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Drinking with Friends: A Cellular Automata Approach to Modeling Peer Influence on Binge Drinking Behavior

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Drinking with friends

A cellular automata approach to modeling peer influence on binge drinking behavior

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Introduction

The heavy consumption and abuse of alcohol among post-secondary students has gained considerable attention in recent decades, influencing a significant body of academic research [2][7][9][15]. Heavy episodic alcohol consumption, known as binge drinking, continues to be a popular social activity among post-secondary students, with a larger proportion of this population engaging in binge drinking than non-students of the same age [7][13].

Binge drinking is defined as the consumption of five or more drinks in a single session[1] (see [3][12]) and has been associated with a number of negative effects, including many with health, behavioral and social consequences [1][5]. Alcohol-related health and wellness concerns are particularly well-documented in recent research. Long-term alcohol abuse is commonly associated with direct toxic effects such as liver and kidney damage [24]. Various health risks impact the post-secondary population in particular, including illness, injury, risky sexual behavior, alcohol dependence, and death [7][22]. Wechsler and Nelson [14] report than an estimated 1700 college-aged students die from alcohol-related injuries every year, a large proportion of which are associated with motor vehicle accidents. Heavy alcohol consumption has also been linked to poor academic attendance and performance, as well as criminal and deviant behavior, including physical and sexual assaults, vandalism, weapon use, drug use and arrest [2][5][7][10][23]. Second-hand impacts of heavy alcohol consumption have also been documented among non-

[1] There is significant variation and debate in the definition of binge drinking among academic literature. Some researchers include gender-specific definitions, such as five drinks per sitting for males, and four for females [6][7] [14]. Others add time constraints to further define a drinking session [5].

bingers and abstainers within the post-secondary environment, including personal and property victimization, and interrupted study and sleep patterns [9][22].

Although its consequences are well documented, binge drinking is a complex behavior associated with and influenced by a variety of environmental, biological and social factors. Within the post-secondary setting, age, gender, family history and ease of accessibility to alcohol, among other factors, have been found to be related to the prevalence of binge drinking [13][15]. In addition, recent research has further stressed the importance of social influences on post-secondary student binge drinking. Such behavior is more prevalent among students involved in athletics and social organizations including fraternities and sororities [14][15][22]. The (actual or perceived) drinking patterns of peers and the approval of friends may also influence one's alcohol consumption [8][9][14]. These findings support the theoretical contributions of social learning theory, which proposes that human behavior, including binge drinking, is learned from interactions through peer groups and exposure to alternate values and norms [22]. With this in mind, investigating the effects of peer influences on binge drinking behavior may provide a better understanding of alcohol consumption in post-secondary students.

Research through simulation modeling

While conventional statistical techniques are able to effectively demonstrate the importance of peer influence on binge drinking, they are limited in their ability to answer more complex questions about such behavior. For example, one may be interested in understanding how different types of social interactions effect the development of binge drinking among groups of college and university students. Similarly, one may be interested in understanding the effect of environmental factors on binge drinking behavior. Through the use of non-linear mathematical modeling techniques, these areas of interest may be explored.

In addition, such techniques may be employed in simulation models to test a variety of scenarios where “what if?” questions may be posed. For example, one may want to know if binge drinking behavior develops differently among populations that have different proportions of drinker types. Alternatively, one may be interested in knowing if populations of binge drinkers change over time when various social and environmental influences change. Through the use of non-linear mathematical modeling, it is possible to capture these complex dynamics and answer research questions that could influence public policy.

With respect to peer influences on drinking behavior, several non-linear mathematical models have been proposed. For example, Gorman, et al developed an agent-based model to examine social dynamics and environmental influences on agents’ drinking behaviors [4]. Through a variety of simulations they were able to demonstrate that contacts between agents were important factors in the social dynamics that influenced drinking. Similarly, Ormerod and Wiltshire developed an agent-based model to analyze the growth of binge drinking in the United Kingdom [11]. Through development of a theoretical model and calibration with survey-based data, the authors were able to show that the imitative behavior spreading across social networks is a reasonable hypothesis to account for the patterns of binge drinking that had been observed in recent years.

