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Dataset Show Case

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Table of Contents (Dataset Show Case)

SMMnet: A Social Network of Games Dataset

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Abstract. *Online games have become a popular form of entertainment, reaching millions of players. These players produce many types of interactions with the games, e.g., a player buys, plays, and comments on a game. Interactions that represent the players' experience are object of study of a very active research area called Player Modeling (PM). This paper presents `SMMnet`: the first dataset for PM that comes from a network of player-game interactions regarding the well-know Super Mario Maker (Nintendo, Kyoto, Japan). `SMMnet` presents a collection of over 880 thousand players that performed nearly 7 million interactions on over 115 thousand game levels. Moreover, we illustrate the diversity of the data with some statistical analyses and examples of studies.*

1. Introduction

The game universe is in constant ascendancy thanks to its popularity. For instance, there are streamers, which are famous players who develop online videos based on games [Gros et al. 2018]. Such ascendancy even created a new category of sports named eSports, which is a competition of professional players playing against each other [Yannakakis and Togelius 2018]. The game industry moves billions of dollars per year. According to Newzoo, a specialist company of game marketing, the estimated value for 2019 is U$ 150 billion.

With this expansion, the application of Artificial Intelligence (AI) in Games is growing with the need for more attractiveness and intelligence [Yannakakis and Togelius 2015]. Researchers focus on understanding the players' experience, *i.e.*, Player Modeling (PM), to study the players' behavior [Yannakakis et al. 2013, Aung et al. 2018]. In addition, from the perspective of game designers, players' behavior is one of the most important factors they must consider when designing the game systems [Lee et al. 2011, Yannakakis and Togelius 2018].

An ongoing research topic is PM in platforms of video games. A platform of video games is a virtual environment in which players interact with games [Eberhard et al. 2018]. The player-game interactions represent relationships of several types, *e.g.*, buy, play, and comment on a game. Each relationship can be represented by a social network, thus a platform of video games has a set of social networks; in this context, we coin the term Social Network of Games (SNG) for them.

For example, the well-known game Super Mario Maker (SMM) (Nintendo, Kyoto, Japan) is in fact a platform of video games of the Super Mario Bros series. In this platform, the players perform many types of interactions, *e.g.*, to play a game level (or simply game), give a "like", break a time record, comment on games created by other players, and elaborate his/her own levels to share online with the world.

Nowadays, there are several game datasets publicly available. Some of them focus on the industry games [Lee et al. 2011, Lin et al. 2017, Aung et al. 2018]; others refer to independent games [Lim and Harrell 2015, Karpouzis et al. 2015]. Nevertheless, these datasets are constrained in Player Modeling and game content exploration without any information from a Social Network of Games, thus making it difficult the study of Social Networks (SN) (*e.g.*, community detection, link prediction, ranking) on this context.

This paper presents the *first* very large and open access SNG dataset: the Super Mario Maker Network Dataset (or `SMMnet`, for short). It is publicly available for download [1]. The dataset provides information about over 115 thousand game levels and over 880 thousand players that performed nearly 7 million interactions of different types with the levels. `SMMnet` serves as a base for learning models, including, but not limited to, Player Modeling, Social Network Analysis, and general Data Mining, *e.g.*, prediction, and pattern discovery.

The rest of this paper is structured as in the following. First, we present formal definitions for Social Network of Games (Section 2). Then, we discuss the new dataset `SMMnet` (Section 3) and its applicability (Section 4). Finally, the last section concludes the paper (Section 5).

2. Social Networks of Games

A Social Network describes interactions and relationships of users in a digital environment [Barabási and Pósfai 2016]. In a network, users represent their relationships by links. There are many types of links, *e.g.*, links denoting social connections, similarity, behavioral interactions, actions, etc [Savić et al. 2019].

Links may also be present in a platform of video games, where players perform many types of interactions with games [Eberhard et al. 2018]. In these platforms, the players can buy, play, comment on a game, etc. Figure 1 illustrates two players p_1 and p_2 interacting (buy, play, comment, etc.) with three games c_1, c_2 and c_3. Each type of relationship form a social network; we coin the term Social Network of Games to refer to them in this paper.

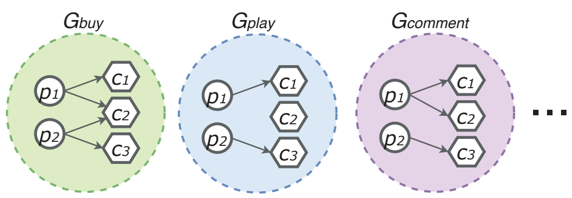


Figure 1. Examples of Social Network of Games.

