Information Consumption and Boundary Spanning in Decentralized Online Social Networks: the case of Mastodon Users

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Abstract
Decentralized Online Social Networks (DOSNs) represent a growing trend in the social media landscape, as opposed to the well-known centralized peers, which are often in the spotlight due to privacy concerns and a vision typically focused on monetization through user relationships. By exploiting open-source software, DOSNs allow users to create their own servers, or instances, thus favoring the proliferation of platforms that are independent yet interconnected with each other in a transparent way. Nonetheless, the resulting cooperation model, commonly known as the Fediverse, still represents a world to be fully discovered, since existing studies have mainly focused on a limited number of structural aspects of interest in DOSNs. In this work, we aim to fill a lack of study on user relations and roles in DOSNs, by taking two main actions: understanding the impact of decentralization on how users relate to each other within their membership instance and/or across different instances, and unveiling user roles that can explain two interrelated axes of social behavioral phenomena, namely information consumption and boundary spanning. To this purpose, we build our analysis on user networks from Mastodon, since it represents the most widely used DOSN platform.

We believe that the findings drawn from our study on Mastodon users’ roles and information flow can pave a way for further development of fascinating research on DOSNs.

Keywords—Mastodon user networks; information consumption; social boundary spanning; bridges; lurking behavior

1 Introduction

The realm of online social networks (OSNs) in the Internet landscape has determined a radical metamorphosis in our lives. Over the past two decades, we observed the advent and the rapid growth of numerous OSN platforms. Their extensive diffusion
across the globe and in our lives dramatically changed how we share information and socialize with each other. These platforms introduced new paradigms and imposed new constraints on the way we communicate within their boundaries.

However, this has eventually exhibited potentially worrying aspects. Since centralized OSN platforms — i.e., hosted and controlled by unique owners — have become pervasive, they started leveraging social media marketing strategies, which exploit targeted advertisements and content personalization to maximize their purposes. Although these choices would presumably increase user engagement and favor the businesses of these platforms, latent side effects are around the corner. Just to mention, there is a risk of running into “information bubbles” or “echo chambers”, with related distortions of social reality. Furthermore, privacy and security concerns might also arise when a single actor handles all user data. Hence, the need for alternatives is evident: social platforms were born to interconnect people, whereas nowadays, they mainly end up doing marketing by exploiting these connections.

Decentralized Online Social Networks (DOSNs) have emerged in response to the aforementioned demanding issues, so as to bring the user back to the center of the social stage and to support spontaneous interactions, no longer biased by marketing mechanisms. Decentralization allows going beyond a single owner, hence giving greater privacy control to the users. The main components to pursue these objectives are the availability of open-source software that users can quickly adopt, and the possibility of connection among different servers — commonly referred to as instances — on which this software runs, which is achieved by leveraging specific communication protocols. This seamless connection between instances leads to a federated model, which allows a user registered to an instance to interact with other users on other instances in a completely natural and transparent way — i.e., without the need for making further subscriptions — similarly to email services. The development of countless platforms based on this federated model has led to the emergence of the so-called federated universe, commonly known as the Fediverse, a widespread social network made up of many instances inherently interconnected with each other. These include Mastodon and Pleroma for microblogging, Pixelfed and Peertube for image and video hosting, resp., Funkwhale for audio hosting, and others.

Mastodon is by far the most popular platform in the Fediverse and the one that has attracted the most attention by the research community. Mastodon is a microblogging platform that offers a user experience in line with Twitter, under many aspects, while including original and valuable functionalities. For instance, Mastodon users can publish content (dubbed toots) and share other people’s content via the boost function (similar to the retweet in its centralized counterpart, Twitter). Furthermore, along with these “traditional” services, the decentralized nature of Mastodon favors the formation of interest-based communities (i.e., individual instances) analogously to what happens in other OSNs such as Reddit. This feature results in an enhanced content management on Mastodon. On the one hand, users can declare some content as inappropriate for a given instance using the content warning feature, while offering a textual complement of such content (i.e., a spoiler); on the other hand, instances’ administrators can explicitly declare the topics of interest that characterize their instances, prohibit some types of contents or even close registrations for their instances. It should be noted that the latter feature only affects the subscription of new users at a specific instance and does not impact on the possibility of interacting with such instances, thanks to the interoperability ensured by the underlying protocols.

From a technical point of view, Mastodon adopts the ActivityPub protocol which provides client-to-server and server-to-server communication capabilities. Combined with subscription mechanisms aimed at retrieving information from remote instances, this protocol supports the aforementioned seamless communication between users of

1https://www.w3.org/TR/activitypub/
different Fediverse instances. The outcomes of this extended followship mechanism on the user experience are manifold. The most noteworthy one is the subdivision of the user timeline into three possible levels of abstraction: home, local, and federated timelines. Specifically, the home timeline contains toots generated by the followed users, whereas the local and federated timelines contain toots created within the home instance and public toots from all (local or remote) users known to it, respectively.

**Related work.** Although recently emerged, decentralized social platforms and their novelties have attracted a certain attention from researchers of various disciplines. Datta et al. [2] investigated the motivations concerning the decentralization of online social networking, exploring various raised challenges and opportunities. Guidi et al. [3] analyzed DOSNs focusing on data management and availability, information diffusion, and privacy; also, they examined limitations and problems associated with the decentralized paradigm.

As previously mentioned, Mastodon has gained particular consideration from the research community [4, 5, 6, 7, 8, 9]. The qualitative interview-based analysis conducted by Zulli et al. [6] sheds light on how Mastodon enables content diversification and community autonomy, supporting horizontal growth between instances rather than vertical growth within instances. Zignani et al. [6, 8] leveraged network analysis to explore the interactions between Mastodon users through a set of structural statistics such as degree distribution, triadic closure, and assortativity. They used these results to compare Mastodon with the platform closest to it from a user experience perspective, i.e., Twitter [10]. According to the in-degree and out-degree distributions analyzed by Zignani et al., Mastodon exhibits a more balanced distribution between followers and followees (with differences ranging between -250 and 250) than Twitter, and a limited presence of bots (around 5%) w.r.t. Twitter (where their fraction of user base was found to be around 15% [10]). Moreover, when focusing on the network formed by reciprocated edges only, the authors found that the local clustering coefficient of nodes stands numerically between the one of Twitter and the one of Facebook. Mastodon also diverges from well-known centralized OSNs in terms of assortativity, as indicated by the lack of correlation between source and destination out-degree, and between source out-degree and destination in-degree. In addition, negative correlation (-0.1) was observed between source and destination in-degrees, which indicates that a user’s popularity is inversely proportional to the users s/he follows. Zignani et al. also evaluated the influence of decentralization on relationships between users [8], revealing how each instance has its own footprint that impacts on the way users connect with each other.

