Preprint of
Pirker, J. (2018). Social Network Analysis in Games User Research. In *Games User Research* (pp. 491-499). Oxford University Press. https://doi.org/10.1093/oso/9780198794844.003.0029

Social Network Analysis in Games User Research

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Key takeaways:

- Introduction to social network analysis; covering network analysis in the context of player and in-game data
- Overview of key elements in network analysis
- Discussion on the possibilities that can be realized through the use of networks and advices on using networks for games user research to understand player behavior in a social context

1. Social Networks in Games – Focus on the Player

In multi-player and social network games, the social interactions – competition or collaboration - between players are an important factor for player engagement and retention. Thus, it is a crucial, but challenging endeavor, to understand better the social structures, dynamics, and interactions between players. One method to investigate the relationship between players is the use of *social network analysis*, which in recent years has become already an important tool to understand user behavior in social media networks, such as Twitter, Facebook, or LinkedIn.

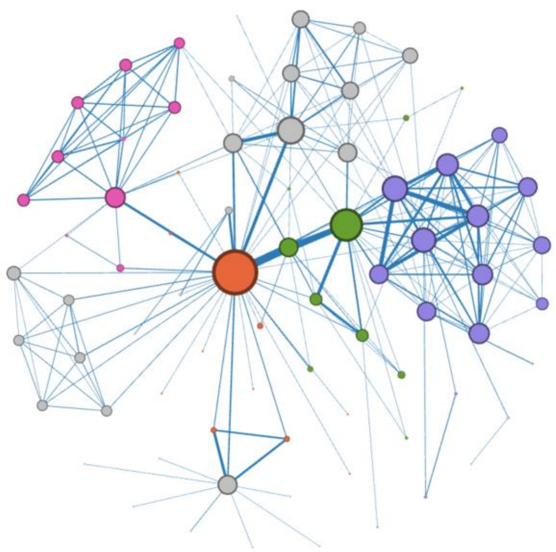

Fig. 1: Example network with about 70 nodes connected through about 230 edges. Larger nodes represent users with more connections.

Social networks are graphs of individuals represented as nodes and their relationship and interactions represented as links between these nodes. They serve as medium for information about behavior, dynamics, and influences in these social structures

(Zheng et al., 2012). Social networks are used to study how individuals are connected to and interact with other individuals. Social network analysis (SNA) is described as the process of investigating social structures with methodologies from network and graph theory (Otte, 2002). SNA became extremely popular as tool to analyze social media networks such as Twitter or Facebook with focus on user relations, the dynamics of the relationships (e.g. how users build relationships or form groups), and the relevance of single users in those networks.

Network Analysis in the domain of games can be used to analyze, visualize, and investigate structures and relationships among players, geographical points, or other in-game elements, which can be represented as mathematical node in a graph structure. These networks can be investigated with different concepts inspired by graph theory. In *social* network analysis the focus is on the social interactions between users or players.

Typical questions we can answer with such concepts are as for instance the following:

- Analyzing individuals:
    - Who are well connected / important players in a network?
    - What is the influence of individuals?
    - Who is the player with the largest reach?
    - Who are players connecting different player groups?
- Analyzing groups and communities:
    - How can we identify groups and communities?
    - How are players connected with each other?
    - Are players more engaged by playing along or together?
    - Are players in groups performing better than players playing on their own?
    - Do connected players share common interests?
- Analyzing social dynamics:
    - How do players connect to other players?
    - How do players build guilds?
    - When a player gets an interesting item to share with other players, how far will it get transmitted?
    - How can we recommend players in PvP matches?

In literature, different examples of social network analysis in games are described. Ducheneaut, et al. (2006), for instance, investigated guilds in *World of Warcraft* as social environments and built social networks within guilds to assess their potential for sociability and to measure the number of social activities. Bovenkamp et al. (2014) investigate different social structures and interactions types to build social networks in *Defense of the Ancients*, *StarCraft*, and *World of Tanks*. Rattinger et al. (2016) look at various networks based on match-data in *Destiny* and combine it with behavioral profiling.

In this chapter a brief introduction of selected topics from social network analysis in the context of games is given. While network analysis without the social focus could be also used to illustrate relationships between in-game places, items, or other elements, which could be connected through links, the focus of this chapter is social network analysis between players.

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2. Social Networks in Games - Essentials

The goal of social network analysis (SNA) in games is to obtain information about relationships between players, identify interesting networks, and map it to interesting features. Typical steps of SNA are (1) mining the data (information about the players), (2) identify interesting networks (through identifying different relationships), (3) analyzing and mapping network data. In the next sections an overview of the process of identifying player networks and how to analyze the networks is given.

2.1. Building Player Networks

To build social networks between players, graph structures are used. Players are represented as *nodes* (v). Relationships between players are represented as *edges* (e) between the nodes (Zafarani, Abbasi, and Liu, 2014). Different forms of interactions and social behavior connect friends, player groups, or similar players. To build these links different forms of interactions can be used.

- *Direct relationships*: Direct (explicit) interactions between players are identified and used (e.g. in-game messaging, friendships, clan memberships).
- *Indirect relationships*: Relationships also can be identified through indirect (implicit) interactions (playing in same matches or opponent matches, same playing time, same in-game location).

In literature we find different examples of relationship information used to create player networks. Rattinger et al. (2016) built networks between players based on different match interactions: playing matches together, playing matches in same team, or in opponent teams. Ducheneaut, et al. (2006) built the networks based on overlapping online time and/or same playing-zone of players connected though guilds. Szell, Lambiotte, & Thurner, (2010) used positive (friendship, communication, trade) or negative interactions (enmity, armed aggression, punishment) to built player networks.

