Department of Management Science and Technology

Network Analysis Of Dave Gibbon’s BlueSky Account

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Abstract

This paper explores the structural properties of a social network derived from Dave Gibbons' Bluesky account, offering insights into community organization, influence dynamics, and connectivity patterns within this online community. Utilizing social network analysis techniques, we examine modularity to identify distinct user groups, centrality measures (betweenness, closeness, PageRank) to pinpoint influential figures, and degree distribution to understand the spread of connections and popularity. Our analysis reveals a network characterized by distinct communities organized around shared interests and professional affiliations, with influence distributed both centrally and locally. We identify key players who bridge communities, facilitate information flow, and shape network-wide discourse. Furthermore, we analyze the network's density and explore local clustering patterns. While acknowledging the limitations of the data and the potential for echo chambers within platforms like Bluesky, particularly those with a specific ideological leaning, this study provides a valuable understanding of the complex interplay between influence, community, and connection in the digital age. The findings highlight the multifaceted nature of influence, the importance of considering both global and local dynamics, and the need for critical awareness of the potential for bias in online social spaces.

Who is Dave Gibbons?

Dave Gibbons is a comic book artist, but in reality, he is more than just an artist—he is a storyteller, a visionary, and a cornerstone of modern graphic literature. Best known for his seminal work on *Watchmen*, a graphic novel that transcended the boundaries of the comic book medium and tried to answer the big question of "Who watches the watchers?". Gibbons etched his name into history by crafting worlds that blur the line between the ordinary and the extraordinary. His intricate line work, meticulous panel composition, and unparalleled ability to convey human emotion through art have made him a beloved figure in the hearts of fans and creators alike.

Born in England in 1949, Gibbons grew up immersed in the golden age of science fiction and comics. From a young age, he was captivated by the bright, bombastic adventures of *Dan Dare* and the ink-stained pages of *The Eagle*. These influences planted the seeds of a career that would later redefine what comics could achieve. Over decades, his artistic style evolved into something entirely his own—bold yet subtle, vibrant yet restrained—imbuing every panel with a sense of purpose and narrative clarity.

Yet, Gibbons's impact goes beyond the art itself. He co-created *Watchmen* with Alan Moore, a work so profound that it challenged the very idea of heroism, deconstructed archetypes, and asked difficult questions about morality, power, and humanity. His visual storytelling brought life to Moore's words, transforming a philosophical narrative into an unforgettable visual masterpiece. The iconic smiley-face button splattered with blood, the symmetry of his nine-panel grids, and the haunting imagery of Dr. Manhattan on Mars—these moments are etched into the collective consciousness of pop culture.

Beyond *Watchmen*, Gibbons has contributed to numerous other legendary works, including *Green Lantern Corps, Doctor Who* and *Kingsman: The Secret Service*. His collaborations with writers like Frank Miller and Mark Millar reflect his adaptability and creative genius. But above all, Gibbons's work resonates because of its deep humanity—it captures not just the heroics of larger-than-life figures but also the vulnerability and flaws that make them real.

Today, as comics evolve into global cinematic universes, Gibbons remains a symbol of authenticity, a reminder of where it all began. His Bluesky account, though modest in following, stands as a small, quiet corner of the digital world—a space where fans can glimpse the man behind the legend. Analysing his network is not just a technical exercise; it is an opportunity to explore how one creator's legacy continues to ripple through time, connecting fans, creators, and dreamers in ways both profound and unexpected.

In a world where heroes are drawn in pixels and printed on glossy paper, Dave Gibbons has shown us that the true power of storytelling lies not in capes or superpowers, but in the ability to reflect the human condition—one panel at a time.

Concept Understanding and Leads for research

This study explores the structural properties of a social network derived from Dave Gibbons' Bluesky account, focusing on community structure, influence, and connectivity. Several key concepts from social network analysis were applied, including:

Modularity: Revealed distinct communities within the network, organized around shared interests, professional affiliations, or geographic location.

Centrality Measures (Betweenness, Closeness, PageRank): Identified influential users based on their position within the network, their role as bridges between communities, and their overall connectivity.

Degree Distribution (In-degree, Out-degree): Showed how connections are distributed across the network, highlighting the presence of active users and the distribution of popularity.

Density: Quantified the overall level of interconnectedness, revealing a sparse network with a denser core of influential users.

Leads for Future Research:

This study provides a foundation for several avenues of future research:

Content Analysis: Analyzing the content shared by influential users and within different communities could provide deeper insights into the topics and themes driving network interactions.

Temporal Analysis: Examining how the network evolves over time, including changes in community structure and shifts in influence, could reveal dynamic patterns of interaction.

Comparative Analysis: Comparing the structure of this network with other social networks, particularly those related to different creative communities, could identify common patterns and unique characteristics.

Qualitative Studies: Conducting interviews or focus groups with users could provide rich qualitative data to complement the quantitative findings, offering deeper insights into motivations and experiences.

Impact of Platform Design: Investigating how the specific design and features of the Bluesky platform might influence network structure and user behavior.

Limitations

This study has several limitations:

Data Scope: The analysis is based on a snapshot of the network at a specific point in time. Network structures are dynamic, and the findings may not be generalizable to other time periods.

Incomplete Data: It is included in the Appendix, that the gender homophily analysis was hampered by incomplete profile data. Future research should explore methods for addressing this limitation.

Methodological Choices: The choice of specific algorithms and parameters (e.g., Louvain method for modularity) can influence the results. Exploring alternative methods could provide additional insights.

Focus on Structure: This study primarily focused on network structure. While structural analysis is valuable, it's important to acknowledge that other factors, such as user behavior and content, also play a significant role in shaping social network dynamics.

Generalizability: The findings may not be generalizable to other social networks or online communities. The specific characteristics of the comics community and the Bluesky platform may influence the results.

Self-Reported Data: The analysis relies on self-reported information in user bios, which may not always be accurate or up-to-date.

Methodology

Nodes

The nodes in this network represent accounts on Bluesky, where each account corresponds to an individual user. These users form a social network based on their connections, representing their followers and the people they follow. The dataset includes 19,242 nodes, comprising Dave Gibbons's followers and the followers of those followers, fetched in an expanded two-level network. Each node is characterized by attributes such as the account's degree, which determines its level of connectivity within the network. The analysis does not include user-generated content but focuses on structural features, such as the relationships between users, their prominence (e.g., degree or influence), and their distribution across the network's modularity clusters.

Edges

The edges in this network represent follower relationships between Bluesky accounts, with the edges being directed to signify the direction of the connection. If one account follows another, a directed edge is drawn from the follower to the account they follow. The dataset contains 29,211 edges, showcasing the intricate web of connections among Dave Gibbons's followers and their extended network. Each edge highlights the interaction and relationship dynamics within the platform, capturing how users are connected through following behaviours. These directed edges allow for the analysis of important metrics such as in-degree and out-degree (number of followers and accounts followed, respectively), which provide insight into user influence and engagement. The edges serve as the backbone for identifying clusters, understanding network density, and analyzing the flow of information or interactions within the Bluesky network.

Dataset Generation

Bluesky Data Collection Using Gephi

The dataset for this analysis was generated using Mattieu Totet*'s bluesky plugin for gephi*, to interact with Bluesky's network. Gephi provides a robust and user-friendly platform for importing, visualizing, and analyzing social network data. The data collection process began by importing Dave Gibbons's followers and expanding the network to include their followers (n+1 degree). This two-tiered approach allowed for the capture of a richer and more comprehensive network structure.

The Bluesky plugin in Gephi enabled seamless integration and extraction of the data directly from the platform's API. This ensured that the data was accurate and ready for immediate analysis. By specifying parameters such as node attributes (account information) and edge attributes (follower-following relationships), the network was structured for detailed study. As we said before, the extracted data consisted of 19,242 nodes (representing accounts) and 29,211 directed edges (representing follower relationships). Gephi's powerful modularity detection and ForceAtlas 2 layout algorithms were then applied to organize and refine the visualization, providing a meaningful representation of community structures and connection patterns within the network.

This method ensured efficiency, accuracy, and flexibility in generating the dataset, making it suitable for in-depth social network analysis.

Social Network Analysis

Graphical representation of the network

A preliminary graphical representation of the network was generated by partitioning the modularity class, where the size of each node corresponds to its degree. The interpretation of this network will be explained as we examine the degree measures. The layout used for visualization in Figure 1 was "Force Atlas 2" in filters of different modules and then unfiltered to present the whole image.

