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Chapter 3

EXPLORING EMERGENCE IN SIMPLE AGENT-BASED MODELS

Marcia R. Friesen*, Kyle Leduc-McNiven, Ken Ferens, Ian Jeffrey and Robert D. McLeod
Electrical and Computer Engineering
University of Manitoba
Winnipeg, Manitoba, Canada

ABSTRACT

This work examines the concept of emergence in agent-based modelling and simulation by modelling several types of agent-based systems and examining simulations for potential emergent phenomena. Emergent phenomena are considered as either emergent behaviour or emergent strategy. Initially, the Netlogo platform is used to develop a rudimentary agent-based model upon which incremental and systematic changes in agent behaviour rules are imposed to examine the points at which emergent behaviour may be detected. Emergent behaviour is defined as agent- and/or group-level phenomena that are not specifically encoded by the modeller. While emergence may be a behavioural whole of the system that is greater than the sum of its parts, it may manifest at large or small scales, may be a complex or a simple phenomenon, and may be counterintuitive or not. Emergent behaviour begins when the outcomes of a simulation cannot be expressly tied back to the encoded

* Corresponding Author: marcia.friesen@umanitoba.ca.

individual agent behavioural rules and profiles. In the second part of this work, an in-house platform is used to explore emergent strategy. Emergent strategy is the view that strategy emerges over time as agents' intentions collide with and accommodate a changing reality. Emergent strategy is a set of actions consistent over time, or a realized pattern which was not expressly intended in the original planning of strategy, i.e., a form of learning that emergences from practice.

Keywords: emergent behaviour, emergent strategy, netlogo, mobile social gameing

INTRODUCTION

Agent based modelling (ABM) is 'bottom-up' systems modelling from the perspective of constituent parts. Systems are modelled as a collection of agents (in social systems, most often people) imbued with properties: characteristics, behaviours (actions), and interactions that attempt to capture actual properties of individuals. In the most general context, agents are both adaptive and autonomous entities who are able to assess their situation, make decisions, compete or cooperate with one another on the basis of a set of rules, and adapt future behaviours on the basis of past interactions. Agent properties may be conceived by the modeller or may be derived from actual data that reasonably describe agents' behaviours – i.e., their movements and their interactions with other agents [1].

The foundational premise and the conceptual depth of ABM is that simple rules of individual behaviour will aggregate to illuminate complex and/or emergent group-level phenomena *that are not specifically encoded by the modeller;* this is the key characteristic of emergence within an ABM. Emergent behaviour may be counterintuitive or surprising, and may be a simple or complex behavioural whole that is greater than the sum of its parts [1]. In a common example of an ABM, a flock of birds given two simple rules – to act to avoid collisions, and to always steer toward the centre of mass of the flock – generate interesting, undulating or wave-like collective behaviour. However, we do not regard "surprise" as an essential component of emergence [2, 3, 4], if only because experience with emergent systems reduces one's sense of surprise. We do, however, welcome surprise as a substantive aspect of hunting for emergence. Paraphrasing Thomas Edison, we might say that "hunting for emergence is 1 percent inspiration, and 99 percent serendipity", and serendipity usually is accompanied by some form of surprise. Also quoting from the lyrics of Green Day, “It's something unpredictable, but in the end it's right”.

More specifically, although there is no doubt that there are considerable emergent phenomena, it is the modelling of such phenomena which is problematic or at least embryonic. An important distinction is made between modelling phenomena and modelling emergence, in that the phrase ‘modelling emergence’ is an oxymoron when one adheres to the premise that emergence cannot be explicitly modelled. Modelling phenomena refers to modelling systems which may demonstrate emergence. The ability of system-level outcomes to elude simple prediction based on the known rules that govern agent behaviour is a cornerstone of emergence. It may be *a posteriori* predictable, but that is sort of cheating.

First, this work examined an agent-based model developed from an existing simple model described by others [5], upon which incremental and systematic changes in agent behaviour rules were imposed. These changes included input conditions, agents’ behavioural preferences, and gender of agents, and the extensions were made to examine the points at which emergent phenomena may be detected.

The simple models initially investigated [1, 5, 6] were those where emergent behaviour has been implied. To prevent to discussion from becoming too cumbersome, the models are conceptual, in line with the objective that “the models should be as simple as possible, but no simpler” [7]. In this case, they can be described simply as two types of agents a minimal number of rules of action and interaction between agents.

The prototypical example is the “Heroes and Cowards” game, also called “Friends and Enemies” or “Aggressors and Defenders”. This behaviour has been studied for several decades [6] and is simulated here as an agent-based model. From this initial model, the behaviour rules in subsequent models are varied by modestly introducing new agent types and/or new rules of and constraints on behaviour. The most interesting variants included the introduction of simple constraints which removed a degree of randomness, ostensibly expected to make the behaviour more predictable and less likely to display emergence. The objective was to see, even in simple models, whether emergent phenomena appear and what the nature of the emergent phenomena may be.

Second, this work examined strategy as an emergent phenomenon, conceptualized as discovering a winning strategy over time within a game. We would argue that a pattern or strategy of play, which may be learned by an agent (real or simulated) is an example of strategy emergence from a system where the rules were simple within an apparently stochastic environment. Specifically, we will explore strategy emergence within a mobile game where human and virtual agents interact. The introduction of the human agent prevents one from inadvertently "hard-coding for emergence" which may be the case, had a human not been in the loop.

