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Application of Liquid Rank Reputation System for Content Recommendation

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CHALLENGES AND VALUE ADDED BY THESIS WORK

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Collaborative Filtering, Content-Based Filtering, Hybrid Models:

- There are Bot Armies which can easily sway the results on Twitter, Telegrams, Youtube, etc.

"Nearly two-thirds of the social media bots with political activity on Twitter before the 2016 U.S. presidential election supported Donald Trump": Source- https://arxiv.org/abs/1810.12398

- Recommendations of the most populat platforms like Twitter, Youtube, etc are easily manipulated by scam channels, reviews and ratings.
- Personalisation on recommendations get overwhelmed with our own following (likes, subscribed, searches).
- Overall the large/most popular content gets recommended (Mathew's Effect).
- **Who will rate the raters?**

Need of the hour is to have a recommendation model just based on unbiased network ratings, following Thesis work leads one step towards that, Liquid Democracy. (Commercial Usage available)

WHAT IS LIQUID RANKING SYSTEM?

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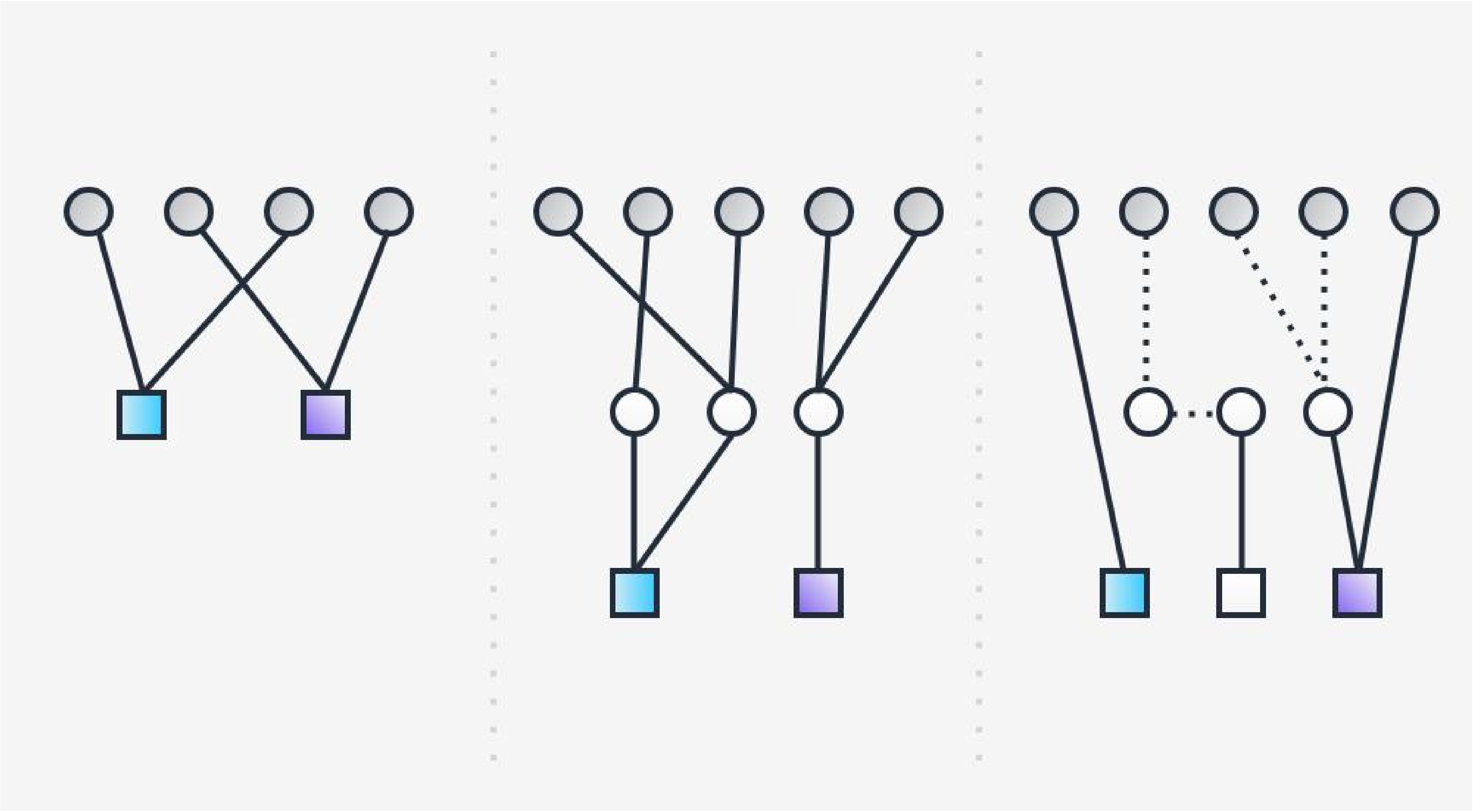

Direct Democracy Representative Democracy Liquid Democracy

What is Liquid Ranking System?

Liquid Democracy is implemented through Liquid Ranking.

- Liquid Ranking is nothing but earned rank in a Liquid Democracy (eg. Decentralised Platforms)
- Most of representative democracies have failed because they were overshadowed by financial powers.
- So, the answers come through the reputation power of individuals for the ranking.
- Each rank is calculated by the individuals on a platform, through features eg. followers, likes, comments, subscribers, etc.

