirty)
- Price data : hourly prices of 9 cryptocurrency pairs (dirty)
- cluster users based on the proportion of tweets they have for each coin (topic overlap measure)
- give equal importance to each user
- average each cluster's average volume and sentiment (parameter-free)

-> compare to the mean of volume and sentiment across all users (vanilla signal)

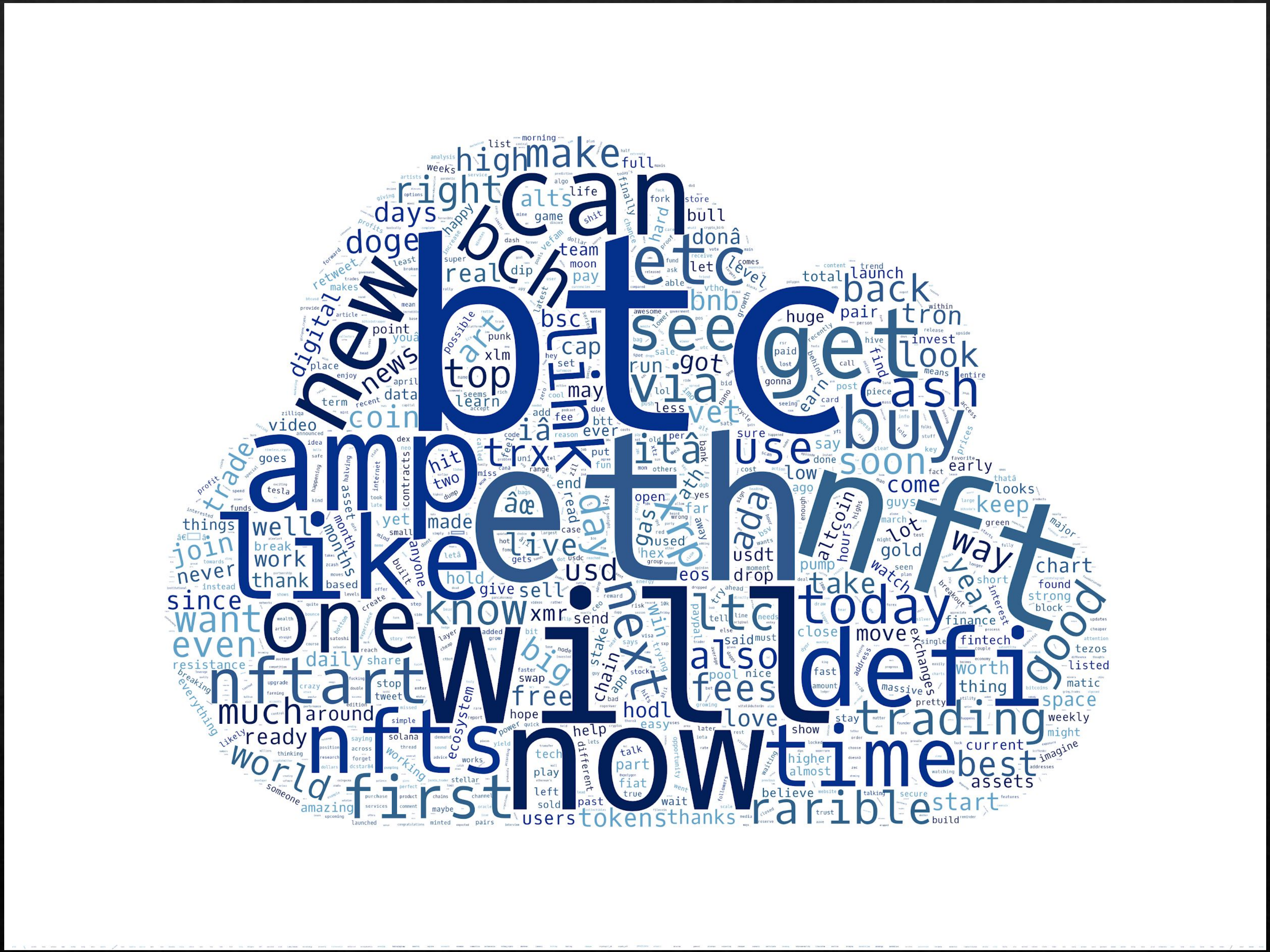
Cluster analysis







All tweets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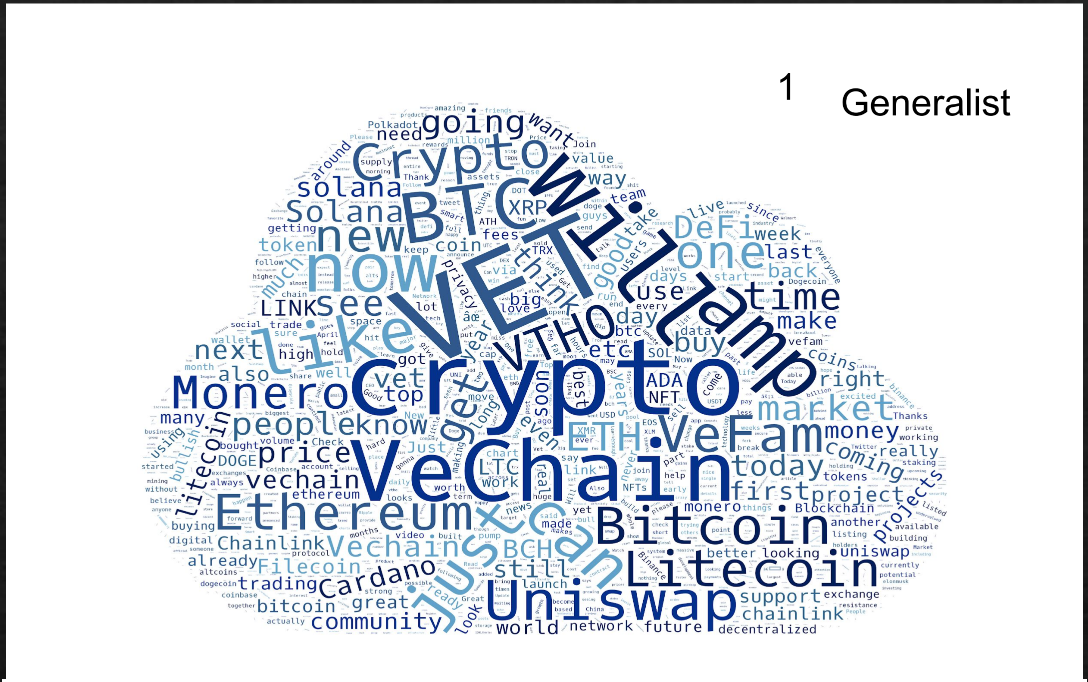
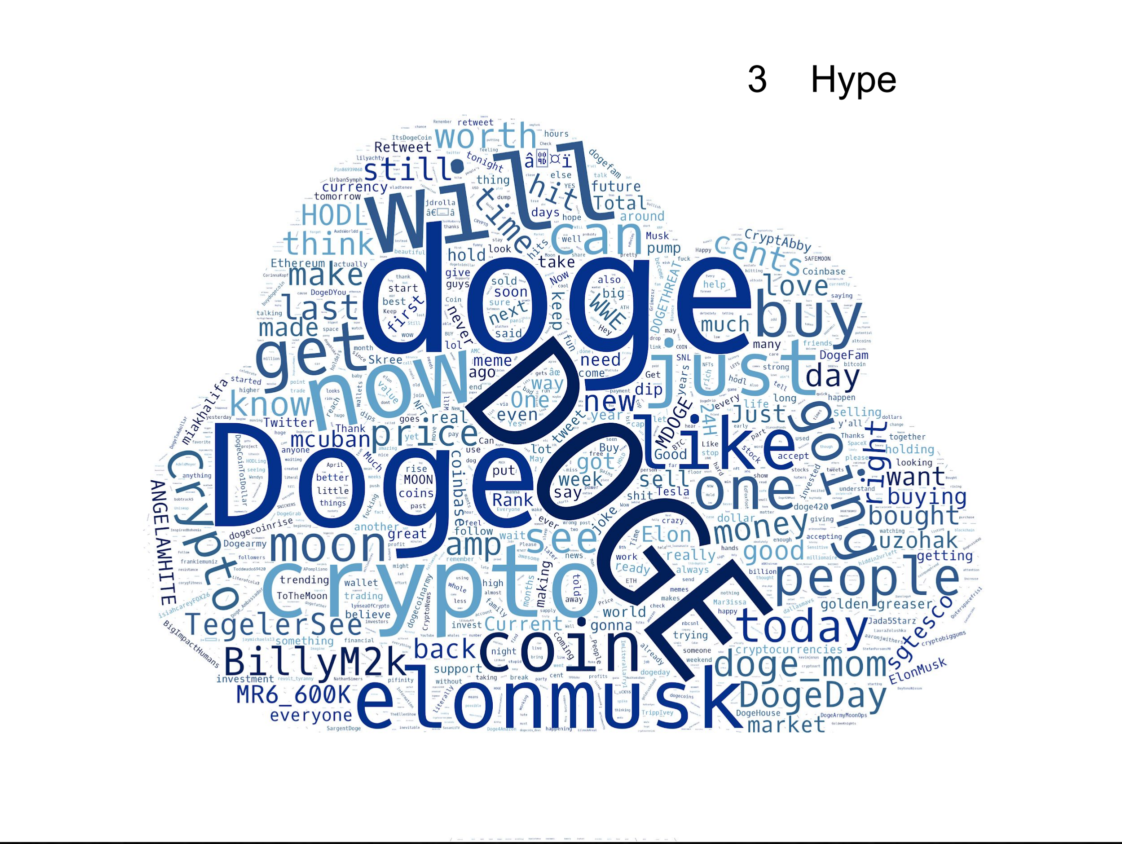
Cluster analysis - word clouds





Cluster analysis - 6 (EOS, all positive)

6
actual technical analysis and trading advice

Encouraging results

Table 1: Signal correlation to 18-hour returns

	Discriminative	Vanilla
BTC	**0.0570**	0.0556
EOS	**0.0235**	0.0203
ETC	**0.0262**	0.0249
ETH	**0.0424**	-0.003
LTC	**0.0787**	0.0608
XMR	-0.007	**0.0047**
NEO	**0.0196**	0.0158
XLM	**0.0494**	0.0377
TRX	**0.0170**	0.0105

Technical limitations

- Price data quality (lots missing dates - increases noise when shifting prices relative to signal)
- Sentiment sparsity - most sentiment is 0
- tweet density - we replaced missing sentiment by 0 (a cluster doesn’t mention a coin for an hour)
- Users are clustered rather than tweets : what to do with “new” users ?

This makes the signal ill-suited for prediction, even for linear regression

Room for improvement

- Social media offer a rich contextual structure. Ideally, one could categorize and cluster all users on Twitter prior to restricting on topics
- Temporal clustering/ graph analysis is challenging but important
- Different clusters should be able to evolve at different timescales/horizons
- Data availability (proportion of missing data) should be a feature for the downstream model
- better Price/Twitter data is mandatory for complexification and actual backtests