In this sense, each relationship forms a social network represented by a directed bipartite graph $G = \{V, E\}$, with edges $e \in E$ of players $p \in V$ interacting with games $c \in V$, therefore $e = (p, c)$. Additionally, these networks change over time because new players/games arrive and new links appear. Therefore, since the graph changes as a function of time, it is a dynamic network [Westaby 2012]. Thereby, SNG has a series of snapshots of static graphs over time.

[1] `SMMnet`. *https://www.kaggle.com/leomauro/smmnet*

Note that a SNG is represented by a set of networks. Therefore, we can study each relationship network individually, given that some algorithms work only on homogeneous networks. Moreover, a SNG can also be represented by a complex network because the set of nodes may be connected by different and possibly overlapping types of relationships [Cherifi et al. 2017]. Also, each node can be represented by a complex object; *i.e.*, game features (*e.g.*, price, type of game, developer) and player features (*e.g.*, age, gender, time of playing).

2.1. Super Mario Maker

Super Mario Maker (SMM) is a platform of video games developed by Nintendo (Kyoto, Japan) for the consoles Nintendo Wii U[2] and Nintendo 3DS/2DS[3]. It was launched in September 2015. In this platform, a player can like and play game levels based on the Super Mario Bros series. Also, the player can create new game levels and share them online with the world. In this sense, SMM can be seen as a Social Network of Games.

In SMM, players present several types of relationships, as it is illustrated in Figure 2. A player can (1) create a game level and (2) play levels created by other players. If a player completes the challenge of the game level, he/she (3) "cleared" the level. The player can also be the (4) first to clear and/or beat the (5) time record of a level. Also, at any time, the player can (6) like a game level. In this sense, this Social Network of Games has six types of relationships.

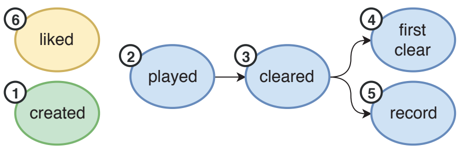


Figure 2. Types of player-game interactions on Super Mario Maker.

3. `SMMnet` Dataset

In this section, we describe the data collection in an automated fashion way. Furthermore, we describe the data, detail a schema for storing `SMMnet` into a Relational Database Management System (RDBMS), and conclude the section with some data analyses.

3.1. Data Collection

The information from Super Mario Maker is available in the website SMM Bookmark[4]. Thus, we elaborated a web crawler to collect the data from the website. A web crawler (or simply crawler) is a computer program that navigates on the world wide web in a systematic and automated way to search and/or collect data [Areekijseree et al. 2018]. To build our crawler, we searched for available Application Programming Interface (API) to retrieve information on the SMM Bookmark; and we found, in Node.js programming language, a set of APIs developed by independent programmers, *i.e.*, without connection with Nintendo.

[2]Nintendo Wii U. *http://bit.ly/nintendo-wii-u-smm* (accessed July 02, 2019).
[3]Nintendo 3DS/2DS. *http://bit.ly/nintendo-3ds-smm* (accessed July 02, 2019).
[4]SMM Bookmark. *https://supermariomakerbookmark.nintendo.net/* (accessed June 28, 2019).

However, the available APIs do not collect players' data, nor they capture the game changes (*e.g.*, new plays) over time. In this sense, we needed to adapt the most recent API, called `super-mario-maker-client`, to collect game changes. Also, we developed two new APIs: (I) `smm-maker-profile`, that collects players' data; and (II) `smm-course-search`, that searches for new game levels; both APIs are public available for download[5]. Figure 3 illustrates our crawler: `smm-course-search` searches for new game levels and stores their IDs into a Database (DB); `super-mario-maker-client` queries the game IDs in the DB and collects the games' data from SMM Bookmark; and, `smm-maker-profile` collects the players' data. It is important to notice that our crawler respects the access policies of the website SMM Bookmark (*i.e.*, *robots.txt*).

