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Evaluating retrieval and summarisation performance of AI-Assistants built with Large Language Models and RAG-techniques (Retrieval Augmented Generation) in the domain of a LMS (Learning Management System)

A subtitle in the language of the thesis

LUDWIG KRISTOFFERSSON

Stockholm, Sweden, 2024

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Abstract

Foobar

Keywords

Canvas Learning Management System, Docker containers, Performance tuning

Sammanfattning

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Nyckelord

Canvas Lärplattform, Dockerbehållare, Prestandajustering

Acknowledgments

I would like to thank FEN for having yyyy. Or in the case of two authors:
We would like to thank xxxx for having yyyy.

Stockholm, May 2024
Ludwig Kristoffersson

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List of acronyms and abbreviations

BERT	Bidirectional Encoder Representations from Transformers
CBOW	Continuous Bag-of-Words
CNN	Convolutional Neural Networks
EC2	Amazon Elastic Compute Cloud
ECM	Expectation-Confirmation Model
ECR	Amazon Elastic Container Registry
ECS	Amazon Elastic Container Service
GAN	Generative Adversarial Network
GPT	Generative Pre-trained Transformers
GQA	Grouped-Query Attention
GRU	Gated Recurrent Units
GUI	Graphical user interface
IR	Information Retrieval
LLM	Large Language Models
LMS	Learning Manegement System
LSTM	Long Short-Term Memory
MMLU	Massive Multitask Language Understanding
MTEB	Massive Text Embedding Benchmark
NLP	Natural Language Processing
ORM	Object-relational mapping
POC	Proof-of-concept
RAG	Retrieval Augmented Generation
RDS	Amazon Relational Database Service
RLHF	Reinforcement learning from human feedback
RNN	Recurrent Neural Network

S3	Amazon Simple Storage Service
seq2seq	Sequence-to-sequence
SMoE	Sparse Mixture of Experts
SNS	Amazon Simple Notification Service
SWA	Sliding window attention
TAM	Technology Acceptance Model
TF-IDF	Term Frequency-Inverse Document Frequency

Chapter 1

Introduction

1.1 Background

This degree project will investigate Large Language Models (Large Language Models (LLM)) and Retrieval Augmented Generation (Retrieval Augmented Generation (RAG)) systems in the form of deploying an AI-Assistant in canvas course rooms. The degree project will investigate how to evaluate these systems in very specialised domains and benchmark various models, approaches and techniques.

The reason this research is important is that LLMs have gained widespread attention and we are likely to see large-scale adoption of these models into various applications. Understanding how to benchmark and evaluate these systems in specialised domains will be crucial to understand how to build these systems, which techniques to use, and which models work well.

Many organisations need to, due to commercial and regulatory compliance, host all AI-models themselves. This aspect is also interesting to evaluate, i.e. how well open source and commercially licensed models compare against the closed source models, such as GPT-4 by OpenAI.

The research will be carried out within the e-learning management object at KTH, who are responsible for the digital learning environment at KTH. The object consists of two teams at the KTH IT department and one team at the digital learning unit at the ITM-school. The university hosts thousands of courses with domain specific information, such as assignments, lectures and schedules, that aren't part of the public domain and therefore not part of the training set of LLMs.

All the work done by KTH IT aims to improve the operations at the university. Among this is reducing the administrative burden undertaken

by teachers and teaching assistants (TAs). KTH IT wants to investigate if AI-assistants can be deployed into the canvas course rooms to reduce the workload of teachers and TAs which would help them focus on teaching, helping students and improve the quality of the education. KTH IT wants to see if it's feasible to deploy an AI assistant into the canvas course rooms.

1.2 Problem

LLMs have gained widespread use since its popularisation by ChatGPT. Their abilities to summarise large bodies of text and follow user instructions have proven very useful in many contexts. However, considering their limited context window (and drawbacks of models with larger context window [1]) deploying useful applications with a chat based interface still rely upon integrating a RAG system, introduced by Lewis et al. [2]. These can retrieve relevant information needed to answer a user's query from outside data sources and inject them into the conversation.

Some announced but currently unreleased models, such as the gemini family of models [**?**], have been reported to show great recall performance and reasoning abilities over millions of tokens. This could significantly reduce the importance of RAG systems in applications which utilise LLMs and external datasets to create intelligent systems with domain specific knowledge. However, even though no exact figures are presented by the Gemini time, inference speed (the time taken to produce a response to a prompt) seems to be significantly slower than shorter contexts. This would again highlight the importance of efficient RAG systems. Still, other approaches than traditional GPUs have been shown recently [3] by the Groq team to greatly increase inference speed.

Evaluating large language models is notoriously difficult. There are objective and automated metrics that can be used for tasks such as evaluating a model's summarisation capabilities, as shown by Basyal and Sanghvi [4]. However, for more complicated evaluations it gets trickier. In their seminal instructGPT paper Ouyang et al. at OpenAI try to evaluate *"how well a model can follow instructions"* [5] which is a very subjective question. They essentially relied upon human labellers to judge the overall quality of each response generated by the model.

In their Gemini-paper the Gemini team discuss the benchmarks used for their largest model. The team states that benchmarks are often designed to test shorter prompts whereas their longer prompts challenge tests used in traditional evaluation methods that rely heavily on manual evaluation. This

highlights the relevance of good evaluation metrics. Regardless of context size or inference speed, evaluation of models tends to be very general. Which makes sense, when considering their general application.

When releasing their Mixtral model [6] the Mistral AI team used a range of benchmark tests, such as MMLU, PIQA, GSM8K etc. Massive Multitask Language Understanding (MMLU) [7] benchmarks a LLMs proficiency in understanding and reasoning across various subjects such as humanities, STEM, and professional and everyday knowledge, by evaluating its performance on 57 tasks, to test its ability to generalise and apply knowledge. PIQA (*Physical Interaction: Question Answering*) [8], evaluates a language models understanding of physical commonsense by asking them to predict the outcome of physical interactions in various scenarios through multiple-choice questions. GSM8K (*The Grade School Math*) [9] tests the ability to solve elementary-level mathematics word problems.

Evaluation of how well LLMs perform is an open research question. As shown above LLM developers often utilise multiple testsuites. These are oftentimes, as shown above, very general tests. When implementing LLMs in practical applications good performance often relies upon very good raw summarisation performance and reasoning abilities. Since the domain specific knowledge is provided to the model, raw built-in knowledge isn't crucial. It is more important for the model to learn the task at hand using very few examples and within the given domain understand the question being asked by a user. Further, as argued by by Siriwardhana et al., the training data of LLMs include the knowledge of datasets such as Wikipedia [10] which means that evaluation methods in very specialised domains hold higher value than generalised domains. These brand new domains, that with certainty haven't been seen during training, tests the models zero-shot, and depending on the implementation, few-shot learning abilities.

The research question for this project is *Which language model and which retrieval techniques do students prefer using?* and *Is it possible to deploy an AI-assistant using a completely open source toolchain?*.

I believe the answer to the first question is that the closed source alternatives will be preferred by the students, however, I think the results will show it is possible to deploy an open source based AI assistant too.

1.2.1 Original problem and definition

The core challenge addressed in this thesis is the effective deployment and evaluation of AI-assistants powered by LLM and RAG techniques

in a specialised domain, specifically within the Learning Manegement System (LMS) of Canvas course rooms at KTH. This involves assessing the practicality and efficiency of integrating AI-Assistants built upon LLMs and RAG techniques into the educational settings to aid in reducing administrative burdens on educators and enhancing student interaction with course materials.

The original problem stems from the need to understand whether AI-assistants can effectively handle the domain-specific data intrinsic to educational platforms that are not included in their initial training datasets. Furthermore, the project aims to compare the efficacy and acceptability of open-source versus proprietary AI models in real-world educational applications.

1.3 Purpose

The purpose of this thesis is two-fold: firstly, to innovate within the educational technology space by integrating AI-assistants to potentially reduce workload and improve informational access within Canvas course rooms. Secondly, the thesis aims to contribute to academic knowledge by providing empirical data on the performance of these AI systems in a controlled educational setting. The dual purpose of this thesis ensures it not only investigates the immediate needs of KTH's digital learning environment but also enriches the scientific community's understanding of applied AI within a specialised domain, such as education.

This research is intended to benefit educational institutions by potentially offering a tool that improves operational efficiency and students by providing an alternative, possibly more effective way of interacting with course content. In addition the research will bring benefits for researchers within AI and education. Ethically, the study focuses on the sustainable development of AI technologies by emphasising open-source solutions, aiming to democratise advanced technological developments and reduce reliance on proprietary models.

1.4 Goals

1. **Technological Efficacy:** To evaluate the accuracy, speed, and reliability of responses by AI-assistants utilising both proprietary and open-source models in handling domain-specific content, such as the course rooms in canvas.

2. **User Preference:** To understand the preferences of students regarding the usability, information quality, and overall experience of interacting with an AI-assistant built upon different models and retrieval techniques.

3. **Operational Feasibility:** To assess the feasibility of integrating an AI-assistant built on fully open-source technologies within an academic setting, considering logistical, technical, and regulatory constraints.

4. **Educational Impact:** To explore the potential of AI-assistants to reduce administrative burdens on educators and improve information accessibility for students.

5. **Comparative Analysis:** To perform a comparative study between various LLM models and RAG-techniques.

1.5 Research Methodology

This project primarily employs an empirical study based on data collection and qualitative insights that will be used to evaluate the implementation of AI-assistants in the educational domain.

1.5.1 System Design and Implementation

Model selection Different models, including proprietary and open-source, with different sizes (number of active parameters), will be tested. The relevant models will be included in the study for testing.

RAG technique selection Various configurations of RAG systems will be tested to identify the most effective method for enhancing the AI's responses with respect to the layout of the data in Canvas course rooms. The relevant techniques will be included in the study for testing.

Implement AI Assistant Design and implement the system that will be used in the study.

Construct study questions Craft the questions that will be asked to students and implement them in the AI assistant.

Find courses to test with Find willing course administrators that want to participate in the study with their students.

1.5.2 Evaluation Design

Study Participants The study will involve students using the AI-assistant and providing feedback on their experiences.

Experimental Setup Controlled experiments will be conducted where participants use different configurations of the AI-assistant for typical student questions.

Data Collection Methods Data will be collected through integrated survey questions within the chat interface, capturing real-time feedback on the AI-assistant's performance and student satisfaction.

1.5.3 Analysis Techniques

Quantitative Analysis Statistical methods will analyse usage data and response accuracy to quantitatively assess the AI-assistant's performance.

Qualitative Analysis Feedback and open-ended responses will be analysed textually to understand user perceptions and contextual effectiveness of the AI-assistant.

This methodology was chosen for its ability to provide a comprehensive evaluation of both the technical capabilities and the practical usability of AI-assistants, offering insights into their potential benefits and limitations in the specific context for this study.

1.6 Delimitations

This project has several delimitations that define the scope and boundaries of the research to ensure a focused and manageable study. The key delimitations are;

- **Model Scope:** The project will not involve the development of new models or the fine-tuning of existing models. This includes LLM and embedding functions. The study will utilise pre-trained models offered by bigger vendors or the open source community.
- **Data Limitations:** Only existing courses within KTH's Canvas LMS will be utilised for the study. No new course content will be created, and no modifications will be made to existing course materials beyond what is necessary for the integration and testing of the AI-assistants.

- **Course Data Access:** The project will not use Canvas APIs for data integration. All interactions with the Canvas platform will be through existing interfaces, or data will be scraped and used from the Canvas web interface.
- **Geographic and Cultural Constraints:** The study is limited to the KTH environment, which may not represent other educational settings in different cultural or geographic contexts or languages. The findings might not be directly transferable to other institutions or countries without additional localisation and adaptation.

1.7 Structure of the thesis

Chapter 2 presents relevant background information about xxx. Chapter 3 presents the methodology and method used to solve the problem. ...

Chapter 2

Background

This chapter provides the necessary background for understanding the research conducted within this thesis. This chapter also showcases the related work for this thesis and how the research relates to it.

2.1 Neural Networks

Neural network models are a type of models within the broader field of machine learning whose design have been inspired by human brains. These models allow computers to recognise patterns and solve complex problems. The backpropagation algorithm was popularised by Rumelhart, Hinton, and Williams [11]. This algorithm efficiently computes the gradient of the loss function with respect to the weights of the network by propagating the error back from the output layer to the input layer. This method is critical to understand all machine learning pipelines because it enables the network to adjust its weights in a way that minimises the error, thereby improving the model's predictions over time.

Building on backpropagation, Yann LeCun et al. [12] introduced the Convolutional Neural Networks (CNN) architecture in 1998. These are a specialised kind of neural network for processing data, such as images, which can be converted to a matrix. CNNs utilise layers with convolving filters that apply the learned weights across subsections of the input data. This reduces the amount of parameters in the network and improves its efficiency.

These are two steps in the evolution of neural network models, particularly the developments in CNNs and other deep learning technologies, are central for setting the stage for even more complex architectures aimed at processing not just visual data, but sequential data such as text. This will eventually lead

to Large Language Models (LLM), which leverage deep learning techniques to understand and *generate* human language. LLMs are built upon the principles of neural networks. Understanding the models we commonly refer to as LLMs involves understanding models such as Transformer models, Bidirectional Encoder Representations from Transformers (BERT), and other encoder-decoder networks.

2.1.1 Recurrent Neural Networks (RNNs)

A Recurrent Neural Network (Recurrent Neural Network (RNN)) is a type of neural network that is good for modelling sequential data. They are significantly different from other neural networks in their ability to maintain memory of previous inputs using an internal state. This state which is maintained inside the network while it's running, will influence the network's output. RNNs proved to be fundamental in tasks where context was crucial, such as language modelling and generation of text.

In an RNN, each neuron, its most basic building block, processes a part of the sequence, receiving both the current input x_t and the output from the previous step h_{t-1}, this is known as the "hidden state". The core of an RNN operation involves updating this hidden state using:

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t + b)$$

where W_{hh} and W_{xh} are the weights for the hidden state and input, respectively, and b is a bias. The updated state h_t is used in the next step to generate the output y_t via:

$$y_t = W_{hy}h_t + b_y$$

However, RNNs often struggle with maintaining a longer context due to problems like vanishing and exploding gradients, as written by Hochreiter and Schmidhuber [13]. This was a problem other RNN models tried to mitigate as it significantly reduce their usefulness in various tasks. The vanishing gradient problem makes it difficult for the RNN to learn connections between events that occur at longer distances in the input sequence because the gradient of the loss function decays exponentially with the length of the input sequence.

