

PARADIGM + DATA-X @ BERKELEY

A project geared towards determining the effect of news articles on crypto-currency prices



What is Paradigm?

Paradigm provides a conversational marketplace for the crypto trading market. It features AI driven tools like automated over-the-counter trading and provides a sophisticated chat tool for institutional traders.

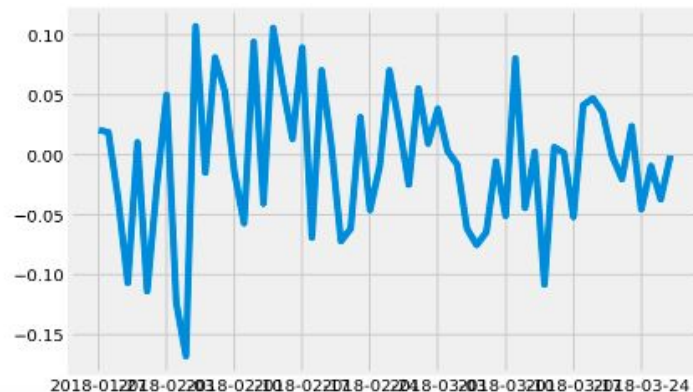
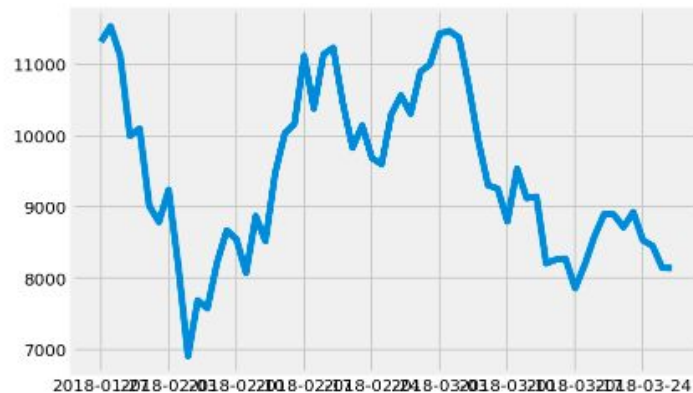
The chat is a combination of several trader tools including counter party discovery, text-to-trade recognition, etc.

The Project Task

Predict whether a news article will have a significant impact on the underlying crypto-asset mentioned in the article.

Details: 1) Event Detection. (2) Quantify significance of event on crypto prices.
(3) Rank importance/influence of article on event. (4) Visually display this importance.

Data Sample



Hypothesis-driven EDA



H1: Strong events (in terms of price change) which are caused by news exist and are common

A strong event caused by news should be easily identifiable since the lag between news and events is expected to be short.

H1 must be rejected

For 1 min , 15 min and 60 min data, one cannot establish a relationship between single news and strong events.

The causal impact of a SINGLE article on news does not exist for strong events. Given that it exists, it is very hard to identify.

Decisions:

**move from intra-day data to daily data
investigate impact of the mass of articles
("sentiment") on price**



Hypothesis-driven EDA

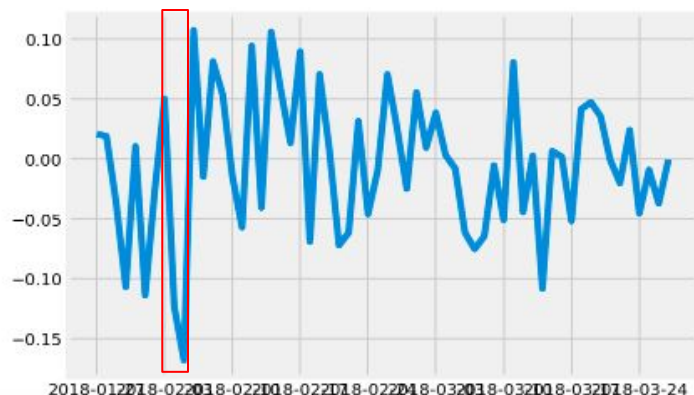
Our data sample has both a big upward and downward trend for which clear sentiment can be identified.

E.g., when the market is falling for 20 days straight, news consistently report “Bitcoin bubble has burst, etc.”

H2: News reflect overall sentiment of the market

Majority of news rather reflect past price movements or repeating other news, possibly building up expectations on future price movements (“sentiment”)

