

CompeteAI: Understanding the Competition Behaviors in Large Language Model-based Agents

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Abstract

Large language models (LLMs) have been widely used as agents to complete different tasks, such as personal assistance or event planning. While most work has focused on cooperation and collaboration between agents, little work explores *competition*, another important mechanism that fosters the development of society and economy. In this paper, we seek to examine the competition behaviors in LLM-based agents. We first propose a general framework to study the competition between agents. Then, we implement a practical competitive environment using GPT-4 to simulate a virtual town with two types of agents, including restaurant agents and customer agents. Specifically, the restaurant agents compete with each other to attract more customers, where the competition fosters them to transform, such as cultivating new operating strategies. The results of our experiments reveal several interesting findings ranging from social learning to Matthew Effect, which aligns well with existing sociological and economic theories. We believe that competition between agents deserves further investigation to help us understand society better. The code will be released soon.

1 Introduction

Competition whose motive is merely to compete, to drive some other fellow out, never carries very far. The competitor to be feared is one who never bothers about you at all, but goes on making his own business better all the time. — Henry Ford

Competition is a key driving force that shapes human societies, influencing various domains such as economics, social structures, and technology development. Understanding these competition mechanisms is essential for comprehending how societies function. Traditional research to study competition has primarily relied on experiments involving real individuals and organizations [Castelfranchi, 1998, Markussen et al., 2014, Drury et al., 2009]. However, they present challenges, such as the inability to control for external variables and considerable time and resource requirements for data collection and analysis [Dafoe et al., 2020]. With the advent of machine learning, there has been efforts using machine learning-based agents to simulate the human society for experiments [Ferber and Weiss, 1999, Drogoul et al., 2002, Panait and Luke, 2005, Buşoniu et al., 2010]. But the capabilities of machine learning models are limited, thus restricting the full autonomy and more actions of the agents.

Recently, the emergence of Large Language Models (LLMs) [OpenAI, 2023, Touvron et al., 2023, Zeng et al., 2023] provides an alternative for social simulations by enabling the creation of autonomous agents [Hardy et al., 2023, Jansen et al., 2023, Argyle et al., 2023, Ziems et al., 2023]. This approach offers several significant advantages. Firstly, it offers controllable agents' behaviors by allowing experimentation in a controlled environment where agents' behaviors can be precisely programmed and regulated. Secondly, agents enable efficient and flexible experiment. Compared to traditional experiments, using agents for simulation is more efficient and flexible, as experimental conditions can be modified

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and adjusted at any time. Moreover, as for data collection, this approach can yield a wealth of data for researchers to conduct in-depth analyses of behaviors and patterns of the agents. Indeed, an emerging body of work has explored these LLM-based agent approaches that simulated various society environments [Park et al., 2023, Gao et al., 2023, Törnberg et al., 2023, Liu et al., 2023a, Akata et al., 2023], with primary focus on agents’ *cooperation* and *collaboration* behaviors, such as software engineering and playing games [Wu et al., 2023, Xi et al., 2023, Abdelnabi et al., 2023]. However, work that examines the concept of *competition* is sparse, which is another important mechanism in human society. Failure to understand the competition aspect could result in one-sided social simulations that do not capture the full spectrum of human interactions, thus limiting their real-world applicability.

In this paper, we seek to address this research gap by investigating the *competition* between LLM-based agents. We first introduce a comprehensive framework for the study of agents’ competition behaviors, forming the foundation of our investigation. This framework provides a structured and formal approach applicable to various scenarios. Guided by our framework, we develop a practical competitive environment (Figure 1) utilizing GPT-4 [OpenAI, 2023] to simulate a virtual town where two types of agents inhabit: restaurant and customers agents. Specifically, the restaurant agents are responsible for managing restaurants and selling food to their customers. The customer agents play the role of judges by selecting restaurants and leaving feedback on their experiences interacting with the restaurants.

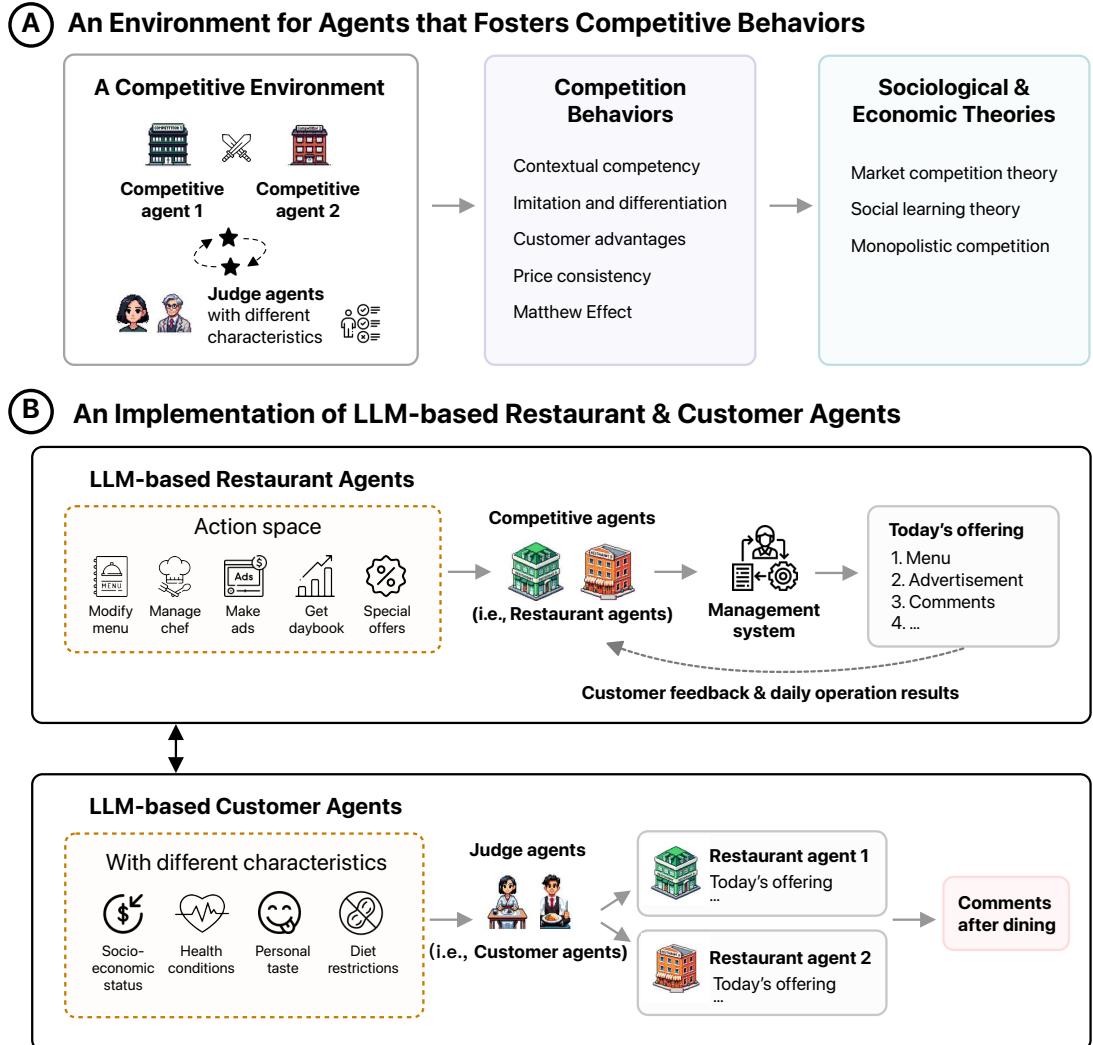


Figure 1: (A) We construct an environment for agents that fosters competitive behaviors, aligning with established sociological and economic theories. (B) We implement LLM-based restaurant agents and customer agents in a competitive environment.

