

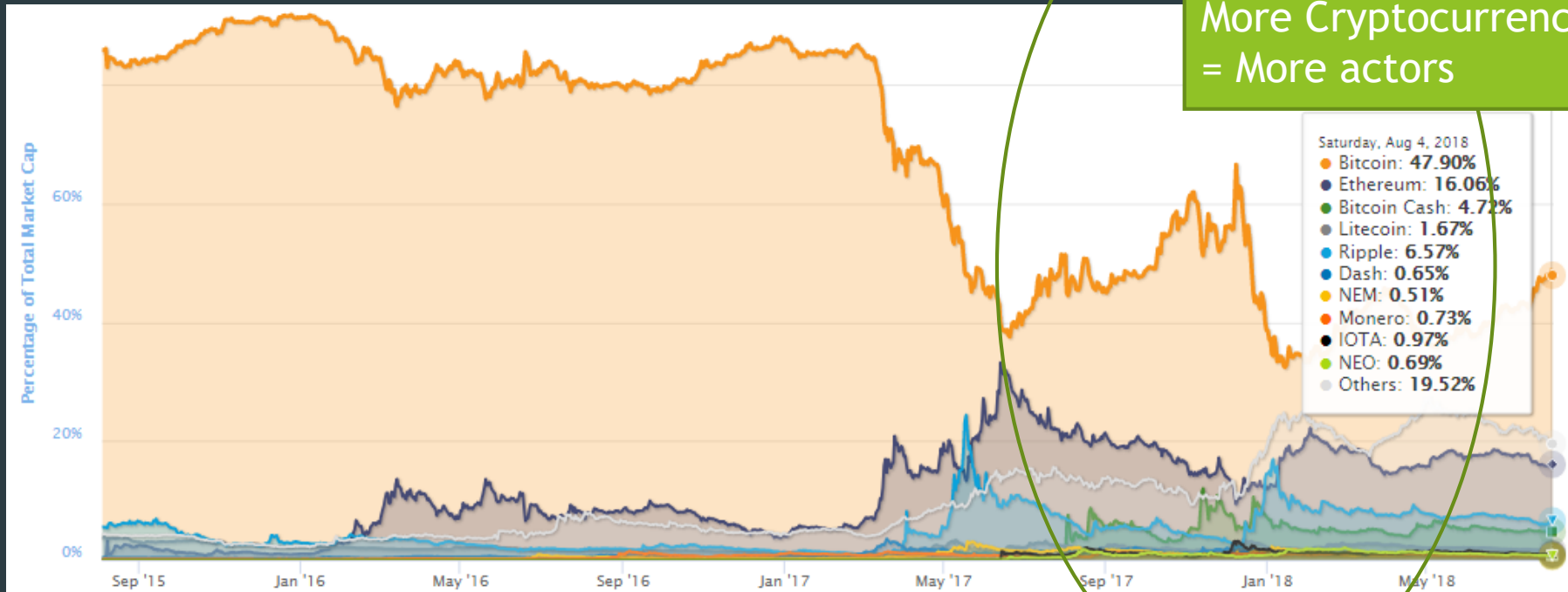
Social network analysis of Cryptocurrencies on Twitter

Use - network analysis techniques

To - Study interaction between Cryptocurrencies

In - Twitter

Motivation



More Cryptocurrencies
= More actors

Motivation(cont.)

- ▶ There are - Many Cryptocurrencies in the market
- ▶ Attract - Many People interested in different Coins
- ▶ Express - Thoughts via Twitter
- ▶ So...

“Can we use Twitter to study social interaction about cryptocurrencies?”

Research Question

- ▶ What is the relationship between cryptocurrencies?
- ▶ And How do they interact to each other?

Why is it important?

