SOCIAL LIVE-STREAMING: TWITCH.TV AND USES AND GRATIFICATION THEORY SOCIAL NETWORK ANALYSIS

James Dux

Department of Interaction Science, Sungkyunkwan University,
Seoul, South Korea

ABSTRACT

The recent explosive growth of live-streaming, particularly video game streaming on Twitch.tv, has led to the development of young communities in a diverse and frequently evolving virtual social space. This study is a Social Network Analysis that aims to uncover how communities are interlocked based on attributes such as Community membership and stream style/type. Additionally, the network geography is related to the Uses and Gratification Theory (UG) that Twitch has been proven to fulfill according to genre and stream type (Sjoblom, Torhonen, Hamari, & Macey, 2017). By collecting data in a user-based fashion and using tools like Gephi, this project presents the Twitch community in a way that reveals users' interest seeking behavior trends. Implications from this study are a resource for: understanding Twitch and live-streaming communities at large, streamers looking for an insight into their audience's interests, and developers seeking the best way to provide and display beneficial content.

KEYWORDS

Social Network Analysis, Uses and Gratification, Twitch.tv, Social Live Streaming, Social Communities

1. INTRODUCTION

Today's internet speeds allow for a new type of media to flourish: live streaming video. Twitch.tv (colloquially known as just 'Twitch') is a prime example of this medium that creates a virtual 'Third Place' where users watch live-streamed videos while interacting with each other simultaneously (Brundl, Matt, & Hess, 2017). 'Streamers' are the performers who broadcast the video while engaging with their live audience 'followers' to varying degrees. Twitch focuses on the streaming of video games such as 'PLAYERUNKNOWN'S BATTLEGROUNDS' (PUBG) and 'League of Legends' (LoL). Why is live-streaming an important subject? Twitch.tv was only founded in 2011, but was bought by Amazon in 2014 for nearly 1 billion US dollars. Twitch.tv boasts 100+ million unique monthly visitors, and about 10 million daily active users (Smith, 2017). Clearly this new type of virtual 'living room experience' has struck a chord with audiences, and deserves further and deeper research.

After thorough literature review of related topics and papers, it is clear that Twitch presents a unique opportunity to learn more about this new digital form of interaction. Previous research has

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proven that live-stream users enjoy and benefit from the social interaction provided by Twitch and similar sites. In particular, the "Co-Experience" provided by this medium has been shown to have a strong influence on the Active and Passive Enjoyment of live-streaming, marking the social aspect as a significant use motivation (Brundl et al, 2017).

Twitch is a social live-streaming site heavily driven by its community (and sub-communities) of streamers and the users who watch, follow, and subscribe to them. The availability of this connection information and the nature of this kind of organization lends itself very well to social network analysis. Social network analysis is "a visual and a mathematical analysis of human relationships", which gives researchers the opportunity to dissect how users in a network are connected by peers (Krebs, n.d.). Not only do social networks reveal connections, but can also be used to discover groupings based on node (individuals') attributes like common interests, communities, and other values. Analysis of these social networks provides benefits to the overall organization and members themselves. For Twitch streamers this might mean insight in where to "strengthen relationships within and across groups"; for Twitch.tv it could mean the ability to provide better 'related content' or to identify key nodes worthy of increased sponsorship (Serrat, 2009). It's clear that social network analysis of Twitch is a worthwhile endeavor that can provide real value for the community and site.

2. LITERATURE REVIEW

2.1. Twitch

Live streaming platforms such as Twitch allow streamers to project live video from their home to viewers over the internet. This video can be sourced directly from their PC for the intent of displaying video game game-play, program use, or any other entertaining/instructional visuals. Twitch in particular is primarily a video game streaming site. Streaming video directly from a webcam is also available. It's very common for streamers to overlay their webcam video inside of their game-play video, so audiences can see their face as the play and talk (see Figure 1). In fact, this method has become expected; viewers enjoy having the opportunity to share in the emotions of the streamer through their facial expressions (Hamilton, Garretson, & Kerne, 2014).

The stream is only half of the Twitch/live streaming equation; the user chat is the other half. The user chat is a simple chat room in which viewers of the stream can communicate with each other (and the streamer) with text and emoticons. The chat is a deeply significant part of the Twitch experience, providing users a way to chat with each other about what's happening on the stream as events unfold. In a 2015 survey of Taiwanese live stream users, 58% of users said they used the chat, and chat room design influenced the intent to use the live stream service (Ho & Yang, 2015). The chat is an integral part of the Twitch experience, morphing what could be a passive video watching experience into a modern participatory, social occasion.

