IT UNIVERSITY OF COPENHAGEN

TikTok StitchGraph:

Characterizing communication patterns on TikTok through a collection of interaction networks

Master's thesis
Data Science
Mads Høgenhaug, Marcus Friis, Morten Pedersen

January 2, 2025
Supervisor: Luca Rossi

ABSTRACT

We present TikTok StitchGraph: a collection of 36 graphs based on TikTok stitches. With its rapid growth and widespread popularity, TikTok presents a compelling platform for study. Its recently introduced research API offers an opportunity to explore the intricacies of its content-remixing stitch feature. Leveraging this, in combination with web scraping, we construct graphs detailing stitch relations from both a video- and user-centric perspective. Specifically, we focus on user multi-digraphs, with vertices representing users and edges representing directed stitch relations. From the user graphs, we characterize common communication patterns of the stitch using frequent subgraph mining, finding a preference for stars and star-like structures, an aversion towards cyclic structures, and directional disposition favoring in- and out-stars over mixed-direction structures. These structures are augmented with sentiment labels in the form of edge attributes. However, the added complexity yields no new insights. Furthermore, no discovered subgraph is statistically significant under a configuration null model. Using these subgraphs for graph-level embeddings together with Graph2Vec, we show no clear distinction between topologies for different hashtag topic categories. Lastly, comparing StitchGraph to Twitter reply networks reveal no major findings with the subgraph analysis and graph embeddings. The dataset and methodology demonstrate one approach to comprising and analyzing network structures from TikTok.

The complete codebase written to create the results for this paper is available in the project repository: https://github.com/Marcus-Friis/thesis

CONTENTS

PREFACE

This project has been a long journey, and throughout the process, we have received many helping hands. First and foremost, we would like to take this opportunity to thank Luca Rossi for being an absolutely outstanding supervisor on all accounts. Working together with him has been both highly educational and a genuine pleasure. We also extend our gratitude to Michele Coscia, for providing much needed support on the technicalities of frequent subgraph mining, Matteo Magnani and Alessia Galdeman, for providing valuable expert feedback on the project, and Marilena Hohmann, for sharing the Twitter data used in the project.

1 INTRODUCTION

In the 21st century, the landscape of public discourse has undergone a significant transformation with the rise of short-form video content platforms such as TikTok, Instagram Reels, and YouTube Shorts. Among these, TikTok has seen a significant increase in popularity, becoming one of the most popular social media services, with more than 1.67 billion active monthly users worldwide (Howarth, 2024). In particular, teens have heavily adopted this new format type (Pew Research, 2023). With the recent introduction of the TikTok Research API (TikTok, 2023), performing large scale studies of TikTok has become a possibility.

The short-form video format has been adopted for all communicative purposes, with content ranging from comedic sketches to serious political debates. This multifaceted nature of TikTok's content makes it a compelling platform to study. The shift from traditional text-dominated social media, such as Facebook and X (formerly known as Twitter), to short-form video content presents new challenges in computationally analyzing public discourse. While natural language processing methods have sufficed for older platforms, the multimodal character of short-form video content introduces analytical challenges that require a combination of visual, auditory, and textual analysis.

TikTok has a plethora of social features. Among these is the *stitch*. The stitch allows users to create a reactionary video of another video, incorporating up to five seconds of the *stitched* video. Similarly, the *duet* allows users to add their own video alongside another user's video in a split screen, floating head, or a green screen format. Unlike stitches, which integrate parts of the original video into the new content, duets display the original and new videos simultaneously and are not bound by the five second rule. This content remixing functionality yields an explicit network structure, where content can have direct connections to other content. This is akin to X's *reply* and *quote* functionality, where posts can be explicit reactions to other posts. Although there exists research on TikTok, most of it is qualitative, and almost no research focuses on studying TikTok as a graph.

This paper presents TikTok StitchGraph: possibly the first graph dataset detailing stitches on TikTok. A stitch network is constructed comprising 36 different hashtags, containing all stitches created in May 2024 using one of said hashtags. The dataset aims to explore and improve understanding of how people communicate using stitches on TikTok. The topological structure of TikTok stitch networks and the content of individual videos are analyzed to uncover patterns and insights into this emerging form of public discourse. Additionally, these findings are compared to Twitter to highlight structural differences and commonalities in how users interact across these two social media platforms. The approach combines basic network analysis, sentiment analysis, frequent subgraph mining, and network embeddings to gain an introductory understanding of the stitch networks collected from TikTok. Specifically, this paper aims to answer the following research questions:

- How can stitch communication on TikTok be studied through the lens of network analysis?
- What stitch patterns are characteristic of TikTok?
- How do the stitch patterns vary between different content themes on TikTok?
- How do the discovered properties of TikTok stitch networks compare with Twitter reply networks?

1.1 AN INTRODUCTION TO TIKTOK

To understand the methods and findings of this paper, one must be familiar with TikTok as a platform and the dynamics that shape its content creation, consumption, and user interactions. This includes understanding the platform's algorithmic structure, the role of trends and challenges, and the unique ways users engage with and remix other users' content with stitches and duets. Throughout this section, multiple TikTok terms and concepts are introduced. For a complete overview, see the Appendix Glossary A.1.

TikTok originated as the Chinese app *Douyin*, launched internationally in 2017. In 2018, it merged with *Musical.ly*, an app introduced in 2014 for sharing lip-sync videos under one minute in length. By 2017, Musical.ly had accumulated 200 million users before being acquired and integrated into TikTok. This historical context shapes TikTok's present-day culture, characterized by its demographic of young users and the popularity of dance videos, as well as the platform's distinctive features for video creation (Savic, 2021).

Users consume TikTok through a personalized video feed, curated by TikTok's proprietary algorithm, commonly referred to as *The Algorithm*. The algorithm presents videos to users, and based on user engagement, it adapts the recommended content. This personalized video feed is known as the *For You Page (FYP)* and is the main attraction of TikTok. Anyone can upload a video and have the algorithm show it in the feeds of other users. The algorithm has strict guidelines towards what content is allowed and will penalize any content that is not compliant with TikTok's policies. This has led users to mask content behind obscure internal ways of speaking and writing, leading to a phenomenon called *algospeak* (Steen et al., 2023).

Other content remixing functionalities include *duets*, *video replies to comments*, and *sound sync*. *Duets* enable users to create collaborative videos in a side-by-side or picture-in-picture format, facilitating interaction through real-time reactions or joint performances. Similarly, *video replies to comments* transform text-based feedback into engaging multimedia interactions. Lastly, *sound sync* lets users create different videos based on the same sound, linking creators through shared auditory elements. These features collectively contribute to an active and creative environment, where users can remix content and interact in different ways. However, by design of the 'For You Page', the exact content being interacted with is heavily influenced by what the algorithm recommends.

TikTok offers a variety of interactive features that shape the way users interact and create content. One of the key features is *hashtags*, which serve as markers for different topics and communities, helping users find and engage with specific content. However, beyond hashtags, TikTok introduced the *stitch* feature in 2020, adding a new layer to communication (TikTok, 2020). This stitch feature is commonly used to create video reactions to other content. Importantly, users cannot stitch a video that is already a stitch of another video. TikTok also gives users control over this feature, allowing them to disable stitching for specific videos or for all of their content. When a video is stitched, the description will show "stitch with @username" and, most of the time[1], provide a direct link to the original video. Throughout this paper, we refer to the user creating the stitch as the "*stitcher*" and the user whose video is being stitched as the "*stitchee*".

[1] We have observed that some users remove the hyperlink from the video description, rendering us unable identify the stitched video.

2 BACKGROUND

This paper collects data for and quantitatively analyzes communication on TikTok. While qualitative methods and ethical considerations regarding TikTok have been fairly well documented, quantitative studies of communication on the platform remain scarce. For this reason, we also look towards similar social network studies conducted on Twitter, leveraging its similarities as a platform to further our understanding of TikTok.

2.1 RESEARCH ON TIKTOK

The digital age has transformed how people engage with the media, moving from passive consumption to active participation. This shift has led to the growth of online communities, where users create and share their own content. This is known as participatory culture, where users are both consumers and creators of media (Jenkins et al., 2015). On platforms like TikTok, features such as stitching and duets enable users to remix and share videos, allowing trends and ideas to spread rapidly. The concept of "produsage" describes how users continuously build on and adapt existing content (Bruns, 2008).

TikTok's stitching feature illustrates this by allowing users to incorporate parts of other videos into their own, blending the roles of creator and consumer (TikTok Newsroom, 2020). This creates an environment where content evolves through collaboration. As Kaur-Gill (2022) shows, TikTok also allows marginalized communities, such as migrant workers in Singapore, to document their poor experiences and challenge the mainstream narratives. Using TikTok's remix features, these workers engage in digital activism, bringing visibility to their unstable living conditions during the pandemic. This aligns with the concept of produsage, where users not only consume content but actively create and remix it, increasing internet exposure for underrepresented voices.

Although these participatory characteristics foster collaboration and community, they also raise legal and ethical questions. According to RippleXN (2023), TikTok's stitch function enables users to engage with existing content in ways that promote viral trends, but also introduces concerns regarding intellectual property. Users must navigate complex questions of content ownership and copyright, as the remixing culture enabled by stitches often blurs the line between original creation and derived work.

Similarly, the internet makes it easy for groups to form and collaborate without formal structures, allowing communities to emerge around shared interests (Shirky, 2008). On TikTok, these communities often form around hashtags, challenges, trends, and interactions. For this study, understanding these patterns is key as we explore how TikTok's stitching feature influences communication. The way users engage through stitching aligns with the ideas of Jenkins et al. (2015), Bruns (2008), and Shirky (2008), creating a space where users build on each other's content and communities grow organically.

Although the role of features such as stitches in content creation has been acknowledged, there has been limited research specifically analyzing how these functions contribute to broader trends and connections within the TikTok ecosystem. In a systematic review of TikTok research, Kanthawala et al. (2022) found that most of the early TikTok studies used content analysis methods and focused on topics such as user behavior and platform governance. However, they noted significant gaps in research that looks into the unique capabilities of TikTok features, including tools like stitches and duets. This oversight underlines the need for studies such as ours, which aim to investigate how TikTok videos, particularly those using the stitching feature, form interconnected networks of content creation. To bridge this gap, researchers can now use TikTok's research API to gather data at scale. The API provides a structured means of collecting information on videos, user engagement, and interactions, offering researchers a more systematic approach to analyzing TikTok's various data.

However, while the API opens up new opportunities for large-scale analyses, it also presents several notable limitations. As Corso et al. (2024) found, the API frequently fails to deliver the full quota of requested data, with researchers often receiving only 65% of the expected content. This issue is made worse because it is unclear when and why some data is missing, especially with older videos that might have been deleted or set to private.

Despite these issues, the TikTok Research API remains a valuable tool for capturing large datasets that were previously inaccessible, and it allows for the examination of features like stitches in more detail than traditional methods. Using this API, this study aims to explore the connections between stitched videos and the broader content networks they form, addressing some of the gaps in understanding how TikTok's unique affordances shape user interaction and content remixing.

2.2 PREVIOUS ANALYSES OF SOCIAL NETWORKS

Social networks have been widely studied, especially on platforms like Twitter[1], which has been a key focus for analyzing how people communicate online. These platforms allow users to interact through direct or indirect connections, forming networks that show patterns of communication, influence, and how content spreads. Twitter's features, like retweets and replies, create clear links between users and their posts, making it easier to study how information flows. For example, a retweet graph maps the connections between users sharing each other's posts, providing a way to analyze how content spreads (Bild et al., 2015).

Research on Twitter has looked at many aspects of communication, such as political influence, user behavior, and network structures. Torregrosa et al. (2020) demonstrate how relevance and centrality within a Twitter network correlate with the spread of extremist discourse, emphasizing that the role of influential users helps shape the flow of content. Lassen and Brown (2011) examine how politicians use the unique features of Twitter to reach their audiences, finding that these features shape communication styles and visibility. Hohmann et al. (2023) explore polarization on the platform, showing how ideological divides and network clustering create echo chambers. Since networks play such a key role in understanding social media, studying similar patterns on other platforms is important.

TikTok's stitch feature provides a way to study communication through explicit connections, similar to how Twitter retweet networks have been analyzed. For instance, studies like Garimella et al. (2018) used Twitter data to model retweet graphs and examine interaction patterns around political events.

Graph theory is an essential tool for studying these communication networks. Metrics such as centrality help identify key users or videos, while community detection reveals clusters of related activity. For example, analyses of Twitter retweet graphs by Cinelli et al. (2021) have demonstrated how interactions often lead to clusters of like-minded users, sometimes forming echo chambers. Although our study does not focus on polarization or ideological alignment, we use similar tech-

[1] In this section, we use the name Twitter to match the platform's name at the time of the studies mentioned. Although now called X, this helps maintain consistency with previous research.

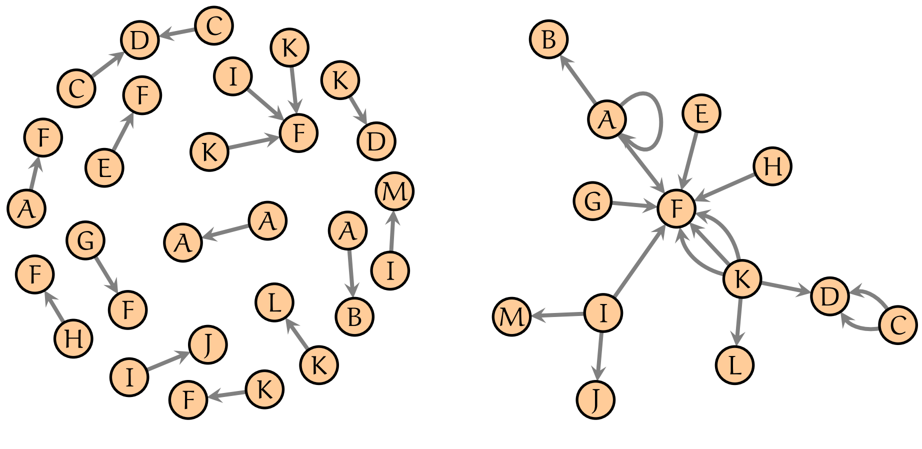
niques, such as centrality metrics to highlight influential nodes, and graph structure analysis to examine topological patterns.

Datasets from Twitter, such as the "Coronavirus Tweet Ids" dataset (Kerchner et al., 2020), provide useful points of comparison. These datasets capture explicit user interactions, such as retweets and replies, which align closely with the stitched relationships in TikTok networks. Although the two platforms differ in format and features, their structural similarities enable direct comparisons through graph analysis.

Prior social network research has focused heavily on Twitter. In this paper, we apply some of the presented methodologies to a newly composed TikTok stitch graph, while in parallel relating the findings to Twitter reply networks from Hohmann et al. (2023). By conducting this analysis, we extend insights from Twitter studies to TikTok, addressing gaps in understanding its unique communication dynamics.

3 DATA & MATERIAL

Our main contribution is composing the TikTok StitchGraph dataset. The dataset consists of stitch videos with metadata, such as user, views, hashtags, etc., and stitch relations between videos. All stitches using one of 36 selected hashtags are collected for all videos created in May 2024. For a video to be included in the dataset, it must be a stitch or a video being stitched. Along with the base TikTok stitch graph dataset, we enrich the data with video transcriptions, detected languages, audio content type, and transcription sentiments. The result is a dataset composed of 36 different graphs, with video metadata and audio data. These can be used in two ways; as **a) video graphs** and **b) user graphs**.



(a) Video graph

(b) User graph

Figure 1: Example user- and video graph, created from a sample of *#biden2024*. Letters denote the user affiliated with the vertex. Video graphs are digraphs, where each vertex is a video and an edge is a stitch relation. They consist solely of stars, with edges being directed towards the central vertex. User graphs are multi-digraphs, where each vertex is a user and each edge is a stitch relation. In user graphs, all patterns can exists including self loops and multiedges.

a) Video graphs are digraphs $G_v = (V, E)$, where vertices are TikTok videos, and edges are directed stitch relations. If video u (the stitcher) stitches video v (the stitchee), there is a directed edge $\{u, v\}$. The affordances and constraints of TikTok dictate the shape that video graphs can take. All video graphs consist of one or multiple stars S_k ranging in size between a dyad S_1, and full star graph $S_{|E|}$, with the directionality always pointing towards the central vertex in the stars. This means that the number of edges $|E|$ for any video graph will range between $\frac{|V|}{2}$ and $|V| - 1$. The number is minimized when the graph consists entirely of dyads S_1, and maximized when the entire graph is a star $S_{|E|}$.

b) User graphs are multi-digraphs $G_u = (V, E)$, where vertices are users, and edges are stitch relations, but between users who stitch each other's videos. If user u stitches a video from user v, then there is a directed edge $\{u, v\}$. Since users can create multiple stitches and be stitched multiple times, the topology of user graphs is not as rigid as that of video graphs. It allows for any arbitrary shapes along with self loops, since users can stitch videos from themselves, and multi-edges, since users can create multiple stitches of a video or different videos from another user. The size of the user graph is constrained by its respective video graph. The number of vertices in the user graph $|V_u|$ ranges from 1 to the number of vertices in the video graph $|V_v|$, depending on the number of unique video creators. The number of edges for both the user- and video graph will always be equivalent $|E_u| = |E_v|$.

3.1 DATA COLLECTION

To compose the TikTok StitcGraph dataset, we use *TikTok's Research API* (TikTok, 2023) and web scraping. Through the API, we collect video metadata. Formally, the only requirement for querying the API is a time period. However, due to API instability[1], we found it helpful to constrain requests further, as it led to more stable API behavior. The API supports filtering by `"create_date"`, `"username"`, `"region_code"`, `"video_id"`, `"hashtag_name"`, `"keyword"`, `"music_id"`, `"effect_id"`, and `"video_length"`. To compose this dataset, we filter by `"hashtag_name"` and `"keyword"` (the video description).