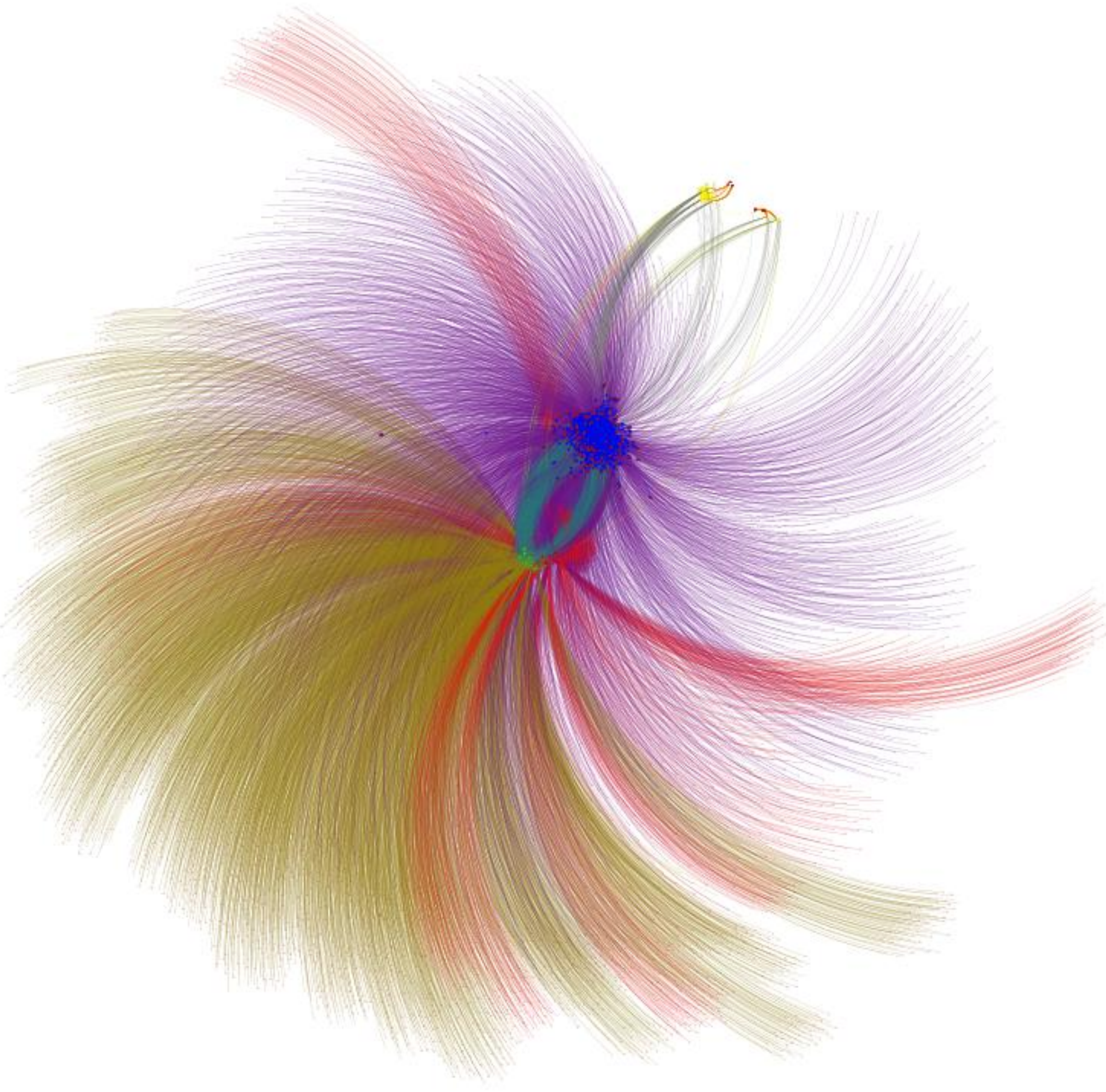

Figure 1: Visualization partitioned by modularity class

Basic topological properties

The network in this study is directed, as edges represent follower relationships on Bluesky, where directionality indicates who follows whom. Initially, the network contains 19,241 nodes and 28,675 edges. However, to focus on more significant nodes and avoid the influence of low-degree accounts, we filtered out nodes with a degree lower than 2, resulting in a reduced network with 3,845 nodes and 13,282 edges. Also, we excluded nodes with self-loops that seemed to be invalid data, so the final edges were 13,280. These steps ensure a cleaner analysis by excluding less relevant accounts and wrong data that do not contribute meaningfully to the network structure.

The network diameter—defined as the longest shortest path between any two nodes in the network (Newman, 2018)—is 13. This suggests that, while the network is large, the longest distance between any two nodes is still relatively moderate. Additionally, the average path length, which is the average of the shortest paths between all pairs of nodes in the network, is 4.2. These metrics reflect in this network the nodes are reasonably well connected, with a path length that is quite manageable given the size of the network.

Betweenness centrality for nodes was calculated using the algorithm developed by Ulrik Brandes in 2001 ("A Faster Algorithm for Betweenness Centrality"). This algorithm helps identify key nodes that act as bridges in the network, facilitating the flow of information across the network. The next steps of the analysis will delve into these centrality measures to further explore the roles of important nodes within the Bluesky community.

Component Measures

Components are well-connected regions of nodes in a network. When a network component's size grows to the total number of nodes (N), it is referred to as a giant component (Newman, 2018). In the current network, the number of Weakly Connected Components (WCC) is 1, indicating that, when the direction of the edges is disregarded, all nodes are part of a single connected structure. However, since the network is directed, the analysis also identified 3,804 Strongly Connected Components (SCCs), which refer to subsets of the network where each node is reachable from every other node within the subset, following the direction of the edges.

Among these 3,804 SCCs, only one is substantial in terms of network size, occupying 80 of the network. The remaining components are minor in comparison and are grouped into a single smaller component. This finding reflects the network's structure, where most nodes are involved in one dominant strongly connected component, while other smaller components exist but have minimal impact on the overall connectivity.

The algorithm used for this analysis is based on **Tarjan's Algorithm** for finding strongly connected components, which is a depth-first search (DFS) based method (Tarjan, 1972). This efficient algorithm, implemented in Gephi, identifies SCCs in linear time by assigning a unique index to each node and tracking low-link values to detect cycles.

As expected, the giant component in this directed network is weakly connected, meaning that, despite the directionality of edges, the overall network forms a single large, connected region. To better visualize the structure of this giant component and its significance, the topological filter "Giant Component" was applied. The resulting visualization clearly illustrates the dominance of this large component:

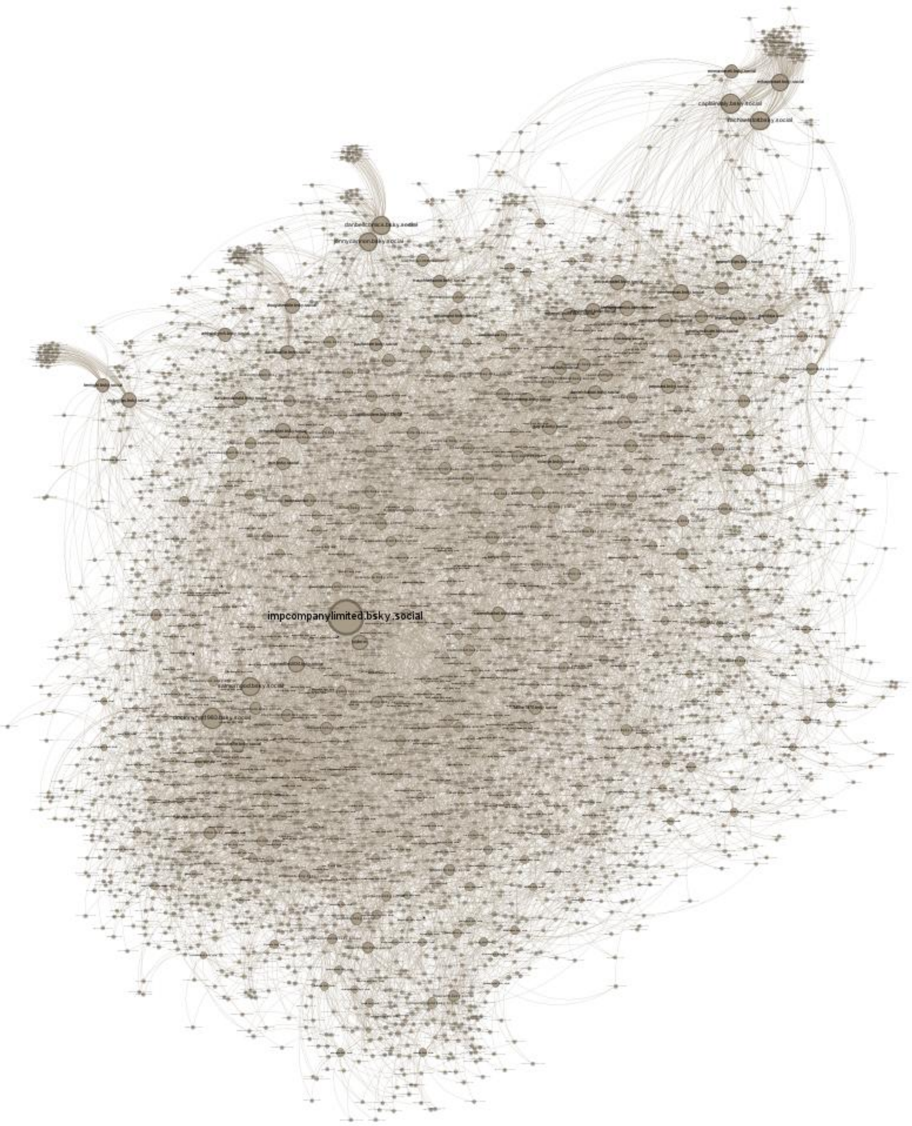

Figure 2: Giant Component

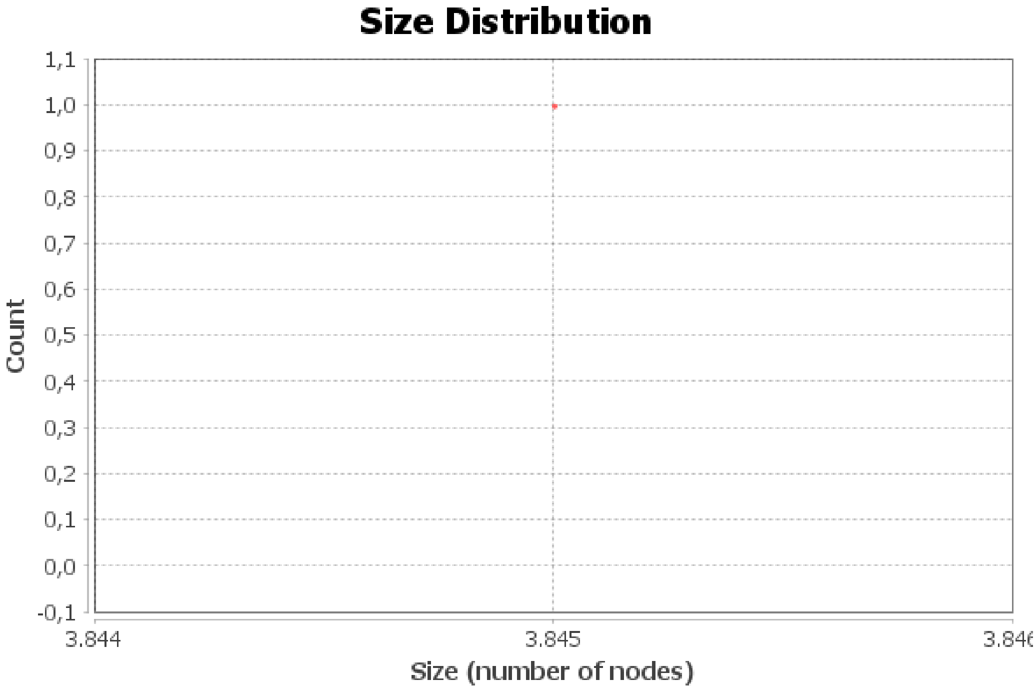

Figure 3: Component Size Distribution

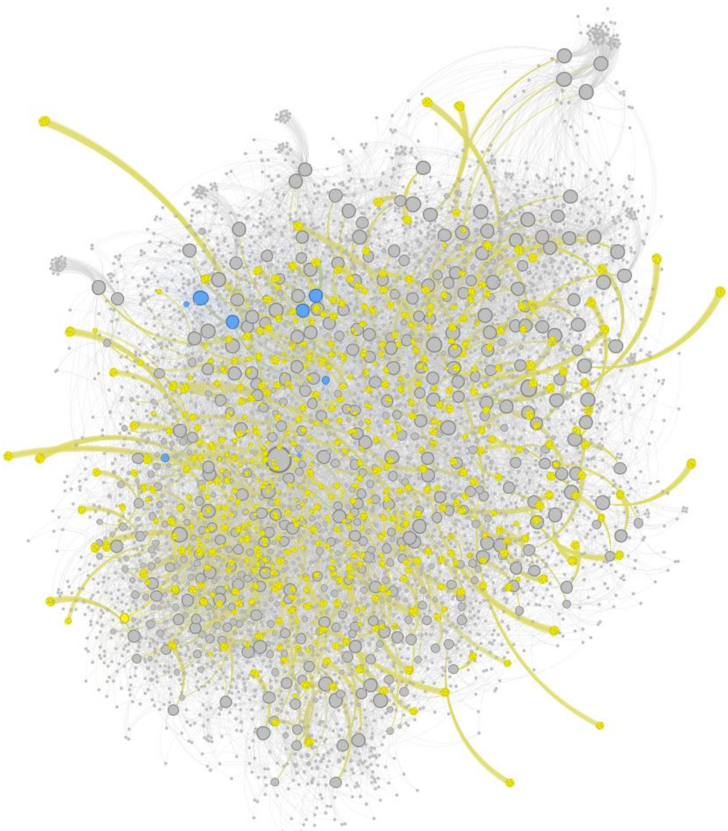

Figure 4: Strongly-Connected Components

Homophily

Community Structure (modularity)

Modularity: Mapping the Communities of Dave Gibbons' Bluesky Network

This section explores the community structure of Dave Gibbons' Bluesky network through modularity analysis. Modularity measures how well a network can be divided into distinct communities or clusters. Nodes within a module are more densely connected to each other than to nodes in other modules. Visualizing these modules helps us understand the organization of the network and identify groups of users with shared interests or affiliations. Gephi, the network analysis software used in this study, employs the Louvain method for modularity optimization. This algorithm is a greedy optimization method that aims to find the best community structure by iteratively moving nodes between communities to maximize the modularity score. It's a widely used and effective approach for community detection in large networks. Figure 6 displays the network, with nodes colored according to their modularity class as determined by the Louvain method. Four distinct clusters have been identified, each revealing a unique facet of the network's composition:

1. Small/Independent Artists and Professionals (Green Cluster, Cluster 0): This cluster represents a group of small and independent artists and comics professionals. Members like Jeff Carlisle, Tom Williams, Richard Bruton, and ArtDroidLynch suggest a community focused on the craft and business of independent comics. The presence of illustrators, designers, and journalists indicates a network centered around creative professionals and industry connections.

