Modeling and Simulation with Agents

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ABSTRACT

Agent based modeling is a extremely effective means of solving complicated problems that are often not easily solved by traditional problem solving techniques. Investigation has identified three primary characteristics that make agents particularly effective: their independent and discrete nature, their ability to deal with feedback easily, and their tendency to exhibit emergent behavior. The independent nature of agents allows them to easily simulate situation such as economic purchasing decisions by multiple customers, stock markets, and social simulations. Complicated feedback loops are also seen in the field of economics, where price changes by one supplier might force a price change by another supplier to stay competitive. Emergent behavior occurs when complicated and unexpected actions manifest themselves as a result of relatively simple programming on the level of the individual agents. This emergent behavior promises significantly more believable and entertaining virtual worlds. These traits and the applications of agents in economic simulation and virtual worlds are discussed in detail in this paper.

General Terms

Agents, Feedback, Diverse Entities, Emergent Behavior

Keywords

Agents, Agent Based Modeling and Simulation, Economic Simulation, Virtual Worlds, Feedback, Diverse Entities, Emergent Behavior

1. INTRODUCTION

Agent based modeling and simulation helps solve complicated problems by using a group of simple, independent, and discrete individuals called agents. Agents are able to simulate complicated environments that contain numerous feedback loops. For this reason, they are highly useful in fields such as economics, sociology, biological sciences, in virtual worlds, and more. This paper highlights the defining characteristics of agents. Two specific applications are discussed in depth, economic systems and virtual worlds. This is concluded with a brief examination of how the traits of agents are effective in each case.

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2. BACKGROUND

An agent is a generally defined as a unique and independent entity that makes decisions based on its environment [13]. In many simulations, an agent simply represents a person. However, there is wide disagreement on the definition of an agent; some modelers consider any independent individual an agent, where some researchers in the field suggest that an agent must have "the ability to learn and modify their strategies as the process unfolds"[3]. Other researchers suggest that agents are autonomous individuals that must be "capable of orderly relations" with each other [1]. Most sources do agree that the discrete nature of agents is integral to their emergent behavior, as discussed in Section 2.3.

2.1 Uses of Agents

Agents are well suited for solving a wide variety of problems that are not as easily solved via traditional means. In fact, some go as far to consider agent based modeling and simulation to be a third way of doing science: inductive logic, deductive logic, and agent based modeling [9]. Deductive logic refers to the system of reasoning where given the truth of the premises, the conclusion must also be true. Inductive logic is where the premises of an argument support a conclusion. Agents allow simulation to be the driving force in solving a problem, bypassing some of the logic that can become overwhelmingly difficult in complicated problems.

The greatest strengths of agents lie in their self-directed, goal-seeking, adaptive nature. Even simple agents, when placed in an environment with other agents, can show complicated behavior. Agents tend to be highly responsive to feedback; often the situation or environment changes as a function of the actions of the acting entities, leading to complex feedback loops, which are discussed in Section 2.4.

2.2 Formal Definition of Agents

Although there is no consensus on a formal definition for an agent, there are some very common traits, identified by Macal and North [9]. Agents are discrete individuals; they are self contained and easily identifiable as one entity. They are oriented towards personal goals, often but not always maximizing a certain objective. Each agent must be self directed and able to function independently of any other agents that are present. These agents must be able to interact with the environment in which they are a part. Less completely accepted is the idea that agents should be able to interact or communicate with other agents. Some sources propose that an agent must be able to adapt behavior over time by modifying its rules of behavior, thus requiring some type of memory.

Some definitions of agents are extremely broad, and arguably, it is often misused. For example, virtual tour guides or personal assistants are sometimes described as agents. These virtual individuals are usually personified with a 3D human-like avatar shown on screen. Often, voice synthesis is integrated into these virtual helpers. However, a single helper interacts with a human, and the image simply serves as a frontend for a rule based system [10]. These virtual individuals should not be considered agents for the purpose of this paper because they do not act independently to achieve some sort of goal. Without a human to guide their actions, they would sit idle.