Liquid Ranking Reputation System

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Computational model of Reputation rating is calculated as

$$\mathrm{R_j} = \sum (R_i * V_{ijt}) + \sum (R_i * F_{ij}) + \sum (R_i * (O_{ijt} + C_{ijt} + D_{ijt} + S_{ijt}) \ *$$

Here

V: Mentions

O: Likes (favourites)

C: Comments (sentiments)

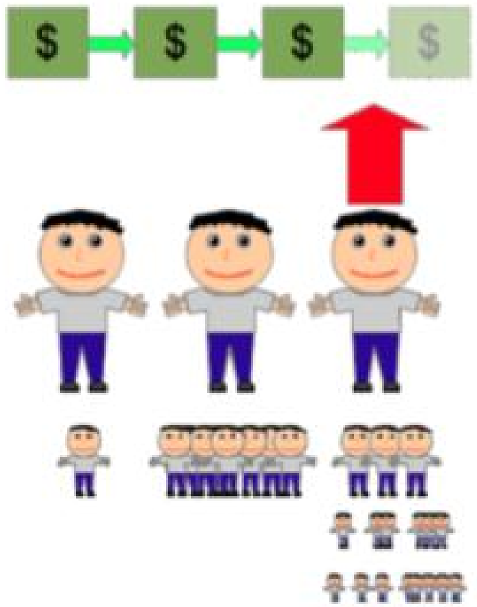
F: Followers

D: Retweets (sharing)

S: Personal Recommendation

- **R_i: Current reputation of i_{th} node (initially considered as 1 for all, "Liquid Weight")**
- **V_{ijt}: It can be implicit rating as positive or negative vote or implicit rating as wire transfer amount ("Rating Weight"), either spent or received, for node j being rated, node i supplying the rating and time t.**

LIQUID RANKING REPUTATION SYSTEM



$$R_i = \Sigma_t \Sigma_j (R_j * V_{ijt})$$

Reputation is Power: Those who earn a better reputation and a greater long-term audience base govern the network.

- In all reputation system provides the distribution of liquid weights while ranking every iteration before normalisation.
- Each part of the algorithm can also have variable weight distribution.
- The algorithm covers not only direct and time independant variable like Followers, but also time dependant variables i.e likes, comments, mentions.
- The thesis opens up a new feature in recommendation using the reputation score, where the reputation of the channel/person can increase/decrease as per his/her acceptance by other fellow members on the platform.
- In the thesis mentions are selected to be the prime feature to consider the reputation score for liquid ranking.

* Kolonin A. et al, Aigents Group & SingularityNet Foundation, 2017

Liquid Democracy in recommendation:
State of the Art

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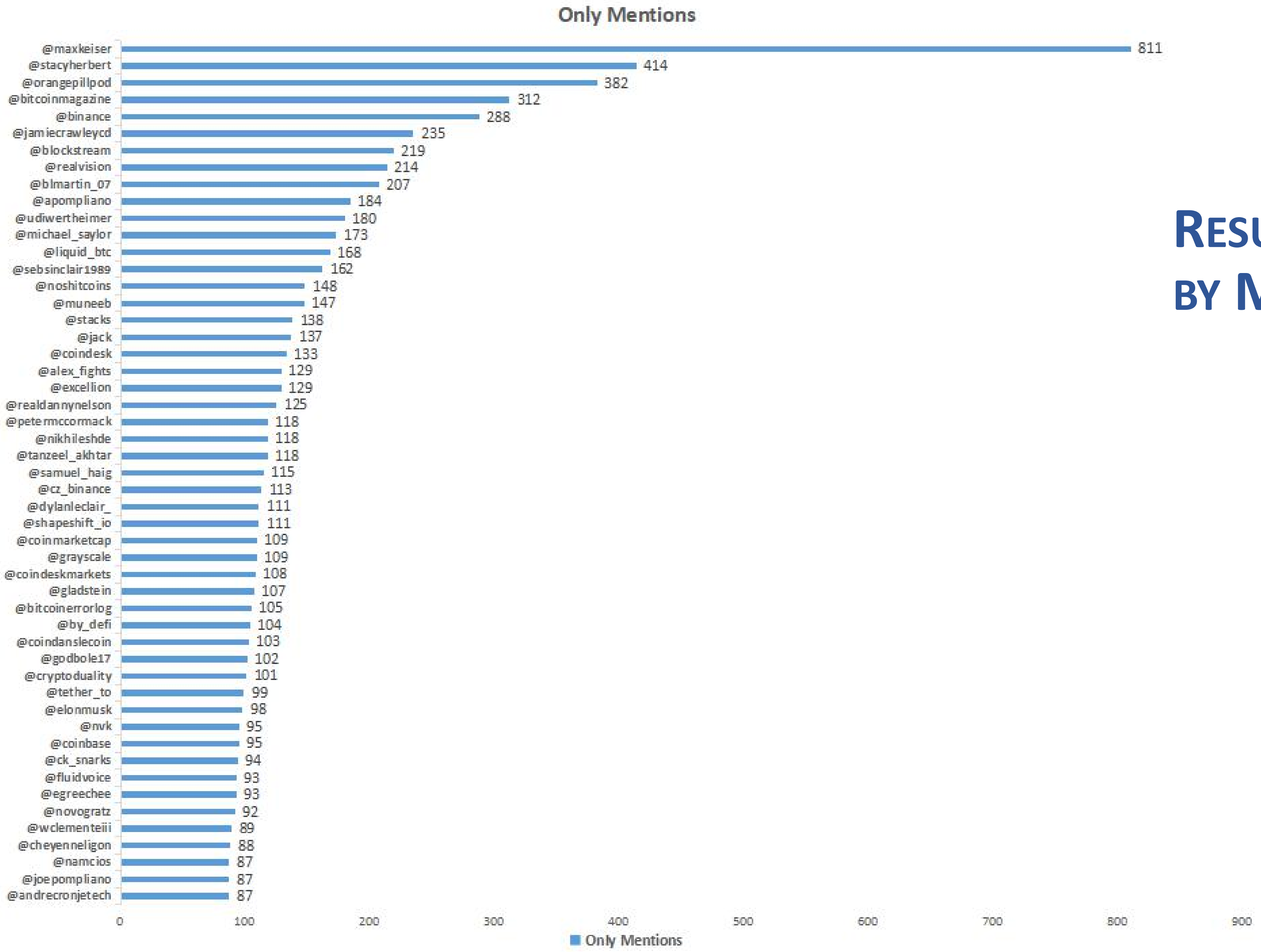
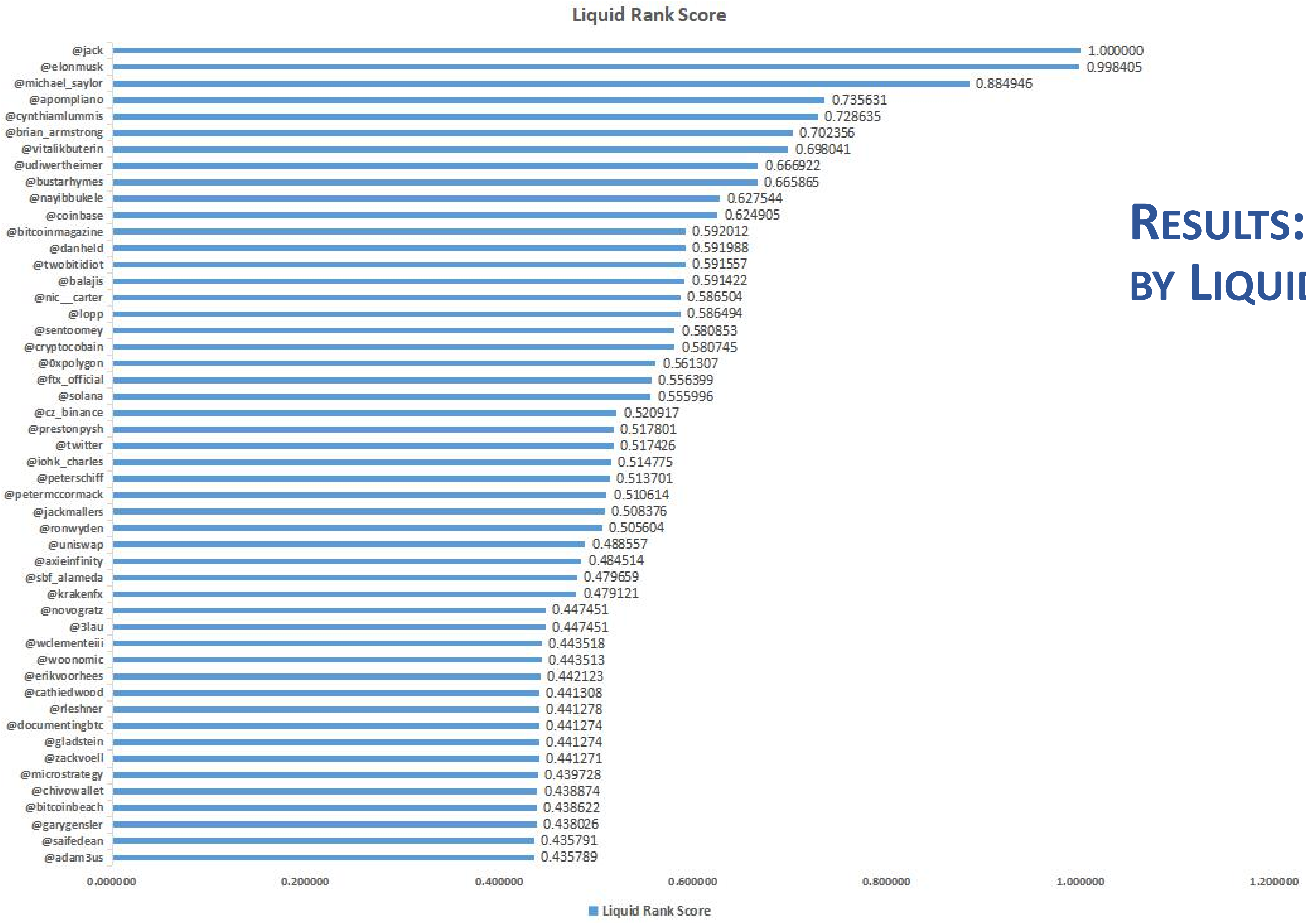
It can be implemented through Liquid Ranking.

