

THE ROLE OF AGENT SYSTEMS IN COMPLEX MODELING AND DECISION MAKING

Jan Kalina

Abstract

Agent systems, particularly multi-agent systems, are becoming increasingly important tools for modeling and decision-making in complex environments, including finance, optimization, and epidemics. These systems simulate interactions between autonomous agents, which are individual entities that make decisions based on predefined rules, enabling the study of decentralized phenomena such as market behavior, social interactions, and information diffusion. By incorporating advanced statistical techniques, agent systems offer a more dynamic and adaptable approach compared to traditional, centralized models, capturing emergent behaviors and optimizing decisions in uncertain environments. This paper explores the role of agent systems in addressing challenges in complex domains, with a focus on their application in finance, optimization, epidemic modeling, and combating disinformation. The integration of agent-based models with principles of statistics and information theory is examined as a key factor driving the effectiveness of these systems in real-world applications. Through this examination, the paper highlights the growing significance of agent systems in tackling modern, decentralized problems that traditional methods have struggled to address.

Key words: multi-agent systems, machine learning, optimization, robust statistics, uncertainty

JEL Code: C63, G17, D85

Introduction

Agent systems and machine learning are increasingly integrated into finance, particularly in areas such as financial technology, algorithmic trading, risk management, decision making, and behavioral finance (Tsfatsion, 2023). The absence of these approaches in traditional finance literature is due to the historical focus on classical financial theories and the more conservative nature of the industry, which has long relied on established methods. However, as the industry faces more complex challenges, these modern methodologies are gaining recognition for their ability to address dynamic and decentralized systems.

The application of agent systems, especially multi-agent systems, has transformed the modeling and analysis of complex financial environments. By simulating interactions among market participants, agent-based models provide valuable insights into phenomena like price bubbles and market crashes (Li et al., 2022). This shift towards decentralized, data-driven modeling is facilitating a more adaptive and nuanced understanding of financial dynamics, which contrasts with the fixed assumptions in traditional economic models. The integration of advanced statistical techniques further enhances the ability of agent systems to optimize decisions in uncertain, ever-changing environments.

Despite their growing influence, several open problems remain in the application of agent systems to finance (Charpentier et al., 2023). One key challenge is the calibration of agent-based models, as accurate and efficient modeling of financial markets requires precise parameterization that is often difficult to achieve with limited or noisy data. Additionally, understanding and predicting emergent behaviors, such as market crashes or systemic risks, remains a complex task, requiring advances in the robustness of agent models (Paccagnan et al., 2022).

This paper has the following structure. Agent systems and their principles are explained in Section 1. The role of statistics and information theory in agent systems is discussed in Section 2. Further sections are devoted to agent systems in specific contexts: in finance in Section 3, in optimization in Section 4, and in epidemics modeling in Section 5. The potential of agent systems to fight against disinformation is discussed in Section 6.

1 Principles of agent systems

Agent systems, or multi-agent systems (MAS), consist of multiple autonomous entities, or agents, which interact within a shared environment to achieve individual or collective goals. These agents can be either software-based or physical entities, each with its own decision-making rules and behaviors. MAS are especially useful for solving complex problems involving decentralized decision-making and distributed control (Mehmood et al., 2023).

From the mathematical point of view, each agent i is represented by a state vector $X_i(t) \in R^n$, which evolves over time according to an update rule f_i . This rule depends on the agent's current state $x_i(t)$ and the states of its neighbors denoted as $x_j(t)$ for $j \in N_i$, where N_i denotes the set of interacting agents. The interactions among agents can be modeled as a network, and the study of MAS often involves analyzing these interactions using techniques from graph theory and dynamical systems.

Agent systems serve a dual purpose in both modeling and decision-making within complex systems. As modeling tools, they simulate decentralized environments by representing autonomous entities that interact with one another and their surroundings. This enables the study of phenomena that are difficult to capture with traditional approaches, such as market behavior, social interactions, or the spread of information. Each agent in the system follows specific decision-making rules or algorithms, making them effective for representing real-world entities like investors, consumers, or organizations. These agents make decisions based on their individual goals, available information, and interactions with other agents, which allows researchers to analyze how individual behaviors lead to emergent system-wide phenomena. Thus, agent systems not only provide a framework for modeling complex systems but also serve as decision-making entities within those models, enabling a dynamic understanding of interactions and outcomes in uncertain and decentralized environments.

Traditional methods for tasks currently solved by agent systems often rely on centralized, statistical, and deterministic approaches, such as linear regression, probabilistic models, time series analysis, optimization techniques like linear programming, or Markov decision processes (MDPs). These methods generally assume predefined relationships and fixed parameters, aiming to solve problems with explicit rules and constraints. In contrast, agent systems model decentralized interactions between autonomous agents, which enables flexibility, adaptation, and the emergence of complex behaviors over time. While traditional methods focus on static environments and simplified assumptions, agent-based models are more capable of handling dynamic, interactive, and uncertain real-world scenarios. This makes agent systems particularly useful for capturing the complexity and subtleties that are often overlooked by traditional methods like statistical modeling or optimization alone.

