Multi agent modelling

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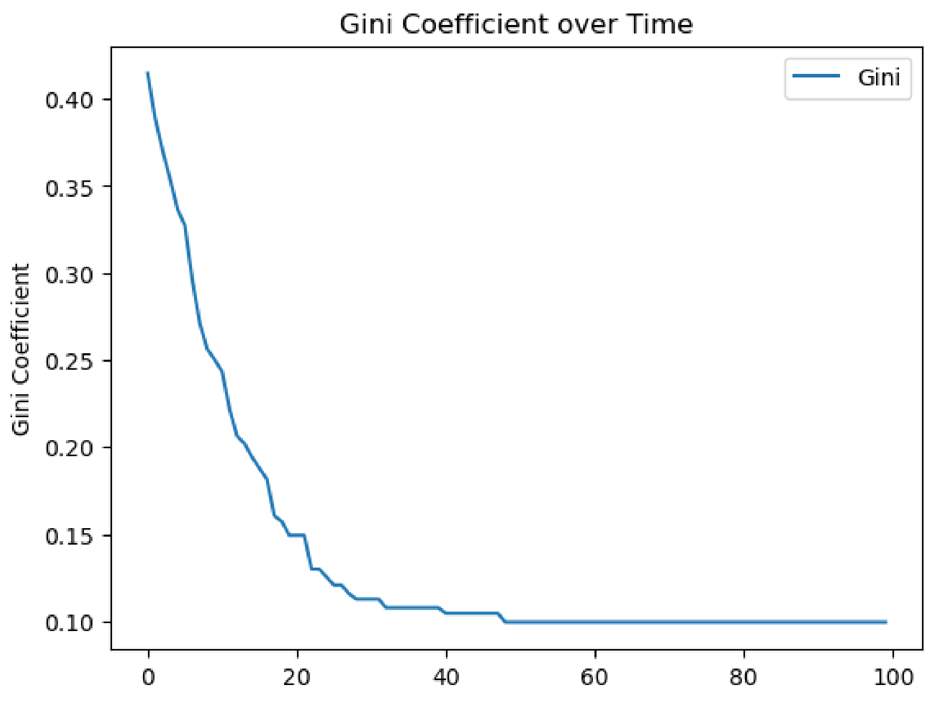
Reflection on Agent-Based Simulations

Part 1 of the Assignment delves into the intricacies of wealth distribution within a simulated environment. This agent-based model presents a scenario where individual agents, each representing an economic entity, engage in the distribution and exchange of wealth. A key feature of this simulation is the use of the Gini coefficient, a statistical measure that captures the degree of inequality in wealth distribution among the agents. The implementation of this measure provides a quantitative method to assess the outcomes of the simulation, offering insights into how wealth is distributed and redistributed over time within the model.

The random allocation of wealth to agents, followed by their interactions leading to wealth exchange, creates a dynamic system. This activity highlights the natural outcomes in these models, where basic rules at an individual level can result in complex behavior in the overall context.

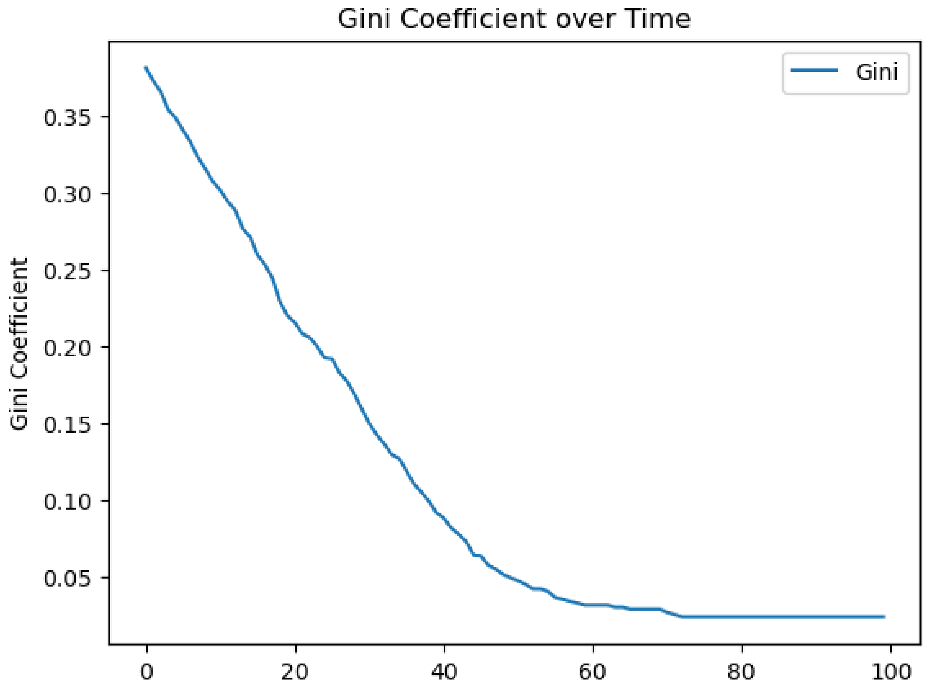
```
Wealth Distribution After 100 Steps:
Wealth: 2, Number of Agents: 61
Wealth: 3, Number of Agents: 39
```