Examples of emergent phenomena found in nature include many insect organizations, colonies and swarms, birds flocking, and fish schooling. Although these real world systems display emergence, the agent based modelling of a system that may demonstrate emergence is fraught with difficulties, as emergence is inherently esoteric and/or ephemeral - that is, difficult to capture objectively. If one has explicitly coded for emergent behaviour, then it is really *not* emergent, as it is an expected or anticipated result. Emergent phenomena is closely aligned to the expression made somewhat familiar by Jacobellis v. Ohio, 378 U.S. Supreme Court 184 (1964), "I know it when I see it".

Emergent Behaviour Within Agent Based Models

Phenomena associated with crowd or group behaviours have been extensively investigated. Existing research on crowds explores how individual behaviors are influenced by the characteristics and behaviours of surrounding people, which – in large enough quantities – can be considered crowds, and how crowd formation and behaviour are impacted by the characteristics of individual people in the crowd [8, 9].

We know intuitively that the nature of crowds and experience of being in crowds varies from culture to culture in accordance with varying cultural norms of personal space, interpersonal interaction, and socialization between sexes. Researchers have investigated pedestrian street crossings where individual agent decisions appear to create a filamentary flow (a group phenomenon) within the larger group of individuals. It is a slight extension of one's local information to include the information of a person or persons one attempts to follow when deciding one's path [8]. This is often modelled by an ABM; however, the apparent emergence of filamentary flow is often somewhat predestined by the programmed local decision rules which only make it *appear* that the stream flow is emerging. In fact, a pre-programmed social decision is made by an agent to follow another agent, provided that the opportunity to follow is deemed better than directly moving forward. For example, if one were to model movement in an analogue to ant colony behaviour where a pheromone trail was emulated, then one would likely induce filamentary flow. On the other hand, if the program merely limited its agent direction to have the agent take the most direct route to their destination, and always to veer to the right if a head-on collision is imminent, and if a group phenomenon of stream flow were then observed out of these very elementary, agent-bounded rules, then one may be able to say that filamentary flow phenomena “emerged” independent of the simple rules of individual behaviour which did not predispose nor favour filamentary flow.

There are also swarm-based models that generate interesting, if not emergent patterns of behaviour, potentially simulating crowd movements. Ants exhibit milling behaviour, i.e., continual circular motion for extended periods, which eventually kills them [10], whereas fish schooling appears to reduce predation [11]. This self-organized pattern, modelled as agents [12], could be considered as emergent, if not necessarily beneficial.

Party Crowds

As with the advice to the White Rabbit from the King in Alice in Wonderland, the White Rabbit put on his spectacles and asked, 'Where shall I begin, please your Majesty?' 'Begin at the beginning,' the King said gravely, 'and go on till you come to the end: then stop.' So too, we will start with replicating the more traditional “Friends and Enemies” or “Heroes and Cowards” parlour game, make some observations, add some minor variations, and conclude with the more interesting emergent behaviour, then stop.

First is a simulation of the game where “simple rules of individual behaviour can lead to surprisingly coherent system level results” [13]. The game is stated as a parlour game where all agents in the model are randomly labelled either A or B for a given simulation. The rules of behaviour state that each agent picks two other agents at random. In the first instance, each agent is to move about, always keeping their respective agent B between themselves and their respective agent A (Cowardly behaviour). In a seemingly small and inconsequential change in the rules of behaviour, each agent always attempts to position *themselves* between their respective chosen agents A and B (Brave behaviour).

The behaviours of the agents are illustrated graphically in Figure 1.

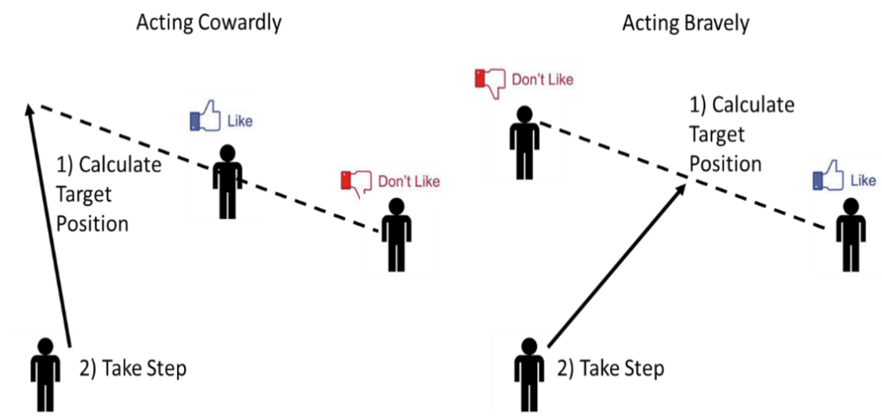


Figure 1. Agent Behaviour. a) Acting Cowardly and b) Acting Bravely.

In the first instance (Cowardly behaviour), the agents (people) mill about in a more or less uniform manner with maximum and equal social distancing, while in the second simulation (Brave behaviour), they immediately tend to cluster. At first, this appears to be a somewhat surprising, unexpected collective behaviour and, by extension, is potentially emergent. However, if the collective outcome is easily predicted from the governing rules for agents (which is arguably the case here), perhaps the agents and their interactions are not sophisticated or diverse enough to trigger a truly emergent phenomenon. It was also noticed in the simulation in [1] that the agents have the ability to teleport across the room as a way to model a wrap-around world; however, that makes the simulation highly unrealistic as a parlor game and makes model-matching with the real world difficult. This feature highlights the impact of the model's boundary conditions: a world that either wraps around in the horizontal or vertical direction has significant impact on how the simulation evolves.

