NETWORK SCIENCE

Twitter vs. Amber Heard: A Network Science Approach to Analyze Tweets During the Depp - Heard Defamation Trial in 2022

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| **Abstract**  Twitter is one of the social media platforms where support and hate can be expressed. We analyzed Twitter data from Kaggle spanning the period January to April 2022 to analyze the tweets during the defamation trial of Johnny Depp, an American actor, and his ex-wife Amber Heard. Three networks were developed—the Tweet Network, the Hashtag Network and the User Network. Sentiment analysis of the Tweet Network revealed mostly negative sentiment for Heard. Community detection using the Louvain algorithm displayed support mostly for Depp. Classification of hashtags in the User network also showed support for Depp. Duplicate tweets and time series of account creation were also explored as possible signs of deliberate propaganda machinery.  **Keywords:** Defamation, Twitter social media analysis, Network Science |

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# **Introduction**

Social media has paved a way for individuals to let their opinions be heard or to sway the opinion of others. Twitter is one such platform where this melting pot of ideas meet. Trending topics of social significance in Twitter usually include those related to current events, politics and celebrities, among others. The case of Johnny Depp vs. Amber Heard, which culminated in April 2022, fascinated global media and outpouring of support or hate for these celebrities were seen in various social media sites including Twitter. Johnny Depp, a popular American actor, sued his ex-wife Amber Heard, for defamation over a The Washington Post op-ed written by Heard in 2018 that referenced sexual violence and domestic abuse (Rosenblatt et al., 2022).

Significance

This study provides a framework for analyzing trending topics using Network Science to  identify the presence of different network topologies and understand the characteristics and implications of these networks.

Related Work

Analyzing Twitter networks derived from users, tweets or hashtags have been of interest to researchers to uncover patterns and detect the presence of manipulation, echo chambers, bots and disinformation. Pacheco et al. (2021) uncovered coordinated campaigns in social networks by building a coordination network and looking at similarities between the identities, images, hashtag sequences, retweets and temporal

patterns of users. Guarino et al. (2020) used the case of the 2016 constitutional referendum in Italy to investigate the structure of communities and propaganda networks to infer polarization of users around a topic, identify users that propagate disinformation and analyze social clusters that played a central role. Khan and Michalas (2020) classified political Twitter users as trustworthy or untrustworthy using random forest and SVM classifiers with computed metrics for social reputation, tweet credibility, sentiment score and H-index core of retweets and likes as features. Zannettou et al. (2019) quantified the influence of state-sponsored trolls on news dissemination in social media platforms including Twitter. Shu et al. (2020) discussed that political disinformation is one of the areas where social media bots are active. Finally, Himelboim et al. (2017) proposed a conceptual classification of Twitter networks based on density, modularity, centralization and the fraction of isolated users as metrics and analyzed the information flow of these network categories.

Scope and Limitations

We used the ‘Twitter Data Amber Heard Social Network Analysis’ dataset on Kaggle (Amberhearddata, 2022) covering tweets made between January to April 2022. Only metadata of the tweets are available and the profile of the users were not disclosed. The dataset focused on studying how influence and the flow of disinformation affected Heard in social media. Thus, it excludes other contexts like promotion of her projects.

# **Data Extraction and Preprocessing**

We compiled three networks from a public dataset in Kaggle (Amberhearddata, 2022) consisting of Twitter metadata on tweets related to Heard and Depp posted in January to April of 2022. The Tweet network was built using individual posts as vertices and replies from one post to another as edges, thus forming a directed graph with vertices pointing towards the source tweet. The Hashtag network was compiled using the top 30 hashtags found in the dataset, along with their co-occurring hashtags as vertices. The frequency of co-occurrences in the same tweet then represented the weight of each edge in this undirected network, while the frequency of the tweet itself in the dataset was added as a node attribute. Finally, the User network was built using frequency of replies from one user to another as edge weights, and individual Twitter user accounts as vertices.