Twitch exists only because of its community. Streamers form the base; they are the ones who produce the content (live streams), displayed on their 'channel'. Viewers support them by tuning in and watching their streams. Revenue for the site comes from ad space and 'subscriptions'. Subscribing to a streamer allows a user to voluntarily pay (certain amount on a monthly basis) a streamer they enjoy. In return, the subscribing user can benefit from things like 'subscriber only mode', when only subscribers are allowed to use the chat, and having unique emoticons available to them (Hamilton et al., 2014). The streamer backbone of Twitch becomes apparent in a 2016 survey which showed that 45.8% of respondents chose ‘Specific twitchers’ as a reason to watch Twitch, followed by ‘Entertainment based on owned game’ at 29.1% (Gandolfi, 2016).

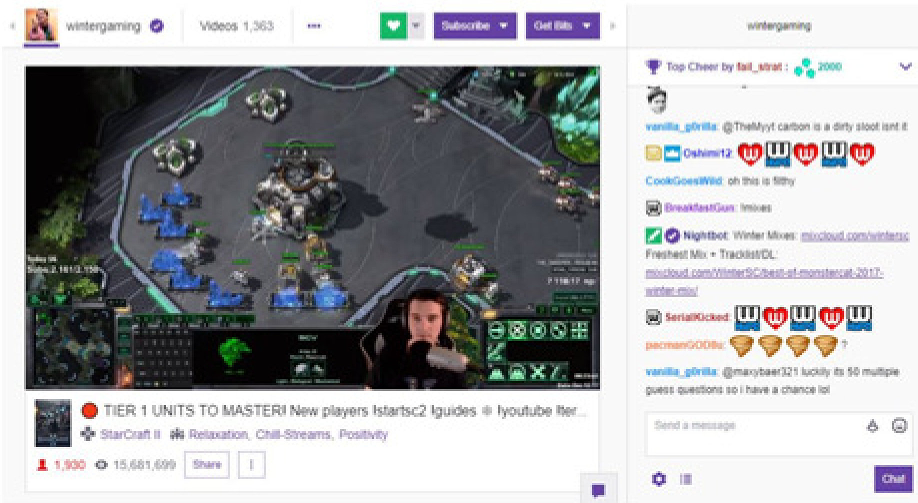

Figure 1. Twitch streamer ‘wintergaming’ plays Starcraft 2 with a webcam overlay of his face. Users participate in the chat on the right of the screen.

2.2. UGT and Twitch

Knowing what functions Twitch offers is the foundation to understanding why people use it. The interest of games appears to be the initial draw, as respondents to a 2014 survey most frequently cited their desire “to learn something about a particular game” as the reason they started watching streams (Hamilton et al., 2014). Thanks to this shared interest, Twitch forms what it known as a ‘Third Place’ for its users, an informal digital meeting place where people happily congregate to enjoy a common interest and socialize with each other (Hamilton et al., 2014). Holbert, Kwak, & Shah (2001) also state “chatrooms and multiplayer games increasingly provide the illusion of face-to-face social interaction and belonging”, further reinforcing Twitch as ‘Third Place’.

To delve deeper into the reasons for using Twitch, researchers have commonly turned toward the ‘Uses and Gratification” (UG) theory. UG is a prominent theory when dealing with personal motivations behind using media ranging from passive television watching to participatory social media use, making UG an appropriate measurement tool for Twitch as well (Sjoblom, Torhonen, Hamari, & Macey, 2017). In UG theory, users are considered to be a conscious ‘fulfillment seeker’. That is, users knowingly and self-reflectively seek out media that will satisfy their personal motivations according to certain guidelines as demonstrated in Table 1 (Sjoblom & Hamari, 2016).

Sjoblom and Hamari (2016) compared the UG need types with Twitch users’ Hours Watched, Streamers Watched, Streamers Followed, and Subscription; their results showed a positive correlation for all need types excepting Personal Integration with ‘Hours Watched’ and ‘Streamers Watched’. Personal Integrative was only positively correlated to ‘Streamers Followed’, and the only need that was negatively correlated to ‘Hours Watched’ and ‘Streamers Watched’, demonstrating a unique characteristic (Sjoblom & Hamari, 2016).

Table 1. The five aspects of UG that were tested by Sjoblom & Hamari, 2016

Table 1
UG need types (West & Turner, 2010, p. 398).