Figure 5: Modularity colours and percentages

2. Help with Illustrating and Storytelling/Amateurs and Comic Lovers (Red Cluster, Cluster 2): This cluster appears to bring together individuals interested in the art of illustration and storytelling, possibly including amateur artists and comics enthusiasts. The presence of accounts like "iBlack AI: image generator," "Valerie Frankel: ghostwriter," and "Films for Breakfast" indicates a diverse range of interests within this cluster, from the technical aspects of image generation to narrative storytelling across different media.

3. UK/EU Artists (Yellow Cluster, Cluster 1): This cluster groups UK and potentially other EU-based artists like Rachael Stott and Emma Vieceli. The inclusion of "captainitaly" (Andrea Schiavone), a prominent Italian artist connected to Emma Vieceli, suggests a broader European artistic community. This tight-knit community likely fosters collaboration, support, and shared experiences specific to the European comics scene.

4. Big Names and Platforms (Blue Cluster, Cluster 3): This largest cluster consists of "big names" in the comics industry, established platforms, and individuals with broader pop culture connections. Accounts like comicbuzz, IMP, Bingbang Comics, Dan Bell Comics, David McDonald, Nir Levie, and "VOICES FROM KRYPTON" suggest a hub of established influence and wider reach. This cluster represents a central node within the network, attracting connections from various other communities.

The modularity analysis, using the Louvain method for optimization, reveals a network organized around distinct professional, geographic, and interest-based communities. The presence of both independent creators and established figures highlights the diverse nature of the network, while the clustering suggests that users tend to connect most strongly with those sharing similar backgrounds or interests. This modular structure influences information flow and collaboration patterns within the network.

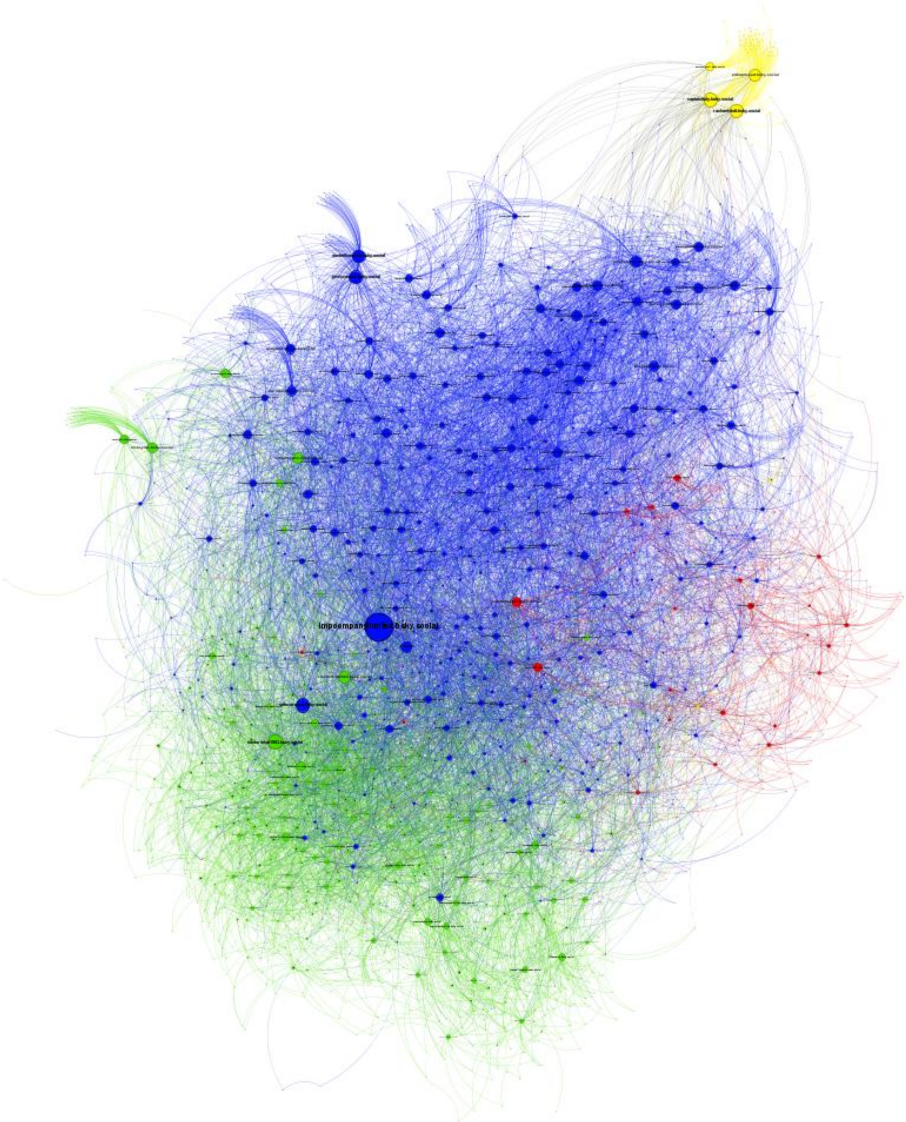

Figure 6: Filtered Network, Coloured by Modularities

Degree Measures

This section examines degree measures within Dave Gibbons' Bluesky network to understand user popularity and its impact on network dynamics. Before delving into the specific findings, it's crucial to define degree centrality and provide some context.

Degree centrality is a fundamental concept in network analysis that measures the number of direct connections a node has with other nodes. In a directed network like Bluesky (where following is a directed action), we distinguish between *in-degree* (number of incoming connections, i.e., followers) and *out-degree* (number of outgoing connections, i.e., accounts followed). Total degree is the sum of in-degree and out-degree, representing the overall connectivity of a node. In this analysis, since all node weights are 1, we are considering the simple, unweighted degree.

Popularity: A high in-degree suggests that a user is popular and receives attention from many other users. In social networks, this often translates to influence and visibility.

Activity: A high out-degree indicates that a user is actively engaging with many other users. This can suggest a user who is curious, engaged, or trying to build a following.

Influence: Users with high total degree, combining both in-degree and out-degree, are often seen as influential hubs within the network. They both attract attention and spread information.

Degree Centrality in Dave Gibbons' Bluesky Network

With an average degree of 3.454, the network exhibits a moderate level of connectivity. Analyzing the degree distribution plots reveals crucial distinctions between total degree, in-degree, and out-degree, challenging initial assumptions about concentrated influence.

- Total Degree Distribution: The total degree distribution, which combines in-degree and out-degree, exhibits a skewed pattern, suggesting the presence of influential hubs.

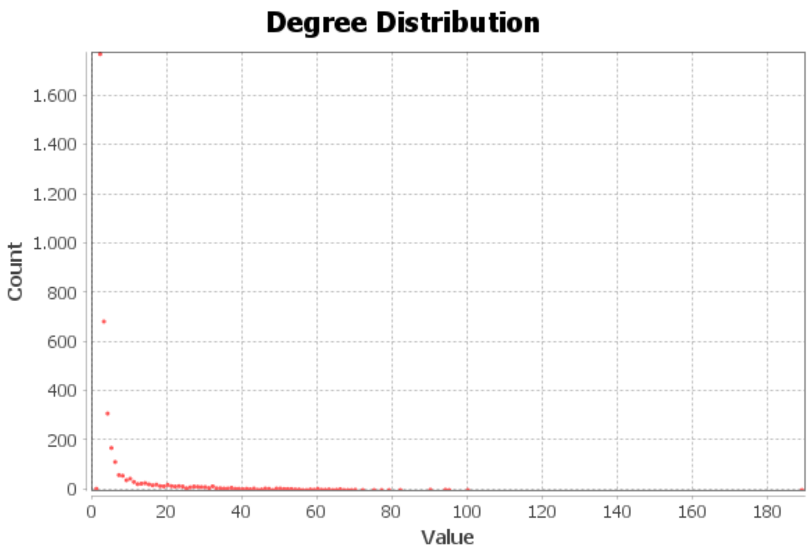

Figure 7: Total Degree Distribution

- In-Degree Distribution: The in-degree distribution shows a less pronounced skew. As we can see in figure 13 the blue cluster, comprising "big names," exhibits a higher concentration of in-degree as we expected, other clusters also have their own "celebrities" with significant follower counts. The key takeaway here is the absence of extremely dominant "hot nodes" in terms of followers. Popularity, while present, is more distributed.

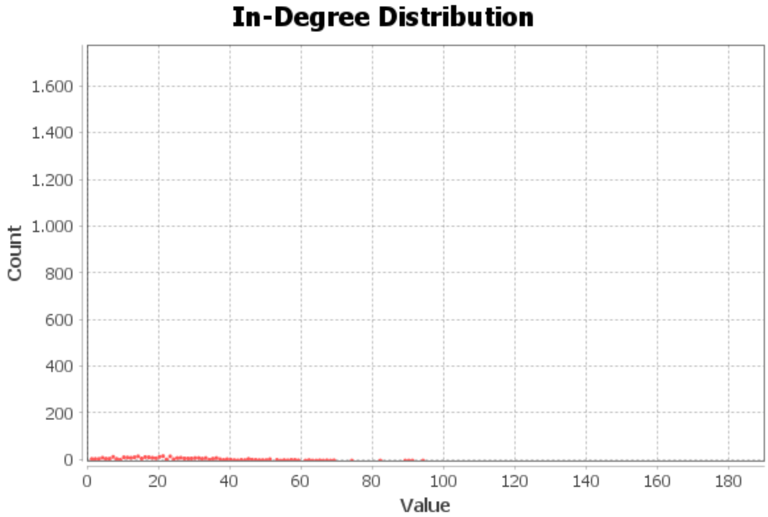

Figure 8: In-Degree Distribution

- Out-Degree Distribution: This distribution is the primary driver of the skew observed in the total degree distribution. A significant number of accounts, including those with high total degree, exhibit a very high out-degree. This suggests a pattern of actively following many accounts, potentially for content consumption, networking, or visibility. It's important to note that many of these accounts like "@doctorwhat" are flagged as spam by the algorithm.

