Project Proposal

Introduction

The rapid advancement of artificial intelligence, particularly Large Language Models (LLMs), has revolutionized macroeconomic research, shifting from traditional models to more sophisticated, data-driven simulations. Although EconAgent has made significant strides in economic modeling by leveraging LLM-empowered agents for realistic simulations, limitations in agent reasoning and employment transition modeling persist.

Our project is important for addressing these limitations and enhancing the accuracy and realism of macroeconomic simulations. By optimizing agent reasoning capabilities and refining the perception of employment transitions, we aim to bridge the gap between theoretical models and real-world economic behavior. This advancement is crucial for more effective policy analysis and economic forecasting.

Our Project Goals include：

- Enhance Agent Reasoning: Improve the decision-making process of EconAgent to better handle complex, multi-dimensional economic factors.
- Refine Perception Module: Integrate job relevance and salary considerations into employment transition modeling, increasing the realism of labor market simulations.

These goals are expected to advance the efficacy of EconAgent, providing a more nuanced and accurate representation of macroeconomic dynamics.

Project Background

1Early empirical statistical models were either less resistant to external shocks or their assumptions were too idealistic. Later, agent-based modeling (ABM) became a promising paradigm. Early ABM relied on predetermined rules, but the restrictions of these rules were too simplified and did not conform to the complex situations in reality. Later ABM used a large amount of data for training to personalize each agent, but this was a huge challenge to computing resources and time costs.

With the development of artificial intelligence technology, individual economic behavior can be elaborately recorded and analyzed, thus the research method has shifted to focus on data-driven modeling. Traditional limited macroeconomic indicators no longer meet the needs. External factors are necessary for a better understanding of macroeconomics. How to combine formulaic indicators with abstract external factors has become the focus of research, so Econagent, a LLM-empowered agent with human-like characteristics for macroeconomic simulations, came into being.

Literature Review

Recent advancements in macroeconomic modeling have shifted focus towards Agent-Based Models (ABMs) as a more promising approach compared to traditional empirical statistical models and Dynamic Stochastic General Equilibrium (DSGE) models. Notable empirical statistical models (Hendry and Richard, 1982; Phelps, 1967) and DSGE models (Christiano et al., 2005) often rely on the assumption of a predetermined economic equilibrium, which limits their ability to capture complex behaviors in the economy.

ABMs offer a significant advantage by allowing diverse agents to interact based on predefined rules or computational models, thus avoiding the assumption of economic equilibrium. This approach enables policymakers to simulate a wide range of policy scenarios and qualitatively assess their impacts on the economy. However, even within ABM, agent modeling approaches—whether rule-based (Tesfatsion and Judd, 2006; Brock and Hommes, 1998) or neural network-based (Trott et al., 2021; Zheng et al., 2022; Mi et al., 2023)M, have limitations. Rule-based models often oversimplify agent behavior, while neural network models rely on extensive training data, which can restrict their ability to fully capture the complexity of economic systems.

2Early empirical statistical models were either less resistant to external shocks or their assumptions were too idealistic. Later, agent-based modeling (ABM) became a promising paradigm. Early ABM relied on predetermined rules, but the restrictions of these rules were too simplified and did not conform to the complex situations in reality. Later ABM used a large amount of data for training to personalize each agent, but this was a huge challenge to computing resources and time costs.

Recent developments in LLM, trained on extensive corpora, have demonstrated human-like capabilities that are increasingly being utilized to construct simulation agents (Wang et al., 2023; Xi et al., 2023). LLM agents offer several key advantages for simulation tasks: they exhibit autonomous adaptive reactions (Team, 2022; Yoheinakajima, 2023), possess human-like intelligence for strategic planning (Wang et al., 2023; Xi et al., 2023), and are capable of effective interaction and communication with other agents or humans (Park et al., 2023; Gilbert and Troitzsch, 2005). These advanced capabilities have led to the widespread application of LLM agents across various fields, including social sciences (Park et al., 2022, 2023; Kovač et al., 2023; Gao et al., 2023b; Jinxin et al., 2023) and natural sciences (Boiko et al., 2023; Bran et al., 2023).

In the realm of economic research, LLM-empowered agents have been explored at three distinct levels: individual rationality or biases in behavior (Horton, 2023; Chen et al., 2023b), planning and cooperation in interactive behaviors (Guo, 2023; Akata et al., 2023), and system-level market simulations (Zhao et al., 2023a; Anonymous, 2024; Chen et al., 2023a).

Project Scope

Our project aims to enhance the EconAgent model by addressing two key areas of improvement: agent reasoning capabilities and the perception module related to employment transitions.

The first modification focuses on improving the agent's reasoning capabilities. Currently, EconAgent employs LLM to simulate agent decisions based on macroeconomic conditions such as inflation, unemployment, and income distribution. However, there is room to optimize the agents' decision-making process in scenarios involving multi-dimensional economic factors.

3Early empirical statistical models were either less resistant to external shocks or their assumptions were too idealistic. Later, agent-based modeling (ABM) became a promising paradigm. Early ABM relied on predetermined rules, but the restrictions of these rules were too simplified and did not conform to the complex situations in reality. Later ABM used a large amount of data for training to personalize each agent, but this was a huge challenge to computing resources and time costs.

For individual agents, we will optimize the memory module. Considering that the current memory module relies on short-term memory and has a single input-output structure, we will introduce long-term memory and streamline the structure to improve the performance and transparency of reasoning.

For multi-agent systems, we will continue to optimize the heterogeneity of each agent, including optimizing the profile of each agent.

