Coursework 2 Report

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Preface

1. In this Agent-Based Model, we will use **MESA** (https://mesa.readthedocs.io/en/stable/), an **ABM framework in Python**. There are at least **two main reasons** to develop ABM in MESA
    a. **Modular Components**, as the Agent and Model are already clearly defined as proper Python Class and have easy interfaces. Not to mention a built-in schedule that can progress the model by one step based on our command
    b. **Built-in tools to enhance result analysis**
2. The ABM created and discussed in this coursework is **modeling real-world financial trading**, especially in the **cryptocurrency market**. The cryptocurrency taken as subject is **Bitcoin** and the fiat currency taken as subject is **British Pound (GBP)**. ABM is the correct approach for this problem, as the **financial trading market is a complex system** consisting of **heterogeneous actors** with **their own decision making rules**. We can also run simulation or what-if scenarios to see how the system and actors within will react toward certain scenario
3. The build of this ABM is **inspired by the similar ABM** for Bitcoin market proposed by Cocco *et al.* [1][3]
4. There are **two main goals** of this coursework, with **several subgoals within**. This will also define the scope of this coursework in general. The main goals and subgoals are
    a. **Comparisons of Performance**
        i. Between **rules of trading** that Agents are using and the **rules variable** that we use (n lag-days)
        ii. Between **Agents** within the created ABM
        iii. Between **created ABM and other similar ABM** (in term of Wealth Acquisition and Price Generation)

b. **Simulation**

    i. **Cyber Attack Scenario**, eliminating 40% of Agents and liquefying all their Bitcoin assets back to fiat currency

Part 1 : Agents

1. **[Nature] Agents** in this ABM will act as **traders** in the **Bitcoin<>GBP** market. There are two main types of traders with their own distinctive natures

    a. **Chartist Traders (CT),** a type of trader that **relies on chart-based analysis** to determine their action, thus the name chartist. As cryptocurrency lacks universally accepted value-relevant fundamentals (such as dividends, interest payments, etc) [2], CT makes sense to be one type of agent. CT will **rely on a set of rules** to **decide their action** at a **given time**. Their main goal is to **gain profit in the fiat currency (GBP)** by opening and closing positions in the Bitcoin market. Further variable that CT is using will be explained in more detail in section 1.1

    b. **Random Traders (RT)**, a type of trader that completely relies on **probability** to determine their action thus the name random traders. Their main goal is to simply **diversify their portfolio** by opening and closing positions in the Bitcoin market. Further variable that random trader is using will be explained in more detail in section 1.1

2. **[Action]** Similar to traders in a real-world trading market, both CT and RT will have **two types of actions**, **opening** and **closing** positions in the market, creating supply and demand in the market and **fluctuating prices**. However, to **simplify the ABM**, we will only **take care of long positions** and **neglecting completely short positions.** Also, both **CT and RT can only open a new position if they have closed their previous position**

3. **[Interaction]** Both CT and RT will have **indirect, endogenous, stochastic, and global interactions**

    a. Both CT and RT have **indirect interactions**. As stated in point 2, their actions in the market will create supply and demand that **fluctuate price** which then **price will affect** CT and RT **next actions**

    b. Both CT and RT **have their own way of determining actions** that always change based on the variables fed to them. As stated in the point above, their actions will affect others in the form of price, creating interaction. Therefore, they are both **endogenous**

c. Both CT and RT have a **probabilistic set of actions.** As stated in the point above, their actions will affect others in the form of price, creating interaction. Therefore, they are both **stochastic**

d. All CT and RT actions are determined by price, which then we can infer that the interactions among them are **global**, although as point 3.a suggests, it is indirect

Task 1.1 : Chartist Traders

Task 1.1.1 : Variable of Chartist Traders

1. There are two sets of rules that CT will use, **Simple Moving Average (SMA) and Exponential Moving Average (EMA)**

    a. **SMA** will calculate the **last n days price average**. If **today's price is below SMA**, the CT agent will **open the position as the price is seen as undervalued**. If **today's price is above SMA**, the CT agent will **close the position as the price is seen as overvalued**. Opening and Closing Rule as stated in Section 1.1 point 2 still applied. **n values** will be varied between **1, 2, 3, 5, 7, and 9** as it represents **near-term trends** [5]

    b. **EMA** will calculate the **last n days price average**, but **weighting recent data more**. If **today's price is above EMA**, the CT agent will **open the position as the trend is seen as bullish (positive)**. If **today's price is below EMA**, the CT agent will **close the position as the trend is seen as negative (bearish)**. Opening and Closing Rule as stated in Section 1.1 point 2 still applied. **n values** will be varied between **1, 2, 3, 5, 7, and 9** as it represents **near-term trends** [5]. The chosen **smoothing factor of the EMA** is **2 / (n+1)**

2. **Both rules will be used to open and close positions**, but **each CT will have their own rule preference**. For the **preferred rule**, it will a**ccount for 80% of the decision** while the **unpreferred one will account for 20% of the decision**. Therefore, there will be 4 subclasses of CT

    a. **Prefer SMA to both open and close positions**. This subclass will then be referred as **R1R1 CT**

    b. **Prefer SMA to open position, but EMA to close position**. This subclass will then be referred as **R1R2 CT**

   c. **Prefer EMA to open position, but SMA to close position**. This subclass will then be referred as **R2R1 CT**

   d. **Prefer EMA to both open and close positions**. This subclass will then be referred as **R2R2 CT**

3. **Number of CT** is roughly **60% of the total Agents**

Task 1.1.2 : Chartist Traders Behaviors

1. In order to gain profit, **CT needs to be able to buy low and sell high**

2. Opening a position when price is below SMA is **taking the fact** that **present's price is cheaper than past's lagging price (undervalued)**, thus interpreted as a good signal to open a position (**buy low**)

3. Closing position when price is above SMA is **taking the fact** that **present's price is more expensive than past's lagging price (overvalued)**, thus interpreted as a good signal to close a position (**sell high**)

4. Opening a position when price is above EMA is **assuming that the trend is bullish or confirmation of reversal pattern (from bearish to bullish)**, thus interpreted as a good signal to open a position and **"ride" the uptrend**

5. Closing a position when price is below EMA is **assuming that the trend is bearish or confirmation of reversal pattern (from bullish to bearish)**, thus interpreted as a good signal to close a position to either **cut loss or take profit**

Task 1.1.3 : Chartist Traders Expectation

1. **Opening using (price < SMA) rule is more speculative than (price > EMA) rule** as **CT does not wait for any bullish trend** and speculatively enter the market once the rule hits. Opening with **(price < SMA) rule is exposing CT to potential loss risk** as the opening position can be hanging quite high. However, if the rule luckily predicts the **hypothetical positive reversal point** (point in which trend is switching from bearish to bullish), the **return is higher than (price > EMA) rule**. This means, **opening with (price < SMA) rule is suitable for risk-seeking CT** while **opening with (price > EMA) rule is suitable for risk-averse CT**

2. **Closing using (price < EMA) rule is more efficient to make profit than (price > SMA) rule** as **CT will "ride" the bullish trend until the reversal pattern is confirmed** before closing position. Compared to

(price < EMA) rule, (price > SMA) is lacking this efficiency when closing position. Despite the efficiency, closing with **(price < EMA) rule** exposes the agent to risk of losing in case of sudden price drop, as EMA is a lagged indicator and the price might already dip when the EMA catches up with the time. Therefore, closing with **(price < EMA) rule is suitable for risk-seeking CT, and (price > SMA) rule is suitable for risk-averse CT**

3. **[Hypothesis]** Based on 2 points above, **the highest profit over time will be achieved by R2R2 agents**, because they are waiting for a reversal pattern for **both opening and closing positions**. With the characteristic of “riding” the trend, R2R2 will surely obtain massive profit especially in bullish market
4. **[Hypothesis] R1R2 and R2R1 agents will have similar profit over time** because their **“risk-sum” are similar**. **R1R2 are both risk seeking when opening and closing position**, while **R2R1 are both risk aversing when opening and closing position**
5. **[Hypothesis]** Although R1R2 and R2R1 have similar performance, **R1R2 will have slightly better profit over time compared to R2R1** due to its “riding” the trend characteristic when closing the position. Its naive open position strategy is compensated with its aggressive take profit strategy
6. **[Hypothesis] R1R1 agents** will have **poorest performance** in term of **profit over time** as it is using **risky rule to open position** but **not trying to compensate** that with aggressive profit making closing strategy

Task 1.2 : Random Traders

Task 1.2.1 : Variable of Random Traders

1. The **probability** of RT to **buy and to sell is both 50%**. This to mimic **uniform randomness** as RT **has no preference at all** for opening or closing positions

2. **Number of RT** is roughly **40% of the total Agents**

Task 1.2.2 : Random Traders Behaviors

1. Due its random stochastic behavior, **RT will generate volume in the market**, thus **introducing volatility to the price**. Without price changing, CT will not make a move at all since the price is stagnant. Therefore, we can say **RT is the initial market mover for the model to run**

2. Furthermore, the **random actions of RT** are also **assumed to mimic the behaviors of real life people trying to diversify their portfolio**. They don't care about profit and loss of one specific financial instrument, but more on "putting their eggs under multiple baskets" to hedge their financial position in general. They can open and close position at anytime without care about the trend, news, etc

Task 1.2.3 : Random Traders Expectation

1. **[Hypothesis]** RT will perform poorer than all subclasses of CT because of its random nature that expose them to opening a very risky position and close it in the worst scenario possible

