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GeoGPT: An LLM-Based Geographic Information System

Using Large Language Models to Create a Natural Language Interface for GIS

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Oppgåve med omfang som kan tilpassast både prosjekt og masteroppgåve

LLMs - GIS-analysens død

(kan justerast seinare)

BAKGRUNN

Nyere modeller for kunstig intelligens har demonstrert spesielt gode evner til å kunne lære av store mengder ustrukturert og semi-strukturert informasjon. ChatGPT fra OpenAi tok verden med storm – og chat-baserte systemer florerer. Kan chat-baserte modeller skapes for å hente ut GIS-data effektivt? Norkart har en stor dataplattform hvor brukere utvikler mot API'er som i stor grad har GIS/Geografiske data i bunn. GeoNorge er en stor datakatalog hvor brukere slår opp, eller søker kategorisert for å finne data. QGIS, Python, PostGIS, FME og andre verktøy brukes ofte til å gjennomføre GIS-analyser – hvor en GIS-analytiker/data-scientist gjennomfører dette.

«*Finn alle bygninger innenfor 100-meters-belte som er over 100 kvm og har brygger*»

Er dette mulig å få til med dagens tilgjengelige chat-modeller?

OPPGAVEBESKRIVELSE

Oppgaven har som hovedmål å undersøke hvordan nyere språkmodeller kan benyttes for å gjennomføre klassiske GIS-analyser ved å bruke standard GIS-teknologi som PostGIS/SQL og datakataloger (OGC API Records fks). Hva finnes av tilgjengelig chat-løsninger? Hvordan spesialtilpasse til GIS-anvendelser? Hvor presise kan en GIS-Chat bli?

Relevante delmål for oppgaven:

1. Kartlegge state-of-the-art
2. Utvikle proof-of-concepts
3. Analysere begrensninger og kvalitet

Oppgaven vil med fordel deles i prosjektoppgave og masteroppgave

- Prosjektoppgave
    - State-of-the-art: Ai-modeller og multi-modal maskinlæring
    - Innhente og utvikle datagrunnlag og API-tilgjengelighet
- Masteroppgave
    - Utvikle proof-of-concepts med tilgjengelige åpne modeller/teknologi
    - Gjennomføre eksperimenter for analyse av kvalitet

Detaljert oppgavebeskrivelse utvikles i samarbeid med studenten.

ADMINISTRATIVT/VEILEDNING

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Hongchao Fan (3D modellering, fotogrammetri, laser)

Abstract

Recent technological developments in Natural Language Processing have led to the emergence of powerful Large Language Models (LLMs) like those powering ChatGPT — an AI-based chat interface created by OpenAI. Such *generative* LLMs have shown to be versatile, and the overarching goal for this master's thesis is to utilize the logical reasoning and code generation abilities of modern LLMs to develop a chat-based GIS that can solve GIS tasks based only on the user's natural language problem formulation. The application, named *GeoGPT*, features three different types of agent which can perform common GIS analyses on OpenStreetMap (OSM) data with little to no help from the user, as demonstrated through experiments. GeoGPT relies on the LLM's *function calling* abilities, which effectively give its agents the ability to use external tools. The agents have different sets of tools, and differ also in the way that they access the OSM data. One agent accesses the data through a PostGIS database, another through an OGC API Features server to download GeoJSON over HTTP, and the third has direct access to shapefiles stored locally in GeoGPT's environment. Experimental results obtained using a new GIS benchmark show that the SQL/PostGIS agent performs best out of the three, getting the most tasks correct while also being the fastest and cheapest. Results from an experiment conducted to evaluate the importance of the quality of the initial prompt/question from the user show that a more detailed prompt formulated as a step-by-step recipe of solving the GIS task, significantly improves GeoGPT's chances of producing a successful answer. Overall, the work done in this thesis shows that an LLM-based GIS like GeoGPT can solve a variety of common GIS tasks based on simple natural language prompts, but that the user's GIS expertise becomes increasingly important as tasks become more difficult.

Sammendrag

Nyvinninger innenfor språkprosessering har ført til fremveksten av store og kraftige språkmodeller, for eksempel modellene som ligger bak ChatGPT — en språkmodell-basert chat-applikasjon utviklet av OpenAI. Slike *generative* språkmodeller har vist seg å være allsidige, og denne masteroppgaven vil utnytte språkmodellenes evner til logisk resonnering og kodegenerering til å utvikle en GIS-applikasjon som kan løse GIS-oppgaver basert på problemformuleringer i naturlig språk. Applikasjonen har fått navnet *GeoGPT*, og tilbyr tre forskjellige agenttyper som gjennom eksperimenter har vist at de kan utføre en rekke ulike GIS-analyser på OpenStreetMap (OSM)-data uten nevneverdig hjelp fra brukeren. GeoGPT utnytter *function calling*, som i prinsippet gir agentene muligheten til å ta i bruk eksterne verktøy. Agentene har blitt tildelt forskjellige verktøy og har også forskjellige måter å aksessere OSM-dataene på. Den ene agenten bruker en PostGIS-database, en annen bruker en OGC API Features-server for å laste ned GeoJSON over HTTP, og den tredje har direkte tilgang til shapefiler lagret lokalt i miljøet som GeoGPT kjører i. Eksperimentelle resultater, basert på en ny GIS-benchmark, viser at SQL/PostGIS-agenten gir korrekt svar på flest oppgaver, i tillegg til å være raskest og billigst. Resultater fra et eksperiment utført for å evaluere betydningen av kvaliteten på problemformuleringen til brukeren, viser at det å gi GeoGPT sekvensielle trinn for å løse problemet forbedrer sjansen betraktelig for at den produserer riktig svar. Samlet sett viser arbeidet i denne masteroppgaven at et språkmodellbasert GIS, slik som GeoGPT, kan løse mange vanlige GIS-oppgaver basert kun på spørringer formulert ved naturlig språk, men også at GIS-ekspertise blir viktigere og viktigere etter hvert som oppgavene blir mer utfordrende.

Preface

This master's thesis is written at the Norwegian University of Science and Technology, for the Division of Geomatics at the Department of Civil and Environmental Engineering. It is the final work of the study programme called Engineering Science and ICT.

I would like to thank Hongchao Fan, my supervisor at the Division of Geomatics, and my two supervisors from Norkart: Alexander Salveson Nossum and Arild Nomeland. I would also like to thank GeoForum and Digin for inviting me to present my thesis at Geomatikkdagene and GeoAI:Konferansen, respectively. Finally, I would like to thank my ever-supporting family for their constant encouragement and support throughout my studies.

Karl Oskar Magnus Holm
Trondheim, 6th June 2024

Contents

Acronyms

AI Artificial Intelligence.

API Application Programming Interface.

BFCL Berkeley Function-Calling Leaderboard.

CQL Common Query Language.

CRS Coordinate Reference System.

DAG Directed Acyclic Graph.

GIS Geographic Information System.

GML Geography Markup Language.

GPT Generative Pre-trained Transformer.

HTML HyperText Markup Language.

HTTP HyperText Transfer Protocol.

JSON JavaScript Object Notation.

Llama Large Language Model Meta AI.

LLM Large Language Model.

MBPP Mostly Basic Python Programming.

NLP Natural Language Processing.

OGC Open Geospatial Consortium.

OSM OpenStreetMap.

PoSE Positional Skip-wisE.

PPO Proximal Policy Optimization.

RAM Random Access Memory.

REPL Read-Eval-Print Loop.

RLHF Reinforcement Learning from Human Feedback.

RNN Recurrent Neural Network.

RoPE Rotary Position Embedding.

SMoE Sparse Mixture-of-Experts.

SQL Structured Query Language.

SSD Solid-State-Disk.

STAC SpatioTemporal Asset Catalog.

UI User Interface.

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1. Introduction

The Introduction will open with section 1.1, which explains the motivation behind this master's thesis. Continuing, section 1.2 will lay out the overarching goals, and formulate three research questions. Section 1.3 explains the research method of the thesis, which should be considered a technical thesis. Section 1.4 will list the main contributions of the work, before section 1.5 gives the reader a high-level overview of the thesis to conclude the Introduction chapter.

1.1. Background and Motivation

The release of OpenAI's *ChatGPT* in November, 2022 (OpenAI, 2022) generated a hype within the general population, and chat-based systems are now flourishing. Furthermore, significant advancements have been made within code generation, which makes LLMs useful for technical tasks, enabling individuals with little to no prior programming experience to carry out computational tasks that require execution of code.

This brings us over to Geographic Information System (GIS) analysis, which has traditionally been "reserved" for GIS *experts*, due to its complexity and steep learning curve. GIS professional are commonly required to know their way around one or more GISs, and should preferably be proficient in programming languages suitable for data science tasks, such as Python or R. Sufficient domain knowledge is also necessary when tackling GIS tasks, like knowing what kinds of data to use for a particular task, and where to find them. All of these points, and more, are barriers to entry for non-experts who wish to make use of powerful GIS tools for their own purposes, but lack the technical know-how required to use them correctly. This challenge serves as the overall motivation behind this master's thesis, which will attempt to mitigate these issues by utilizing the vast background knowledge and code generation abilities of modern Large Language Models (LLMs), to make GIS analysis more approachable to non-experts.

1.2. Goals and Research Questions

Deriving from the motivation described in the section above, the overarching goal of this master's thesis is to investigate the possibilities of utilizing LLMs to create a natural language interface with a system that is capable of solving GIS-related tasks. The overall hypothesis is that modern LLMs possess a sufficient understanding of common GIS workflows which, when paired with their excellent code generation abilities, should enable them to solve a variety of such tasks.

Based on this overarching goal, three research questions have been constructed and are listed below:

1. Can an LLM-based system solve common GIS tasks?
2. What are core challenges in developing LLM-based GISs?
3. Can an LLM-based GIS replace GIS professionals?

1.3. Research Method

This master's thesis will be of a technical character, and will revolve around the development of a "proof of concept". The usefulness of this "proof of concept" will be evaluated through experiments, which will help answer the research questions listed in section 1.2. This report will predominantly serve to highlight the contributions of the proof of concept and the experiments, as these activities constituted the bulk of the time spent on the master's thesis.

1.4. Contributions

Below is a brief description of the main contributions of this master's thesis:

1. A chat-based GIS named *GeoGPT*, powered by LLMs, that can perform tasks commonly solved using GIS software.
2. A new GIS benchmark that will help give insigth into the ability of a system like GeoGPT to solve common GIS tasks when provided only with a natural language problem formulation.
3. An investigation into the open question of the extent to which GeoGPT can replace GIS professionals.

1.5. Thesis Structure

Below is an outline of the thesis' structure:

- Chapter 2 introduces the theory and tools necessary for the reader to be familiar with in order to understand the rest of the work. It also provides insight into the work that has been done on autonomous, LLM-based systems, particularly within the field of geomatics.
- Chapter 3 will lay out GeoGPT's architecture, providing both a high-level overview and details on important parts of the system.
- Chapter 4 presents the experimental setup, the datasets utilized, and the results obtained from these experiments, along with their evaluations.

- Chapter 5 discusses the experimental results in light of the research questions, and addresses additional points of discussion that arise from these results.
- Chapter 6 suggests potential areas of improvement in GeoGPT that are suitable for future research.
- Chapter 7 will conclude this master's thesis, reiterating the main contributions of the work.

2. Background Theory and Related Work

NB! Parts of this chapter is reused material from the specialization project (Holm, 2023) that preceded this master's thesis. The following sections have been reused, with some minor adjustments: subsection 2.1.2, subsection 2.1.3, and subsection 2.4.1.

Chapter 2 will lay a theoretical basis for the work done in this master thesis, providing the reader with the necessary knowledge to understand the contributions of the work. Section 2.1 will focus on Large Language Models (LLMs). First, subsection 2.1.1 will introduce the terms "token" and "context window", which are used frequently throughout this thesis. Thereafter, subsection 2.1.2 will present the component that most modern LLMs are based upon — namely the Transformer — and the attention mechanism that powers it. Continuing, subsection 2.1.3 will present some of the leading LLMs as of 6th June 2024, both proprietary and open-source ones. Subsection 2.1.4 will then present the concept of *prompt engineering*, which is a structured way of composing input to an LLM, before subsection 2.1.5 concludes section 2.1 by introducing *function calling*, a way of allowing LLMs to use external tools. Section 2.2 will give a brief intro to LangChain, a Python library that is used extensively throughout GeoGPT's code base. Section 2.3 will introduce the reader to PostGIS and OGC API Features, which are geospatial technologies that are used within GeoGPT. Section 2.4 will present work that in some way relates to this thesis. Subsection 2.4.1 present work where LLMs are applied for geospatial purposes, while subsection 2.4.2 describes different patterns that can be applied to LLM-based agents to improve their performance.

2.1. Large Language Models

This section will give the reader an overview of the inner workings of Large Language Models. LLMs are a type of neural networks that excel at language processing. They can be developed for different Natural Language Processing (NLP) tasks, for instance text classification, masked language modelling, and text generation. While they all have their use cases, only text generation will be relevant for this thesis. Generative LLMs are designed to understnad and generate sequences of text, and are the types of models behind technologies like OpenAI's *ChatGPT* (OpenAI, 2022).

2.1.1. Tokens and Context Window

While us humans understand sentences as sequences of words, LLMs perceive them as sequences of **tokens**. An LLM possesses a fixed set of unique tokens in its vocabulary, from which it constructs words and sentences. Tokens can be entire words, short character sequences (subwords), or single characters Ali et al. (2024). Figure 2.1 illustrates how OpenAI's GPT-3.5 and GPT-4 models *tokenize* an English sentence. Notice how some words are deconstructed into more than one token. For example, the word "revolutionizing" is split into its stem, "revolution", and its suffix, "izing". Figure 2.2 shows how this process applies to other suffixes as well. This way, the model only has to learn the meaning of "revolution", and can append different suffixes to modify its function within a sentence, as opposed to learning the meaning of an entirely new token for each version of the word.

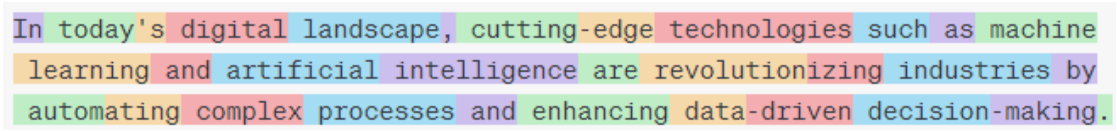

Figure 2.1.: Tokenization of an English sentence using the GPT-3.5 Turbo and GPT-4 tokenizer

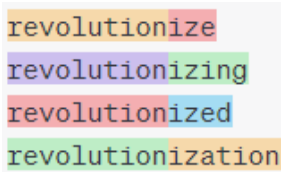

Figure 2.2.: Tokenization of the word "revolution", with different suffixes

The **context window** of an LLM is the range of tokens that an LLM is able to process (Zhu et al., 2024, p. 1). When an LLM generates text, it does so by generating a new token based on the tokens it sees in the span of the context window. A larger context window will allow the LLM to take more and longer documents as context, and generate output based on these. Leveraging sophisticated techniques like Rotary Position Embedding (RoPE) (Su et al., 2024) and Positional Skip-wisE (PoSE) training (Zhu et al., 2024), researchers have been able to efficiently extend the context window of open-source models like, for instance, Meta AI's Llama models (introduced in subsubsection 2.1.3).

2.1.2. Attention and the Transformer Architecture

Titling their paper Attention Is All You Need, Vaswani et al. suggest that their attention-based Transformer architecture renders network architectures like Recurrent Neural Networks (RNNs) redundant for machine translation purposes, due to the Transformers superior parallelization abilities and the shorter path between combinations of position

input and output sequences, making it easier for the model to learn long-range dependencies (Vaswani et al., 2017, p. 6). The Transformer is able to process multiple positions in the input sequence simultaneously, unlike RNNs, which is purely sequential.

Furthermore, the Transformer employs *self-attention*, which enables the model to draw connections between arbitrary parts of a given sequence, bypassing the long-range dependency issue commonly found with RNNs. Basically, this makes it easier for the model to "remember" what parts from earlier in the input sequence when generating new tokens. An attention function maps a *query* and a set of *key-value pairs* to an output, calculating the compatibility between a query and a corresponding key (Vaswani et al., 2017, p. 3). Looking at Vaswani et al.'s proposed attention function (2.1), we observe that it takes the dot product between the query Q and the keys K, where Q is the token that we want to compare all the keys to. Keys similar to Q will get a higher score, i.e., be *more attended to*. Finally, everything is passed into the softmax function[1], shown in (2.2), which normalizes the distribution of probabilities. The final matrix multiplication with the values V, the initial embeddings of the input tokens, will yield a new embedding in which all individual tokens have some context from all other tokens. The attention mechanism is improved by multiplying queries, keys, and values with *learned* weight matrices that are obtained through backpropagation. Self-attention is a special kind of attention in which queries, keys, and values are all the same sequence.

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{2.1}$$

$$\text{softmax}(\mathbf{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}. \tag{2.2}$$

Attention blocks can be found in three places in the Transformer architecture, which is displayed in Figure 2.3. The Transformer, which was created for machine translation tasks, has two main parts: the *encoder* (the left part of Figure 2.3) and the *decoder* (the right part of Figure 2.3). The encoder learns the representation of the origin language from a given input sequence, while the decoder learns the representation in the target language and generates the output sequence. Below is an example of Norwegian to German translation, showcasing the different ways that the attention mechanism is used:

1. In the encoder block, to perform self-attention on the Norwegian input sequence.
2. In the decoder block, to perform self-attention on the German output sequence.
3. In the decoder block, to perform *cross-attention* (also known as encoder-decoder attention), where each position in the decoder attends to all positions in the encoder.

Vaswani et al. managed to achieve new state-of-the-art results for machine translation tasks, with their introduction of the Transformer architecture. The Transformer represented a breakthrough in the field of NLP, and is the fundamental building block of

[1] https://en.wikipedia.org/wiki/Softmax_function (last visited on6th June 2024)

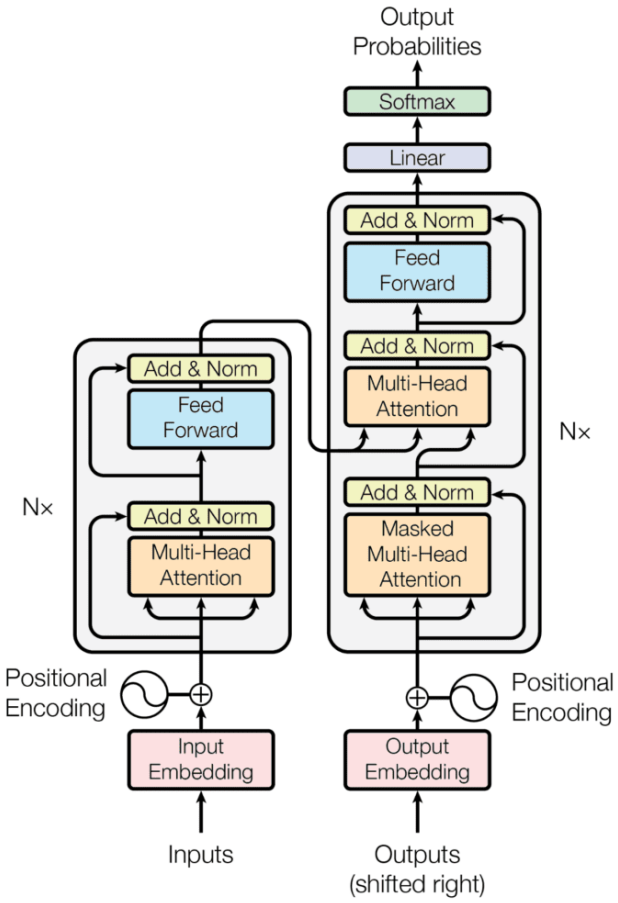

Figure 2.3.: The encoder-decoder architecture of the Transformer (Vaswani et al., 2017, p. 5)

most modern LLMs. Though designed for machine translation, the architecture has later proved effective for numerous downstream tasks, and for a variety of modalities.

2.1.3. State-of-the-Art Decoder-Only Large Language Models

While the work of Vaswani et al. (2017) is still considered perhaps the greatest breakthrough in NLP, most moderns LLM do not apply the exact encoder-decoder architecture of the Transformer. The evolution following the Transformer has favoured generative decoder-only models, focusing entirely on the generative component of the Transformer, with the goal being to create models that can produce coherent and context-aware text.

The GPT Family

Generative Pre-trained Transformer (GPT) is an LLM that was introduced by OpenAI in 2018 (Radford et al., 2018). Specifically designed for text generation, the GPT is essentially a stack of Transformer *decoders*. It demonstrates through its vast pre-training on unlabelled data that such *unsupervised* training can help a language model learn good representations, providing a significant performance boost while alleviating the dependence on *supervised* learning, which requires labelled training data. The model employs masked *multi-head attention*, which runs the input sequence through multiple attention heads in parallel. It is restricted to seeing only the last k tokens, with k being the size of the context window, and is tasked with predicting the next one.

Training consists of two stages: the above-mentioned unsupervised pre-training process, and supervised fine-tuning. The former is used to find a good initialization point, essentially teaching the model to imitate the corpora that it is trained on. This, however, will naturally produce undefined behaviour where the model rambles on uncontrollably, simply attempting to elaborate upon the input sequence it is given to the best of its abilities. It is therefore necessary to fine-tune the model on target tasks in a *supervised* manner. Radford et al. (2018, p. 4) explain how the model can be fine-tuned directly on tasks like text classification, but how other tasks require the conversion of structured inputs into ordered sequences, as is the case when fine-tuning for tasks like multiple choice. Figure 2.4 shows this *inlining* process, which is required because the pre-trained model was trained on contiguous sequences of text. In the case of ChatGPT, OpenAI used Reinforcement Learning from Human Feedback (RLHF) (Christiano et al., 2023) by employing a three-step strategy: first training using a supervised policy, then using trained reward models to rank alternative completions produced by ChatGPT models, before fine-tuning the model using Proximal Policy Optimization (PPO) (Schulman et al., 2017), which is a way of training AI policies. This pipeline is then performed for several iterations until the model produces the desired behaviour (OpenAI, 2022).