Agent-based models, however, have some limitations. Applications of agent-based models in the social sciences often involve human agents with complex behavior and psychology that are difficult to quantify and calibrate. As a result, caution must be taken when interpreting the quantitative outcome of such models when the accuracy of the inputs is questionable [25]. In addition, agent-based models require the description of individual units which can be computationally intensive and time consuming [25], limiting the number of agents included in a simulation, as well as their detail and level of interaction.

In this project, we adopt Cellular Automata (CA) modeling as a means to focus solely on the elements of concern: individual state (binging) and local interactions (peer pressure). CA models are well suited for exploring the dynamics that occur within a population, and are useful for visualizing the clustering behaviour of communities. With this more abstract approach, it is possible to simulate large populations with reasonable computational requirements.

Cellular automata modeling

In a CA model, a population can be represented in a two dimensional square grid where each cell represents an individual in the population [17]. The state of each cell can vary depending on pre-determined rules. These rules are derived from an existing theoretical framework describing a particular phenomenon and are used to model what is happening in the real world. A CA model can effectively capture social interactions that happen over time [16][19]. Since each cell has the capability of holding the information pertaining to that cell, changes can be recorded. In general, CA models measure time discretely, in other words, progress through time is represented as a series of time steps. The cells capture the information at each time step and their states can alter through successive time steps [20].

In order to simplify the complexity of human behavior, CA modeling must make assumptions which are supported by research. While each cell in a CA model can potentially be influenced by surrounding cells, this model accounts for only four neighbors: north, south, east and west. The assumption here is that individuals are not impacted by everyone that physically surrounds them, but only those people they have social contact with. This type of neighborhood is called the von Neumann neighborhood.

In this CA model the social interactions progress through time steps. The cells capture the information at each time step and alter their state through successive steps. These updates happen simultaneously following the pre-determined transition rules. We assume this model to have a constant population even though there are processes of births, deaths, immigrations and emigrations in any population.

The model

This model represents a social community of individuals with a high-risk of binging behavior that extends beyond the physical boundaries of a specific geographical area. Specifically, we consider a community of post-secondary students and their direct social acquaintances. This community consists of three types of individuals.

- Non-Binger (NB)
- Occasionally Binger (OB)
- Frequently Binger (FB)

An individual can only play a single role at a time. Over time individuals can transition from one state to the next based on predetermined rules. For example, an OB can become a FB due to social interaction, and later become a NB following a health problem. The purpose of this study is to analyze the evolution of a fixed population in a community of such individuals.

Model design

This CA model integrates social influences and transition rules. The cells in the grid interact as individuals would in a social community. The cells change over time as they receive and give social influence to their neighbors. After each iteration, the grid is updated to reflect the modifications. Since this is a scenario-based model, the variables can be set according to input data and adjusted to reflect possible changes in the community. Although the cells are stationary, the state of the cell can vary. This reflects the change in social state individuals may experience during their life course. These changes occur as a result of social influences and experiences. We selected the von Neumann neighborhood and use the average of the surrounding cells to describe these social interactions. Further, at any given time only a random subset (i.e., one to four) of the neighbors exert social influence on a cell.

Modeling Process

The process of developing this model was similar to that described in [18]. We began by surveying existing literature in order to generate a conceptual model of the phenomena under study. We found that for binge drinking, while its characteristics and effects have been well studied, the role of peer pressure is less well understood. Clearly it is important: within the post-secondary setting, direct peer influences may include pressure to consume alcohol by offering a drink, buying a round, or encouraging drinking games [21]. Social influences may also be indirect or passive in nature, associated with perceived norms of heavy drinking among peer groups, and general accessibility to alcohol within the post-secondary education setting [9][15]. Ambiguity can be discouraging for a modeling project, but it is precisely due to the difficulty of performing real-world experimentation and study on this topic that makes this kind of attempt useful.

