

Agent-Based Simulations for Protocol Design, Tokenomics, and Risk Analysis

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Agenda

- 1 Introduction
- 2 Modeling Steps
- 3 Demo

What are Agent-Based Models?

A programmed world where multiple **agents** live in an environment and interact with each other through **actions**.

- Agents can represent:
 - individuals (humans, wallets, network nodes)
 - organizations/abstract entities (DAOs, protocols)
- Actions:
 - economic (send/receive, buy/sell, deposit/withdraw)
 - social (vote, follow/unfollow)

What can you do with an ABM simulation?

- For users / investors:
Manage risk by stress-testing the protocol with hypothetical market events like hacks and price crashes.
- For protocol / DApp engineers:
Make design decisions (e.g. fee rates, reward tokenomics) by simulating all possibilities and optimize for the best outcome

Traditional Method vs ABM

Macro-level simulation

- Only measures aggregate outcomes (net gains/losses)
- More assumptions required
- Fixed parameters

Agent-based simulation

- Measures individual-level & aggregate outcomes
- Less assumptions required
- Customizable parameters

"All models are wrong, but some are useful."

Step 0: Understand your protocol

Ask questions like:

- Who are the primary group of actors involved in the ecosystem?
- What can each actor do?
- What rules does the system set for agents?
- Is there any tokens involved and if so how do they flow?

Exercise

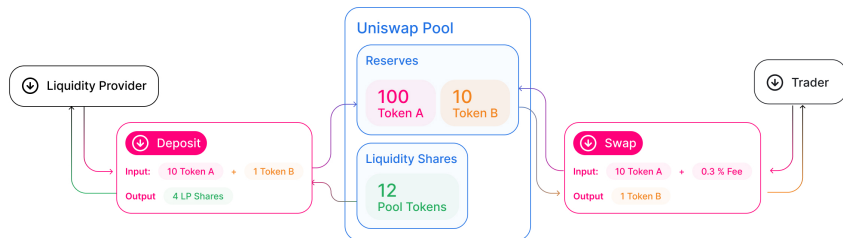
Pick a protocol / DApp and try to answer these questions.

Step 1: Build a flow chart

A flow chart is the best way to start modeling complex systems like DeFi protocols. Be sure to include:

- Agent-agent interactions
- Agent-protocol interactions
- Flow of funds / native tokens

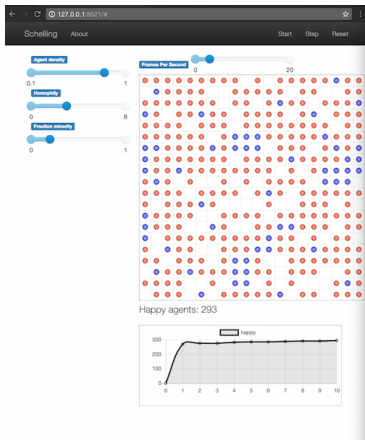
Recommended tool: Draw.io (open source)



Mesa

Open-source Python library for agent based models and simulations

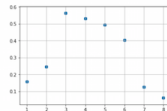
- Easy to use (entry-level OOP knowledge)
- Built-in analysis and visualization modules



```
In [10]: def get_segregation(model):  
    ...  
    Find the % of agents that only have neighbors of their same type.  
    ...  
    segregated_agents = 0  
    for agent in model.schedule.agents:  
        segregated = True  
        for neighbor in model.grid.neighbor_iter(agent.pos):  
            if neighbor.type != agent.type:  
                segregated = False  
                break  
        if segregated:  
            segregated_agents += 1  
    return segregated_agents / model.schedule.get_agent_count()
```

Now, we set up the batch-run, with a dictionary of fixed and changing parameters. Let's hold everything fixed except for Homophily.

```
In [11]: fixed_params = {"height": 10, "width": 10, "density": 0.8, "minority_pc": 0  
variable_params = {"homophily": range(1,9)}  
  
In [12]: model_reporters = {"Segregated_Agents": get_segregation}  
  
In [13]: param_sweep = BatchRunner(SchellingModel,  
    variable_parameters=variable_params, fixed_paramet  
iterations=10,  
max_steps=200,  
model_reporters=model_reporters)  
  
In [14]: param_sweep.run_all()  
80it [00:02, 27.26it/s]  
  
In [15]: df = param_sweep.get_model_vars_dataframe()  
  
In [16]: plt.scatter(df.homophily, df.Segregated_Agents)  
plt.grid(True)
```



Step 2: Create agent classes

Code Structure

```
class TestAgent(mesa.Agent):  
  
    def __init__(self, unique_id, model):  
        super().__init__(unique_id, model)  
        self.unique_id = unique_id  
        self.model = model  
        self.attr_X = 0  
        self.attr_Y = 0  
  
    def step(self):  
        # observe state and perform actions  
  
    def action_name(self, args):  
        # single action function
```

- Subclass *mesa.Agent*
- Define **attributes** and **actions**.
- Define a **step** (policy) function

Step 3: Create model class

Code Structure

```
from mesa.time import RandomActivation

class TestModel(mesa.Model):
    def __init__(self, params, seed=None):
        super().__init__()
        self.schedule = RandomActivation()
        for i in range(100):
            agnt = TestAgent(i, self)
            self.schedule.add(agnt)
        self.datacollector = mesa.DataCollector(
            agent_reporters={"x": "attr_X"})

    def step(self):
        self.add_remove_agents()
        self.schedule.step()
        self.datacollector.collect(self)
```

- Subclass *mesa.Model*
- Create an initial state
- A mechanism to add / remove user agents each step
- Assign agents to a scheduler
- Create data collectors

Step 4: Calibration and estimation

Aim: Assigning values to parameters and initial conditions in order to reproduce real-world behavior.

Methods:

- Direct observation from data / protocol parameters
e.g. 5% inflation rate on token, 15% node commission
- Statistical estimation (minimize distance from real data)
e.g. monthly new users, daily ETH prices
- Meta-modeling

For a list of data sources and tools for on-chain analytics, see sites.google.com/view/mingxuanhe/resources

Step 5: Simulation

Data tracking: *mesa.DataCollector*

Track both aggregate variables (e.g. TVL, total fees) and individual agent variables (e.g. distribution of token balance, top and bottom performance of agents)

Tips:

- Run multiple batches on different random seeds and aggregate (Monte Carlo)
- Change the protocol parameters to explore “parallel universes”
- Disaster simulation: large drop in prices, large withdrawal of liquidity, etc.

Step 6: Visualization (optional)

Use *mesa.visualization.modules*

Available modules:

- Charts: bar chart, line chart, pie chart
- Grids: canvas grid, hex grid
- Network visualization
- User-settable parameter (slider / choice / number input)

Example: An ABM for Uniswap V2 AMM

- Agents: 1000 traders, 50 liquidity providers, 1 liquidity pool for token pair X and Y
- Actions: traders can swap, LPs can add/remove liquidity
- Agent attributes:
 - Trader: holding of token X and Y
 - LP: holding of token X and Y, holding of LP tokens
 - Pool: balance of token X and Y, fee rate, constant product K
- Performance metrics: TVL, slippage, impermanent loss

Extensions to the Toy Model

- Different types of traders: arbitrageurs, speculators, noise traders - each type has a different trading pattern in response to state variables
- Multi-pool model: Pool competition, triangle arbitrage,

References I

Token Engineering Commons. (2022). Token engineering fundamentals module 4 [<https://tokenengineering.net/course/tef-module4/>].

Uniswap. (2022). How uniswap works.

<https://docs.uniswap.org/contracts/v2/concepts/protocol-overview/how-uniswap-works>