This led to the development of more sophisticated variants like Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU)s were developed. LSTMs [13], use input, output, and "forget gates" to manage information flow, which allows them to maintain stable gradients. GRUs, which was proposed by Cho et al. [14], simplifies this by merging the gates

and states, reducing complexity while preserving performance across various tasks.

2.1.2 Sequence-to-Sequence Models

Sequence-to-sequence (seq2seq) models are designed to process sequences of data, such as text or speech, and generate corresponding output sequences. Sutskever et al. [15] were the first to introduce these models which typically consist of two main components: an encoder and a decoder. The encoder will process the input and convert it into a dense vector. This vector encodes the entire input sequence which is then passed to the decoder, which generates the output. This architecture proved very useful in certain tasks such as translating text between languages. Bahdanau, Cho, and Bengio built upon this concept with attention mechanisms [16] which would allow the decoder to focus on a specific piece of the input for small parts of the output, which improved the models ability to focus on longer sequences.

2.1.3 Transformer Models

The Transformer model, introduced by Vaswani et al. [17], was a new approach for seq2seq networks, with a self-attention mechanism which was different from the recurrent design of RNNs. The new transformer architecture introduced by Vaswani et al. allowed the network to weigh the importance of different tokens in the input data irrespective of their sequential position. Where a token is a sequence of characters that can be treated as a single logical entity in the input and output sequence.

The key innovation of the Transformer is its ability to handle dependencies between single tokens or sequences of tokens at long distances from each other. This makes the transformer architecture especially good at understanding context in text data.

The introduction of the transformer model was foundational in the field, and today most models use this architecture, see section 2.3 and 2.3.2.

2.1.4 BERT and Advances in Encoder-Decoder Models

BERT was introduced by Devlin et al. [18] in 2018 and was a major improvement within natural language processing. The BERT model optimised token representations bidirectionally which means that it was refining the understanding of each token by looking at the tokens before and after each token. BERT was built on the transformer model's encoder which allowed for

pre-training on large text corpora, followed by fine-tuning for various tasks such as sentiment analysis and question answering.

Encoder-decoder models are important in machine learning for tasks that involve converting one sequence into another, such as machine translation or speech-to-text. In this type of model the encoder processes the input sequence and compresses information into what's known as a context vector, this is a condensed representation of the input data. The decoder takes this context vector and generates an output sequence token by token. Each of these two components may be built using recurrent networks, convolutional networks, or more commonly nowadays, transformer architectures.

In contrast to traditional encoder-decoder models, encoder-only models, such as BERT, focus on generating an output based on an input without the need for a decoder. These models are typically used for tasks that require deep understanding of language context like sentence classification.

Decoder-only models, like the Generative Pre-trained Transformers (GPT) (see section 2.3), focus on generating sequences from a given context or starting point. These models are very good in situations where the model needs to exhibit "creative" properties, such as when generating text completions.

Parallel to BERT, other encoder-decoder models like the Transformer [17] and seq2seq networks with attention mechanisms [16] have shown great results when translating sequences in tasks like machine translation, exemplified by Google's Neural Machine Translation system [19], and speech recognition, as seen in Apple's Siri voice assistant [20].

2.2 Generative AI

Generative AI is a term used to describe a subset of artificial intelligence technologies that are designed to create new content. This can be images such as with DALL-E [21], text with models like GPT-3 [22] or movies [23]. These models are capable of generating realistic and arguably novel outputs by understanding and simulating the underlying structure of the training data. One of the most popular frameworks in Generative AI includes Generative Adversarial Network (GAN)s, introduced by Goodfellow et al. [24], which consist of two neural networks, the generator and the discriminator. These two networks will compete against each other. The generator creates items that are as realistic as possible, and the discriminator evaluates them. This process runs until the discriminator can no longer accurately separate generated items from the training data.

2.3 State-of-the-Art Large Language Models

LLM represent a significant breakthrough in Natural Language Processing (NLP). They are capable of understanding and generating text similar to that written by humans. In recent years, several cutting-edge LLMs have been developed by prominent companies and research institutions that have gained wide-spread use. This section gives an overview of some notable examples of these advanced LLMs.

2.3.1 OpenAI's GPT Series

OpenAI's GPT series of language models have over the past few years featured some of the most widely used language models. GPT-1 was first released in 2017 followed by GPT-2, GPT-3, and GPT-4 (with various variants of these models). GPT-3, in particular, with its 175 billion parameters, has demonstrated strong capabilities in tasks such as text completion, question answering, and even code generation [22]. These models are some of the most widely used models, primarily due to their popularisation by the product from the same company, ChatGPT [*].

2.3.2 Mistral

Mistral is a french firm that has released a few models that has gained widespread adoption in the open source community. As of writing, *Mistral-7B-Instruct-v0.2* had 2,297,845 million downloads on huggingface last month [†], and Mixtral-8x7B-Instruct-v0.1 had 628,927 [‡].

Mistral 7B v0.1 [25] was their first major model to get widespread notoriety. The model is a 7-billion-parameter language model which was small enough to run on consumer-grade GPUs. The model utilised Grouped-Query Attention (GQA)[26] and Sliding window attention (SWA) [27] techniques to achieve impressive results across various benchmarks, including reasoning, mathematics, and code generation tasks. *Mistral 7B v0.1 instruct* is a related fine-tuned model.

The "instruct" version of generative AI models, such as the Mistral 7B, has been fine-tuned to follow prompted instructions. In contrast, the base model simply generates output based on the provided prompt. This process was first

[*] chat.openai.com
[†] The huggingface page for Mistral-7B-Instruct-v0.2
[‡] The huggingface page for Mixtral-8x7B-Instruct-v0.1

published by the team at OpenAI [5], however it's also employed by mistral and other model vendors. This approach is commonly used for models deployed in AI assistants or chat applications.

The *Mixtral of Experts* model [6], is a variant of the Mistral model that introduces a Sparse Mixture of Experts (SMoE) architecture, as described by Jiang et al. *Mixtral-8x7B-Instruct-v0.1* employs 8 feedforward blocks (experts) in each layer, with a router network selecting two experts for processing and combining their outputs at each timestep. The model has access to 47 billion parameters, but effectively only utilise 13 billion parameters during inference, which makes the model easier to deploy on GPUs with less amounts of memory.

2.3.3 Google's Language Models

Google has two major families of model, the first being the Gemini family, as introduced in a series of papers by Google's team [28], consists of models like Gemini Ultra, Pro, and Nano, each of these models are designed for specific applications and more importantly size of GPU. Where the larger models require enterprise-grade GPUs that are expensive to operate. Gemini 1.5 extended on these models with an even larger context window by effectively processing and recalling information across millions of tokens in a multi-modal context (tokens include both text, audio and image tokens) [29]. This is the first model to demonstrate resilience to the problem first described by Nelson et al. where the model would be biassed towards instructions or data in the beginning and end of larger prompts [1].

Goggles Gemma family of models [30] represents Google's effort to provide state-of-the-art, lightweight models to the open source community. These models, available in sizes of 2 billion and 7 billion parameters. The models demonstrate worse performance against their Gemini class of models across all tasks such language understanding and reasoning. However, the Gemma models' size make them easier to deploy on smaller consumer-grade GPUs.

2.3.4 The LLama family of models

In February 2023, Meta AI released LLaMA [31] in four distinct sizes: 7, 13, 33, and 65 billion parameters. The model utilised features such as SwiGLU activation functions, rotary positional embeddings, and root-mean-squared layer-normalisation to achieve comparable results to OpenAIs GPT-

3 model. Despite being initially released under a noncommercial licence, the weights of LLaMA were leaked, prompting widespread unauthorised use. This accelerated its adoption across various applications.

Later in July of 2023, Meta released LLaMA-2 [32] which was built upon the foundational models of its predecessor with enhanced data sets of 2 trillion tokens, fine-tuning capabilities, and improved dialogue system performance through specialised LLaMA-2 Chat models, these are similar to the instruct models mentioned in section 2.3.2. LLaMA-2 had a 40% larger training corpus and extended the context length to 4,000 tokens. The release included model sizes from 7 to 70 billion parameters. These models were released under a similar licence to the first LLaMA models.

Recently, in April 2024, Meta AI released LLaMA-3, this time with two models, one 8 billion parameter model and one 70 billion parameter model. These were open source and available online * from day one under a commercial licence. The model was pre-trained on approximately 15 trillion tokens. Meta announced an, as of writing, future release of a 400 billion parameter model.

2.3.5 Notable other vendors

Besides the major players such as OpenAI, Google, and Meta, there exists a vast array of players, of varying size, that also develops language models. These include, but are not limited to, Anthropic, IBM and DeepMind (which is also a part of Google).

2.4 Prompt engineering

Prompt engineering is the name given to the technique that evolved from the use of language models. This is the task of optimising the performance of a LLM such as GPT-4, LLaMA, and others. This involves crafting the input text, or *"prompt"* to these models in a way that guides them to produce desired outputs [33, 34].

Prompt engineering is defined as the practice of designing input prompts that maximise the efficacy and accuracy of LLM outputs. It is a key factor in the success of deploying LLM-based applications. The process of prompt engineering involves several key techniques. A prompt should, according to Chen et al. include clear instructions and enough contextual details to guide

*The GitHub repository for LLaMA-3

the model towards providing the expected answer in the expected format. There are numerous advanced techniques such as "role-prompting", zero-shot, one-shot, and few-shot prompting that can improve the performance of LLM.

For instance, Kathiriya et al. [33] demonstrates that role-prompting produces responses with heightened professional relevance. Similarly, Chen et al. highlight how few-shot prompting can refine the model's ability to perform complex analytical tasks by providing some targeted examples. Both of these studies show how prompt engineering techniques can improve performance.

Figure 2.1, taken from the paper published by Chen et al. [34] illustrates an example of role-prompting. In this example the LLM is instructed to assume the role of an expert in artificial intelligence, which aligns its responses with specific professional knowledge.

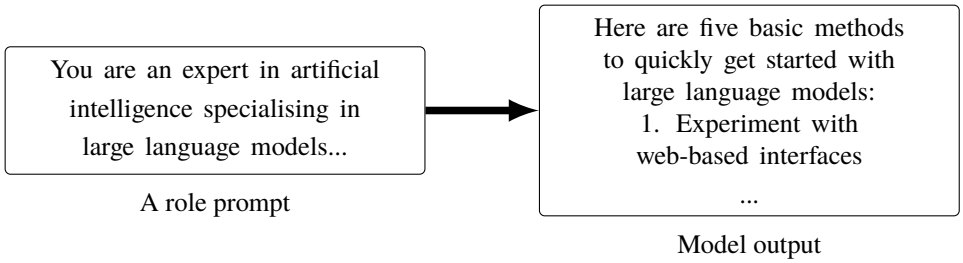

Figure 2.1: Role prompting example.

Another technique known as few-shot prompting, is shown in figure 2.2, taken from the paper written by Kathiriya et al. [33]. With this technique the model is provided with multiple examples to better understand the task. If only one example is given, this is referred to as "one-shot" prompting. Similarly, if no example is given, then the prompt is referred to as a "zero-shot" prompt.

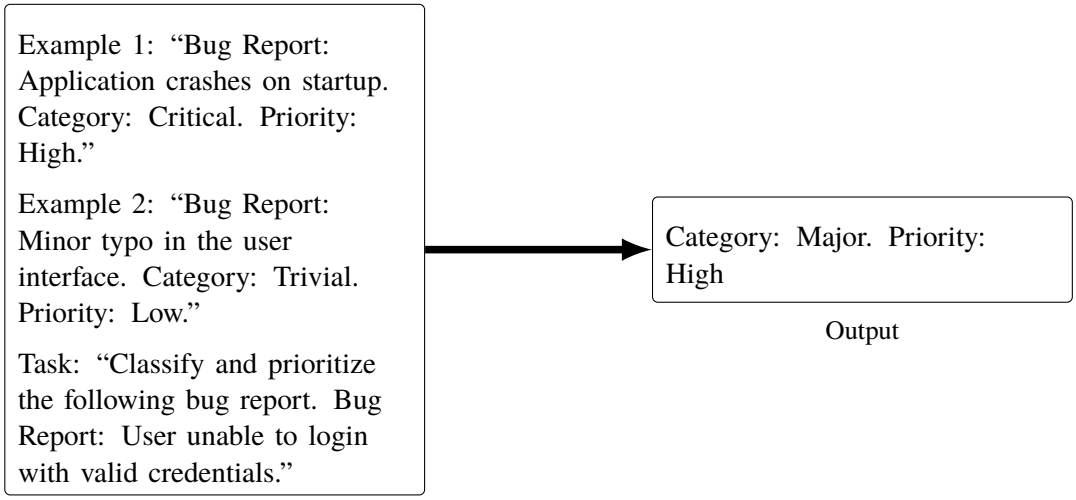

Figure 2.2: Few-shot prompting example.

2.5 Evaluating LLM performance

When an LLM vendor, such as Mistral, releases a new model its performance is evaluated using a series of well-established benchmarks. These benchmarks are essential for understanding the model's capabilities in various cognitive tasks. This includes tasks such as mathematical reasoning, language understanding and program synthesis. This practice helps to quantify the models' performance and provides a method to compare its performance against previously released models [9, 35, 36].

When Mistral released its first major model they used table 2.1 to compare its results against the LLaMA family of models. There are numerous benchmarks included in the table, that test various abilities of the model. For example, the *GSM8K* benchmark includes thousands of grade-school level maths problems that are designed to test mathematical reasoning [9]. Benchmarks like MBPP assess a model's ability to understand and generate programming code from natural language descriptions [35]. A test like *MMLU* measures general world knowledge and problem solving ability [7]. Lastly, the *PIQA* benchmark, challenges a model with physical common sense questions [37]

Model	MMLU	HellAs	PIQA	Arc-e	Arc-c	HumanE	MBPP	Math	GSMBK
LLaMA 2 7B	44.4%	71.1%	77.9%	68.7%	43.2%	11.6%	26.1%	3.9%	16.0%
LLaMA 2 13B	55.6%	70.7%	80.8%	75.2%	48.8%	18.9%	35.4%	6.0%	34.3%
LLaMA 1 33B	56.8%	83.7%	82.2%	79.6%	54.4%	25.0%	40.9%	8.4%	44.1%
LLaMA 2 70B	69.9%	85.4%	82.6%	79.9%	56.5%	29.3%	49.8%	13.8%	69.6%
Mistral 7B	62.5%	81.0%	82.2%	80.5%	54.9%	26.2%	50.2%	12.7%	50.0%
Mixtral 8x7B	**70.6%**	**84.4%**	**83.6%**	**83.1%**	**59.7%**	**40.2%**	**60.7%**	**28.4%**	**74.4%**

Table 2.1: Table used by Mistral to compare the performance of *Mixtral 8x7B* to *Mistral 7B* and the Llama family of models.