2.3 Emergent Behavior

Emergent behavior occurs when a series of simple individuals work together and show unexpected behavior that is significantly more complicated than than what a single individual could do. Although emergent behavior is a key feature of agent based simulations, it is also seen in nature. An obvious example is seen with many insects. Termites work together to create large mounds with very complicated temperature control structures, even though no single termite plans to produce a specific mound [16, 17]. Emergent behavior is often characterized as being very difficult to predict given only the rules that govern the individuals. Small changes to the environment or the rulesets that govern agents can greatly affect the resulting behavior of the system as a whole [3].

One simple example of emergent behavior is flocking. In a flocking simulation, agents generally model birds, fish, or insects. There are three simple rules for each agent [11]:

- Separation: Agents will avoid collisions with each other.
- Alignment: Agents will attempt to point the same direction as their neighbors.
- Cohesion: Agents will try to stay near other agents.

These three simple rules implemented in a set of a few hundred agents create a very realistic set of clearly identifiable flocks [18], as seen in Figure 1. Most importantly, these flocks have no centralized control; no specific birds in the flock act as leaders or take on any role different from any of the other birds. Each individual in the simulation has a limited view of its surroundings and acts according to that information. Figure 1 illustrates a simulation using very basic flocking rules. The flocks that form continually recombine and split into different flocks in a manner very reminiscent of biological flocking [11].

Flocking has numerous applications. One example is document clustering. Cui et al., [5] represented a set of documents as a set of agents. Key words in each document were identified and the agents moved across a field, moving towards documents with similar keywords and away from those with different keywords. Implementation of this model is primarily a matter of defining the cohesion element to be a function of the keywords in nearby documents. Separation and alignment do not play as significant of a role. This model was very effective in clustering the documents based on their overall topic [5].

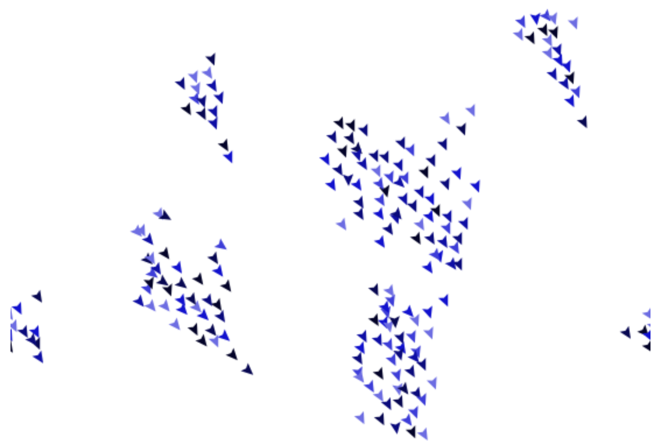

Figure 1: A flocking simulation generated using NetLogo [18].

2.4 Feedback

Agent simulations tend to deal with feedback loops more easily than inductive or deductive systems. Feedback occurs when the output of a system is looped back into the system as an input. Essentially, the output of the system is one of the factors that drives the next set of choices made in the system. Agent based simulations tend to run iteratively, where time steps occur to advance the simulation. The choices that the agents make in one iteration depend on what choices were made in the previous iteration. In the case of one-step logical systems, the calculations must take this feedback information into account by complicating the single step equation. This creates recurrence relations that are very difficult to solve analytically.

One simple example of these feedback loops is a stock exchange where each person's buying decisions affect the market, which will affect the buying decisions on the next day. Use of an agent based framework inherently provides both discrete individuals, and a mechanism to deal with the feedback of a constantly changing environment, both of which can be difficult to model inductively or deductively.

2.5 Agents as Diverse Entities

Many agent based simulations benefit from allowing multiple types of agents to exist in the simulated world. These fundamentally different agents allow modelers to represent distinct groups or even different entities without complicating the model as a whole. The design of each agent may still quite simple and intuitive.

An example of the benefit of these diverse entities can be seen in the field of economics. Real life economic systems can contain a variety of different entities, such as individual traders, consumers, corporations, financial institutions, and governments. Each entity could be modeled as a different type of agent. Environmental phenomena such as weather or natural resources can even be modeled in the same simulations as additional agents [14]. An example of this will be discussed in detail in Section 3.2.

2.6 Agent Uses

Agents enable simulation and research in many fields that previously suffered from modeling difficulties. These fields may contain many complicated feedback mechanisms which are either not understood or extremely difficult to model directly. In agent based systems, the complicated behavior will often emerge as a function of the simply and easily modeled actions of a set of individual agents. Many fields, such as economics, cannot always do direct experimentation, as discussed in Section 3.1.