- ▶ **It fulfils research gaps...**

- ▶ Most research focused on price prediction and modelling but
“No one studied user interactions in Social network”

- ▶ **Benefits investors**

- ▶ Make market more transparent
 - ▶ Dependency between cryptocurrencies will be revealed
 - ▶ User behaviours will be revealed
 - ▶ **Investor can use insights to create trading strategies.**

Design

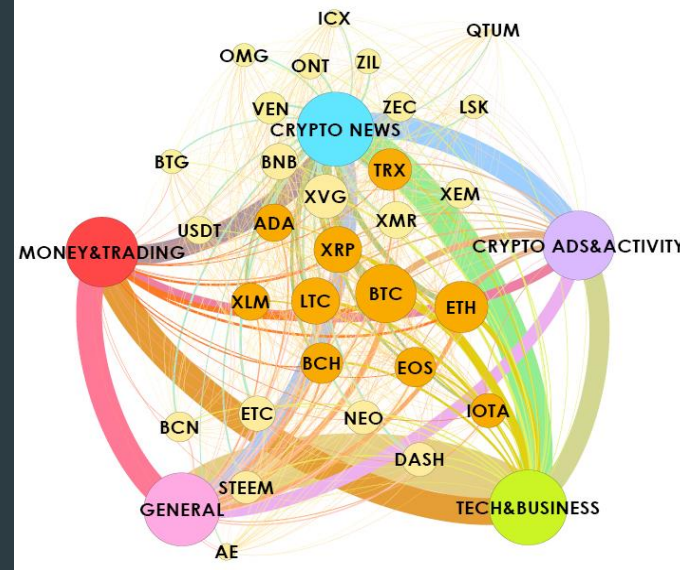
► Analyse 2 networks

1. Hashtag Co-occurrence Network

- It contains Hashtag that co-occurred with **Cryptocurrencies** hashtags
- To study: “How each coin is talked about in social network?”

2. User Network

- Users who actively tweet about **Cryptocurrencies**
- To study: “How users who like different coins interact to each other?”



Workflow

Collect tweets
and Clean data

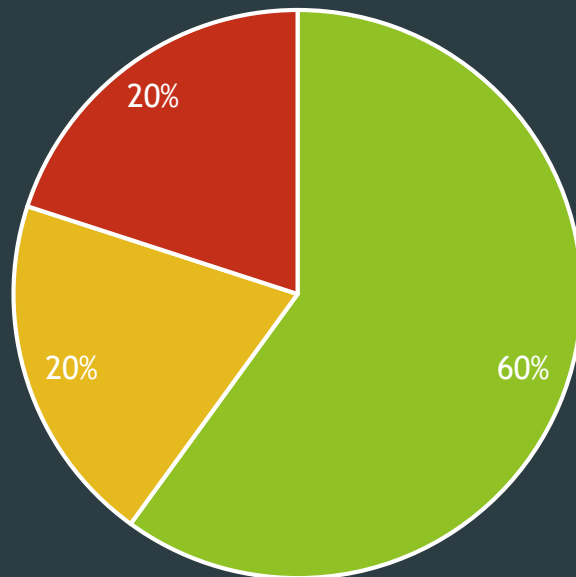
Analyse hashtag
co-occurrence
network

Collect users
and Clean data

Analyse users

Report

My Effort



■ Data Preparation

■ Analysis

■ Report

Collect Tweets
and Prepare data

Analyse hashtag
co-occurrence network

Collect users
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Report

- ▶ **Collect data:** Tweepy API, Search for Tweets containing hashtags of top-30 cryptocurrencies in the market Ex.

- ▶ 45 days (13 May - 26 June 2018)

- ▶ **Clean data:**

- ▶ Exclude Bots : Botometer API + Manual
 - ▶ Exclude Retweet & Tweets with Non-English hashtag
 - ▶ Keep only important hashtag
 - ▶ To choose the Threshold, we need Robustness test! -> **Top-4000 hashtags**

- ▶ **Find co-occurring hashtags**

- ▶ Exclude hashtags that co-occurred by chance.
 - ▶ Keep only $P(A,B) > P(A)P(B)$

bitcoin	btc	
ethereum	eth	ether
ripple	xrp	
bitcoincas	bch	
eosio	eos	
litecoin	ltc	

Collect Tweets
and Clean data

Analyse hashtag
co-occurrence network

Collect users
and Clean data

Analyse users

Report

► Raw data

Tweets	~ 6 millions
Users	~ 600 k

► Cleaned data

Users	~ 140 k	
Total Hashtags	~ 100 k	
Hashtags > threshold	~ 4 k	← Node
Co-occurring Hashtags Pairs	~ 320 k	
Co-occurring Hashtags Pairs (Excluding by chance)	~ 310 k	← Edges

