Incorporating Game Theory and Nash Equilibrium Concepts to Predict Social Network Community Behaviors

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Abstract—In June 2016, there were an estimated 1.55 billion active users on the most popular social media platform, Facebook[1]. As of April 26th, 2017, there were an estimated 700 million active users on Instagram, our main social media platform for this research. As the number of users on social media platforms increases, a problem of great significance becomes clear: the increasing amount of negativity within the communities. Our goal in this paper is to use the concepts of game theory and Nash Equilibrium to solve this problem. We create a game that has two social media users, or players, trying to extend their outreach while keeping a positive community. Using five variables collected from various Instagram profiles, we create cost and payoff functions for the decision making part of game theory. We implement those functions and make several discoveries: contrary to popular belief, the comments and negative comment percentage are not correlated; the number of followers directly affects the number of likes on a user's posts; the cost function output increases with the payoff function output in a strong positive correlation; and that a follower number increase on an account will almost always result in an increase in number of comments. Future work could explore implementing our functions with the Gambit library for game theory and incorporating the mathematical portion of Nash Equilibrium into our solution.

Index Terms—Game theory, cost function, payoff function, social media, negativity, community management

1 Introduction

2 Introduction

With the growing popularity of social media, community behaviors became linked to the number of people in a users follower-base and how they responded to the users posts. Instagram users are constantly competing against each other in a race, each vying to get more followers, more likes on their posts, more comments on their posts, more views of videos, etc. Keeping this information in mind, we used game theory to cast two Instagram users as players in a game where both of the players are trying to obtain the optimal community. This optimal community has the maximum amount of followers possible with no negativity. People who strive to have a large follower base have the cost of possibly having more negativity within their community.

The purpose of this project is to see how game theory can predict the actions of modern-day social media. Game theory is based on two users who are both trying to achieve the same thing. In the game we created, the aim of these players is to be Instafamous(having a large quantity of followers and being widely known by other Instagram users). However, they might lose followers because of the negativity in their community. Thus, they will obviously try to expel this negativity. Our aim is for these players to be able to reach their aim of instafame, while satisfying their desire for a positive community. Therefore, Nash Equilibrium is the most obvious concept to use.

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Nash Equilibrium is a well-known concept in game theory. Nash Equilibrium is found when neither player changes his or her strategy when the other player reveals his or hers. In other words, when no player has the incentive to change their strategy after all players strategies are revealed, Nash Equilibrium is found. Nash Equilibrium finds the strategy that has the least risk for both players, allowing both to be able to achieve their desired outcome even though each player has multiple strategies to choose from. In Nash Equilibrium, every player wins. This applies to our game because all users, or players, are able to achieve their desired outcome, which is increased outreach or popularity and decreased negativity which takes the form of hate and spam comments on posts.

3 Related Work

Much research has been done using Nash Equilibrium. Liu et al. [2] based a study on making a game among multiple mobile users. This game will consist of two decentralized data offloading mechanisms trying to achieve Nash Equilibrium. Additionally, Fortetsanakis et al. [3] incorporated game theory and finds the Nash Equilibrium to develop an outline for analysing any outliers of utility functions of providers. Another paper that incorporates game theory is Masson et al. [4] created a model based on News Feed and how it applies to the posting behavior of users that are competitive. While using a bit of the Nash Equilibrium, they later proposed an algorithm where it estimates the amount of messages that flow through each news feed. In the subject of Bayesian Nash Equilibrium, Xia et al. [5] proposed a game to comprehend the uncertain cooperation between nodes using Bayesian Nash equilibrium. Nash equilibrium can be complicated, and Hajibagheri et al. [6] addressed the complication of communities in social networks. Their final attempt created a graph that was related the the Nash equilibrium.

Under two-player games, Hou et al. [7] presented a game in which two players continue to simultaneously run while the variables are below a threshold. Assuming the second player is aware of a set of rules laid out by the first player, the second player can chose to violate or follow this set of rules. Similarly, Dextreit and Klmanovsky [8] exemplified the application of game theory using a two-person game with the players constantly responding to the previous actions. Rahmes et al. [9] determined multiple strategies for decision making by using their proposed model. On the other hand, Lee et al. [10] introduced a game in which a player changes its attributes to maximize their payoff by comparing against other users and maximizing their payoff. Similarly to Lee et al., Lin et al. [11] developed a model of user behavior, and designs strategies for simulating user cooperation with peers. Additionally, Zhang et al. [12] attempted to discover covert nodes within social media and networks. Using regular nodes, they had potentially discovered hidden nodes. In response to being sure of finding hidden nodes, Yang et al. [13] proposed a method of a way to discover hidden nodes within social networks using a model to analyze and calculate different nodes within the network. Li et al. [14] also suggested a method of faster caching of videos by storing popular videos to give users faster video services.

