Eötvös Loránd University – Faculty of Informatics

Computer Science MSc – Artificial Intelligence Specialization

First Assignment

Collective Intelligence

Agent-Based Modelling Task

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BUDAPEST

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Restaurant Recommendation Ecosystem

An Agent-Based Simulation of Social Influence on Restaurant Choice

Overview

Purpose. The model investigates how **social influence** and **economic inequality** jointly shape restaurant success and market concentration. Customers choose restaurants based on price, quality, and distance preferences, while **influencers** advertise venues that can afford to hire them. The goal is to examine whether the feedback between income and advertising leads to **monopolization**.

Entities, State Variables, and Scales.

- **Customers**: move randomly until hungry; then they select the most suitable dining option. After eating for several ticks, they leave the restaurant and continue exploring after a short cooldown phase.
- **Influencers**: wander freely across the map. When hired, they advertise the 'sponsoring' restaurant for a fixed duration, attracting nearby customers within their `meet-radius`.
- **Restaurants**: six colored cuisine zones placed symmetrically around the origin on a toroidal grid ($N \times N$). Each has *price*, *quality*, *cuisine*, and *money.*. Initial capital is allocated using a **softmax distribution** to create adjustable wealth inequality. They earn money from customer visits, but also pay periodic maintenance costs; once their funds fall below zero, they close permanently.

Process Overview and Scheduling. At **setup**, all agents start at the origin; restaurant patches are initialized with softmax-weighted starting budgets. Each tick:

1. **Influencers** move randomly, promoting the restaurant they are hired by until their contract ends.
2. **Customers** choose and visit restaurants, pay, and exit after eating.
3. **Restaurants**handle maintenance, hire influencers if wealthy, or close when bankrupt.
4. The simulation stops automatically when only one restaurant remains active or when the maximum tick limit is reached.
5. Data are collected for income inequality, top share, and surviving restaurants.

Design Concepts

Emergence: unequal restaurant performance and spontaneous monopolies arise from individual decisions and social contagion.
Adaptation: ustomers re-evaluate choices each hunger cycle; restaurants react via influencer hiring.
Sensing: customers detect influencers within the `meet-radius`.
Interaction: influencer halos redirect customer flow and redistribute economic activity.
Stochasticity: random initialization of attributes, positions, and capital.
Observation: global metrics such as income inequality (Gini index), top restaurant share, number of active influencers, and surviving restaurants are continuously tracked.

Details

Initialization. Six restaurants (Thai, Mexican, Italian, Japanese, Indian, Greek) are placed equidistantly. All customers and influencers start at (0,0). Restaurant capital heterogeneity is controlled by `softmax-variance`.

Input Data. No external data used; parameters (e.g., `num-customers`, `num-influencers`, `meet-radius`, `hunger-rate`, `influencer-duration`, `influencer-price`, `maintenance-cost`) are user-defined sliders.

Submodels.

- **Restaurant-Score:** combines weighted attributes for decision-making.
- **Hunger-Cycle:** manages transitions between wandering, hungry, and cooldown.
- **Influencer-Campaign:** handles influencer hiring, promotion duration, and spatial advertising effects.
- **Economic-Balance:** updates restaurant income, deducts maintenance, triggers influencer hiring, and processes bankruptcy events.

Experiments & Results

Two-Factor Design. To explore the emergence of market inequality, a two-dimensional parameter sweep was conducted using NetLogo's `BehaviorSpace`. The first factor, **softmax-variance** ($0-20$), controls the heterogeneity of initial restaurant capital - higher values create stronger wealth inequality at startup. The second factor, **num-customers** ($10-250$), determines market size. Each parameter pair was repeated 20 times with different random seeds.

Outcome Measures. Two global indicators were recorded:

- **Gini-income:** inequality index of restaurant earnings (0 = equal, 1 = monopoly);
- **Top-restaurant-share:** fraction of total income captured by the single richest restaurant.

Both were averaged over 20 replications, and 95% confidence intervals were computed for each grid cell.

Parameter Ranges.

Parameter	Range	Step
softmax-variance	$0-20$	1
num-customers	$10-250$	5
simulation length	10000 ticks	–
replications	20 per cell	–

Results Overview. Figure 1 shows the heatmap and contour of mean Gini-income. Low variance and small customer populations yield moderate inequality, while increasing either variable amplifies divergence until a sharp transition appears around *softmax-variance* ≈ *5–7*. Beyond this region, one or two restaurants accumulate most income, signaling a **tipping point** from balanced co-existence to monopolization.