2 The role of statistics and information theory in agent systems

Agent systems rely heavily on statistical methods and information theory to interpret and optimize agent behavior, model agent interactions, and evaluate various outcomes in complex environments. Given that agents often operate under conditions of uncertainty and incomplete information, these techniques are crucial for ensuring the effectiveness of the system in dynamic scenarios.

In agent systems, Bayesian inference plays a significant role in decision-making by allowing agents to continuously update their beliefs based on new data. This process helps minimize uncertainty, enabling agents to make more informed decisions that improve overall system performance. Bayesian methods are particularly effective in environments where

information is incomplete or noisy, as they allow agents to adjust their understanding of the world as more evidence becomes available.

Monte Carlo simulations are another important statistical tool used in agent systems. These simulations model random processes within the system, allowing agents to evaluate the potential outcomes of different decisions under varying conditions. By running numerous simulations, agents can assess the probability of various scenarios, which aids in optimizing their behavior and improving decision-making strategies. Monte Carlo methods are particularly useful when analytical solutions to complex problems are not available, making them invaluable in uncertain environments (Li et al., 2022).

Entropy, a concept from information theory, is central to understanding uncertainty within MAS. Entropy quantifies the degree of disorder or unpredictability in a system and is used to evaluate how much information is required to reduce that uncertainty. In the context of agent systems, entropy helps model the degree of uncertainty agents face and can guide their decision-making processes by indicating when more information is needed. This measure enables agents to adapt their behaviors in response to changing environmental conditions, ultimately enhancing their ability to make accurate decisions.

Robust statistical methods are also employed in agent systems to ensure that the system remains reliable even in the presence of noisy or imperfect data (Kalina and Tichavský, 2022). They are designed to perform well despite the presence of outliers or inaccuracies in the data, making them essential in real-world applications where data quality may be variable. They allow agent systems to maintain stability despite the challenges posed by imperfect information or by high dimensionality (Kalina and Rensová, 2015).

The integration of information theory into MAS further enhances their ability to handle uncertainty and adapt to dynamic environments. By providing a mathematical foundation for understanding and quantifying information, information theory supports the design of more efficient and effective decision-making algorithms for agents. This approach enables agents to learn from their interactions and adjust their strategies over time, improving their performance in uncertain and dynamic environments.

In summary, statistical methods and information theory are indispensable for the functioning of agent systems. They provide the tools necessary for agents to model uncertainty, update their beliefs, and optimize their behaviors in complex, dynamic settings. By integrating these techniques, MAS can handle uncertainty more effectively, adapt to changing environments, and make more informed decisions, making them highly suitable for applications in areas such as economics, robotics, and artificial intelligence.

3 Agent systems in finance

Often in the simulations of financial markets, agent-based models are used to study the interactions between various market participants, such as investors, traders, and institutions, and to observe the emergent behavior of market dynamics. These simulations provide valuable insights into phenomena like market crashes, price bubbles, and volatility by simulating how individual agents' actions and decisions can collectively lead to large-scale market events. By modeling diverse behaviors and strategies, agent-based models offer a more nuanced understanding of market fluctuations compared to traditional models. In addition to simulating market interactions, agent systems are also widely applied to solve portfolio optimization problems, where agents represent investors making decisions about asset allocation. These models use various approaches, such as reinforcement learning and Monte Carlo simulations, to optimize portfolio returns while managing risk. By continuously adapting to changing market conditions, these techniques help identify strategies that improve investment outcomes and achieve better long-term returns, even in the face of uncertainty (Charpentier et al., 2023).

An interesting application was presented by Dvořáková and Danko (2024), who suggested a simplified framework to model the mortgage crisis, demonstrating how individual decisions made by banks and households can collectively lead to large-scale market outcomes, potentially triggering a financial crisis. The study uses agent-based modeling, a powerful simulation technique ideal for capturing complex, decentralized systems. By applying graph theory, the model represents a network of banks that issue mortgages, monitoring the repayment patterns, defaults, and the transmission of financial shocks as insolvent banks transfer their losses to connected institutions. The research explores how variations in these factors influence outcomes like unpaid debts, bank failures, and household bankruptcies. The findings from the simulation provide insight into how a mortgage crisis could emerge in a hypothetical economy under different scenarios (Li et al., 2022).

