Title: Agent Based Simulation for Decision Making

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Introduction

Agent-based simulation is a valuable approach for studying the potential influence of individuals on a group of agents. This simulation method is often employed to model real-life scenarios, offering insights into social influence dynamics and facilitating a better understanding of various phenomena. It can be particularly useful for examining situations such as social interactions in settings like bars, decision-making processes within companies, or the impact of individuals on a larger population. It is important to acknowledge that agent-based simulations are theoretical constructs that may not perfectly reflect real-world scenarios. When applied to real data, deviations can arise due to the presence of additional factors that may not be fully captured in the simulation. However, despite these limitations, agent-based simulations provide a valuable tool for exploring and studying complex social dynamics and phenomena, shedding light on the potential effects of individual behaviour within a larger context.

Theoretical description

The development of this simulation involves representing individual opinions as a binary state, specifically denoted as 0 and 1, which can be interpreted as "yes" or "no" respectively. At the beginning of the simulation, a fraction 'x' of the agents is assigned either state 0 or state 1. To better understand the outcomes and exit probabilities, a Monte Carlo simulation approach is employed. To facilitate this simulation, a one-dimensional vector is created, comprising all the agents and their respective states. This vector, referred to as "spins," is initially modified by changing all the 0 values to -1. This adjustment allows for easier calculation of energy in the simulation. The spins in the vector are distributed with a fraction 'x', which, in this case, is set to 50%.

To incorporate the convincing ability of each agent, a parameter 'p' is introduced. 'p' represents the convincing probability and takes a value between 0 and 1 ($0 < p < 1$). For example, 'p' could be set to 0.1, 0.5, or 0.9. If 'p' is 0.5, it implies that the probability of convincing a positive spin (1) for a "yes" agent is higher compared to convincing a negative spin (-1) for a "no" agent. The specific rules for changing decisions can be defined based on the context, and the calculation of energy for each spin can be related to the 'Ising-Lenz' model. By implementing this simulation framework and considering the energy calculations, the dynamics of the system and the evolution of individual decisions can be studied. Rules of how energy for every agent is calculated, is shown on figure 1.

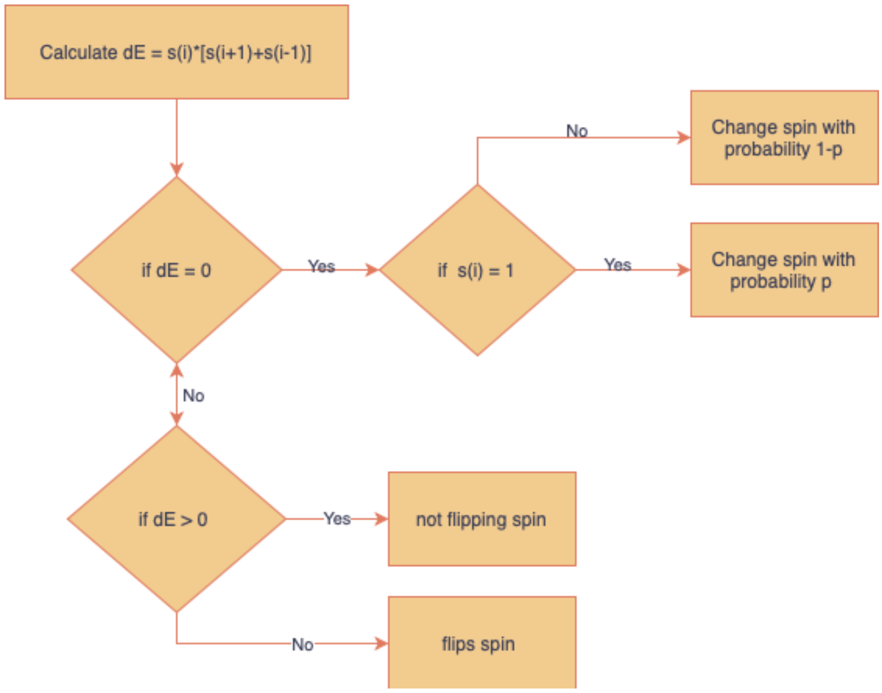

Figure 1 Algorithm for flipping or not flipping a spin of agents.