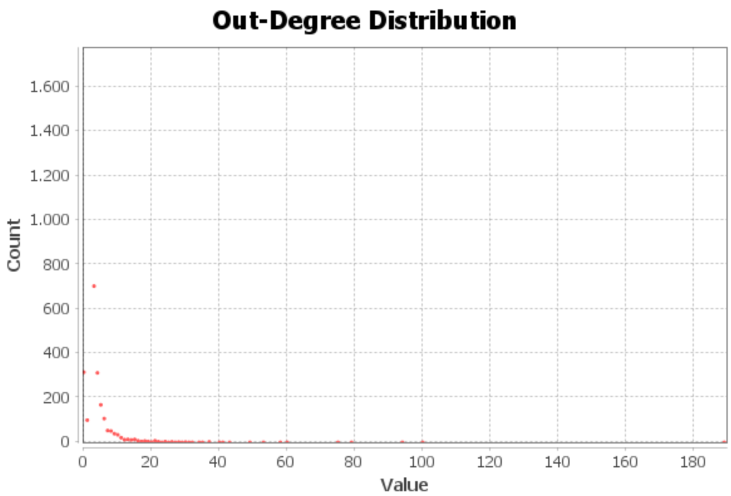

Figure 9: Out-Degree Distribution

By visualising the data, we can see a pattern:

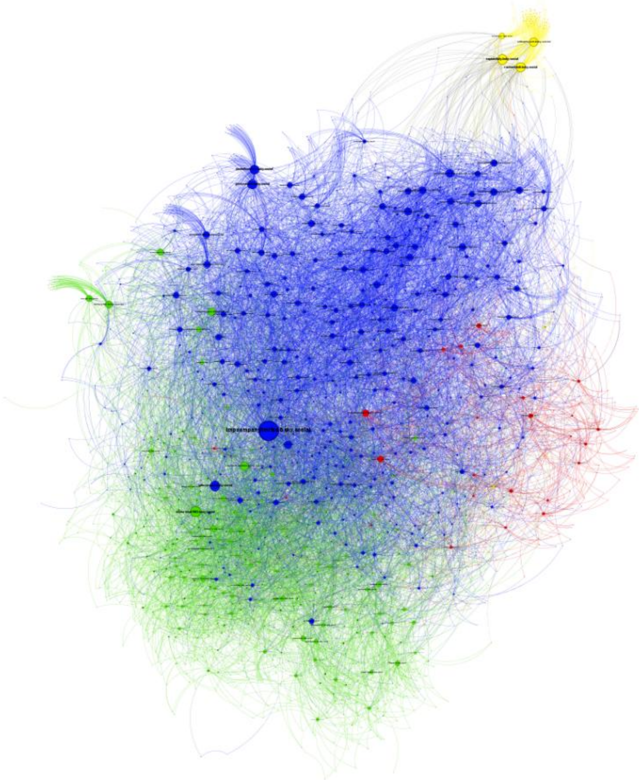

Figure 11: Total-Degree Visual

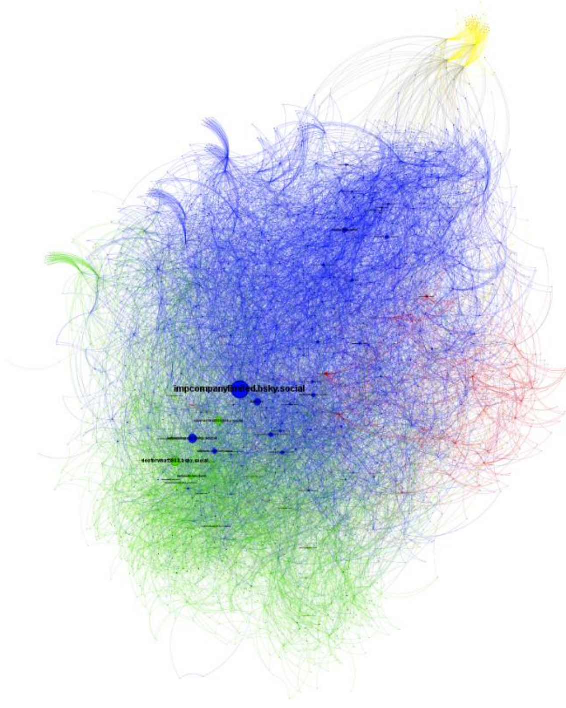

Figure 10: Out-Degree Visual

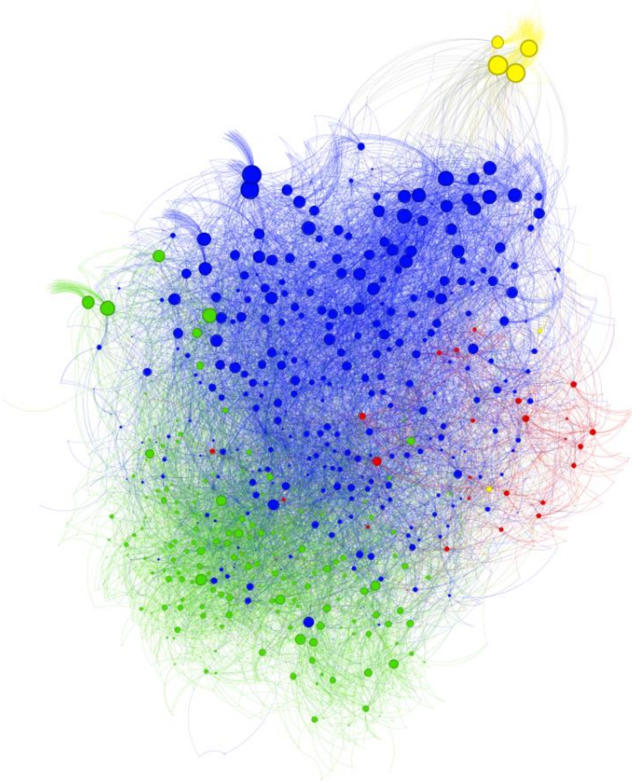

Figure 12: In-Degree Visual

By taking a closer look at the data we can confirm that the top degree accounts are primarily characterized by high out-degree, not in-degree. This means they are actively following a large number of accounts, not necessarily attracting a disproportionate share of followers.

The analysis reveals that the initial focus on total degree masked a crucial distinction:

- High Out-Degree: Active Engagement: Accounts with high out-degree are actively participating in the network by following a large number of users. This reflects activity and a desire to connect with a broad range of content and users.
- High In-Degree: Distributed Popularity: While some accounts have higher in-degree (follower counts) than others, the distribution is relatively more even than expected in a typical social network. This suggests a more distributed influence, with various communities having their own popular figures. Also, this community can be described as niche, so the absence of huge hubs is understandable.

For the above reasons, we decided to highlight the accounts with high In-Degree and present that as more important. It's valuable to note that we do not see any account belonging in cluster 2, as we would expect. This amplifies that conclusions of the modularity analysis.

Label	Modularity Class	In-Degree
captainitaly.bsky.social	1	94
rachaelstott.bsky.social	1	91
danbellcomics.bsky.social	3	90
jonnycannon.bsky.social	3	89
erikapriceart.bsky.social	1	82
johnfreeman.bsky.social	3	74
westonfront.bsky.social	3	69
nickxylas.bsky.social	0	69
richardbruton.bsky.social	0	68
marclaming.bsky.social	3	67
alexpaknadel.bsky.social	3	67

Centrality Measures

Betweenness and Closeness Centrality: Unveiling Influence and Community Structure

This section analyzes betweenness and closeness centrality within Dave Gibbons' Bluesky network to illuminate influential users and the network's community structure. Figure 13 visualizes betweenness centrality, colored by modularity, revealing key bridging nodes that connect distinct communities. This analysis, coupled with the observed modularity structure, offers insights into the dynamics of this network.

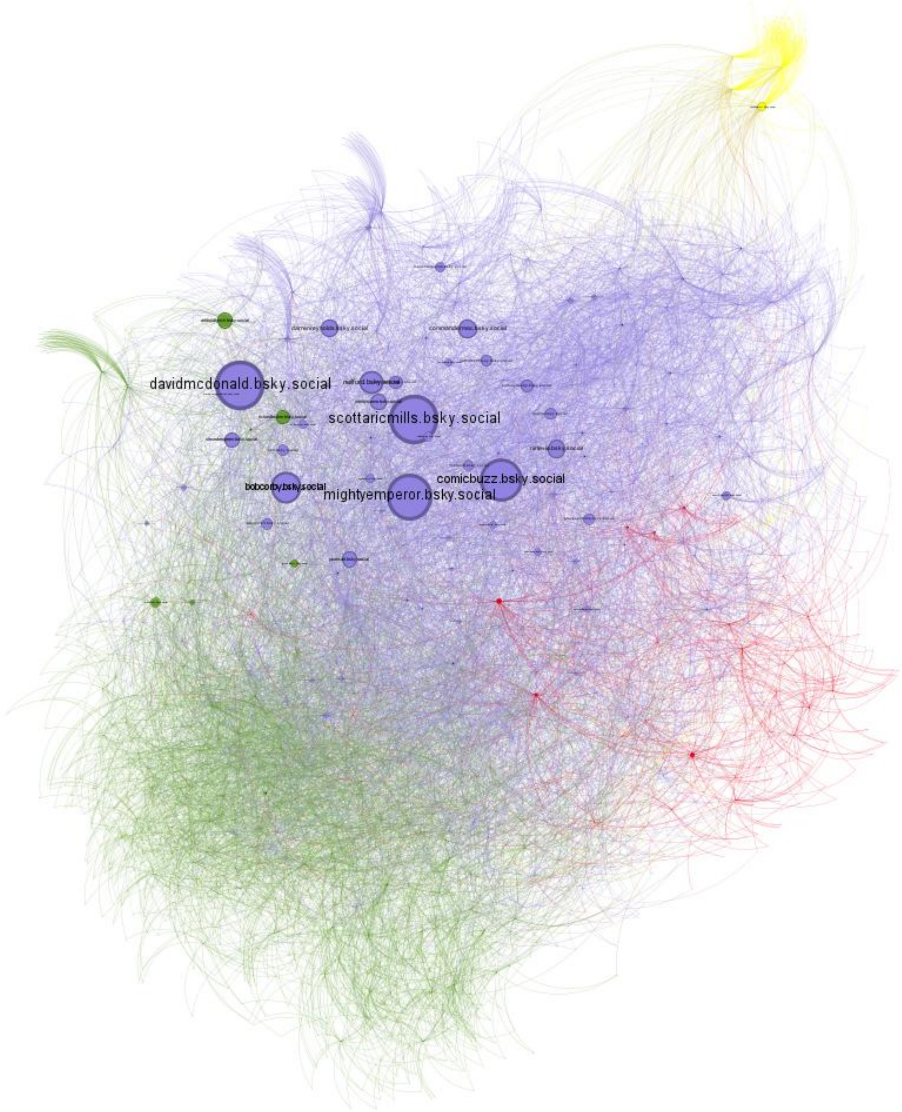

Figure 13: Betweenness centrality, colored by modularity

Betweenness Centrality: Gatekeepers of Information Flow

Betweenness centrality measures the number of shortest paths traversing a given node. High betweenness signifies a node's role as a crucial intermediary, influencing information flow between disparate network regions. As expected the "blue cluster", characterized by the presence of "big names" and actors, attracts a significant portion of the betweenness centrality. This suggests that these influential figures act as central hubs, drawing connections from various parts of the network. The high betweenness within this cluster underscores the concentration of influence and information flow around these prominent individuals. The top 5 accounts are:

