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Decentralized Networks Growth Analysis: Instance Dynamics on Mastodon

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Abstract. Federated social networks have become an appealing choice as alternatives to mainstream centralized platforms. In the current global context, where the user's activity on various social networks is monitored, influenced and manipulated, alternative platforms that offer the possibility of owning and controlling one's own data are of great importance. Mastodon stands out among decentralized alternatives in the fediverse.

In this study, we conduct a time-based dynamics analysis of Mastodon instances within a specific period. Our results show a growth pattern of instances in terms of accounts in certain periods of time, and due to social events, reinforcing our assumption of it being already trusted as a decentralized platform. Our work holds significance in the wider context of studying and understanding the adoption and evolution of decentralized platforms as ethical alternatives to Big Tech platforms.

Keywords: social networks · fediverse · Mastodon · decentralized systems · privacy in networks

1 Introduction

The *fediverse* is a network of networks of federated servers, i.e., that operate in a decentralized manner. It mostly uses open-source software, and ActivityPub as a communication protocol, that is also a World Wide Web Consortium (W3C) [12] standard. Networks in the fediverse have come to the attention of the general public mostly in recent years, as they represent more ethical and privacy-respecting alternatives to centralized Big Tech networks. Monitoring, profiling, and privacy issues in general have existed on networks centrally controlled by companies, as data collection, and (third-party) data sharing is their main business model. Decentralized networks are seen as more ethical because they give the opportunity of owning and controlling one's data, there is no data collection and sharing for profit. Thus, they are alternatives that currently respect the freedom from non-interference, as Coeckelberg talks about the same freedom issues in general about AI in [3]. This study is focused on the most popular and growing platform on the fediverse, Mastodon.

Mastodon uses the aforementioned ActivityPub protocol, which provides a client-to-server API for content management and a server-to-server API. The

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protocol utilizes the term "actors" to represent users who have accounts on servers. Servers are often called "instances". Each user has an *inbox* for incoming messages and an *outbox* for outgoing messages. Within the client-to-server architecture, notifications are published to the sender's outbox, and to view them, the actors must request access. In federated server settings, notifications are dispatched directly to the intended recipient's inbox, and only this setup offers subscription functionalities. Moreover, the sender needs a followers list, and non-federated actors must know all senders. This fosters a unique inter-server communication environment where data is stored and shared selectively based on actor type and server federation [6].

Mastodons software is free and open-source. A user can establish an independent Mastodon instance, or register on one of the instances that offer account registration, and accounts on different instances can communicate with each other through a *federated timeline*. Three types of feeds can be accessed: a) Home feed, where the user can see posts from people they follow, b) Local feed, where the user can see posts from all people from the specific instance they belong to, c) the Federated feed, where the user can see posts from all other instances of Mastodon [8]. As opposed to relying on recommender algorithms to track users' behaviour and show posts accordingly for increasing engagement as is in centralized platforms, these three types of feeds offer a more randomized selection of posts. Additionally, there is an Explore feed where the user can view the most popular posts by users in various instances. While most Mastodon instances are public, there are also private ones, where the owner of the instance can admit people to the server based on their discretion. Mastodon provides functionalities, such as posting, replies, favourites, bookmarks and hashtags. Mastodon saw a spike in popularity around *November 2022*, after the acquisition of Twitter and the switch of ownership in October 2022, a change that seems disliked by Twitter users [21]. The number of unique users on Mastodon almost doubled since the Twitter acquisition, from just a little less than 5 million in early November 2022 to 8.7 million in March 2023 [19]. We also prove this growth for some instances in this work. Our motivation is to study the adoption of these decentralized alternatives and the growth rate, investigating the following main research questions:

– what insights about time-based dynamics and account creation growth-rates can we identify on Mastodon?
– what insight do the centrality metrics give us regarding influential accounts on Mastodon?
– what initial insight can we get regarding group and community structure on Mastodon?

In this work, we have analyzed the effects of the recent influx of users and instances that affect the dynamics and structure of Mastodon, motivated by the opportunity to investigate how a social networking platform evolves during a period of rapid growth. We report a longitudinal analysis of several Mastodon instances and our insights into the structure of the largest Mastodon instance. The structure of the paper is as follows. In Sect. 2 we discuss related work, we elaborate on our dataset and methodology in Sect. 3, Sect. 4 presents our analysis and results, and we conclude the paper, also discussing future work in Sect. 5.

