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On modelling multi-agent systems based on large language models

Eugeny Yu. Shchetinin[1], Tatyana R. Velieva[2], Lyubov A. Yurgina[3], Anastasia V. Demidova[2]

[1] Financial University under the Government of the Russian Federation, 49, Leningradsky Pr, Moscow, 125993, Russian Federation

[2] RUDN University, 6 Miklukho-Maklaya St, Moscow, 117198, Russian Federation

[3] Sochi Branch of RUDN University, 32 Kuibyshev St, Sochi, 354340, Russian Federation

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Abstract. The article studies the effectiveness of implementation of multi-agent systems based on large language models in various spheres of human activity, analyses their advantages, problems and challenges. The results of the research have shown that multi-agent systems based on large language models have significant potential and wide opportunities in modelling various environments and solving various tasks.

Key words and phrases: multi-agent systems, large language models, society modeling

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1. Introduction

Artificial intelligence has undergone significant changes in the last few years, rapidly moving from basic automation to sophisticated generative models. Large language models (LLMs) such as GPT-4o or Gemini, which can understand and create human-like text, have pushed the boundaries of MAShine learning, enabling unprecedented applications in content creation, customer support, and other areas. These advances have shown how AI can process and interpret vast amounts of data, but it operates within a set of constraints, often lacking the flexibility to adapt in real time [1, 2].

A new paradigm, known as agent-based artificial intelligence (AI), is emerging that has the potential to revolutionize the role of AI: from simply interpreting and responding to prompts to autonomously managing complex tasks. This leap promises a future in which AI not only improves productivity and decision-making, but also autonomously navigates dynamic environments, making it a transformative technology for all fields of application.

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One of the most promising and rapidly growing areas of AI today is the field of multi-agent systems (MAS), as they have the potential to rethink the way MAShines interact and solve complex problems. These systems decline from traditional approaches to AI, allowing autonomous agents to collaborate, communicate, and coordinate their actions to achieve common goals in dynamic environments. From healthcare to finance, logistics to entertainment, MAS are poised to revolutionize a variety of industries through the use of collective intelligence and adaptive behavior.

Traditional large language models, while powerful, have limitations. First, LLMs are trained on huge amounts of data that represent a snapshot in time, limiting their knowledge to the date the training data was collected. Consequently, they are unaware of events and information that have emerged since the last update to the training data, limiting their usefulness in scenarios that require up-to-date data. Additionally, adapting monolithic models like LLMs is a complex and resource-intensive task, as they require significant amounts of data and computational power to fine-tune their behavior.

Another key limitation is that standard LLMs operate without context-sensitive access to user information or databases. For example, if someone queries a model to determine available vacation days, a typical LLM cannot retrieve this information because it does not have access to personalized, secure data. While traditional LLMs can help with tasks such as document summarization or text composition, they are insufficient when users need specific answers based on real-time or customized data sources.

In addition, the structure of LLMs makes it difficult to add components in order to dynamically verify or validate results. Although they can generate answers based on patterns in their data, they cannot autonomously access external databases or tools to validate or augment their answers. This limits their accuracy and flexibility when solving complex problems that may require multi-step solutions using real-world data. Agent-based AI overcomes these limitations by integrating modular components (real-time search tools, logic verifiers, and specialized databases) that extend the capabilities of LLMs beyond static answers. With the flexibility to access external resources and perform complex tasks, agent-based AI combines the language processing capabilities of LLMs with the precision of rule-based programming. This enables AI systems to generate accurate, context-aware answers in a wide range of applications, opening the way to new levels of usefulness and responsiveness [3–5].

The article analyzes problems and challenges of development and implementation of distributed intelligence based on LLM in various social spheres.

2. Multi-agent systems based on large language models

Multi-agent systems (MAS) are a paradigm in which different agents, each with specialized roles, collaborate to achieve common goals. This approach improves problem solving efficiency by providing robustness and adaptability that are difficult to achieve with individual agents. In MASs, agents can be programmed to perform specific tasks and interact with each other, allowing for a decentralized method of solving complex problems. These systems work well in environments where tasks can be distributed among agents with different expertise, allowing for simultaneous execution of tasks and real-time problem solving.