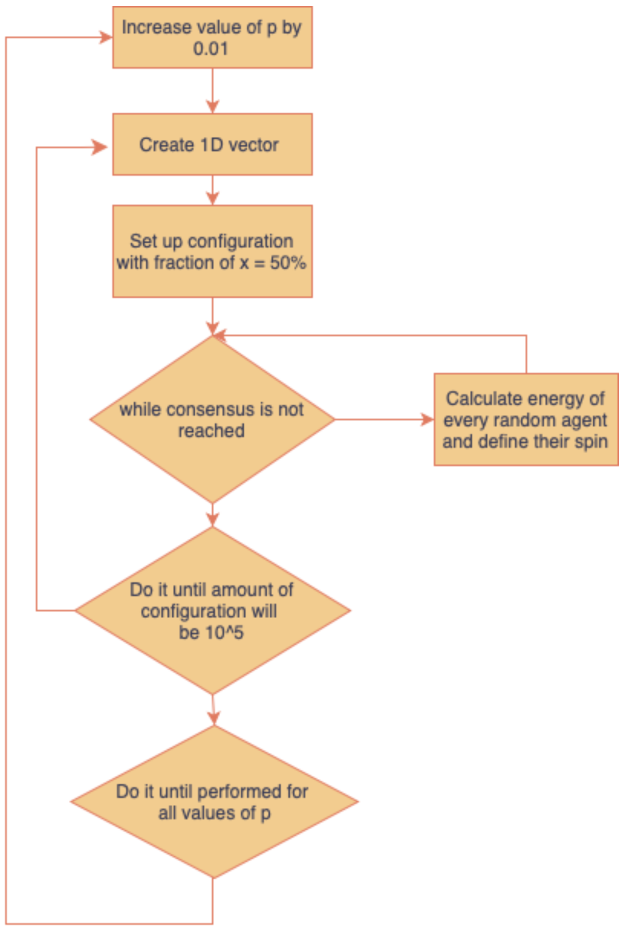

Figure 2 Diagram showing algorithm of simulation

In the simulation described, the process begins with a loop that increments the value of 'p' by 0.01 in each step. This loop generates 100 different values of 'p', ranging from 0 to 1. For each 'p' value, several configurations (as specified) are created and simulated.

For each configuration, a one-dimensional vector is constructed representing the agents' opinions, with an equal fraction of "yes" and "no" agents (50% each). Subsequently, a random agent and their neighbours are selected from the vector. The energy difference, denoted as 'dE', is calculated for this agent and its neighbours, considering periodic boundary conditions. The decision of whether to change the agent's spin or not is determined by an algorithm that follows a flipping or non-flipping strategy, as depicted in Figure 1. This process is iterated continuously until a consensus is reached, meaning that all agents are convinced to either say "yes" or "no" (i.e., all spins have a value of 1 or -1). Rules of changing decision of agents is described as picture on figure 3.

This iterative procedure is carried out for each 'p' value, resulting in the calculation of 10^5 configurations for every 'p' value in the simulation. The aim is to observe the dynamics and the achievement of consensus under different 'p' values, as the system evolves, and agents potentially change their opinions based on the calculated energy differences.

For this simulation code in python was developed.