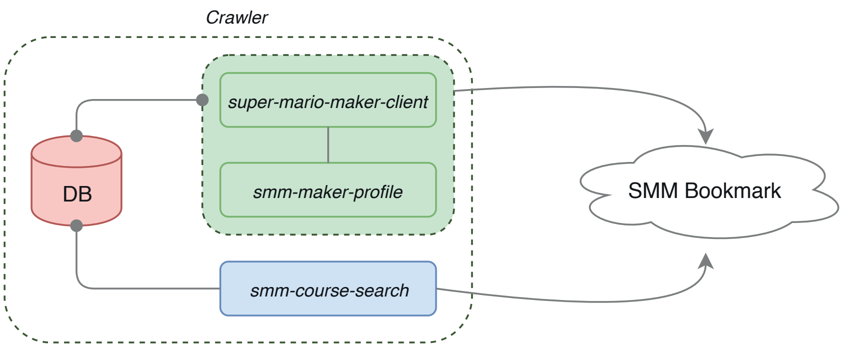


Figure 3. Crawler: Data collector structure.

However, the data collector suffered with bandwidth limits, as SMM Bookmark servers responded to a page request in around 2.7 seconds, making it impracticable to explore the whole network. Because of scalability considerations, we had to focus on a small set of games, maximizing the edge coverage over these groups of nodes aiming to preserve the community structure of the network sample [Areekijseree et al. 2018].

Therefore, we selected data from four nationalities to be collected: France (FR), Germany (DE), Canada (CA) and Brazil (BR). We selected FR, DE and CA countries for being the most active communities, right after United States and Japan, for which a huge number of levels were created per day, making it impractical to capture. We also selected BR to be a South America representative. Finally, the collection was performed during almost five months, from 16 Nov 2017 to 10 Apr 2018. The game changes from these countries were collected at every two hours.

3.2. Data Description

The `SMMnet` data is split into seven CSV (Comma-Separated Values) files: (1) COURSES.CSV, game level data; (2) COURSE-META.CSV, temporal changes on levels; (3) PLAYERS.CSV, players data; (4) PLAYS.CSV, plays; (5) CLEARS.CSV, clears; (6) LIKES.CSV, likes; and (7) RECORDS.CSV, time records over time. Figure 4 illustrates a schema with non-normalized tables to store the `SMMnet` into a Relational Database Management System (RDBMS). It is composed of seven tables, each one for one CSV file, that includes the levels, players, and the changes over time.

[5]npm. *https://www.npmjs.com/ leomaurodesenv* (accessed June 29, 2019).

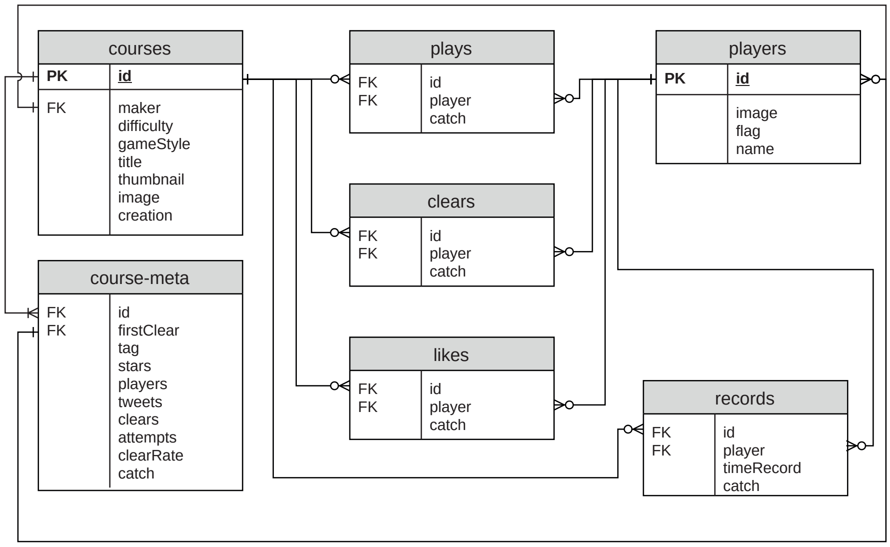


Figure 4. Schema for `SMMnet`.

COURSES.CSV presents static metadata from SMM levels. For example, level id (*string*, primary key), difficulty (*string*), game style (*string*), who created the game level - maker (*string*, foreign key), title (*string*), thumbnail link (*string*), image link (*string*), and creation date (*datetime*). Additionally, COURSE-META.CSV presents temporal changes on these levels, *i.e.*, tags (*string*), number of plays (*int*), number of tweets (*int*), clears (*int*), attempts (*int*), and likes (*int*) over time. All temporal tables have a "catch" field (*datetime*) that informs when the tuple was captured.