Customers possess different characteristics, such as income, taste, health, and dietary restrictions.

Within this simulated environment, the restaurant agents compete with one another as they strive to attract and retain customers. This competition serves as a driving force, compelling the restaurant agents to evolve and adapt continually and progressively. The restaurant agents response to this competition by developing innovative operating strategies to outperform their rivals.

Our experiments reveal several interesting findings:

- **Contextual Competency of LLM-based Agents:** Our initial discovery confirms that LLMs can accurately perceive and operate within competitive contexts, forming the foundation for effective simulation experiments.
- **Immitation and Differentiation among Competitors:** Our observations indicate that competing agents engaged in mutual learning while striving for differentiation, a phenomenon consistent with *social learning theory* [Bandura and Walters, 1977]. This creates a conducive learning environment alongside competitive interactions.
- **Market competition and customer benefits:** Our research demonstrates that competition among agents leads to improved service quality and more tailored approaches to meet customer needs, which aligns with *market competition theory* [Ahn, 2002]. These findings emphasize the importance of adopting customer-centric strategies for success in competitive environments.
- **Price Consistency:** Our observations indicate that in competitive environments, there is a noticeable trend of price convergence.
- **Matthew Effect:** Our study reveals a Matthew Effect [Rigney, 2010] in the restaurant competition. This phenomenon manifests as a self-reinforcing cycle where popular restaurants gain even more popularity while lesser-known establishments continue to receive minimal attention. Our analysis indicates this is because imbalanced access to information.
- **Strategies in Competition:** Our study further reveals that agents employ undisclosed tactics in competitive environments, such as introducing package and discount deals to attract customers from different affordability ranges.

The contributions of this paper are three-fold:

1. *A competitive framework for LLM-based agents.* Shifting the focus from cooperative behaviors of agents that have been primarily studied, we pioneer a comprehensive framework specifically designed to analyze competitive interactions between LLM-based agents.
2. *An implementation of a simulated competitive environment.* We operationalize our proposed framework by developing a specialized competitive environment in the context of restaurant management and competition, where restaurant agents compete for customer engagement, thereby providing a structured platform for analyzing agent behaviors.
3. *Novel insights into competitive dynamics.* We observed various competition behaviors from LLM-based agents in our extensive experiments that align with existing sociological and economic theories, informing future research and design implications.

2 Building the Competitive Environment

In this section, we explain the competitive environment of our study, including our proposed general framework of studying competition behaviors of agents (see Section 2.1), an overview of the study environment and components (see Section 2.2), followed by detailed explanations of the several components depicted in our framework (from Section 2.3 to Section 2.4).

2.1 A general framework of studying competition behaviors of agents

Competition means that people need to compete for limited resources to make themselves thrive in an environment. We first propose a general framework to study the competition behaviors of agents. As shown in Figure 2, our framework, referred to as “*CompeteAI*”, consists of four major components.

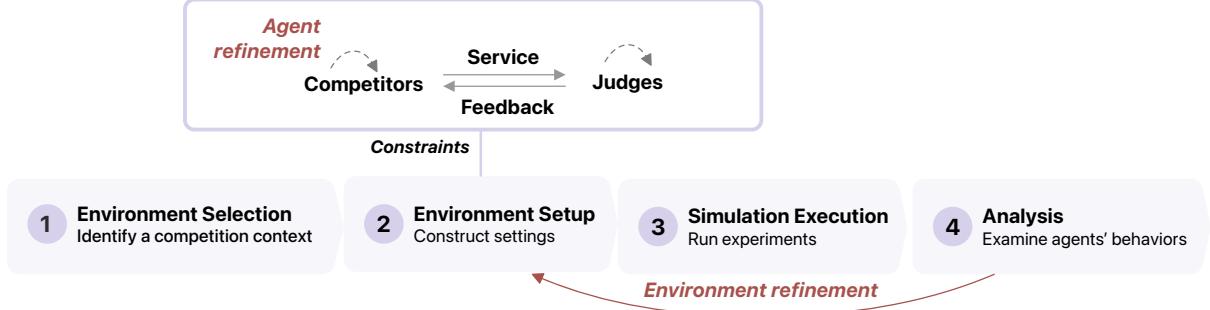


Figure 2: A general framework for studying the competition between AI agents. Our framework consists of four main components: environment selection, environment setup, simulation execution, and analysis. Environment setup is the key component, where competitors and judges interact with each other and keep refreshing (the dotted arrows) based on the feedback.

First, in **Environment Selection**, we identify an appropriate competition context for competition—this could range from competitive games, to company-customer interactions, and to other races as the main study environment. Second, in **Environment Setup**, we construct the chosen setting, leveraging the existing agent frameworks, such as CAMEL [Li et al., 2023b] or AutoGen [Wu et al., 2023] for adaptation. Third, in **Simulation Execution**, we run a series of experiments to capture the interaction processes between different agents within the established environment. Lastly, in **Analysis**, we observe, analyze, and summarize the behaviors from the experimental results to derive insights.

Of note, the most important component is to create a competitive environment, where designers should meticulously consider the *competitors*, *judges*, and *interactions* between them (e.g., competitors provide *service* to the judges and judges provide *feedback* to the competitors). *Constraint* is necessary for this component to succeed, such as resource constraints and service constraints for the competitors, or money constraints and buying constraints for the judges. The design of the constraints is inspired by the *resource dependence theory* [Hillman et al., 2009] where competition for resources can influence the behavior of an organization, relationships with other organizations, and strategies for survival and success. The design of these components highly depends on the competition situation. Designers should also pay attention to their interactions, iterations (since most competitions require feedback and rerun), and results management.

We now introduce the key concepts of our framework, including environment, competitors, judges, constraints, service and feedback, and agent refinement.

- **Environment:** The simulated space where competitions occur, typically facilitated by LLM-based agents.
- **Competitors:** The primary subjects who perform certain actions to gain advantages, such as attracting more customers or securing more votes.
- **Judges:** Entities that receive services from competitors and influence their success, such as customers in a retail setting or voters in an election.
- **Constraints:** Rules designed to level the playing field in competitions. Examples include limiting dining choices to one restaurant per meal or one vote per person in elections.
- **Service and Feedback:** Competitors offer services to win over judges, who in turn provide feedback that informs future competitor actions.

