Introduction to Computer Simulations in Social Science: Modelling Collective Behaviours

Maxime L. D. Nicolas* [1]

[1] *University College London*

February 27, 2024

Abstract

This course explores computer simulations in social sciences, focusing on simple applications in economics. It challenges the traditional view of rationality in economics and defines the economy as a complex system. It explores the mechanisms of contagion, social pressure, and herd behaviour, and their implications across different fields such as politics, psychology, sociology, and economics. The course covers simulations of the Weidlich-Lux opinion dynamics and Ising models, highlighting their applications in understanding market dynamics.

Contents

1 Introduction: Rationality vs Complexity **1**
1.1 The Representative Agent in Economics . . . 1
1.2 The Economy as a Complex System . . . 1

2 Contagion, Social Pressure, and Herd Behaviour **2**
2.1 Politics: The Bandwagon Effect and Public Opinion . . . 2
2.2 Sociology: Peer Pressure and the Asch Conformity Experiments . . . 2
2.3 Psychology: The Spread of Emotional Contagion . . . 2
2.4 Entrepreneurship and business: Success breeds success . . . 3
2.5 Economics: Collective Behaviour in Economics . . . 3

3 Application: Simulation of models **3**
3.1 Weidlich-Lux opinion dynamics model . . . 3
3.1.1 The model . . . 4
3.1.2 Simulations . . . 4
3.2 Ising model and social applications . . . 6
3.2.1 What is the ising model? . . . 6
3.2.2 The model . . . 7

4 Conclusion **10**

*University College London, 66-72 Gower St, WC1E 6EA London UK. E-mail address: `m.nicolas@ucl.ac.uk`

1 Introduction: Rationality vs Complexity

1.1 The Representative Agent in Economics

The hypothesis of rationality in economics is a cornerstone concept assuming that individuals consistently make decisions aimed at maximising their personal benefit or satisfaction, given all the available information. This concept forms the foundation of rational choice theory and provides a framework for interpreting economic and social behaviours. Originating in the 18th century, notably with the work of Adam Smith, this theory suggests that individuals engage in a cost–benefit analysis to choose their own best option. Rational choice theory is built around the notions of individuals as rational actors, that engage in a cost–benefit analysis to choose their own best option implying the pursuit of self-interest, illustrated by the principle of the *invisible hand*. Based on the rational choice theory, the behaviour of a representative agent is used to draw conclusions about the behaviour of the society as a whole. For example, in economic models, the representative agent might be used to predict how changes in policy or economic conditions will affect aggregate consumption, saving, and investment behaviours. Beyond economics, the rationality hypothesis is also applied in fields like political science, sociology, and philosophy.

However, this hypothesis ignores the role of interactions among individuals within economic systems and assumes that decisions are made in isolation without considering the influence of others. This perspective fails to account for social interactions such as imitation, social pressures, and herd behaviour, challenging the notion of a purely individualistic decision-making process. [Keynes(1936)] first criticised the assumption that investors rely solely on available information for their decisions, using his *'beauty contest'* analogy. He described investors as trying to forecast "what average opinion expects the average opinion to be" and characterised herding behaviour as "[conforming] with the behaviour of the majority or the average" [Keynes(1937)]. He argued that investors might instead benefit from aligning their choices with the majority's sentiment, underscoring the significant role of mass psychology in economic decisions, thus illustrating the limitations of the rationality hypothesis in capturing the full complexity of economic behaviours and phenomena.

In economics, interactions often manifest as imitation strategies, where individuals adopt the crowd's behaviour, without taking into account their own information. These strategies have prompted numerous studies seeking to explain the origins of financial instability. Pioneering work by [Shiller et al.(1984)Shiller, Fischer and Friedman] suggested that fads and trends, rather than individual motivations, often drive investors' choices. Such behaviours can create positive feedback loops, leading to booms and triggering speculative bubbles and crashes [Lux(1995), Sornette(2009)]. They are also linked to what [Shiller(2015)] describes as "irrational exuberance," a profound excess of collective optimism that drives prices beyond their fundamental values.

1.2 The Economy as a Complex System

Similarly to how physicists model complex systems, where numerous particles interact in ways that lead to unpredictable and emergent phenomena, the economy is characterised by intricate interactions among numerous actors[1]. In such complex systems, components—also known as agents—include individuals, companies, institutions, and governments, all interconnected and interacting. These agents have the ability to adapt to the environment and to the actions of other agents, leading to a rich variety of collective behaviours and phenomena. Just like the interactions among particles in a physical system can lead to the emergence of complex patterns and behaviours and result in unforeseen dynamics.