The collaborative nature of MASs is particularly useful in scenarios that require distributed intelligence and decision making. Each agent in the system acts autonomously, but their actions are coordinated to achieve the overall goals of the system. This structure provides flexibility and resilience, as the system can continue to function effectively even if individual agents fail or are removed. In addition, MASs can adapt to changing conditions and requirements, making them suitable for dynamic and complex applications such as logistics, autonomous vehicles, and resource management.

At its core, a MAS consists of multiple autonomous entities, or agents, each with unique capabilities, knowledge, and goals. These agents interact with each other and with the environment, often making decisions based on local observations and rules. Unlike centralized AI systems, where one person makes all decisions, in a MAS, intelligence is distributed across multiple agents, allowing for decentralized decision making and emergent behavior that can adapt to changing conditions [6].

Agent-based AI belongs to systems that have some degree of autonomy, capable of making decisions, planning actions, and learning from experience to achieve specific goals without ongoing human intervention. Agent-based AI systems are designed to possess “agency”, meaning they can autonomously perform tasks on behalf of users or other systems by developing their own workflows and using available tools. Unlike traditional large language models that respond to queries within given parameters, agent-based AI can adapt and learn from new data and user interactions, plan and execute complex, multi-step tasks, interact with external tools and databases, and improve over time through feedback and continuous learning [7, 8].

3. Multi-agent systems based on LLM

The integration of LLM into MAS marks a significant advance in the development and capabilities of MAS. LLM-based MAS leverage LLM’s reasoning, planning, and decision-making capabilities, enabling agents to perform tasks that require a high degree of cognitive processing. These systems can understand and generate human-like text, making them ideal for applications involving natural language processing and interaction. LLM can help agents better understand each other’s goals and strategies, facilitating smoother collaboration and efficient task execution.

LLM-based agents can conduct complex dialogues, interpret contextual information, and make informed decisions based on vast amounts of data. This ability is especially useful in scenarios where agents must understand subtle instructions or collaborate on tasks that require deep reasoning. By using LLM, MAS can improve their ability to solve complex and dynamic problems, providing more robust and adaptive solutions than traditional approaches. This level of collaboration is essential in environments where precise coordination and adaptive response are critical to success [9].

3.1. Topology of multi-agent systems

Topology in the context of MAS refers to the arrangement or structure of different agents in the system and how they interact with each other. This concept is important to understand the communication patterns, coordination mechanisms and overall effectiveness of MAS. Here is a deeper understanding of what topology means and what its implications are. MASs can be divided into different topological types depending on the roles and interactions of the agents. The topology of MAS influences on how agents communicate, coordinate and perform tasks, which affects the effectiveness and reliability of the system as a whole.

3.2. Peer-to-peer topology

In a peer-to-peer topology, agents operate at the same hierarchical level. Each agent has its own role and strategy, but no agent has a hierarchical advantage over others. This topology supports cooperation and competition in achieving common goals without centralized leadership. Decentralized decision-making allows agents to work independently, but still contribute to achieving the overall goals of the system. This approach ensures equal status for all agents, which is especially suitable for problems that require collective decision-making and shared responsibility.

3.3. Hierarchical topology

Hierarchical topologies include a leader and one or more followers. The leader agent is responsible for direction, planning, and strategic decision making, while the follower agents carry out tasks based on the leader's instructions. This centralized decision-making process allows for a clear separation of roles and responsibilities, making it effective in scenarios that require coordinated efforts under the direction of a central authority. The role of the leader agent is critical to ensuring that the overall strategy is consistent and that tasks are aligned with the system's goals.

