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Common Crowd Dynamics: Shaping Behavioral Intention Models

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COMMON CROWD DYNAMICS: SHAPING BEHAVIORAL INTENTION MODELS

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As the human population grows, so too does the need to understand human behavior. One particularly important aspect of human behavior is how it changes within conglomerations of people, i.e. crowds. In this thesis, a method for modeling crowd behavior is proposed. This method draws inspiration from the concept of behavioral intention and the related forces of attitudes, influences, and social norms. These topics are first defined and detailed, followed by a survey of related research. Next, the model is presented and adapted to three common crowd dynamics, each stressing a different component of behavioral intention. Observations are made about these models, and extensions to the models and directions for future research are considered.

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CHAPTER 1

INTRODUCTION

The capacity to predict and better understand human behavior is a powerful tool for improving nearly any computational endeavor that involves human interaction: architecture design, evacuation planning, crowd control, disaster response, anti-drug campaigns, etc. The opportunity for such study has never been better. As the human population has grown in number and spread across the planet, so too has the opportunity for humanity to demonstrate special forms of behavior observed when masses of people gather together and form crowds. Crowd studies have been further augmented by the maturation of the social and psychological sciences and by the development of computer technology powerful enough for modeling and simulation.

Alongside contributing factors such as industrialization and the rise of cities, Reicher (2001) marks the French Third Republic as the "birthplace of crowd psychology". Reicher supports this claim with an example of the debate between Scipio Sighele and Gabriel Tarde in the 1890s. This debate concerned how to determine criminal responsibility in the crowd, struggling to distinguish between individual and crowd forces. It is a problem that merits investigation to this day. The 1890s also saw Gustave le Bon (1895) develop his theories of the crowd mind, observing that concentrated masses of people are more than just the sum of their component individuals; other forces must be at work. The rising prevalence of crowds and opportunities to observe them have continued to spawn new lines of research and debate throughout the twentieth century and into the twenty-first.

Related to and often part of crowd research is the study and modeling of individual behavior. The term "individual" does not imply that such models isolate a person from others. Rather, individual behavior models incorporate endogenous attitudes originating from within the person and account for the outside effects of physical and social influences. Which forces are most important, their effects, and how they interact with each other is a target of extensive study, and many different models have been proposed. Among these models are Ajzen and Fishbein's theory of reasoned action (1981) and other models descended from and inspired by it. The variety of model components – the different types of attitudes, influences, and social norms – are also the subjects of their own studies.

In this thesis, the concepts of behavioral intention and the theory of reasoned action are applied to crowd behavior, more specifically three common crowd dynamics. The first and current section provides an overview of the types of research and the applicability of said research. The second section provides background information about crowds and behavioral intention. Two models of behavioral intention, the theory of reasoned action and the theory of planned behavior, are detailed, and the models' components of attitudes, influences, and social norms are each investigated further. The third section describes some of the latest state of the art related research concerning behavior models and crowd dynamics, from social studies to proposed models to simulations in virtual environments. The fourth section proposes a model for crowd behavior inspired by the theory of reasoned action and its adaptation to three scenarios commonly found in human societies. Lastly, the fifth section draws some final conclusions and suggestions for extension and future areas of study.

CHAPTER 2

BACKGROUND

The concepts of "crowd" and "intention" may seem intuitive, but nevertheless, an accumulated literature has served to weed out inaccuracies and misconceptions, providing a firm foundation on which researchers may communicate. First, crowds are defined and their importance, internal processes, relationships, and simulation are investigated. Some historical context is also provided, showing some trends in opinion over the past century. Next, behavioral intention is described in greater detail, and various models of intention are also explored. Behavioral intention may be viewed as a complex web of interacting internal and external factors. Among these factors are attitude, influence, and social norms. These factors are examined more closely at the end of this section.

Crowds

As the world approaches (or has exceeded, by some estimates) seven billion people, planet Earth has become increasingly crowded. A crowd exists wherever humans gather en masse: sports stadiums, stock exchange floors, enthusiasts conventions, political protests, etc. Musse and Thalmann (1997) define crowds as "a large group of individuals in the same physical environment, sharing a common goal". These crowds may be viewed as a hierarchy: individuals are collected into groups, and the resulting groups are collected into a crowd (Musse & Thalmann, 2001).

The ubiquity of human crowds means research and understanding has a wide variety of applications, from psychology to transportation research and architecture (Treuille, Cooper, & Popivic, 2006). Sociologists often study crowds' responses to extreme stimuli, such as natural disasters and social upheaval, but Musse and Thalmann (1997) stress the importance of studying normal crowd behavior. “Normal” refers to the type of behavior that is not a response to change but the typical response to a constant environment. Another reason that improving the current understanding of crowd behavior is so important lies with the unavoidable nature of social interaction. The purest, most elemental form of individual behavior is difficult to model due to social interference; the complexities of interrelationships always exist (Musse & Thalmann, 2001). Therefore, a better understanding of crowd behavior may also reveal new avenues for thinking about individual behavior.

Crowd behavior is the set of actions resulting from people's intentions (i.e. planned actions not yet committed), beliefs (i.e. internal status), knowledge (i.e. information about the environment), and perceptions (i.e. sensory input of the environment). When crowd behavior is treated as a set of actions, the question remains of how to interpret human control in a crowd. Do the actions produce effects analogous to a particle system, or maybe crowds are more akin to a flock or behavioral system?

Musse and Thalmann observe that these micro and macro approaches have different properties. A particle system has no hierarchy and follows simple rules much like a physical particle system employing charged fields. Flocks on the other hand consist of two levels, the flock and the agent, where individuals in the flock express limited intelligence and act according to their local surroundings. Lastly, a behavioral system uses defined rules, organizational structures, and assumes a greater level of human intelligence of its agents than either flocks or particle systems.

The study of crowd behavior involves observing a variety of group effects on the crowd. These effects may be classified into a number of categories, among which are polarization, the sharing and adding effects, and domination (Musse & Thalmann, 1997). Polarization is the formation of two or more groups within the crowd that possess diverging characteristics. The sharing effect involves others' actions influencing individuals, while the adding effect involves others' actions influencing entire groups. The domination group effect occurs during the rise of a leader or leaders in the social hierarchy, their influence spreading to lower members of the hierarchy.

Observing the above effects and attempting to quantify them is a delicate process. Translating observations of real-world crowds into models and simulations can be similarly delicate, and Berk (1974) argues that many of the problems in simulating crowds result from epistemological issues. Quantifying the concept of the mind is a difficult endeavor, especially when it comes to crowd behavior. This difficulty fosters different interpretations and approaches to a working model, starting at a fundamental level: Berk notes that early researchers disagreed concerning the rationality of crowd behavior.

Reicher (2001) argues that the scarce study of crowds has largely been separated from psychological research. In Le Bon's (1895) classic work on crowds, individuals lose their normal psychological capacities when in a crowd and act with a primal irrationality. Individuals trade their sense of self and responsibility in exchange for strength of numbers, and the loss of self-interest leads to the irrational behavior of the group mind, even leading to putting one's own health at risk (similar thinking is expressed in deindividuation theory). Into the early 1900s, crowd psychology consisted merely of explanations that served only to reinforce unscientific assumptions about crowd behavior; the crowd was anonymous, random, and unknowable (Reicher, 2001). Reicher's main criticism of this approach is that Le Bon's arguments are too divorced from social context and give the crowd too much credit for its behavior.

Two principles which support the above criticism have grown stronger over the past century. The first principle is that crowd behavior mirrors its culture and society. Reicher provides an example of the English food riots in the early 1800s. The riots were triggered not by primitive hunger but by the social transition to a market-based economy and the wrongdoing perceived by the population. The second principle is that crowd behavior in turn alters society. The resulting social changes of the crowd-society relationship may be viewed on three levels. At the individual level, crowd behavior changes how people view themselves as social actors; participation strengthens ideology. Secondly, crowds serve as a fertile ground for new ideas to develop and spread. Lastly and most drastically, crowds can alter whole societies. Reicher points to any revolution for evidence of the powerful potential inherent in a crowd-society relationship.

In addition to Le Bon's idea of the irrational group mind, another common theme in early crowd research is that collective behavior entails deviant behavior (Couch, 1968). This theme followed from how Le Bon viewed collective behavior as a pathological form of behavior. Among these old ideas, Couch identifies several stereotypes and provides arguments against them. The suggestibility stereotype indicates that the passions of the crowd cause it to be easily manipulated by outside forces. Couch counters that if crowds are so suggestible, then why do outside authorities have so many problems dispersing them? Crowds are often ill prone to acquiesce to authority. Against the destructiveness stereotype, while the crowd may be responsible for relatively minor property damage, most of the destruction is caused by the established authority which often causes loss of life. Against the emotionality stereotype, the forces acting against the crowd are often as emotional as the crowd they face, and individuals often encounter emotionally charged situations outside the crowd, so there is little to distinguish the emotion in a crowd from any other emotional event. Couch too suggests abandoning the line of thought that crowd behavior is abnormal and instead recognize crowds as a legitimate social system with unique qualities.

Granovetter (1978) proposes an improvement to the classic way of thinking about collective behavior, that collective behavior somehow strips away “civilized” behavior and exposes some feral element underneath. Instead, outcomes are explained by norms, beliefs, preferences, motives, etc., and failing crowd norms and beliefs are replaced with new ones. However, knowing the new (or possibly old) norms and beliefs is necessary but not sufficient for explaining outcomes. Also needed is a model for how individual preferences interact with each other. This model differs from a simple “everyone joined group A because they all believed in A”. Instead, it addresses how a heterogeneous collection of beliefs interacts and aggregates across a rational, heterogeneous population.

Thresholds form a crucial part of Granovetter's model for decision-making processes. For example, should a person join a riot? The affirmative decision becomes more appealing as the size of the riot increases; a larger riot means a lesser chance of getting personally identified and apprehended. Even individuals with opposing beliefs may find themselves in the same crowd if they possess similar thresholds. Granovetter suggests a variety of applicable situations for the threshold model: “diffusion of innovations” such as technology adoption, population migration, leaving a social gathering, the voting bandwagon effect, worker strikes, etc. Other examples include the spread of rumors, where people need to hear from multiple sources before believing new information, and the spread of diseases, where people need to contact a number of infected before contracting the illness.

The above discussion of crowds has proposed a few arguments against the early ideas of crowd irrationality and deviancy. If at one end of the spectrum is impulsive crowds acting in a haze of passion, then at the other end of the spectrum is the use of game theory and its rational players' strategies used to describe crowd behavior. In decision theory, a player acts to maximizes rewards or minimize costs. Berk (1974) approaches crowd behavior using both decision theory and collective decision-making, crediting individuals with a large degree of rationality. It should be noted, however, that it is possible to simultaneously act rationally and incorrectly and that the rationality of a person may be measured in degrees.

Treated as a game, a player is a single person, and individuals increase their payoffs when they collaborate. This rationality is justified by a series of examples where groups of people are intuitively attributed as incapable of rational behavior but exhibit the opposite. Mental patients have been observed to develop a value system that minimizes discipline by authorities while simultaneously maximizing their ability to coerce each other. Other examples include the calculation behind conflict among gang members, the proposed rational self-interest in juvenile property crimes, and civil disorders that communicate social problems to an outside audience.

While crowds may be naturally observed in the real world, simulating models on a computer serves as a way to more easily compare model behavior with observed behavior. The simulation of crowds started gaining momentum in the 1990s due to the rise in cheap computing power and research's applicability to planning areas for human traffic (Briano & Revetria, 2008). The simulation of human crowds, however, is made difficult by both complexity and subtlety (Treuille et al., 2006). An individual's motion and their interaction with the surrounding environment is relatively simple in simulation; the interactions and relationships between a network of individuals is not.

One popular type of model used in computer simulations is the agent-based system. Agent-based simulations possess a strength for mirroring real-world individual decisions. They account for each individual's unique state and allow for unique parameters which lead to interesting heterogeneous behavior. However, agent-based simulations can be difficult to develop behavioral rules for and are computationally expensive. Local path planning often yields unrealistic movement as well.

Realistic movement involves simulated crowd behaviors consistent with observed real-world crowds using collision avoidance and response at the individual level (Pelechano, Allbeck, & Badler, 2007). Animating a large crowd involves studying locomotion, path planning, and navigation as well as simulating behavior using cognitive models. Different model approaches struggle in different ways to define the motion of a crowd of agents. The social forces model looks approximately like particle movement; it is unrealistic but handles high densities. Rule-based models typically do not use collision detection or repulsion, instead using waiting rules which work better with low-density crowds. They are realistic but work best when handling low densities. Cellular automata models limit spatial movement to a grid. This cell grid interferes with high-density crowds, causing it to be both unrealistic and best for low densities.

Behavioral Intention

Human decision behavior has been studied by researchers hailing from a variety of fields: artificial intelligence, psychology, cognitive science, and decision science (Lee & Son, 2008). This research has also yielded a variety of behavior models. For simulating crowd behavior, Lee and Son used the Belief-Desire-Intention (BDI) framework. The BDI model is based on folk psychology, meaning it does not use cognition theories which incorporate the physical processes of thought. Instead, it describes human behavior and reasoning using terms common in human language: belief is the information assumed by the individual and may be incomplete or incorrect, desire is the state a person wishes to achieve, and intention is the person's committed desire. Using the BDI model as inspiration, Briano and Revetria (2008) worked with another framework called PECS (Physical, Emotional, Cognitive, Social). An evolution of the BDI framework, the PECS model incorporates human social behavior.

The Theory of Reasoned Action

Another model for human behavior is the Theory of Reasoned Action (TRA), developed by Ajzen and Fishbein (1981). In the TRA, behavioral decisions are determined by intention. Intention in turn is composed of two components: attitude, which Bock et al. (2005) describe as “behavioral beliefs”, and social norms, which Bock et al. describe as reflections of “normative beliefs and [the] motivation to comply with [those] beliefs”. Muduganti, Sogani, and Hexmoor (2005) take these terms and interpret behavioral intention as the weighted sum of attributes shown in Equation 1. When endogenous attitude is affected by outside social forces, subjective norms in the TRA serve the purpose of bridging the gap between attitude and behavior (Ryan, 1982).

$$\begin{gathered} Behavioral\ intention = Weight_{Attitude} * Attitude \\ + Weight_{Subjective\ Norms} * Subjective\ Norms + Error \end{gathered}$$

Equation 1. A Behavioral Intention Model. Behavioral intention is represented as a weighted sum of attributes.

As the TRA's focus is on behavioral intention, a distinction should be made between behavioral intention and goal intention (Sheppard, Hartwick, & Warshaw, 1988). Behavioral intention is limited to an individual's committed desire to perform an action and does not involve what the longer term goals resulting from that action may be. As an example from the domain of education, a behavioral intention may be to attend class. This differs from the goal intention of attaining an A grade, which is a possible outcome of the behavior.

Ryan (1982) argues that belief formation and change drive the TRA forward and distinguishes between different types of beliefs. Descriptive beliefs are formed by direct experience. Information beliefs involve accepted information from an indirect source, while inferential beliefs are derived via inference. These inferential forces allow attitudinal beliefs and normative beliefs to affect each other.

Bock et al. (2005) also identify different motivational forces behind intention, which they divide into three categories: economic, social-psychological, and sociological. Economic forces exist when people are motivated by some form of utility, such as wealth, resources, or other forms of satisfaction. Social-psychological forces spur people to action because, by participating, people feel better about themselves and desire to strengthen their relationship with others as well as their access to the benefits such a relationship may entail. Lastly, sociological forces improve the working atmosphere of the organization. Bock et al. include terms such as "fairness, innovativeness, and affiliation" in this latter category.

The TRA has been used with success to model consumer behavior (Sheppard et al., 1988). Not only predicting intention and behavior, the TRA located consumers' attempts to change their behavior, answering the *where* and *how* of behavioral change in relatively simple terms. With these results, Sheppard et al. summarize the goal of the TRA as:

> [to] predict the performance of *any voluntary act, unless intent changes prior to performance* or *unless the intention measure does not correspond to the behavioral criterion in terms of action, target, context, time-frame and/or specificity*. (p. 325; emphasis theirs)

As long as the component terms are used within limits of compatibility, the TRA becomes a powerful tool in predicting human behavior and revealing the process by which that behavior arose.