Initially, the Gini coefficient is high, indicating inequality in wealth distribution. Over time, the coefficient decreases, suggesting wealth becomes more evenly distributed among agents. After 100 steps, most agents have 2 or 3 units of wealth, further indicating reduced inequality.

(0, 5)

```
Wealth Distribution After 100 Steps:
Wealth: 8, Number of Agents: 1
Wealth: 9, Number of Agents: 68
Wealth: 10, Number of Agents: 31
```

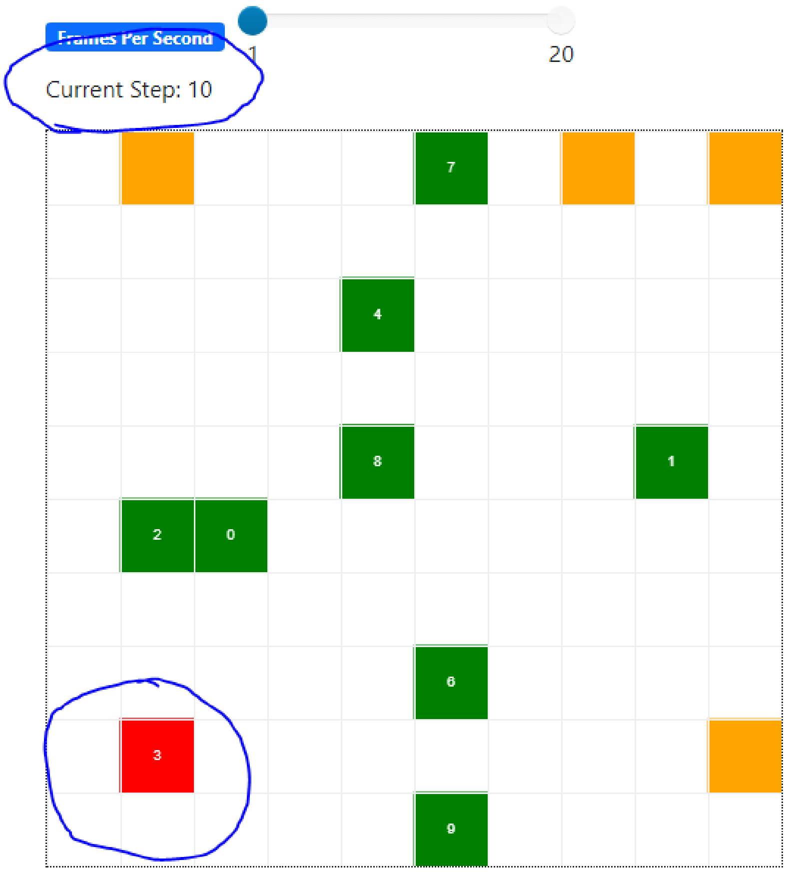


It illustrates a decline in the Gini coefficient over time, indicating a trend towards more equal wealth distribution among agents. After 100 steps, most agents (68) have 9 units of wealth, with fewer agents (1) having 8 or 10 units, demonstrating a narrow wealth range.