Collect Tweets
and Clean data

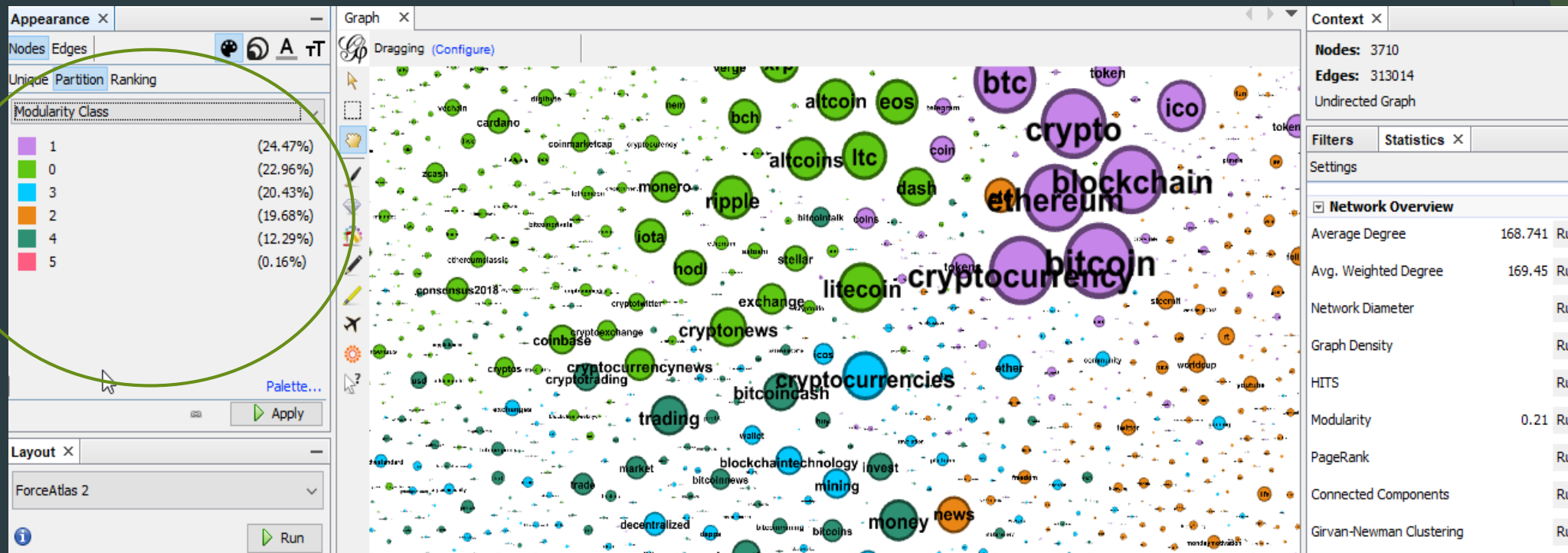
Analyse hashtag
co-occurrence network

Collect users
and Clean data

Analyse users

Report

- Build hashtag co-occurrence network
 - Node = hashtag and Size = how often it co-occurred with others
- Perform Community Detection - Group related hashtags to “Topic”



Collect Tweets
and Clean data

Analyse hashtag
co-occurrence network

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Report

- **Perform Community Detection** - to cluster groups of hashtags strongly related

1_crypto_news	2_crypto_ads	3_general	4_bussiness_tech	5_trading
altcoins	crypto	news	cryptocurrencies	money
altcoin	cryptocurrency	usa	fintech	trading
cryptonews	blockchain	love	technology	investing
hodl	ico	entrepreneur	business	cryptotrading
cryptocurrencynews	token	worldcup	tech	invest
exchange	airdrop	follow	finance	investment
coinbase	coin	rt	mining	forex
consensus2018	tokens	success	blockchaintechnology	market
bittrex	free	music	ai	trade
cryptoexchange	tokensale	art	iot	stocks
cryptos	erc20	trump	future	gold
coinmarketcap	coins	twitter	currency	wallstreet
dgb	giveaway	retweet	decentralized	cash
moon	bounty	youtube	startup	investors
cryptotwitter	telegram	facebook	china	trader
dogecoin	airdrops	video	icos	usd
digibyte	airdropalert	life	marketing	investor