We proceeded to develop a mathematical model describing the various categories of binge drinkers, and how change in category occurs. A computational model was built, and preliminary experimentation showed the behavior resulting from the proposed model. From this evidence, we returned to the conceptual and mathematical models, and revised them. This process continued iteratively, noting new behavior, and making changes as our understanding improved or as new questions were raised. We retained intermediate models so that variations in modeling binge drinking can be compared. Through this exploration of the theoretical space associated with modeling binge drinking, we were able to identify some model characteristics that matched our understanding of the phenomena, and some that did not.

This approach is well suited to problems like this where the existing research does not yet fully explain how a process takes place. Combining mathematical modeling with computational simulation allows researchers to develop a possible model of the target phenomena and then test it in action to see if its behavior matches real data and experience, and is also consistent in a logical sense, i.e., the entities and mechanics in the model behave as expected. If the design results in behavior that runs contrary to the intention of the model, such as static behavior when dynamic phenomena are being modeled, or if there is a lack of expected interaction between entities, these are problems with the model itself. With complex phenomena, such problems may only become obvious through experimentation of the model in various scenarios, thus this is not a trivial step in this kind of research.

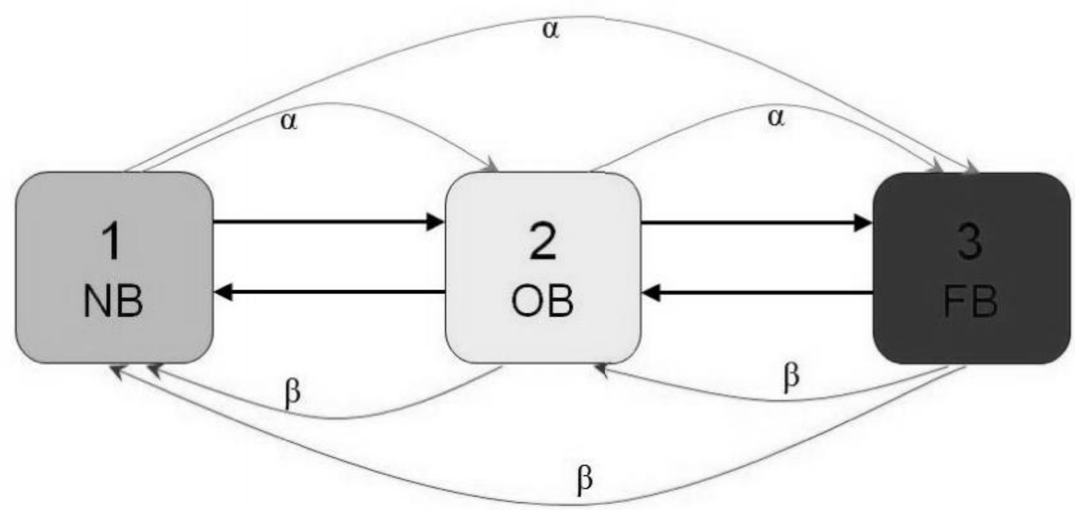


Figure 1: Model of drinking transitions

A deterministic model for binging

Let $k \in \{1,2,3\}$ denote the state of each individual, where 1 is for NB, 2 is for OB and 3 is for FB. Let the location of each individual s in the grid be denoted by (i,j) and $N_s = N_{ij}$ show the neighborhood of (i,j). We assume $1 \leq N_s \leq 4$. For each individual (i,j) in the grid we define $C_{ij}(t)$ as the social counter of the individual (i,j) at time t. Suppose s is of type k' for $k' \in \{1,2,3\}$ and $v_{kk'}$ denotes the values of the social influence of an individual of type k on s in the neighborhood N_s. Then we define

$$C_{ij}(t) = C_{ij}(t-1) + \epsilon + \sum_{k \in N_{ij}} v_{kk'} \qquad (1)$$

The parameter ij a randomly determined value with a normal distribution centered on zero. Using gure 1 values of $v_{kk'}$ are $\alpha > 0$ or $\beta < 0$ based on the type of surrounding neighbors.