Many economic phenomena emerge from the interactions of agents rather than being the result of a single entity's actions. For example, market trends, economic cycles, and financial crises are not the direct result of one individual's decisions but emerge from the complex interplay of many agents' decisions. By viewing the economy as a complex system, economists and researchers can gain an understanding of the underlying dynamics and potential for unpredictable and emergent behaviour, leading to more robust economic theories and policies.

[1]For further reading on the application of complexity analysis in the social sciences, see [Miller and Page(2009)]. For insights into why the economy can be viewed as a complex system, refer to [Arthur(2009)] and [Bouchaud(2009)].

2 Contagion, Social Pressure, and Herd Behaviour

In this section, we explore the reasons behind interactions within social systems, such as contagion, social pressure, and herd behaviour. These behaviours have been extensively documented across various disciplines, including politics, psychology, sociology, entrepreneurship, and economics.

2.1 Politics: The Bandwagon Effect and Public Opinion

In politics, the phenomenon where voters are influenced by opinion polls and tend to vote in the direction predicted to win is often referred to as the "bandwagon effect."[2] This effect suggests that individuals may choose to support the candidate or party that appears to be more popular or likely to win, based on the trends shown in opinion polls. The bandwagon effect is a form of social proof, where people's decisions are influenced by the perceived actions or beliefs of others, under the assumption that the majority view is the correct or desirable one. The bandwagon effect in politics illustrates how voters are not always purely rational actors making decisions in isolation but are instead influenced by the social context and the perceived preferences of others. This can lead to a form of strategic voting, where individuals vote not necessarily for their first choice but for the option they perceive as most viable based on public opinion trends. Several studies such as [Mutz(1995), McAllister and Studlar(1991), Marsh(1985)], have documented the bandwagon effect in political voting behaviour. This suggests that media coverage, particularly the kind that focuses on who is winning or losing, can influence where campaign contributions go, as donors want to back the likely winner. This can also influence voters, who may perceive the leading candidate as the best choice.

2.2 Sociology: Peer Pressure and the Asch Conformity Experiments

The Solomon Asch experiment [Asch(2016)], conducted in the 1950s, is a key study in social psychology that demonstrated how people conform to group pressure. In the experiment, participants were asked to guess line lengths in a group setting where other participants intentionally chose incorrect answers. The study found that individuals often conformed to the group's wrong choices, highlighting the strong influence of perceived majority opinions on individual decisions. the Asch experiment sheds light on why individuals might follow the majority's lead, even against their own better judgement.

2.3 Psychology: The Spread of Emotional Contagion

A recent study by [Kramer et al.(2014)Kramer, Guillory and Hancock], analysed Facebook data to investigate whether emotional states could be transferred to others through social media content. The study in question explores emotional contagion through Facebook by manipulating the emotional content in users' News Feeds[3]. It found that reducing positive content led to fewer positive posts and more negative posts by users, and vice versa. The data involved over 689,000 Facebook users, analyzing over 3 million posts. The main findings suggest that emotions expressed by others on social media can influence our own emotions, providing evidence of emotional contagion on a large scale through social networks.

[Hill et al.(2010)Hill, Rand, Nowak and Christakis] examines the spread of long-term emotional states, specifically "contentment" and "discontent", across a social network using a modified susceptible-infected-susceptible (SIS) model, termed the SISa model. This model incorporates both spontaneous infection and transmission through social contact. The research used data from the Framingham Heart Study to demonstrate that both positive and negative emotional states can spread like infectious diseases, with the probabilities of becoming content or discontent influenced by the number of similar emotional contacts within one's social network. The study found that contentment and discontent have transmission rates, recovery rates, and spontaneous infection parameters, providing a perspective on how emotions can propagate through social ties over time.

[2] For a complete definition of the bandwagon effect, see [Schmitt-Beck(2015)]

[3] This study is controversial due to ethical concerns about the manipulation of users' emotions without their explicit consent, raising questions about privacy, consent, and the psychological impact of social media platforms.

2.4 Entrepreneurship and business: Success breeds success

[Salganik et al.(2006)Salganik, Dodds and Watts]'s experiment involved creating an online music platform where participants could listen to, rate, and download songs. They were divided into different "worlds" with varying visibility of others' choices. In some worlds, participants could see the download counts (indicating popularity) of songs chosen by previous participants, while in others, this information was hidden. The experiment found that songs that became popular in one world didn't necessarily do so in others, demonstrating how social influence and visibility of others' preferences can significantly shape individual choices and perceived quality of music. This study highlights how social influence can shape cultural markets and create unpredictable success patterns.