Economic simulations benefit particularly from agent based models. The complexity in many economic models is directly a result of the simple goals of each individual maximizing what is best for themselves. Further discussion of this field occurs in Section 3.

Social interactions are effectively modeled in several cases using agent systems [9]. In the Sugarscape model, an artificial society was modeled and found to exhibit a variety of characteristics common to simple societies. Behaviors such as trade, wealth, disease, and conflict between multiple distinct communities appeared in this simulated society [9]. A more pragmatic example is a social simulation modeling the development of housing segregation patterns [13, 2]. In this simulation, it was determined that racially segregated neighborhoods could form when only a small percentage of people actively choose to move away from unlike neighbors.

Agents have been used in political simulations for identifying key processes in the formation of national identity [9]. In cognitive sciences, emotions and their roles in social behavior have been investigated [6]. The spread of disease and and modeling population fluctuations (the classic predator vs. prey model) are just two of many uses in the biological sciences [9]. In the area of human-computer interaction, agents are used in a variety of video games, in some cases playing the role of announcers [7]. In other cases, all of the computer controlled characters are modeled with agents [4], or in *The Sims*, the players have the role of guiding complicated agents with a basic model of emotions [19].

Despite all of the benefits to problem solving with agents, they tend to be more computationally expensive than other methods, especially when compared to more straightforward logical reasoning. An example of this can be seen in a simple biological predator/prey model. Consider a world populated with wolves and sheep, where the wolves need to eat sheep to survive. In these systems, population cycles tend to develop, as increases in the number of wolves cause the number of sheep available to decrease. At that point, many wolves die of starvation and the sheep flourish. The high availability of sheep allows the growth of the wolf population, and the cycle repeats. This process can be modeled fairly easily with differential equations, if the modeler has a sufficient math background and knowledge of the system. The system could also be modeled iteratively, calculating a new population for both groups after each time step. Finally, the most computationally expensive approach is to actually model each individual sheep and wolf on a 2D grid and allow them to interact. In the final case, the population cycles should simply emerge in the model. This approach does, however, have the advantage of being simple to modify; new variables can be added without rewriting any equations. In the age of inexpensive and abundant computer power a model that is more computationally complex but easy to develop is often a better choice than one that is difficult to develop.

3. APPLICATIONS IN ECONOMICS

Agent-based simulations are particularly well suited for research in economics, primarily because of the difficulty in performing real-world experiments [9], as discussed below. The concept of agents immediately offers a few helpful constructions; a set of independent individuals making decisions that are based on a changing environment is exactly what an economist generally wishes to model.

3.1 The Role of Simulation in Economics

Agent based simulations are effective in economics where actual experimentation is simply impossible. Direct experimentation is generally impossible; researchers cannot directly manipulate a market in a meaningful way, nor would they be able to create a 'control' market to see the effect of their changes. As a result, simulation is a vital tool for economists. Furthermore, economic simulations are characterized by complicated and recurring feedback loops that interrelate multiple sets of sometimes differentiated individuals and the environment. Modeling these complicated interactions is a strength of agent systems [9, 13, 14, 2].

3.2 Agent Modeling in Electricity Markets

Consider an example of electricity markets. Researchers wanted to determine how deregulating an electricity market would affect bulk electricity prices. Traditional analytical and statistical tools are rendered useless because of the complexity of the market processes [14]. In Tesfatsion's model [14], she gave the agents the ability to participate in discriminatory-price auctions, where buyers and sellers make purchase decisions as a function of the price per unit. Despite the obvious nature of these transactions, the exact purchase decision is difficult to model directly, because of the feedback nature of these purchases. Price changes directly affect the quantity of a product that is sold, which is leads to further price changes. Each individual electricity producer was modeled as an autonomous agent with a simple learning system that allowed it to develop a supply strategy.

Different strategies were created for the set of buying agents; these agents purchased electricity the way an average homeowner would [14]. Typically, homeowners use a consistent amount of electricity without paying attention to price fluctuations. These two different types of agents interact both within their group and with the other set of agents.