In [11], we recently contributed to studying the decentralized paradigm through Mastodon from a different perspective, i.e., the instance level. First, we created an updated and highly representative dataset of the relationships between Mastodon users, upon which we inferred a network model capturing the relationships between Mastodon instances. Leveraging this model, we delved into the main structural characteristics of Mastodon, taking a macroscopic as well as a mesoscopic perspective, also analyzing the Mastodon instance network backbone. Our earlier study revealed a fingerprint characterizing the network of Mastodon instances, through which we distinguish Mastodon from the most widely used centralized OSNs. Also, we spotted the development of a mutual-reinforcement mechanism between instances to reduce the potential sectorization bias deriving from the decentralization, which is a feature further strengthened by an emerging modular structure between the instances. In this regard, we provided insights into the nature of the communities of Mastodon instances, unveiling the main factors that influence their development, e.g., topics, languages, and temporal processes. We also shed light on the linkage mechanism between instances which shows a negative degree correlation, thus revealing how users tend to interact regardless of the relevance of their “home” instance. Finally, we evaluated the evolution of the platform
and its role within the Fediverse during the last few years, assessing the achievement of
its structural stability and the temporal consolidation of the role of the most relevant
instances.

It is worth noticing that, being developed on an up-to-date crawling of Mastodon
corresponding to a much larger network than in previous studies, our earlier work
in [11] has set the current state-of-the-art data for modeling Mastodon; however, de-
spite the in-depth investigation made on this data, all findings drawn from our earlier
study are at instance level only.

**Contributions.** Our research work hence aims to fill a lack of study on user rela-
tions and roles in DOSNs, and in this respect we want to pursue two main interrelated
goals:

- First, since DOSNs embrace a myriad of instances, we are interested in under-
  standing whether and to what extent interesting, decentralization-driven user
  behaviors arise within the membership instances, across different instances, or
  even correspond to mixed behaviors. This might favor the comprehension and
  the modeling of the information flow within and between multiple instances.

- Second, since the human-centric approach of DOSNs undervalues artificially
  imposed interactions, such as those deriving from boosting or advertisement
  mechanisms, we want to assess how users shape their roles in a more spontaneous
  social networking context. In this respect, our focus is on user roles that are
  essential to explain two interrelated axes of behavioral phenomena in online
  social networks, namely information consumption and boundary spanning. The
  dualism between information consumption and boundary spanning can indeed
  profoundly affect the scope of the information flow within a network and its
  fluidity, e.g., whether information flows rapidly and spreads widely or remains
  confined to specific areas of the network.

To the best of our knowledge, no works have been proposed so far to analyze user
roles and behaviors in DOSNs based on the above aspects. Note also that our perspec-
tives on the aforementioned aspects of interest in this work are totally independent
from knowledge about textual or media contents produced and exchanged through
the Fediverse, thus exploiting only the topological information of the user relation
network.

To conduct our research study, we shall focus on the most widely known and
representative Fediverse platform, i.e., Mastodon, which is hence the best suited as
case in point for investigating on the DOSN landscape. Moreover, this also allows
us to capitalize on up-to-date data resources and relating findings from our earlier
work [11].

Our roadmap to delve into the understanding of the above discussed aspects will
be developed so as to pursue a number of objectives that can be summarized into the
following research questions:

**Q1 – The User Network structure:** What are the main structural characteristics of
the network of following relations between Mastodon users?

**Q2 – Representative instances:** Are the users belonging to the most relevant Mastodon
instances representative of the entire user network?

**Q3 – Boundaries and bridges:** Are Mastodon users involved in inter-instance links
and how do they act as local bridges?

**Q4 – Over-consumption:** Are there Mastodon users who tend to over-consume, i.e.,
lurk, others’ information? Is this behavior bounded to the membership instances
or it spans across the instance boundaries?

**Q5 – Dual role users:** Are there users who behave as both lurkers and bridges within
their own instance?
Q6 – Alternate role users: Can user behavior vary according to the observation scale? That is, can a user be a lurker within her/his instance and simultaneously act as a bridge between instances, or vice versa?

Plan of the paper. The remainder of the paper is organized as follows. Section 2 introduces to the Mastodon data and the network models we used in our analysis. Section 3 presents our structural analysis of the Mastodon user networks, by first considering the full set of users and their relations, then focusing on a representative subset of the user network corresponding to a selection of the most relevant instances in Mastodon. Section 4 provides insights into user roles that are relevant to boundary spanning and information consumption behaviors for the users in Mastodon. Section 5 summarizes the main lessons learned from our analysis, while Section 6 concludes the paper and provides pointers for future research.

2 Data Extraction and Network Modeling

In our earlier work [11], we developed a privacy-friendly crawler upon the publicly available Mastodon REST APIs to build an up-to-date and highly representative dataset. It is worth emphasizing that, to preserve privacy requirements, we relied on authenticated requests only, i.e., those towards the instances that allowed accountable requests through their APIs, and we also avoided using any scraping tools.

To account for the decentralized nature of Mastodon, we leveraged on the instances.social website, which politely keeps track of the Mastodon instances panorama. In particular, this website enabled us to locate some “seed” instances (i.e., the online ones at the time of crawling) from which we started our exploration of the Mastodon Fediverse. By getting information on the timelines of about 900 instances, we reached more than 80,000 users, who represented the starting point of a breadth-first-search to discover new connections and, consequently, more users. In this regard, we point out that although the toots (delivered over the timelines of the seed instances) were inspected to discover the corresponding users, the toot data was never stored, therefore our study described in this work is totally agnostic of textual contents. Furthermore, the interactions between users in terms of incoming and outgoing links were anonymized through proper hashing functions at the time of their acquisition.

After processing the fetched data, we came up with about 1.4M unique users and 18M unique links between them, traversing more than 16,000 instances. The protocol underlying Mastodon, i.e., ActivityPub, supports seamless communication between all the Fediverse platforms. This implies that the data obtained by means of the APIs can in principle also concern interactions between Mastodon instances and instances pertaining to other services in the Fediverse. Therefore, using the aforementioned instances.social and the fediverse.party platforms we discerned the Mastodon instances within our dataset, splitting them into online and temporarily offline ones, where the latter correspond to instances that keep an inactive status for at most two weeks (according to the instances documentation provided by instances.social). As a result, we discovered 6,960 Mastodon instances, among which 1,116 were online.

Upon the extracted data, we built networks whose entities (i.e., nodes) represent users, and we modeled their relationships either at the level of the whole Mastodon network or at the level of individual instances. Let us denote with $U$ the set of users and with $I$ the set of instances available in the extracted Mastodon data. We define the Mastodon user network as a directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where the node set $\mathcal{V}$ contains pairs $(u, i)$, with $u \in U$ and $i \in I$, and the edge set $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ corresponds to

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2https://docs.joinmastodon.org/api/
3https://instances.social/
4https://fediverse.party/en/mastodon
the set of following relations, such that any \((x, y) \in \mathcal{E}\) with \(x = (u, i)\) and \(y = (v, j)\) means that user \(u\) in instance \(i\) follows user \(v\) in instance \(j\); note that \(u\) may coincide with \(v\) only if \(i \neq j\).

Given a target instance \(i \in \mathcal{I}\), we define the instance-specific user network of \(i\) as the directed subgraph \(G_i = (V_i, E_i)\) induced from \(\mathcal{G}\), such that \(V_i = \{u | (u, i) \in \mathcal{V}\} \subseteq \mathcal{U}\) and \(E_i\) is the set of edges \((u, v)\) with \(u\) following \(v\) in instance \(i\).

Given a set of target instances \(\mathcal{M} \subset \mathcal{I}\), we define the network of the relations between users of the instances \(\mathcal{M}\), dubbed merged network, as the directed subgraph \(G_M = (V_M, E_M)\) induced from \(\mathcal{G}\), such that \(V_M = \{u | (u, i) \in \mathcal{V} \land i \in \mathcal{M}\} \subseteq \mathcal{U}\) and \(E_M\) is the set of edges \((u, v)\) with \(u\) following \(v\) in some instance of \(\mathcal{M}\).