Need type	Description	Media examples
Cognitive	Acquiring information, knowledge, comprehension	Television (news), video ("How to Install Ceramic Tile"), movies (documentaries or films based on history e.g., The Other Boleyn Girl)
Affective	Emotional, pleasant, or aesthetic experience	Movies, television (sitcoms, soap operas)
Personal integrative	Enhancing credibility, confidence, and status	Video ("Speaking With Conviction")
Social integrative	Enhancing connections with family, friends, and so forth	Internet (e-mail, chat rooms, Listservs, IM)
Tension release	Escape and diversion	Television, movies, video, radio, Internet

Overall, Twitch displays the ability to satisfy UG motivations with "social interaction, learning and entertainment" as "important aspects of spectatorship" (Sjoblom & Hamari, 2016). Twitch UG satisfaction was further investigated by Sjoblom et al. (2017) where the unique characteristics of game genre and stream type were related to UG needs, revealing that the unique characteristics of game genres and stream types watched were correlated with different motivations. Even more significant was the fact that stream type had more impact on affecting user gratifications than did game genre (Sjoblom et al., 2017). This reinforces the notion of Twitch being a 'Third Place', allowing users to informally seek use gratification by dividing themselves into groups/streams based on interest in not just game genre, but also in the stream type or 'atmosphere' that has been developed by the streamer (Hamilton et al., 2014).

It is clear that all UG needs contribute in some way to the way users watch streams, and that these UG needs also affect users' choice of stream (Sjoblom & Hamari, 2016; Sjoblom et al., 2017). Beyond how stream type and content (such as genre) affect the UG needs for Twitch, there is the effect of stream size and possibly other factors playing into users' stream choices.

In addition to the above-mentioned stream attributes, the size of the stream also plays a role in the interactivity and social usability of Twitch. Hamilton et al. (2014) make specific note of the effect of stream size: "as streams scale up, information overload renders chat unreadable…… participants become frustrated with the difficulty of interacting in these streams", possibly leading to users seeking smaller, less populated streams. This is directly backed by Sjoblom et al.'s (2017) finding that Social Integrative and Personal Integrative UG needs are a part of Twitch users' motivation. The interaction between streamers and their audience is affected by the size of the stream.Streamers generally reported that they could interact effectively with 100-150 viewers by reading comments on stream, taking game play suggestions, and so on; beyond that number interaction was often unmanageable and the social aspects, even between users, was diminished (Hamilton et al. 2014).

A curious finding about the relation between stream type and game genre emerges when looking at the size of communities as a whole. Churchill and Xu (2016) found in a social network analysis of streamers that the Casual Streaming culture is the largest, followed by the Speed-Running culture, and finally the Competitive culture. The claim is that this ranking comes from the technical difficulty of games, Casual being the easiest to understand and Competitive being the most difficult and technically intensive (Churchill & Xu, 2016). However, Sjoblom et al. (2017) show in their UG study that when factoring game genre and stream/culture type together, Competitive stream types offer more, and more significant UG need satisfaction than Speed-running stream types, indicating that perhaps the Competitive community should be larger

(Sjoblom et al., 2017). These two types provide similar levels of motivation when only considering stream type. Taking this anomaly into account, extra consideration should be given to what streams users choose and the multitude of factors at play.

During their social network analysis of Twitch, Churchill and Xu (2016) visualized communities by specific games and community/culture types (Competitive, Casual, and Speedrun). Strong connections between game franchises were found, along with fairly well integrated cultures. During this study, however, only large, popular streamers who followed other streamers were considered. The inclusion of smaller streams of varying types might have an impact in subsequent studies. This is because, as mentioned by Hamilton et al. (2014), the size of streams/streamers impact the quality of socialization and therefore possibly users' habits.

Twitch itself provides a platform for every game (e.g. League of Legends, Warframe), every genre (e.g. Action, Real-time Strategy), and every stream/culture type (e.g. Speed Running, Casual). Users then filter this multitude of streams based on their personal interest, style, and motivations such as entertainment based on owned games, evaluation of non-owned games, or the ability to comment on the game (Gandolfi, 2016).

3. METHOD

This study aims to construct an exploratory social network analysis of Twitch, expanding on previous efforts with a focus on how communities are possibly affected by UG afforded by different types/cultures of streams, as well as game genre and stream size. Recently introduced by Twitch is browsing by 'Communities' that includes sections like 'VarietyStreaming', 'Positivity', and 'eSports', allowing another level of social network comparison. There is also the availability of coding streams based on their culture/type. This represents a move away from the traditional classification of streams by game or genre, and presents the opportunity for a fresh look at community structure.

3.1. Research Questions

RQ1) How does Twitch's social network look considering stream size, but before partitioning based on stream attributes?

RQ2) How does Twitch's social network look when based on streams' Community Membership Type?

RQ3) How does Twitch's social network look when based on stream Type (eg Competitive, Casual, Speedrunning,Social, or Learn)?

RQ4) How does Twitch's social network look when based on game genre?

RQ5) How does Twitch's social network look when based on a modularity algorithm?

RQ6) What can detailed views of single nodes reveal about the network?

RQ7)Which streams are key in terms of degree centrality, and how does this compare to their follower size and other traits?