Interest also exists in testing the limits of this model by applying it to situations somewhat outside the familiar framework, such as when committed actions are not entirely under the performer's control or when the target person is not in a situation to possess a fully formed intention. Since the model applies only to behavioral intention, the model's power weakens from interference by external factors, otherwise known as uncertainty in the intention-performance relationship. As an example in consumer behavior, a person may have the intention to buy a certain item, but the item may become too expensive or is physically unavailable. Therefore, the intention cannot lead to the desired action.

Since the TRA concerns itself with a single behavior, modifications need to be introduced for choosing among alternatives. Sheppard et al. mention a greedy approach in which intention is measured towards each competing option and the strongest one is chosen. Another method selects the choice with the most positive attitude and subjective norm.

The TRA model struggles to represent the importance of intending actions which are doomed to failure as well as the consequences of that failure. A distinction needs to be made between behavioral intention and committed intention; the model weakens when predicting what a person actually ends up doing. An intention may fail due to the reasons described above: uncontrollable interference or choosing an alternative. In these situations, intentions should become estimates, and estimates require additional considerations.

The Theory of Planned Behavior

To address some of these identified weaknesses, Ajzen (1991) proposed the Theory of Planned Behavior (TPB) which is an extension of the theory of reasoned action. The TPB focuses on what Ajzen calls “cognitive self-regulation”, using a dispositional approach to prediction. The theory still measures behavioral intention, what Ajzen calls “motivational factors that influence a behavior”, but it incorporates Perceived Behavioral Control (PCB) into the model, the belief in ease of execution of a behavior. The concept of PBC originates from previous studies investigating behavioral control's relationship with predicting behavior. For example, Ajzen and Madden (1986) demonstrated that the addition of behavioral control contributed to the more accurate predicting of class attendance and final grades in students. As in the TRA, attitudes and subjective norms continue their role as predictors in the TPB.

Both the TRA and TPB imply that a person's attitudes are formed after careful consideration of the available information (Conner & Sparks, 2005). General attitudes on their own fail to accurately predict specific behaviors (Ajzen, 1991). Traits, discussed in the “Attitude” section, similarly fail. One workaround to this problem has been to combine many behaviors together and use the aggregate as an indicator of behavioral disposition, but this overly broadens predictive power. Generalizations and aggregations may not help directly with specifics, but they do inform other factors that do help with specifics. Behavioral intention serves as a buffer between attitudes and behavior since attitudes were found to poorly predict behavior directly (Conner & Sparks, 2005). However, how attitudes translate into intentions is less clear. Conner stresses the need for compatibility, “when both are assessed at the same level of specificity with regard to [action, target, context, and time]”.

An attitude may be viewed as the sum of products: beliefs that an action will lead to some consequence times the evaluation of that consequence. This calculation is not performed by the individual every single time but rather is stored in memory. A subjective norm may be viewed as another sum of products: the perceived significant other's normative belief times the motivation to comply with the significant other. In this case, the distinction between normative beliefs and behavioral beliefs may be arbitrary, but the distinction is still useful. Lastly, PBC may also be viewed as a sum of products: the frequency of a factor times the inhibiting (or promoting) power of that factor. These products often possess weights which vary by the target person and behavior.

Also important to the model are salient beliefs, the subset of beliefs that a person uses in a given situation (Ajzen, 1991). Ajzen distinguishes between three kinds of salient beliefs: behavioral, normative, and control. Each type of salient belief corresponds to a component of the TPB. Behavioral beliefs inform attitudes. Normative beliefs inform subjective norms, and control beliefs inform perceptions of behavioral control.

Ajzen stresses that given different situations, the above components may have varying levels of importance and admits that the relationship between the factors requires greater understanding. Since PBC was introduced to account for factors outside a person's control, situations where a person has a high degree of volitional control typically weakens the predictive power of PBC (Armitage & Conner, 2001). Similarly, in situations where intention has little effect on behavior (situations with low volitional control), PCB has a direct relationship with behavior. The TPB may also have a weakness in not accounting for past behavior, which is arguably the best predictor of future behavior (Armitage, 2005). Armitage points to such related phenomena as habit formation and “practice makes perfect”, where in the latter, repetition leads to mastery which leads to an increase in perceived behavioral control.

Attitude

Described earlier as “behavioral beliefs”, attitudes are the psychological constructs used to describe an individual's perspective towards their material and immaterial environment. Ajzen and Fishbein (2005) identify two types of attitude. The first type consists of general attitudes towards physical objects, social groups, events, or other general targets, while the second type consists of specific attitudes towards specific behaviors with respect to similar targets. Describing attitudes as the modern day “crown jewel” of social psychology, Crano and Prislin (2006) write that an attitude represents “an evaluative integration of cognitions and affects experienced in relation to an object”. Varying the strength of an attitude also varies an evaluation's persistence and the consistency of the attitude-behavior relationship.

Ajzen (2005) defines attitude as a “latent, hypothetical construct” which affects entities in observable ways. This reduced definition applies to traits as well, but traits and attitudes are distinguished by their internalized direction. Where traits point inwards towards the individual, attitudes are directed outwards into the environment. Attitudinal responses evaluate an object, i.e. to have an opinion about something, where traits inform the tendency of a response, e.g. to be cautious. Attitudes are considered more prone to change given new input. Traits, however, are less mercurial.

Directed towards some external object, attitudes are measured by the individual’s responses to the object, which Ajzen divides into three categories. Cognitive responses perceive object characteristics. Affective responses indicate a change in the individual's emotional state. Conative responses encompass any potential or executed actions towards the object. Classifying responses into these three categories may require subjectivity, especially when distinguishing cognitive and affective reactions. Which is chiefly responsible in a given situation: the metaphorical “heart” or “head”?

The three attitudinal responses may also be interpreted as three components that work together to form an attitude. Ajzen describes this relationship as a hierarchy, where the cognitive, affective, and conative components form the first-order factors and attitude is the second-order factor. When a response is measured using this structure, the observed attitude predisposes the three categories of responses. Predisposition does not imply universal agreement, however. For example, an alcoholic may possess an emotional reliance on alcohol despite knowing that the substance ultimately causes harm. Though there are such exceptions, correlation among the three components is the rule.

The process by which an attitude forms should be distinguished from the process by which an attitude changes (Crano & Prislin, 2006). Attitude formation results from conditioning or even mere exposure to a received message. Attitude change, on the other hand, may be a bit more involved and is represented by two types of models. Dual-process models, as the name suggests, use a two-step process of message reception followed by attitude change. Examples include the elaboration likelihood model and the heuristic/systematic model. Single-process models use a single cognitive process that accounts for both source and message effects. An example single-process model is the cognition in persuasion model.

The study of attitudes formed the original basis of social psychological research (Ajzen & Fishbein, 2005). From the 1930s to the 1970s, however, attitudes were shown to be poor predictors of behavior, and the relevance of the attitude construct in predicting behavior was called into question. The attitude-behavior inconsistencies came in two varieties: literal inconsistencies, where intentions do not lead to action, and evaluative inconsistencies, where the expressed attitude does not lead to action.

Proposed reasons for the attitude-behavior inconsistencies included response biases. To avoid biased responses, researchers attempted to use indirect approaches for gathering data, but the updated results proved no more valid. Another explanation attributed the inconsistencies to the single dimensionality of attitude. Attitude was believed to be multi-faceted, a property which may have been lost when expressed in a single value. This gave rise to attitudinal components: cognitive (logical attitudes), affective (emotional attitudes), and conative (volitional attitudes). These measures, however, strongly intercorrelated and still could not account for the inconsistencies.

To overcome these problems, the limits of attitudes must be understood. Ajzen and Fishbein explain that attitudes despite the problems above can still predict behavior but only if the behavior broadly represents the attitude domain. This idea leads to the principle of aggregation, that attitudes indicate broad behavioral dispositions, and the principle of compatibility, that attitude and behavior must involve the same action, target, context, and time. Using the principles of aggregation and compatibility, the resulting attitude-behavior consistency possesses three categories of moderators: meta-attitudinal, self-interest, and assessment related (Crano & Prislin, 2006). Example moderators include accessibility, certainty, temporal stability, etc.

Recent research on attitudes has investigated the difference between deliberate attitudes and automatic attitudes, also known as explicit attitudes and implicit attitudes, respectively (Gawronski & Bodenhausen, 2006). Explicit attitudes involve self-reported evaluations, while implicit attitudes are inferred from response latency measures. Modern persuasion models have performed well in explaining how different messages influence explicit messages. Implicit attitude changes, however, are less understood. Gawronski and Bodenhausen suggest that this lack of understanding is due to much of the research either not making the required distinctions or assuming implicit attitudes are stable, resulting from long-term experiences.

Influence

Regardless of the situation, if two individuals are within proximity to each other, the effects of influence are inevitable (DePaulo & Friedman, 1998). Influence is the tendency for one to complement, reciprocate, converge, or compensate their behavior given the behavior of another. Therefore, influence is a form of coordination, and as an individual's social network changes, so too does the experienced influence.

The power of influence should not be underestimated. Kahan (1997) argued that when considering committing a crime, the debate within the individual is not limited to weighing the costs and benefits of the crime itself. Supplementing criminal behavior are the forces of social influence and the criminal tendencies of other individuals. The power of social influence on criminal behavior has even been used as extenuating factors in murder trials (Colman, 1991). As such, a society wishing to deter criminal behavior should enact laws that not only inflict penalties on the perpetrator but also mold the population's social weight ascribed to the crime (Kahan, 1997).

Behaviors driven by social influence may be viewed as goal-oriented (Cialdini & Trost, 1998). The force of social influence is strongest when a behavior services multiple goals. Cialdini and Trost list three goal categories: “to behave effectively, to build and maintain relationships, and to manage self-concept”. Effective behavior is a rational goal because it allows people to reap greater payoffs from their actions. Social relationships need to be built and maintained due to the perceived social rewards that come with conformity, as social deviants are shunned. The dominant culture is not necessarily the target of conformity; the higher valued culture of a peer group may substitute. The third goal category, self-concept, is the positive image of oneself, i.e. self-esteem or an established identity. Without an objective means to establish self-concept, one must look to similar others as a means for self-evaluation.

Social influence consists of three major components: social norms, conformity, and compliance. (Social norms are addressed in the next section.) Conformity involves changing one's behavior to match the behavior of others (Cialdini & Goldstein, 2004), and serves three powerful personal goals: to improve accuracy of perception, gain approval of desirable others, and to avoid a deviant self-concept (Cialdini & Trost, 1998). When the motivation is to increase correctness of perceptions and behavior, the influence component is known as informational conformity (Cialdini & Goldstein, 2004). When the motivation is to gain societal approval, it is known as normative conformity. These two motivations, while conceptually distinct, appear with less distinction theoretically and empirically, and overall, the goal of accuracy simply causes one to conform to a perceived consensus.

The last major component of social influence, compliance, refers to an acquiescence to a request, either implicitly or explicitly (Cialdini & Trost, 1998). Cialdini and Trost list six psychological principles popular among compliance professionals: reciprocity, consistency, social validation, liking, authority, and scarcity. Compliance, like conformity, also has a goal of accuracy (Cialdini & Goldstein, 2004). A rational individual desires to achieve goals efficiently and reap the most rewards, and to do so requires interpreting information accurately. By complying with incoming messages, the expected result is to improve accuracy of perceptions. Another goal of compliance is the goal of affiliation. A fundamental aspect of humans is to associate with one another. By complying with social cues, the expected result is to build a stronger social network.

Influence is not necessarily a one-way process with the large group influencing the small group; it works both ways (Cialdini & Trost, 1998). During conflict arising from challenging the status quo, an individual may choose the minority opinion, which confers some informational advantage (a process known as “conversion”). The majority opinion may also be a viable option when it offers a larger network of social support (a form of compliance). When a majority opinion is contrary to a person's existing beliefs, a comparison process begins where internal ideals are compared to the external ideals of the majority opinion. When a contrary minority opinion is perceived, the individual undergoes a more rigorous validation process that tests for accuracy. After this process, the message is either internalized or rejected. However, a distinction should be made between internalization and the public expression of an internal status. Majority influences appear to favor both public and private, direct forms of expression, while minority influences favor private, indirect expression. No matter the case, when accuracy is the salient goal, people tend to rely on the consensus heuristic/majority position.

The consensus heuristic, however, does not guarantee accuracy. Postmes, Spears, and Cihangir (2001) investigated the effect of group norms on the quality of group decisions, more specifically the effect of consensus norms versus critical thought. It was found that groups relying on consensus norms unreliably arrived at correct decisions. The poor performance of consensus groups was attributed to their preference for shared information, i.e. they overvalued information known to all group members. Though consensus norms are the result of group cohesion, Postmes et al. argue that cohesion is ultimately not the source of poor decisions.

Rather, a group's history plays an important role in the formation of consensus norms, critical group norms, and the quality of group decisions.

Helbing and Molnar (1995) incorporated concepts from social influences into a social force model. The social force model subjects pedestrians to social forces and has been shown to describe self-organization of observed pedestrian behavior. This pedestrian model shares many similarities with the behavior of gases and fluids. People are simulated as particles that behave according to social rules, i.e. changes in velocity are attributed to changes in motivation, not changes in physical force applied to the person (Kirkland & Maciejewski, 2003).

Using three different types of force terms, the model's forces are a measure of internal motivations to move a certain way (Helbing & Molnar, 1995). Each particle is motivated to acquire a certain velocity which represents the rational desire to take the shortest route at a comfortable speed. Particles also maintain a certain distance from other pedestrians and environmental borders. This represents the "private sphere" or "territorial effect" of the pedestrian. Getting too close to these spheres increases discomfort, caused in part by the increased risk of collision. Particles also respond to different types of attractive effects which represent movements towards friends, a street performer, a visually appealing window display, etc.

Social Norms

A standard part of collective action theory, the zero contribution thesis postulates that rational agents require externally enforced rules in order to cooperate and achieve group interests, even when the group interests would benefit the rational agent (Ostrom, 2000). Situations involving the zero contribution thesis have the structure of an n-person prisoner's dilemma game. Despite the dilemma, cooperative behavior is observably widespread. People have been commonly observed to organize themselves to benefit the group. Examples include labor unions, tax payers, voters, etc. Research has struggled to synthesize this observed behavior with the zero contribution thesis into a revised theory of collective action. Among the proposed revisions is to add two additional types of norm-using players which facilitate opportunities for collective action and cooperation: conditional cooperators and willing punishers. How did these types of players come into existence? An evolutionary approach proposes humans evolved to naturally learn social norms and indirectly to generate norm-using players.

In cooperation norms, the use of sanctions is a key part of enforcement and may even be driven by non-selfish motives (Fehr & Fischbacher, 2004). Human cooperation is based specifically on the conditional cooperation norm: cooperate if the group cooperates; defect if the group defects. Conditional cooperators are players that cooperate only when they believe others will reciprocate (Ostrom, 2000). They compose a large proportion of the population, experiments suggesting 40-60 percent. Such players occupy an important roll in the early rounds of games by convincing others to contribute. The threshold in required belief that others will reciprocate varies over the population. Regardless of the threshold, accumulated disappointment leads to decreased numbers of participating conditional cooperators. Therefore, it is beneficial to incorporate mechanisms that prevent this downward cascade.

The second type of norm-using player is the willing punisher. Willing punishers punish those who under-perform or free ride. Free riders are a common problem in cooperative scenarios that involve the public good problem, where a good becomes “public” when no group member can be excluded from the good's consumption (Fehr & Fischbacher, 2004). Punishment often takes the form of sanctions and is an important component of an organization's survival (Ostrom, 2000). One common form of punishment is shame. Shame is not equivalent to guilt, the former being imposed by others, while the latter is a self-imposed punishment for failing to uphold a social norm. Willing punishers may also reward those who perform above the minimum required, assuming the role of "willing rewarders".

Conditional cooperators and willing punishers may use social norms to promote collective action, but what exactly defines a social norm? Kandori (1992) defines social norms as "the specification of desirable behavior together with sanction rules in a community". Social norms are an understanding shared across a group of people concerning which actions are required, acceptable, or forbidden (Ostrom, 2000) and generally consist of the traditions and taboos within a society (Cialdini & Trost, 1998). However, a social norm consists not of codified laws but of understood rules and expectations of behavior, deriving its power from the social network, not the legal system. A norm is considered "social" when it is shared by multiple people and is sustained by the people's approval or disapproval (Elster, 1989). It should be noted that individuals within a society may adhere to norms to different degrees and that norms may be more representative of the collective as a whole rather than a random member individual (Cialdini & Trost, 1998). Individuals use the norms of their peers as the standard by which they assess their own behavior (Schultz, Nolan, Cialdini, Goldstein, & Griskevicius, 2007). The group affected by a social norm can vary widely in size, from a small family to a national society (Fehr & Fischbacher, 2004).