### 3 User Network Structure

In this section we begin with answering our first research question (Q1), i.e., understanding the main structural traits of the user network in Mastodon (Section 3.1). Next, we take the opportunity of investigating on the presence of noisy or irrelevant user relations according to requirements specified for their membership instances (Section 3.2). This eventually leads us to answer our second research question (Q2) by identifying and analyzing the subset of the user network corresponding to the most relevant instances in Mastodon (Section 3.3), which will be used as our workbench for the subsequent user behavioral analysis.

#### 3.1 The Mastodon user network

As our first action towards the understanding of behaviors of Mastodon users, we gained a comprehensive view of the main features of the Mastodon user network, both from a macroscopic and mesoscopic perspective.

In the first data column of Table 1 we report the main structural characteristics analyzed. First, it stands out the high numbers of nodes and edges available in our network, which indeed captures a large fraction of the existing Mastodon user base. We also notice a reasonable fraction of source nodes (i.e., users having only outgoing links), which would include newcomers at the time of the data acquisition, and in general users that take a peripheral role in the platform; moreover, the fraction of sink nodes (i.e., users having only incoming links) is quite small, which would indicate a moderate presence of users who do not appear to be interested in establishing or reciprocating connections with other Mastodon users.

Another helpful indicator concerning the linkage between users is expressed by the degree correlation or degree assortativity, i.e., the probability that a link between two nodes depends on their respective degrees [12, 13]. Given the observed value, which is slightly negative yet close to zero, it happens that the Mastodon user network is an uncorrelated network: this turns out to be explained due to a very interesting trait of Mastodon, since the lack of degree correlation highlights how users relationships within Mastodon are generally driven by genuine interests, and not biased by recommendation mechanisms within or across instances.

We further delved into the relationships between users by investigating aspects of transitivity (i.e., the likelihood that two incident edges are completed by a third one, thus forming a triangle) and local clustering coefficient (i.e., how strongly connected are the neighbors of a node); the latter was measured by averaging either over all nodes (indicated as “full averaging” in Table 1) or only nodes with degree greater than one. The relatively higher local clustering coefficient w.r.t. the transitivity is

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5 At the time of writing of this work, we achieve a coverage that ranges between 62% and 78% of the full audience of Mastodon, according to the fediverse.party and instances.social websites, respectively.
Table 1: Main structural characteristics of the user networks derived from Mastodon.

|                        | User network (full) | User network (filtered) | Top-5 instance merged user network |
|------------------------|---------------------|-------------------------|-----------------------------------|
| #nodes                 | 1,315,739           | 1,237,985               | 657,712                           |
| #edges                 | 17,252,347          | 16,239,329              | 8,227,553                         |
| density                | 1e-05               | 1e-05                   | 2e-05                             |
| % sources              | 34.2%               | 34.7%                   | 29.7%                             |
| % sinks                | 7.5%                | 6.7%                    | 3.1%                              |
| average degree*        | 21.925              | 22.007                  | 21.445                            |
| average in-degree      | 13.112              | 13.118                  | 12.509                            |
| degree assortativity*  | -0.040              | -0.042                  | -0.072                            |
| degree assortativity  † | -0.032              | -0.033                  | -0.048                            |
| transitivity*          | 0.003               | 0.003                   | 0.002                             |
| clustering coefficient*| 0.393               | 0.398                   | 0.401                             |
| clustering coefficient (full averaging)* | 0.315 | 0.323 | 0.357 |
| reciprocity            | 32.8%               | 32.2%                   | 28.6%                             |
| average path length    | 5.326†              | 5.312†                  | 5.088 (5.162†)                    |
| #strongly connected components | 565 (125) | 526 (129) | 223 (125) |
| #weakly connected components | 327 | 320 | 141 |
| modularity by Louvain  | 0.737               | 0.736                   | 0.688                             |
| #communities by Louvain| 580 (125)           | 578 (111)               | 384 (89)                          |
| modularity by Louvain* | 0.717               | 0.717                   | 0.658                             |
| #communities by Louvain* | 565 (127)           | 518 (109)               | 412 (90)                          |
| modularity by Leiden*  | 0.743               | 0.741                   | 0.688                             |
| #communities by Leiden* | 629 (138)           | 629 (127)               | 417 (97)                          |
| #communities by Infomap| 594 (53)            | 568 (52)                | 273 (48)                          |
| #communities by Infomap* | 359 (19)           | 349 (19)                | 178 (17)                          |

* Statistic calculated by discarding the edge orientation
† Statistic calculated as $\ln(N)/\ln(\ln(N))$, where $N$ denotes the number of nodes

not surprising, given the low density of the network. Moreover, when coupled with the moderate fraction of reciprocal edges (i.e., closed loops of length 2), this hints at the presence of strong local connectivity. At the same time, the average path length is quite low, about 5.

To understand the community structure of the Mastodon user network, we resorted to the widely used [Louvain](https://github.com/nicolasdugue/DirectedLouvain) and [Infomap](https://www.mapequation.org/infomap/) methods, along with the more recent [Leiden](https://github.com/rap86/leidenalg) method. Louvain exploits a hierarchical greedy approach based on two phases, modularity optimization and community aggregation, which are repeated until there are no more changes to be made on the communities and a maximum of modularity is achieved. Infomap optimizes the Map equation, which leverages the information-theoretic duality between finding community structures in a network and minimizing the description length of the movements of a random walker in a network. The Leiden method is designed to improve upon the Louvain method, by providing guarantees on the connectivity of the discovered communities through an iterative algorithm that includes local moving and community aggregation stages, with the addition of an intermediate stage of refinement of the community connectivity. We used both the undirected and directed implementations of the Louvain and Infomap algorithms, whereas for the Leiden algorithm, we used the only available undirected
Table 2: Size of the top-5 relevant Mastodon instances and their aggregation (merged network).

| Instance          | #nodes | #edges   | density |
|-------------------|--------|----------|---------|
| mastodon.social   | 305 968| 3 408 327| 4e-05   |
| pawoo.net         | 306 753| 4 329 562| 5e-05   |
| mastodon.xyz      | 16 076 | 35 631   | 1e-04   |
| mstdn.io          | 16 853 | 112 805  | 4e-04   |
| octodon.social    | 7 082  | 34 493   | 7e-04   |
| merged network    | 657 712| 8 227 553| 2e-05   |

3.2 Filtering out noisy instances

In our structural analysis of the Mastodon user network, we also considered to measure the effects of simplification of the network in terms of pruning of user relations involving potentially noisy or irrelevant instances. To this purpose, here we capitalize on related findings from our previous study [11], in which we assessed the relevance of the instances according to the number of links they receive. In this regard, we observed statistical significance (based on a Kolmogorov-Smirnov test) of a lognormal fitting of the in-degree distribution when removing the instances that are pointed by less than 51 other instances.

Performing this pruning step on our Mastodon user network implies the removal of approximately 100k nodes and 1M edges; nonetheless, it should be noticed that the main characteristics of the Mastodon user network structure have remained substantially unchanged. In fact, as shown in the central column of Table 1, all statistics are in line with those relating to the original network. Such consistency allows us to argue that the most relevant instances strongly determine the backbone of the whole Mastodon user network, also ensuring its robustness w.r.t. the removal of potentially noisy elements.