All of these benchmarks are essential for developers and researchers to understand the limitations and capabilities of AI models. They ensure continuous improvements and innovations in the field. Each benchmark is sourced and created differently. Some models are tested against just a single benchmark such as OpenAI's codex model (now deprecated) [36]. However, most general purpose language models such as those released by Mistral, OpenAI, Meta, Google and more use a common set of benchmarks such as those in table 2.1 [6, 38, 31, 29].

2.6 Web crawling

Web crawling is a technique to systematically browse the World Wide Web to index the content of websites for search engines and other applications using automated programs known as web crawlers [39, 40]. This is a process that's crucial for the operation of search engines.

A web crawler starts with a list of URLs to visit. As the crawler visits these URLs, it identifies all the hyperlinks on the page and adds them to a database of known URLs to visit. After visiting a URL the crawler employs a method of selecting the next url to visit, which may be one of the hyperlinks it just found on the current page, or any url it might have found before. This method may vary depending on the implementation of the crawler. This process continues until a defined stop condition.

While the primary application of web crawling is in web search engines, it can also be used within various other domains. Web crawlers can be used for everything from monitoring changes in web pages to gather data from specific intranets or corporate knowledge bases.

Implementing an efficient web crawler involves addressing multiple technical challenges. These are primarily constructing an efficient crawler that can visit and process urls at scale. Additionally, the crawler must be able to

index the content found on those websites, which may include various media types such as plaintext, images or document formats such as PDF.

2.7 Information Retrieval

Information Retrieval (IR) refers to the process of returning relevant information from a corpus of documents. The field primarily focuses on the retrieval of text data and is a core part of many applications such as search engines or AI agents.

The objective of information retrieval is to find material within an unstructured database [41]. This usually involves resolving the relevant documents in response to a user query. Information retrieval systems are usually measured against precision and recall metrics. These show how relevant the documents returned were, and how many of the relevant documents were returned.

$$\text{Precision} = \frac{\text{Number of Relevant Documents Retrieved}}{\text{Total Number of Documents Retrieved}} \tag{2.1}$$

$$\text{Recall} = \frac{\text{Number of Relevant Documents Retrieved}}{\text{Total Number of Relevant Documents in the Corpus}} \tag{2.2}$$

The core of IR is indexing and search algorithms. To index a corpus means processing all the documents in the corpus into a data structure that can later be used for retrieving docs. Search algorithms utilise this index to find documents that match the user's query [41].

The second problem of IR is to rank the returned documents. This is problem with many possible solutions.

2.7.1 Term frequency inverse document frequency

Term Frequency-Inverse Document Frequency (TF-IDF) is a measurement used to evaluate how important a word is to a document in a collection or corpus. This means it is a relative metric that is unique to the corpus being indexed. TF-IDF is calculated by multiplying two values

1. How many times a term appears in a document
2. The inverse document frequency of the term across a set of documents

Term frequency is calculated using the following formula

$$\text{TF}(t, d) = \frac{\text{Number of times term } t \text{ appears in document } d}{\text{Total number of terms in document } d} \tag{2.3}$$

The inverse document frequency is calculated using this formula

$$\text{IDF}(t, D) = \log\left(\frac{\text{Total number of documents in the corpus } D}{\text{Number of documents containing term } t}\right) \tag{2.4}$$

The complete formula for TF-IDF is the following

$$\text{TF-IDF}(t, d, D) = \text{TF}(t, d) \times \text{IDF}(t, D) \tag{2.5}$$

This formula means the relevance for a token increases with the number of times that term appears in the document, but is offset by the frequency of the term in the entire corpus. This is a good way of adjusting for the fact that some words are generally more common than others, such as "a", "the", etc. [41].

2.7.2 Embedding Functions

Vector embeddings are a way of representing text or other media content, such as images, as a numerical vector that encapsulates their features. Figure 2.3 illustrates how a token, in this case *cat* and *dog*, is encoded into a vector.

$$\texttt{cat} \rightarrow \{0.042, 0.112, 0.236, 0.368, 0.491, 0.623, 0.784, 0.895, \ldots, 0.931\}$$

$$\texttt{dog} \rightarrow \{0.157, 0.209, 0.330, 0.501, 0.579, 0.619, 0.755, 0.832, \ldots, 0.874\}$$

Figure 2.3: Example embeddings for "cat" and "dog" strings.

For text content such a feature could be something abstract about a word that's even true in several languages. In text processing, one typically leverages the neural network of a language model to understand the contexts and co-occurrences of tokens. These networks have usually been trained on very large corpora of text and are thereby very good at placing semantically similar

tokens close to each other in a vector space. For example, *football* and *soccer* may appear in similar contexts, leading the network to locate them near each other in a "meaning space", as can be seen in figure 2.4. Measured with something like levenshtein distance, the words are very far from each other, even though we know they are synonymous in many contexts. Processing text with a neural network and representing it with a vector can allow computers to perform complex tasks like text prediction with an understanding akin to human cognitive judgments [42].

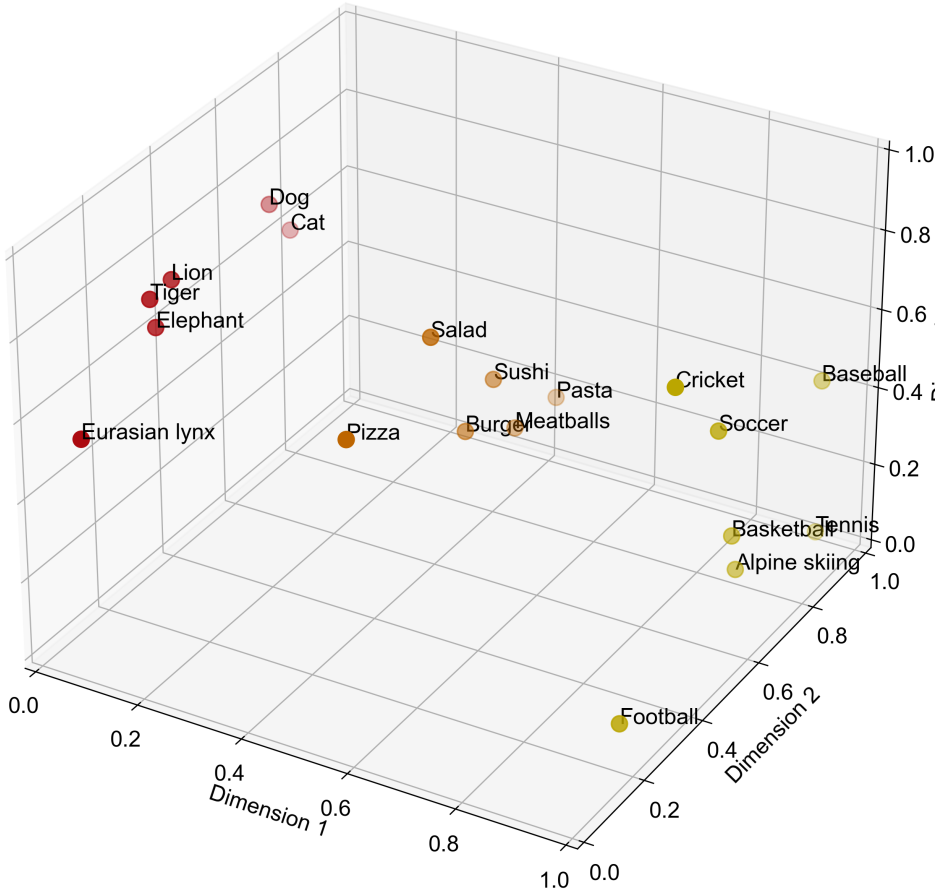

Figure 2.4: Simplified 3D space with simplified embeddings for various words

There are numerous types of models and techniques that have been developed to efficiently compute vector embeddings. One such is Continuous Bag-of-Words (CBOW) and Skip-gram models, introduced by Mikolov et

al. [42]. These were early yet foundational methods for generating word embeddings. These models leverage large corpora to predict tokens from their context (CBOW), or with the context from the tokens (Skip-gram). Both of these techniques leverage the trained models ability to learn semantic and syntactic nuances of the tokens in the training corpus [42, 43].

Advancements in vector embedding technologies enhance NLP tasks such as text classification and sentiment analysis. Embedding models that can process language or images with nuance and precision are crucial for accurate real-world applications [44].

There are new Embedding functions released often, built-upon different language models and employing various different techniques. The evaluation of these embedding functions often remains constrained to a narrow set of tasks. Muennighoff et al. [45] tried to address this issue by introducing Massive Text Embedding Benchmark (MTEB), which spans 8 embedding tasks covering a total of 58 datasets and 112 languages. The leaderboard is currently actively maintained on hunggingface *.

Two models that rank highly on the leaderboard is Salesforce's open source *SFR-Embedding-Mistral* model which exemplifies advancements in embedding technology for text retrieval tasks [46]. Similarly, OpenAI has developed several closed source embedding models that also rank highly on the MTEB leaderboard [47, 48].

Embeddings are often used to compare documents against each other, or against a given user query. This is often done by computing similarity scores between words, phrases, or documents, which are represented as vectors in the embedding space. These scores quantify the closeness, or "similarity" between different texts.

The similarity between two vector representations is typically measured using the cosine similarity metric. This calculates the cosine of the angle between two vectors. This metric ranges from -1 (the exact opposite document) to 1 (the exact same document), with 0 indicating orthogonality (no similarity). The cosine similarity $\text{sim}(u, v)$ between two vectors u and v is defined as:

$$\text{sim}(u, v) = \frac{u \cdot v}{\|u\|\|v\|} \tag{2.6}$$

where $u \cdot v$ is the dot product of the vectors u and v, and $\|u\|$ and $\|v\|$ are the Euclidean norms of both vectors.

*Massive Text Embedding Benchmark (MTEB) Leaderboard on Huggingface

2.8 RAG

RAG is the process of integrating retrieval mechanisms into the generative models. This approach effectively combines the strengths of both retrieval and generative language modelling to enhance a model's ability to accurately recall factual information by utilising an external knowledge base during the generation process [2].

RAG was developed to address the limitations of large pre-trained language models that could compress a large training corpus into its weights, but could struggle with accessing and precisely manipulating this information when required. The term "hallucination" would come to describe the event where models would "recall" incorrect information, as shown in figure 2.5.

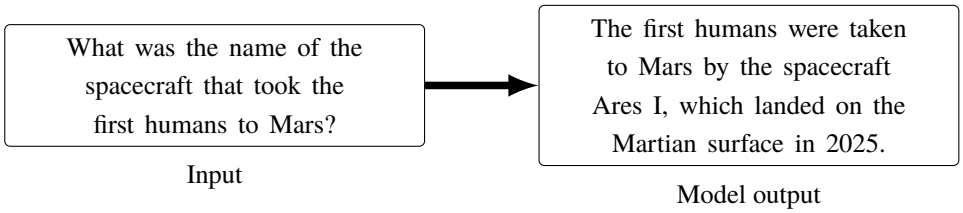

Figure 2.5: An example of how a model can hallucinate an answer to a question.

The fact that language models tend to have a propensity to hallucinate, and the simple fact that it is very time consuming to train language models, mean these models would often lag behind in knowledge-intensive applications where correctness is crucial. The integration of a non-parametric memory, or an external knowledge base, allows these models to retrieve relevant information during the generation process and thereby producing more accurate responses [2].

In a typical RAG setup, the systems architecture is split into two main components: the retriever and the generator. The retriever is a language model trained to search and fetch relevant documents. Nowadays, this process often utilises dense vector representations of documents (see section 2.7.2) which enables efficient and effective search [49].

The returned documents are then fed into the generator, this is a seq2seq model, which then synthesises the information into coherent text. The generator is often instructed to only use authoritative facts that are returned from the retriever and not rely on its internal knowledge for factual statements. This dual-component approach allows RAG to dynamically access a large

corpus of knowledge while maintaining its ability to generate fluent and contextually appropriate language [2]. This method has shown significant improvement over a purely parametric-approach in various tasks such as question answering and fact verification [22, 50].

When google announced Gemini 1.5 [29] they claimed it could effectively recall knowledge over prompts as large as a million tokens. It remains to be seen if the hallucination, training-time and context length problems can be overcomed and remove the need for a RAG system when building knowledge-intensive applications on-top of a LLM.

2.9 AI Assistants

AI assistants is a type of AI-system that is designed to support human users by performing tasks that typically require human intelligence. Stuart Russell and Peter Norvig wrote in *Artificial Intelligence: A Modern Approach* that an assistant should interact with their environment to achieve specific goals rationally and effectively [51].

AI assistants must be good at NLP for effective communication with humans in addition to good knowledge representation such as with a RAG toolchain. The assistant must also possess good reasoning and decision-making abilities, as those exhibited by a modern LLM. An assistant should also utilise machine learning to improve from user interactions.

2.10 Measuring usability and acceptance of new technologies

To assess how effectively a user can interact with a technology, for instance, an AI assistant, Jakob Nielsen's "Usability Engineering" [52] is a seminal book that defines usability in terms of learnability, efficiency, memorability, safety, and satisfaction. All of these can be measured through specific metrics. The IBM Computer Usability Satisfaction Questionnaires, developed by Lewis [53], offer a tool that's been validated through the years to measure these dimensions.

Interactions with AI agents through conversation is very affected by the agent's ability to engage in social dialogue. Bickmore and Cassell [54] discuss the importance of dialogue in building engagement long-term between users and conversational agents. Their conversational agents communicated over the

phone, but their framework for understanding the qualitative feedback from users about their experiences can also be applied with an AI assistant.

Technology Acceptance Model (TAM) was introduced by Davis [55] and is particularly relevant for examining the acceptance of new technologies such as AI assistants. TAM suggests that perceived usefulness and ease of use are key factors for whether a new technology is accepted and used. The model is useful for investigating users' attitudes towards the utility and usability of new technologies, not the least of which is AI and AI assistants.

Expectation-Confirmation Model (ECM) was introduced by Bhattacherjee [56] in 2001 and it extends the understanding of user satisfaction beyond initial acceptance which is outlined in TAM. ECM includes user expectations, perceived performance, and confirmation of expectations into the satisfaction assessment. This model is especially useful in assessing whether a technology meets or exceeds the users' expectations over time.

