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LLMS - The Death of GIS Analysis?

An Investigation into Using Large Language Models
to Make GIS Analysis Simpler, Faster, and More
Accessible

Specialization Project in Computer Science and Geomatics, June 2024

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Abstract

To be
written

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1. Introduction

1.1. Background and Motivation

The field of Large Language Models (LLMs) is an emerging one. Fan et al. (2023, p. 2) found that the proportion of papers about LLMs¹ to arXiv has skyrocketed since 2020, with a six-times increase in percent points from 2022 to 2023. They write that prompt engineering has been extensively used as a way to improve code generation (Fan et al., 2023, p. 7)

1.2. Goals and Research Questions

The overarching goal of this specialization project is to investigate how Large Language Model (LLM) can be utilized to make GIS analysis simpler, faster, and more accessible. As exemplified in the task description provided by Norkart (see appendix A), such a system should be able to create a meaningful response to a query such as:

"Find all buildings within a 100-meter belt that are above 100 meters above sea level and have docks."

The task then is to investigate how modern language models can be used to perform classical GIS analyses using standard GIS technologies like PostGIS and geospatial data catalogues adhering to OGC or STAC standards. Based on the task description I have constructed three research questions that I will attempt to answer in this specialization project report:

1. What is the potential of LLM-based GIS analysis?
2. How can OGC API Features be used in an overlay analysis using ChatGPT-4?
3. How can we give ChatGPT-4 access to external tools?

Researching the potential of using LLMs in GIS could uncover new methodologies for spatial analysis, predictive modeling, and decision-making. The aim with RQ1 would be to assess the capabilities and limitations of integrating machine learning algorithms with Geographic information systems (GISs), and also touch on how a mature LLM-based GIS could impact the daily work of (human) GIS professionals.

¹Including articles whose title or abstract includes "LLM", "Large Language Model", or "GPT".

1. Introduction

RQ2 focuses on the feasibility of using the OGC API - Features Standards in a typical overlay analysis within a conversational AI context like ChatGPT-4, having the users be able to express themselves using natural language queries. An answer to RQ2 would describe how OGC APIs can be called and manipulated in a flexible manner during a conversation to perform spatial queries or analyses, like intersecting layers or filtering features based on certain criteria.

RQ3 delves into the technical and ethical considerations of expanding ChatGPT-4's capabilities through integration with external tools, such as GIS software or data analytics platforms. It would explore options for secure and efficient data exchange, and assess the implications of such access in terms of data privacy and user consent.

1.3. Research Method

My research methods consist of a literature study and a set of experiments/proofs of concept, the latter of which is described in detail in chapter 4.

1.3.1. Literature Study

I set out by deciding on some search terms, and used a "snowball sampling" technique to find relevant articles. Table 1.1 shows the number of search results on various sites.

In order to evaluate large amounts of literature, a strategy of filtering out papers that are *not* relevant was put in place. The strategy involves reading the least time-consuming and more information-packed sections first, and then reading other parts of the paper if it is deemed relevant to the project. Figure 1.1 shows the order in which the different types of elements/sections commonly were read, and at any point in this pipeline the paper could be deemed irrelevant, and would subsequently be discarded from the literature study. The literature study is presented in chapter 3.

1.3.2. Experiments

Three experiments were conducted in order to answer the research questions listed in section 1.2. As the literature study is the main focus of this specialization project, the experiments are not very in depth, but serve to support some of the claims that are made about the potential of an LLM-based GIS agent. The experiments are presented in chapter 4.

1.4. Contributions

The main contributions of this specialization project are listed below:

1. Gather relevant literature to facilitate development of a state-of-the-art LLM-based GIS agent.
2. Perform experiments on ChatGPT-4, investigating its abilities in manipulating geospatial data of different formats and access channels.

1. Introduction

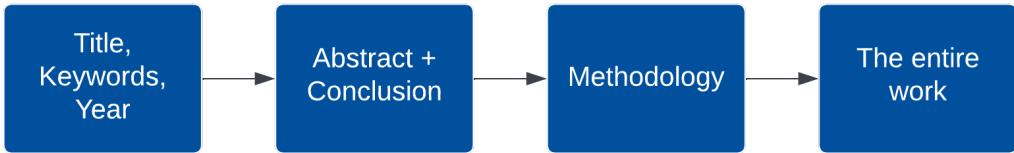


Figure 1.1.: Seaching strategy

Keyword	arXiv	Google Scholar	Web of Science
Large Language Model	5,101	5.76e6	36,463
Geographic Information System	588	7.36e6	50,688
Geospatial standard	55	295,000	3,363
Prompt engineering	1,081	1.02e6	24,281
Retrieval-augmented generation	491	3,050	19
Text embedding	4,730	402,000	16,193
LLM fine-tuning	917	10,200	22

Table 1.1.: Literature study search results

1.5. Thesis Structure

The thesis is divided into four main sections:

- Chapter 2 introduces the theory, tools, and methods necessary to understand the work.
- Chapter 3 discusses previous work related to this thesis.
- Chapter 4 explains the experimental plan and setup, and lists the results of these.
- Chapter 5 discusses some of the finding of the experiments, and other considerations when developing an LLM-based GIS agent.
- Chapter 6 sums up the work and points to ways it can be improved or extended in the future.

2. Theory

Disclaimer: I will reuse parts of a paper I wrote in the theory module called "TDT13 - Advanced Text Analytics and Language Understanding" in this chapter 2 chapter. This includes subsection 2.1.1 and subsection 2.1.3.

Chapter 2 of this specialization project will talk about the leading technologies in the field of Large Language Model (LLM), which in itself is a subfield of Natural Language Processing (NLP). section 2.1 will go over the leading LLM models, their strengths and weaknesses, and briefly mention differences in model architecture. Section 2.3 will name the most prominent providers of LLM services.

Figure 2.1 shows an actor map which includes stakeholders, providers, and other groups and organizations that could have some relevance to an autonomous LLM-based GIS-agent. Following subsections will go over the different groups and explain why they are included in the actor map.

2.1. LLMs

This section will open with an explanation of the building block of modern Large Language Models, namely the Transformer, which employs self-attention. Subsection 2.1.2 and subsection 2.1.3 will then discuss the two most famous families of LLMs, namely the GPT's and the BERT's, as well as the brand new multimodal Gemini model from Google, and various open-source alternatives. Section 2.2 will then enlighten the reader about the different ways in which Large Language Models can be benchmarked and how we can measure the quality of a natural language response produced by an LLM.

2.1.1. Attention and The Transformer Architecture

Vaswani et al. (2017) managed to achieve new state-of-the-art results for machine translation tasks with their introduction of the Transformer architecture. The Transformer has later been proved effective for numerous downstream tasks, and for a variety of modalities. Titling their paper *Attention Is All You Need*, Vaswani et al. suggest that their attention-based architecture renders Recurrent Neural Networks (RNNs) redundant, due to its superior parallelization abilities and the shorter path between combinations of position input and output sequences, making it easier to learn long-range dependencies (Vaswani et al., 2017, p. 6).