The API is limited with regards to stitches, as it does not have any native functionality for querying stitches or getting stitch relations[2]. However, when a stitch is created, TikTok will automatically put "#stitch with @*username*" in the video description along with a hyperlink to the stitched video. The hyperlink to the stitchee is only available on the TikTok website or app and not through the API. This means that we cannot create the desired network purely through the API. Instead, we need to use a combination of API requests and web scraping to collect the data. The result is the following three-step pipeline: querying stitch video metadata through the API, scraping the IDs of videos being stitched from TikTok's website, and querying the API for the metadata of the stitched videos. The collection process is repeated for each of the 36 selected hashtags for May 2024. This process is seen in Figure 2.

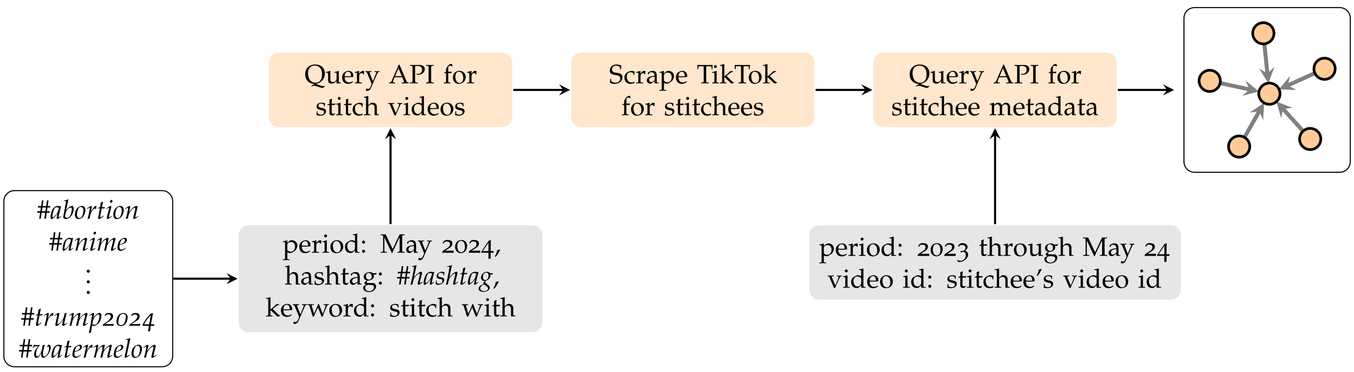


Figure 2: Flowchart illustrating the data collection pipeline. The process begins by querying the API for videos that are stitches of specific hashtags. Next, web scraping is used to extract the original video (the *stitchee*) by navigating to the TikTok site of the stitch video. Using Selenium, the link to the stitchee is extracted from the hyperlink, thus yielding the stitch relation. Finally, the API is used again to retrieve metadata for the stitchee, completing the data collection process.

Query API for stitch videos: The first step of the data collection pipeline is to query TikTok's API for stitch videos. Since the API does not provide direct support for identifying stitches, we employ a workaround method. Specifically, we leverage

[1] Note that the API instability heavily constrained the possibilities for the project, and any query too large would crash the API with error `500 Internal Server Error`.

[2] This is not true as of November 2024. A field called `video_mention_list` has been added to the API, which contains a list of users tagged in a video. However, when we did the project, this feature did not exist.

TikTok's default behavior of automatically including "#stitch with @*username*" in the video description when creating stitches.

To identify stitch videos, we query for those that meet three criteria: (1) the video description must contain the phrase "stitch with ", (2) the video must have been posted in May 2024, and (3) the video must include one of the hashtags for which we are collecting data. This process may yield some false positives (videos that are not stitches but contain the phrase "stitch with "), but these are filtered out in later stages of the pipeline. To maximize the capture of actual stitch videos, we filter only by the "stitch with " phrase at this stage. The result of this step is a list of candidate stitches along with their metadata.

Scrape TikTok for stitchees: Once the stitch videos are identified, the source video of the stitches must be found to create a graph structure. Unfortunately, the TikTok API does not provide a way to link stitches to their source videos, as this information is absent from the metadata. However, TikTok's website and app include a hyperlink to the source video within the video description when creating a stitch. Consequently, we employ web scraping to collect stitchees and their relationships. Using Selenium with Python, we simulate a browser, access the TikTok site of each stitch video, and extract the link to the corresponding source video. This process is repeated for all the collected stitches, resulting in an edge list stating which video each stitch stitches.

There are instances where no link can be found; this is mainly due to either the video having been removed, the video not actually being a stitch and therefore not having a hyperlink, or the user having altered their description and thus removing the link to the original video. If any of these are true, we remove the stitcher from the dataset.

Query API for stitchee metadata: Once the stitch relationships are collected, the stitchee metadata must be collected. From the previous step, we have collected all stitchee video IDs, which we can use to query the TikTok API. The central challenge with this process is that the stitchee videos may be from any point before May 2024, not necessarily from that specific month. To address this, we make multiple API calls, collecting data dating back to January 2023[3]. This step provides the metadata for the stitchees, completing the data collection. At the end of this process, we have constructed a graph structure with the edge list scraped from TikTok and vertex metadata gathered through the TikTok API.

3.1.1 Hashtags - Filtering and Selection Criteria

To constrain the scope of the dataset, 36 hashtags are selected for which to gather stitch graphs. This gives us 36 distinct graphs for analysis and comparison. The hashtags are chosen based on three criteria: comparable size, topic/community focus, and predominantly English language content. These are guiding criteria, but were not strongly enforced in our selection. The size criterion is there to limit the impact of size differences on the analysis of TikTok graphs. The topic/community focus criterion means that the hashtag should be centered on a topic, event, or community of people. The intent is to find hashtags where a conversation occurs such that users communicate using stitches. Lastly, the English language criterion guarantees that we can work with the auditory component of the videos, facilitating future NLP analysis. These criteria lead to the selection seen in Table 1, and these are the 36 hashtags for which we collect graphs.

Each hashtag has been assigned to one of three categories: *Shared Interest*, *Entertainment*, or *Political*. These categories are an attempt to reflect the overarching themes of the hashtags and offer an additional dimension for comparing network topologies, contents, and metadata. Hashtags are selected to similarly cover all three categories. While some hashtags could fit into multiple categories, the assign-

[3] While it would be beneficial to go further back than this, the API rate limits make this impractical.

Shared Interest	Entertainment	Political
Anime	ASMR	Abortion
Booktok	Catsoftiktok	Biden2024
Gaming	Challenge	Blacklivesmatter
Gym	Comedy	Climatechange
Jazz	Conspiracy	Election
Kpop	Dogsoftiktok	Gaza
Lgbt	Football	Guncontrol
Makeup	Learnontiktok	Israel
Minecraft	Movie	Maga
Plantsoftiktok	News	Palestine
	Science	Prochoice
	Storytime	Trump2024
	Tiktoknews	
	Watermelon	

Table 1: Categorization of each collected hashtag. Each of the 36 collected hashtags are assigned one of three categories: *Shared Interest*, *Entertainment*, or *Political*. The category assignment is assigned manually based on the nature of the observed content.

ment reflects the predominant use or context observed. For example, #*lgbt* could align with both Shared Interest and Political; however, watching videos from said hashtag showed that it is predominantly used to engage in a community of like-minded people instead of as a forum for political discussion, and for this reason is assigned to Shared Interest. Similarly, while #*comedy* might suggest a specific interest, it is categorized as Entertainment to reflect its broader context. The line between these categories can be ambiguous and the specific assignment of hashtags could arguably be changed, yet this framework allows for meaningful comparisons within and across groups. The hashtag #*watermelon* is particularly ambiguous, as it encompasses both occasional "viral food" recipes and a historic association with the Palestinian flag. Recently, this symbolism has resurfaced on TikTok as a form of algospeak, enabling users to discuss Palestine while avoiding algorithmic penalties. However, we find that during the time period in which the data was gathered, TikTok users predominantly used it to refer to actual watermelons. Therefore, it is categorized as Entertainment.

3.2 THE COLLECTED DATASET

The collected StitchGraph dataset is comprised of 36 hashtags, with one video- and user graph for each. The video graphs follow the star structure as described in the beginning of this section. For example, clustering is nonexistent, the undirected diameter is at most 2, and the graphs are sparse. Descriptive statistics of the video graphs are presented in Table 2. The number of vertices in all the collected hashtags ranges from 10 to 6702, with #*guncontrol* and #*comedy* being the smallest and largest, respectively. The smallest networks consist of entirely dyads, while #*kpop* is the most pure star-like video graph, with a global degree centralization (Freeman, 1978) of 0.21. This is directly reflected in #*kpop*'s ratio between number of vertices in the largest weakly connected component and the full graphs' number of vertices. Although this is not usually a direct indicator of degree centralization in other graphs, the topological constraints of video graphs mean that this is directly related to the ratio of vertices in the largest weak component.

Hashtag	|V|	|E|	#Components	|V| in LCC	Degree centralization
comedy	6702	3737	2965	23	0.00
booktok	4810	2792	2018	74	0.01
anime	2351	1363	988	113	0.05
storytime	2330	1385	945	141	0.06
lgbt	2111	1183	928	30	0.01
palestine	1550	841	709	20	0.01
gaming	1371	759	612	35	0.02
maga	1311	689	622	10	0.01
football	1293	680	613	27	0.02
catsoftiktok	1205	745	460	89	0.07
news	1197	653	544	11	0.01
trump2024	1120	600	520	19	0.02
kpop	1100	737	363	237	0.21
makeup	1069	626	443	68	0.06
gaza	1034	555	479	12	0.01
dogsoftiktok	993	560	433	12	0.01
gym	929	480	449	10	0.01
israel	816	433	383	5	0.00
learnontiktok	792	413	379	5	0.00
movie	782	433	349	23	0.03
challenge	668	345	323	5	0.00
blacklivesmatter	527	275	252	7	0.01
science	451	235	216	6	0.01
conspiracy	435	227	208	6	0.01
election	401	210	191	6	0.01
watermelon	339	180	159	9	0.02
biden2024	281	145	136	4	0.01
asmr	214	107	107	2	0.00
minecraft	169	94	75	14	0.07
prochoice	162	99	63	21	0.12
tiktoknews	150	76	74	3	0.01
plantsoftiktok	140	71	69	3	0.01
abortion	98	52	46	5	0.03
climatechange	92	46	46	2	0.00
jazz	32	16	16	2	0.00
guncontrol	10	5	5	2	0.00
Shared interest	1408.2	812.1	596.1	58.6	0.05
Entertainment	1253.6	698.3	555.4	25.9	0.02
Political	616.8	329.2	287.7	9.4	0.02

Table 2: Selected metrics for each of the 36 collected video graphs, with aggregate rows in the bottom for each category. For the full video graph table, see Appendix A.3 Table 5.

With the videos collected, the user graphs are constructed and presented in Table 3. The number of edges between a video graph and its corresponding user graph is equivalent, due to user graphs being multi-digraphs, where each edge is a stitch between users. Although the user graphs have no structural constraints, they all display some of the same properties. Most notably, all of the graphs have essentially 0 reciprocity and clustering. Furthermore, there is a large discrepancy between the undirected and directed diameters (d_u and d), as well as the average undirected path length, L_u and the average path length L in the largest weakly connected component. Many of the largest components display high degree centralization, with 5 of them achieving a score of 1, meaning that they are stars.

	Full graph					Largest weakly connected component						
Hashtag	|V|	|E|	#Components	D	D_u	|V|	|E|	L	L_u	C_u	Reciprocity	Degree centralization
comedy	4608	3737	1135	2	19	1838	2032	1.02	7.24	0.00	0.00	0.03
booktok	3540	2792	1119	4	24	844	925	1.28	8.43	0.00	0.00	0.09
storytime	2036	1385	762	2	7	173	189	1.47	2.36	0.00	0.00	0.89
lgbt	1685	1183	566	2	14	365	373	1.04	6.62	0.00	0.00	0.10
anime	1605	1363	443	4	16	646	771	1.53	6.97	0.00	0.01	0.17
palestine	1236	841	434	1	14	144	148	1.00	5.95	0.00	0.00	0.22
catsoftiktok	1059	745	354	2	11	142	146	1.00	5.03	0.00	0.00	0.45
gaming	1023	759	325	4	17	243	266	1.72	6.98	0.01	0.00	0.13
football	935	680	321	2	13	73	81	1.11	5.32	0.00	0.00	0.27
dogsoftiktok	919	560	385	1	5	13	12	1.00	2.21	0.00	0.00	0.61
makeup	915	626	345	2	5	68	68	1.00	1.97	0.00	0.00	1.00
kpop	906	737	236	3	13	344	365	1.03	3.45	0.00	0.00	0.69
gaza	801	555	269	2	11	109	116	1.01	4.51	0.00	0.00	0.29
news	784	653	255	2	6	73	180	1.00	2.11	0.00	0.00	0.90
trump2024	768	600	202	2	14	272	303	1.13	5.88	0.00	0.00	0.10
gym	742	480	297	2	9	74	80	1.00	3.61	0.00	0.00	0.48
maga	644	689	106	3	12	414	557	1.03	4.56	0.00	0.00	0.16
israel	594	433	183	2	22	141	153	1.00	8.07	0.00	0.00	0.07
movie	583	433	199	3	12	71	89	1.22	4.71	0.03	0.00	0.26
challenge	485	345	191	2	10	35	54	1.13	4.76	0.00	0.00	0.13
learnontiktok	464	413	131	6	9	79	134	2.45	3.76	0.16	0.03	0.15
science	411	235	182	1	5	11	10	1.00	2.55	0.00	0.00	0.51
blacklivesmatter	388	275	119	2	8	64	65	1.02	3.46	0.00	0.00	0.41
conspiracy	365	227	150	2	4	11	12	1.00	1.96	0.00	0.00	0.88
election	334	210	131	1	6	11	10	1.00	2.80	0.00	0.00	0.39
watermelon	290	180	119	1	6	17	16	1.00	3.15	0.00	0.00	0.29
asmr	191	107	92	1	2	6	5	1.00	1.67	0.00	0.00	1.00
minecraft	151	94	66	1	3	14	13	1.00	1.86	0.00	0.00	1.00
biden2024	188	145	50	2	11	63	69	1.39	4.55	0.00	0.00	0.23
prochoice	141	99	46	1	4	30	30	1.00	2.69	0.00	0.00	0.67
tiktoknews	120	76	49	1	2	8	7	1.00	1.75	0.00	0.00	1.00
plantsoftiktok	96	71	58	1	6	8	8	1.00	2.71	0.00	0.00	0.24
abortion	87	52	37	1	3	6	5	1.00	1.67	0.00	0.00	1.00
climatechange	86	46	43	1	3	4	3	1.00	1.67	0.00	0.00	0.33
jazz	32	16	16	1	1	2	1	1.00	1.00	0.00	0.00	-
guncontrol	10	5	5	1	1	2	1	1.00	1.00	0.00	0.00	-
Shared interest	1069.5	812.10	347.1	2.4	10.8	260.8	287	1.16	4.36	0.00	0.00	0.43
Entertainment	946.4	698.29	308.9	2.0	7.9	182.1	211.9	1.17	3.47	0.01	0.00	0.53
Political	439.8	329.17	135.4	1.6	9.1	105	121.7	1.05	3.90	0.00	0.00	0.35

Table 3: Selected metrics for each of the 36 collected user graphs, with metrics for both the full graphs and their largest weakly connected components, and with aggregate rows in the bottom for each category. Despite no topological constraints, user graphs all display no clustering or reciprocity, a significant difference between directed and undirected path lengths, and a high degree centralization in their largest component. For the full user graph tables, see Appendix A.3 Tables 6 and 7.

In addition to the metrics presented in the tables, we also noted some observations about the nature of stitches. As expected, stitchers generally have much fewer views than the stitchee, with the stitchee on average having 12 thousand times as many views, showing tendencies of it being e.g. regular users stitching popular clips and adding their perspective or reaction. Similarly, the follower count of the stitchees is approximately 38 times higher than that for the stitchers[4], and the total user-likes is approximately 40 times greater. We also find that only 18% of the stitched videos use the same hashtag as the stitcher, based on our scraped data, indicating that stitches are not confined to a single "community". A notable example of a stitchee exhibiting multiple of these properties is a video by a semi-popular user. It begins with the words, 'What do other girls have on the walls in their bedroom?' and includes only the hashtag *#greenscreen*, due to the use of TikTok's official greenscreen effect. The video is stitched 486 times across 19 hashtags, with stitchers responding by showcasing their bedroom walls usually decorated with a poster or something similar relating to the used hashtag, despite no community affiliation from the stitchee.

3.2.1 Limitations of the Collected Data

The collected dataset is constrained by both collection-specific and general TikTok limitations. Collection-specific constraints include the period of video creation, the timing of data collection, and the reliance on a hashtag-based collection method. The dataset consists entirely of stitches created in May 2024, with no stitches collected from other periods. However, we note that the majority of stitches occur shortly after the original video is uploaded: on average, 31% of stitches occur within one day and 82% within 30 days of the original upload. While the stitch videos were created in May 2024, data collection transpired during Autumn 2024, meaning that videos had ample time to be removed, made private, or affected by changes in API behavior. Furthermore, the hashtag-based collection method introduces inherent limitations, as it captures only stitches associated with a predefined set of hashtags, rather than the entirety of stitch communication on the platform.

TikTok also imposes several constraints on data collection. First, we rely on the official TikTok research API, and any filters or constraints of the API directly affect the collected data. During our research, we encountered frequent back-end issues with the API, including recurring error codes (e.g., `500`), which made certain hashtags unavailable for collection. For example, we were unable to collect data for *#freepalestine* due to persistent API errors. Second, the API lacks a native feature to identify stitches, leading to us using "stitch with " as a proxy. However, users can remove this from their description, causing such videos to be excluded from the dataset. Additionally, some users create "fake stitches" that replicate the functionality of a stitch but without utilizing the official TikTok stitch feature. Although these videos appear as stitches to viewers, they lack the affordances of official stitches, such as including "stitch with " in the description. Lastly, for a stitch to be collected, the creator must be public, aged 18 or over, and the video must not belong to Canada (TikTok, 2024).