Task 1.3 : Market Environment

Task 1.3.1 : Assumption

In this ABM, the market will **represent all exchanges** in which Bitcoin is traded in the whole world. However, we are **simplifying the created market because of time and resource constraints**. Here are the assumptions that we are taking to simplify the market

1. ABM is taking **1st January 2020 as the starting point**, thus all **initial variables will refer to that point of time**. This includes **number of traders**, **Bitcoin price in GBP**, **number of Bitcoin** available in the market, and **number of Fiat** available for trading

2. **Only 37.39% of Bitcoin addresses are actively transaction**, and the rest have very limited financial value [7]. Out of this 37.39%, **only 5% are**

based in the UK [6]. We assume only UK based addresses will transact using GBP in the Bitcoin market. We will take this into account when **determining the initial number of agent**

3. Due to **computational limitations**, we will **diminish the number of agents** that we acquire from point 2 **by a factor of 200,000**

4. **Only 60% of total Bitcoin are transactable** [3]. This will diminish the number of available of Bitcoin in the model as well

5. From 1st January 2020 to 31st October 2023, **number of traders are estimated to grow 25.7% every year** [9], thus every **month** we will **add 25.7% new traders spread to monthly basis** to the model

6. From 1st January 2020 to 31st October 2023, the **number of bitcoins is estimated to grow by 7.6% annually** [8], thus we will add this factor to the model. The **newly added bitcoin will be spread to monthly basis and assigned to random group of agents** using **Gibrat** principle [3]

    a. [Disclaimer] Adding 60% of new bitcoin to the system does not make sense and does not represent real life scenarios from 2020 to 2023. It will disrupt the model as well. Therefore we propose better approach as explained above in point 6

7. In order to **highlight the effectiveness of rule that agents are using**, agents will use **all-in strategy** whenever they open or close positions in the market

8. Since we are **neglecting short position**, then price change formula will **only take the factor of number of open and close positions** to estimating demand and supply

9. To simplify the model, we are **reducing the Satoshi number to 4 digits** instead of 8 [11]

10. To simplify the model, **we assume that the agents only have GBP as their capital at any time they enter the model**. At the **beginning of time**, we **will spread the number of fiat available uniformly** among agents (both CT and RT) available at that particular time. For **new agents** introduced to the model, they will also **take the same number of fiat** as their initial capital

Task 1.3.2 : Market Variable

1. **Total number of days** from 1st January 2020 to 31st October 2023 is **1400 days**, therefore the **ABM will take this number as the number of maximum steps** for simulation

2. **Initial number of agents** on **1st January of 2020** is **596,493,484** [9]. Taking account of the **37.39%** factor mentioned in Section 1.3.1 point 2, this will diminish the number to **223,028,914**. Taking account of the **5%** factors mentioned in Section 1.3.1 point 3, this will diminish the number to **11,151,445 agents.** Taking account of the **200,000** factors mentioned in Section 1.3.1 point 3, this will diminish the number to **56 agents**. We will use this number as the initial number of agents in the model. This number will **grow every 30 steps by 2%** to follow Section 1.3.1 point 5

3. **Price change** is determined by using **Petrov formula** [10]. The formula is stating that if **volume of open is more than short**, then the **price will increase** by certain factors. If **volume of open is less than short**, then the **price will decrease** by certain factors. Volume itself is defined as the number of bitcoin that is either open or close at a given time, mimicking the supply and demand in the market

    a. $\Delta Nn = Vopen - Vclose$

    b. $price\ change = \left\lfloor \alpha \cdot sgn(\Delta Nn) \cdot \sqrt{|\Delta Nn|} \right\rfloor$

    c. α value is $\frac{\sqrt{2}}{2}$, sgn is the sign of ΔNn, and [] represents floor function

4. **Initial number of bitcoin transactable** on **1st January of 2020** is **18,141,643.75** [8]. Taking account of the **60%** factor mentioned in Section 1.3.1 point 4, this will diminish the number to **10,884,986**. Taking account of the **200,000** factors mentioned in Section 1.3.1 point 3, this will diminish the number to **54.4249.** We will use this number as the initial number of bitcoin in the model

5. **Initial number of GBP Volume in Bitcoin market** on **1st January of 2020** is **14,011,191,757** [12]. Taking account of the **200,000** factors mentioned in Section 1.3.1 point 3, this will diminish the number to **70,056.** We will use this number as the initial number of GBP in the model. It means **each agent will possess 1251 GBP**. We will use this as the initial capital of each agent in the model

6. **Initial price of bitcoin** on **1st January of 2020** is **5,433.85** [12], and we will use this number as the initial price of bitcoin

Part 2 : Agent Performance Comparison

Task 2.1 : Variation of n vs Performance

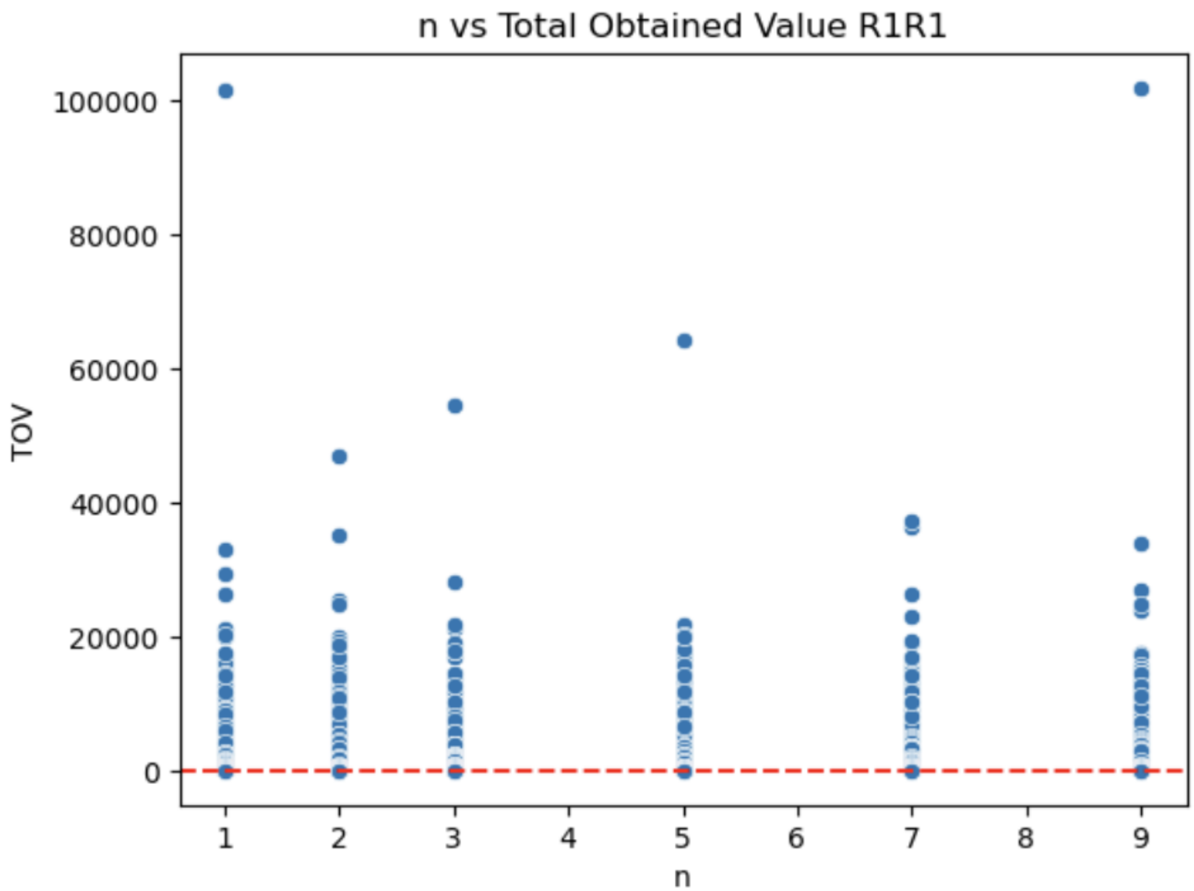
In this section, we will **compare the behavior changes of agents based on lag-days (n) in both SMA and EMA** and see its impact towards the **performance of the chartist agents**. As stated in Section 1.1.1 point 1a, we will use **1, 2, 3, 5, 7, and 9 as the value of n** because it represents **near-term trends** [5] as chartist traders in real life are also operating in the near-term window**.** We will discuss all types of chartist agents individually and try to compare all of them by the end of the section. **All the data** presented below is **captured at the last step, which represents 31st October 2023**. In each agent, we will take a closer look into

1. **Total Obtained Value (TOV)** : The **total number of obtained fiat and bitcoin by an agent at a given time t**. The formula is $TOV = (fiat_t + bitcoin_t) - fiat_0$. If the agents are still holding bitcoin when calculating the value, bitcoin will be converted to fiat for a price at time t. **In this scenario, all t will be equal to 1400**. For TOV, we will take a closer look into **spread of TOV** and **statistics summary based on n**

2. **Open Position** : The **total number of open positions of all agents** that fall under a specific group **at a given time t**. If it's the R1R1 open position, then it only takes into account R1R1 agents. For Open Position, we will take a closer look into **statistics summary based on n**

To obtain the data below, **we run the model more than once** to get a **better understanding of agents' interaction and statistical meaning**. Unfortunately, due to **time and resource constraints**, we only run it for **3 times** and aggregate the results.