OpenAI's API currently features three flagship models, which are all proprietary: the GPT-3.5 Turbo model, which is fast and inexpensive; the GPT-4 Turbo model, which as of 6th June 2024 is described by OpenAI as their "previous high-intelligence model"; and lastly, GPT-4o, their "fastest and most affordable flagship model".[2] The GPT-4o has

[2] https://openai.com/api/ (last visited on 2nd June 2024)

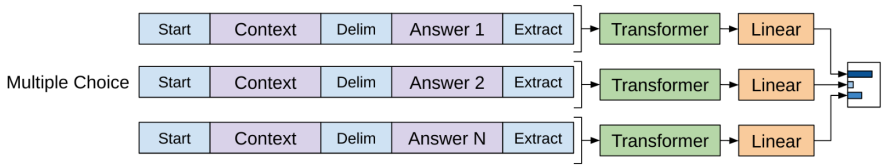

Figure 2.4.: A subsection of a figure illustrating from a paper on the GPT model, showing how multiple choice tasks need to be *inlined* so that they can be used for fine-tuning. This is because the GPT is trained on ordered sequences (Radford et al., 2018, p. 4)

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unique multi-modal abilities and can reason across audio, vision, and text in real time, according to OpenAI.[3]

The Gemini Family

The suite of models known as *Gemini* is Google's latest response OpenAI's GPT models. The Gemini 1.0 suite (Gemini Team et al., 2024a), released in December 2023, is the first suite of Gemini models and includes three different versions: *Ultra*, *Pro*, and *Nano*. These are listed in descending order in terms of size. The models of the Gemini 1.0 suite are multi-modal, supporting text, image, audio, and video. Gemini 1.0 Ultra displayed new state-of-the-art performance on most major benchmarks, but performed significantly worse on the *HellaSwag* benchmark compared to the latest GPT-4 model at the time. The HellaSwag benchmark measures a model's common-sense understanding, and the models scored 87.8% and 95.3%, respectively. Supporting a context length up to 1M tokens, Gemini 1.0 Ultra surpassed Claude 2.1's context window of 200k with a wide margin (see the next paragraph for more on the Claude models), and with the release of Gemini 1.5 Pro in February 2024 came also the possibility of utilizing a context window of up to 10M tokens, though in production this number is currently limited to 1M tokens (Gemini Team et al., 2024b; Pichai and Hassabis, 2024). Furthermore, Gemini 1.5 *Pro* outperforms Gemini 1.0 *Ultra* in some capabilities despite using significantly less training compute (Gemini Team et al., 2024b, p. 31).

The Claude Family

Developed at Anthropic, Claude is the third major suite of proprietary LLMs. Anthropic has helped push in the direction of long-context LLMs, with their Claude 2 model (released in November 2023) being the first to support up to 200k tokens (Anthropic, 2023, p. 9). Latest in line is Claude 3, a family of language models that — much like the Gemini family — features three models of different sizes: *Opus*, *Sonnet*, and *Haiku*. Again, these are listed in descending order in terms of size. The Opus model offers the most advanced capabilities, and outperforms GPT-4 and Gemini 1.0 Ultra on most

[3] https://openai.com/index/hello-gpt-4o/ (last visited on 2nd June 2024)

benchmarks (Anthropic, 2024, p. 6). Haiku is Anthropic's fast and economical option, while Sonnet serves as a balance between Opus' complexity and Haiku's speed.

Open-Source Alternatives

As mentioned, OpenAI's GPT models, Google's Gemini models, and Anthropic's Claude models are all proprietary. This prevents developers from downloading these models and making improvements and customizations to them. This has led to the emergence of a number of *open-source* LLMs.

The **Llama** family of LLMs, developed at Meta AI, is perhaps the most famous open-source option to the proprietary LLMs. At the time of writing, their latest LLM is the *Llama 3* model (Meta AI, 2024), which comes in two sizes: 8B and 70B parameters. Both models display state-of-the-art performance on most major benchmarks compared to other open-source alternatives, and the 70B model even surpasses proprietary models like Gemini 1.5 Pro and Claude 3 Sonnet on certain benchmarks.

Mistral AI is one of the most prominent actors in the world of open-source LLMs. Their debut model, the *Mistral 7B*, outperformed Llama 2 13B (the best open-source LLM at the time) across all the benchmarks they evaluated (Jiang et al., 2023). Mistral AI has also gained fame for their Sparse Mixture-of-Experts (SMoE) architecture, which was introduced with the *Mixtral 8x7B* model (Jiang et al., 2024). Mixtral 8x7B shares the same architecture as Mistral 7B, except that each layer of the model is composed of 8 feed-forward blocks. Using a router at each layer, Mixtral 8x7B is able to use only 13B out of a total of 47B parameters during inference, keeping cost and latency low.

Along with their Gemini models, Google released a family of open-source models called **Gemma**, which are based on the same research conducted for the Gemini models (Gemma Team et al., 2024). Gemma comes in two sizes: 2B and 7B parameters. At its release, the Gemma 7B surpassed Llama 2 13B and Mistral 7B in 11 out of 18 benchmarks. Note, however, that Llama 3 8B has improved upon its predecessor, and now also performs better than Gemma 7B, overall.

2.1.4. Prompt Engineering

Prompt engineering refers to a structured process of constructing input to an LLM. In a chat-based context like that of ChatGPT, the prompt generally consists of a series of messages. These messages can hold one of three different roles,[4] each listed below:

- **System**: Generally used to set the behaviour of the LLM assistant, giving the assistant a specific personality or information on how to answer the user.
- **User**: A message from the human user that the assistant should respond to.
- **Assistant**: A message generated by the AI/LLM.

[4] https://platform.openai.com/docs/guides/text-generation/chat-completions-api (last visited on 2nd June 2024)

White et al. (2023) stress the importance of prompt engineering to efficiently converse with LLMs. They provide a catalogue of prompt patterns that aim to help enforce certain qualities in the output generated by the LLM. These patterns are organized into six categories (White et al., 2023, p. 4):

- **Input Semantics**: Clarifying what information is fed into the LLM and how this input should be used to generate responses.
- **Output Customization**: Strategies to guide how the LLM should format and structure its responses.
- **Error Identification**: Methods of identifying and resolving errors in the outputs produced by the LLM.
- **Prompt Improvement**: Techniques to improve the quality of both the input provided to the LLM and the output it generates.
- **Interaction**: Strategies for enhancing interactions between the user and the LLM.
- **Context Control**: Controlling the contextual domain within which the LLM operates.

Patterns that turned out useful to GeoGPT — the main contribution of this thesis — include the *Template* pattern (Output Customization), the *Reflection* pattern (Error Identification), and the *Infinite Generation* pattern (Interaction). The *Template* pattern allows the user or the system to define a template for the LLM to fill out. This is closely related to *function calling*, which is discussed in subsection 2.1.5. Also related to function calling is the *Reflection* pattern, which allows the LLM to inspect its own output in order to identify and correct errors. The *Infinite Generation* pattern lets the LLM generate output indefinitely without requiring the user to re-enter the conversation after each generated message. This pattern is important when developing agentic behaviours.

2.1.5. Function Calling LLMs

Function calling — also known as *tool calling* — was first introduced by OpenAI in April 2023 (Eleti et al., 2023). Function calling allows developers to provide function definitions to an LLM, and have the LLM decide, based on the current context, *if* the function should be invoked, and what *parameters* should be used as input to the function. Code Snippet 2.1 shows a description of a function that performs a mathematical division. It is specified by its name, description, and its two parameters: the dividend and the divisor, both of which are required. This function definition has a corresponding function in code written by the developer, which can now be invoked when the LLM deems it necessary. After a function has been invoked using the parameters specified by the LLM, the LLM can then be prompted once more, now with the output of the function invocation. This way, function calling makes it possible to give an LLM *hooks* into the real world, and provides a more reliable way for developers to integrate LLMs into applications.

```
{
  "type": "function",
  "function": {
    "name": "divide",
    "description": "Performs a mathematical division.",
    "parameters": {
      "type": "object",
      "properties": {
        "dividend": {
          "description": "The number to be divided (numerator).",
          "type": "number"
        },
        "divisor": {
          "description": "The number by which the dividend is divided (denominator).",
          "type": "number"
        }
      },
      "required": ["dividend", "divisor"]
    }
  }
}
```

Code Snippet 2.1: Example of a function definition for a tool that performs divison. It is specified by a name and description, and its two parameters: the dividend and the divisor, both of which are required.

Function calling can be used to provide correct and up-to-date information. Having the LLM use function calling for information retrieval also make them more transparent, making it possible to trace a claim back to its source, something that is normally hard to do with LLMs. Another use case is code execution. Take this rather simple function signature:

```
execute_python_code(code: string) -> string
```

Such a function could take a string of Python code and return the standard output that results from executing that code. This is the principle behind what was previously known as ChatGPT's "Code Interpreter" mode, where ChatGPT serves as a code executing agent that can generate, execute, and self-correct its own code. Similar functions can be constructed for SQL, making it possible for LLMs to work against relational databases. Furthermore, as Eleti et al. (2023) describes, function calling can also be used to extract structured data from text.

An initiative amongst researchers at Berkeley (Yan, Fanjia et al., 2024) lead to the creation of a benchmark that aims to evaluate the LLM's ability to call functions and tools. The benchmark, named Berkeley Function-Calling Leaderboard (BFCL), includes four different test scenarios: *single function*, where the LLM is provided with a single function

definition; *multiple function*, where 2 to 4 functions are passed, and the model must select the appropriate function; *parallel function*, where the model needs to determine how many functions should be called; and *parallel multiple function*, a combination of parallel function and multiple function. Some models support different levels of function calling natively, while others have to be carefully prompted to help accommodate function calling abilities. As of 6th June 2024, a prompted version of GPT-4-0125-Preview tops the leaderboard.[5]

2.2. LangChain

LangChain (LangChain AI, 2022) is an open-source project that provides tooling which simplifies the way that developers interface with LLMs. As the name suggests, LangChain revolves around *chains*. Chains are Directed Acyclic Graphs (DAGs), which can be constructed from so-called *runnables*. LangChain is supported by a large community of developers, and has components that simplify interaction with LLMs, like prompt templates, output parsers, toolkits for function calling purposes, and off-the-shelf agents.

Common use cases for LangChain are:

- Building chatbots for question answering that use semantic retrieval from a document store.
- Creating agents with access to external tools by leveraging function calling.
- Creating code executing agents for Python, SQL, or other programming languages.

In January 2024, LangChain AI rolled out a framework called LangGraph, which is built on top of the LangChain ecosystem. While *chains* are well-suited for DAG workflows, they are not easily adapted to cyclic graphs. LangGraph, however, is specifically designed to simplify development of cyclic graphs for LLM applications, which are commonly used to create agent-like behaviours (LangChain AI, 2024). A LangGraph *graph* is a set of nodes that pass around and modify a state dictionary. The nodes are connected by edges that define what node can follow another node. Edges can be conditional, meaning the state produced by the originating node decides which edge is followed to the next node. This allows for complex logic and simplifies implementation of advanced agent patterns, some of which are discussed in subsection 2.4.2.

2.3. Geospatial Databases and Data Catalogues

This section will discuss the geospatial technologies that were used in this master's thesis.

[5] https://gorilla.cs.berkeley.edu/leaderboard.html (last visited on 6th June 2024)

2.3.1. PostGIS

PostGIS (*PostGIS* 2001) is an open-source extension for the PostgreSQL database that adds support for storing, indexing, and querying geospatial data. Data can be stored in both two and three dimensions, and they can take the form of points, lines, polygons, and more. Geospatial types can be stored along with a spatial index, which can significantly reduce search time for their geometries. GiST (Generalized Search Tree)[6] is commonly used in PostGIS to take advantage of various tree-based search algorithms that are developed to retrieve spatial features quickly.

PostGIS also comes with a plethora of spatial database functions that are used to analyse and process geospatial data. These function's names are prefixed with `ST_`- (short for "spatio-temporal"), with examples including `ST_DWITHIN`, `ST_BUFFER`, and `ST_TRANSFORM`. Code Snippet 2.2 shows a typical PostGIS query for retrieving building outlines within a bounding box.

```
1 SELECT *
2 FROM osm_buildings_polygons
3 WHERE type = 'house'
4   AND ST_Intersects(geom, ST_MakeEnvelope(min_lon, min_lat, max_lon,
      max_lat, 4326));
```

Code Snippet 2.2: PostGIS example code for retrieving outlines of buildings of type 'house' within a bounding box specified by coordinates in the WGS 84 map projection

2.3.2. OGC API Features

OGC API Features is an API specification developed by the Open Geospatial Consortium (OGC) that defines modular API building blocks for interacting with *features*, which are real-world objects (Open Geospatial Consortium, 2022). This includes blocks for creating, modifying, and querying features on the Web. A typical OGC API Features server implements these building blocks for HTML, GeoJSON, and GML. These are called *requirement classes*, though none of them are strictly required. The HTML requirement class gives the consumer of the API a visualization of the features in a web map in the browser, whereas the GeoJSON and GML requirements classes are typically meant for use in other applications. An OGC API Features server consists of a number of collections containing items/features. Figure 2.5 illustrates the structure of such a server.

The development of the OGC API Features specification is divided into several parts that are meant to build on each other. Here are the five parts that are listed on OGC's websites:[7]

[6] https://en.wikipedia.org/wiki/GiST (last visited on 2nd June 2024)
[7] https://ogcapi.ogc.org/features/ (last visited on 2nd June 2024)

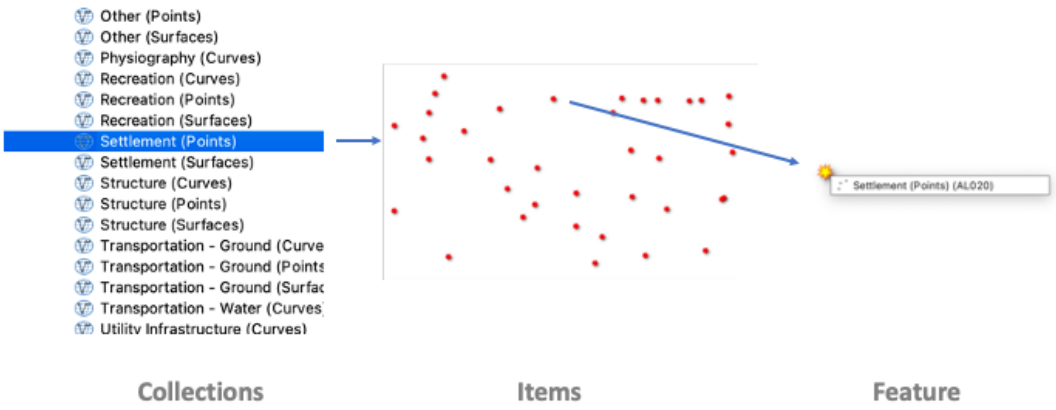

Figure 2.5.: The general structure of a typical OGC API Features server. The server would have a number of collections, which in turn have a number of items/features that have geographical components. The consumer of the API can request a collection of items, or individual features. The figure was retrieved from https://features.developer.ogc.org/ on 29th April 2024.

- Features - Part 1: Core[8]
- Features - Part 2: Coordinate Reference Systems by Reference [9]
- Features - Part 3: Filtering[10]
- Features - Part 4: Create, Replace, Update and Delete[11]
- Features - Part 5: Schemas[12]

Part 1 specifies the core capabilities which were described in the first paragraph of this section, while parts 2-4 specify additional capabilities. Part 2 allows for retrieval of features in Coordinate Reference Systems (CRSs) different to the default WGS 84 reference system. Part 3 enables filtering of features using Common Query Language (CQL), which is a language similar to SQL, so that consumers of the API can retrieve subsets of a given collection. Code Snippet 2.3 shows two examples of CQL queries:

```
1 \\ Example 1
2 county in ('Akershus', 'Buskerud', 'Ostfold')
```

[8] https://docs.opengeospatial.org/is/17-069r4/17-069r4.html (last visited on 2nd June 2024)
[9] https://docs.ogc.org/is/18-058r1/18-058r1.html (last visited on 2nd June 2024)
[10] https://docs.ogc.org/DRAFTS/19-079r1.html (last visited on 2nd June 2024)
[11] https://docs.ogc.org/DRAFTS/20-002.html (last visited on 2nd June 2024)
[12] https://docs.ogc.org/DRAFTS/23-058r1.html (last visited on 2nd June 2024)

```
3
4 \\ Example 2
5 DWITHIN(the\_geom, Point(63.4265, 10.3960), 1, kilometers)
```

Code Snippet 2.3: Examples of two simple CQL filters: Example 1 filters for all features whose `county` attribute is either 'Akershus', 'Buskerud', or 'Ostfold'; Example 2 checks whether a feature's geometry is within 1 kilometer of the point specified by the latitude and longitude 63.4265, 10.3960.

Part 4 defines how an OGC API Features server should handle addition, replacement, modification, and removal of features. Part 5 explains how features can be defined by a logical schema and how these schemas are published. In addition to parts 1 through 5, several other *proposed* extensions have emerged, such as the *Search* extension, which would allow for multi-collection queries, or the *Geometry Simplification* extension which proposes the use of simplification algorithms for retrieving simplified versions of a collection.[13]

2.4. Related Work

The related work is divided into two main parts: subsection 2.4.1, which presents research investigating potential use cases of LLMs in the field of geospatial information technology; and subsection 2.4.2, which includes examples of three different types of patterns that can be used in LLM-based agents.

2.4.1. Using LLMs for Geospatial Purposes

Roberts et al. (2023) investigated the extent of GPT-4's geospatial awareness through a set of case studies with increasing difficulty, starting with general factual tasks and moving up to more complex questions such as generating country outlines and travel networks. They found that GPT-4 is "skillful at solving a variety of application-centric tasks", almost having the ability to "see", despite the fact that they only have the ability to read and generate *text*[14] Roberts et al. showed that the LLM can function as a travel assistant, providing trip suggestions when given requirements for the trip, and that it can give more or less correct start- and end locations of certain bird migration paths. While it quickly became obvious that a lot of geospatial context have been embedded within the model during the vast pre-training, the open question of whether this is memorization or reasoning is a central one. The variability of tasks the experiments leads the authors to conclude that it is unlikely that all of this is memorization, but they say that some things appear to be memorized.

Mooney et al. (2023) examined the performance of ChatGPT in a GIS exam, aiming to evaluate its understanding of various geospatial concepts, highlighting the model's

[13] https://github.com/opengeospatial/ogcapi-features/tree/master/proposals (last visited on 2nd June 2024)

[14] Note that multi-modal models were not particularly widespread when they wrote their paper.

capabilities and limitations. Both GPT-3.5 and GPT-4 were test, and they delivered performances equivalent to grades of D and B+, respectively. Additional experiments were conducted for more specialized areas of GIS, including True/False questions about spatial analysis, and simple tasks in applied GIS workflows. Experiments on the latter showed that GPT-4 was able to correctly answer a relatively complex GIS task involving seven different datasets, which required seven steps in order to obtain a perfect score. Generally, GPT-4 outperformed GPT-3.across all tasks. Both models clearly showcased their strong capabilities, but the authors highlight a range of challenges if such models are to be applied for real tasks. They say which the multi-modal nature of GIS makes it difficult to apply the LLMs directly.

Li and Ning (2023) state that "autonomous GIS will need to achieve five autonomous goals: self-generating, self-organizing, self-verifying, self-executing, and self-growing.". They propose a divide-and-conquer-based method to address some of these goals, where they split the overall problem into sub-problems. Furthermore, they propose a simple trial-and-error approach to address the self-verifying goal. Even with its shortcomings, the solution that Li and Ning (2023) provide, called *LLM-Geo*, produced good results in various case studies by providing executable assemblies in a Python environment when given URLs to relevant data sets along with a user-specified query.

Zhang et al. (2023) use the LangChain framework to combine different GIS tools in a sequence to solve various sub-goals, focusing on using the semantic understanding and reasoning abilities of LLMs to call externally defined tools. They named this framework *GeoGPT*. The externally defined tools are described by names and descriptions, the latter of which contains information about the function's input parameters and output types. Tools are defined for the collection, processing, analysis, and visualization of geospatial data. The effectiveness of the system is showcased through case studies, where GeoGPT performed actions like land use classification and raster-to-vector conversion using the externally defined tools.

2.4.2. Agent Patterns

LLM-based agents can be implemented in many different ways, and researchers have developed a plethora of *agent patterns* that seek to make improvements to areas where LLMs tend to be less effective. This section will briefly explain three different types of agent patterns that were considered during the development of GeoGPT.

The **multi-agent** pattern takes inspiration from human collaboration, consisting of multiple specialized agents that work together to achieve a common objective. MetaGPT (Hong et al., 2023) is an LLM-based multi-agent system consisting of agents with human-level domain expertise. Using an assembly line paradigm, where the overall goal is divided into subtasks, Hong et al. showed that MetaGPT could generate more coherent solutions compared to the previous state-of-the-art multi-agent systems. MetaGPT achieved a new state-of-the-art performance on the HumanEval and Mostly Basic Python Programming (MBPP) benchmarks (Hong et al., 2023, p. 7), demonstrating the potential of the multi-agent pattern. AutoGen (Wu et al., 2023) and crewAI (Moura, 2024) are other examples of frameworks geared towards the multi-agent pattern.

Patterns that employ **self-reflection** are commonly used with autonomous LLM-based agents. *Reflexion* (Shinn et al., 2023) is a framework that reinforces agents through linguistic feedback, essentially allowing the agent to reflect upon the outcomes of its actions. The framework utilizes three distinct models: an *Actor* model responsible for generating text and actions; an *Evaluator* model which assesses the quality of the outputs from the Actor; and a *Self-Reflection* model that generates reinforcement cues for the Actor based on the output and quality assessment of the other two models. Together, these three models form a loop that will run until the Evaluator deems the output from the Actor to be correct.

Step-by-step reasoning is another pattern that has proved to be efficient in helping LLMs produce correct responses. Wei et al. (2023) demonstrated that so-called *chain-of-thought prompting* can be used for enhancing reasoning in LLMs, where the prompt to the LLM includes examples of how to reason for tasks *similar* to the one being solved. By helping the LLM with decomposing multi-step problems into intermediate steps, Wei et al. managed to achieve state-of-the-art accuracy on the GSM8K benchmark of maths word problems.

3. GeoGPT

GeoGPT's source code is available in this GitHub-repository: https://github.com/oskarhlm/masters-thesis.

This chapter will give a detailed description of the inner workings of *GeoGPT*, the thesis' proposed solution to an LLM-based GIS. GeoGPT is a webpage that features a chat interface and a web map. Users can ask questions through the chat interface and receive answers as text and/or geometries in the map. GeoGPT features *three* different agent types: an *OGC API Features* agent, a *Python* agent, and an *SQL* agent. Their differences will be explained in this chapter.

Section 3.1 will give a high-level overview of GeoGPT's architecture. GeoGPT employs a client-server architecture, where the server is supported by auxiliary services such as databases and API endpoints. The client is a chat-based web GIS, and the server, which hosts the above-mentioned agents, is responsible for streaming responses to the client in the form of chat messages, and GeoJSON files that can be added to the map on the client. Section 3.2 will delve into the architecture of the generic tool agent that is implemented by each of GeoGPT's three agents. This section will also discuss the external tools that the agents have at their disposal, as well as prompt engineering techniques used within GeoGPT.

3.1. High-Level Application Architecture

The two main parts of GeoGPT is its web client and its server. They are highlighted in green and blue in Figure 3.1, respectively. This is where all of GeoGPT's source code is located. The server is connected to three data sources: a folder containing shapefiles, a *PostGIS* database, and an OGC API Features server. It also uses a Redis database, which is responsible for storing conversations between the user and GeoGPT, and OpenAI's inference API, which is responsible for text generation. Sections 3.1.1 through 3.1.4 will provide further details on the components that make up GeoGPT.