2 Related Work

Research on Mastodon instance dynamics has been scarce but some recently conducted work exists since it's a fairly new network and has existed since 2016. We will discuss some relevant work next.

2.1 Network Analysis of Mastodon

Zignani et al. conducted one of the first large-scale studies on Mastodon users in 2018 [23]. The research focused on analyzing the existing dataset from Mastodon at the time and studying the network growth and relationships between instances. They found differences with mainstream social media platforms, as users tend to follow other users and instances based on interests, rather than popularity. In 2021, more extensive research has been conducted by La Cava et al. in [8]. They built upon Zignani's datasets and analyzed the data from that time, as Mastodon grew five times since the last big research on large sets of data. This new study reinforces Zignani's findings and provides further insight into connections between users from multiple instances within the fediverse. La Cava researched network instances of Mastodon on a macroscopic and mesoscopic level and analyzed how these instances evolve. This study concluded that Mastodon has achieved "structural stability and a solid federative mechanism among instances" [8]. In 2022, La Cava et al. followed up their research by studying the relations and roles of the users in Decentralized Open Source Networks (DOSNs) [9]. They state that links between users on Mastodon are interest-based and not artificially stimulated, resulting in a decoupled network. The researchers found that there are two main roles the users can have on the platform: bridge or lurker. A bridge user is someone who is active in more than one instance and acts as a bridge between these instances. A lurker user is someone who rarely contributes on a Mastodon instance, but they are considered active users as they stay online on the platform and "consume information". The aforementioned works report positive conclusions regarding Mastodon, such as its ability to enable community autonomy, technical development as a social enterprise, quality engagement, and niche communities [24].

2.2 User Migration from Twitter to Mastodon

Zia et al. analyzed the migration of users from Twitter to Mastodon in the weeks of the Twitter acquisition. They found out that new users have mostly registered on a popular instance, such as mastodon.social. They explain this as a metric for centralization in Mastodon, as 96% of users are registered in the top 25% of biggest instances [22] and users do this because they are used to networking in large social media platforms, like Twitter. Moreover, they state that only a fraction of users who migrated to the largest instance of Mastodon will migrate again to a more specific instance based on their preferences for the topic. Furthermore, Zia et al. identify the two main reasons why a user would leave Twitter: 1) Ideological reason - the user does not agree with the new company's actions; 2) Following account reason - people they follow migrated there already. In 2023, La Cava et al. studied the user migration from Twitter to Mastodon using the same timeframe examined by Zia et al. The authors focus on the structure of the social media platform, the engagement of community members, and the language they use to communicate, all from the perspective of Twitter and what drives a Twitter user to migrate to Mastodon. The results are surprising, as they discovered that users networking in sparse communities are more likely to migrate to Mastodon [7]. Additionally, users who engaged in conversations on Twitter regarding popular migration hashtags, such as #TwitterMigration, have a greater tendency to migrate to Mastodon. The authors in [22] have found that one of the reasons for people adopting Mastodon is related to data control, because it provides the ability to control personal data, and consequently also more control over the use of personal data by (third-party) data mining activities, as opposed to Big Tech platforms, in which users have no control over their data, except for what is provided by legislation such as e.g., GDPR in the EU. Centralization tendencies in the context of account distribution on Mastodon are studied by the authors in [11], who report that 96% of users join 25% of the largest instances.

3 Methodology

3.1 Dataset

To comprehensively analyze Mastodon, a thorough data collection strategy was essential. This involved data crawling, which facilitated the gathering of extensive and meaningful information about both accounts and instances of Mastodon. To accomplish this, a series of software crawlers were developed using C#, which were designed to interact with the Mastodon REST APIs [13]. It was essential to select a method that would permit access to the necessary data without the risk of modifying the content of the server. Upon execution of the GET methods, the resulting data was received in JSON format. The Mastonet package [10], a .NET library was utilized, for efficient handling of the Mastodon API methods in C#, as it's specially designed to facilitate easy interaction with Mastodon APIs. The data was collected between 15th of April to 7th of June for the 5 instances, and the data for single-user instances was collected on 6th of August.