3.3 ENRICHING THE GRAPHS WITH CONTENT INFORMATION

The collected stitch graphs detail the topology of the stitch relations between videos and between users. These stitches themselves are videos, and they contain information that the graphs in isolation cannot describe. While metadata such as views, hashtags, video descriptions, etc. have been collected, gathering further video content data is beneficial for deepening our understanding of the domain. The multi-

[4] For practical API rate limit reasons, this calculation is based on a subset of hashtags, namely: *#blacklivesmatter*, *#climatechange*, *#election*, *#jazz*, *#kpop*, *#maga*, *#movie*, *#science*, and *#tiktoknews*.

modal nature of videos makes this a non-trivial task, as truly understanding each video requires understanding speech, audio, visual content, cultural context, and trends.

To limit the scope of this paper, we work purely with speech content. Specifically, we extract the sentiment of each video, adding an extra dimension to the graph data. Sentiment analysis is chosen because it captures the emotional tone of speech, offering a meaningful feature that aligns with our goal of enriching the graph without overcomplicating the task. Despite the fact that more complex tasks could provide deeper insights, sentiment serves as an exemplary addition to the data, while furthering our understanding of the domain. To this end, we also classify the audio type to identify whether a video contains speech. This classification step is crucial to ensure that sentiment analysis is applied only to relevant content. The resulting process is depicted in Figure 3.

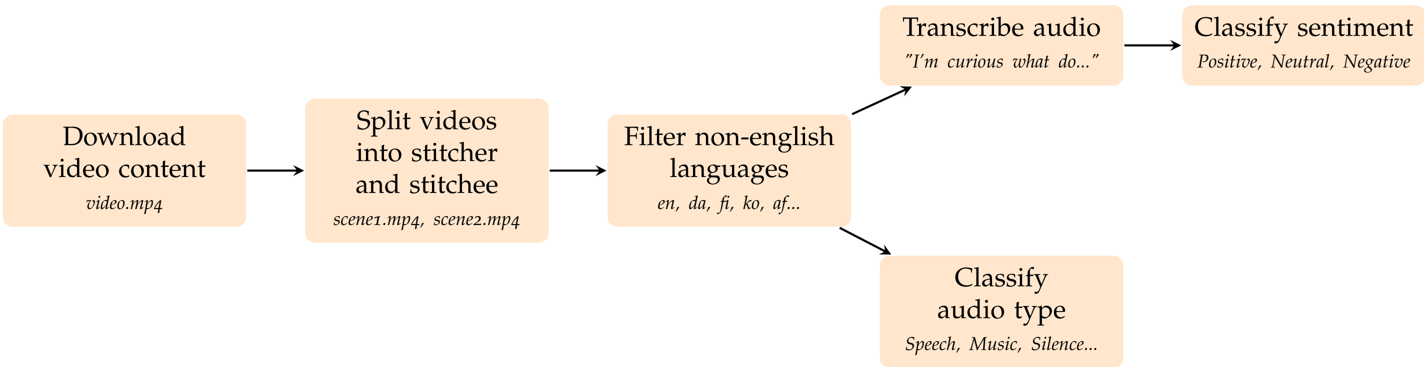


Figure 3: The process by which videos are enriched with content data. Specifically, the video's spoken language, audio type, transcription, and sentiment are extracted.

Download video content: The first step of the augmentation pipeline is downloading videos. Specifically, we download all available stitches and not the stitched videos. Neither TikTok's API nor the app supports downloading videos. Instead, we use *Pyktok* (Freelon, 2024), an unofficial Python library for collecting TikTok data. With this library, we download all available collected stitches, amounting to 86%, with the remaining 14% not being available for download, either due to being removed or made private. This resulted in 20299 total downloaded videos.

Split videos into stitcher and stitchee: The stitch videos that we obtain contain both the stitcher and stitchee parts in the same video. Since we aim to process the reactions to the stitched content, we separate the stitchers from the stitchees by splitting videos. To this end, we use the Python library *scenedetect* (Breakthrough, 2024), which detects scene changes by analyzing variations in the HSL (Hue, Saturation, Lightness) color space. Specifically, the adaptive detection method identifies abrupt cuts using a rolling average of color differences, and classifies a scene shift when the rolling average is above a set threshold. Using the adaptive detection method, we detect the scene shift that transitions from the stitchee part to the stitch part.

The specific scene detection strategy, as described by Algorithm 1, is to detect all scene shifts that occur within the first five seconds with a set adaptive threshold. TikTok stitches can only include up to five seconds of the stitched content, which can be leveraged to focus scene shift detection exclusively on the first five seconds of stitches. If one or more scene shifts are detected, the videos are split at the last detected scene. If no scenes are detected, lower the adaptive threshold and repeat. This process is repeated for adaptive thresholds 9, 6, and 5. If no scenes are detected with any of the thresholds, the videos are split at the five second mark, which also

Algorithm 1 Pseudocode for splitting videos into stitcher and stitchee

```
Input: A stitch video
Output: The respective stitcher and stitchee parts of the video
thresholds ← [9, 6, 5]                                ▷ Adaptive threshold for detecting scenes
splitPoint ← 5                                        ▷ Default split point
videoSegment ← ExtractSegment(video, 0, 5)            ▷ Only use the first 5s
for threshold in thresholds do
    sceneShifts ← DetectSceneShifts(videoSegment, threshold)
    if length(sceneShifts) > 0 then
        splitPoint ← GetLastSceneShift(sceneShifts)
        break
    end if
end for

SplitVideoAt(video, splitPoint)                       ▷ Split video at detected split point

function DetectSceneShifts(videoSegment, threshold)   ▷ From scenedetect
    return list of timestamps where scene shifts are detected based on threshold
end function
```

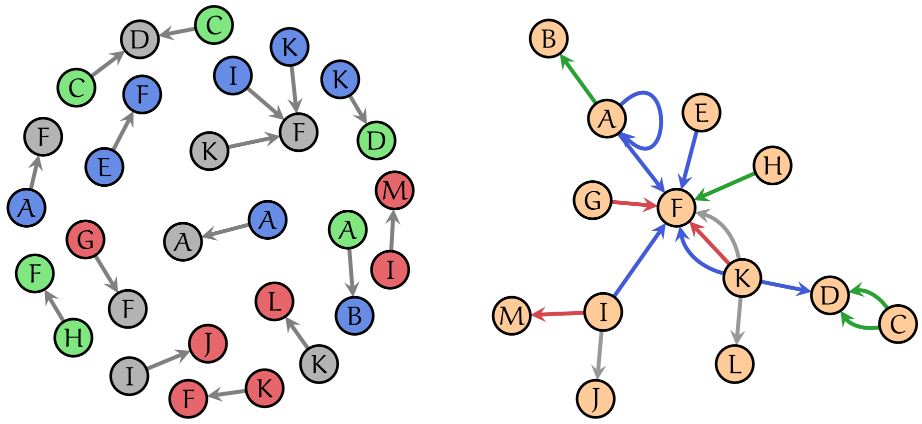
serves as a default split point in alignment with the five second limit for TikTok stitches.

Filter non-English languages: Many of the collected videos are in languages other than English. Since the applied sentiment analysis model is designed exclusively for English-language content, only videos in English are transcribed. To identify the language of each video, OpenAI's Whisper Model (Radford et al., 2022) is used, offering functionalities to classify the language of audio and video files, among other features.

Classify audio type: TikTok videos often feature various audio types. Since our goal is to extract the sentiment of videos, it is essential to distinguish between speech and non-speech audio, such as music or other sounds. To achieve this, we apply Google's *MediaPipe Audio Classifier* (AI, 2024), which classifies the audio type for each second of a video. This dimension provides insight into the dominant audio type within a video, which itself is useful for gaining a deeper understanding of the content, while also being useful for filtering transcriptions.

Transcribe audio: To extract the textual component of each video, each English video is transcribed; both the stitch and the stitchee parts. Similarly to the *Filter non-English languages* section, we also use the Whisper model but for transcriptions. The model has six sizes ranging from *tiny* (39 million parameters) to *turbo* (809 million parameters). As we do not possess expensive computing hardware, we opted to use the *base* model (74 million parameters). A known limitation of Whisper is its 30-second context window, which requires padding or pruning videos to this duration. An alternative approach would involve processing the audio input in batches. In our dataset, the proportion of videos shorter than 30 seconds varies between hashtags. For example, 18% of the videos in the hashtag #*abortion* are shorter than 30 seconds, while this percentage increases to 40% for #football and 75% for both #*comedy* and #*dogsoftiktok*. In contrast, hashtags such as #*storytime* predominantly feature videos longer than 30 seconds, reflecting a different narrative style. However, we assume that the 30-second context limitation aligns well with TikTok's nature as a short-form video platform, where the general sentiment or core message of a video is often conveyed within the first 30 seconds.

Classify sentiment: To enrich the analysis of TikTok communication, we incorporate the sentiment analysis into the user graphs. While our focus is the communication structure, sentiment analysis provides additional insight while still allowing for comparison with Twitter, helping to explore whether platform differences influence communication dynamics. We use *VADER Sentiment Analysis* (hereafter referred to as VADER) (Hutto and Gilbert, 2014) to analyze the transcribed text from stitcher videos, classifying the sentiment into positive, neutral, or negative categories. When videos are unavailable for download, or when no transcription exists, they are labeled with a separate 'no content' label. The result of the sentiment classification is sentiment augmented graphs, where video- and user graphs have assigned sentiments on the stitch relations, illustrated in Figure 4. This enriched user graph enables frequent subgraph mining with sentiment-labeled edges, facilitating the identification of patterns tied to specific sentiment categories.



(a) Sentiment video graph **(b)** Sentiment user graph

Figure 4: Example user- and video graph, created from a sample of *#biden2024*, augmented with sentiment. Possible sentiment labels are positive, neutral, negative, and no content. In the video graph, each video (vertex) is assigned the sentiment of the video transcription. Transitioning to the user graph, each video (edge) is assigned the sentiment of the stitcher's transcription. Thus, it models user's reactions towards other user's content. This figure is an extension of Figure 1.

3.4 TWITTER: A COMPARATIVE PERSPECTIVE

Twitter serves as an important point of comparison in this study. Unlike TikTok's video-based, multimodal content, Twitter's reply networks are focused on text-based interactions, where users respond directly to tweets and other replies. For this paper, we use existing Twitter data, provided by Hohmann et al. (2023), and presented in Table 4. This data, from which we construct the reply networks, centers around six topics and events: gun control, pro-choice, abortion, a vice presidential debate, a second presidential debate, and the U.S. Supreme Court ruling on Obamacare. This is fundamentally different from our StitchGraph dataset, which consists of all stitches from specific hashtags, while the Twitter dataset is a collection of tweets containing at least one of a couple keywords per overall topic. The datasets are composed by Hohmann et al. (2023) but originate from a collection of previous research. Due to the differing data sources, the specific data collection details vary between networks, and as such, it is important to be mindful of the diverse data collection practices when using the data. The dataset reflects a snapshot of political discourse from around a decade ago. Since then, the political landscape surrounding key issues such as abortion and gun control has evolved significantly, influenced by changes in public opinion, policy changes, and new social movements. This gap highlights the need to be aware of changes over time, as the discussions around these topics today may diverge significantly from then.

The Twitter reply networks are multi-digraphs, where vertices are users that have tweeted tweets that conform to the data collection criteria, and edges are

Topic	Full graph $\|V\|$	$\|E\|$	#Components	D	D_u	Largest weakly connected component $\|V\|$	$\|E\|$	L	L_u	C_u	Reciprocity	Degree centralization
Second debate	1556	3248	163	2	14	986	2584	1.00	5.01	0.00	0.00	0.20
Election	1381	2266	367	1	14	734	1296	1.00	5.29	0.00	0.00	0.08
VP debate	1330	2756	158	2	12	932	2325	1.00	4.80	0.00	0.00	0.18
Abortion	1081	1277	186	6	18	690	946	1.91	7.09	0.00	0.01	0.10
Guncontrol	284	239	116	2	6	11	11	1.23	3.05	0.00	0.00	0.14
Obamacare	74	108	27	1	4	12	11	1.00	1.83	0.00	0.00	1.00

Table 4: Selected metrics for the Twitter reply networks for both the full graphs and their largest weakly connected components. These are comparable with the TikTok user graphs, with edges mapping interactions (replies) between users.

replies directed from the replying user to the source user. This is similar to the TikTok user graphs, where the vertices are users, and edges are the stitch relations between them. Although Twitter allows for replying to a reply, unlike stitches on TikTok, there is still very little reciprocity.

To also compare sentiment findings, we apply VADER to analyze the sentiment of tweets, obtaining a sentiment score for each one. In contrast to TikTok, Twitter is a text-dominated platform, and all tweets contain a textual component, meaning that sentiment analysis can be performed on all tweets.

4 METHOD

This paper examines the structural patterns of TikTok stitch networks to quantitatively compare the topologies of different graphs and hashtag categories in TikTok StitchGraph. By analyzing whether hashtags within the same category exhibit structural similarity, the goal is to uncover patterns in how users interact and communicate on the platform. Two main approaches are employed: subgraph analysis and graph representation learning. Subgraph analysis identifies recurring subgraphs that form the observed communication patterns within stitch networks, while graph representation learning focuses on deriving graph-level embeddings to represent the networks in a lower-dimensional space, enabling the evaluation of similarities and differences between hashtag groups within the learned vector representation. By combining subgraph analysis with graph embeddings, both micro-level patterns (e.g., motifs like star structures or chains) and macro-level patterns (e.g., clustering of hashtag categories) are detected. This dual approach facilitates a more comprehensive understanding of the communication dynamics on TikTok.

The presented methodology is only applied to user graphs, and not video graphs. The focus is on user graphs because they capture broader interaction patterns between users, and because of the platform-enforced constraints on video graphs. Analysis of user graphs reveals insights into user stitch behavior. Furthermore, the results of the methods are compared with Twitter reply networks to offer context and perspective from a similar well-studied social network.

4.1 FREQUENT SUBGRAPH MINING

To identify characteristic stitch patterns on TikTok, the *subgraphs* that constitute the observed TikTok stitch user graphs are examined. The objective is to identify the *motifs* that characterize communicative patterns on TikTok. To this end, *frequent subgraph mining* is employed, a technique used to discover subgraphs that appear repeatedly within a graph (Coscia, 2021). Specifically, *transactional graph mining* is applied, aiming to identify subgraphs that frequently occur across a collection of graphs. In practice, this involves pruning the subgraph search space by constraining the minimum required *support* of a subgraph. In a transactional setting, the support of a subgraph is the number of graphs in the graph set with which the subgraph is *isomorphic*, as illustrated in Figure 5. Note that this is fundamentally different from *single graph mining*, where support is defined as the number of isomorphisms between a subgraph and a single graph. An important implication of the transactional setting is that the mined subgraphs may vary in how representative they are of specific graphs. Under the transactional support definition, a subgraph is treated as equally representative of all graphs in which it appears, even if its frequency within the graphs differs.

The need for isomorphism checks makes the process of frequent subgraph mining computationally intensive. Isomorphism itself is an NP-intermediate problem (Aaronson, 2016), and mining frequent subgraphs requires frequent isomorphism checks. This makes it difficult to implement frequent subgraph mining ourselves, and instead we opt for existing implementations, namely *gSpan* (Yan and Han, 2002) and *MoSS* (Borgelt and Berthold, 2002). We use these to mine undirected and directed structures, respectively.

In this study, subgraphs are mined from both standard user graphs and sentiment-augmented user graphs. This approach enables us to analyze the purely topological

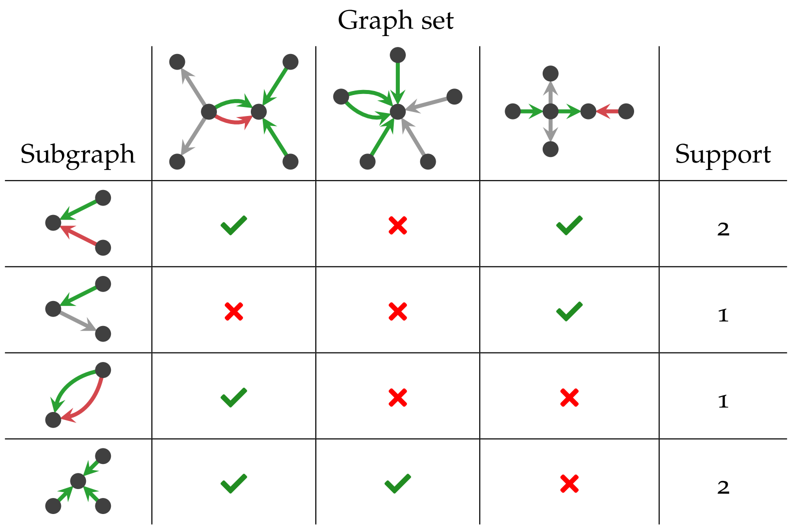


Figure 5: The figure illustrates transactional frequent subgraph mining. Four example subgraphs are compared against the graph set to determine whether each subgraph is isomorphic to any induced subgraph from the graph set. The support of a subgraph is defined as the number of graphs in the set, where the subgraph appears. A checkmark ✔ indicates that the subgraph is found in a graph, while a cross ✘ indicates it is not.

structure of stitch communication, as well as the influence of sentiment on these topological patterns. This is done by assigning an *edge color* (edge attribute) to each edge based on the sentiment of the stitch. Specifically, stitchees are assigned sentiment as an edge color since the goal is to find patterns in the reactions. We create four classes of sentiment; a positive, neutral, negative, and missing content class.