3.2. Collection/Sampling

A total of 175 streams were selected. First, 75 streams were selected from Twitch's Communities. A specific community was selected and automatically sorted by live-viewers. A stream must have had more than one live-viewer and more than 100 followers to have been selected. Streams were selected systematically by amount of live viewers; approximately 10% of the Community's streams were selected each time. Additionally, 100 streams were selected from 'TwitchSwitch', a website that generates a link to a random Twitch stream, with at least one live-viewer.

Streams were required to have at least 100 followers to be more likely to guarantee links between nodes. Streams of all sizes were desired for diversity. Smaller streams are valued for their representation of increased streamer-follower interaction, and larger streams for generating edges as popular media (Hamilton et al. 2014).

3.3. Nodes

Each node represents a stream. Each node has certain attributes to help group them. Existing attributes are:

-Number of Followers (stream size)

-Game Played

Other attributes had to be assigned by the researcher. These are:

-Type of Stream (casual – streamers play a game, competitive – streamers play competitively against other players [in leagues or for ranks], speed running – players race to complete a game as fast as possible, social – streamers are doing some other activity, learn – streamers note on their stream that they try to teach a game)

-Genre (the genre of the game being played, ie First Person Shooter (FPS), Multiplayer Online Battle Area (MOBA), Massively Multiplayer Online (MMO), In-Real-Life (irl), Sports, Horror, Strategy, Card, Sandbox, Adventure, Fighting, Role Playing Game (RPG), etc)

-Community Membership Type (General – belongs only to social communities, Competitive – belongs only to competitive/game communities, Mixed – belongs to at least one social and at least one competitive/game community, None – belongs to no communities. Streamers choose which communities they want to join. Streams can belong to up to three communities at a time. Due to the infinite amount of communities available, streamers were coded into one of the four classifications.)

3.4. Edges

Edges are determined by actual users. That is, followers that streams share in common. The weight of the edge is determined by the amount of followers in common.

3.5. Programs/Resources

Twitch.tv, TwitchTools.com, TwitchSwitch.tv, Gephi, Python, Microsoft Excel

3.6. Process

Once node information from Twitch was recorded into an Excel sheet, the stream's ID was given to TwitchTools.com to retrieve a list of its followers in CSV format. A Python script was used to compare stream follower files. The followers were sorted by 'Notification' and then 'Follow Date, only the first 5000 followers were compared. 'Notification' means the user receives a notification when that stream comes online, 'Follow Date' is the date when the user started to follow the streamer. These were chosen to best represent habitual stream watchers. The amount of followers in common between streamers was used to determine the weight of edges between streams. This node and edge information was fed into and analyzed with Gephi.

When analyzing, edges with a weight of less than two were filtered out. This is to slightly increase the meaningfulness of the graph, as there were quite a few edges with a weight of only one. This caused eight of the nodes to be excluded from the final graph, leaving 167 nodes. The layout algorithm used was Force Atlas 2, and edges are undirected. Edge weight plays a role in determining the shape of the network.

4. RESULTS

RQ1) How does Twitch's social network look considering stream size, but before partitioning based on stream attributes?

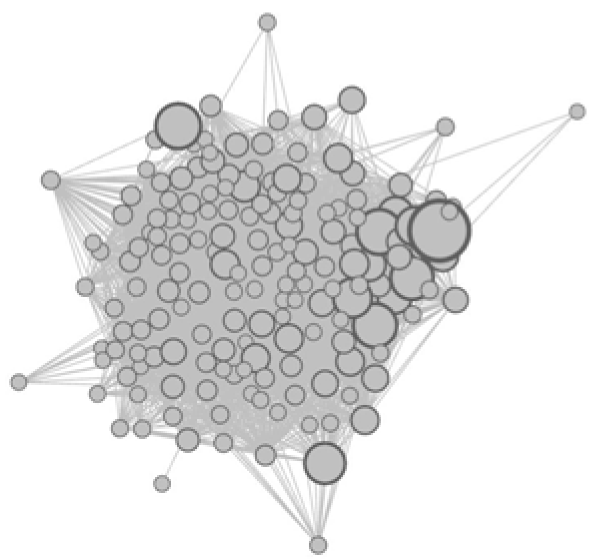

Figure 2. Nodes are presented simply, without any groupings. The size of the nodes is relative to the amount of followers they have.

Overall, the social graph is quite compact with few outliers. Nearly every node has a connection to more than one other node. Analysis provides an Average Degree of 38.299, an Average Path Length of 1.87, Diameter of 4, and Density of .221. This data and Figure 2 show a quite tightly knit community despite the number of nodes. Notable is that some of the largest nodes are actually near the outside of the graph, when generally the largest nodes would be expected to be more central. In fact, many of the central nodes small and medium sized. This shows the significant factor of interactivity that smaller streams can deliver above larger streams (Hamilton et al. 2014). Due to the data collection method, it can be hypothesized that many people visit and follow these larger streams, but they do not visit them as habitually (no 'Notification') as smaller streams.