3.2 Ensuring the Validity of Collected Data

To ensure the validity and reliability of this research, cautious data cleaning and pre-processing steps were applied post-crawling. This included handling missing or inconsistent data, such as null values, and formatting the data appropriately for further analysis. The gathered data involving certain account information, such as user ID, username, account name or display name is deliberately excluded from this work in accordance with privacy rules and our principles in protecting user identities. Even IDs were anonymized by adding noise. This approach is designed to enhance the transparency of our investigative results while ensuring that the privacy of a user is maintained. We give utmost importance to privacy, so we are not only guided by GDPR but with privacy as a human-rights principle. Our data served for an in-depth longitudinal examination of the evolution and progression of Mastodon as a DOSN. Table 1, shows a summary of the dataset:

Table 1. Summary of data collected from all five instances

Mastodon instance	Type of data collected	Amount of data collected
mastodon.social	general account information	87,210 accounts (8% of userbase)
mastodon.social	account following information	864,588 accounts
mastodon.cloud	general account information	125,329 accounts (50% of userbase)
mstdn.social	general account information	30,728 accounts (15% of userbase)
mastodon.online	general account information	23,885 accounts (13% of userbase)
mastodon.world	general account information	21,608 accounts (13% of userbase)
mastoturk.org	general account information	40 accounts
single-user instances	general instance information	4908 instances

4 Dynamics Analysis and Results

This section investigates the analysis of gathered data from multiple Mastodon instances. Python was utilized for the analysis of the dataset. The NetworX and NetworKit libraries were used for analyzing the mastodon.social instance, focusing on gaining insights into centrality metrics, communities, and groups. NetworkX is a library that specializes in complex network and graph creation, manipulation, and analysis [4]. NetworKit is a comprehensive open-source toolkit that specializes in high-performance network analysis [20]. The analysis of the data was conducted on a personal computer, and Habrok - the high-performance computing cluster of the University of Groningen [2], which proved efficient in performing large-scale network analysis.

4.1 Account Number Dynamics

This section navigates through various data points acquired by evaluating the dates of account formations on numerous instances across different time markers/checkpoints. This investigation offers insight into the evolution, adaptation, and patterns of each five Mastodon instances from which general account information has been gathered, as explained in Table 1. The visualization of the data throughout this study has been implemented using Python, specifically utilizing the Matplotlib [5] and Pandas [14] libraries. The graph in Fig. 1, offers a visual representation of the evolution of instances over the years since the year each instance was created. We found that there was a growth peak across all 5 instances in 2022. However, 2023 was marked by a big contraction for all instances, except mastodon.social. The latter kept almost a constant growth of users over the first 5 months of 2023. Figure 2 shows that all instances experienced user growth in November 2022, while for mastodon.social this was not significant. Furthermore, we see a continuous decrease in new accounts following December 2022 for all instances going into 2023.

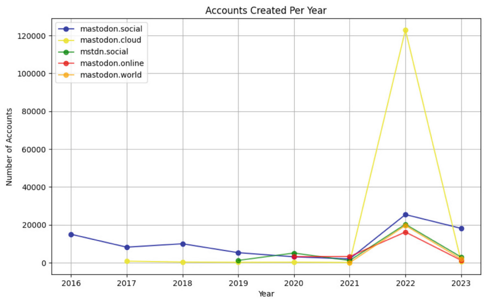

Fig. 1. Yearly evolution of the number of registered users on 5 instances

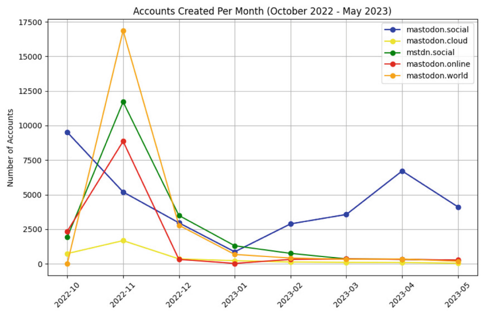

Fig. 2. Monthly evolution of the number of newly registered users on five instances after the Twitter ownership change