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

2. Theory

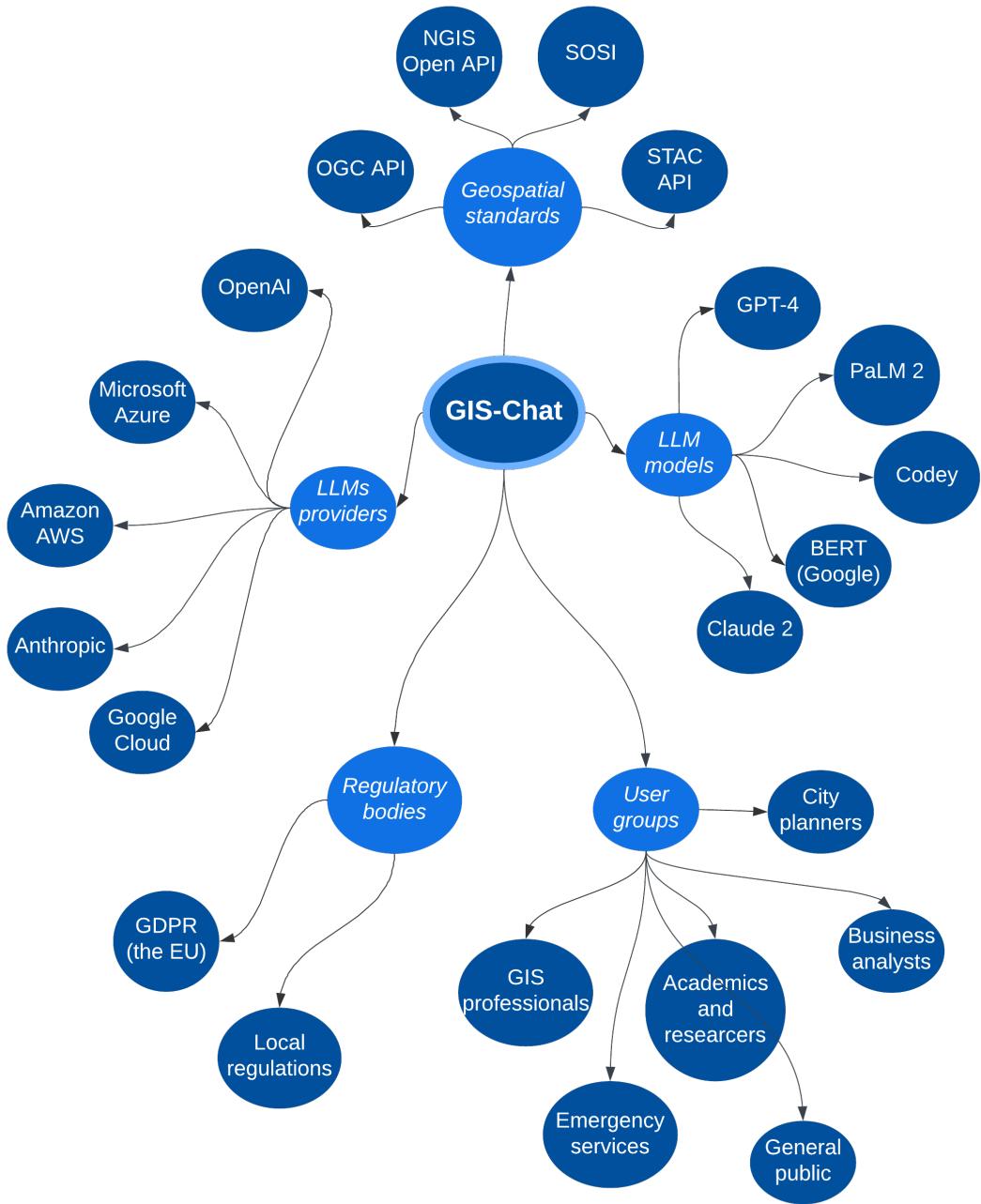


Figure 2.1.: Actor map for stakeholders, providers, and other groups and organizations that could have some relevance to an autonomous LLM-based GIS-agent.

2. Theory

commonly found with RNNs. 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 we take 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, e.g., be *more attended to*. These differences in attention are further emphasized by applying the softmax function. The final matrix multiplication with the values V , being the initial embeddings of all input tokens, will give us a new embedding in which all tokens have some context from all other words. We improve the attention mechanism by multiplying queries, keys, and values with weight matrices learned through backpropagation. Self-attention is a special kind of attention in which queries, keys, and values are all the sequence.

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

Attention blocks can be found in three places in the Transformer architecture (Vaswani et al., 2017, p. 5) (I will use machine translation from Norwegian to German as an example):

1. In the encoder block to perform self-attention on the input sequence (which is in Norwegian)
2. In the decoder block to perform self-attention on the output sequence (which is in German)
3. In the decoder block to perform cross-attention (or encoder-decoder attention) where each position in the decoder attends to all positions in the encoder

The Transformer represented a breakthrough in the field of NLP, and is the fundamental building block of LLMs like BERT.

2.1.2. The GPT Family

Generative Pre-trained Transformers (GPTs) are a type of LLM first introduced by OpenAI in 2018 (Radford and Narasimhan, 2018). Specifically designed to perform text generation, it is essentially a stack of Transformer *decoders*, and demonstrates through its vast training on unlabelled data help a language model learn good representations, providing a significant performance boost, while alleviating the dependence on supervised learning. While the original Transformer architecture as described by Vaswani et al. (2017) was intended for machine translation, thus having encoder to learn the representation of the origin language representation of a given input sequence and an encoder to learn the representation in the target language and perform cross-attention between the two, the GPT is designed only to *imitate* language. By applying masked multi-head attention, the model is restricted to only see past k (with k being the size of the context window) tokens and is tasked to predict the next one.

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Training consists of two stages: unsupervised pre-training and supervised fine-tuning. The former is used to find a good initialization point, essentially teaching the model to imitate the corpora it is trained upon. This results in a model that will ramble on uncontrollably, just trying to complete the input sequence it's given to the best of its knowledge, however this will produce undefined behaviour. It is therefore necessary to fine-tune the model on a target task with supervision. Radford and Narasimhan (2018, p. 4) explain how the model can fine-tune directly on tasks like text classification, but how one for other tasks needs to convert structured inputs into ordered sequences 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) 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). This pipeline is then performed for several iterations until the model produces the desired behaviour (OpenAI, 2022).

2.1.3. The BERT Family

Bidirectional Encoder Representation from Transformers (BERT), introduced about four months after release of paper on the GPT architecture (Radford and Narasimhan, 2018), is a family of language models which was first introduced in 2018 and is designed to facilitate a wide range of downstream tasks (Devlin et al., 2019, p. 5). The BERT architecture consists of stacked bidirectional Transformer *encoders*. This makes BERT unsuitable for text generation, unlike the *decoder*-based GPT architecture. However, the self-attention in the encoder, in which tokens can *see* both past and future tokens, mechanism allows for training of deep bidirectional representations, facilitating a wide range of NLP tasks. The input sequence is transformed into embeddings (vector representations). These per-token embeddings include information about the meaning of the word itself, the meaning of the sentence/segment it belongs to, and the token's position in the full input. These embeddings then pass through a stack of Transformer encoders (12 and 24 for **BERT_{BASE}** and **BERT_{LARGE}**, respectively), allowing the model to learn more complex patterns and of different granularities (token, sentence, document) (Devlin et al., 2019, p. 5).

In the BERT framework, there are two training steps, namely the pre-training and fine-tuning procedures. BERT is pre-trained on two NLP tasks. One is Masked Language Modelling (MLM), in which 15% of words are masked with the special [MASK] token and are left for the model to predict (Devlin et al., 2019, p. 4). The MLM task helps the model learn bidirectional representations. The second of the two unsupervised tasks used during pre-training is Next Sentence Prediction (NSP), where the special [CLS] token (found at the start of each tokenized sequence) is used to predict if a sentence B follows A. During this pre-training step, the input sequence looks like this:

[CLS] this is sentence A [SEP] and this is sentence B [SEP]

The [CLS] token is used to label sentence B as either **IsNext** or **NotNext**.

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BERT is normally fine-tuned to specific downstream tasks by using the [CLS] token, which captures an aggregated representation of the input sequence. This vector representation can then be used as input to a classification layer for tasks like multi-label classification and regression.

2.1.4. Gemini

As of writing, Google’s Gemini (Gemini Team and Google, 2023) (introduced on December 6th 2023) is the latest addition to the field of LLMs. Being fundamentally designed for multimodality, it is able to reason between text, images, video, audio, and code. It is released in different sizes: the Gemini Ultra, the Gemini Pro, and the Gemini Nano. The Gemini Ultra produces state-of-the-art performance on 30 of 32 widely-used academic benchmarks, and performs worse than OpenAI’s GPT-4 on only one benchmark, the HellaSwag benchmark for common-sense reasoning for everyday tasks. Gemini Ultra outperforms GPT-4 on the MMLU benchmark, various reasoning benchmarks, and shows significant improvements in maths and code related benchmarks (Gemini Team and Google, 2023, p. 7). Gemini performs better than OpenAI’s multimodal equivalent of GPT-4V in all (Gemini Team and Google, 2023, p. 12).

Like the GPT architecture, Gemini is built on top of Transformer decoders, and trained to accommodate various modalities, supporting interleaved sequences of text, image, audio, and video as inputs (Gemini Team and Google, 2023, pp. 3–4). This highlights one of the greatest strengths of the Transformer architecture, namely that it can be adapted for multiple modalities. Commonly, multimodal AI architectures consist of an ensemble of models, one for each given modality, with different representations that can be difficult to combine. The Transformer solves this issue and provides a common architecture that can be trained end-to-end.