# **Results and Discussion**

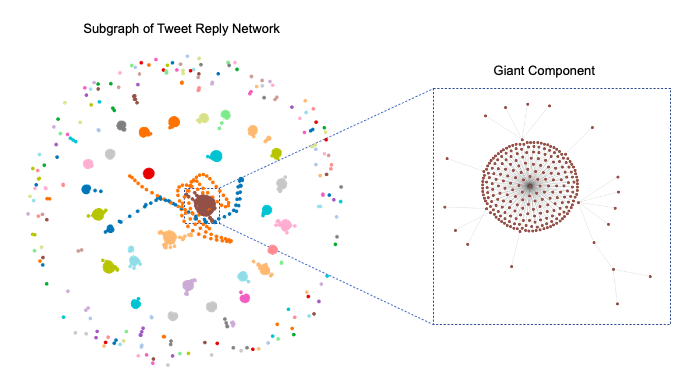
Tweet Network

The Tweet network is a graph with 553,733 vertices and 106,921 edges. The log-log plot of the degree (k) distribution, which is closely mirrored by the same plot for in-degrees (kin), indicates that the network is scale-free, implying preferential attachment for replying to tweets that gain visibility. The same cannot be said for the out-degrees (kout), which exhibit a binary distribution, following from the restriction that each tweet can reply to at most one other tweet.

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| Chart, scatter chart  Description automatically generated  Figure 1A | Chart, scatter chart  Description automatically generated  Figure 1B | Chart, bar chart  Description automatically generated  Figure 1C |

**Figure 1. Tweet Network Degree Distribution.**The network is scale-free as seen from the degree and in-degree log-log plots but exhibit a binary distribution for the out-degree.

The high proportion of nodes with kout=0 as well as the low network size relative to the network order immediately reveal that the graph is not connected, with numerous isolated nodes. Plotting a subgraph of the network including the giant component showed us three patterns of conversations in relation to the controversies surrounding Heard and Depp, namely: semi-viral tweets which spur numerous but short reply chains (one example being the giant component with its radial structure), long conversation chains, and small components representing tweets with zero or very few (typically at most 1 or 2) replies. No tweet went truly viral in the sense of inciting thousands of replies within the study, with the giant component having 261 nodes. Regardless of the component structure, clustering remains at zero for all tweets, again stemming from the inherent restriction on the social media platform that a tweet cannot reply to multiple posts simultaneously.



**Figure 2. Tweet Network Subgraph Including the Giant Component.** The subgraph reveals three patterns of conversations surrounding the controversies between Amber Heard and Johnny Depp.

The component size distribution aligns with the degree distribution, indicating few long conversation chains, and that component orders are proportional to the degree of their central hub (for components with a radial structure).

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| A picture containing histogram  Description automatically generated | *Number of components:* 446,812  *Components with 1 node (posts with no replies):* 376,306  *Components with 2 or more nodes (posts with replies):* 70,506  *Mean component order*: 1.239  *Order of Giant component*: 261 |

**Figure 3. Tweet Network Component Order Distribution.**  The plot indicates few long conversation chains.

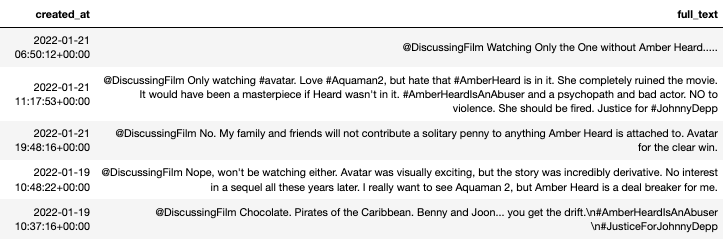
We then proceeded to perform sentiment analysis on the tweets in the network, using Twitter-RoBERTa-base for Sentiment Analysis obtained from Hugging Face. Sentiment analysis is a Natural Language Processing (NLP) technique that classifies whether text has positive, negative, or neutral sentiment (Gupta, 2018). The model is RoBERTa-base and was fine-tuned for sentiment analysis using the TweetEval benchmark and trained on 124 million tweets from January 2018 to December 2021 (Hugging Face, 2021). RoBERTa is a robustly optimized technique for pretraining NLP systems that improves on Google's self-supervised method, Bidirectional Encoder Representations from Transformers, or BERT. BERT is a ground-breaking method that obtained cutting-edge results on a variety of NLP tasks by using unannotated text from the web rather than a language corpus tagged particularly for a certain task. RoBERTa extends BERT's language masking method, in which the system learns to detect purposely hidden text segments inside otherwise unannotated language instances (Meta AI, 2019).​​

Owing to computational limitations in analyzing a network of this size, we focused on the giant component, with 261 nodes and 260 edges. It has a radial structure that is centered on a node which represents a tweet by user @DiscussingFilm, posted last January 19 asking about preferences between two movies to be released later this year, ‘Aquaman and the Lost Kingdom’ and ‘Avatar 2.’ Unlike most Twitter accounts,  @DiscussingFilm does not contain personal thoughts but instead is a “source for quick reliable news and ... content,” mostly concentrated on films and television series, boasting a “[h]ome for healthy and liberating discussion.”