The sequence diagram in Figure 3.2 shows how the different parts of the system interact with each other when the user first loads GeoGPT and enters a question into its chat interface. The initial page load triggers the creation of a session object in the Redis database, where the rest of the conversation will be stored. The diagram also illustrates the client-server relationship between the web UI and the LangChain server. Further details on the sequence diagram will be discussed later in this chapter.

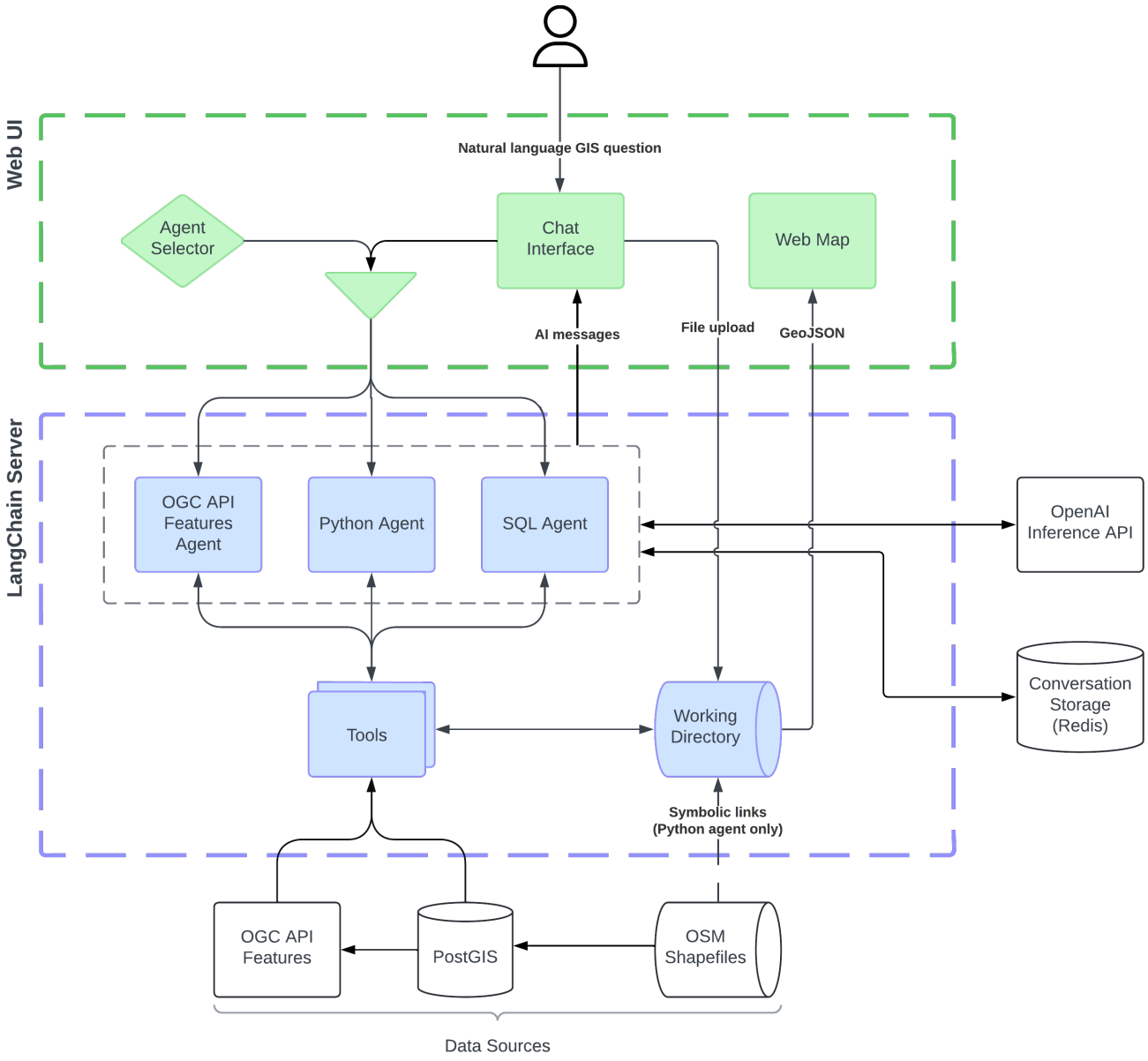

Figure 3.1.: Architecture overview highlighting the client-server architecture of GeoGPT, and the major components that make up the Web UI (in green) and the LangChain Server (in blue). Auxiliary services like databases and external APIs are shown in white.

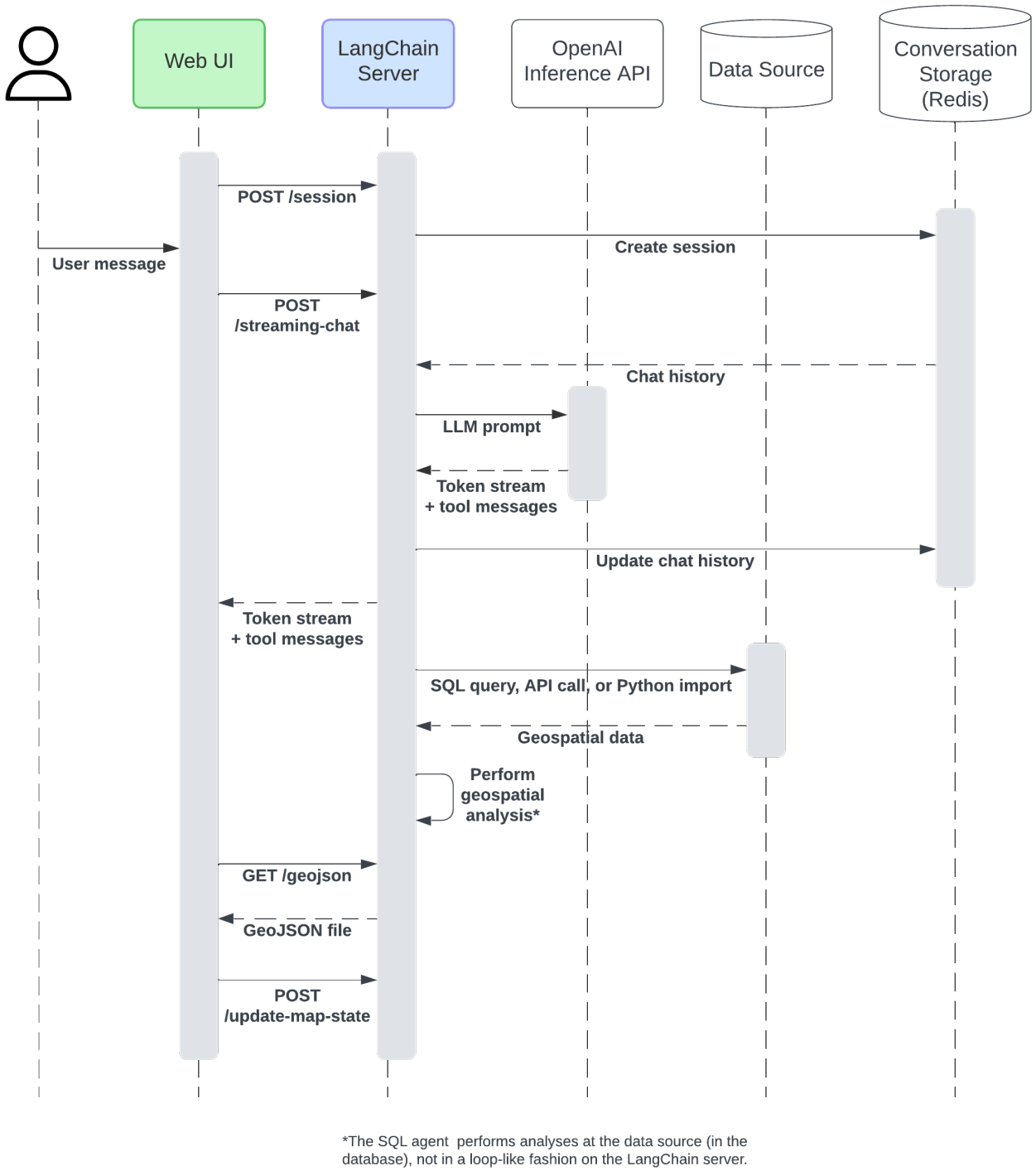

Figure 3.2.: Sequence diagram showing the information flow as the user sends a message to GeoGPT.

3.1.1. LangChain Server

The *LangChain Server* is the heart of GeoGPT, and is where all the Large Language Model (LLM)-related logic is situated. It is responsible for taking user messages passed from the web client to the server's `/streaming-chat` endpoint, and returning a stream of AI messages generated by an LLM. The AI messages include textual messages, which are streamed token-by-token, and tool messages, which are discussed in section 3.2. Table 3.1 shows a complete list of the endpoints exposed by the server, and how they are used by the client.

Table 3.1.: Summary of the endpoints exposed by the LangChain server

Endpoint	**Method**	**Description**
/session	GET	Takes a `session_id` as a query parameter, allowing the client to continue on a pre-existing session.
/session	POST	Creates a new session with an empty conversation.
/streaming-chat	GET	Endpoint for chatting the LLM. Takes a `message` as a query parameter and returns an event stream, allowing for token streaming from server to client.
/update-map-state	POST	Used to send the state of the client map to the server. Keeps the server updated on what layers are present in the map, their color, etc.
/geojson	GET	Takes a `geojson_path` as a query parameter. Allows the client to retrieve a given GeoJSON file that is stored in the working directory on the server.
/upload	POST	Allows the client to upload one or more files to the working directory on the server.

The LangChain server features GeoGPT's three different agent types. These are listed below:

- **OGC API Features Agent** – Retrieves data from an OGC API Features server, and uses Python to perform analyses on this data.
- **Python Agent** – Accesses and manipulates shapefiles using Python code.
- **SQL Agent** – Interacts with data stored in a PostGIS database.

The agents are responsible for taking messages from the users and utilizing the *external tools* available to them through the LLM's function calling abilities (see subsection 2.1.5) to find answers to the users' geospatial questions. The tools available to each of the agents are presented in subsection 3.2.2.

The agents use OpenAI's inference API to access LLMs to generate text and function calls. Prompt engineering techniques are used within the agents to produce prompts that can be used as input to these LLMs. These techniques are described in further detail in subsection 3.2.3.

The agents have access to a working directory where they can store files on-disk, which is reset to its default state each time the web client is reloaded. The agents can access the files in the working directory through some of the tools that are presented in subsection 3.2.2, one of which allows the agents to add GeoJSON files stored in the working directory to the map on the web client. The sequence diagram in Figure 3.2 shows how the client requests a GeoJSON file using the server's `/geojson` endpoint, an action triggered by this tool, which is called `add_geojson_to_map`.

3.1.2. Redis for Conversation Storage

Redis (Sanfilippo, 2009) is a fast in-memory database that is often applied as a caching database that sits on top of some persistent database. It can also be used for vector-based storage, or as a simple NoSQL database. The latter option is the way that it is used in GeoGPT's architecture, and its sole purpose is to store conversations between GeoGPT and its users. Whenever a user starts a conversation with GeoGPT, a session object is created in the Redis database, as the sequence diagram in Figure 3.2 shows. This object holds an array that holds all the messages of the the conversation. This array is written to every time the human or GeoGPT produces a message.

Storing messages, either in memory as a simple array or in a database like Redis, is crucial to enable multi-message conversations. In order for an LLM to act as a conversational agent, a chat history needs to be included in the prompt. In the case of GeoGPT, the entire chat history is included. This has the advantage of providing the LLM with the complete context for the conversation, but the disadvantage of potentially bloating the context window. Furthermore, as the chat becomes longer, each new token will be both more expensive and take longer to get generated. A long chat history could also make the resulting prompt exceed the token limit of the LLM, meaning that more tokens are passed to the LLM than can fit in its context window. This issue was not considered much for this project.

3.1.3. Shapefiles, PostGIS, and OGC API Features

18 shapefiles were downloaded into GeoGPT's environment. These are the geospatial data that GeoGPT's agents will have at their disposal when the user asks a GIS-related question. The data are discussed in detail in subsection 4.1.4. For GeoGPT's Python agent, these shapefiles are "copied" to its working directory using symbolic links.[1] This

[1] https://en.wikipedia.org/wiki/Symbolic_link (last visited on 2nd June 2024)

way, the Python agent can access the files in the download directory where the *actual* file is stored, by using the path to a file in the working directory, which *points* to the real file. This makes the startup of GeoGPT much faster, since it does not copy the actual contents of the files from the download directory to the working directory.

For the SQL agent, a PostGIS database was deployed using Docker, and populated with the shapefiles described above. The files were given spatial indexes to speed up retrieval of features. For the OGC API Features agent, an OGC API Features server was added on top of the PostGIS database, as Figure 3.1 shows. The server was deployed using the `pramsey/pg_featureserv` Docker image (CrunchyData, 2024), which requires a connection string to the PostGIS database. Any table in the database which has a geometry column and a specified Coordinate Reference System (CRS), will be exposed on the server. The server offers functionality like bounding box filtering, result limiting, and CQL filtering. These are added as query parameters in the URL used to fetch a collection's items, for instance:

```
.../collections/{collection_id}/items.json?limit=1000&filter=name IS
NOT NULL&bbox=10.3388,63.3693,10.4590,63.4500
```

In the internals of the server, this URL will be converted to an SQL query that will be run against the database. Results of the query will be returned as GeoJSON. The current implementation of *pg_featuresserv* only supports a maximum of 10,000 features per request. Code Snippet 3.1 shows an example of how CQL code is converted into SQL code:

```
1 \\ CQL code passed through the `filter` query parameter
2 within(geom, POINT(0 0))
3
4 \\ SQL code that will be run agains the database
5 ST_Within("geom",'SRID=4326;POINT(0 0)'::geometry)
```

Code Snippet 3.1: Example of how a CQL filter checking if a point at coordinates (0, 0) resides within a feature's geometry, is converted by the OGC API Features server to the corresponding SQL code

3.1.4. Web UI

GeoGPT's user interface is made using SolidJS,[2] a JavaScript framework for creating websites. As Figure 3.3 shows, it consists of a chat interface, a web map, and an agent selector located above the chat interface. The chat interface was designed to imitate the interface of OpenAI's ChatGPT. Here, the user can ask geospatially related questions for GeoGPT to answer. AI message tokens and tool messages are streamed from the

[2] https://www.solidjs.com/

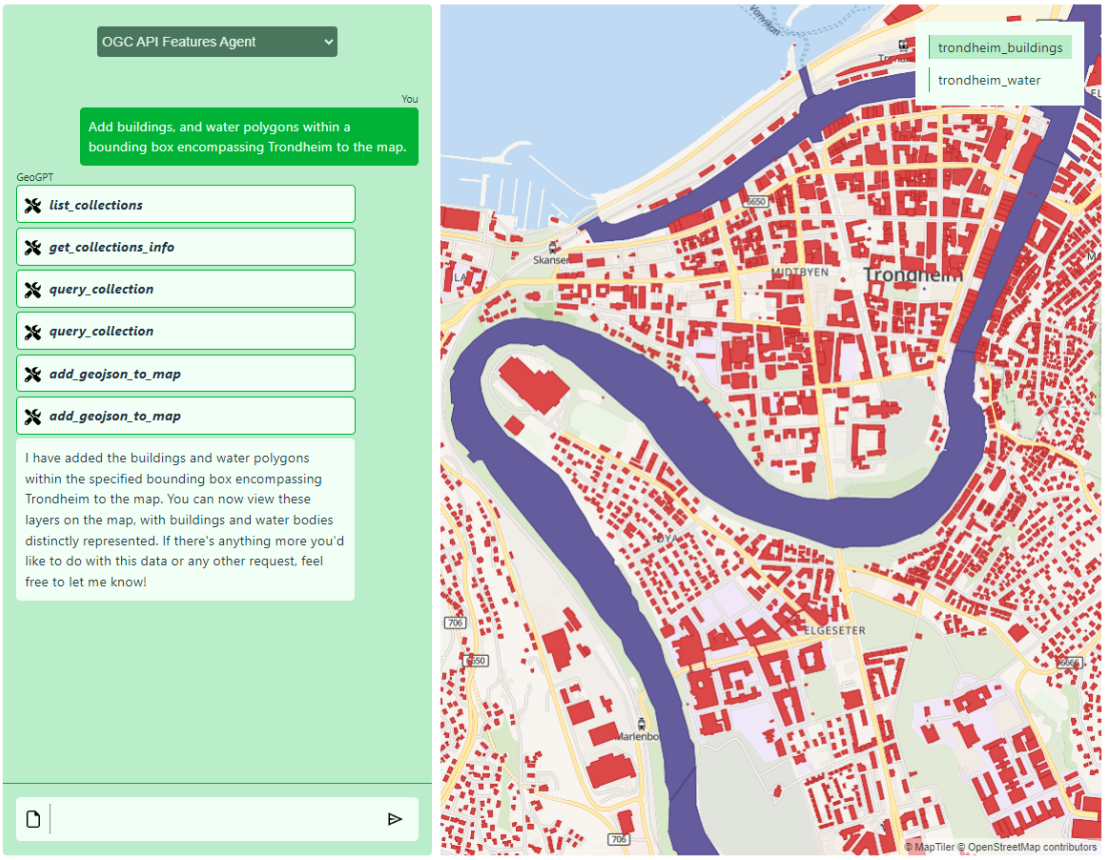

Figure 3.3.: GeoGPT's web UI, which features a chat interface and a web map that displays results from analyses. In this example, the user has asked GeoGPT to add water and building geometries for Trondheim to the map. This was successful, as layers named `trondheim_water` and `trondheim_buildings` were added by GeoGPT, after a series of tool calls.

LangChain server and added to the chat, which helps the user follow GeoGPT's thought process as it is solving a problem. The generated text is generally streamed in the Markdown format.[3] A library called *showdown*[4] is used to convert the Markdown to HTML, ensuring that tables, code blocks, lists, and other elements are properly rendered in the browser. Left of the input field on the bottom of the chat is a file upload button. Files that are uploaded here will be added to the working directory on the LangChain server, as Figure 3.1 shows.

The map is created using MapLibre,[5] an open-source fork of Mapbox. A base map from

[3] https://en.wikipedia.org/wiki/Markdown (last visited on 2nd June 2024)
[4] https://github.com/showdownjs/showdown (last visited on 2nd June 2024)
[5] https://github.com/maplibre/maplibre-gl-js (last visited on 2nd June 2024)

OpenStreetMap (OSM) is used, fetched through a mapping platform called MapTiler.[6] GeoJSON files that are fetched from the server will be added to the map with a random colour. On the top-right of the map is an overlay listing all layers that are currently present in the map. Using the arrow keys on this list will change the z-index of the selected layer in the map.

3.2. Agent Architecture

GeoGPT's agents have a common underlying architecture, which is illustrated in subsection 3.2.1. They differ, however, through their assigned *tools*, which are described in subsection 3.2.2. Other slight differences are seen in the way that they are prompted. The prompting strategy used for GeoGPT will be discussed in subsection 3.2.3.

3.2.1. LangGraph Agent Implementation

The agentic behaviour of GeoGPT is implemented using LangGraph, which was described in section 2.2. Figure 3.4 illustrates the flow between the various nodes that make up the agent, and also shows the prompt engineering approach used in GeoGPT. A state dictionary is passed between, and updated by, the nodes. This state includes the chat history, the path to GeoGPT's working directory, a list of the current files in this directory, as well as other less important state.

The `__start__` node serves as the entry point of the agent. At this point, only one message is present in the state, namely the initial message from the user. The `__start__` node points to the `Prompt Engineering` node, where a prompt is constructed and passed on to the `agent` node. In the `agent` node, this prompt is passed to an LLM, so that a response can be generated. This response could contain text and/or instructions to invoke some tool. Therefore, the current state, now containing both the user message and the AI message, is sent to the conditional node called `agent_should_continue`. This node simply checks if the last AI message includes instructions to call some tool. If this is the case, we should proceed to the `action` node.