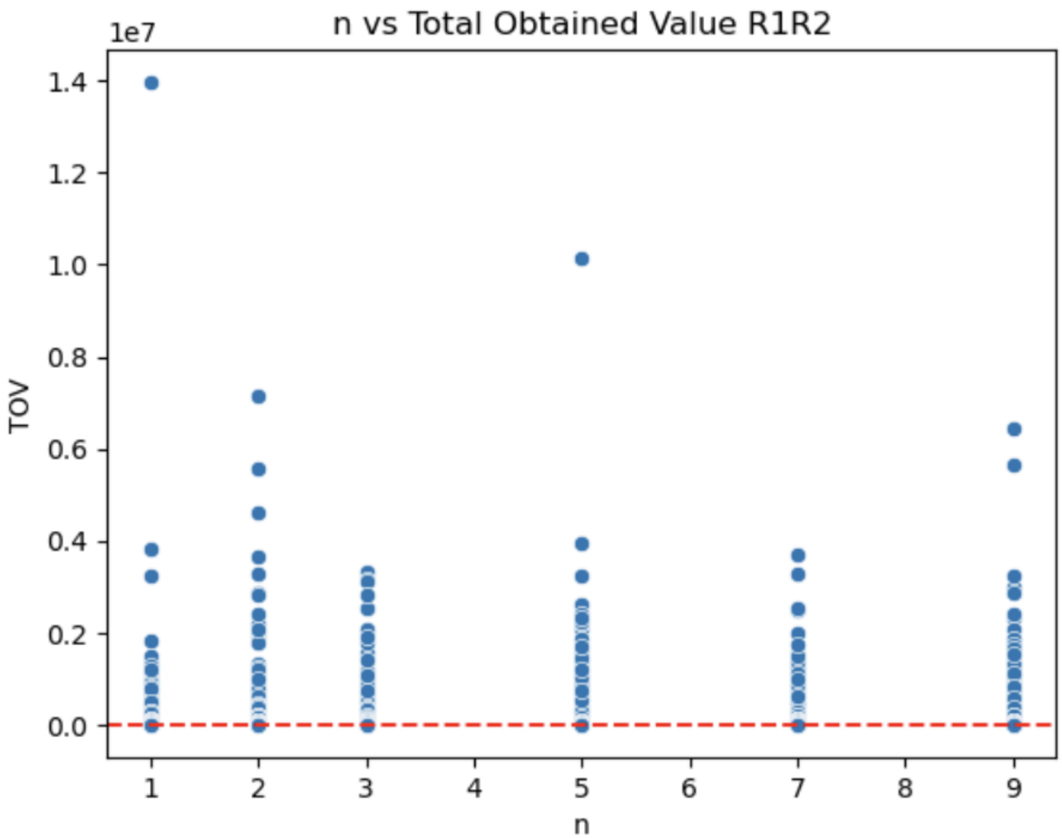
Task 2.1.1 : R1R1 Agent



chartist_day_reference	TOV Mean	TOV SD	TOV Max	TOV Min
1	1721.749308	4291.385967	101596.9254	3.0032
2	1812.675550	3359.999605	46960.5489	0.0000
3	1701.623672	3260.806020	54496.4885	0.0000
5	1667.931205	3286.556426	64210.7660	1.7226
7	1722.251761	3152.470271	37293.8680	0.0000
9	1845.483324	4233.137913	101782.1495	0.0000

chartist_day_reference	Open Pos Mean	Open Pos SD
1	112.900000	2.999649
2	107.476316	4.501913
3	103.493827	0.500182
5	104.064220	5.001883
7	107.547597	3.501264
9	124.635539	6.501535

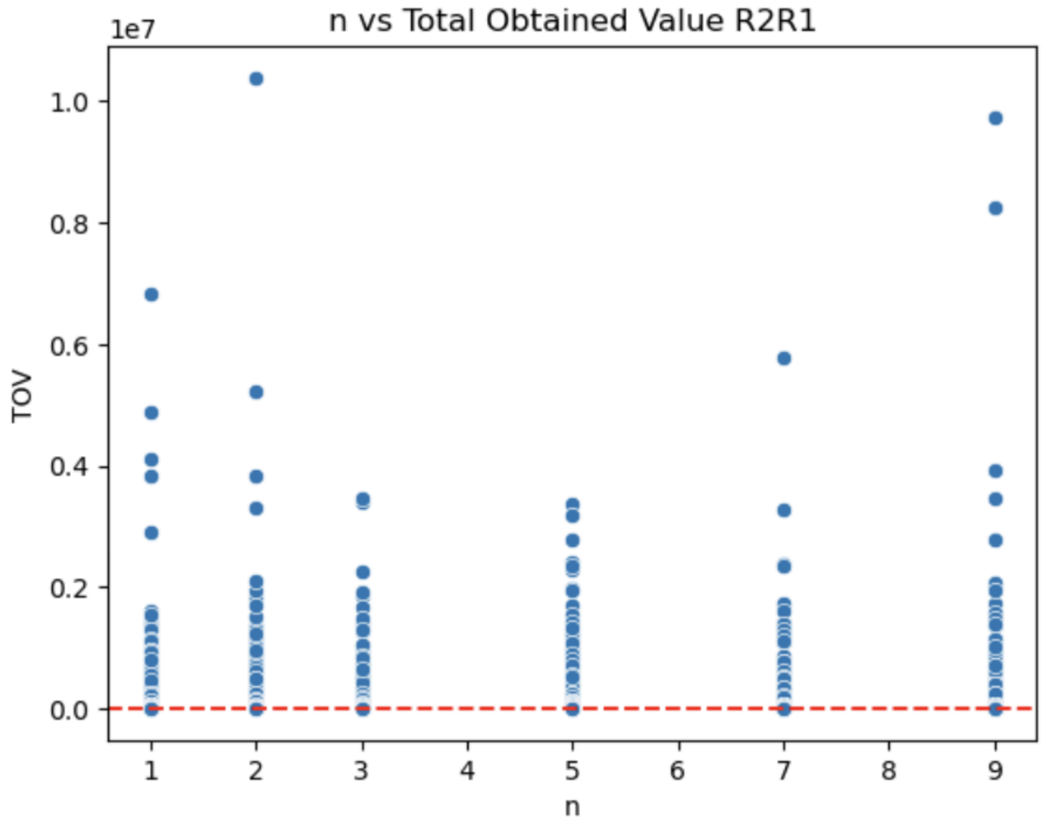
Task 2.1.2 : R1R2 Agent



chartist_day_reference	TOV Mean	TOV SD	TOV Max	TOV Min
1	75451.815692	463328.369540	1.397118e+07	0.0000
2	92080.286880	403870.976652	7.128729e+06	0.0000
3	86945.587797	306343.301688	3.316382e+06	7.6008
5	82900.865520	404840.349455	1.014849e+07	0.0000
7	68443.782788	261224.492879	3.703200e+06	2.8498
9	80874.040623	354678.365705	6.421329e+06	9.2734

chartist_day_reference	Open Pos Mean	Open Pos SD
1	286.180426	19.496423
2	307.132510	7.001628
3	305.041152	2.000400
5	311.336554	14.504919
7	295.609555	9.503283
9	301.105600	11.003896

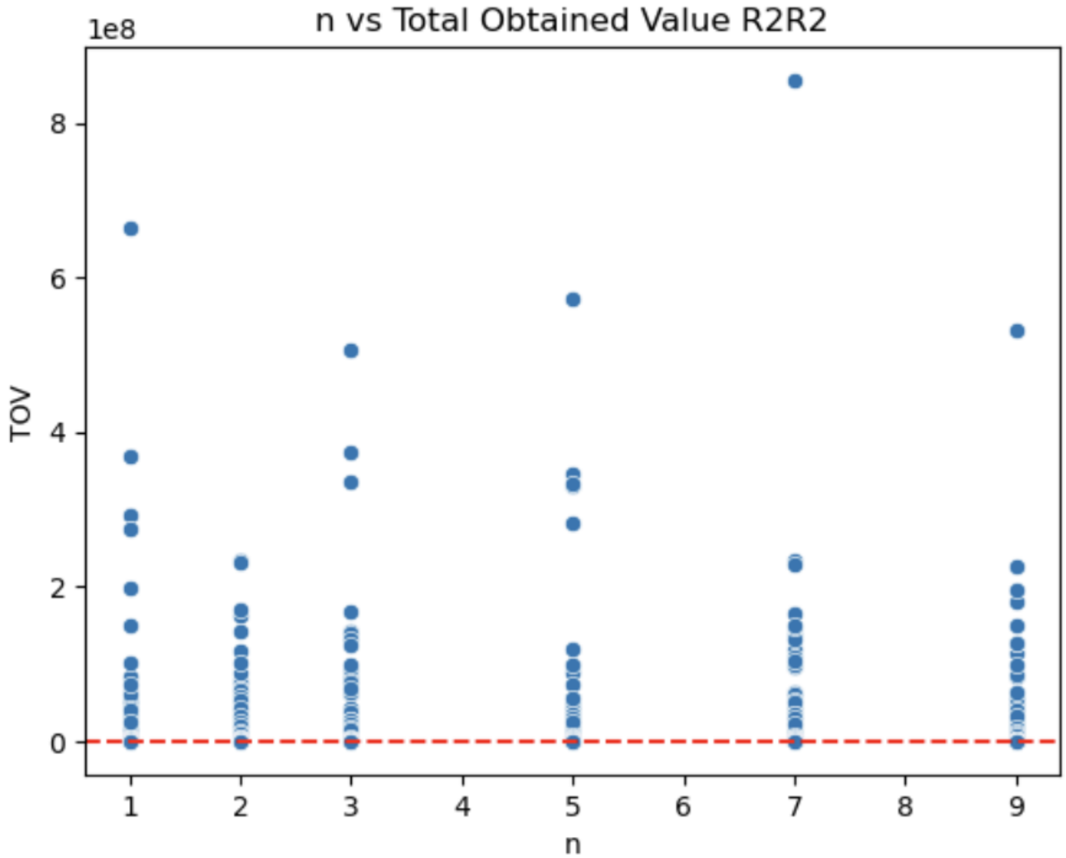
Task 2.1.3 : R2R1 Agent



chartist_day_reference	TOV Mean	TOV SD	TOV Max	TOV Min
1	81966.276863	350512.753905	6.824788e+06	19.5800
2	82504.895723	419195.851180	1.038462e+07	22.4320
3	66458.375922	244189.684354	3.473314e+06	19.0600
5	71770.092148	267712.300514	3.355093e+06	15.1506
7	69449.351370	283508.095433	5.792554e+06	17.8018
9	85605.400306	455970.810841	9.734126e+06	20.4803