2.1.5. Open-Source Alternatives

Seeing as the state-of-the-art models of today (GPT-4 and now, Google’s Gemini) are all closed-source, it is important to note that there are viable open-source alternatives out there that. This section lists the most prominent ones.

LLaMA 2

Perhaps the most famous open-source LLM, Meta AI’s LLaMA 2 is a powerful family of pre-trained and fine-tuned LLMs that outperformed open-source chat models on most benchmarks Touvron et al. (2023). It also shows great results in terms of safety, even outperforming the closed-source ChatGPT-0301 model. The training process of LLaMA is similar to that of the GPT model (see subsection 2.1.2). Pre-training is performed using an optimized auto-regressive transformer which is trained from a large corpus of unstructured data. It is the fine-tuned using various alignment techniques, and the authors also share a new technique they call Ghost Attentions, which aims to control

2. Theory

dialogue flow over multiple turns. RLHF and Proximal Policy Optimization (PPO) are important techniques used to get the desired behaviour out of the model.

Many flavours of LLaMA have been trained. Most notably is, Code LLaMA (Rozière et al., 2023), a family of LLMs fine-tuned for code, scoring at 53% and 55% on HumanEval and MBPP, respectively. Vicuna-13B is another example, which is a LLaMA model fine-tuned on user-shared conversations collected from ShareGPT (a website where users can upload ChatGPT conversations). At its release in March 2023, it achieves more than 90% quality of OpenAI ChatGPT and Google Bard, while also outperforming the original LLaMA model.

Mistral

Mistral 7B (AI, 2023) is another open-source LLM, claiming to be “the most powerful language model for its size to date”. Being a 7.3B parameter model, it is quite small compared to other models, such as the 1.76T parameter GPT-4 model. Mistral 7B outperforms the LLaMA 2 13B on all benchmarks, and approaches CodeLlama 7B performance on code. It uses a sliding window attention mechanism, which yields a linear compute cost of $O(\text{sliding_window.seq_len})$.

2.2. Benchmarking and Evaluation of LLMs

There are several ways of benchmarking Large Language Models but this section will focus on HumanEval, Multitask Language Understanding (MMLU), and Grade School Math 8K (GMS8K). According to metrics displayed on the various pages for these datasets found on [PapersWithCode](#), they seem to be the three most common datasets for measuring the different abilities of a given LLM.

Not fin-
ished

2.2.1. Evaluation Metrics

Perplexity

Perplexity measures the degree of uncertainty in predicting the next word in a sequence, based on the preceding words. This is done by calculating the negative average log-likelihood. A lower score indicates better performance.

Human Evaluation

Human evaluation, though an obvious evaluation metric, can be powerful. Human evaluators can manually score generated text based on a range of criteria, including relevance, fluency, coherence, and overall impression.

BiLingual Evaluation Understudy (BLEU)

BiLingual Evaluation Understudy (BLEU) provides a quick, inexpensive, and language-independent method of automatic machine translation, allowing researchers to rapidly

2. Theory

home in on effective modelling ideas (Papineni et al., 2002). BLEU shows the BLEU formula, which takes the geometric mean of the corpus' modified precision score and then multiplies it by an exponential brevity penalty factor. (2.2) shows the result when taking the log of the function, which makes the ranking behaviour more apparent (Papineni et al., 2002, p. 5).

$$\log \text{BLEU} = \min \left(1 - \frac{r}{c}, 0 \right) + \sum_{n=1}^N w_n \log p_n \quad (2.2)$$

Recall-Oriented Understudy (ROUGE)

The Recall-Oriented Understudy (ROUGE) metric aims to automatically determine the quality of a summary by comparing it to ground truth summaries produced by humans. (2.3) shows the ROUGE-N formula, which is the n-gram recall between a candidate summary and a set of the aforementioned ground truth summaries.

$$\text{ROUGE-N} = \frac{\sum_{S \in \{\text{ReferenceSummaries}\}} \sum_{\text{gram}_n \in S} \text{Count}_{\text{match}}(\text{gram}_n)}{\sum_{S \in \{\text{ReferenceSummaries}\}} \sum_{\text{gram}_n \in S} \text{Count}(\text{gram}_n)} \quad (2.3)$$

Diversity

Diversity is an important measure to assess the predictability of a model. n-gram diversity is a common metric. Other methods to measure diversity aim to find the semantic diversity between generated sequences.

2.2.2. Benchmarks

HumanEval

HumanEval is a dataset of handwritten problems used to measure functional correctness for synthesizing programs for docstrings (Chen et al., 2021, pp. 2–4).

Multitask Language Understanding

First introduced by Hendrycks et al. (2021) Multitask Language Understanding is a way of testing a Large Language Model's multitask accuracy, covering 57 tasks including mathematics, computer science, and others.

Grade School Math 8K

This is a dataset made to measure an LLM's abilities to perform mathematical arithmetic.

2.3. Large Language Model (LLM) Providers

Not finished

2. Theory

2.3.1. Huggingface

2.3.2. OpenAI

2.3.3. Microsoft Azure

2.3.4. Google Cloud

2.3.5. Amazon Web Services

2.3.6. Anthropic

2.4. Geospatial Standards

2.4.1. International Standardization Work

OGC Api Standard

The Open Geospatial Consortium (OGC) API Standards serve as the glue in the field of Geographic information system (GIS), paving the way for interoperability and data exchange between diverse systems. Leveraging common web protocols like HTML and supporting multiple data formats including JSON, GML, and HTML. The OGC API standard provides a modular architecture consisting of a core specification and various extensions. This modularity allows for flexibility, enabling users to customize their services according to specific needs. According to their webpages, they provide 80 different standards, each for a specific geospatial purpose. Notable examples are 3D Tiles, CityGML, GeoTiff, and OGC API - Features (OGC, 2023).

OGC API Standards function as modern replacements to older standards like WMS and WFS, and presents an evolved and more adaptable framework for spatial data operations, setting the stage for future innovations in the GIS domain.

STAC Api Standard

The SpatioTemporal Asset Catalog (STAC) API is a standardized way to expose collections of spatial temporal data for online search and discovery. Built upon a JSON core, it aims to be a uniform and flexible environment from which developers can customize the API infrastructure to their domain. STAC API provides a powerful query language that allows users to search by various parameters like time, location, and keywords, making widely applicable. The STAC community has also defined specification in order remove the complexity associated with having to create unique pipelines when consuming different spatial-temporal collection. The significance of the STAC API lies in its ability to democratize access to large volumes of geospatial data. By offering a common standard for data cataloguing and discovery, it reduces the barriers that often exist due to incompatible data formats. Developers or GIS professionals can take advantage of this through built-in tooling in QGIS, a desktop GIS for viewing, editing, and analysing spatial data, or through third-party packages in the Python and R programming languages. The

2. Theory

API is also accessible through the command line interface when using GDAL (*STAC Tutorials* n.d.).

As OGC board member Chris Holmes puts it: "The STAC API implements and extends the OGC API — Features standard, and our shared goal is for STAC API to become a full OGC standard." (Holmes, 2021).

2.4.2. Norwegian Standardization Work

Geospatial standardization work has been on the agenda of Norwegian governing powers for decades and have materialized in frameworks/collaborations like Geovekst and Norge digitalt, as well as the SOSI file format. Subsection 2.4.2 will delve into the work that has been done and what is expected for the future. The reasoning for the conclusion of this section is that the constraints of this specialization project is set by the Norwegian borders, and thus it is important to be aware of the standards that apply.

ChatGPT
place-
holder
text
- will
rewrite

SOSI

Samordnet Opplegg for Stedfestet Informasjon (SOSI) is a Norwegian file format for storing and exchanging geospatial data. It was first introduced in 1987 and has since approached international standards, the most important arenas currently being ISO/TC 211 and OGC (Mardal et al., 2015). SOSI is the adopted Norwegian standard for creating and delivering digital geographic data, administered by the Norwegian Mapping Authority (Statens kartverk) (Mæhlum and Rød, 2023).

In a SOSI dataset, terrain points, lines, and polygons are represented by their coordinates and classified into various object types according to the SOSI object catalog standard. However, there are few GIS systems that can read SOSI data directly, so data in SOSI format usually needs to be converted to another GIS-readable data format (Mæhlum and Rød, 2023).

Geovekst

Geovekst is a collaborative initiative in Norway aimed at collecting, managing, and distributing geospatial information. Established in 1992, it is a partnership between national, regional, and local government bodies, as well as several private companies. Geovekst's primary focus is on creating a comprehensive, standardized geographical database for Norway that is easily accessible and updated regularly. It has played a vital role in various planning and development projects across the country, from urban planning to environmental conservation.