- **Agent Refinement:** Both competitors and judges adapt based on interactions, such as updating strategies or sharing information among peers.
- **Environment Refinement:** The design of the environment could further be refined according to the process of the study to better simulate the real-world scenarios and achieve the trade-off between simulation resources (API fees, hardware and software constraints) and real-world scenarios.

Our general framework serves as an ideal testbed for creating a diverse competitive environment to study the behaviors of agents. It has the potential to be extended to various practical environments and situations. More importantly, our environment can be used to simulate social competitions between agents. Observing and analyzing this offers valuable insights for a better understanding of competition and inspires more interesting future research. In the following, we provide a specific implementation of the competitive environment based on the proposed framework.

2.2 Environment Overview

In this section, we describe our practical environment implemented guided by the general competition framework. Specifically, we set the environment to be a small town with only two types of entities: 2 restaurants and 14 customers. We assume that each customer cannot cook and must go to one of the restaurants to eat. To make our observations easier, we assume that one customer should eat once at one restaurant every day. For profit, restaurants must compete with rival to attract more customers. In this paper, both restaurants and customers are powered by LLM-based agents, which are GPT-4 [OpenAI, 2023]. The detailed introduction of our environment is shown in Figure 3.



- ⇒ **Environment:** A virtual town with only restaurants and customers.
- ⇒ **Competitors:** Two LLM-based agents (i.e., restaurants).
- ⇒ **Judges:** LLM-based agents as customers with different characteristics.
- ⇒ **Constraints:**
 - 1) Customers cannot cook
 - 2) One customer should have one meal every day at one restaurant
 - 3) There are housing and facilities costs for the restaurants every day
 - 4) There will only be the starting fund for each restaurant to operate
- ⇒ **Service & Feedback:** Restaurants provide food to the customers and customers leave comments to the restaurants.
- ⇒ **Agents Refinement:** Restaurants update their menu or operations based on customer feedback. Customers update their comments to restaurants.

Figure 3: Our simulated virtual town consists of two types of agents: restaurant agents that are served as competitors and customer agents as examples of judge agents. Key concepts of our proposed framework include Environment, Competitors, Judges, Constraints, Service and Feedback, and Agents Refinement. Note that environment refinement is not included here since this is out of the scope of the virtual town.

As shown in Figure 1, each restaurant is managed by an LLM-based agent to offer food to customers on daily basis. Specifically, the restaurant is operated via several pre-defined actions such as “modify menu”, “manage chef”, and “make advertisements” to serve customers of the day. Then, each customer receives the information from each restaurant and chooses between them. After their meal, customers leave comments as feedback to the restaurants. We assume the system runs for N days until one of the restaurants decides to quit the race, or until we stop the game.

There are four challenges in making this simulation practical. Firstly, for most LLM-based agents, their inputs and outputs are both in textual formats. It is non-trivial to enable them to interact with the real environment. Therefore, both restaurants and customers need real systems to emulate the possible actions. Secondly, agents should be sufficiently diverse to trigger more competitive behaviors. In the real world, users have diverse preferences. Some customers may prefer vegetarian food, while others prefer fast food. Thirdly, the validation of is non-trivial. Sophisticated simulations are ultimately approximations of real-world conditions. It is imperative to rigorously assess how well agents’ behaviors within these simulations correspond to empirical human actions in real-world contexts. This ensures that the simulation is not only internally consistent but also externally valid. This is a challenge that requires partnerships

with restaurants and domain experts. Lastly, the scalability of the system should also be considered, e.g. potentially scalable to more agents with greater diversity to simulate more complex scenarios.

In the following, we introduce how to overcome these challenges in our implementation.

2.3 Competitors

In this study, we employ LLM-based agents as restaurant managers. Real-world restaurants involve complex operations like hiring staff, crafting menus, and advertising—tasks beyond the scope of text-based LLMs that lack real-world sensing capabilities [Dafoe et al., 2020]. To address this, we use carefully designed and detailed prompts to contextualize the scenario for agents and build a comprehensive restaurant management system accessible with APIs, which enables agents to manage the restaurant more effectively. For the ease of implementation and result analysis, we limit the competitive landscape to two restaurants. However, our framework can be readily used to incorporate more restaurants.

Figure 4 shows the process of a restaurant agent. Each one is granted a certain number of starting funds to hire chefs, make menus, make advertisements, and do other things. First, each restaurant receives a daybook recording the history of income, expenses, comments from customers, and so on. Information of its rivals (i.e., the other restaurant) is also provided, including the menu and the number of customers. The agent then analyzes all information and designs a plan for next day such as hiring a new chef or updating the menu. The restaurant agents are told through prompts that all operations are performed through the management APIs we created. Table 1 shows the supported APIs in the system. Then agent interacts with the restaurant management system to serve the customers.

Note that all actions should be performed in the feasible action space. Any actions falling outside of this space will not elicit a system response. However, it is essential to acknowledge that certain new strategies and plans may arise organically. These emergent strategies, which are not explicitly included in the prompts or the predefined APIs, are documented as anticipated outcomes of our study. This naturally

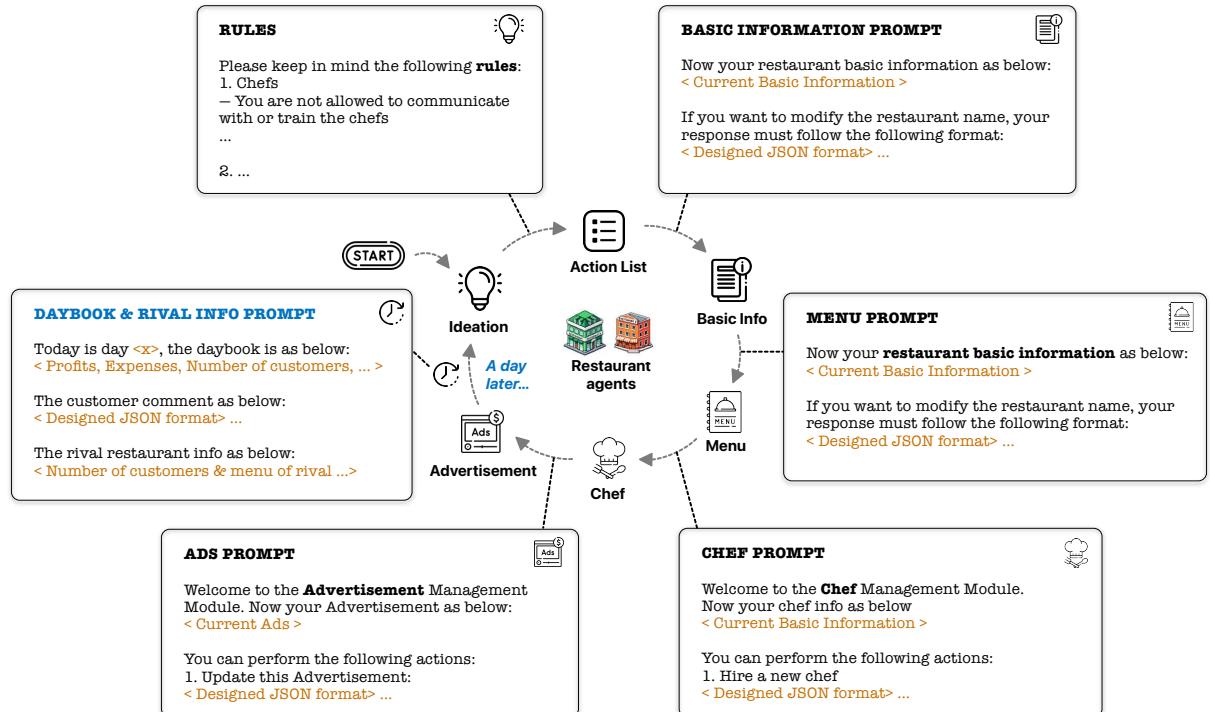


Figure 4: An overview of the process of operating restaurants among the competitors (i.e., two restaurants). On each day, the restaurant receives the daybook and the information for the rival. Then, the agent manages the restaurant prompted by the basic information prompt, menu prompt, chef prompt, and ads prompt. More details are in the main text.

