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Deconstructing cultural appropriation in online communities: A multilayer network analysis approach

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ABSTRACT

In this study, we introduce a novel multilayer network model designed to analyze complex social phenomena in online communities. The model captures intricate relationships between users, content, and specific aspects of social phenomena, providing a comprehensive framework for understanding these interactions. We applied this model to a dataset of over 1 million Reddit comments from January to April 2022, filtered for cultural appropriation-related keywords. Our quantitative analyses, based on Social Network Analysis techniques, revealed significant findings. For instance, a subreddit exhibited the highest user interaction, indicating a substantial level of engagement on this topic. Furthermore, the distribution of key contents across different subreddits was non-uniform, suggesting diverse levels of engagement across communities. The results of this research underscore the potential of our approach in providing a nuanced understanding of social phenomena in online communities, thereby contributing to future research in this field.

1. Introduction

Cultural appropriation, a complex and controversial issue, has become increasingly prevalent in online communities. This term refers to the act of adopting elements from a culture that is not one's own, often without understanding or respecting the significance of those elements in their original cultural context. This can encompass various aspects, including fashion, art, and language (Sádaba, LaFata, & Torres, 2020; Sharifonnasabi, Bardhi, & Luedicke, 2020; Young, 2010; Ziff & Rao, 1997). The issue with cultural appropriation lies in its potential to perpetuate stereotypes, marginalize certain groups, and appropriate cultural elements without proper understanding or context (Beverland, Eckhardt, Sands, & Shankar, 2021; Kleinman & Kleinman, 1996; Matthes, 2019; Young & Haley, 2009). The choice of studying cultural appropriation relies on:

1. Relevance and timeliness: cultural appropriation discussions have intensified with the rise of global interconnectedness. Studying it offers insights into contemporary cultural dynamics.
2. Diverse opinions on this topic: a rich area for analysis. This diversity provides a comprehensive view of the discourse.
3. Implications for online communities: platforms like Reddit have become key venues for cultural appropriation discussions. Analyzing these can offer insights into online community dynamics.
4. Gap in existing research: even if the topic has been studied elsewhere, its dynamics on Reddit remain underexplored, presenting an opportunity for this study.

With the advent of online communities, the ease of accessing and sharing cultural elements has increased, often without a comprehensive understanding of their significance. This has led to a surge in instances of cultural appropriation in online

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spaces (Cordes & Merskin, 2019; Dey, Lal, Balmer, Pandit, & Saren, 2018; Wooley-Snider, 2018). In recent years, cultural appropriation has sparked intense debates in online communities (Barua, 2022). Numerous instances involving celebrities have been reported, with accusations primarily circulating on platforms like Instagram and Twitter. For instance, pop singer Adele faced accusations of cultural appropriation after sharing an Instagram picture of herself wearing a traditional African hairstyle. Similarly, celebrities such as Ariana Grande, Kim Kardashian, Katy Perry, and Kylie Jenner have faced backlash on social media for appropriating various aspects of different cultures.[1] Understanding the dynamics of cultural appropriation is crucial due to its significant implications for social justice and cultural respect. This phenomenon, prevalent in online communities, often involves the adoption of cultural elements without a comprehensive understanding of their significance in their original cultural context. Given the vast and diverse user base of Reddit, it serves as a microcosm of global online communities, making it an ideal platform to study the nuances of cultural appropriation. By examining cultural appropriation on Reddit, we aim to:

1. Capture a broader spectrum of opinions: unlike platforms like Instagram and Twitter, which are often dominated by celebrity voices and mainstream media, Reddit offers a space for grassroots discussions, providing a more comprehensive view of public opinion on cultural appropriation.
2. Understand the evolution of the discourse: Reddit's threaded discussion format allows for the tracking of how conversations on cultural appropriation evolve over time, offering insights into how perceptions change and which arguments gain traction.
3. Identify patterns and trends: by analyzing discussions on Reddit, we can identify patterns in how cultural appropriation is discussed, which can inform strategies for fostering more informed and respectful conversations on the topic.

In this study, we introduce a novel multilayer network model and analysis framework specifically designed to study social phenomena in online social platforms. We choose to apply this model to Reddit, a popular online platform, using cultural appropriation as our case study. By doing so, we hope to provide a comprehensive understanding of cultural appropriation in online communities, contributing to the broader discourse on this important social issue.

The choice of Reddit as the platform for this study is motivated by several factors. First, Reddit is a popular online platform that hosts a wide range of discussions on various topics, including cultural appropriation. Despite this, there is a noticeable lack of specific studies that have been conducted to understand cultural appropriation on Reddit. While there have been studies on cultural appropriation on other popular social media platforms such as Twitter (Bass, 2020; Mosley, 2021; Nilsson, 2022; Siems, 2019), Reddit remains largely unexplored in this context. Second, Reddit's structure and nature make it a suitable platform for studying social phenomena. As noted by Massanari (2017), Reddit's algorithm, governance, and culture can support a variety of discussions, making it a rich source of data for studying social phenomena. Similarly, Singer, Ferrara, Kooti, Strohmaier, and Lerman (2016) observed that Reddit's user sessions can provide insights into online performance and behavior, which can be valuable in understanding the dynamics of social phenomena like cultural appropriation. Therefore, this paper aims to fill this research gap by proposing a novel multilayer network model to represent the discussion on a social phenomenon and applying it to Reddit.

Social Network Analysis (SNA) is a robust methodology that provides insights into the relationships and patterns within social networks. It has been extensively applied to study various social dynamics, such as the spread of information and ideas, the formation and dissolution of groups, and the influence of key players in a network (Almars, Li, & Zhao, 2019; Chen, Kou, Wang, & Zhao, 2021; Dakiche, Tayeb, Slimani, & Benatchba, 2019; Lai, Tambuscio, Patti, Ruffo, & Rosso, 2019; Xu, Rui, He, Wang, & Hadzibeganovic, 2020; Zhang et al., 2019). In this study, Social Network Analysis (SNA) is first utilized to identify and analyze key players in the discussion on a social phenomenon within a multilayer network model. These key players are individuals or entities that significantly influence the spread of discussions or content, distinguished by their position within the network and their role in the diffusion process. SNA is also used to understand the propagation of specific content related to a social phenomenon, analyzing how content is shared within the network and providing insights into the dynamics of discussions. Furthermore, SNA is employed to analyze the spread of specific sub-types of a social phenomenon, studying how its different forms are discussed and spread within the network. Through the application of SNA to the multilayer network model, a comprehensive understanding of the dynamics and patterns of cultural appropriation in online communities is achieved. This approach allows for the identification of key players, analysis of content spread, and study of the diffusion of different forms of cultural appropriation, providing valuable insights into this complex social phenomenon.

Multilayer networks, also known as multiplex or interconnected networks, represent a significant advancement over traditional single-layer networks. They allow for a more nuanced representation of complex systems by capturing relationships between different types of nodes and edges (Kivelä et al., 2014). In the context of this study, multilayer networks are particularly important because they provide a more comprehensive view of the relationships and patterns within a social platform like Reddit. This is crucial when studying complex social phenomena, which involves a multitude of interactions and discussions that cannot be adequately represented by a single-layer network. For instance, in online social platforms, multilayer networks can be used to represent different types of discussions on various topics (Bonifazi, Breve, Cirillo, Corradini, & Virgili, 2022). This allows us to capture the full complexity of these discussions, including how they are interconnected and how they evolve over time. Multilayer networks have also found applications in other fields. For example, in neuroscience, multilayer networks are used to represent the interactions between different brain regions and to model changing brain dynamics over time (Muldoon & Bassett, 2016). The use of multilayer networks in this study is crucial for capturing the intricate dynamics of cultural appropriation in online communities. By providing a

[1] https://www.seventeen.com/celebrity/g22363821/cultural-appropriation-examples-celebrities/

more comprehensive view of the relationships and patterns within the platform, multilayer networks enable a deeper understanding of this complex social phenomenon.

The paper is structured as follows. In Section 2 we present the objectives of this research and its main contributions. In Section 3 we analyze past literature on the themes discussed in this paper. In Section 4 we define the multilayer network model for the representation of social phenomena and its projections. In Section 5 we present some possible analyses specialized for the model. In Section 6 we present our experimental campaign on Reddit. In Sections 7 and 8 we discuss our findings and draw conclusions for the paper.

2. Research objectives and contributions

In this paper, we introduce a novel multilayer network model tailored for the representation of social phenomena in online communities. This model captures intricate relationships between users, content, and specific aspects of social phenomena, offering a more comprehensive view of the relationships and patterns within online platforms. Coupled with our proposed set of quantitative analyses based on Social Network Analysis (SNA), we aim to unlock deeper insights into the dynamics and patterns of social phenomena in online communities. Given the limited exploration of cultural appropriation in the context of Online Social Platforms (especially Reddit), using a Social Network Analysis approach, our study fills a significant gap in the literature and offers fresh insights into this contemporary and relevant social issue.

To achieve this, we have delineated the following specific objectives:

1. **Development of a multilayer network model:** our primary objective is to introduce a novel multilayer network model that captures the intricate relationships between users, content, and specific aspects of social phenomena.
2. **Quantitative analyses:** building on the model, we aim to design quantitative analyses rooted in Social Network Analysis techniques. These analyses are crafted to unveil significant patterns and dynamics within the model.
3. **Application to Reddit data:** with our model and analyses established, we endeavor to apply this framework to a dataset of Reddit comments. This dataset, encompassing over 1 million comments from January to April 2022, has been curated for cultural appropriation-related keywords. Through this, we aspire to delve into the phenomenon of cultural appropriation within online communities.
4. **Evaluation of the model:** our concluding objective is to assess the efficacy of our multilayer network model and the associated analyses in offering a nuanced understanding of social phenomena in online spaces.

Through the realization of these objectives, our ambition is to enrich the understanding of social phenomena in online communities and to furnish a powerful tool for subsequent research in this domain. Moreover, by centering our research on cultural appropriation on Reddit, we aim to deliver actionable insights for online community moderators, educators, and advocates, thereby promoting more enlightened and respectful dialogues on this topic. The contributions of this paper are:

- The introduction of a novel multilayer network model to depict a social phenomenon, encapsulating the intricate relationships between users, content, and sub-types of the social phenomenon.
- The elaboration on projections and combined projections of the multilayer network, facilitating a holistic view of the relationships and patterns within the digital platform.
- The proposition of a set of quantitative analyses grounded in Social Network Analysis to comprehend a social phenomenon, tailored for the multilayer network model and its projections.
- The application of the multilayer network model and the suggested analyses to explore the cultural appropriation phenomenon on Reddit.