Unlike other geospatial initiatives, Geovekst emphasizes shared responsibilities and costs among its partners. This cooperative model ensures consistent data quality and efficient use of resources. It utilizes a variety of data sources, including aerial photographs, laser scans, and mapping, making it a rich resource for both public and private sectors. Moreover, its open-access policy allows for wider dissemination of geospatial information, thus encouraging innovation and informed decision-making across multiple disciplines.

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Norge digitalt

Established in 2005, Norge Digitalt is a more recent framework compared to Geovest and is the name of Norway's national spatial data infrastructure. Norge Digitalt primarily involves governmental bodies (national, regional, and municipal), but also educational and research institutions and companies with responsibilities on a nation-wide scale; examples include Telenor and local and regional energy companies (Norge Digitalt, 2023, p. 6). Norge Digitalt aims to coordinate and streamline all geospatial activities in Norway, making it easier for users to discover, access, and use spatial data.

One key feature of Norge Digitalt is its focus on international standards and interoperability. While Geovest is primarily a national initiative, Norge Digitalt aims to integrate Norway's geospatial data with that of other European countries. It supports a wide range of data formats and follows international standards, including those set by the Open Geospatial Consortium (OGC). The framework also provides various tools and services, like metadata catalogues and web services, making it a comprehensive solution for geospatial data management and distribution in Norway.

2.5. User Groups

There are several user groups that could take advantage of an AI-based agent with general geographic and GIS knowledge. Questions can span from simple retrieval questions such as "How many people live in Trondheim" and "How long is the drive from Oslo to Bergen?", to more complicated questions that require problem-solving abilities and reasoning. While it is difficult to obtain dataset over common queries, Kumar (2023), creator of the chatbot app Pocket AI¹, shared a dataset of ~13k user queries from his app along with classifications of these. Salient categories were:

- "task oriented" (23.1%)
- "informational" (20.2%)
- "social" (16.2%)
- "personal advice and self-improvement" (13.1%)

The main takeaway from these numbers is that the main motivation for use is productivity.

This aligns with the results of Skjuve et al. (2023) from their questionnaire-based study performed in late January 2023, about three months after its release (OpenAI, 2023). The goal with the study was to find out *why* people use ChatGPT. They found that most participants (55%) are motivated by productivity, and specifically applying it for routine tasks, information retrieval, text generation and writing support, and software development (Skjuve et al., 2023, pp. 17–21). Table 2.1 shows all categories and their

¹<https://github.com/varunon9/pocket-ai>

2. Theory

frequencies. There were 197 samples in total, and more than one category could be assigned to each sample. It is worth noting that the study is likely to have included early adopters, and might therefore make the results less representative for the time at which this report is written (7th December 2023), now that use patterns have become more established (Skjuve et al., 2023, p. 37).

Table 2.1.: Categories and frequency of ChatGPT usage (Skjuve et al., 2023, pp. 16–17).

Category	% (n)
Productivity	55% (109)
Novelty	51% (101)
Fun and amusement	20% (41)
Creative work	18% (34)
Social interaction and support	9% (18)
Other	7% (15)

Given that the main reason people use conversational AI is for productivity, whether in a professional, academic, or personal context, such technology could be highly beneficial in a geospatial setting. 67 out of the 197 participants in Skjuve et al. (2023, p. 18) highlighted "ChatGPT's ability to understand complex queries" and that it is "efficient in alleviating the need to experiment with different phrasings of the query", as is often needed when 'Googling' for an answer to a specific question. This ease of information retrieval, along with its problem-solving abilities (Skjuve et al., 2023, p. 20), could also make conversational AIs highly relevant for geospatial purposes, and in the field of GIS.

One could imagine a range of potential user groups that could benefit from such an artificial, and spatially aware, companion. A couple of suggestions user groups are presented in Figure 2.1. Perhaps the most obvious one is that of the GIS professionals. While a AI-based GIS agent more capable than the average GIS professional currently far from becoming a reality, such an agent could help suggest strategies of solving a particular problem using the input data available and the end goal, or it could help solve mundane tasks in an automated way in order to allow the GIS professional to allocate more time to creative and complex tasks.

Closely related is city planners. Though often less knowledgeable in the field of GIS, they are increasingly dependent upon geospatial analysis in order to make informed decisions. Having an easy-to-use GIS ready at any moment could prove both time- and cost-saving. The same goes for business analysts and people involved in academia. The *time* variable is especially important to the emergency services. At the impact of a natural disaster like a flood or forest fire, geospatial analysis could prove lifesaving. Having powerful geospatial knowledge even in the absence of a GIS professional is therefore important in order to focus resources to areas where the situation is most pressing.

An AI agent with geospatial awareness could also be useful to the general public. One may want to find suitable biking routes or good hills to do interval running in, or to

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know what areas are prone to flooding, when buying a house. Most people do not have the knowledge or time to perform such analyses themselves, so an automated AI-based agent could prove useful here.

2.6. Ethical and Privacy Concerns

Although an AI-based GIS agent could prove powerful, there are some ethical pitfalls in terms of regulations and privacy concerns. If such an agent is to make decision on behalf of humans it is important that one can hold someone accountable in the case where something goes wrong. If an AI-based agent is tasked to lead firefighters to the tactically optimal locations in order to quench the fire, but misleads them and traps them inside the fire, who is then to blame? Sparrow (2007) provides an interesting angle on this issue, though related the role of artificially intelligent robots in modern warfare.

Furthermore, it is important that it is impossible to use the AI for immoral purposes, such as finding the optimal location in which to dissolve poison into people's drinking water. Work has been done with newer LLMs to prevent them from producing dangerous, misinformed, or toxic text—it is widely discussed in the technical report of the latest GPT model (OpenAI, 2023, pp. 11–14)—but there have been cases where these issues haven't been considered well enough².

The General Data Protection Regulation (GDPR) entered into applicability in the European Union in 25th of May 2018, and although not a member of the European Union, Norway incorporated the GDPR in July the same year due to its membership of the European Economic Area. The GDPR imposes stricter regulations about data privacy, meaning people have more control over their personal data, and that businesses get a level playing field in terms of what customer information is available (Datatilsynet, n.d.). With data privacy being more relevant than ever in this information age we find ourselves in, we must make certain that AI-based GIS agents are unable to access and spread information of private or sensitive character, even if such information has become publicly available by accident—as was the case when the Norwegian Broadcasting Corporation (NRK) was able to (legally) obtain accuracy geolocations of central people in the Norwegian army from a commercial London-based company³.

²The LaMA-based Alpaca model, developed at Stanford University, was taken offline after being shown to produce misinformation, toxic text: https://www.theregister.com/2023/03/21/stanford_ai_alpaca_taken_offline/

³Link to news article in Norwegian: <https://www.nrk.no/norge/xl/norske-offiserer-og-soldater-avslortet-av-mobilen-1.14890424>

3. Related Work

The related works are divided into three sections, each being relevant to the project in different ways. Section 3.1 is the most obviously relevant section, discussing works in which LLMs were employed to perform tasks in the geospatial realm. Section 3.2 delves into different prompt engineering and planning strategies that could be useful to make an autonomous GIS agent perform better and more reliably. Section 3.3 discusses Retrieval Augmented Generation (RAG), that is, how one can provide an autonomous LLM-based agent with external contributions tooling and up-to-date information.

3.1. GIS with LLMs

A substantial body of work have been done in recent years to assess the geospatial knowledge of LLMs, and how they can be fine-tuned or embedded into frameworks to serve downstream tasks.

3.1.1. Geospatial Context in LLMs

Scherrer and Ljubešić (2020) were able to show that BERT can be fine-tuned to accurately predict geolocations from textual input, by winning a shared task on predicting geolocations from Twitter/Jodel messages in a workshop in 2020 (Gaman et al., 2020). By converting the task into a double regression problem, where they predicted latitude/-longitude pairs from the output [CLS] representation of BERT models. For a subtask on a Swiss Jodel dataset, they were able to achieve a median distance of 15.72 km from the ground truth, showing that LLMs can be trained correlate lingual features and geolocations.