Table 1: The action space (APIs) that agents can leverage.

API	Properties	Action Space
basic_info	name, rent, money, status	Get information & Modify restaurant name
chef	name, salary	Hire / Fire chef & Adjust chef salary
menu	name, price, cost_price, description	Add / Delete / Get / Modify item in menu
advertisement	content	Get / Modify advertisement
comment	day, name, score, content	Get all comments
daybook	profit, expense, num_of_customer, and so on	Get daybooks

leads us to a question: can agents develop new skills and strategies not in the original action space? In Section 3.6, we present empirical evidence that agents spontaneously generate innovative strategies, such as offering packages and discounts to attract customers.

2.4 Customers

Customers are judges in our environment, and it is important to include diverse customers to trigger more findings. To this end, we introduce *characteristics* to each customer to enhance their diversity. The characteristics comprise several factors: income, taste, health condition (e.g., diabetes), and dietary restrictions (e.g., vegetarians). All characteristics information is set by prompts and fed to the system to be remembered as eternal characteristics. For instance, one customer with middle-level income loves gluten-free food and another one is high-level income and fond of vegetarian.

Figure 5 shows the process of each customer. After the construction based on their characteristics, the information from two restaurants is shown to them, including the name of the restaurant, customer score, advertisement, menu, and comments. Each customer must choose one restaurant based on their own characteristics and the provided restaurants' information. Meanwhile, customers should provide reasons for better analyzing their choice later. Then, the scores for dishes are saved in the restaurant system. According to the scores and other information, each customer gives a score and comment (on their selected dishes or all dishes?), which will become dining experience for future customers.

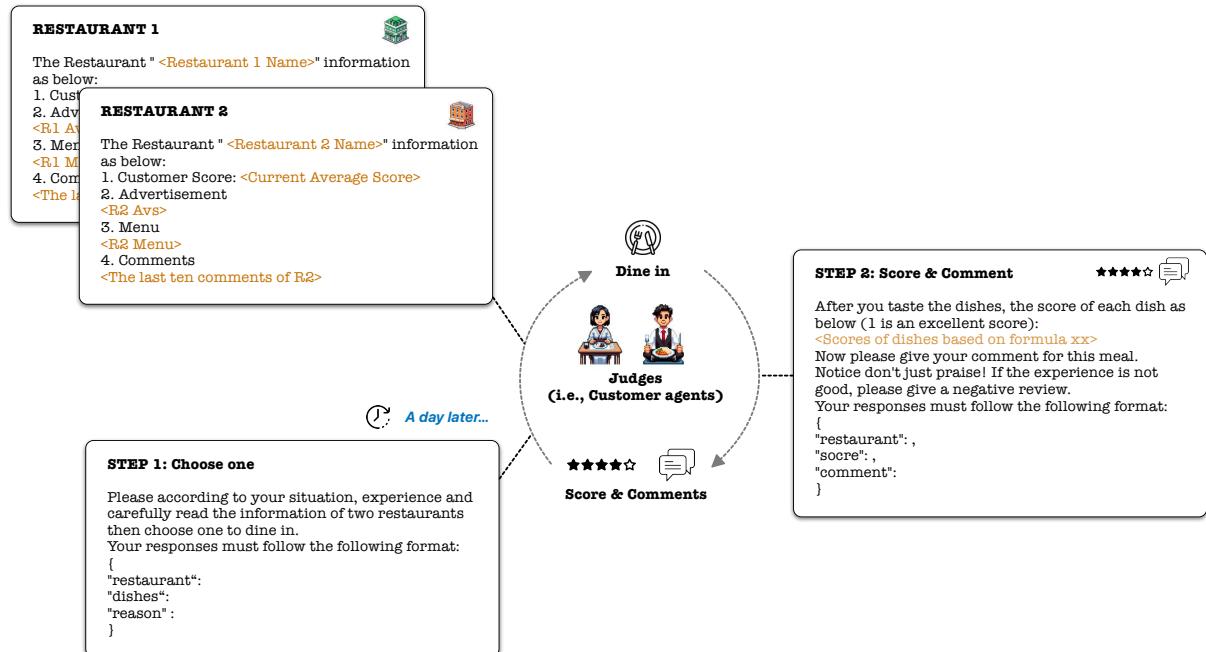


Figure 5: The detailed customer dining process. On each day, each customer receives the information from two restaurants and selects one to dine. After meal, customers leave comments and scores.

3 Analysis and Results

In this section, we present our observations by running the experiment 15 times due to the limited constraint and budget in API service.¹

3.1 Contextual competency

Our first and the most fundamental finding is that **LLM-based agents can perceive and operate within the competition context.** This is essential for this study, where LLMs are expected to have a holistic understanding of the competitive environment in addition to merely comprehending the instructions.

We show a case study to support this observation. In the following, one of the restaurant agents receives the daybook and the rival information, then analyzes the information as follows:

Restaurant agent

First, we could add more description to our menu to highlight the quality of ingredients used and the care put in to prepare the dishes. This will not only showcase the value customers will receive but will also provide necessary information for those with dietary restrictions.

The agent adds more detailed descriptions to menu items to better convey information to customers (key observations are marked in red):

Restaurant agent

I also noticed that **our competitor has a wider selection on their menu**, including beverages like French Wine and Cafe au Lait, as well as vegetarian-friendly dishes. To expand our menu, I would like to consider **adding some French coffee and wine options**, as well as at **least one more vegetarian dish**.