We conduct all frequent subgraph mining on both the complete TikTok user graphs and their largest weakly connected components. All mined subgraphs are subsequently compared with Twitter graphs and relevant configuration models to compute their support for these. For this reason, we use iGraph's isomorphism function (`subisomorphic_vf2`) for computing the support in subgraphs after they are mined[1] to have a comparable support between TikTok, Twitter, and configuration models. In conjunction with mining both undirected and directed graphs, we mine both purely structural patterns and sentiment patterns, resulting in eight separate frequent subgraph mining runs.

When mining subgraphs, all self-loops are removed, but due to computational constraints, multi-edges are removed in the non-sentiment graphs. Although gSpan cannot find multigraph subgraphs, it can find simple subgraphs from a multigraph. MoSS can find multi-graph subgraphs, but it does not support self-loops. When computing the support of each mined subgraph, all self-loops and multi-edges are removed from the graph set, as their presence hinders isomorphism checks in iGraph[2].

4.1.1 Undirected Subgraph Mining with gSpan

To mine undirected subgraphs, we use gSpan (Yan and Han, 2002). gSpan uses a minimum DFS code technique to build a lexicographic order of graphs and then sub-

[1] Note, in our experiments, we occasionally observed a slight difference between iGraph's computed support and the mined support from gSpan or MoSS. In this paper, we always report iGraph's computed support unless stated otherwise.

[2] As of `iGraph 0.11.6`, `subisomorphic_vf2` does not support self-loops. Furthermore, despite no documentation stating missing support for multi-edges, we empirically found that two non-isomorphic graphs can falsely return as isomorphic by iGraph if the subgraph contains a multi-edge.

sequently uses a depth first search strategy to mine frequent connected subgraphs. For this study, we use a C++ implementation of gSpan, provided by Yan (2009), and ran the experiments in a Pop!-OS environment. To do this, all graphs are converted into a .gspan file format, and provided to the algorithm. gSpan supports mining from graphs with multi-edges, but does not support finding multi-edge subgraphs. We mine subgraphs down to a support threshold of 60% without constraints on subgraph size.

4.1.2 Directed Subgraph Mining with MoSS

To mine directed subgraphs, we use Molecular Substructure Miner (MoSS) (Borgelt and Berthold, 2002). MoSS is another frequent subgraph mining algorithm, originally developed for mining subgraphs in molecules. We use it to mine directed frequent subgraphs, as gSpan does not support edge direction. Specifically, we use a special implementation from Borgelt (2022), implemented in Java, that supports general-purpose directed subgraph mining. MoSS employs a depth first search strategy to explore the search tree of possible subgraphs in a strategy similar to Eclat (Zaki et al., 1997), and prunes the search tree using support-based, size-based, and structural-based pruning. Pruning limits the search space based on the minimum support threshold, the maximum subgraph size limit, and ensures that each subgraph appears only in one branch of the search tree. In mining TikTok graphs, we prune the search tree by limiting the maximum substructure size to $|V| = 4$ as the search tree grew too large for larger substructures and resulted in memory issues. MoSS does not support self-loops, but has no other topological restrictions. Using edge attributes in the form of sentiment classes prunes the search tree enough allowing for multi-edge mining, whereas with the unattributed version, we ran into computational constraints, leading us to mine simple no-sentiment substructures.

4.1.3 Discovering Motifs

While the discovered subgraphs provide insight into the common patterns in the different graphs, this does not mean that these are significant. These subgraphs could appear in any graph of similar size. If a subgraph is significant, it is referred to as a motif. To discover motifs, the subgraphs should be compared to a relevant null model (Coscia, 2021). A common choice for a null model is the configuration model, which preserves the degree distribution of the original graph while randomizing their connections. Comparison to this null model reveals whether the candidate motifs are significant or a product of the degree distribution. To account for randomness in the configuration models, 10 configuration models are instantiated for each user graph. Comparisons to configuration models are only conducted for non-attributed graphs, meaning we do not do this for sentiment graphs.

4.2 GRAPH EMBEDDINGS

Graph embeddings provide a powerful framework to represent relationships and interactions in complex systems. By simplifying high-dimensional and intricate network structures, they map these systems into a lower-dimensional vector space, with the goal of capturing their structural and topological properties in numerical form.

In this study, graph embeddings are applied to analyze the structure of user graphs. Specifically, we embed and cluster 36 distinct graphs, each representing a specific hashtag. These hashtags are divided into three predefined groups based on their themes (see Section 3.1.1). By studying embeddings and their clusters, we evaluate whether hashtags within a specific theme share structural properties distinct from those in other groups, offering insight into how stitch patterns vary between content topics.

4.2.1 Graph Representation Learning with Graph2Vec

To encode the graphs, we use *Graph2Vec* (Narayanan et al., 2017), implemented by the Karate Club library (Rozemberczki et al., 2020). As a method for graph representation learning, Graph2Vec encodes entire graphs into fixed-length embeddings, preserving both structural and topological characteristics. Inspired by *Word2Vec* (Mikolov et al., 2013) and *Doc2Vec* (Le and Mikolov, 2014), Graph2Vec represents individual graphs as "documents" and rooted subgraphs as "words." Using the Weisfeiler-Lehman relabeling strategy (Shervashidze et al., 2011), it captures both local and global features of the graphs. Graph2Vec adapts Doc2Vec's skip-gram model, where the context window corresponds to the neighborhood captured by the Weisfeiler-Lehman relabeling. This skip-gram approach helps learn vector representations, which can be applied to tasks such as clustering and classification. However, like many neural representation learning methods, Graph2Vec is somewhat opaque: while we can observe the final embeddings and evaluate them in downstream tasks, it is difficult to pinpoint which specific graph structures map to particular dimensions of the resulting vectors, making it a black box algorithm. Due to the limitations of the Karate Club Library, we only apply Graph2Vec on simple graphs, i.e. we prune self-loops and multi-edges from the graphs. Lastly, Graph2Vec does not support edge-attributed graphs, and hence we refrain from embedding the sentiment graph with Graph2Vec.

4.2.2 Bag-Of-Subgraphs - A subgraph-based Graph Representation

To represent entire graphs, a Bag-Of-Subgraphs approach is employed. The mined subgraphs from frequent subgraph mining can be used to define a subgraph-graph occurrence matrix to extract vector representations for entire graphs. This approach is analogous to the Bag-Of-Words model, but instead of using a vocabulary of words as basis vectors, it leverages subgraph isomorphisms. With this approach, each graph is represented as a collection of subgraph occurrences, ignoring their specific positions or arrangement within the graph. This yields, in contrast to Graph2Vec, an interpretable embedding space, where each dimension can be explained as the presence of a specific subgraph. This approach can be applied to all variants of graphs, since we mine undirected, directed, sentiment-undirected, and sentiment-directed subgraphs.

4.2.3 Clustering and Group Analysis

After embedding the graphs, we cluster them using HDBSCAN (Campello et al., 2013; Pedregosa et al., 2011), a density-based algorithm that identifies clusters of varying sizes without requiring a predefined number of clusters. This approach helps group similar network structures and uncover hidden patterns within the embeddings. This is used as a means to investigate whether hashtags of the same category display similar graph properties in the embedding space and thus cluster together. For example, we can examine whether political hashtags form distinct clusters that differ significantly from entertainment- or shared-interest hashtags. If detected clusters overlap with the assigned categorization of hashtags, it points to graph topology being dependent on the nature of the hashtag. To evaluate this, Normalized Mutual Information (NMI) is applied to calculate the overlap between the two partitions.

5 RESULTS

We introduce the TikTok StitchGraph dataset. From this, applying the presented methodology, we present a look into the foundational subgraphs, and how the collected hashtags relate in their topology. All results are derived from analyzing the largest weakly connected component of the networks.

Importantly, the sentiment results are skewed by human error. *#challenge*, *#football*, *#makeup*, and *#minecraft* are all missing some sentiment labels. *#makeup* and *#minecraft* are only missing a small portion, *#football* is missing all edges not classified as speech by the applied audio classifier, and *#challenge* is missing essentially all sentiment labels. This directly impacts the mined sentiment subgraphs and their support, and the sentiment Bag-Of-Subgraphs graph representations. Results based on these should be interpreted accordingly.

5.1 TIKTOK SUBGRAPHS AND MOTIFS

In this section, we present the findings of the subgraph analysis. The results are illustrated through figures that show various subgraphs. Each subgraph is accompanied by two numbers indicating the support for TikTok and Twitter, respectively (TikTok | Twitter). Importantly, the reported support values represent transactional support and should be interpreted accordingly.

This section is organized as follows: First, we highlight observations regarding cyclic subgraphs and their absence in the mined results. Next, we examine the hierarchical relationships among subgraphs and the relative prevalence of stars and chains. This is followed by an exploration of adding sentiment and directionality as dimensions in the analysis, comparing TikTok's patterns to those observed on Twitter. Lastly, we discuss the absence of any significant motifs under the used null model.

5.1.1 Subgraphs

The first notable observation is the lack of cyclic subgraphs. As seen in Figure 6, the most common cycle is a square, with a support of 16. This support is low enough such that subgraph mining will not find any subgraph that is a supergraph of a cycle. Interestingly, the support of cycles with an even number of vertices is consistently higher than that of cycles with an odd number of vertices. An odd-numbered cycle means that a user has to be both a stitcher and a stitchee for these cycles to occur. This is indicative of it being rare for a user to both stitch and be stitched, which is also reflected by the mean 38 magnitude difference in the number of user followers between stitchers and stitchees. In contrast, this tendency is not observed in the Twitter data. Instead, all reported cyclic subgraphs occur almost equally, with most of them having Twitter support 4.

Given that cycles are not present in any mined subgraph, the complete subgraph hierarchy of up to six vertices can be mapped out, as presented in Figure 7. From it, the hierarchy of subgraphs is apparent, illustrating how the support of any child subgraph is at most equal to its parent. We see that stars and star-like patterns generally have slightly higher support than chains and chain-like patterns. Furthermore, we note that, without cycles, any mined subgraph will always be an interpolation between stars and chains.

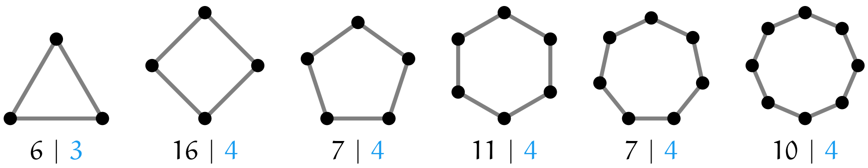


Figure 6: The figure shows the cyclic subgraphs identified within the largest connected components of user graphs, ranging from a triangle to an octagon. The numbers beneath denote the support of the subgraph in TikTok and Twitter in that order.

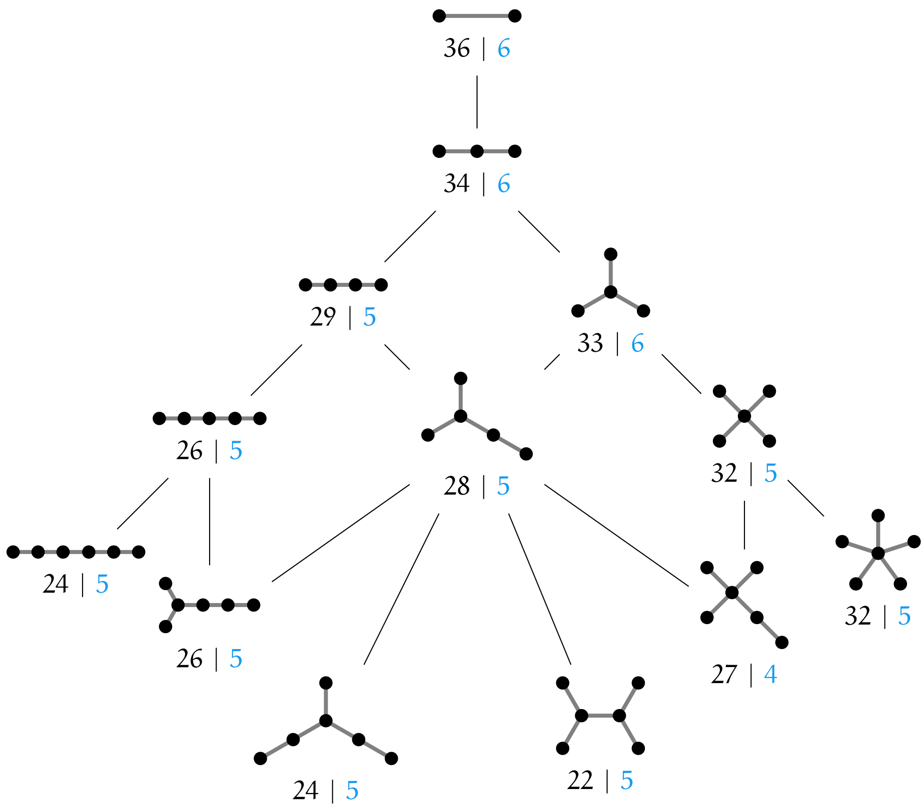


Figure 7: The figure shows the frequent undirected subgraphs identified in TikTok user graphs using gSpan on the largest connected component. The lines between subgraphs illustrate their hierarchical relationships, where each subgraph extends from the one above. The numbers are the supports of the given subgraphs in TikTok and Twitter respectively. Simpler structures, such as dyads S_1 ($\text{support} = 36$), form the foundation, while more complex patterns like chains and star-like structures emerge as extensions with lower support. This highlights how TikTok stitch patterns evolve, often around central hubs or sequential interactions.

These findings are also true going beyond subgraphs with six vertices, as seen in Figure 8. The most common substructure with more than six vertices is a six-star S_6, which appears in 29 user graphs' largest weak component. This aligns with the notion of central users often acting as hubs, either for generating reactions or being highly active in reacting to others. This is a general trend for most of the subgraphs, with pure stars having higher support than pure chains. In fact, for subgraphs where $|V| \geqslant 8$, the pure chain does not appear within the mined set of graphs with a minimum support threshold of 21. The rest of the subgraphs are somewhere in between stars and chains, often occurring in the form of stars extended with a chain, or a chain connecting two stars. The support for these interpolations appears to correlate with the degree to which they resemble a star or a chain. By comparison, the chains' support is generally equal to the stars' support in Twitter networks, indicating a preference for chains when compared to TikTok.

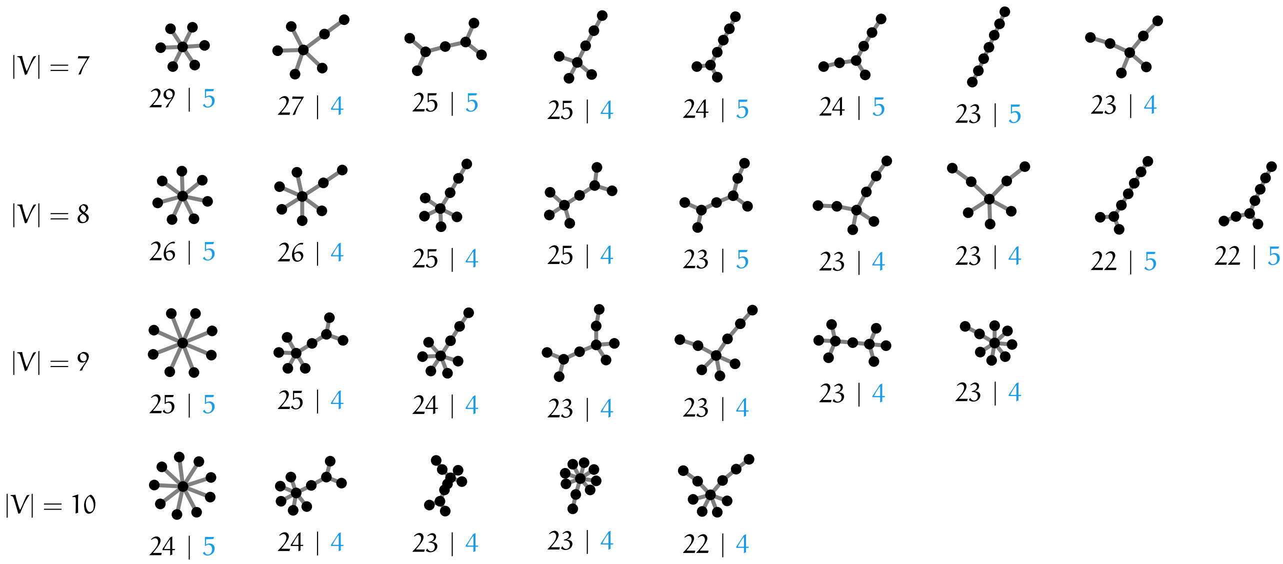


Figure 8: The figure displays frequent subgraphs with seven or more nodes in the user graphs, grouped by their number their number of vertices $|V|$, down to support threshold 22 (see the full figure in Appendix A.4 Table 8). The numbers are the support in TikTok and Twitter respectively. Generally, stars and star-like patterns are the most common for each size, with chains and chain-like patterns having systematically lower supports.

Nuancing the subgraphs with direction provides further insight into the tendencies in stitch behavior. As reflected by the lack of odd-numbered cycles, a user being both stitched and stitching another user is rare. This is further reinforced by the directed subgraphs in Figure 9, showing an out-two-star has support 34, an in-two-star has support 33, but a mixed-direction two-star has support 22, meaning it is comparatively uncommon for a user to both stitch and be stitched. The same trend is reflected in all larger structures, with three-stars S_3 having out-star support 32, in-star support 31 and mixed-star support 17 or 14 based on the specific directionality. Conversely, Twitter exhibits relatively uniform levels of support across in-, out- and mixed-direction two-stars S_2. Moreover, three-stars S_3 display interesting supports. Although the in- and out-three-star S_3 Twitter support is comparable, the two mixed-direction three-stars S_3 vary greatly compared to all previous Twitter support patterns.

From the figure, the square from above is also specified with direction. As hypothesized, the square consists of two users collectively stitching two other users, forming a weak cycle. This pattern has equivalent support with the undirected square, and no other directed squares are mined, leading to this structure largely explaining the undirected squares support.