- davidmcdonald.bsky.social (0.001825): As a comics writer,editor and publisher, this account occupies a prominent position, bridging multiple modules. This suggests a role as a conduit for information and interactions within the comics community, connecting creators, readers, and related groups.
- scottaricmills.bsky.social (0.001801): An Ignatz award-winning graphic novelist mixing lovable characters with an undeniable sense of humanity (just like Gibbons), this account mirrors the pattern of davidmcdonald.bsky.social, bridging communities within the comics sphere. This reinforces the importance of these individuals in facilitating connections within this creative domain.
- mightyemperor.bsky.social (0.001683): This account, while less descriptive (Bio states: "I am not here"), also exhibit high betweenness, suggesting their involvement in connecting different segments of the network. As we will see later, he plays even bigger role than someone would expect! Further investigation into their activity and connections is warranted to understand their specific roles.
- comicbuzz.bsky.social (0.001567): One account we sure expected to have high betweenness is Comic Buzz, a Pop-Culture reporter team that covers comics, anime, games and movies, and of course keep the network informed.
- bobcorby.bsky.social (0.001133): As a retired engineer, cartoonist, and organizer of the Small Press & Alternative Comics Expo (SPACE), this account bridges the professional and independent spheres of the comics world.

It's valuable to note that all these accounts did not show high in-degree. This leads to the conclusion that in order to influence information flow accounts not only need a high following but they need to be active and share more content and reposts to become more powerful in the network in terms of betweenness centrality.

Modularity and Closeness Centrality

In network theory, harmonic closeness centrality measures how efficiently a node can access other nodes in a network, even when the network is disconnected. Unlike traditional closeness centrality, which is undefined for unreachable nodes, harmonic closeness centrality accounts for these cases by summing the reciprocals of shortest path distances (Newman, 2018). A higher score indicates that an account is well-positioned to quickly reach a large portion of the network. If an account wants to increase its visibility in a specific community, connecting with an account that has high harmonic closeness centrality can help them reach a broader audience more quickly. Unlike betweenness centrality, which highlights key intermediaries, harmonic closeness centrality emphasizes nodes that are structurally well-placed for efficient communication.

Notably, the "green" cluster exhibits a high concentration of closeness centrality. As previously observed, this cluster comprises small and independent comics professionals. Their high closeness centrality suggests a strategic approach to network engagement. They likely follow prominent figures within the industry while also cultivating a substantial following of their own. This "controlled following," potentially driven by marketing considerations, positions them as active participants in the network's information exchange. They are not overly selective in their follow patterns like more famous people, likely due to the need to connect with a broad audience.

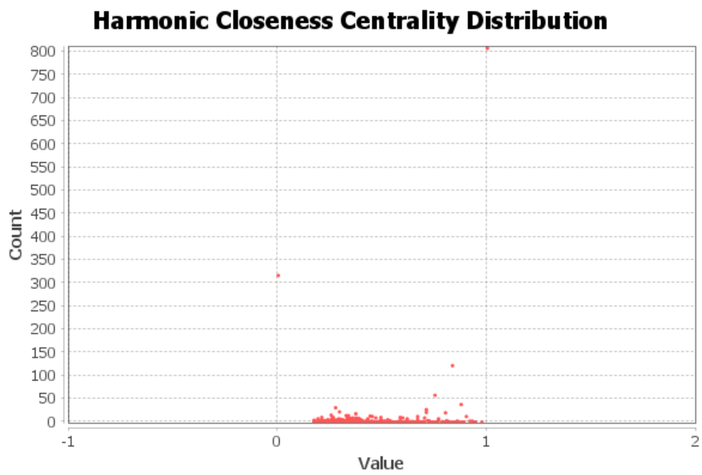

Figure 14: Harmonic Closeness Distribution

The following plot illustrates the distribution of harmonic closeness centrality within Dave Gibbons' Bluesky network:

Figure 15: Harmonic Closeness Visualisation

Synthesis: Bridging the Gap

The interplay between betweenness centrality, closeness centrality, and modularity reveals a nuanced picture of influence and community structure within Dave Gibbons' Bluesky network. The high-betweenness nodes, particularly within the blue cluster, act as central hubs connecting diverse communities. Concurrently, the green cluster of independent professionals, characterized by high closeness centrality, actively engages with both influential figures and their own followers, demonstrating a strategic approach to network participation. These findings highlight the importance of considering multiple centrality measures in conjunction with community structure to fully understand the dynamics of social networks.

Graph Density

This section examines the overall density of Dave Gibbons' Bluesky network, providing insights into the level of interconnectedness among its users. Graph density measures the proportion of potential connections that are actual connections within the network. A density of 1 indicates a complete graph (where every node is connected to every other node), while a density of 0 indicates a graph with no connections.

The overall density of the Bluesky network is 0.001, suggesting a relatively sparse network. This is a common characteristic of large social networks, where the number of potential connections far exceeds the number of actual connections. However, analyzing the density of the network's core reveals a different picture.

Filtering the network to exclude nodes with a degree less than 75 reveals a density of 0.025. Further filtering to exclude nodes with a degree less than 100 yields a density of 0.058. These increasing density values with higher degree thresholds demonstrate that the more highly connected accounts form a significantly denser core within the network. This observation suggests that while the network as a whole might be sparsely connected, the most influential and active users are much more likely to be interconnected with each other.

This finding aligns with previous observations about the distribution of degree centrality. The presence of high-degree "hubs," primarily driven by out-degree (accounts followed), creates a densely connected core within the broader, more sparsely connected network. These core users, actively engaging with a substantial number of other influential accounts, form a tightly knit group that likely plays a significant role in shaping information flow and influencing network-wide discussions. The increasing density with higher degree thresholds emphasizes that this interconnectedness is particularly pronounced among the most active and influential members.

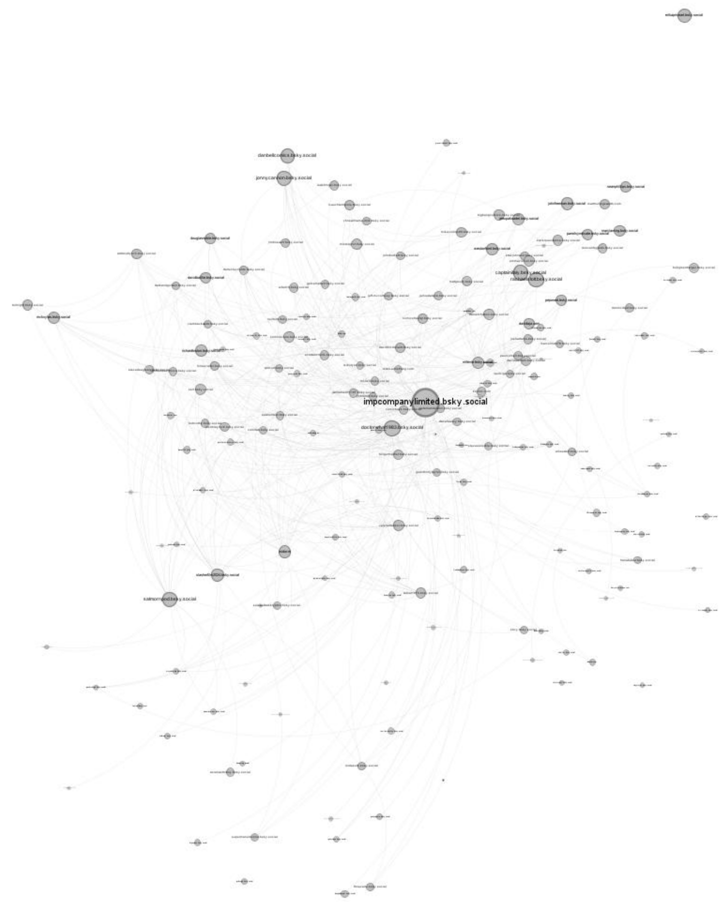

Figure 16: Density for Nodes with Degree Higher than 75

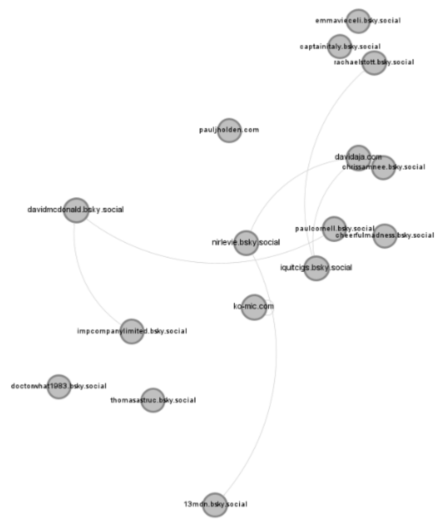

Figure 17: Density for Nodes with Degree Higher than 100

Page Rank

This section explores PageRank within Dave Gibbons' Bluesky network to identify potentially influential users. PageRank, an algorithm famously used by Google to rank web pages, measures the importance of a node within a network based on the quantity and quality of its connections. In directed networks like Bluesky, where connections have direction (following), PageRank provides a valuable measure of influence, taking into account not just how many followers an account has, but also the importance of those followers. It's preferred over eigenvector centrality in directed graphs because eigenvector centrality can be more susceptible to issues with directed cycles. The specific algorithm used in this analysis, as implemented in Gephi, is described by Page, Brin, Motwani, and Winograd (1999) in "The PageRank Citation Ranking: Bringing Order to the Web."

PageRank was calculated for the network, with self-loops (accounts following themselves) removed to avoid skewing the results. The algorithm iteratively distributes "importance" or "influence" throughout the network based on connection structure. The resulting PageRank scores reflect the relative influence of each account. The sum of all PageRank scores is expected to be close to 1 (in this case as calculated in Excell, 0.998932), with any slight deviations due to rounding during the calculation.

