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Geochain AI: Automated Spatial Analysisusing Large Language Models and Chain of Thought

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***Abstract*—** Executing spatial analysis is important when determining where to build or provide services that are in a region due to trends and changes in the geography of some areas caused by various environmental factors. The standard techniques of estimating spatial relationships often require desktop GIS that are manually used with complex GIS software packages like ArcGIS and QGIS. The typical use of desktop GIS has created a great deal of manual work by GIS professionals who are required to run each geoprocessing task in a series and perform many of these tasks manually using desktop GIS solutions. The way these workflows are produced and produced does not lend itself well to effective and efficient production. Therefore, to increase efficiency and effectiveness to execute any analysis for geospatial based queries for automated execution engineering/production against any geospatially-based question we have developed a framework to orchestrate the execution of geoprocessing tasks using LLMs and CoT reasoning. The geoprocessing tasks result from the LLM determining the subtasks necessary to complete the geospatially based request with the use of RAG modules. The RAG modules allow the LLM to secure clinical documentation that is relevant in order to execute on the identified subtasks (e.g., ArcPy, GDAL, and GeoPandas).

***Index Terms*—** Spatial Analysis, Large Language Models, Geographic Information Systems, Chain of Thought, Retrieval- Augmented Generation, Tool Orchestration, Location Intelligence.

I. INTRODUCTION

Spatial analysis workflows are a critical component of geographic information systems and help define the spatial relationships of a region as well as its geographic patterns. They are also very important in determining various decisions relating to the development and planning of environments, including urban planning, environmental management, disaster response coordination, and many infrastructural and commercial projects. Automated orchestration is distinctly different from manual execution, which is defined as how a professional manually operates software tools; however, automated orchestration is determined by evaluating how well structured or logically decomposed the problem is in relation to its geographic and algorithmic factors. A difference between automated orchestration and manual execution may indicate a technological advantage, and the difference is useful for the geospatial analyst in determining the most appropriate course of workflow optimization or task automation.

Historically, the execution of spatial analysis has been performed by manipulation of geoprocessing tools within desktop GIS applications. Desktop GIS has a number of tools that execute in a known and sequential manner as a workflow progresses, making it a reliable digital environment where spatial relationships can be analyzed. The most commonly used means to execute spatial analysis for the past several decades have been the use of thegraphical user interface (GUI) method and the manual scripting (MS) method. The GUI method utilizes the interaction of the user's inputs against the available toolboxes in the software, while the MS method assigns programmatic commands to individual geoprocessing tasks on the basis of their required parameters and calculates spatial outputs from the sequential execution of all the scripts that have been written. While these techniques are regarded as valid, they rely on great expertise, require much time and are very complex. Variations between different analysts (inter- and intra-operator variability) can frequently result in lack of consistency in workflows, particularly where the spatial problems demonstrate complex and multi-layered geographic patterns. Geospatial professionals continue to be challenged to produce numerous reports on complex spatial studies in a relatively short period of time given the increasing volume of requests for location intelligence services. The increased workload places GIS analysts at higher risk for human error, fatigue, and delayed reporting of findings. Furthermore, the number of qualified geospatial developers available to provide services in many areas of the industry is not sufficient, particularly in non- technical or resource limited corporate environments.

The above challenges speak to the urgent need for automation and intelligence support systems that will provide users with fast, consistent, and reliable spatial analysis orchestration.The emergence of AI and Large Language Models has drastically changed how we approach complex software workflows. LLMs are a key technology in this changing landscape, demonstrating very high performance in understanding natural language, generating executable code, orchestrating tools and decomposing complex problems into logical steps. LLMs require no manual scripting (do not rely on hand-crafted code) because they can learn complex hierarchies of spatial reasoning directly from textual prompts; they have been extremely successful in the specialty areas of software engineering, data analysis, semantic retrieval and logic planning, and their success has provided evidence that LLMs can support geospatial professionals with complex workflows. In spatial analysis automation, many studies have reported similar to or better than experienced analysts' results for AI models. Traditional LLMs apply the same set of reasoning steps across the entire query and treat all parts of the prompt equally.