3. Related literature

Social media and social networks have become significant topics of research in various fields, including social sciences and humanities. Several research papers have explored the impact and characteristics of social media platforms, such as Facebook, Twitter, and Instagram, on social phenomena and human behavior (Hidayati, 2019; Hoxha, 2021; Jader, 2021; Yefanov & Tomin, 2020). One aspect that researchers have focused on is the role of social media in communication and information sharing. Social media platforms have provided a new avenue for individuals to express their thoughts, opinions, and experiences (Eschmann, Groshek, Chanderdatt, Chang, & Whyte, 2020; Jader, 2021; Yefanov & Tomin, 2020). Users can interact with each other, share content, and engage in discussions, creating a sense of community and facilitating the exchange of information (Hidayati, 2019; Hoxha, 2021; Jader, 2021; Yefanov & Tomin, 2020). Furthermore, researchers have explored the characteristics of social media platforms and their effects on user behavior. Social media platforms have also been studied for their role in facilitating social interaction and information sharing (Hoxha, 2021).

One social phenomenon that has garnered significant attention in the past is cultural appropriation (Bickford & Warren, 2020; Cherid, 2021; Jessup, 1991; Malik, Zakki, Riaz, et al., 2021; Mosley & Biernat, 2021; Young, 2010). Cultural appropriation refers to the act of taking elements of one culture and using them in a way that is disrespectful or harmful to the members of that culture. This can include things like using traditional symbols or artifacts without understanding their significance, wearing traditional clothing in a manner that mocks or belittles the culture, or using language or linguistic elements in a way that is insensitive or exploitative.

Cambridge Dictionary[2] defines cultural appropriation as "the act of taking or using things from a culture that is not your own, especially without showing that you understand or respect this culture". A number of studies have focused on identifying and understanding the dynamics of cultural appropriation in different contexts, including social media platforms (Cordes & Merskin, 2019; Dey et al., 2018; Wooley-Snider, 2018). These studies have employed a variety of methodologies, including data analysis and ethnographic research, to explore the ways in which cultural appropriation is articulated, resisted, and negotiated in online spaces. For instance, Dey et al. (2018) investigated the ways in which young British South Asian adults express and reinforce their dual cultural identities through the appropriation of selfies. While this approach provided rich, qualitative insights, it was primarily focused on a specific demographic and cultural context. Cordes and Merskin (2019) examined the use of social media strategies to combat cultural appropriation of indigenous cultures and identities. They explored the politics of representation and cultural appropriation, as well as the experiences of Native American people, and proposed ways to prevent it. However, the study was primarily focused on specific strategies and did not explore the broader dynamics of cultural appropriation on social media. Wooley-Snider (2018) focused on the representation of Native American women on social media amid cultural appropriation, sexual objectification, and modern invisibility. However, the study was limited in its scope and did not explore the broader implications of these findings for other marginalized groups or for the dynamics of cultural appropriation more generally. While these studies provide valuable insights into the dynamics of cultural appropriation in specific contexts, they do not employ a generalizable approach that can be applied to study any social phenomenon. Moreover, they do not apply Social Network Analysis, a powerful methodology for studying the complex interactions and dynamics within online communities.

In this context, multilayer networks have been widely used to represent users and their interactions in various domains, such as hashtags in tweets (Gori, Martinez, Marteleto, Rodrigues, & Sereno, 2023; Türker & Sulak, 2018), sentiment classification of tweets (Golev & Sushkina, 2022; Singh, Mitra, & Singh, 2020), fake news identification (Pierri, Piccardi, & Ceri, 2020), detecting topic authoritative social media users (Logan, LaCasse, & Lunday, 2023; Nguyen, Wang, Dai, & Dow, 2021; Oro, Pizzuti, Procopio, & Ruffolo, 2017), and identifying conflicts in online discussions (Zhu & Zhang, 2022). These studies have demonstrated the effectiveness of multilayer networks in capturing complex relationships and identifying key players in different scenarios. The study presented by Logan et al. (2023) models user interactions on Twitter as a weighted, directed network. The researchers used topic modeling to induce a directed multilayer network, which helped identify influential users and highly connected groups of individuals. This study underscores the importance of understanding the dynamics of online social networks in order to effectively leverage them for social influence outcomes. In the context of public health, Gori et al. (2023) analyzed Twitter data related to the COVID-19 pandemic and found that the frequency of selected keywords could significantly explain future COVID-19 cases and deaths in one locality. Golev and Sushkina (2022) focused on the consistency of comments to news texts published in social networks. They found that the consistency of the original text determined the consistency of comments, highlighting the importance of the original text in shaping online discussions. Finally, Zhu and Zhang (2022) proposed a nearly-linear time algorithm for minimizing the risk of conflict by modifying the initial opinions of a small number of nodes. This research underscores the importance of algorithmic solutions in managing and mitigating conflicts in online social networks.

A more similar study to the one discussed in this paper is proposed by Bonifazi et al. (2022). The authors thought of a general multilayer network approach to investigate discussions on a social network, using a Twitter dataset containing tweets about opinions on COVID-19 vaccines. It extracts a set of relevant hashtags for each line of thought (i.e. pro-vaxxer, neutral, and anti-vaxxer) and uses a multilayer network model to figure out that the anti-vaxxers tend to have denser and more cohesive networks than pro-vaxxers, leading to a higher number of interactions among anti-vaxxers. The paper also compares its approach with one based on single network analysis and shows that its model is more effective in identifying influential users. This approach is different from the one proposed in this paper. Indeed, our proposed model can be used to represent and study any social phenomenon, not just one specific topic or behavior. It also fully highlights the dynamics within a social network, from communities to contents and topics, making it a more comprehensive tool for social network analysis.

Table 1 provides a comparative analysis of the previous works with the one presented here.

4. Modeling a social phenomenon

In this section we introduce our multilayer model to represent a social phenomenon. In Section 4.1 we are going to formalize the multilayer model. In Section 4.2, we are going to present how we can work with this model.

Before we delve into the formal definition of the multilayer model, it is important to understand the rationale behind the choice of this model and its suitability for studying social phenomena in online social platforms. The multilayer network model is a powerful tool for representing complex systems, where entities are interconnected in multiple ways (Bianconi, 2018; Melançon, Renoust, & Ren, 2021; Williams et al., 2021). This model allows us to capture the richness of interactions and relationships that exist in an online social platform. In our study, we formalize a multilayer network model that encapsulates various aspects of online platforms. This model comprises three distinct layers:

1. User Layer: this layer encapsulates the individual users on the platform.
2. Content Layer: this layer is dedicated to the content that users interact with.
3. Social Phenomenon Layer: this layer focuses on the specific sub-types of the social phenomenon under investigation.

[2] https://dictionary.cambridge.org

Table 1
Comparison of previous multilayer network research with the current work.

	Methodology	Focus	Applicable to
Chen, Lerman, Ferrara, et al. (2020)	Data set of tweets	COVID-19 pandemic	Specific to COVID-19
Hern et al. (2018)	Sentiment analysis	Cybersecurity	Specific to cybersecurity
Thomas, Cary, Smith, Spears, and McGarty (2018)	Social media analysis	2015 European refugee crisis	Specific to refugee crisis
Freuler (2016)	Social media analysis	Syrian refugee crisis	Specific to Syrian refugee crisis
Dey et al. (2018)	Qualitative approach	British South Asian adults	Specific demographic contexts
Cordes and Merskin (2019)	Social media analysis	Indigenous cultural identities	Specific strategies and cultures
Wooley-Snider (2018)	Social media analysis	Native American women	Specific to Native American women
Türker and Sulak (2018)	Multilayer networks	Hashtags on Twitter	Twitter hashtags only
Singh et al. (2020)	Multilayer networks	Sentiment analysis of tweets	Specific to sentiment analysis
Pierri et al. (2020)	Multilayer networks	Disinformation detection	Specific to disinformation
Oro et al. (2017)	Multilayer networks	Influencers	Specific to influential users
Nguyen et al. (2021)	Multilayer networks	Malicious accounts	Specific to malicious behavior
Bonifazi et al. (2022)	Multilayer networks	Online discussions	Specific to online discussions
Logan et al. (2023)	Multilayer networks	Twitter interactions	Specific to Twitter interactions
Gori et al. (2023)	Multilayer networks	COVID-19 pandemic	Specific to COVID-19
Golev and Sushkina (2022)	Multilayer networks	News in social networks	Specific to online discussions
Zhu and Zhang (2022)	Multilayer networks	Minimizing risk of conflict	Specific to conflict minimization
Ours	Multilayer networks	Any social phenomenon	Multiple social phenomenon

These layers are interlinked through various types of interactions, forming a complex web of relationships that mirror the intricate dynamics of online platforms. The proposed multilayer network model offers a comprehensive perspective on social phenomena in online platforms, leveraging the expressiveness of multilayer models (Aleta & Moreno, 2019; Boccaletti et al., 2014). By segregating users, content, and social phenomena into interconnected layers, we can delve deeper into the mechanisms of discussion and propagation of social phenomena on these platforms.

4.1. Formal definition of the multilayer model

First of all, we need to introduce the model able to represent social phenomena on an online social platform. We propose an undirected multilayer network model, denoted as $\mathcal{M}$, to represent social phenomena on an online social platform.

Definition 1 (*Multilayer Network Model*)**.** $\mathcal{M} = \langle U, C, S, E \rangle$ is a multilayer network model consisting of three interconnected layers: the User layer U, the Content layer C, and the Social phenomenon layer S. Each layer is an undirected network.

Definition 2 (*User layer*)**.** The User layer is defined as $U = \langle N_u, E_u, L_u \rangle$, where each node $u_i \in N_u$ represents a user of the social platform. An edge $(u_i, u_j, l_u) \in E_u$ exists between two distinct nodes if these users belong to the same community. The label of the edge, $l_u \in L_u$, represents the specific community which the users belong to, where L_u is the set of edge labels of this layer.

In the User layer, if two users belong to more than one community, multiple edges will exist between them, each with a distinct label representing the different communities they both belong to. For instance, if u_i and u_j are both members of communities X and Y, there would be two edges between u_i and u_j, one with label X and another with label Y.