In the `action` node, these instructions are used to invoke tools that execute some code. These LLM-generated instructions specify the *name* of the tool, and suitable tool *parameters* that will be passed to this tool (see subsection 2.1.5 for more details on how *function/tool calling* works). Code Snippet 3.2 shows an example of such a tool. This tool is called `sql_db_query`, and takes a string of SQL code that is executed against a database. After such a tool has been invoked, the return value from the tool are appended as a tool message to the chat history, as Figure 3.4 shows. If the state of the system has now changed because of the tool invocation, a system message is added to the chat history. Figure 3.5 illustrates this behaviour, where a mid-conversation system messages is added to inform the agent about updates to the state of the system (this further discussed in subsection 3.2.3). We can now loop back to the `Prompt Engineering` and `agent` nodes, so that the LLM can react to the results from the tool invocation. This cyclic behaviour

[6] https://www.maptiler.com/ (last visited on 2nd June 2024)

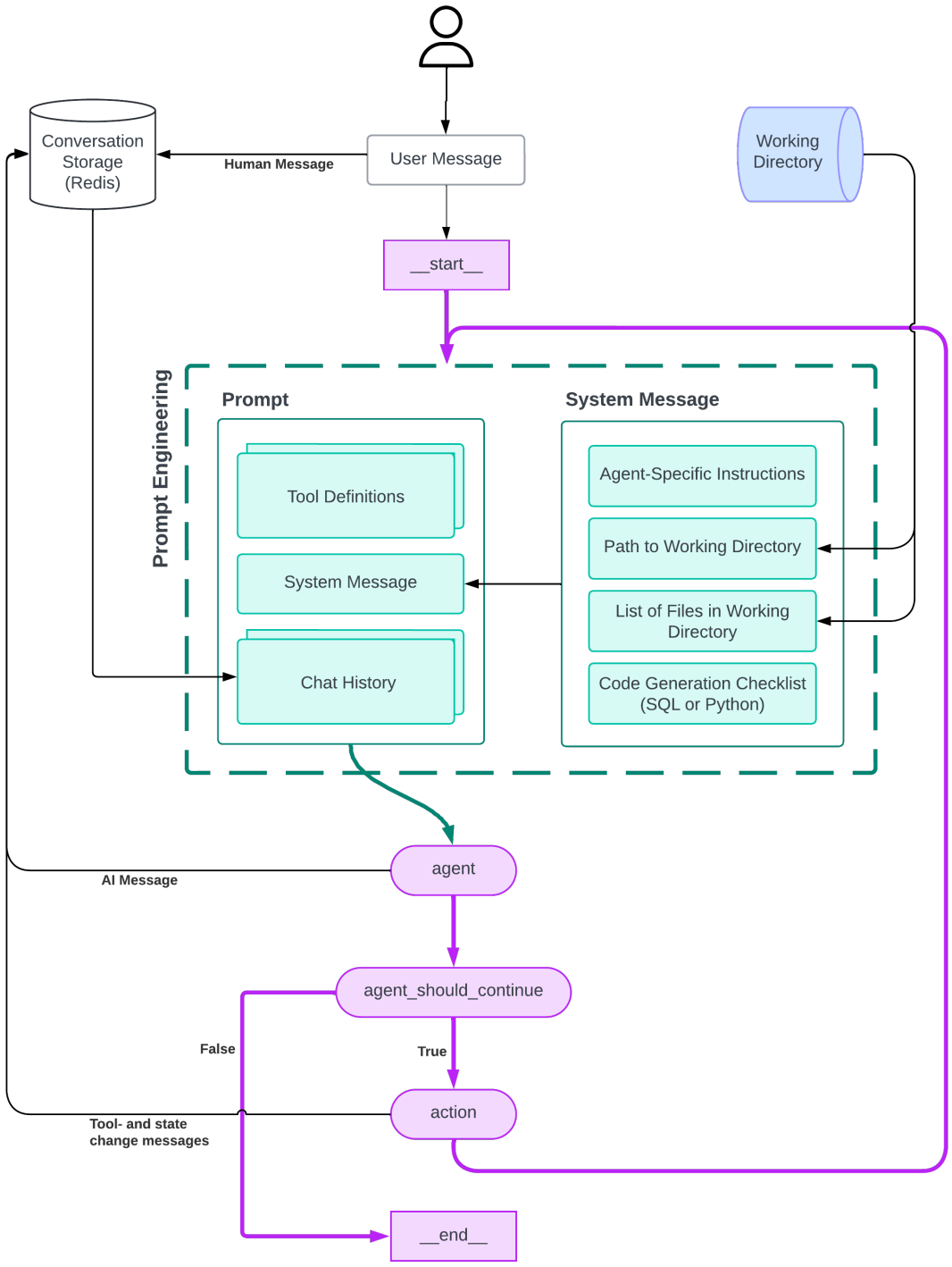

Figure 3.4.: Generic tool agent graph including the prompt engineering approach. Purple nodes and edges are what makes up the *LangGraph* graph, while teal-coloured parts are related to prompt engineering.

allows the agent to repeatedly call tools to try and answer the question from the user. When the agent finds no reason to call any more tools, `agent_should_continue` will return `False` so that the termination node, `__end__`, is reached. At this point, the agent has hopefully answered the question from the user.

```python
class QuerySQLDataBaseInput(BaseModel):
    query: str = Field(..., description='SQL query to be executed.')
    layer_name: str = Field(
        ..., description='Descriptive name for the data.')


class QuerySQLDataBaseTool(BaseSQLDatabaseTool, BaseTool):
    name: str = "sql_db_query"
    args_schema: Type[BaseModel] = QuerySQLDataBaseInput
    description: str = "Execute SQL queries and manage the results."

    def _run(self, query: str, layer_name: str) -> str:
        try:
            # Execute the query and load the result into a DataFrame
            df = pd.read_sql(query, self.db._engine)

            # Convert WKB to geometries and create a GeoDataFrame
            df['geom'] = df['geom'].apply(
                lambda x: wkb.loads(x, hex=True))
            gdf = gpd.GeoDataFrame(df, geometry='geom')

            # Save the result as GeoJSON
            filename = f'{layer_name}.geojson'
            WorkDirManager.add_file(filename, gdf, save_as_json=True)

            # Return a summary of the SQL query result to the LLM
            return f"Query returned {len(gdf)} features."

        except SQLAlchemyError as e:
            # Inform the LLM of errors in the code
            return f"Error: {str(e)}"
```

Code Snippet 3.2: A simplified version of a tool called `sql_db_query`. The tool is written in Python and executes SQL code against a PostGIS database. The LLM will specify the `query` and `layer_name` parameters, both of which are strings. The `query` will be executed against the PostGIS database, and the results will be saved as GeoJSON under the name "layer_name".geojson, in GeoGPT's working directory.

Figure 3.5.: Example of a chat history, mid-conversation. GeoGPT elects to invoke the `sql_db_tool` to get a polygon for Nordland county, before adding it to the map using the `add_geojson_to_map` tool. Tool- and system messages help ensure GeoGPT that the actions it takes are successful.

Table 3.2.: Overview of GeoGPT's agent types and their assigned tools

Agent Type	**Tools**
OGC API Features	`list_collections`
	`get_collections_info`
	`query_collection`
	`python_repl_ast`
	`add_geojson_to_map`
Python	`get_shapefile_info`
	`python_repl_ast`
	`add_geojson_to_map`
SQL	`sql_db_list_tables`
	`sql_db_schema`
	`sql_db_query`
	`add_geojson_to_map`

3.2.2. Tools

Table 3.2 shows an overview of the tools that are available to each of the agents. As described in subsection 2.1.5, these are defined by a name, a description of the tool's functionality, and a description of the parameters that the tool expects. The tools are written by the developer of the system. Code Snippet 3.2 shows a tool written in Python that is executes LLM-generated SQL code against a PostGIS database.

The OGC API Features agent has access to a total of five tools. **`list_collections`**, which takes no parameters, sends a GET request to the `/collections` endpoint of the OGC API Features server and uses the response to construct a list of the available collections. This tool gives the agent an overview of what collections are available. Using the response from `list_collections` the agent can now invoke the **`get_collections_info`** tool. This tool takes a list of collection names and returns relevant information for each of these collections. This includes the JSON response from the "landing page" of the collection, which includes details such as the collection description, spatial extent, and available attributes. Furthermore, a list of common values for certain high-cardinality attributes is included in the tool's response, as exemplified by Code Snippet 3.3. The percentages are obtained by querying a large number of features from the `/collections/{collection_id}` endpoint, and calculating their prevalences.

```
Property: fclass
    tree: 71.1%
    peak: 27.2%
    beach: 0.9%
    cave_entrance: 0.5%
    spring: 0.2%
    cliff: 0.1%
    volcano: 0.0%
```

Code Snippet 3.3: Prevalences of common values for the *fclass* property of the *osm_natural_points* collection

The **query_collection** tool is used to retrieve features from a collection. It takes a collection name, a CQL filter, a bounding box, and a layer name. Based on these parameters, an URL like this is constructed:

```
https://localhost:9001/collections/{collection_id}/items.json?limit=10000&filter={cql_filter}&{bbox}
```

The features retrieved from this query are saved in GeoGPT's working directory as "{layer_name}.geojson". The message returned from the tool reads something like this: "Query returned 5627 features." If the GeoJSON itself was returned as a tool message, this would quickly bloat the context window of the LLM, and therefore it is avoided.

Common for the OGC API Features agent and the Python agent is the **python_repl_ast** tool. This tool takes a string of Python code, executes it, and returns whatever the code prints to the standard output. If the code errors, the error message is returned instead. This Python tool is the main way for these two agents to perform geospatial analyses. The code is executed in a so-called Read-Eval-Print Loop (REPL). An advantage of using REPLs is that code can be executed in blocks, with variables from one block being shared with other blocks. This means that if the first block loads a large file into memory, which is often a time-consuming operation, then the subsequent blocks can reuse this in-memory variable without reloading the file. This allows the LLM to quickly retry if the subsequent code blocks should error. The Python agent also has a tool called **get_shapefile_info**, which works similarly to `get_collections_info`.

add_geojson_to_map is the only tool that is common for all three agent types. The tool's job is to add layers to the map on the client. It takes two parameters: the name of a GeoJSON file stored in GeoGPT's working directory, and a layer name. Invoking the tool will send a message to the client, which includes the full path to the file on the server. The client will then make a GET request to the server on the `/geojson` endpoint, asking for the contents of this file to be returned so that it can be added to the map. The sequence diagram in Figure 3.2 illustrates this behaviour.

The SQL agent has tools very similar to the OGC API Features agent. **sql_db_**

`list_tables` is a tool that will list all the available database tables, along with their description. `sql_db_schema` takes a list of table names and returns information about their attributes, the prevalence of different values in high-cardinality columns, and other details about these tables, much like `get_collections_info`. `sql_db_query` accepts arbitrary SQL code that will be executed against the database. Code Snippet 3.2 shows a simplified version of this tool. The tool will make sure that query results that has a geospatial component will be stored as GeoJSON in GeoGPT's working directory, so that the geometries can be added to the map on the client, using the `add_geojson_to_map` tool.

3.2.3. Prompt Engineering

The prompt that is passed to GeoGPT's agents consists of tool definitions, a system message, and a chat history, as Figure 3.4 and Figure 3.7 show. It is constructed before every invocation of the *agent* node, where it is passed to an LLM so that it can generate an answer. LLMs have no inherent memory, so in order to have a chat conversation, the entire chat history needs to be passed with the prompt.[7]

Figure 3.4 shows that there are four elements to the main system message:

1. Agent-specific instructions
2. A path to the working directory
3. A list of the current files in the working directory
4. A checklist that the LLM should use when generating code

Figure 3.7 shows the prompt passed to GeoGPT's SQL agent where the user has asked which county is the largest by size. The agent-specific instructions include information intended to give the LLM contextual awareness and hints on how it should work towards solving tasks. We start by telling LLM that it's a "helpful GIS agent/consultant that has access to an SQL database containing OpenStreetMap data". This is a common way of giving LLMs a persona, which results in responses like the one in Figure 3.6. Continuing, we give it some information on how to string tool calls together to solve tasks. We tell it to first list available tables, then look up the schemas of the relevant tables, and then, using the information gathered, to construct an SQL query to answer the user's request. We also remind it that it needs to add the result of the analyses to the map, using the `add_geojson_to_map` tool.

[7] Several strategies have been developed by researchers to avoid having to pass the entire chat history to the LLM each time, as this will eventually bloat the context window, making token generation slower and worse in quality. Strategies include picking only the n last messages in the chat history, passing a summary of the chat instead of entire messages, or utilizing knowledge graphs.

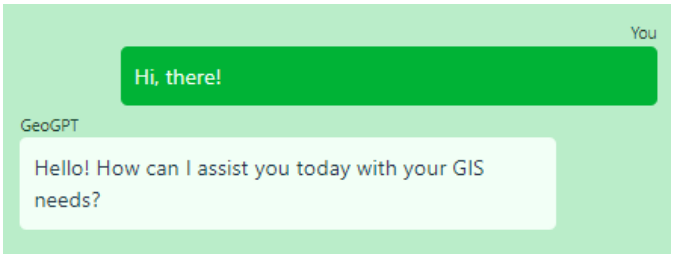

Figure 3.6.: Conversation showcasing the effect of giving an LLM a persona through the system message

The next two parts of the system message concern GeoGPT's working directory. Having a working directory is important to control which files the agent has available, and also to make sure it doesn't save files to the folder on the LangChain server where GeoGPT's source code is located, as this would bloat the actual source code. First, we tell the LLM where the working directory is located. This is especially important for the OGC API Features agent and the Python agent, as they need to manually read and write to the paths of the files in the working directory, using the Python code they generate. Second, we list the files that currently reside in the working directory. In the prompt in Figure 3.7 there "are currently no files written to the working directory", but if there were any, they would be listed in a bullet point list in place of this message.

The final part of the system message is a checklist to inform the LLM about common pitfalls it could run into when generating code. The checklist in Figure 3.7 is tailored for GeoGPT's SQL agent. A similar checklist for Python is provided for the other two agents, with reminders about using metric CRSs when doing area calculations, etc.

Normally, conversation-based prompts for LLM contain only a single system message, at the very start of the conversation. GeoGPT, however, features a — to the author's knowledge — novel usage of system messages. As Figure 3.5 shows, system messages are appended mid-conversation, providing updates about state changes in the system. These are generated in the `action` node (see Figure 3.4). The first system message is added because a new file has been added to the working directory, as a result of invoking the `sql_db_query` tool. Such messages help GeoGPT stay up-to-date on what files it has available, and in Figure 3.5, it uses this information immediately to add the new file to the map using `add_geojson_to_map`. Another system message is eventually added to tell the GeoGPT that client map has been modified. This message helps ensure GeoGPT that the invocation of `add_geojson_to_map` was successful. If it wasn't, then the system message would inform it about this.

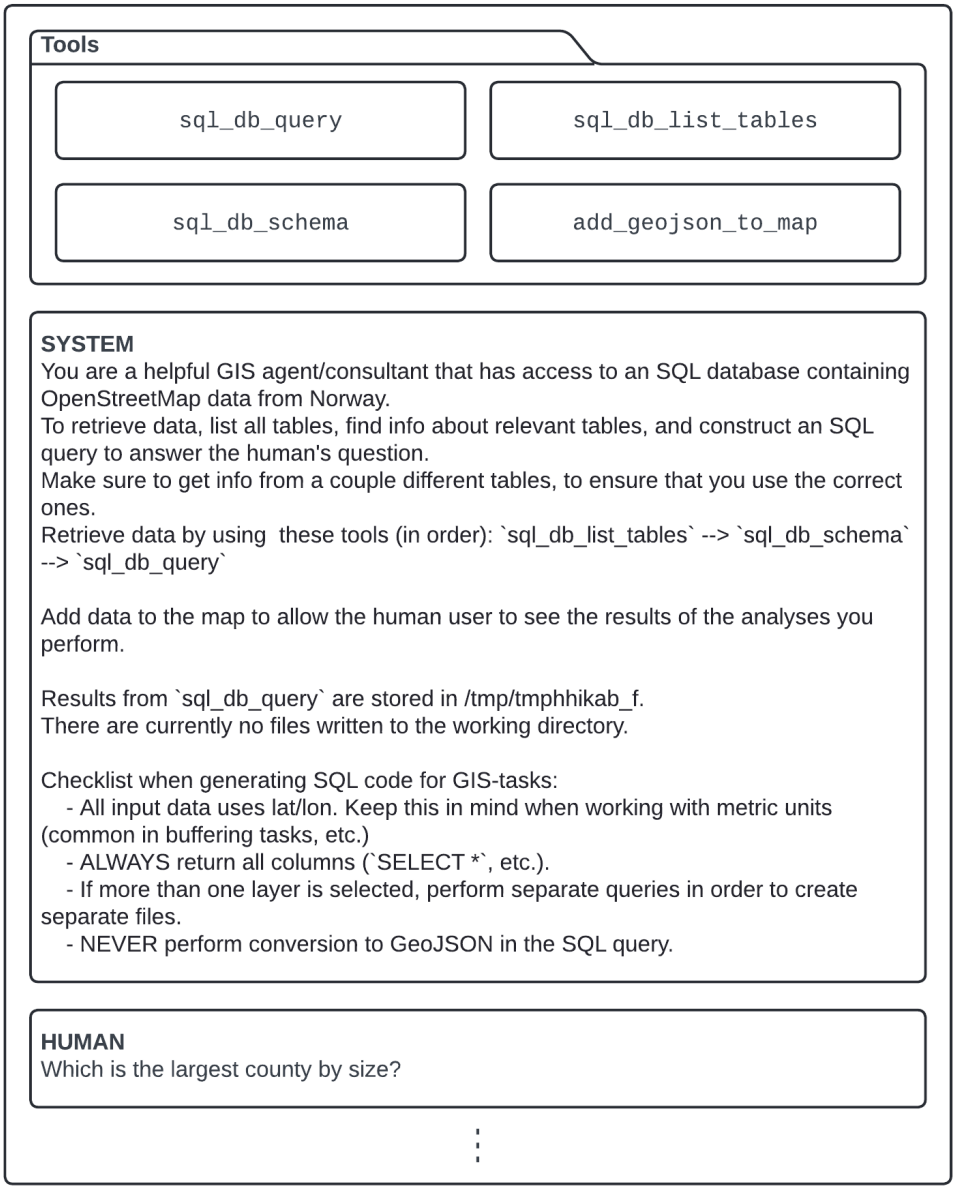

Figure 3.7.: Initial prompt to GeoGPT as the user asks a question. The prompt includes tool definitions, the main system message, and the chat history (which currently only includes the initial message from the user).

4. Experiments

Section 4.1 of the Experiments chapter will describe the methodology and rationale behind the two experiments conducted in this thesis. The first experiment, presented in subsection 4.1.1, assesses GeoGPT's ability to solve common GIS tasks through a new GIS benchmarking dataset. The other experiment, presented in subsection 4.1.2, will assess the importance of the quality of the prompt passed from the user to GeoGPT. Subsection 4.1.4 lists the datasets used in the experiments. Section 4.2 presents the experimental results and offers interpretations of the findings from the experiments. It will also present several example results, including screenshots of the application and code that generated by GeoGPT.

4.1. Experimental Setup

This section will explain the concept and setup of the two experiments mentioned in the paragraph above. Section 4.1.1 will describe the setup for the GIS benchmark experiments, while subsection 4.1.2 will explain the setup for the prompt quality experiment. Subsection 4.1.3 describes the hardware on which the experiments were conducted, and the specific LLMs that were used.

4.1.1. GIS Benchmark Experiment

The first experiment will measure the abilities of GeoGPT's three agent types to produce correct answers to GIS tasks. It will also measure cost and latency for the generated answers, and the agent's ability to produce similar answers, consistently (repeatability). To do this, a benchmarking dataset was constructed. This is a set of 12 GIS-related questions with corresponding correct answers, which can be viewed in its entirety in Table A.1. Each of the 12 questions will be asked three times per agent type. Thus, the total number of experimental runs becomes the following:

$$12 \text{ questions} \cdot 3 \text{ agent types} \cdot 3 \text{ repetitions} = 108 \text{ experimental runs}$$

The following sections, named "Outcome Evaluation", "Cost and Latency", and "Repeatability", will go into detail on the different ways that the results are evaluated.

Outcome Evaluation

Each of the 108 GeoGPT-generated answers will be manually evaluated based on how well they answered the question, and this *outcome* will be annotated as one of the following:

success, *partial success*, and *failure*. Table 4.1 shows the guidelines used when assigning outcome scores.

Table 4.1.: Guidelines for evaluating the outcomes of tests

Outcome	**Guideline**
Success	The question was answered correctly and little to no follow-up from the user was required to produce the desired outcome. No false assumptions were made by the system when answering the question.
Partial Success	Portions of the question were answered correctly or semi-correctly, and/or some follow-up from the user was required to guide the system toward the solution.
Failure	The question was answered incorrectly, and/or false assumptions were made by the system while attempting to answer the question.

Cost and Latency

The application is hooked up to LangChain's tracing system, *LangSmith*.[1] Apart from being a useful tool for debugging purposes, it provides a simple way to obtain detailed data on token usage and latency for a particular run, as well as the total cost of the run, in American dollars. Further details, and screenshots of LangSmith's interface, can be found in Appendix B.

Box plots will be used to compare these three metrics for the different agents. The box plots follow the description for box plots found on Wikipedia.[2,3] Box plots allow us to easily see where the 0th (Q_0), 25th (Q_1), 50th (Q_2), 75th (Q_3), and 100th (Q_4) percentiles of the datasets lie, as well as the dataset's outliers. Outliers are those data points that fall more than 1.5 times the interquartile range (the distance between Q_3 and Q_1) above Q_3 or below Q_1.

Repeatability

Another aspect that the GIS benchmark experiment will try to evaluate, is the consistency of the system — its ability to produce similar responses, repeatedly. The outcome scores are encoded using the ordinal encoding presented Table 4.2. A higher value indicates a better outcome. Standard deviations are calculated for each triplet of identical test

[1] https://www.langchain.com/langsmith (last visited on 2nd June 2024)
[2] https://matplotlib.org/stable/api/_as_gen/matplotlib.pyplot.boxplot.html (last visited on 2nd June 2024)
[3] https://en.wikipedia.org/wiki/Box_plot (last visited on 2nd June 2024)

samples (samples where the question and the agent type remained the same), using these encoded outcomes. This will serve as a suitable measure for assessing repeatability.

Table 4.2.: Ordinal encodings for outcome scores

Outcome	**Encoded Value**
Success	2
Partial Success	1
Failure	0

4.1.2. Prompt Quality Experiment

A second experiment is constructed to evaluate the importance of the quality of the initial question/prompt from the user. As stated in the Background and Motivation chapter, part of the motivation for developing an LLM-based GIS like GeoGPT is to make GIS more accessible to non-experts. It is therefore interesting to assess the extent to which a carefully constructed prompt by a GIS expert can enhance the system's output.

For these experiments, the three hardest questions from the GIS benchmark experiment were picked. Then, for each of these questions, a *novice*-level and an *expert*-level prompt was constructed. The novice-level prompt is as simple as possible, while the expert-level prompt is more elaborate and written as a step-by-step recipe for solving the problem. Despite their differences, the prompts should ideally produce the same answer.

4.1.3. Hardware and LLM Version

All experiments were conducted on a Lenovo ThinkPad E490, which has an Intel® Core™ i7-8565U CPU @ 1.80GHz processor, 15.8 GB usable RAM, and 256 GB SSD storage. Everything but the LLM inference (text generation) was done locally. LLM inference was done using OpenAI's Inference API.

It is worth noting that two slightly different models were used during testing. This is due the release of the `gpt-4-turbo-2024-04-09` model in mid-April. According to OpenAI, "this new model is better at math, logical reasoning, and coding" compared to `gpt-4-0125-preview`,[4] which is the model that was used for the first experimental runs. At `gpt-4-turbo-2024-04-09`'s release, a decision was made to use this for the remaining experimental runs. The runs that had already been conducted were not re-run due to time constraints and a confidence that these slight model upgrades would not significantly change the outcome of the experiments.

[4]OpenAI has a GitHub repository containing the code they use to evaluate their Large Language Models (LLMs) and benchmark results for OpenAI models and reference models from other companies: https://github.com/openai/simple-evals (last visited on 2nd June 2024)

4.1.4. Datasets

A total of eighteen datasets were used in the experiments, all downloaded from a website called "Geofabrik".[5] *Geofabrik*, which is German for "geo factory", is a company that "extract, select, and process free geodata". They have gathered data from OpenStreetMap and published them as a collection of shapefiles, dividing them into categories such as "places of worship", "points of interest", and "traffic". Data can be downloaded for different regions of the world, but for the experiments conducted in this thesis, only data for Norway was used. Table 4.3 lists the datasets, along with short descriptions of their contents, and the number of features for each dataset. Common for all datasets is their *fclass* attribute, which is short for *feature class*. Some datasets have additional attributes, such as the *maxspeed* attribute in the road dataset and the *type* attribute in the building dataset. Figure 4.1 shows a plot containing four selected datasets, constrained to a bounding box of Trondheim. This plot was created by GeoGPT.