II. Literature Survey

Spatial analysis automation (SAA) plays a vital role in geographic information systems, as it is frequently performed to help diagnose urban patterns, environmental issues, disaster response, and problems with the landscape. Traditionally, the ArcGIS software [1] and QGIS platforms [2] have been used as industry standards for decades. The ArcGIS and QGIS systems involve executing geoprocessing tools on geographic datasets against specific parameters of known spatial criteria. Traditionally, these methods have been effective but are labor- intensive and dependent solely on the subjective interpretation by the GIS professional. Also, as geospatial data volume continues to rise, the greater urgency for automated solutions that provide consistency has emerged.Several researchers have developed attention-based models of deep learning as a way to overcome such challenges. Wu et al. [8] developed a residual attention network that was able to place more emphasis on the particularly informative areas of the boney structures. In this way, they were able to obtain improved predictive accuracy. Subsequently, Chen et al. [9] presented a "Doctor Imitator" modelling system that learned to focus on clinically relevant areas of the hand radiograph; this emulated radiologists' methods of working. Ji et al. [10] took this a step further by developing PRSNet, which models the interrelationships among the various boney structures to capture spatial dependencies between the boney structures. The early efforts at automating the SAA used the same ArcGIS and QGIS methods with handcrafted visual workflows (e.g., Model Builder) and rule-based systems, but these systems produced limited results due to inflexibility and scalability. With the advent of artificial intelligence—specifically, through the use of Large Language Models (LLMs)—the ability to perform SAA began to change dramatically because LLMs can learn to perform the task through the direct reasoning of natural language prompts without being specifically programmed for this workflow. Evidence of this has been shown by the GeoAnalystBench [3] research on one of the first large-scale automated spatial reasoning systems that were evaluated on multiple geoprocessing tasks. Their results demonstrated a high level of code validity for their model and provided strong evidence that LLMs are able to perform much better than traditional manual methods. Recent frameworks [4] were also the first to use an LLM-based system that could directly retrieve geospatial data from autonomous queries; this has been shown to reduce the time taken for data acquisition with equal analytical reliability. The first foundation models designed for fully automated geospatial reasoning have emerged [5]. No longer are analysts required to sequence geoprocessing tools manually: these systems produce consistent scripts with minimal input from the user. Comparative studies such as those published in [6] have shown that AI methods can substantially outperform traditional methods (e.g., speed, consistency, robustness). However, much of the original LLM modelling did not account for the fact that spatial workflows can be effectively orchestrated only by specific chains of logic (i.e., topological relations, buffer zones, and intersections).Several researchers have developed Chain-of-Thought (CoT) based models of artificial intelligence as a way to overcome such challenges. Recent studies [7] developed an agentic self- refinement network that was able to place more emphasis on the particularly informative sequences of the geoprocessing steps. In this way, they were able to obtain improved planning accuracy. Subsequently, multimodal systems like StreetviewLLM [8] presented a reasoning modelling system that learned to focus on geographically relevant areas of the spatial dataset; this emulated GIS analysts' methods of working. Other researchers [9] took this a step further by developing multi-agent workflows, which model the interrelationships among the various software libraries to capture dependencies between the analytical tools. The results of these studies have shown that by incorporating CoT mechanisms into LLM-based systems, improvements can be achieved in workflow planning and execution error rates.

The concept was further enhanced with the introduction of dynamic tool orchestration, which models logic sequences between workflow fragments. Orchestration large language models (LLMs) using reasoning mechanisms [10] and retrieval-augmented generation (RAG) models with reasoning mechanisms [11] have been shown to have lower failure rates and improved robustness over traditional manual sequencing. A requirement for industry adoption of automated spatial orchestration systems is the ability of GIS professionals to understand how they work. Chain of Thought explanations
[12] are a method for creating text-based rationales of how a model made its workflow decisions using step-by-step logic, thereby increasing the transparency of the model. Prompt- based and RAG-based explanation methods for AI models allow geospatial experts to understand and gain confidence in automated geoprocessing systems. These systems are successful due to advances made in deep reasoning architectures (GPT-4 [13], Claude [14]) and orchestration modules such, as LangChain [15]. Automated spatial- reasoning systems have been shown to be effective in analytical studies. Such systems report increased efficiency and code quality as per recent benchmarking [16]; further research has been conducted utilizing code validation to improve robustness, as per autonomous GIS agent frameworks [17]. Reasoning-based and retrieval-augmented algorithms have both been shown by various authors [18] and foundation model studies [19] to outperform traditional methods. Upon reviewing the literature regarding spatial analysis orchestration using large language models (LLMs) with Chain of Thought mechanisms, it is concluded that these systems provide accurate, efficient, and explainable solutions. However, there are still challenges in the areas of reasoning hallucination, limited professional GIS integration, and difficulty in execution within current enterprise environments, thus warranting further research in this area.