3.3 Narrowing the focus: the top-5 instances

We further investigated the impact of instance selection on the main traits of the Mastodon user network by focusing on the most important instances. Again following the lead of [11], we selected the top-5 instances by relevance, according to the maximization of a threefold criterion based on number of registered users, number of involved links, and data access permission policy; this resulted in the following selection of instances: mastodon.social, pawoo.net, mastodon.xyz, mstdn.io and

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https://github.com/vtraag/leidenalg
Table 2 provides a summary of their size information. We then created the user network upon these instances according to the *merged network model* (defined in Section 2).

On this merged network, we replicated the structural analysis carried out on the whole and pruned user-networks, in order to unveil whether and to what extent the user network of the top-5 instances can be considered representative of the entire Mastodon user network. As shown in the rightmost column of Table 1, the similarity between the statistics on the top-5 instance merged network and the corresponding ones of the whole user network is evident, which supports our above hypothesis of representativeness of the Mastodon user network. Note that, as concerns the average path length, we managed to calculate it exactly on the merged network, while for the much larger full and filtered networks we were forced (due to computational issues) to an approximation generally valid for random scale-free uncorrelated networks (cf. Table 1); in this respect, the approximated values of average path length appear to be very close to the exact value computed on the top-5 instance merged network.

To further strengthen our hypothesis, we also examined the in-degree distributions and the community size distributions of the three user networks under evaluation. As shown in Figure 1, for both in-degree and community size, the three networks have box plots that are very close to each other. In particular, concerning the in-degree distributions, the medians are equal to 1,092.5, 1,078.5, and 846, for the full, filtered, and merged networks, respectively; moreover, the median of the community size distributions settles on 3 for all the considered networks. This is remarkable, as not only confirms the relatively low relevance of the instances removed from the entire user-network, but more interestingly, it indicates that the network of the top-5 instances can effectively be used as a proxy for the Mastodon user relations; in addition, by focusing on a small number of large instances, this proxy can in principle enhance our interpretability of the behavioral patterns to discover in the Mastodon user relations.

Upon the above findings and remarks, we chose to narrow our focus on the top-5 instance merged network in the subsequent behavioral analysis of Mastodon users.

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Note that, according to the instances.social website, the top five ranked instances might partly be changed, since the time of our crawling of the Mastodon network, w.r.t. one or all of the criteria we considered for the instance selection.
Boundaries, bridges, and over-consumption

In this section we delve into the relations between users in top-5 instance merged network in order to discover user roles that are relevant in terms of two particular behavioral phenomena, namely boundary spanning and information consumption. We elaborate on the former in Section 4.1 and on the latter in Section 4.2, which will lead us to answer our Q3 and Q4 research questions, respectively.

4.1 Instance boundaries and bridges

Here we will focus on those Mastodon users that are involved in inter-instance links and on how they can be regarded and scored as local bridges in the Mastodon user network (Q3).

Shell nodes and inter-instance edges. In Table 2, we notice that the sum of the number of nodes and edges over the top-5 instances are 652,732 and 7,920,818, respectively, which differs from the size of the merged network.

We inspected our data looking for the reasons of the above fact, and found that the additional 4,980 nodes and 306,735 edges in the merged network take a specific role therein. Given a merged network \(G_M = (V,E)\), we define the aforementioned two types of entities as follows:

- Shell nodes: a node \((v,i)\) \(\in V\) is said a shell node if \(\nexists (u,j) \in V : i = j \land ((u,j),(v,i)) \in E \lor ((v,i),(u,j)) \in E\).

- Inter-instance edges: \(((u,j),(v,i)) \in E\) is said an inter-instance edge if \(i \neq j\).

Loosely speaking, a shell node is a user linked to users of other instances only, while an inter-instance edge is a link for users of different instances. The Mastodon top-5 instance merged network has indeed 4,980 shell nodes and 306,735 inter-instance edges; the distribution of such nodes w.r.t. the various top-5 instances is shown in Figure 2 whereas details about the distributions of the inter-instance edges will be considered later (cf. Table 5).

Visualization of the inter-instance subnetwork. In order to get more insights into the linkage between instances, we visually inspected the inter-instance subnetwork, which models the edges connecting nodes that belong to different instances in the top-5 instance merged network.
Figure 3: Illustration of the inter-instance subnetwork. Nodes correspond to users belonging to the instances composing the top-5 instance merged network and only inter-instance edges are drawn. Nodes are colored according to their membership instances, i.e., mastodon.social (blue), pawoo.net (red), mastodon.xyz (green), mstdn.io (magenta), and octodon.social (orange). The color of an edge corresponds to the color of the source instance. The displayed layout is based on the force-directed drawing ForceAtlas2 model. (Produced by using the Graphistry service, available at https://www.graphistry.com.)
Figure 4: Zoom-in views from Fig. 3. Nodes are colored according to their membership instances, i.e., *mastodon.social* (blue), *pawoo.net* (red), *mastodon.xyz* (green), *mstdn.io* (magenta), and *octodon.social* (orange). The color of an edge corresponds to the color of the source instance.
As it can be observed from Figure 3, several interesting patterns emerge. The first eye-catching aspect is the pervasiveness of mastodon.social (colored in blue), which appears to be dominant in establishing user relationships across instances. The roots of this phenomenon plausibly lie in the relevance of mastodon.social since it is commonly recognized as one of the supporting pillars of the Fediverse and the first instance of the Mastodon project. The central area of Figure 3 is characterized by a particularly intense mix of colors, indicating the presence of user connections that involve all the instances in the network; this is clearly consistent with the key principle of the Fediverse as an ecosystem made of independent yet cooperating instances.

Through a detailed inspection of the network in Figure 3, we also spotted some regions showing further relevant patterns, such as a strong linkage between users of some pairs of instances or a dense interleaving among multiple instances’ users. In this regard, as shown in Figure 4 (a), resp. Figure 4 (b), there is a tight connectivity among users of mastodon.social with users of mstdn.io, resp. users of mastodon.social with users of mastodon.xyz. An analogous situation can be observed in Figure 4 (c), where a strong coupling between users of mastodon.social and users of pawoo.net emerges, with the addition of some sporadic users belonging to mstdn.io, which are nonetheless well connected with the other two instances.

Moreover, it is worth noticing how the pairwise interactions between (users belonging to) different instances occur with remarkable intensity even among the largest instances, as shown in Figure 4 (c). This trait is particularly interesting, since although such instances can definitely be regarded as self-sufficient and represent stand-alone social platforms — given their remarkable size — their users tend to interact outside the boundaries so as to gain a more global user behavioral experience.

Figure 4 (d) illustrates two regions of the network characterized by two different patterns: a particularly marked connection between users of mastodon.social and users of mstdn.io (on the left), which is also massively involved in a linkage with users from pawoo.net, and another group of users from different instances (as shown by a mix of colors, on the right). The latter hints at a comprehensive connectivity between all the instances composing the merged network, as also confirmed by the identification of other regions characterized by users belonging to different instances, i.e., Figures 4 (e) and (f). These events observed in the merged network reveal that the boundary spanning spotted so far is not limited to pairwise instance links, but it involves multiple instances. As a consequence, we can argue that Mastodon users fully exploit the potential of seamless interaction between independent instances provided by the platform.