4.2 Network-Influence Based on Centrality Metrics

We applied the three well-known centrality metrics to our dataset: Degree Centrality, Closeness Centrality and Eigenvector Centrality. The subsequent analysis derived from each centrality measure facilitated the identification of accounts of high relevance and influence within the network, specifically those ranking in the top 20 of each list [17]. The centrality algorithms were applied to 87.210 mastodon.social accounts, that have a total following of 864,588 accounts, from 18.847 Mastodon instances. The Degree Centrality quantifies the number of connections or neighbours for an account. The account's centrality increases with its number of connections. Accounts with a high degree centrality are typically those exhibiting high levels of activity or interaction within the network [17]. Closeness Centrality offers another perspective on node significance within a network, emphasizing the 'distance' between nodes rather than just the quantity of connections [18]. The algorithm that was used for this metric is calculated as the inverse of the average of the shortest path between a vertex and all other vertices. Nodes with high Closeness Centrality have shorter average distances, enabling efficient information dissemination [17]. Regarding the research on mastodon.social, nodes with high Closeness Centrality play crucial roles in rapid information spread. Proximity to other nodes aids effective communication. Higher Closeness Centrality implies greater centrality within the digital community [17]. Eigenvector Centrality measures the importance of a node by the quantity and quality of its connections. It accounts for connections' centrality. High Eigenvector Centrality involves connections with other highly central nodes, amplifying an account's significance [18]. Accounts exhibiting high Eigenvector Centrality meet at least one of the following criteria: they have many connections, they are connected to important neighbours with high centrality or both.

Centrality Analysis Results. Through an evaluation of the results from these centrality measures, we determined that a group of six accounts matched consistently across all three centralities, indicating their importance within the network. They were present in the top 20 accounts across all centrality measures. The frequency of these accounts across all three centrality measures acknowledges their significance within the mastodon.social network, and signifies considerable influence.

Figure 3, shows the results of the centrality metrics. The six accounts that match across all centralities are labelled as 'account number 1' through 'account number 6'. In order to protect the privacy of an account and adhere to the imposed security guidelines, as explained in Sect. 3.2, the original user IDs of the accounts within the top 20 of all centrality metrics are not shown.

4.3 Community Analysis Using the Louvain Algorithm

We also conducted a community detection analysis, utilizing the Louvain algorithm. The Louvain algorithm was developed for discovering communities in large networks with high modularity partitions. Additionally, it helps reveal the complete hierarchical community structure inherent in the network, providing different views in community detection [1]. The Louvain algorithm was applied to

Degree Centrality

Rank	Account	Centrality Value	In-Degree
1	account number 1	0.05878297961917077	337195
2	user ID	0.023555755522578988	582
3	account number 2	0.01990430112874702	807022
4	user ID	0.017510094415021275	25515
5	user ID	0.017080987801111978	1926
6	account number 3	0.013903748263621821	169788
7	account number 4	0.011863467759751188	23394
8	account number 5	0.01137884330900187	264972
9	user ID	0.01078665304937502	1178
10	user ID	0.00992265671355225	2042
11	user ID	0.009473887532428778	3807
12	account number 6	0.009402176993177089	410747
13	user ID	0.009249502941867042	2401
14	user ID	0.009044780918519478	7820
15	user ID	0.008962660784860285	1765
16	user ID	0.008881697272801928	1461
17	user ID	0.00887938402960026	421
18	user ID	0.008797263895941067	2527
19	user ID	0.00872324011348771	2275
20	user ID	0.008385506606044273	1709

Closeness Centrality

Rank	Account	Centrality Value
1	account number 1	0.4830497522156526
2	account number 2	0.4254915672022477
3	account number 6	0.3906102067421265
4	account number 4	0.38697401004409443
5	account number 5	0.3867693391239043
6	user ID	0.38654241124480465
7	user ID	0.38632662733303774
8	account number 3	0.3819866920727121
9	user ID	0.38146678687071084
10	user ID	0.38130742412610585
11	user ID	0.38121072711547593
12	user ID	0.38078466799837224
13	user ID	0.3804126258188334
14	user ID	0.3803086846502627
15	user ID	0.37863192013191443
16	user ID	0.3786224663998586
17	user ID	0.37691004192633143
18	user ID	0.37614128596552054
19	user ID	0.37577858442331047
20	user ID	0.375318611748689