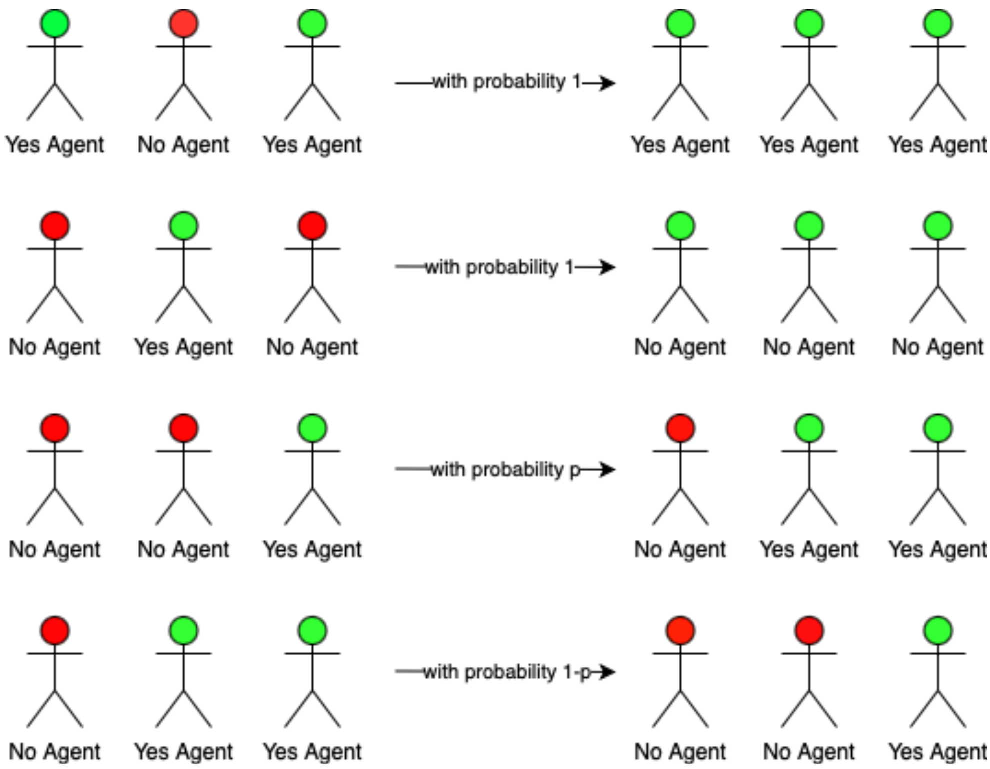

Figure 3 Showing rules of behaviours of agents

Results of simulation

The main objective of this simulation was to analyse the relationship between the convincing ability of the yes-agents ('p') and the likelihood of reaching a positive consensus state ('E'). The exit probability 'E' represents the fraction of configurations in which a positive consensus is achieved. To investigate this relationship, the simulation generated various values of 'p' and calculated the corresponding exit probabilities 'E'. The resulting values were recorded and organized in Table 1, providing a comprehensive overview of the simulation outcomes.

Table 1 serves as a valuable reference for understanding the behaviour of the simulation. It highlights specific 'p' values that can be considered significant milestones in comprehending the overall process. Notably, the table reveals that when the convincing ability of the yes-agents ('p') is set to 50%, the exit probability 'E' is also approximately 50%, specifically measured at 0.49664. This finding implies that in the context of the simulation, there is an intriguing symmetry between the convincing ability of the agents and the likelihood of reaching a positive consensus state. With a convincing ability of 50% ('p' = 0.5), the simulation suggests that there is a 50% probability of achieving a positive consensus state. By examining the data presented in Table 1, it’s possible to also discern valuable insights regarding the minimum convincing ability of the yes-agents required for achieving a positive consensus in all configurations.

The observed common features and characteristics among different systems within a universality class can be attributed to the nature of the plot itself. Specifically, the graph generated from the data exhibits a distinct pattern reminiscent of a step function. It is important to note that altering the size of the vector used in the simulation could potentially impact the resulting graph. Figure 4 displays the plot generated using the provided data. The distinctive step-like nature of the graph suggests abrupt changes or transitions in the system's behaviour. Universality class can be seen in this example as phase transition that occurs after critical point.

E	0.0	3,00E-05	0.0001	0.00015	0.00036	0.00095	0.00202	0.00489	0.01253	0.03179
p	0.37	0.38	0.39	0.4	0.41	0.42	0.43	0.44	0.45	0.46
E	0.07923	0.18706	0.3741	**0.49664**	0.61637	0.81442	0.92097	0.96771	0.9872	**0.99471**
p	0.47	0.48	0.49	**0.5**	0.51	0.52	0.53	0.54	0.55	**0.56**
E	0.99772	0.9992	0.99965	0.99987	0.99991	0.99995	0.99999	**1.0**		
p	0.57	0.58	0.59	0.6	0.61	0.62	0.63	**0.64**		

Table 1 Significant values from output of simulation.

The search focused on identifying the first 'p' value for which 'E' equals 1. Upon examining the data, it was observed that the first occurrence of 'E = 1' is found at 'p = 0.64'. However, it was also noticed that there are multiple preceding 'p' values that exhibit 'E' very close to 1. To ensure a more conservative approach and account for potential fluctuations, the last 'p' value with 'E' close to 0.99 was considered.

The value that meets these criteria is 'p = 0.56', where 'E' is approximately 0.99471. By rounding the value, we can consider it as effectively reaching a positive consensus with a probability of 1. This determination is significant as it indicates that for 'p ≥ 0.56', all configurations in the simulation consistently lead to a positive consensus state. It provides valuable insights into the critical threshold of convincing ability required to ensure a reliable and predictable outcome in terms of achieving unanimous agreement among the agents.