Subsequently, we adapted an ABM version of the above-referenced "Friends and Enemies" parlour game by U. Welinski within Netlogo [14]. Netlogo is an ABM framework (https://ccl.northwestern.edu/netlogo/) that is freely available with low threshold programming requirements, making it ideal to explore interesting ABM phenomena and to potentially witness emergent behaviour. The potential of Netlogo is succinctly expressed in the paradigm of Wolfram's experimental mathematics that includes the use of computation for (1) gaining insight and intuition; (2) discovering new patterns and relationships; and (3) using graphical displays to suggest underlying mathematical principles, etc. among others [15]. These notions are ideally suited to ABMs.

The parlour game in Netlogo is called “Heroes and Cowards” and can be found in the Netlogo library under the IABM Chapter 2 folder which accompanies the Netlogo installation. The game is also discussed in the accompanying book by Wilenski [5] (chapter 2). Simple modifications and a bug fix as suggested by U. Welinsky were undertaken when the model was initially explored.

There are a number of variations that a person can implement to reproduce the results of Bonabeau’s parlour game, at least “on the face of it”. The most interesting of the new variations introduced was ordering of agents (people) as they arrive at the party. In this modification, rather than randomly selecting “Friends” and “Enemies”, the order of arrival was used to set “Friends” and “Enemies”. This was viewed as constraining the system by slightly reducing the degree of stochastic or random processing. As an aside, in other types of problems such as in integrated circuit placement and routing problems (NPC problems), the problem becomes easier when the I/O assignments are removed. Here constraints are introduced which resulted in significantly more interesting and arguably less predictable behaviour, as will be demonstrated.

One can also remove the agent teleportation ability (which effectively precludes a wrap-around world and is by default very easy to do in Netlogo) and assign additional properties to the agents (for example, assign gender to each agent and create rules for the selection of agents A and B based on gender (same, opposite, one of each, etc.). Although this only adds one more level of specificity, it may be just enough to elude simple prediction, which arguably is a cornerstone of emergence.

Scenario 1: Gender-Modified ABM

In the first instance, gender extensions to Bonabeau and Welinski’s models of “Heroes and Cowards” were made. In a modified genderized version of the ABM, two modes were supported: an agent could select two other agents either at random or an agent could select the other agent(s) based on similar gender.

Figure 2 illustrates the outcomes of a gendered modification of the ABM, with Figure 2a as the initial conditions. In Figure 2b, the agents select their A and B agents at random and the agents attempt to position themselves between the agents they have selected (Brave behaviour). In Figure 2c, the agents select their A and B agents from the same gender and again attempt to position themselves between the agents they have selected (Brave behaviour)). The simulation of Figure 2c demonstrates the following stylized properties of social systems, without having designed them into the underlying model assumptions:

- Brave individuals with arbitrary friend/enemy genders tend to aggregate.
- Brave individuals with the same friend/enemy genders tend to aggregate or cluster by gender (at least, they do so in a wrap-around world).

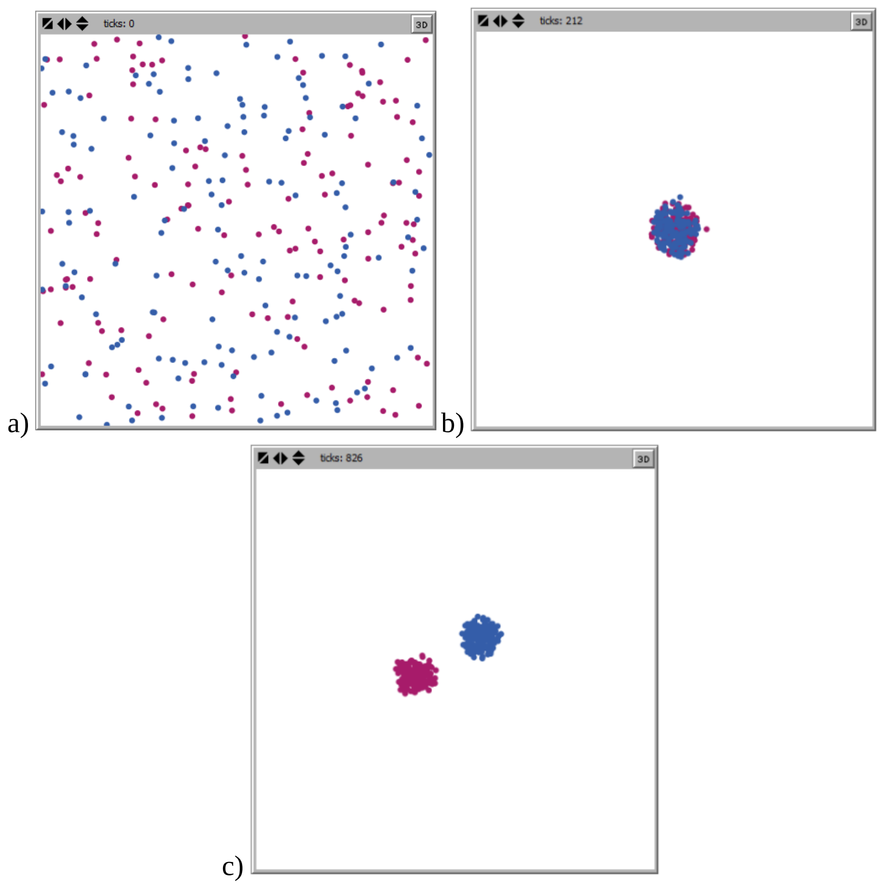


Figure 2. Gender-modifed ABM with a) Initial party-goer locations b) Homogeneous cluster and c) Segregated clusters.