- Liquid Ranking algorithm is developed to work as a hybrid feature for content recommendation (a dynamic recommendation model).
- Each rank can be calculated by the individuals on a platform, through features eg. followers, likes, comments, subscribers, etc (we have used Mentions in Twitter Data)
- Liquid Ranking algorithm is tested to get the opinion leaders or most influencial channels in the given time frame for crypto news versus just based on the mentions of channels.
- Dataset scrapped from Twitter contained 37605 tweets by 10000+ channels/accounts on Twitter.
- Cold Start or "higher level friends" in our case were passed by selecting initial 30 channels which are pro-active cryptocurrency related accounts.
- The top 50 channels recommended (on both scales) were rated on 0-2 scale (for qualitative analysis). Crypto data. 0 is given to channels which have least influence and 2 to most influent. Hence "Relavant" Channels are those which have score of 2, and the rest are considered as "Irrevelant".

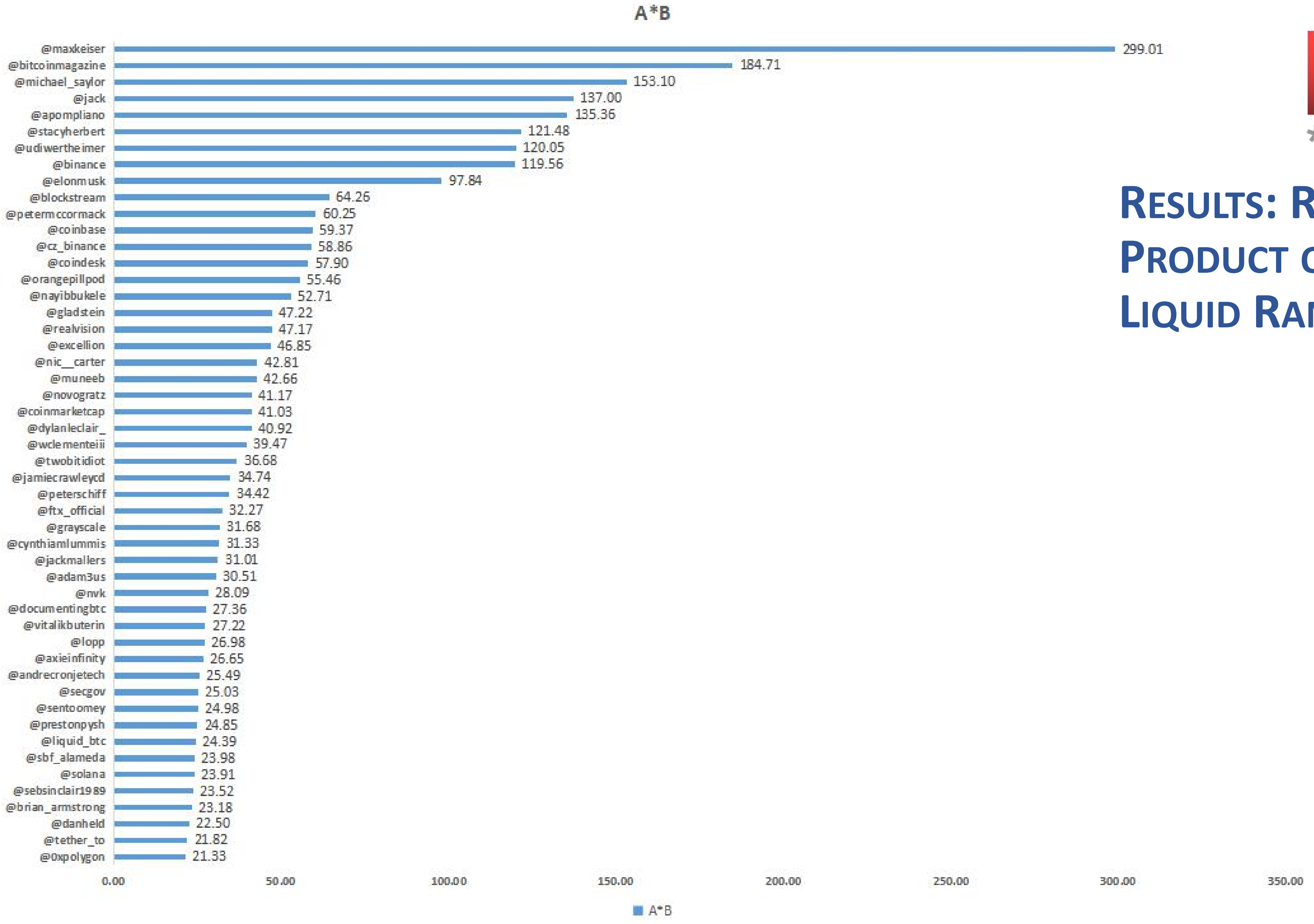
RESULTS: RANKING BASED BY MENTIONS



Results: Ranking Based by Liquid Rank Score



Results: Ranking Based on Product of Mentions and Liquid Rank Score



Results Qualitative Analysis: Decision Support

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Results Qualitative Analysis: Average Precision