Other models for the same problem have included even more different types of agents, such as the power generation company, the transmission company, the distribution company, the customer, the demand agents, and system operators. Each of these different types of agents has a set of different goals and attributes. The complexity of this system creates feedback loops, where small changes in the pricing of the transmission company affects everything from the customer's electricity pricing to profit margins of the generating company [9]. Figure 2 illustrates some of the agents and interactions that might exist in a model such as this one.

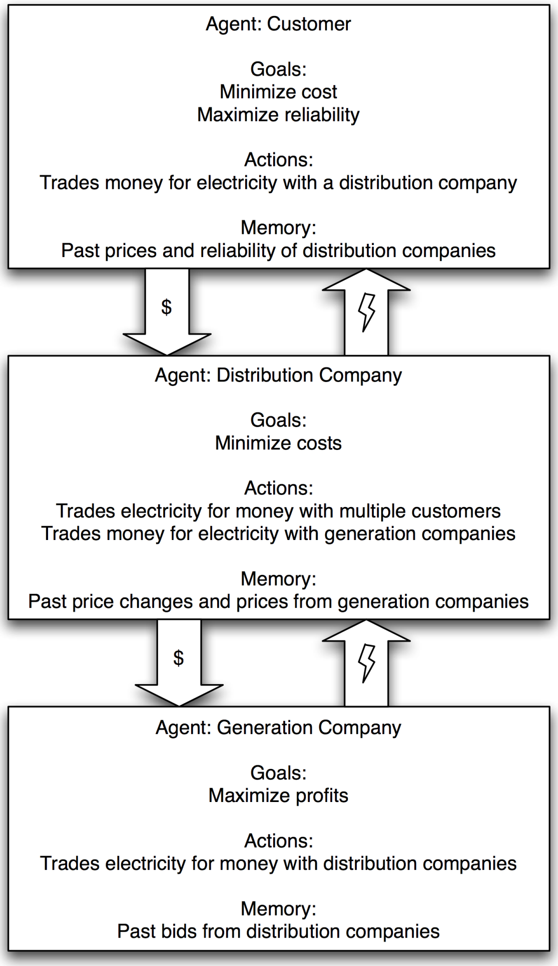

Figure 2: This is a simplification of an example in [9]. Here three unique agents, the customer, distribution, and electricity generation company, interact in a electricity market.

These models lead to a number of interesting conclusions. For example, the optimal pricing strategy for a given entity evolves and changes several times before converging. The complicated series of changes that leads to the final pricing strategy occur because of the feedback in the system, as each entity adjusts its strategy to respond to the changes of its competitor. Another important result was that some entities may collude[1] when no specific code existed to support this communication between entities [14]. This finding could be very significant in antitrust lawsuits where there are allegations of price collusion.

[1]In economics, price collusion occurs when two corporations that sell the same product meet and agree to set the price of the product artificially high. The oil cartel, OPEC, functions this way.

4. APPLICATIONS IN VIRTUAL WORLDS

A key component of any virtual world is believable inhabitants. These virtual worlds are generalized as computer simulated environments created for users to interact within. Virtual worlds include both many types of video games, training simulations, social meeting places, and more. For example, space agencies and aerospace agencies use them for training. In the military, mission briefs can be more clearly conveyed with a fly through of a virtual world. In order to make these virtual worlds believable, immersive, and more interesting, Non-Player Characters (NPCs) are added. These NPCs are computer controlled entities that also inhabit the world, along-side the human controlled characters. Many modern video games can be considered a subset of virtual worlds; the game itself occurs inside a world created for the game, much like fantasy worlds are created in many works of fiction.

The value of agents is readily apparent in many virtual worlds because of the obvious correlation between discrete goal-driven agents and entities in a world. The variety of research in virtual worlds [4, 10, 12, 1, 3] and the fast paced global game development industry [19, 7] makes the flexibility of agents particularly valuable.

4.1 Agents as Non-Player Characters

Virtual worlds, and particularly the subset of video games, require a set of believable people, creatures, animals, or other entities to fill it and bring it to life. A significant portion of computer games include the human player interacting with NPCs controlled by an artificial intelligence system. Although it depends on the genre of the game, in many cases, the more human-like the computer controlled characters behave, the better. Players tend to find AI systems to be rigid and unsatisfying, and would prefer more meaningful and immersive interactions with NPCs [4].