chartist_day_reference	Open Pos Mean	Open Pos SD
1	302.488980	1.500572
2	277.320104	29.983879
3	291.040541	6.002398
5	284.000000	0.000000
7	297.837746	10.002956
9	285.893196	4.000297

Task 2.1.4 : R2R2 Agent



chartist_day_reference	TOV Mean	TOV SD	TOV Max	TOV Min
1	4.031068e+06	3.097225e+07	6.635893e+08	24.5672
2	3.579018e+06	1.732378e+07	2.351739e+08	33.3420
3	4.256796e+06	2.778561e+07	5.066750e+08	32.4716
5	4.286362e+06	3.034275e+07	5.721206e+08	26.2304
7	4.537373e+06	3.322600e+07	8.550811e+08	26.8778
9	3.629727e+06	2.385193e+07	5.309796e+08	28.4252

chartist_day_reference	Open Pos Mean	Open Pos SD
1	353.993197	1.000544
2	370.546256	33.923207
3	344.474691	7.504179
5	359.518560	1.500729
7	354.481799	25.008749
9	360.295154	27.985445

Task 2.1.5 : Preliminary Discussion

Before we jump into the explanation based on the spread and statistics summary above, we need to **better understand the effect of n in trading rules** that the agents are using

1. **SMA and EMA** rules are **both calculating average prices in the last n days**. This is important **information** as the agent will know **how "good" or "bad" the price is today to open or close a position** in the market compared to past data from their perspective. So both SMA and EMA can be used to **estimate today's price value**, whether it is **undervalued or overvalued**
2. However, the **difference between SMA and EMA** lies in the fact that EMA is using **weighted average to calculate the average number** by adding a certain **weight factor** to the more recent data. This factor is defined as **smoothing factor**
3. The **smoothing factor** that is used in this ABM is **2 / (n + 1)**. This has meaning that
    a. **If n = 1**, then the **EMA value is similar to SMA**. However, since the **rule is different** (for SMA, if the price is lower, it is a signal to buy. For EMA, it is the other way around), the **behavior of the agents will not be the same**. If agent R1R1 and R1R2 are opening new positions in the market, then it means R2R1 and R2R2 will not do anything. If agent R1R1 and R2R1 are closing their positions in the market, agent R1R2 and R2R2 will not do anything. We call this n=1 effect
    b. **If n = 2**, then the **EMA is weighting recent data more than older data by ratio of 2:1** towards the result average
    c. **If n = 3**, then the **EMA is weighting recent data and older data by the same ratio 1:1** towards the result average
    d. **If n > 3**, then the **EMA is weighting older data more than recent data** and the **factor is increasing if we increase the n-value**

Task 2.1.6 : Explanation

Based on the graphs and statistics summary above, we can see the **maximum possible TOV is achieved by R2R2 agent by huge margin,** gaining a staggering **855M GBP**. **This aligns with our hypothesis in Section 1.1.3 point 3** regarding the highest earning agents. On the other hand, the lowest performance of all is R1R1 agents, and by a huge margin as well. **This aligns with our hypothesis in Section 1.1.3 point 6**.

This phenomenon is the result of "riding" the trend that R2R2 possesses and also opening position only when reversal pattern is confirmed. The **optimum value of n for R2R n=7**, but **it has no linear correlation** between varied values of n. For standard deviation, it has positive correlation with the average, as the price increases the SD values are also increasing. However, in **n>7**, the **performance starts to decline**. This makes sense as **too high n value will make the agents too late** in adapting to the market situation and detecting reversal patterns.

The performance of **R1R2 and R2R1 agents are similar**, but **R1R2 are slightly better** than R2R1 (based on average, maximum, and minimum values). **This aligns with our hypothesis in Section 1.1.3 point 4 and 5** regarding R1R2 and R2R1 agents' performance.

What is interesting is the effect of n value toward those two agents. **R1R2 performs stabler at n=2**, but reaches **its maximum potential in n=1 and n=5.** This is due to the effect of n when opening positions using SMA and closing with EMA. The **lower the value of n**, the **more risky when opening** but **less risky when closing** the position, which may result in a big win scenario. The same applies to the **higher the value of n**, the **less risky when opening** but **more risky when closing** the position as **it tries to anticipate a false reversal pattern**, which may result in a big win scenario as well. This also explains why n=2 is more stable as the value lies between n=1 and n=5.

For **R2R1**, it reaches its **maximum potential in n=9**, very **similar to R1R1**. Both types of agents are **closing with SMA strategies** that **lack the capability to ride the bullish pattern**. Therefore, the **more lagged the indicator the better** as it gets time to at least ride the early pattern before finally the SMA value catches up and closes the position. It **ironically utilizes the lagged indicator** to **still be able to gain the profit.**

Task 2.2 : Type of agent Performance

Based on our discussion in task 2.1, we can say that

1. **Both R1R1 and R2R1** agents perform best at **n = 9**
2. **R1R2** agents perform best at **n = 5** (based on maximum and average TOV)
3. **R2R2** agents perform best at **n = 7**

To be able to see the difference in performance, **we will only take this n-value to compare between agents.** Also, it is intended to **reduce bias** because some agents are performing well in several n values, while the others are only in 1 value. Also, the **gap among agents is too big**, which will widen if we combine the data of all n. Random agents are not affected directly by n value at all

In this section, we will **compare the performance of agents based on 3 categories**

1. **Total Obtained Value (TOV)** : The **total number of obtained fiat and bitcoin by an agent at a given time t**. The formula is $TOV = (fiat_t + bitcoin_t) - fiat_0$. If the agents are still holding bitcoin when calculating the value, bitcoin will be converted to fiat for a price at time t. **In this scenario, all t will be equal to 1400**

2. **Open Position** : The **total number of open positions of all agents** that fall under a specific group **at a given time t**

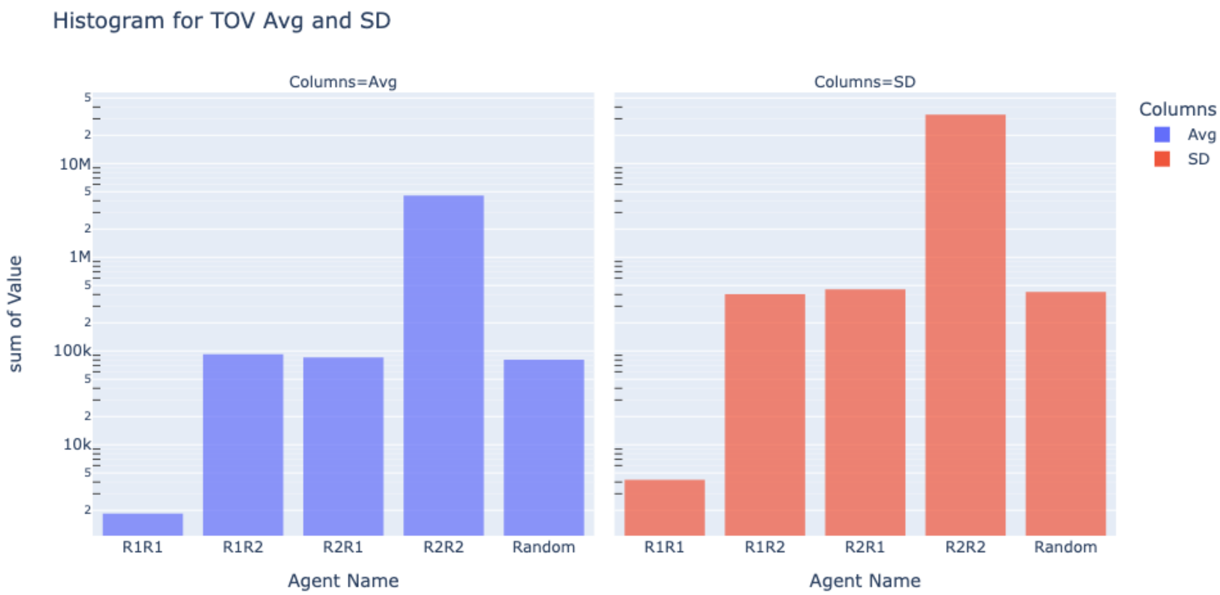
3. **Bitcoin : Fiat Ratio** : The split ratio between Bitcoin and Fiat in agents portfolio, and this value is calculated using this formula $TOV = bitcoin_t * bitcoin\_price_t / fiat_t$

All the data presented below is **captured at the last step, which represents 31st October 2023**.