[Van de Rijt et al.(2014)Van de Rijt, Kang, Restivo and Patil] investigates how initial success, regardless of merit, can lead to further successes, a phenomenon often referred to as the "Matthew effect" or "success-breeds-success" dynamics. The Kickstarter experiment explored how projects' visibility of funding and backer count can create a contagion effect, where potential backers are influenced by the apparent popularity and support of a project. This phenomenon, akin to social proof, suggests that people are more likely to fund projects that are perceived as successful or popular, based on the visible support from others. This dynamic highlights the importance of social influence in crowdfunding platforms and the potential for projects to gain momentum through visible indicators of success.

2.5 Economics: Collective Behaviour in Economics

[Welch(2000)] investigates the influence of security analysts' buy or sell recommendations on subsequent analysts' recommendations. It finds that recent recommendations have a significant impact on the next two analysts, suggesting a herding behaviour. This is important because it shows that analysts tend to follow each other rather than rely solely on independent analysis, which can lead to fragile market conditions. The study develops a new statistical methodology to quantify this herding effect, contributing to our understanding of how information and behaviours aggregate in financial markets and potentially leading to market inefficiencies or bubbles. investigates why financial analysts often make similar forecasts. The study suggests analysts may herd, or align their predictions with the consensus to avoid the risk associated with outlier forecasts. This behaviour could be driven by professional incentives, peer influence, or the desire to maintain reputation, potentially impacting market perceptions and investment decisions.

In 1995, management gurus Michael Treacy and Fred Wiersema reportedly bought 50,000 copies of their book "The Discipline of Market Leaders" to make sure it made The New York Times Best Seller list. Despite mediocre reviews, this initial boost helped the book to continue selling well enough to maintain its bestseller status without further interventions.[4].

3 Application: Simulation of models

This section is dedicated to introduce two closely related models that are used in social science to model collection behaviour. They are particularly well suited to model the economy.

3.1 Weidlich-Lux opinion dynamics model

The Weidlich-Lux model [Weidlich(1971), Weidlich(2006), Lux(1995)] initially introduced by Weidlich in 1971 in quantitative sociology is used to model opinion dynamics integrating social influence and individual preferences. The model helps to understand the polarisation within society, such as political affiliations and technology adoption.

The Weidlich-Lux opinion dynamics model is versatile and can be applied across various domains such as the stock market context where the model represent the decision-making process of investors regarding buying or selling stocks. This is particularly relevant in understanding how market sentiments and individual investor preferences influence market dynamics. Investors often look to the actions of their peers as a source of information, leading to herd

[4]This event was documented in a 1996 Bloomberg article titled "Did Dirty Tricks Create a Best Seller?"

behaviour. A positive sentiment (or *bullish*) outlook can lead investors to buy, while a negative sentiment (or *bearish*) outlook can lead to selling.

3.1.1 The model

In this context, agents represent investors who hold either an optimistic (*bullish*) sentiment if they anticipate a price rise or a pessimistic (*bearish*) sentiment otherwise. The investor population at any given time t is divided into two groups, n_+ and n_-, representing the number of optimistic and pessimistic agents, respectively. The total number of investors is $2N = n_+ + n_-$, and the mean sentiment is expressed by the sentiment index:

$$x = \frac{n_+ - n_-}{2N} \quad \text{where} \quad x \in [-1, 1]$$

Here, $x > 0$ (or $x < 0$) indicates a dominance of optimistic (or pessimistic) agents, and $x = 0$ signifying a balanced view of the society. The model is characterised by the possibility for investors to switch their opinions from one state to another (+ and -), driven by individual transition probabilities that determine the sentiment dynamics. Assuming a homogeneous population, each individual has identical transition probabilities per time unit, denoted by p_+ for switching from (-) to (+) and p_- for switching from (+) to (-). The system configuration is described by $n = (n_+ - n_-)/2$. The transition rates are modelled as exponential functions:

$$\begin{cases} p_+(n) = v\exp(U) \\ p_-(n) = v\exp(-U), \end{cases}$$

where v is a parameter defining the switching frequency between groups and $U(\cdot)$ is a function describing factors influencing sentiment transition rates. In the basic form of the model, $U(\cdot)$ depends only on the current population configuration, as indicated by the sentiment index x :

$$U = \alpha_0 + \kappa n = \alpha_0 + \alpha_1 x,$$

with $\alpha_1 = \kappa N$ and $Nx = n$. The model's parameters are as follows: (i) The constant bias factor α_0 describes an individual's preference toward an opinion, unaffected by others' views. A positive α_0 increases the likelihood of an agent switching from (-) to (+), and vice versa for a negative α_0. (ii) The contagion parameter α_1, representing the herding effect, quantifies the strength of sentiment contagion or herd behaviour, illustrating how group pressure can influence an individual towards the majority opinion. A higher positive α_1 increases the transition probability towards the prevalent sentiment, especially as $|x|$ increases.