2.11 Related Work

2.11.1 The Open Source Models by Mistral and Meta

Mistral and Meta have both released a series of open-source models within their respective LLaMA and Mistral families. They've both made substantial contributions to the field of NLP. The LLaMA models offered very capable models that could fit within different computing envelopes, with various levels of compute capacity [31, 32]. Similarly, Mistral's models, including *Mistral-7B* and its Mixtral variants, have been made widely available and demonstrated robust capabilities. While the performance of these models is noteworthy, their most significant impact lies in their open-source licensing. This approach has democratised access to cutting-edge research and models, significantly accelerating the pace of innovation in the field compared to proprietary models from vendors such as OpenAI.

2.11.2 The Proprietary Models by OpenAI

The models released by OpenAI, which includes all the models from GPT-1 through GPT-4 have led the field across most benchmarks and text capabilities. Each new model has incorporated architectural improvements, larger datasets and new training methodologies. All of which have increased the models' ability to understand complex text structures and generate coherent text. OpenAI's contributions primarily lie in their scaled transformer

architectures and fine-tuning techniques [22]. OpenAI have also done major advancements in LLM alignment research, for instance with their development of *instructGPT* [5]. InstructGPT was an effort to get models to follow human instructions. This was done through a combination of techniques such as Reinforcement learning from human feedback (RLHF) and supervised learning. These techniques have also shown to be able to increase truthfulness and reduce toxicity in the model's output, which may have been inherent in the models' training dataset.

2.11.3 Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks

The introduction of RAG by Lewis et al. has been crucial for the development of NLP systems. The model they proposed has been shown to combine the generative power of a LLM with the factual accuracy of verified knowledge bases. From a research perspective, RAG is a method of addressing "hallucinations" in generative models [2]. "Hallucinations" refers to instances where a LLM asserts a fact that is provably untrue as though it were accurate, see figure 2.5. With the techniques proposed by Lewis et al. a system can be constructed around the model that ensures only verified facts are used to answer input prompts.

2.11.4 Gemini 1.5: Unlocking Multimodal Understanding Across Millions of Tokens of Context

There are two dominant theories for how AI systems will be constructed. The first theory advocates for a RAG-based approach. As discussed in sections 2.8 and 2.11.3, RAG effectively integrates an external knowledge base into an AI system. However, there is the alternative theory of longer context windows. The context window refers to the maximum amount of tokens the model can consider at one time when generating responses. The context window typically consists of the input prompt, whatever extra content has been added to the model (could be multi-modal content such as images) and the models' output. With a large enough context window, theoretically, an entire knowledge-base could be incorporated into a prompt. This would remove the need from intercepting the models generation process, which is the core component of RAG, since the entire knowledge base is part of the prompt.

Previously, Liu et al. has shown that models with larger prompts have a bias towards the beginning and the end of the prompt [1]. This effectively

meant that a knowledge base with similar facts injected into the beginning or end of the prompt would have a higher likelihood of being included in the response, regardless of their correctness.

When Google announced their Gemini 1.5 model they released results that suggest that it could process and integrate information across vast context windows using an extended transformer architecture [29]. The model could do this without a bias in precision or recall depending on where the data existed in the prompt. Even though this model isn't widely available yet, Google's results suggest that it is possible to construct a model that can fit a large knowledge base within the context window of a LLM.

Larger context windows generally require larger models which are more expensive to run. Larger prompts also take longer compute responses for. It remains an open research question whether the necessity of RAG-systems will remain in the future.

2.11.5 Measuring Massive Multitask Language Understanding

The MMLU benchmark was introduced by Hendrycks et al. in 2020 to provide a framework for evaluating LLM across a broad range of tasks [7]. The test covers tasks in fields such as elementary mathematics, US history, computer science and law. It is designed to test a model's world knowledge and problem solving abilities. The benchmark is significant as it is the current most widely used general intelligence test on LLMs.

As highlighted by many, not the least Google in their Gemini 1.5 paper [29], there is a pressing need for new benchmarking approaches. Traditional benchmarks do not sufficiently challenge new models, especially in the multimodal domain where text, images, video, and audio are combined [29]. Current evaluation methods rely heavily on human labelling and annotation, they are increasingly seen as inadequate for more complex prompts and responses.

In addition most benchmarks are biassed towards the training dataset of the models. The model's general intelligence is measured by data that is available to the model during training. This includes historical events, facts and problems. For instance, included in the training set are programming problems very similar to the programming problems included in benchmarks such as *PIQA* [37]. To test the models true intelligence there is a need for benchmarks that measure the models abilities on data it hasn't seen before.

Chapter 3

Method or Methods

This chapter outlines the methodologies and procedures used for conducting the research described in this thesis. The focus is on presenting the chosen methods for data collection, analysis, and evaluation of the deployment and effectiveness of AI-assistants within Canvas course rooms at KTH.

3.1 Research Process

The research process within this thesis consisted of three main phases. This section will outline each phase and what the purpose was.

3.1.1 Prof of concept

The study will aim to achieve an assistant using open source and permissively licensed LLMs and RAG techniques, that is comparable to the current best in class models provided under less permissive licesnses and are only available through properitery APIs. Considering that this is a fairly complex task, the research started with a long phase of constructing various proof of concepts.

There would be two main proof of concepts, one using proprietary models and RAG techniques, and one strictly using software that is under open source licenses and can be self-hosted.

3.1.2 Implementation of study software

The second phase consists of constructing the software that will be used during the study. This software is the actual AI assistant and all it's components, such as the course room crawler and indexer, the infrastructure to run LLMs

at scale and a Graphical user interface (GUI) to interact with the assistant. This software also needs to be able to exchange various different components that are the subject for the study, such as the LLM being used in a chat. Furthermore, the software needs to be able to record user interactions and responses to questions.

3.1.3 Conduct the study at KTH

This phase consists of deploying and monitoring the assistant in the course rooms that have enrolled in the study. This might involve modifying the software such that it works in the new course room, or ensuring that there is enough capacity on the platform to sustain the new users.

3.1.4 Analyse results

TODO.

3.2 Research Paradigm

This research in this thesis follows a pragmatic approach that blends aspects of the study from positivist paradigms to investigate the practical application and user reception of AI assistants generally within the educational setting. Additionally, it seeks to determine which technologies perform best by analysing segmented responses to user queries based on the specific technologies used to generate the answers. The pragmatic approach supports using mixed methods to answer the research questions effectively, focusing on 'what works' as the basis for knowledge claims. The positivist elements of the study will quantify which technologies deliver the fastest responses and yield the most usage among users. Participants will be exposed to one technology from a predefined set, selected through random sampling. This methodological approach allows for a positivist analysis to determine which technology is the fastest and most preferred by its users.

The collection and analysis of the feedback from the participants in the study is an interpretivisit approach to answer the questions of more subjective nature. These are questions like which technologies or models generate the most accurate results, or answers that are more preferred by users.

To summarise, initially the chatbot is deployed (positivist approach), followed by the collection and analysis of user feedback (interpretivist approach) to understand the broader implications of AI-assistant technology

in specialised domains such as education. This method aims to understanding the functional capabilities of the AI-assistant in addition to its practical utility and acceptance by end-users, students and teachers.

3.3 Data Collection

The data collection in this study comes from two sources;

- The AI-assistant software built to conduct this research. This includes metrics from the usage of the system, in addition to integrated survey components of the system such as responses to questions from users of the system.
- Responses to coursework questions from students in selected courses that are part of the study, submitted as part of their course requirements.

3.3.1 Data collected by the software constructed for this study

The AI-assistant software was constructed to record various pieces of data, these can be grouped into four categories, operational data, usage data, performance data, feedback data. The data collected by the AI-assistant is anonymous. No personal information was recorded by the system, aside from any information that may have been submitted as part of a question by the user to the assistant.

3.3.1.1 Operational data

The operational data refers to data collected by the system to function. This includes information in or about the course rooms such as the various pieces of content found in a course room and their relations. This can be lecture slides, lab assignments, links to external sites etc.

3.3.1.2 Usage data

Usage data in system refers to data that is generated when users use the system. This includes session information and its metadata, chat information such as which course room a chat is associated with and which messages were sent by the user and the ai-assistant in each chat.

3.3.1.3 Performance data

Various metrics regarding the performance of the system is also computed and kept. These include metrics such as how quickly a model generates a response to a given prompt and how long the response. Also, how quickly a vector embedding was computed and how quickly the index returns documents.

3.3.1.4 Feedback data

The feedback data is the most intentional data tracked by the system. This includes questions injected into the chat at specified intervals. These questions and intervals are the same for all users. The questions have a predefined set of answers and the system tracks which of the answers a user selects, or if they don't select any answer at all. In addition binary thumbs up/down questions are also asked about certain responses from the system.

3.3.2 Data collected by questions in the coursework

TODO. Do this section when more is known about the answers here...

3.3.3 The participants in the study

The study sources its participants from courses from course administrators that have volunteered for their courses to participate in the study. The courses were found by emailing course responsibles at the EECS school at KTH in addition to connections of the supervisors of this thesis. The participants in the study are students in the following courses:

- LD1000 Lär dig lära online 2.0 credits
- DD1380 Javaprogrammering för Pythonprogrammerare 1.5 credits
- MG2040 Assembly Technology 6.0 credits
- LD1006 Kognitiv psykologi för lärare: Matematikundervisning 3.0 credits
- DD1349 Projektuppgift i introduktion till datalogi 3.0 credits
- DD2419 Project Course in Robotics and Autonomous Systems 9.0 credits
- DD1367 Software Engineering in Project Form 9.0 credits

3.4 Experimental design and Planned Measurements

Participants in the study will be randomly assigned to groups, each of which will use a specific set of technologies and techniques. This random assignment will be managed by software written for this study, and it will apply to every chat session started with the assistant by the participating student. Each group will utilise a unique configuration based on one of these predefined parameters;

- The language model used to run the chat. This is the LLM that is used to generate chat replies within the chat. It's also used for the internal logic of the assistant. This internal logic consists of tasks such as identifying whether the user asked the assistant a question that needs data from the knowledgebase.
- The RAG technique and technology used to access the indexed data. This could be TF-IDF or an embedding function. It it's the latter the group also have a defined embedding model assigned.
- Post processing of the retrieved documents. This is a boolean flag that configures the assistant to post process documents before inserting them into the context window for the configured LLM to generate an answer with.

The software allows for questions to be inserted into a chat the participant is having using the following two triggers.

1. After a participant has had n chats and is sending the m:th message in that chat
2. After a student clicks one of the frequently asked questions

Each of these triggers allows for inserting any given number of questions into the chat. Any question has to follow one of the following templates;

a) A question, such as *"Was this a good answer?"* accompanied with a "thumbs up" or a "thumbs down" button to answer the question with.

b) A question, such as *"How accurate did you find this answer?"* with a set of answers to select from such as *Very accurate*, *Somewhat accurate*, *Neither accurate nor inaccurate*, *Somewhat inaccurate*, *Very inaccurate*.

With these configurations, the experiment aims to measure the impact of the predefined parameters on users' responses to the questions posed during the chats at the configured triggers.

3.5 Test environment

3.5.1 Software

To reproduce the results of this study the software that was written to crawl course rooms, index their content and host the chat with the assistant is available in its entirety on github, see Appendix A.

3.5.2 Configuration

There is quite a bit of configuration needed to get the software operational. The *README* in the source code extensively covers how to run the software in most common environments, see Appendix A.

3.5.3 Data and access to canvas

To run the AI assistant with data from an actual course room the bot needs to have access to a canvas through a KTH registered user. Due to time constraints the option to use the official Canvas API was abandoned early in the planning of this study. The softwares' crawler therefore needs the cookies of an authenticated user with access to the course rooms included in the study.

note: maybe explore publishing the course content of some course rooms? As like a downloadable from the github repo or something?

3.5.4 Models

The software constructed for the study utilise the transformers python library * maintained by HuggingFace. The library manages the download and loading of the open source LLMs and embedding models used in the thesis. This also means that if the models are no longer available on the huggingface registry, or the registry is nonoperational, the models have to be obtained by other means. The open source models that are supported by the software are the following models

*The GitHub page for the transformers library /github.com/huggingface/transformers

- The Mistral-7B-Instruct, provided by MistralAI, *
- The Gemma-7B, provided by Google, †
- The Falcon-7B, provided by TII UAE, ‡
- The SFR-Embedding-Mistral, provided by Salesforce, §
- The Meta-Llama-3-8B-Instruct, provided by Meta, ¶

In addition to the open source models the software also supports experiments using some proprietary models by OpenAI. The two models that are supported are the *GPT-4* model and the *text-embedding-3-large* embedding model ‖. Both of these are accessible using the python API ** which require an OpenAI subscription and API key.

3.5.5 Hardware

The study software should be able to execute on most common hardware and most parts of the application are not particularly compute intensive. The notable exception to this is the worker processes in the LLM Service part of the software that, depending on the model, run quite intensive compute loads. That is unless the agent runs either of the proprietary cloud hosted models provided by OpenAI.

If the agent is running one of the LLMs it can run, such as the *Mistral 7B instruct* model, the agent needs access to a quite capable GPU. For the supported models this needs to be a GPU with at least 24 GB of video memory. Example of such graphics cards are *NVIDIA GeForce RTX 3090*††, *NVIDIA TITAN RTX*‡‡ or *NVIDIA A10 Tensor Core*§§. This used servers on AWS, specifically the G5 instances (g5.4xlarge) equipped with *NVIDIA A10 Tensor*

*huggingface.co/mistralai/Mistral-7B-Instruct-v0.2
†huggingface.co/google/gemma-7b
‡huggingface.co/tiiuae/falcon-7b
§huggingface.co/Salesforce/SFR-Embedding-Mistral
¶huggingface.co/meta-llama/Meta-Llama-3-8B-Instruct
‖platform.openai.com/docs/guides/embeddings/
**github.com/openai/openai-python
††nvidia.com/sv-se/geforce/graphics-cards/30-series/rtx-3090-3090ti/
‡‡nvidia.com/en-eu/deep-learning-ai/products/titan-rtx/
§§nvidia.com/en-us/data-center/products/a10-gpu/

Core GPUs [*]. The open source embedding models such as *SFR-Embedding-Mistral* can be run on CPUs, which only require the same amount of RAM available to run the models.

3.6 Assessing reliability and validity of the data collected

3.6.1 Validity of method

To research how well AI-assistants work in a specialised domain, other methods could've been used. For instance, instead of building an assistant and deploying it, the thesis could've explored similar domains and drawn conclusions from the success of similar systems in similar domains. However, actually implementing an assistant and evaluating its efficacy using standard methods such as TAM and ECM is a more accurate way of measuring the research questions laid out.