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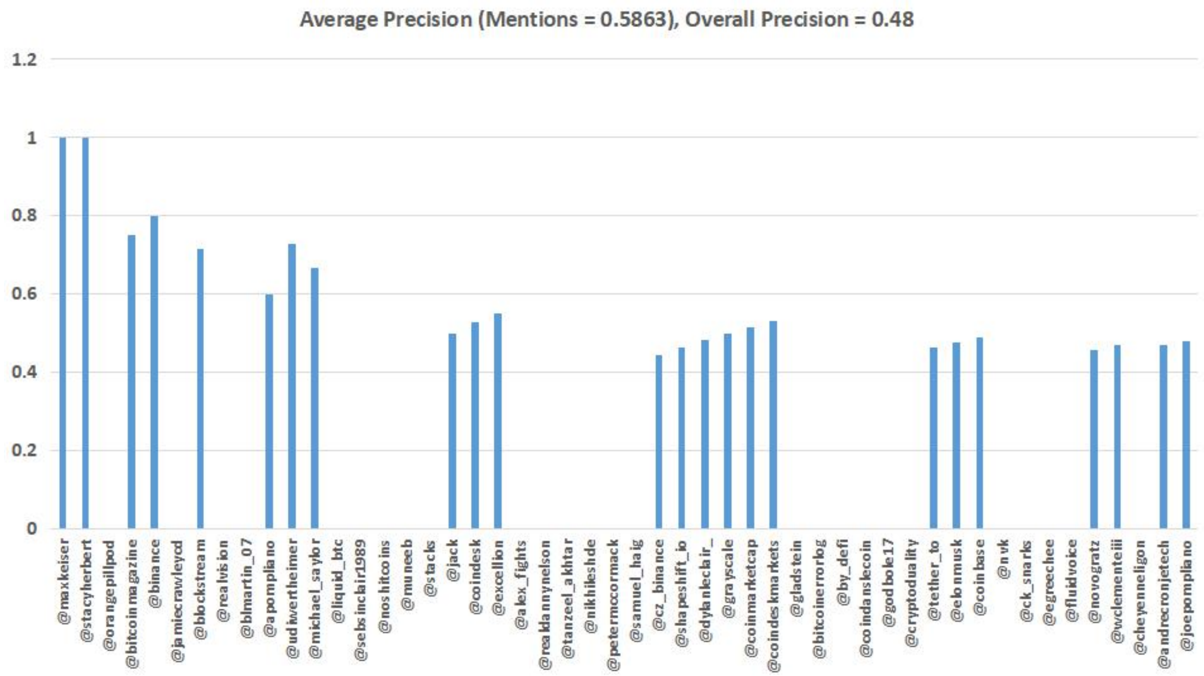
