AI Assistants and Agents in Geographic Information Systems

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Abstract. This Ph.D. project focuses on the design, implementation, and evaluation of an AI Assistant for Geographic Information Systems (GIS). This assistant will interpret and execute GIS tasks based on natural language descriptions, directly addressing the critical shortage of GIS specialists in municipal councils, particularly in Portugal. The aim is to empower non-expert users to autonomously perform essential GIS tasks while also providing advanced support for experienced professionals. The research methodology encompasses the development of a prototype AI Assistant, the fine-tuning of a language model for GIS-specific operations, and the establishment of a comprehensive evaluation framework to assess its effectiveness and efficiency. Furthermore, this project will lay the foundational groundwork for an AI Agent capable of autonomously performing more complex GIS tasks, extending beyond user assistance. The expected results include a functional AI Assistant prototype, a robust training framework and dataset, and a detailed evaluation demonstrating its utility in real-world GIS scenarios.

1 Introduction

Geographic Information Systems (GIS) are frameworks for gathering, managing, and analyzing data rooted in location. They are invaluable for urban planning, environmental monitoring, and resource management, enabling informed decision-making through spatial data analysis. However, an observed challenge in municipal councils, particularly in Portugal, is the shortage of GIS specialists, as noted by experts, including my supervisors. This shortage hinders the effective use of GIS technologies, leading to inefficiencies and missed opportunities for data-driven decision-making. AI Assistants and Agents, powered by language models (LMs), present a promising solution to bridge the knowledge gap for non-GIS experts, enabling them to perform necessary tasks independently through natural language interaction. For GIS-expert users, these AI-driven systems can also serve as powerful aids in performing more complex and specific tasks.

Therefore, the research question guiding this project is as follows.

How can a language model-based AI Assistant and Agent interpret and execute tasks within GIS platforms, and what is its effectiveness and efficiency?

2 AI Assistants vs AI Agents

Before moving on to the details of the project, it is important to clarify the distinction between AI Assistants and AI Agents, as we have found different definitions of these terms. For this project, we will use the definitions proposed by IBM [10], because in our opinion they seem to be the most comprehensive and clear.

An AI Assistant, powered by an LM, is a system characterized by its conversational AI interface, the need for an initial prompt and ongoing user input to perform tasks, and task specialization through fine-tuning. However, it is only capable of taking actions explicitly stated in the prompt, such as drafting an email or summarizing a document, rather than independently deciding to perform related unprompted tasks. Besides that, the adaptation and evolution of the assistant are only possible with the release of new versions.

Conversely, an AI Agent only needs an initial prompt to initiate a sequence of actions by identifying tasks, breaking them into subtasks, and orchestrating the execution of these tasks by invoking the necessary external tools. An AI Agent is composed of four main components: the *LM "Brain"*, which manages the entire workflow; *Memory* which is subdivided into *short-term* and *long-term* memory allowing the agent to continually learn; *Tools* which are external tools that the agent can invoke to perform tasks; and *Planning* which breaks down tasks into actionable subtasks.

3 State of the art

Through a systematic literature review, which will be submitted to an international journal, we could identify two predominant collaborative author clusters in the field of AI Assistants and Agents for GIS. The first cluster, with the China University of Geosciences (Wuhan, China) as a common affiliation, is responsible for publishing [24, 27, 28, 29, 30, 31]. The second cluster, primarily associated with The Pennsylvania State University (University Park, USA), published [16, 22, 1, 2, 20].

As the main findings of the literature review:

- **AI Assistants:** The first cluster of authors, with a fine-tuned Small Language Model (SLM), was able to achieve a performance equivalent to a Large Language Model (LLM) for GIS-knowledge tasks [29][2]. If this finding can be generalized to other domains, it could significantly reduce the computational costs associated with using LLMs, making AI Assistants more accessible and efficient, without a significant loss in performance.
  Regarding the most common use cases, assistants are being developed and tested for code generation [17, 11, 8, 5], chatbots in geoportals [14, 15, 25], and retrieval of location-based information from text [9, 13, 7].

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[2] To differentiate between SLMs and LLMs, we will use Microsoft's definition, which sets the threshold at 10 billion parameters [18].

- **AI Agents:** There is not yet a fully AI Agent for GIS, based on the definitions presented in Section 2, but efforts are being made towards that. The *Planning* component is the most explored so far, which in our view is understandable given the current model context length limitations for the *Memory Component* and being one of the first steps in an agent workflow [26, 19, 16, 6, 30, 24, 28]. Additionally, the *Tools Component* is also being explored, with a focus on integrating GIS-specific tools into the agent workflow [20, 2, 16].