Links can be undirected (connected both ways), directed (connection only one way), or weighted (e.g. by a number indicating the number of interactions).
For a simple classification we can identify three different network structures based on properties of links:

- Undirected networks (Links are undirected)
- Directed networks (Links are directed)
- Weighted networks (Links are weighted)

Figure 2 gives an overview of different graph types. Figure 2a represents an undirected graph: all three players are connected with each other. Figure 2b illustrates a directed graph, in which only the relationship between player A and player B is bidirectional and all connections to player C are only one way (e.g. player A and player B are following updates of player C, but not vice versa). The graph represented in Figure 2c additionally contains weights, which could be used illustrate a measurement of number of interactions (e.g. number of matches played together, numbers of messages sent,…).

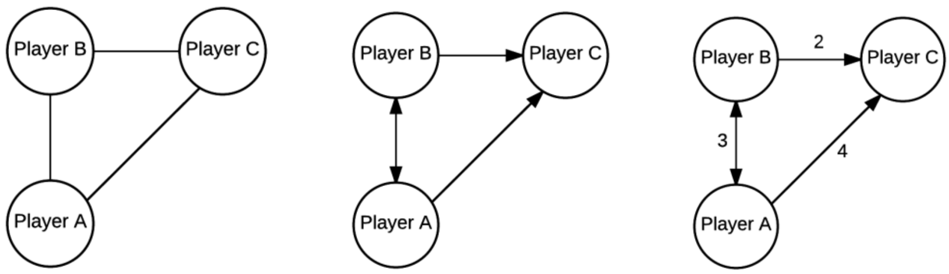

Fig. 2: (a) undirected graph (b) directed graph (c) directed weighted graph

The resulting networks can be then used to analyze the relationships, identify key players and weak players, or find sub-graphs and communities. The mathematical representation of a network is an adjacency matrix correlating the links to the nodes.

2.2. Analyzing Player Networks

There are different metrics from graph theory to analyze and investigate networks. In this section the most important metrics are briefly described to give a first overview of the possibilities of graphs. Further details and the mathematical background can be found in (Zafarani, Abbasi, and Liu, 2014). These metrics can be used as for instance to identify weak or key players, which are important for the existence and the robustness of the network. Game designers and operators can then try to include elements to motivate these players.

The *degree* (d) of a node (player) represents the number of links to other nodes (players). A high degree represents a high number of friends, interactions, or matches played together, respectively. In directed graphs, additionally *in-degrees* (edges towards node) and *out-degrees* (edges away from node) are described. To measure the ***centrality*** of players different metrics can be used including various features. The *degree centrality* measures the number of connections of players based on the degree. Looking at directed graphs, the in-degree centrality describes the prestige or level of activeness of the player (many interactions with other) and the out-degree centrality describes the gregariousness. Other forms of centrality measures also consider for example the number of friends of friends (e.g. PageRank).

To measure the ***closeness*** (distance) in graphs between two nodes, the number of paths (links) between nodes is counted. This information is important to analyze how fast information would spread between two players, or how likely they will befriend. If two people in the network are connected through a common friend, the chance that also these players are starting to interact is higher (Rapoport, 1953). To measure the centrality of players in term of “being close to all other players”) the *closeness centrality* is used.

To identify the ***connectivity*** between nodes, the links are investigated: weak links are links connecting sub-graphs. These links are often very important to connect different groups with each other. A link is described as bridge if it is connecting sub-graphs –

the removal of such a link would disconnect the sub-graphs. Even though players in a bridge connection might not have essentially a lot of connections, they are still considered as an important part of the graph in the sense of connecting groups (Easley and Kleinberg, 2010). It is crucial to identify and motivate such players to keep the social connection between subgroups. This measure is described as *betweenness centrality*.

Another way to look at graphs is to look at subgraphs, also known as *communities*, clusters, or groups. In player research this is an important aspect to identify groups of players strongly connected to each other. When playing games player form groups based on e.g. interests, playing habits, playing times, or geographical zones. These groups are not essentially related to in-game clans, or official groups, and therefore also not explicitly visible. The identification of such groups could be used as for an instance for recommendation systems or player classification.

The nodes and edges of the networks can be mapped to supplementary in-game information, such as playing behavior, in-game performance, weapon or tool preferences, or also demographical data. Mapping such information to social network metrics can help identifying motivators, issues, or influences on in-game performance or in-game behavior.

2.4. Conclusion and Next Steps

In multi-player games, one of the most important motivators for players is the social aspect. The use of networks in the domain of games user research can give valuable insights in social interactions, structures, and dynamics in the game. Based on different forms of interactions also various kinds of networks can be created. Typically, social networks give game designer and operators insights in social aspects such as key or weak individuals in a group or community, which are essential for the robustness and the connection between the players and different player groups. The identification of such players can help to introduce additional motivators to strengthen the network. However, networks cannot only be used to look closer at individual players, but also to identify entire player groups. For matchmaking and recommendation systems, the use of social networks can for instance help to identify indirect or implicit communities to engage social playing.

In this chapter, only a first very brief overview on social network analysis in the context of games user research and player behavior analysis was given. However, this a broad and complex topic and this chapter was only designed as first introduction. To get more information on this topic readers are advised to study further books on social network mining and analysis books like (Scott, 2000) or (Zafarani, Abbasi, and Liu 2014) and try first social analysis tools such as Gephi.

Next steps

- Gephi – Open Source Software to visualize and analyze networks, https://gephi.org/
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