**Figure 4. Central Post in Tweet Network Giant Component.** The central node represents a tweet asking about movie preferences between two movies, one starring Amber Heard.

Sentiment analysis was performed on the tweets comprising the giant component in reply to the original post, and it was found that despite the relative harmlessness of the post and Twitter account, it incited largely negative sentiments against Heard. The overall negative sentiment in the component is depicted on the graph in Figure 6, but this does not prevent some replies of positive tweets, possibly for humorous effect.



**Figure 5. Sample Tweets in Giant Component.** The original tweet generated a network of negative sentiments against Amber Heard.

It can also be noted that replies outside of the radius structure tend to be mostly of opposite sentiments. This may account for the counter arguments and attempts of influence between users.

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**Figure 6. Giant Component of the Tweet Reply Network with Sentiment Classification.** Most nodes exhibit negative sentiments toward Amber Heard, based on the pretrained NLP model Twitter-RoBERTa-base for Sentiment Analysis.

## Hashtag Network

The Hashtag network with its edges defined by co-occurring hashtags on the same tweet is effectively a projection of the Tweet-Hashtag bipartite network. We limited the network to the top 30 hashtags and their co-occurring hashtags, to focus on the most relevant hashtags and reduce noise, similar to Guarino et al (2020). This consequently modifies the distribution to lessen both the number of high-degree, low-frequency hubs while also eliminating tens of thousands of links to low-degree nodes, as evident from the comparison in Figure 7.

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**Figure 7. Hashtag Network Degree Distribution Comparison (All Hashtags vs Top 30 Hashtags and Co-Occurrences).** Nodes are reduced, modifying the degree distribution by focusing on top 30 hashtags.

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**Figure 8. Hashtag Network Clustering Distribution.** Nodes tend to have very high or very low clustering.

The resulting Hashtag network based on the top 30 tweets formed a fully connected undirected graph with 20,689 vertices and 55,106 edges. Figure 8 shows how the clustering distribution is bimodal, with numerous hashtags being highly clustered, i.e. used frequently in conjunction with other popular hashtags, as well as a similar number of less-used or poorly connected hashtags.

Given the connectedness of the graph and its clustering distribution, we sought to identify communities of hashtags that were often used in the same tweets. Applying the Louvain method provided 14,836 communities with modularity of 0.119, but of these communities only 6 comprised more than one node (Figure 9). These were considered to be the communities of interest, and we labeled them as Communities A to F, accordingly, and plotted their subgraph as seen on Figure 10.

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**Figure 9. Distribution of Nodes in Hashtag Communities.** Only 6 communities have more than 1 node.

The low modularity indicates weak division among the communities overall. Interpreting the communities by looking at their member-hashtags seem to confirm this, as most of the hashtag communities sided with Depp, albeit expressed in different forms. These ranged from fandom, petitions to support his films or boycott studios in alignment with Depp’s interest, or outright misogyny against Heard. Only Community F was in support of Heard, and this was the smallest among the 6 communities with only 14 hashtags, indicating rare co-occurrence of these hashtags with others circulating in Twitter. This accounts for the difficulty in locating the nodes in Figure 10.

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**Figure 10. Hashtag Network Subgraph for Communities A to F.** There is weak separation among the communities, which are dominated by Community A.