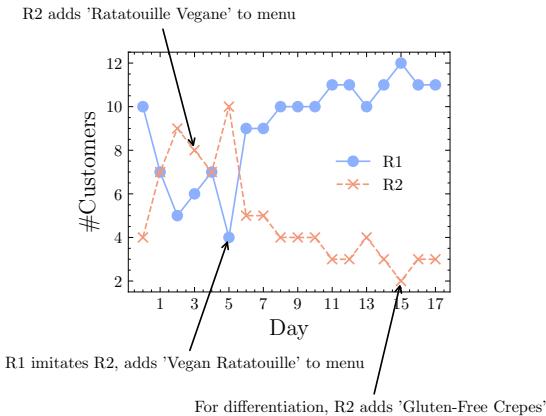
When comparing the menu with that of the rival, the agent finds the menu is less diverse. To address this, it plans to introduce some dishes that are similar to those on the rival's menu:

Restaurant agent

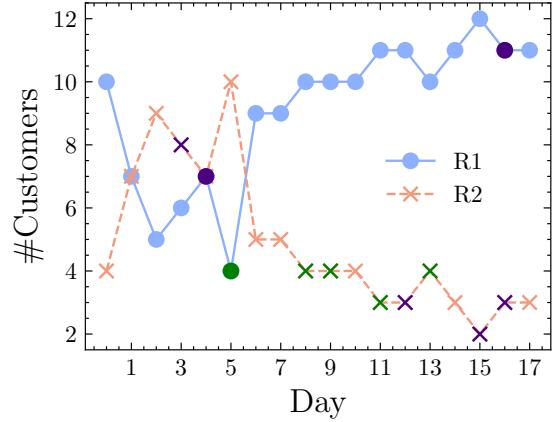
Second, monitoring the competition reveals that **their prices are generally lower than ours**, which could be why they are drawing in more customers. It would be beneficial to consider a review of our pricing strategy.

The agent also notices that its prices of dishes are higher than the rival's and doubts that could be the reason why the rival's restaurant is more attractive to customers. Then, it decides to adjust the pricing strategy accordingly.

Through this example, we find that the agent is capable of analyzing its rival and making adjustments accordingly. This proves that agents have a holistic understanding of the competitive environment. Further analysis shows that the action of “analyze competitor” occurs in all simulations. Therefore, the LLM-based agents are considered to have an excellent understanding of the competitive context.



(a) One restaurant learns from the other to add similar dishes, while still differentiates by adding different ones.



(b) An overview of both behaviors. Red and blue represent imitative and differentiated behaviors, respectively.

Figure 6: Imitation and differentiation of two restaurants during competition.

3.2 Imitation and differentiation

Our second observation indicates that **in competition, competitive agents both imitate each other and strive to differentiate themselves from their rivals**. This finding is in line with Bandura's social learning theory and product differentiation phenomenon. The former stating that individuals learn new behaviors through observation and imitation [Bandura and Walters, 1977], the latter asserting that competitors typically seek to distinguish their products or services to attract specific target markets.

Overall Findings: As shown in Figure 6(a), after Restaurant 2 introduces a “vegan” attribute to its menu on Day 3, Restaurant 1 notices this change on Day 5 and decides to add “vegan” attribute in its own menu. The same example in Figure 6(b) abstractly represents imitative behaviors in red and differentiated behavior in blue. We observed that these two behaviors repeatedly occur in each restaurant during competition. By the end of the competition, both restaurants share 8 identical dishes, with Restaurants 1 and 2 offering 3 and 2 unique dishes, respectively.

Imitation: As demonstrated in Figure 6, the agents actively observe and adapt to the strategies of their competitors. In the recorded interaction, on Day 5, Restaurant 1 said:

Restaurant agent

Analysing the menu of "La Maison de la Côte," they offer a wider variety, including several vegan options. To cater to a broader demographic, we should consider introducing some vegan dishes.

This statement confirms that Restaurant 1 actively monitors the actions from Restaurant 2, identifies gaps in their own offerings, and adapts to better meet customer needs, exemplifying the principles of social learning theory.

Monopolistic Competition: Competitions in our environment can be approximated as monopolistic competition [Smith, 1937], where there are multiple sellers in the market, but no single entity has enough influence to dictate market prices. In our case, there are two restaurants, which cannot communicate with each other, preventing any collusion to establish a monopoly.

Product differentiation: Product differentiation is an important phenomenon in monopolistic competition. When both restaurants share the same style (e.g., French cuisine) and initial funding, their menus should theoretically be similar. However, to attract more customers, restaurants usually add unique dishes to distinguish them from their rivals. This is evident in the following example:

¹As a reference, the average API fee for successfully running the experiment once is \$20.

Restaurant agent

To differentiate ourselves from the competition, we'll offer a variety of dishes catering to different dietary needs, like gluten-free and vegan options. This will help us tap into a niche market that most other French restaurants might ignore.

Dynamic changes in two behaviors: When facing a competitive disadvantage, restaurants tend to closely monitor their competitors, resulting in an increase in both imitative and differentiated behaviors. As shown in Figure 6(b), on Day 3, the number of customers in Restaurant 2 significantly exceeded that of Restaurant 1, facilitating imitative behavior in Restaurant 1. After Day 7, the number of customers in Restaurant 1 continues to exceed Restaurant 2. Consequently, Restaurant 2 exhibited a considerable amount of both imitative and differentiated behavior, while Restaurant 1 displayed minimal engagement in these behaviors. These findings demonstrate that competitive disadvantages prompt restaurants to intensify their focus on their rivals.

Combined effects of two behaviors: If two restaurants share the same settings (cuisine type, initial funding), their menus naturally tend to be similar. However, differentiation reduces this similarity, while imitation increases it, ultimately leading to a dynamic equilibrium. As shown Figure 7, through the combined effects of two behaviors, the proportion of similar and different dishes remains stable: mostly similar but with a few distinctive offerings.

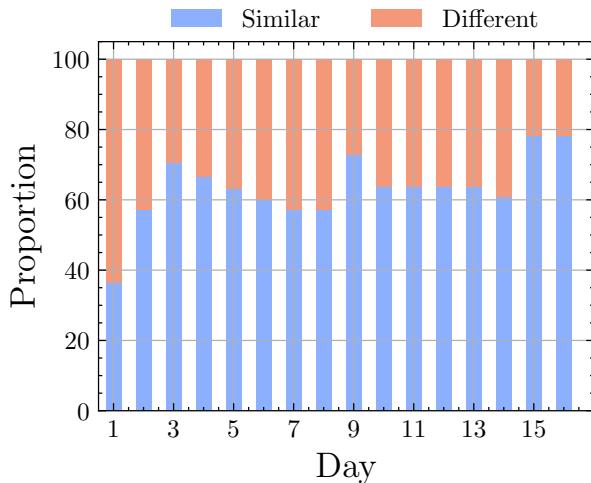


Figure 7: Illustration of the proportion of similar and different dishes between the two restaurant agents. For example, if both of their menus have 10 dishes where 6 of them are similar, the proportion is 60%.

In short, imitation and differentiation are common behaviors in monopolistic competition [Salop, 1979]. These effects lead to high similarities in the menus of the two restaurants. Moreover, the frequency of these behaviors is intricately linked to the competitive position of organizations within the competition.

3.3 Market competition and customer benefits

Competition benefits customers by giving them more choices and motivating competitors to improve. In a highly competitive market, customers have more options, forcing competitors to focus more on meeting their needs and enhancing service quality. At the same time, due to the presence of rivals, competitors must strive to raise their standards to gain a competitive edge. This dynamic environment encourages innovation, efficiency, and customer-centric service, ultimately benefiting customers. These observations are well aligned with the *market competition theory* [Ahn, 2002].