Rules:
We assume that at the initial state $C_s(t)$=0 for each cell *s* in the grid.

Case I: *s* is a NB (*s*=1)

- if $C_s(t)$<-1 for *T* time steps then *s* becomes an OB (*s*=2)
- if $C_s(t)$<-10 then *s* becomes a FB (*s*=3) in the next time step

Case II: *s* is a OB (*s*=2)

- if $C_s(t)$<-1 for *T* time steps then *s* becomes a FB (*s*=3)
- if $C_s(t)$<-10 then *s* becomes a FB (*s*=3) in the next time step
- if $C_s(t)$> 1 for *T* time steps then *s* becomes a NB (*s*=1)
- if $C_s(t)$> 10 then *s* becomes a NB (*s*=1) in the next time step

Case III: *s* is a FB (*s*=3)

- if $C_s(t)$>1 for *T* time steps then *s* becomes an OB (*s*=2)
- if $C_s(t)$>10 then *s* becomes an OB (*s*=1) in the next time step

Here *T* is the number of time steps needed to effect change in individuals, and 1 and -1 are considered as threshold values for gradually changing the states of individuals. The thresholds 10 and -10 are considered for major circumstances that force individuals to change their states to 1 or 3, respectively.

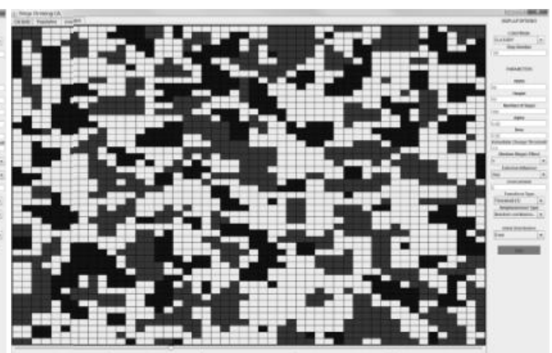
Simulation Details
The binge drinking cellular automata application was developed in Java, and as such can run on any common operating system. Many parameters can be altered, including the dimensions of the grid and length of the simulation. Currently, grids of roughly 10,000 cells or less are supported. Execution time for an experiment can vary between a fraction of a second up to one minute for large grids and/or long simulations (2000 or more steps). Short execution times for experiments are a priority since it allows for more responsive and interactive exploration of the configurations of the simulation. The program features tabbed output allowing visualization of the cellular automata itself, as shown in Figure 2, as well as plots of interesting metrics, including population distributions and average cell value. Plot functionality is supported by the versatile JFreeChart library.

Experimental Results
Due to the exploratory nature of the development of this model, many possible configurations of parameter values and options were available for running experiments. The experiments described here used a 50 cell by 50 cell grid, and were run for 600 steps. Various options were tested on our threshold model using the base parameter values. Plots of the distributions of the populations of cell classes can be seen in Figure 3. The options tested were

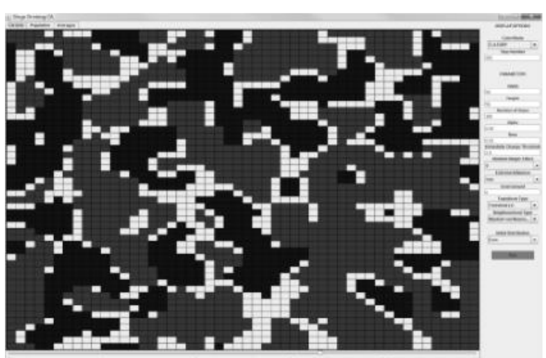
- Whether or not cells in the extreme binging categories (NB and FB) can change
- Whether initial cell values are distributed evenly across categories, or are distributed based on relationships found in a survey.

