#h1 Chapter 33 – Agent-Based Modeling

#h2 A new science

#h3 33.1 - Introduction

#pg As our infrastructure, process, operations, and architectural designs continue to grow in complexity, we need new ways of understanding how interconnected systems at different levels of organization work together, and when the fail to work together. Designing a new airplane is done with the help of computer-aided design tools, and the resulting computer models can be used in a variety of simulations for testing. This digital twin of the aircraft we are designing can be used in simulations, subjecting our design to physical constraints and forces, for example in a simulated (i.e., digital) wind tunnel, or the effect of outside forces, like the wear and tear of moving parts over time due to heating, friction, and strain. Although this can of design process is now very common, a more recent development is now considering not just the solution we are designing, with its physical and/or moving parts, the physical constraints imposed on it, and the specifications needed to be met to create a safe, efficient, and cost-effective new technology. Instead, it focuses on the complex interaction between the solution between designed and the key players that will interact with it.

The approach is called Agent Based Modeling (or ABM).

#pg ABM is a helpful tool when studying complex systems and/or environments. Systems and environments are made of many parts, all of them imposing some constrains and affordances to the larger system. We can think of these systems as physical, like the planets revolving around our sun in our solar system, or the system can be more abstract, like a game, a herd, flock or pack of animals, or an economy, or an ecosystem, even societies, belief systems and religions can be modeled as systems with parts. An environment can be an abstraction of a real physical environment, like an operating room. We can model the things we consider important, like any ingress and egress to the OR, or the position of the various parts of equipment. At the same time, we can leave out other things, such as the paint color of the wall. Some of the parts are more interesting than others, and we refer to them as agents. Agents too can take on many forms, but what sets them apart from the apart from the other parts in the system is that agents have agency. The agents have goals, internal states, can receive (limited) information about their environment and influence it by means of action. In other words, the agents aren't passive in their environment, changing behavior only when perturbed. Instead, they work actively within their environment to reach their goals. However, that doesn't mean these agents need to be intelligent, consciousness, moral, ethical lifeforms capable of complex goal directed problem solving. Anything can be a goal. Consider a thermostat. It has a clear goal: maintain a particular temperate set by the user. It can sense its environment by measuring its temperature, and it can influence its environment by turning on the heat, or cooling system. Finally, it has internal states, such as 'heating' or 'cooling on' or 'idle'. AMB focuses on understanding the interplay between environment and the agents in it. Even for moderately complex systems, it becomes impossible to describe all states and transitions between them fully from first principles. In complex systems, the behavior of its part and the evolution of this behavior depends crucially on the initial state the system was in. As they evolve over time, the behavior of such system can be erratic and even chaotic, before returning to a more stable state or predictable transitions between states. Imagine three spherical objects (e.g., planets or billiard balls), each with its own mass and initial velocity and position find themselves close enough together to exert an influence over each other, by means of a gravitational pull. Each of three objects is attracting the two other ones, moving towards each other, and being catapulted away like a sling shot when they get too close (this is how some planetary mission get spacecrafts where they need to be in reasonable time: the sun and larger planet's gravitational pull can slingshot a man-made probe towards its destination at great speed). As a result, the three objects move in a continuous but unpredictable dance around each other. Outside of physics, ABM is used to help understand regularities and structure of complex systems that give rise to emergent properties not directly deducible from examining each part in detail. Think of the flocking of swarms of birds, the coordinated behavior of ants, bees and termites that result highly effective and stable societies. and the construction of efficient physical structures like beehives and termite mounds. Each individual ant or bee is likely to be completely unaware of the bigger plan, having no insights into its individual contributions to the emergent whole. Instead, each operates with a small number of very simple rules to follow. It is when collection of such agents each selfishly tries to follow those rules, we might see unexpected collective and complex behavior arise. The agents have rules, but they are also constrained by their environment. This is where ABM has the potential to become an essential tool for designing and embedding new technologies, including AI, into our environments. We can ask ourselves what aspects of the environment we place our agents in is both necessary and sufficient for the emergent behaviors of the agents to be observed. And with that, we can improve the design of such environments digitally before it is 1) build 2) the agents interacting with it find it is deeply flawed in how it constrains the agents.

#h3 33.2 - Agent-Based Modeling aided Design

#pg There are many complex systems of interest at MSK, some of which are likely to be improved on with insights gleamed from ABM. For example, we can model the dynamics of a hierarchical organization to understand whether the specifics of such a system can cause bottlenecks for the flow of information. Similarly, we can model the logistics and supply chains necessary in running a large treatment center, on the lookout for disruptions that occur at various tipping points: a point in time during which a complex system changes from one regime of behaviors to another very different regime. Tipping points are very heard to anticipate. In complex system, we simply can't fully predict every single state a system can be in, as only the slightest difference in initial conditions make the outcome unpredictable. Modeling and simulating the system instead, over many different initial conditions, might reveal and help us gain insight in the sudden changes in system behavior that might occur. Before making this more concrete and relevant to the work here at MSK, we will briefly discuss a few simpler models that are often used to introduce ABM as a method.