Ex. Cryptocurrencies hashtags

bitcoin	ethereum	ripple	bitcoincash
btc	eth	ripple	bitcoincash
btcdsd	ether	ripplet	bitcoin_cash
hitbtc	ethereum	xrp	bch
btcdnews	myetherwallet	xrpbtc	bchpls
freebtc	ethereum	xrpthesta	bchforeveryone
btcpri	etherium	xrppcomm	bchusd
btcturk	ethusd	xrpparmy	ibch
bitebtc	ethereummining	xrpusd	bchfaucet
btcm	etherc	xrpsymbol	
btctrading	etherdelta	instaxrp	
wearebtcp	ethbtc	xrpcommunity	
btcpics	ethlend	xrpnyc	
btcfx	ethereummark		

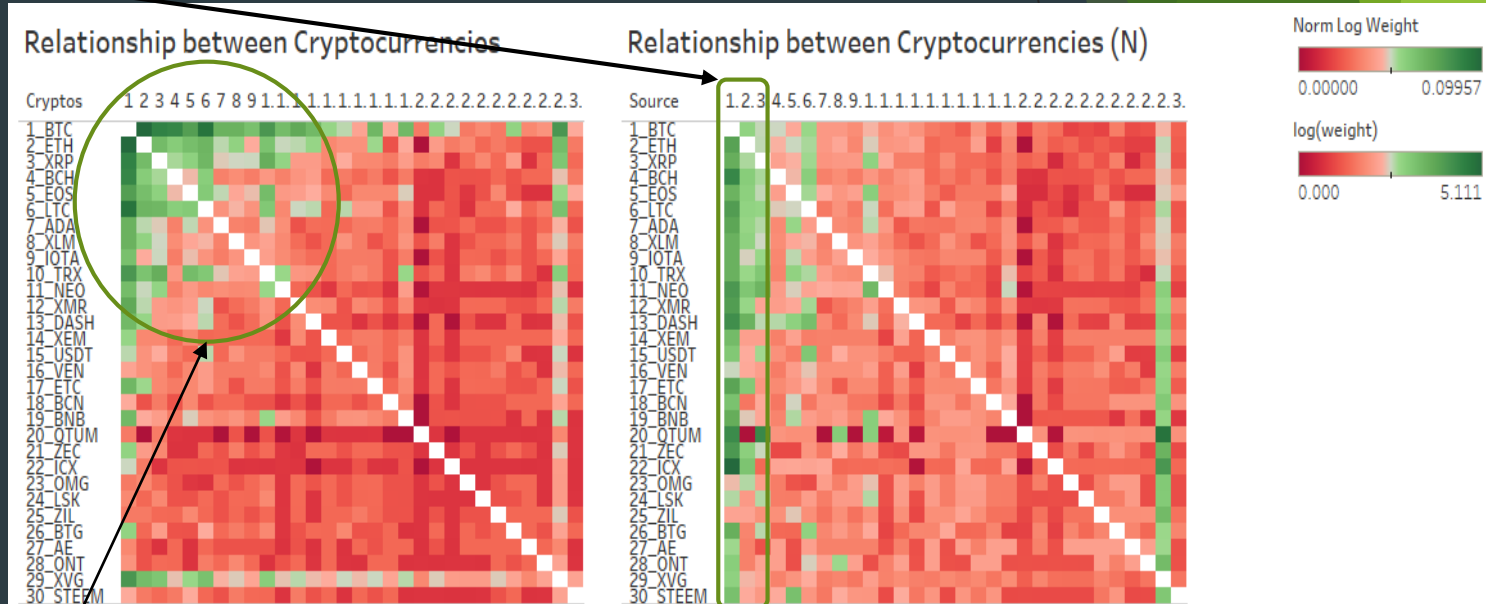


-
- The figure consists of three main parts: a network diagram and two heatmaps.
- Network Diagram:** A complex network of nodes and edges. Nodes are represented by colored circles and labeled with cryptocurrency abbreviations (e.g., BTC, ETH, XRP, ADA, XLM, LTC, BCH, EOS, IOTA, DASH, STEEM, AE, BNB, TRX, XMR, XEM, ZEC, LSK, QTUM, ICX, OMG, ONT, ZIL, VEN, BTG, USDT, ADA, XVG, XRP, XLM, LTC, BCH, EOS, IOTA, DASH, STEEM, AE) and community categories (e.g., MONEY&TRADING, CRYPTO NEWS, CRYPTO ADS&ACTIVITY, TECH&BUSINESS, GENERAL). Edges represent relationships between these entities, with colors corresponding to the community categories.
- Heatmaps:** Two heatmaps showing the relationship between communities and 30 cryptocurrencies. The top heatmap is titled "Relationship between Cryptocurrencies and Communities" and the bottom heatmap is titled "Relationship between Cryptocurrencies (N)". Both heatmaps use a color scale for log(weight) from 3.091 (red) to 7.860 (green). The top heatmap has a color scale from 0.02019 (red) to 0.05088 (green). The bottom heatmap has a color scale from 0.02019 (red) to 0.05088 (green). The heatmaps show the relationship between communities (CRYPTO-NEWS, TECH&BUSINESS, CRYPTO-BUZZ&ADS, GENERAL, TRADING) and 30 cryptocurrencies (1_BTC, 2_ETH, 3_XRP, 4_BCH, 5_EOS, 6_LTC, 7_ADA, 8_XLM, 9_IOTA, 10_TRX, 11_NEO, 12_XMR, 13_DASH, 14_XEM, 15_USDT, 16_VEN, 17_ETC, 18_BCN, 19_BNB, 20_QTUM, 21_ZEC, 22_ICX, 23_OMG, 24_LSK, 25_ZIL, 26_BTG, 27_AE, 28_ONT, 29_XVG, 30_STEEM).