Table 4.3.: Datasets used in the experiments

Dataset	**Type**	**Description**	**#Features**
Buildings	Polygon	Contains building outlines. Its *type* attribute can have values like "house", "university", and "restaurant".	4,147,645
Land Use	Polygon	Represents areas designated to different purposes and activities. Its *fclass* attribute can have values like "forest", "farmland", and "residential".	541,452
Natural	Point	Contains outlines of various objects found in nature. Its *fclass* attribute can have values like "beach", "glacier", and "cave_entrance".	119,725
Natural	Polygon	Similar to the point data equivalent.	6,665

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[5] https://download.geofabrik.de/europe/norway.html (last visited on 2nd June 2024)

Table 4.3 continued from previous page

Dataset	Type	Description	#Features
Places of Worship	Point	Common values for *fclass* attribute: "christian", "buddhist", and "muslim".	311
Places of Worship	Polygon	Similar to the point data equivalent.	2,520
Places	Point	Common values for *fclass* attribute: "farm", "village", and "island".	178,997
Places	Polygon	Similar to the point data equivalent.	5,689
Points of Interest	Point	Common values for *fclass* attribute: "tourist_info", "bench", and "kindergarten".	117,677
Points of Interest	Polygon	Similar to the point data equivalent.	45,825
Railways	Line	Common values for *fclass* attribute: "rail", "subway", and "tram". Also has True/False attributes *bridge* and *tunnel*.	14,008
Roads	Line	Common values for *fclass* attribute: "rail", "subway", and "tram". Has additional attributes *oneway*, *maxspeed*, *bridge*, and *tunnel*.	1,741,929
Traffic	Point	Common values for *fclass* attribute: "crossing", "street_lamp", and "parking".	98,860
Traffic	Polygon	Common values for *fclass* attribute: "parking", "pier", and "dam".	45,623
Transport	Point	Common values for *fclass* attribute: "bus_stop", "ferry_terminal", and "railway_station".	91,627

Continued on next page

Table 4.3 continued from previous page

Dataset	Type	Description	#Features
Transport	Polygon	Similar to the point data equivalent.	935
Water	Polygon	Common values for *fclass* attribute: "water", "wetland", and "river_-bank".	1,861,199
Waterways	Line	Common values for *fclass* attribute: "stream", "river", and "canal".	833,253

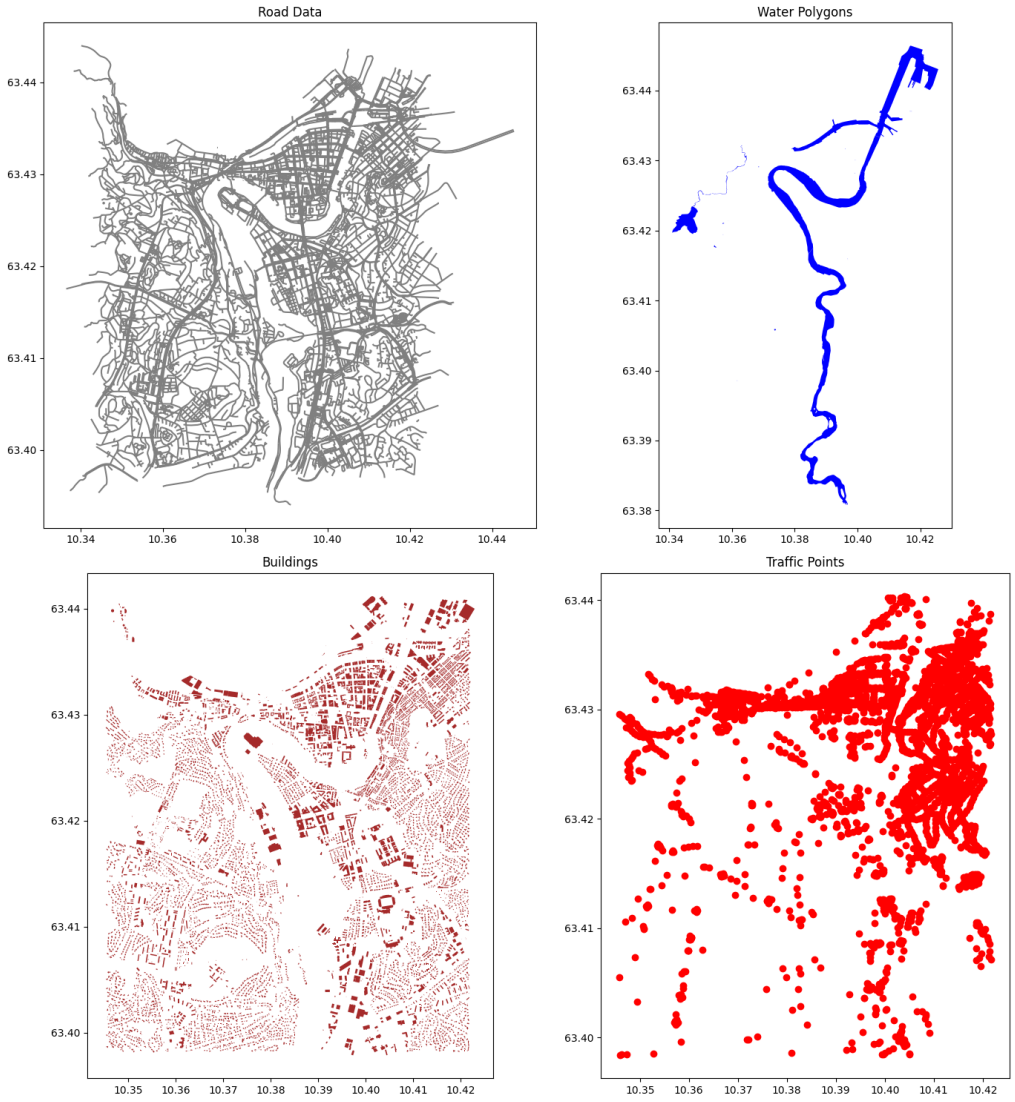


Figure 4.1.: A plot of four selected datasets constrained to a bounding box of Trondheim. From top-left, clockwise: road lines, water polygons, traffic points, and building polygons. These plots were generated by GeoGPT.

4.2. Experimental Results

Subsection 4.2.1 and subsection 4.2.2 will present the results from the experiments presented in subsection 4.1.1 and subsection 4.1.2, respectively. Visualizations for this section were created using Matplotlib,[6] a Python library suitable for creating bar charts, box plots, etc.

4.2.1. GIS Benchmark — Results

Outcome Evaluation

Figure 4.2 shows a bar chart for the outcome distribution between GeoGPT's three agents. The OGC API Features agent and the Python agent have comparable results, whereas the SQL agent performs significantly better than the other two. The SQL agent has a success rate of 69.4%, while the other two share a success rate of 38.9%. Possible reasons for this are discussed in section 5.2 of the Discussion.

Figure 4.2.: Outcome distribution between GeoGPT's different agent types. The OGC API Features and Python agents perform similarly, whereas the SQL agent outperforms them by a significant margin.

[6] https://matplotlib.org/ (last visited on 2nd June 2024)

Cost and Latency

Figure 4.3 displays a box plot with a logarithmic y-axis that shows answer latencies between the different agent types, that is, the time taken by the agents to produce answers. Here we can see that the SQL agent spends the least amount of time per task. The OGC API Features agent has a slightly higher median, but with a few time-consuming outliers. The Python agent is the odd one out with a median of ~ 82 seconds, a $Q3 \sim 293$ seconds, and a $Q4 \sim 984$ seconds, in addition to a couple of high-latency outliers. The large gap from the Python agent to the other two agents it largely due to the Python agent's tendency to load large datasets into memory. For instance, when attempting the task of calculating the difference between a polygon outlining Oslo and water polygons within it (see Table A.1 for the task formulation), the Python agent used nearly 40 minutes on the entire task. 94% of the time was spent executing the code in Code Snippet 4.1. The main reason for the long execution time is line 8, where the whole `osm_landuse_polygons.shp` dataset is loaded into memory. This dataset has a size of ~ 1.4 GB and a total of 1,861,199 polygon features, and loading such amounts of data in this way is very time-consuming. The Python agent was the only agent with such issues because the OGC API Features agent is limited to 10,000 features per request, and the SQL agent does not load the data into memory like the other agents do.

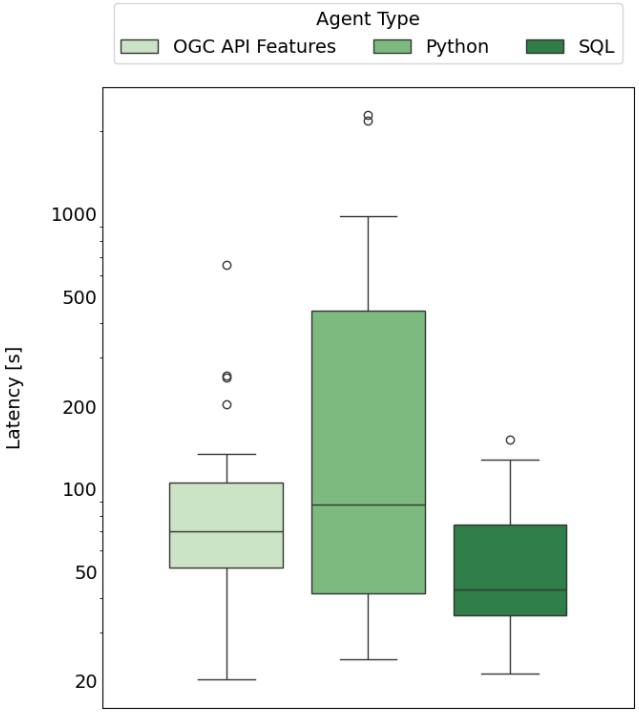
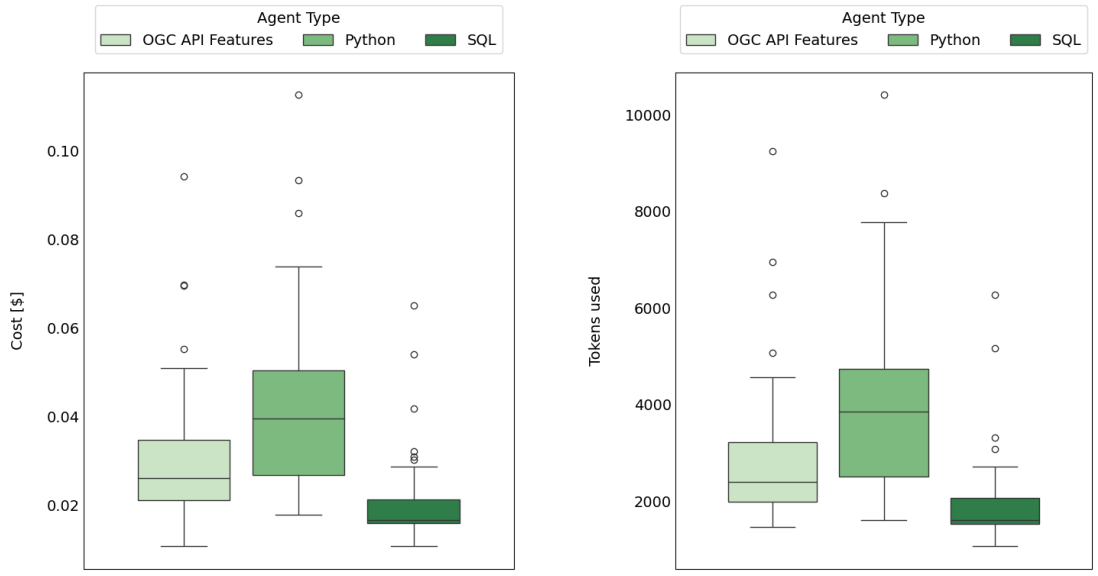


Figure 4.3.: Box plots comparing the time taken to generate answers between GeoGPT's agent types. Again, the SQL agent performs best, while the Python agent is the odd one out with very high latencies compared to the other two.

Figure 4.4 shows box plots for token usage and cost per run. Naturally, these figures appear very similar, since prices for the input tokens and generated output tokens are fixed for the models used. According to OpenAI's webpages,[7] they charge $10 per million input tokens and $30 per million output tokens for their GPT-4 Turbo model. From the results of the experiments, a ratio of approximately $10.7 per million tokens — either input *or* output — was calculated, which is closest to the input token price. This shows that *a lot* more input tokens were used, compared to output tokens.



(a) Average cost per answer between the agent types

(b) Average token usage per answer between the agent types

Figure 4.4.: Cost and token usage between GeoGPT's different agent types. These plots are highly correlated, but will differ somewhat because of the imbalance between input and output tokens.

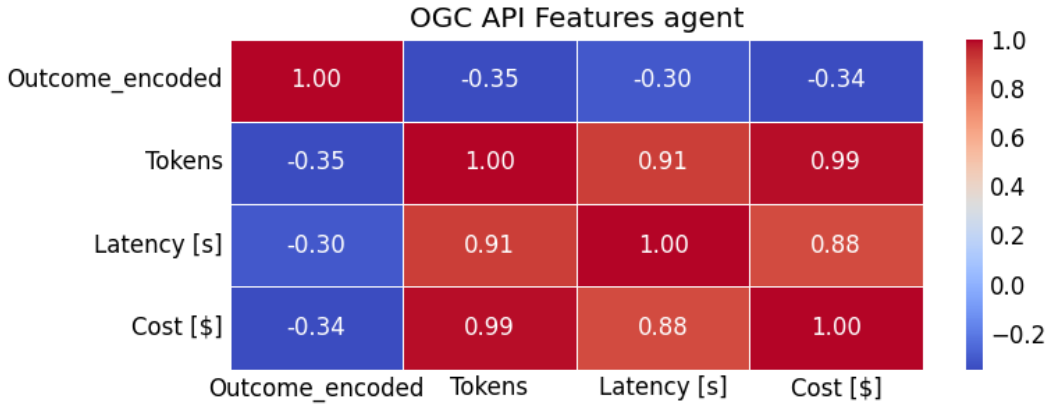
An observation that can be made from the correlation matrices in Figure 4.5 is that the correlation between latency and token usage is inconsistent between the agent types. The OGC API Features agent and SQL agent have strong correlation between these metrics, but the Python agent has next to none. This supports the observation that, for the Python agent, code execution time — particularly the time spent on expensive imports — is likely the main contributor to the high latency.

Another observation that can be made from Figure 4.5 is the slight negative correlation between the encoded outcome and each of the following variables: token usage, latency, and total cost. This suggests that a task that takes longer to complete, and has a higher token usage, is *less* likely to produce a successful outcome. Possible reasons as to why this is the case will be explored in subsection 5.3.1 in the Discussion.

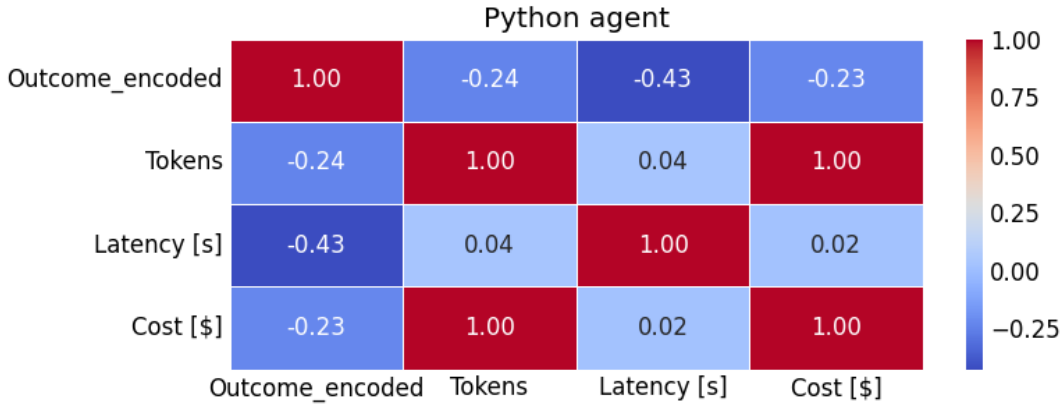
[7] https://openai.com/pricing (last visited 2nd June 2024)

```
1  import geopandas as gpd
2
3  # Paths to the shapefiles
4  landuse_path = '/tmp/tmpsutdy6it/osm_landuse_polygons.shp'
5  places_path = '/tmp/tmpsutdy6it/osm_places_polygons.shp'
6
7  # Load the data from shapefiles
8  landuse_gdf = gpd.read_file(landuse_path)
9  places_gdf = gpd.read_file(places_path)
10
11 # Filter out 'residential' areas from the landuse data
12 residential_gdf = landuse_gdf[landuse_gdf['fclass'] == '
   residential']
13
14 # Compute the spatial difference to exclude residential areas from
    the places data
15 oslo_outline = gpd.overlay(places_gdf, residential_gdf, how='
   difference')
16
17 # Path for the output GeoJSON file
18 output_path = '/tmp/tmpsutdy6it/oslo_outline_no_residential.
   geojson'
19
20 # Save the resulting GeoDataFrame to a GeoJSON file
21 oslo_outline.to_file(output_path, driver='GeoJSON')
22
23 # Output the path to the saved file
24 print(output_path)
```

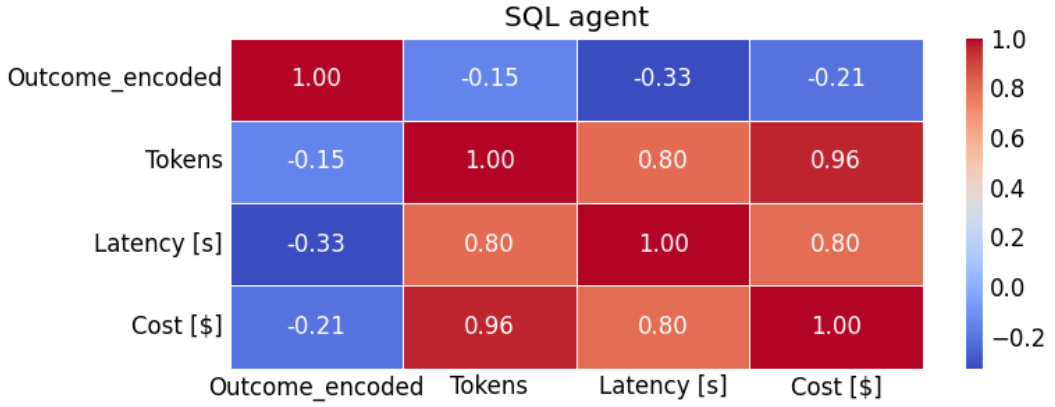
Code Snippet 4.1: GeoGPT-generated Python code designed to compute the difference between the outline of Oslo, the Norwegian capital, and residental features within it. The execution time of this code block was $\sim$ 36 minutes, mostly due to line 8.



(a) Correlation matrix for the OGC API Features agent



(b) Correlation matrix for the Python agent



(c) Correlation matrix for the SQL agent

Figure 4.5.: Correlation matrices for the metrics recorded during the GIS benchmark experiment for the three agent types

Repeatability

Table 4.4 shows the average standard deviation of the encoded outcomes for each agent type, as well as the mean of these three standard deviations. These numbers indicate that there is a notable amount of inconsistency in GeoGPT's answers when task and agent type stays the same, on average deviating with more than a third of an outcome category (0.376 for the encoded values).

Table 4.4.: Standard deviations of encoded outcomes for GeoGPT's agent types

Agent Type	**Outcome Std. Deviation**
OGC API Features	0.552
Python	0.337
SQL	0.241
Mean	0.376

Successful Responses

Figure 4.6 shows a successful response from GeoGPT's SQL agent when asked how many counties the Glomma river runs through.[8] GeoGPT correctly lists all four correct counties in a numbered list. Code Snippet 4.2 shows the code generated by GeoGPT for the second invocation of `sql_db_query`. The second invocation is nearly identical to the first one, but in the first invocation the geometry column was not included in the response, meaning GeoGPT was unable to add the results to the map. The tool informs GeoGPT about this, and the agent therefore decided to run the query again, now making sure to include the geometry column in the query result, before adding the resulting GeoJSON file to the map using the `add_geojson_to_map` tool. A follow-up message instructed GeoGPT to "Add Glomma to the map", allowing for visual verification that the answer it gave was correct.

[8] This run was not part of the results used for evaluation due to a bug in the `sql_db_query` tool that caused it to unnecessarily execute queries twice. GeoGPT's response would not be different had the bug not been present for the run, but it would have taken longer to complete.

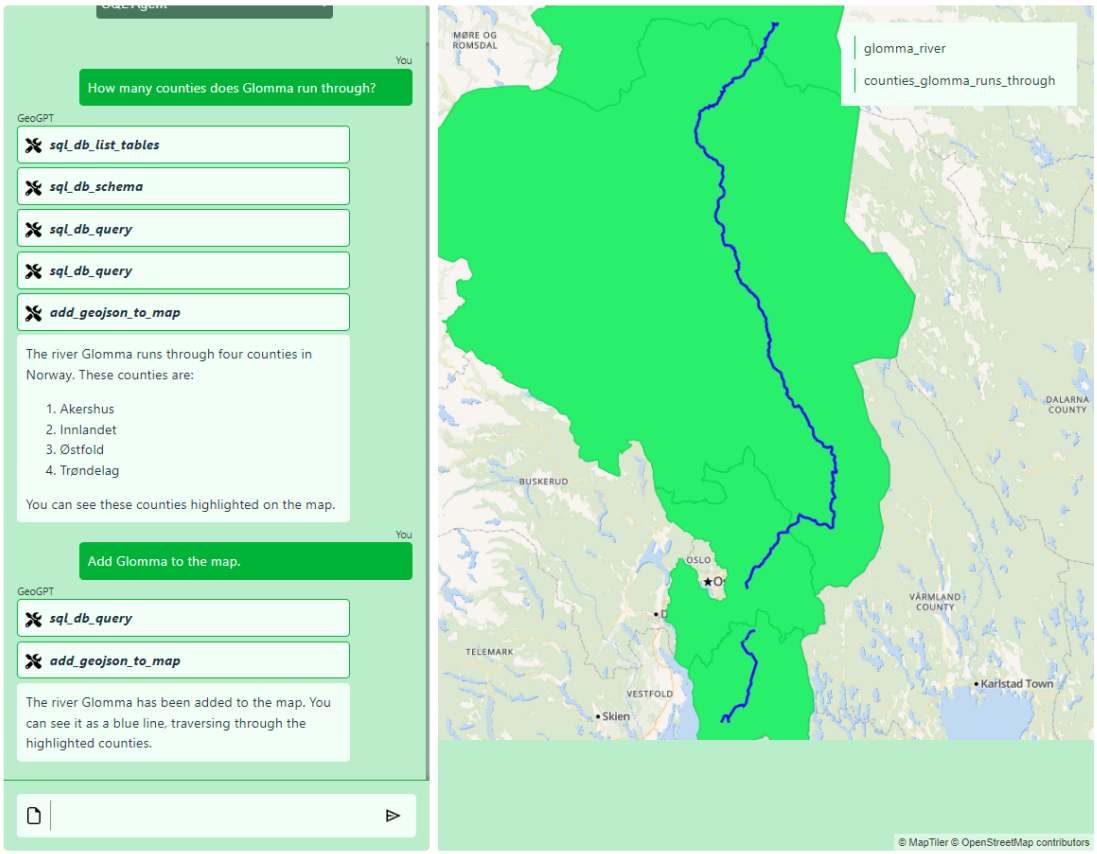


Figure 4.6.: Successful response from GeoGPT's SQL agent when asked how many counties the Glomma river runs through. Using the tools available to it, GeoGPT's SQL agent was able to to find that the river Glomma runs through the following counties: Akershus, Innlandet, Østfold, and Trøndelag. A follow-up message was added to make GeoGPT add the river geometries to the map, to do a visual for verification of its results.

```sql
WITH river AS (
    SELECT geom
    FROM osm_waterways_lines
    WHERE fclass = 'river' AND name ILIKE 'Glomma'
),

places AS (
    SELECT geom, name
    FROM osm_places_polygons
    WHERE fclass = 'county'
)

SELECT DISTINCT places.name AS county_name, places.geom AS geom
FROM river, places
WHERE ST_Intersects(river.geom, places.geom);
```

Code Snippet 4.2: GeoGPT-generated SQL code to retrieve the counties that the Glomma river runs through. The `ST_Intersects` function from PostGIS was used to find the intersection between the river data and the county polygons, and the names and geometries of the counties were included in the result.