Definition 3 (*Content layer*)**.** The Content layer is defined as $C = \langle N_c, E_c, L_c \rangle$, where each node $c_k \in N_c$ represents a piece of content on the platform. An edge $(c_k, c_l, l_c) \in E_c$ exists between two distinct content nodes if they are associated with the same topic. The label of the edge, $l_c \in L_c$, represents the topic associated with the content, where L_c is the set of edge labels of this layer.

Definition 4 (*Social phenomenon layer*)**.** The Social phenomenon layer is $S = \langle N_s, E_s, L_s \rangle$, where each node $s_l \in N_s$ represents a specific sub-type of the social phenomenon. An edge $(s_l, s_m, l_s) \in E_s$ connects sub-types that share a specific relation. The label of the edge, $l_s \in L_s$, represents the type of relation between the sub-types, where L_s is the set of edge labels for this layer.

In the Social phenomenon layer, a sub-type can be considered as a distinct category or aspect of the social phenomenon that is being examined. Relations between sub-types could be based on similarity (if the sub-types share common characteristics), causality (if one sub-type leads to another), or association (if the sub-types are related but not directly causally linked). The label l_s captures this specific relation, providing a nuanced understanding of the interconnections between different aspects of the social phenomenon.

Definition 5 (*Multilayer edges*)**.** E is the set of multilayer edges connecting nodes across the three layers, indicating associations between users and contents and between contents and social phenomenon sub-types.

For example, consider a scenario on a social media platform focusing on cultural appropriation:

- In the User layer, imagine a user node u_i representing "Alice", an active user of the platform. Alice participates in various cultural discussion forums and communities. Alice's interactions and memberships in these communities are symbolized by edges connecting u_i to other users in these communities.

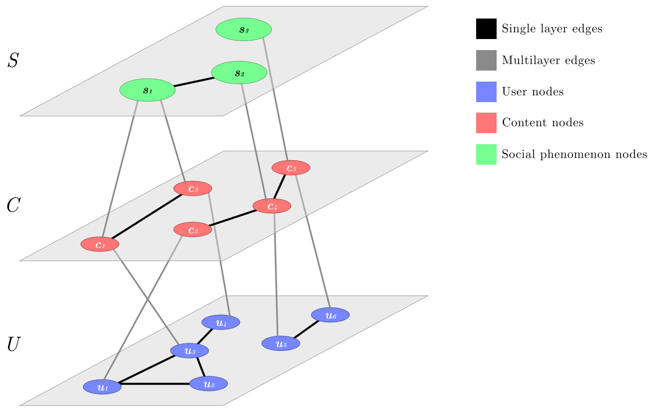

Fig. 1. Graphical representation of $\mathcal{M}$.

- In the Content layer, consider a content node c_k representing a blog post discussing the use of cultural symbols in fashion. This post is connected to other content nodes that explore similar issues, such as the cultural significance of traditional attire or debates around cultural appropriation in the fashion industry.
- In the Social phenomenon layer, a node s_l represents the sub-type "cultural appropriation in fashion". This node is linked to other nodes that denote various sub-types of this phenomenon, such as "cultural appropriation in food", "cultural sensitivity", and "cross-cultural influences".
- Multilayer edges interconnect these layers. For instance, an edge $(u_i, c_k) \in E$ links Alice's user node u_i in the User layer with the blog post node c_k in the Content layer, indicating her engagement with this post. An edge $(c_k, s_l) \in E$ connects the blog post node c_k with the "cultural appropriation in fashion" node s_l in the Social phenomenon layer, signifying the relevance of the post to discussions around cultural appropriation in the context of fashion.

It is important to note the absence of multilayer edges between the User layer and the Social phenomenon layer, emphasizing that sub-types are semantically linked to content rather than directly to individual users. Fig. 1 provides a graphical representation of our multilayer model, illustrating the three layers and their interconnections.

The figure illustrates the three layers of the multilayer network model. In this example, the User layer contains six nodes, connected by edges if they belong to a same community. The Content layer is made up of five nodes, linked together if they share a set of common topics. Content nodes are linked to user nodes through multilayer edges, representing an interaction of the user with the content, including the posting activity. Ideally, each content should be posted by a user, but the model is flexible and can also handle cases where contents are not linked to specific users. The Social phenomenon layer contains three nodes, connected by edges that represent the associations between sub-types of the phenomenon being studied. While the model can be used to represent different social phenomena, this paper focuses on the analysis and study of a single social phenomenon. Content nodes and Social phenomenon nodes are connected by multilayer edges if the content relates to a sub-type of the social phenomenon being studied.

4.2. Projections of the multilayer model

In the context of multilayer network analysis, we introduce the concept of *projections*. A projection is a transformation of the multilayer network model that focuses on the relationship between two specific layers, allowing for a more targeted analysis of the network's structure. This simplification allows us to analyze and understand the relationships and patterns within the multilayer network model more effectively.

Definition 6 (*Projection*)**.** A projection of the multilayer network model is a transformation that simplifies the network by focusing on the relationship between two specific layers. Formally, given a layer $M = \langle N_m, E_m, L_m \rangle$ in the multilayer network, we can project it onto another layer $M' = \langle N_{m'}, E_{m'}, L_{m'} \rangle$. The resulting projection, denoted as $M^{M'}_{L_m} = \langle N_m, E_{mm'}, L_m^{m'} \rangle$, retains the same set of nodes N_m from the layer M. On the other hand, an edge between two nodes $m_1, m_2 \in N_m$ is included in $E_{mm'}$ if there exists a multilayer edge $e \in E$ that links both m_1 and m_2 to the same node $m' \in N_{m'}$. The edge label $l_m^{m'} \in L_m^{m'}$ indicates whether the connected nodes have a similar or different relationship in the original layer M.

Fig. 2 provides a visual representation of this concept. To illustrate this concept, let us consider the projection of the User layer onto the Content layer. In this projection, each node represents a user, and two nodes are connected if the corresponding users have interacted with the same content. This projection allows us to analyze the patterns of user interactions based on the content they interact with.

However, it is important to note that these projections may not fully capture the complexity of the social platform. To address this, we introduce the concept of combined projections.

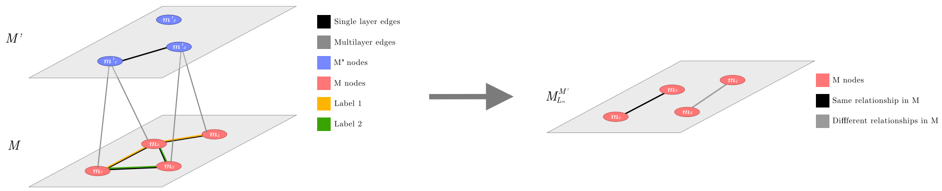

Fig. 2. Example of a generic projection $M_{L_m}^{M'}$.

Definition 7 (*Combined Projection*)**.** A combined projection in a multilayer network model is a transformation that extends the concept of a simple projection by considering additional layers or projections. Formally, given an existing projection $M_{L_m}^{M'}$ and another layer or projection $M'' = \langle N_{m''}, E_{m''}, L_{m''} \rangle$, we define a combined projection as $M_{L_m}^{M',M''} = \langle N_m, E_{mm'm''}, L_m^{m'm''} \rangle$. This combined projection retains the node set N_m from the original layer M. An edge between two nodes $m_1, m_2 \in N_m$ is included in $E_{mm'm''}$ if, and only if, there exists multilayer edges in E connecting m_1 and m_2 to nodes in both M' and M''. The edge label $l_m^{m'm''} \in L_m^{m'm''}$ indicates whether the connected nodes have a similar or different relationship in $M_{L_m}^{M'}$.

This approach allows for a more comprehensive analysis of the complex and multi-dimensional relationships present in the network. For example, consider a scenario where we want to understand how user interactions with certain types of content relate to specific social phenomena. We first project the Content layer onto the User layer, forming a projection based on user-content interactions. Next, we project this onto the Social phenomenon layer, creating a combined projection that links users to sub-types of the social phenomenon via their interactions with content. This combined projection allows us to analyze how user engagement with specific topics or types of content is associated with different aspects of the social phenomenon. Such an analysis could reveal patterns like certain topics being more influential in shaping user perceptions of a social issue, or how user communities cluster around specific content types in relation to the social phenomenon.

In summary, projections and combined projections are essential tools in our multilayer network model, allowing us to analyze and understand the complex relationships and patterns within the social platform.

5. Studying a social phenomenon

Once we have our multilayer model and the projections of interest, we are able to define many different analyses to study the social phenomenon of interest. Surely, we can use all well-known Social Network Analysis techniques on single layers U, C, and S. However, the focus of this paper is to think of some novel analyses to better understand a social phenomenon in an online social platform through a multilayer perspective. In the following subsections, we are going to define some of them, that could be of highest interest in the context we are going to analyze. It should also be said that flexibility of the model can bring to the definition of many of them, depending on the goal of the analysis. Theoretical insights can be found in Appendix A.

5.1. Identify key players in the diffusion process

In the context of social networks, key players and influential users refer to distinct roles. Influential users, often known as opinion leaders or influencers, shape discourse within the network due to their large following or recognized expertise. Key players, however, are individuals or entities crucial in spreading a specific topic or idea within the network. They may not necessarily shape discourse but are vital in its propagation. To identify these key players, we utilize centrality measures such as Degree centrality, Betweenness centrality, and Eigenvector centrality. By identifying users with high centrality values, we can pinpoint key players in the diffusion process. These users are likely to have a significant influence on the spread of topics related to the social phenomenon under study due to their extensive connections and interactions with other users. Projecting these key players onto the Content layer allows us to understand the specific topics they are spreading. This projection provides insights into the specific topics being diffused by these key players, offering a more nuanced understanding of the diffusion process.

In summary, using centrality measures to identify key players in the diffusion process and analyzing their interactions with specific content and topics can yield valuable insights into the patterns and dynamics of the social phenomenon within the network. This information can inform strategies for managing the spread of the phenomenon and fostering more positive interactions within the online community.

5.2. Understand key contents and topics

To comprehend the discourse surrounding a social phenomenon, it is essential to identify influential content. We employ metrics like PageRank, Degree centrality, and Clustering coefficient to gauge the influence and propagation of specific content. By identifying contents with high values in these metrics, we can pinpoint specific contents that are rapidly propagating among users. These contents are likely to be key in the diffusion process of specific topics, as they are being viewed and interacted with by a large number of users. Projecting this information onto the User layer allows us to understand the specific users driving the spread of these topics and the most influential communities in the discussion.