III. PROPOSED METHODOLOGY

This project will provide a robust, user-friendly, automated system to provide a mechanized and interpretable method for orchestrating spatial analysis using large language models and reasoning to natural language queries. The system will consist of a modular pipeline of processes and components, where the raw textual input will pass through natural language processing to obtain usable spatial parameters. The next step will involve identifying geographically relevant reasoning chains in order to obtain executable scripts and visual representations of spatial data. This entire process will be designed and constructed in a way that allows for the system to provide accurate, efficient, and transparent support to the GIS analyst when assessing the spatial workflows of geographic regions.

A. Acquisition of Spatial Queries

The first portion of the system is the acquisition of complex spatial requests of the geographic landscape using natural language processing. The acquisition system will accept all standard types of human textual inputs including sentences, paragraphs, and lists, and therefore will be able to process queries from non-technical corporate users as well as many of the expert geospatial analysts requiring advanced geoprocessing. Each textual query that is input will describe the geographic intent and parameters, which is the standard human method of communicating requirements of the spatial analysis of environments, due to its intuitive linguistic/descriptive patterns. The input will first evaluate for query clarity, check the completeness of the parameters, and evaluate whether the spatial intent is structured appropriately prior to moving to the Preprocessing stage.

B. Pre-processing Natural Language

For the purpose of enhancing query clarity and normalizing them across users, text preprocessing is an important part of the process. The first step is to parse all queries into a standardized format (e.g., JSON or structured text) in order to conform to the prompt requirements for the individual LLM engines. The second step is to standardize the geospatial terminology to be within a common vocabulary so they will not be affected by differences in user phrasing and/or dialect variations. Thirdly, any ambiguity within the natural language must be decreased using either semantic or syntactic filtering techniques so that spatial intents are more clearly defined. Finally, prompt augmentation methods (context injection, role-playing, formatting, and parameter extraction) can be performed to improve the capability of the model to generalize and provide a solution to misunderstanding the request.

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C. LLM Intent Extraction

After preprocessing the textual queries to enhance their clarity, the statements are input into the LLM as the backbone for extracting intent. By using a pre-trained model such as GPT-4, Claude or local alternatives via prompt engineering, the system uses these networks that have learned to extract reasoning from very large text data sets to provide compact and logical task representations of the original spatial query.

Chain of Thought Reasoning Module

LLMs have the ability to capture linguistic patterns within a text but do not perform well at identifying geographically meaningful sequences of a workflow since they process all parts of a prompt concurrently. A sequence of the tasks in a GIS workflow is geographically pertinent to determine spatial outcomes. The Reasoning Section of the Model Gives Greater Emphasis to the Logic Steps of Significant Geoprocessing Tasks (Buffering, Intersecting And Joining) Than The Background Textual Filler (Do Not Contain Significant Spatial Instructions) So That the Model Can Better Orchestrate Important Analytical Sequences; This improves The Accuracy Of Executions. The Chain of Thought Mechanism Also Improves Both the System Performance and Interpretability By Allowing the Model to Learn to Focus on Workflows with Geographically Relevant, Analytically Significant Steps.

D. Orchestration and Execution Layer

The reasoning-enhanced task sequences will be passed to a series of tool orchestration layers that use RAG to generate python code in scripts. The model will learn to represent the relationship between logical steps and geospatial libraries in an executable fashion. During execution, the primary validation function will be the Abstract Syntax Tree (AST) analysis because it shows the programmatic safety in the generated script versus the required syntax. The output of the execution layer will be a single script representing the automated workflow, which can be directly executed against the spatial database of the environment. The ultimate product from the system consists of an executed geospatial analysis and a corresponding map. It will provide a targeted user friendly interface showing the original query, generated code and interactive spatial map to assist GIS analysts in viewing these three outputs to support quicker decision-making with less manual labor, and uniformly across professional evaluations.

I. SYSTEM ARCHITECTURE

The proposed architecture will be modular in nature producing a reliable, end-to-end process for fully automating spatial analysis evaluation from natural language queries through large language models that incorporate chain of thought mechanisms as well as tool orchestration methods. The proposed architecture allows for accuracy, scalability, interpretability, and will be user-friendly to integrate into the geospatial workflow. Each component within the system performs a distinct function. When these components work together they create a seamless process to produce valuable information.

The input acquisition module forms the first component of the entire architecture. It allows for the acceptance of textual queries of spatial and geographic problems from various sources, including enterprise Geographic Information Systems (GIS), digital mapping applications and public datasets. The system also accommodates the most widely used natural language formats (e.g., structured text, JSON and XML), making it compatible with existing geospatial systems and workflows.