3.1.2 Simulations

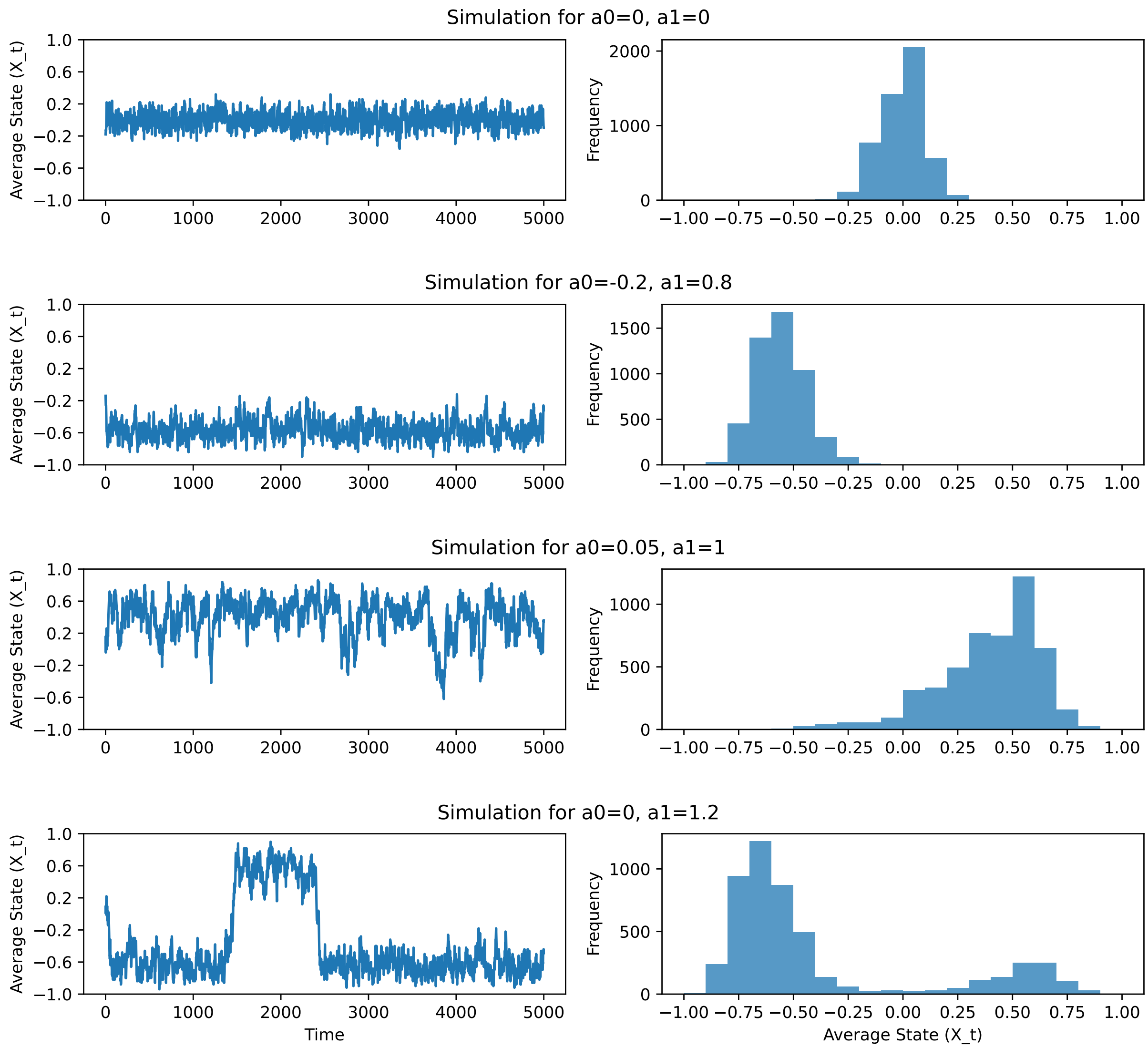
The simulation follows the steps describe by the pseudo code on Listing 1.The function initialises the states of N*2 agents and iterates over a specified number of observation points. At each point, it calculates the average opinion state and updates the states based on computed transition probabilities.

Different simulations under different parameter settings are depicted in Figure 1, demonstrate various equilibrium states. Each scenario reflects unique dynamics in opinion formation and evolution. On the left, the plots show results for the evolution of the aggregate sentiment of the society and on the right, histograms for the distributions under different parameter settings.