Testing whether or not cells in the most extreme categories could change was investigated since it seemed conceivable that people entrenched in a given behavior would not be susceptible to peer influence. After all four possible combinations of the options were run, some patterns emerged. If the cells in extreme categories do not change, then the CA as a whole quickly becomes dominated by the extreme categories. Any OB cells are eventually influenced by neighbors of one extreme or the other, until no mid-value cells remain. If cells of the extreme values can change, a short initial period is characterized by a flourishing of mid-values, but these are soon after absorbed into large, distinct clusters of extreme value. The use of the survey relationships for setting up experiments had a clear effect, since NB make up more than half of the total population. In this case, NB eventually dominated all the cells if extreme values were capable of changing; if extremes could not change, the OB cells still overwhelmingly changed state to NB. Notably, in all of these experiments the extreme classes end up dominating the cell grid.

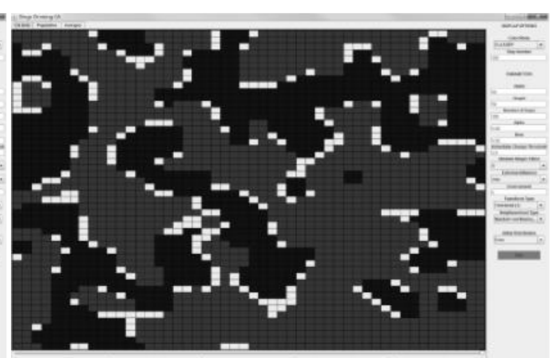
(a) Initial conditions



(b) After 100 steps



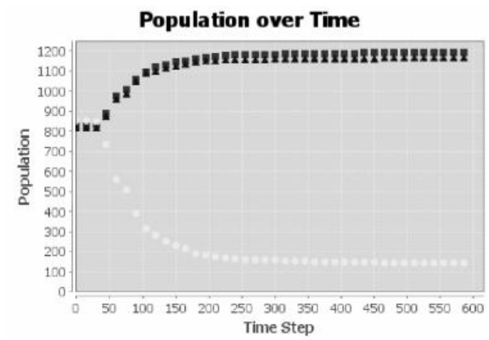
(c) After 200 steps



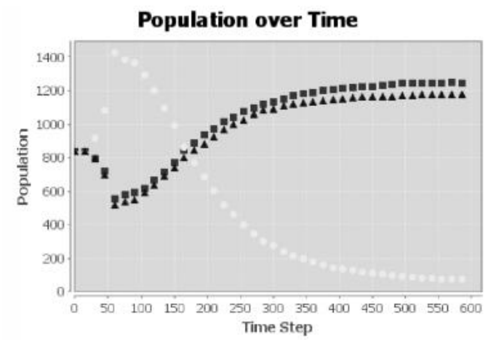
(d) After 300 steps

Figure 2: Binge drinking cellular automata

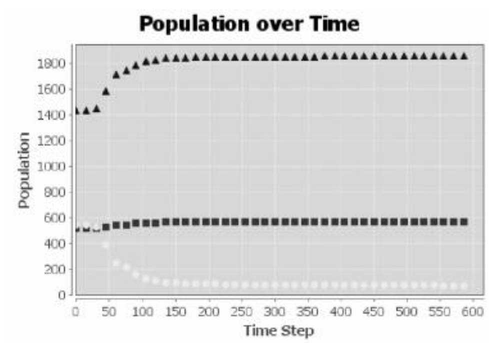
Experiments varying the strength of influence were also performed. The strength of positive influences (i.e., against binge drinking) is determined by α; the strength of negative influences by β. They are usually set at 0.02, which allows for gradual but noticeable change over the lifetime of an experiment. If these values are equal, changing them simply alters the rate of change in the model. However, the model behaves differently if α and β are not equal. With α set to less than β, if extremes cannot be influenced, the stronger force initially converts more OB cells, but once there are primarily only extremes left, the effect is minimal, since the remaining cells are entrenched in their behavior. If extremes can be influenced, the stronger force wins out eventually, dominating all cells. However, converting FB to NB, or vice-versa, is still a slow process. Figure 4 shows two runs of the model with β (negative influence) higher than α (positive influence).