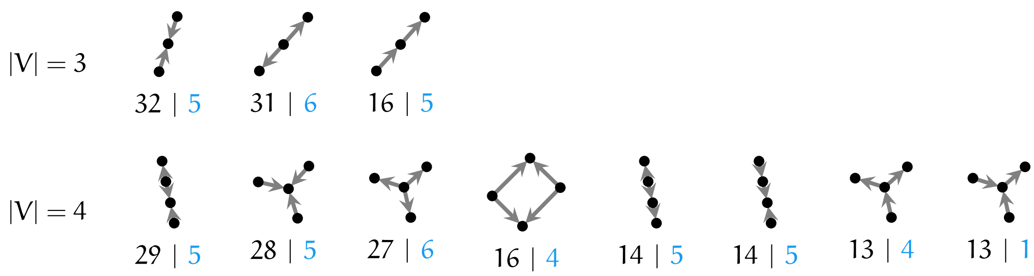


Figure 9: The figure shows the frequent directed subgraphs identified in the user graphs. Due to computational constraints, the analysis was limited to subgraphs with four or fewer nodes. We observe that chains and star structures with mixed direction occurs a lot less frequently than those with consistent directionality.

To determine whether any mined subgraph is a motif, subgraphs are compared to relevant null models. Doing this did not reveal significant motifs for undirected and directed subgraph mining. This result is likely due to the choice of null model, the simplicity of the mined subgraphs, and the specific support definition. Configuration models preserve the degree distribution, and many of the simple structures are explained by the degree distribution. For instance, stars can be entirely explained by the degree distribution: high-degree central nodes and low-degree peripheral nodes (each with an out-degree of 1) will occur with equal prevalence in a configuration model. Other mined subgraphs are often star-like patterns, and in combination with the large size of many user graphs, the subgraphs are likely to emerge by chance based on the given degree distribution. This is further perpetuated by the support definition. Each subgraph only has to appear once for it to count towards the support, meaning the support definition does not account for differences in frequency within the user graphs and configuration models.

5.1.2 Sentiment Subgraphs

Adding sentiment as a dimension yields the subgraphs illustrated in Figure 10. From these we see that positive and negative edges have a support of 30, missing sentiment edges 27, and neutral edges 22. An explanation for the maximum support of 30 lies in the size of the largest components, as ten user graphs have a largest component size of $|V_{lcc}| \leqslant 11$. Outside of these surface-level observations, no clear trends emerge with regard to sentiment patterns.

A notable observation is the lack of anything between pure stars and chains, unlike in the previous subgraph mining. In fact, subgraphs with $|V| \geqslant 5$ consist of purely stars, further indicating that TikTok stitch networks are dominated by this pattern. Although no mechanism prevents other subgraphs from appearing, the likely reason for their absence is the increased number of possible subgraphs, especially due to the limited largest component sizes. As four new edge classes are introduced, the possible subgraphs increase exponentially.

Building on the undirected sentiment subgraphs, Figure 11 introduces directionality as an additional dimension. However, no new unexpected patterns emerge with regard to the combination of sentiment and direction.

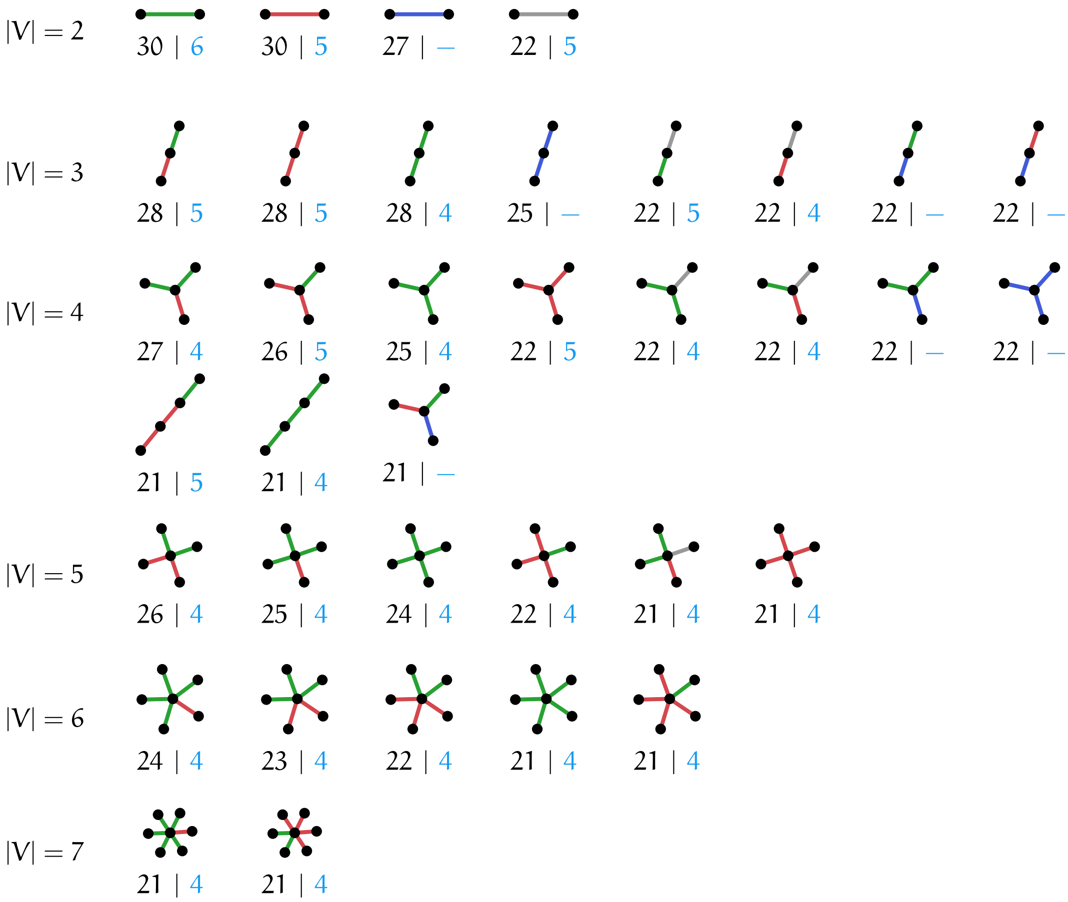


Figure 10: The subgraphs identified in Figure 7, enriched with sentiment labels. Green edges represent positive sentiments, red for negative, gray for neutral, and blue for missing sentiments. The subgraphs highlight how sentiment influences the structure of user interactions. Star-like structural patterns dominate, reflecting either central user receiving reactions, or a central user reacting. If a subgraph contains a missing sentiment edge, the Twitter support is undefined.

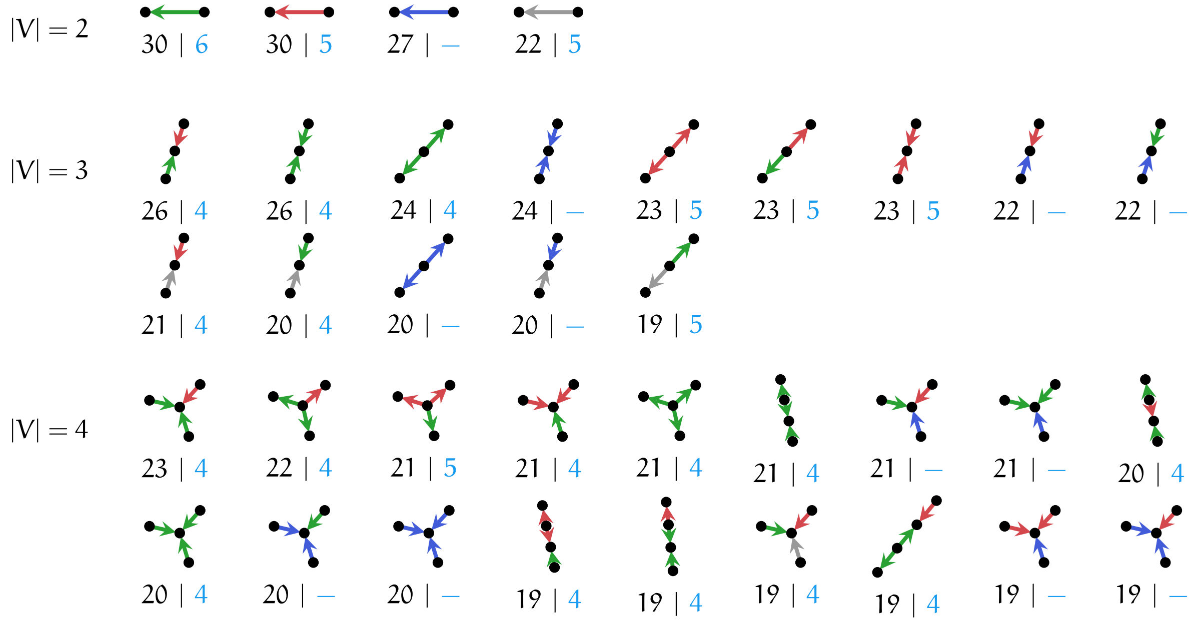


Figure 11: Mined sentiment subgraphs, extending Figure 10 with direction, showing all subgraphs with support $\geqslant 19$. The full figure can be found in Appendix A.4 Figure 14.

5.2 GRAPH EMBEDDINGS

To compare the collected graphs with clustering, we employ various graph embedding techniques to find a representation that facilitates vectorized comparisons. To this end, we employ two approaches: we apply the graph representation learning algorithm Graph2Vec, and we use the identified subgraphs in a Bag-Of-Subgraphs approach, leading to the results seen in Figure 12.

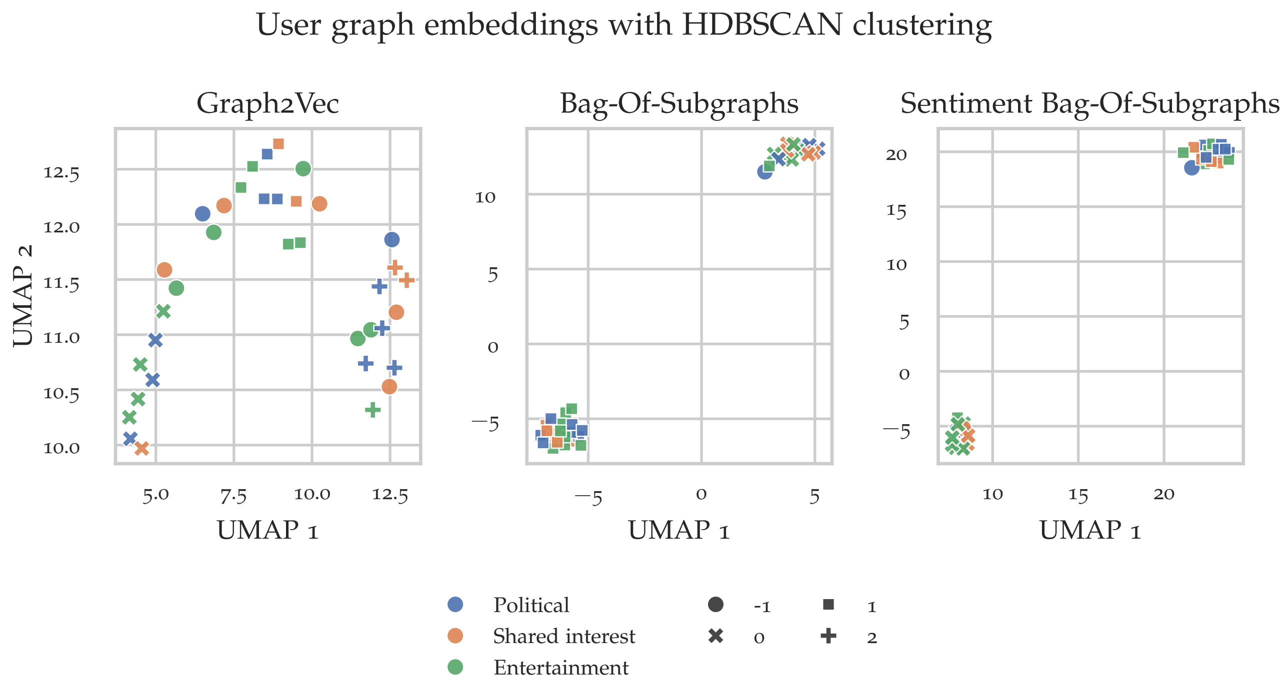


Figure 12: Comparison of user graphs across three embedding spaces, labeled by assigned hashtag categories, clustered using HDBSCAN, and subsequently dimensionality reduced with UMAP. They reveal no separation between graphs corresponding to different categories. This observation is further reinforced by the minimal overlap between the assigned categories and the clusters identified by HDBSCAN.

Inspecting the figure reveals no clear separation between graphs of different categories in any embedding space, indicating no relationship between the graph topologies and the categorization in the embedding spaces. Moreover, in the Graph2Vec representation, three clusters are detected, whereas both Bag-Of-Subgraphs reveal only two clusters. Investigating the driving mechanism behind this partitioning, we find that the size of the graphs almost entirely explain the clustering. In the Graph2Vec space, the average graph size for cluster 0 is 6.3, 1 is 55.9, and 2 is 230.7, and the same trend is observed in the other two representations, showing a strong positive correlation between cluster assignment and graph size. These detected clusters show no overlap with the categorization. Calculating Normalized Mutual Information (NMI) between the categorization and the detected clusters supports this observation, with NMI values ranging from 0.001 to 0.054, further confirming the lack of overlap. Alternative embedding methods are presented in Appendix A.5 Figures 15, 16, and 17.

Similar to the previous results, Figure 13 reveals no clear distinction between TikTok user graphs and Twitter reply networks across both variants of Bag-Of-Subgraph. However, in the Graph2Vec embedding space, larger Twitter graphs occupy a distinct region compared to TikTok graphs, suggesting potential differences in graph structures for larger graphs. Consistent with observations in the TikTok-only analysis, graph size remains the primary factor driving separation across all

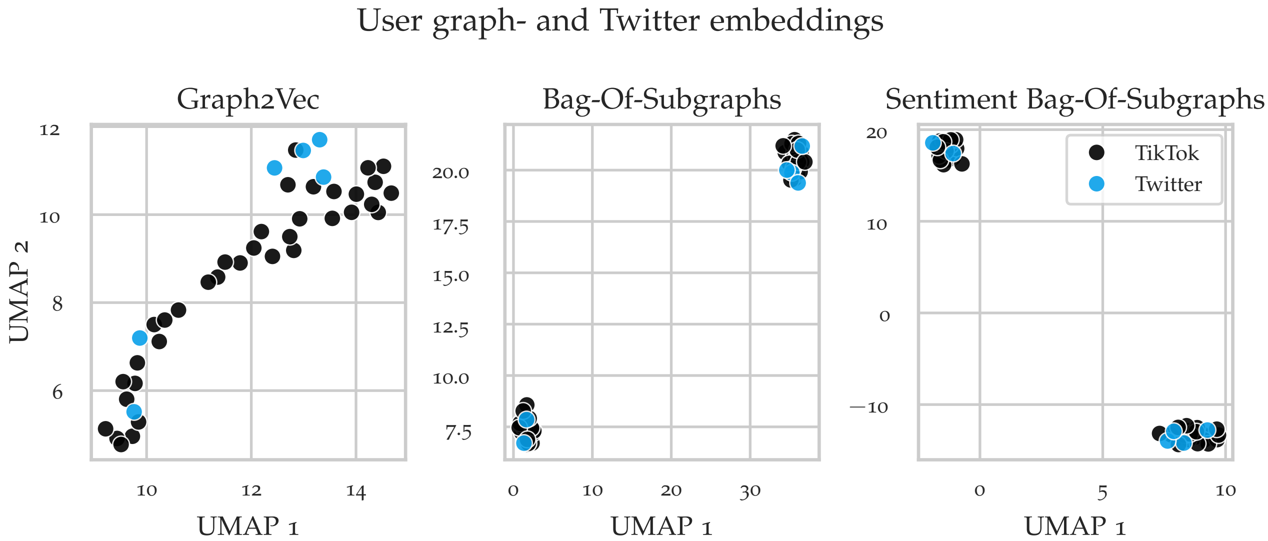


Figure 13: Comparison of user graph embeddings from TikTok and Twitter across three embedding spaces, dimensionality reduced with UMAP. While no distinct separation is observed for most graphs, larger Twitter graphs appear to occupy a slightly different region compared to TikTok graphs in the Graph2Vec embedding space. No such distinction is evident in either Bag-Of-Subgraphs.

embedding spaces. Smaller Twitter graphs tend to cluster near smaller TikTok user graphs, while larger graphs from both platforms are similarly grouped. Overall, the embeddings do not show strong platform-specific grouping for the majority of graphs.

6 DISCUSSION

The TikTok StitchGraph dataset offers numerous avenues for exploration and analysis. The presented data collection, methodology, and results, comprise one approach to deepening insights into TikTok stitch patterns, yet they are limited by the assumptions of the specific approach, and other equally interesting findings could be explored with an alternate strategy. In this section, the findings and implications of the results are discussed, along with proposals for improvements and future research directions.

6.1 TIKTOK STITCHGRAPH: A FIRST ATTEMPT AT UNDERSTANDING TIKTOK STITCHES

We have collected the TikTok StitchGraph dataset: a starting point to study TikTok's stitch-based interactions, covering 36 hashtags across different topics. The graph structures, comprising both video and user graphs, generally exhibit sparse, star-like patterns with high degree centralization, short path lengths, low clustering, and low reciprocity. Together, they reflect how stitches on TikTok often center around key videos and/or users. These observations frame the shape of TikTok stitch communication, as further backed up by the subgraph analysis.

The data collection process involved some uncertainty in what data could be collected, particularly in the early stages of this project. As of creating this project, we experienced major instability issues, and while the API was improved by the developers during this time, it constrained the possibilities for what data could be obtained, and what downstream analyses could be performed. Furthermore, the lack of a built-in method for identifying stitch connections required indirect methods, such as using the phrase "stitch with" in video descriptions, which may have introduced gaps or inaccuracies in the dataset.