It should be noticed that the force-directed layout (ForceAtlas2) we used for drawing the network emphasizes the peripheral positioning of portions of the network, such as those corresponding to the above cases, in which there exists a higher connectivity among a bunch of nodes of two or few instances than with nodes of the other instances.

Bridges. The above discussed boundary entities relate to another aspect of interest to our analysis of the merged network, which is the presence of nodes connected by edges acting as local bridges at varying degrees.

An effective method to identify such edges is to measure for each pair of linked nodes their topological overlap, or normalized embeddedness [17], which is the fraction of common neighbors a pair of connected vertices has. Indeed, edges acting as bridges are expected to share few or no neighbors, and in fact the topological overlap enables smoothing the notion of local bridge, so that the lower the topological overlap of a linked pair of nodes, the higher the strength of their link as local bridge. Originally conceived for undirected networks, the topological overlap has also been adapted to directed networks. Following [15], the directed topological overlap (DTO) for an edge

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Table 3: Percentage of Mastodon users regarded as strong-bridges and bridges for selected cut-off thresholds of the nDTO score percentiles.

| Network           | #Nodes | #Strong-bridges (%) | nDTO Score |
|-------------------|--------|---------------------|------------|
|                   |        | (w/o sources and sinks) | 5th | 10th | 25th |
| mastodon.social   | 305,968 | 121,585 (39.7%) | 61.5% | 64.6% | 70.9% |
|                   |         | 81,112 (26.5%)    |           |       |      |
| pawoo.net         | 306,753 | 97,590 (31.8%)   | 50.6% | 53.9% | 61.8% |
|                   |         | 38,842 (12.7%)   |           |       |      |
| mastodon.xyz      | 16,076  | 12,521 (77.9%)   | 85.3% | 86.2% | 88.8% |
|                   |         | 1,086 (6.8%)     |           |       |      |
| mastodon.xyz      | 16,853  | 4,414 (26.2%)    | 75.1% | 82.6% | 86.2% |
|                   |         | 290 (1.7%)       |           |       |      |
| octodon.social    | 7,082   | 1,436 (20.3%)    | 64.8% | 68.9% | 74.4% |
|                   |         | 626 (8.8%)       |           |       |      |
| merged network    | 657,712 | 238,042 (36.2%) | 56.0% | 59.7% | 66.8% |

(u, v) is defined as:

\[ DTO(u, v) = \frac{|N_{out}^u \cap N_{in}^v|}{(|N_{out}^u| - 1) + (|N_{in}^v| - 1) - |N_{out}^u \cap N_{in}^v|} \]

where \( N_{out}^u \) and \( N_{in}^v \) denote the out-neighbors and in-neighbors of the nodes \( u \) and \( v \), respectively. Note that the DTO is defined only for edges \((u, v)\) such that \( |N_{out}^u| > 1 \) and/or \( |N_{in}^v| > 1 \); otherwise, for isolated dyads, the DTO is assumed to be zero.

Since our focus is on users rather than links, we define the node-centric DTO (nDTO) of a node \( u \) as follows:

\[ nDTO(u) = \frac{1}{|N_{in}^u \cup N_{out}^u|} \left( \sum_{v \in N_{in}^u} DTO(v, u) + \sum_{v \in N_{out}^u} DTO(u, v) \right) \]

The application of the node-centric DTO measure produces a ranking of the nodes, whereby higher ranks (i.e., lower scores) correspond to stronger bridge nodes. (Note that, for the sake of readability, in the DTO and nDTO definitions we have omitted the reference to the membership instances of \( u \) and \( v \)).

Table 3 shows the percentage of nodes corresponding to selected percentiles of nDTO score over each of the top-5 instances as well as the whole merged network. As it can be noted already for the 5-th percentile, it stands out that more than a half of the node set is identified as bridges, with peaks above 75% in mastodon.xyz and mstdn.io.

We also quantified the existence of nodes showing a strong status as bridges. We identified such nodes, dubbed strong-bridges, as the nodes having a nDTO score equal to zero. In Table 3, we report the number of strong bridges for each of the top-5 instances: compared to the total number of nodes, the percentage of strong bridges appears to be always significant, ranging from about 20% (octodon.social) to about 78% (mastodon.xyz).

We also evaluated the impact of source and sink nodes on the overall percentage of strong bridges found in our analyzed networks. As reported in Table 3, even by filtering out such nodes, the portion of strong bridges remains evident, unveiling a relatively low bias due to source and sink nodes at least in the largest networks, where the percentage of strong bridges ranges from about 13% in pawoo.net to above 27% in mastodon.social.
Table 4: Percentage of Mastodon users regarded as lurkers w.r.t. selected cut-off thresholds based on the LurkerRank score percentiles.

| network          | 95th | 90th | 75th |
|------------------|------|------|------|
| mastodon.social  | 2.8% | 7.7% | 30.1%|
| pawoo.net        | 4.3% | 9.3% | 28.3%|
| mastodon.xyz     | 2.0% | 6.0% | 73.6%|
| mstdn.io         | 4.6% | 8.9% | 77.6%|
| octodon.social   | 38.7%| 41.6%| 56.3%|
| merged network   | 3.7% | 9.0% | 24.3%|

4.2 Over-consumption

In this section, we answer our fourth research question (Q4) regarding the identification of users that tend to over-consume information produced by others. To this purpose, we take a particular perspective on this problem, which relies on the theory of lurking behavior analysis [19, 20].

A key concept in this theory is that (online) social networks are characterized by a participation inequality principle, whereby the crowd of a social network does not actively contribute, rather it mostly remains hidden or “silent”, without taking an active role in the visible participation and interactions with other members. This kind of users should not be trivially regarded as totally inactive users (i.e., registered users who do not use their account to join the online community), rather a silent user can be perceived as someone who gains benefit from information produced by others (e.g., reading posts and comments, watching videos, etc.) without mostly giving back to the online community; within this view, these users are also called lurkers. It has been shown in several works (e.g., [19, 20, 21, 22, 23]) that lurking is normal and also an active, participative and valuable form of online behavior, including a form of cognitive apprenticeship that corresponds to legitimate peripheral participation. In this respect, lurkers might have a great potential in terms of social capital, since they acquire knowledge from the community; therefore, when engaged, they become beneficial for the propaganda and development of the community.

Modeling and analyzing lurking behaviors has been formulated as an eigenvector-centrality-based node ranking problem, which is totally content-agnostic, as it does not require other information than the graph topology [18]. The LurkerRank method was designed to assign each user a score expressing her/his lurking status. In Appendix, we report the mathematical details of this method. It should be noted that the LurkerRank method applies to a network graph with reversed edge-orientation, therefore hereinafter we shall consider any edge \((u,v)\) as a link from \(u\) to \(v\) where \(v\) is a follower of \(u\).