**Table 1. Top Hashtags per Community based on the Frequency Node Attribute.** Most themes show support for Depp

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| **Community** | **Top Hashtags** | **Themes/Patterns** |
| A  4721 nodes | BoycottWarnerBrothers, JusticeForJohnnyDepp, BoycottFantasticBeasts3, AmandaHeard, AmberHeardIsTheRealAbuser, JusticeForJohnnyDeppVirginia2022, JohnnyDepp, AmberHeard, BoycottWB, PaulBettany | Support for Depp  Boycott of WB\* |
| B  942 nodes | amberheardperjury, AbuseHasNoGender, SpreadTheWord, AmberHeardIsAnAbuser, AmberHeardIsALiar, MenToo, AmberHeardIsADangerToOthers, AmberHeardIsAProvenLiar, karma, AmberHeardDeservesPrison | Dislike for Heard |
| C  288 nodes | JohnnyDeppIsInnocent, JohnnyDeppisInnocent, IStandWithJohnnyDepp, WeAreYourWarriors, JusticeforJohnnyDepp, IAmADeppWarrior, JohnnyDeppDeservesJustice, LoveProtectSupportJD, NoJohnnyNoMoney, ISupportJohnnyDepp | Support and fandom for Depp |
| D  278 nodes | johnnydepp, johnnydeppisinnocent, depphead, justiceforjohnnydepp, ДжонниДепп, SundayThoughts, amberheardisaliar, amberheardisanabuser, defamation, justiceforjohnnydeppvirginia2022 | Support for Depp,  Mostly lowercase tweets |
| E  66 nodes | StopTheShock, MinamataFilm, Minamata, JusticeForMinamata, TheAcademy, minamata, minamatafilm, Oscars, love, Oscar | StopTheShock movement\*\*, Minamata film/disease, Oscars |
| F  14 nodes | JohnnyDeppisawifebeater, HappyBirthdayAmberHeard, IStandWithAmberHeard, misogyny, JUSTICEFORAMBERHEARD, JohnnyDeppIsAnAbuser, JohnnyDeppisarapist, freeamberheard, MentalHealthAwarenessMonth, justiceforamberheard | Support for Heard |

*\* Warner Bros. Studios cast Amber Heard in the film “Aquaman” and removed Johnny Depp from the cast of the “Fantastic Beasts” franchise, triggering petitions for boycott (Nugent, 2020)*

*\*\* StopTheShock is a movement to ban electric shocks to punish people with disabilities, typically neurotypical disorders such as autism (American Association of People with Disabilities, 2018). This is possibly conflated with Minamata disease, a neurological disease from mercury poisoning, as featured in a film “Minamata” starring Depp (Minamata (2020), 2021).*

A comparison of Networks C and F on Figures 11 and 12 respectively highlights the stark difference in the level of diversity of support for the two celebrities.

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**Figure 11. Hashtag Communities C.** This hashtag community shows diverse expressions of support for Depp.

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**Figure 12. Hashtag Communities F.** This hashtag community centered around #IStandWithAmberHeard shows little diversity in expressions of support for Heard.

Finally, we constructed a graph of only the top 30 hashtags using the Fruchterman-Reingold layout at 100 iterations, given the ability of the layout to visualize the strength of clustering within the subgraph (Hansen, et al. 2011) The graph shows that #IStandWithAmberHeard, the only hashtag in the list in clear support of Heard, was the farthest node with stronger clustering among the rest.

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**Figure 13. Top 30 Hashtags.** The #IStandWithAmberHeard hashtag has greater distance from other hashtags, which are more tightly clustered and are largely in support of Depp.

## User Network

We built the User network with 203,498 vertices and 81,321 edges, finding the network analogous to the Tweet network in that replies from one user to another comprise the edges of the directed graph. The key difference is that one user may reply to multiple users, allowing for a non-binary out-degree distribution, as well as clustering. Figures 14 and 15 show the scale-free degree distribution, and the clustering distribution, respectively.

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| A picture containing scatter chart  Description automatically generated  Figure 14A | Scatter chart  Description automatically generated  Figure 14B | Scatter chart  Description automatically generated with low confidence  Figure 14C |

**Figure 14. User Network Degree Distribution.** The network is scale-free as seen from the degree, in-degree, and out-degree log-log plots.

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**Figure 15. User Network Clustering Distribution.** The nodes exhibit a wide range of clustering, implying the presence of communities.

While there still remain a number of isolated users, the opportunity for interaction with multiple nodes in the User network allowed for the formation of a large giant component, consisting of 152,145 nodes out of the 203,498 total users. We again plotted the component order distribution with the giant component as a clear outlier, as well as a subgraph of the network (Figures 16 and 17). We observed how the giant component is surrounded by many smaller, disconnected components with chain-like and radial structures. For the giant component, we show only the 10-core to overcome computational limitations in rendering the plot.