Figure 4.7 shows a partially successful attempt from GeoGPT's Python agent to calculate the number of trees along Munkegata in Trondheim. While setting a definitive answer to such a question is difficult, the correct answer was set to 100 trees, assuming a 20-meter buffer around the line segments that make up the road. In Code Snippet 4.3, we can see how GeoGPT loads the road data around Munkegata in Trondheim, using an approximate bounding box to avoid retrieving roads named "Munkegata" in other cities (there is one in Oslo). It then filters and saves the loaded data to only include features named "Munkegata". In the following code block, shown in Code Snippet 4.4, GeoGPT gets the tree data by filtering the `osm_natural_points` dataset on the `fclass` attribute, before loading the road data for Munkegata from Code Snippet 4.3, converting both datasets to a metric CRS, creating a buffer around the road data, performing an intersection between the buffer, and finally printing the `tree_count` to the standard output. This answer was evaluated as a *partial success*.

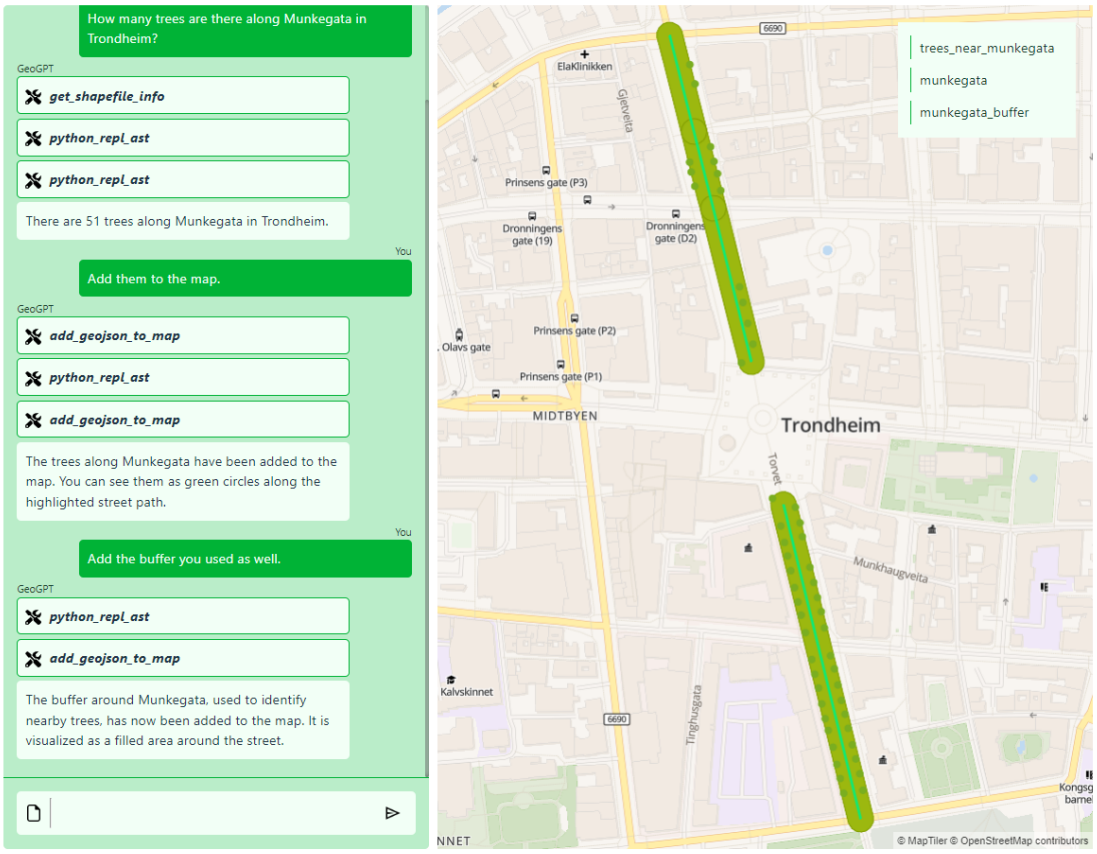


Figure 4.7.: Partially successful response from GeoGPT's Python agent when asked how many trees there are along Munkegata in Trondheim. It managed to find the road segments corresponding to Munkegata in Trondheim, but created a slightly too small buffer around it, which did not cover all the relevant trees.

```python
import geopandas as gpd

# Load roads data with a focus on Munkegata
roads_path = '/tmp/tmpl8zsdj6m/osm_roads_lines.shp'
munkegata_bbox = (10.3910, 63.4270, 10.4030, 63.4330) # Approximate
    bounding box around Munkegata
munkegata_roads = gpd.read_file(roads_path, bbox=munkegata_bbox)

# Filter for Munkegata
munkegata = munkegata_roads[munkegata_roads['name'] == 'Munkegata']

# Save filtered Munkegata road to GeoJSON
munkegata_path = '/tmp/tmpl8zsdj6m/munkegata.geojson'
munkegata.to_file(munkegata_path, driver='GeoJSON')

print(munkegata_path)
```

Code Snippet 4.3: GeoGPT-generated Python code to retrieve Munkegata in Trondheim. The bounding box, which is generated from GPT-4's background knowledge, covers a suitable area in the center of Trondheim, where Munkegata is located. This step is important, as a road named "Munkegata" can also be found in Oslo, which is located in a *completely different* part of Norway.

```python
from shapely.geometry import box
import geopandas as gpd

# Load the trees points
natural_points_path = '/tmp/tmpl8zsdj6m/osm_natural_points.shp'
trees = gpd.read_file(natural_points_path)

# Filter for trees
trees = trees[trees['fclass'] == 'tree']

# Load Munkegata road
munkegata_path = '/tmp/tmpl8zsdj6m/munkegata.geojson'
munkegata_road = gpd.read_file(munkegata_path)

# Project to UTM for accurate distance measurement
munkegata_utm = munkegata_road.to_crs(epsg=32633)
trees_utm = trees.to_crs(epsg=32633)

# Buffer Munkegata by 10 meters to include nearby trees
tree_buffer = munkegata_utm.buffer(10)

# Spatial join trees within buffered Munkegata
trees_near_munkegata = gpd.sjoin(trees_utm, gpd.GeoDataFrame(geometry=
```

```
    tree_buffer), how='inner', op='intersects')

# Count the number of trees
tree_count = trees_near_munkegata.shape[0]
print(tree_count)

# --> 51
```

Code Snippet 4.4: Python code to calculate the number of trees along Munkegata in Trondheim. The datasets were converted to a metric CRS (WGS 84 / UTM zone 33N), before a buffer around the road data from Code Snippet 4.3 was created and used to find the intersection with the tree data. 51 trees were found, but ideally ~ 100 should be returned.

```python
import geopandas as gpd

# Define the file path for the roads shapefile
shapefile_path = '/tmp/tmpr1hvr_c5/osm_roads_lines.shp'

# Read the shapefile with a condition on maxspeed being >= 70
roads_gdf = gpd.read_file(shapefile_path)
roads_high_speed_gdf = roads_gdf[roads_gdf['maxspeed'].astype(float)
    >= 70]

# Save the filtered GeoDataFrame as GeoJSON
output_geojson_path = '/tmp/tmpr1hvr_c5/oslo_high_speed_roads.geojson'
roads_high_speed_gdf.to_file(output_geojson_path, driver='GeoJSON')

print(output_geojson_path)
```

Code Snippet 4.5: GeoGPT-generated Python code that saves high-speed roads with a misleading filename. This was the source of error that lead to the result in Figure 4.8. GeoGPT assumed that the `osm_roads_lines.shp` included road data only for *Oslo*, when in reality it includes data for the *whole of Norway*.

Unsuccessful Responses

This section will highlight some limitations in the current version of GeoGPT. Figure 4.8 illustrates an issue sometimes encountered with GeoGPT, which will be a central topic in the Discussion. Here, the Python agent has failed to recognize that the road datasets it has available is in fact for the whole of Norway, not just Oslo, the country's capital. As Code Snippet 4.5 shows, the agent performs the correct analysis based on the assumption it has already made, but the answer is far from what the user enquired, due to this false assumption about the data.

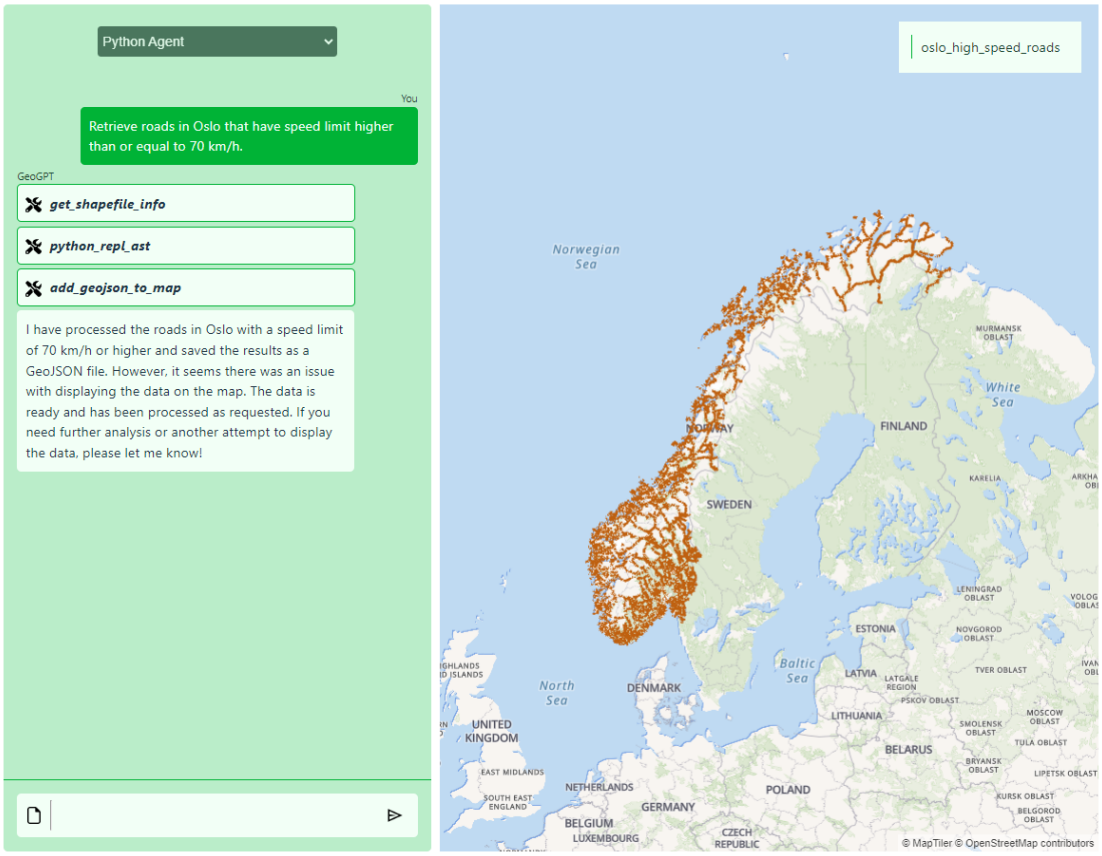


Figure 4.8.: Unsuccessful attempt by GeoGPT's Python agent to retrieve high-speed roads in Oslo. The figure shows roads throughout *the whole of* Norway with speed limits of 70 km/h or higher, but it should only have shown those in Oslo, the Norwegian capital.

Figure 4.9 shows an unsuccessful attempt from GeoGPT's OGC API Features agent to create a geodesic line between Oslo Airport Gardermoen and Bergen Airport Flesland. Code Snippet 4.6 shows GeoGPT's attempt to download a point feature with the name of "Oslo Airport". It turns out that no such point feature exists, and only a polygonal feature in another dataset is available for the airport. The same is the case for Bergen Airport. GeoGPT made many attempts at fetching point data for the airports, but of course none of them returned any results.

Eventually, GeoGPT downloads a set of features from the `osm_transport_points` collection twice, naming them "oslo_airport.geojson" and "bergen_airport.geojson". It then produces the code shown in Code Snippet 4.7, where it selects the first point feature in each collection and *assumes* that their coordinates correspond to the two airports. These two features actually correspond to are Rakkestad Airport and a bus stop on a road along Ofotfjorden in Nordland. In addition to this mistake, subsequent attempts at creating a geodesic line between the locations were unsuccessful.

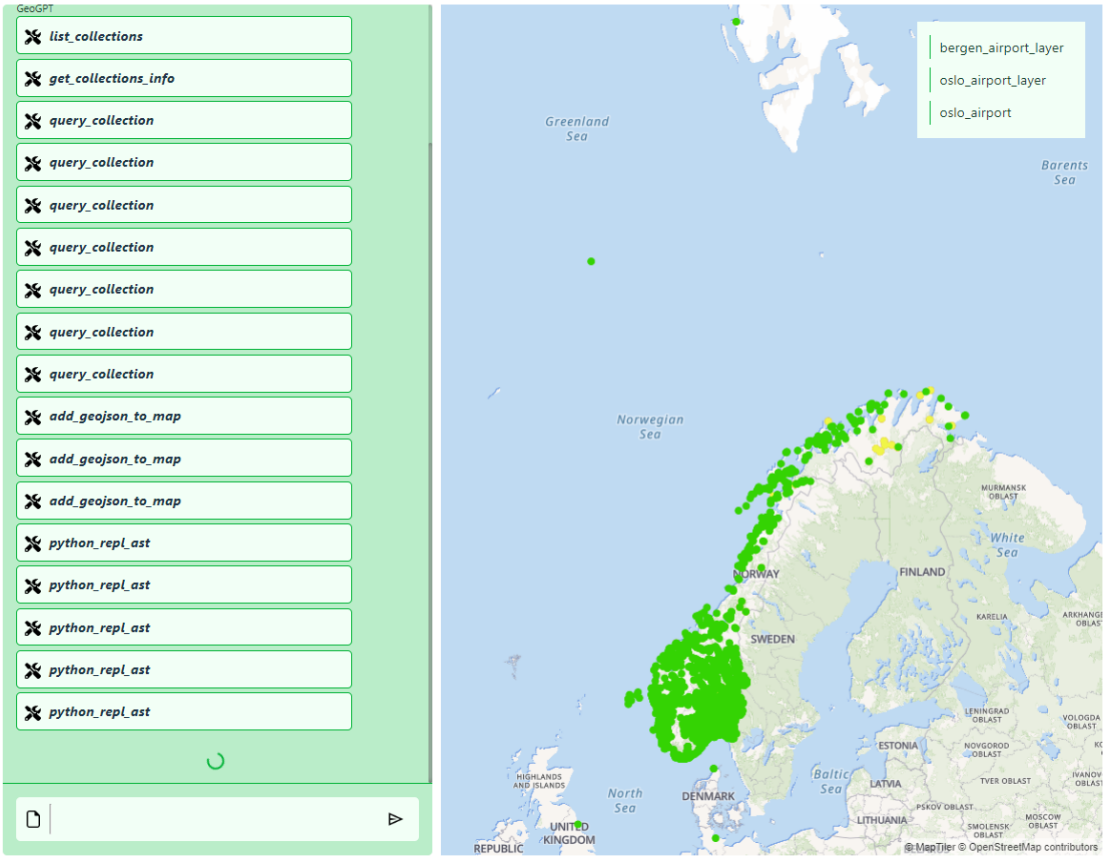


Figure 4.9.: Unsuccessful attempt by GeoGPT's OGC API Features agent to create a geodesic line between Oslo Airport Gardermoen and Bergen Airport Flesland. GeoGPT has added datasets to the map, assuming they contain airport point data, when in reality they contain traffic point data for the whole of Norway. The result should have been a geodesic line between Gardermoen, located in the southeast of Norway, and Flesland, located in the southwest of Norway.

```
{
  "collection_name": "public.osm_transport_points",
  "cql_filter": "fclass='airport' AND name='Oslo Airport'",
  "layer_name": "oslo_airport"
}

-> No features were found at http://localhost:9001/collections/public.
    osm_transport_points/items?limit=10000&filter=fclass='airport' AND
    name='Oslo Airport'.
Try to change the parameters, or make them less restrictive.
```

Code Snippet 4.6: Invocation of the `query_collection` tool that returned no features. This is because there are no features named "Oslo Airport" in the `public.osm_transport_points` collection. The JSON object contains the parameters sent to the tool, and the text after the "`->`" is the message returned from the tool.

```
import geopandas as gpd

oslo = gpd.read_file('/tmp/tmpwlojm_1k/oslo_airport.geojson')
bergen = gpd.read_file('/tmp/tmpwlojm_1k/bergen_airport.geojson')

oslo_coords = oslo.geometry[0].coords[0]
bergen_coords = bergen.geometry[0].coords[0]

oslo_coords, bergen_coords

# -> ((11.3469259, 59.397229), (16.919517, 68.3459))
```

Code Snippet 4.7: GeoGPT-generated Python code that picks the first feature from two collections that include various point data, in the *hope* that they correcspond to Gardermoen and Flesland. This was of course not the case.

4.2.2. Prompt Quality Experiment — Results

Figure 4.10 shows the outcomes of the experiments where the importance of the quality of the user's initial prompt was evaluated. It is clear to see that *expert*-level prompting significantly outperforms *novice*-level prompting, the latter of which failed to produce fully responses. It is worth noting, however, that the questions picked were the three hardest ones from the GIS benchmark experiment.

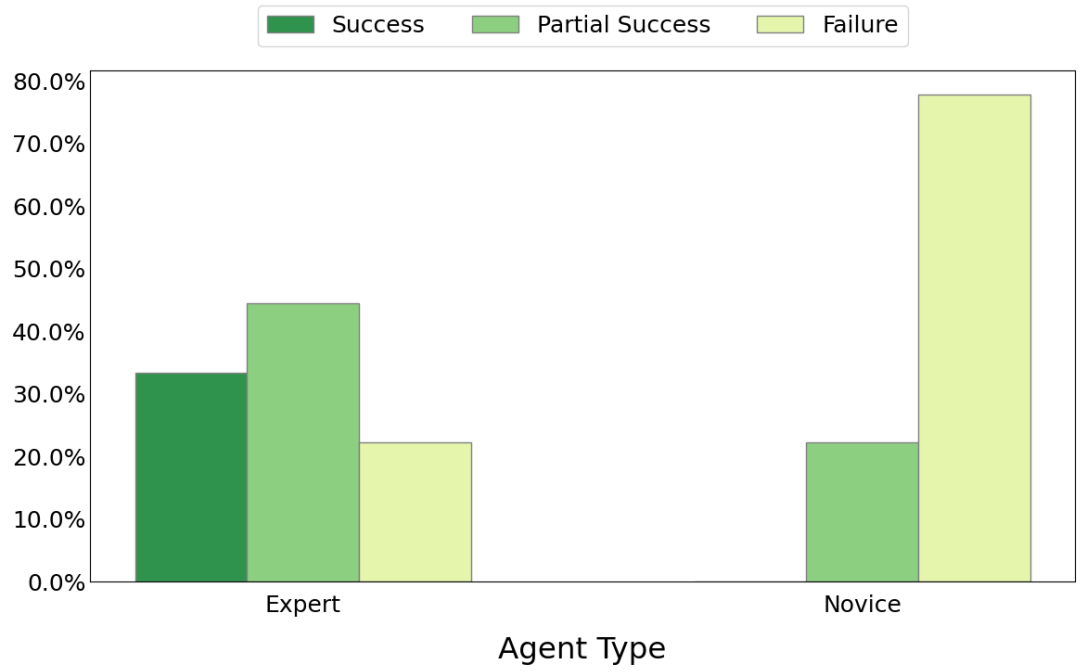


Figure 4.10.: Outcome distribution for different levels of prompt quality. Using novice-level prompting, GeoGPT failed to produce fully successful responses, but using the more elaborate expert-level prompt, GeoGPT performed much better.

Figure 4.11 compares the responses that GeoGPT's OGC API Features agent managed to produce for the different prompt levels on the task of counting the number of trees along the road named "Munkegata" in Trondheim (see Table A.1). The *novice*-level prompt reads as follows:

> "Could you count how many trees there are on Munkegata street in Trondheim?"

The *expert*-level prompt includes a series of instructions:

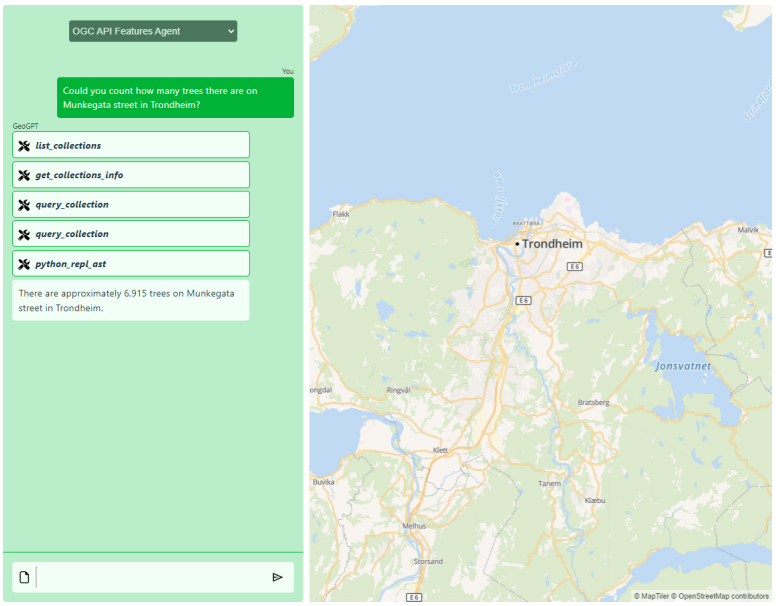
> "1. List all datasets that could possibly include trees.
> 2. Find the correct feature class and filter the relevant dataset to access tree data

for Trondheim. Use a bounding box to reduce the number of trees to analyse.
4. Fetch road data for Munkegata. Use a bounding box for Trondheim in case there are streets elsewhere named Munkegata.
5. Convert both datasets to a suitable metric CRS and add a 20-meter buffer around the road data.
6. Find all trees that lie within this buffer and count them.
7. Present the findings with a map highlighting the roads and the trees."