3.6.2 Reliability of method

The methods used in this study, including those for measuring user acceptance of the tool, are considered reliable. However, the results of the study will be heavily impacted by the type of users using the tool. Given the research is taking place at the division of robotics at a technical university, the participating courses are mostly technical courses with tech savvy students. To reproduce the results of this study it would have to closely reproduce the student population participating in the study. To increase the reliability of the method in this study the research could have been performed at a wider array of universities with a more diverse student population.

3.6.3 Data validity

TODO: after the results section has been written.

3.6.4 Reliability of data

TODO: after the results section has been written.

[*] aws.amazon.com/ec2/instance-types/g5/

3.7 Planned Data Analysis

TODO: after the results section has been written.

3.7.1 Data Analysis Technique

TODO: after the results section has been written.

3.7.2 Software Tools

TODO: after the results section has been written.

3.8 Evaluation framework

TODO: after the results section has been written.

3.9 System documentation

Appendix A includes links to the source code developed for the research in this thesis. The source code includes a *README* with comprehensive instructions for how to build, run and deploy the software.

Chapter 4

What you did

4.1 Proof of Concepts

The following section will outline the various Proof-of-concept (POC) applications that were built before the actual software that was written to conduct the research outlined in this thesis. Each POC will outline what it was trying to accomplish and what the outcome was.

4.1.1 Langchain based applications

Langchain is a company [*] and framework [†] for building context aware reasoning applications. The framework allows for easy composition of language models and RAG techniques and tools that makes it easy to build chatbots with a connected knowledge base. This section outlines some POCs that were made with the langchain framework.

4.1.1.1 GPT-4 and text-embedding-3-large

To build a chat application with an AI-assistant that has access to an external knowledge base, one of the most popular approaches is to use langchain to connect the following four parts.

1. A LLM, such as GPT-4 to run the chat.
2. A LLM, such as GPT-4 to run the query construction.

[*] langchain.com
[†] python.langchain.com

3. An embedding function, such as OpenAI's text-embedding-3-large used to index and query documents.

4. A vector store, such as ChromaDB, that stores the vector embeddings and associated documents *

.

In this configuration, Lanchain acts as the glue connecting these components and handling tasks like chunking larger documents. The goal of this POC was to test a common approach for building AI assistants and evaluate its potential for use in the full study. A video can be seen here that showcases this POC.

4.1.1.2 Mistral 7B v0.2 and e5-large-v2

There was a POC constructed that had the same approach as the one outlined in 4.1.1.1 with the notable requirement that all tools had to be under an open source licence. This meant the GPT-4 model and text-embedding-3-large models couldn't be used. A similar version of the same POC was made that used the Mistral 7B v0.2 model and the embedding function e5-large-v2 [57]. These are both under an open source licence and are freely available on Huggingface †. This POC did however suffer from poor performance in initial tests for retrieval and performance. It was difficult to tune the prompts to get decent performance. This POC showed it was difficult for the researcher to get good performance out of certain models using the langchain framework.

4.1.2 Custom applications

This section outlines some major and minor POCs that were made without any frameworks that are popular LLM applications, aside from very common python libraries such as pytorch and hugginface's transformers library.

4.1.2.1 Simple Python API for models on Huggingface

Langchain and similar tools support running language models locally. However, working with the prompt templates in less advanced models than GPT-4 and achieving good retrieval and chat performance was challenging. Therefore, a simple POC was developed to create higher-level Python

*trychroma.com/

†huggingface.co/mistralai/Mistral-7B-Instruct-v0.2 huggingface.co/intfloat/e5-large-v2

abstraction APIs on top of the Hugging Face Transformers library that could be integrated into completely custom solutions. These APIs include examples like those shown in listings 4.1 and 4.2. A short video can be seen here that demonstrates a chat application (without an integrated knowledge base) built on-top of these simple APIs.

Listing 4.1 High level API on-top of Huggingface's tranformers library that can be used for generating text using models available on Huggingface.

```
def load_hf_model(
    model_path: str,
    device: str
) -> (transformers.AutoModelForCausalLM, transformers.AutoTokenizer):
    """
    Loads a Hugging Face causal language model and its tokenizer for a given
    model path and device.
    """

def generate_text(
    model: transformers.AutoModelForCausalLM,
    tokenizer: transformers.AutoTokenizer,
    device: str,
    params: Params,
    prompt: str
) -> str:
    """
    Generates text from a prompt using the specified model, tokenizer, and
    generation parameters.
    """

async def generate_text_streaming(
    model: transformers.AutoModelForCausalLM,
    tokenizer: transformers.AutoTokenizer,
    device: str,
    params: Params,
    prompt: str
) -> AsyncGenerator[str, None]:
    """
    Asynchronously generates text from a prompt, yielding tokens incrementally.
    Useful for streaming responses.
    """

def _tokenise_inputs(
    tokeniser: transformers.AutoTokenizer,
    input_texts: list[str],
    max_length: int = 8192
) -> dict:
    """
    Tokenizes the input texts with padding and truncation.
    """

def should_stop_generating(
    output_token_ids: list,
    tokenizer: transformers.AutoTokenizer,
    params: Params,
    token_id: int
) -> bool:
    """
    Determines whether to stop generating text based on stop conditions.
    """
```

Listing 4.2 High level API on-top of Huggingface's tranformers library that can be used for generating vector embeddings using models available on Huggingface.

```
def load_hf_embedding_model(
    model_path: str,
    device: str
) -> (torch.nn.Module, transformers.AutoTokenizer):
    """
    Loads a Hugging Face embedding model and its tokenizer for a given model
    path and device.
    """

async def compute_embedding(
    model: torch.nn.Module,
    tokeniser: transformers.AutoTokenizer,
    text: str
) -> List[float]:
    """
    Computes and returns the normalized embedding for a given text using the
    specified model and tokenizer.
    """

def _compute_model_embeddings(
    model: torch.nn.Module,
    tokenised_inputs: dict
) -> torch.Tensor:
    """
    Computes the model embeddings from the tokenized inputs.
    """
```

4.1.2.2 Mistral 7B v0.2 and Opensearch

The goal with this POC was to build a version of the RAG application that didn't use a vector embedding function. Instead, this POC would utilise a traditional search service such as Elasticsearch or Opensearch. These implement "traditional" search algorithms such as TF-IDF, as outlined in section 2.7.1. This POC was very easy to implement and showed great promise.

4.1.2.3 Post processing for smaller models

When working with models that don't produce the best scores on public benchmarks, such as MMLU, there are a number of techniques that can be employed that could improve the performance of a RAG system. These generally smaller models suffer from worse scores on precision and recall

benchmarks. This means they are worse at recalling facts injected into the conversation by a RAG pipeline. One of the techniques that can be used is post-processing retrieved documents before they are inserted into the chat. There are a number of ways of achieving this. One of the techniques that was tried, and eventually implemented in the final study, was to use a post-processing mechanism, where each of the retrieved documents are passed through a post-processing function, which reduce the size of the document, as shown in Equation 4.1 and Equation 4.2.

$$R = \text{LLM}\left(Q, \{D_i\}_{i=1}^{N}\right) \tag{4.1}$$

Where:

- R is the generated response.
- LLM is the language model function.
- Q is the user query.
- $\{D_i\}_{i=1}^{N}$ are the matching documents retrieved from the index.

$$R = \text{LLM}\left(Q, \{\text{PP}(D_i, P)\}_{i=1}^{N}\right) \tag{4.2}$$

Where:

- PP is the post-processing function.
- P is the post-processing prompt.

There are different strategies for the prompt that reduce the size of the document. This prompt can instruct the language model to extract quotes from the document related to the query, summarise key facts related to the query, or a number of other methods. The one that was chosen for the final study was extracting quotes as this showed the most potential. Figure 4.1 and Figure 4.2 illustrate this process.

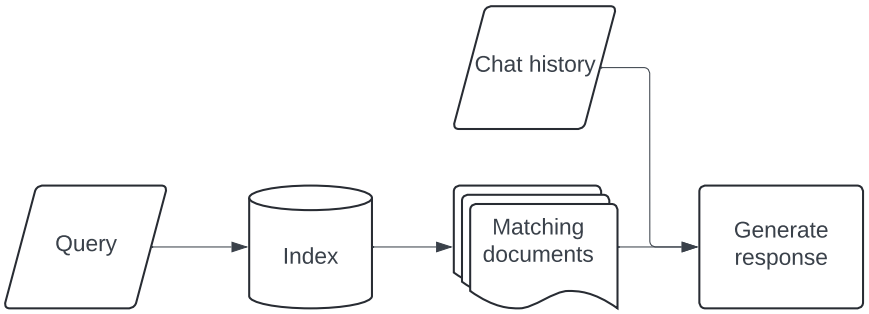

Figure 4.1: Diagram that shows how documents are injected into the chat, without post-processing

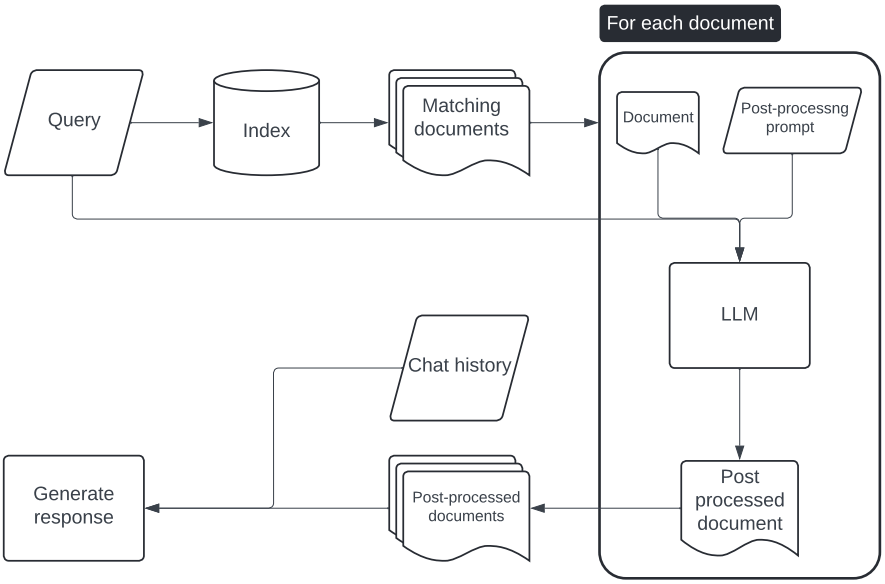

Figure 4.2: Diagram that shows how documents are post-processed before they are injected into the chat

4.1.2.4 Too much processing

Processing the documents to be smaller in size such that smaller models could accurately recall facts from retrieved documents was investigated until the

point where additional processing would no longer improve the quality of the answers,

There were additional efforts put towards investigating the processing of documents to be smaller in size. The goal was to enable smaller models to accurately recall facts from the retrieved documents. This process continued until additional processing no longer improved the quality of the answers. There were POCs produced that for instance processed the documents during the indexing phase in addition to the retrieval phase. During the indexing the documents were compiled into smaller "facts" that were indexed on their own. However, reducing the documents in size decreased the retrieval algorithms, both TF-IDF algorithms and embedding functions.

Some processing however could improve the performance. Such as including a summary of the entire document with each chunk of that document. In summary, pre-processing the documents, and chunks of each document, during the indexing process, did increase the system's ability to produce accurate answers to user queries. However, processing the documents too much was found to eventually lead to a reduction in accuracy.

4.2 The architecture of the software

This section will outline the final software that was constructed to investigate the research question in this thesis. The section will describe the goal of the software, what components it consists of, how each component works and showcase how it helps students get answers to their questions.

4.2.1 What the purpose of the software is

The purpose of the software is to crawl canvas course rooms and index their data into a knowledge base. The software should expose this knowledge base in a chat based application integrated into the same course room it has crawled. The tool should be able to randomly sample a configuration of models and tools for indexing, retrieval and chat between users of the tool. Finally, the tool should inject questions into the chat and track the necessary data points to investigate the research question of this thesis outlined in section 1.2.1.

4.2.2 Overall architecture

The software is primarily written in python, with a service-based architecture. This means it is divided into distinct domain specific services, each handling

specific domains and functionalities. These services handle one of four things, LLM-, Download-, Index- or Chat-functionality.

These services are written in such a way that they can be incorporated into any executable within the project. There are numerous executables within the application, these are;

- A graphical user interface, which is a web-based application
- A HTTP rest API
- A websocket server
- A job-runner that execute background tasks from a queue
- A worker node for the LLM service that keep a LLM in-memory ready to generate a response to a prompt for the given model

Figure 4.3 shows an overview of the architecture of the software written to conduct the research and which components are called by other components.

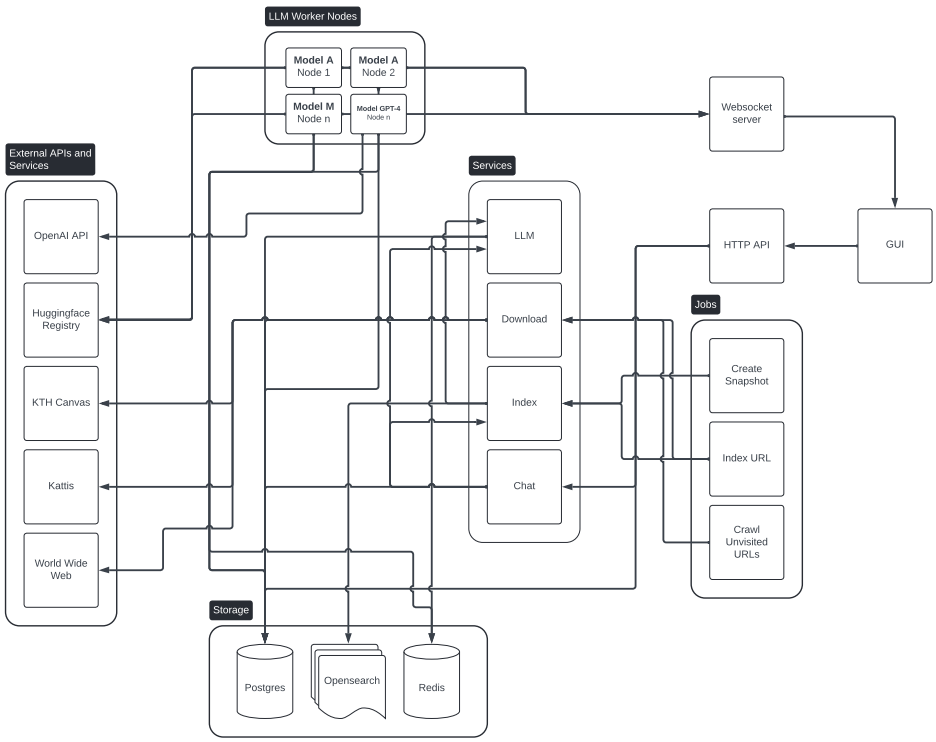

Figure 4.3: Diagram that shows the system architecture of the software constructed to run the study

4.2.3 Dependencies

The software is written on-top of numerous python and javascript libraries, these are documented in their entirety in the systems source code repository. In addition, the software needs the following major dependencies to operate.