Roberts et al. (2023) investigated extent of GPT-4’s geospatial awareness through a set of case studies with increasing difficulties, starting with general factual tasks and finishing with complex questions such as generating country outlines and travel networks. The authors find that GPT-4 is “skilful at solving a variety of application-centric tasks”, almost having the ability to “see”, despite being a language model and thus only being able to interface with the world through sequenced, textual input. Examples include its ability to perform as a travel assistant in providing itinerary suggestions for a trip when provided with requirements, and its ability to provide start and end locations bird migrations generally correct, and in some cases highly accurate. While it becomes obvious that a lot of geospatial context have been embedded within the model during the vast pre-training, the question whether this is memorization or reasoning is a central

3. Related Work

one. The authors suggest that variability of tasks in their experiments deems it unlikely that it is all memorization, but they say that some things appear to be memorized.

Mooney et al. (2023) examined the performance of ChatGPT in a Geographic information system (GIS) exam, aiming to assess its ability to grasp various geospatial concepts, highlighting its capabilities and limitations. Experiments were conducted on GPT-3.5 and GPT-4, which 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 workflow. Experiments on the latter showed that ChatGPT-4 was able to correctly answer a relatively complex GIS tasks involving seven different datasets, requiring seven steps in order to obtain a perfect score. Generally, ChatGPT-4 outperformed ChatGPT-3.5 in all tasks. While clearly powerful, the authors highlight a range of limitations, among which the multimodal nature of GIS, which would hinder a straightforward application of existing models.

Unlu (2023) discussed importance of enabling LLMs to recognize and interpret geospatial data, and how OpenStreetMap (OSM) can play an important role in offering LLMs linguistic access to vast cartographic datasets. He exemplifies this claim through a proof of concept in which he performs small-scale fine-tuning on an LLM with 1B parameters, using an artificial supervised datasets curated by the more capable ChatGPT 3.5-turbo, which functions as a teacher model, generating prompt-answer pairs for given preprompts. The fine-tuned model displays promising ability of answer questions about a location's attributes, allowing the user to inquire about things like tourist appeal and potential profitability of businesses in the vicinity of the given location. Unlu emphasizes the method's strengths for small datasets and minimal computational settings. The study also investigated the idea of using embeddings of the curated prepromts. Experimenting with average GLOVE embeddings, he showed that the latent structure of verbal descriptions of OSM data can yield insightful patterns. This, he argues, can prove useful when creating Retrieval Augmented Generation (RAG) applications aimed at allowing users to retrieve geospatial information in a prompt-based manner.

3.1.2. Autonomous GIS

Li and Ning (2023) states that “autonomous GIS will need to achieve five autonomous goals: self-generating, self-organizing, self-verifying, self-executing, and self-growing.”, and provide a “divide-and-conquer”-based method to address some of these goals. Furthermore, they propose a simple trial-and-error approach to addressing the self-verifying goal. They also highlight need of a memory system in a mature Large Language Model (LLM)-based Geographic information system (GIS) system, referring to the use of vector databases in autonomous agents like AutoGPT (Richard, 2023). Even with its shortages, the solution that (Li and Ning, 2023) provide, called LLM-Geo, is able to solve provide good solutions in various case studies by providing executable assemblies in a Python environment when provided with URLs to relevant data sets, along with a user-specified query.

Zhang et al. (2023) use the LangChain framework (Chase, 2022) in order to combine different GIS tools in a sequence in order to solve different sub-goals, and focuses on

3. Related Work

using the semantic understanding and reasoning abilities of LLMs like (e.g., ChatGPT) to call externally defined tools, employing the LLM as an agent or controller. The authors take great inspiration from the AutoGPT framework (Richard, 2023). The externally defined tools are described (manually) by its name and description. Said description contains information about the input parameters and output types of the tools/functions. Tools are defined for geospatial data collection, data processing and analysis, and data visualization. The effectiveness of the system is showcased in four case studies.

Qi et al. (2023) discuss how LLMs can be used in spatial data management, facilitating a system that can learn from both structured and unstructured data, the latter of which is possibly the greatest strength of modern LLMs. They highlight the opportunity that LLMs provide in reducing the barrier to information retrieval for the general public, and discuss how these strengths can be used in spatial data management by leveraging a spatial database system trained from both structured and unstructured data, allowing for seamless access to spatial knowledge, also for those with little or no expertise in querying a spatial database. With that in mind, they envisage to use *machine learning models as a spatial database* (MaaSDB), which when trained on structured and unstructured spatial data can *generate query answers directly* instead of retrieving data from tables, the latter of which has been the most common way of using machine learning in database query processing. From conducting preliminary studies they present a system of LLM-based system of query analysers, query plan generators, and a query result generators to handle natural language user queries. They propose a Generative Adversarial Network (GAN)-based model to generate tabular data, seeing if such a model can remember the key characteristics of the data. Such a model will have a *generator G* that will produce a record a *discriminator D* that will classify whether the generated record resembles a real record. The results of this approach are promising, and further prompt-based test performed on ChatGPT demonstrates its potential to learn spatial knowledge and answer queries. While potentially powerful, they highlight a range of challenges of implementing their proposed system, such as hallucination, the limited availability of structured spatial data, generalizability issues, and the problem of updating the trained models when the underlying data changes.

3.2. Prompt Engineering and Planning Strategies

Large Language Models have shown great abilities in problem-solving and decision-making tasks, but generally struggle as they are presented with larger and more complex tasks. Also, seeing as they are pure stochastic machines, the output is seldom reproducible. While the temperature parameter of the GPT models help serve as a control mechanism for this randomness, it does not guarantee fully predictable text generation. These issues have led people into investigation *prompt engineering* and various techniques for helping the models form plans when faced with large and complex tasks, both of which aim to guide the model into producing the desired response.

Zhou et al. (2023) introduces a framework called Language Agent Tree Search (LATS) "that synergizes the capabilities of LLMs in planning, acting, and reasoning.". As of

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3. Related Work

writing (October 30th, 2023), the LATS framework is the highest scoring model on the HumanEval benchmark, demonstrating state-of-the-art performance on decision-making tasks in a range of diverse domains. LATS performs a sequence of operations in succession until the task at hand is solved. These are *selection*, *expansion*, *evaluation*, *simulation*, *backpropagation*, and *reflection*. Employing Monte Carlo Tree Search they enable the LLM-based to select the among n sampled options while still exploring other promising alternatives, using a heuristic to rank alternatives. Though a shared space of thoughts and actions, the framework supports both reasoning and decision-making tasks. Observation and self-reflection abilities enables LATS to use external feedback, which proved valuable when testing the framework on different benchmarks, some of which were discussed in subsection 2.2.2.

3.3. Retrieval Augmented Generation

RAG is tightly interwoven with explainable AI, being a framework for retrieving facts from an external knowledge base to allow a LLM-based agent access to accurate up-to-date information (Martineau, 2023). A common problem when working with language models, especially those designed to be general-purpose, is hallucination; that is, when the model provides an answer that is completely wrong but in a very convincing manner. While progress is being made with newer models even the better ones, like GPT-4, gives an incorrect answer about 1 out 5 times, and even worse for certain categories of queries (for instance 'code' and 'business') (OpenAI, 2023, p. 10). Retrieval Augmented Generation can help mitigate this problem.

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3.3.1. LangChain

LangChain (Chase, 2022) is an open-source project that provides tooling that can be used to create autonomous AI agents. It is designed to help with prompt management and optimization, creating chains of calls to LLMs, data augmentation, autonomous agent creation, and memory-related tasks.

3.3.2. Microsoft Semantic Kernel

Microsoft Semantic Kernel is an SDK that functions as the brain of an autonomous agent and provides connectors to models and memory, and connects to triggers and actions.

3.3.3. AutoGPT

Richard (2023) will try to split a task into subtasks and use the internet and other tools in an automatic loop to solve the task/subtasks.

4. Experiments and Results

Three experiments were conducted in this specialization project. Section 4.1 will explain how the experiments were conducted, and section 4.2.

4.1. Method: Experimental Plan and Setup

The experiments conducted for this report have been planned to answer the research questions described in section 1.2.

4.1.1. Experiment 1: Testing ChatGPT's Ability to Perform Geospatial Analysis

Tests were performed to assess ChatGPT's ability to perform geospatial analysis. The testing approach is inspired by the work of Roberts et al. (2023) (see section 3.1), who did experiments with increasing difficult on GPT-4 to characterize what GPT-4 knows about the geographical world, highlighting both capabilities and limitations. These focused on GPT-4's general geospatial awareness, and were not concerned with GIS-related tasks. Therefore, I will refer to Roberts et al. (2023) when highlighting its somewhat surprising geospatial awareness abilities, and focus my efforts to displaying its potential for use in the world of GIS. I will do this by constructing various tests that try to reflect its GIS knowledge.