To answer the research question Q4, our main goal is to understand whether and to what extent lurkers of an instance are target nodes of an information flow coming either from the same instance or from a different instance. To this purpose, we compute the LurkerRank method to each of the top-5 instance networks as well as to the merged network. In Table 4, we report the percentage of users identified as lurkers for selected percentiles of LR values, where LR symbol is used to denote the scoring function of LurkerRank (cf. Appendix). Looking at the table, we notice that the merged network as well as each of the top-5 instances, but octodon.social, show a percentage of lurkers that is below 5% and 10% for the 95th and the 90th percentile, respectively, while for octodon.social, the percentage values at 95th and 90th percentiles are comparable and set around 40%. However, when extending to the 75th percentile, the percentage of users increases to at least approximately 30% (for mastodon.social and pawoo.net), with a peak above 70% in mastodon.xyz and mstdn.io. Note also that the increment
Table 5: Percentage of outgoing edges, resp. incoming edges, between pairs of selected instances that correspond to edges towards, resp. from, lurkers. Percentiles refer to LurkerRank scores.

| source instance | target instance | #edges | edges to lurkers | edges from lurkers |
|-----------------|-----------------|--------|------------------|-------------------|
|                 |                 |        | 95th  | 90th  | 75th  | 95th  | 90th  | 75th  |
| mastodon.social | mastodon.social | 1488327 | 12.6% | 15.1% | 25.3% | 0.4%  | 0.6%  | 2.2%  |
|                  | pawoo.net       | 45713  | 3.4%  | 8.3%  | 19.5% | 1.5%  | 1.9%  | 5.3%  |
|                  | mastodon.xyz    | 46069  | 5.8%  | 7.7%  | 44.4% | 0.8%  | 1.0%  | 2.4%  |
|                  | mstdn.io        | 29245  | 7.0%  | 9.6%  | 26.8% | 0.8%  | 1.0%  | 2.4%  |
|                  | octodon.social  | 29935  | 5.9%  | 8.7%  | 22.1% | 0.9%  | 1.1%  | 3.0%  |
| pawoo.net        | mastodon.social | 29572  | 48.5% | 49.4% | 54.7% | 1.0%  | 1.4%  | 4.8%  |
|                  | mastodon.xyz    | 4329562| 13.4% | 16.8% | 31.8% | 0.1%  | 0.2%  | 0.8%  |
|                  | mstdn.io        | 3192   | 3.3%  | 6.4%  | 43.7% | 0.5%  | 0.7%  | 2.3%  |
|                  | octodon.social  | 945    | 11.7% | 19.2% | 39.8% | 0.1%  | 0.1%  | 0.6%  |
| mastodon.xyz     | mastodon.social | 36428  | 19.5% | 21.8% | 34.7% | 1.0%  | 1.9%  | 10.8% |
|                  | pawoo.net       | 6684   | 1.3%  | 6.6%  | 17.8% | 2.8%  | 5.9%  | 30.5% |
|                  | mastodon.xyz    | 35631  | 4.5%  | 8.9%  | 46.2% | 0.0%  | 0.1%  | 3.0%  |
|                  | mstdn.io        | 1417   | 9.5%  | 12.8% | 41.6% | 0.4%  | 0.6%  | 4.2%  |
|                  | octodon.social  | 2404   | 3.2%  | 5.9%  | 14.6% | 0.2%  | 0.6%  | 5.2%  |
| mstdn.io         | mastodon.social | 28523  | 15.2% | 16.7% | 23.2% | 1.8%  | 2.7%  | 12.6% |
|                  | pawoo.net       | 6691   | 1.6%  | 4.9%  | 13.3% | 5.7%  | 8.3%  | 35.5% |
|                  | mastodon.xyz    | 863    | 6.2%  | 8.1%  | 24.7% | 1.0%  | 1.9%  | 15.8% |
|                  | mstdn.io        | 112805 | 4.5%  | 6.6%  | 25.3% | 0.0%  | 0.0%  | 0.7%  |
|                  | octodon.social  | 626    | 7.7%  | 11.8% | 22.0% | 1.3%  | 2.7%  | 18.4% |
| octodon.social   | mastodon.social | 34148  | 17.6% | 19.1% | 28.0% | 2.5%  | 7.5%  | 14.5% |
|                  | pawoo.net       | 84     | 0.0%  | 0.0%  | 0.0%  | 4.8%  | 4.8%  | 6.0%  |
|                  | mastodon.xyz    | 2281   | 4.4%  | 5.9%  | 18.8% | 1.1%  | 3.0%  | 5.8%  |
|                  | mstdn.io        | 941    | 10.1% | 13.3% | 39.3% | 1.0%  | 1.9%  | 5.5%  |
|                  | octodon.social  | 34493  | 20.8% | 24.3% | 37.2% | 0.5%  | 1.2%  | 7.7%  |

Information consumption. Once the lurkers at varying degrees were identified within the merged network, we investigated the links towards lurker nodes of a specific instance w.r.t. the overall incoming links, in order to understand how much the information flow is “consumed” by (i.e., it is directed to) lurkers, and whether this occurs internally or externally to their membership instance.

We report the results of our analysis in Table 5, under the column “edges to lurkers”, for each pair of the top-5 instances — including self-pairing, i.e., within-instance links — and for various lurking score percentiles. At a first glance, it can be noted a certain variety in the percentage values, which indicates a remarkable differentiation of information consumption by lurkers within and across the various instances.

On the one hand, there is an evidence of information flow directed to lurkers from inside their membership instance, although this happens at different extents; in particular, at the 95th percentile, the percentage of links directed to lurkers ranges from 4.5% in mstdn.io and mastodon.xyz to about 21% in octodon.social.

On the other hand, however, there is also a remarkable amount of information flow directed to lurkers from outside their membership instance. In this respect, the mastodon.social instance turns out to be the best target for lurkers, given the highest percentages of links coming from the other instances (and mastodon.social itself) and directed to lurkers. In particular, we notice a considerable amount of information flow from pawoo.net to lurkers in mastodon.social, which is about 50% of the connections from pawoo.net to mastodon.social. Also, mastodon.xyz and mstdn.io lurkers tend to absorb most information from outside, while pawoo.net is particularly relevant as on octodon.social appears to be at a significantly lower rate than for the other instance networks.
Figure 5: Graphical illustration of the information flow between the top-5 Mastodon instances, modeled from information producers to information consumers. Self-loops and flow values (cf. Table 5) are omitted to avoid cluttering. Each flow has the same color as the source instance.

Overall, the above remarks highlight an important trait of the Mastodon network as a mix of within-instance and across-instance information consumption of its users. Figure 5 provides an illustration of the information flow between the top-5 instances, which complements our understanding from the results shown in Table 5 by highlighting a sort of mutual reinforcement among such instances, in terms of information production, resp. consumption, behaviors exhibited by their users.

Information spreading. Analogously to the previous analysis, we examined how the outgoing links from an instance might be originated by lurkers.

Clearly, as expected from the definition of lurking behavior, lurkers do not contribute much to the diffusion of the information they consume, which is indicated by the small percentage values reported in Table 5 under the column “edges from lurkers”. However, some exceptions stand out. In particular, already at the 95th percentile, lurkers of mastodon.xyz, mstdn.io and octodon.social contribute to spread information towards pawoo.net in a non-negligible way. This trend strengthens at the 90th percentile and, for mastodon.xyz and mstdn.io, is boosted at the 75th percentile (with peaks above 35% from mstdn.io to pawoo.net). The above is remarkable as we recall that pawoo.net tends to attract lurkers belonging to other instances (e.g., mastodon.social and octodon.social), and conversely, we also spotted that lurkers from all the other instances (especially from mastodon.xyz, mstdn.io, octodon.social) might contribute to the diffusion of information towards pawoo.net.