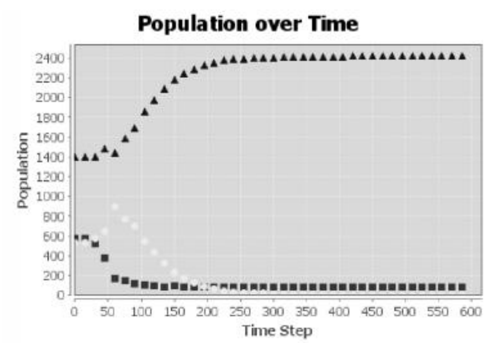
(a) Even distribution, extremes do not change



(b) Even distribution, extremes can change



(c) Survey distribution, extremes do not change

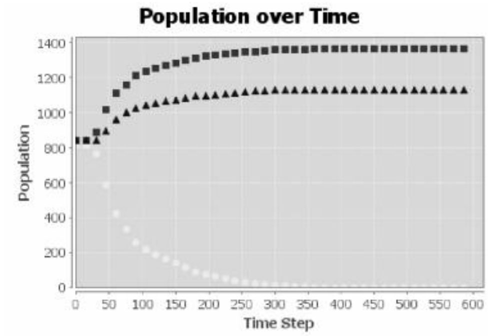


(d) Survey distribution, extremes can change

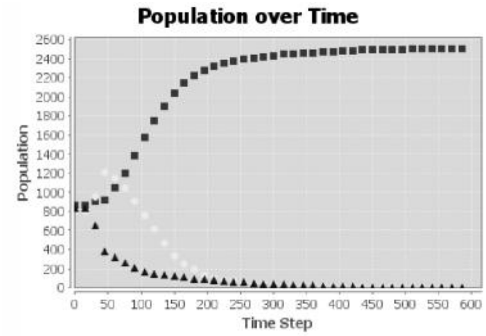
■ Non-Bingers (NB) ● Occasional Bingers (OB) ▲ Frequent Bingers (FB)

Figure 3: Experiments on population distributions

In the base model, OB have no influence on similar neighbors. One alternate to this is for OB to have an effect equal to α-β. Thus, they have a positive effect on each other if α is greater than β, and a negative effect if the reverse is true. However, this alternate rule simply accelerates any overall change in cell value. OB cells drift towards extreme values more quickly, and the overall state of the system approaches a steady state rapidly. This is true whether or not extreme values can be influenced.



(a) Extremes do not change



(b) Extremes can change

■ Non-Bingers (NB) ● Occasional Bingers (OB) ▲ Frequent Bingers (FB)

Figure 4: Experiments on influence strength, $\alpha = 0.02$, $\beta = 0.03$

Conclusions

The models included in this paper present initial exploratory experimentation that is part of ongoing research into the social factors associated with binge drinking behavior. The cellular automata approach proves to be a promising method for investigating peer influences as it allows for both local and global population effects to be considered while taking into account the dynamics of various types of social and environmental influences. In the current work we adopted a simple approach that allows us to vary the flexibility of binge drinking classifications, the distribution of initial behavior classifications, and the strength of positive and negative types of influences.

Results of the experiments revealed several interesting patterns of social behavior including considerable variation in the speed at which individuals change their binge drinking habits. Such findings are encouraging at this early stage as they could lead to more significant discoveries in future research. For example, with further refinement to the model including the specification of positive and negative influences, the results of experimentations could lead to important policy implications for effective intervention strategies. It can also be used to support research employing more traditional methods, such as by suggesting what kind of questions should be asked in future surveys. We hope that this shows how simulation modeling can be used even during exploratory phases of research.

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