Analyse users

- ▶ Community detection again - to find group of coins strongly related
- ▶ “How likely that **coin X** will be mentioned **with coin Y**?”
 - ▶ “High-ranking cryptocurrencies are more likely to be mentioned with other cryptocurrencies than the low-ranking ones”



“High rank strongly related to each other”
= “People often mention high ranking together”

Collect Tweets
and Clean data

Analyse hashtag
co-occurrence network

Collect users
and Clean data

Analyse users

Report

1. Take top-1000 users most often tweet about cryptocurrencies as “Based users”
 - ▶ Aims to build network of users who are active in cryptocurrencies
2. Collect friends of based users and their connections -> Painful! due to Twitter limitation
 - ▶ Collect user data -> friends & followers of base users -> keep only users with ≥ 10 links to base
 - ▶ Collect friendship between them
 - ▶ Collect tweets of these users
3. Create user vectors - to measure how much they are interested in each coin and topic.
 - ▶ A User Score = $P(\text{\#coin hashtag}) = \text{\#coin hashtag} / \text{\#total hashtags}$

uid	screen_name	bitcoin	ethere	ripple	bitcoin	eosio	litecoir
_99712395	cloudbreak79	0.165698	0.005814	0.002907	0.002907	0	0.380814
_94561172	vmediahero	0.333333	0.333333	0	0.333333	0	0
_94523500	NeerajNeeraj876	1	0	0	0	0	0
_94519511	danielk15350934	0.333333	0.333333	0	0	0	0
_96705306	WennMoon	0.333333	0.333333	0	0	0	0
_99934346	MikeJam50406782	0.307692	0	0	0	0	0
_99888927	Prene15	0	0	0	0	0	0
_90285150	TheseriousJ1973	0.2	0	0.022222	0.044444	0	0
_95092274	NhaNgoaiCam	0	0	0	0	0	0



Collect Tweets
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Report

1. **User Correlation Analysis - Find correlation between coin scores of each user**

- ▶ If users like a specific coin, which other coins they're likely to like?

2. **Homophily Analysis - assortative measure**

- ▶ If users like a specific coin, how likely their friends will also like it?
- ▶ How likely users who share the same preference will know each other?