As with everything, there are caveats. The segregation of genders is less distinct or non-existent in the non-wrap-around world and also becomes less apparent as the population of agents increases, for reasons which are somewhat self-evident (centre of mass argument).

It should be noted that the observed segregation of party goers, albeit a natural phenomenon at real parties, is a consequence of initial conditions of the random placement of agents. It is also a consequence of wrap-around boundary conditions. Without the wrap-around boundary conditions, the simulation returns to that of aggregation.

Scenario 2: Non-Wraparound Worlds and Visual Insights

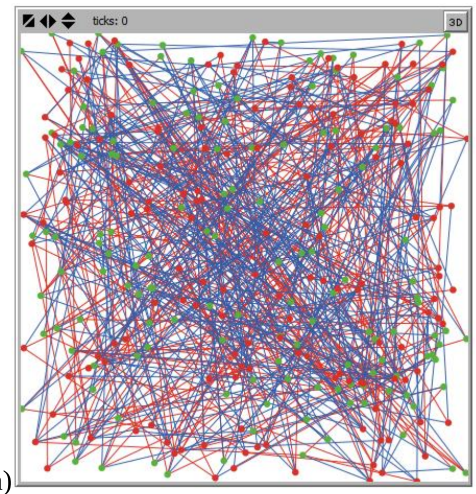
Figure 3 illustrates the parlour game in a world that does not wrap around and where the agent acts cowardly and attempts to position itself such that its selected agent B is always between itself and its selected agent A. This does not result in “everyone in the room will mill about in a seemingly random fashion”, as expected in [1], but rather something that is possibly unexpected: the agents systematically occupy the perimeter of the room. The expected milling about only occurs when the world wraps-around.

Figure 3. Potential emergent behaviour.

Arguably, Figures 2c and 3 potentially illustrate some form of emergence. The clusters formed are neither obvious nor predictable from the rules governing agent behaviour, and the occupancy of agents along the perimeter is not as anticipated, given that one was expecting a more uniform movement pattern.

More interesting and somewhat unexpected is the situation when links between friends and enemies are displayed as shown in Figure 4. Links are very easily created and displayed in Netlogo. In Figure 4, the red links are between enemies with the blue links between friends.

a)



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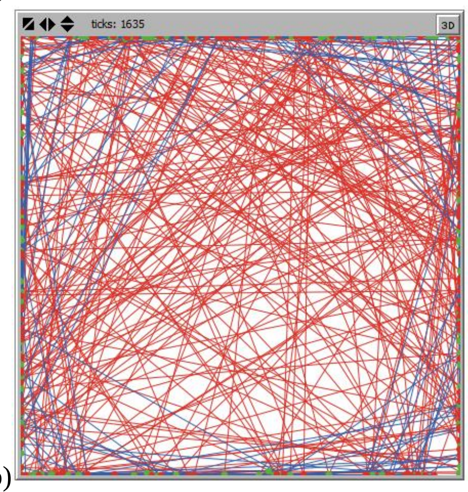


Figure 4. Potentially interesting or unexpected result. a) Initial conditions and b) Final result.

Perhaps it is not surprising that the links with enemies are the ones that eventually traverse the room, illustrating that enemies tend to socially distance themselves from one another while attempting to keep friends close. In a bit of humour, this is somewhat opposite to the advice of "Michael Corleone" in The Godfather Part II (1974), written by Mario Puzo and Francis Ford Coppola: "My father taught me many things here — he taught me in this room. He taught me — keep your friends close but your enemies closer" [16]. This behaviour was noticeable as a consequence of being able to use a graphical display to explore underlying mathematical principles.

These extensions demonstrated within the "Heroes and Cowards" party game associated with assigning gender to agents and/or allowing the world to wrap-around or not is no doubt interesting. Notwithstanding, there is still some gas in the tank when it comes to exploring this simple parlour game further, and as such, we return to the King's directive.

Scenario 3: Ordering of Agents upon Arrival

In this scenario, agents (people) are assigned enemies and friends as they enter the parlour, based on their order of arrival. Agent i, will have agent i+1 (the next to arrive) as a friend, and will have agent i-1 (the agent who arrived just prior) as an enemy. This is clearly a high degree of ordering, denoted LinearWrap (Scenario 3a) since the enemy of agent i would be i-1 mod (number of agents in the simulation) and the friend of agent i would be i+1 mod (number of agents in the simulation) (Figure 5a). In a more technical parlance, this configuration is akin to a bidirectional circular buffer.