In the first scenario, both constant bias factor (a_0) and contagion parameter (a_1) are zero. In this scenario, the absence of bias ($a_0 = 0$) and contagion ($a_1 = 0$) results in individuals changing their opinions independently, leading to random fluctuations of the sentiment index around zero. This represents a balanced societal state where no opinion prevails. The lack of bias and contagion implies that there's no inherent preference for any opinion and no influence from the collective sentiment, resulting in equilibrium without a dominant direction.

The second scenario incorporate a negative bias ($a_0 = -0.2$) towards negative opinions and a moderate contagion parameter ($a_1 = 0.8$).The negative bias leads to a tendency towards negative opinions, with the contagion effect causing

Figure 1: Caption



```
1. Initialization:
  Randomly initialize opinion states of all agents, Nt, to either 1 or -1.

2. Simulation Loop:
  For each observation point obs in 1 to nb_obs:
    Calculate the average opinion state, Xt = mean(Nt).
    Compute transition probabilities based on Xt:
      U_ = a0 + a1 * Xt
      p_bear = v * exp(-U_) * deltat
      p_bull = v * exp(U_) * deltat
    Update opinion states:
      For each agent i in 1 to N*2:
        Draw a random number r from a uniform distribution [0, 1].
        If Nt_i == 1 (If the agent's current state is positive):
          If r < p_bear:
            Nt_i = -1 (Switch to negative state)
        Else (If the agent's current state is negative):
          If r < p_bull:
            Nt_i = 1 (Switch to positive state)
    Append Xt to the list of average states X.
```

Listing 1: Pseudo code to simulate from the Weidlich-Lux model

more pronounced fluctuations and a general skew towards negative states. The predisposition towards negativity, reinforced by moderate herding behaviours, results in a societal inclination towards negative sentiments, with fluctuations reflecting this bias.

A slight positive bias ($a_0 = 0.05$) combined with strong contagion ($a_1 = 1$). The society exhibits significant fluctuations due to the strong contagion, with a general but not overwhelming tendency towards positive states influenced by the slight bias. The minimal positive bias nudges societal sentiment towards positivity, which is then amplified by strong herding behaviours, leading to dynamic fluctuations with a positive skew.

The last scenario has no bias ($a_0 = 0$) and a strong contagion parameter ($a_1 = 1.2$). The absence of bias combined with strong contagion leads to extreme polarisation, with society quickly switching from one extreme the other. This results in a highly volatile and polarised societal state, where sentiment can dramatically swing between extremes based on initial conditions.

3.2 Ising model and social applications

3.2.1 What is the ising model?

The Ising model represents a theoretical framework used to understand ferromagnetism. Ferromagnetism characterises materials that possess the ability to maintain a net magnetic moment, essentially becoming magnets, even in the absence of an external magnetic field. In such materials, atomic magnetic moments align uniformly due to the quantum-mechanical exchange interaction among adjacent electron spins, even without an external magnetic force. This phenomenon is observable in ferromagnetic materials, including but not limited to iron, cobalt, nickel, and certain alloys, which can preserve their magnetic orientation post the removal of an applied magnetic field. These materials find extensive applications across various domains, such as in the manufacturing of hard drives, electric motors, and generators.

At the Curie temperature (Tc), iron transitions from ferromagnetic to paramagnetic properties, where it is no longer able to sustain a net magnetic moment due to the thermal agitation that disrupts the orderly alignment of magnetic moments. For iron in its pure form, this critical temperature is established at 770°C (1438°F) or 1043 K. Below this threshold, the thermal energy is insufficient to disrupt the magnetic moments' alignment, allowing iron to exhibit strong ferromagnetic characteristics by aligning its magnetic moments cohesively, thereby generating a significant magnetic field.

The Ising model, originally developed to describe ferromagnetism in solid-state physics, has found surprising applications in modeling the stock market and various social phenomena due to its ability to capture complex systems' emergent behaviors from simple interactions. This model illustrates how local interactions among components can lead to the emergence of global order or patterns, a feature commonly observed in social and economic systems.

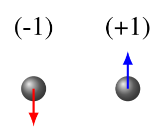
In the context of the stock market, traders' decisions can be analogised to the magnetic spins in the Ising model. Each trader, like a magnetic spin, can adopt one of two states: buying or selling (akin to spin up or down in the Ising model). The decision of each trader is influenced by a combination of their individual inclinations and the behaviour of their peers, mirroring the local interactions among spins in the Ising model. This analogy allows the model to capture the herd behaviour often observed in financial markets, where the collective actions of traders can lead to large-scale trends or sudden market shifts, akin to phase transitions in physical systems.