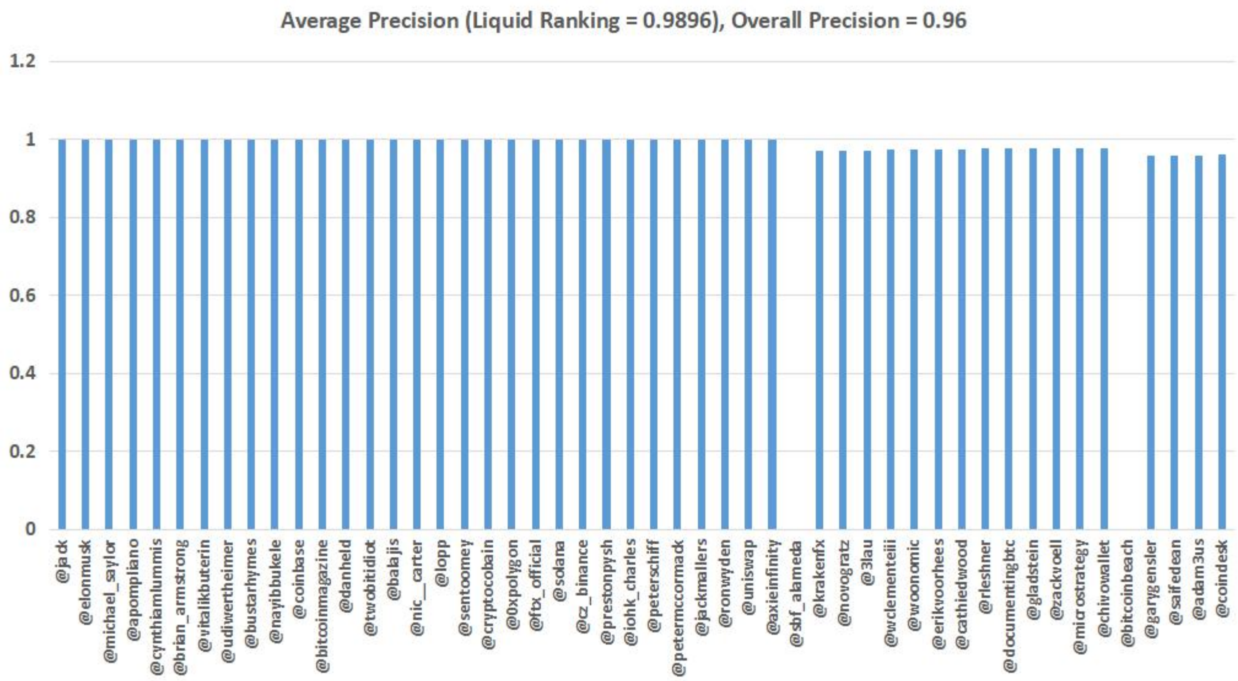
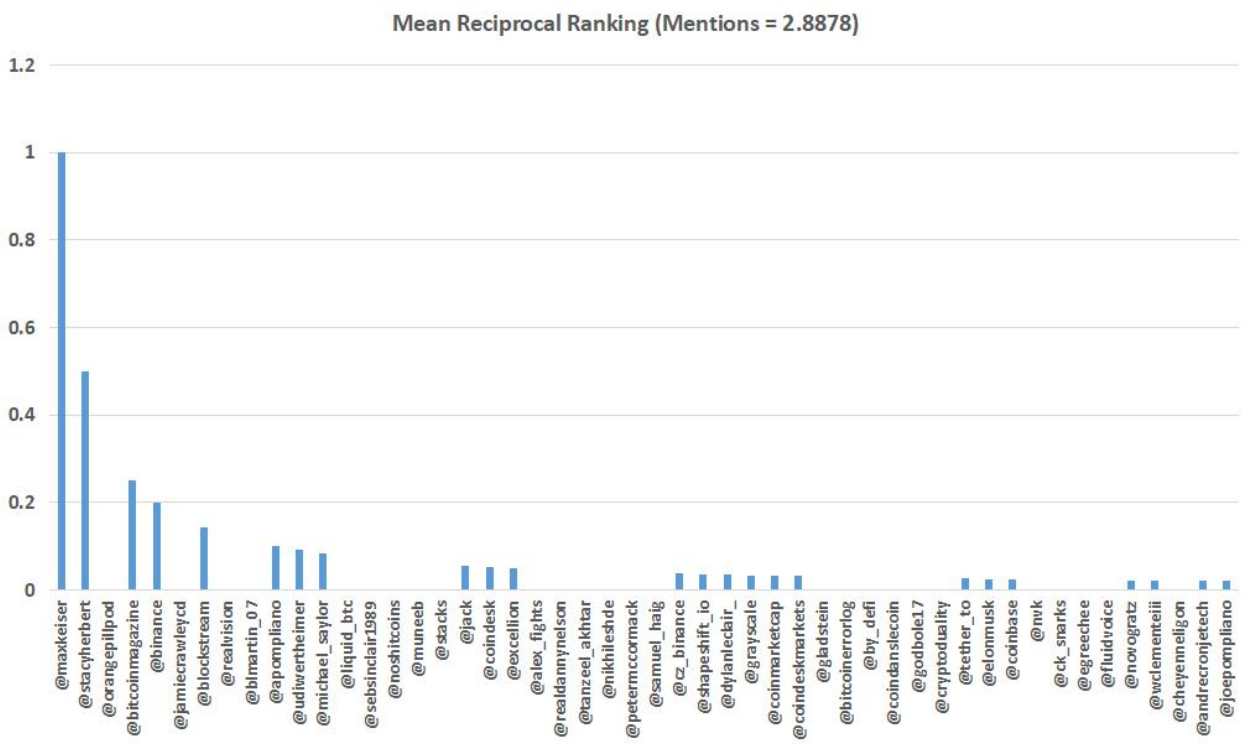
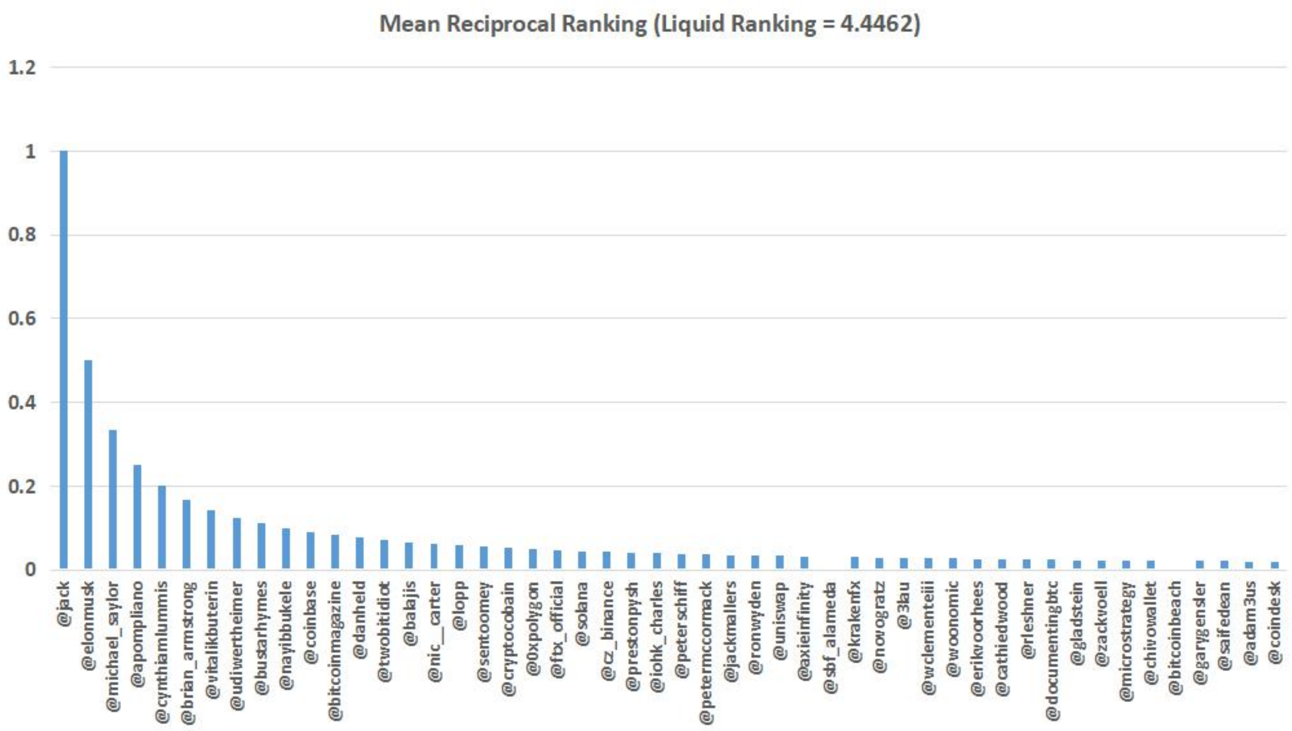