3.4. Nested topology

A nested topology combines peer-to-peer and hierarchical structures to create a flexible system in which agents can form substructures to solve complex problems. These substructures operate either through peer-to-peer interactions or through hierarchical command chains within the larger system. This dual approach allows agents to leverage the benefits of both peer-to-peer and hierarchical mechanisms to facilitate efficient task execution and coordination. The flexibility of nested topologies allows agents to dynamically create subsystems as needed, increasing the overall adaptability and efficiency of the system [10].

3.5. Dynamic topology

Dynamic topologies are characterized by the roles, relationships, and number of agents changing over time. This inherent adaptability of the system allows it to reconfigure itself in response to changing tasks and conditions. This flexibility is essential for maintaining efficiency and effectiveness in rapidly changing environments. Agents within a dynamic topology can join or leave the system as needed, ensuring the system's resilience and ability to adapt to new tasks.

This high degree of flexibility and adaptability makes dynamic topologies particularly suitable for environments in which task requirements change frequently. For example, in a multi-agent system designed to respond to natural disasters, the number and roles of agents can be changed depending on the situation. This capability allows the system to deploy additional resources or reassign tasks as the disaster scenario evolves, ensuring an effective and coordinated response. The ability to dynamically adapt to new information and circumstances increases the overall stability and effectiveness of the system in managing complex, unpredictable situations [11, 12].

4. Planning in multi-agent systems

Planning in MASs is a critical process that includes both global and local planning. Effective planning ensures that agents can work together effectively, adapt to dynamic conditions, and ultimately achieve the system's goals [13].

4.1. Global planning

Global planning involves understanding the overall task and developing work processes that take advantage of each agent's specialization. This high-level planning phase is necessary to establish the basis for the system operation and ensure that all agents work in concert to achieve the overall goal.

- Task Decomposition: The first step in global planning is to decompose the main task into smaller, more manageable sub-tasks. This requires analyzing the task requirements and breaking them down into components that can be performed by individual agents or groups of agents.
- Workflow Design: Once the tasks have been decomposed, work processes are designed to define how the tasks will be performed. This includes defining the sequence of activities, communication protocols, and the roles of each agent. The goal is to maximize the efficiency and capabilities of each agent by making effective use of their specialized skills.
- Task Allocation: Assigning tasks to agents based on their specialization and capabilities is a critical part of global planning. This ensures that each agent works on tasks that best suit their strengths, resulting in improved overall system performance.
- Alignment with overall goals: Ensuring that individual tasks are aligned with the overall goals of the system is critical. This alignment helps maintain consistency in the system actions and effectively achieve desired results.

4.2. Local planning

Local planning focuses on decomposing the tasks assigned to each agent into manageable subtasks. This detailed level of planning ensures that agents can effectively complete their tasks and contribute to the collective goal.

- Subtask decomposition: Each agent takes its assigned tasks from the global plan and further decomposes them into specific actions that it can perform. This may include detailed planning of the steps, resources needed and expected results for each subtask.
- Execution strategies: Agents develop strategies for effectively completing their subtasks. This includes planning the sequence of actions, optimizing resource use, and scheduling tasks to meet deadlines or milestones.
- Goal alignment: Even at the local level, it is important for agents to ensure that their actions are consistent with the collective goals. Agents must continually adapt and update their plans based on feedback and changes in the environment to stay aligned with the overall goal.

4.3. Planning challenges

To ensure effective planning in MAS, several challenges must be addressed:

- Designing effective workflows: Designing effective and flexible workflows is challenging, especially in a dynamic environment. Workflows must be robust enough to handle uncertainty and adapt to changes in the system or task requirements.
- Iterative processes: Managing iterative processes to improve intermediate results is essential. This includes refining plans based on feedback, optimizing performance through iterative cycles, and ensuring continuous improvement in task execution.
- Coordination and communication: Ensuring effective coordination and communication between agents is critical to the success of the system. Agents must be able to share information, agree on roles, and synchronize their actions to achieve a collective goal.