4.3 Dual role users

Our fifth question (Q5) concerns unveiling the existence of Mastodon users that take a twofold role as lurkers and bridges. To this purpose, for each of the top-5 instances and the merged network, we analyzed the overlap between a set of lurkers and a
Table 6: Dual role users in the top-5 instance networks and in the merged network.

| network            | #nodes  | LR@95th ∩ nDTO@5th | LR@90th ∩ nDTO@10th | LR@75th ∩ nDTO@25th |
|-------------------|---------|-------------------|-------------------|-------------------|
| mastodon.social   | 305,968 | 0.7%              | 5.1%              | 26.1%             |
| pawoo.net         | 306,753 | 1.6%              | 4.9%              | 20.4%             |
| mastodon.xyz      | 16,076  | 1.1%              | 4.9%              | 72.3%             |
| mstdn.io          | 16,853  | 0.5%              | 7.3%              | 76.6%             |
| octodon.social    | 7,082   | 37.6%             | 39.5%             | 51.5%             |
| merged network    | 657,712 | 1.5%              | 6.0%              | 18.9%             |

set of bridge users, selected from their respective ranking solutions according to the percentile thresholds used in the previous analysis, such that each set pair refers to the same percentile proportion (i.e., 95th vs. 5th, 90th vs. 10th, and 75th vs. 25th).

Table 6 reports on the results of our analysis. The octodon.social instance shows by far the largest percentage of users exhibiting the dual role, which is already above 37% w.r.t. the toughest overlap (i.e., LR@95th ∩ nDTO@5th), then settling around 51% for the smoothest overlap (i.e., LR@75th ∩ nDTO@25th). Note that the latter point corresponds to an increase rate that is much lower than for the other instances, where the percentages of dual roles keep far below 10% w.r.t. the two largest overlaps while increasing up to a minimum of 20% (pawoo.net) and a maximum of 77% (mstdn.io) w.r.t. the overlap LR@75th ∩ nDTO@25th. Interestingly, this is in accord with the higher, resp. lower, smoothness in the role identification shown by octodon.social, resp. the other instances, for varying scoring percentiles, as we already observed in our previous analysis (cf. Table 5). Moreover, the difference in percentages corresponding to the LR@75th ∩ nDTO@25th between the two largest instances (i.e., mastodon.social and pawoo.net) and the other three instances also depends on the size of their respective user-bases: in fact, as the number of users in an instance gets smaller, the volume of information produced becomes more limited, and hence their users tend not only to consume it but also to act as information flow facilitators; by doing this, they can contribute keeping the instance sustainable with fresh contents and timely interactions.

Considering the merged network, there is evidence of a certain presence of dual role users — thus indicating that a dual role behavioral phenomenon can also occur in a cross-instance context — with percentages that are in line with some of the instances, particularly pawoo.net.

**Alternate role users.** Here we consider our sixth research question (Q6). The goal is to understand whether by mixing the scales of observation, i.e., either locally within an instance or globally at the level of the merged network, distinct behaviors of users may arise. As for the previously analyzed research questions, we focus on lurkers and bridge users, thus aiming to identify whether users can be regarded as lurkers inside their membership instance yet as bridges in a cross-instance environment, and vice versa.

In Table 7, we report the percentage of users of a given instance that are identified as users showing a lurking role locally and a bridging role globally (upper subtable). As it can be noted, while a few cases (below 2%) are already identified w.r.t. LR@95th(L) ∩ nDTO@5th(G), this alternate behavior becomes more evident w.r.t. larger overlaps, on all instances though at different extents. These results allow us to understand how the information flow moves within a decentralized context. An intra-instance (or local) lurker is a user who tends to absorb information, while an inter-instance (or global) bridge is a user who contributes to connect multiple regions of a network of instances.
Table 7: Mastodon users who behave differently according to the observation scale, i.e., locally within their instance (denoted with superscript \((L)\)) or globally at the level of merged network (denoted with superscript \((G)\))

| users          | mastodon.social | pawoo.net | mastodon.xyz | mstdn.io | octodon.social |
|----------------|-----------------|-----------|--------------|---------|---------------|
| LR95@95th \(L\) ∩ nDTO95th \(G\)  | 0.6%            | 1.6%      | 0.8%         | 0.3%    | 1.2%          |
| LR90@95th \(L\) ∩ nDTO90th \(G\)  | 4.8%            | 5.0%      | 2.7%         | 2.4%    | 36.2%         |
| LR75@95th \(L\) ∩ nDTO75th \(G\)  | 25.0%           | 21.2%     | 66.7%        | 72.7%   | 45.1%         |
| nDTO95th \(L\) ∩ LR95th \(G\)     | 0.2%            | 3.1%      | 0.3%         | 0.1%    | 0.1%          |
| nDTO90th \(L\) ∩ LR90th \(G\)     | 0.7%            | 12.2%     | 0.4%         | 0.2%    | 0.1%          |
| nDTO75th \(L\) ∩ LR75th \(G\)     | 13.3%           | 26.6%     | 2.7%         | 1.2%    | 0.5%          |

It follows that the users having this dual scale-dependent role are those who, while consuming locally produced information, enable the information coming from their instances to flow into the Fediverse, thus becoming potential information facilitators. Moreover, as already partially unveiled in our previous analysis on dual role users, the higher percentages of alternate role users generally found for instances with a smaller user base suggest a tendency of users in such instances to act as a touch-point and interconnect different regions that cross the instance boundaries.

In Table 7, we also report the percentage of users of a given instance that are identified as users showing a bridging role locally and a lurking role globally (bottom subtable). We observe that the percentage values are generally much lower than the previously discussed behavioral case. This should not be surprising since if a user takes a within-istance bridge role, s/he is already committed to broker information and hence will likely be less inclined to absorb information from the outside. Nonetheless, in this scenario, mastodon.social and pawoo.net represent an exception, showing non-negligible overlaps of alternate role users under less restrictive percentile thresholds. We tend to ascribe this phenomenon to aspects related to the topology of those instances; in particular, the sparsity of connections over a large user base would favor some users to absorb information from other instances while acting as bridges locally.

5 Discussion

Here we summarize the main findings that raised from our extensive analysis of the Mastodon user relations.

To answer our first research question (Q1), we explored the main structural characteristics of the Mastodon user network. Among the noteworthy facts, we observed a lack of degree correlation, which should be ascribed to a form of spontaneous connectivity between users that relates to the absence of boosting mechanisms for “artificial” interactions, such as those due to the widely used recommendation strategies adopted by the centralized OSNs. From a mesoscopic perspective, based on Louvain, Leiden, and Infomap community detection methods, the user networks exhibit a moderately high modularity (around 0.7) and a high number of communities; this trait, which indicate the existence of small densely connected groups of users tailored to specific shared interests, appears to be consistent with the spontaneous connectivity trend in Mastodon.

Remarkably, all the specific traits discovered on the full user-network remained valid also after our step of graph pruning aimed at removing irrelevant instances. This was further strengthened when we considered a set of instances able to represent the entire Mastodon user network, as outlined by our second research question (Q2). To this purpose, supported by some pertinent results from the study in [11], we focused on the five most relevant instances in Mastodon. After evaluating their main structural features and finding high consistency with the results obtained on the full user-network, we concluded that the top-5 instance network can be regarded as representative of the
whole Mastodon user network, and indeed we used it in our subsequent tasks of user behavior analysis.