To obtain the data below, **we run the model more than once** to get a **better understanding of agents' interaction and statistical meaning**. Unfortunately, due to **time and resource constraints**, we only run it for **3 times** and aggregate the results.

Task 2.2.1 : Total Obtained Value

```
TOV Statistics
  Agent Name           Avg            SD
0       R1R1  1.845483e+03  4.233138e+03
1       R1R2  9.208029e+04  4.038710e+05
2       R2R1  8.560540e+04  4.559708e+05
3       R2R2  4.537373e+06  3.322600e+07
4     Random  8.077220e+04  4.251428e+05
```



According to the data above, we can see that the TOV of **R2R2 dominates other agents by quite a big margin** (please note that the diagram has exponential y-axis). This aligns with what we discuss in Section 2.1.6, in which R2R2 agents are **able to "ride" the bullish trend** thus providing them with a good closing strategy.

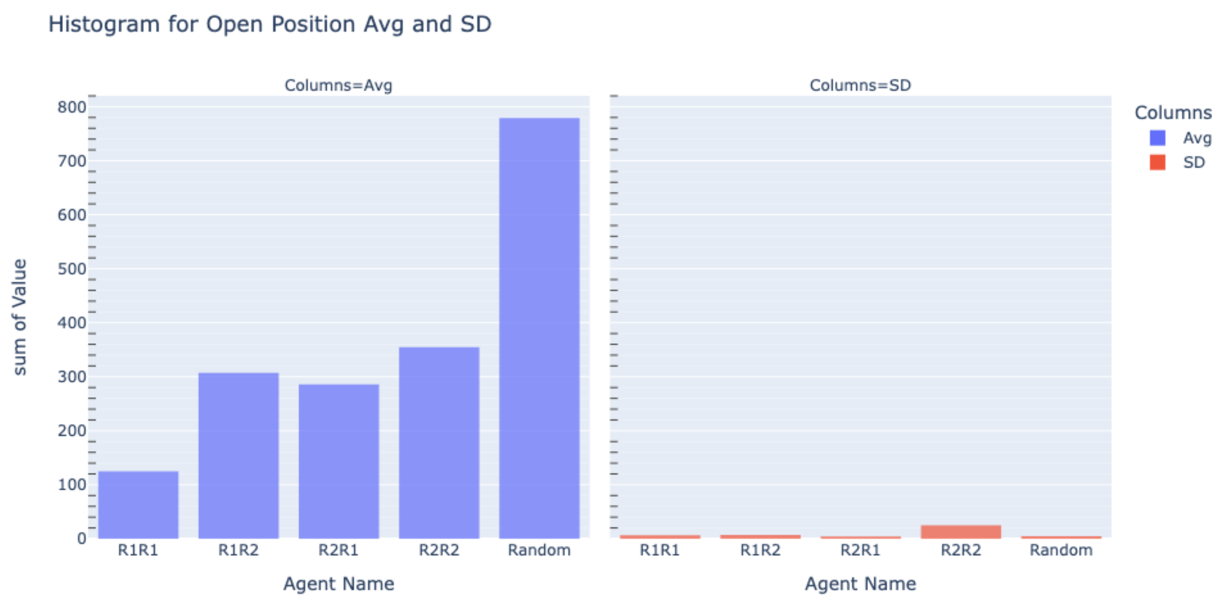
Also, the **similarity of performance between R1R2 and R2R1 with the condition that R1R2 performs slightly better** proves our hypothesis in Section 1.1.3 point 4 and 5 and aligns with the explanation in Section 2.1.6. Although they are similar, the reason why they are bagging good enough profit is different. For **R1R2**, it is because they possess **"riding" the trend capabilities**, while for **R2R1** is because they are relying on **high delay of SMA indicator** (and also **luck**) to gain **profit**.

What is surprising is that **random traders perform better compared to R1R1**, and **not too far apart from both R1R2 and R2R1**. This means **random movement is good enough** to **obtain profit** and **R1R1 agents simply fail to read the market**.

Task 2.2.2 : Open Position

Open Position Statistics

	Agent Name	Avg	SD
0	R1R1	124.635539	6.501535
1	R1R2	307.132510	7.001628
2	R2R1	285.893196	4.000297
3	R2R2	354.481799	25.008749
4	Random	779.000000	5.000831



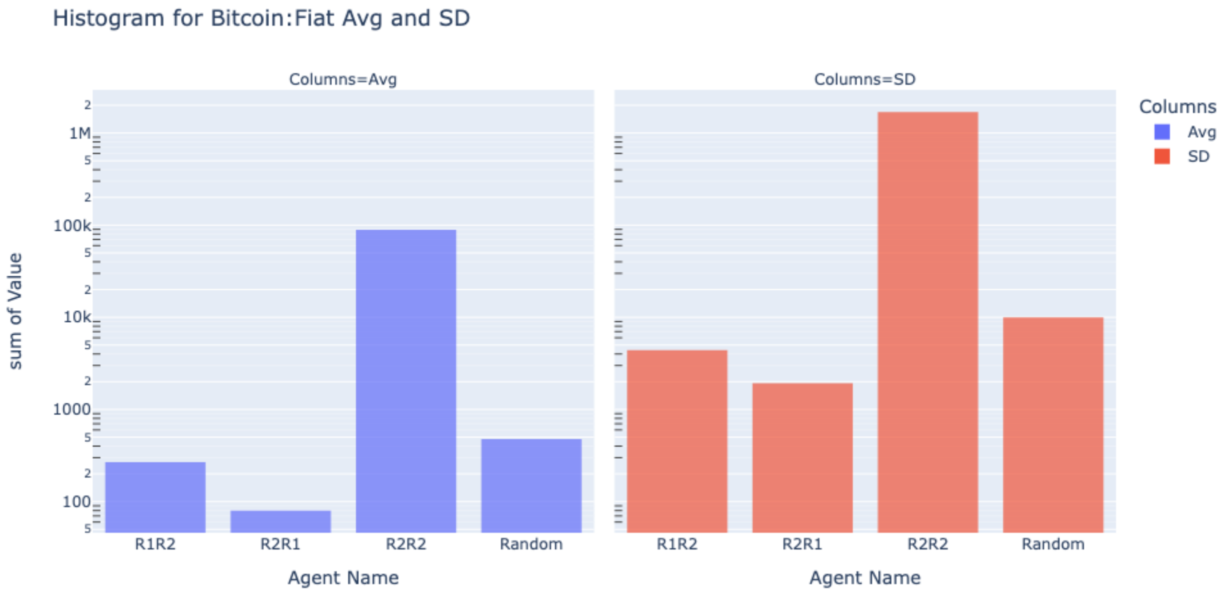
According to the data above, the **number of open positions of Random agents** are **very high compared to other agents**. This is due to the random movement that it possesses as they **do not have any specific criteria to close their position**. However, their tendency to not close their position resembles a **"holding" maneuver** in the real world. Therefore, it explains the reasoning why Random Agent is performing better compared to R1R1 and similar to R1R2 and R2R1. Random Agent is **riding the bullish trend** of Bitcoin trend over time by **holding it**. The value of that bitcoin is simply increasing by itself without the need for the Random Agent to trade anything. Basically **they are doing nothing** to **gain profit**.

R1R2, R2R1, and R2R2 agents are **simulating active trading** in the market by having **medium value of open positions in the market**. They are providing good dynamics to the market ecosystem.

However, for **R1R1**, their **open position is so low compared to the other** (less than half of other agents average). This means it does not have a good strategy to open positions in the market, resulting in it **to hold into fiat instead of trading bitcoin**.

Task 2.2.3 : Bitcoin/Fiat Ratio

```
Ratio Bitcoin vs Fiat
  Agent Name           Avg            SD
0       R1R1      0.000000  0.000000e+00
1       R1R2    267.043720  4.404027e+03
2       R2R1     79.846960  1.922969e+03
3       R2R2  89278.090835  1.688421e+06
4     Random    477.370751  9.950790e+03
```



According to the data above, the **ratio of R2R2 agents is significantly high** (please note that the diagram has exponential y-axis). This means, the **majority of R2R2 TOV** is actually coming from the **opening and holding position rather than closing position**. As the price is rising in a bullish trend, the TOV of R2R2 is also skyrocketing. Not to mention, the exponential effect of additional bitcoin that is gained through the Gibrat principle that favors them as the richest agents within the system.

And also based on the data above, we can see that the ratio of **Random agents is higher than both R1R2 and R2R1**. This proves our hypothesis in Section 2.2.2 in which **Random Agents are gaining profit through holding Bitcoin rather than trading it**.

Part 3 : Model Validation

Task 3.1 : Input Validation

All **input validations are following Section 1.3** as it also describes all the input parameters that we use and all justification behind those selected parameters and values.