Negative Sentiment



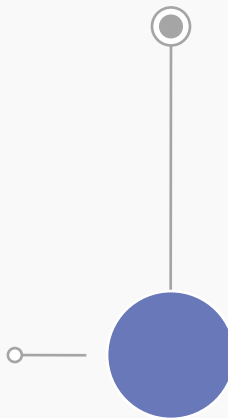
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3513  "It's hard to put in words how life-changing b...
3514  As Regulators Tighten The Noose, Cryptocurrenc...
3515  Build a Cryptocurrency Price Tracker in 5 Minutes
3516  The Objective-Realist vs. the Crypto-Evangelist.
3517  Bitcoin set for worst week since 2013 as crypt...
3518  Could Price Manipulation Be Killing Bitcoin?
3519  Bitcoin Is the 'Biggest Bubble in Human Histor...
3520  Unfazed by cryptocurrency crash, miners flocks...
3521  Initial coin offerings, explained - CNET
3522  Bitcoin Price Hits Floor, Bounces Back Above $...
3523  Bitcoin Investors Have Lost Nearly $87 Billion...
3524  Bitcoin falls below $8,000 as value plummets f...
3525  Smell of doubt in Bitcoins online
3526  Bill Gates once stayed up until 4am to write a...
3527  Bitcoin set for worst week since 2013 as crypt...
3528  8 Reasons Bitcoin Has Lost $175 Billion in Mar...
3529  Here's Why Bitcoin Is Plunging Again Today
3530  Bitcoin value plunges after misleading report ...
3531  Bitcoin's huge arbitrage play just vanished as...
3532  Espionage malware snoops for passwords, mines ...
3533  Fileless WannaMine Cryptojacking Malware Using...
3534  Ex-ice tea maker Long Blockchain backs off bit...
3535  Weekly Threat Report 2nd February 2018
3536  19-year-old bitcoin millionaire: You should in...
3537  Bitcoin Has Worst Week Since 2013, Briefly Tum...
Name: title, Length: 84, dtype: object
```

Hypothesis-driven EDA

Given that overall sentiment is indicative of future price movements, we could label those articles which share the sentiment to be important.

E.g. negative articles will be important when overall sentiment is negative.

We can make a scoring if we can determine how “negative” an article is.



H3: Since H2 = true, there might be a causal impact of sentiment on price (e.g. “self-fulfilling prophecy”)

Sentiment reflects both past price movements but might also be an indicator of future price movement -> e.g. Self-fulfilling prophecy.

Decision on next steps

“Event-based approach”: try to label news articles (significant vs. not) and then predict the label via NLP

Major advantage: Given that we have labels, we can accurately predict the label (see last year’s solution).

Major concern: it is extremely hard to label data without introducing enormous bias.

“Sentiment-based approach”: consider an article to be important if it shares the overall sentiment.

Major advantage: we avoid labeling data and possibly establish a causal relation between sentiment and price.

Major concern: no variance in importance of articles. All articles might be important if sentiment persists for a long time.

both approaches involve extensive NLP, so we can start off with NLP and postpone final decision.



How do we ensure reliability and accuracy of our process and pipeline?

Baseline Modeling: Codebase Demo

```

4499 Bitcoin Price Technical Analysis - BTC/USD Cr...
4500 Ethereum Price Technical Analysis - ETH/USD Cr...
4501 Bitcoin Will Stabilize, Hit $50K by 2019: Ben-Wer
4502 Bitcoin Will Stabilize, Hit $50K by 2019: Ben-Wer
4503 College kids using Bitcoin to pay for 'huge dr...
4504 College kids using Bitcoin to pay for 'huge dr...
4505 Bitcoin drops below $4,200 for first time in t...
4506 Bitcoin drops below $4,200 for first time in t...
Name: title, dtype: object

```

These articles do not seem to be very relevant to immediate price changes.

Minute Price: Top negative event

```

In [33]: strongest_changes = btc_1

strongest_changes = strongest_changes.sort_values(by = ["log_close"], ascending = True)
strongest_changes.head()

```

```

Out[33]:

```

	Timestamp	Open	High	Low	Close	Volume_BTC	Volume_Currency	Weighted Price	log_close	year	hour	minute	Date	
1818349	2018-03-06 05:58:00.000	8483.22	8488.00	8240.29	8258.18	354.382107	3.186228e+06	4340.478216	-0.028140	2018	...	8	18	2018-03-06
181884	2018-03-05 22:01:01.42000	8483.00	8483.00	8364.85	8365.00	235.726598	1.894339e+06	8072.746965	-0.022033	2018	...	9	17	2018-03-05
1819005	2018-03-06 23:13:00.000	8295.44	8800.00	8860.00	8860.00	139.030717	8.527980e+05	8704.088686	-0.022508	2018	...	20	15	2018-03-06
1811086	2018-03-02 12:33:00.000	8483.01	8483.01	8116.54	8330.80	258.829886	1.803791e+06	8390.803032	-0.018054	2018	...	15	15	2018-03-02
1818378	2018-03-06 05:45:00.000	8483.17	8483.17	8324.24	8341.00	184.538380	1.582464e+06	8386.039423	-0.017673	2018	...	8	45	2018-03-06

[Link to Youtube Video Presentation](#)

Workflow of ML Approach

RNN Model:

Predict sentiment of articles

- Built an RNN model from scratch
- Used NLP to convert articles into input

OUTPUT:

- Articles defined as having a predicted sentiment of positive or negative
- A metric that represents the relation of the article to crypto-currency price from [0,1]
- Model has **70% accuracy**

RNN Model:

Predict sentiment of articles

- Leverage the RNN model to label articles
- Added features to define relationship between the sentiment and impact

OUTPUT:

- Added features relating to the four quadrants below:

		Impact on Price	
		Increase	Decrease
Sentiment	Positive		
	Negative		

RNN Model:

Predict sentiment of articles

NEXT STEPS:

- Use all article features and engineered features in ML model
- Use traditional machine learning to predict impact on price
- Try different models (Logistic Regression, Random Forest etc.)

OUTPUT:

- Predicted degree of impact of an article on crypto-currency price