Social norms, though frequently discussed and used in research, still require additional study in terms of their origins, what defines their content, and how they are enforced. Concerning origins, social norms may form whenever an individual's action affects others in a positive or negative way, though Fehr and Fischbacher admit this view is not wholly uncontested. A norm may arise from survival techniques, which evolve into traditions distanced from their original function (Cialdini & Trost, 1998). Another possibility is that norms arise from a set of rules that society has agreed upon, forming the standard of interaction between individuals. From a societal-value perspective, social norms originate arbitrarily and gain power through cultural acceptance. Therefore, the social norm is not inherently beneficial. Antithetical to this approach, social norms may originate from behaviors that accomplish group goals, proposing an inherent beneficial quality to the social norm.

Social norms are compatible with the economics axiom that agents are rational (Kandori, 1992). Therefore, social norms must exist because the self-interested community sustains them. They must provide certain benefits to those that follow them, what Kandori calls “proper incentives... in every respect”. To provide such incentives, deviants must be punished and the failure to punish must also be punished.

Two opposing lines of thought straddle the extreme ends of economic theory (Elster, 1989). On one end is Adam Smith's instrumental rationality, that human behavior is pulled by the prospect of future rewards. On the other end is Emile Durkheim, who advocated social norms as a behavioral motivator, that humans are pushed from behind by “quasi-inertial forces”. These opposing views draw the distinction that social norms are not outcome-oriented like typical rational actions. Rather, they are either unconditional or the conditions are not future-oriented, fueled by the strong emotions that they can trigger. However, social norms can be guided by self-interest when self-interest determines which norms among many are chosen for a given situation.

The above principles separate social norms from other types of norms. Where social norms are not outcome-oriented, moral norms involve consequences and outcomes. Legal norms require an enforcer motivated by self-interest, whereas social norms are enforced by community sanctions. Private norms are similarly enforced by guilt but typically are not shared with others. Additionally, social norms should be distinguished from habits and compulsive neuroses which are kept private and do not generate guilt on their own.

Social norms both incite and guide human action (Schultz et al., 2007). Therefore, they have actively been used in marketing campaigns and used as a tool in changing drug and alcohol consumption, eating disorders, gambling, littering, etc. Normative messages deployed in the field have had mixed success in changing behavior, sometimes encountering boomerang effects where the person affected acts in an opposite manner in order to assert their freedom.

In broadcasting normative messages, it is important to distinguish between the different types of social norms a message may target. The following norm types, however, are not disjoint sets (Cialdini & Trost, 1998). Some messages target the descriptive norm, a behavioral factor that describes "perception of prevalence", the behavior common to a given situation (Schultz et al., 2007). Descriptive norm messaging may attempt to correct the perception that certain behaviors are more widespread than they actually are. However, since deviant behavior is considered to be both above or below the descriptive norm, the message may discourage some while actually encouraging others. Aside from descriptive norms, other messages target the injunctive norm, what Schultz et al. describe as "perceptions of what is commonly approved or disapproved within a culture". Injunctive normative messages can reduce the boomerang effect by strengthening an injunctive norm so that it overrides a related descriptive norm. Lastly, the subjective norm, defined by the belief that others desire a certain course of action, is particularly important in predicting behaviors and intentions (Cialdini & Trost, 1998). Defining a subjective norm using other norms is relatively simple. The target individual determines the injunctive norms of significant others in their social network and the others' willingness to adhere to those norms. This perception of other's injunctive norms results in a subjective norm.

CHAPTER 3

RELATED WORK

In this section a survey of related work pertaining to behavior models, behavioral intention, and crowd simulation is described and discussed. The behavior models interpret human action in some interesting ways, and they are accompanied by practical applications and meta-analyses. Following the studies of intention, a more in-depth look of the studies of crowds is performed, beginning with crowd formation and transitioning into crowd simulation, human user involvement, macro-level approaches, and simulated evacuations.

Behavior Models

The theory of reasoned action has inspired many models for human behavior. The technology acceptance model draws inspiration from the TRA (Schepers & Wetzels, 2007). In the technology acceptance model, “perceived usefulness” and “perceived ease of use” gauge an individual's attitude towards the use of a technology. The subjective norm's predictive power in this model has possessed mixed results. Schepers' and Wetzels' meta-analysis of a variety of studies showed, however, that the subjective norm possessed significant influence over perceived usefulness of a technology and the behavioral intention to use that technology.

Another model related to the the theory of reasoned action is the MODE model, which stands for “Motivation and Opportunity as DEterminants” (Fazio & Towles-Schwen, 1999). The MODE model typically requires broad motivations to be accurate. In the MODE model, attitudes are activated either consciously or spontaneously, and the activated attitude biases perception of information concerning the attitude object (Ajzen & Fishbein, 2005). This property of attitudes results in the model distinguishing between two classes of attitude-behavior processes (Fazio & Towles-Schwen, 1999). The first class is behaviors involving conscious deliberation. In this class, relevant attitudes are compared to the behavior in question, and alternative behaviors are considered. The second class is spontaneous reaction where attitudes immediately inform a behavior without being consciously considered. Ajzen and Fishbein (2005) concede the work shows encouraging results but point out the model's assumption that only strong attitudes (as opposed to all attitudes) are activated may be false. They also indicate other issues with linking general attitudes to specific behaviors.

Gawronski and Bodenhausen (2006) also worked with attitudes, proposing the associative-propositional evaluation model which assumes a distinction between explicit and implicit attitudes. In doing so, it provides theoretical backing for ideas such as evaluative conditioning, cognitive dissonance, priming, and persuasion.

Lee and Son (2008) attempted to build a comprehensive model for human decision behavior (which includes decision making and decision planning), integrating aspects of previous models which Lee and Son categorize as engineering, psychological, and economical. Their model used Bayesian belief networks, decision field theory, and probabilistic depth first search. Their extensions to the BDI framework showed promising results of simulated human behavior in dynamic and intricate situations.

Similarly, Cho et al. (2008) used the BDI framework for crowd simulation. In their model-based approach, an agent's beliefs represented their perceptions of the environment, while their desires and intentions represented candidate and selected actions, respectively. This perception-action relationship empowered agents to adaptively react to a dynamic environment. Two weaknesses to their approach, however, were the lack sequential actions and cooperative leadership. Cho et al. suggest the addition of planning mechanisms to strengthen the model.

Bock et al. (2005) observed diffusion of knowledge within a firm where knowledge was stored within individuals and must be shared across the organization. They found that people are prone to hoard knowledge rather than share it and are influenced by personal and contextual forces. Even if there exists a system to share knowledge, people have to be encouraged to use it, and counter to intuition, extrinsic rewards may actually suppress an individual's tendency to share knowledge. Bock et al. interviewed executives concerned with knowledge management to determine motivations and beliefs of individuals. They classified the types of motivational forces into three categories (see the "Background" section) and hypothesized that increasing these motivational forces would lead to a greater intention to share knowledge.

Muduganti, Sogani, and Hexmoor (2005) attempted to better understand the reasons why people are accepting of certain technologies while rejecting others. Also under investigation was what causes the "middle ground" situation of a technology being used for a short time or experiencing an oscillating degree of use. Attitudes, subjective norms, and behavioral intentions were distributed on a bell curve ranging from 1 to 7, while an error term ranged from -1 to 1. The subjective norm was adjusted when intention exceeded a threshold. One of the goals was to avoid the use of cumbersome questionnaires to gather data, instead using a computer model. The model tried to improve beyond existing models of user acceptance of information technology. Causal models were considered too "cross-sectional" and temporally "static", while individual reasoning models' narrow focus missed social influences and group decision making.

In other work with behavioral intention, Ryan (1982) explored the model by testing for variable interdependencies. The resulting data indicated that the interdependencies were very complex and formed a variable network. Why not combine the variables if they are so related?

Ryan argued that the data indicated variables that were “distinct but related” and that the merging of variables would be an oversimplification.

Sheppard, Hartwick, and Warshaw (1988) analyzed the TRA in terms of its applications to situations not entirely suited to the original framework. They surveyed a long list of previous studies and assessed the intention-performance relationship as well as the attitude/subjective norm-intention relationship. Ultimately, they found many instances where researchers may have stretched the model's capabilities a bit far, yet the model's predictive power did not collapse under the stress.

The elements of the TPB – attitudes, subjective norms, and PBC – have been used to predict non-donors' intentions to donate blood (Robinson, Masser, White, Hyde, & Terry, 2008). Robinson et al. proposed that the subjective norm may inconsistently contribute to the predictive power of the TPB when surveying donors and non-donors. They extended the TPB by adding factors known to be important in blood donor research: descriptive norms (what behavior significant others ultimately choose), moral norms (the moral obligation to donate blood), anticipated regret (an affective component), and donation anxiety (another affective component). A questionnaire was used to measure the above components on a 1 to 7 scale. In the end, the extended model performed better than the original standard model with 70% variance in donation intention accounted for. Also, it was found that negative feelings of regret made strong motivators to donate blood.

The TPB has also been used in the domain of physical activity research (Armitage, 2005). Regular physical activity is an excellent cancer and disease deterrent, yet many people still do not get enough exercise. While the TPB has been successfully used to predict initiation of an exercise plan, Armitage was curious about longer term maintenance. The paper addresses two

TPB limitations in particular: the TPB's ability to predict sustained physical activity as mentioned above and the TPB's weakness in not using past behavior information. Results showed that PBC was a very important contributor to committing exercise, and that a successful exercise plan also enhanced PBC.

The TPB has been tested by meta-analysis for its effectiveness (Armitage & Conner, 2001). Armitage and Conner collected 185 studies and tracked how well results were predicted by the TPB. The model was found to account for 27% variance in behavior and 39% variance in intention. PBC accounted for more variance in studies where behavior measures were self-reported as opposed to objectively reported or observed. It was also determined that the subjective norm was a weak predictor in intention, but this may have been due to poor measuring techniques or the construct of subjective norms requiring expansion.

Crowd Models

The nature of the crowd's life cycle, how crowds form and disperse, has accrued some interest. Lacks, Gordon, and McCue (2005) investigated crowd formation at the scene of a crime. They discovered a relationship between the nature of a homicide, the resulting crowd size, and how that crowd interacts with law enforcement. Murder scenes provoked increasingly unusual behavior from gathering crowds, indicating the emergence of new norms in the society.

Christou (2010) observed that the life cycle of a crowd is composed of three basic stages. Crowds start with the individual, which grows into a crowd (i.e. “formation”) and eventually decays back into separate individuals (i.e. “dispersion”) as shown in Figure 1. The goal of the project was to build a generic model representing these stages and transitions. Individuals in the model are represented as a vector of attribute values and a personal goal they need to achieve. Crowds are then formed by a set of individuals with similar goals; the crowd disperses after the goal is satisfied. The model was applied to situations of crowd formation around a point of interest, e.g. a car accident, and the crowd continued to grow due to a compulsion by people to join crowds even if they cannot perceive the original point of interest.

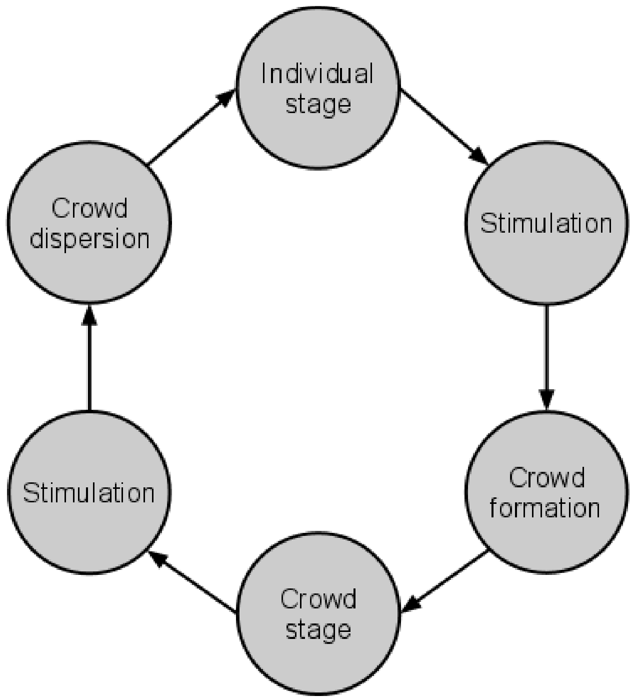

Figure 1. The Crowd Life Cycle Model. Crowds form and disperse in response to a variety of stimuli.

Some researchers identify the many available computer models as being overly simplistic or too focused on a single phenomenon. Fridman and Kaminka (2007) applied Festinger's (1954) social comparison theory, which generalizes across social phenomena, to a model for crowd behavior with the expressed purpose of addressing this problem. The basic principle of the model is that when humans are unable to objectively determine their internal state, they will turn to similar members and evaluate their behavior via comparison, i.e. imitation. The supposed prevalence of such behavior strengthens the model's generality. The model demonstrates many natural behaviors similar to real-world human crowd behavior.

Continuing with perceived narrow focus as a recurring weakness in existing models, Fridman and Kaminka (2009) developed another general cognitive crowd model based on social comparison theory as well as a method for evaluating the model's behavior. The model uses a "contagion" algorithm to simulate social comparison behavior and was developed using the Soar cognitive architecture combined with the GameBots virtual environment. This environment provided a dynamic, 3D world for the agents to move in. The method for evaluation consisted of questionnaires given to humans observing the model simulation, with question format resembling "Were any agents working together?" and "Were there any leaders?". The gathered data suggests that the computer model matches many characteristics observed in a real-world scenario.

Guy et al. (2010) proposed a new algorithm called "PLEdestrians" for simulating large heterogeneous crowds. The goal of this particular simulation was to achieve interactive rates using the Principle of Least Effort; hence the "PLE". A desktop PC could simulate crowds consisting of thousands of agents. Using PLEdestrians, each agent in the crowd calculates a trajectory that is energy efficient and avoids collisions. The model exhibits emergent phenomena observed in real-world crowds: lane formation, crowd compression, and edge and wake effects. Results were compared with previous studies and real-world video of crowds. Both quantitative performance analysis and qualitative comparisons to the video data showed promising results. Limitations to the model include an over-simplified means of calculating energy efficiency based on walking in a straight line. Also, the human representation is a simplified rigid disc instead of the relatively pliable shape humans actually are.

In a similar effort to improve simulation runtime, Guy, Lin, and Manocha (2010) proposed a new trajectory planning algorithm simulating human movement, called RCAP

(Reciprocal Collision Avoidance for Pedestrians). The algorithm assumes implicit cooperation among agents, resulting in a sharing of the collision avoidance workload. Based on a provably sound algorithm for simulating robots, it adds a “human touch” by incorporating human traits to better simulate human collision avoidance, e.g. adding personal space, delayed response times, etc. The model was evaluated against human walking data. In terms of path similarity, real-world data fit well with the simulated data, and the improvements added negligible computation time over the original algorithm. In terms of collision response, the model was observed to match a similar human response pattern of observe and react, followed by a maintenance phase.

Pelechano et al. (2007) faced the problem of simulating both the crowd's local motion and global wayfinding behavior in a dynamically changing environment. Their attempt to realistically and naturally simulate the above motion while maintaining a high crowd density required the combination of psychological and physiological rules into a social forces model. The resulting model is heterogeneous with different traits distributed among the agents. Over long distances, “tangential” forces steer the agents, while over short distances, motion is achieved through collision avoidance and pushing due to conflicts in personal space tolerances.

Balancing local motion and global navigation is a common problem. In another approach, a precomputed roadmap of the static environment is used for global wayfinding on the macroscopic level (Van den Berg, Patil, Sewall, Manocha, & Lin, 2008). The model has built-in safeguards against unnatural oscillatory behaviors, and individual agents have local runtime planning and collision avoidance but do not coordinate with each other, instead performing their own calculations. Agents do not repel each other. Rather, they focus only on collision avoidance and reaching the desired destination. Van den Berg et al. credited this property with generating realistic emergent behaviors. They applied the model to three scenarios: a stadium, an office evacuation, and city crosswalks. Natural behaviors were observed, including lane formation. The model's strengths and weaknesses were credited to its simplicity: speedy computation at the cost of no rules of thumb and some unnatural behaviors demonstrated in specific circumstances. Performance evaluations showed that the distributed model scaled nearly linearly.