Meanwhile, combining the players and levels by links (*e.g.*, played, liked, cleared, and time records), forms the Social Network of Games. Thus, we need to correlate the tables COURSES and PLAYERS. PLAYERS.CSV presents the players' data, *i.e.*, id (*string*, primary key), player's image (*string*), name (*string*), and nationality - flag (*string*). While, we use auxiliary tables, PLAYS.CSV, CLEARS.CSV, LIKES.CSV, and RECORDS.CSV, to link the player and level tables over time, using a "catch" field.

Therefore, PLAYS.CSV, CLEARS.CSV, and LIKES.CSV only have three fields, *i.e.*, level id (*string*, foreign key), player (*string*, foreign key), and catch (*datetime*). Meanwhile, RECORDS.CSV has one more field, *i.e.*, time record in milliseconds (*int*).

Table 1 presents the number of tuples of each table. This dataset presents 115 thousand levels that 880 thousand players around the world played 3.94 million times, cleared 2.05 million times with 117 thousand time records, and liked 619 thousand times. In summary, the `SMMnet` is split into seven files that can be stored into a RDBMS, such as PostgreSQL, Oracle, and MySQL. The next section presents more dataset characteristics.

3.3. Dataset Characteristics

Figures 5 and 6 illustrate the proportion of the game styles and game difficulties of levels, respectively. Considering Figure 5 and Table 2, 51.7% of the levels follow the game style Super Mario Bros U, 21.2% follow Super Mario Bros, 19.0% follow Super Mario World, and 8.1% follow Super Mario Bros 3. Note, there is a high preference for the most recent game style (*i.e.*, Super Mario Bros U), followed by the oldest game style (*i.e.*, Super Mario

Table 1. Quantity of tuples in each table.

Table	Data
COURSES	115k
COURSE-META	292k
PLAYERS	884k
PLAYS	3,940k
CLEARS	2,050k
LIKES	619k
RECORDS	117k

Bros). In this sense, we presume that the most recent style prevails through the new visual and gameplay characteristics, while the oldest style stands out due to the memory of the most traditional style of the Super Mario Bros series.

Figure 6 and Table 3 show the percentages of courses according to their difficulties. In order of difficulty, 25.8% of the courses are considered easy, 44.6% are normal, 24.1% are expert, and 5.4% are super expert. To the best of our knowledge, there is no rule to define the game difficulty; SMM platform establishes the difficulty of a level automatically.

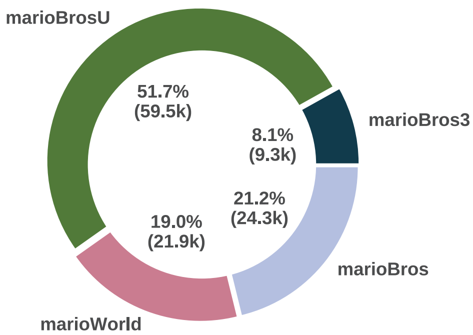


Figure 5. Game levels styles.

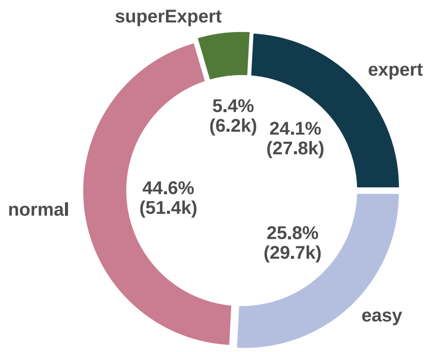


Figure 6. Game levels difficulties.

Table 2. Game levels styles.

Style	Data
marioBrosU	59.5k (51.7%)
marioBros	24.3k (21.2%)
marioWorld	21.9k (19.0%)
marioBros3	9.3k (08.1%)

Table 3. Game levels difficulties.

Difficulty	Data
easy	29.7k (25.8%)
normal	51.4k (44.6%)
expert	27.8k (24.1%)
superExpert	6.2k (05.4%)

The total number of interactions (*i.e.*, plays, clears, records and likes) made by players is 6,729,000. Among them, 3,941,378 refer to interactions of the type play, while 2,051,809 are clears, 117,126 are time records, and 618,687 are likes. Figure 7 shows the types of interactions on the top-100 game levels with the highest number of interactions. As we can see, many plays, likes and clears exist, but few time records occur because a level usually has few broken records.

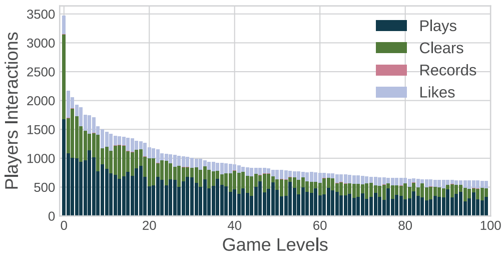


Figure 7. Dataset: Sum of the players interactions by level for the top-100 most popular game levels.