RQ2) How does Twitch's social network look when based on streams' Community Membership Type?

Introduced as a beta feature in February 2017, Twitch's 'Communities' are "self-organizing, public groups centered around specific activities"; these communities act as a way for users to more easily discover streams that are more pertinent to their interests (Karsevar, 2017). Figure 3 reveals that 'General' community streams are strewn throughout the graph, likewise with 'None'. General (more social focused) streams form the 'core' of the network. This comes as no surprise seeing as relaxed and socially open streams such as these represent several of the Uses and Gratification traits like Social and Personal Integration. 'Competitive' community streams are a bit scattered, but show a couple of clear groupings, indicating users' interest in certain gaming mechanics, and then branching off to social streams as well. Interestingly, 'Mixed' community streams are a bit scattered as well, but are often found clumped next to the two Competitive groupings. It's possible these mixed streams form a type of bridge as followers express their intents of satisfying different UG needs while moving between more social and competitive communities.

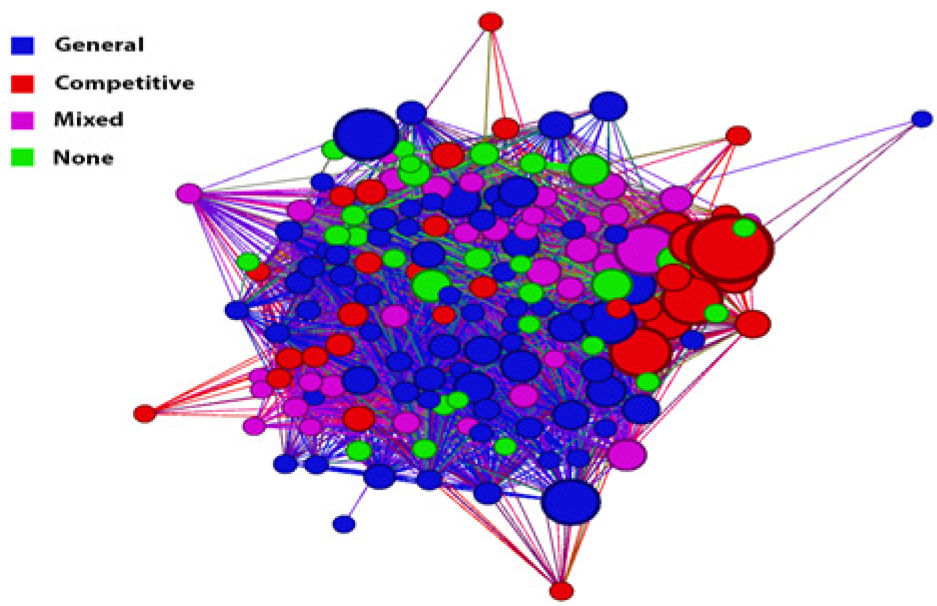

Figure 3. Nodes (streams) are partitioned by Community Membership Type, and sized depending on the number of overall followers.

RQ3) How does Twitch's social network look when based on stream Type (eg Competitive, Casual, Speedrunning, Social, or Learn)?

This classification for streams is based on previous research by Sjoblom et al. (2017). Streams were coded by the researcher based on how the streamer described their stream, or lacking a self-description, a stream type was assigned depending on the style of game-play or culture. For instance, streams which did not display a particular game were assigned 'Social', and streams that mentioned competitive play were assigned 'Competitive'.

Immediately obvious in Figure 4 is that groupings are much clearer by stream Type than they are by Community Membership (Figure 3). This may suggest a couple of things. First, Community Membership is more complicated than the coding allowed for. Second, Community Membership (which is user-decided) is a more esoteric [social] marker than an appropriate stream identifier. More research is needed.

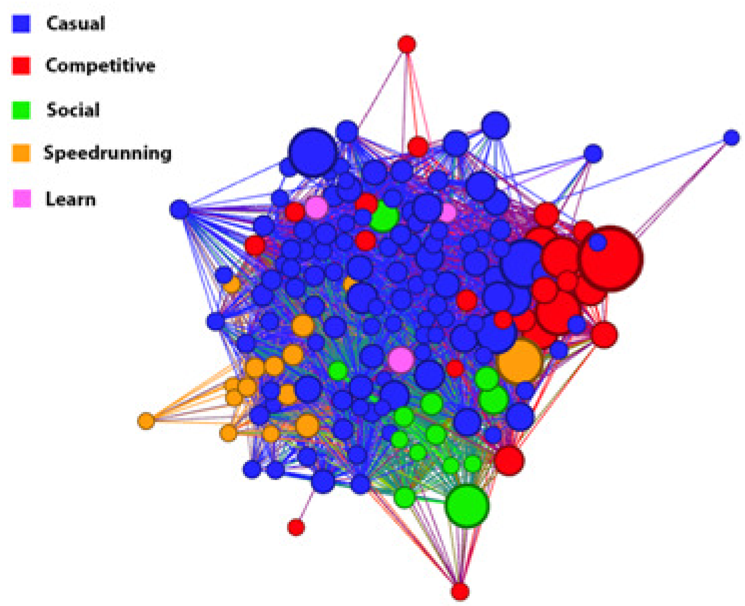

Figure 4. Nodes (streams) are partitioned by stream Type and sized depending on the number of overall followers.