The above crowd models have all attempted to simulate crowds in a generic context. The next two research projects, however, apply crowd modeling to more specific domains. The first was by Sarmady, Haron, and Talib (2007). They used a multi-agent model to simulate the crowds of the Tawaf area, which becomes extremely crowded during the Hajj season. While more detailed human behavior models were available, they ultimately opted to incorporate a simpler one due to the need to simulate tens of thousands of individuals. As a result, instead of a a more complex social forces model (which is considered for use in future studies), a cellular automata model is used for microscopic movement. Individuals are given parameters and intentions which map to a series of actions, which in turn map to a series of macroscopic movements. Static path tables are used for macroscopic behaviors so that a circular movement around the simulated Kaaba is maintained. It is hoped that this continued research will produce a better understanding of this social phenomenon and increase the safety of the Kaaba's millions of annual pilgrims.

In addition to situations of extreme crowding like the example above, it has been observed that drunkenness mixed with crowds can also lead to injury. Moore, Flajslik, Rosin, and Marshall (2008) investigated the causes of violence in intoxicated crowds by building a model that could help answer the how and why intoxication increases aggressive behavior. They argued that intoxication disrupts social behaviors, and by disrupting social behaviors, emergent affiliative behaviors that would minimize stress are also disrupted. Therefore, intoxication leads to increased stress in crowded environments, and increased stress leads to aggression and violence. The above ideas were incorporated into a particle model of human behavior, representing intoxication by destabilizing particle trajectories. When simulating the model, two groups were placed on opposite ends of a narrow hallway, and each particle was given a point at the opposite end of the hallway to walk towards. In “sober” trials, the model displayed emergent lane-forming behavior. In “intoxicated” trials, lane formation was disrupted and velocities towards goals were reduced. However, the model is based on data obtained from real-world sober crowds only, and Moore et al. argued that better data was needed based on real-world intoxicated crowds.

In some situations, it is useful to effect change within the crowd by applying external forces. Kirkland and Maciejewski (2003) used the social force model to simulate pedestrian flow and human crowds. They introduced into the simulation autonomous robots to directly influence the behavior of the crowds, encouraging lane formation, while discouraging chaos and traffic jams. These robots, attracted by the crowds of people, attempt to influence behavior by moving at a velocity different from the surrounding people and by using auditory and visual cues. Though their work was very preliminary, Kirkland and Maciejewski showed that introducing a heterogeneous element like a robot can alter the dynamics of a situation. Their next goal became to deploy a robot that could create an attractive social force.

A similar project proposed a method for directing virtual crowds using navigation fields (Patil, Van den Berg, Curtis, Lin, & Manocha, 2010). This method uses a social force model to handle local collision avoidance. Agents are directed by user-defined guidance fields, even at interactive rates, while still retaining individual goals. Guidance fields can also be obtained from video data of real-world crowds. Regardless of how they are created, these fields are then unified into a smooth navigation field. The transition from guidance field to navigation field eases manipulation of the navigation field while still maintaining precision. While the combination of interactivity and real-time feedback allows users to more effectively control crowd behavior, the model may not be capable of exhibiting certain macroscopic crowd behaviors.

Another possible application of human-computer interaction involves the populating of virtual spaces with simulated crowds. Gayle and Manocha (2008) observed a problem in sparsely populated virtual worlds such as Second Life, which reduces immersion of human players and creates an undesired sense of lifelessness. They developed techniques to populate the world with agents capable of autonomously avoiding collisions while navigating virtual paths, leading groups, and sometimes participating in a group. Their approach is based on a centralized server network topology where each agent is connected to the server (or a group of servers with a shared database). Agents possess local and global navigation models: the local model is based on social forces with the workload placed on client machines, and the global model is based on cell decomposition with the workload handled by server. Up to 18 agents were simulated (the maximum number of available Second Life accounts), and real-time interactive performance was achieved. Bandwidth posed a limiting factor, but it was estimated that one client could support 8-15 agents and still maintain desired performance.

Rather than use virtual crowds to serve human participants, sometimes human participants are used to further virtual crowd research. A lack in commonly accepted validation methods for crowd simulation models has been observed (Pelechano, Stocker, Allbeck, & Badler, (2008). Pelechano et al. proposed “a level of presence achieved by a human in a virtual environment”, i.e. immersion, as a metric for virtual crowd behavior. Four different types of models were implemented for human participants to interact with – social forces, rules based, cellular automata, and HiDAC (Pelechano et al., 2007) – and were evaluated for qualities that could harm presence in a virtual environment: shaking, discrete movement, overlapping with other agents, no communication between agents, agents unable to push each other, etc. The researchers then created a virtual cocktail party, adding to the agents communication, locomotion, and idling animations. Human participants were then inserted into the party using a head-mounted display, tracking sensors, etc. Participants performed simple tasks in the virtual environment and then filled out a questionnaire rating the achieved presence of the different models. Using the data gathered from the questionnaires and other sources, they were able to determine many positive qualities of the simulations, such as predictable human reactions to virtual crowd behaviors, as well as areas for improvement, such as improved auditory and haptic feedback.

Many of the previous studies described above have largely modeled crowds on a microscopic level where individual behaviors are simulated in detail. The following studies simplify individual behavior to varying degrees in favor of a greater macroscopic perspective. Musse and Thalmann (1997) explored the relationship between a crowd of autonomous virtual humans and their emergent behavior, where group behavior was defined by a user, but individual behavior was determined by a random process. The model also incorporates sociological concepts to represent certain behaviors.

In future work, Musse and Thalmann (2001) addressed the problems of how to model crowds using a hierarchical structure, how to distribute that structure, and how to account for behaviors of different complexities. In approaching these problems, crowds were treated as hierarchies. Three courses of action were made available to agents in these crowds: they could follow their script (i.e. “programmed behavior”), react to events (i.e. “reactive or autonomous behavior”), or be directed by a user (i.e. “guided behavior”). The resulting model was called the ViCrowd model. Based on a flocking system, it uses a group-based as opposed to an individual-based approach, resulting in improved performance.

Treuille et al. (2006) developed a crowd model based on continuum dynamics using dynamic potential fields and velocity fields for navigating among moving obstacles. The focus was on large groups with common goals. As such, the simulation is not agent-based. Instead, it uses per-particle energy minimization with a continuum perspective. The resulting model may not be as general, but it does require less computational power.

Reducing a model's demands for computer cycles is especially important for models that are best simulated at interactive rates. Narain, Golas, Curtis, and Lin (2009) wanted to do just that with a model of very large crowds. This model represents crowds simultaneously as discrete individuals and as a single continuous system. The latter systems takes the form of a continuum fluid, complete with density and flow velocity. Narain et al. introduced the concept of the “unilateral incompressibility constraint” (UIC) to the large-scale continuous system, which constrains fluid movement by incorporating local collision avoidance. The UIC speeds up the simulation by serving as a large-scale collision avoidance step. The model was found to efficiently handle hundreds of thousands of agents; it could even simulate one million agents at 3 frames per second. Limitations include only local/adjacent collision avoidance, and proposed improvements included the use of social rules for more realistic behaviors.

The above study divided the crowd into two levels and simulated both simultaneously. In this next study, a similar approach was taken with three levels. Ivancevic, Reid, and Aidman (2010) proposed a new model of crowd behavior dynamics that incorporates entropic geometrical principles with the goal of improving the predictive theory of crowd behavior. The model operates on three “synergetic” levels – macro, meso, and micro – and attempts to explain crowd behaviors and behavior transitions by measuring these three levels simultaneously. The macro level involves individual behavior dynamics which is then generalized for behavioral-compositional crowd dynamics using a micro-level formalism. The meso level in between these two consists of aggregate statistical-field dynamics. Crowd dynamics were formulated as entropy in three steps: as individual behavior, as a non-equilibrium transition phase where the micro-level brings changes to the macro-level, and then as collective behavior. Future work looked to add 3D simulations to bring the model a visual representation and also to study abrupt changes in crowd behavior.

One of the most practical benefits of crowd research is the better understanding and planning of human evacuations. When disaster strikes, people typically flee the danger zone as quickly as possible. Problems arise at choke points, where exits leading away from danger become clogged with humans. Since improving evacuation rates has a direct impact on saving lives, it makes for a popular research topic. Kamkarian (2009) used a multi-agent system to model crowds trapped in indoor spaces. The model is inspired by swarm behavior and grid communications, applying a least effort algorithm to the agents. Agents move toward the exit as fast as possible and in as straight a line as possible. The model was used to measure evacuation rates in different scenarios where the placement of the exit changed.

In a study of communication's effect on evacuation rates, Pelechano and Badler (2006) developed “Maces”: the Multi-Agent Communication for Evacuation Simulation. Maces' focus is on unknown environments; agents must explore and share discoveries with each other. Exploration involves wayfinding, a cognitive factor of navigation which involves four components: a cognitive map for remembering the environment, an orientation to position oneself within the map, the ability to explore and learn the environment, and navigational ability. Maces uses local motion driven by Helbing's model (Helbing, Farkas, & Vicsek, 2000) and inter-agent communication, which improved evacuation rates.

In emergency evacuations, each individual has a desired velocity but is often unable to attain that velocity due to congestion. Maury, Roudneff-Chupin, and Santambrogio (2010) interpreted these qualities as the incompressibility constraints of a fluid. Where a micro-level approach would treat individuals as rigid discs, their model uses a macro-level approach, instead being concerned with density, gradient structure, and gradient flow. Since it takes a macro-level view of the crowd, the model is unable to trace the paths taken by individuals. Therefore, individual strategies, such as avoiding congested areas, can not be directly incorporated into the model. However, the macroscopic approach produces natural motion where no movement would exist in a microscopic model.

Gawronski and Kulakowski (2011) investigated virtual human crowds attempting to leave a room through a small exit. They simulated this problem using the generalized force model and the model parameters of Helbing et al. (2000), determining that the probability of trying to exit the simulated room was 10 percent, given 150 people. This suggested that in crowds of hundreds, the individual’s mind has little power over moving its body to a desirable location; numerous other forces overwhelm the individual's control. To raise the probability above 50 percent required the addition of a number of helping forces, but determining the number of helpers was made difficult due to the problem’s complexity.

CHAPTER 4

THE MODELS

Presented in this section are three models representing three broadly defined scenarios. These scenarios are common in natural settings and can be generalized to include many other examples of crowds. Each model emphasizes one of the three components in the behavioral intention formula. These three components may be ordered in terms of increasing social scope: attitude from endogenous sources, influence to the relationships between individuals, and social norms to the relationships between individual and society. The first model emphasizes attitudinal forces when simulating an exhibition floor. The second model emphasizes influential forces during an evacuation. The third model takes a closer look at the role of different types of norms in the formation of seating arrangements. No single model is used to represent all three scenarios because the relative importance of any one component and the relationships between the components vary by scenario (Ajzen, 1991).

These models are inspired by the theory of reasoned action (Ajzen & Fishbein, 1981), where intentions lead to behaviors. Behavioral intention may be interpreted as the sum of products (Conner & Sparks, 2005) of weighted attitudes and subjective norms (Muduganti et al., 2005). This existing model can be extended by adding components (Robinson et al., 2008), resulting in Equation 2. Further augmentation may take the form of thresholds, which form an important part of the decision-making process (Granovetter, 1978; Muduganti et al., 2005), and a greedy approach can be used for choosing among alternatives (Sheppard et al., 1988).

$$Behavioral\ intention = Weight_{Attitude} * Attitude + Weight_{Influence} * Influence + Weight_{Social\ Norms} * Social\ Norms + Error$$

Equation 2. The Modified Behavioral Intention Model. Based on Equation 1, behavioral intention is represented as a weighted sum of attributes of increasing scope.

The above ideas were adapted to models implemented in NetLogo, an environment for modeling multi-agent systems (Wilensky, 2010). NetLogo provides a simple editor and an easy to use programming language where agents and a virtual environmental can be quickly defined and simulated. The editor is just one tab within a larger NetLogo program. Another tab contains a graphical representation of the virtual environment as well as buttons, controls, and displays that the user may define. No compilation is required; the user may alter code in one tab and can view the effects immediately in the other.

The user interfaces and complete source code for the following three models may be found in the appendices.

The Museum

The setting of the first model is a museum exhibition floor, but a grocery store, hotel lobby, strip mall, or amusement park also serve as appropriate metaphors. What all these settings have in common is an open floor on which pedestrians amble from one location to another. Static points of interest are spread across the floor, and overcrowding is typically not a concern. Keeping with the museum setting, agents represent museum attendees, and the points of interest represent the various artifacts which compose the exhibition.

This setting provides a conduit for chiefly observing attitude's effects on behavior by decreasing the importance of influence and social norms while simultaneously increasing the importance of attitudes. Influence's prominence is diminished by the typical calm, open atmosphere. The physically open space reduces the physical influence nearby agents may exert on each other, and since each agent attends the exhibition on their own, cognitive influences are reduced as well by limiting an agent's social network.

The effect of social norms are diminished to different degrees depending on the norm. As a social setting, museums inherently include a host of general rules. For example, attendees are expected to respect the personal space of others, nor should they yell, harass, or steal; these are virtually universal norms. More specific to the museum scenario, attendees understand that they should not touch the exhibits. A real world museum's policy could include many additional norms, but they are beyond the scope of this more general model. Most importantly, by entering the museum each attendee is assumed to be a willing participant and as such willingly follows the social contract.

The above diminishing effects leave attitude as the greatest contributing factor to an attendee's behavior. The museum becomes the backdrop in which a visitor's movement is largely independent of external forces, instead determined by internal, endogenous attitude. The attendee enters through a single entrance, wanders the show floor, and eventually leaves through the exit. As they wander, attendees perceive various portions of the exhibition and make internal evaluations of each exhibit's compatibility with themselves.

For attitudes to function as a better predictor of behavior, general attitudes must predict general behaviors and specific attitudes must predict specific behaviors (Ajzen, 1991; Conner & Sparks, 2005). Since the museum scenario is believed to be a situation that stresses attitudes, the attitude portion of the model is further divided into three subtypes – affective, conative, and cognitive (Ajzen and Fishbein, 2005) – as shown in Equation 3.

$$Attitude = Attitude_{Affective} + Attitude_{Conative} + Attitude_{Cognitive}$$

Equation 3. Dividing Attitude into Components for Greater Specificity.

These attitude components are used to evaluate the attractiveness of each exhibit in the museum. The affective factor represents an appreciation for a piece's appeals to emotion. The conative factor represents a willingness to react physically, and the cognitive factor represents an appreciation for appeals to logic. In the simulation, each of the attendee's attitude components ranges from 1 to 7 and is randomly generated over a normal distribution with a mean of 4 and a standard deviation of 1. A random floating point number ranging from 0 to 1 is used as an attitude weight. Each museum exhibit also possesses corresponding values of *appeal*. These values are assigned as random floating point numbers ranging from 1 to 7. The distance between the attendee's attitudes and an exhibit's appeal represents compatibility between the two entities, as shown in Equation 4. Because the affective, conative, and cognitive factors are approximated via equal weighting, the resulting differences are averaged together.

$$Compatibility = \frac{|(a.A_{Aff} - e.A_{Aff})| + |(a.A_{Con} - e.A_{Con})| + |(a.A_{Cog} - e.A_{Cog})|}{3}$$

Equation 4. Calculating Compatibility Between Exhibit and Attendee. *a* is the attendee, *e* is the exhibit, and A_{Aff}, A_{Con}, and A_{Cog} are the respective attitude components of affective, conative, and cognitive.

Despite their reduced roles, the museum attendee is still affected by influential and normative factors. Influence is represented by *pliancy*, an attraction to exhibits that attendees nearest the target attendee express interest in. Social norms are represented by *crowd affinity*, the willingness of the target attendee to view exhibits that have attracted a large number of viewers. These variables are generated using the same method as the attitude terms.

Agents are given *age* and *energy* parameters that limit their time spent at the museum. Energy values decay over time; the rate of decay decreases if visited exhibits are more compatible with the agent. *Age* represents duration of agent activity, starts at 0, and simply increments for every tick the agent exists in the simulation. Attendees also have an *attention span* which determines how long they will focus on a target exhibit. When that focus is broken by a randomized process, the attendee targets a new exhibit, maintaining a list of unexplored exhibits to choose from next.

The simulation begins with a fixed number of exhibits placed in a circular configuration and a single attendee at the entrance. Whenever the current population is less than the maximum population cap (designated as *num-attendees*), an additional attendee is created every tick in the upper right corner of the virtual space. Upon creation, aside from their randomly determined parameters as described above, the attendee also selects the nearest exhibit as the initial target. Therefore, the simulation begins devoid of attendee agents, but after a short amount of time has elapsed, a large population of agents exists to amble about the exhibition floor.