3. **User Influence factor analysis**

- ▶ What makes a user become influential in cryptocurrency social network?

Collect Tweets
and Clean data

Analyse hashtag
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Collect users
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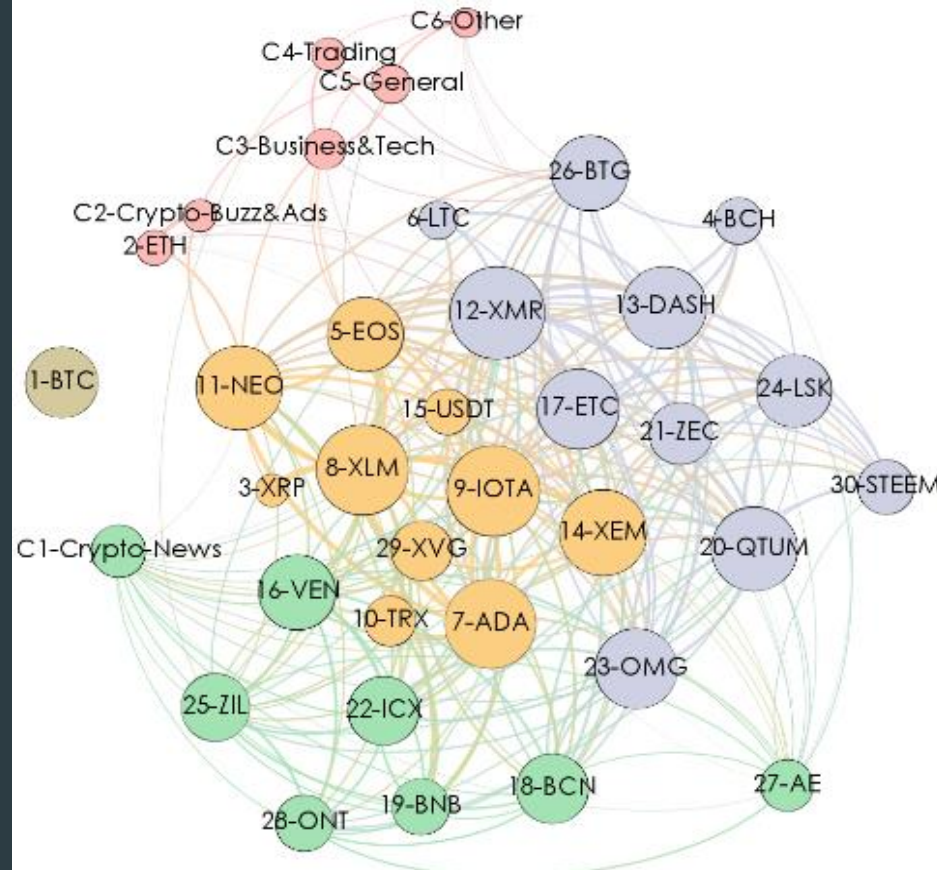
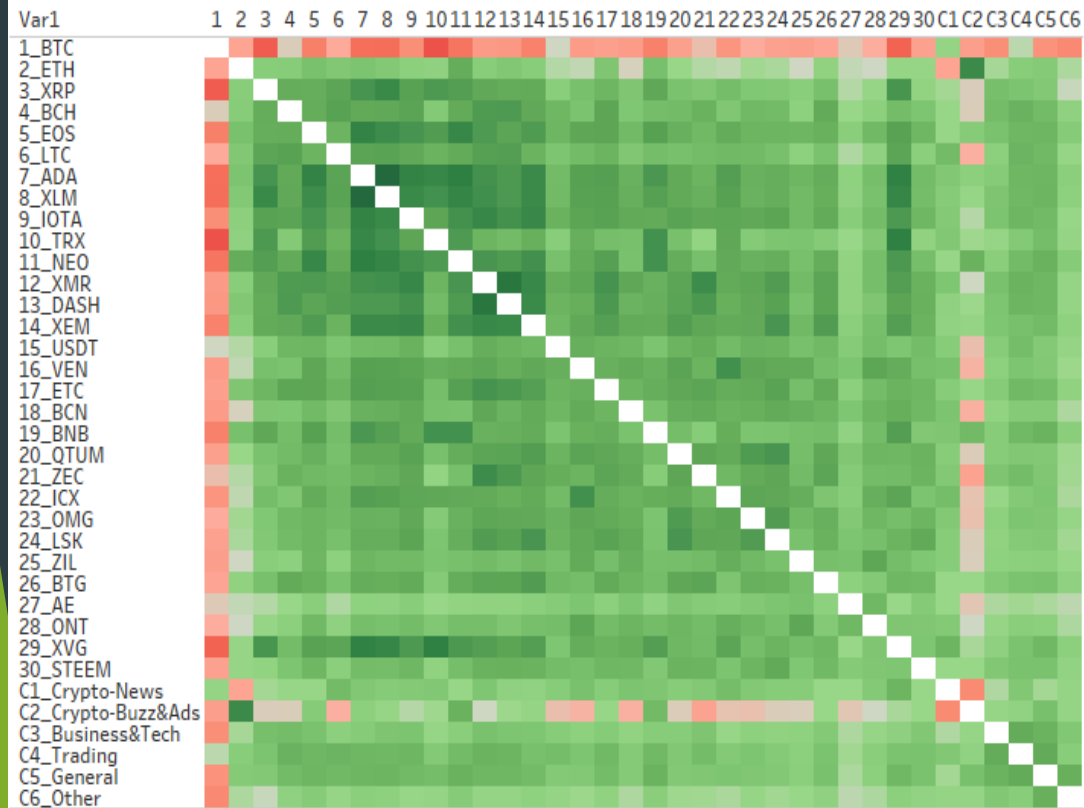
Analyse users