The StitchGraph dataset focuses exclusively on stitches collected in May 2024 centered around 36 selected hashtags. Alternate collection criteria could yield further insights into the domain of TikTok communication. Future work directions could include exploring other interaction types, such as duets, replies to comments, or other TikTok features useful for building a graph structure. Additionally, structuring the dataset as a single graph could facilitate analyses such as single graph mining, community detection, and link prediction. Another direction might involve changing the video selection criteria. For instance, one potential approach is building datasets around specific events or trending topics, instead of using a hashtag-based approach set in May 2024. The reliance on hashtags excludes a significant portion of TikTok communication, especially cross-community interactions not tied to specific hashtags.

6.2 UNREALIZED POTENTIAL OF VIDEO CONTENT

This paper's primary focus is on analyzing stitches as graphs. However, a stitch is a video and is by nature multi-modal. Currently, the multi-modality of videos is only used for transcriptions of videos to extract sentiment. While this serves as an exemplary additional dimension to the graph structure, there is an untapped potential in the complexity of TikTok videos, both in terms of extracting additional attributes, and as a stand-alone research subject. Furthermore, the findings from the sentiment labels are limited by human error related to the #*challenge*, #*football*, #*makeup*, and #*minecraft* graphs.

The applied sentiment analysis method relies on classifying sentiment on video transcriptions. This simplistic approach, while useful for speech-dominated videos, is limited in its capacity and utility. Many videos on the platform align with TikTok's origin as a hub for lip-sync content, rather than a platform primarily focused on spoken communication. Some hashtags such as #*storytime* and #*gaza* have extensive speech, while others such as #*dogsoftiktok* and #*kpop* feature less spoken language. Sentiment of transcriptions is less representative for these hashtags with comparatively less speech. For these, incorporating visual and auditory data could support more nuanced sentiment detection, similar to that in Lai et al. (2023).

Although sentiment serves as an interesting dimension in the subgraph analysis, there is unrealized potential in exploring it further. The current approach does not fully leverage the rich, multi-modal information in TikTok videos, highlighting possibilities for deeper and more diverse analysis tasks. Exploring sentiment analysis further shows that there is a difference in mean sentiment between political and non-political hashtags. Using VADER's computed normalized, weighted composite score for each video reveals that the Political hashtags score a mean of 0.03 compared to Entertainment's 0.14 and Shared Interest's 0.17. This indicates a clear difference in the sentiment of hashtags based on the content type. One direction to explore could be using the stitch graphs as signed networks, looking into their balance, and relating this to their categorizations.

Going beyond sentiment also yields new opportunities. We classify audio types, yet these are not utilized beyond light exploratory data analysis. Modeling stitch interactions with more complex labels such as whether a stitch is a reaction to a prompt, a discussion of opinions presented in the stitchee, or something entirely different, could shed light on unexplored dynamics of TikTok stitches.

6.3 SUBGRAPH ANALYSIS AND THE ABSENCE OF MOTIFS

The subgraph analysis points to stars and star-like structures dominating stitch graphs, exhibiting well-defined directional patterns, and an aversion towards cycles. However, given the current transactional setting and the choice of null model, no subgraphs can be considered motifs. Expanding subgraphs with sentiment labels does not provide additional insights into sentiment patterns or the defining topology, apart from further validating the observed preference for star patterns.

The first notable observation from the subgraph analysis is the lack of cyclic substructures. No cyclic structures pass the minimum support threshold. This is useful, as it means any discovered substructure also contains no cycles. The directed subgraphs further expand on this, with mixed-direction two-stars S_2 being much less frequent than in- and out-two-stars. Along with the infrequency of odd-numbered cycles and the observed view-, like-, and follower count differences between stitcher and stitchee, it points to patterns of stitches mostly being directed from lesser-known users to popular users, and it being rare for popular users to create stitches. This potential mechanism of TikTok serves as a direction for future research, diving deeper into how the platform affordances shape the TikTok stitching meta.

Despite the characteristics of the discovered subgraphs, none qualify as motifs under the null model. There are two reasons for this: the choice of configuration model as null model and the transactional support definition. Stars and star-like patterns are identified as important structures in stitch graphs, with smaller chains connecting stars into larger components. However, stars are entirely explained by their degree distribution which a configuration model preserves, and as such are not considered statistically significant. This, in conjunction with the transactional support, means they are likely to occur at least once in a configuration model, and thus be deemed not significant. Another support definition could alleviate this to a degree. However, the simplistic degree distribution of the stitch graphs limit what other patterns can occur.

Picking alternative null models could reveal motifs. For instance, the simple Erdös-Rényi random graph provides a less restrictive baseline, preserving the number of vertices and edges. Under this model, the directed square from Figure 9 qualifies as a motif, with a support of 16 in user graphs compared to 8 in random graphs. The relaxed constraints of random graphs make identified motifs less meaningful. A more appropriate comparison could involve analogous social media graphs. Although this project draws comparisons with Twitter, the limited sample size diminishes its utility. Collecting a substantial set of comparable graphs from social media platforms could help to discover motifs that distinguish TikTok from other platforms.

The subgraph analysis is extended with sentiment labels. The supports in isolation reveals no surface-level insights into stitch patterns. However, it is currently not compared to any relevant null model, and consequently, is it is unknown whether any of the mined patterns are significant, making it infeasible to draw conclusions about specific subgraphs. Future work should compare sentiment subgraphs to a relevant null model if this direction is further explored.

Sentiment labels exemplify one approach to augmenting stitch graphs with additional attributes. Frequent subgraph mining supports both vertex and edge attributes, and any information that can be attributed to either of these could be explored with this method. For instance, an alternative to sentiment labels could, for example, be exploring the role of influencers in the subgraphs of stitch graphs. By leveraging user metadata, vertices could be assigned influencer labels and subsequently mined for subgraph patterns and potentially motifs, functioning as avenues for new insights in stitch patterns.

6.4 EMBEDDINGS AND TOPIC-TOPOLOGY RELATIONS

Using Graph2Vec and the Bag-Of-Subgraphs approach, user graphs are represented in vector format. However, doing so reveals no clear relationship between topic and topology, as both approaches primarily capture size-related features rather than topic-specific differences.

Graph2Vec is employed as a graph representation learning technique to encode the structural properties of the stitch graphs into an embedding space. The embeddings provide a spectrum of user graphs, yet show no clear separation between graph categories. Graph size is the primary factor influencing the placement of graphs in the embedding space, with larger graphs clustering towards the upper regions of the UMAP scatter plot (Figure 12). Similarly, the Bag-Of-Subgraphs embeddings also reflect a reliance on size, as they primarily capture subgraph frequencies proportional to the graphs' sizes. The embeddings reveal two distinct groupings of data points, which are differentiated by few a subgraphs being present in one set of graphs and absent in the other. This method is also limited by the lack of motifs from the subgraph analysis. A more nuanced set of subgraphs and a non-binary approach accounting for subgraph frequency could improve separation between graphs.

Comparisons with Twitter reply networks reveal similar limitations in distinguishing structural features related to content themes, highlighting how size-related factors dominate in the embeddings of both platforms. Larger Twitter graphs display minor separation from the larger user graphs in the Graph2Vec space, yet these are not captured using clustering. There is no separation in the Bag-Of-Subgraphs spaces, likely due to the subgraphs being mined from TikTok. Without using subgraphs distinct to Twitter, it might not capture unique patterns exclusive to Twitter.

Further research should consider graph sizes to minimize its influence as the primary differentiator. Alternatively, sampling strategies could be employed to sample random subsets of vertices, mitigating size-related biases. This approach is effective, provided the graphs are sufficiently large, ensuring that the sampled subset remains representative of the original structure.

6.5 TIKTOK AND TWITTER: A COMPARATIVE DISCUSSION

Reflecting the TikTok findings in the Twitter reference graphs reveals some differences in simple network metrics, yet little difference in subgraphs and graph embeddings. Various factors contribute to this, including data collection specifics, the amount of data, the applied preprocessing, and the differing roles of replies versus stitches.

Firstly, the details of data collection are fundamentally different. The Twitter data does not employ a hashtag-centric strategy, is from a different time period and range, and applies rules to the selection of included users. These differences are significant as they influence the structure of the graphs and the implications of our findings. The limited sample of six Twitter graphs also constrain the representativeness of the findings. To reduce uncertainty, more graphs are necessary, as the results are currently too dependent on the specifics of the compared graphs.

The nature of the reply is also different from that of the stitch. On TikTok, there are multiple features for interacting with other users, both in text and video format. The stitch is just one of many social features and is used less compared to its sibling, the duet. In contrast, the reply is the primary function for publicly reacting and adding to others' tweets.

With the applied methodology, there is little to no observed difference between TikTok and Twitter. One reason is the preprocessing of the graphs. For almost all applied techniques, graphs are required to be simple. This reduces some of what makes Twitter unique, as it is more prone to self-loops and multi-edges than TikTok. Furthermore, communication outside the largest component appears to be generally more nuanced in the Twitter graphs.

For future research, it would be beneficial to either compose or obtain more comparable Twitter data on a larger scale. This would facilitate deeper insights and could serve as a relevant null model for motif discovery.

7 CONCLUSION

This paper set out to compose and analyze TikTok StitchGraph through the lens of network analysis. Despite technical instability, uncertainties, and limitations, 36 distinct networks based on hashtags are successfully constructed, describing the use of the TikTok stitch functionality on both a user- and video level. By applying a combination of basic network analysis, graph augmentation with sentiment analysis, subgraph mining, and graph embeddings to user graphs, communication with stitches is analyzed to characterize what makes the stitch unique in a user-centric network context. Notably, the graphs show no clustering, no reciprocity, and high local degree centralization.

Using transactional frequent subgraph mining, the mined subgraphs reveal patterns that form the building blocks of TikTok user graphs, with stars and star-like structures being the most frequently occurring substructures. Additionally, video metadata, edge directionality, and the scarcity of cyclic subgraphs indicate that it is rare for users who stitch to also be stitched. Despite this, no discovered subgraphs can be considered as statistically significant motifs under applied configuration null models, indicating that the discovered subgraphs are explained by the degree distribution of user graphs. This also holds true for sentiment enriched subgraph mining, revealing no patterns with regards to the sentiment of stitches.

The graph embeddings further expose the limitations of the current dataset and methods. By applying Graph2Vec and a Bag-Of-Subgraphs approach, graphs are represented and compared in vector spaces, yet they reveal no relation between the embedding of a graph and its related topic category. Instead, they primarily capture the size of graphs, forming clusters of similarly sized networks.

Comparing these findings to six obtained Twitter graphs reveals minor differences. Outside of descriptive statistics, both subgraph analysis and graph embeddings show that Twitter is seemingly comparable to TikTok, displaying similar support patterns in subgraphs and no clear separation in embeddings. These finding are however constrained by the small sample of Twitter graphs, and the fundamental differences in data collection.

Combining all the results paints a picture of TikTok stitch graphs showing clear patterns for stitch behavior with regards to directionality, an aversion towards cycles, and a preference for stars and star-like structures, that are comparable to structures on Twitter.

8 ACKNOWLEDGMENTS

In this project, we have used various generative AI tools. Specifically, GitHub Copilot was employed to assist with coding tasks, Writefull was used to enhance the quality of our writing, and ChatGPT for a combination of both. In particular, generative AI was not used to create original text, but was strictly limited to improving and clarifying the content we had already written. This means that generative AI was never used to introduce new content or new ideas and conclusions that we had not already written ourselves. A common example prompt used a lot for this paper is:

> Here is an excerpt from an academic paper:
> [INSERT TEXT HERE]
> Improve the wording of the last sentence.

As for code assistants, GitHub Copilot was primarily used for code completion. ChatGPT was used primarily to debug existing code. For example, a common prompt was:

> The below Python code throws an error, please help to identify why.
> [INSERT CODE HERE]
> We get this error:
> [INSERT ERROR HERE]

These are rough examples of prompts that exemplify the way we used generative AI.

BIBLIOGRAPHY

Aaronson, S. (2016). $P \stackrel{?}{=} NP$, pp. 1–122. Cham: Springer International Publishing.

AI, G. (2024). Mediapipe audio classifier. https://ai.google.dev/edge/mediapipe/solutions/audio/audio_classifier. Accessed: 2024-12-19.

Bild, D. R., Y. Liu, R. P. Dick, Z. M. Mao, and D. S. Wallach (2015). Aggregate characterization of user behavior in twitter and analysis of the retweet graph. *ACM Transactions on Internet Technology (TOIT) 15*(1), 1–24.

Borgelt, C. (2022, October 31). Moss - molecular substructure miner version (3.0). Retrieved October 9, 2024, from https://borgelt.net/moss.html.

Borgelt, C. and M. R. Berthold (2002). Mining molecular fragments: Finding relevant substructures of molecules. In *2002 IEEE International Conference on Data Mining, 2002. Proceedings.*, pp. 51–58. IEEE.

Breakthrough (2024). Pyscenedetect: Video scene cut detection and analysis tool. Accessed: 2024-12-19.

Bruns, A. (2008). *Blogs, Wikipedia, Second Life, and Beyond: From Production to Produsage*. Digital formations. Peter Lang.

Campello, R. J. G. B., D. Moulavi, and J. Sander (2013). Density-based clustering based on hierarchical density estimates. In J. Pei, V. S. Tseng, L. Cao, H. Motoda, and G. Xu (Eds.), *Advances in Knowledge Discovery and Data Mining*, Berlin, Heidelberg, pp. 160–172. Springer Berlin Heidelberg.

Cinelli, M., G. D. F. Morales, A. Galeazzi, W. Quattrociocchi, and M. Starnini (2021). The echo chamber effect on social media. *Proceedings of the National Academy of Sciences 118*(9), e2023301118.

Corso, F., F. Pierri, and G. De Francisci Morales (2024). What we can learn from tiktok through its research api. In *Companion Publication of the 16th ACM Web Science Conference*, pp. 110–114.

Coscia, M. (2021). The atlas for the aspiring network scientist.

Freelon, D. (2024). pyktok: A simple module to collect video, text, and metadata from tiktok. https://github.com/dfreelon/pyktok. Accessed: 2024-12-19.

Freeman, L. C. (1978). Centrality in social networks conceptual clarification. *Social Networks 1*(3), 215–239.

Garimella, K., G. De Francisci Morales, A. Gionis, and M. Mathioudakis (2018). Political discourse on social media: Echo chambers, gatekeepers, and the price of bipartisanship. In *Proceedings of the 2018 world wide web conference*, pp. 913–922.

Hohmann, M., K. Devriendt, and M. Coscia (2023). Quantifying ideological polarization on a network using generalized euclidean distance. *Science Advances 9*(9), eabq2044.

Howarth, J. (2024). Top social media platforms in 2024. https://explodingtopics.com/blog/top-social-media-platforms. Accessed: 2024-11-05.

Hutto, C. and E. Gilbert (2014, May). Vader: A parsimonious rule-based model for sentiment analysis of social media text. *Proceedings of the International AAAI Conference on Web and Social Media 8*(1), 216–225.

Jenkins, H., M. Ito, and d. boyd (2015). *Participatory Culture in a Networked Era: A Conversation on Youth, Learning, Commerce, and Politics*. Polity.

Kanthawala, S., K. Cotter, K. Foyle, and J. Decook (2022, 01). It's the methodology for me: A systematic review of early approaches to studying tiktok.

Kaur-Gill, S. (2022). The cultural customization of tiktok: subaltern migrant workers and their digital cultures. *Media International Australia 186*(1), 29–47.

Kerchner, D., L. Wrubel, and D. Smith (2020). Coronavirus tweet ids.

Lai, S., X. Hu, H. Xu, Z. Ren, and Z. Liu (2023). Multimodal sentiment analysis: A survey.

Lassen, D. S. and A. R. Brown (2011). Twitter: The electoral connection? *Social science computer review 29*(4), 419–436.

Le, Q. and T. Mikolov (2014, 22–24 Jun). Distributed representations of sentences and documents. In E. P. Xing and T. Jebara (Eds.), *Proceedings of the 31st International Conference on Machine Learning*, Volume 32 of *Proceedings of Machine Learning Research*, Bejing, China, pp. 1188–1196. PMLR.

Mikolov, T., K. Chen, G. Corrado, and J. Dean (2013). Efficient estimation of word representations in vector space.

Narayanan, A., M. Chandramohan, R. Venkatesan, L. Chen, Y. Liu, and S. Jaiswal (2017). graph2vec: Learning distributed representations of graphs. *arXiv preprint arXiv:1707.05005*.

Pedregosa, F., G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and Édouard Duchesnay (2011). Scikit-learn: Machine learning in python. *Journal of Machine Learning Research 12*(85), 2825–2830.

Pew Research (2023). Teens, social media and technology 2023. https://www.pewresearch.org/internet/2023/12/11/teens-social-media-and-technology-2023/. Accessed: 2024-11-07.

Radford, A., J. W. Kim, T. Xu, G. Brockman, C. McLeavey, and I. Sutskever (2022). Robust speech recognition via large-scale weak supervision.

RippleXN (2023). Understanding stitch on tiktok: A creative tool and its legal implications. https://ripplexn.com/insights/understanding-stitch-on-tiktok-a-creative-tool-and-its-legal-implications. Accessed: 2024-10-22.

Rozemberczki, B., O. Kiss, and R. Sarkar (2020). Karate Club: An API Oriented Open-source Python Framework for Unsupervised Learning on Graphs. In *Proceedings of the 29th ACM International Conference on Information and Knowledge Management (CIKM '20)*, pp. 3125–3132. ACM.

Savic, M. (2021). Research perspectives on tiktok its legacy apps| from musical.ly to tiktok: Social construction of 2020's most downloaded short-video app. *International Journal of Communication 15*(0).