I will use the Elveg 2.0 dataset (The Norwegian Mapping Authority, 2019), along with cadastral data. In order to assess ChatGPT's ability to read and understand different data formats, the data will be provided in both SOSI, GML, and GeoJSON format. Datasets for the first two formats were downloaded from <https://geonorge.no>, while the GeoJSON datasets were created using a custom Bash script which converts from GML to GeoJSON using the `ogr2ogr` program from GDAL. The Elveg 2.0 dataset contains a range of different layers for different types of geometries. In order to simplify the experiments, only the layer named "Fartsgrense" (eng. "Speed limit") was used fro Elveg 2.0.

Below are the questions that were asked, in rising order of predicted complexity.

1. “Provide a summary of the file contents, highlighting the file’s most salient features.”
2. “Provide a visual representation of the file contents.”
3. “Find the mean location of the building locations.”
4. “Extract all roads with a speed limit greater than or equal to 80 km/h.”

4. Experiments and Results

5. "Select all buildings located within 50 metres of a high-speed road (speed limit >= 80 km/h)."
6. "Find the area best suited for expansion to accommodate residential buildings."

Some follow-up questions are added when needed, in order help the model understand the questions or when it stops and asks for permission to go forth with analysis.

4.1.2. Experiment 2: Comparing File Upload and API Calling in ChatGPT-4

Another important thing to test is the issue of providing ChatGPT with relevant files on which it can perform analysis. ChatGPT Plus users will have access a range of advanced features, including web browsing with Bing, Dall-E Image Generation, and Code Interpreter. The latter of these allows the user to manually upload files into the chat instance and perform advanced analyses on the contents of these, which is what was used to upload the datasets for the tests above. While this is very powerful, having to manually upload files poses some limitations. A more flexible system should be capable of accessing web APIs in real time.

A dataset containing the border of Drammen Municipality was used to test compare ChatGPT's ability to perform analyses on manually uploaded data, versus data handed through it from passing a URL address. The data conforms to the GeoJSON standard and contains a FeatureCollection object with a single Feature, namely the border. When file/URL has been provided, ChatGPT is simply asked to present a visual presentation of its contents.

4.1.3. Experiment 3: Testing ChatGPT's Ability to Perform Overlay Analysis using OGC API Features and LangChain

Experiments on RQ3 will test different tools and techniques intended to give an LLM access to up-to-date information and external tools (see section 3.3 on Retrieval Augmented Generation). The main focus will be on how one can use a tool like LangChain hook up a conversational AI with sophisticated functionality found in various GIS software.

Experiments on RQ2 will require three different elements:

1. Provide ChatGPT with API URL(s) to relevant data collections corresponding with the OGC API - Features specification
2. Prompts to ChatGPT-4 using the "Code Interpreter" beta feature
3. Gold standard/expected output for the given combination of input data and prompts

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These experiments will be limited to the collections found at <https://alenos-tester001.azurewebsites.net/>. This example OGC API was created by Norkart's Alexander Salveson Nossum for with the purpose of testing OGC API Features on Norwegian data. It was created using `pygeoapi`¹, which is a Python server implementation of the OGC API suite

¹<https://pygeoapi.io/>

4. Experiments and Results

	SOSI	GML	GeoJSON	Shapefile
Summary	No	Yes	Partially	Partially
Plotting	-	When guided	When guided	Yes
Mean location	-	When guided	Yes	No
Filtering	-	No	Yes	Yes
Buffer + Intersect	-	No	No	No
Planning for expansion	-	No	Partially	No

Table 4.1.: Overview of the ability of ChatGPT’s Code Interpreter to handle various geospatial data formats

of standards. It allows for deployment of a RESTful OGC API endpoint using OpenAPI, GeoJSON, and HTML.

4.2. Experimental Results

4.2.1. Results for Experiment 1

As Table 4.1 shows, ChatGPT’s Code Interpreter is unable to read and write SOSI files. It was unable to manipulate the data directly and was also unable to convert the file into a more suitable format, failing to convert it GeoJSON using GDAL’s `ogr2ogr`. SOSI is therefore excluded from Table 4.1, which shows the successfulness of ChatGPT to perform analyses on various file formats.

Furthermore, ChatGPT’s Code Interpreter did not manage to properly analyze the GML data without guidance. It created a parser that was difficult to use for further analysis. When guided into using the GeoPandas library, which accepts GML data, it managed to plot the contents and calculate a centroid. The buffering and intersection task “was interrupted due to its time-consuming nature”, and it did not make an attempt at solving the planning task due to inability to analyze the GML files.

With the GeoJSON data, ChatGPT had difficulties reading the files and could not provide a good summary consistently. It *was* able to plot the data, but that had to be done in separate responses for each of the datasets. It was able to find the high-speed roads, but could not figure out which buildings were within a 50-meter buffer of these. However, when asked to plan for expansion to accommodate residential buildings, it managed to achieve a result close to what was expected in the “Buffer + Intersect” task. It accomplished this by creating a grid and figuring out which grid cells were within 50 meters of a high-speed road. This did not extract a subset of the building points—which would have been the desired output—but it had some minor value in terms of visualization (see Figure 4.1). Though the result is useful, it was closer than in the GML attempt to what would be an expected response.

Using the shapefile formatted data, ChatGPT was able to produce a decent summary of the data, but the attribute names were cut off after about 10 characters. It was,

4. Experiments and Results

however, able to produce quite good visual representations of both dataset, colouring the roads differently by their speed limits and the buildings by their building type.

4.2.2. Results for Experiment 2

Figure 4.2a and Figure 4.2b shows the results when providing ChatGPT-4 with the GeoJSON for the outline of Drammen municipality using the file upload functionality and providing it and URL to an API endpoint, respectively. While handling the direct file upload with bravura, it struggled when provided the URL. When provided the URL, its first response was that “there was a problem with establishing a connection to the website”, after trying to process the request using Code Interpreter. When guided (twice) to try accessing the URL using its web browsing abilities, it was eventually able to read the data. In the subsequent prompt it was asked to provide a visual representation, but failed to do so successfully as Figure 4.2b shows. The reason for this was its decision to “truncate the dataset for brevity, using a subset of the full coordinate list” (see Listing 4.1).

Listing 4.1: ChatGPT code that truncates coordinates

```
# ...

# Extracted coordinates from the JSON data
coordinates = [
    [9.976278541184014, 59.71166107645171],
    [9.975715936016496, 59.71206324390201],
    [9.975270250797282, 59.71243147807226],
    # ... Truncated for brevity, using a subset of the full
    # coordinate list
    [9.964929990238785, 59.774609947672644]]
]

# ...
```

