Agent-Based Modelling – Glosten Milgrom Model

TEAM 1 - THE INFORMED TRADERS

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Agenda

1. What is the Agent Based Model ?
2. Targets and achievements
3. Detailed analysis of one particular experiment
4. What we have learnt

Introduction to the Glosten Milgrom Model

Glosten Milgrom Model simulates the process of information impacting the formation of transaction price in a market maker market.

In particular, the key is the market maker learning the true fundamental value of the traded security from the information contained in the orders she received.

Agents:

- Informed traders I, taking up $\mu \times 100\%$ of the trader population
- Uninformed traders U, with $p(buy) = \gamma$
- A market maker M, who does not have inventory issues

Introduction to the Glosten Milgrom Model – pseudo code

```
Traded security value V sampled from Bernoulli(σ) ∈ {high, low}
for every trader coming to the market maker:
    if informed trader:
        action = buy order if V == high else sell order
    elif uninformed trader:
        action sampled from Bernoulli(γ) ∈ {buy order, sell order}
    if buy order:
        market maker provides ask price  # The learning part.
        transaction price = ask price
    elif sell order:
        market maker provides bid price   # The learning part.
        transaction price = bid price
    Terminate loop when market maker has learned what V is
```

Introduction to the Glosten Milgrom Model (cont'd)

Some highlights of the model settings:

- M cannot distinguish between U and I.
- But M knows the value of σ, μ, and γ.
- Traders are always active, i.e., they never choose to not submit an order.
- There only exist fully informed and fully uninformed traders.

Targets and Achievements

1. Exploring the parameters of the model (Appendix 1)
2. Importance of market maker’s initial belief to the learning process (Appendix 2)
3. Additional strategy to uninformed traders – opportunity of being inactive (Appendix 3)
4. Introduction of new agents - partially informed traders

Additional agent and Parameter

I : $fully\ informed\ trader$

- μ_i: $the\ fraction\ of\ fully\ informed\ trader$

P : $partially\ informed\ trader$

- μ_p : $the\ fraction\ of\ partially\ informed\ trader$
- η : $confidence\ of\ making\ correct\ orders$

U : $Uninformed\ trader$

M : $Market\ Maker$

Eta (η)

$Eta(\eta)$ represents the confidence that Partially informed trader(P) makes correct orders.

- $\eta = 0.95$: 95% of actions are rational (e.g., buy when he should)
- $\eta = 0.05$: 95% of actions are irrational(e.g., buy when he shouldn't)

Thus,

- if $\eta > 0.5$, M receives more correct information from P
- if $\eta < 0.5$, M receives more deceiving information from P