Shervashidze, N., P. Schweitzer, E. J. Van Leeuwen, K. Mehlhorn, and K. M. Borgwardt (2011). Weisfeiler-lehman graph kernels. *Journal of Machine Learning Research 12*(9).

Shirky, C. (2008). *Here Comes Everybody: The Power of Organizing Without Organizations*. Penguin Press.

Steen, E., K. Yurechko, and D. Klug (2023). You can (not) say what you want: Using algospeak to contest and evade algorithmic content moderation on tiktok. *Social Media + Society 9*(3), 20563051231194586.

TikTok (2020). New on tiktok: Introducing stitch.

TikTok (2023). Research api. https://developers.tiktok.com/products/research-api (Accessed on January 2, 2025).

TikTok (2024). Codebook. https://developers.tiktok.com/doc/research-api-codebook. Accessed: December 11, 2024.

TikTok Newsroom (2020). New on tiktok: Introducing stitch. https://newsroom.tiktok.com/en-us/new-on-tiktok-introducing-stitch. Accessed: 2024-11-05.

Torregrosa, J., Á. Panizo-Lledot, G. Bello-Orgaz, and D. Camacho (2020). Analyzing the relationship between relevance and extremist discourse in an alt-right network on twitter. *Social Network Analysis and Mining 10*, 1–17.

Yan, X. (2009). Software - gspan: Frequent graph mining package. Accessed: 2024-10-02.

Yan, X. and J. Han (2002). gspan: Graph-based substructure pattern mining. In *2002 IEEE International Conference on Data Mining, 2002. Proceedings.*, pp. 721–724. IEEE.

Zaki, M. J., S. Parthasarathy, M. Ogihara, W. Li, et al. (1997). New algorithms for fast discovery of association rules. In *KDD*, Volume 97, pp. 283–286.

A APPENDIX

A.1 GLOSSARY OF TIKTOK TERMS

Algorithm TikTok's recommendation system, which curates content shown to users based on their interactions, preferences, and trends.

Captions Text added to videos by creators, providing context or commentary.

Comment A user response left on a video, allowing interaction and discussion between viewers and creators.

Descriptions Brief summaries or context provided in text under the video, often used to explain content or include hashtags. Descriptions are created by video creators upon uploading a video..

Duet A feature that lets users create a side-by-side video with another user's video, often for reactions, responses, or collaborations.

Follower A user who has chosen to subscribe to another user's content, receiving updates and recommendations.

For You Page (FYP) A personalized feed, where the shown videos are determined by the TikTok recommendation algorithm.

Hashtag Keywords preceded by a hash symbol (#) that categorize and tag content, making it discoverable by users searching for specific themes or topics.

Sounds/Use of Other's Sound Audio clips that users can borrow and use in their own videos, often leading to viral trends.

Stitch A feature on TikTok that allows users to use a clip from another user's video and add their own response or continuation.

Trends Popular themes, challenges, or types of content that gain widespread attention on the platform.

User An individual with an account on TikTok who can create, watch, and interact with videos.

Video Reply to Comment A feature allowing creators to respond to a comment with a new video, linking the response directly to the original comment.

A.3 FULL DATA TABLES

Hashtag	Category	|V|	|E|	#Self -loops	#Multi -edges	#Components	|V| in LCC	Density	D	D_u	L	L_u	Degree assortativity	C_u	Reciprocity	Degree centralization	Closeness centralization	Betweenness centralization
comedy	Entertainment	6702	3737	0	0	2965	23	0.00	1	2	1.00	1.41	-	0.00	0.00	0.00	0.13	0.00
booktok	Shared interest	4810	2792	0	0	2018	74	0.00	1	2	1.00	1.72	-	0.00	0.00	0.01	0.18	0.00
anime	Shared interest	2351	1363	0	0	988	113	0.00	1	2	1.00	1.84	-	0.00	0.00	0.05	0.18	0.00
storytime	Entertainment	2330	1385	0	0	945	141	0.00	1	2	1.00	1.90	-	0.00	0.00	0.06	0.20	0.00
lgbt	Shared interest	2111	1183	0	0	928	30	0.00	1	2	1.00	1.54	-	0.00	0.00	0.01	0.14	0.00
palestine	Political	1550	841	0	0	709	20	0.00	1	2	1.00	1.36	-	0.00	0.00	0.01	0.10	0.00
gaming	Shared interest	1371	759	0	0	612	35	0.00	1	2	1.00	1.53	-	0.00	0.00	0.02	0.12	0.00
maga	Political	1311	689	0	0	622	10	0.00	1	2	1.00	1.15	-	0.00	0.00	0.01	0.06	0.00
football	Entertainment	1293	680	0	0	613	27	0.00	1	2	1.00	1.38	-	0.00	0.00	0.02	0.06	0.00
catsoftiktok	Entertainment	1205	745	0	0	460	89	0.00	1	2	1.00	1.90	-	0.00	0.00	0.07	0.25	0.01
news	Entertainment	1197	653	0	0	544	11	0.00	1	2	1.00	1.26	-	0.00	0.00	0.01	0.11	0.00
trump2024	Political	1120	600	0	0	520	19	0.00	1	2	1.00	1.31	-	0.00	0.00	0.02	0.09	0.00
kpop	Shared interest	1100	737	0	0	363	237	0.00	1	2	1.00	1.97	-	0.00	0.00	0.21	0.35	0.05
makeup	Shared interest	1069	626	0	0	443	68	0.00	1	2	1.00	1.85	-	0.00	0.00	0.06	0.18	0.00
gaza	Political	1034	555	0	0	479	12	0.00	1	2	1.00	1.29	-	0.00	0.00	0.01	0.09	0.00
dogsoftiktok	Entertainment	993	560	0	0	433	12	0.00	1	2	1.00	1.38	-	0.00	0.00	0.01	0.15	0.00
gym	Shared interest	929	480	0	0	449	10	0.00	1	2	1.00	1.12	-	0.00	0.00	0.01	0.04	0.00
israel	Political	816	433	0	0	383	5	0.00	1	2	1.00	1.12	-	0.00	0.00	0.00	0.08	0.00
learnontiktok	Entertainment	792	413	0	0	379	5	0.00	1	2	1.00	1.09	-	0.00	0.00	0.00	0.05	0.00
movie	Entertainment	782	433	0	0	349	23	0.00	1	2	1.00	1.47	-	0.00	0.00	0.03	0.12	0.00
challenge	Entertainment	668	345	0	0	323	5	0.00	1	2	1.00	1.07	-	0.00	0.00	0.00	0.04	0.00
blacklivesmatter	Political	527	275	0	0	252	7	0.00	1	2	1.00	1.13	-	0.00	0.00	0.01	0.05	0.00
science	Entertainment	451	235	0	0	216	6	0.00	1	2	1.00	1.11	-	0.00	0.00	0.01	0.05	0.00
conspiracy	Entertainment	435	227	0	0	208	6	0.00	1	2	1.00	1.13	-	0.00	0.00	0.01	0.05	0.00
election	Political	401	210	0	0	191	6	0.00	1	2	1.00	1.12	-	0.00	0.00	0.01	0.06	0.00
watermelon	Entertainment	339	180	0	0	159	9	0.00	1	2	1.00	1.20	-	0.00	0.00	0.02	0.08	0.00
biden2024	Political	281	145	0	0	136	4	0.00	1	2	1.00	1.06	-	0.00	0.00	0.01	0.04	0.00
asmr	Entertainment	214	107	0	0	107	2	0.00	1	1	1.00	1.00	-	0.00	0.00	0.00	0.00	0.00
minecraft	Shared interest	169	94	0	0	75	14	0.00	1	2	1.00	1.48	-	0.00	0.00	0.07	0.13	0.01
prochoice	Political	162	99	0	0	63	21	0.00	1	2	1.00	1.71	-	0.00	0.00	0.12	0.24	0.01
tiktoknews	Entertainment	150	76	0	0	74	3	0.00	1	2	1.00	1.03	-	0.00	0.00	0.01	0.02	0.00
plantsoftiktok	Shared interest	140	71	0	0	69	3	0.00	1	2	1.00	1.03	-	0.00	0.00	0.01	0.02	0.00
abortion	Political	98	52	0	0	46	5	0.01	1	2	1.00	1.15	-	0.00	0.00	0.03	0.08	0.00
climatechange	Political	92	46	0	0	46	2	0.01	1	1	1.00	1.00	-	0.00	0.00	0.00	0.00	0.00
jazz	Shared interest	32	16	0	0	16	2	0.02	1	1	1.00	1.00	-	0.00	0.00	0.00	0.00	0.00
guncontrol	Political	10	5	0	0	5	2	0.06	1	1	1.00	1.00	-	0.00	0.00	0.00	0.00	0.00
	Shared interest	1408.20	812.10	0.00	0.00	596.10	58.60	0.00	1.00	1.90	1.00	1.51	-	0.00	0.00	0.05	0.13	0.01
	Entertainment	1253.64	698.29	0.00	0.00	555.36	25.86	0.00	1.00	1.93	1.00	1.31	-	0.00	0.00	0.02	0.09	0.00
	Political	616.83	329.17	0.00	0.00	287.67	9.42	0.01	1.00	1.83	1.00	1.20	-	0.00	0.00	0.02	0.07	0.00

Table 5: Full table of video graph metrics.

Hashtag	Category	|V|	|E|	#Self -loops	#Multi -edges	#Components	|V| in LCC	Density	D	D_u	L	L_u	Degree assortativity	C_u	Reciprocity	Degree centralization	Closeness centralization	Betweenness centralization
comedy	Entertainment	4608	3737	32	104	1135	1838	0.00	2	19	1.01	7.23	-0.01	0.00	0.00	0.01	-	0.04
booktok	Shared interest	3540	2792	266	91	1119	844	0.00	4	24	1.14	8.35	-0.06	0.00	0.00	0.02	-	0.03
storytime	Entertainment	2036	1385	56	58	762	173	0.00	2	7	1.11	2.38	-0.07	0.00	0.00	0.07	-	0.01
lgbt	Shared interest	1685	1183	48	13	566	365	0.00	2	14	1.02	6.53	-0.07	0.00	0.00	0.02	-	0.03
anime	Shared interest	1605	1363	67	73	443	646	0.00	4	16	1.36	6.95	-0.10	0.00	0.00	0.07	-	0.09
palestine	Political	1236	841	22	19	434	144	0.00	1	14	1.00	5.43	-0.06	0.00	0.00	0.03	-	0.01
catsoftiktok	Entertainment	1059	745	30	9	354	142	0.00	2	11	1.02	3.98	-0.16	0.00	0.00	0.08	-	0.01
gaming	Shared interest	1023	759	30	20	325	243	0.00	4	17	1.36	6.74	-0.12	0.01	0.00	0.03	-	0.03
football	Entertainment	935	680	34	31	321	73	0.00	2	13	1.03	4.11	-0.07	0.00	0.00	0.03	-	0.00
dogsoftiktok	Entertainment	919	560	23	4	385	13	0.00	1	5	1.00	1.51	-0.10	0.00	0.00	0.01	-	0.00
makeup	Shared interest	915	626	45	11	345	68	0.00	2	5	1.01	2.15	-0.13	0.00	0.00	0.07	-	0.01
kpop	Shared interest	906	737	44	21	236	344	0.00	3	13	1.03	3.42	-0.24	0.00	0.00	0.26	-	0.14
gaza	Political	801	555	9	12	269	109	0.00	2	11	1.00	4.18	-0.08	0.00	0.00	0.04	-	0.01
news	Entertainment	784	653	12	84	255	73	0.00	2	6	1.01	2.10	0.41	0.00	0.00	0.08	-	0.01
trump2024	Political	768	600	3	15	202	272	0.00	2	14	1.07	5.83	-0.05	0.00	0.00	0.04	-	0.06
gym	Shared interest	742	480	24	12	297	74	0.00	2	9	1.00	3.22	0.02	0.00	0.00	0.05	-	0.01
maga	Political	644	689	5	70	106	414	0.00	3	12	1.02	4.55	0.00	0.00	0.00	0.10	-	0.15
israel	Political	594	433	3	14	183	141	0.00	2	22	1.00	7.68	0.00	0.00	0.00	0.02	-	0.03
movie	Entertainment	583	433	13	30	199	71	0.00	3	12	1.05	3.76	-0.05	0.01	0.00	0.05	-	0.01
challenge	Entertainment	485	345	17	36	191	35	0.00	2	10	1.02	3.07	0.15	0.01	0.00	0.05	-	0.00
learnontiktok	Entertainment	464	413	13	15	131	79	0.00	6	9	1.99	3.12	-0.10	0.06	0.01	0.08	-	0.02
science	Entertainment	411	235	4	2	182	11	0.00	1	5	1.00	1.46	-0.08	0.00	0.00	0.01	-	0.00
blacklivesmatter	Political	388	275	2	4	119	64	0.00	2	8	1.00	3.09	-0.05	0.00	0.00	0.07	-	0.02
conspiracy	Entertainment	365	227	3	9	150	11	0.00	2	4	1.00	1.54	0.20	0.00	0.00	0.02	-	0.00
election	Political	334	210	5	2	131	11	0.00	1	6	1.00	1.72	-0.12	0.00	0.00	0.02	-	0.00
watermelon	Entertainment	290	180	9	0	119	17	0.00	1	6	1.00	2.05	-0.04	0.00	0.00	0.02	-	0.00
asmr	Entertainment	191	107	8	4	92	6	0.00	1	2	1.00	1.15	0.66	0.00	0.00	0.02	-	0.00
biden2024	Political	188	145	1	6	50	63	0.00	2	11	1.22	4.33	-0.11	0.00	0.00	0.08	0.69	0.08
minecraft	Shared interest	151	94	9	0	66	14	0.00	1	3	1.00	1.58	-0.14	0.00	0.00	0.08	-	0.01
prochoice	Political	141	99	2	2	46	30	0.01	1	4	1.00	2.45	-0.22	0.00	0.00	0.14	0.45	0.04
tiktoknews	Entertainment	120	76	4	2	49	8	0.01	1	2	1.00	1.41	0.01	0.00	0.00	0.05	-	0.00
plantsoftiktok	Shared interest	96	71	33	4	58	8	0.01	1	6	1.00	1.82	0.67	0.00	0.00	0.02	-	0.00
abortion	Political	87	52	2	0	37	6	0.01	1	3	1.00	1.38	-0.16	0.00	0.00	0.05	-	0.00
climatechange	Political	86	46	2	1	43	4	0.01	1	3	1.00	1.09	0.73	0.00	0.00	0.01	-	0.00
jazz	Shared interest	32	16	0	0	16	2	0.02	1	1	1.00	1.00	-	0.00	0.00	0.00	0.00	0.00
guncontrol	Political	10	5	0	0	5	2	0.06	1	1	1.00	1.00	-	0.00	0.00	0.00	0.00	0.00
	Shared interest	1069.50	812.10	56.60	24.50	347.10	260.80	0.00	2.40	10.80	1.09	4.18	-0.02	0.00	0.00	0.06	0.00	0.03
	Entertainment	946.43	698.29	18.43	27.71	308.93	182.14	0.00	2.00	7.93	1.09	2.78	0.05	0.01	0.00	0.04	-	0.01
	Political	439.75	329.17	4.67	12.08	135.42	105.00	0.01	1.58	9.08	1.03	3.56	-0.01	0.00	0.00	0.05	0.38	0.03

Table 6: Full table of user graph metrics.