4. Experiments and Results

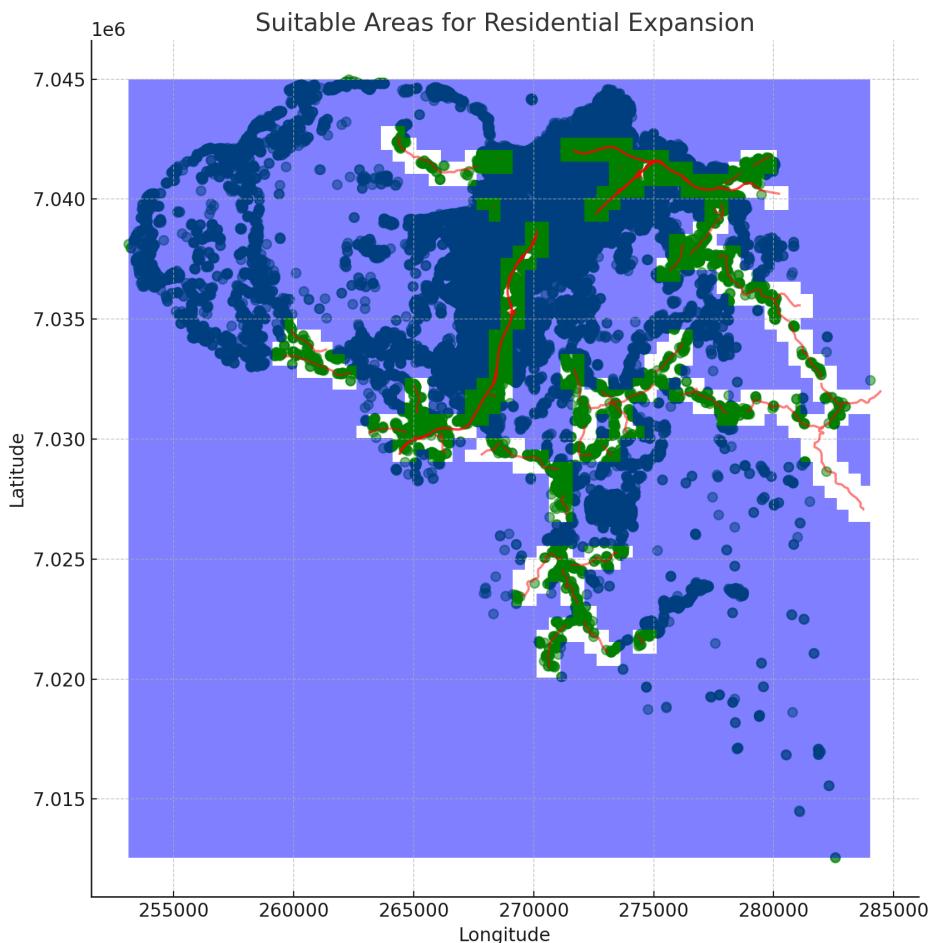


Figure 4.1.: The result of ChatGPT when asked to “Find the area best suited for expansion to accommodate residential buildings”, using provided GeoJSON datasets. Potentially suitable areas for residential expansion are depicted in blue.

4. Experiments and Results

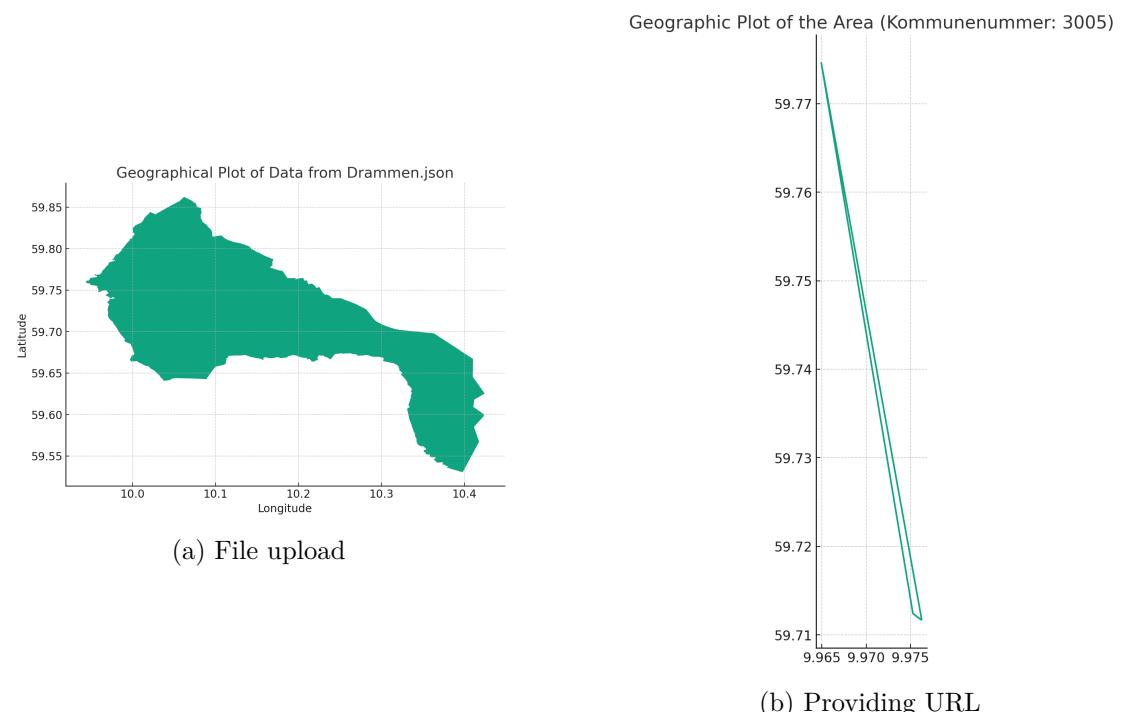


Figure 4.2.: Comparison of the resulting outline of Drammen when using file upload (a) and providing an URL to an API endpoint (b) with ChatGPT-4

5. Discussion

5.0.1. Using the In-Built ChatGPT Code Interpreter for Geospatial Analysis

When using ChatGPT’s Code Interpreter with file uploads, it became apparent that it runs in a Linux environment, and that it uses a mounted drive in the `/mnt` director, which is used for temporarily mounted filesystems. From the initial experiments where the same data in different file formats was tested it tried to a GDAL command (`ogr2ogr -f "GeoJSON" {converted_geojson_path} {sosi_file_path}`) to perform a conversion from SOSI to GeoJSON, the latter of which is far easier to manipulate in a Python environment. This test failed, and the system’s response was that “the `ogr2ogr` tool is not available in this environment”.

This result was not very surprising, especially since the driver needed to read and write SOSI files—which is called *fyba* and is developed by The Norwegian Mapping Authority¹—is almost certainly not available in the standard Linux environment for ChatGPT’s Code Interpreter. Seeing as the SOSI standard still is widely used for Norwegian geospatial purposes (though expected to be exchanged with the GML format in the future), it is important for an LLM-based GIS agent focused on the Norwegian market to be able to handle this file type.

The inability to manipulate the Linux environment using by the Code Interpreter clearly poses some limitations on the systems. A solution to the problem is to create a custom environment on a server and implement agent-like capabilities by other means (LangChain, AutoGPT, AutoGen, etc.). Having the agent run on an environment that we control ourselves gives us greater flexibility, and we can then allow the agent to access powerful GIS tooling, such as the GDAL library. This also allows us to avoid having to perform I/O on a mounted directory (in the `/mnt` directory), which can increase the speed of reads and writes.

5.0.2. Mitigating ChatGPT’s Inability to Access Web APIs

As results of experiment 2 (see subsection 4.2.2) showed, ChatGPT-4 struggles when provided with URLs to external Web APIs, even when prompted to use its web browsing abilities and pairing them with its Code Interpreter. These issues are not present when using direct file upload, in which case the model appears to save the uploaded file in a temporary file directory in on a mounted drive in its Linux environment. While it can be hard to interpret the inner workings only from the code samples, it appears that it

¹<https://github.com/kartverket/fyba>

5. Discussion

does not do this by default after fetching data from an external API. It appears from the results, in which it *truncates* the file and “store’s” the content directly in code, thus attempting to store the entire file in the context window of the LLM. The context window of the ChatGPT-4 model is currently at 32,000 tokens (the new GPT-4 Turbo has a context length of 128,000 tokens). While these are of significant size, they are not meant to (or able to) store large file, and thus it becomes a limiting factor when the file contents grow large, which is not uncommon for geospatial files.

This is a significant limitation of using ChatGPT-4 out of the box, and one should therefore look into other ways of handling web requests and subsequent storing of the received data. Techniques within Retrieval Augmented Generation (RAG) can help here, and tools like LangChain or OpenAI’s own “GPTs”² can help solve this issue.

²<https://openai.com/blog/introducing-gpts>

6. Conclusion and Future Work

6.1. Conclusion

6.2. Future Work

Seeing as this is a specialization project that will transition into a larger master thesis, the points discussed in this section will be key parts of the plan for the work carried out in the latter.

6.2.1. Test regime

In order to test the feasibility of different language models to serve as the brain of an autonomous GIS agent, a testing regime should be developed. In the examples of autonomous GIS agents described in the literature study of this report (see section 3.1), results have generally been presented in the form of case studies (Li and Ning, 2023; Zhang et al., 2023). This type of qualitative testing is entirely appropriate to showcase the possibilities of the technologies but may be insufficient when comparing performance of different systems. In the latter case a quantitative approach would probably be preferable.

One idea is to create a test dataset which consists of inputs and corresponding desired outputs of typical GIS tasks. Inputs would in this case be natural language queries inputted by a mock user, and the output would be what you would expect a GIS professional to return when given the same tasks/queries. Inputs should reflect the varying level of GIS knowledge in the different user groups (see section 2.5). Outputs could be files with typical geospatial extensions (.shp, .geojson, .sosi, etc.), or they could adhere to API schemas specified by geospatial standards (see section 2.4).