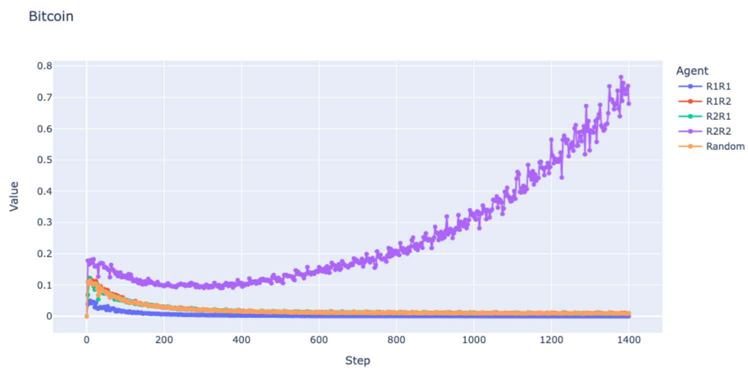
Task 3.2 : Output Validation : Agent Performance

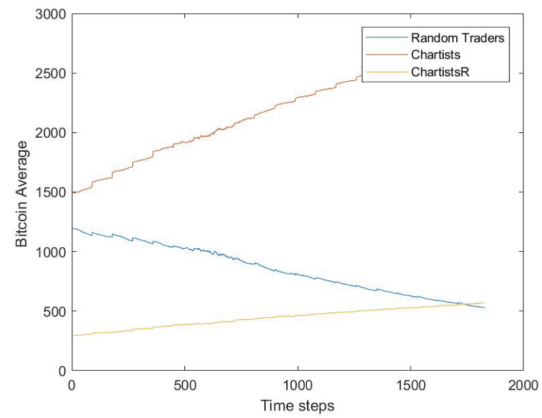
In this section, we will **validate the agent performance in our ABM with the result of Cocco's model [1] based on 3 categories**

1. **Amount of Bitcoin :** The **total number of bitcoin possessed by an agent at a given time t**. We will compare the trend over time
2. **Amount of Fiat** : The **total number of fiat possessed by an agent at a given time t**. We will compare the trend over time
3. **Total Obtained Value (TOV)** : The **total number of obtained fiat and bitcoin by an agent at a given time t**. We will compare the trend over time

Task 3.2.1 : Bitcoin

ABM vs Cocco's ABM





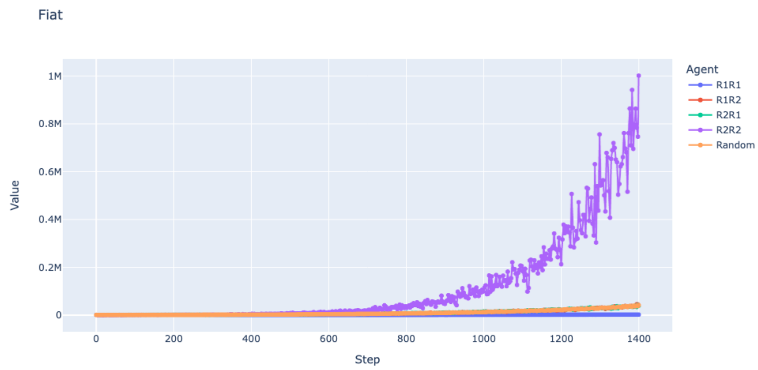
Based on the trend above, we can see that **R2R2 Chartist agents have the same tendency as Cocco's Chartists and Chartist$_r$ to obtain more bitcoin** over time. However, there is a slight difference at the **beginning of the simulation** in which R2R2 bitcoins are **declining** but then gaining momentum and **rising exponentially** after that. This is because R2R2 is using a simpler strategy to open and close positions compared to Cocco's chartists that are using more technical signals to decide their actions. This results in the R2R2 agents to **often close their position at the beginning of the simulation** as the rules hit, resulting in the decline at the beginning of the graph. However, due to **Gibrat's principle**, it creates a s**nowball effect on R2R2 bitcoin possession** since **they are the major shareholder of bitcoin at any given time**, thus explaining the exponential trend after that.

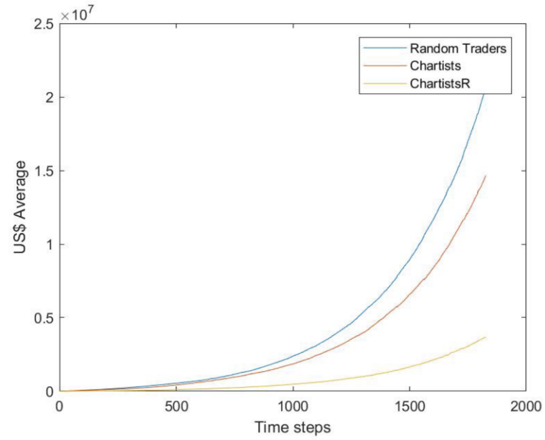
However, for R1R2, R2R1, R1R1 Chartists, and Random agents have the same tendency as Cocco's Random Traders, in which their number of bitcoins is decreasing over time. The reasoning for these agents' behaviors are the same as R2R2 agents at the beginning of the simulation. They are constructed using simpler trading strategies, resulting in them often **closing their position at the beginning of the simulation**. However, since they are minor **shareholders of bitcoin**, their bitcoin possession is actually declining as it cannot balance the rate of position closing by the agents.

Overall, the output of this ABM is similar as Cocco's ABM, but with slight difference due to rules that are used and also implementation difference of market dynamic (Gibrat's principle, etc)

Task 3.2.2 : Fiat

ABM vs Cocco's ABM





Based on the trend above, we can see that **R2R2 Chartist and Random agents have the same tendency as Cocco's Chartists and Random Agents to obtain more fiat exponentially** over time. However, the **results are inverted**. In the ABM, R2R2 Agents exponential growth is far greater than Random Traders, while in the Cocco's ABM they are not far apart and Random Traders is performing better in terms of gaining fiat.

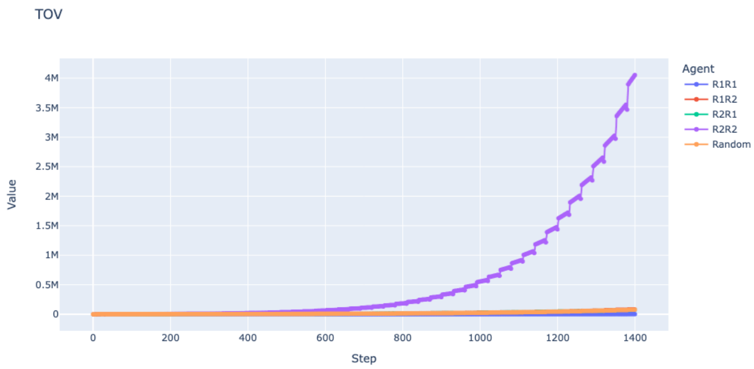
For **R1R2, R2R1, R1R1 Chartists**, they are also **growing exponentially** but the **factor is far less than R2R2 and Random agents**. This is not the case in Cocco's ABM, as the exponential growth factor among agents are not vastly apart.

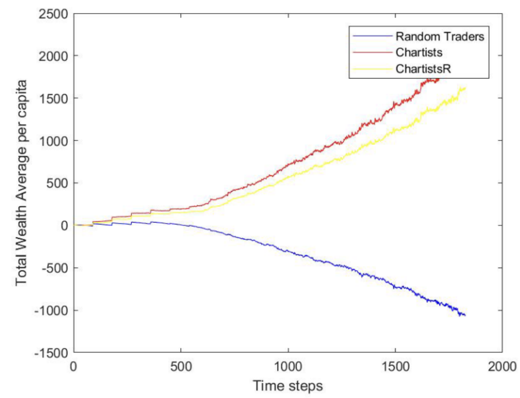
This phenomenon is also **related to the Gibrat principle** that we put into the ABM. When **R2R2 obtains the bitcoin this way**, they technically gain **this bitcoin for free**, and when they convert this to fiat, it technically will boost their fiat in general.

Overall, the output of this ABM is similar as Cocco's ABM, but with slight difference due to rules that are used and also implementation difference of market dynamic (Gibrat's principle, etc)

Task 3.2.3 : Total Obtained Value

ABM vs Cocco's ABM





Based on the trend above, we can see that **R2R2 Chartists have the same tendency as Cocco's Chartists and Chartist$_r$ to gain more total value obtained exponentially** over time. This is the result of the trend in bitcoin and fiat as well, as the total value obtained is also related to the growth of both Fiat and Bitcoin.

For **R1R2, R2R1, R1R1 Chartists**, they are also **growing slightly in terms of total value obtained** but the **factor is far less than R2R2**. This is not the case in Cocco's ABM, as the exponential growth factor among Chartist agents are not vastly apart.

What is interesting is that in Cocco's **ABM**, the **total value obtained by the Random Traders are declining over time while random agents in this ABM are not**, showing that Cocco's random traders are bearing the loss **exponentially**. The **hypothesis** of this phenomenon is because the **probability of opening and closing position between this ABM and Cocco's ABM are not the same**, resulting in Gibrat's principle of Bitcoin distribution to cover up for potential loss of Random Agent.

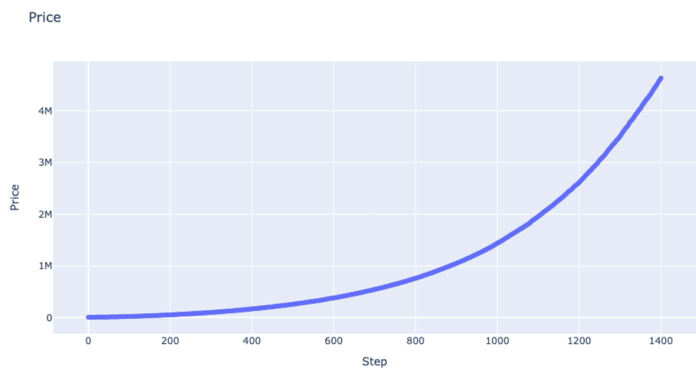
In the ABM, we can also see a **jagged pattern**. It is actually the **effect of adding new agents so the TOV average dropped** a little since we are initializing its fiat with the same initial fiat value in the beginning. And then there will be a **spike after that**, since we are also **adding new bitcoins to the system**.