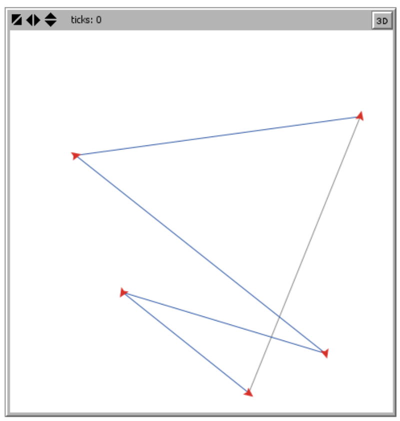
In a variation of Scenario 3, the same friend and enemy relationships are enforced but without wrapping the connection at the first and last to arrive. While still highly ordered, this is denoted LinearNoWrap (Scenario 3b), as the enemy of agent 0 would be agent 0's own enemy and the friend of the last agent to arrive would be their own friend as shown in Figure 5b). This configuration is akin to a traditional queue.

The degree of randomness in the simulation is reduced due to both being ordered, as well as ensuring that each agent has a unique friend and a unique enemy, which would not be the case if friends and enemies were selected at random with replacement.

In response to the question of emergence - whether group dynamics can be anticipated once one is familiar with the agent rules of behaviour – the answer posited here is 'no', in that surprising and interesting patterns emerge. In our estimation, the patterns and collective behavior that emerge are as least as interesting as those associated with Wolfram's cellular automata and/or

Conway's game of life [17]. However, we are not conjecturing that these simple parlour game patterns are universal computational machines, but rather that they illustrate convincingly "on the face of it" emergence, if nothing else.

Simulating Scenarios 3a and 3b leads to the most interesting patterns in our progression through rudimentary ABMs with variations, as illustrated in Figures 6 and 7, respectively. It should be qualified as being *potentially* more interesting, as emergence is often in the eye of the beholder. Figure 6 illustrates Scenario 3a as a progression from initial conditions to knot like patterns followed by disentanglement into a closed loop (a bit like visualizing knots in topology, without the headache). Figure 7 illustrates Scenario 3b as a progression from initial conditions to knot-like patterns, followed by disentanglement into a string.

a) 

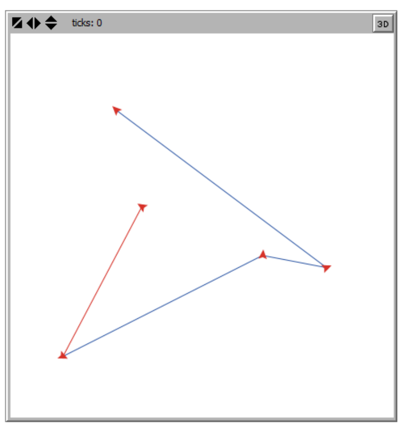
b) 

Figure 5. a) LinearWrap, 5b) LinearNoWrap.

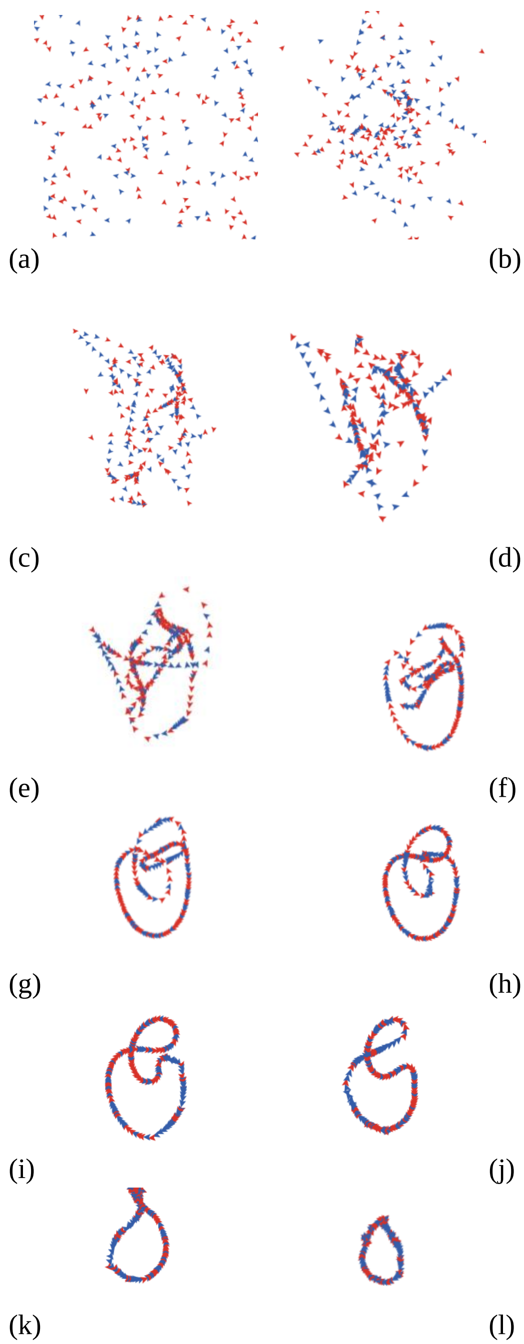


Figure 6. Evolution of scenario 3(a): LinearWrap (Figure 5a).

It should be noted that for visualization purposes, the agent shape has been changed to their Netlogo default arrow shape.

These patterns are quite amusing to watch in real time as they traverse and dart about the screen, not unlike partiers at parties forming a conga line (also a form of emergence in real social systems and notably amusing to watch and/or participate in).