Figure 2 shows an example execution of the museum simulation. The green upper right and red lower left squares represent the entrance and exit, respectively, to the virtual environment. Pentagons represent individual exhibits, while circles represent the attendees. Attitude values are represented by a color's brightness – the brighter the color, the greater the value. Which attitudinal component is displayed may be manipulated by a drop-down menu in the simulation's user interface. In Figure 2, attendee cognitive parameters are displayed in magenta and exhibits' cognitive appeal values are in cyan.

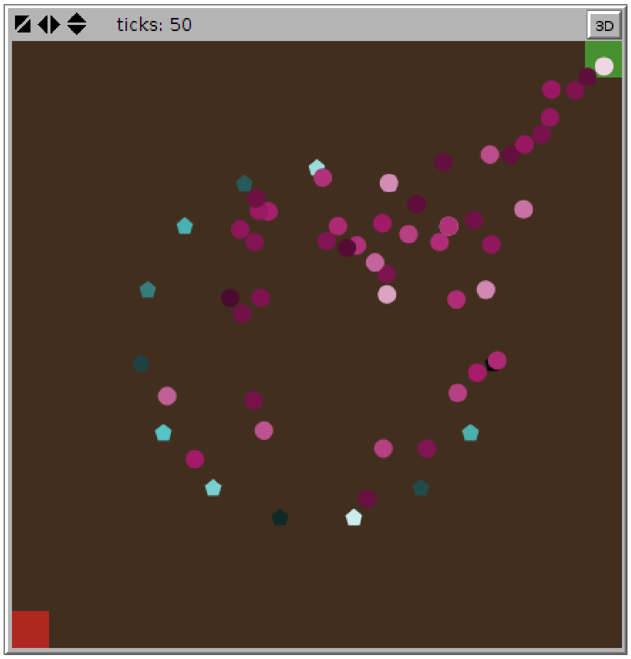

Figure 2. Commencing the Museum Simulation. Circular attendees visit pentagonal exhibits; brightness represents cognitive parameters.

The passage of time during the simulation is measured in ticks. During each tick, each agent undergoes a decision-making process that determines their next action. The first phase of this process involves updating their list of unvisited exhibits. If their current location is also the location of an exhibit, that exhibit is removed from the list. The second phase is the motion phase in which a target exhibit is chosen and pursued. The attendee starts by checking their energy. If their energy level is less than or equal to zero, they make their way towards the exit. Otherwise, the attendee makes a check against their attention span parameter. The smaller their attention span, the greater chance the attendee has of switching to another target exhibit. Whether they change targets or not, the attendee then walks towards their exhibit of choice. In the third and final phase, agents increment their age value and decrease their energy. Energy decay is determined by a simple distance function comparing the attendee and the nearest exhibit. Exhibits with values closely resembling the corresponding values of the attendee results in slower energy decay.

Behavioral intention expresses itself during the second phase, specifically when choosing a new target exhibit. The process of choosing an exhibit is shown in Figure 3.

```
 1. If rand(0, 1) < w_A
 2.      t = mostCompatibleExhibit()
 3. Elseif rand(1, 7) < I
 4.      If targetOf(nearestNeighbor) ∊
 5.           unexploredList
 6.           t = targetOf(nearestNeighbor)
 7.      Else
 8.           t = mostCompatibleExhibit()
 9.      Endif
10. Else
11.      t = mostCrowdedExhibit()
12. Endif
```

Figure 3. The Attendee Process for Choosing a Target Exhibit. w_A is the attitude weight, *t* is the attendee's target exhibit, and *I* is the influence component of pliancy.

First, the attendee makes a check against their *attitude weight*. The greater the weight's value, the better chance that attitudes will be used in making a decision. If the check succeeds, the target becomes the exhibit in the unvisited list that is most compatible with the attendee. If the check fails, either influence or normative parameters are used to make the decision. Given a successful check against an attendee's *pliancy*, the attendee will choose the same target as the nearest other attendee (Figure 3, line 6). If this target has already been visited, however, the attitude method becomes the fallback option. Otherwise, social norms are used, and the attendee targets the exhibit with the most nearby attendees, i.e. the most crowded exhibit (Figure 3, line 11). This process is summarized in the state diagram of Figure 4. Using the above steps, behavioral intention becomes a process in which each attendee forms an intention about where they would like to go next within the virtual environment. This intention may not result in committed action, however, due to the overriding compulsion to leave the environment once energy levels are depleted.

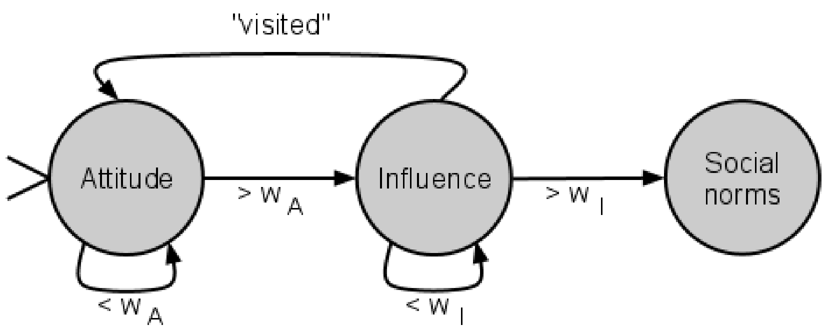

Figure 4. The Attendee's Decision-making Process. Random checks compared to weights determine how the decision is made.

This model demonstrates the importance of location when placing points of interest. Exhibits that appeal to the most people should be readily accessible in order to retain people's attention and prolong visits. Perhaps room planners want to direct viewers along certain paths; they would need to consider each exhibit's appeal to different types of people. Figure 5 plots the fluctuating average age of attendees during the exhibition. Increasing trends represent periods where attendees are viewing the exhibits, while decreasing trends represent periods where attendees are leaving and new attendees are being created. New attendees have age 0 and therefore lower the average age in the graph. This information could be used to predict and control flow between an entrance and an exit via placement of points of interest. Producing periodic fluctuations in average age indicates attendees entering and leaving in groups. Very little fluctuation indicates a more regular flow of individuals.

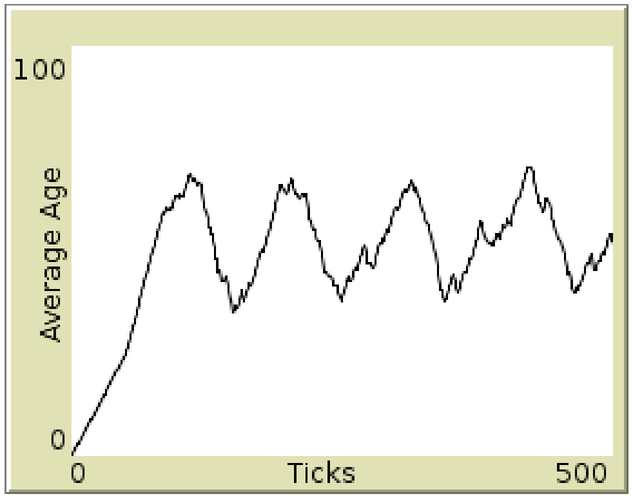

Figure 5. Museum Attendee Average Age over Time.

The Station Platform

The second model represents a station platform, which may be found near a train, bus, or subway depot. The station platform is included as a common crowd scenario to represent areas of high density, where people push and shove as they try to reach a common Point Of Interest (POI), e.g. a train's open door, an entry gate, or an exit gate. A second dynamic arises in this scenario with the addition of a negative POI, which may represent a bomb or a threatening criminal. The negative point creates alarm in people who perceive it, which spreads across the crowd and causes a change in priorities; people now desire to evacuate the premises. This scenario strengthens the power of the influence component above attitude and social norms. Attitudes are largely the same across the crowd; they must reach the target destination. Many social norms, especially those involving personal space, are weakened due to the limited availability of space.

In this model, influence takes two forms: physical influence and mental influence. Physical influence, what is termed *physical enmity* in the model, represents the force an agent is willing to exert on others to push them away. This is inspired by the social force model (Helbing and Molnar, 1995) where particles emit force fields that push and pull each other due to changes in motivation. Mental influence, more specifically *alarm acquisition* in this model, represents how quickly an agent will acquire an alarmed status from others nearby. The two forms of influence function as a compliance component that people use to increase the accuracy of their perceptions (Cialdini and Goldstein, 2004).

If influence is the means of acquiring alarm from others, attitude is the means of creating alarm by reacting to a negative perception. Even if they are not directly or indirectly alarmed by the negative POI, a passenger that witnesses everyone else leaving in the opposite direction is compelled by their *follow affinity* parameter to due likewise, representing a social norm of sensitivity to crowd motion. Similar to the parameters in the museum model, each parameter ranges from 1 to 7 and is randomly generated over a normal distribution with a mean of 4 and a standard deviation of 1. Also, each passenger's *alarm level* is initiated to zero.

The virtual environment of the station platform consists of a square field divided in half by a barrier, impenetrable save for a single opening in its center. A variable number of passenger agents are created south of the barrier. When the simulation begins, each agent attempts to move towards the bottom center of the screen, representing some POI. This motion is countered by the physical influence passengers exert on each other.

Physical influence is represented by directed edges connecting the agents. Edges are created as a function of an agent's physical enmity and a globally defined physical weight. The two parameters form a product which forms the radius of a "circle of influence". The agent at the center creates a directed edge towards other agents that fall within this circle. However, edges only connect agents that possess line of sight, i.e. edges do not intersect the central barrier.

A typical execution of the station platform simulation can be viewed in Figure 6, where passengers push each other and try to get closer to the bottom center of the environment.

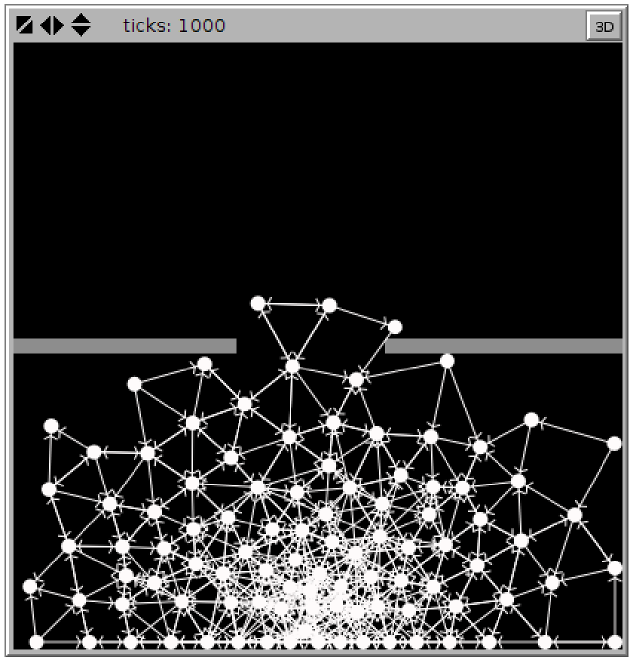

Figure 6. A Simulated Crowd at a Station Platform. The barrier is represented by gray rectangles, passengers by white circles, and influences by directed edges.

With the initial environment, passengers, and influence edges created, each tick of the simulation then proceeds to model the motion of the passengers. This process begins by first calculating each passenger's basic trajectory, ignoring the influence network. In this step, passengers are placed into one of three categories: "calm and not following", "calm and following", or alerted. The categorization process is shown in Figure 7.

```
1. If alarmLevel < A
2.      If w_N * N < unevacuatedPopulation
3.           t = bottomCenter
4.      Else
5.           t = top
6.      Endif
7. Else
8.      t = top
9. Endif
```

Figure 7. The Passenger Process for Choosing a Destination. *A* is the attitude component of alarm creation, w_N is the norm weight, *N* is the norm component of follow affinity, and *t* is the passenger's target destination.

"Calm and not following" passengers, the default state, are those who move towards the bottom center of the environment (Figure 7, line 3). "Calm and following" passengers have not been alerted either directly or indirectly but proceed to exit the bottom half of the environment regardless due to a social norm of "follow the herd", i.e. everyone else is leaving for an unknown reason, so the passenger leaves too (Figure 7, line 5). This behavior is triggered when a certain percentage of the total population leaves the area, exceeding the passenger's *follow affinity* threshold. The third category of passenger, alarmed passengers, also make their way to the exit (Figure 7, line 8). Alarmed passengers use their *alarm creation* parameter as a threshold that their current alarm level must exceed. This parameter also represents the level of alarm a passenger assumes when directly perceiving a negative POI. Once categorized, passengers move towards their appropriate destination. Figure 8 represents this decision process as a state diagram.

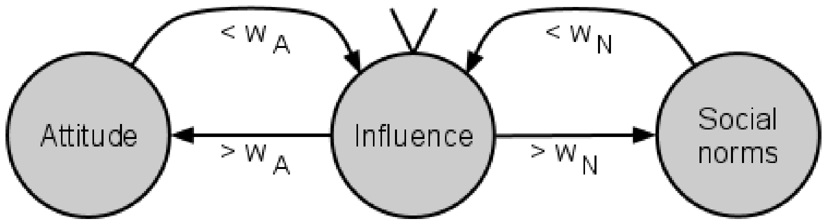

Figure 8. The Passenger's Decision-making Process. Attitudes and social norms form intentions after thresholds are exceeded.

A maintenance phase follows after the move step in which the influence network is updated. New edges are created between agents (between passengers or a negative POI) using the process described earlier, and old edges that connect agents too far apart are destroyed.

With the network updated, the next step uses this network to communicate alarm between passengers and exert influence on the motion of the passengers. The process of alarm creation and transmission is shown in Figure 9.

```
 1. If isNeighbor(offender)
 2.      If alarmLevel < wA * A
 3.           alarmLevel = wA * A
 4.      Endif
 5. Else
 6.      alarmp = mean(N1.alarmLevel,
 7.                    N2.alarmLevel,
 8.                    ... ,
 9.                    Nn.alarmLevel)
10.      alarmLevel += (alarmp - alarmLevel)
11.                    * wIM * IM
12. Endif
```

Figure 9. The Passenger Process for Creating and Spreading Alarm. w_A is the attitude weight, A is the attitude component of alarm creation, $alarm_p$ is the perceived alarm, N is the set of neighbors, w_{IM} is is the mental influence weight, and I_M is the mental influence.

Alarm is initially created by passengers with a direct connection to a negative POI and is the product of a passenger's *alarm creation* parameter multiplied by a global attitude weight (Figure 9, line 3). Alarm may also be acquired from neighboring passengers. Each passenger takes the average alarm level of its neighbors, compares the resulting mean value to its current alarm level, and adjusts up or down accordingly (Figure 9, lines 10-11). The result is a source of alarm propagating across a network, represented in Figure 10 as different shades of red. After calculating mental influence, physical influence is represented by a repulsive force exerted by the network connections. The force algorithm used is built into NetLogo and is similar to Fruchterman and Reingold's (1991) layout algorithm. The algorithm imbues edges with a spring-like elasticity and results in passengers moving themselves out of the way of others in order to satisfy their personal space requirements, the NetLogo procedure for which is shown in Equation 5.

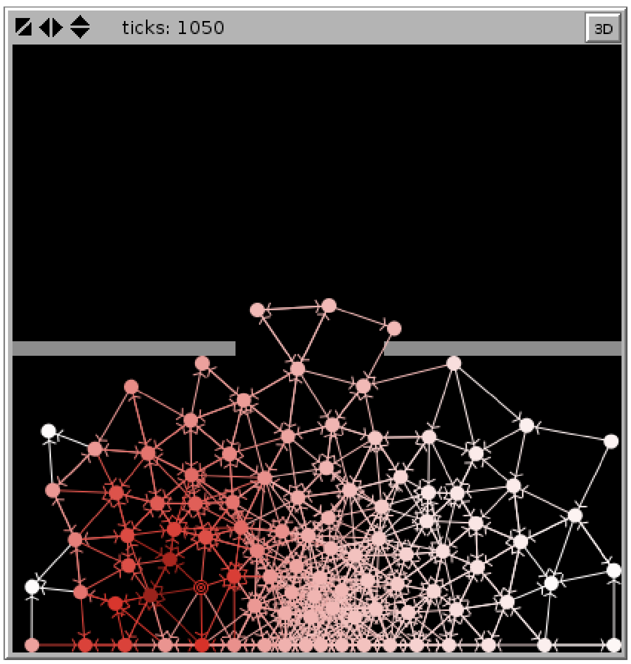

Figure 10. Alarm Propagating Across the Crowd. Alarm is represented by shades of red. The target symbol represents a negative POI.

$$layout - spring(\{p, N\}, e_O, 0.1, w_{IP} * I_P, 0)$$

Equation 5. Creating Passenger-passenger Repulsion. *{p, N}* is the set of a passenger and its neighbors, e_O is the set of outward edges, *0.1* is the force exerted along the edges, w_{IP} is the physical influence weight, I_P is the physical influence, and *0* is the global passenger repulsion. A more detailed explanation of the layout-spring procedure may be found in the online NetLogo Dictionary.