– Scalability: As the number of agents and the complexity of tasks increases, maintaining effective planning becomes increasingly difficult. The system must scale efficiently to handle a large number of tasks without sacrificing performance and coordination [14].

5. Agent memory and information retrieval

Effective memory management is critical to the operation of MAS. The ability to store, manage, and retrieve information allows agents to work more intelligently and collaboratively. Here, we take a closer look at the types of memory used in MAS and the challenges associated with them.

5.1. Types of memory

Short-term memory is used during the ongoing interaction, is transient, and does not persist after the conversation ends. This type of memory helps agents keep track of the immediate context and perform tasks in real time. For example, during negotiations between agents, short-term memory is used to store the most recent offers and counteroffers, allowing agents to make informed decisions based on the most recent information received from the exchange.

Long-term memory stores historical requests and responses, providing context for future interactions. This type of memory helps agents recall and learn from past experiences, thereby improving their performance over time. For example, a customer service agent can use long-term memory to recall previous interactions with a customer, allowing them to provide more personalized and effective assistance based on the customer's history and preferences.

Integrating large language models with external databases improves the accuracy and relevance of MAS responses. This type of memory allows agents to access vast amounts of information that is not stored internally. For example, agents can use external stores to obtain updated weather or stock price information that is important for decision making but is not stored in their internal memory. With this capability, agents can provide informed and timely responses using comprehensive and relevant data sources [15].

Episodic memory captures interactions within a system and allows agents to refer to past interactions to improve problem solving. This type of memory is similar to human episodic memory, which recalls specific events or episodes. For example, in a multi-agent system designed to respond to emergency situations, agents can use episodic memory to recall past emergency scenarios and apply the lessons learned to current situations. This ability allows agents to use historical data to improve decision making and performance in a dynamic and complex environment.

The consensus memory in a MAS serves as a single source of common information for agents, ensuring consistency and smooth interaction. This is essential for maintaining a common understanding and coordinated actions across the entire system. For example, in a collaborative robotics system, the consensus memory ensures that all robots have the same map of the environment and understand their respective tasks and positions. This common knowledge base allows agents to work together to make informed decisions that contribute to the overall efficiency and effectiveness of the system [16].

5.2. Memory management issues

– Hierarchical Storage: Managing a hierarchical storage where different agents have different levels of access and needs can be complex. Ensuring that sensitive information is protected while providing the necessary access to the relevant data requires robust access control

mechanisms. Implementing multi-level access control and encryption can help manage multi-level storage effectively and ensure that only authorized agents have access to sensitive information. This approach ensures the protection of critical data while maintaining the efficiency and functionality of the system by providing agents with appropriate access according to their roles and requirements.
- Maintaining the integrity of the consensus memory: Ensuring the integrity of the consensus memory is very important as any tampering or unauthorized changes can lead to system failures. Maintaining a consistent and accurate consensus ledger is essential for effective collaboration between agents. The use of distributed ledger systems can ensure a secure and immutable record of shared information, thereby enhancing the integrity of the consensus memory. This approach ensures that all agents have access to reliable and tamper-proof data, which is necessary for coordinated and efficient operations in the system.
- Effective communication and information sharing: Ensuring effective communication and information sharing between agents is necessary for coordinated actions, since miscommunication or data loss can disrupt the operation of the system. Developing reliable communication protocols and redundancy mechanisms can ensure reliable information sharing and reduce the risk of miscommunication. This approach helps maintain the integrity and efficiency of the system, allowing agents to effectively collaborate and achieve common goals despite possible communication problems.
- Use of episodic memory: Effective use of episodic memory to improve responses to new queries requires retrieving and using contextually relevant past interactions, which requires sophisticated algorithms to accurately match current queries with past experiences. Advanced machine learning techniques, such as memory-enhancing neural networks, can help agents effectively recall and apply past experiences to new situations. This approach allows agents to improve their decision-making and problem-solving capabilities by drawing on a rich history of relevant interactions, resulting in more informed and effective responses.
- Scalability and efficiency: As the number of agents and task complexity increases, maintaining effective memory management becomes increasingly challenging. The system must scale to handle larger volumes of data and more complex interactions without degrading performance. Scalable storage architectures and distributed storage solutions can support the growth of MAS, ensuring that the system remains efficient and effective as it expands. This approach allows the system to cope with increased demands while maintaining high performance and reliability, ensuring smooth operation in increasingly complex and data-rich environments [17, 18].