The following table presents the top 10 accounts ranked by PageRank:

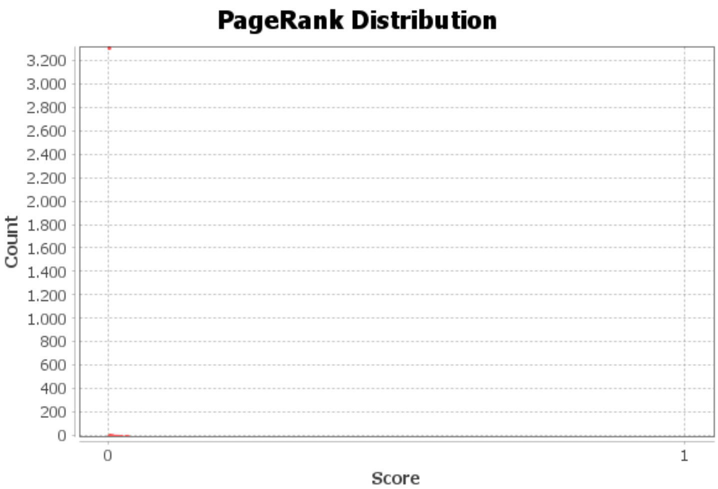

Figure 18: PageRank Distribution

Label	Pagerank
nicksetchfield.bsky.social	0.032303
bobayres.bsky.social	0.029412
darrenreynolds.bsky.social	0.021731
timotron1.bsky.social	0.017442
petersanderson.bsky.social	0.015494
olde1973.bsky.social	0.013744
sarakocher.bsky.social	0.013476
davidmcdonald.bsky.social	0.011234
stevedeegreen.bsky.social	0.01048
neilford.bsky.social	0.009918

The accounts listed above have the highest PageRank scores, indicating their potential influence within the Bluesky network. These users are not just popular (having many followers), but they are also followed by other influential accounts, creating a reinforcing loop of influence. Here are some key observations:

- Top Influencers: nicksetchfield.bsky.social, bobayres.bsky.social, and darrenreynolds.bsky.social emerge as the top three influencers based on PageRank. Their high scores suggest that they are central figures in the network, attracting attention and potentially shaping discussions.
- Diverse Influence: The list includes a range of accounts, suggesting diverse areas of influence within the network. Further investigation into the content shared by these accounts is needed to understand the specific nature of their influence.
- olde1973.bsky.social's: Despite having a relatively low follower count, olde1973.bsky.social appears in this list, suggesting that their influence might be more nuanced than simple follower counts indicate. Their connections to other influential users likely contribute to their PageRank score.
- davidmcdonald.bsky.social's Consistent Importance: As observed in previous analyses, davidmcdonald.bsky.social consistently appears as a significant node, reinforcing their role as a key player within the network.

Implications:

PageRank provides a valuable measure of influence within directed networks. The accounts identified above likely play a significant role in:

- **Information Dissemination:** They are well-positioned to spread information and ideas within the network.
- **Opinion Leadership:** Their influence may extend to shaping opinions and trends.
- **Engagement:** They likely play a key role in fostering discussions and interaction within their respective communities.

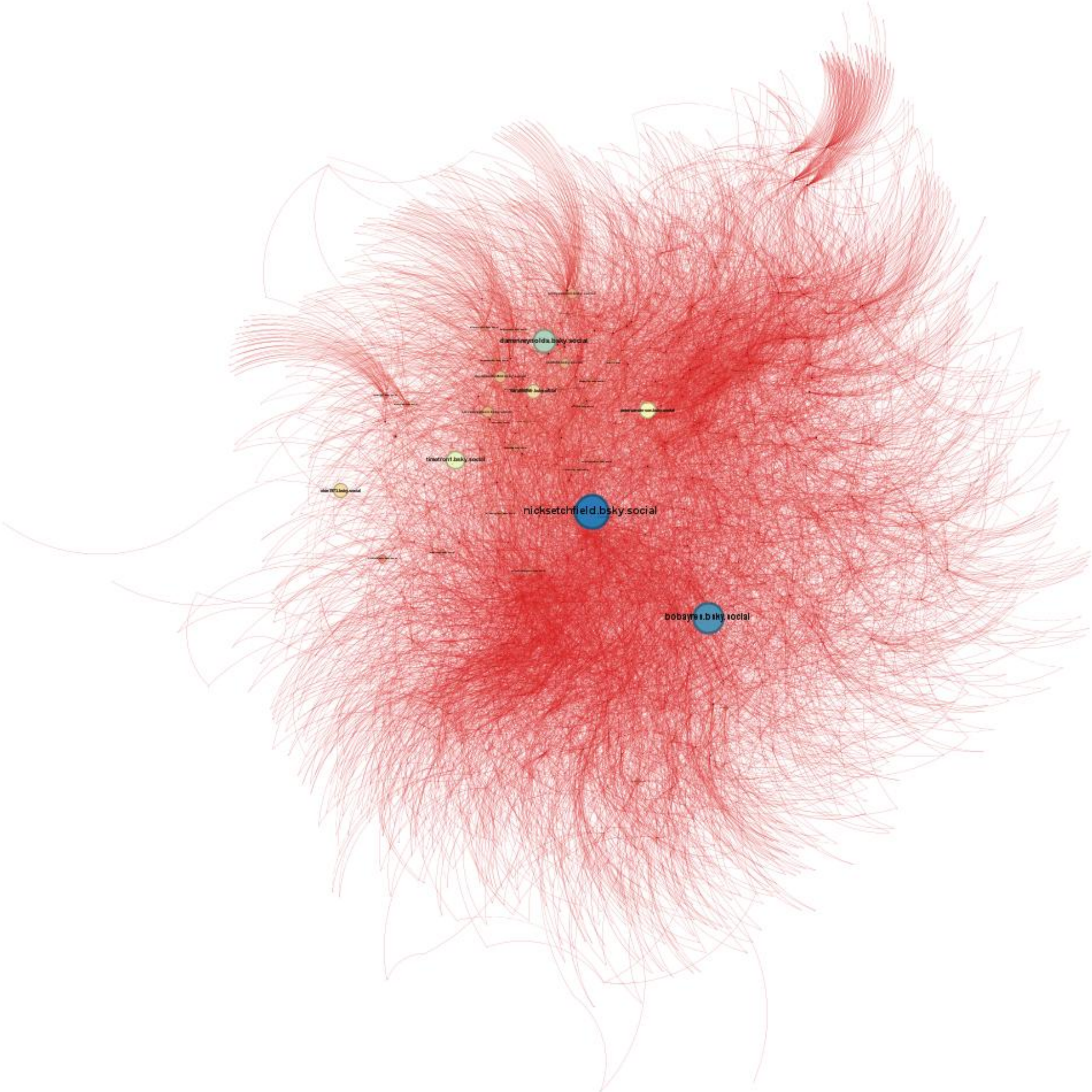

Figure 19: PageRank Visualisation

Community Specialists:

This section delves into the identification of "community specialists" within Dave Gibbons' Bluesky network. While previous analyses have examined influence and connectivity at the network level, this section focuses on identifying key players *within* each of the modules identified through modularity analysis. Community specialists are individuals who are highly influential *within* their specific community but may not necessarily have a high global influence across the entire network. They are crucial for maintaining community cohesion, shaping local discussions, and fostering a sense of shared identity.

To identify community specialists, we employed a two-step process:

1. Module Isolation: Each module identified through modularity analysis was isolated as a sub-network.

2. Betweenness Centrality Calculation: Betweenness centrality was calculated *within* each isolated module. This allowed us to identify nodes that are central to the communication and information flow *within* their respective communities. We chose betweenness centrality for this purpose as it highlights nodes that bridge different parts of the *local* network, emphasizing their role in connecting members within the community.

The analysis revealed several community specialists across the different modules.

- Within the "Small/Independent Artists and Professionals" module (Green Cluster), artdroidlynch.bsky.social stands out with high betweenness centrality. As an 2000AD Comic Artist, 2000AD being an company David Gibbons used to work, this account is very likely to be as important as the centrality suggests. The second name by size is Richard Bruton, who is another 2000AD artist, fact that amplifies our results. He is followed by Tom Williams and Jeff Carlise, both of whom are great artists, the latter of them being a strng voice of politics, standing against right-wing behaviours. These profiles play a crucial role in connecting different segments of this community, potentially linking artists with writers, journalists, or other professionals.
- In the "Big Names and Platforms" module (Blue Cluster), comicbuzz.bsky.social exhibits high betweenness centrality, reflecting its role as a central platform for information and discussion within this community.
- The "UK/EU Artists" module (Yellow Cluster) shows Rachael Stott and Emma Vieceli as community specialists, both female artists from the UK. Their high betweenness within this module highlights their importance in connecting artists within this specific geographic and professional community.
- The " Help with Illustrating and Storytelling/Amateurs and Comic Lovers" module (Red Cluster) highlights again IblackAI, a tool that mostly likely amateur artists use to design comics with the use of AI image generation and Valerie Frankel, a known ghostwriter as community specialists. Their high betweenness within this module reflects the need of younger and ambitious artists for help to create their own art, and be part of the comic community as creators.