The overall market trend, or "magnetisation," in this context, represents the aggregate sentiment or prevailing direction in the market, which can also influence individual agents' decisions. Positive magnetisation might represent a bullish market trend, encouraging more buying behaviour, while negative magnetisation could indicate a bearish trend, leading to increased selling.

3.2.2 The model

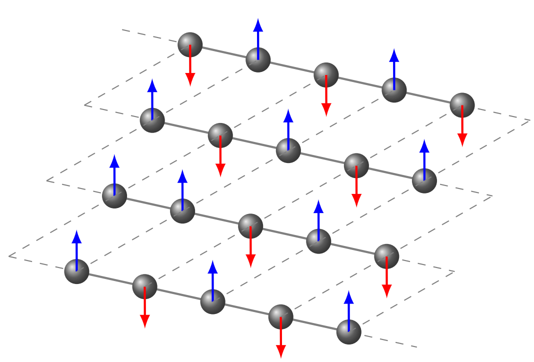
The Ising model is composed of discrete variables representing atomic spins' magnetic dipole moments, which can adopt either of two states: +1 or -1 as show on Figure 5.

Figure 2: Spins in one of the two states (+1 or -1).



These spins are arranged in a lattice as show on Figure 3, allowing each spin to interact with its neighbours. Each spin functions like a miniature bar magnet, aligned collectively. Altering the orientation of one magnet requires energy input due to resistance from neighbouring magnetic fields, as these magnets naturally favour alignment. This effect is modelled by considering that spins interact with their nearest neighbours, generating an interaction energy dependent on their relative alignments.

Figure 3: Two-dimensional square-lattice Ising model.



The model uses a probabilistic approach to determine state transitions, comparing the calculated energy change to a randomly generated number to decide whether a spin will flip. This decision-making process is influenced by

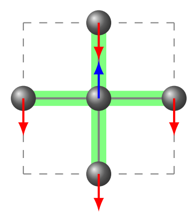
```
For timeStep = 1 to totalSimulationTime
    For rowIndex = 1 to latticeRows
        For columnIndex = 1 to latticeColumns
            # Compute energy change for a potential spin flip
            energyChange = ComputeEnergyChange(rowIndex, columnIndex)

            # Compare to thermal fluctuation
            If exp(-energyChange / (BoltzmannConst * CriticalTemp)) > Random(0, 1)
                # Flip the spin
                FlipSpin(rowIndex, columnIndex)
            End If
        End For
    End For
End For
```

Listing 2: Pseudo code to simulate from the Ising model

the system's temperature, particularly in relation to the critical temperature, Tc, utilising Boltzmann's probability distribution to model the likelihood of spin inversion. For instance, consider a random box in our lattice of spins, along with its four nearest neighbours represented on Figure 4.

Figure 4: Spin interaction with its four nearest neighbours.



The energy change associated with a spin flip, denoted as $E_{\text{flip,}}$, is given by the expression:

$$E_{\text{flip}} = -J \sum_{\text{neighbour}=1}^{n} s_{\text{neighbour}}$$

Here, J represents the exchange energy, a constant that quantifies the strength of interaction between adjacent spins. The variable n corresponds to the number of nearest neighbours, and $s_{\text{neighbour}}$ signifies the spin value of a neighbouring atom. In a one-dimensional lattice, this summation encompasses the two immediate neighbours adjacent to the spin under consideration. For a two-dimensional lattice, the summation extends to include neighbours to the right, left, above, and below the spin in question, and so forth for higher dimensions.

The decision to transition to a new spin state is determined probabilistically. If the ratio derived from the system's dynamics exceeds a randomly generated number x, with $0 < x < 1$, the new state is adopted. Conversely, should this ratio fall below x, the system retains its original state. The probability of a spin flip is governed by the Boltzmann distribution, expressed as:

$$e^{-E_{\text{lip}}/kT_{\text{c}}}$$

where T_c denotes the critical temperature at which the system undergoes a phase transition, and k is the Boltzmann constant. This distribution is widely used due to its applicability across a range of systems, including but not limited to thermodynamic and statistical mechanics contexts.

Listing 2 presents the pseudo code to simulate from the Ising model where:

- "**ComputeEnergyChange (rowIndex, columnIndex)** " is a placeholder for the function that would calculate the energy change (E_{flip}) associated with flipping a spin at a particular lattice site identified by 'rowIndex' and 'columnIndex'.

- The condition exp (-energyChange / (BoltzmannConst * Criticaltemp)) > Random $(0,1)$ represents the Metropolis criterion in a simplified form, comparing the probability of a spin flip, determined by the Boltzmann factor e^{-E_{lip}/kT_c}, against a random number between 0 and 1 .