6. Bringing agent-based AI to industry

One of the main reasons why agent-based AI is a breakthrough in AI research is its ability to combine flexibility with precision. LLMs excel at processing and generating human-like text, making it easy for users to interact with AI using natural language commands. They can generate responses or actions based on subtle, context-sensitive understanding, which is useful in scenarios where traditional programming may not be able to handle all possible situations. Traditional programming, on the other hand, offers structured, deterministic algorithms that are ideal for tasks that require precision, repeatability, and verifiability. Agent-based AI systems leverage the flexibility of LLMs to solve problems that require dynamic responses, while relying on traditional programming to provide rigorous rules, logic, and performance. This combination allows AI to be both intuitive and precise [18].

Autonomy is another distinctive feature of agent-based AI systems. They can operate independently and autonomously perform certain tasks without the need for constant human supervision, enabling continuous operation in environments where human supervision is limited or unnecessary. Autonomous systems can support long-term goals, manage multi-stage tasks, and track progress over time.

6.1. Autonomous management of marketing campaigns

An agent-based AI tasked with managing a marketing campaign can autonomously perform various stages of campaign management, from content creation to performance analysis. For example, an agent might start by developing targeted content based on audience data and recent engagement trends. It would then distribute that content across multiple platforms–social media, email, or websites – and track the campaign's performance in real time. As engagement data comes in, the AI can dynamically adjust its strategy, such as shifting budget to more effective channels or changing the tone of messaging to resonate with a specific demographic. If a certain ad format is underperforming, the AI can replace it with a more effective one. This capability not only optimizes campaign results, but also allows marketers to focus on creative strategy and innovation. The agent can work continuously, ensuring that the campaign always aligns with business goals and adapting in real time to maximize ROI.

6.2. Monitoring health status and adjusting treatment in real time

In healthcare, agent-based AI could be a game changer in patient care by continuously monitoring a patient's vital signs, medication adherence, and other health metrics. For example, an agent could track data from wearable devices, such as heart rate, blood pressure, and oxygen levels, and compare these metrics with historical data and clinical guidelines. If any metrics fall outside safe parameters, the agent could alert medical staff or automatically adjust the treatment plan, such as increasing medication dosage or recommending diagnostic testing.

For chronic conditions such as diabetes, an agent can continuously analyze blood glucose levels and suggest dietary adjustments to the patient in real time. By autonomously monitoring patient data and providing clinicians with actionable insights, agent-based AI supports proactive and responsive treatment, potentially improving patient outcomes and reducing hospital visits. It allows healthcare professionals to focus on complex and sensitive care while the AI handles routine monitoring and adjustments [19].

6.3. Autonomous cybersecurity surveillance and threat response

In the cybersecurity space, agent-based AI can act as a vigilant and tireless guard, constantly monitoring network traffic, system logs, and user behavior for potential threats. For example, an agent can monitor access patterns to a company's systems, identifying any unusual activity that might indicate phishing attacks, malware intrusions, or unauthorized access attempts. If a particular user's behavior deviates significantly from the norm—such as multiple failed login attempts or accessing sensitive data outside of normal hours—the AI can flag this as suspicious and immediately initiate security protocols.

Additionally, AI can analyze incoming network traffic for signs of distributed denial of service (DDoS) attacks, blocking potentially malicious IP addresses in real time. When a threat is detected, AI can autonomously deploy countermeasures, such as isolating affected servers or restricting access to compromised accounts. This level of autonomous threat response allows organizations to maintain robust security even in the face of rapidly evolving cyber threats, while requiring minimal human intervention for routine security monitoring [12, 20].