5.3. Analyze community dynamics

The analysis of community dynamics is a crucial aspect of understanding the diffusion of a social phenomenon. Communities, conceptualized as clusters of users with shared interests or similar activities, can significantly influence the diffusion process. Community dynamics, referring to the changes and interactions within groups of users sharing common interests, play a crucial role in understanding the spread of a social phenomenon. These dynamics, including community formation, evolution, and interaction, can significantly influence how a phenomenon diffuses within a network. Thus, analyzing these dynamics provides valuable insights into the spread of such phenomena. We utilize metrics such as Modularity, Community size, and Community embeddedness to analyze the role and influence of specific communities in the diffusion process. By identifying communities with high values in these metrics, we can gain insight into the role that specific communities play in the diffusion of a sub-type of the social phenomenon. These communities are likely to be central to the diffusion process, as they are well connected and influential within the network. Projecting these communities onto the Social phenomenon layer allows us to understand the specific sub-types of the social phenomenon that are most prevalent within these communities. This can help us understand how the phenomenon is being spread and what factors may be driving its diffusion within specific communities.

5.4. Identify key sub-types of the social phenomenon

The analysis of specific sub-types of the social phenomenon is a crucial aspect of understanding its diffusion. This analysis can provide insights into the mechanisms of diffusion and inform strategies to influence the spread of the phenomenon. We employ measures like Clustering coefficient, Triadic closure, and Sub-graph centrality to identify and analyze the most prevalent sub-types. By identifying sub-types with high values in these metrics, we can pinpoint specific sub-types that are most common in the contents posted by users. These sub-types are likely to be key in the diffusion process of the social phenomenon, as they are well connected, frequently shared, and influential within the network. Projecting this information onto the Content layer allows us to understand the specific content driving the spread of these sub-types. This information can inform strategies to influence the spread of the social phenomenon and promote desirable outcomes.

5.5. Demonstration of the proposed model

To elucidate the versatility and applicability of our methodology, we offer a generalized example that integrates the multilayer network model, projections, and quantitative analyses. Imagine an online social platform where users actively engage by sharing diverse content. Within this context, let us consider *User A* shares *Content 1* and *User B* shares *Content 2*. Both pieces of content relate to a broader category, termed here as *Topic X*. In our multilayer network model, nodes representing *User A*, *User B*, *Content 1*, *Content 2*, and *Topic X* are instantiated in their respective layers. Relationships are then established as: *User A - Content 1*, *User B - Content 2*, *Content 1 - Topic X*, and *Content 2 - Topic X*.

Delving into projections, a projection on the User layer would manifest a direct connection between *User A* and *User B*, given their shared interest in *Topic X*. Such a projection streamlines the network, spotlighting user-to-user interactions and shared interests. Subsequently, the quantitative analyses introduced earlier can be applied to these projections. As an illustration, Degree Centrality could be employed to pinpoint influential users within the network. In this hypothetical scenario, both *User A* and *User B* would register a Degree Centrality of 1 in the User layer projection, signifying their individual content contributions. Likewise, leveraging PageRank on the Content layer could highlight trending or impactful content. Here, both *Content 1* and *Content 2* would likely register a high PageRank, denoting significant user engagement.

This demonstration aims to underscore the adaptability and coherence of our multilayer network model, projections, and quantitative analyses. It showcases the potential to unravel intricate dynamics across various social phenomena within online platforms, emphasizing the model's broad applicability beyond any specific topic or theme.

6. Experiments with the multilayer model

In this section, we are going to specialize the framework presented in Section 4. In particular, we use the model to study the phenomenon of *cultural appropriation*. We do this by applying the analyses we presented in Section 5. It is crucial to note that our choice of the cultural appropriation dataset is primarily to demonstrate the potentiality and robustness of our framework. While the insights derived might be specific to this dataset, the overarching goal is to showcase the adaptability and capability of the proposed method across diverse social phenomena. All the experiments, including dataset download and elaboration, are done on a Ubuntu 20.04 LTS virtual server with 96 GB of RAM and 16-core CPU.

Table 2
Descriptive analysis of our dataset.

Parameter	Value
Number of comments	20,102
Number of authors	16,976
Number of subreddits	1590
Number of unique topics	5263

6.1. Dataset

In our study, we use a dataset that includes all comments from Reddit that were available for download in the first four months of 2022, from January 1st to April 30th. We choose to focus on comments, as they provide a representative sample of the topics being discussed. Reddit posts often contain links or images without full text, so comments are a better representation of the topics discussed. We obtained the data from `pushshift.io`, which provides easy access to historical Reddit data. To ensure that our dataset is relevant to the topic of cultural appropriation, we filtered comments using specific keywords related to this phenomenon. These keywords include terms such as "traditional symbol", "artifact", "cultural misappropriation", "traditional clothing", "cultural appropriation", "language appropriation", "linguistic appropriation", "cultural stereotypes", "cultural misrepresentation", "cultural insensitivity", "religious appropriation", "cultural exploitation", and "cultural commodification". This ensures that our dataset is primarily focused on comments specifically discussing cultural appropriation, allowing us to concentrate our analysis on this particular topic.

Our dataset includes the following features:

- `id`: a unique alphanumeric string to identify a comment;
- `author`: the commenter's name;
- `subreddit`: the subreddit in which the comment was posted;
- `body`: the full text of the comment.

To construct our multilayer network model, we add two more features to our dataset that are not directly obtained from Reddit:

- `topics`: the topics discussed in the comment;
- `sub-types`: the sub-types of cultural appropriation identified in the comment.

We use OpenAI's GPT-3 Ada model[3] to extract the topics discussed. We choose this model because it is fast and recommended by OpenAI for keywords extraction. It is important to note that natural language processing is not the focus of our paper, and we use GPT-3 only to extract the topics discussed in the comments. We prompt GPT-3 using the phrase "Comment: {body}\n\nTopics:" with a temperature of 0.5, and a maximum output of 60 tokens.

In order to ensure the quality and relevance of our data, we implement a comprehensive cleaning process. This process is conducted both automatically, using Natural Language Toolkit (NLTK) and regular expressions (regex), and manually, to ensure the accuracy of the data. Firstly, we remove all deleted authors and subreddits from the dataset. Subreddits with only one comment and those that has only one author posting in them are also excluded, as they would not provide sufficient data for our analysis. Secondly, we filter out comments that has fewer than four words. Given the complexity of the social phenomenon we are studying, comments with fewer than four words are deemed unlikely to contribute meaningful insights. Thirdly, we remove words not actually representing topics of discussion and comments without topics. This is done to ensure that our analysis focus solely on relevant discussions related to the social phenomenon. Lastly, we clean the topics by removing links, hashtags, and non-English words. This step is crucial in ensuring that our analysis is based on coherent and meaningful discussions. Through this comprehensive cleaning process, we are able to refine our dataset and ensure that our analysis is based on relevant and meaningful data. We provide a descriptive analysis of our dataset in Table 2.

All analyses are performed using Python 3 and its libraries Pandas, for data manipulation, and NetworkX, for model implementation. Our dataset and all analyses can be found in the Github repository https://github.com/ecorradini/CulturalAppropriation. In our analyses, we consider six sub-types of cultural appropriation, identified in the comments by specific keywords in the body: `A` (appropriation of traditional symbols and artifacts), `M` (misappropriation of traditional clothing or fashion), `L` (linguistic appropriation), `S` (stereotyping and misrepresentation of cultures), `I` (insensitivity towards religious and cultural practices), and `E` (exploitation of cultural traditions for commercial gain). It is important to note that a single comment can discuss more than one topic and refer to more than one sub-type.

[3] https://openai.com

Table 3
Descriptive analysis of layer U.

Parameter	Value
Number of nodes	16,976
Number of edges	2,642,943
Density	0.01834
Number of connected components	1172
Size of the maximum connected component	21

Table 4
Descriptive analysis of layer C.

Parameter	Value
Number of nodes	20,102
Number of edges	75,168,155
Density	0.37205
Number of connected components	200
Size of the maximum connected component	19,890

Table 5
Edges defined for layer S.

Node	Node	Relationship
A	M	Similarity
A	S	Association
A	I	Causality
A	E	Causality
M	S	Causality
M	I	Association
M	E	Causality
L	S	Association

6.2. Specialization of the multilayer network model to the dataset

In this section, we describe how we tailor our multilayer model for the given dataset. The User layer, denoted as U, contains all the authors who wrote comments in the dataset. Each author is represented as a node $u \in N_u$. Two authors $u_i, u_j \in N_u$, are connected by an edge $(u_i, u_j, l_u) \in E_u$ if they both wrote comments in the same subreddit, which is the label of the edge. In our experiments, communities are identified by the subreddit name. As shown in Table 3, the User layer has a relatively low density, indicating that the network consists of multiple connected components of varying sizes, with the largest connected component being small in size.

The Content layer, denoted as C, contains all the comments in the dataset. Each comment is represented as a node $c \in N_c$. Two comments, $c_i, c_j \in N_c$, are connected by an edge $(c_i, c_j, l_c) \in E_c$ if they share at least one common topic. The set of common topics is the label of the edge. Table 4 shows a descriptive analysis of the layer C. The Content layer has a relatively high density, with the largest connected component being much larger than the others, suggesting that the network has at least one dominant topic among all the comments.

The Social phenomenon layer, denoted as S, contains the sub-types of cultural appropriation identified in the previous section. This layer has six nodes in total, and the edges between them are shown in Table 5. The relationships between the sub-types are defined as follows:

- Similarity: this relationship exists between two sub-types if they share common characteristics or features. For example, two sub-types might be similar if they involve the same kind of activity or behavior within the social phenomenon.
- Association: this relationship exists between two sub-types if they are related or connected in some way, but not directly causally linked. For example, two sub-types might be associated if they often occur together or if they are part of the same broader category within the social phenomenon.
- Causality: this relationship exists between two sub-types if the occurrence of one sub-type leads to or influences the occurrence of another. For example, one sub-type might cause another if the behavior or activity represented by the first sub-type directly leads to the behavior or activity represented by the second sub-type.