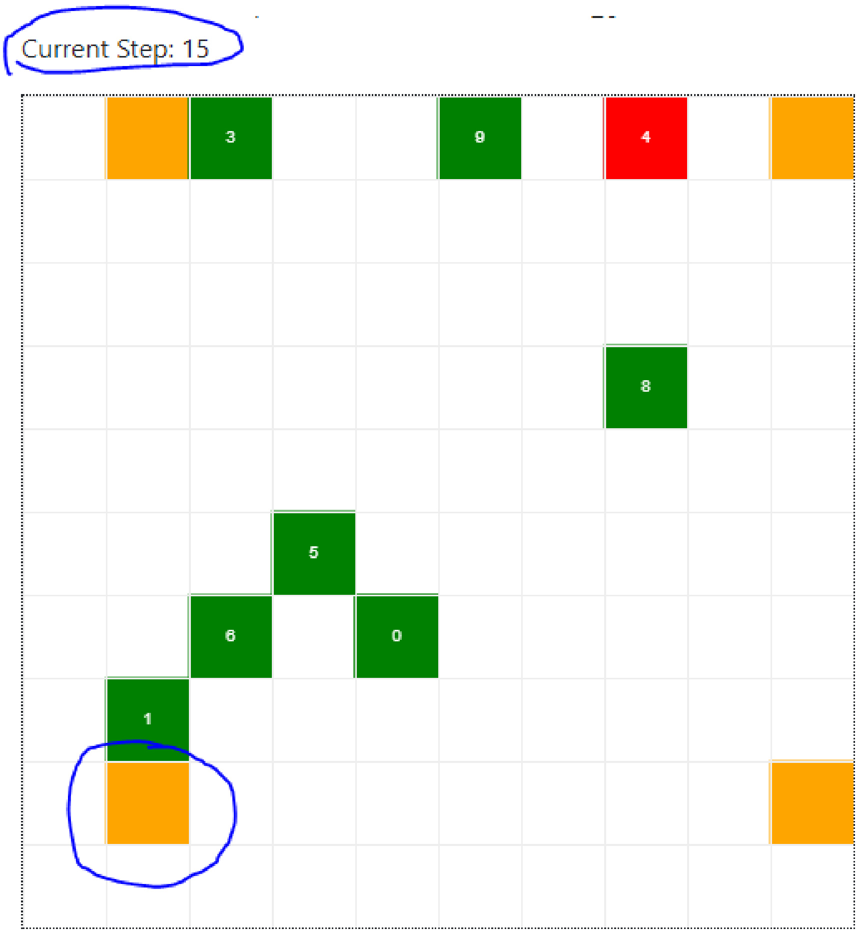
(0, 20)

Analyzing Parking Lot Dynamics through Simulation

The visualization aspect of this simulation is especially noteworthy. It transforms abstract ideas like agent movement and space occupancy into something you can see. This not only improves comprehension but also lays the groundwork for improving the management of real-world parking spaces.



ID nr 3 just entered a parking space.



The car has left after 3-5 steps.

```
RuntimeError: This event loop is already running

Socket opened!
{"type":"reset"}
{"type":"get_step","step":1}
Car with id 3 parked after 1 steps
{"type":"get_step","step":2}
Car with id 9 parked after 2 steps
{"type":"get_step","step":3}
{"type":"get_step","step":4}
{"type":"get_step","step":5}
Car with id 3 parked after 2 steps
{"type":"get_step","step":6}
{"type":"get_step","step":7}
{"type":"get_step","step":8}
{"type":"get_step","step":9}
Car with id 3 parked after 3 steps
{"type":"get_step","step":10}
{"type":"get_step","step":11}
{"type":"get_step","step":12}
{"type":"get_step","step":13}
{"type":"get_step","step":14}
Car with id 4 parked after 14 steps
{"type":"get_step","step":15}
```

The image above illustrates the output when a car has parked

Comparing the two simulations shows how flexible agent-based modeling can be. One simulation looks at an economic idea, while the other deals with a common daily situation. Both use agent-based modeling to make complex ideas simpler and easier to understand.

Conclusion

Reflecting on these simulations, we learned that agent-based modeling is a powerful tool for both understanding complex systems and finding solutions to real problems. The ability to visualize and analyze these models provides valuable insights, making complex systems more accessible and easier to read and understand.

In conclusion these simulations do not only demonstrate the power of modeling but also offer a deeper understanding of the complexities and nuances of both economic and everyday systems.