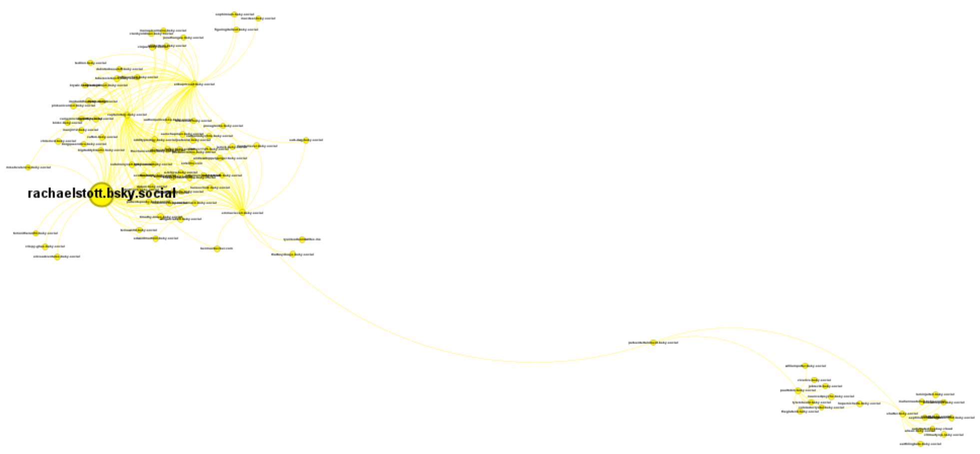

Figure 20: Yellow Cluster Specialists

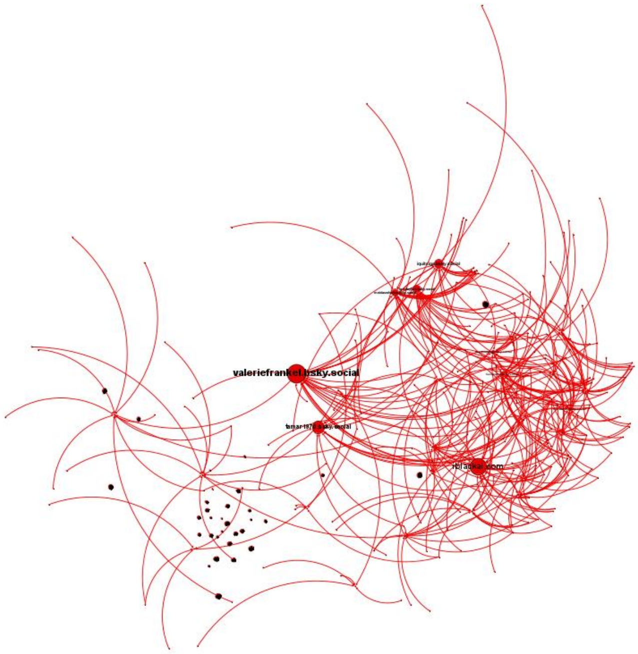

Figure 21: Red Cluster Specialists

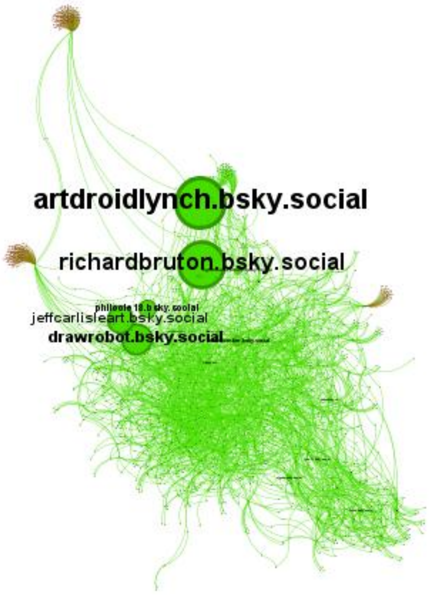

Figure 22: Green Cluster Specialists

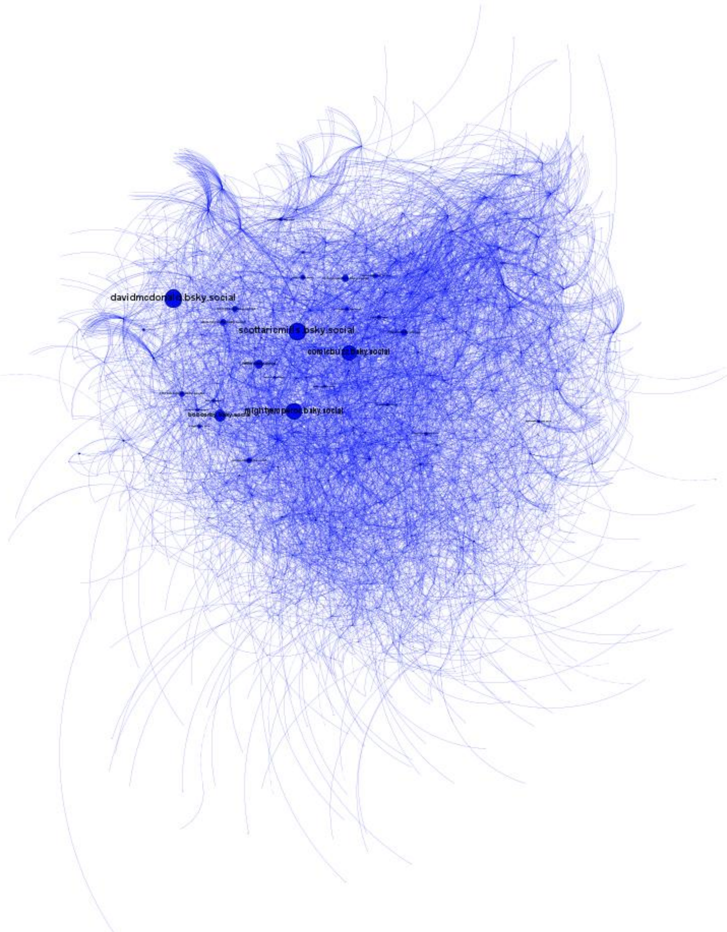

Figure 21: Blue Cluster Specialists

Interpretation:

The identification of community specialists provides a more granular understanding of influence within the network. These individuals may not be globally influential, but they are vital for the functioning and cohesion of their respective communities. They likely play a key role in:

- Local Information Flow: They facilitate the exchange of information and resources within the community.
- Community Building: They contribute to creating a sense of shared identity and belonging.
- Knowledge Sharing: They may act as points of contact for specific expertise or information within the community.

Connecting to Previous Findings:

This analysis complements the earlier findings on modularity and centrality. While modularity revealed the overall community structure, this analysis highlights the key players *within* those communities. The community specialists identified here may or may not have high global centrality scores. Their importance lies in their *local* influence and their role in connecting members of their specific communities, so they are important and should be considered for strategic choices like “marketing campaigns” of the next title from Gibbons!

Implications:

Understanding the role of community specialists is crucial for comprehending the full complexity of influence within the network. These individuals, while potentially less visible at the global level, are vital for the health and activity of their respective communities. Their presence suggests a more distributed model of influence, where different individuals hold sway within different spheres of the network.

Further Analysis:

Further research could explore the specific types of information or resources shared by community specialists and how their influence shapes discussions and activities within their respective modules. Combining this analysis with qualitative studies, such as interviews or focus groups, could provide deeper insights into the roles and motivations of these key community members.

Conclusion: Weaving the Threads of Connection, Amidst Echoes

Dave Gibbons' Bluesky network, a vibrant tapestry of creators, professionals, enthusiasts, and influencers, offers a fascinating glimpse into the intricate dynamics of online communities. Our exploration of this network, guided by the principles of social network analysis, has revealed a rich and nuanced structure, challenging simplistic notions of influence and highlighting the importance of diverse perspectives. Yet, it also compels us to consider the potential for echo chambers and the reinforcement of existing biases within such online spaces.

We began by mapping the network's contours, identifying distinct communities clustered around shared interests, professional affiliations, and geographic proximity. The Louvain method illuminated these modules, revealing a network organized around hubs of independent artists, dedicated enthusiasts, UK-based creators, and established industry giants. This modularity underscores the human tendency to connect with like-minded individuals, forming communities of shared identity and purpose. However, in the specific context of Bluesky as an alternative to X (formerly Twitter), particularly one associated with a predominantly left-leaning user base, this tendency towards community formation may also contribute to the creation of echo chambers, where dissenting voices are marginalized, and ideological homogeneity is reinforced.

Delving deeper, we explored the intricate pathways of influence and connection. Centrality measures revealed key players who shape information flow and potentially guide network-wide discourse. Betweenness and closeness centrality highlighted individuals who bridge different communities, acting as vital conduits for cross-pollination of ideas. PageRank, considering the "quality" of connections, identified influential voices who resonate within the network, while bridging centrality emphasized those who connect otherwise disparate groups. These individuals, strategically positioned within the network's architecture, wield influence that extends beyond mere popularity, shaping the landscape of conversations and trends. However, within a platform leaning ideologically in one direction, this influence may serve to amplify existing viewpoints rather than fostering open debate.

Yet, influence is not solely concentrated at the global level. Our analysis of degree distribution revealed a more nuanced picture, with high out-degree accounts actively engaging with a broad range of users, and in-degree revealing a more distributed form of popularity. Furthermore, the identification of "community specialists" underscored the importance of local influence. These individuals, deeply embedded within their respective modules, play a vital role in fostering community cohesion and driving local discussions. They may not be global celebrities, but their influence within their niche is undeniable.

The network's density, while relatively sparse overall, revealed a denser core among influential users, highlighting the tendency for the most active and engaged members to connect with each other. This interconnectedness within the core suggests a potential for rapid information exchange and collaboration among key players. However, within a platform already inclined toward a particular ideology, this dense core may further solidify existing viewpoints and limit exposure to alternative perspectives.

Finally, our exploration of bridging centrality highlighted the crucial role of individuals who connect otherwise disparate communities. These "bridges" facilitate the flow of information and ideas across community boundaries, fostering a more integrated and interconnected network. The case of olde1973.bsky.social, with high bridging centrality despite a modest following, reminded us that influence can take many forms and that connections between communities are not always reflected in simple follower counts. Yet, even these bridging connections may primarily serve to reinforce shared ideological assumptions if the network itself is relatively homogenous.

In conclusion, Dave Gibbons' Bluesky network is a complex ecosystem of interconnected individuals, each playing a unique role in shaping the network's dynamics. From the global influencers to the local community specialists, from the active engagers to the bridging nodes, each user contributes to the rich tapestry of connections that make up this online community. However, it is crucial to acknowledge the potential for echo chambers and the reinforcement of existing biases within platforms like Bluesky, particularly given its association with a specific ideological leaning. While this network, like the world it reflects, is a testament to the power of human connection, the formation of communities, and the diverse ways in which influence can be wielded and shared, it also serves as a reminder of the importance of seeking diverse perspectives and challenging our own assumptions, even within spaces that seem to connect us with like-minded individuals. Understanding these dynamics allows us to appreciate the complex interplay of influence, community, and connection in the digital age, while also remaining critically aware of the potential pitfalls of online echo chambers and ideological homogeneity.

Appendix

Several additional analyses were conducted to explore other potential aspects of the network structure, including gender homophily and local clustering patterns (triangles, cluster coefficient). These analyses, along with a more detailed discussion of their methodologies and results, are included here in the Appendix, because while these analyses provide some interesting insights, they did not form the primary focus of this study due data limitations for gender homophily, potential biases in local clustering measures and insufficient confidence results. We chose to include them in the paper, for completeness.

Appendix A: Gender Homophily Analysis

Homophily, the tendency of individuals to associate with those similar to themselves, is a common phenomenon in social networks. This section explores potential homophily based on gender within Dave Gibbons' Bluesky network. Given the substantial proportion of user bios where gender could not be determined, the analysis focuses on *self-described* gender indicators. However, it's important to acknowledge the limitations of this approach. Identifying gender within user bios based solely on keywords is inherently challenging and prone to inaccuracies. While the comics community generally values diversity and respect for gender equality, fact that is multiplied by the Bluesky platform, with its association with a predominantly left-leaning user base, many users may not explicitly state their gender in their bios or use language that is ambiguous or ironic (e.g., "I love to annoy my wife"). Furthermore, the chosen keyword lists are not exhaustive and may not capture the full spectrum of gender expressions and identities. While these keyword lists were used to categorize accounts as "female," "male," or "non-binary," it's crucial to recognize the potential for bias and misclassification.

The use of an AI model trained on a larger dataset of user bios could potentially improve the accuracy of gender categorization, but this was beyond the scope of the present study due to resource constraints.

Despite these limitations, a keyword-based approach was employed to identify self-described gender within user bios. Accounts were assigned to "female," "male," or "non-binary" categories based on the presence of the following keywords:

- Female keywords: "she", "her", "mother", "mom", "daughter", "girl", "woman", "female", "wife", "sister"
- Male keywords: "he", "him", "dad", "son", "father", "boy", "man", "male", "husband", "brother"
- Non-binary keywords: "they", "them", "lgbtq", "non-binary", "genderqueer", "transgender", "agender", "bigender", "genderfluid", "demigender", "two-spirit", "androgynous", "gender non-conforming"

Crucially, a large portion of user bios (approximately 50% across all modularity classes) did not contain enough information to reliably infer gender. These "unknown" cases were excluded from the present analysis, and the percentages presented below reflect the distribution *among the accounts where gender could be identified*.