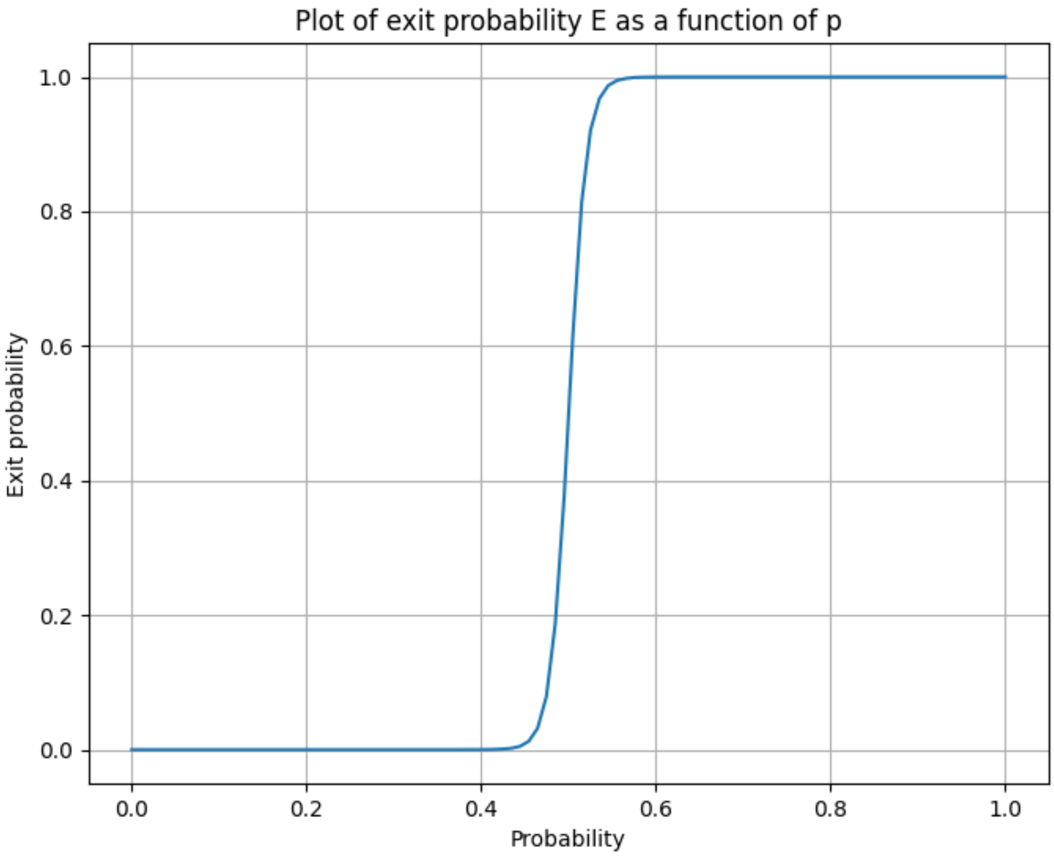

Figure 4 Plot of exit probability 'E' as a function of calculated for 10^5 configurations and vector size N =50

Conclusion

In conclusion, the simulation aimed to explore the relationship between the convincing ability of the yes-agents ('p') and the likelihood of reaching a positive consensus state ('E'). Through analyzing the data recorded in Table 1, it became evident that a convincing ability of 50% ('p' = 0.5) resulted in a corresponding exit probability 'E' of approximately 50%. This symmetry between 'p' and 'E' indicates an intriguing connection between the convincing ability of the agents and the achievement of a positive consensus state. Moreover, by examining the graph generated from the data, which exhibited a step-like pattern, it was possible to identify the critical threshold of '$p \geq 0.56$' where 'E' consistently reached 1, indicating a reliable and predictable outcome of unanimous agreement. These findings provide valuable insights into the behavior of the simulation and contribute to our understanding of the relationship between convincing ability and consensus achievement among the agents.

The outcome illustrated by the graph representing the function exhibits a captivating resemblance to that of a step function, characterized by a series of distinct, well-defined intervals of stability before undergoing an abrupt and pronounced transition to a new state which is 1. This critical point is like a pivotal juncture where the behaviour of system undergoes a notable shift, signalling a substantial change in its dynamics. Remarkably, this altered state persists consistently throughout the remaining steps of the probability graph, highlighting the enduring influence and impact of the initial critical transition. This observation underscores the significance of identifying and understanding the critical point in comprehending the overall behaviour and trajectory of probability values for decision making of individuals in such a complex system.