In the station platform model, a passenger's attitude towards the negative POI, mental influence of neighbors, and social norms forms an intention that involves reaching either the bottom or top of the environment. However, physical influences often overpower these intentions due to other passengers sharing similar goals in a crowded space. Figure 11 shows a typical execution of the simulation which demonstrates these concepts. Passengers which were originally determined to reach the bottom center of the screen are alarmed either directly by the negative POI or indirectly by nearby passengers. When their alarm level exceeds a threshold, shown in deeper shades of red, they attempt to leave the bottom half of the environment. As more and more passengers similarly attempt to leave, physical crowding causes bottlenecking at the single exit.

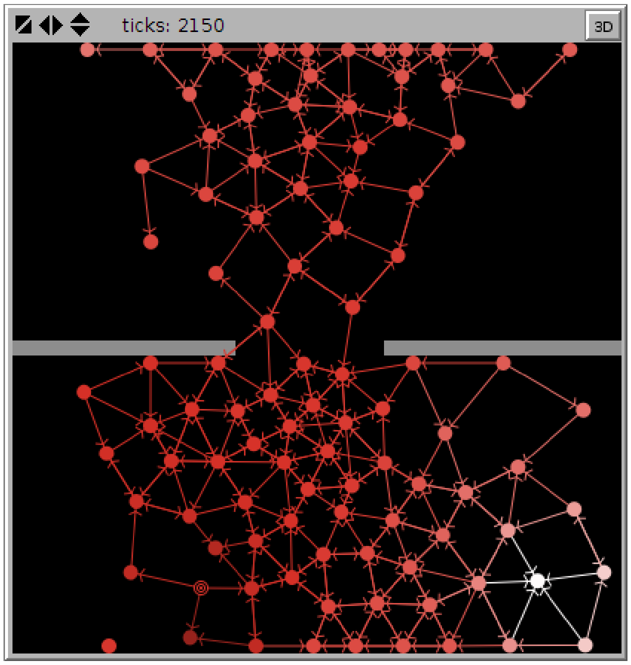

Figure 11. A Station Platform Crowd in Mid-evacuation.

This scenario demonstrates some interesting crowd behavior. First, the crowd phenomenon of congestion around an exit is readily observed. This congestion may be attributed to the interfering forces passengers apply to each other. The size of the exit may be adjusted during the simulation, and wider gaps allow for decreased evacuation times. However, the gap in the barrier also exposes some problems with this particular simulation specifically dealing with corners. Certain collision detection problems results in a vibrating pattern of motion with passengers. While this does not cause agents to become stuck, the motion is unrealistic and should be eliminated in future work. Other interesting behaviors concern the transmission of alarm over the network. If passengers nearest the negative POI possess particularly low *alarm creation* parameters, they fail to propagate enough alarm in others to cause a change in behavior. Similarly, if passengers are alarmed but possess high *physical enmity* values, they avoid others and fail to transmit the alarm. By avoiding others, passengers may also fail to properly acquire alarm.

These observations lead to possible applications for the model. The concept of alarm transmission can be expanded into a more general form or made more specific to another domain in order to further study information diffusion across a network of people. While the station platform model resembles an evacuation, it does not simulate evacuation behaviors specifically. However, the model and virtual environment could be tailored to better predict evacuation behavior, especially to investigate the importance of alerting participants that an evacuation is taking place.

The Classroom

The third scenario represents a school classroom, which shares some similarities with a seating problem or a resource allocation problem. Students enter the classroom and one by one, they choose a seat. Which seat they choose is a function of which seats are available and the interacting forces of personal and social preferences. An attitude value represents the student's personal feelings towards sitting near the front and center of the classroom, and an influence value takes into account the number of occupied seats adjacent to a candidate desk. What this scenario seeks to focus on, however, is the power of social norms.

There are many different types of social norms (Schultz et al., 2007), and the subjective norm's performance in predicting behavior may require expansion (Armitage & Conner, 2001). Therefore, different types of norms are incorporated into the student's decision making process. In the classroom scenario, one social norm of particular strength is the expectation that people are to sit near the front and center. Another norm is a norm of consistency, that once a person has chosen a seat, they are expected to choose the same seat the following day. By incorporating pressures encouraging consistency, the classroom model attempts to address a perceived weakness in the original theory of reasoned action, which does not account for past behaviors. If this norm was absolute in its power, then the first day would determine the final seating arrangement, but this is rarely the case. Instead, the strength of the norm interacts with students' varying levels of norm adherence coupled with attitudinal and influential forces.

The simulation begins by creating a set of students. Each student has their intention parameters initialized to values ranging from 1 to 7 and randomly generated over a normal distribution with a mean of 4 and a standard distribution of 1. These students are positioned along the bottom of the virtual environment. Above them are positioned a grid of desks. During each tick of the simulation, one student is randomly chosen who picks a vacant desk to sit in. The desk selection process is shown in Figure 12.

```
1. If rand(0, 100) < wN1 * N1
2.      t = mostFrontCenter(availableDesks)
3. Elseif rand(0, 100) < wN2 * N2
4.        AND previousDesk ∊ availableDesks
5.      t = previousDesk
6. Else
7.      t = mostCompatibleDesk()
8. Endif
```

Figure 12. The Student Process for Choosing a Desk. w_{N1} and N_1 are the respective norm weight and norm of sitting towards the front and center of the classroom, w_{N2} and N_2 are the respective norm weight and norm of sitting in seat used previously, and *t* is the student's target desk.

The desk selection process consists of two checks. The first check compares a random number to the product of the "sit near the front" norm and the student's personal adherence to the norm. If the check succeeds, then the student sits at the closest available seat to the front and center of the classroom (Figure 12, line 2). If the students fail to adhere to the norm, then another similar check occurs using the "sit in the same seat" norm multiplied by the student's adherence. Successful adherence causes the student to sit in their previous seat (Figure 12, line 5). If the seat is unavailable or the student again fails to adhere to a norm, another selection process begins in which attitudes and influences are used to choose the desk (Figure 12, line 7).

The overall decision process is summarized in the state diagram of Figure 13, and the attitude-influence selection subprocess is shown in Figure 14.

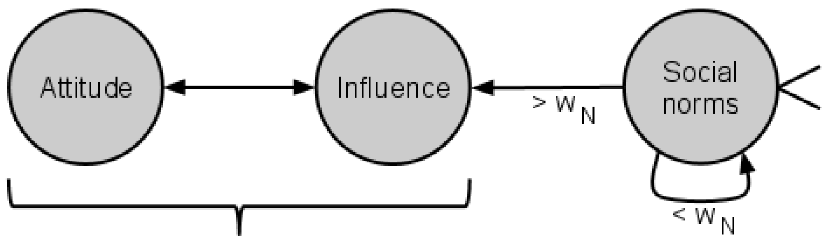

Figure 13. The Student's Decision-making Process. If social norms are not used, attitudes and influences combine to take their place.

```
1. d = distance(closestDesk, furthestDesk)
2. d_preferred = A * d
3. candidateDesks = closest3(desks, d_preffered)
4. t = closest(candidateDesks, I)
```

Figure 14. The Student Process for Determining the Most Compatible Desk. *closestDesk* is the desk closest to the front and center, *furthestDesk* is the desk furthest from the front and center, and *d* is the distance between the two. *A* is the attitude towards sitting near the front, and $d_{preferred}$ is the transformation of that attitude into a distance. *candidateDesks* is the set of 3 desks with a distance from the front and center closest to $d_{preffered}$. *t* is the student's target desk, the candidate desk with a crowding level closest to *I*, the influence exerted by neighboring occupied desks.

A student's attitude parameter represents their personal feelings towards sitting near the front of the class. This attitude is translated into a region of space pivoting around the closest front and center desk (Figure 14, line 2). Larger values form regions closer to the front and center, while smaller values form regions further away. The three vacant desks closest to this region form a list of candidates (Figure 14, line 3), and a single desk is chosen from the list by comparing the number of occupied desks near each candidate to the student's preference for crowding (Figure 14, line 4), e.g. if a student possesses a low tolerance for crowding, then the candidate desk with the least number of adjacent occupied desks will be selected.

The decision process repeats until all students are seated. A resulting seating arrangement may be found in Figure 15 which shows 20 students seated after their second round of choosing desks. Desks are represented by small, brown squares. Students are represented by person-shaped symbols and an identification number. After choosing a desk, a color code indicates how the choice was made. Purple follows the “sit in the same seat” norm, red follows the “sit nearest the front” norm, and blue indicates that a combination of attitude and influence factors were used.

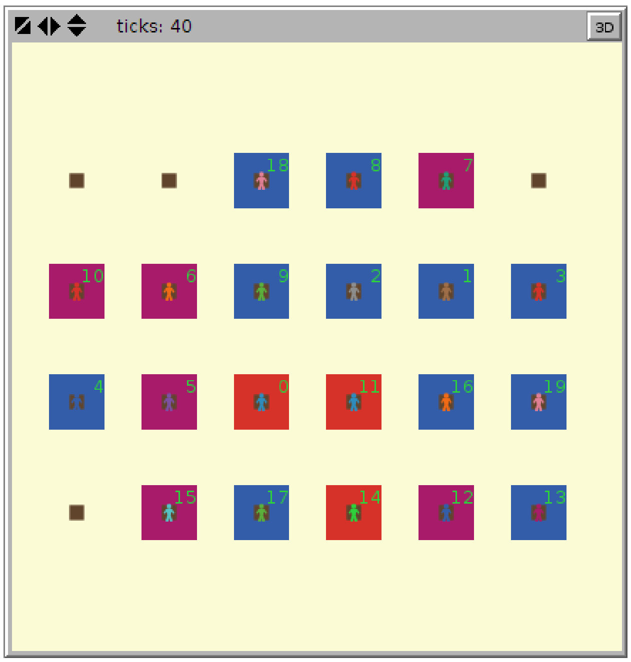

Figure 15. A Classroom of Seated Students. Purple, red, and blue indicate “sit in the same seat” and “sit near the front” norms and using attitudes and influences, respectively.

The classroom model explores a couple scenario-specific norms and their interaction with attitudes, influences, and behavior. Even when social norm strength was made very strong, however, individual moderate adherence diminished overall impact on behavior. If attitude, influence, and social norms are evaluated by scope, then the social norms – the outermost “shell” – were likely too broad to generate the desired crowd behaviors on their own. This model also attempted to improve a possible weakness of the theory of reasoned action by combining norms with knowledge of past behavior. However, the model only accounts for the most recent desk choice and might be improved with an expanded memory of past actions.

CHAPTER 5

CONCLUSION

In this thesis, behavioral intention and attitude, influence, and social norm components were applied to three scenarios that represent common crowd dynamics: ambulation about an open hall, high density evacuation, and crowd resource allocation. The result was three related models that explored different facets of crowd behavior by stressing the different components. Some properties of crowd behavior were simulated directly, while others emerged from the interaction between agents. Phenomena of interest included oscillating population levels in the museum, weakened norm adherence in the classroom, congestion at the exit of the station platform, and the (lack of) propagation of alarm.

These phenomena showed that the intention components of attitude, influence, and social norms are applicable and flexible when simulating crowd behavior. However, these components are best utilized within certain limits represented as expanding levels of scope. The model was shown to be highly adaptable, though the ease of adaptation varied among the scenarios. Certain successes found in one model – particularly the model of the station platform, which demonstrated some of the most promising displays of crowd behavior – could be adapted for use in the other models.

The flexibility demonstrated by the concepts underlying all three models also means that many future modifications can be made to either improve existing performance or to investigate new ideas. For example, past behavior is also an important factor for predicting future behavior (Armitage, 2005), so future work could involve adding dynamic components to the agents where internal parameters are adjusted by perceptions of the environment. Other work could involve attempting to replicate additional emergent crowd behaviors, such as lane formation, using behavioral intention.

These models may be adapted for point of interest placement, information diffusion, or different types of social networks. Ultimately, a better understanding of crowd behavior leads to better models of human behavior both in the crowd and as individuals, and that means improved evacuation planning, architecture design, etc. for anywhere humans gather.

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APPENDICES

APPENDIX A

USER INTERFACES

Some variables in NetLogo are neither declared nor initialized within the NetLogo code. These variables are declared and initialized from the NetLogo user interface. Therefore, in addition to the source code made available in appendices B through D, reproductions of the NetLogo user interfaces, found on the following pages, are also necessary to run the simulations.

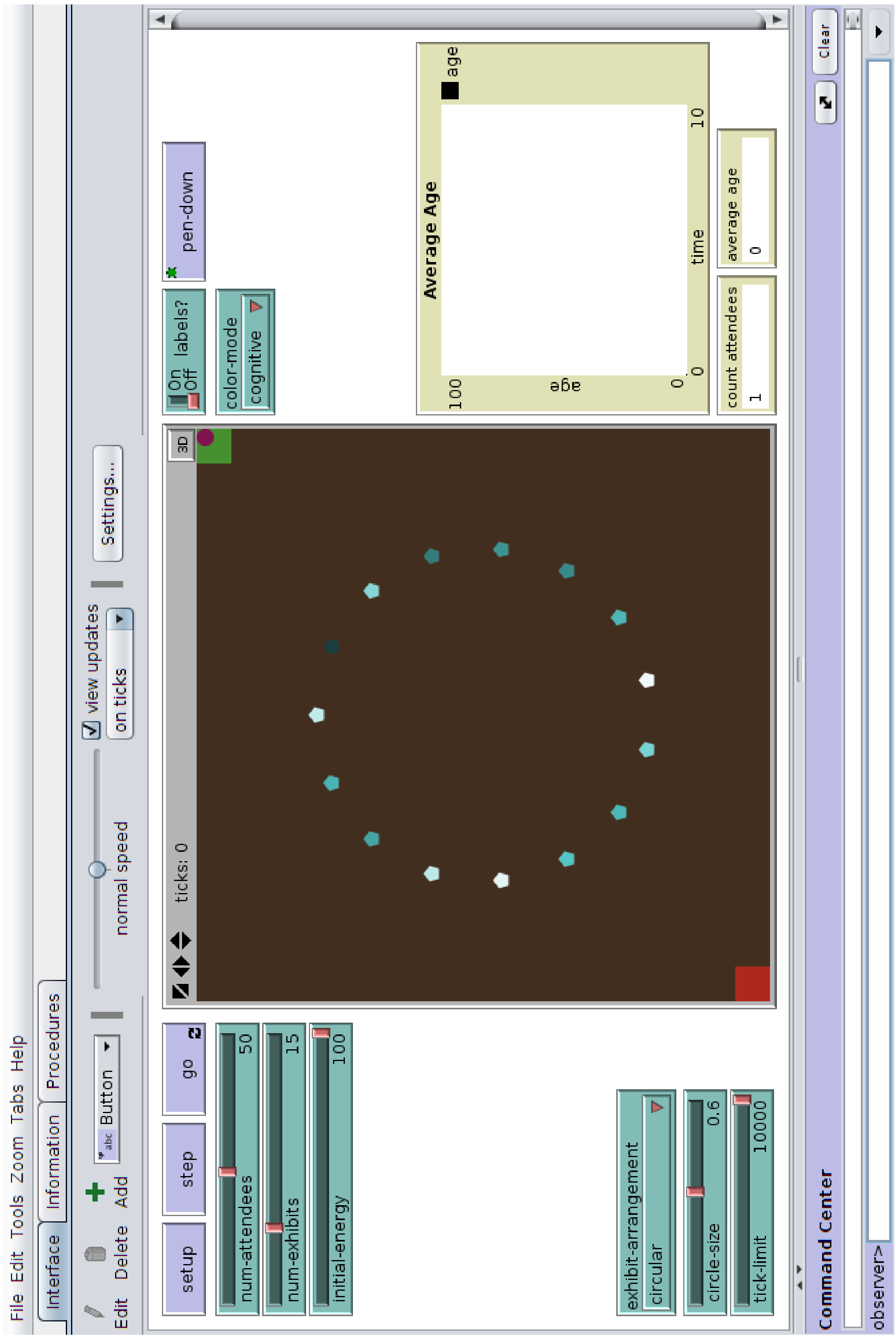

Figure A1. The NetLogo User Interface for the Museum Model.