It is essential to understand the implications of this exclusion:

- Significant Data Loss: Excluding 50% of the data introduces a substantial bias. The results may not be representative of the entire network.

- Potential for Skew: It's possible that the 50% of accounts with identifiable gender differ systematically from the 50% where gender is unknown. This could skew the results in unpredictable ways.

Therefore, the results presented below should be interpreted with extreme caution. They reflect *explicitly stated* gender affiliations within *only half* of the user bios and should not be generalized to the entire network.

Findings:

The following table presents the distribution of self-described gender across the modularity classes (excluding "unknown" cases):

Modularity Class	Female (%)	Male (%)	Non-Binary (%)
0	44.46	55.17	0.37
1	45.42	54.04	0.54
2	38.41	61.42	0.18
3	42.43	57.20	0.37

Among the accounts where gender could be identified, there is a slight tendency towards male representation across all modularity classes. However, the proportions are not drastically skewed, suggesting that gender homophily, if present, is not the primary driver of community formation in this *subset* of the network. While a slight male predominance is observed in the *identifiable* accounts across communities, this observation cannot be extrapolated to the entire network. Future research, addressing the challenge of incomplete profile data, is necessary to understand the true role of gender in shaping the network's structure. This analysis serves primarily as a demonstration of the limitations of relying solely on self-reported information and highlights the critical need for more complete data to study social phenomena like homophily accurately.

Appendix B: Local Clustering Analysis

Triadic Closure

This section briefly addresses local clustering patterns within Dave Gibbons' Bluesky network, specifically examining triangles and the cluster coefficient. While local clustering is undoubtedly an important aspect of social networks, the potential for degree-based biases in triangle counts and the cluster coefficient necessitates a cautious approach. Despite not forming the basis of our primary analysis, we have included this brief discussion of triangles and the cluster coefficient to provide a more thorough picture of the network's characteristics.

Triangles, formed by three mutually connected nodes, are often used to assess the prevalence of triadic closure—the tendency for "friends of friends" to become connected. Below we see the result table:

impcompanylimited.bsky.social	99

artdroidlynch.bsky.social	42
fhnavarro.bsky.social	30
koldoazpitarte.bsky.social	29
termight.bsky.social	26
richardbruton.bsky.social	26
nirlevie.bsky.social	24
scottaricmills.bsky.social	22
nickxylas.bsky.social	22

While the analysis of triangles reveals that certain accounts participate in a significant number of triadic relationships (e.g., impcompanylimited.bsky.social with 99 triangles), triangle counts can be heavily influenced by the degree of a node. High-degree nodes are more likely to participate in triangles simply by virtue of having more connections. This can lead to misinterpretations, where a node appears to be highly clustered simply because it has many connections, rather than because it's embedded in a particularly dense community.

Cluster Coefficient:

The cluster coefficient, which measures the proportion of a node's neighbors that are also connected to each other, provides another perspective on local density. While we have calculated the cluster coefficient for all nodes and identified 45 nodes as "stars" (cluster coefficient of 1), indicating that all their neighbours are mutually connected, we have chosen not to focus on this metric for similar reasons as with triangle counts. As discussed previously, the cluster coefficient can be misleading for low-degree nodes, as even a single connection will result in a coefficient of 1. Furthermore, even for higher-degree nodes, the cluster coefficient primarily reflects local clustering, which may not be representative of the node's overall position and influence within the broader network.

Bridging Centrality

This chapter explores bridging centrality within Dave Gibbons' Bluesky network. Bridging centrality measures the extent to which a node connects different communities or modules within a network. Unlike betweenness centrality, which focuses on shortest paths, bridging centrality specifically emphasizes connections *between* communities, regardless of path length. Nodes with high bridging centrality act as crucial links, facilitating communication and information flow across community boundaries.

Figure 24 visualizes the network, with node sizes scaled according to their bridging centrality scores. Three accounts stand out due to their larger node size, indicating higher bridging centrality:

- olde1973.bsky.social: This account, seen again with high PageRank, exhibits a high bridging centrality, suggesting its role in connecting distinct communities within the network. The account's bio describes the user as a "successful comedian, writer, and artist," with a focus on "dog and Cancer." This diverse set of interests likely contributes to their bridging role, connecting individuals interested in comedy, writing, art, and potentially even those interested in astrology or pet-related topics. However, a notable discrepancy exists between their visual prominence (due to high bridging centrality) and their relatively low follower count (21) and following count (66). This highlights an important point: bridging centrality is distinct from popularity. olde1973.bsky.social's value lies in their connections *between* communities, not necessarily their overall popularity. Interestingly, despite their lower follower count, olde1973.bsky.social also emerged with a high PageRank score, indicating that their connections are considered to be of high quality or importance within the network. This further emphasizes their potential role as a bridge between otherwise disparate communities.

- mightyemperor.bsky.social: As noted in previous sections, this account has consistently emerged as significant in various centrality measures. Its high bridging centrality reinforces its importance as a connector within the network, spanning across community boundaries.
- comicbuzz.bsky.social: Also previously identified as significant, this account's high bridging centrality aligns with its role as an online platform covering pop culture. It likely serves as a bridge between different interest-based communities within the network.

Connecting with Previous Findings:

The prominence of mightyemperor.bsky.social and comicbuzz.bsky.social in both betweenness and bridging centrality highlights their crucial role in connecting different parts of the network. While betweenness emphasizes their importance in shortest path communication, bridging centrality underscores their connections *between* communities, regardless of the specific paths involved. This suggests that these accounts not only facilitate information flow but also play a role in integrating diverse perspectives and fostering broader network cohesion.

The emergence of olde1973.bsky.social as a key bridging node, despite not being as prominent in betweenness centrality, adds a new dimension to our understanding of the network's structure. Its high bridging centrality, coupled with its high PageRank score, suggests that it may connect communities that are not well-integrated through shortest paths. This account, with its eclectic mix of interests as indicated in its bio, could be facilitating communication or information exchange between otherwise disparate groups, highlighting its importance in bridging structural gaps within the network.

The identification of these bridging nodes provides valuable insights into the network's dynamics:

- Cross-Community Communication: Bridging nodes facilitate the flow of information, ideas, and influence across community boundaries, promoting broader network awareness and potentially fostering collaboration.
- Integration of Diverse Perspectives: By connecting different communities, these nodes contribute to a more integrated network, exposing users to a wider range of viewpoints and potentially reducing echo chamber effects.
- Potential Gatekeepers: While bridging nodes can foster positive exchange, they also have the potential to act as gatekeepers, controlling or filtering the flow of information between communities.

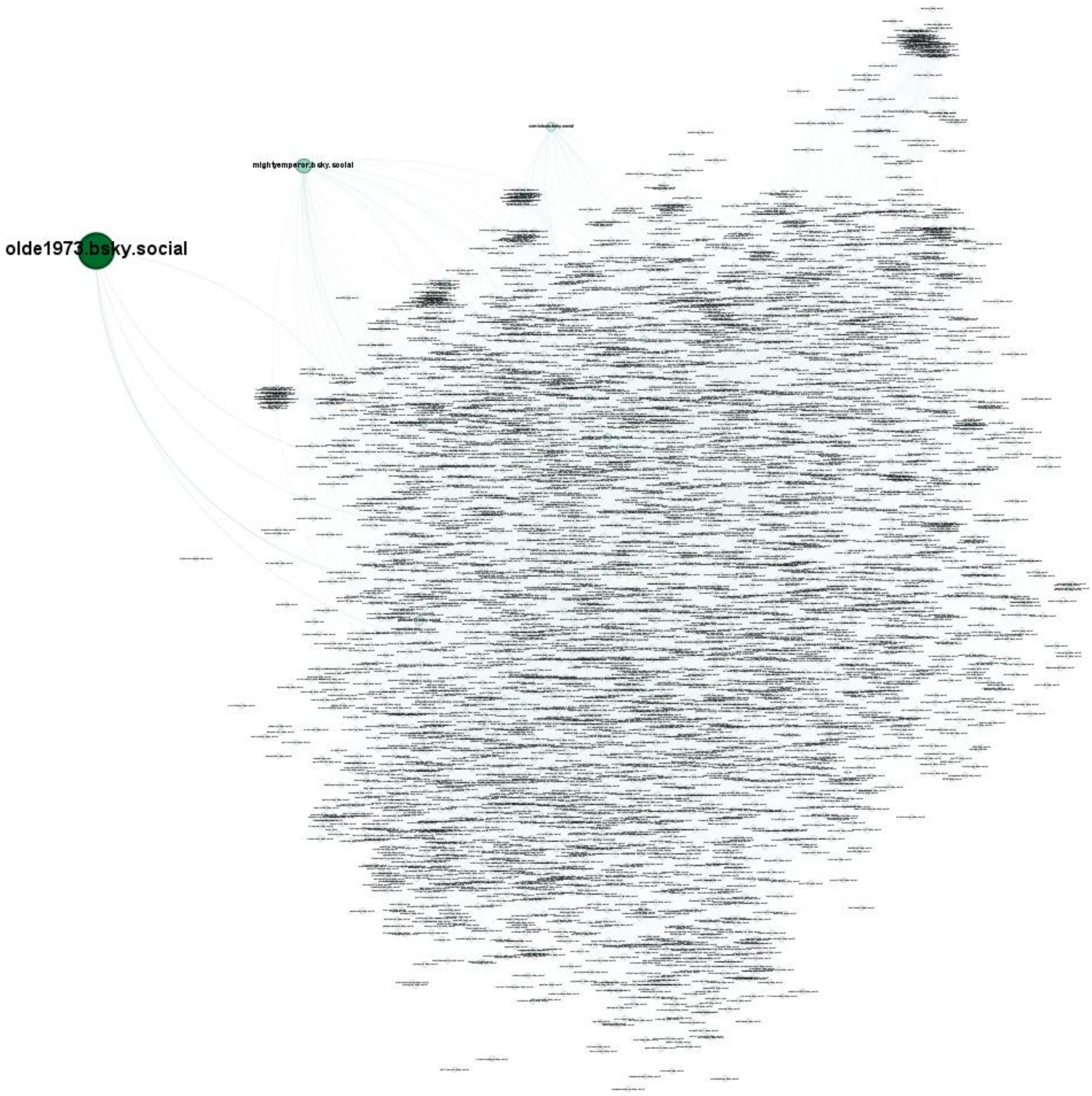

Figure 24: Bridging Centrality Visualisation

Further research is needed to explore the specific nature of the connections made by these bridging nodes and the communities they link. Analyzing the content shared and the interactions facilitated by these accounts can provide a deeper understanding of their roles in shaping network-wide communication and influence. Investigating the communities connected by olde1973.bsky.social, in particular, could reveal previously unseen connections and pathways within the network. The diverse interests indicated in their bio suggest a potentially broad reach across different segments of the network. Further analysis, such as a qualitative analysis of their interactions and a community-specific analysis, is needed to fully understand the nature of their bridging role and the communities they connect. This discrepancy underscores the importance of considering multiple metrics and exploring the nuances of network connections beyond simple follower/following counts.

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Figures