To answer our third research question (Q3), we investigated the linkage between Mastodon users accounting for the instance boundaries. We indeed found out a significant fraction of inter-instance links and of shell nodes (i.e., users having connections with other instances’ users only), thus unveiling an evident boundary-spanning phenomenon, as also confirmed by our visual inspection in Figs. 3 and 4. We delved into the boundary-spanning mechanisms in Mastodon through the identification of users acting as bridges at varying degrees. To this purpose, by leveraging the notion of directed topological overlap, we discovered a widespread presence of bridge users, with a non-negligible fraction of what we called strong-bridges, i.e., users having a topological overlap equal to zero. Interestingly, this still holds even by removing the source and sink nodes from the network. Therefore, we can state the existence of structurally strategic nodes holding connections between across-instance regions of the network, which positively impacts on the effectiveness of information flow between the users over all Mastodon.

As for our fourth research question (Q4), we modeled the information over-consumption phenomenon through the Mastodon user network in terms of lurking behaviors. As thoroughly discussed in the literature, lurkers are silent users who tend to mostly consume information from the others’ actions rather than produce information; but at the same time, by holding a certain social capital and given their pervasiveness in a social network, such users might significantly contribute to boundary spanning and information flow phenomena. In this regard, we built our analysis upon a theoretically well-founded content-agnostic eigenvector-centrality ranking method, LurkerRank. Our goal was twofold: to understand whether and to what extent lurkers of an instance are target nodes of an information flow coming from other users, and whether this involves the membership instance or the other instances. In this regard, we found out that lurkers are present, at varying degrees, over all the selected instances under study, with mastodon.social being the preferred instance for information consumption by lurkers. In general, information consumption is not confined to the membership instance, but it extends beyond the boundaries of the instances, so as to further capitalize on the information exchanged through different regions of the Mastodon user network. Furthermore, we unveiled that lurkers are also involved in information spreading processes between instances, even in a non-negligible way as it happens for users in pawoo.net that are linked to (i.e., follow) lurkers of the other instances.

Our last research questions regarded the existence of users who show a dual lurker-bridge role, either simultaneously through the whole user network and the instance-specific subnetworks (Q5), or alternately as a function of the observation scale, i.e., inter-instance and intra-instance perspective (Q6). We found a relatively small fraction of users acting both as lurkers and bridges within their own instances; since these users normally over-consume but have also the potential of disseminating information, they could be regarded as information flow facilitators. This trait is present through all the merged network, and is particularly evident in the smallest instances, where the produced information is limited to the size of the audience in those instances, and hence an amplification is needed. Concerning the alternate and scale-dependent behavior, we spotted the existence of users acting as local (i.e., on their own instances) lurkers and global (i.e., between instances) bridges, whereas the contrary does not hold. Reasonably, the former trait allows users to disseminate information from their own instances outwards, while the latter is unnecessary as they are already responsible for the intra-instance information spreading. As a final remark, we believe that such dual/alternate-role users can be regarded as highly strategical ones, as their complementary structural functionality makes them ideal candidates to determine the speed and scope by which the information flows within Mastodon, and more generally, in a decentralized social context.
6 Conclusions

Decentralized Online Social Networks (DOSNs) aim to bring the social paradigm back to its roots made up of spontaneous interactions and genuine interests, in contrast to the marketing-driven engagement mechanisms typically adopted by the centralized OSNs. To guarantee a user-centric vision, DOSNs support the creation of independent and self-hosted servers seamlessly connected among each other. Nevertheless, this metamorphosis of the online social media environment could change how some of the fundamental components underlying human relationships appear and evolve via the Internet.

In this work, we have provided a number of insights into DOSN user relations and behaviors, using as a case in point Mastodon, the most-known service of the Fediverse.

We analyzed the Mastodon user network to answer six research questions encompassing the main structural characteristics of the following user relations, the impact due to the most representative instances on the user network, across-instance boundary spanning and bridges, over-consumption and information flow, dual and alternate role users.

Our future work plan includes further investigation on the impact that decentralization has on user behaviors and how the latter adapt to allow information flowing quickly and across instances. In this regard, we are interested in defining a suitable multilayer network model for the user relations in order to support the characterization and analysis of the duality and mutual reinforcement between information-production and information-consumption behaviors as a function of the users’ timelines and instance-based contexts.

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Appendix

Lurker ranking methods, originally proposed in [24, 18], are designed to mine silent user behaviors in the network, and hence to associate each user with a score indicating her/his lurking status. Since the basic assumption of lurking behaviors is related to the amount of information a user receives, the key idea in the definition of lurker ranking methods is that the strength of a user’s lurking status can be determined based on three main principles, namely over-consumption, authoritativeness of the information received, non-authoritativeness of the information produced.

The first principle corresponds to the evidence of a disproportion between information-consumption over information-production exhibited by a user. The second principle relates to the importance as information producers of a user’s followees (i.e., in-neighbors), while the third principle related to the low importance as information producer of a user with respect to her/his followers (i.e., out-neighbors).

These principles are implemented in a ranking model so as to differently weighing the contributions of a node’s in-neighborhood and out-neighborhood. For the sake of brevity here, we will refer to only one of the formulations described in [24, 18], which is that based on the full in-out-neighbors-driven lurker ranking, hereinafter named as LurkerRank (LR).

Given a directed social graph \( G = (V, E) \), where any edge \((u, v)\) means that \(v\) is follower of \(u\), the LurkerRank LR(v) score of node \(v\) is defined as:

\[
LR(v) = \alpha[L_{in}(v) (1 + L_{out}(v))] + (1 - \alpha)p(v)
\]

where \(L_{in}(v)\) is the in-neighbors-driven lurking function:

\[
L_{in}(v) = \frac{1}{|N_{out}^v|} \sum_{u \in N_{in}^v} \frac{|N_{out}^u|}{|N_{in}^u|} LR(u)
\]

and \(L_{out}(v)\) is the out-neighbors-driven lurking function:

\[
L_{out}(v) = \frac{|N_{in}^v|}{\sum_{u \in N_{in}^v}} \sum_{u \in N_{out}^v} \frac{|N_{in}^u|}{|N_{out}^u|} LR(u)
\]

where \(\alpha\) is a damping factor ranging within \([0, 1]\) (usually set to 0.85), and \(p(v)\) is the value of the personalization vector, which is set to \(1/|V|\) by default. To prevent zero or infinite ratios, the values of the in/out-neighborhood size of a node are Laplace add-one smoothed. As a result, the higher the LR score of a node, the higher its likelihood to be regarded as a lurker in the network under study.

It should be noted that the actual meaning of “received information” modeled by the links in the LurkerRank input graph can depend on the specific context of network analysis; in practice, it refers to either a social graph (i.e., a linked pair \((u, v)\) means that \(v\) is follower of \(u\)) or an interaction graph (e.g., \(v\) likes or comments \(u\)’s posts). LurkerRank has been extensively evaluated on both scenarios [18, 25]. Nonetheless, although both social and interaction relations are indicators of information consumption by users, the information on interaction data that can be acquired from a real
social network might be significantly sparse, and our context of study does not make an exception to this. Therefore, in this work LurkerRank is applied to a followship graph, which corresponds to the Mastodon user networks defined in Section 3 (with reversed edge-orientation).