Agent systems and the maximum entropy portfolio approach are closely related in the context of financial modeling and optimization. In an agent-based framework, each agent, representing an investor or financial institution, makes decisions about portfolio allocation based on available information and a set of rules or strategies. These agents aim to maximize their utility or returns while managing risk, and one way to model such decision-making is through the maximum entropy portfolio approach. This method seeks the portfolio allocation that maximizes uncertainty (or entropy) subject to constraints like expected returns and risk

levels (Večeř et al., 2024). The agents, in this case, can be designed to iteratively adjust their strategies based on observed market data and their evolving beliefs, effectively simulating how individual decisions lead to market-wide portfolio allocations. The maximum entropy principle is particularly useful in agent systems as it offers a robust framework for dealing with incomplete information and uncertainty, allowing the agents to explore a wide range of possible outcomes while still adhering to financial constraints. Therefore, integrating the maximum entropy approach into agent-based models provides a powerful tool for simulating complex, dynamic financial systems and optimizing portfolio decisions under uncertainty (Charpentier et al., 2023).

4 Agent systems and optimization

Agent systems and optimization are closely related, especially when modeling decision-making processes in complex environments. In agent-based modeling, agents represent autonomous entities that interact with each other and their environment to achieve specific goals. These goals often involve optimization problems, where agents seek to improve their outcomes based on predefined criteria (Chen et al., 2024).

Optimization in agent systems can take many forms, such as maximizing utility, minimizing cost, or achieving a balanced allocation of resources (Paccagnan et al., 2022). For example, in financial markets, agents may optimize portfolio allocation by adjusting their investments to maximize returns while minimizing risk, often using techniques such as reinforcement learning or Monte Carlo simulations. In such cases, the agents iteratively update their strategies based on feedback from the environment, seeking the optimal solution. Moreover, optimization techniques, like genetic algorithms or gradient-based methods (Kalina and Matonoha, 2020), can be used to enhance the decision-making abilities of agents, allowing them to adapt to changing conditions and improve their performance in dynamic, uncertain environments. Thus, agent systems provide a powerful framework for solving optimization problems in decentralized, multi-agent contexts.

5 Agent systems in epidemics modeling

Agent systems have been increasingly used in epidemic modeling, with COVID-19 serving as a significant case study, to simulate the spread of the virus and assess the impact of various interventions. In these models, agents represent individuals or groups within a population, each with distinct behaviors, health statuses, and interactions with others. By using agent-

based modeling, researchers can simulate how individuals make decisions regarding social distancing, vaccination, or mask-wearing, and how these choices affect the transmission dynamics of the virus. The agents interact within a virtual environment that reflects real-world factors such as geographic location, demographics, and the availability of healthcare resources. These systems allow for the exploration of various scenarios, including the effectiveness of different public health strategies and the potential outcomes of government interventions (Fan et al., 2024). Agent systems in COVID-19 modeling offer valuable insights into the complex and dynamic nature of pandemics, helping policymakers make more informed decisions in managing and mitigating the effects of the virus.

A realistic epidemic model on the level of individual municipalities was proposed in Datta et al. (2022), who used agents to simulate the behavior of individuals and their social contacts in New York State. This simulation of various scenarios for a partial reduction of social contacts also included modeling of the effect of state interventions against the pandemic. The theoretical model exploiting graph structures to explain inter-individual contacts was validated on Big Data. The whole study illustrates that epidemic models and predictions primarily require to have experience in statistics and informatics and to deploy suitable artificial intelligence machinery.

6 Agent systems and disinformation

Agent systems are increasingly being applied to study and combat the spread of disinformation, as they provide a powerful framework for simulating how false information spreads within social networks and how it can be detected and countered through targeted interventions.

6.1 Agent systems for modeling the spread of disinformation

Agent systems provide a robust framework for modeling the spread of disinformation across social networks, where each agent consumes, shares, and propagates information. The dynamics of how information, especially misleading or false content, spreads can be analyzed through the lens of information theory, which considers how information is transmitted, encoded, and processed within the system. In this context, agents are responsible for interpreting and passing on information, with each agent representing a node in the network. The entropy associated with misinformation can be calculated to assess the uncertainty or disorder in the information flow, providing insights into how disinformation distorts the network's information landscape (Franceschi et al., 2022). These models can then be used to

develop strategies to reduce the entropy and increase the accuracy of information transmission, helping to mitigate the harmful effects of disinformation.

6.2 The mathematical foundations of agent systems in disinformation modeling

The mathematical models used in agent systems rely on principles of information theory or game theory to explain how information is disseminated and processed by agents. Concepts like information entropy and mutual information are key to understanding the effectiveness of interventions in combating disinformation. In these models, agents use information to make decisions, with the uncertainty associated with the information quantified using entropy measures. Reliable algorithms help agents optimize their decision-making processes, balancing the need for information with the risk of misinformation. Bayesian inference further enhances these models by enabling agents to update their beliefs based on new information, improving how they process uncertain or incomplete data (Chen et al., 2024). This integration of information theory strengthens the simulation's accuracy, ensuring that agents respond to the flow of information in ways that reflect real-world dynamics (Franceschi et al., 2022).