The second enhancement targets the perception module, particularly in the context of employment transitions. In EconAgent’s current framework, when an agent becomes unemployed, the system only adjusts the agent's propensity to work in subsequent months. However, this overlooks a critical aspect: the relationship between the new job offer and the agent’s previous job, in terms of both job content and salary. Our project seeks to incorporate these factors into the agent’s decision-making process, allowing agents to evaluate job offers based on their relevance to previous roles and the potential financial impact. This added layer of consideration will improve the realism of labor market dynamics in the simulations, as agents will behave more similarly to real-world individuals who weigh job relevance and financial stability when deciding on future employment.

Moreover, we will carefully design a series of parameters that will be passed into the system through the UI, which will affect the entire environment, such as location (country, city), tax/fiscal policy (related to the government), time (year, month), interest rate/monetary policy (related to the central bank), etc.

By targeting these two areas, our project seeks to build upon the foundational work of EconAgent, enhancing both the reasoning and perception modules to offer more robust and realistic simulations of macroeconomic behavior. Ultimately, these improvements aim to bridge the gap between academic simulations and real-world economic behavior, ensuring that EconAgent can model more realistic and complex economic phenomena.

4Early empirical statistical models were either less resistant to external shocks or their assumptions were too idealistic. Later, agent-based modeling (ABM) became a promising paradigm. Early ABM relied on predetermined rules, but the restrictions of these rules were too simplified and did not conform to the complex situations in reality. Later ABM used a large amount of data for training to personalize each agent, but this was a huge challenge to computing resources and time costs.

Integrating advanced reasoning techniques into the existing EconAgent framework poses a significant challenge. The existing model was designed with a specific set of assumptions and algorithms, and introducing sophisticated reasoning methods requires careful alignment with these underlying structures. This process may necessitate substantial modifications to the current architecture, including adjustments to the decision-making algorithms and the data processing pipelines.

Enhancing the perception module to incorporate job relevance and salary correlations also introduces complexity. The current framework does not account for these additional factors, which means thatIt is necessary to introduce a new model to process such information separately.

Ensuring that the new reasoning and perception enhancements are compatible with the existing simulation structures is a critical constraint. The integration process must address potential conflicts between the new and existing components, such as inconsistencies in data formats, processing methods, or simulation outputs. This requires rigorous validation and testing to ensure that the new components work harmoniously within the established framework.

Advanced reasoning and perception techniques may increase the computational demands of the model. Ensuring that the enhanced EconAgent remains computationally efficient is essential for practical applications, particularly when scaling up simulations to handle large datasets or complex scenarios.

Thorough validation and testing will be required to ensure that the enhanced model produces accurate and reliable results. This involves not only verifying the correctness of the new components but also assessing their impact on the overall simulation outcomes. Ensuring that the enhancements improve the model's performance without introducing biases or inaccuracies is a key challenge.

References

[5]Early empirical statistical models were either less resistant to external shocks or their assumptions were too idealistic. Later, agent-based modeling (ABM) became a promising paradigm. Early ABM relied on predetermined rules, but the restrictions of these rules were too simplified and did not conform to the complex situations in reality. Later ABM used a large amount of data for training to personalize each agent, but this was a huge challenge to computing resources and time costs.

HENRY DavidF, RICHARD J F. On the formulation of empirical models in dynamic econometrics[J]. Research Papers in Economics,Research Papers in Economics, 1982.

CHRISTIANO L J, EICHENBAUM M, EVANS C L. Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy[J/OL]. SSRN Electronic Journal, 2005. http://dx.doi.org/10.2139/ssrn.284956. DOI:10.2139/ssrn.284956.

TESFATSION L, JUDD KennethL. Handbook of Computational Economics, Volume 2: Agent-Based Computational Economics[J]. 2006.

TROTT A, SRINIVASA S, WAL D, et al. Building a Foundation for Data-Driven, Interpretable, and Robust Policy Design using the AI Economist[J]. Research Papers in Economics,Research Papers in Economics, 2021.

GROUP F. The Rise and Potential of Large Language Model Based Agents: A Survey[J].

Yoheinakajima. 2023. Babyagi. https://github. com/yoheinakajima/babyagi. (Accessed on 01/10/2023).

PARK J, O'BRIEN JosephC, CAI CarrieJ, et al. Generative Agents: Interactive Simulacra of Human Behavior[J]. 2023.

PARK J, POPOWSKI L, CAI CarrieJ, et al. Social Simulacra: Creating Populated Prototypes for Social Computing Systems[J]. 2022.

BOIKO DaniilA, MACKNIGHT R, GOMES G. Emergent autonomous scientific research capabilities of large language models[J]. 2023.

HORTON JohnJ. Large Language Models as Simulated Economic Agents: What Can We Learn from Homo Silicus?[J]. 2023.

GUO F. GPT Agents in Game Theory Experiments[J]. 2023.

6Early empirical statistical models were either less resistant to external shocks or their assumptions were too idealistic. Later, agent-based modeling (ABM) became a promising paradigm. Early ABM relied on predetermined rules, but the restrictions of these rules were too simplified and did not conform to the complex situations in reality. Later ABM used a large amount of data for training to personalize each agent, but this was a huge challenge to computing resources and time costs.

GAO C, LAN X, LI N, et al. Large Language Models Empowered Agent-based Modeling and Simulation: A Survey and Perspectives[J]. 2023.

7Early empirical statistical models were either less resistant to external shocks or their assumptions were too idealistic. Later, agent-based modeling (ABM) became a promising paradigm. Early ABM relied on predetermined rules, but the restrictions of these rules were too simplified and did not conform to the complex situations in reality. Later ABM used a large amount of data for training to personalize each agent, but this was a huge challenge to computing resources and time costs.