- A postgres database
- A opensearch index
- A redis in-memory storage

4.2.4 Courseroom Crawler

The software contains a job that is run every minute, which checks if a new snapshot should be taken of a course room. A snapshot contains all urls and their content that was crawled from a course room. A piece of content may be a canvas webpage, a file hosted on canvas, an external url or file etc.

If a new snapshot is created of a course room the crawler will immediately crawl the course room. The crawler has global rules it follows for all course rooms, certain pages are ignored and how some content should be indexed. For instance, some common tools, such as the programming assignment tester kattis [*] have a known format. The crawler employs specific crawlers for these common sites and tools to ensure a high-level of data quality. The crawler was built upon the playwright framework developed by Microsoft [†]. This is a browser automation framework, mostly used for end-to-end testing of web applications. Using a browser to crawl websites is more compute-intensive than simply requesting the html files without rendering them. The benefit of using a browser, and actually rendering the content of the pages, is that content that's requested by scripts on the page gets loaded and can be extracted.

Ideally, the public canvas HTTP API [‡] should be used to ensure the highest level of data quality and a more reliable connection. However, this API had been disabled by KTH IT and would've taken time and resources to get access to.

[*] More information about how kattis is used at universities can be found here kattis.com/universities

[†] playwright.dev/

[‡] Documentation for the API can be found here canvas.instructure.com/doc/api/

4.2.5 Database design

All database interactions has been built on-top of the python Object-relational mapping (ORM) peewee *. An ORM is a technique for converting data between a relational database and objects native to the program. A full entity relation diagram can be seen in figure 4.4.

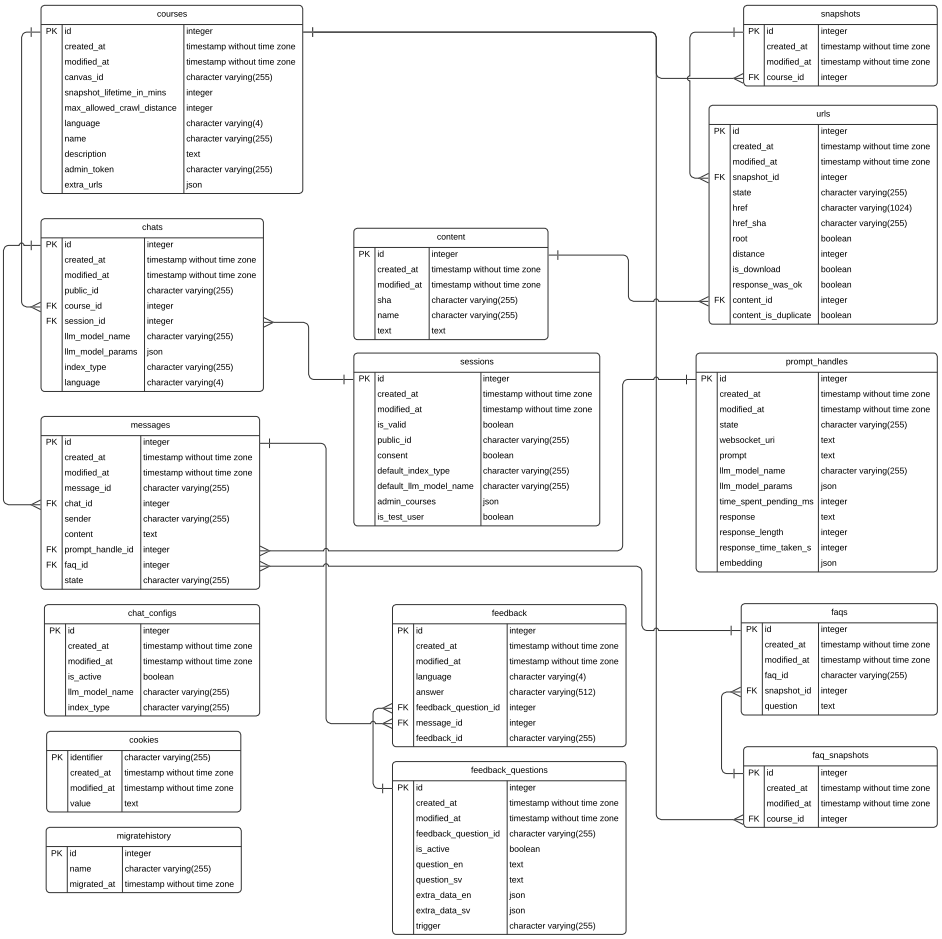

Figure 4.4: A diagram that shows the complete schema for the database

4.2.6 Document index

Opensearch, which started as a fork of the popular search engine Elasticsearch, serves as a full text search backend and document store for the software.

*docs.peewee-orm.com

The opensearch server also stores each vector embedding for all supported vector embedding functions used in the study. Opensearch is also used in the software to compute similarity scores for the computed vector embeddings of all documents, utilising the k-NN algorithm for efficient nearest neighbour search. This enables rapid retrieval and ranking of relevant documents based on their vector similarities which is one of the key research goals of this thesis. Listing 4.3 shows an example of a document indexed in a snapshot of a course room that participated in the study.

Listing 4.3 Example of an indexed document from the course *DD1367 Software Engineering in Project Form 9.0 credits* which participated in the study.


```
{
  "name": "Communication guidelines: DD1367 HT23 Programvarukonstruktion...",
  "text": "Document chunk: 1/1\nDocument summary: The document provides...",
  "text_raw": "Due to the mass amount of daily emails, I would like to...",
  "url": "https://canvas.kth.se/courses/43604/modules/items/765971",
  "sfr_embedding_mistral": [
    0.012644807808101177,
    -0.007494120392948389,
    0.005445912480354309,
    ...
  ],
  "text_embedding_3_large": [
    -0.009533963166177273,
    0.01081753708422184,
    -0.01858356036245823,
    ...
  ]
}
```


4.2.7 Running large language models at scale

One of the principal requirements for the study software was the ability to investigate the impact of different LLM on the experience of the user. This could impact the recall abilities of the system due to the models involvement in both understanding what the user is searching for and for summarising that information. Additionally, large embedding models would also be investigated within the scope of the study.

Proprietary models, such as those provided by OpenAI and are studied in this thesis, are always executed on the model vendors infrastructure and are accessible only via an HTTP API. These APIs are not compute-intensive

for the consuming application, such as the one developed for this thesis. However, open-source models, like the Mistral family of models, are available for anyone to run. One of the goals of this thesis was to investigate the feasibility of running such applications with all necessary dependencies on-premise. This involved executing these models within the application. This presents an engineering challenge, as these models are not very mature yet, and the infrastructure for running them is not well developed.

For the software in this study an *LLM-service* was developed. This service presented a high-level API that could be used by any part of the application, such as the chat-service, for producing messages, or the indexing service, for producing summaries or embeddings. The API had a high-level function that took a model name, model parameters and prompt to execute, and returned a prompt handle as a response. The data model for a prompt handle can be seen in its entirety in figure 4.4, but in addition to the provided arguments, this kept the necessary queuing information for the system to function, some performance metrics and the output of the model.

In the background the service provides the infrastructure for organising a virtually unbounded number of worker-nodes for each model. Any worker node keeps the model running in memory, which could be either in CPU or GPU memory. Loading the model into memory is a time-consuming operation, which was one of the driving reasons for this approach. This architecture allows for scaling the service to keep up-with-higher demand for prompt-completions. Heavy load could be caused by for instance, many users using the system simultaneously, or indexing one or more course rooms simultaneously.

Organising systems like this have many difficulties, particularly regarding the distributed nature of this architecture and the compute intensiveness of model inference. For instance, since the execution time of a prompt can be upwards of a minute, the worker nodes need the ability to stream the response back to an end user in real-time token-by-token, to provide a good user experience. For this reason a websocket service was implemented, that allows the end-user application to listen for tokens being produced over a websocket that the producing node is directly connected to. More advanced queue techniques, such as a Kafka queue, could have been implemented instead of using a database table with distributed mutex locks in Redis. However, for rapid implementation and prototyping, the chosen approach was adequate for the software in this thesis.

4.2.8 Assigning a chat configuration to a user

The system supports defining multiple chat configurations, each consisting of a specific set of tools and models for the user's chat experience. A chat configuration consists of;

- **A Language Model**: This is the LLM used for generating assistant responses and computing internal agent functionality such as the post processing of documents, if that's enabled for the config.
- **Retrieval Technique**: The method used for information retrieval, either an embedding model or full-text search.
- **Embedding Model**: Specifies the embedding model if used.
- **Document Processing**: Indicates whether documents should be post-processed before being inserted into the chat context (see section 4.1.2.3).

Any configuration can be selectively enabled or disabled based on the experimental requirements.

When a user accesses the system for the first time, a configuration is randomly assigned to ensure an unbiased distribution among users. Once assigned, the configuration remains consistent for the lifetime of that user's account. This is however only true if the user uses the same browser, a new browser would result in a separate account.

4.2.9 Gathering user feedback

The software was designed to facilitate user feedback collection. This feedback is gathered through a fairly flexible feedback entity, which integrates questions in the configured language of the course. A feedback questions are triggered by specific conditions, such as:

- After the response for the n-th message is sent in the m-th chat a user has had, where n represent the number of messages in the current chat and m the number of chat a user have had in total.
- After generating a response to a frequently asked question.

These triggers were chosen to capture the user experience over a certain period, enabling control over the duration of system usage when analysing the users response to each feedback question.

The feedback question format was designed to be extensive. There were two formats implemented for the research in this thesis. These formats were multiple choice questions, and binary *thumbs up* / *thumbs down* questions. Figure 4.5 and 4.6 showcase these two formats respectively.

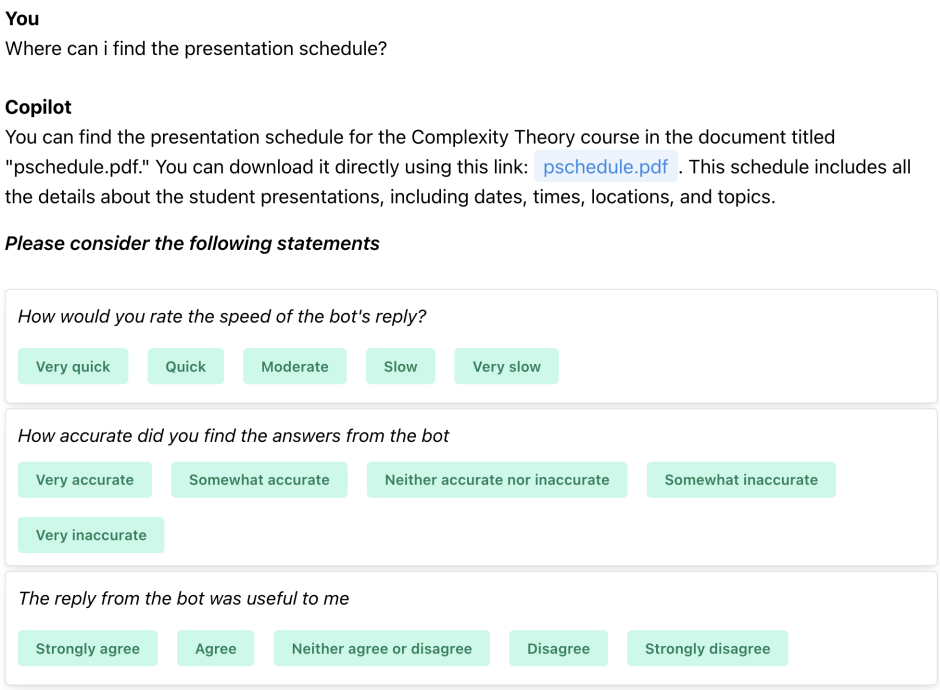

Figure 4.5: Example of a number of multiple choice questions inserted into the chat

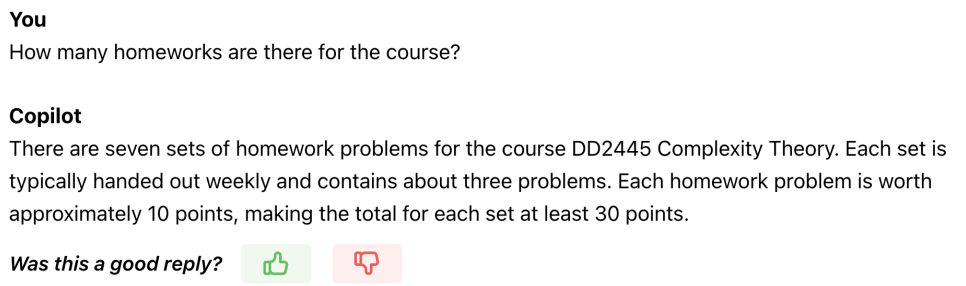

Figure 4.6: Example of a thumbs up/thumbs down question inserted into the chat after the user clicks on a FAQ.

4.2.10 User interface

The assistant built for the system was designed to live within the LMS used at KTH, known as canvas. Each couse in canvas is assigned a course room. This course room contains all the information a participant in the course might need, such as course announcement, assignments and modules. Figure 4.7 shows the course room of one of the courses that participated in the study. The GUI for the assistant designed for this thesis, was designed to live within the courseroom as an iframe.

The software constructed for this study was designed to integrate with KTH's LMS, Canvas. Each course in Canvas has a designated course room that contains all information for students in the course. This includes announcements, assignments, modules and more. Figure 4.7 shows the course room of one of the participating courses in the study. The GUI for the assistant, developed for this thesis, was embedded within the course room as an iframe, accessible through the course sidebar in the web, and navigation menu in the Canvas mobile app.