6.3 Developing systems to combat disinformation: The traffic light model approach

To tackle the challenges posed by disinformation, we propose the following theoretical model that integrates principles of information theory, aiming to quantify and respond to the spread of false information. The idea is to exploit entropy as the measure of the disorder or uncertainty associated with different pieces of content, helping to determine the severity of disinformation. Agents in the system assess information based on factors such as its dissemination rate, reach, and impact, all of which contribute to the overall information entropy in the network. The disinformation score calculated by agents reflects the level of uncertainty or misinformation within the system, with higher entropy levels indicating greater risk. This score then feeds into the categorization system (green, yellow, or red) allowing for timely interventions. By incorporating information-theoretic principles into the model, we ensure that the system is responsive to shifts in information flow, allowing for more accurate detection and mitigation of disinformation over time.

Conclusion

This paper provides an overview of the growing role of agent systems, particularly multi-agent systems, in modeling and decision-making in complex environments such as finance,

optimization, epidemic modeling, and disinformation. By simulating decentralized interactions, multi-agent systems offer a dynamic approach that enhances the understanding of emergent behaviors and decision-making in uncertain environments. The integration of statistical techniques and information theory further optimizes these systems. While the paper does not introduce original ideas, it contributes by synthesizing existing knowledge and discussing the increasing importance of agent-based models in addressing decentralized, real-world problems that traditional methods struggle to tackle. Future research is planned for the study of insolvencies in the Czech Republic, aiming to analyze and predict the outcomes of financial crises, providing insights into the effectiveness of various interventions and policy decisions.

Acknowledgements

The work was supported by the project 24-11146S of the Czech Science Foundation.

References

- Charpentier, A., Élie, R., Remlinger, C. (2023): Reinforcement learning in economics and finance. *Computational Economics*, 62, 425–462.
- Chen, Q., Jiang, L., Qin, H., Al Kontar, R. (2025): Multi-agent collaborative Bayesian optimization via constrained Gaussian processes. *Technometrics*, 67, 32–45.
- Datta, A. Winkelstein, P., Sen, S. (2022): An agent-based model of spread of a pandemic with validation using COVID-19 data from New York State. *Physica A*, 585, 126401.
- Dvořáková, K., Danko, K. (2024): Agent-based modeling of the financial crisis and the role of financial literacy in this process. *Proceedings RELIK 2024*, 21–36.
- Fan, Q., Li, Q., Chen, Y., Tang, J. (2024): Modeling COVID-19 spread using multi-agent simulation with small-world network approach. *BMC Public Health*, 24, 672.
- Franceschi, J., Pareschi, L., Zanella, M. (2022): From agent-based models to the macroscopic description of fake-news spread: the role of competence in data-driven applications. *Partial Differential Equations and Applications*, 3, 68.
- Kalina, J., Matonoha, C. (2020): A sparse pair-preserving centroid-based supervised learning method for high-dimensional biomedical data or images. *Biocybernetics and Biomedical Engineering*, 40, 774–786.
- Kalina, J., Tichavský, J. (2022): The minimum weighted covariance determinant estimator for high-dimensional data. *Advances in Data Analysis and Classification*, 16, 977–999.

- Kalina, J., Renšová, D. (2015): How to reduce dimensionality of data: Robustness point of view. *Serbian Journal of Management*, 10, 131–140.
- Li, T., Zhao, Y., Zhu, Q. (2022): The role of information structures in game-theoretic multi-agent learning. *Annual Reviews in Control*, 53, 296–314.
- Mehmood, U., Roy, S., Damare, A., Grosu, R., Smolka, S.A., Stoller, S.D. (2023): A distributed simplex architecture for multi-agent systems. *Journal of Systems Architecture*, 134, 102784.
- Paccagnan, D., Chandan, R., Marden, J.R. (2022): Utility and mechanism design in multi-agent systems: An overview. *Annual Reviews in Control*, 53, 315–328.
- Večeř, J., Richard, M., Taylor, S. (2024): Portfolio optimization beyond utility maximization: the case of driftless markets. *European Journal of Finance*, 31, 318–347.
- Tesfatsion, L. (2023): Agent-based computational economics: Overview and brief history. In Venkatachalam, R. (ed.): *Artificial intelligence, learning and computation in economics and finance. Understanding Complex Systems*. Springer, Cham, pp. 41–358.

Contact

Jan Kalina

The Czech Academy of Sciences, Institute of Computer Science

Pod Vodárenskou věží 2, 182 00, Prague 8, Czech Republic

& Charles University, Faculty of Mathematics and Physics

Sokolovská 83, 186 75 Prague 8, Czech Republic

kalina@cs.cas.cz