The multilayer network model integrates these layers into a single model, allowing us to analyze the relationships and dynamics between different layers. Table 6 provides a descriptive analysis of the multilayer edges. It shows that each node in layer U is linked to at least one node in layer C, as the posting activity is included in the possible interactions between these two layers. Additionally, there are over 5,000 additional edges between nodes in layer U and layer C that are not related to the posting activity. In our case, the other possible interaction of a user with a comment, in addition to the posting activity, is replying to another comment. The same logic applies to the relationship between layers C and S, where each comment is linked to at least one sub-type of cultural appropriation.

Table 6
Descriptive analysis of multilayer edges.

Parameter	Value
Number of edges between U and C	22,439
Number of edges between C and S	158,978
Number of nodes in U not linked to C	0
number of nodes in C not linked to S	0

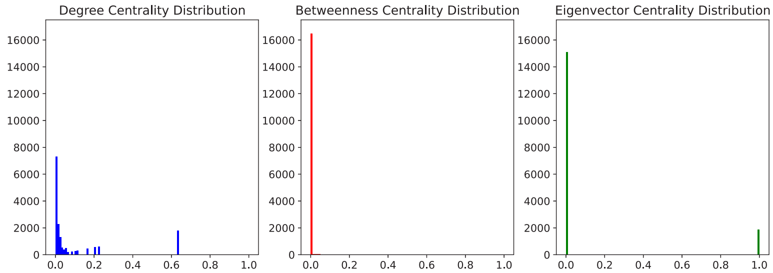

Fig. 3. Distributions of values of Degree, Betweenness, and Eigenvector centralities for the User layer.

Table 7
Descriptive analysis of $K^C_{L_c}$.

Parameter	Value
Number of nodes	3834
Number of edges	691
Number of isolated nodes	3254
Density	$9.40 \cdot 10^{-5}$

6.3. Experiments on key players in the diffusion process

In this first experiment we are going to analyze users. To identify the key players in the diffusion process of information inside the network, we first compute the Degree centrality, Betweenness centrality, and Eigenvector centrality of all users in the User layer. To ensure that the centralities are comparable, we normalized them using the min–max normalization method, which maps the values to a new scale between 0 and 1. Fig. 3 shows the distributions of the values of the three centralities in the User layer. A notable observation from this figure is the high number of users with centralities close to zero across all metrics. However, peaks observed near 0.6 for Degree centrality and near 1 for Eigenvector centrality indicate the presence of influential users.

We apply the Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) method to identify key players in the diffusion process (see Appendix B for more details). The users are ranked based on their relative proximity and the top users, with a relative proximity value higher than the average, are identified as the key players. The results reveal that a mere 22.6% of the total users in the User layer, amounting to 3834 users, are pivotal, accounting for a staggering 85% of the total interactions in the network. The density of the sub-network obtained from these key users is also significantly higher, with a value of 0.30683, which represents an increase in value of 1569.34% from the density of the User layer. This suggests that the key users play a crucial role in the spread of information in the network, as they are highly connected and have a large number of interactions with other users. Their central position in the network makes them potential trendsetters, shaping the narrative and influencing the broader community. This finding highlights the importance of considering the role of key users in the study of social phenomena.

We can now study what are the main topics discussed by this group of key users. To do this, we have to first build the sub-network of the User layer containing only the key users and the corresponding edges $K = \langle N_k, E_k, L_k \rangle$. Here, $N_k \subseteq N_u$ is the set of nodes, we have a node for each key user; $E_k \subseteq E_u$ is the set of edges between key users; $L_k \subseteq L_u$ is the set of labels associated to the edges of the network. Then, we need to project the sub-network K with the Content layer. As we have seen in Section 4.2, we need a new network $K^C_{L_c} = \langle N_k, E_{kc}, L^k_c \rangle$. Each node $k \in N_k$ is a key user. Two nodes $k_i, k_j \in N_k$ are linked by an edge $(k_i, k_j, l^k_c) \in E_{kc}$ if they have interacted with the same content in C. The label l^k_c of the edge is the set of topics discussed in the content. Table 7 shows a descriptive analysis of the obtained projection.

This result shows that only a small fraction of the key users (580), i.e., non-isolated nodes, are driving the discussion in the Content layer. The low density of the network and the high number of isolated nodes suggest that most of the key users are not interacting with the same content or with each other. This fragmentation might be indicative of diverse perspectives or the existence of multiple sub-communities within these key players, each championing different narratives. Fig. 4 shows a list of the top 50 most discussed topics between non-isolated key users in our network. The figure shows that a lot of the topics discussed are related to culture, food, and appropriation. This not only underscores the relevance of these subjects in the current discourse but also hints at the broader socio-cultural dynamics at play. Some other topics discussed include immigration, language, fashion, religion, and

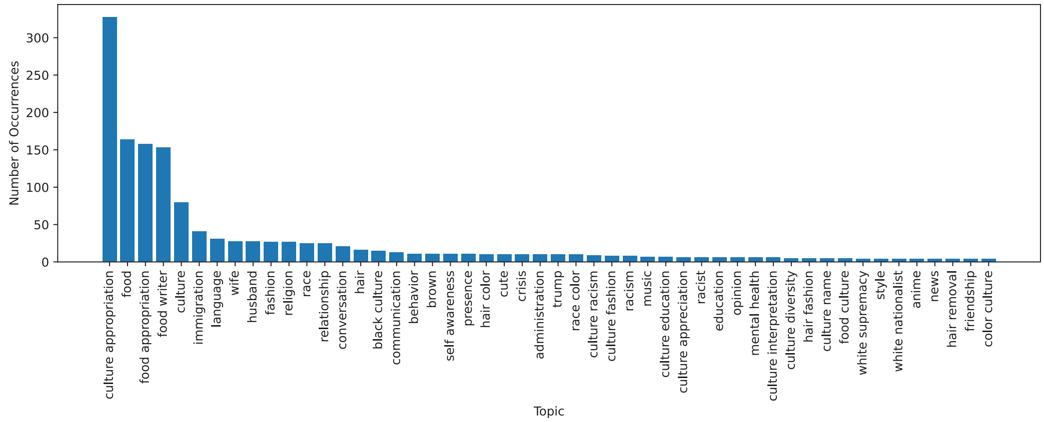

Fig. 4. Distributions of top 50 most discussed topics by the 580 key users.

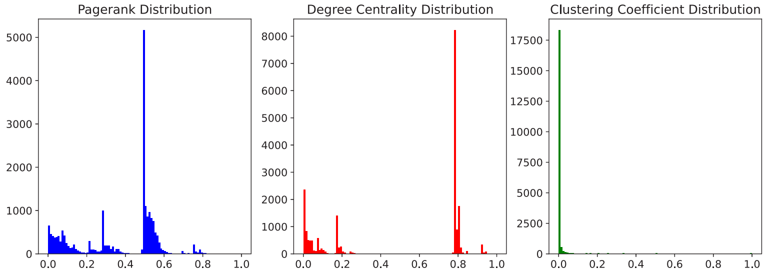

Fig. 5. Distributions of values of PageRank, Degree centrality, and Clustering coefficient for the Content layer.

race. The results suggest that the key users in the network are interested in a wide range of topics and are actively discussing these topics with each other. Understanding the topics that are being discussed among key users can give us valuable insights into the interests and concerns of this group and can help us understand the diffusion of social phenomena in the network.

6.4. Experiments on key contents and topics

In this second experiment, we are going to analyze the contents in the Content layer of our multilayer network. Our aim is to understand the spread of specific pieces of content and identify the key factors driving their diffusion. To achieve this, we are going to measure three metrics: PageRank, Degree centrality, and Clustering coefficient. These metrics provide a comprehensive understanding of how specific pieces of content are spreading and being interacted with in the network. Fig. 5 shows the distributions of these three metrics in the Content layer.

As we can see from this figure, the values of PageRank and Degree centrality in the Content layer are pretty high. Indeed, for PageRank we have four peaks, one near 0, a second around 0.3, the biggest near 0.5, and the smallest around 0.8. We have four peaks on Degree centrality too. The biggest peak is around 0.8. This observation underscores the fact that a significant portion of the content shares overlapping discussion themes. The distribution of Clustering coefficient follows a power law, indicating that most nodes have a low number of triangles formed by their neighbors. This means that most contents do not belong to densely connected clusters, and their neighbors tend to be only loosely connected.

It is also worth noting that the intersection between the nodes with the highest PageRank and the nodes with the highest Degree Centrality is relatively large, with 5838 nodes in common. This overlap signifies that the most influential content pieces in the network are also the ones that resonate with the most recurrent discussion themes. We first define the sub-network $T = \langle N_t, E_t, L_t \rangle$, where $N_t \subseteq N_c$ is the set of nodes containing the 5,838 key contents, $E_t \subseteq E_c$ is the set of edges between these nodes, and $L_t \subseteq L_c$ is the set of labels associated with the edges. In T, we computed the distribution of the topics most discussed in the edges. The distribution of the topics most discussed in the edges of this sub-network is illustrated in Fig. 6, displaying the percentage of each topic's occurrence.

As we can see from the figure, the topic "culture appropriation" is the most present in the edges. This is expected, as it is one of the most generic topic and the dataset is focused on culture appropriation. However, it should be also noted that all the key contents are mainly focused on a single topic. This suggests that the diffusion of the key contents is mainly driven by the discussions around this topic, instead of a variety of different ones.

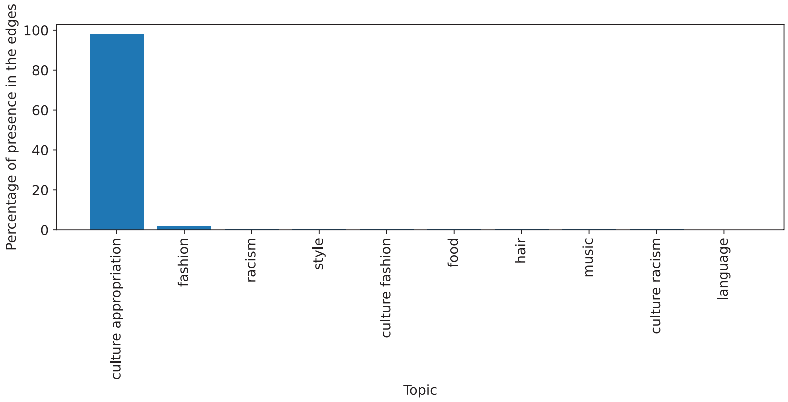

Fig. 6. Percentage of presence of the most discussed topics in the edges of T.