As compared to Figure 3 (General community being moderately related to 'Casual' type streams), Figure 4 again shows that Casual streams to make up the bulk and core of the network. Casual type streams had the highest degrees of centrality, acting as a bond between more focused cultures. 'Speedrunning', 'Competitive', and 'Social Streams' were quite tight-knit. This suggests that users congregate to a specific culture/interest, and then branch out to satisfy other needs like Tension use gratifications (or vice versa). No community really has a monopoly on large or small streams, signifying that users still can attain Social or Personal Integrative gratification across cultures and stream styles. Speedrunning does however have the largest concentration of small streams, possibly adding credence to Churchill and Xu's (2016) study that stated the small attraction of highly technical streams compared to less technical general streams.

RQ4) How does Twitch's social network look when based on game genre?

Figure 5 shows the social network based on game genres, listing the top ten. Heavily prevalent is the First Person Shooter (FPS) genre, likely due in part to the current popularity of PUBG. FPS games like PUBG and Counter-Strike are scattered across the Competitive and Casual regions

(Figure 4) likely because of their ability to satisfy multiple UG stream needs; they can be highly technical (Cognitive UG), provide in-game socialization (Social/Affective UG), and can be cinematic (Tension UG). Adventure games make up almost the entire Speedrunning type streams due to their single-player nature, but are still found elsewhere throughout the network. Multiplayer Online Battle Arena (MOBA) games lend themselves well to the Competitive streams thanks to their top-down views of small scale battles, but are still found throughout the network. In-Real-Life (IRL) is relegated to Social streams, as Social streams are defined as doing something other than a game. The IRL designation is given unless the streamer lists a specific activity (like music or art), so general IRL activities (chatting) greatly trump specific non-game activities at this time.

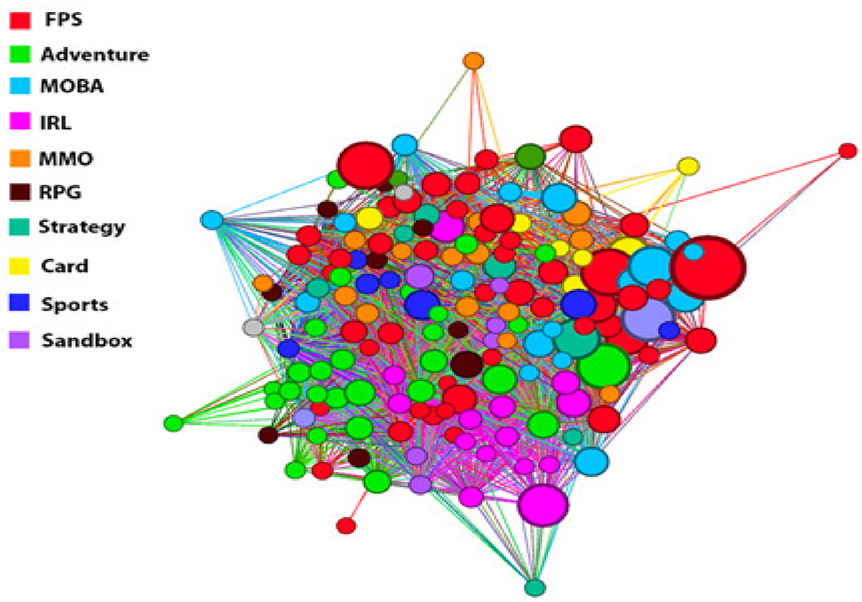

Figure 5. Nodes (streams) are partitioned by game genre and sized depending on the number of overall followers.

In general, game genres don't have too many boundaries when it comes to Community Membership or even stream Type. Streamers are simply using the games as a tool to interact with their community, a common bonding type. Sometimes a specific tool (Adventure or MOBA) helps reach a certain type of follower, but the social heart of Twitch allows genres to span the entire network.

RQ5) How does Twitch's social network look when based on a modularity algorithm?

Running the social network through a modularity algorithm produces results close to consistent with assigned variables like stream type. In this algorithm, the network was divided into 6 sections with no knowledge about the nodes' attributes stream communities, types, genres, etc. Figure 6 is the result of automatically generated 'communities' or sections of the network. Without assigning meaning to the nodes, parts of the network still match together. These 'organic' communities provide the insight of the mixing and dividing of users' interests. Again, competitive and speedrunning cultures stand out clearly. As communities from Figure 3 were mixed at the top, they are here as well. At the bottom, there is the collusion of General/Mixed communities and casual/social type streams.