While $\mu_i = 0$

$\eta = 0.95$

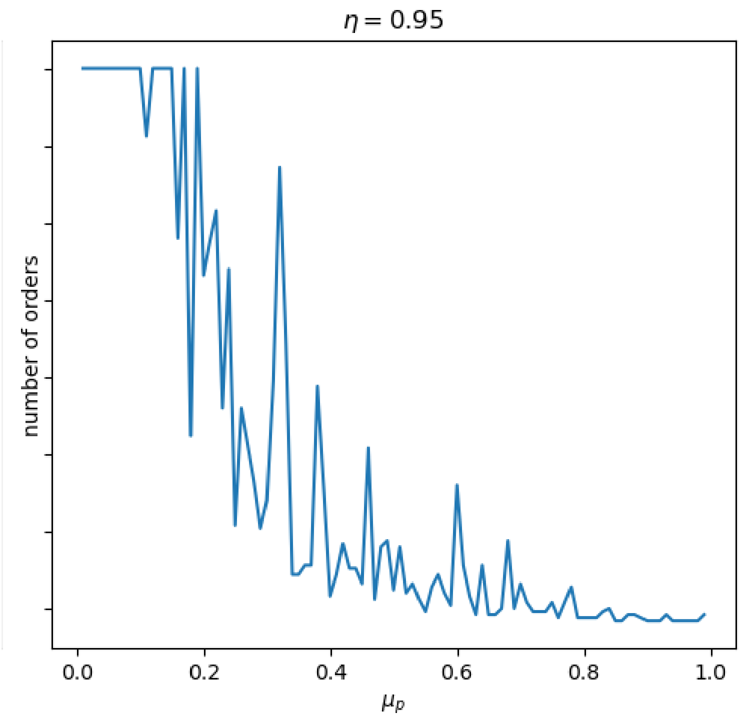

Figure 1 - learning efficiency when eta = 0.95

$\eta = 0.05$

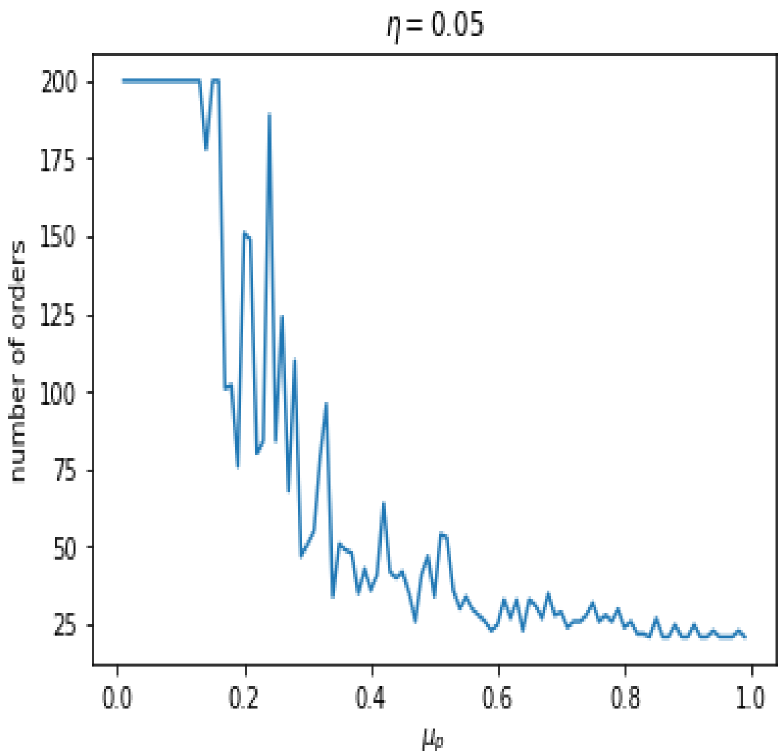

Figure 2 - learning efficiency when eta = 0.05

Whether M receives rational or irrational orders, she still can learn from the information and converge the learning process.

The correctness of what M learns

$(if\ \mu_i = 0)$	$\eta = 0.95$ (Correct Info)	$\eta = 0.05$ (Deceiving Info)
True intrinsic value is	V_H	V_H
Market Maker learns	V_H	V_H

Table 1: An example of what Market Maker learns from different information

The correctness of what M learns (cont’d)

- Intuitively, we expect M to arrive at an incorrect conclusion when there is much false information.

- Surprisingly, M manages to learn correctly even with false information.

- M knowing eta allows her to translate the irrational behaviour somehow and obtain the correct conclusion.

Summary of the project

- Implement and simulate agent based model from scratch
- Sensitivity analysis of parameters
- Experimenting with different agents and strategy sets
- Analysing agent's behaviour as well as systemic dynamics
- Intuitive belief might not be reflected in empirical results
- Use of Python for implementation and analysis

Thank you for your attention

Feel free to reach out for further information and you can view additional analysis slides in appendix

Appendix 1 - Sensitivity analysis of parameter μ

- Next information parameter which is crucial to the market maker learning is μ the fraction of informed traders in the market
- In the GM model the normal behaviour of the model has a constant parameter μ
- In actual markets this parameter varies when the market maker receives orders so what is the sensitivity of μ ?
- Agent-based model is simulated with a varying μ to analyse learning efficiency

Simulation results (Figure 3) :

- For low values of μ (less informed traders) market maker does not learn
- When market maker learns the efficiency increases with μ (directly proportional)
- Overall, this indicates the high levels of sensitivity