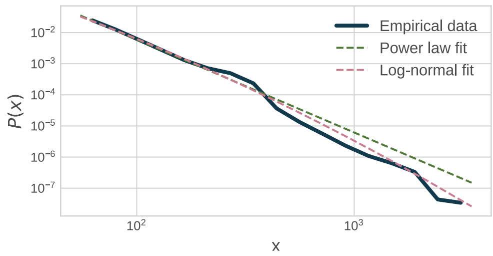
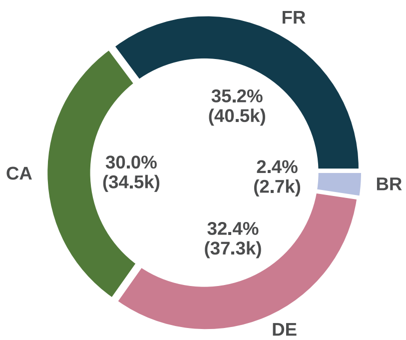


Figure 8. Probability Density Function for the top-100 most popular game levels; with power-law and log-normal estimates.

The interaction data in Figure 7 presents a few levels with high interaction and a fast decrease. This behavior is similar to a power-law, which is very common in Social Networks, including few popular and many unpopular objects [Newman 2005]. In this dataset, only 0.13% (151) levels received more than 500 interactions and the majority 99.87% (114,881) has interactions ranging from 0 to 500. Figure 8 reports a Probability Density Function plot for the top-100 most popular game levels. As it can be seen, it exhibits a similar behavior of a power-law [Clauset et al. 2009] and log-normal distribution estimates [Mitzenmacher 2004].

In `SMMnet`, there are over 880 thousand players that performed 7 million interactions on over 115 thousand levels. Besides, as mentioned before, we selected four nationalities, collecting 41 thousand levels from FR, 37 thousand from DE, 34 thousand from CA, and three thousand from BR. Figure 9 and Table 4 summarize this information. This is a substantial amount of data to infer knowledge about the players and games in at least four different countries. Additionally, there are no missing values.

Figure 9. Game levels by country.



Country	Data
France (FR)	40.5k (35.2%)
Germany (DE)	37.3k (32.4%)
Canada (CA)	34.5k (30.0%)
Brazil (BR)	2.7k (02.4%)

Table 4. Game levels by country.

4. Applicability

The `SMMnet` dataset can be used in several applications, *e.g.*, Social Network and Artificial Intelligence in Games studies. Next, we present some studies for motivating potential users of the dataset to find other creative uses.

4.1. Social Networks

It is possible form at least three types of graphs in this dataset, *i.e.*, static graphs, dynamic graphs, and complex networks. Exploring a static graph requires to observe the social network at a specific timestamp (snapshot), *e.g.*, a social network of likes from the last day. In a dynamic graph, the social networks change over time. Thus, it is necessary to elaborate temporal graphs at each given time interval, *e.g.*, a social network of likes for each day. Meanwhile, in a complex network, it is necessary to take into account the multiple relationship types and/or complex objects, *e.g.*, a social network with plays and clears links.

In this sense, we emphasize that this dataset can be used in different scenarios. `SMMnet` can be explored in many social network studies, including, but not limited to: (1) community detection, to identify communities of players (*e.g.*, similar players); (2) link prediction, *e.g.*, infer what games a player will play on a network of plays; and (3) ranking, *e.g.*, sort the popular games, or influential players.

4.2. Artificial Intelligence in Games

Researchers attest that companies invest in production of new games with graphics and interactive qualities by using artificial intelligence techniques [Lucas 2009, Yannakakis 2012]. Besides, games are advantageous test-bed to algorithms because they offer a simulated environment in which many factors are reacting simultaneously.

This dataset offers many artificial intelligence applications. We highlight some possibilities: (1) Data Mining, supervised or unsupervised learning (*e.g.*, clustering to identify similar games' characteristics); and (2) Player Modeling, extract characteristics from the players' activities in the social networks.

4.2.1. Detecting Influential Players

`SMMnet` has already been used in some studies that illustrate its usefulness in Player Modeling. Researchers used this Social Network of Games dataset to detect the game influencers (or simply influencers), that is, players with high influence in creating new trends by publishing online contents (*e.g.*, videos, blogs, forums) [Moraes and Cordeiro 2019].