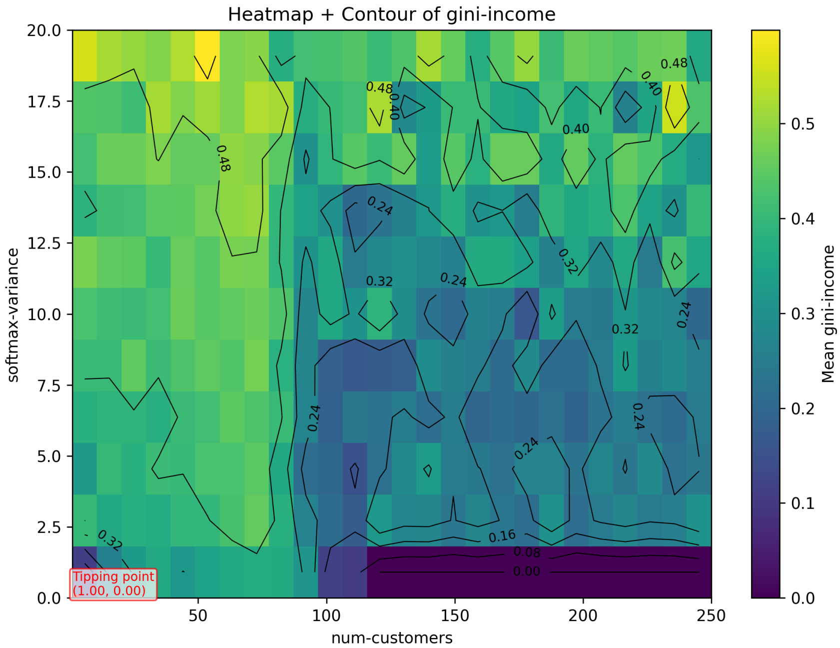

Figure 1: Heatmap + contour of mean Gini-income. The lower-left corner indicates the estimated tipping region.

A similar pattern is evident in the **top-restaurant-share** (Figure 2), confirming that above the threshold, a single restaurant dominates the market with over 80 - 90% of total earnings.

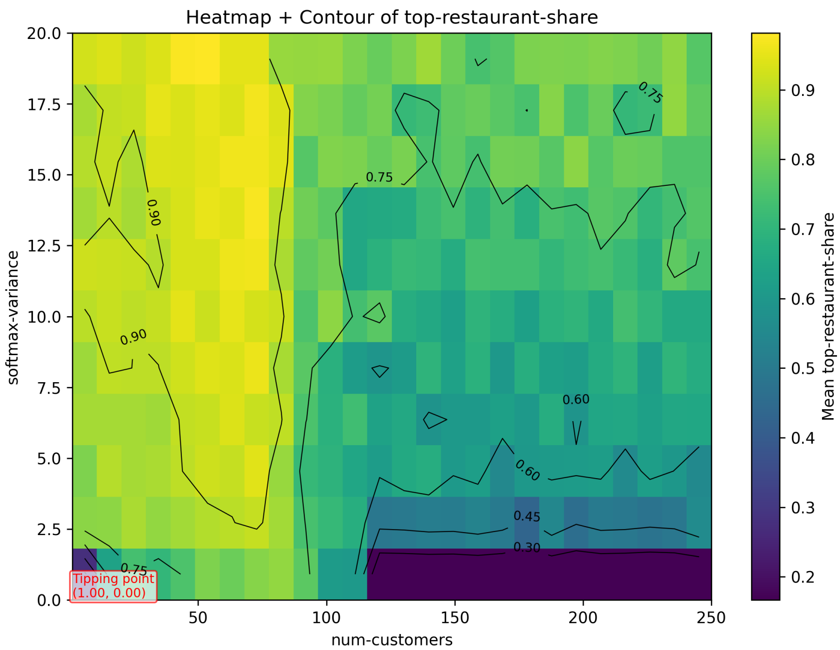

Figure 2: Heatmap + contour of mean top-restaurant-share. Increasing capital variance or population size fosters monopoly formation.

To illustrate the dynamic regimes, Figure 3 plots representative time series at three levels of *softmax-variance*. Under low inequality, income shares remain stable; at high inequality, one restaurant rapidly overtakes all others - a clear phase transition driven by feedback between advertising and income.

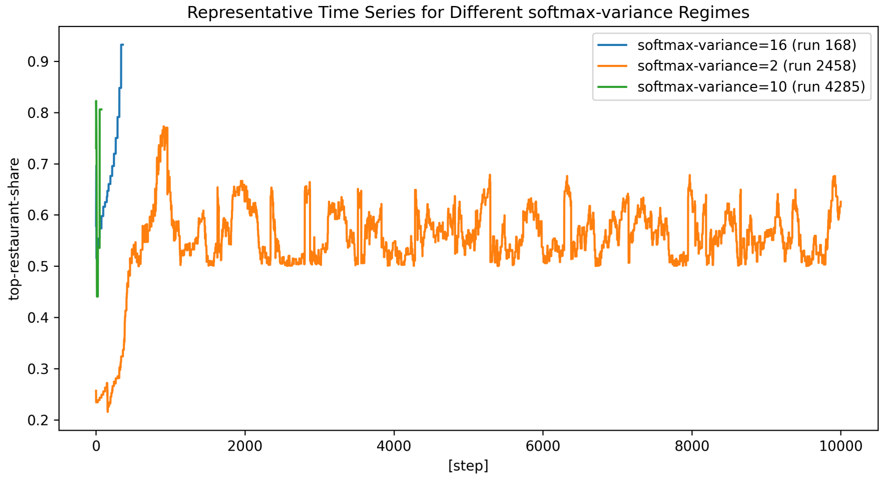

Figure 3: Representative time series of top-restaurant-share across softmax-variance regimes.

Takeaway. The model reveals a social–economic tipping point: beyond a critical initial wealth disparity, influencer-based marketing self-reinforces success, leading to extreme market concentration and restaurant extinction.

Limitations. Customer learning and restaurant pricing remain static; introducing adaptive preferences or dynamic pricing could yield more realistic cycles of boom and recovery. Future work could also extend to multi-city or time-varying influencer networks.