Hashtag	Category	|V|	|E|	#Self-loops	#Multi-edges	#Components	|V| in LCC	Density	D	D_u	L	L_u	Degree assortativity	C_u	Reciprocity	Degree centralization	Closeness centralization	Betweenness centralization
comedy	Entertainment	1838	2032	5	60	1	1838	0.00	2	19	1.02	7.24	-0.22	0.00	0.00	0.03	0.17	0.25
booktok	Shared interest	844	925	23	26	1	844	0.00	4	24	1.28	8.43	-0.23	0.00	0.00	0.09	0.14	0.52
anime	Shared interest	646	771	7	56	1	646	0.00	4	16	1.53	6.97	-0.25	0.00	0.01	0.17	0.17	0.57
maga	Political	414	557	1	67	1	414	0.00	3	12	1.03	4.56	-0.14	0.00	0.00	0.16	0.25	0.36
lgbt	Shared interest	365	373	0	4	1	365	0.00	2	14	1.04	6.62	-0.35	0.00	0.00	0.10	0.22	0.68
kpop	Shared interest	344	365	2	16	1	344	0.00	3	13	1.03	3.45	-0.47	0.00	0.00	0.69	0.50	0.96
trump2024	Political	272	303	1	15	1	272	0.00	2	14	1.13	5.88	-0.32	0.00	0.00	0.10	0.21	0.46
gaming	Shared interest	243	266	3	9	1	243	0.00	4	17	1.72	6.98	-0.32	0.01	0.00	0.13	0.19	0.50
storytime	Entertainment	173	189	0	16	1	173	0.01	2	7	1.47	2.36	-0.29	0.00	0.00	0.89	0.81	0.99
palestine	Political	144	148	0	4	1	144	0.01	1	14	1.00	5.95	-0.42	0.00	0.00	0.22	0.24	0.70
catsoftiktok	Entertainment	142	146	0	4	1	142	0.01	1	11	1.00	5.03	-0.53	0.00	0.00	0.45	0.20	0.72
israel	Political	141	153	0	9	1	141	0.01	1	22	1.00	8.07	-0.22	0.00	0.00	0.07	0.13	0.57
gaza	Political	109	116	0	6	1	109	0.01	2	11	1.01	4.51	-0.49	0.00	0.00	0.29	0.30	0.67
learnontiktok	Entertainment	79	134	0	3	1	79	0.02	6	9	2.45	3.76	-0.23	0.16	0.03	0.15	0.34	0.59
gym	Shared interest	74	80	0	7	1	74	0.01	1	9	1.00	3.61	-0.46	0.00	0.00	0.48	0.44	0.89
news	Entertainment	73	180	0	79	1	73	0.03	1	4	1.00	2.11	-0.00	0.00	0.00	0.90	0.79	0.83
football	Entertainment	73	81	0	7	1	73	0.02	2	13	1.11	5.32	-0.27	0.00	0.00	0.27	0.18	0.51
movie	Entertainment	71	89	0	11	1	71	0.02	3	12	1.22	4.71	-0.00	0.03	0.00	0.26	0.26	0.57
makeup	Shared interest	68	68	0	1	1	68	0.01	1	2	1.00	1.97	-	0.00	0.00	1.00	1.00	1.00
blacklivesmatter	Political	64	65	1	1	1	64	0.02	2	8	1.02	3.46	-0.43	0.00	0.00	0.41	0.44	0.84
biden2024	Political	63	69	1	6	1	63	0.02	2	11	1.39	4.55	-0.49	0.00	0.00	0.23	0.25	0.69
challenge	Entertainment	35	54	2	19	1	35	0.05	2	10	1.13	4.76	0.15	0.00	0.00	0.13	0.23	0.61
prochoice	Political	30	30	1	0	1	30	0.03	1	4	1.00	2.69	-0.24	0.00	0.00	0.67	0.52	0.86
watermelon	Entertainment	17	16	0	0	1	17	0.06	1	6	1.00	3.15	-0.45	0.00	0.00	0.29	0.37	0.68
minecraft	Shared interest	14	13	0	0	1	14	0.07	1	2	1.00	1.86	-	0.00	0.00	1.00	1.00	1.00
dogsoftiktok	Entertainment	13	12	0	0	1	13	0.08	1	3	1.00	2.21	-0.84	0.00	0.00	0.61	0.64	0.80
conspiracy	Entertainment	11	12	0	2	1	11	0.11	1	3	1.00	1.96	-0.30	0.00	0.00	0.88	0.88	0.96
election	Political	11	10	0	0	1	11	0.09	1	6	1.00	2.80	-0.03	0.00	0.00	0.39	0.42	0.66
science	Entertainment	11	10	0	0	1	11	0.09	1	5	1.00	2.55	-0.27	0.00	0.00	0.51	0.50	0.74
plantsoftiktok	Shared interest	8	8	1	0	1	8	0.14	1	6	1.00	2.71	-0.44	0.00	0.00	0.24	0.28	0.44
tiktoknews	Entertainment	8	7	0	0	1	8	0.12	1	2	1.00	1.75	-	0.00	0.00	1.00	1.00	1.00
abortion	Political	6	5	0	0	1	6	0.17	1	2	1.00	1.67	-	0.00	0.00	1.00	1.00	1.00
asmr	Entertainment	6	5	0	0	1	6	0.17	1	2	1.00	1.67	-	0.00	0.00	1.00	1.00	1.00
climatechange	Political	4	3	0	0	1	4	0.25	1	3	1.00	1.67	-0.50	0.00	0.00	0.33	0.42	0.44
guncontrol	Political	2	1	0	0	1	2	0.50	1	1	1.00	1.00	-	0.00	0.00	-	-	-
jazz	Shared interest	2	1	0	0	1	2	0.50	1	1	1.00	1.00	-	0.00	0.00	-	-	-
	Shared interest	260.80	287.00	3.60	11.90	1.00	260.80	0.08	2.20	10.40	1.16	4.36	-0.36	0.00	0.00	0.43	0.44	0.73
	Entertainment	182.14	211.93	0.50	14.36	1.00	182.14	0.06	1.79	7.57	1.17	3.47	-0.27	0.01	0.00	0.53	0.53	0.73
	Political	105.00	121.67	0.42	9.00	1.00	105.00	0.09	1.50	9.00	1.05	3.90	-0.33	0.00	0.00	0.35	0.38	0.66

Table 7: Full table of largest weak component user graph metrics.

A.4 FULL FREQUENT SUBGRAPH MINING FIGURES

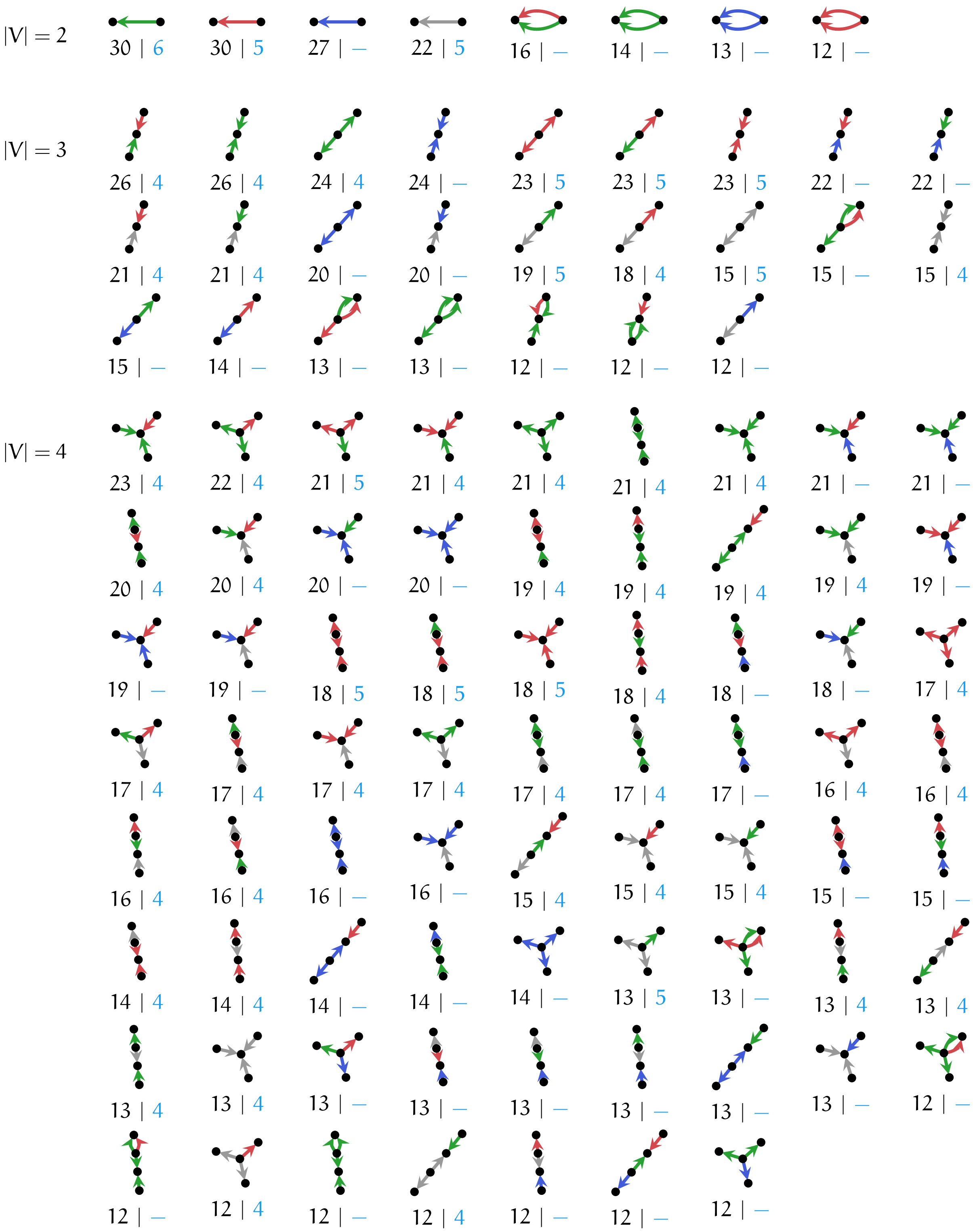


Figure 14: Full figure of all mined directed sentiment subgraphs for subgraphs up to $|V| = 4$ and down to support 12. This figure uses the support computed by MOSS, which means multi-edges can occur, and the specific supports of subgraphs can differ from figure 11.

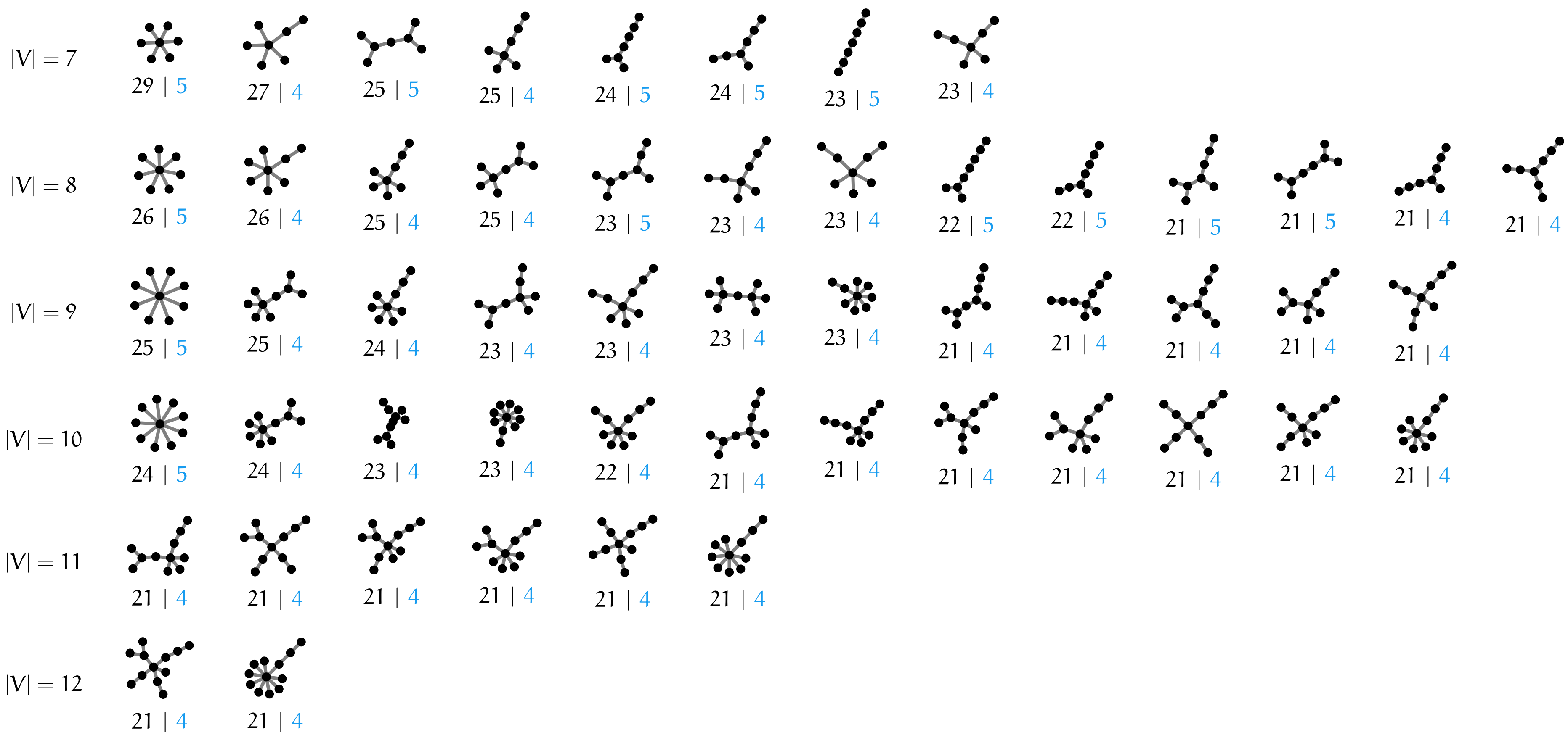


Table 8: Full figure of larger undirected subgraphs.

A.5 ALTERNATIVE GRAPH EMBEDDING SCATTER PLOTS

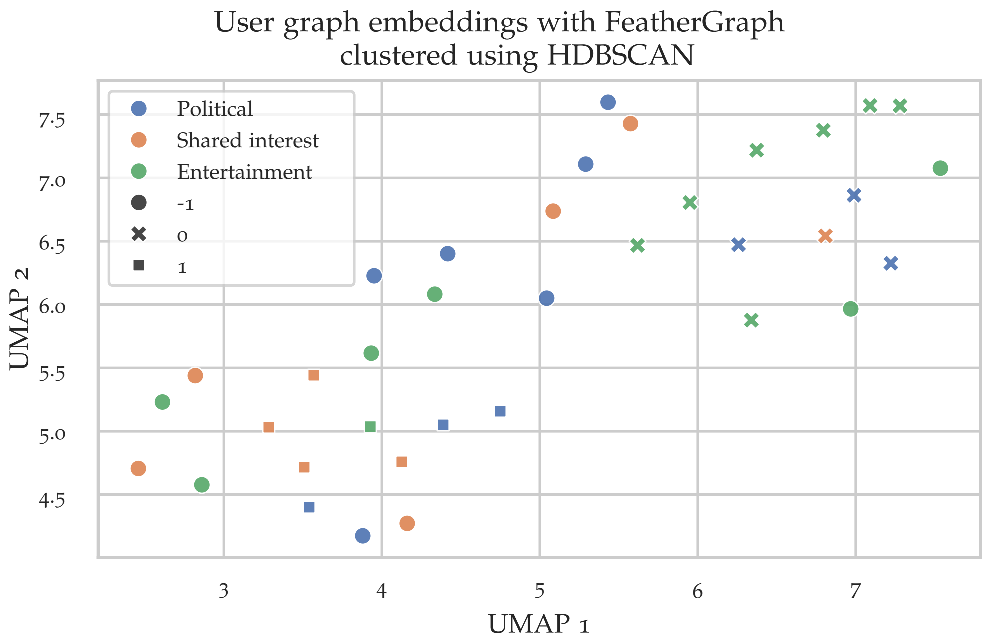


Figure 15: FeatherGraph embeddings of user graphs.

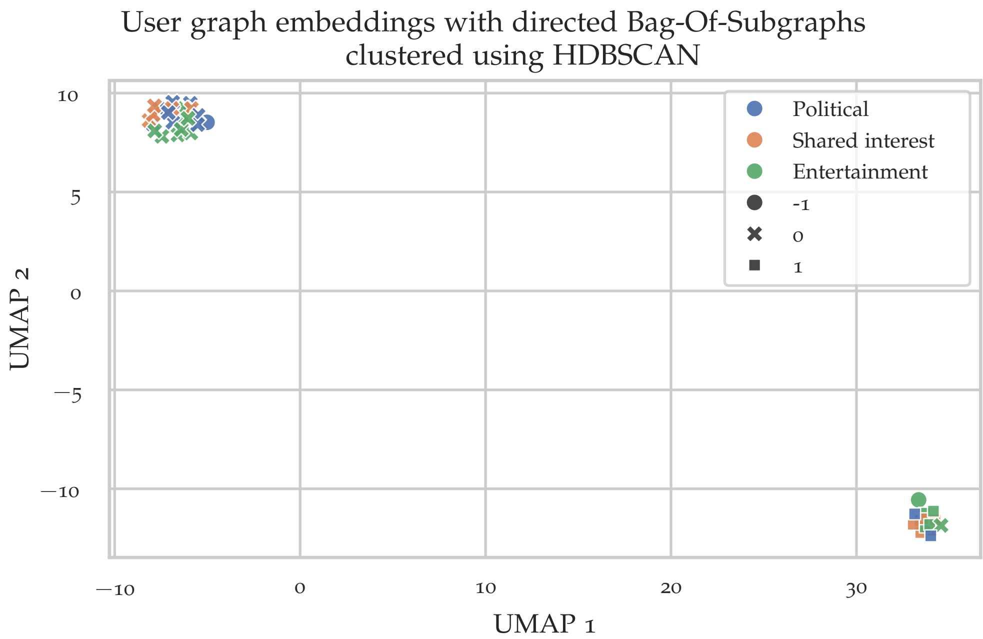


Figure 16: Bag-Of-Subgraphs with directed subgraphs.

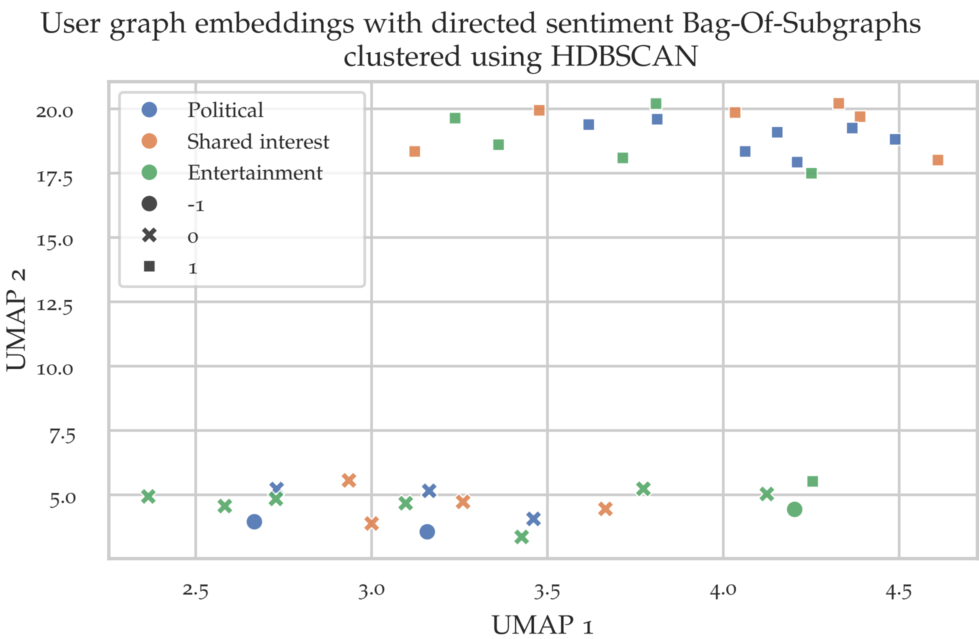


Figure 17: Bag-Of-Subgraphs with directed sentiment subgraphs.