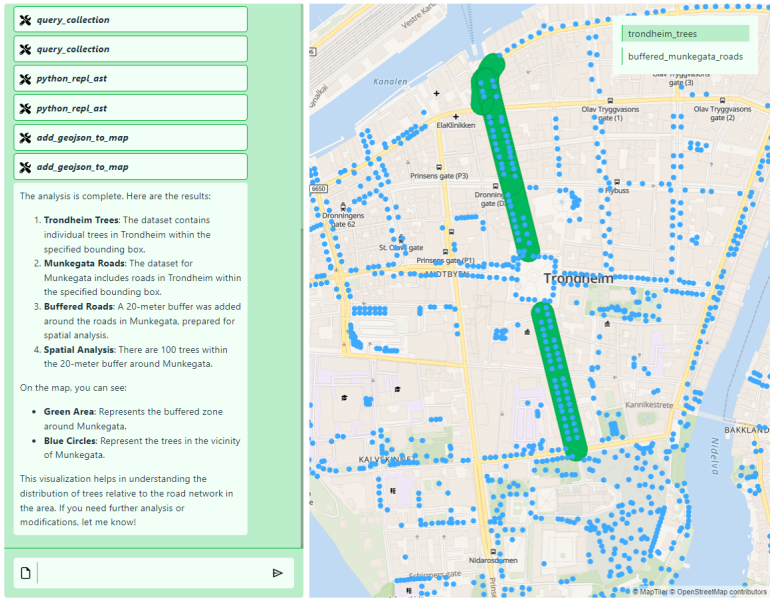
When using the novice-level prompt, GeoGPT was unable to produce the correct outcome, and confidently answered that there are "approximately 6,915 trees on Munkegata street in Trondheim", which is far from being true. When solving the task, GeoGPT made a series of oversights that lead to this result. First, it failed to take into account that there may be more than one street in the dataset named "Munkegata", missing the important step of applying a bounding box filter to the query. A similar mistake was made when retrieving the tree data. Due to the upper limit of 10,000 features per request to the OGC API Features server, it's crucial to narrow down the query to ensure that all relevant features are retrieved, rather than just a subset of them. GeoGPT's request lacked a bounding box, resulting in a randomly distributed subset of 10,000 trees, scattered across the whole of Norway. A third mistake occurred when GeoGPT calculated a *bounding box* around the retrieved road data instead of creating a *buffer*. Using a buffer would have produced a more accurate result. The bounding box that was created spanned from Trondheim to Oslo, thus including far more trees than was intended.

The expert-level prompt, on the other hand, provided the necessary guidance for GeoGPT for this specific task, steering it clear of the issues it encountered with the novice-level prompt. As OpenAI themselves stated, "some tasks are best specified as a sequence of steps".[9] Furthermore, they say that writing explicit steps required to solve a task "makes it easier for the model to follow them".

[9] https://platform.openai.com/docs/guides/prompt-engineering/strategy-write-clear-instructions (last visited on 2nd June 2024)



(a) Novice-level prompting



(b) Expert-level prompting

Figure 4.11.: Comparison between novice- and expert-level prompting of GeoGPT's OGC API Features agent on the task of calculating of the number of trees along Munkegata in Trondheim. Using the novice-level prompt, GeoGPT found 6,915 trees (far too many). However, using the expert-level prompt, it was able to find the correct number of trees and add the appropriate layers to the map.

5. Discussion

Section 5.1 of the Discussion chapter will suggest a place for an application like GeoGPT in the field of GIS. Thereafter, section 5.2 will present possible reasons as to why the SQL agent outperforms the OGC API Features and Python agents. Section 5.3 will address problems encountered during the development of GeoGPT, as well as issues discovered during testing. Finally, section 5.4 will describe a semi-failed attempt at implementing a multi-agent architecture for GeoGPT and provide suggestions as to why this wasn't successful.

5.1. GeoGPT's Place in the Field of GIS

As stated in the section on Goals and Research Questions, one of the goals of this thesis is to see if an LLM-based systems can replace GIS professionals. Results from the prompt quality experiment, as detailed in subsection 4.2.2, indicate that GIS professionals are not immediately threatened. As Figure 4.11 shows, expert-level prompting is highly necessary to make GeoGPT consistently produce the desired outcomes for more complex tasks.

It is, however, clear that LLM technologies have significant potential to automate tasks that GIS professionals are commonly faced with. The benchmarking results from subsection 4.2.1 show that a system like GeoGPT is able to successfully solve a wide range of GIS task. GeoGPT has proven that it can handle real datasets, including some very large ones. For example, the dataset containing water polygons includes 1,861,199 features (see Table 4.3). Furthermore, many of the questions in the GIS benchmark (see Table A.1) are not very technically phrased, showing that expert-level prompting is not necessary for simpler tasks. GeoGPT can therefore serve as a helpful companion — much like GitHub Copilot[1] for software developers — that can quickly solve simple, repetitive tasks, alleviating the workload on GIS professionals, while being a powerful option for less experienced users.

By using a Large Language Model in a GIS context, one can also take advantage of their built-in geospatial awareness, which is learned during the vast pre-training process. This geospatial awareness was demonstrated by Roberts et al. (2023) (see subsection 2.4.1 for more details). The knowledge within the LLM can therefore help solve tasks when the available data is insufficient. For instance, the GPT-4 model which was used in the experiments was able to generate quite accurate bounding boxes for several different Norwegian cities, and it was also able to generate very accurate coordinates for places

[1] https://github.com/features/copilot (last visited 2nd June 2024)

like Aker brygge in Oslo. This became useful in one of the tests in the GIS benchmark, as GeoGPT occasionally failed to find the point data for Aker brygge in the data provided (it should possible to find in the `points_of_interest` point dataset). Using the LLM's background knowledge for tasks that do not require a high degree of accuracy could prove quite useful.

On the other hand, the results from the repeatability study of the GIS benchmark experiment, show that the randomness of LLMs gives reason to doubt the answers that GeoGPT produces. The standard deviations in Table 4.4 shows GeoGPT's answers are not always consistent. Furthermore, a common problem with many LLMs is that they will often deliver overly confident answers in response to questions they do not know the answer to. This is problematic, as a user with limited GIS experience will generally not be capable of detecting when GeoGPT generates a believable, but completely false answer. An example of this was seen as GeoGPT was asked which county is the largest by size. This question was asked a total of nine times in the GIS benchmark experiment, across the different agents, and was answered incorrectly a total of four times (see Table A.2). The incorrect answers typically stated the following:

> "The largest county by size is **Finnmark**, with an area of approximately **646,150 square kilometers**."

The correct answer to the question, based on the data available to GeoGPT, is "Nordland", which area is calculated to about 80,5 thousand square kilometres. To the inexperienced user, it is difficult to know whether this answer can be trusted. An experienced GIS user could, however, inspect the code produced by GeoGPT to see if it makes sense. A GIS professional should also be able to recognize that 646,150 square kilometres is far greater than the actual size of Finnmark, and reason that the cause is probably the use of the wrong projection, one that gets distorted at higher latitudes.

Lin et al. (2023, pp. 1–2) write that the issue with uncertainty in LLMs is a challenge that "has attracted limited attention until recently", highlighting the "forbiddingly high" dimensionality of the output space as one of the key hindrances to a reliable way of measuring confidence. Therefore, until there is a reliable way of measuring the uncertainty of an LLM's response, this will remain a limitation of *all* LLM-based systems.

5.2. Why Does the SQL Agent Outperform the Other Agents?

The experimental results presented in section 4.2 show that GeoGPT's SQL agent outperforms both the OGC API Features agent and the Python agent, and with a significant margin. As Figure 4.2 in subsection 4.2.1 shows. This section will present possible reasons for this performance gap.

5.2.1. Likely Higher Prevalence of PostGIS Examples During Pre-Training

A possible reason for the performance gap between the SQL agent and the other two, is the fact that PostGIS is a very established technology, with its first stable release dating back to 2001.[2] The other agents rely on Python libraries like GeoPandas[3] in place of PostGIS, which is a less established technology. As of 6th June 2024, Google Scholar returns $\sim$ 22.600 results for "PostGIS" compared to $\sim$ 3.650 for "GeoPandas". This large difference in search results is likely correlated with the respective prevalences of the two technologies in the data that the GPT model used in the experiments was trained upon, data which is obtained through web scraping (Radford et al., 2019, p. 3). If this is the case, it is likely that the model will be better at generating PostGIS code.

5.2.2. Limitations with the OGC API Features server

A common source of error with several of the failed runs with the OGC API Features agent, was its inability to fetch more than 10,000 features from the OGC API Features server. The limit of 10,000 features is specified in the OGC API Features standard (Open Geospatial Consortium, 2022), which states that no more than 10,000 features should be returned in a single response. Accompanied by such a large response, however, should be a "`next`" link that should point to the next set of 10,000 features. This way, the server could effectively return more than 10,000 features. Unfortunately, as of 6th June 2024, the latest version of *pg_featuresserv*, which was used to deploy the server, does not support this feature,[4] which represents a significant limitation to the current OGC API Features agent in GeoGPT.

Furthermore, the lacking support for multi-collection queries is, in the author's opinion, a limitation to the current OGC API Features specification. A proposal draft for an extension that supports this has been created,[5] but it is unclear whether it will be accepted into the specification. This extension, called *Search*, would allow for more complex CQL queries that are not easily specified using query parameters. Code Snippet 5.1 shows one of the multi-collection query examples included in the proposal draft. The ability to construct such queries could make retrieval of features much more efficient, possibly making the Python tool in GeoGPT's OGC API Features agent redundant. The query in Code Snippet 5.1 would not be possible using the current OGC API Features specification, and currently GeoGPT would have to download the two collections, load them into memory using Python, and do the query there. Using multi-collection queries that are converted into PostGIS queries could also speed up analysis, as PostGIS is generally faster than Python.

[2] https://en.wikipedia.org/wiki/PostGIS (last visited 2nd June 2024)
[3] https://geopandas.org/en/stable/ (last visited 2nd June 2024)
[4] https://github.com/CrunchyData/pg_featureserv/blob/master/FEATURES.md (last visited 2nd June 2024)
[5] https://github.com/opengeospatial/ogcapi-features/tree/master/proposals/search (last visited 2nd June 2024)

```
\\ SQL query for fetching lakes within Algonquin Park
SELECT lakes.*
FROM lakes
JOIN parks ON ST_Intersects(lakes.geometry, parks.geometry)
WHERE parks.name = 'Algonquin Park';

\\ Corresponding CQL query (would return a tuple of parks and lakes)
POST /search   HTTP/1.1
Host: www.someserver.com/
Accept: application/json
Content-Type: application/ogcqry+json

[
    {
        "collections": ["parks","lakes"]
        "filter": {
            "and": [
            {"eq": [{"property": "parks.name"},"Algonquin Park"]}
            {"contains": [{"property": "parks.geometry"},
                           {"property": "lakes.geometry"}]}
            ]
        }
    }
]
```

Code Snippet 5.1: Multi-collection CQL query using the *Search* extension proposed for the OGC API Features specification. This *one* query will retrieve the polygon for "Algonquin Park" and every lake contained within the park.

5.3. Where GeoGPT Struggles

This section will present two issues that emerged from the Experiments. Subsection 5.3.1 will address an issue that occurs when GeoGPT gets stuck, trying to solve a task by repeatedly making similar, unsuccessful attempts. Subsection 5.3.2 will discuss GeoGPT's *self-verification* abilities, and how they could be improved.

5.3.1. Walking Into Dead Ends

As pointed out in subsection 4.2.1, the correlation matrices in Figure 4.5 of the metrics from the GIS benchmark experiment show that the encoded outcome has a negative correlation with each of the following variables: token usage, latency, and total cost. This suggests that runs which use more time and tokens, are less likely to result in successful outcomes. GeoGPT's tendency to get stuck in "dead ends" might explain this. The example in Figure 4.9 shows this well: GeoGPT tries to query the same collection many

times (using the `query_collection` tool) in more or less the same way, trying to retrieve data for Oslo Airport Gardermoen and Bergen Airport Flesland. It does not find any features, and it struggles to realize that the collection it is querying might not even contain the data it is looking for. This results in an almost endless loop of unsuccessful tool calls, and consequently, high latency for an unsuccessful outcome, and many tokens used.

Peysakhovich and Lerer (2023) suggest, regarding current LLMs, that "relevant information located in earlier context is attended to less on average". This might explain why GeoGPT occasionally gets stuck attempting the same thing over and over, as it may have forgotten options from earlier in the context window. Furthermore, GeoGPT's endless responses tend bloat the context window with tool messages. A bloated context window leads to higher token usage and inference time per call to the LLM, which slows the system down even further.

5.3.2. Self-Verification

As discussed in the section on Related Work, Li and Ning (2023) introduce five goals for autonomous agents, one of which is *self-verifying*, the system's ability to test and verify its actions. GeoGPT is already doing self-verfication through mid-conversation system messages that verify that a file has been saved to the working directory, or that a layer has been added to the map on the client. This does not, however, fix the issue where GeoGPT works with data that is different to what it believes it to be. An example of this issue was presented in the section on "Unsuccessful Responses" in subsection 4.2.1, where GeoGPT believed it was working with data only for Oslo, when in reality the data was for the whole of Norway.

A possible way of doing self-verification that mitigates these kinds of issues is to utilize multi-modal LLMs. Figure 5.1 shows how a multi-modal GPT-4 model can correctly identify that the map layer resulting from the above-mentioned unsuccessful analysis is incorrect, based only on a screenshot of the map. Using such multi-modal LLMs, GeoGPT could verify its answers visually, giving it a rough idea of whether the geometries it added to the map seem reasonable in relation to what they are meant to represent.

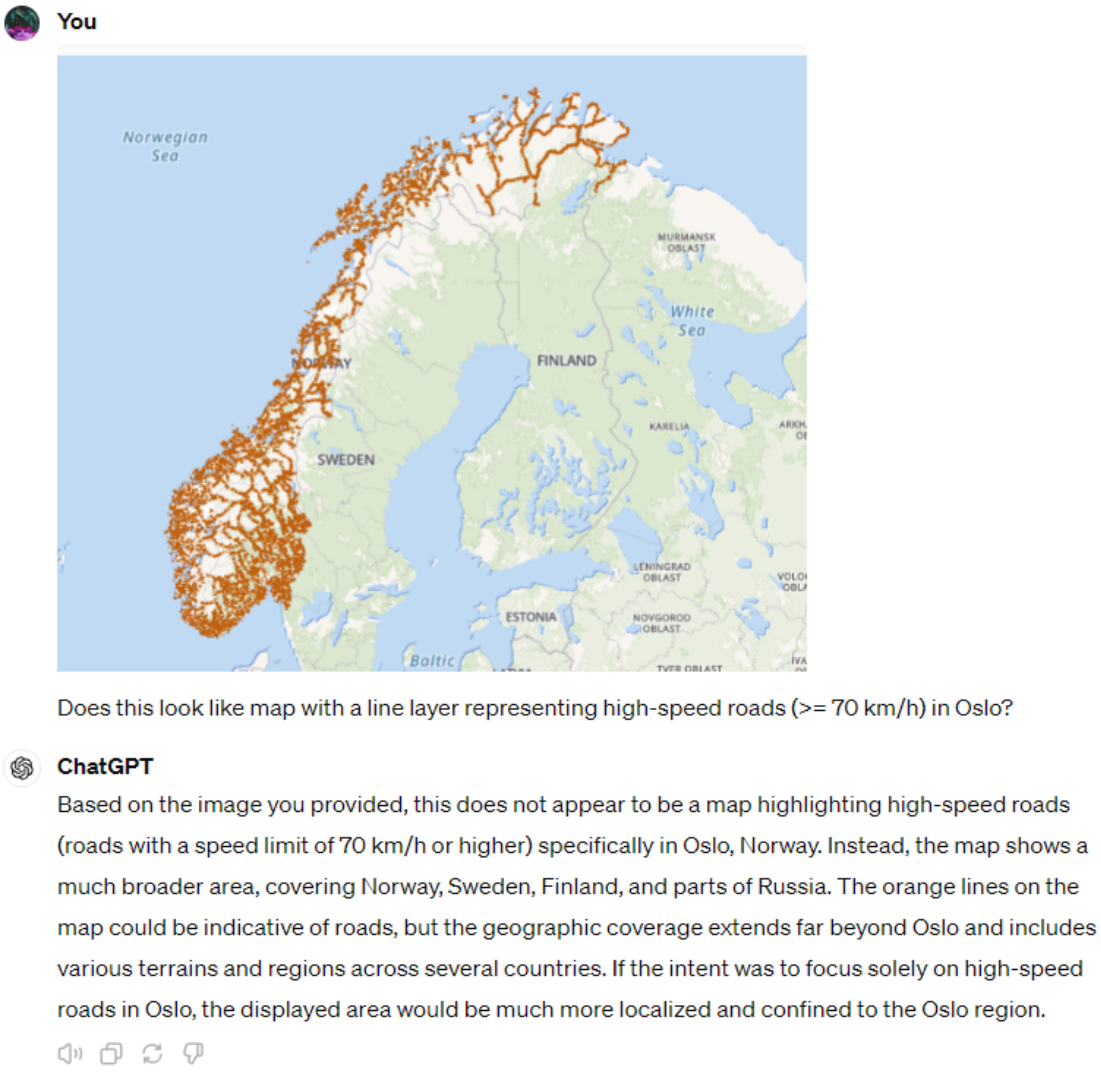


Figure 5.1.: ChatGPT's multi-modal GPT-4 correctly identifying that the map layer intended to show high-speed roads in Oslo in fact "extends far beyond Oslo". The initial question from the user asked GeoGPT to retrieve roads in Oslo with speed limit greater than or equal to 70 km/h, but the results contains all roads in *Norway* with speed limit greater than or equal to 70 km/h.

5.4. Multi-Agent Architectures

An attempt was made to create a multi-agent version of GeoGPT that employs three different sub-agents: one for data retrieval, one for data analysis, and one for map interaction. Each agent will get a collection of tools, which will be relevant for the sort of tasks they will be asked to solve. These agents are orchestrated by a *Supervisor* agent, which takes messages from the user and assigns tasks to the appropriate sub-agents. Figure 5.2 shows how a supervisor node takes a user message and gets the option of selecting which sub-agent is to solve the next sub-task. This approach was inspired by the technologies mentioned in subsection 2.4.2 (Agent Patterns).

Initial tests on a multi-agent version of the OGC API Features agent were conducted, but the implementation turned out to both increase the latency of the system and be a source of confusion for the LLM. It is possible, however, that such an architecture could be useful as the number of tools available to the agent grows — seeing as a large number of functions could probably start confusing the LLM — but for the current version of GeoGPT, the multi-agent pattern seemed to only get in the way.

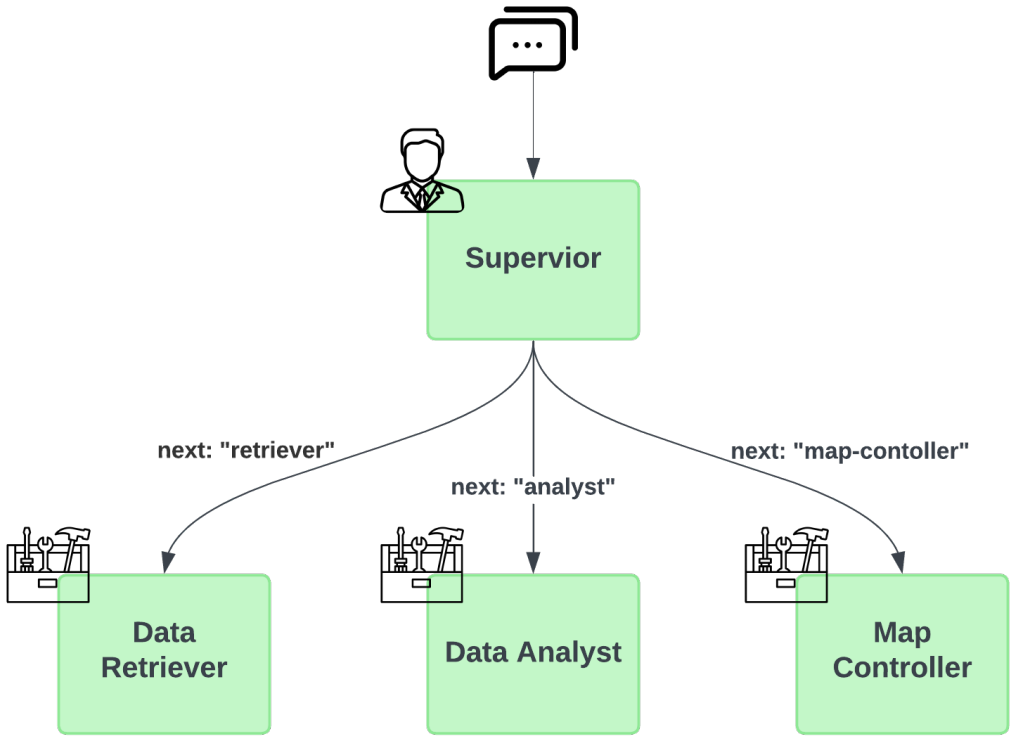


Figure 5.2.: Illustration of a multi-agent implementation for GeoGPT's OGC API Features agent, where an agent supervisor takes in a user message and gets to select which sub-agent is to solve the next sub-task

6. Future Work

This chapter will present challenges that are reserved for future work. Section 6.1 addresses a limitation with the experiments conducted in this thesis, and emphasizes the need for experiments that investigate the ability of a system like GeoGPT to answer questions where there are no concrete answers, and where ethical considerations and assumptions must be made. Section 6.2 highlights the need for testing different models for for use in LLM-based GISs. Section 6.3 discusses automated data discovery. Currently, to use GeoGPT, the user has to provide it with data through, for instance, a geospatial database, but not all users will have the technical know-how required to set up such a database themselves.

6.1. Measuring Ability to Answer Questions That Have No Clear Answer

The experiments conducted in this thesis focused on the system's ability to answer questions that have concrete and *correct* answers. However, GeoGPT's ability to answer questions of a subjective nature — questions that have no *one* correct answer — was not tested. For instance: what would happen if we asked GeoGPT to find a suitable route from A to B that is as *safe* as possible? How would it interpret such a request? Would it only take into account the speed limit and road type? Would it be able to assess socio-economic aspects of areas that the route crosses, for instance avoiding "bad neighbourhoods" at nighttime? Would it decide to incorporate weather forecasts into the analysis? Future research should find methods to measure the ability of LLM-based GIS agents to provide appropriate and safe answers to such questions.

6.2. Comparing Different Models

GeoGPT is based around OpenAI's GPT-4 Turbo model but, as subsection 2.1.3 showed, there are numerous competitors. Future research should look into the possibility of swapping out GPT-4 Turbo with other models, first and foremost those with good function calling abilities, as this necessary for GeoGPT to work as intended. A benchmark comparing results for different models would be a natural way of building upon the results of this thesis.

Future research should especially look into the viability of using open-source models. In a report interviewing 500 companies on their LLM adoption, 46 percent stated their preference for open-source models going into 2024 (Wang, Sarah and Xu, Shangda,

2024). *Control* and *customizability* turns out to be the two most important factors into enterprise's open-source appeal, allowing for increased control over proprietary data and ability to effectively fine-tune models, respectively.

6.3. Automated Data Discovery

The experiments in this thesis were based upon a pre-existing collection of geospatial datasets that were made available to GeoGPT in different ways. GeoGPT is currently reliant on the user providing data either as a geospatial database, through an OGC API Features server, or as a collection of geospatial files that can be manipulated through Python code. A fully autonomous GIS agent should, however, be able to search the web for suitable datasets. For instance, if a user wishes to perform a noise analysis for a particular location in Norway, the agent should be able to search a website like Geonorge[1] for datasets related to noise (firing ranges, roads, etc.), download these, and then perform the analysis. Initial test were conducted with Geonorge in this thesis to see if this was possible, but the results were inconsistent.