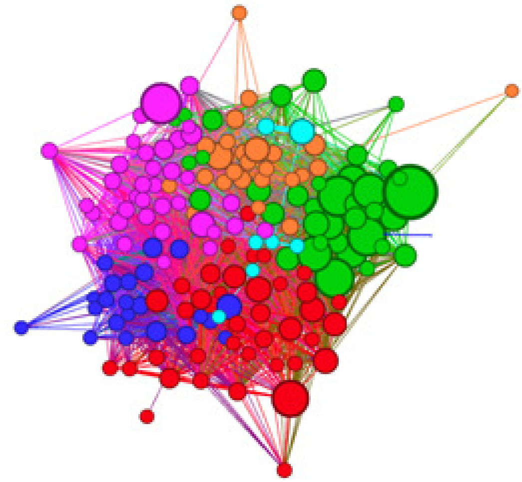

Figure 6. The network when run through a modularity algorithm to produce 6 sections.

RQ6) What can detailed views of single nodes reveal about the network?

By focusing on specific nodes, 'case studies' about the network and its nodes are possible. The stream with the most followers, 'dreamhackcs', is a 'Competitive' type stream, and belongs to the 'Competitive'community. It's connected to nearly all of the other Competitive streams as kind of a key figure for that stream type (Figure 6). Despite its size and importance to Competitive streams, it's not nearly as central as some of the other Casual type streams, or even compared to the other Competitive streams. This is likely due to the fact that 'dreamhackcs' is a special use stream that live-broadcasts large competitive events (Dreamhack Tournament) and reruns, but is not a typical stream run by a single streamer.

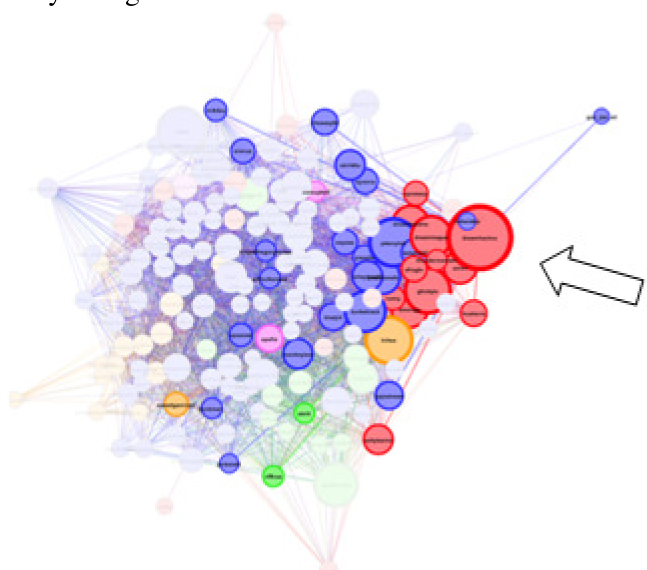

Figure 7. A focused view of 'dreamhackcs'. See Figure 4 for network legend.

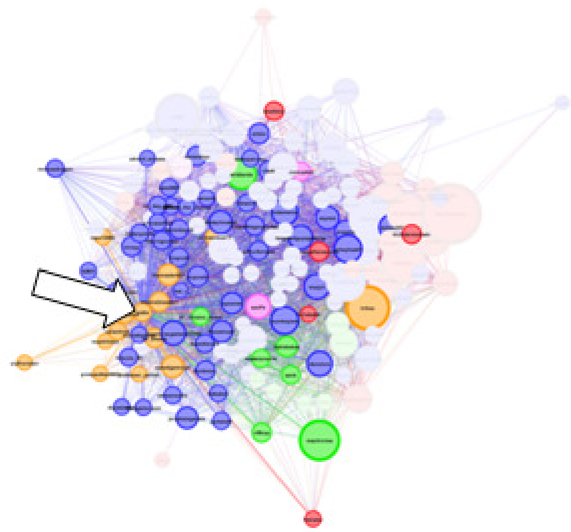

Figure 8. A focused view of ‘reabs’. See Figure 4 for network legend.

‘reabs’ is a Speedrun type node (Figure 7). Despite being close to the outskirts of the network, it is still connected to almost every other Speedrun node, showing a tight-knit community. ‘reabs’ is also connected to the majority of Casual nodes, despite being a purely Competitive Community Member. Like Figure 3, this might suggest that Community Membership might not have too big of an impact in what users stay within. Instead, users may allow their UG needs to lead the way and search out a stream like ‘reabs’ for certain gratifications, and the Casual streams for other gratifications.