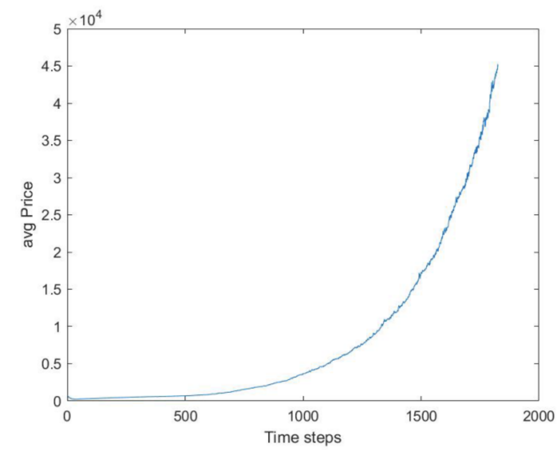
Overall, the output of this ABM is similar as Cocco's ABM, but with slight difference due to rules that are used and also implementation difference of market dynamic (Gibrat's principle, etc)

Task 3.3 : Output Validation : Price

In this section, we will **validate the price formed in our ABM with the result of Cocco's model [1] and also the existence of unit-root property in the Market** as one of the stylized facts of Bitcoin Market [13] **.** The unit-root property is a property of a time series data in which they are exhibiting stochastic or random walk behavior, thus making them non-stationary. It means it is difficult to predict future values solely based on historical data.

Task 3.3.1 : Price Trend





The **price trend** generated by this **ABM is similar to Cocco's ABM** price trend. It exhibits exponential growth, although **Cocco's ABM is steeper** than this ABM. This phenomenon is the result of **Cocco's initial assumption** that the number of **bitcoin growth is 60% every 90 days**, which **contradicts** what we are using in **Section 1.3.1 point 6**. Despite the difference in magnitude, as we also use the same approach of adding new bitcoin to the system over time, the end **result pattern is also similar.**

Task 3.3.1 : Unit-Root Properties

```
test_stats : 0.6395718890426881
P-Value : 0.988551462401689
Critical Value : {'1%': -3.4449982835447894, '5%': -2.8679986379826814, '10%': -2.5702102140862397}
```

In order to **examine the properties of unit-root**, we will use **Augmented Dickey-Fuller test**. The **null hypothesis** (H_0) of this test is the **bitcoin price exhibits unit root properties / random walk**. The alternative **Hypothesis** (H_a) is that the **bitcoin price does not exhibit the random walk trend**. To be able to reject (H_0), we need to **calculate both test statistics and compare it with critical values of 1%, 5%, and 10%**. Also, we need to take a closer look into P-Value which indicates the probability of test_stats to happen.

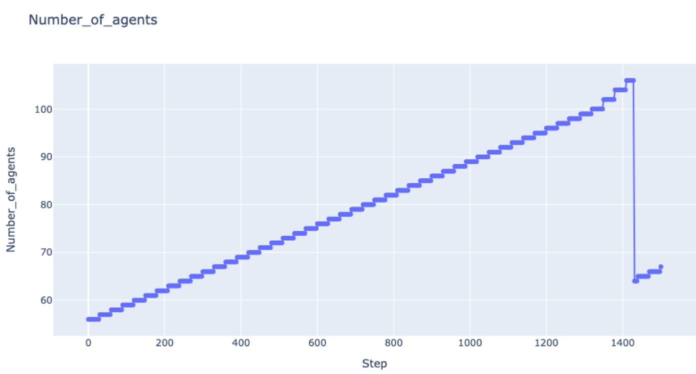
Based on the data above, we can see that **test stats values are above all critical values listed**, with a **very high p-value 0.9885** (98.85% probability). Therefore, using these information, **we cannot reject the** (H_0), thus making the **price generated in this ABM to possess unit-root properties**. This **aligns with [13] and [1]**.

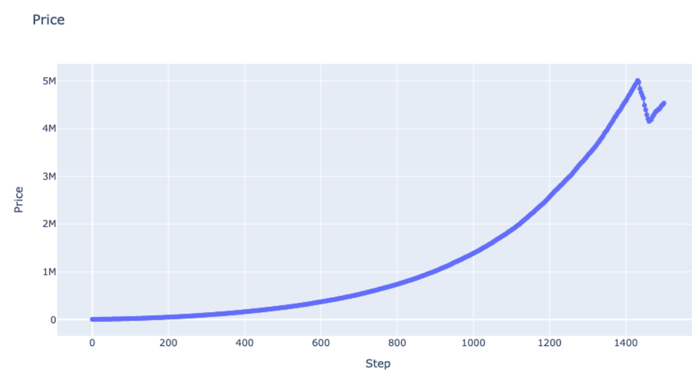
Part 4 : Cyberattack on Bitcoin

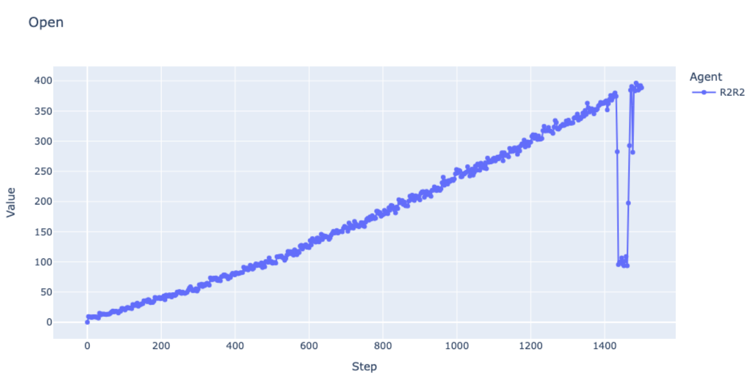
Task 4.1 : Pre-Discussion

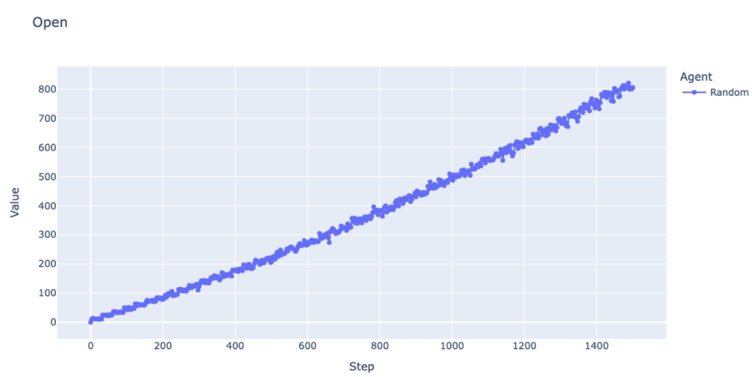
On the 1st December 2023 (step 1430), we want to simulate a **Bitcoin attack**, in which the hacker would **take out 40% of the total agents** and **sell their bitcoin to the market**. **Hypothetically**, this will create **imbalance of supply and demand** at that point, and **price will drop significantly and instantly**. The **price drop will trigger R1R2 and R2R2 agents** to **sell their bitcoin** when the **EMA values catch up with the sudden drop**, thus **prolonging the drop even more** because of abundant supply with less demand. However, this **bearish trend will stop once** the demand starts to rise again due to **all opening rules** (both R1 and R2) **finish estimating the downtrend**. The **rebound process is even faster** due to the existence of **Random Agents** as well. To prove our hypothesis, let's take a closer look into the graphs.

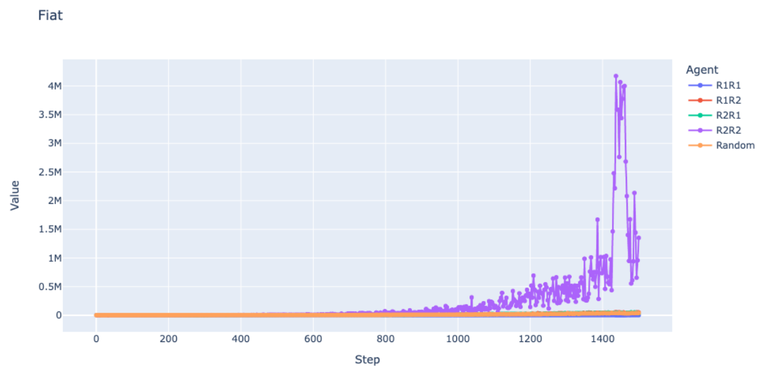
Task 4.2 : Graphs

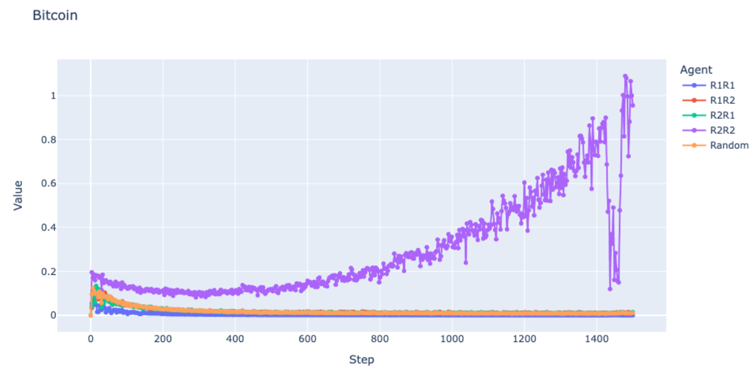












Task 4.3 : Discussion

As stated in Section 4.1, a massive drop of number of agents will occur in Step 1430. However, this is not the only effect of the hacker attack. **Sudden price drop will also occur** since the hacker is **selling all the attacked agents' bitcoin to the market**, creating an imbalance of supply and demand in the market (**supply >> demand**). This is proven by the **sudden dip of the price at the same time of sudden drop of number of agents**. After a couple of steps, this price sudden drop phenomenon will then trigger **all agents that use EMA to close position** to actually close their position. This is due to the fact that EMA value finally catches up with the drop and starts to detect a bearish trend. This closing position phenomenon will then make the Fiat graph to increase drastically while Bitcoin graph to decrease at nearly the same amount.