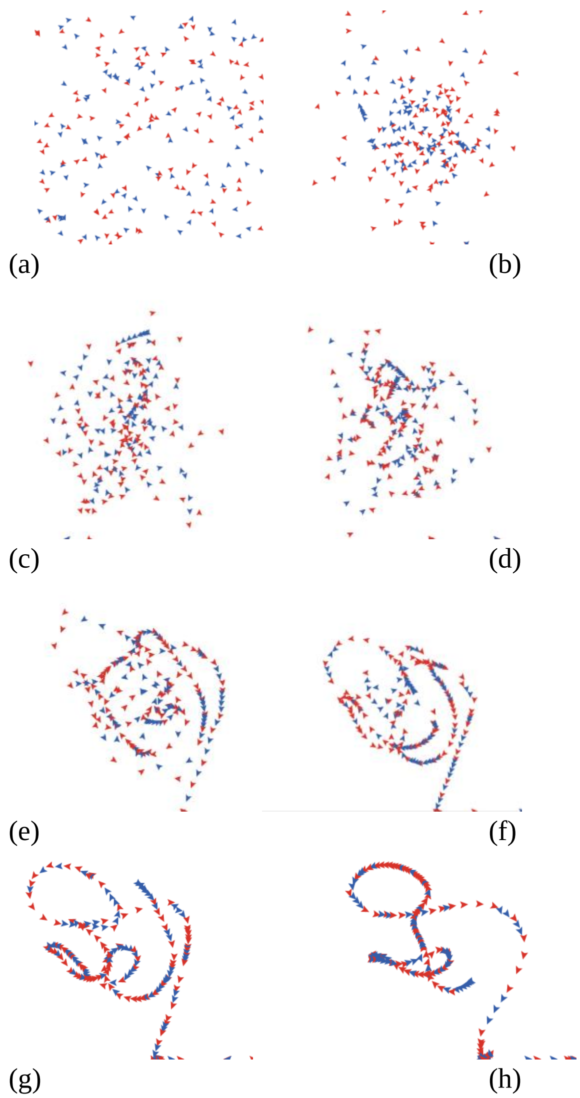


Figure 7. (Continued)

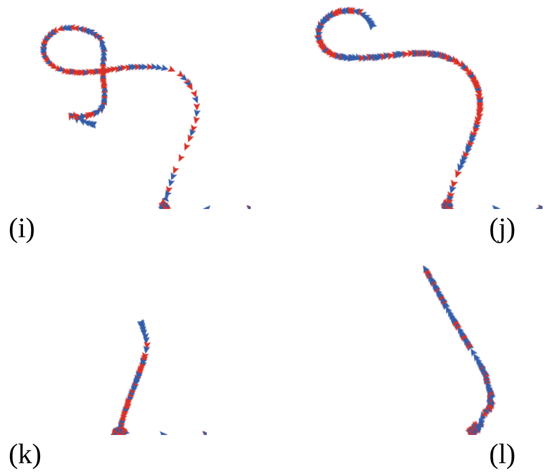


Figure 7. Evolution of scenario 3(b): LinearNoWrap (Figure 5b).

A further modification is that the partygoers are a mixed group of those who act bravely as well as cowardly, rather than the whole population of agents acting in one way or the other. This change enhances the visual appeal and is not necessary to generate these patterns. The macroscopic behaviour is similar to that when the partygoers are all of one type but not quite as interesting. For example, when everyone acts bravely, the agents tend to aggregate a bit sooner than when mixed. The mixed strategy was introduced by Welinski in Chapter 2 of [5].

Another parameter that was added here was a degree of crowd avoidance. In general, the agents in Netlogo can occupy the same space, so a mild form of collision avoidance was introduced. At present the agent will move directly towards the target unless the number of agents within a cone view of 60 degrees and less than 30 steps range is greater than 10% of the party-goers. If the 10% threshold is exceeded, the agent will simply move in a random direction. This simple form of collision avoidance is easily introduced as a behaviour within Netlogo.

We have made our simple extensions to the “Heroes and Cowards” model available in the Netlogo Model Commons [18]. The visualizations are viewable on YouTube [19].

EMERGENT STRATEGIES

In examining potential emergent strategy, our discussion will focus on developing or discovering a winning strategy over time. Specifically, we will explore strategy emergence within a mobile social game within a human and virtual agent environment as discussed in Chapter 8 of [5]. We argue that this pattern (strategy), which may be learned by an agent, human or simulated, and which may not even able to be described completely, is an example of an emergent strategy. As with more traditional spatial-temporal ABMs examined in the proceeding section, strategy emergence would have to develop from a system where the rules were simple within an apparently stochastic environment. This latter discussion resonates with emergent strategy examined within organizational behaviour (e.g., [20]).

We have developed a mobile social game for the purpose of teasing out potential strategy learning. The game is a simple variation or modified version of the card game War, played on a mobile device. The mobile game variant is played with only five cards dealt face-up from a deck of 52, and as such, each player knows only the value of their own cards. The cards can be played in any order, high card wins for each round, and a game (playing your 5 cards) would typically last 20 seconds. As a prototype configuration for exploring emergent strategy, a human player plays against a bot. While an obvious scoring system would be to award a single point for each round, our version employs a weighted scoring system, recognizing that a narrow victory is more satisfying than a blowout. Hence there is now an opportunity for a player to learn a winning strategy over time.

At this time, the game is loosely considered an ABM consisting of autonomous agents (humans) and agent bots. However, there is presently no opportunity built-in to collaborate or collude in beating the bots, although there are opportunities for learning or adaptation (both human and machine). A competitive game was the simplest setting we could envision to explore the relatively new concept of (modelling) toward observing an emerging strategy.