Table 8
Descriptive analysis of $T^U_{L_u}$.

Parameter	Value
Number of nodes	5838
Number of edges	1025
Number of isolated nodes	4603
Density	$6.016 \cdot 10^{-5}$

We are now going to project T into the User layer, to see which are the users linked to the key contents. To do this we define the projection of T in the User layer as $T^U_{L_u} = \langle N_t, E_{tu}, L^C_u \rangle$. We have a node for each key content, two nodes are linked by an edge if they have an interaction from the same user. Each edge is labeled by the community the user belongs to. First of all it is interesting to note that 1475 users interacting with key contents belong to the set of key users found in the previous experiments. This overlap accentuates the pivotal role these key users play in shaping the discourse, acting as the primary conduits for the diffusion of these influential content pieces. Table 8 shows a descriptive analysis of $T^U_{L_u}$.

The results of the projection of the key contents sub-network on the User layer indicate that there is a significant number of isolated nodes, which suggests that many of the users who interacted with the key contents did not interact with each other. This may indicate that the diffusion of these contents was driven by a few highly active users, who shared the contents with their respective communities. The low density of the projection further supports this idea, as it indicates that the connections between users who interacted with the same key contents are sparse. This may also suggest that the users who interacted with the key contents had diverse interests and engaged with different contents. Overall, these results suggest that the diffusion of the key contents was not driven by a cohesive community, but rather by a few active users who shared the contents with their respective networks.

The key contents were posted on 271 different subreddits. So, there is not just a single subreddit driving the discussion on cultural appropriation, but many of them. Fig. 7 shows the distribution of the number of key contents for each of the top 50 subreddits.

As we can see from the figure, the subreddit “AmItheAsshole” is the one producing more interaction between users. However, there is not an actually dominant subreddit for key contents. Indeed, the distribution decreases smoothly. It is also interesting to note that 2237 out of 5838 key users posted contents on “AmItheAsshole” subreddit. The fact that this subreddit produces the most interaction between users is a significant finding since it suggests that this particular community is engaging and perhaps more open to discussing the topic of cultural appropriation. However, the distribution of key contents across the different subreddits is not uniform, indicating that different communities have different levels of engagement with cultural appropriation. This diversity underscores the multifaceted nature of discussions around cultural appropriation, with different communities offering unique perspectives and nuances. This could be due to factors such as the topic of discussion, the community’s rules, and norms, among other things. Moreover, the fact that a significant proportion of key users posted on the “AmItheAsshole” subreddit suggests that this community is particularly active and engaged. This could be because the subreddit is specifically designed for users to discuss if they were in the wrong in a particular situation, and as such, users are more willing to engage in discussions and debates.

6.5. Experiments on community dynamics

In this third experiment, we aim to analyze the dynamics of communities in the User layer of the multilayer network. To understand the dynamics of communities, we will measure three metrics: Modularity, Community size, and Community embeddedness. By identifying communities that have high values in any of these metrics, we can identify specific communities that are central to the diffusion process of the sub-type of the social phenomenon. The modularity of the User layer is equal to 0.5369. Fig. 8 shows the scatter plot of the relation between Community size and Community embeddedness.

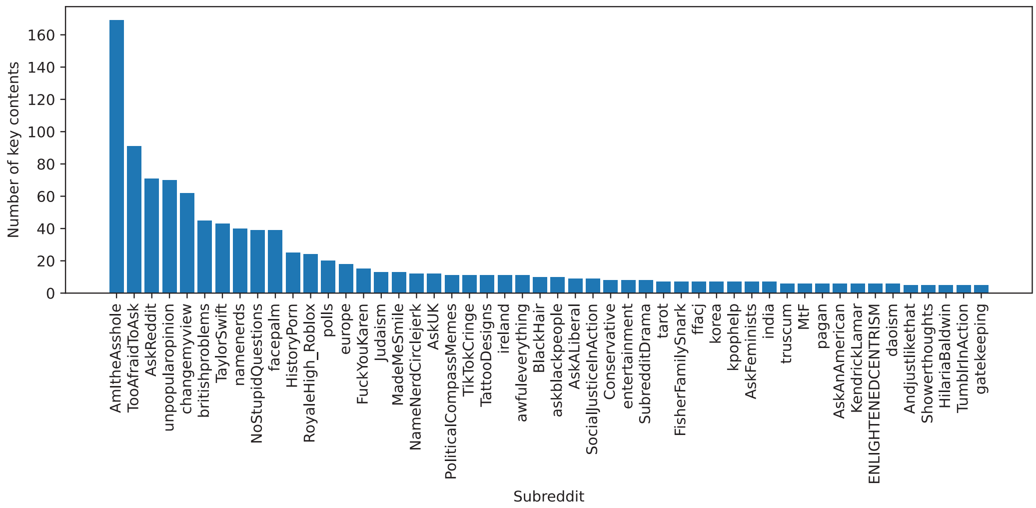

Fig. 7. Number of key contents for each subreddit.

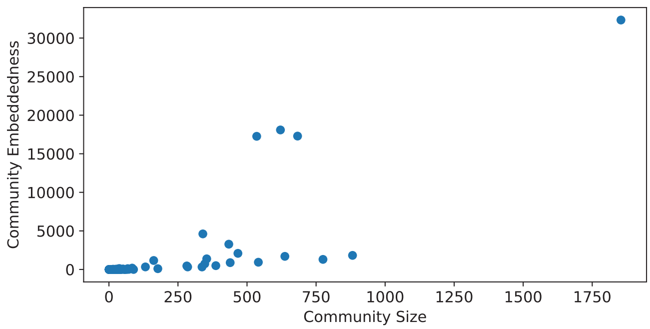

Fig. 8. Scatter plot of Community size and Community embeddedness for the User layer.

The value of Modularity indicates a strong structure in the network, with clear community divisions. In the scatter plot, we can see that there is a general trend of low community embeddedness at increasing community size, with a few notable outliers. Many communities have community embeddedness values less than 5000, even when their community size is around 1000. However, there are three communities with a community size of around 700, but with significantly higher community embeddedness values, near 20,000. The most striking outlier in the scatter plot is a single community with a community size of 1854 and an extremely high community embeddedness value of 32,338. Further analysis revealed that this community consists of a significant portion of key users we found in Section 6.3 - 1850 out of the 1854 members in this community. The large community with high Community embeddedness suggests that a large community can also have high levels of interconnectedness and integration, despite the general trend of low Community embeddedness at increasing community size. These outliers, particularly the community with a size of 1854 and an exceptionally high community embeddedness value, underscore the pivotal role of key users in shaping the discourse within communities.

We want now to study the cultural appropriation sub-types discussed in this particular community. In order to do so, we must first build a sub-network of the User layer that contains only the users of this community and their corresponding edges, $B = \langle N_b, E_b, L_b \rangle$. Here, $N_b \subseteq N_u$ is the set of nodes, where we have a node for each user in the community, $E_b \subseteq E_u$ is the set of edges between these nodes, and $L_b \subseteq L_u$ is the set of labels associated with the edges. We now need to project the Content layer on the Social phenomenon layer. To do this, we must build a new network, $C^S_{L_s} = \langle N_c, E_{cs}, L^c_s \rangle$. Each node $c \in N_c$ represents a piece of content. Two nodes $c_i, c_j \in N_c$ are linked by an edge $(c_i, c_j, l^c_s) \in E_{cs}$ if they are linked through a multilayer edge to the same sub-type in the Social phenomenon layer. The label l^c_s of the edge is the set of sub-types they refer to. Finally, we must project B into $C^S_{L_s}$. To simplify, we will call this new network $B^C_{L_s} = \langle N_b, E_{bc}, L^c_s \rangle$. We have a node in N_b for each user in the biggest community. Two nodes are linked by an edge in E_{bc} if they interacted with the same content. The labels in L^c_s represent the set of sub-types the users have discussed. Table 9 shows a descriptive analysis of this projection.

The projection has a relatively low number of edges compared to the number of nodes, indicating that the majority of users in the community do not discuss the same cultural appropriation sub-type. The density of the projection is also very low, suggesting that the connections between users are sparse. This may indicate that the members of this community have diverse interests and

Table 9
Descriptive analysis of $B^C_{L_s}$.

Parameter	Value
Number of nodes	1854
Number of edges	291
Number of isolated nodes	1600
Density	0.000169

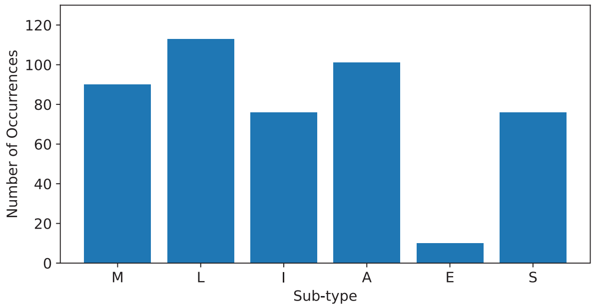

Fig. 9. Number of occurrences of each sub-type in the edges of $B^C_{L_s}$.

Table 10
Descriptive analysis of S.

Parameter	Value
Average clustering coefficient	0.55
Triadic closure	6
Sub-graph centrality	3.2

engage with different contents. The presence of a significant number of isolated nodes further supports this interpretation. Fig. 9 shows the number of occurrences of each sub-types in the edges of $B^C_{L_s}$.

As we can see from this figure, the sub-type occurrences in the edges of the projection support the idea that the majority of users in the community do not discuss the same cultural appropriation sub-type. The occurrence of different sub-types with similar frequency, except for sub-type "E" which has significantly fewer occurrences, suggests that the members of this community have diverse interests and engage with different contents.

6.6. Experiments on key sub-types of the social phenomenon

In this fourth experiment, we are going to analyze the Social phenomenon layer to understand the spread of specific sub-types. We use three metrics to describe the Social phenomenon layer: clustering coefficient, triadic closure, and sub-graph centrality. The results of these metrics are presented in Table 10. These results suggest that the sub-types in the Social phenomenon layer are well connected, as indicated by the high average clustering coefficient of 0.55. The triadic closure of 6 indicates that there are many triangles of relationships between sub-types, further emphasizing their interconnectedness. The sub-graph centrality of 3.2 sheds light on the pivotal role certain sub-types play in shaping the discourse on the social phenomenon, acting as central nodes in the spread of discussions.