RESULTS QUALITATIVE ANALYSIS: MEAN RECIPROCAL RANKING





FUTURE SCOPE OF THESIS

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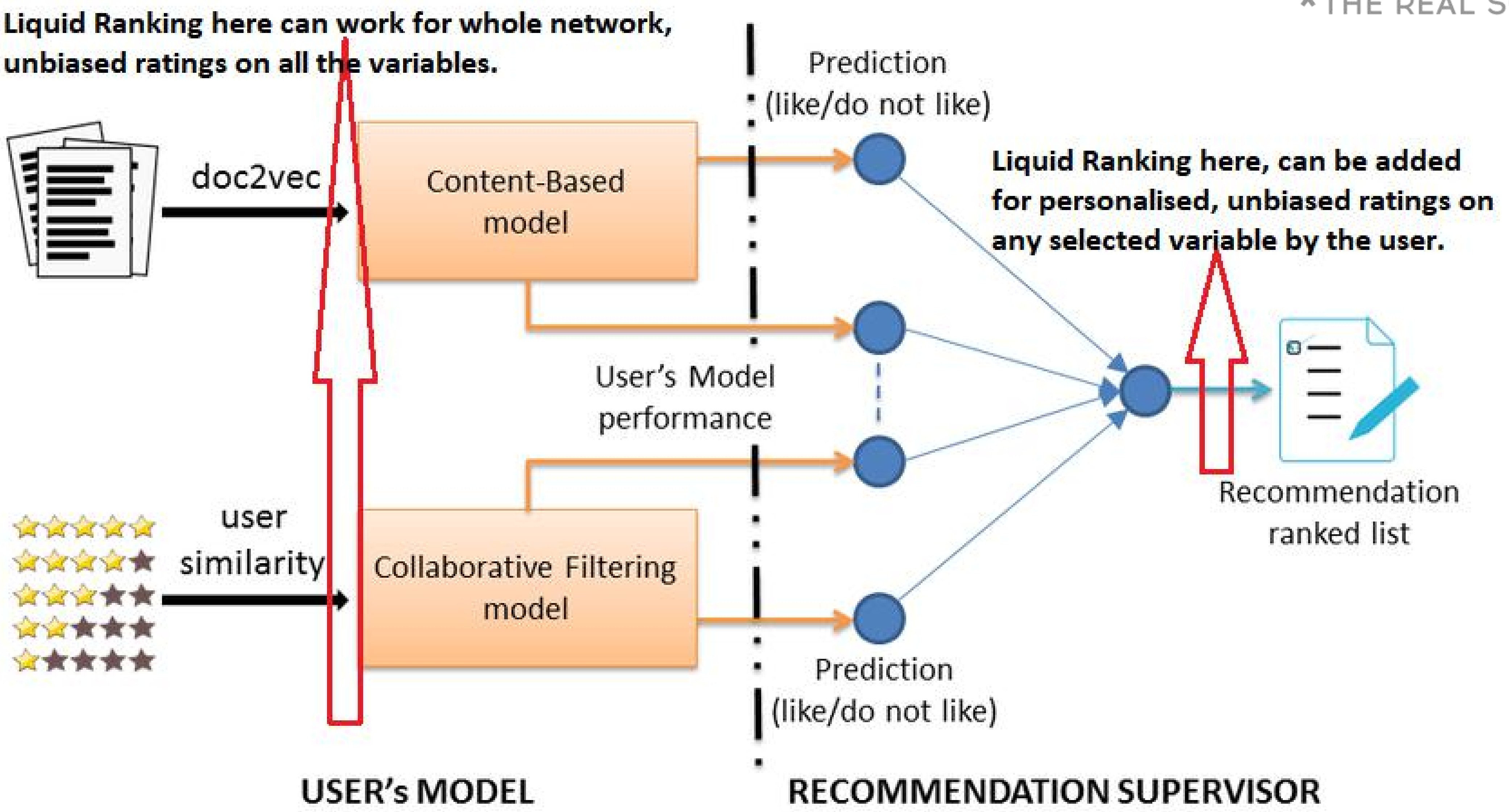
- Liquid Ranking can directly be implemented in the account of social media channel or an online store where Cold Start would be handled by the reputation of our friends and people whom we already follow.
- Later this reputation would ripple to more recommendations, starting from our social circle.
- Liquid Ranking on multiple attributes can make not only personalised recommendation much better, but also will help new content provider or say here in the case less influential channels also to be recommended (who are producing good work and talked about in our social circle, not viral but surely liked and effective content)
- One thing has to be considered that Liquid Ranking, considers the time period of the usage or search, which makes recommendations dynamic and fresh everytime.