#h3 33.3 - Game of Life

#h3 33.4 - Flocking

#h3 33.5 - Segregation

#h3 33.6 - Evacuation Model

#pg The last model we will discuss is the most relevant to how we envision ABM to be used to guide and aid in the design of our physical infrastructure and embedding of new technologies within it. In a famous paper, XXXX created a simulation in which humans had to evacuate a space, in response to some adverse event, for example a fire breaking out. Think of the complexity of each agent in that simulation. Each of them a human individual, a highly complex biological entity, with his or her personal goals, drives, motivations, agendas, perspectives. Each of them a human individual of physical dimensions, detailed but also limited sensory inputs, and a range of possible interactions with its environment at its disposal (screaming, whispering, waving, sitting down, jumping, singing). What was groundbreaking in the approach taken by XXX was to deem almost all that irrelevant. Instead, he choose to model human individuals as digital grains of sand. And the only rule these sand agents were given was to move out of the space. If the space is mostly empty, everyone will be hardly impeded by any other individual. However, make the space too crowded (the tipping point), and suddenly, the agents will end up in each other’s way. And as with sand, the agents now behave as particles, causing friction between those touching and slowing down their progress towards escaping the space. When we model this behavior, we can change the environment in which this happens. We assume the agents will always follow the same rule, so to have as many people escape in as little time as possible, we can look to the environment to facilitate this. This approach yielded some interesting and unexpected design principles, very likely not the ones a human architect would consider. For example, as you can see in figure 23223, placing a large round column in front of the exit improves the number of agents escaping the space within some unit of time. Turns out a round column in the way does 2 beneficial things. First its roundness decreases friction between it and the agents, preventing many agents from getting stuck. Second, it effectively splits the agents in two subsets (one going around the column in way direction, the other one in the other direction). This decreases the number of agents close together, and as such decreases the friction between agents, and allows agents to move faster towards the exit.

#h3 33.7 - Designing an ICU

#pg Using the above logic, we propose we can use ABM to test the interplay between the environment (the physical layout of the ward, with its affordances and constraints) and the agents in it (clinicians, like nurses and doctors, patients, family, members, supporting staff, etc.). For example, how do we design an ICU that scales gracefully as the number of people in it is increased? Can we observe and understand possible tipping points using an agent-based model to redesign, rethink and prevent it from happening? Imagine the clinicians (mostly nurses) on the ICU, attending to the patients, which includes taking their vitals, administering medications, drawing blood, answering patient questions, and escalating the care if needed (if a patient suffers a cardiac arrest, for example). In most hospitals, the nurse's station functions as. a base of operations. From it, clinicians are dispatched by their schedule or patient demands to attend to them. This creates substantial foot traffic in expensive real estate that isn't designed with space in mind or as a priority. With a reasonable number of patients, this system can operate without too many delays. However, just as in the fore fire example above, at a certain point there are too many patients needing to many interaction touchpoints, and with one additional patient, a system in flow might become a system in grid lock. ABM might be able to predict those tipping points, or other adverse and unforeseen emergent ill effects the design of an environment can have. It informs and forces designers, engineers, and other stakeholders to reimagine the environment to mitigate these ill effects.

#h3 33.8 - Combining Approaches

#pg ABM allows us to observe and hopefully understand the emergent properties (good or bad) we might encounter in a complex system of agents and environment. In conventional ABM, the agents typically only follow a small number of local rules. For example, in the flocking model, one rule was simply to in the same direction as the agents closest to you. It is a local rule, because it only specifies what action the agent can take to optimize its goal. It doesn't factor in the fate of the other agents. The agent is behaving selfishly in its own interest, not the greater good. Yet collectively, such local rules can have very complex consequences to the system. But if we want to tackle more interesting scenarios, we might have to make our agents a bit smarter, and a bit more adaptive. At the same time, observing a tipping point in the interaction and environment is not enough. We need to be able to iterate on the design so we understand what aspect of the environment is responsible for this tipping point, we can work towards redesigning the environment within the constraints of the entire physical space to prevent the tipping point from happening. The ordering of this and the previous two sections on genetic algorithms and reinforcement learning is not random. We think that a combination of the three methodologies can help us (re)imagine and design spaces less or even not subject to emergent but disruptive and thus decremental scenario. First, rather than keeping the various agents in the model simple and static, following only a few rules, we can use reinforcement learning to create adaptive AI agents, mimicking the adaptive process of humans interacting with their environment. Second, the environment as well can be implementing some intelligent optimization process. For this, genetic algorithms can be used to create, mutate, and combine environments if they are associated with a higher fitness. Over time, both the environment and agents will evolve, hopefully towards a stable and optimal solution, and if so, likely to a solution human designers would have probably never even contemplated or considered.

#h3 33.9 - Demos

#h3 33.10 - References