If we take a closer look at the Random Agent behavior, they don't change at all since **their strategy is not depending on the price at all**. Therefore, any effect on the price will not change their behavior at all.

Part 5 : New Agents

Task 5.1 : Deffuant Agent

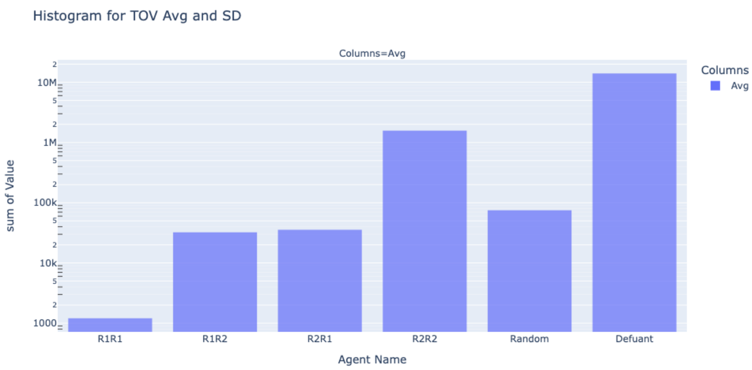
1. **[Nature] Deffuant Agents** will act as **traders** in the **Bitcoin<>GBP** market but will **heavily rely on the opinion of other agents** to decide their **action**. They **will not take a look into price value**, because in their train of thoughts, it is already embedded in the other agent's opinion or actions. In the real world, this type of agent is well known as **Sentiment Trader (ST)** [14].
2. **[Action]** Similar to CT and RT, ST will have **two types of actions**, **opening** and **closing** positions in the market, creating supply and demand in the market and **fluctuating prices**

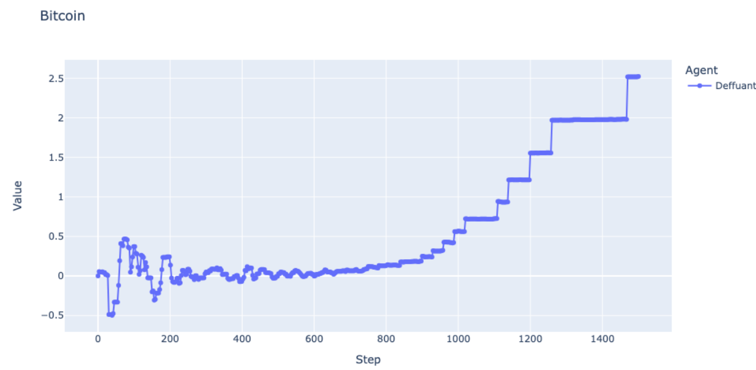
3. **[Interaction]** ST will interact both with CT and RT. Their interaction would be direct, exogenous, stochastic, and global
    a. ST will have **direct interactions with other agents**, although the opinion value will not be important for other types of agents
    b. ST completely relies on other agents to decide their action. Therefore, they are both **endogenous**
    c. Similar to CT and RT, ST will have a probabilistic **set of actions.** Therefore, they are both **stochastic**
    d. ST are interacting with all agents to form opinions that they will then use to decide next actions to take. Therefore, their interaction is **global**
4. **[Variables]** ST will try to estimate other agents' opinion towards the market by using a stochastic approach and threshold of tolerance. The **tolerance level (d) value** chosen is **0.7**, as it is the optimum value for opinion to converge that I obtain during Tutorial 5. In the **dynamic market, the opinion needs to be flexibly updated**, otherwise the action taken by the **agent will be lagging behind** and **exposing the agent to multiple risks at once**
5. **[Variables] Opinion** in ST agents will **determine whether the agent will open or close a position and how much assets that they use using a stochastic approach**. The opinion ranges between 0 to 1 (float), in which it **represents the probability to open or close position** and also the **amount of assets to be traded**. For **buying**, ST will use the **opinion as it is**, while for **selling** it will **inverse it first**
    a. For example, opinion = 0 means 0% open position, or 100% closing position entirely (cash-out)
    b. opinion = 0.2 means 20% chance to open position using 0.2 of fiat, or 80% to sell 0.8 of bitcoin
    c. Opinion = 0.6 means 60% chance to open position using 0.6 of fiat, or 40% to sell 0.4 of bitcoin
    d. Note that ST will follow CT and RT rules, in which they can only open one position at a time and need to close it before they can open a new one
6. [Step by Step] For an ST agent to decide on action, the mechanism will follow this step by step
    a. At t=0, all agents will have opinion set to 0
    b. Everytime an agent beside ST (can be either CT or RT) is opening position, their opinion will be set to 1
    c. Everytime an agent beside ST (can be either CT or RT) is closing position, their opinion will be set to 0
    d. Everytime an ST agent is stepping, it will take random agents and try to find the absolute difference of opinion between them. If it

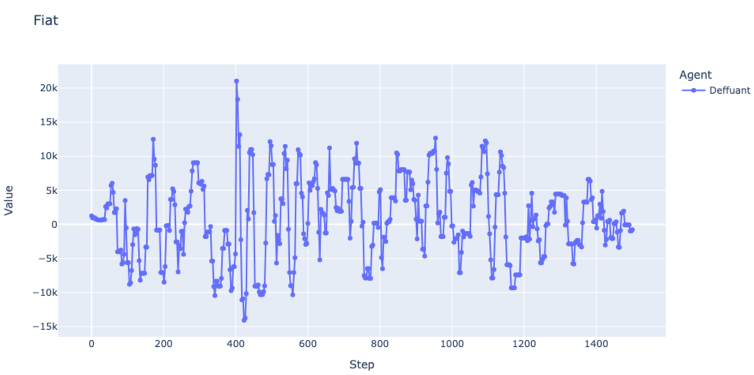
is below the d value, then continue to the step e). Otherwise skip to the step f)

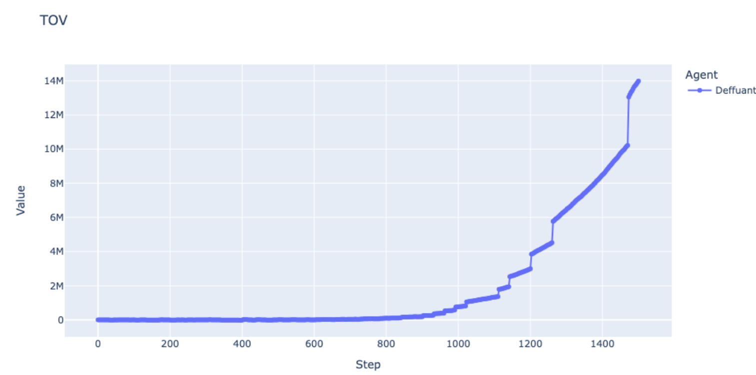
e. It will then update its opinion by the average of its own opinion with the other agent opinion
f. Based on its current is_close value, the agent will decide to either open or close position using its current opinion as the stochastic reference

Task 5.2 : Deffuant Agent Performance









1. From the chart above, we can see that the performance of Deffuant Model at step 1500 even beats R2R2 agents by a quite high margin (please note that y-axis is exponential)
2. The TOV Value and Bitcoin graph is not impacted by the Bitcoin disruption due to hacker attack
   a. The reason for this is they are constantly trading based on opinion and rather than using all-in strategy, they are spreading their portfolio based on the current sentiment of the market. By doing that, Deffuant Agent managed to maintain high value TOV despite the environmental changes by relying on market sentiment

Part 6 : Result Discussion

Based on what we already discussed above, there are several main points that we can take out from this ABM experiment

1. Using parameters and agents that we define in Section 1, we **successfully create a model** in which **Chartist Traders and Random Traders are trading bitcoin in a virtual market and producing stylized facts of Bitcoin price**, in this case unit-root properties. The price trend in this ABM cannot be predicted solely based on past data and it is not stationary
2. **Exponential Moving Average Rule** is **far more significant compared to Simple Moving Average** in terms of opening and closing positions i**n order to gain maximum profit**
3. The **Bitcoin market is highly volatile and highly affected by many external factors** such as **news, sentiment, and etc**. Therefore, it is not possible to use this ABM to predict the future price of Bitcoin. **Adding those external factors** to this ABM is **not feasible** and also a**dds another layer of complexity without any guarantee that will be useful** as we need to do a lot of **calibration and estimation**. However, this ABM is still **useful to at least understand multiple agent types behavior** in stylized fact Bitcoin market and **simulate it under several scenarios** such as hacker attack, sudden positive and negative news, domino effect of other cryptocurrency, and so on
4. **New types of agents** that can do **sentiment analysis or opinion analysis** are definitely **useful** as it can **enrich the decision making process** of the agents, especially in uncertain scenarios. **Further experiment of this type of agent needs to be done** to actually **assess its impact in real life scenarios**

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