Future Scope of Thesis



Reviewer's Advice

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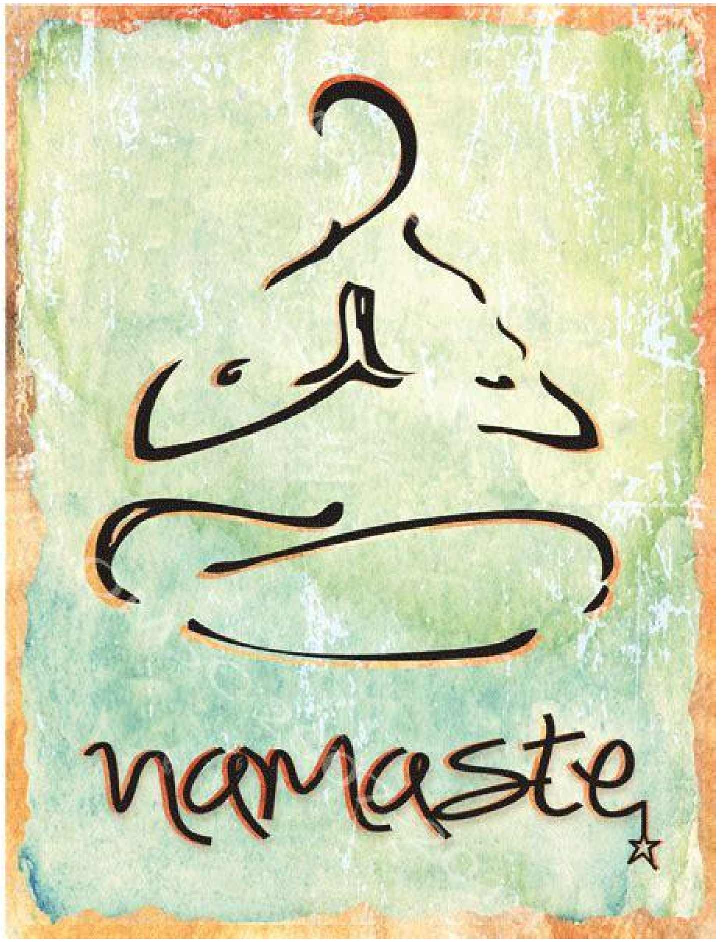
- To improve the quality of work by adding more metrices, else it is comparative to PageRank, HITS methods, etc.
- The present dissertation is an application of elaborative and powerfull liquid rank reputation system. Its true the best results can be seen with more metrices, but this is among the primary stages of using reputation system for recommendation models. I have tried to rank the dataset with followers on Twitter also, but it would skew the results towards the large channels or the most influential people on Twitter.
- PageRank have limitation of considering the benchmark of authenticated pages to have more value than any other pages on web. Thus, if linked by these High Value pages gives higher index to the page tagged. Reputation system is a dynamic and flexible set of algorithm, the value of the most rated node can be hampered or decrease by negative ratings or in our case it may arise when the particular high reputation channel is not active in the discussion, hence its worth will not be considered at all.


namaste


youtube
netflix
count_vectorizer
history
ratings
python
recommended
filtering
content
learn
based
amazon
for
scikit
pandas
movies
csv
cosine_similarity
dataframe

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- Proof of Reputation as Liquid Democracy for Blockchain https://steemit.com/blockchain/@aigents/proof-of-reputation-as-liquid-democracy-for-blockchain

- Liquid Democracy for Distributed AI Systems https://blog.singularitynet.io/reputation-consensus-and-liquid-democracy-based-on-open-ledger-protocol-for-distributed-ai-systems-ffc2e6f387d1

Appendix: Liquid Rank Reputation System for Content Recommendation Dataset

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Identifying Opinion Leaders by Mentions and Liquid ranking:

- DATASET: Sample dataset from Twitter and Reddit on Cryptonews Feed has been taken for finding opinion leaders (or can be considered as recommendation for new channels on twitter which are having impact on the related topic in that time frame)
- Only Twitter Data is selected upon to build the algorithm of Content Recommendation System, dataset contain 37605 tweets and more than 10k channels (twitter accounts).
- Opinion Leaders are found on the basis of the "Mentions" by the selected channels which were used to fetch data in that time frame.
- Considering direct mentions by the channels as the area of interest to find new recommendation ranking.

Appendix: Liquid Ranking for Content Recommendation

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Identifying opinion leaders by liquid ranking:

Initial Phase Algorithm used to build the Architecture for Content Recommendation:

$$\mathrm{R_j} = \sum (R_i * V_{ijt})$$

Architecture: Code has been built from scratch currently, will need updation according to new features in future.

- Initially reputation score was given as 1 to everyone.
- Opinion Leaders are found on the basis of the "Mentions" by the selected channels, these mentions work as Weights (multiplier) to build new reputation score.
- Every loop of reputation scoring, follows normalisation of data (within positive range)
- The end results are as follows.