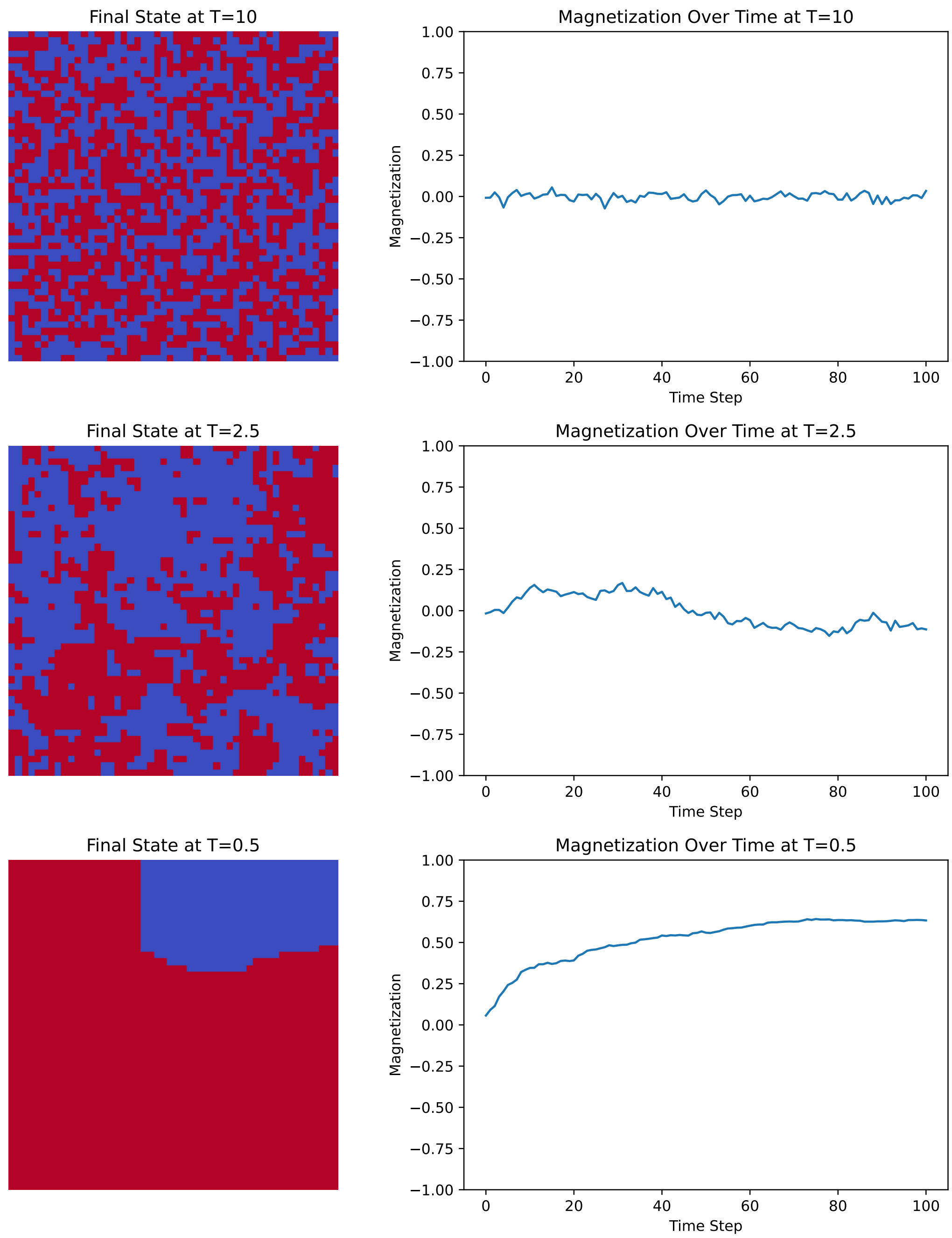
- "**FlipSpin (rowIndex, columnIndex)**" is a placeholder for the function that would actually flip the spin at the specified lattice site if the condition is met.

By varying the parameters J and T_c, one can observe the system's response to these changes. For instance, a system may exhibit instability under certain conditions, as illustrated in Figure 5, whereas under different parameters, it may achieve a stable state, characterised by regions of uniform spin orientation.

In the given system, disorder prevails with the net magnetisation near zero. However, in the same simulation conducted at a lower temperature the dynamics shift. The interactions among spins become predominant, leading to their alignment and the manifestation of distinct phases within the model.

Over time, the system evolves towards full magnetisation. This transition is anticipated to occur at a certain temperature, marking the shift from a ferromagnetic to a paramagnetic state.