Eigenvector Centrality

Rank	Account	Centrality Value
1	account number 1	0.1576459071285379
2	account number 2	0.113727031078251
3	user ID	0.0937611080202121
4	account number 6	0.09074283390580973
5	user ID	0.08070474187095202
6	user ID	0.07669990577372751
7	account number 5	0.07635074129558776
8	account number 4	0.07467908760428067
9	account number 3	0.07445223401460625
10	user ID	0.07440618957475256
11	user ID	0.07008762414775739
12	user ID	0.06943184064843247
13	user ID	0.058680700909157925
14	user ID	0.058000711931680285
15	user ID	0.05733213869387007
16	user ID	0.05687037727168223
17	user ID	0.05639234633002446
18	user ID	0.056128267983078066
19	user ID	0.055991941180353416
20	user ID	0.05495721225861871

Fig. 3. Centrality metrics results

the account following information dataset, which has a total of 864,588 accounts, from multiple Mastodon instances.

Results of the Community Analysis. The results of the community analysis with the Louvain algorithm, concluded that there are 98 communities in the gathered data, which includes all the following accounts from the collected source users. Of the 98 communities, the community with the highest number of nodes has 236.477 nodes. Apart from this, many communities have below 100 nodes, the smallest ones have 2 nodes. To gain more insight into these communities a filter was applied based on several nodes, keeping only communities with more than 100 nodes. The results show 37 communities. From an initial dataset of 87.210 accounts from mastodon.social, we have found that users registered on it belong to communities pertaining to 18.847 unique instances, showing a big diversity of communities, as shown in Table 2. These results show that the users of mastodon.social are not stuck inside one instance, but they want to see posts and read opinions from users with different backgrounds on different instances. Within those 18.847 instances, all five instances from which we collected general account information are shown in Table 3, within the top 15 most popular instances in the results of the community analysis. The 6 accounts that appear within the top 20 of all centrality metrics as explained in Sect. 4.2 were searched within the obtained communities. The account that has the highest values among all centrality metrics, referred to as account number 1, belongs to the largest community. Furthermore, four users, namely account number 3, 4, 5 and account number 6 all belong to the second largest community, which has 160.374 nodes. The user referred to as account number 2 belongs to the third largest community, which has 104.886 nodes. These accounts belong to well-known people, such as the founder of Mastodon, a famous book author, a well-known Star Trek actor, a Washington Post tech reporter and the official Mastodon account. These accounts are influential based on centralities and community analysis.

Table 2. Type and Count of instances

Type	Count
Number of unique instances	18.847
Number of nodes	864.588
Number of mastodon.social nodes	321.717
Number of Non-mastodon.social nodes	542.871

Table 3. Instance and Count

Instance	Count
mastodon.social	321.717
mstdn.social	25.494
mastodon.online	19.245
mas.to	16.670
mastodon.world	14.387
fosstodon.org	9.387
pawoo.net	9.067
infosec.exchange	9.025
hachyderm.io	8.166
mastodonapp.uk	7.618
mstdn.jp	7.329
mastodon.cloud	7.240
troet.cafe	6.704
mastodon.lol	6.580
mastodon.art	6.412

4.4 Following Group-Based Analysis

This section illustrates the analysis of user groups present within the collected data from the mastodon.social platform, focusing specifically on the interaction patterns captured in the 'following' account data. The dataset that was analyzed is the account following information dataset, which has a total of 864,588 accounts, from multiple Mastodon instances.

Initially, the structure of the dataset represented directed graphs, where each edge (source_id and target_id pair) corresponds to a 'following' relationship. It is important to note that in the original context, not all 'following' relationships are mutual. Out of an aggregate of 8.36 million edges in the dataset, 718.824 edges were extracted that represent associated 'following' relationships, yielding 359.412 pairs of nodes. This subset, accounting for approximately 8.6% of the total number of edges, is the primary focus of this section of the analysis.