While the inputs should be fairly simple to construct there are several questions to be answered in regard to the outputs:

- How does one evaluate the accuracy of the output?
- How should the AI agent respond when the user does not specify an output file format?
- How does one evaluate the usefulness of outputs to questions that should not return geospatial files, e.g. answers to general questions about geo-related subjects?

These are questions outside the scope of this specialization project. They will, however, be pursued in my master thesis.

6. Conclusion and Future Work

6.2.2. Framework for Planning, Acting, and Reasoning

6.2.3. Embeddings

6.2.4. Fine-Tuning

To be
written

6. Conclusion and Future Work

Bibliography

- AI, M. (2023). Mistral 7B.
- Chase, H. (2022). LangChain.
- Chen, M., Tworek, J., Jun, H., Yuan, Q., Pinto, H. P. d. O., Kaplan, J., Edwards, H., Burda, Y., Joseph, N., Brockman, G., Ray, A., Puri, R., Krueger, G., Petrov, M., Khlaaf, H., Sastry, G., Mishkin, P., Chan, B., Gray, S., Ryder, N., Pavlov, M., Power, A., Kaiser, L., Bavarian, M., Winter, C., Tillet, P., Such, F. P., Cummings, D., Plappert, M., Chantzis, F., Barnes, E., Herbert-Voss, A., Guss, W. H., Nichol, A., Paino, A., Tezak, N., Tang, J., Babuschkin, I., Balaji, S., Jain, S., Saunders, W., Hesse, C., Carr, A. N., Leike, J., Achiam, J., Misra, V., Morikawa, E., Radford, A., Knight, M., Brundage, M., Murati, M., Mayer, K., Welinder, P., McGrew, B., Amodei, D., McCandlish, S., Sutskever, I., & Zaremba, W. (2021). Evaluating Large Language Models Trained on Code.
- Datatilsynet. (n.d.). General Data Protection Regulation.
- Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding.
- Fan, A., Gokkaya, B., Harman, M., Lyubarskiy, M., Sengupta, S., Yoo, S., & Zhang, J. M. (2023). Large Language Models for Software Engineering: Survey and Open Problems.
- Gaman, M., Hovy, D., Ionescu, R. T., Jauhainen, H., Jauhainen, T., Lindén, K., Ljubešić, N., Partanen, N., Purschke, C., Scherrer, Y., & Zampieri, M. (2020). A Report on the VarDial Evaluation Campaign 2020. *Proceedings of the 7th Workshop on NLP for Similar Languages, Varieties and Dialects*, 1–14.
- Gemini Team & Google. (2023). *Gemini: A Family of Highly Capable Multimodal Models* (tech. rep.).
- Hendrycks, D., Burns, C., Basart, S., Zou, A., Mazeika, M., Song, D., & Steinhardt, J. (2021). Measuring Massive Multitask Language Understanding.
- Holmes, C. (2021). SpatioTemporal Asset Catalogs and the Open Geospatial Consortium.
- Kumar, V. (2023). What are people asking to ChatGPT?
- Li, Z., & Ning, H. (2023). Autonomous GIS: The next-generation AI-powered GIS.

Bibliography

- Mæhlum, L., & Rød, J. K. (2023). SOSI. *Store norske leksikon*.
- Mardal, G., Borreb, M., Christensen, L., Jetlund, K., Ryghaug, P., & Hokstad, I. (2015). Nasjonal strategi for videreutvikling av SOSI.
- Martineau, K. (2023). What is retrieval-augmented generation?
- Mooney, P., Cui, W., Guan, B., & Juhász, L. (2023). *Towards Understanding the Geospatial Skills of ChatGPT: Taking a Geographic Information Systems (GIS) Exam*.
- Norge Digitalt. (2023). *Generelle vilkår for Norge Digitalt-samarbeidet* (tech. rep.).
- OGC. (2023). OGC Standards.
- OpenAI. (2022). Introducing ChatGPT.
- OpenAI. (2023). GPT-4 Technical Report.
- Papineni, K., Roukos, S., Ward, T., & Zhu, W.-J. (2002). Bleu: A Method for Automatic Evaluation of Machine Translation. In P. Isabelle, E. Charniak & D. Lin (Eds.), *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics* (pp. 311–318). Association for Computational Linguistics.
- Qi, J., Li, Z., & Tanin, E. (2023). MaaSDB: Spatial Databases in the Era of Large Language Models (Vision Paper).
- Radford, A., & Narasimhan, K. (2018). Improving Language Understanding by Generative Pre-Training.
- Richard, T. B. (2023). AutoGPT: The heart of the open-source agent ecosystem.
- Roberts, J., Lüdecke, T., Das, S., Han, K., & Albanie, S. (2023). GPT4GEO: How a Language Model Sees the World's Geography.
- Rozière, B., Gehring, J., Gloeckle, F., Sootla, S., Gat, I., Tan, X. E., Adi, Y., Liu, J., Remez, T., Rapin, J., Kozhevnikov, A., Evtimov, I., Bitton, J., Bhatt, M., Ferrer, C. C., Grattafiori, A., Xiong, W., Défossez, A., Copet, J., Azhar, F., Touvron, H., Martin, L., Usunier, N., Scialom, T., & Synnaeve, G. (2023). Code Llama: Open Foundation Models for Code.
- Scherrer, Y., & Ljubešić, N. (2020). HeLju@VarDial 2020: Social Media Variety Geolocation with BERT Models. *Proceedings of the 7th Workshop on NLP for Similar Languages, Varieties and Dialects*, 202–211.
- Skjuve, M., Bae Brandzaeg, P., & Følstad, A. (2023). Why People Use ChatGPT.
- Sparrow, R. (2007). Killer Robots. *Journal of Applied Philosophy*, 24(1), 62–77.
- STAC Tutorials. (n.d.).

Bibliography

- The Norwegian Mapping Authority. (2019). *Elveg 2.0* (tech. rep.).
- Touvron, H., Martin, L., Stone, K., Albert, P., Almahairi, A., Babaei, Y., Bashlykov, N., Batra, S., Bhargava, P., Bhosale, S., Bikel, D., Blecher, L., Ferrer, C. C., Chen, M., Cucurull, G., Esiobu, D., Fernandes, J., Fu, J., Fu, W., Fuller, B., Gao, C., Goswami, V., Goyal, N., Hartshorn, A., Hosseini, S., Hou, R., Inan, H., Kardas, M., Kerkez, V., Khabsa, M., Kloumann, I., Korenev, A., Koura, P. S., Lachaux, M.-A., Lavril, T., Lee, J., Liskovich, D., Lu, Y., Mao, Y., Martinet, X., Mihaylov, T., Mishra, P., Molybog, I., Nie, Y., Poulton, A., Reizenstein, J., Rungta, R., Saladi, K., Schelten, A., Silva, R., Smith, E. M., Subramanian, R., Tan, X. E., Tang, B., Taylor, R., Williams, A., Kuan, J. X., Xu, P., Yan, Z., Zarov, I., Zhang, Y., Fan, A., Kambadur, M., Narang, S., Rodriguez, A., Stojnic, R., Edunov, S., & Scialom, T. (2023). Llama 2: Open Foundation and Fine-Tuned Chat Models.
- Unlu, E. (2023). Chatmap : Large Language Model Interaction with Cartographic Data.
- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & Polosukhin, I. (2017). Attention Is All You Need.
- Zhang, Y., Wei, C., Wu, S., He, Z., & Yu, W. (2023). GeoGPT: Understanding and Processing Geospatial Tasks through An Autonomous GPT.
- Zhou, A., Yan, K., Shlapentokh-Rothman, M., Wang, H., & Wang, Y.-X. (2023). Language Agent Tree Search Unifies Reasoning Acting and Planning in Language Models.

Appendices

A. Task Description from Norkart



Faculty of Engineering Science and Technology
Department of Civil and Environmental Engineering

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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

A. Task Description from Norkart



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Detaljert oppgavebeskrivelse utvikles i samarbeid med studenten.

ADMINISTRATIVT/VEILEDNING

Ekstern veileder: (en eller flere)

Mathilde Ørstavik, Norkart

Rune Aasgaard, Norkart

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Aktuelle vegglearar og ansvarleg professor ve NTNU (den som har fagansvar nærmest oppgåva):

Terje Midtbø (GIS, kartografi, visualisering)

Hongchao Fan (3D modellering, fotogrammetri, laser)