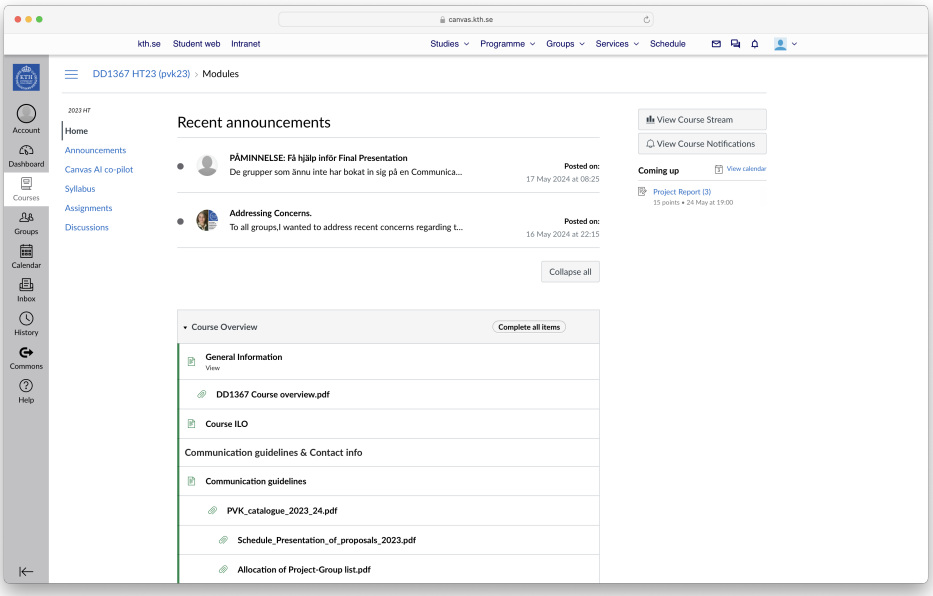

Figure 4.7: The course room of DD1367 Software Engineering in Project Form 9.0 credits in canvas

The system utilise a script that compiles the most common questions. These are displayed each time a user starts the application, as can be seen in figure 4.8. This allows the user to quickly understand what other students have asked the tool, and quickly start a conversation.

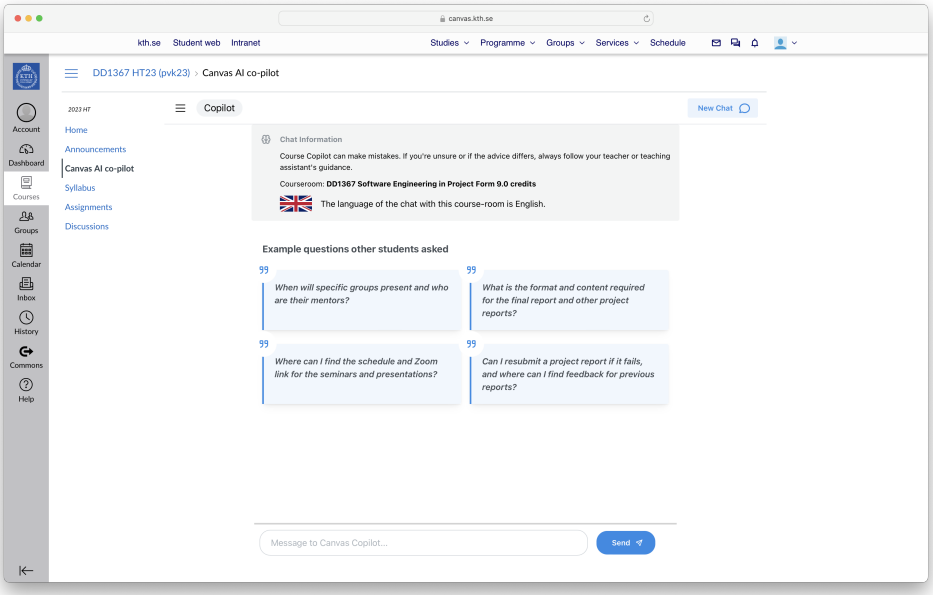

Figure 4.8: The chat UI with frequently asked questions shown before the user sends their first message

Overall, the GUI of the tool is very simple as can be seen in figure 4.9. It allows users to send and receive messages from the tool. The responses from the assistant support some rich formatting, such as bold fonts. Links to cited documents are highlighted and forwards the user to the corresponding page or file in canvas when clicked. A video demonstration of the software being used by a student can be seen here.

Any teacher or TA can be granted administrative privileges which yields them access to a list of all chats that have been had between students and the assistant in their course, as can be seen in figure 4.10. This allows them insights into what the chatbot is responding to the students questions.

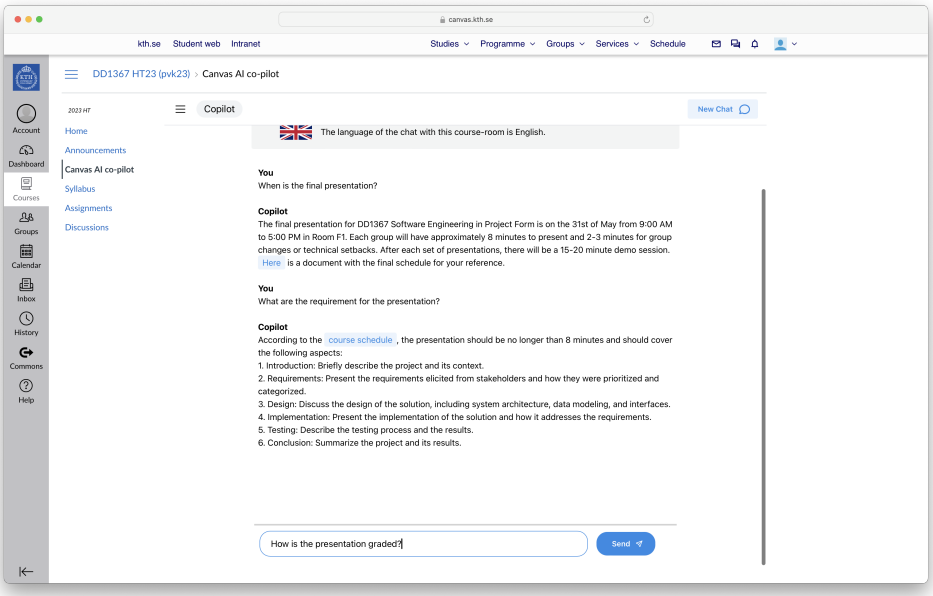

Figure 4.9: A short conversation with the assistant

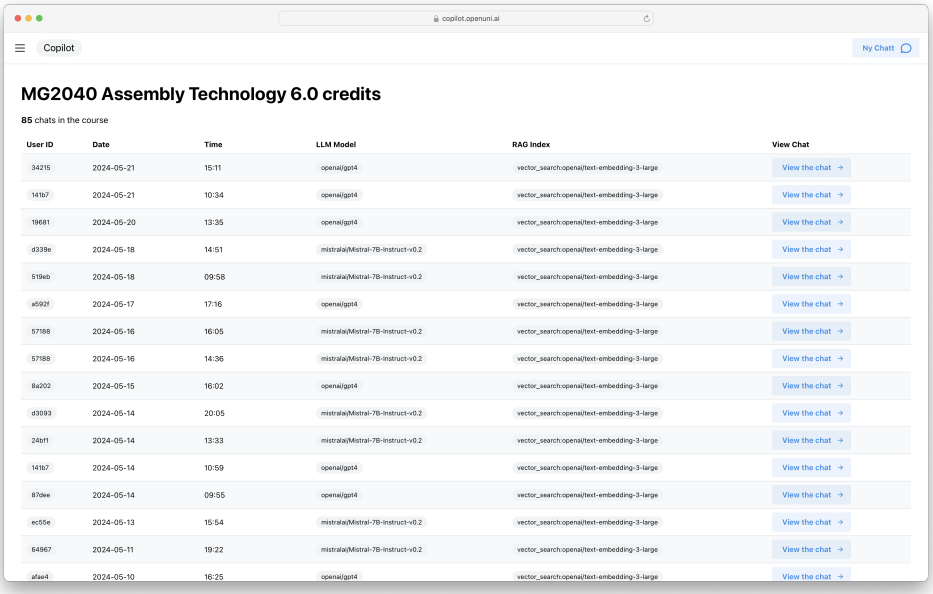

Figure 4.10: The view available to teachers and TAs that shows all conversations students have had with the assistant

4.3 How the software is deployed

Considering the nature of running LLMs at scale the software had quite compute-intensive requirements. Due to sponsorship from KTH Innovation there were credits accessible on Amazon AWS that were available to use for the study. This meant AWS was a suitable cloud infrastructure provider to deploy the software that was built for the study.

AWS has hundreds of services of varying levels of abstraction. The requirements on the infrastructure for this study was primarily that it had to support GPU heavy compute-workloads. Since the software was built to be packed into Docker images, the infrastructure had to support connecting GPU devices to the running Docker containers. AWS Amazon Elastic Container Service (ECS) supports creating *"Task Definitions"* and executing them in services that are hosted on their fully managed *Fargate* platform, or hosting them on regular Amazon Elastic Compute Cloud (EC2)-instances. The latter has a wide array of instance definitions to choose from, of which multiple has one or more GPU devices connected. The ECS platform was therefore chosen as the main deployment platform for the software. The entire system architecture can be seen in figure 4.11.

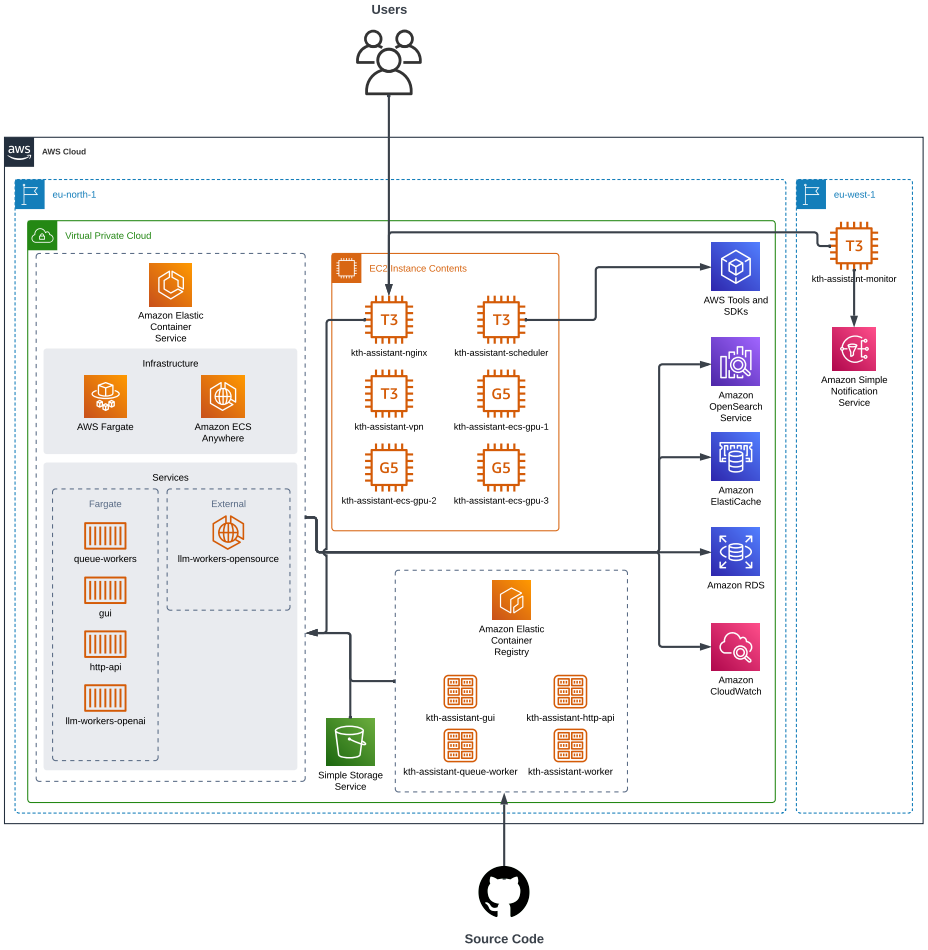

Figure 4.11: Diagram that shows how the software was deployed on Amazon AWS

In the repository for the source code there are a few github workflows, one of which builds the executables for the project. The executables are four docker images, these are:

- **HTTP API:** This docker image runs the HTTP and Websocket servers for the software.
- **GUI:** This runs a small node server that servers the user interface for the software.
- **LLM Worker:** This runs a worker node for a given LLM in the system

- **Queue Worker:** This executes a pool of worker nodes for the jobs that can be dispatched in the system

Each of these images are published to their respective Amazon Elastic Container Registry (ECR)-registry. The ECR are themselves used as source for the task definitions in ECS. Together with configuration stored in Amazon Simple Storage Service (S3) the image and task definition are deployed into services in ECS. These services can be scaled independently of each other, and use different hosting environments depending on their workload.

Each service can be scaled manually or put in auto scaling groups. The only service that would see any considerable load is the *LLM-worker* containers. However, since they need to keep the LLM in-memory in order to provide real time answers to users, it can't be scaled using traditional metrics such as CPU or memory usage. No sophisticated auto-scaling was configured, since it was deemed unnecessary for this study. Instead, the study relied upon a schedule maintained by a simple script that during certain peak hours scaled up the infrastructure necessary to run more nodes for each enabled LLM or embedding function.

Traditional services in AWS were used for running the respective component of the application. One postgres server was deployed in Amazon Relational Database Service (RDS), an in-memory Redis cache was created in *Amazon ElastiCache* and an OpenSearch cluster was created in *Amazon OpenSearch Service*. Logs from all services and software components were collected in *Amazon CloudWatch*.

Whilst the service was operational keeping track of whether the system was operational became a priority. During the initial development and deployment it became necessary to track if the service was up and running and be notified of any outages. Therefore a simple playwright script was built that simulated a student entering a question in each course room on a rotating schedule. This would publish a message on a Amazon Simple Notification Service (SNS) topic that would trigger an email if a response couldn't be produced by the system.

Chapter 5

Results and Analysis

This chapter will present and analyse the results of the research conducted in this thesis.

5.1 Feasibility of building an AI assistant on open source technologies

One of the goals of the research in this thesis was, as outlined in section 1.4, to assess the feasibility of building an AI-assistant on open-source technologies and deploying the agent in an academic setting. This section will outline the results and showcase the impact open source tooling had on the implementation of the AI assistant.

5.1.1 How popular was the system

The system was developed during the spring of 2024 and gradually deployed to seven real courses at KTH starting on the 18th of April 2024. The students in the courses that participated in the study held a total of 596 chats. As can be seen in figure 5.1 these steadily increased through over the course of the study as students initiated new chats with the assistant.