Report

1. User Correlation Analysis

- “Users who like altcoins are likely to like other altcoins around their ranks, while users who actively talked about the top ranks, Bitcoin and Ethereum, show less interest in altcoins but more engagement in general topics”.

Spearman Correlation



Collect Tweets
and Clean data

Analyse hashtag
co-occurrence network

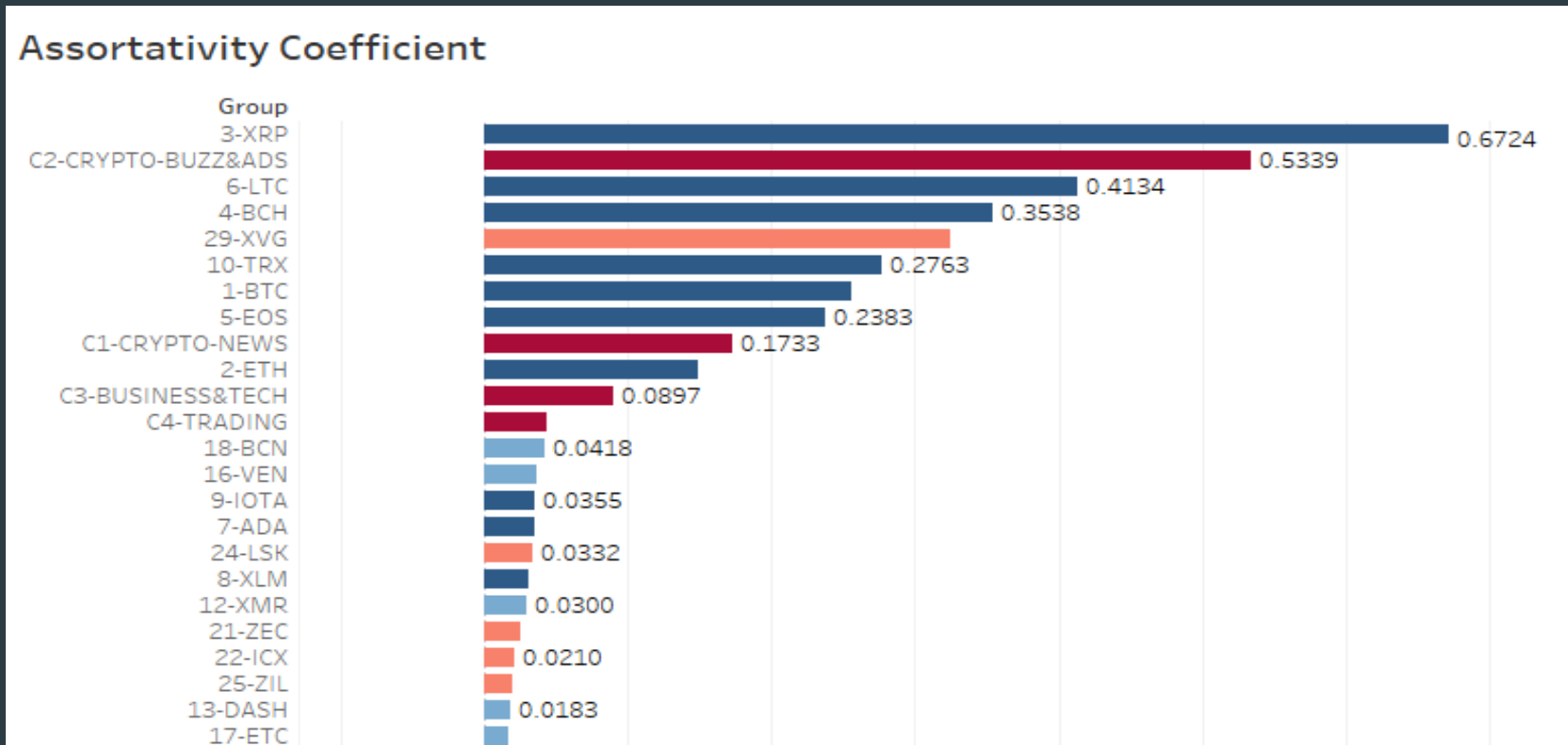
Collect users
and Clean data

Analyse users

Report

2. Homophily Analysis

- If users like a specific coin, how likely their friends are going to like it?
 - Users who like top-10 (Dark Blue) tends to know each other more than the users who like coins in lower ranks



Collect Tweets
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Analyse hashtag
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Report

3. User Influence factor analysis

- ▶ What makes a user become influential in cryptocurrency social network?
 - ▶ User who focus in some specific coins or user who talk about many coins in general?
 - ▶ Measure by Entropy = How diverse coins that a user talk about ?
- ▶ Influence = Be often retweeted
 - ▶ Perform linear regression:

```
Call:
lm(formula = rt_count ~ followers_count + friends_count + entropy +
    twt_count + hashtag_count + lifetime_twt_count, data = MyData)
```

Residuals:

Min	1Q	Median	3Q	Max
-199071	-428	-221	2	519835