The game is played in an iterative fashion, and the bot maintains one of several pre-set strategies throughout the entire set of iterations. The strategies are purposely not revealed here. Five rounds complete one game, and the number of games (iterations) has been set at 100. This number allows for significance in inferring whether the human player evolved a winning strategy over time vs. winning by chance. The game has some features in common with other competitive games, although it has been designed to be of short duration in an iterative fashion.

Presently, the game consists of levels, for which the bot plays a strategy for each level without variation in strategy while at that level. After 100 iterations the player may level up if they have learned a winning strategy. Here the agents are both players and bots. Feedback is immediate: the result of each game is scored with tie games ignored. At the end of 100 iterations or games, the strategy of overall play is presented to the player as a distribution associated with play, provided the player discovered or evolved a winning strategy. Although the cards are dealt from a deck of 52, they are ranked for each game as 1 (lowest) through 5 (highest) for strategy presentation purposes.

A winning strategy by the human player was defined as consistent play tending to 2 standard deviations above random play, with random play having a 50/50 probability of winning. This provides a P-value of less than 0.05 and would be considered significant as opposed to winning by chance. Effectively, the result would imply a 2.8% chance of winning by luck alone and would lend evidence to an emergent strategy having developed over the 100 iterations. It is possible to win by luck, but it is also highly unlikely [21].

Figure 8 displays a login and welcome screen. A subsequent screen explains the basic features and rules of the game, including disclosure that one is playing against a bot and that the bot is using one strategy consistently for 100 iterations of play for each level.

Figure 9 illustrates an initial set-up for a round and an example of play. The human player's cards are face up while the bots are face down. In Figure 9, the human player played a Queen while the bot played a 2. As this was a lopsided win, the points awarded are calculated as 13-(Value(Queen) – FaceValue(2 Hearts)). This is a heuristic introduced to reflect a minimal number of points for a lopsided victory.

Figure 8. Login and welcome screen.

Figure 10 represents strategies that evolved or had been learned to beat the bot's strategy. This histogram represents the order in which the cards were played on average over 100 hands. For the first strategy, the player was more likely to lead with a low card followed by higher valued cards and ending with mid-range cards. This particular strategy was learned by (RDM) after 200 iterations. A winning strategy was not considered learned after 100 iterations, and hence a second round of 100 was played before levelling up (ties are ignored). For the second strategy, the player was more likely to lead with a mid-level card followed by higher valued cards and ending with low value cards. This particular strategy was learned by (RDM) after the next 100 iterations after levelling up. Figure 11 displays the records at this point in time as well as upon levelling up a second time.

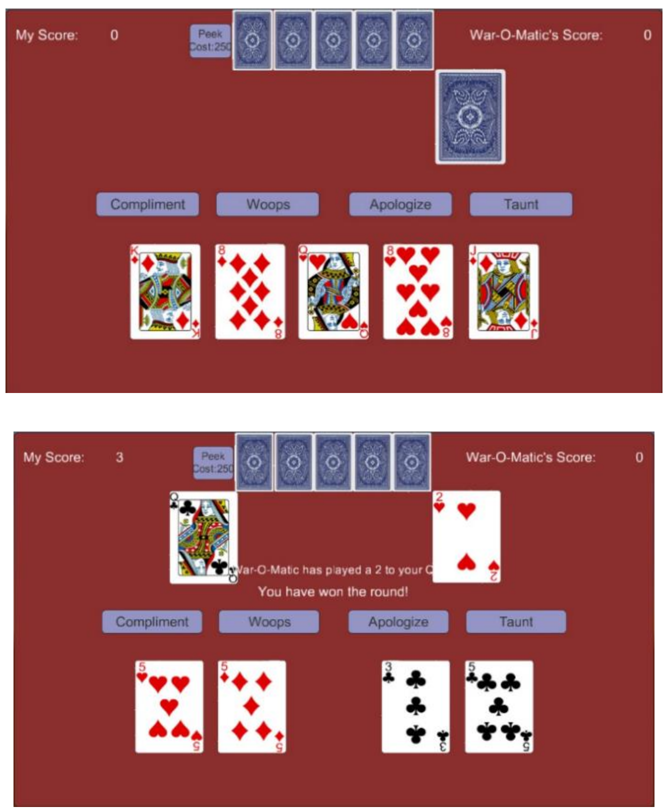


Figure 9. An example of an initial set-up for an iteration of play and an example of play.