3.3.1 Competition improves the service quality

Competitors enhance their service quality to prevent rivals from exceeding their services.

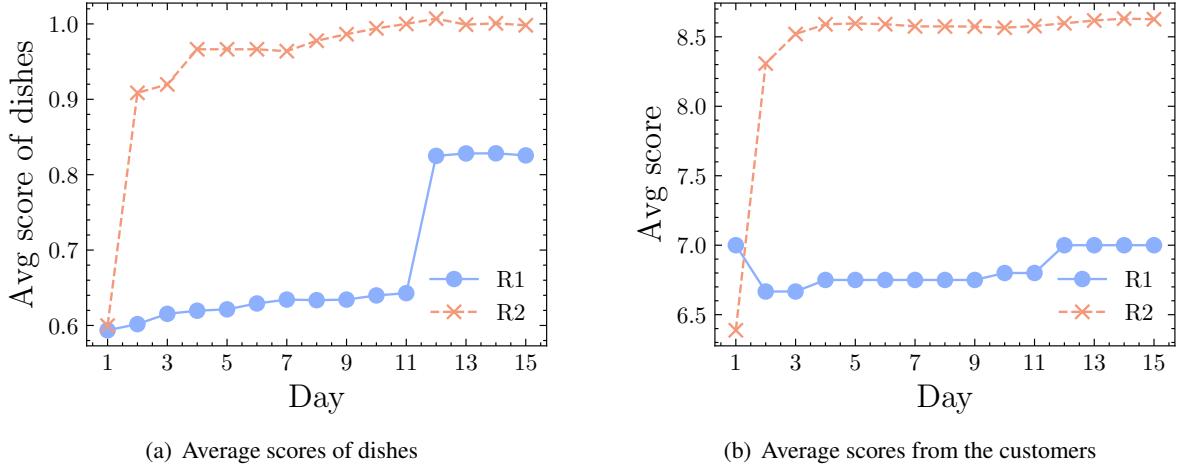


Figure 8: The average scores of dishes and customers are getting improved over time.

In our competitive environment, the quality of dishes plays a pivotal role in shaping the overall service quality. We recognize that the quality of dishes is associated with the dish price, cost price, and chef level. To gauge dish quality, we formulate several key assumptions to underpin our assessment: 1) The taste of dishes exhibits a positive correlation with the skill levels of chefs, which is tied to their salary. 2) The quality and taste of the dishes are linked to both the original price and the selling price.

Motivated by these assumptions, we introduce a mechanism (an empirical formula according to our experience playing with this environment) to evaluate the score s for each dish:

$$s = 0.5 \times \frac{c}{p} + 0.5 \times \frac{f}{5000},$$

where c is the cost, p is the price, and f is the salary for the chef.

Figure 8(a) show the average score of dishes increased over time and Figure 8(b) demonstrates the growth of customer scores over time in the same experiment.

3.3.2 Competitors cater to the customers

Competitive agents cater to the customer needs to help them obtain advantages in the competition. Those prioritizing customer insights are better positioned to adapt, innovate, and thrive amidst competition.

Table 2 shows the agent responses tailored to different customer needs. Different characteristics of customers may lead to various needs. For instance, people with diabetes seek dishes with reduced sugar content, while those with limited income prioritize cost-effective options. Those needs exist in the comments, which are then received by the agents to make some arrangements to satisfy.

Table 2: Examples of customer needs and restaurant behaviors.

Customer need	Agent behavior	Type
Vegetarian	Add “Vegetarian Ratatouille” to the menu	Dietary restriction
Diabetes	Change “Tarte Tatin” to “Low-Sugar Tarte Tatin”	Dietary restriction
Seafood	Add “Seafood Bouillabaisse” to the menu	Taste
Noodles	Add “Zucchini Noodles” to the menu	Taste
More affordable	Price reduction & Add “Budget-Friendly Set” to the menu	Income

In the following two examples, the agent carefully reads customers' comments, understands their requirements, and then makes modifications.

Restaurant agent

Looking at the customer feedback, ... , we should consider adding a few more vegetarian-friendly and low-sugar options to cater to customers with specific dietary requirements.

Restaurant agent

Some customers found our prices a bit high, although ..., We'll review our pricing strategy, perhaps introducing a few more affordable dishes to cater to a wider customer base.

Note that agents not only understand customers from their direct requirements, but also analyze customers for *long-term* changes. In the following example, the agent collects comments and records for a few days; then it finds a trend: "the growing trend towards vegetarianism".

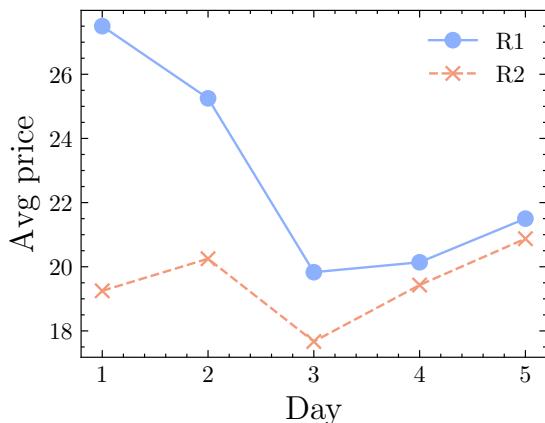
Restaurant agent

Given the feedback and the growing trend towards vegetarianism, it would be prudent to include another flavorful vegetarian dish on the menu.

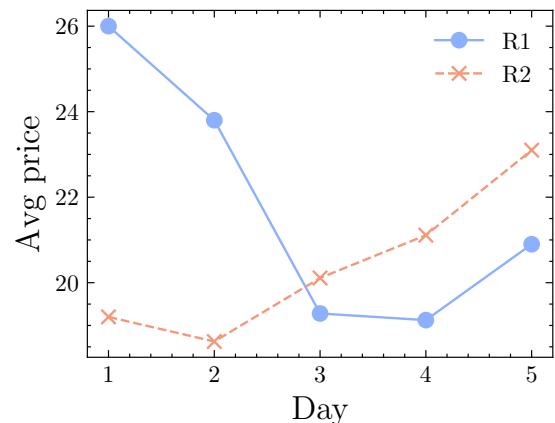
3.4 Price consistency

An intriguing finding is the gradual consistency of dish prices in two restaurants of the same style as time progresses. It aligns with monopolistic competition, as visually depicted in Figure 9.

Overall Findings: Figure 9(a) shows the average price changes of similar dishes in two restaurants. On Day 1, there is a significant price difference between them and Restaurant 1 starts reducing them rapidly on Day 2. The prices of both restaurants reach the same level on Day 3. On Day 5, the prices



(a) The average prices of *similar* dishes in two restaurants tend to be consistent over time.



(b) The average prices of *all* dishes in two restaurants tend to be consistent over time.

Figure 9: The prices of dishes tend to be consistent with each other.

almost converge to the same value. At the same time, Figure 9(b) shows the average prices of their menus over time. We also observe that the prices of all dishes tend to be consistent gradually.