Regarding the trends in the development of these AI Assistants and Agents, is the predominance of the use of *self-instruction*, proposed by Wang et al. [23], to overcome the scarcity of human-labeled training data in the fine-tuning process. This framework consists of using LMs to generate synthetic data and gaining notoriety after Taori et al. [21], demonstrating that it can be used to fine-tune SLMs for specific tasks with a performance comparable to that of LLMs, despite the significantly smaller size of the SLMs. This was the approach used by the first cluster of authors in the previously mentioned work [29]. In addition to that, identical results were achieved by Wei et al. [24], Hou et al. [8], Zhang et al. [28, 31].

Although *self-instruction* presents a promising approach to address the scarcity and cost associated with creating high-quality human-annotated data for fine-tuning, several measures were implemented to mitigate LM hallucination or inaccurate content. Examples include prior expert refinement to address inaccuracies or incompleteness in the generated data [31], the removal of low-quality instructions [29, 31], and restricting the model context to a specific domain [29].

3.1 Research Gaps

Two main research gaps were identified in the literature review:

- **Model Context Protocol (MCP) and Agent2Agent (A2A)**: These two protocols, proposed by Antrophic [3] and Google [4] respectively, are designed to enhance the interoperability of AI Agents across different platforms and domains. However, they have not yet been applied to GIS. Given that these protocols were launched this year, we anticipate an initial wave of research in this area for GIS.
- **Reinforcement Fine-tuning (RFT):** A potential alternative to *self-instruction* that does not involve synthetic data generation and that is not being used in the literature. RFT is a technique that enables LMs to learn from user interactions by adapting responses based on feedback, with the primary challenge being the definition of an appropriate reward function. This can be achieved automatically through a reward model or by employing a specific RFT technique known as *Reinforcement Learning from Human Feedback* (RLHF) ([12]), which, as its name suggests, uses human feedback to learn and adapt to user preferences. Notably, only [17] has indicated plans to explore RLHF in future research.

Although the integration of these research gaps will depend on external collaborations and their defined use cases, we will keep them in mind for future project relevance. For example, MCP could connect the AI Assistant to GIS databases or processing software, and RFT could lead to a personalized assistant that adapts to user workflows.

4 Expected Results

The expected results of this PhD project include:

- **An AI Assistant for GIS Platforms:** This assistant will be powered by a specialized, potentially fine-tuned, language model for GIS operations. Users will interact with it via a user-friendly interface, initially through text and later potentially through voice. It will be able to perform tasks like generating graphs from datasets and creating reports from spatial data. The specific functionalities will be further defined through collaboration with a municipal council.
- **A Training Framework and Curated Dataset:** To effectively fine-tune the language model, we'll establish a thorough training framework. The specific dataset composition and types will be determined in partnership with a municipal council, focusing on real-world applicability (e.g., vector data, raster data, geospatial databases, or specific municipal records). We will also explore *self-instruction* for generating synthetic data if real labeled data is scarce. Our approach will involve comparing different language models and fine-tuning strategies to identify the most effective combination.
- **An Evaluation Framework:** A rigorous evaluation framework will be established to quantitatively and qualitatively assess the AI Assistant's effectiveness and efficiency in executing GIS tasks. This framework will incorporate established metrics from the literature for measuring key performance indicators such as accuracy of task execution, user satisfaction, and time efficiency.
- **Foundational Work Towards an Autonomous AI Agent:** Building upon the success of the AI Assistant, this project will undertake initial steps toward extending the previous results to an AI Agent. This agent should possess the capability to autonomously perform more advanced GIS tasks, including breaking down complex problems into subtasks, orchestrating the use of multiple GIS tools, and self-correcting its operations.

5 Conclusion

The first year of this Ph.D. project has been dedicated to conducting a systematic literature review, which has provided valuable insights into the current state of AI Assistants and Agents in GIS. Furthermore, exploratory contacts with potential external partners have been initiated to explore the possibility of collaboration in the development and evaluation of the AI Assistant prototype in real-world scenarios. The following years of this project will be dedicated to the development of the expected results.

During the all project, we will follow the latest trends in the literature and industry to ensure that the developed AI Assistant is aligned with the most recent advancements in the field. Additionally, we will also undertake a continuous learning process through several online courses to deepen our understanding of the underlying technologies and methodologies used in the development of AI Assistants and Agents.

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