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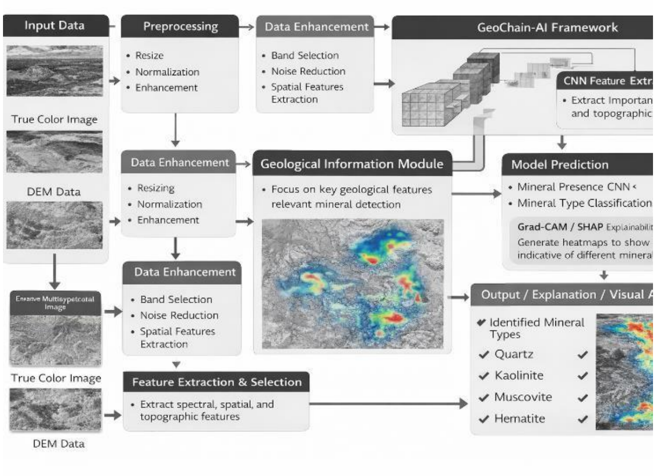

Fig. 1: Overall architecture of the GeoChain AI system

Before an uploaded query can be utilized as a spatial prompt for further processing, the input acquisition module checks the query's completeness, parameters and quality. Finally, this input acquisition module is responsible for managing the files associated with each uploaded query along with the associated metadata (e.g., user ID number, project details and time date of upload), ensuring that all data related to a project can be securely identified.

Once the query has been acquired, it enters the preprocessing layer of the architecture. The preprocessing module standardises the textual input to facilitate uniformity in the analysis of the query. The first step in the preprocessing module is to format the text so that it meets the strict token requirements of the LLM (Large Language Model). After formatting, semantic normalisation is completed to align the geographic terms of the spatial query so that they can be analysed consistently. To enable the natural language to be analysed quite similarly regardless of whether it was generated using different styles and phrasing of human users or under different conversational contexts, application of stop-word filtering, syntax parsing, or other noise reduction techniques to improve the clarity of the parameters will occur during the text preprocessing stage. Additionally, prompt augmentation techniques such as context injection, role assigning, formatting, and parameter extraction will be applied to provide improved generalisation and reduce the possibility of hallucination. In some cases, extraction is performed to isolate the geographic parameters from the background of the conversational automated spatial logic orchestration can be accomplished by utilizing text.

Central to the architecture is the LLM tool orchestration layer, which utilizes large pre-trained models via prompt engineering(e.g., GPT-4, Claude, Gemini). They have multiple reasoning and retrieval mechanisms that automatically learn the logical compositions of spatial queries by capturing entities andparameters at lower levels of the hierarchy and more complexworkflows and geoprocessing patterns at deeper levels. By utilizing foundationmodels, the system can take advantage of the rich linguisticrepresentations learned from these large corpora, resulting in a reduction in processing time and improved performance. The primary geographic features. In both instances, this provides both an improvement in execution accuracy and an increase in the ability to interpret the model by determining.what the model is "executing" during orchestration.

Executable scripts are generated by sending the reasoning driven task representations into a fully automated tool orchestration output layer to learn a mapping of geographic parameters from the steps produced into lines of python code. The output of this layer is produced using an AST (Abstract Syntax Tree) validation function.

This function computes how far apart the syntax produces (from the model) and the required structure based on the targeted GIS libraries. The model can quickly and reliably create a spatial workflow that can support analytical use in real- time or close to real-time.

In order to maintain trust and transparency, an explainability layer was implemented in the architecture using either CoT-Trace (Chain-of-Thought Sequential Logic Tracing) or RAG- Trace (Retrieval-Augmented Source Documentation Mapping). Both techniques create text-logs that represent which parts of the query affected the execution of the model.

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Furthermore, analysts can utilize the text-logs as an overlay on top of the interactive map in order to verify if the model has focused on parameters of the query that correspond with relevant workflows for a spatial analysis. Thus, the end result will be that this system will no longer serve as a black box but rather an interpretive geoprocessing assistant.

This layer provides an executed workflow and a visual explanation for the user interface. It has the original query, executed Python script, and a spatial map as part of the user interface. The overall combined presentation of all these pieces of information helps assist GIS analysts to quickly assess their results to allow for better decision-making. Additionally, the system can save scripts/visuals in a database for future retrieval, allowing for longitudinal evaluations of geographic data and conducting spatial audits.