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| Icon  Description automatically generated | *Number of components:* 152,145  *Components with 1 node (users with no replies):* 137,183  *Components with 2 or more nodes (posts with replies):* 14,962  *Mean component order*: 1.338  *Order of Giant component*: 32,183 |

**Figure 16. User Network Component Order Distribution.** The giant component is an outlier in the component order distribution

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**Figure 17.  User Network Subgraph Including the 10-Core of the Giant Component.** The User Network consists of one giant component of interacting users surrounded by smaller chains and groups of users

Given that users may also reply multiple times to the same user, we opted to use the number of such replies for each directed user pair as edge weights attributes, rather than creating parallel edges, to aid in community detection. 267 communities were identified within the giant component using the Louvain Method, with modularity of 0.591. Due to limitations in computational power, we opted to plot sample communities rather than the entire giant component.

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**Figure 18. Distribution of Nodes in User Communities.** The number of nodes per user community skews heavily right.

The users were then classified into 5 categories based on the hashtags used, referring to the top hashtags previously identified. Out of 182,538 users, 119,183 did not use any hashtags. 56,767 were classified as pro-Depp, 6,214 users were neutral, 357 used hashtags that were indicative of support for both Depp and Heard, and only 17 users were classified as pro-Heard. It can be observed in Figure 20 that the randomly selected communities are dominated by accounts that do not utilize hashtags, followed by pro-Depp accounts.

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**Figure 19. User Classifications based on Hashtags.** Most users don’t use hashtags when tweeting, but those that do mostly use hashtags that are supportive of Depp.

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Fig. 20A

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| Fig. 20B | |
| **Fig. 20. Sample Communities in the User network.** Based on hashtags, the user network is dominated by supporters of Depp. | |

## Possible Propaganda

We also looked at possible propaganda or disinformation from the three networks by looking at some features, similar to the approach of Khan and Michalas (2020). Possible indicators include the presence of duplicate tweets and spikes in account creation that may be attributed to bots or paid user activity.

After classifying tweets as pro-Heard or pro-Depp based on hashtags, we found 12 out of 2,091 pro-Heard tweets (0.57%) that were duplicated. These all comprised the lone hashtag #IStandWithAmberHeard, with no additional text, thus providing little context as to whether the tweets are organic.  11 of the tweets were tweeted by the same user named “justiceforamber” and the other was tweeted by the user named “hotelshrimp”. Meanwhile, of the 495,522 tweets found that clearly supported Depp based on the hashtags used, 54,623 or 11.02% were duplicates, some of which were lengthy tweets using emojis and special characters (example on Figure 21). While the proportion of duplicate pro-Depp tweets may appear inauthentic, further investigation still be performed to see if tweets were posted by bots or social media trolls to influence the public opinion on the judgment of Depp v. Heard hearing.



**Figure 21. Sample Duplicate Tweet from Pro-Johnny Tweets.** Duplicated tweets were posted days apart, with lengthy use of emojis and special characters

Further circumstantial evidence of deliberate propaganda in favor of Depp was the timeline of user creation, with the number of new accounts peaking at the end of April just when the testimonial of Depp ended.

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**Figure 22. Timeline of New Account Creation, Jan-April 2022.** User creation peaked on April 25 when Depp concluded his testimony

# **Conclusion and Recommendations**

Social media has a big role to play in shaping the opinions of the society. This study demonstrated the use of network science in analyzing tweets by building three networks - the Tweet Network, the Hashtag Network and the User Network. Classic network statistics such as degree distribution and clustering distribution were used to analyze the network topology. Sentiment analysis on the Tweet network showed mostly negative sentiment for Heard, Community detection using Louvain algorithm for the hashtag network revealed mostly support for Depp, and polarity of users based on their hashtags showed support for Depp. Initial work on classifying disinformation against Heard was also explored by looking at duplicate tweets and user creation activity, which may be characteristics of social media bots.

Possible Use Cases

This type of analysis lends well to analyze leanings of users for any topic. This can be used by political analysts, sociologists, publicists in having a data driven approach to identify support or opposition  for a particular cause or person.

Future Work

This dataset only looks at a section of time and only one social media platform. Evaluation of user behavior and hashtags across different platforms can be compared, and temporal analysis of the network. Moreover, a correlation of the time series analysis between timing of user creation and negative posts against Heard may unearth additional information that can inform of propaganda proliferation, presence of social media bots and identification of troll accounts for malicious intents.

**Availability of data and materials**

The datasets used are available at Kaggle [16]. Jupyter notebook codes are available from the corresponding authors on reasonable request.

**Competing interests**

The authors declare that they have no competing interests.

**Funding**

Not applicable

**Author’s contributions**

The authors compiled the network from available data and created all network visualizations. All authors read and approved the final manuscript.

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