In the category of security, Gasior et al. [15] presented a security-based solution to the job scheduling problem in Cloud Computing infrastructures. Additionally, White et al. [16] tried to increase the amount of security in online social networks(OSN) since new threats have risen. Game theory is used to create a game with several scenarios in which the hacker might attack the security systems. Roy et al. [17] surveyed various network security papers to give readers a better understanding of game theory applied to cyber security.

Much research has been done about game theory in networks. Azadjalal et al. [18] proposed a method that, for an active users trust network, determines the effectiveness coefficient for the users in that network. Reiffers-Masson et al. [19] showed a competition between multiple information sources from a social network group in order to maximize the visibility of the players, especially of his/her messages sent inside of a community. Jiang and Xu [20] presented a game theory-styled approach for community detection in dynamic networks. However, their approach does not work for overlapping cases. In response to overlapping cases, Zhao et al. [21] proposed an algorithm Co-game which detects communities in dynamically-sized networks.

Along the lines of nodes and their behaviors, Feng et al. [22] proposed a method to improve the travel of packets of information by monitoring selfish behaviors of various nodes and improving the packet forwarding. Alternatively, Wang et al. [23] attempted to discover patterns of spread among gossip within various social networks.They discovered that there is a range of uncertainty factor when dealing with humans. Along the same lines, Pavlidou et al. [24] surveyed a variety of routing models based in game theory, while under the assumption that all of the nodes may not be cooperating with the others efficiently.

4 Methods

Nash Equilibrium finds the solution in a game that is equally beneficial for both players. Although we did not use Nash Equilibrium, we use the basic principles, finding the optimum middle ground for two players, to create our equations and formulas. Our games Nash Equilibrium would be an *optimally balanced* community. The definition of *optimally balanced*, in this case, is having the outreach and the negativity stabilize each other's effects. An account that is *optimally balanced* will have maximum outreach and minimum negativity.

We minimized the number of variables because the more variables present, the more difficult it becomes to incorporate game theory. The different types of variables that will be used are followers, number of likes on their second-to-most-recent post (for accuracy), total number of posts, total number of comments on the second-to-most-recent post, and negative comments percentage (as a decimal). The two functions to be used in this project are the cost and the payoff functions *(see Equations 1 and 2)*. The cost is going to represent the amount of negativity in the community and the number of hate and spam comments. The payoff function is the outreach of the user. Simply put, it is how much popularity the user gains by forfeiting their desire for a positive and accepting community among their followers and commenters. These functions are implemented throughout the algorithm and code using five variables.

Before being able to incorporate our game into game theory, we must first define our game. Our game is a two-person cooperative game in which the two users compete to reach the most optimum community. In this case, we classify an optimum community as one where the user has the most outreach among the community, but the least negativity.

$$\frac{fl + cn}{\frac{1}{2}(p + np)} \tag{1}$$

$$\frac{cnlp}{f} \tag{2}$$

4.1 Models

To denote player 1 and player 2 as well as their set of actions, we use the models $u \epsilon U$ and $w \epsilon W$. Both of which consist of two actions-blocking users and posting. Assuming that $x(t)$ is the state of followers or the total number of followers at the point in the moveset, we create the function $x(t+1) = J(x(t), u(t), w(t))$ which will predict the number of followers based on the moves of the two accounts. The function J is equivalent to $J = K(x(t), w(t), u(t)) - L(x(t), w(t), u(t))$. K is our payoff function in Equation 1 and L is the cost function in Figure 2. Our payoff and cost functions are increased or decreased by an arbitrary value a dependent upon whether the move was the blocking of another user or upload to their timeline. Blocking users results in a decrease in both the payoff and cost functions; posting results in increases in both functions. We will use both $u = U_{GT}(x, w)$

and $w = W_{GT}(x, w)$ as our control policies, representing each community at the beginning of the moveset. We will use the equations in Figure 3 through 6 to determine the best move for each player, dependent on the others previous move. $u = \check{U}(w)$ and $w = \check{U}(u)$ are both being used to calculate the best move for one player based on how the other players move resulted. Either $u = \check{U}(w)$ or $w = \check{U}(u)$ must satisfy Figure 3 and 4 or 5 and 6 in order to be played.