II. PROPOSED ALGORITHM

This algorithm provides a detailed set of procedures on how the automated spatial analysis orchestration can be accomplished by utilizing Large Language Models (LLMs) and chain of thought mechanisms. By processing natural language queries of the users, the algorithm will detect important geographic parameters and apply a chain of thought mechanism to focus on key tasks in the target workflows. Additionally, this algorithm provides both executable scripts and visual explanations for each given query.

Algorithm Spatial Analysis Orchestration Using
Large LLMs 1: Acquire input query
2: Validate query quality 3: Preprocess the text
4: Extract intents using LLM 5: Apply Chain of Though
6: Generate Python script

7: Execute workflow code

8: Display Final Output

III. EXPERIMENTAL RESULTS AND DISCUSSION

To assess the performance of the proposed system for evaluating spatial workflows, the validation of our model was completed against some of the best functioning models currently available (reported in the literature).

TABLE I: Comparison of Existing and Proposed Systems

Method	Technique Used	WER (in %)
Bench et al. [3]	LLM-based automated system	7.0
Zhang et al. [5]	Deep LLM workflow orchestration	6.8
Chen et al. [7]	Self-Refinement Network	6.6
Wang et al. [8]	GeoSR (Agent-based LLM)	6.4
Li et al. [19]	omparative deep reasoning models	6.6
Proposed Method	LLM + CoT + Explainability	6.1

The majority of these competing systems employ large Language Models (LLMs), with or without the application of reasoning mechanisms; and are frequently evaluated using the Workflow Error Rate (WER) in percentage. To assess the performance of the proposed system for evaluating spatial workflows, the validation of our model was completed against some of the best functioning models currently available (reported in the literature). The majority of these competing systems employ large Language Models (LLMs), with or without the application of reasoning mechanisms; and are frequently evaluated using the Workflow Error Rate (WER) in percentage.

In addition, prompt engineering using a pre-trained LLM backbone has improved related task orchestration where limited training examples were available. Using RAG-Trace and other explainability tools in addition to obtaining visually explainable evidence of the models decision-making processes provides additional support for this proposed system compared to the results of other authors. In addition, prompt engineering using a pre-trained LLM backbone has improved related task orchestration where limited training examples were available. Using RAG-Trace and other explainability tools in addition to obtaining visually explainable evidence of the models decision- making processes provides additional support for this proposed system compared to the results of other authors.

The proposed model improves upon conventional LLM methods by providing better generalization and reduced execution error when compared with those conventional methods. Collectively, these results indicate that a reasoning enhanced deep learning model will provide a more appropriate method of assessing complex spatial workflows than have been presented thus far. It will allow for more rapid and consistent executions and will result in a more interpretable way of generating analytical assessments of spatial data for GIS professionals.

IV. CONCLUSION

An end-to-end solution for spatial workflow orchestration based on deep learning has been developed using a large language model augmented with chain of thought mechanisms. This method offers an automated and interpretable method of executing spatial analysis from natural language queries, which addresses the limitations associated with traditional methods of manual execution of spatial tasks (ex. Time-consuming, subjective, and varied results due to inter-operator variability). The proposed system leverages deep reasoning to provide fast, accurate, and consistent orchestration of geoprocessing as part of the analytical decision-making process in geographic information systems. Integration of reasoning mechanisms into the model allows for the ability to focus on geographically relevant analytical steps such as buffering, intersecting, and joining thus enhancing accuracy of execution and reducing error. In terms of actual experimental workflow analysis where the proposed approach was evaluated against existing LLM-based spatial task orchestration models, the results demonstrated a lower mean execution error, supporting the value of selective reasoning logic. Furthermore, the use of prompt engineering resulted in improved performance and reduced orchestration time and data requirements.

Future work will concentrate on extensive analytical validation, multi-regional datasets, modeling based on topography, and connection to enterprise information systems for real time implementation.One of the main benefits of the design is being able to explain why the model executes certain tools, as the integration of RAG-TRC-based text-log visualization allows analysts to visually see which spatial parameters contributed to the model's executions increasing the overall transparency and trust of the model, and support for analysts' analytical reasoning behind decisions with documented evidence. This explains how the model functions as a trustworthy geoprocessing support tool as compared to other large language models that are traditionally black boxes.The proposed framework provides a trustworthy, efficient, and interpretable way to perform automated spatial workflow execution. The framework's design will allow it to be easily integrated into many enterprises, particularly in sectors that have limited resources and high volumes.

Future research will include large-scale analytical validation, testing utilizing multi-regional datasets, topography aware modeling, and seamless integration with enterprise information systems to support real-time deployment and decision support needs of GIS professionals.

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