Now, we aim to project the Social phenomenon layer onto the Content layer to gain a deeper understanding of the diffusion of the sub-types of the social phenomenon. We create a new network, $S^C_{L_c} = \langle N_s, E_{sc}, L^s_c \rangle$, where each node $s \in N_s$ represents a sub-type of the social phenomenon. Two nodes $s_i, s_j \in N_s$ are linked by an edge $(s_i, s_j, l^s_c) \in E_{sc}$ if they are discussed by the same content in the Content layer. The label l^s_c of the edge is the set of contents that discuss both sub-types s_i and s_j. Such a projection is invaluable in understanding the diffusion patterns of the social phenomenon, revealing which sub-types act as catalysts in driving discussions and which ones are more peripheral. By analyzing the centralities of the nodes in the projection, we can understand which sub-types are most central and important in the diffusion of the social phenomenon. Additionally, by weighing the centralities with the number of common contents in the edges, we can further understand the significance of the relationships between sub-types in the diffusion process. The results shown in Figs. 10(a) and 10(b) give us insight into the spread and importance of different sub-types of the social phenomenon. Fig. 10(a) shows the average number of contents discussing each sub-type, indicating which sub-types are being discussed more frequently. Sub-types A and M have the highest values, with over 1000 contents discussing each of them on average. This dominance suggests that these sub-types might be central to the broader discourse on the social phenomenon. On the other hand, sub-types E and L have the lowest values with only 333 and 337 contents discussing them, respectively.

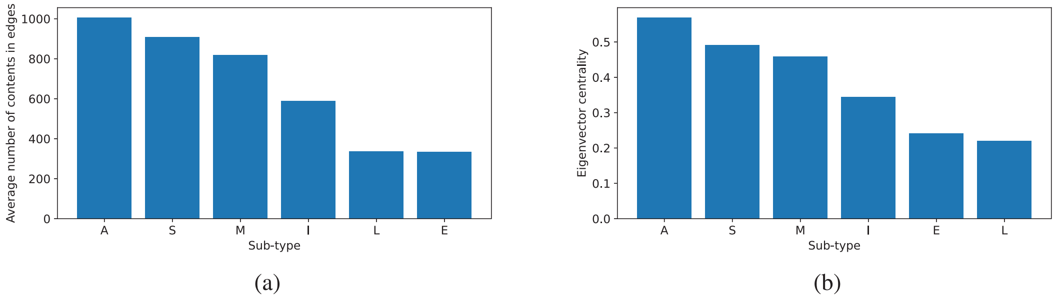

Fig. 10. (a) Average number of contents discussing each sub-type. (b) Eigenvector centrality values of each sub-type.

7. Discussion

This paper proposes a novel multilayer network model that can be used to analyze social phenomena on online social platforms. The multilayer network is a network model consisting of three layers: User layer, Content layer, and Social phenomenon layer. The User layer represents the users of the online social platform, while the Content layer represents the different types of content shared on the platform. The Social phenomenon layer represents the specific sub-types of the social phenomenon being studied. Each layer is an undirected network, and all interactions are labeled by a set of possible labels. The layers are connected by multilayer edges, allowing for the identification of patterns and relationships across them. The model is flexible, allowing for the creation of projections to analyze and understand the relationships and patterns within the multilayer network model. Projections can be combined, providing a more comprehensive view of the relationships and patterns within the social platform.

The model is then specialized to analyze the social phenomenon of cultural appropriation on the online platform Reddit. The study utilizes a dataset of comments related to cultural appropriation, providing insights into various aspects of the Reddit platform:

- The first experiment reveals that influential users in the network are typically part of tightly-knit and often small communities. This indicates that the dissemination of information is influenced not only by community size but also by factors such as topic of discussion and community engagement. This challenges the conventional wisdom that larger communities are the primary drivers of information dissemination, highlighting the nuanced dynamics of online discussions.
- The second experiment examines the spread of specific content and identifies the key factors driving their dissemination. Results indicate that content with common discussion topics holds the most significance in the network. Furthermore, it emphasizes the role of a select group of proactive users in content diffusion, suggesting that targeted interventions or collaborations with these users could significantly influence discourse.
- The third experiment explores the relationships between users and subreddits in the network. The findings reveal varying levels of engagement with cultural appropriation across different communities, with the subreddit "AmItheAsshole" displaying notable activity and involvement in discussing this topic. This insight is invaluable for stakeholders aiming to engage in or moderate discussions on cultural appropriation, directing them to the most active and influential communities.
- The fourth experiment analyzes the Social phenomenon layer and the diffusion of sub-types. Findings suggest that sub-types "appropriation of traditional symbols and artifacts" and "misappropriation of traditional clothing or fashion" are important and frequently discussed in the Social phenomenon layer, while sub-types "exploitation of cultural traditions for commercial gain" and "linguistic appropriation" are less important and less frequently discussed. The results also highlight the interconnectedness of sub-types and their relationships with specific contents in the network. The ability to pinpoint which sub-types dominate discussions and which remain on the periphery is a testament to the model's capability to offer actionable insights for researchers, policymakers, and community managers.

The theoretical implications of our research are significant. Unlike existing approaches, our multilayer network model and the proposed analyses offer a novel perspective on the study of social phenomena in online communities. This model, with its unique capability to capture intricate relationships between users, content, and specific aspects of social phenomena, provides a more comprehensive framework for understanding these interactions. The concept of cultural appropriation, at its core, revolves around the act of adopting elements from a culture without understanding or respecting their original significance. The theoretical base for this concept is rooted in understanding power dynamics, cultural exchange, and the potential marginalization of certain groups. In the digital age, the study of cultural appropriation in the context of social media is paramount due to the platform's global reach and immediate impact. Social media amplifies voices but can also perpetuate stereotypes and misrepresentations at an unprecedented scale. Understanding cultural appropriation in this context informs us about the broader societal dynamics, the perpetuation of cultural stereotypes, and the potential for both positive and negative cultural exchanges. This distinct approach contributes to the theoretical understanding of social phenomena in online communities, setting our research apart from existing work.

In terms of practical implications, our research provides unique insights into the dynamics and patterns of cultural appropriation in online communities. Our approach allows for a more nuanced understanding of the hotspots of engagement and the diverse ways communities engage with cultural appropriation. By identifying these patterns, we can better understand the implications of online discourse on real-world cultural dynamics and interactions.

Furthermore, even if cultural appropriation is the focus of our experiments, it is important to note that our multilayer network model and analysis framework can be applied to different social phenomena. The versatility of our approach allows for adaptation to different contexts and topics, highlighting its potential to reshape the discourse on various online social phenomena. Future research can leverage this model to explore diverse social phenomena, potentially revealing new insights and deepening our understanding of their manifestation and evolution in online communities.

8. Conclusions

This paper has presented a novel multilayer network model for the representation of cultural appropriation in online communities. We have shown how this model can be used to capture the complex relationships between users, content, and sub-types of the social phenomenon, and how projections and combined projections can be used to gain a more comprehensive view of the relationships and patterns within the social platform. We have also proposed a set of quantitative analyses based on Social Network Analysis to understand a social phenomenon, which can be applied to the multilayer network and its projections. Finally, we have specialized the multilayer network model and the proposed analyses to the study of cultural appropriation in Reddit. It is pertinent to highlight that the primary objective of this paper was to demonstrate the potential and applicability of multilayer network analysis in the realm of social media. The depth and width of insights achievable through this method are vast. By delving deeper into the intricacies of multilayer networks, researchers can uncover nuanced patterns, relationships, and dynamics that might remain hidden in traditional single-layer network analyses. Our multilayer approach offers a richer, more holistic view of social phenomena, allowing for a more comprehensive understanding of the multifaceted interactions and intricacies inherent in online communities. Future research can indeed explore the depth and breadth of insights further, leveraging the robustness of the multilayer network analysis approach.

While this study focused on cultural appropriation, the model can be extended to study other forms of discrimination or bias in online communities, such as racism, sexism, or homophobia. This would help us understand the underlying mechanisms that lead to these social phenomena and develop strategies to mitigate their negative effects. Applying the model to other online social platforms, such as Twitter or Instagram, is another promising direction. This would allow us to understand the dynamics of social phenomena across different platforms and communities. Adding temporal properties to the model could enable us to study the evolution of these phenomena over time, providing insights into how they start, spread, and evolve. Advanced techniques such as Graph Neural Networks (GNNs) could also be explored to improve the representation and analysis of the multilayer network. By learning from the complex patterns of user interactions and engagements, GNNs can provide a deeper insight into various aspects of the network, from user influence to the spread of content. Their ability to capture the nuanced relationships between users and content means they can predict trends and behaviors with a higher degree of accuracy than traditional methods. For instance, they can anticipate how certain content might propagate based on historical data and the underlying structure of the network. Integrating GNNs into our framework holds the promise of significantly enhancing the depth and precision of our analyses, leading to a more comprehensive understanding of social phenomena in online communities. Finally, the model and analyses can be extended to other critical social phenomena, such as the spread of misinformation or the formation of extremist groups. This would allow us to understand the underlying mechanisms that lead to these phenomena and develop strategies to mitigate their negative effects.

CRediT authorship contribution statement

Enrico Corradini: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data and code are available at https://github.com/ecorradini/CulturalAppropriation.

Appendix A. Theoretical measures for studying social phenomena

In the paper, we mention various metrics to analyze the social phenomena in online platforms using our multilayer model. This appendix delves deeper into the theoretical underpinnings of these metrics. The subsequent sections provide a comprehensive theoretical explanation of these metrics, emphasizing their relevance and applicability in the context of our study. The inherent flexibility of our model allows for the definition and adaptation of various metrics, depending on the specific objectives of the analysis.

A.1. Identify key players in the diffusion process

In network theory, the identification of key players is paramount for understanding the dynamics of information flow. Different roles, such as influential users and key players, have distinct theoretical implications.

Influential Users vs. Key Players: influential users, also termed as opinion leaders or influencers, are theoretically posited to shape the discourse within a network. Their influence stems from a large following or a recognized expertise in a domain. On the other hand, key players might not have the same level of discourse-shaping influence but are crucial in the propagation of specific topics or ideas within the network. Their role is more about dissemination than creation of discourse.