Other players follow the influencers looking for entertainment and credible information about the games. Consequently, game companies invest in influencers to perform marketing for their products. However, it is not a trivial task to detect game influencers among thousands of players. Moraes and Cordeiro (2019) proposed a framework to extract temporal aspects of the players' actions, and then detect the influencers by performing a classification analysis.

Figure 10 illustrates the framework proposed by Moraes and Cordeiro (2019), which is split into three steps: network modeling; player modeling; and classification analysis. In the network modeling process, they model the social network of developments (G_{dev}) and likes (G_{like}); both graphs are dynamic and directed bipartite. G_{dev} represents a network of player creations, *i.e.*, the player who created each game level.

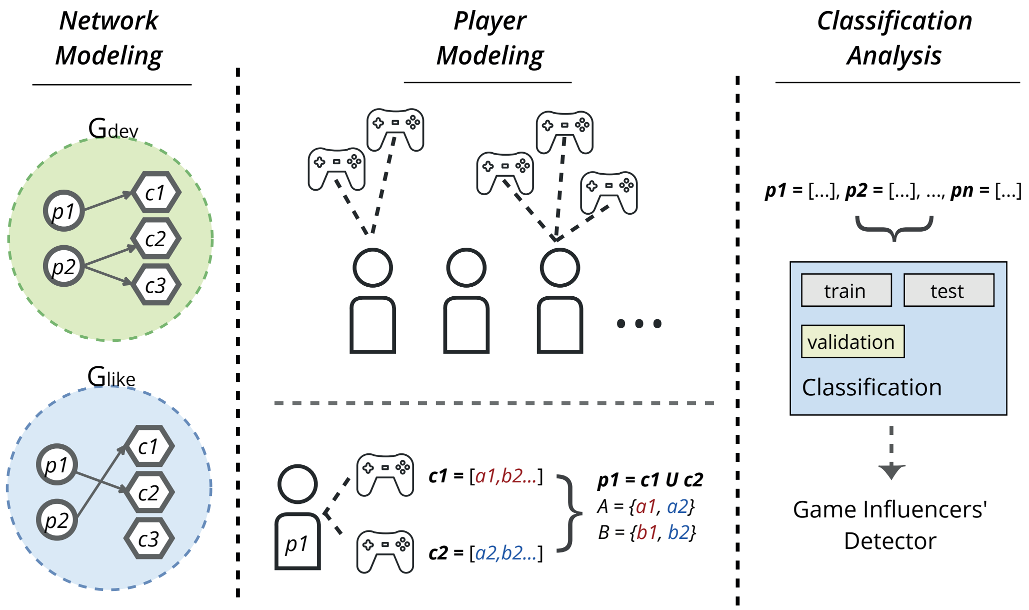


Figure 10. Framework for Detecting Game Influencers.

Meanwhile, G_{like} represents a network with game levels liked by players; it is a network of the levels liked over time.

In the player modeling step, the researchers extracted a set of game levels created by each player, using the G_{dev} network. For each game level it was modeled a data stream of likes over time, using the G_{like} network. For each data stream of likes, it was extracted a series of features, and then combined to represent the player's features of its creator. Therefore, a player was represented by a combination of his/her games' features.

In classification analysis, they evaluated 28 classification algorithms using the players' features. The best classifier (Logistic Regression) reached high accuracy (87.1%) and f1-score (85.7%) to detect the game influencers. Note that player labels (*i.e.*, ground truth) were created manually by observing their activity on popular gaming sites. The authors also executed a validation, which demonstrated that the proposed framework automatically detects influencers with high precision even when using data from distinct countries for testing and training.

5. Conclusion

In this paper, we presented `SMMnet`: the *first* dataset for Social Networks of Games (SNG). SNG is a set of social networks in which the players perform many types of interactions with games, *e.g.*, buy, play, and like a game. In this sense, an SNG can be represented by a set of social networks or a complex network. Also, these networks can change over time; therefore, they have dynamic graphs as function of time.

`SMMnet` was extracted from the well-known game Super Mario Maker (Nintendo, Kyoto, Japan). This dataset presents a collection of over 880 thousand players that performed nearly 7 million interactions on over 115 thousand levels. Besides, we present a schema to store this dataset into a Relational Database Management System. Finally, we highlighted the applicability of this dataset in the research fields of Social Networks and Artificial Intelligence in Games. However, its limitation is not having internal data of the game levels, only metadata from social networks. In addition to the presented sample studies, we believe that researchers and game designers will find further creative proposals for this dataset.

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