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	9.606e+02	3.143e+02	3.056	0.00225	**
followers_count	4.960e-01	7.887e-03	62.898	< 2e-16	***
friends_count	-4.654e-01	3.321e-02	-14.015	< 2e-16	***
entropy	-2.123e+02	1.190e+02	-1.785	0.07438	.
twt_count	-1.962e-01	1.305e-01	-1.504	0.13273	
hashtag_count	2.095e-01	4.679e-02	4.477	7.68e-06	***
lifetime_twt_count	-2.293e-02	1.102e-02	-2.082	0.03740	*

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 8390 on 8410 degrees of freedom
Multiple R-squared: 0.3246, Adjusted R-squared: 0.3241
F-statistic: 673.6 on 6 and 8410 DF, p-value: < 2.2e-16

Questions addressed in this dissertation

Hashtag co-occurrence network

- ▶ How is **coin's ranking** related to the **social interaction**?
 - ▶ Top ranks are mentioned in various topics
 - ▶ High-High ranks are strongly related.
 - ▶ High-Low ranks has stronger relationship than Low-Low = Low attaches to High
- ▶ How likely that **coin X** will be mentioned **in topic Y** ?
- ▶ How likely that **coin X** will be mentioned **with coin Y**?

User network

- ▶ If users like a specific coin, **which other coins they're likely to like?**
- ▶ If users like a specific coin, **how likely their friends will also like it?**
- ▶ How likely users who share the **same preference** will **know each other?**
- ▶ **What makes a user influential** in cryptocurrency social network?