TUTORIALS 5, 6, 7

DATA-DRIVEN BUSINESS AND BEHAVIOUR ANALYTICS

Introduction

In the next tutorials, you will build an agent-based model (ABM) that aims to explain price formation in prediction markets. Each tutorial will focus on a different part of the model, broadly based on what you have learned in the previous week.

Tutorial 5 - week 8

In this tutorial, you will need to build an agent-based model of the Deffuant model for opinion dynamics, as seen in class, but assuming agents are part of a network. The specifications of the the model are the following:

1. There are N agents.
2. At $t = 0$ agents have opinions $0 < o < 1$ drawn from a uniform random distribution between 0 and 1.
3. Every time step, agent i is picked at random. Agent j is picked randomly from agent i's neighbours.
4. If $|o_i(t) - o_j(t)| >= d$, nothing happens. Otherwise, agent i and j update their opinion according to the following equations:

$$o_i(t+1) = o_i(t) + \mu(o_j(t) - o_i(t))$$
$$o_j(t+1) = o_j(t) + \mu(o_i(t) - o_j(t))$$

5. This process repeats for $\tau = \frac{N}{2}T$ times, where T represents the unit of time (i.e., the number of time steps it takes to to sample $\frac{N}{2}$ agent pairs).

There are two ways to build this model, the quick one and the smart one. The quick one is by using matrices and arrays to keep track of the agent opinions the network. However, when we build agent-based models, we usually need classes to deal with all the possible changes and to make the most out of object-oriented programming. Using classes to do build this model is the smart approach. This means that in the next tutorials you will only have to add features, without having to rewrite code from scratch, regardless of what the other features will be.

Tutorial 5, exercise 1

Build the opinion dynamics model described above, by using N=100 agents on a Barabasi-Albert network, $d = \mu = 0.5$, $T = 30$. Plot the evolution of opinions by drawing a scatter plot of all agents' opinions as a function of T.

Tutorial 5 - exercise 2

Repeat exercise 1 but now use a small-world network and an Erdos-Renyi netowrk. Compare the results obtained on these three networks and discuss.

Tutorial 5 - exercise 3 [OPTIONAL]

Repeat exercise 1 for $d \in \{0.1, 0.3, 0.7, 0.9\}$. Discuss the results by comparing them with those obtained using $d = 0.5$.

Tutorial 6 - week 9

In this tutorial, you will build the market in which agents participate. The market is a prediction market on single event E, which can have outcomes $E \in \{0, 1\}$. Agents are picked randomly to participate in the market, and buy or sell a contract in the following way: if agent i is chosen to participate in the market, they can either buy or short sell a contract, whose payoff is 1 if E = 1, and 0 otherwise. Since agent i believes that $P(E = 1) = o_i$, they will buy a contract only if the current price $\pi < o_i$, and sell (or short sell) it if $\pi > o_i$. They will neither buy or sell if $\pi = o_i$. The demand of agent i (i.e. the number of contracts traded), D_i, is proportional to the distance between their opinion and the price, and is described by $D_i(t) = o_i(t) - \pi(t)$. That is, the more mispriced the agent believes the contract is, the more they will trade. The excess demand (ED) is simply the sum of each agent's demand, multiplied by a noise term $\nu \approx N(0, 0.05)$, as follows: $ED(t) = |\nu| \sum_i D_i(t)$. Price gets updated every day following this equation: $\pi(t + 1) = \pi(t) + ED(t)$, with $0 \leq \pi(t) \leq \ \forall t$

Tutorial 6 - Exercise 1

Based on the information above, and the opinion dynamics model you built last week, build the environment of the ABM (i.e. the market). *Hint:* Use the information above to derive the time-dependent probability of an agent to participate in the market. Assume that the market lasts 50 days.

Tutorial 6 - Exercise 2

A study has shown that trading volume in prediction markets exhibits a power-law growth which depends on the number of days until the end of the market, such that $V(t) = (T_{max} - t)^{-\lambda}$, where T_{max} is the duration of the market, and $\lambda = 2.44$ [1]. Incorporate this result into the model.

References

[1] V. Restocchi, E. Gerding, and F. McGroarty. Statistical properties of volume and calendar effects in prediction markets. *Physica A: Statistical Mechanics and its Applications*, 523, 2019.