The specialty of monopolistic competition: In monopolistic competition, no business has total control over the market price, but they have the freedom to set prices. For-profit, they must continuously monitor market trends, competitor actions, and consumer demands to develop effective pricing strategies.

Core manifestation: In our environment, two restaurants must adjust strategies according to rivals and customers. When there is a significant difference between restaurants, the one with higher price, forced by the rival's lower price, will be compelled to reduce its prices. On the contrary, the one with a lower price will raise the price to make a profit. So before arriving at the same level, two restaurants' prices always show a trend of approaching.

Limited price reduction: Because of the existing cost price, competitors can not reduce price limitless.

No joint markup: Competitors can not communicate with each other, so cooperation is impossible.

3.5 Matthew Effect

In our study, we observed a phenomenon reminiscent of the Matthew Effect [Rigney, 2010], wherein entities with an initial competitive edge continue to accrue benefits, leaving others in a perpetual state of catch-up, leading to unequal growth and opportunities. This effect is widely recognized in various domains, including education [Walberg and Tsai, 1983] and science funding [Bol et al., 2018].

Below, we elaborate on how our findings offer practical insights into the manifestation of the Matthew Effect in the context of LLM-based agents, specifically within the dynamics of restaurant customer traffic and feedback mechanisms.

Overall Findings: As shown in Figure 10, on Day 1, most of customers choose Restaurant 1 due to its affordability, diverse menu offerings, and other factors, resulting in a satisfying experience. As a result, Restaurant 1 receives the most customer comments, allowing them to make adjustments based on this valuable information. In contrast, Restaurant 2 has few customers and their comments. This makes Restaurant 2 unable to obtain the latest information. On Day 2, since Restaurant 1's menu caters more to customers and there is very little information about Restaurant 2, most customers continue choosing Restaurant 1. This makes Restaurant 2 get into trouble, and this pattern persists daily.

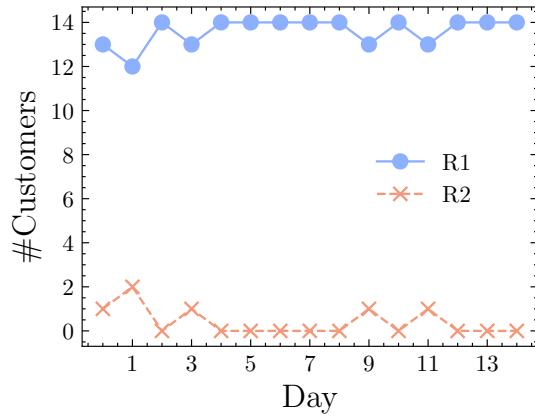


Figure 10: The Matthew Effect during the competition.

Core Manifestation: At the beginning, Restaurant 1's inherent advantages, such as cost-effectiveness and menu diversity, set it on a trajectory of accumulating further benefits. As it continues to receive and act on customer feedback, its offerings become more refined. Conversely, Restaurant 2, lacking such initial advantages, finds itself caught in a feedback void, leading to a persistent disparity in benefits between the two establishments.

Significance of Initial Factors: It is evident that initial attributes, notably Restaurant 1's affordability and diverse menu, are important in catalyzing the feedback loop. This observation resonates with the

Matthew Effect's principle, highlighting the criticality of starting advantages.

Disproportionate Growth Patterns: The evolving dynamics, where Restaurant 1 thrives, and Restaurant 2 faces challenges, epitomize the uneven growth trajectories central to the Matthew Effect.

Information Asymmetry: A standout observation from our study is the skewed information access. Restaurant 1's iterative improvements, fueled by consistent customer feedback, emphasize the role of information in shaping competitive stances.

In short, our findings underscore the profound impact of initial advantages and the pivotal role of feedback in creating a self-perpetuating cycle of success for some and challenges for others, aligning with the principles of the Matthew Effect. We will further discuss how situating our findings in the context of the Matthew Effect holds profound practical implications for the development, deployment, and democratization of LLMs in competitive scenarios in the Discussion section.

3.6 Agents propose new strategies in the competition

We further observe that agents can propose some new strategies in the competition including the addition of *packages* and *discounts* to obtain advantages. Note that the “new” strategies are not previously prompted or implied, which is rather interesting.

3.6.1 Packages

In the menu, the restaurant agent adds a single dish and adds packages to attract more customers by packing several dishes into one package with a satisfactory price. For example:

Restaurant agent

To cater to middle-class affordability, I will introduce a "Meal of the Day" combo that includes a main dish, dessert, and drink at a slightly lower cost.

3.6.2 Discounts

Discounting is an effective way to attract and retain customers. This strategy is also proposed by agents in our experiments. For example:

Restaurant agent

I would like to introduce a 'Customer's Choice Dish of the Month'. This will include collecting monthly feedback from customers about their favorite dishes, and the one with the highest votes will be featured as a special for the next month with a small discount.

4 Discussion

4.1 Alignment with existing theories and why?

As shown in Table 3, our study has revealed that LLM-based agents can make several competition behaviors that align well with existing sociological and economic theories. But *why* do agents possess these behaviors still unexplored due to the black-box nature of the large language models we adopted (GPT-4). A possible explanation could be that the models are well-trained on a massive corpus that contains texts from diverse disciplines such as psychology, sociology, and economy [OpenAI, 2023]. Therefore, we doubt that the model could have already memorized these popular theories and examples, leading to these “common” behaviors triggered by our prompts.

Table 3: The map from phenomenons to theories

Phenomenon	Theory
Imitation	Social learning
Differentiation	Product differentiation in monopolistic competition
Customer advantages from competition	Market competition theory
Price consistency	Monopolistic competition
Matthew Effect	Theory about Matthew Effect

4.2 Beyond the alignment

An interesting question that arises following the above analysis is: can LLM-based agents behave *more* than just following existing knowledge in the training data? Can they cultivate *new* intelligence? We believe this could be profoundly important to perform new studies in sociology and economics, leveraging agents to uncover new rules, laws, or even theories.

Additionally, the observed behaviors are well aligned with existing theories, indicating that they are also aligned with human values [Gabriel and Ghazavi, 2021], which may trigger interest from the value alignment community to perform research in an agent-based environment. This work can then be considered as the baseline for such alignment research where more complex algorithms can be introduced.

4.3 Broader implications for AI adoption

Recognizing the presence of Matthew Effect in LLM competition can inform strategies for adopting and improving newer or smaller LLM agents. By understanding the challenges they might face due to initial disadvantages, strategies can be developed to level the playing field.

The Matthew Effect, when observed in the realm of LLMs, can lead to monopolistic behaviors or concentrated power among a few dominant models. Recognizing this effect is crucial for ensuring diversity fairness, and broad access in the AI landscape.

By understanding the dynamics of the Matthew Effect in LLM-based competition, researchers and developers can better design training protocols, feedback mechanisms, and integration strategies to ensure that even agents with initial disadvantages have the opportunity to thrive.