Appendix: Qualitative Analysis

- Channels only rated 2(max) are considered to be relevant.
- Ratings are given considering, the number of tweets, number of tweets everyday, retweets, likes and comments.
- There are almost 8500+ channels, only top 50 of each mention based and liquid ranking were considered.
- Liquid ranking feature can be added to a recommendation model as a layer, for personalise and dynamic recommendation.
- How Personalised: e.g. considering Twitter data, personal connections' following can be used as base of liquid ranking to get recommendations.
- How dynamic: Each feature used as base of liquid ranking can be seen as a timestamped transaction, hence the recommendation can be dynamic.

Appendix: Results

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	A	B	C	D	E	F	G	H	I	J	K	L
1	Channel	Mentions	Followers(*50k)	Relevance	Rank	Rank Liquid		Rank Mentions	Channel	Liquid Rank	Followers(*50k)	Relevance
2	@maxkeiser	811	9	**2**	1	73		18	@jack	13.026331	120	**2**
3	@stacyherbert	414	3	**2**	2	136		40	@elonmusk	13.005549	1348	**2**
4	@orangepillpod	382	1	1	3	871		12	@michael_saylor	11.527602	40	**2**
5	@bitcoinmagazine	312	38	**2**	4	12		10	@apompliano	9.5825747	26	**2**
6	@binance	288	134	**2**	5	53		113	@cynthiamlummis	9.4914364	2	**2**
7	@jamiecrawleycd	235	1	1	6	523		166	@brian_armstrong	9.1491218	20	**2**
8	@blockstream	219	4	**2**	7	135		126	@vitalikbuterin	9.0929092	58	**2**
9	@realvision	214	6	1	8	262		11	@udiwertheimer	8.6875413	3	**2**
10	@blmartin_07	207	1	1	9	3943		282	@bustarhymes	8.673775	76	**2**
11	@apompliano	184	26	**2**	10	4		54	@nayibbukele	8.174591	64	**2**
12	@udiwertheimer	180	3	**2**	11	8		41	@coinbase	8.1402214	84	**2**
13	@michael_saylor	173	40	**2**	12	3		4	@bitcoinmagazine	7.7117446	38	**2**
14	@liquid_btc	168	1	1	13	920		131	@danheld	7.7114306	10	**2**
15	@sebsinclair1989	162	1	1	14	858		73	@twobitidiot	7.7058154	5	**2**
16	@noshitcoins	148	1	0	15	2054		267	@balajis	7.7040598	12	**2**
17	@muneeb	147	2	1	16	**162**		62	@nic__carter	7.6399985	6	**2**
18	@stacks	138	2	1	17	653		102	@lopp	7.6398648	8	**2**
19	@jack	137	120	**2**	18	1		114	@sentoomey	7.56638	4	**2**
20	@coindesk	133	48	**2**	19	52		168	@cryptocobain	7.5649767	11	**2**
21	@excellion	129	4	**2**	20	93		129	@0xpolygon	7.31177	20	**2**
22	@alex_fights	129	1	1	21	3661		78	@ftx_official	7.2478364	7	**2**
23	@realdannynelson	125	1	1	22	3900		111	@solana	7.2425833	22	**2**
24	@tanzeel_akhtar	118	1	1	23	3899		27	@cz_binance	6.785631	92	**2**
25	@nikhileshde	118	1	0	24	3904		97	@prestonpysh	6.7450535	7	**2**
26	@petermccormack	118	9	1	25	**29**		232	@iohk_charles	6.7056342	17	**2**
27	@samuel_haig	115	1	0	26	2055		68	@peterschiff	6.6916368	12	**2**
28	@cz_binance	113	92	**2**	27	24		25	@petermccormack	6.6514253	9	**2**
29	@shapeshift_io	111	2	**2**	28	**702**		74	@jackmallers	6.6222773	5	**2**
30	@dylanleclair_	111	2	**2**	29	74		173	@ronwyden	6.5861694	11	**2**

Appendix: Results

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31	@grayscale	109	11	2	30	160	152	@uniswap	6.3641014	16	2
32	@coinmarketcap	109	82	2	31	58	81	@axieinfinity	6.3114437	16	2
33	@coindeskmarkets	108	2	2	32	#N/A	94	@sbf_alameda	6.2481915	1	1
34	@gladstein	107	3	1	33	44	184	@krakenfx	6.241188	22	2
35	@bitcoinerrorlog	105	1	1	34	804	46	@novogratz	5.828651	9	2
36	@by_defi	104	1	1	35	2057	332	@3lau	5.8286385	5	2
37	@coindanslecoin	103	1	1	36	2056	47	@wclementeiii	5.7774131	10	2
38	@godbole17	102	1	0	37	3901	121	@woonomic	5.7773537	20	2
39	@cryptoduality	101	1	0	38	2058	115	@erikvoorhees	5.7592437	12	2
40	@tether_to	99	4	2	39	291	147	@cathiedwood	5.7486197	24	2
41	@elonmusk	98	1348	2	40	2	574	@rleshner	5.7482297	2	2
42	@coinbase	95	84	2	41	11	72	@documentingbtc	5.7481805	13	2
43	@nvk	95	2	1	42	129	33	@gladstein	5.7481749	3	2
44	@ck_snarks	94	1	1	43	316	546	@zackvoell	5.7481391	1	2
45	@egreechee	93	1	1	44	3902	181	@microstrategy	5.7280375	3	2
46	@fluidvoice	93	1	0	45	5669	141	@chivowallet	5.7169218	3	2
47	@novogratz	92	9	2	46	36	169	@bitcoinbeach	5.7136333	1	1
48	@wclementeiii	89	10	2	47	38	116	@garygensler	5.7058662	5	2
49	@cheyenneligon	88	1	0	48	3903	103	@saifedean	5.6767554	4	2
50	@andrecronjetech	87	6	2	49	156	64	@adam3us	5.6767345	9	2
51	@joepompliano	87	7	2	50	199	19	@coindesk	5.6711941	48	2

Appendix: End Results

- **LIQUID RANKING CODE: https://github.com/xenvik/Recommendation-Model/blob/main/Liquid_Ranking.py**
- **RANK COMPARISON (BY MENTIONS AND LIQUID RANKING):** Final_Results.xlsx