[1] https://www.geonorge.no/ (last visited on 6th June 2024)

7. Conclusion

This thesis has shown the viability of using Large Language Model (LLM) technology to create autonomous agents aimed at GIS analysis. *GeoGPT*, the proposed solution, shows through a new GIS benchmark containing question and answer pairs for common GIS tasks, that it is able to utilize the logical reasoning and code generation abilities of modern LLMs like GPT-4 to solve a wide range of such tasks. The user interacts with GeoGPT through a webpage that consists of a chat interface resembling that of OpenAI's ChatGPT, and a web map where results from analyses can be displayed. The user can type GIS questions into the chat interface, which GeoGPT will attempt to answer through text and/or by adding geometries to the map. GeoGPT relies heavily on *function calling*. This is a way of giving function/tool definitions to an LLM, essentially enabling it to *invoke* these external tools (which run code created by the developer) by specifying the name of the tool and suitable parameters that will be passed to it.

Featuring three different agent types, GeoGPT shows that it can manipulate geospatial data in different ways. GeoGPT's SQL agent accesses data directly from a PostGIS database, its OGC API Features agent interacts with an OGC API Features server that resides on top of the PostGIS database, and its Python agent utilizes shapefiles in GeoGPT's local environment. The agents have different sets of tools that allow them to work with their data. Included in the SQL agent's collection of tools, is a tool that takes a string of SQL code that will be run against the PostGIS database, thus enabling the agent to perform GIS analyses. The OGC API Features and Python agents both have access to a similar tool that allows them to run Python code. Other tools include tools to list database tables or collections in the OGC API Features server, and a tool to geometries to the map on the client.

Two sets of experiments were conducted. The first revolves around the GIS becnhmark, comparing the three agent types to see which is best at solving common GIS-related tasks. Results from this experiment show that the SQL agent outperforms the other two, with a success rate of 69.4% compared to 38.9% for each of the others.

The second set of experiments evaluates the importance of the quality of the question from the user. Questions were formulated in two different ways: a simple formulation, resembling a user with little GIS experience, and a more accurate and detailed formulation, resembling a user with extensive GIS experience. The results from the experiment show that providing GeoGPT with a higher quality initial problem formulation greatly increases the likelihood of the system to produce a successful outcome. This suggests that a user's GIS experience is still very valuable, even as we face a reality where highly sophisticated LLMs can be used to automate away numerous technical tasks.

Thus, with the goal of investigating how Large Language Models can be utilized to

make GIS analysis simpler and more approachable, this thesis has demonstrated the potential of using LLMs for this purpose. The thesis has shown a promising way forward and showcased a novel method of using LLMs to enable non-GIS experts to undertake advanced GIS analysis with the help of a system like GeoGPT.

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A. Experimental Attachments

A.1. GIS Benchmark Experiment — Questions and Test Results

Table A.1.: Questions for GIS benchmark experiment

Query ID	Query	Correct Response
aker_brygge_national	Which is the closest railway station to Aker brygge?	Nationalteateret
cliff_clusters	Locate clusters of cliffs, each containing more than 10 cliffs, with cliffs within each cluster no more than 0.1 degrees apart.	Should be about 8-9 clusters.
county_names	What are the names of the counties in found in the data?	Nordland, Telemark, Troms, Rogaland, Vestland, Trøndelag, Vestfold, Buskerud, Akershus, Østfold, Innlandet, Møre og Romsdal, Agder Finnmark
glomma_counties	How many counties does Glomma run through?	4. Trøndelag, Innlandet, Akershus, and Østfold.
largest_county	Which is the largest county by size?	Nordland
nidarosdomen_polygon	Retrieve a polygon of Nidarosdomen.	Adding a polygon of Nidarosdomen to the map.
num_trees_munkegata	How many trees are there along Munkegata in Trondheim?	Giving the correct number of trees (about 70-80).

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Table A.1.: Questions for GIS benchmark experiment

Query ID	**Query**	**Correct Response**
oslo_bergen_geodesic	Create a geodesic curve between the airports of Oslo and Bergen.	A geodesic, slightly curved line between Gardermoen and Flesland.
oslo_residental_diff	Provide an outline of Oslo but exclude residential areas by computing their difference.	The polygonal outline of Oslo with cutouts where there area areas classified as residental.
oslo_roads_gte_70_kmh	Retrieve roads in Oslo that have speed limit higher than or equal to 70 km/h.	Adding corresponding line segments to the map.
vestfold_bbox	Find the coordinates that define a the extent of a rectangular bounding box that encompasses the county of Vestfold.	(9.7553357, 58.720455, 10.6750198, 59.674011)
viken_dissolve	Combine the countries that correspond to the historical country of Viken into a single feature.	Display the outline of Viken, based on the outlines of Buskerud, Akershus, and Østfold, that are found in the data. Should be dissolved, i.e., no borders.

Table A.2.: Results from GIS benchmark experiment

Query ID	Agent Type	Outcome	Latency [s]	Tokens
aker_brygge_national	oaf	partial success	87.16	3347
aker_brygge_national	oaf	partial success	97.85	3042
aker_brygge_national	oaf	partial success	70.36	4563
aker_brygge_national	python	partial success	68.10	4736
aker_brygge_national	python	partial success	49.48	2192
aker_brygge_national	python	partial success	76.84	4270
aker_brygge_national	sql	success	63.51	2569
aker_brygge_national	sql	success	151.46	6273
aker_brygge_national	sql	success	103.98	5169
cliff_clusters	oaf	partial success	93.21	3047
cliff_clusters	oaf	partial success	134.62	3713
cliff_clusters	oaf	failure	253.77	6956
cliff_clusters	python	failure	66.42	5421
cliff_clusters	python	failure	125.96	4650
cliff_clusters	python	failure	109.29	4768
cliff_clusters	sql	failure	39.36	1633
cliff_clusters	sql	failure	75.27	3085
cliff_clusters	sql	success	31.64	1632

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Table A.2.: Results from GIS benchmark experiment

Query ID	**Agent Type**	**Outcome**	**Latency [s]**	**Tokens**
county_names	oaf	success	78.08	2389
county_names	oaf	success	67.45	2399
county_names	oaf	failure	20.23	1471
county_names	python	success	44.33	2532
county_names	python	success	30.50	2355
county_names	python	success	31.09	2355
county_names	sql	success	64.21	1874
county_names	sql	success	52.28	1880
county_names	sql	success	47.62	1886
glomma_counties	oaf	success	69.73	2253
glomma_counties	oaf	success	65.57	1945
glomma_counties	oaf	success	67.37	2397
glomma_counties	python	success	663.22	3658
glomma_counties	python	failure	295.93	4388
glomma_counties	python	success	285.23	2281
glomma_counties	sql	success	102.48	1828
glomma_counties	sql	success	25.01	1266
glomma_counties	sql	success	21.36	1064
largest_county	oaf	success	41.82	1713
largest_county	oaf	success	71.82	2223
largest_county	oaf	failure	47.00	1797
largest_county	python	failure	29.37	2415
largest_county	python	failure	41.95	2810
largest_county	python	failure	40.55	2407

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Table A.2.: Results from GIS benchmark experiment

Query ID	Agent Type	Outcome	Latency [s]	Tokens
largest_county	sql	success	40.08	1771
largest_county	sql	success	28.51	1474
largest_county	sql	success	38.30	1381
nidarosdomen_polygon	oaf	success	29.82	1923
nidarosdomen_polygon	oaf	success	31.73	1909
nidarosdomen_polygon	oaf	success	31.61	1922
nidarosdomen_polygon	python	success	35.10	4510
nidarosdomen_polygon	python	success	25.36	3649
nidarosdomen_polygon	python	success	33.35	3663
nidarosdomen_polygon	sql	success	29.64	1546
nidarosdomen_polygon	sql	success	90.61	1529
nidarosdomen_polygon	sql	success	39.39	1513
num_trees_munkegata	oaf	failure	75.60	2977
num_trees_munkegata	oaf	failure	80.13	2984
num_trees_munkegata	oaf	failure	57.66	2407
num_trees_munkegata	python	partial success	122.99	3930
num_trees_munkegata	python	failure	916.13	2362
num_trees_munkegata	python	failure	911.18	8385
num_trees_munkegata	sql	failure	80.41	1359
num_trees_munkegata	sql	failure	67.41	2626
num_trees_munkegata	sql	failure	31.86	1359
oslo_bergen_geodesic	oaf	failure	652.88	9253
oslo_bergen_geodesic	oaf	failure	102.38	3360

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Table A.2.: Results from GIS benchmark experiment

Query ID	**Agent Type**	**Outcome**	**Latency [s]**	**Tokens**
oslo_bergen_geodesic	oaf	failure	258.52	6271
oslo_bergen_geodesic	python	partial success	118.54	6683
oslo_bergen_geodesic	python	partial success	129.40	7782
oslo_bergen_geodesic	python	failure	373.37	10412
oslo_bergen_geodesic	sql	failure	97.79	2710
oslo_bergen_geodesic	sql	failure	73.78	2575
oslo_bergen_geodesic	sql	failure	127.43	3318
oslo_residental_diff	oaf	failure	119.39	2373
oslo_residental_diff	oaf	partial success	114.92	3033
oslo_residental_diff	oaf	success	121.17	2621
oslo_residental_diff	python	success	673.96	4013
oslo_residental_diff	python	failure	2190.08	3867
oslo_residental_diff	python	failure	2290.09	3650
oslo_residental_diff	sql	success	42.49	1537
oslo_residental_diff	sql	failure	94.35	2485
oslo_residental_diff	sql	success	52.14	1790
oslo_roads_gte_70_kmh	oaf	partial success	44.44	1959
oslo_roads_gte_70_kmh	oaf	failure	58.61	1989
oslo_roads_gte_70_kmh	oaf	partial success	35.55	1961
oslo_roads_gte_70_kmh	python	failure	983.76	3912

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Table A.2.: Results from GIS benchmark experiment

Query ID	Agent Type	Outcome	Latency [s]	Tokens
oslo_roads_gte_70_kmh	python	failure	757.70	3819
oslo_roads_gte_70_kmh	python	failure	849.06	3827
oslo_roads_gte_70_kmh	sql	success	43.88	1542
oslo_roads_gte_70_kmh	sql	success	37.26	1577
oslo_roads_gte_70_kmh	sql	success	38.38	1566
vestfold_bbox	oaf	failure	56.33	2001
vestfold_bbox	oaf	partial success	50.38	3177
vestfold_bbox	oaf	success	55.82	2480
vestfold_bbox	python	success	24.08	1612
vestfold_bbox	python	success	33.63	2366
vestfold_bbox	python	success	42.36	2808
vestfold_bbox	sql	success	23.76	1188
vestfold_bbox	sql	success	47.35	1932
vestfold_bbox	sql	success	23.30	1182
viken_dissolve	oaf	success	52.24	2336
viken_dissolve	oaf	success	204.07	5078
viken_dissolve	oaf	failure	133.40	3985
viken_dissolve	python	success	68.23	6099
viken_dissolve	python	success	86.32	6007
viken_dissolve	python	partial success	89.98	6461
viken_dissolve	sql	partial success	34.58	1553
viken_dissolve	sql	success	34.72	1540

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Table A.2.: Results from GIS benchmark experiment

Query ID	**Agent Type**	**Outcome**	**Latency [s]**	**Tokens**
viken_dissolve	sql	partial success	37.36	1543

A.2. Prompt Quality Experiment — Questions and Test Results

Table A.3.: Questions for prompt quality experiment

Query ID	Level	Formulation
oslo_bergen_geodesic	novice	Please plot the shortest flight path on a map between Oslo and Bergen's airports.
oslo_bergen_geodesic	expert	1. Get info on all potentially relevant datasets. The airports are possibly stored as polygons in the available data. 2. Filter those datasets for airports and list the names of the airports. 3. Retrieve the geographic coordinates for Oslo Gardermoen Airport (OSL) and Bergen Flesland Airport (BGO) by filtering on the names you found. 4. If no name was found, try a different dataset and go back to step 2. 5. Utilize available tools to draw a geodesic curve that represents the shortest path on the earth's surface between these two points. 6. Present the findings with a map highlighting the largest county.
oslo_roads_gte_70_kmh	novice	Draw roads in Oslo where you can drive at least 70.
oslo_roads_gte_70_kmh	expert	1. Retrieve an outline of Oslo. 2. Calculate max/min lat/lon values for this bounding box, and use it to retrieve a subset of the road data. 3. Select road segments within the outline from step 1 that have a max speed >= 70. 4. Present the findings with a map highlighting the selected roads.
num_trees_munkegata	novice	Could you count how many trees there are on Munkegata street in Trondheim?

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Table A.3.: Questions for prompt quality experiment

Query ID	**Level**	**Formulation**
num_trees_munkegata	expert	1. List all datasets that could possibly include trees. 2. Find the correct feature class and filter the relevant dataset to access tree data for Trondheim. Use a bounding box to reduce the number of trees to analyse. 4. Fetch road data for Munkegata. Use a bounding box for Trondheim in case there are streets elsewhere named Munkegata. 5. Convert both datasets to a suitable metric CRS and add a 20-meter buffer around the road data. 6. Find all trees that lie within this buffer and count them. 7. Present the findings with a map highlighting the roads and the trees.

Table A.4.: Results from prompt quality experiment

Query ID	**Agent Type**	**Level**	**Outcome**
oslo_bergen_geodesic	sql	novice	failure
oslo_bergen_geodesic	oaf	novice	failure
oslo_bergen_geodesic	python	novice	failure
oslo_bergen_geodesic	sql	expert	failure
oslo_bergen_geodesic	oaf	expert	failure
oslo_bergen_geodesic	python	expert	partial success
oslo_roads_gte_70_kmh	sql	novice	partial success
oslo_roads_gte_70_kmh	oaf	novice	partial success
oslo_roads_gte_70_kmh	python	novice	failure
oslo_roads_gte_70_kmh	sql	expert	success
oslo_roads_gte_70_kmh	oaf	expert	partial success
oslo_roads_gte_70_kmh	python	expert	success
num_trees_munkegata	sql	novice	failure
num_trees_munkegata	oaf	novice	failure
num_trees_munkegata	python	novice	failure
num_trees_munkegata	sql	expert	partial success
num_trees_munkegata	oaf	expert	success
num_trees_munkegata	python	expert	partial success

B. LangSmith

LangSmith[1] is a DevOps platform made as a part of the LangChain ecosystem. It allows the developer of LLM-based applications to test, deploy, and monitor applications. LangSmith was used during both the development and testing of GeoGPT. Figure B.1 shows the main page for a LangSmith project, in this case the project which is hooked up to GeoGPT. This page gives a list of all of GeoGPT's runs, and metrics like latency, token usage, and total cost in dollars, for each run. This is where the metrics recorded in the experiments (see Table A.2) were obtained.

Figure B.2 shows the trace of a given run of GeoGPT. In the sidebar to the left, is a complete list of all the LangChain runnables that were invoked during the run. On its right, is an overview of the inputs and outputs of the runnable that is currently selected. This page is very useful for debugging purposes.

[1] https://www.langchain.com/langsmith

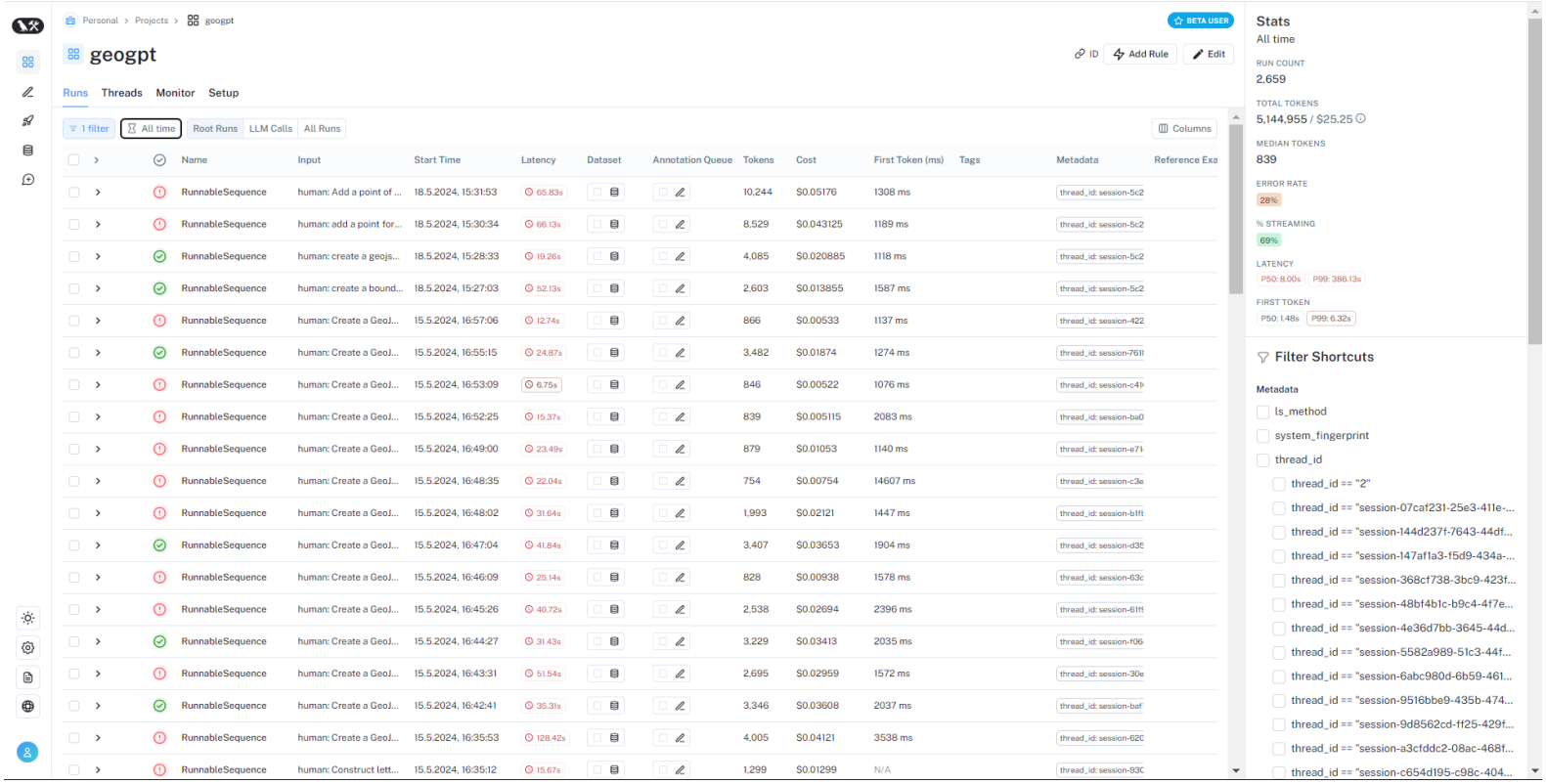

Figure B.1.: Main page for a LangSmith project, in this case the “geogpt” project

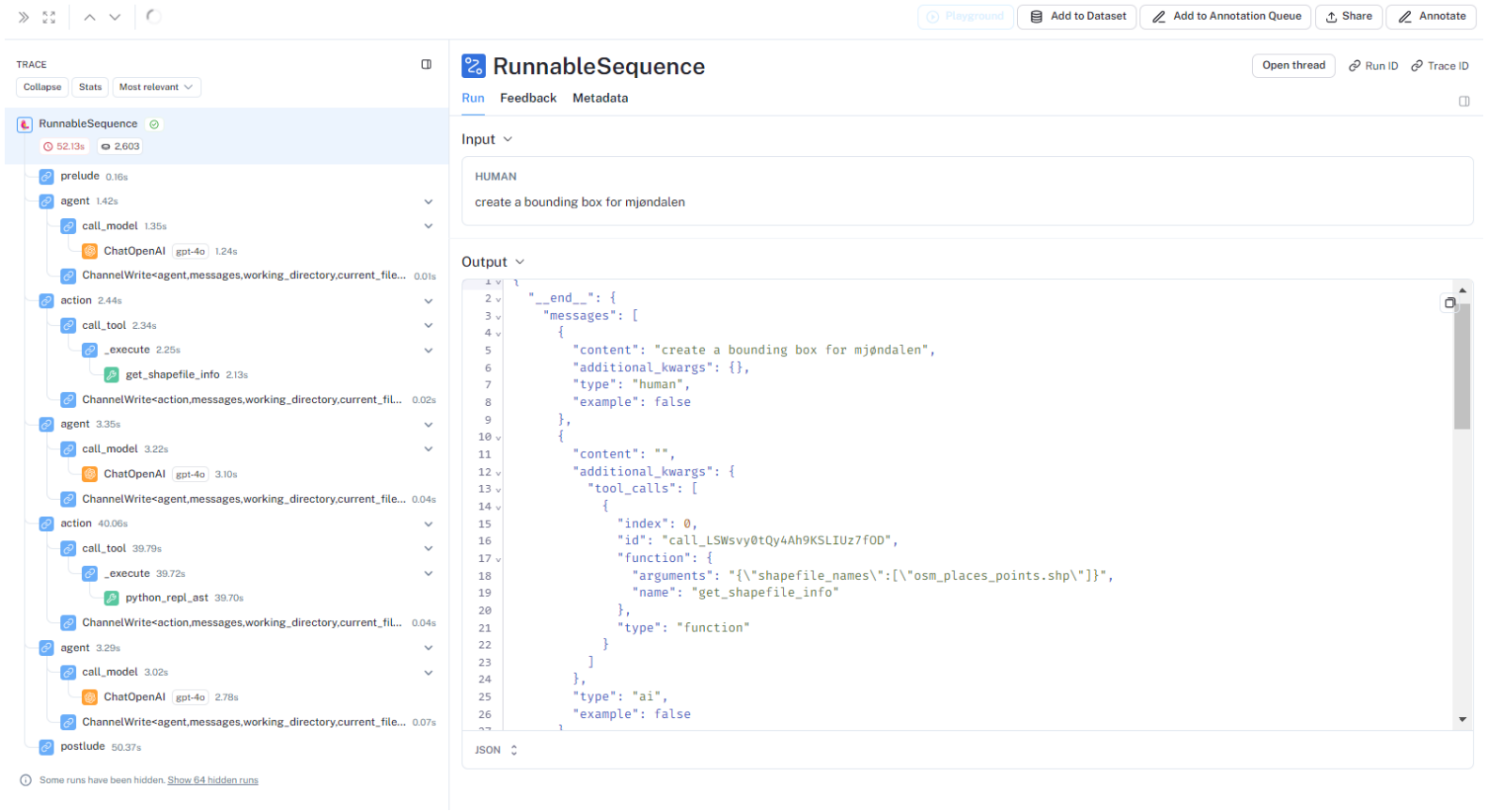

Figure B.2.: LangSmith trace for a GeoGPT run