Oblivion, 2006, by Bethesda Softworks, is one recent large scale commercial computer game that featured agent-like modeling. *Oblivion* uses a system called Radiant AI, which is described as giving "every NPC a set of 'needs' (such as hunger) that they will [attempt] to fulfill" [15]. Although the promotional material strongly suggests this form of artificial intelligence is completely revolutionary, other evidence suggests it is essentially an agent based AI system, albeit one of the first in a major game.

This agent AI system proved to be too powerful and not suited for the context of a game. Several interesting and somewhat unexpected[2] behaviors were observed [15].

> One character was given a rake and the goal "rake leaves"; another was given a broom and the goal "sweep paths," and this worked smoothly. Then they swapped the items, so that the raker was given a broom and the sweeper was given the rake. In the end, one of them killed the other so he could get the proper item.
>
> ...
>
> In one test, after a guard became hungry and left his post in search of food, the other guards followed to arrest him. The town people looted the town shops, due to lack of guards.

[2]And therefore emergent.

In the end, Bethesda Softworks significantly reduced the AI system by limiting the scope of the interactions the NPCs were capable of [15].

4.2 Modeling Virtual Emotions

Varied types of emotional modeling has proven effective in several independent cases to create realistic and immersive behavior, where the player feels "drawn into" the virtual world [19, 4, 6]. In *The Sims*, a particularly popular commercial game, the player guides several unique and somewhat autonomous people through their daily lives. The goal of each individual is to maximize their happiness, which is a function of having a set of needs met. One interaction might be cooking and eating a meal; although this interaction fulfills the agent's hunger, it's not a particularly fun activity (unless that agent enjoys cooking) [19]. Thus, complicated feedback relationships develop, so finding an optimal solution to maximizing an individual's happiness is difficult, thus making the game a game.[3]

Chaplin et al. [4] developed a model based on the psychological foundations of emotions. They chose to use drive theory, where biological needs lead to an emotional response, which then is the driving force in the next action. The emotions of fear, anger, sadness, and happiness were chosen. Fear causes an agent to distance himself from an agent they have low relationship values with. Anger occurs when another agent is using a resource that this agent wants. Sadness occurs when drive settings are low and happiness when they are high. These basic emotions are also identified in Davis [6].

These drive settings are similar to the ones modeled in *The Sims* [19], which include social, energy, rest, and heat. Values in each of these categories represent the physical state of an individual agent. For example, someone might be tired (low energy and rest), lonely (low social rating), and hot (high heat rating). Since this agent seems to have pretty negative drive settings, they would likely find themselves unhappy. Thus, an agent's actions are not only driven by a need to optimize their drive ratings (get some sleep to become better rested), but are also affected by their current emotional state. A tired agent is not inherently prone to violent actions, but one that is tired and angry that another agent is using the only available bed resource might take a violent action.

This model is quite effective at creating a sustainable set of balanced interactions between agents. Intuitively, the actions of agents make more sense, show more variety, and are easily understood by observers. Given the small set of stimuli and emotional outputs, these emotionally driven models result in very realistic environments. The agents behaved in a way that humans would expect a person would in the given environment [4]. In general, that is an improvement over many typical interactions between NPCs and their environment.

5. CONCLUSIONS

A variety of uses for agents and their dynamic and emergent behavior has been presented. In particular, their applications in economics and virtual worlds were discussed. Agent based simulations are effective in economic research, particularly so given that direct experimentation is often not possible. The independent nature of agents makes them well suited for modeling individuals in an economic system or entities in an exchange market. In virtual worlds, agents help create an immersive environment with interactions that are much more sensical and varied, much more like what human observers expect. These complicated behaviors are largely possible through a few key features of agents: They are capable of complex emergent behavior seemingly beyond the bounds of their apparently simple individual programming. Their independent nature allows them to easily handle complex feedback situations. Finally, a system may contain a diverse quantity of agents where differently programmed agents take different roles in a simulation.

Agents have a bright future in scientific simulation in a variety of fields and in other applications, such as virtual worlds. Computing power is becoming cheaper and more readily available, so complicated agent based simulations are more possible now than ever before. These developments will lead to more immersive virtual worlds and video games with more enjoyable NPCs. Research that was previously difficult or even impossible is now being conducted with agent based simulations. I expect to see the use of agent based models and simulations increase in a many fields.

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