7. Discussion

However, as exciting as the prospects of agent-based AI are, they are not without problems. Ethical considerations, such as ensuring that these systems make decisions in line with human values, are paramount. The complex nature of AI models can make decision-making processes difficult to understand and interpret, creating accountability and trust issues, especially in high-stakes applications. There is also the question of liability – who is responsible if an agent-based AI makes a mistake? Data privacy and security are another major concern as these systems become increasingly autonomous and handle increasingly sensitive information. Robust safeguards are needed to protect against misuse or security breaches.

While agent-based AI promises transformative applications across industries, it also poses challenges related to trustworthiness. The accuracy and reliability of the information provided by AI agents ideally requires human oversight, but with agent-based AI, this oversight can be compromised. This challenge arises from the probabilistic nature of large language models, which are inherently non-deterministic and can sometimes produce "hallucinations" – answers that seem plausible but are actually incorrect. If data sources are limited or if the wrong processing step occurs, agent-based AI can generate unfounded assumptions or misleading answers. These inaccuracies are especially problematic in sensitive areas such as healthcare or legal advice, where accurate and verified information is important for ensuring safety, compliance, and overall trust.

8. Conclusion

Multi-agent systems exhibit remarkable collective intelligence and the ability to adapt to changing conditions, making them useful for solving complex problems and modeling social processes. Despite the existing problems, the potential benefits of agent-based AI are too great to ignore. As research in this area advances, we can expect to see increasingly sophisticated AI agents that can collaborate with humans in ways we have only seen in science fiction. The key to harnessing the full potential of agent-based AI lies in striking the right balance between autonomy and human control. Thoughtful design of such systems and careful consideration of ethical implications will enable us to create AI agents that complement human capabilities rather than replace them.

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Information about the authors

Shchetinin, Eugeny Yu.—Doctor of Physical and Mathematical Sciences, Lecturer of Artificial Intelligence Department (e-mail: riviera-molto@mail.ru, ORCID: 0000-0003-3651-7629, ResearcherID: O-8287-2017, Scopus Author ID: 16408533100)

Velieva, Tatyana R.—Candidate of Physical and Mathematical Sciences, Senior lecturer of Department of Probability Theory and Cyber Security (e-mail: velieva-tr@rudn.ru, ORCID: 0000-0003-4466-8531)

Yurgina, Lyubov A.—Ph.D. of Pedagogical Sciences, Head of the Department of Mathematics and Information Technology of the Sochi branch of RUDN University (e-mail: yurgina_la@pfur.ru, ORCID: 0009-0004-4661-5059)

Demidova, Anastasia V.—Candidate of Physical and Mathematical Sciences, Assistant Professor of Department of Probability Theory and Cyber Security (e-mail: demidova-av@rudn.ru, ORCID: 0000-0003-1000-9650)

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О моделировании мультиагентных систем на основе больших языковых моделей

Е. Ю. Щетинин[1], Т. Р. Велиева[2], Л. А. Юргина[3], А. В. Демидова[2]

[1] Финансовый университет при Правительстве Российской Федерации, Ленинградский проспект, д. 49, Москва, 125993, Российская Федерация

[2] Российский университет дружбы народов, ул. Миклухо-Маклая, д. 6, Москва, 117198, Российская Федерация

[3] Сочинский институт (филиал) Российского университета дружбы народов, ул. Куйбышева, д. 32, Сочи, 354340, Российская Федерация

Аннотация. В статье изучается эффективность внедрения мультиагентных систем на основе больших языковых моделей в различных сферах человеческой деятельности, анализируются их преимущества, проблемы и задачи. Результаты исследования показали, что мультиагентные системы на основе больших языковых моделей обладают значительным потенциалом и широкими возможностями в моделировании различных сред и решении различных задач.

Ключевые слова: искусственный интеллект, финансовые риски, большие данные