5 Related Work

5.1 Large language models and agents

Large language models (LLMs) [OpenAI, 2023, Touvron et al., 2023, Zeng et al., 2023] attracted considerable attention owing to their exceptional proficiency in a wide range of natural language understanding and generation tasks [Wang et al., 2023b, Xiao et al., 2023, Chen et al., 2023a, Zhou et al., 2023, Li et al., 2023a]. Building upon this foundation, there has been a burgeoning area of research that utilizes LLMs as central controllers to create autonomous agents capable of human-like decision-making [Wang et al., 2023c, Xi et al., 2023, Huang et al., 2023, Wang et al., 2023a, Li et al., 2023c, Chang et al., 2023]. Studies have indicated that while exhibiting effective experiential learning [Zhao et al., 2023], leveraging multiple LLMs through cooperation and debate can further enhance their capabilities [Abdelnabi et al., 2023]. This is achieved by integrating multiple LLMs into a cohesive group and designing specific interaction mechanisms. These agents engage in proposing and deliberating unique responses and thought processes over multiple iterations, resulting in better generation quality. This insight has led to the development of several noteworthy approaches. For instance, AutoGen [Wu et al., 2023] introduces a novel framework that facilitates the development of LLM applications using multiple customizable, conversational agents capable of collaborative problem-solving. The applications of these collaborative LLM-based agents

are diverse, including task planners [Wang et al., 2023d, Song et al., 2023], simulators in behavioral economics studies [Horton, 2023], and judges in specific domains [Chan et al., 2023].

Our work distinguishes itself from prior research, which primarily investigates agents' behaviors in cooperation scenarios [Dafoe et al., 2020, Li et al., 2023b]. Instead, our evaluation focuses on studying LLM-based agents under a *competition* scenario, an area that has received relatively less attention but holds equal significance.

Moreover, our work contributes to the evaluation protocols of LLM-based agents by emphasizing a unique aspect. Instead of relying solely on quantitative metrics [Liu et al., 2023b, Jin et al., 2023], our evaluation methodology is naturally inspired by classic sociological and economic theories that prioritize a careful interaction process and meticulous observations to assess these agents' performance. This detailed and iterative process may also trigger new interest in future research on LLM-based agents.

5.2 Cooperation and competition

The relationship between cooperation and competition has been a long-standing subject of research in the fields of economics, biology, and social sciences [Stapel and Koomen, 2005, Khanna et al., 1998, Luo et al., 2022, Deutsch, 2011]. This relationship has been explored through a combination of empirical studies and agent-based simulations.

Empirical studies have provided valuable insights into the dynamics of cooperation and competition [Porter, 2008, Kosfeld and Von Siemens, 2011]. For instance, Markusen et al. [2014] found that inter-team competition can serve as a catalyst for intra-team cooperation by stimulating improvements in relative group performance. Chen [2008] further highlighted the intricate interplay between cooperation and competition in real-world scenarios. In the realm of AI and computer science, there exists a substantial body of literature dedicated to investigating the dynamics of cooperation and competition among AI models or agents within simulated environments [Dafoe et al., 2020, Drury et al., 2009]. Castelfranchi [1998] introduced a framework for modeling social environments using AI agents, encompassing elements such as cooperation, groups, and organizations. Building upon this foundation, Dafoe et al. [2020] and Zhang et al. [2023] proposed open problems in cooperation AI, aiming to enhance the joint welfare of a group, thereby contributing to the understanding of these dynamics in artificial environments. In our work, we leverage LLM-based agents, known for their profound natural language understanding and reasoning capabilities, to effectively stimulate human behaviors and probe the intricate interactions within a novel **competition** scenario. Our contribution bridges a significant gap in the literature by addressing the under-explored dimension of competition in AI and computer science. Moreover, our work distinguishes itself from recent contributions such as Chen et al. [2023b] by introducing a versatile competition framework adaptable to diverse competitive situations.

5.2.1 Social Learning Theory and Market Competition Theory

Social learning theory [Bandura and Walters, 1977] posits that individuals learn new behaviors through observation, imitation, and modeling. This paradigm has found applications in various domains such as psychology, education, and sociology [Latham and Saari, 1979, Deaton, 2015, Davis and Luthans, 1980]. It serves as a robust framework for comprehending the intricate interplay between individual cognition and external influences in learning.

In this work, we explore the application of social learning theory by scrutinizing the behaviors of LLM-based agents in an interactive environment. Through comprehensive experiments, we successfully elucidate how LLM-based agents exhibit efficient social learning behaviors, and establish their potential utility in simulating complex dynamics in various disciplines social science.

Market competition theory [Smith, 1937] elaborates on how companies and organizations compete for consumer attention and finite resources within a marketplace [Smith, 1937], which plays a vital role in understanding economic dynamics, shaping business strategies, and informing public policy decisions [Hirschleifer, 1978].

In this study, we delve into the applicability of market competition theory by investigating how competition among LLM-based agents influences their learning processes and decision-making mechanisms. Through meticulous empirical study, we have found compelling evidence that when these agents engage in competitive environments, they exhibit substantial enhancements in service quality and capacity to adapt their strategies to meet the diverse and evolving needs of their customers. These findings underscore the importance of embracing customer-centric strategies to achieve success in competitive market landscapes.

6 Limitations and Future Directions

While this study offers a valuable initial exploration of LLM-based agents in a competition scenario, it should be considered a stepping stone for more comprehensive research in this domain. Specifically:

- **Sample Size and Diversity.** Due to the constraints imposed by the GPT-4 API limitations, our experiments did not involve a significant number of restaurants and customers. We see this not as a hindrance but as an opportunity for future research to build upon our work by expanding the number of interacting agents to gain insights into more complex consumer behavioral studies and business decision-making.
- **Text-Based Interactions.** Our current framework leverages GPT-4, the most adept text-based Language Learning Model (LLM), which predominantly relies on textual data. We acknowledge that real-world environments often involve multi-modal interactions and inputs, such as image, video, and audio. As more sophisticated multi-modal LLMs become publicly available on a large scale, we anticipate that future studies could offer a more holistic view.
- **Version-Specific Findings.** The results in this paper are based on GPT-4 version `gpt-4-0613`. We acknowledge that future API updates may affect the results. To facilitate direct comparisons, we recommend utilizing the same API version. Meanwhile, we encourage researchers to adapt and enhance LLM-based frameworks to accommodate the rapid advancements in language model technologies, ensuring the continued relevance and applicability of their findings.

These limitations not only outline the boundaries of the present study but also pave the way for targeted, in-depth research that could further enrich our understanding of machine learning applications in the context of restaurant-customer interactions.

7 Conclusion

We introduced a general framework called CompeteAI to study the dynamics of competition using large language model-based agents. By instantiating the framework as a virtual town with restaurant and customer agents, we extensively explored the competition behaviors of agents. Our study revealed several interesting findings in accordance with classic sociological and economic theories. To conclude, our work confirmed that LLM-based agents can be used for simulating the competition environment, providing research experience for future studies on sociology, economics, and human study.

Disclaimer

We leveraged LLM-based agents to generate plans for running a restaurant or writing a comment. Our study does not output any irresponsible or risky words.

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