Centrality Measures: the concept of centrality is foundational in network theory. It quantifies the importance of nodes within a network. Three primary centrality measures are employed to identify these key players:

- *Degree Centrality:* rooted in the work of Freeman (1979), degree centrality, denoted as $\delta(u)$, is a measure of a node's immediate connections. Mathematically, it is the number of edges incident on a node, represented as $\delta(u) = \sum_v A_{uv}$, with A being the adjacency matrix. The theoretical implication of high degree centrality is that the node can directly interact with a large portion of the network. However, it does not account for the depth or quality of these connections.
- *Betweenness Centrality:* this measure, also introduced by Freeman (1979), captures a node's role as a bridge or gatekeeper in the network. It quantifies the number of shortest paths between nodes that pass through a given node. The formula $\beta(u) = \sum_{s \neq u \neq t} \frac{\sigma_{st}(u)}{\sigma_{st}}$ represents this, where σ_{st} is the total shortest paths from node s to node t. Theoretically, nodes with high betweenness centrality can control or influence the flow of information.
- *Eigenvector Centrality:* based on the work of Bonacich (1987), this measure evaluates the quality and influence of a node's connections. It is defined using the principal eigenvector of the adjacency matrix. The theoretical underpinning is that nodes connected to other high-centrality nodes are more influential.

Implications for Diffusion: from a theoretical standpoint, nodes (or users) with high centrality values are pivotal in the diffusion process. Their extensive connections and interactions amplify the spread of topics or ideas. Furthermore, projecting these central nodes onto different layers, such as the Content layer, can provide deeper insights into the nature and specifics of the diffusion process.

In essence, the centrality measures, rooted in network theory, offer a robust framework to understand the dynamics of diffusion in networks. By identifying and analyzing these key players, one can derive actionable insights to influence the spread and nature of information within the network.

A.2. Understand key contents and topics

The theoretical understanding of content and topic dynamics in networks is pivotal for grasping the nuances of discourse surrounding a social phenomenon. Network metrics provide a lens through which the influence and propagation of specific content can be analyzed. Three primary metrics, PageRank, Degree centrality, and Clustering coefficient, are employed in this context:

- *PageRank:* rooted in the foundational work of Abdo, Ismail, and Eladawy (2009) and Page, Brin, Motwani, and Winograd (1998), PageRank is a recursive algorithm that measures the importance of nodes in a network. Theoretically, it is based on the premise that the importance of a node is determined not just by the number of links it has, but also by the quality or importance of those links. The formula $\varrho(c) = (1-d) + d \sum_{c' \in M(c)} \frac{\varrho(c')}{L(c')}$ captures this, where the damping factor d accounts for the probability that a user will continue clicking on links. A high PageRank theoretically indicates a node's significant influence within the network.
- *Degree Centrality:* as introduced by Freeman (1979), degree centrality in the context of content quantifies the interconnectedness of a piece of content with others. It measures how many other contents a specific content shares topics with. Theoretically, a high degree centrality indicates that a content is central to many discussions or topics, serving as a hub in the content network.
- *Clustering Coefficient:* based on the work of Boccaletti, Latora, Moreno, Chavez, and Hwang (2006), Fagiolo (2007) and Watts and Strogatz (1998), the clustering coefficient provides a measure of the degree to which nodes in a graph tend to cluster together. In the context of content, it provides insights into how topics or contents are interconnected. A high clustering coefficient theoretically suggests that if two pieces of content share a common link with a third one, they are also likely to be linked together, indicating closely knit topic clusters.

Implications for Content Diffusion: from a theoretical standpoint, contents with high values in these metrics are more likely to propagate rapidly among users. They serve as focal points or hubs in the content diffusion process. Furthermore, projecting this content-centric information onto user-centric layers, such as the User layer, can provide deeper theoretical insights into the dynamics of content consumption, dissemination, and influence.

In essence, these network metrics, deeply rooted in network theory, offer a robust theoretical framework to understand the dynamics of content and topic diffusion in networks. By analyzing and understanding these metrics, one can derive a comprehensive understanding of content dynamics within a network.

A.3. Analyze community dynamics

Community dynamics, rooted in network theory, offer a profound understanding of the interactions and evolutions within groups of users in a network. The theoretical exploration of these dynamics is pivotal for comprehending the diffusion mechanisms of social phenomena. Communities, from a theoretical standpoint, can be visualized as dense subgraphs or clusters within a larger network, where members share common interests or engage in similar activities. The dynamics within these communities, such as formation, evolution, and interaction patterns, can significantly influence the diffusion trajectories of various phenomena within the network. Three primary metrics are employed to delve deeper into these dynamics:

- *Modularity:* introduced by Silva, Comin, and da F. Costa (2022) and Newman (2006), modularity is a metric that quantifies the strength of division of a network into communities. Theoretically, a high modularity value indicates that the network has a strong community structure, with dense connections within communities and sparse connections between them. The formula $\mu = \frac{1}{2m}\sum_{ij}[A_{ij} - \frac{k_i k_j}{2m}]\delta(c_i, c_j)$ captures this essence, emphasizing the difference between the actual number of edges within communities and the expected number in a random network.
- *Community Size, $\sigma(C)$:* the size of a community is a straightforward metric, representing the number of users or nodes within a specific community. Theoretically, a larger community might wield more influence or activity within the network. However, size alone does not capture the nuances of connectivity or the community's relative influence.
- *Community Embeddedness, $\zeta(C)$:* this metric, rooted in the idea of network integration, measures the extent to which a community is intertwined with the rest of the network. We can compute it as $\zeta(C) = \sum_{n_C \in N_C} \sum_{n \in N_u(n_C)} [partition(n) \neq C]$ captures this, emphasizing the connections a community has with nodes outside its boundary. Theoretically, a high embeddedness indicates a community that, while cohesive, is not isolated and actively interacts with the broader network.

Implications for Diffusion Analysis: from a theoretical perspective, communities with high values in these metrics play pivotal roles in the diffusion processes of specific sub-types of social phenomena. They act as epicenters of information dissemination, influencing the trajectory of diffusion within the network. By projecting these community-centric insights onto layers representing specific phenomena, one can derive a comprehensive theoretical understanding of how specific topics or sub-types spread and the underlying factors driving their diffusion.

In essence, the theoretical exploration of community dynamics, underpinned by these metrics, provides a robust framework for understanding the intricate patterns of information flow and influence within networks.

A.4. Identify key sub-types of the social phenomenon

The diffusion of a social phenomenon is often not uniform; it comprises various sub-types or facets that spread differently within a network. The theoretical understanding of these sub-types is paramount to grasp the intricacies of the diffusion process. By employing network metrics, we can delve deeper into the structural properties of these sub-types, shedding light on their prominence and influence within the network. Three primary metrics are instrumental in this exploration:

- *Clustering Coefficient, $\iota(s)$:* rooted in graph theory and introduced by Boccaletti et al. (2006), Fagiolo (2007) and Watts and Strogatz (1998), the clustering coefficient quantifies the interconnectedness of nodes. In the context of social phenomena, a high clustering coefficient for a sub-type indicates its tendency to co-occur or be discussed alongside other sub-types. Theoretically, this suggests that certain sub-types might be inherently linked, either due to their nature or due to external factors influencing their co-discussion.
- *Triadic Closure, $\tau(s)$:* the concept of triadic closure, as defined by Opsahl (2013), is grounded in the idea of transitivity in relationships. It measures the likelihood of two nodes being connected if they share a common neighbor. The formula $\tau(s) = \frac{n_{\text{closed}}(s)}{n_{\text{closed}}(s)+n_{\text{open}}(s)}$ captures this essence, emphasizing the interconnectedness of sub-types within the network. Theoretically, a high triadic closure suggests that sub-types are not isolated entities but are part of a more intricate web of relations.
- *Sub-graph Centrality, $\psi(s)$:* introduced by Estrada and Rodríguez-Velázquez (2005) and Kumar et al. (2022), sub-graph centrality offers a measure of the importance of a node by considering the entire structure of the sub-graph it forms. The formula $\psi(s) = \sum_{k=0}^{\infty} \frac{(A'^k)_{ss}}{k!}$ encapsulates this, emphasizing the centrality of a sub-type based on its connections and the overall structure of its sub-graph. Theoretically, a high sub-graph centrality indicates a sub-type's pivotal role within the network, suggesting its influence and prominence.

Implications for Diffusion Analysis: from a theoretical standpoint, sub-types with high values in these metrics are likely to be central in the diffusion process. They act as nodes of influence, driving the spread of the broader social phenomenon. By projecting these insights onto other layers, such as the Content layer, we can derive a comprehensive theoretical understanding of the mechanisms driving the spread of these sub-types and the content that amplifies their diffusion.

In essence, the theoretical exploration of social phenomenon sub-types, underpinned by these metrics, provides a robust framework for understanding the intricate patterns of diffusion within networks.

Appendix B. TOPSIS method

The Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) is a multi-criteria decision-making method. Originally proposed by Hwang and Yoon (1981), the method is designed to determine the best alternative from a set of alternatives based on multiple criteria. The fundamental concept behind TOPSIS is to identify solutions that are closest to the ideal solution and farthest from the negative ideal solution (Behzadian, Otaghsara, Yazdani, & Ignatius, 2012).

B.1. Basic concept

Given a matrix of alternatives and criteria, the method involves the following steps:

1. *Normalization of the Decision Matrix*: this step transforms all the criteria values into a comparable scale, typically ranging between 0 and 1.
2. *Weighted Normalized Decision Matrix*: each criterion is assigned a weight based on its importance. The normalized decision matrix is then multiplied by these weights.
3. *Determination of Ideal and Negative Ideal Solutions*:
   - The ideal solution is the best value for each criterion across all alternatives.
   - The negative ideal solution is the worst value for each criterion across all alternatives.
4. *Calculation of Separation Measures*: for each alternative, the Euclidean distance to the ideal solution (d_{positive}) and the negative ideal solution (d_{negative}) is computed.
5. *Calculation of Relative Proximity to the Ideal Solution*: the relative proximity of each alternative to the ideal solution is calculated using the formula:

$$\text{Relative Proximity} = \frac{d_{\text{negative}}}{d_{\text{positive}} + d_{\text{negative}}}$$

6. *Ranking of Alternatives*: alternatives are ranked based on their relative proximity values. The alternative with the highest relative proximity is considered the best.

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