Results of the Analysis of Groups. The dataset was transformed into multiple undirected graphs, each edge now signifying a mutual 'following' relationship between two nodes. This transformation facilitates the examination of 'cliques' within the collected data. The clique algorithm was applied only to undirected graphs with more than 2 nodes. These groups are characterized by a high density of internal connections, that are often of significant interest in the exploration of social dynamics, influence spread, and community detection. The results are shown in Table 4 Moreover, the top 20 nodes manifesting the highest frequency within the identified cliques were further isolated. The node exhibiting the greatest frequency appears in 1.338.364 cliques, which constitutes 63% of all discovered cliques and the node occupying the 20th position in this ranking appears in 483.960 cliques, corresponding to 23% of all cliques. A particularly fascinating discovery within this set of top 20 nodes is that all nodes represent users from a

Table 4. Summary of the group analysis

Type	Count
Total number of undirected graphs	443
Number of undirected graphs with more than 2 nodes	109
Size of the largest graph	49.399
Total number of cliques	2.130.032
Average number of cliques in graphs with more than 3 nodes	19.541,577981651375
Size of the largest clique	27

specific country who are active on mastodon.social. However, none of these users appears in the maximal clique of 27 nodes identified in the analysis. According to Netblock, a globally recognised internet monitor operating at the intersection of digital rights, cybersecurity, and internet governance, several social media platforms, such as Twitter, Facebook, and Instagram [15] were limited at the specific country point when we saw this peak. Upon conducting more research, there have been found no indications of any such restrictions imposed on the use of Mastodon. These findings suggest that a substantial number of tightly-knit user groups from the specific country have been active on mastodon.social until the spring of 2020. It is highly plausible that these groups migrated from the aforementioned restricted platforms, leveraging mastodon.social as an alternative platform. We do not want to reveal the specific country, for security reasons, but it is clear that at the point we saw the spike, the use of other platforms was restricted due to political reasons.

4.5 Analysis of Turkish Accounts

Following our discovery of users from a specific country described in Sect. 4.4, we decided to further pursue detecting groups of users from a certain country around a specific event. Thus, we looked into users from Turkey following the earthquake that occurred in February 2023. We retrieved 120 Turkish users over 6 instances, including the five initial instances and mastoturk.org. This natural event happened on the 6th of February, and 2 days after the earthquake, Twitter was restricted in Turkey [16]. Indeed, we found that there was a number of newly registered Turkish users on Mastodon, shown in Fig. 4. Firstly, there is the November surge in new users, because of the takeover of Twitter, followed by a small increase in registered users in February 2023, right after the earthquake.

4.6 Individual-Account Instance Analysis

We also conducted an analysis of single-user instances. In total, we have retrieved 4908 instances that have only one user. We collected data regarding instance creation and we found out that out of these 4908 instances, 1959 instances were created in November 2022.

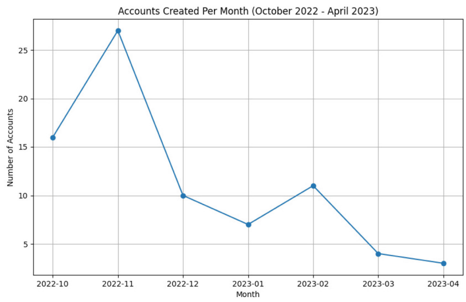

Fig. 4. Monthly evolution of the number of newly registered users from Turkey

5 Conclusion and Future Work

The main objective of this study was to conduct a comprehensive study of Mastodon and its account growth. mastodon.social is the largest instance within Mastodon and provides the most comprehensive information among all instances. The collection of data proved to be a lengthy process, taking part over the course of two months. Although the gathered data does not encapsulate all accounts within an instance, its comparison with the information available on The Federation, a website for gathering statistics about nodes in the fediverse, matches the most important result, which is that instances from Mastodon encountered an increase in the number of newly registered users in November 2022. Upon evaluating the communities within multiple mastodon instances, we found that the accounts from a single instance interacted with accounts on more than 18.000 unique instances. These results confirm the significant diversity in a decentralized network. The study of groups within mastodon.social revealed millions of groups of users within less than 10% of the gathered data. This indicates that there are multiple closely connected groups of people that use Mastodon to network among themselves. Furthermore, this analysis determined that Mastodon is seen as a platform that provides a safe online environment in terms of freedom of expression and freedom from non-intervention. Our future work is focused on our interest in studying if eco-chambers exist in Mastodon.