RQ7) Which streams are key in terms of degree centrality, and how does this compare to their follower size and other traits?

Initially, the most noticeable trait of the centrality heat map is that the largest nodes/streams do not represent the most connective nodes (Figure 9). When compared to Figure 4, the most central nodes are Casual. As Twitch satisfies UG needs, these nodes seems to provide a great even ground for viewers, a kind of comfortable starting point that attends to many needs like Cognitive gameplay and Affective streamer interaction. Also notable is the fact that highly central nodes are often medium sized. Too small, and a stream doesn’t provide enough interaction. Too large, and a stream overwhelms the user with interaction.

Competitive nodes are often also quite central. The base reason for Twitch is to act as a platform for streaming game content, and it’s clear users still move between social/Casual streams and more serious Competitive streams. Speedrunning is quite mixed in terms of centrality. Speedrunning can be quite a specific interest, and this is represented in the centrality map. It’s likely the furthest streams have a specific focus, drawing a dedicated crowd. And yet, as in Figure 7, this crowd still mingles with very central/Casual streams.

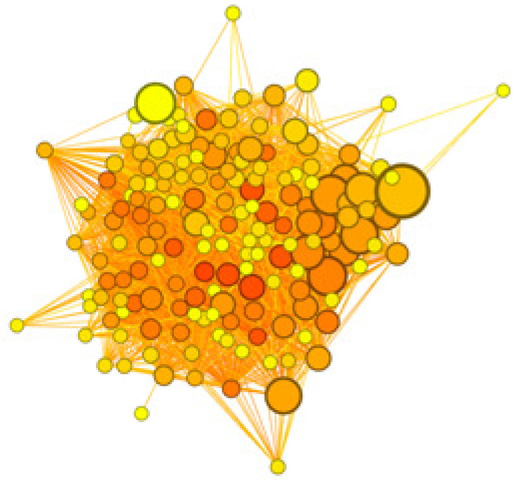

Figure 9. A network 'heat map' of centrality. Darker means a higher degree of centrality (more connections).

5. CONCLUSION / DISCUSSION

Compared to traditional media, social live-streaming sites like Twitch are relatively new. Twitch itself is often in a state of change as trends and streamers come and go, updates are applied, technologies become more accessible, and the internet culturefluctuates. Even Twitch's Communities section had been added within one year of this study. This study was performed to impart a beginning understanding of the nature of Twitch's social network onto the audience.

This study found that Community Membership didn't segregate nodes into sections as well as stream types. This suggests that Communities may be kind of vague, being that they are streamer-defined (ie streamers can create/join any community), or, the method used to define them wasn't selective enough. There are an infinite amount of communities, which may make it difficult for streams to define themselves, or for users to find an appropriate stream that includes all/most of the streams that would satisfy their UG needs. Well defined communities, however, could be extremely beneficial.

Therefore, this researcher would like to suggest an improved way of classifyingstreams. Communities (especially large ones) as they are, often don't correlate quite well with stream type or the game played. A way of breaking down and defining streams may help users find the streams they desire. Since Communities are already streamer-defined, it's not impossible that Twitch could provide a streamer or user-driven filter system. Streamers could add certain filters to their stream regarding the usual peak viewer count, usual game and game genre, type of stream, and so on. Likewise, users could also be given the power to help define streams/filters.

The method of connecting streams, by followers-in-common and by Notification, was successful. It helped avoid large streams dominating the network by size alone. Streams of all sizes were allowed shine in the network based on habitual users as they do on Twitch itself. Smaller and mid-sized streams often had high centrality (especially Casual types) due to their increased interactivity (smaller streams better suited for socializing). Larger streams like 'Dreamhackcs' (Competitive type) helped form the hubs of their respective stream types.Frequent connections between all social circles were found, even from very focused cultures such as Speedrunning.

Twitch is indeed an open community, offering a diverse range of topic and interests, yet linked together by the social experience provided. The existence of specific communities lets users swim around within the overall network to find a stream to satisfy whatever their needs might be.

Due to the ever-evolving nature of Twitch and social sites, this research has some limitations. For instance, streams can have membership in multiple communities. For this study, this node attribute had to be codified based on their Community Memberships, not on their exact communities due to the infinite possibilities. Future research may want to consider a way in which to include this variable. Additionally, stream type and game played can change. Again, these variables were assigned based on the stream at the time of data collections. Classification is unending for continually changing social sites and evolving media. It is also very difficult to dictate the perfect genre for a game, as a game may have both RPG and Adventure elements, so the researcher must code the genre as what appears to be the primary genre. Following studies may benefit from incorporating a system where the genre of games in a stream can be better defined and compared. As this was exploratory research, future research on a specific network trend, or expansion of a specific community, genre, or stream type might be interesting.

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