Figure 5: Simulation results from the Ising model



4 Conclusion

By simulating the interactions among agents and their response to the change of parameters, the models can provide insights into how collective behaviours emerge from individual decisions. This includes the formation of bubbles or crashes, where the alignment of buying or selling behaviours among agents leads to significant market movements. Furthermore, by adjusting parameters in the model, which can represent external market volatility or uncertainty, one can study how market stability and agent behaviours change under different conditions.

This approach allows economists and financial analysts to explore complex market dynamics, understand the conditions under which extreme market events may occur, and investigate the effects of collective behaviours on market trends, all within the conceptual framework provided by the Ising model.

One can mention that this kind of models, in their basic form it doesn't take into account the influence of Key Opinion Leaders: Influential investors or analysts can sway market sentiments significantly. The model can simulate the impact of such influencers on the overall market dynamics, showing how a single opinion can propagate through social networks and affect the market.

References

[Arthur(2009)] Arthur, W.B., 2009. Complexity and the economy, in: Handbook of Research on Complexity. Edward Elgar Publishing.

[Asch(2016)] Asch, S.E., 2016. Effects of group pressure upon the modification and distortion of judgments, in: Organizational influence processes. Routledge, pp. 295–303.

[Bouchaud(2009)] Bouchaud, J.P., 2009. The (unfortunate) complexity of the economy. Physics World 22, 28.

[Hill et al.(2010)Hill, Rand, Nowak and Christakis] Hill, A.L., Rand, D.G., Nowak, M.A., Christakis, N.A., 2010. Emotions as infectious diseases in a large social network: the sisa model. Proceedings of the Royal Society B: Biological Sciences 277, 3827–3835.

[Keynes(1936)] Keynes, J.M., 1936. The general theory of employment, interest, and money. Springer.

[Keynes(1937)] Keynes, J.M., 1937. The general theory of employment. The quarterly journal of economics 51, 209–223.

[Kramer et al.(2014)Kramer, Guillory and Hancock] Kramer, A.D., Guillory, J.E., Hancock, J.T., 2014. Experimental evidence of massive-scale emotional contagion through social networks. Proceedings of the National academy of Sciences of the United States of America 111, 8788.

[Lux(1995)] Lux, T., 1995. Herd behaviour, bubbles and crashes. The economic journal 105, 881–896.

[Marsh(1985)] Marsh, C., 1985. Back on the bandwagon: The effect of opinion polls on public opinion. British Journal of Political Science 15, 51–74.

[McAllister and Studlar(1991)] McAllister, I., Studlar, D.T., 1991. Bandwagon, underdog, or projection? opinion polls and electoral choice in britain, 1979-1987. The Journal of Politics 53, 720–741.

[Miller and Page(2009)] Miller, J.H., Page, S.E., 2009. Complex adaptive systems: an introduction to computational models of social life: an introduction to computational models of social life. Princeton university press.

[Mutz(1995)] Mutz, D.C., 1995. Effects of horse-race coverage on campaign coffers: Strategic contributing in presidential primaries. The Journal of Politics 57, 1015–1042.

[Van de Rijt et al.(2014)Van de Rijt, Kang, Restivo and Patil] Van de Rijt, A., Kang, S.M., Restivo, M., Patil, A., 2014. Field experiments of success-breeds-success dynamics. Proceedings of the National Academy of Sciences 111, 6934–6939.

[Salganik et al.(2006)Salganik, Dodds and Watts] Salganik, M.J., Dodds, P.S., Watts, D.J., 2006. Experimental study of inequality and unpredictability in an artificial cultural market. science 311, 854–856.

[Schmitt-Beck(2015)] Schmitt-Beck, R., 2015. Bandwagon effect. The international encyclopedia of political communication , 1–5.

[Shiller(2015)] Shiller, R.J., 2015. Irrational exuberance, in: Irrational exuberance. Princeton university press.

[Shiller et al.(1984)Shiller, Fischer and Friedman] Shiller, R.J., Fischer, S., Friedman, B.M., 1984. Stock prices and social dynamics. Brookings papers on economic activity 1984, 457–510.

[Sornette(2009)] Sornette, D., 2009. Why stock markets crash: critical events in complex financial systems. Princeton university press.

[Weidlich(1971)] Weidlich, W., 1971. The statistical description of polarization phenomena in society. British Journal of Mathematical and Statistical Psychology 24, 251–266.

[Weidlich(2006)] Weidlich, W., 2006. Sociodynamics: A systematic approach to mathematical modelling in the social sciences. Courier Corporation.

[Welch(2000)] Welch, I., 2000. Herding among security analysts. Journal of Financial economics 58, 369–396.