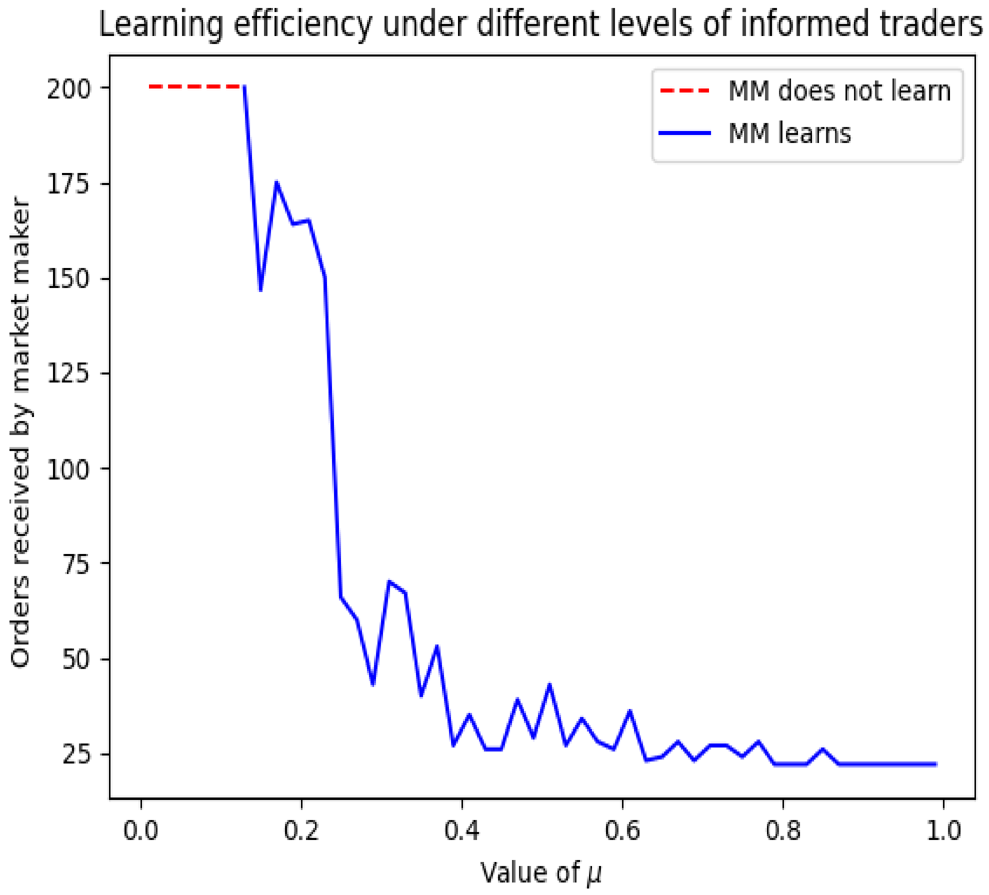

Figure 3 - learning efficiency with varying μ

Appendix 2 - Importance of initial belief σ

- For the market maker to provide a price to the traders requires the use of Bayesian inference to update her probability of σ which determines the market maker's belief of the asset value being either V^H or V^{L}.
- Normal behaviour of ABM assumes that σ = 0.5, which indicates high entropy of the marker maker's initial belief.
- We will now update the market maker's initial belief when she knows the market trend is either bullish or bearish.
- $Market\ Maker\ Learnining\ Efficiency = Number\ of\ orders\ recieived\ to\ learn\ true\ value\ of\ asset$
- We update initial belief to 0.4 which indicates marker maker belief is that the market is bullish. We also update the value of sigma to mildly bullish/bearish market conditions and extreme bullish/bearish market conditions.
- Results: Learning efficiency does not change. Market maker initial belief is not important.

Market maker belief is that market is Bullish

Market type	Intial belief	Sigma	Efficiency
Normal	0.5	0.50	49.02
Bullish	0.4	0.25	50.31
Bearish	0.4	0.75	49.08

Figure 4- learning efficiency in mildly bullish/bearish conditions

Market maker belief is that market is Bullish

Market type	Intial belief	Sigma	Efficiency
Normal	0.5	0.5	48.71
Bullish	0.4	0.1	49.56
Bearish	0.4	0.9	51.51

Figure 5- learning efficiency in extreme bullish/bearish conditions

Appendix 3 - Inactive Trader

- New feature for uninformed traders to remain inactive.
- Parameter θ (theta) which decides the probability of uninformed traders submitting an order or making a trade.
- Impact on learning process of Market Maker with varying theta and hence the efficiency:
  - θ = 1 implies original Glosten Milgrom Model.
  - θ decreases Market Maker’s efficiency increases.
  - θ increases Market Maker’s efficiency decreases.
- Impact on Liquidity on the Market with varying theta.
  - High θ implies higher chances of UI of submitting random traders.
  - Low θ implies higher chances of remaining inactive or less orders submitted

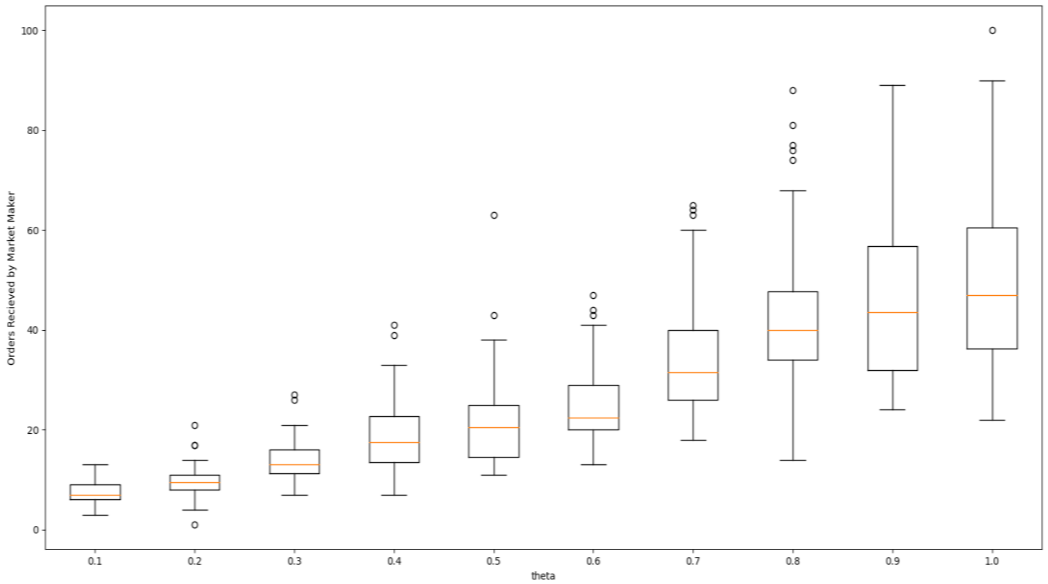

Figure 6 - learning efficiency with varying theta