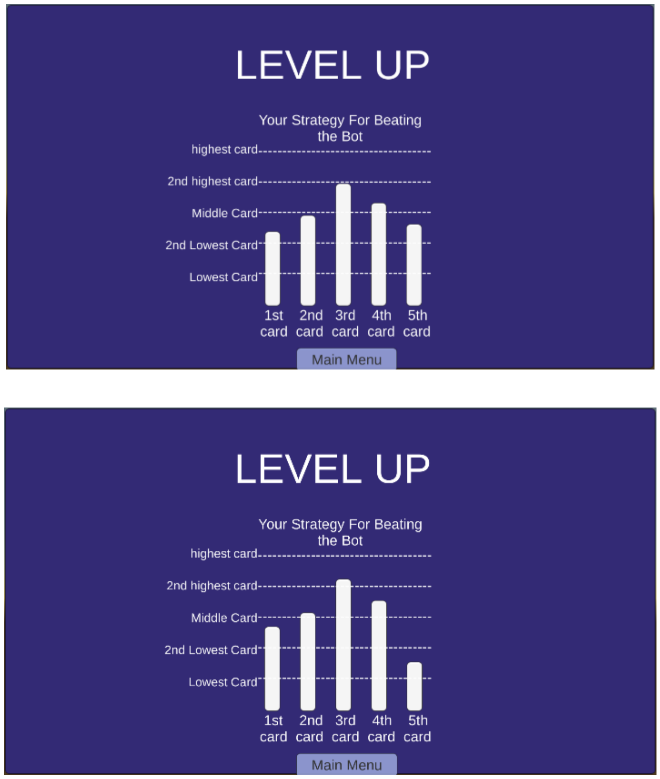
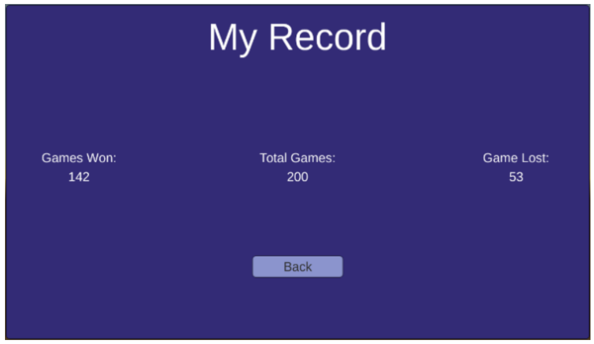


Figure 10. An example the strategy evolved (learned) to beat the bot (level 1 and level 2).

Figure 12 illustrates the results from beating the final strategy level.

Table 1 presents some limited attempts at beating the bot and learning a winning strategy. Of those listed below, Kevin, Farnaz and Fernando most efficiently learnt winning strategies against the bot. One person continued play to level 4 where a randomly selected strategy from level 1, 2 or 3 was selected by the bot (unfortunately they did not report intermediate scores).

At this time, the game is loosely considered an ABM. It is closely aligned to an ABM that relies on data input from humans, sensors, as well as potentially bots, and at times referred to as a participatory ABM [22, 23]. As mentioned, our ABM framework consists of autonomous agents (humans) and agent bots and at this time there is no opportunity for agents to collaborate or collude in beating the bots. Agent interaction is limited to one human agent and one bot agent, regardless of how many may be playing against bots. Yet, as one plays, one does get a feeling of developing a strategy, particularly as one starts accumulating wins. The opportunity to recognize a pattern and exploit it is present.



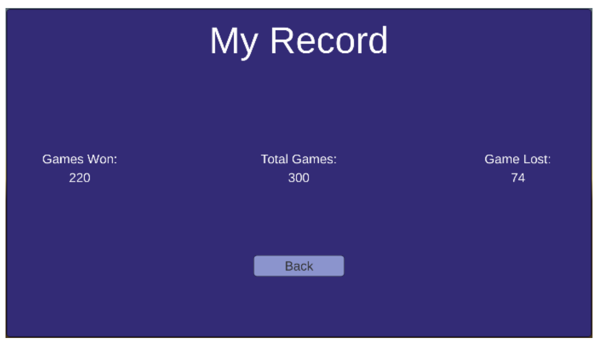


Figure 11. A cumulative record illustrating a strategy was learned significantly above beating the bot by pure chance (level 1 and level 2).

Figure 12. A cumulative record illustrating a strategy was learned significantly above beating the bot by pure chance (final level 3).

Table 1. Example of play and cumulative scoring

User	Level 1		Level 2		Level 3		Level 4	
	win	loss	win	loss	win	loss	win	loss
Bob	142	53	220	74	292	101		
Ken	70	30						
Kevin	85	12	160	34	219	50		
Mehrdad	80	16					317	72
Sridhar	69	28	208	87				
Farnaz	80	19	162	35	256	51		
Rahul	75	26						
Fernando	76	23	149	50	213	83		
Monjurul*	80	71						

* Did not level up.

Although it is difficult to draw any profound conclusions from the limited number of samples above, it seems that for the majority of players they had no difficulty in detecting a pattern and beating the bot. For a small number of players it was also evident that they were unable to detect a pattern and arrive at a winning strategy. The players who played and developed winning strategies in the most optimal manner were Kevin and Farnaz. This is not by any means a Randomized Control Trial, quite the contrary, the players were all graduate students in Electrical and Computer Engineering and self-selected. Their real value was in helping to test the platform itself and coincidentally provide some initial data. Improvements to this type of game would be to allow a person to learn a strategy based on their last 100 games as opposed to levelling up in blocks of 100 as it is currently. Also the number of 100, along with system performance issues and relatively frequent disconnects was discouraging to players. A suggested number of iterations or games being 50 before levelling up was a common theme among the volunteers.

The next phase of the emergent strategy development will be to use the framework where the bot attempts to learn a player's strategy over time and adapts a strategy to beat a human.

CONCLUSION

Emergence may be thought of as a macro-scale effect with unique and distinct qualities, which arises as a result of micro-scale interactions, independent of and unforeseeable from the modelling decisions made at the micro-scale in agent-based simulation. This work looked more deeply into the simple parlour game “Friends and Enemies”, and made several minor modifications that brought about interesting emergent patterns of behaviour. The second part of the chapter explored the emergence of a strategy within the context of a mobile game. This work is newer and represents yet unexplored areas for ABMs and their interaction with human agents.

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