References

1. Blondel, V.D., Guillaume, J.L., Lambiotte, R., Lefebvre, E.: Fast unfolding of communities in large networks. J. Stat. Mech. Theory Exp. **2008**(10), P10008 (2008)
2. Center for Information Technology, University of Groningen: Habrok high-performance computing cluster. Technical report, University of Groningen (2023). https://wiki.hpc.rug.nl/habrok/start. Accessed multiple times during June and July 2023
3. Coeckelbergh, M.: The Political Philosophy of AI: An Introduction. Wiley, New York (2022)

4. Hagberg, A.A., Schult, D.A., Swart, P.J.: Exploring network structure, dynamics, and function using NetworkX. In: Proceedings of the 7th Python in Science Conference (SciPy2008), pp. 11–15. Pasadena, CA USA, August 2008
5. Hunter, J.D.: Matplotlib: a 2D graphics environment. Comput. Sci. Eng. **9**(3), 90–95 (2007)
6. Ilik, V., Koster, L.: Information-sharing pipeline. Serials Librarian **76**(1–4), 55–65 (2019)
7. La Cava, L., Aiello, L.M., Tagarelli, A.: Get Out of the Nest! Drivers of social influence in the #Twitter migration to Mastodon (2023)
8. La Cava, L., Greco, S., Tagarelli, A.: Understanding the growth of the Fediverse through the lens of Mastodon. Appl. Netw. Sci. **6**(1), 64 (2021)
9. La Cava, L., Greco, S., Tagarelli, A.: Information consumption and boundary spanning in decentralized online social networks: the case of mastodon users. Online Soc. Netw. Media **30**, 100220 (2022)
10. Lacasa, G.G.: Mastonet (2017). https://github.com/glacasa/Mastonet. Accessed 20 Apr–7 June 2023
11. Lee, K., Wang, M.: Uses and gratifications of alternative social media: why do people use mastodon? (2023)
12. Lemmer-Webber, C., Tallon, J., Shepherd, E., Guy, A., Prodromou, E.: ActivityPub. W3C Recommendation 20180123, World Wide Web Consortium, January 2018. https://www.w3.org/TR/activitypub/
13. Mastodon: Mastodon API documentation. https://docs.joinmastodon.org/methods/. Accessed 20 Apr–7 June 2022
14. McKinney, W.: Data structures for statistical computing in Python. In: van der Walt, S., Millman, J. (eds.) Proceedings of the 9th Python in Science Conference, pp. 56–61 (2010)
15. Netblock.org: Twitter, Facebook and Instagram restricted in Venezuela on day of planned protests, November 2019. https://www.netblock.org/. Accessed 15 July 2023
16. Netblock.org: Twitter restricted in turkey in aftermath of earthquake, February 2023. https://netblocks.org/reports/twitter-restricted-in-turkey-in-aftermath-of-earthquake-oy9LJ9B3. Accessed 28 Aug 2023
17. Newman, M.: Measures and metrics. In: Networks. Oxford University Press, July 2018
18. Riveni, M.: Mathematics of networks - centrality. Lecture notes. Social Network Analysis, University of Groningen (2022)
19. SocialHome: The Federation (2023). https://the-federation.info/. Accessed 30 Mar 2023
20. Staudt, C., Sazonovs, A., Meyerhenke, H.: NetworKit: an interactive tool suite for high-performance network analysis. CoRR abs/1403.3005 (2014). https://arxiv.org/abs/1403.3005
21. Stokel-Walker, C.: Twitter may have lost more than a million users since Elon musk took over. MIT Technol. Rev. 1 (2022)
22. Zia, H.B., He, J., Raman, A., Castro, I., Sastry, N., Tyson, G.: Flocking to mastodon: tracking the great Twitter migration (2023)
23. Zignani, M., Gaito, S., Rossi, G.P.: Follow the "Mastodon": structure and evolution of a decentralized online social network, pp. 541–550 (2018)
24. Zulli, D., Liu, M., Gehl, R.: Rethinking the "social" in "social media": insights into topology, abstraction, and scale on the mastodon social network. New Media Soc. **22**(7, SI), 1188–1205 (2020)