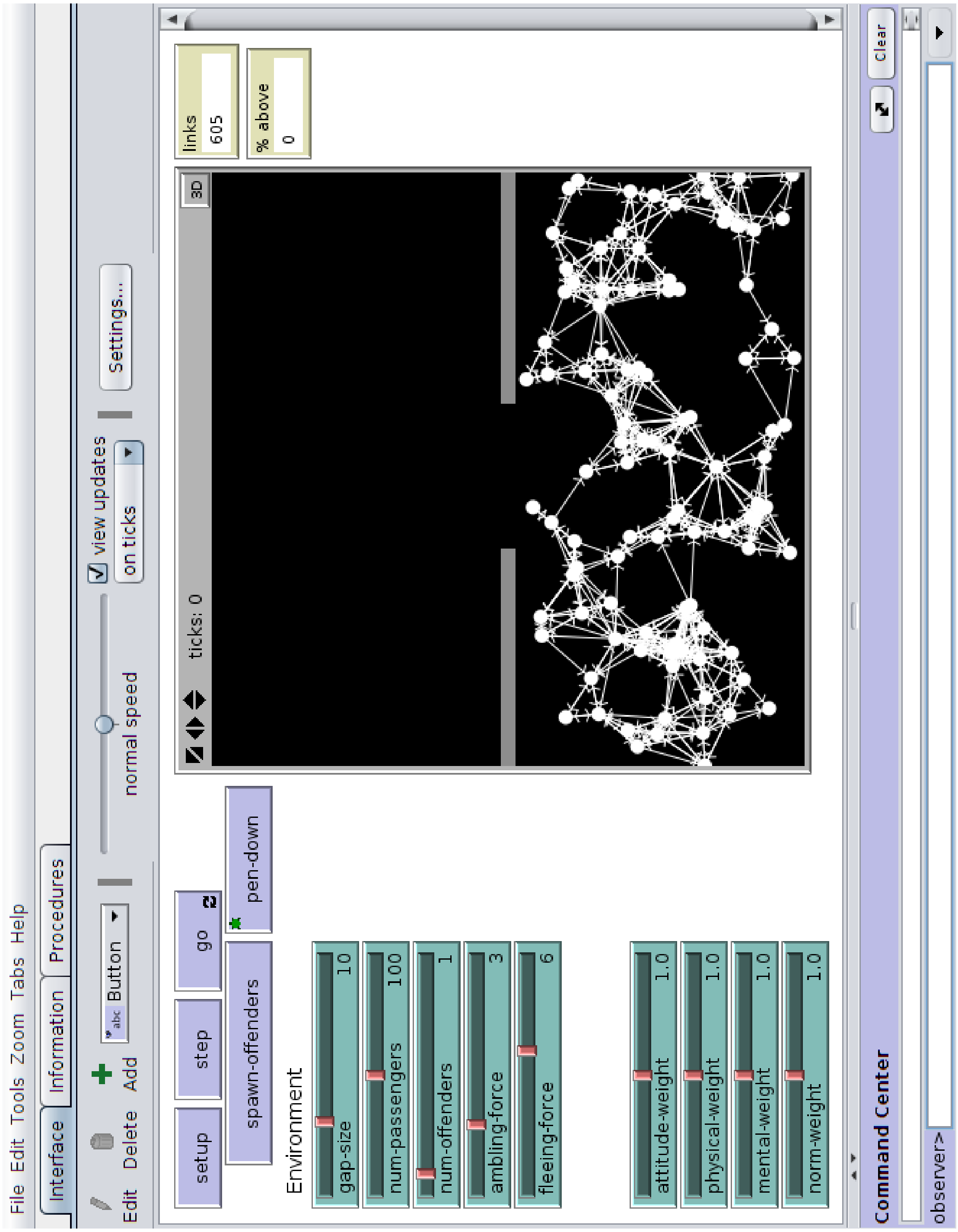

Figure A2. The NetLogo User Interface for the Station Platform Model.

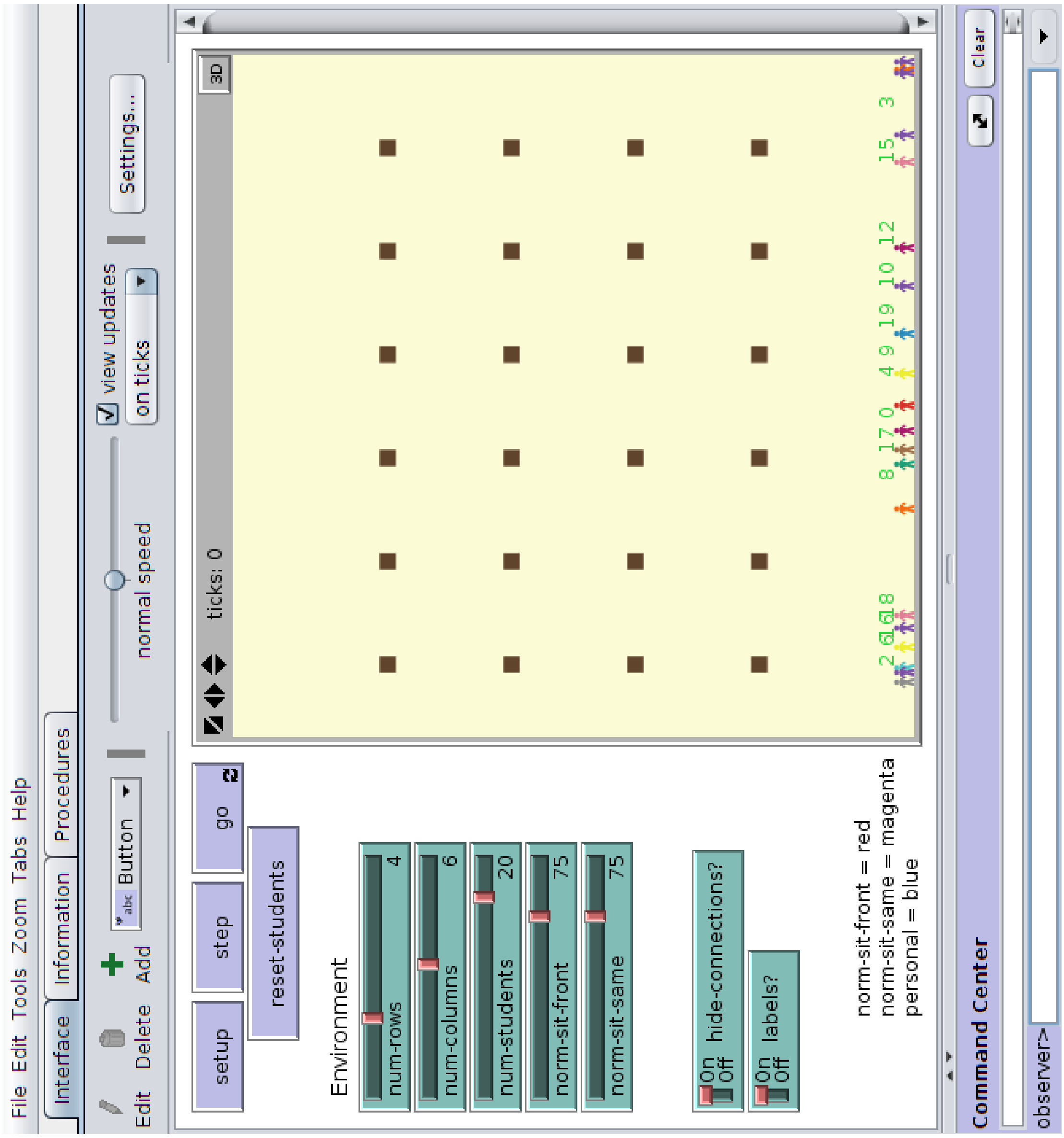

Figure A3. The NetLogo User Interface for the Classroom Model.

APPENDIX B

THE MUSEUM SOURCE CODE

```
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;; File: The Museum.nlogo
;; Author: Marcel Bouchard
;; Date: 19 July 2011
;;
;; The purpose of this model is to incorporate behavioral intention
;; concepts into an exhibition floor simulation, stressing attitude
;; components
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

;; turtle breed: the exhibit
breed [exhibits exhibit]
exhibits-own [
  ;; each exhibit possesses three types of appeal
  affective-appeal  ;; emotional appeal
  conative-appeal   ;; behavioral appeal
  cognitive-appeal  ;; cognitive appeal
]

;; turtle breed: the attendee
breed [attendees attendee]
attendees-own [
  ;; the three factors that compose attitude
  affective-factor ;; appreciation for appeals to emotion
  conative-factor  ;; willingness / prone to react physically
  cognitive-factor ;; appreciation for appeals to thought
  attitude-weight
  ;; representations of influence and social norms
  pliancy        ;; attraction to exhibits targetted by nearest attendees
  crowd-affinity ;; attraction to exhibits with many nearby attendees
  ;; other simulation components
  age            ;; the number of ticks the agent has been alive
  energy         ;; overall willingness to remain at the exhibition
  attn-span      ;; likelihood to remain at an exhibit
  target-exhibit ;; current exhibit to travel towards
  unexplored     ;; the set of exhibits not yet visited
]

;; prepare the simulation
to setup
  clear-all
  setup-patches
  setup-turtles
  setup-colors
  display-labels
  do-plots
end

;; set all the patches to their default state
to setup-patches
  ask patches [
    set pcolor (brown - 3)
```

```
    ;; paint the NE and SW corners to designate entrance and exit
    if (pxcor > max-pxcor - 2) and
      (pycor > max-pycor - 2) [set pcolor (green - 1)]
    if (pxcor < min-pxcor + 2) and
      (pycor < min-pycor + 2) [set pcolor (red - 1)]
  ]
end

;; set all the exhibits and attendees to their default state
to setup-turtles
  ;; first, set up the exhibits
  set-default-shape exhibits "pentagon"
  create-exhibits num-exhibits [
    set affective-appeal ((random-float 6) + 1)
    set conative-appeal ((random-float 6) + 1)
    set cognitive-appeal ((random-float 6) + 1)
  ]
  ;; arrangement depends on the chosen type from the drop-down menu
  if (exhibit-arrangement = "random") [
    ask exhibits [setxy random-xcor random-ycor]
  ]
  if (exhibit-arrangement = "circular") [
    layout-circle exhibits (max-pxcor * circle-size)
  ]
  ;; second, set up the first attendees
  set-default-shape attendees "circle"
  create-attendees 1
  ask attendees [
    setup-default-attendee
  ]
end

;; set default values for a given attendee
to setup-default-attendee
  set age 0
  ;; set position
  setxy max-pxcor max-pycor ;; move to north east corner
  set heading 180           ;; face south
  ;; set behavioral intention components
  set affective-factor (random-normal-1-7 4 1)
  set conative-factor (random-normal-1-7 4 1)
  set cognitive-factor (random-normal-1-7 4 1)
  set attitude-weight (random-float 1)
  set pliancy (random-normal-1-7 4 1)
  set crowd-affinity (random-normal-1-7 4 1)
  ;; set other variables
  set energy initial-energy
  set attn-span (random-float 1)
  ;; initially target closest exhibit
  set target-exhibit (min-one-of exhibits [distance myself])
  ;; initialize the set of unexplored exhibits to all exhibits
  set unexplored exhibits
end

;; produce a random number from 1 to 7 using a normal distribution
;; arg1 is the mean, arg2 the standard deviation
to-report random-normal-1-7 [arg1 arg2]
```

```
  let number (random-normal arg1 arg2)
  if (number < 1) [set number 1]
  if (number > 7) [set number 7]
  report number
end

;; select the appropriate coloring scheme
to setup-colors
  if (color-mode = "affective") [
    ask exhibits [set color (scale-color green affective-appeal 1 7)]
    ask attendees [set color (scale-color violet affective-factor 1 7)]
  ]
  if (color-mode = "conative") [
    ask exhibits [set color (scale-color blue conative-appeal 1 7)]
    ask attendees [set color (scale-color orange conative-factor 1 7)]
  ]
  if (color-mode = "cognitive") [
    ask exhibits [set color (scale-color cyan cognitive-appeal 1 7)]
    ask attendees [set color (scale-color magenta cognitive-factor 1 7)]
  ]
end

;; draw indicator labels
to display-labels
  ask turtles [set label ""]
  if labels? [
    ask attendees [set label age]
    if (color-mode = "affective") [
      ask exhibits [set label (precision affective-appeal 2)]
    ]
    if (color-mode = "conative") [
      ask exhibits [set label (precision conative-appeal 2)]
    ]
    if (color-mode = "cognitive") [
      ask exhibits [set label (precision cognitive-appeal 2)]
    ]
  ]
end

;; draw various data to graphs
to do-plots
  set-current-plot "Average Age"
  set-current-plot-pen "age"
  if (any? attendees) [
    plot mean ([age] of attendees)
  ]
end

;; advance the entire simulation by one tick
to step
  ask attendees [
    update-exhibit-list
    move-attendee
    alter-energy
    set age (age + 1)
  ]
  equalize-attendance
```

```
  exit-attendees
  setup-colors
  display-labels
  tick
  do-plots
end

;; remove explored exhibit from unexplored list
to update-exhibit-list
  if (any? exhibits-here) [
    ;; unexplored is updated to remove the exhibit at the attendee's
    ;; location
    let current-exhibit (one-of exhibits-here)
    set unexplored (unexplored with [who != [who] of current-exhibit])
  ]
end

;; move the attendee towards the appropriate destination
to move-attendee
  ifelse (energy > 0)
  [
    ;; possibly change targets
    if ((random-float 1) > attn-span) [
      change-target
    ]
    face target-exhibit
    ;; move toward target exhibit
    ifelse (distance target-exhibit < 1)
      [move-to target-exhibit]
      [forward 1]
  ]
  [
    ;; energy expired, so proceed to exit
    facexy min-pxcor min-pycor
    forward 1
  ]
end

;; choose the target exhibit depending on a variety
;; of internal and external forces
to change-target
  ifelse ((random-float 1) < attitude-weight)
    ;; using attitude
    [set target-exhibit (best-exhibit-for self unexplored)]
    [
      ifelse (((random-float 6) + 1) < pliancy)
        ;; using influence: attempt to let nearest neighbor pick target
        [
          let nearest-neighbor (min-one-of attendees [distance myself])
          let possible-target ([target-exhibit] of nearest-neighbor)
          ;; if target is not on unexplored list, revert to attitude
          ifelse (any? (unexplored with [who = [who] of possible-target]))
            [set target-exhibit possible-target]
            [set target-exhibit (best-exhibit-for self unexplored)]
        ]
        ;; using norms: target most crowded exhibit
        [
```

```
          set target-exhibit (max-one-of exhibits [
            count (attendees with [(distance myself) < 2])
          ])
        ]
    ]
end

;; given an attendee and set of exhibits, report the most compatible exhibit
;; most compatible exhibit is the exhibit with most similar attributes
to-report best-exhibit-for [attnd exhibit-set]
  report min-one-of exhibit-set [(
    abs ([affective-appeal] of self - [affective-factor] of attnd) +
    abs ([conative-appeal] of self - [conative-factor] of attnd) +
    abs ([cognitive-appeal] of self - [cognitive-factor] of attnd)
    ) / 3
  ]
end

;; decay energy depending on attributes of nearest exhibit
to alter-energy
  ;; find nearest exhibit
  let nearest (min-one-of exhibits [distance myself])
  ;; energy decay is the mean of differences
  set energy (
    energy - (
      abs ([affective-appeal] of nearest - affective-factor) +
      abs ([conative-appeal] of nearest - conative-factor) +
      abs ([cognitive-appeal] of nearest - cognitive-factor)
    ) / 3
  )
end

;; create a new attendee if below maximum population
to equalize-attendance
  if (count attendees < num-attendees) [
    create-attendees 1 [
      setup-default-attendee
    ]
  ]
end

;; remove attendees at the exit
to exit-attendees
  ask attendees [
    if (pcolor = ([pcolor] of patch min-pxcor min-pycor)) [die]
  ]
end

;; advance simulation indefinitely
to go
  if ticks >= tick-limit [stop]
  step
end
```