$$J(x, \check{U}(w), w) >= J(u, w) \tag{3}$$

$$\forall u \epsilon U, w \epsilon W \tag{4}$$

$$J(x, \check{U}(u), u) >= J(u, w) \tag{5}$$

$$\forall u \epsilon U, w \epsilon W \tag{6}$$

4.2 Formulation

In the creation of our payoff and cost function, we use the following variables:

- f as the total number of followers
- l as the total number of likes on the second to most recent post
- c as the number of comments on the second to most recent post
- n as the percent of negativity within the comments on the second to most recent post. If the percent was 0, we recorded it as 0.01 to keep our equations from reaching 0
- p as the number of posts a user has posted on their account

The payoff function shows the outreach the account has in society. Within our payoff function, we created the equation in Equation 1 by assuming cn will be the total number of negative comments and that the negative comments were not posted by a follower of the user. Assuming these users are not followers of the account, we can incorporate them into our outreach function because the user has a further outreach than noted by the follower variable. We multiply followers by likes, assuming all of the user's followers have seen all of the posts the user posted. We do not incorporate the number of negative users in this part of the payoff equation.

The second part of the payoff function averages the number of posts to the number of assumed negative posts, or posts in which the majority of comments are negative. From here, we divide the number of people the account's posts have impacted by the average of negative and positive posts.

Using the same variables mentioned in the payoff function, we create our cost function in Figure 2. The cost function finds the number of negative comments (obtained by multiplying c by n) and multiplies by the number of likes to determine how many people were affected by the negative comment. We do this because negativity is often a spiraling effect, where once there is some negativity, it increases. Next, we take the output of cnl and multiply it by the number of posts p to determine the number of people negativity has affected in the entire community. Finally, we divide the output of $cnlp$ by the number of followers f to determine the percent of followers directly affected by the negativity in the comments. The output of this equation may be greater than one depending upon the variables of the user, so we can assume all of the users in the community were affected in this instance. Using the Bertrand Model of Duopoly and changing variables, Equations 1 and 2 show the output to be graphed and compared to find the desired outcome.

5 Results

5.1 Experiment

To implement our cost and payoff functions in order to find the arbitrary value a, we wrote a short program in Python, which is a popular programming language. Within Python, we used the Numpy and Pandas libraries. For the graphs, we used Microsoft Excel's graphing features. Our dataset consisted of about 50 different users on Instagram, and comprises their username, number of followers, the number of likes on the second-to-last post, the total number of posts that the user has made, the number of comments on the second-to-last post, and the percentage of negative comments in the second to last post. These features of our dataset were used as our variables in our functions to be plotted. We use the generated dataset to implement our equations and functions. Finally, when dealing with or dataset, we graph the results in an attempt to shed more light on correlations. This could be potentially used to find the arbitrary value a to be used in further implementations. We used these variables to simulate the possible changes and stages throughout an account. We keep the variables as rigid as possible in an attempt to keep our formulas simplified.

5.2 Data

From the dataset we used, we received the graphs in Figures 1 through 4.We were able to determine loose correlations between the number of followers and the number of comments, and our cost and payoff functions. Within these graphs, we removed outliers from our dataset to better discover correlations. Using our cost compared to payoff graph in Figure 4, we were able to determine that there is a positive correlation between the cost and payoff.

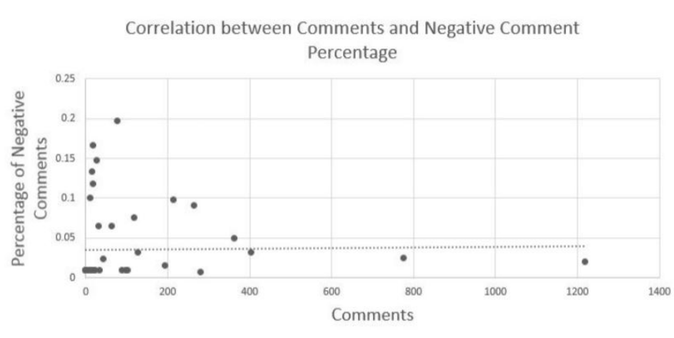

Fig. 1. Correlation Between Comments and Negative Comment Percentage

Figure 1 shows that the number of comments does not really seem to have any link with negative comments percentage, shown by the virtually nonexistent correlation.