APPENDIX C

THE STATION PLATFORM SOURCE CODE

```
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;; File: The Station Platform.nlogo
;; Author: Marcel Bouchard
;; Date: 19 July 2011
;;
;; The purpose of this model is to incorporate behavioral intention
;; concepts into a station platform simulation, stressing influence
;; components
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

;; turtle breed: the passenger
breed [passengers passenger]
passengers-own [
  ;; attitude: degree of reaction towards offender
  alarm-creation ;; also doubles as a threshold for fleeing
  ;; influences:
  physical-enmity   ;; physical
  alarm-acquisition ;; mental
  ;; social norm: join mass exodus
  follow-affinity
  ;; other variables
  alarm-level
]
;; link breed: passenger-to-passenger links
directed-link-breed [passenger-links passenger-link]

;; turtle breed: the offender
breed [offenders offender]
;; link breed: links with the offender
directed-link-breed [offender-links offender-link]

;; prepare the simulation
to setup
  clear-all
  setup-patches
  setup-passengers
end

;; set all the patches to their default state
to setup-patches
  ask patches [
    set pcolor black
    ;; divide the world in half with a barrier
    ifelse (gap-size = 0)
      ;; barrier with no gap
      [if (pycor = 0) [set pcolor grey]]
      ;; barrier with gap
      [if (pycor = 0)
        and ((pxcor < gap-size / -2)
          or (pxcor >= gap-size / 2)) [set pcolor grey]
      ]
  ]
```

```
end

;; set all the passengers to their default state
to setup-passengers
  set-default-shape passengers "circle"
  ;; create passengers on unique patches
  create-passengers num-passengers [
    set color white
    ;; place passengers below the barrier
    set xcor random-xcor
    set ycor (random-float (min-pycor + 1)) - 1
    correct-position
    ;; set behavioral intention attributes
    set alarm-creation (random-normal-1-7 4 1)
    set physical-enmity (random-normal-1-7 4 1)
    set alarm-acquisition (random-normal-1-7 4 1)
    set follow-affinity (random-normal-1-7 4 1)
    set alarm-level 0
  ]
  setup-passenger-links
end

;; recursively place turtle below barrier in unique position
to correct-position
  if (any? (other turtles-here)) [
    set xcor random-xcor
    set ycor (random-float (min-pycor + 1)) - 1
    correct-position
  ]
end

;; produce a random number from 1 to 7 using a normal distribution
;; arg1 is the mean, arg2 the standard deviation
to-report random-normal-1-7 [arg1 arg2]
  let number (random-normal arg1 arg2)
  if (number < 1) [set number 1]
  if (number > 7) [set number 7]
  report number
end

;; build a network based on proximity and line of sight
to setup-passenger-links
  ask passengers [
    let weighted-enmity (physical-enmity * physical-weight)
    create-passenger-links-to (other passengers with
      [((distance myself) < weighted-enmity)     ;; establish distance
        and (has-line-of-sight? self myself)]) [ ;; establish LOS
      set color ([color] of end2)
    ]
  ]
end

;; report false if the line joining two turtles intersects a barrier
to-report has-line-of-sight? [turtle1 turtle2]
  ;; turtles in the same room automatically have LOS
  if ([ycor] of turtle1 > 0) = ([ycor] of turtle2 > 0) [
    report true
```

```
  ]
  let x1 ([xcor] of turtle1)
  let y1 ([ycor] of turtle1)
  let x2 ([xcor] of turtle2)
  let y2 ([ycor] of turtle2)
  ;; calculate the x-intercept of the line between two turtles
  let x-intercept 0
  ifelse (x2 - x1 != 0)
    [
      let slope ((y2 - y1) / (x2 - x1))
      set x-intercept (round (-1 * y1 / slope + x1))
    ]
    [set x-intercept x1]
  ;; report false if x-intercept hits a barrier
  if (x-intercept < gap-size / -2) or (x-intercept >= gap-size / 2) [
    report false
  ]
  report true
end

;; advance the entire simulation by one tick
to step
  if (mouse-down?) [
    process-mouse
  ]
  setup-patches
  move-passengers
  update-offender-connections
  update-passenger-connections
  exert-influence
  enforce-barrier
  setup-colors
  tick
end

;; move passengers depending on intenal and external factors
to move-passengers
  let below-rating ((count passengers with [ycor < 0]) / num-passengers * 7)
  ask passengers [
    ifelse (alarm-level < alarm-creation)
      [
        ifelse (follow-affinity * norm-weight < below-rating)
        [
          ;; calm passengers travel towards the bottom
          ifelse (ycor >= 0.9)
            [facexy 0 0.8]
            [facexy 0 min-pycor]
        ]
        [
          ;; not alerted, but leaving because everyone else is
          ifelse (ycor <= -0.9)
            [facexy 0 -0.8]
            [set heading 0]
        ]
        if (can-move? (ambling-force / 100)) [forward (ambling-force / 100)]
      ]
      [
```

```
        ;; alarmed passengers travel towards the gap then fan out
        ifelse (ycor <= -0.9)
          [facexy 0 -0.8]
          [
            set heading 0
          ]
        if (can-move? (fleeing-force / 100)) [forward (fleeing-force / 100)]
      ]

  ]
end

;; kill offender links that are too long and create new ones
to update-offender-connections
    ask offender-links [
      let kill? false
      let weighted-enmity (([physical-enmity] of end2) * physical-weight)
      ifelse (link-length >= weighted-enmity)
        ;; kill links that are too long
        [set kill? true]
        ;; kill links that intersect barriers
        [set kill? (not (has-line-of-sight? end1 end2))]
      if kill? [die]
    ]
    setup-offender-links
end

;; build a network around the offenders
to setup-offender-links
  ask offenders [
    create-offender-links-to (passengers with
      [((distance myself) < (physical-enmity * physical-weight))
        and (has-line-of-sight? self myself)]) [
      set color ([color] of end2)
    ]
  ]
end

;; kill passenger links that are too long and create new ones
to update-passenger-connections
  ask passenger-links [
    let kill? false
    let weighted-enmity (([physical-enmity] of end1) * physical-weight)
    ifelse (link-length >= weighted-enmity)
      ;; kill links that are too long
      [set kill? true]
      ;; kill links that intersect barriers
      [set kill? (not (has-line-of-sight? end1 end2))]
    if kill? [die]
  ]
  setup-passenger-links
end

;; use links to spread information and move passengers
to exert-influence
  ask passengers [
    ;; offenders create alarm in passengers
```

```
    ifelse (any? my-in-offender-links)
      [
        if (alarm-level < (alarm-creation * attitude-weight)) [
          set alarm-level (alarm-creation * attitude-weight)
        ]
      ]
      [
        ;; spread alarm to linked passengers
        if (any? out-passenger-link-neighbors) [
          let perceived-alarm (mean
            ([alarm-level] of out-passenger-link-neighbors))
          let shift ((perceived-alarm - alarm-level)
            * alarm-acquisition * mental-weight)
          set alarm-level (alarm-level + shift / 7)
        ]
      ]
    ;; enforce boundaries on alarm-levels
    if (alarm-level > 7) [set alarm-level 7]
    if (alarm-level < 0.01) [set alarm-level 0]
    ;; offender-passenger repulsion
    layout-spring
      (turtle-set self)                   ;; the set of turtles
      my-in-offender-links                ;; the set of links
      0.1                                 ;; force exerted by link
      (physical-enmity * physical-weight)  ;; link target length
      0                                   ;; global turtle repulsion
    ;; exert passenger-passenger influence
    layout-spring
      (turtle-set self out-passenger-link-neighbors)
      my-out-passenger-links
      0.1
      (physical-enmity * physical-weight)
      0
  ]
end

;; move any passengers within the barrier onto the correct side
to enforce-barrier
  ask turtles [
    if (ycor < 1) and (ycor > -1) [
      ifelse (pxcor >= gap-size / -2) and (pxcor < gap-size / 2)
        [
          ;; turtles within gap are adjusted left or right
          if (pycor = 0) [
            if (xcor < (ceiling (gap-size / -2)))
            or (xcor > (floor (gap-size / 2))) [
              set xcor pxcor
            ]
          ]
        ]
        ;; turtles within barrier are adjusted up or down
        [
          ifelse (ycor >= 0)
            [set ycor 1]  ;; top half
            [set ycor -1] ;; bottom half of the barrier
        ]
    ]
```

```
  ]
end

;; color turtles and links
to setup-colors
  ;; color turtles according to their alarm-level
  ask passengers [
    set color (scale-color red alarm-level 9 0)
  ]
  ask offender-links [
    set color ([color] of end2)
  ]
  ask passenger-links [
    set color ([color] of end2)
  ]
end

;; advance the simulation indefinitely
to go
  ifelse ((count (passengers with [ycor < 0])) > 5)
    [step]
    [stop]
end

;; remove existing offenders and spawn new ones
to spawn-offenders
  ask offenders [die]
  set-default-shape offenders "target"
  create-offenders num-offenders [
    set color red
    set xcor random-xcor
    set ycor (random-float (min-pycor + 1)) - 1
    correct-position
  ]
end

;; use mouse input to create an offender
to process-mouse
  ask offenders [die]
  set-default-shape offenders "target"
  create-offenders 1 [
    set color red
    set xcor mouse-xcor
    set ycor mouse-ycor
  ]
end
```

APPENDIX D

THE CLASSROOM SOURCE CODE

```
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;; File: The Classroom.nlogo
;; Author: Marcel Bouchard
;; Date: 19 July 2011
;;
;; The purpose of this model is to incorporate behavioral intention
;; concepts into a classroom seating simulation, stressing social norm
;; components
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

;; turtle breed: the desk
breed [desks desk]

;; turtle breed: the students
breed [students student]
students-own [
  prefer-front         ;; preference to sit near front
  prefer-alone         ;; preference towards desks with empty neighbors
  norm-front-adherence ;; strength of adherence to norm of
                       ;; "sit near front"
  norm-same-adherence  ;; strength of adherence to norm of
                       ;; "sit in same seat"
  previous-desk        ;; number of desk from previous turn
]

;; prepare the simulation
to setup
  clear-all
  setup-patches
  setup-students
  setup-desks
  ask links [
    if (hide-connections?) [hide-link]
  ]
  display-labels
end

;; set patches to their default state
to setup-patches
  ask patches [set pcolor (yellow + 4)]
end

;; create students along the bottom of the room
to setup-students
  set-default-shape students "person"
  create-students num-students [
    set prefer-front (random-normal-1-7 4 1)
    set prefer-alone (random-normal-1-7 4 1)
    set norm-front-adherence (random-normal-1-7 4 1)
    set norm-same-adherence (random-normal-1-7 4 1)
    set previous-desk -1
    set xcor random-xcor
```

```
  ]
end

;; produce a random number from 1 to 7 using a normal distribution
;; arg1 is the mean, arg2 the standard deviation
to-report random-normal-1-7 [arg1 arg2]
  let number (random-normal arg1 arg2)
  if (number < 1) [set number 1]
  if (number > 7) [set number 7]
  report number
end

;; create and arrange desks
to setup-desks
  set-default-shape desks "square"
  create-desks (num-rows * num-columns) [
    setxy max-pxcor max-pycor
    set heading 0
  ]
  ask desks [
    set color (brown - 2)
  ]
  arrange-desks
  network-desks
end

;; arrange desks into a grid formation
;; note: code inspired by Uri Wilensky's "Party" model
;;       as included with NetLogo
to arrange-desks
  ;; determine the interval between rows and columns
  let row-interval (floor ((world-width * 0.75) / num-rows))
  let column-interval (floor (world-width / num-columns))
  ;; store patches that serve as points on the grid
  let grid patches with [
    ;; space rows and columns evenly
    ((pycor mod row-interval) = 0) and
    ((pxcor mod column-interval) = 0) and
    ;; only add patches under the limit
    (floor (pycor / row-interval) < num-rows) and
    (floor (pxcor / column-interval) < num-columns)
  ]
  ;; determine the shift necessary to center rows and columns
  let y-shift (floor ((max-pycor - ([pycor] of (max-one-of grid [pycor])))
      / 2))
  let x-shift (floor ((max-pxcor - ([pxcor] of (max-one-of grid [pxcor])))
      / 2))
  ;; place desks onto unique grid locations
  ask desks [
    move-to (one-of (grid with [not (any? (other desks-here))]))
  ]
  ;; shift desks to center
  ask desks [
    set xcor (pxcor + x-shift)
    set ycor (pycor + y-shift)
  ]
end
```

```
;; link adjacent desks together
to network-desks
  ask desks [
    ;; link with nearest column neighbors
    let same-column ((other desks) with [xcor = ([xcor] of myself)])
    create-links-with (same-column with-min [distance myself]) [
      set color black
    ]
    ;; link with nearest row neighbors
    let same-row ((other desks) with [ycor = ([ycor] of myself)])
    create-links-with (same-row with-min [distance myself]) [
      set color black
    ]
    ;; link with nearest neighbors not in same row or column
    let diagonals ((other desks) with [
      (xcor != ([xcor] of myself)) and
      (ycor != ([ycor] of myself))
    ])
    create-links-with (diagonals with-min [distance myself]) [
      set color black
    ]
  ]
end

;; draw indicator labels
to display-labels
  ask turtles [set label ""]
  ask patches [set plabel ""]
  if labels? [
    ask students [
      if (patch-at 1 1 != nobody) [
        ask patch-at 1 1 [
          set plabel ([who] of myself)
          set plabel-color lime
        ]
      ]
    ]
  ]
end

;; advance the simulation by one tick
to step
  ask links [
    ifelse (hide-connections?)
      [hide-link]
      [show-link]
  ]
  ifelse (any? students with [ycor = 0])
    [
      ask one-of students with [ycor = 0] [
        choose-desk
      ]
      display-labels
      tick
    ]
    [
```

```
      stop
    ]
end

;; move all students to the front of the classroom
to reset-students
  setup-patches
  ask students [
    setxy random-xcor min-pycor
  ]
  display-labels
end

;; sit at an unoccupied desk
to choose-desk
  ;; convert student norm adherence into weights between 0 and 1
  let weight1 ((norm-front-adherence - 1) / 6)
  let weight2 ((norm-same-adherence - 1) / 6)
  ;; isolate the set of empty desks
  let available-desks (desks with [not (any? students-here)])
  ifelse (random 100) < (norm-sit-front * weight1)
    [
      ;; follow the norm of sitting in the front
      move-to (min-one-of available-desks [distancexy (max-pxcor / 2) 0])
      ask patch-here [set pcolor red]
      ask neighbors [set pcolor red]
    ]
    [
      ifelse (previous-desk >= 0) and
      (member? (desk previous-desk) available-desks) and
      (random 100) < (norm-sit-same * weight2)
        [
          ;; follow the norm of sitting in previous seat
          move-to (desk previous-desk)
          ask patch-here [set pcolor magenta]
          ask neighbors [set pcolor magenta]
        ]
        [
          ;; isolate the most preferred desk of those available,
          ;; disregarding norms
          let pick (find-best-desk self available-desks)
          move-to pick
          set previous-desk ([who] of pick)
          ask patch-here [set pcolor blue]
          ask neighbors [set pcolor blue]
        ]
    ]
end

;; given a student and desk set, report the most preferred desk
to-report find-best-desk [arg-student arg-desks]
  ;; find desks closest and furthest to front and center
  let closest-desk (min-one-of desks [distancexy (max-pxcor / 2) 0])
  let furthest-desk (max-one-of desks [distancexy (max-pxcor / 2) 0])
  ;; define region as the distance between the above two desks
  let distance-region -1
  ask closest-desk [
```

```
    set distance-region (distance furthest-desk)
  ]
  ;; transform prefer-front [1 7] into a
  ;; preferred distance [0 distance-region]
  let ratio (abs (([prefer-front] of arg-student) - 7) / 6)
  let preferred-distance (ratio * distance-region)
  ;; find candidate desks that are close to this preferred distance
  let candidates -1
  ifelse ((count arg-desks) < 3)
    [
      set candidates arg-desks
    ]
    [
      set candidates (min-n-of 3 arg-desks [
        abs ((distance closest-desk) - preferred-distance)
      ])
    ]
  ;; report the candidate desk with the most compatible level of crowding
  let preferred-crowding ((abs (([prefer-alone] of arg-student)
        - 7) / 6) * 8)
  report (min-one-of candidates [abs (preferred-crowding
        - find-num-student-neighbors)])
end

;; report the number of neighbor desks with seated students
to-report find-num-student-neighbors
  report (count (link-neighbors with [any? (students-here)]))
end

;; advance the simulation indefinitely
to go
  step
end
```

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