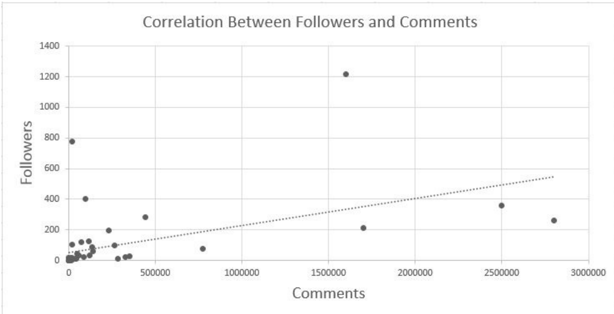

Fig. 2. Correlation Between Followers to Comments

Figure 2 shows a strong positive correlation between the number of followers a user has and the number of comments on their post(s). This strong correlation shows that an increase in the number of followers a user has normally results in an increase in the number of comments The more followers a user has, the more comments they will have.

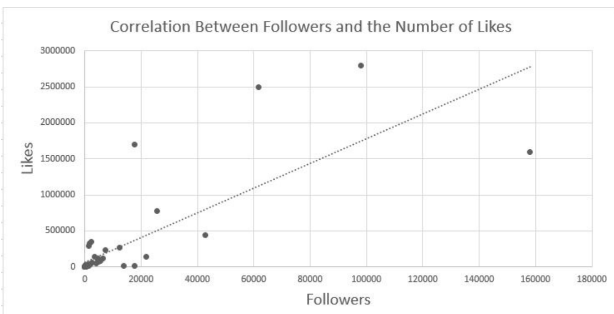

Fig. 3. Correlation Between Followers and Likes on a Post

Similar to Figure 2, Figure 3 shows that an increase in the number of followers will lead to an increase in the amount of likes that user's post has. This is not necessarily a bad thing, seeing as how there can not be any negativity in the number of likes on a post.

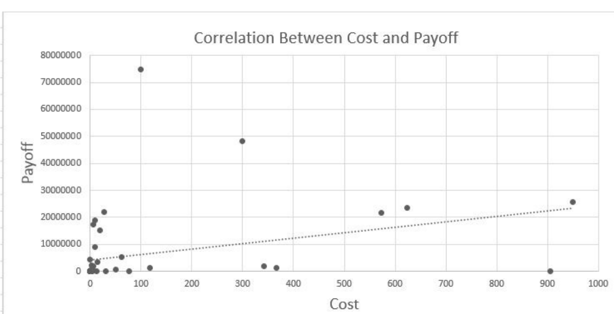

Fig. 4. Correlation Between Comments and Number of Posts

Since the cost function is the overall negativity in the community and the payoff function is the user's outreach, Figure 4 shows that a greater outreach and popularity is accompanied by greater negativity.

6 Discussion

Over the course of this paper, our solution to the problem of predicting trends in community member's actions showed how the different aspects of social media can reflect the most likely beneficial outcome of the user's possible action choices.

In this paper we were trying to solve the problem of reaching the optimum community size in social media platforms, or a community with minimized negativity and maximized outreach. In order to solve this issue, we proposed a payoff and cost function of outreach and negativity, respectively. Before implementing game theory, we attempted to discover the value of the number of followers and negativity would change as the moves went on. We were unable to discover this value, and also unable to implement game theory due to technical limitations.

After conducting the experiment, the team discovered that our predictions were inaccurate, but have the potential to be accurate with further research and fewer limitations. Due to limitations of both time and equipment, we were unable to attempt to apply the Python library Gambit for game theory and fully test our solution. This will likely be the first and most important way to further our study. Within our study, there are other ways our methods and results can be improved. One task to improve our experiment would be to alter our functions in order to determine if the methods we used were flawed, as well as expanding the dataset in order to compile a more complete list of users and variables. Furthermore, changing the cost and payoff functions to be able to take a wider range of variables as well as less rigid variables into account in order to allow flexibility in the scope of social media platforms.

6.1 Implications of the Research on the Field of Study

The solution that can potentially be reached with further studies can be applied to several other social media platforms. However, in these other platforms, they may require a program to detect any hate or spam comments with the posts. Beyond social media applications, our solution can be adapted for both marketing and politics. With in politics, it can be used by politicians attempting to maximize their popularity and minimize the amount of negativity they receive. In the marketing aspect, our solution can be used because companies want to maximize the popularity of their products, increasing profits, and minimize the negativity directed at their product or company.

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