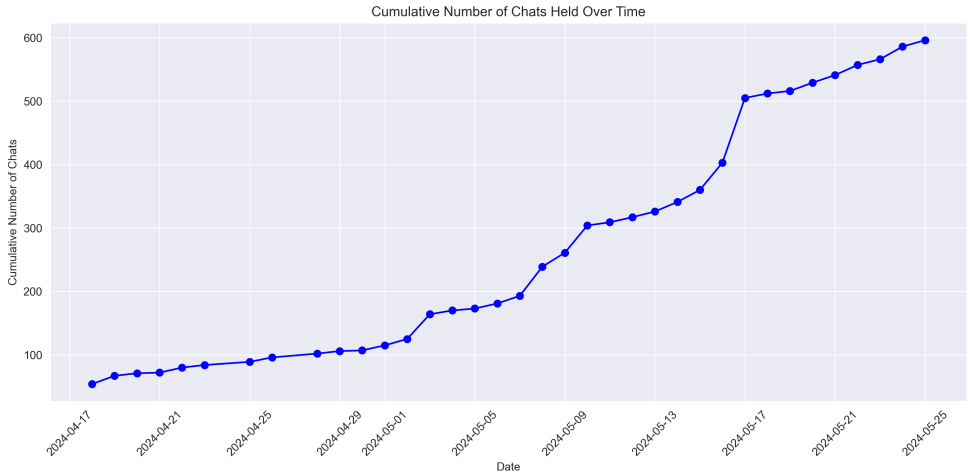

Figure 5.1: Cumulative number of chats started by users participating in the study

Separating the chats initiated in the separate course rooms we observe that some courses followed a fairly linear increase in the number of chats. One example of this is the course *MG2040 Assembly Technology 6.0 credits*, which can be seen in figure 5.2.

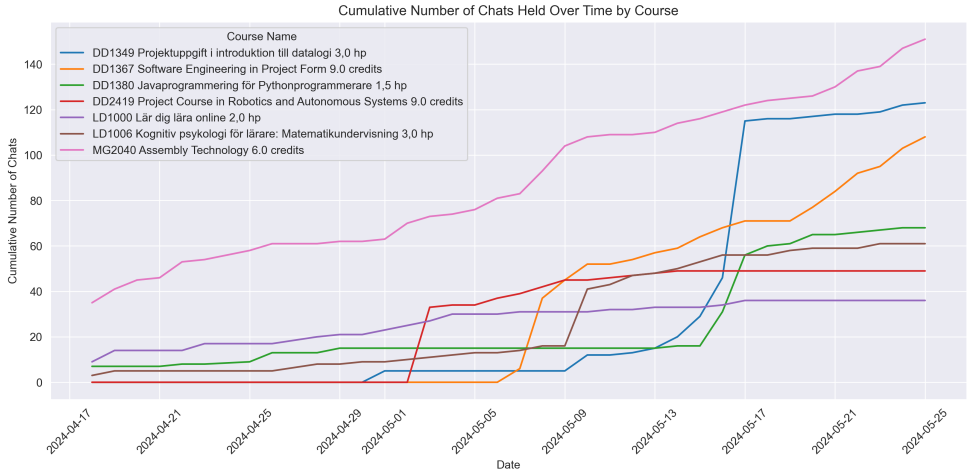

Figure 5.2: Cumulative number of chats started by users participating in the study in each course

Looking at other courses in figure 5.2 it is evident that not all courses follow the same pattern as *MG2040*. Some courses initially have very few chats due to the chatbot not being deployed simultaneously across all courses. Table 5.1

details the start dates for each course. For instance, *DD1349 Projektuppgift i introduktion till datalogi 3,0 hp* exhibits a steep increase in users when it launched, followed by no further growth. This is because the course officially ended shortly after the chatbot was introduced. In all courses participating in the study, the chatbot was deployed well after the courses had already begun, therefore a similar pattern can be seen in many other courses.

Course	Go live date
LD1000 Lär dig lära online 2,0 hp	2024-04-17
LD1006 Kognitiv psykologi för lärare: Matematikundervisning 3,0 hp	2024-04-17
MG2040 Assembly Technology 6.0 credits	2024-04-17
DD1349 Projektuppgift i introduktion till datalogi 3,0 hp	2024-05-01
DD2419 Project Course in Robotics and Autonomous Systems 9.0 credits	2024-05-03
DD1367 Software Engineering in Project Form 9.0 credits	2024-05-07
DD1380 Javaprogrammering för Pythonprogrammerare 1,5 hp	2024-05-13

Table 5.1: The start dates for each course, when the bot was deployed in each canvas course room.

Figure 5.3 shows the total number of chats held in each course. The course *MG2040* held the most, 151 chats. *DD1349* held the second most and *DD1367* the third most, 123 and 108 chats respectively.

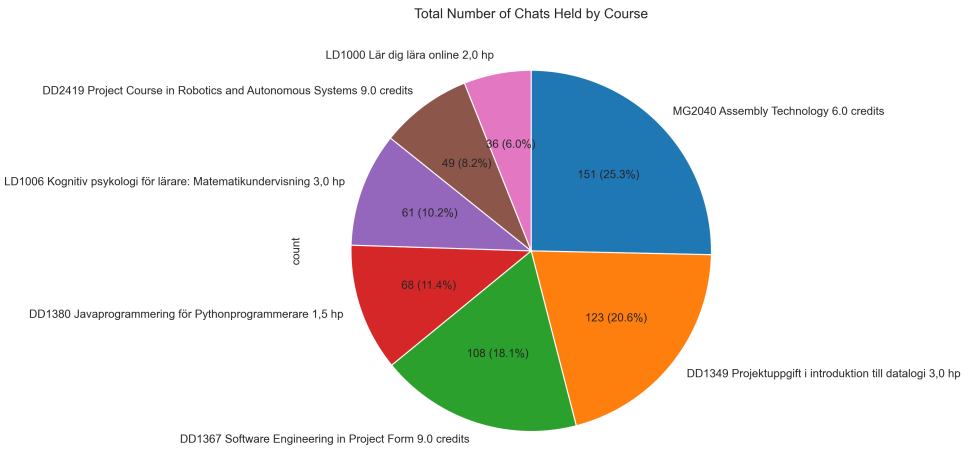

Figure 5.3: Number of chats held by in each course

Looking at the number of sessions created in Figure 5.4 and Figure 5.5, we can see a similar pattern linear pattern. A session is started whenever a user loads the application without already having loaded it before. A session is not tracked between devices, therefore a user would have two sessions if the same

user accessed the chat on two different devices, such as a desktop and a mobile phone. However, the same session is used across courses.

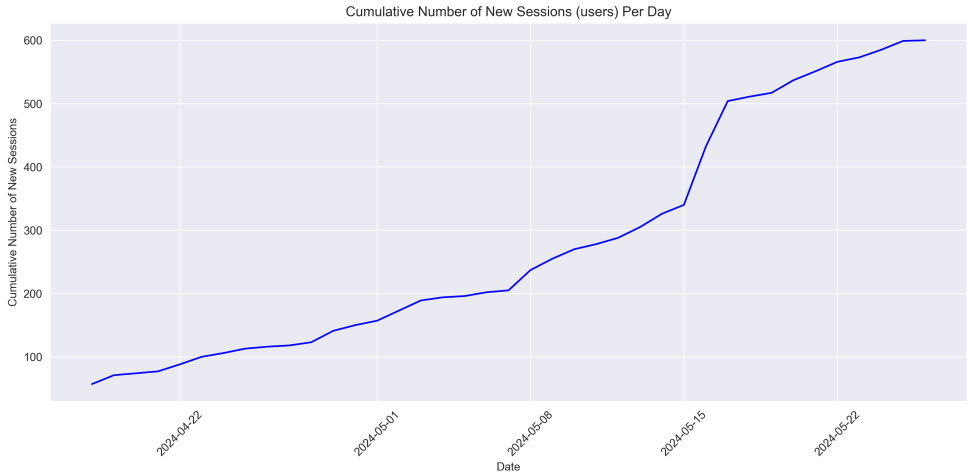

Figure 5.4: Cumulative number of sessions per day

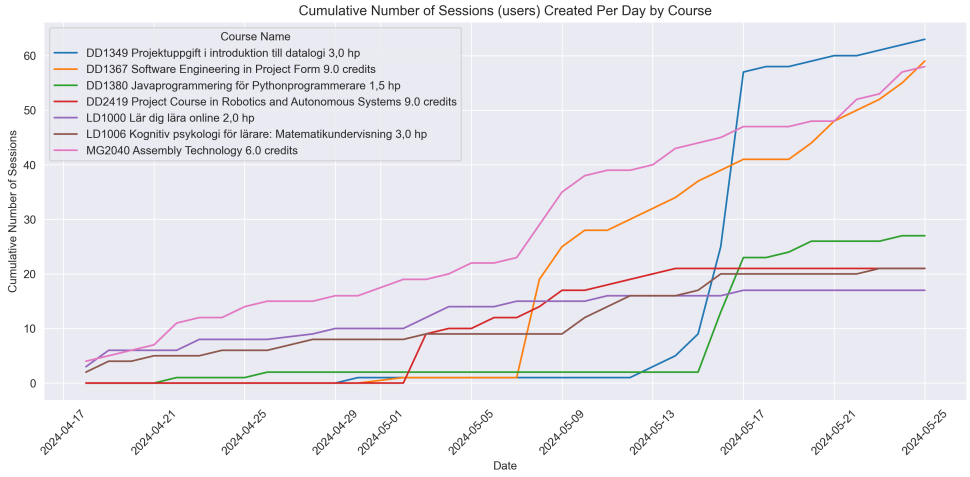

Figure 5.5: Cumulative number of sessions per day in each course

Looking at the distribution of how many chats and messages is sent per session, as seen in figure Figure 5.6 and Figure 5.7 we can see that it was very common for users to only start one or two chats. Most users sent quite a few messages though. The average user held 2.22 chats and sent 9.57 messages.

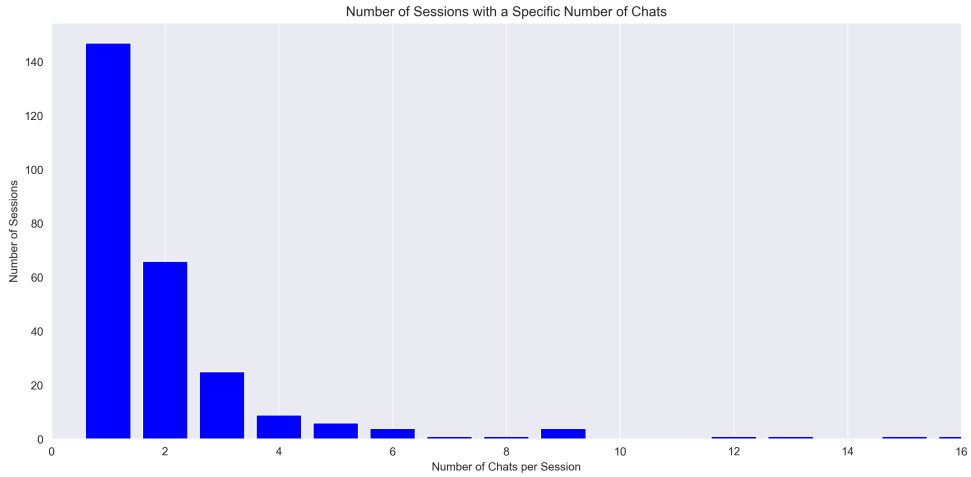

Figure 5.6: Number of sessions with each number of chats

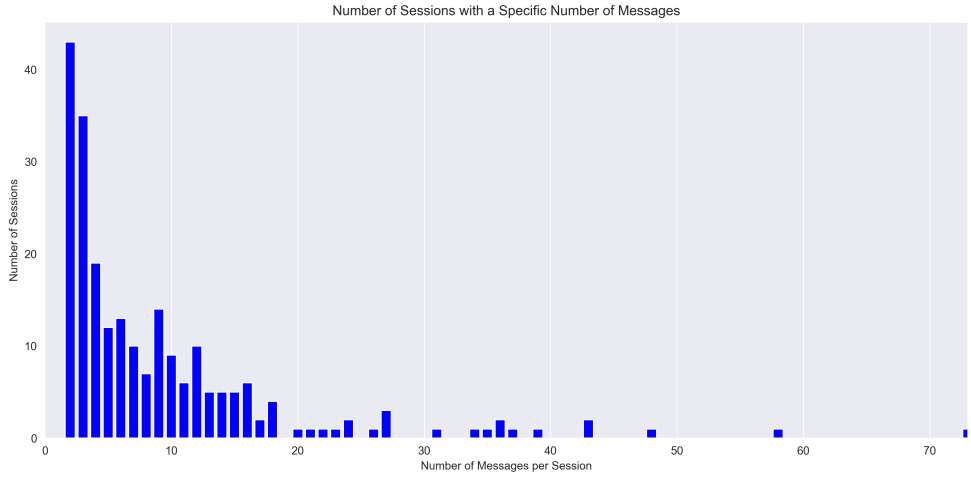

Figure 5.7: Number of sessions with each number of messages

5.1.2 Open source v. Proprietary LLMs

5.1.3 Open source v. Proprietary Embedding functions

5.2 The impact of different LLM models on the speed, accuracy and reliability of responses

This section will present and analyse the gathered data on user preference and technological efficacy of different tools and technologies such as different RAG toolchains and LLM, as outlined in section 1.4.

5.3 Qualitative analysis of user responses

This section will present an analysis of the free text answers users have provided in the forms that have been presented in the participating courses.

5.4 Reliability Analysis

5.5 Validity Analysis

Chapter 6

Discussion

diskussion här

Chapter 7

Conclusions and Future work

7.1 Conclusions

7.2 Limitations

7.3 Future work

Due to the breadth of the problem, only some of the initial goals have been met. In these section we will focus on some of the remaining issues that should be addressed in future work. ...

7.3.1 What has been left undone?

The prototype does not address the third requirment, *i.e.,* a yearly unavailability of less than 3 minutes; this remains an open problem. ...

7.3.1.1 Cost analysis

The current prototype works, but the performance from a cost perspective makes this an impractical solution. Future work must reduce the cost of this solution; to do so, a cost analysis needs to first be done. ...

7.3.1.2 Security

A future research effort is needed to address the security holes that results from using a self-signed certificate. Page filling text mass. Page filling text mass. ...

7.3.2 Next obvious things to be done

In particular, the author of this thesis wishes to point out xxxxxx remains as a problem to be solved. Solving this problem is the next thing that should be done. ...

7.4 Reflections

One of the most important results is the reduction in the amount of energy required to process each packet while at the same time reducing the time required to process each packet.

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Appendix A

Source Code

The source code used to conduct the research in this thesis is available in its entirety at github.com/nattvara/kth-assistant.

Appendix B

Something Extra

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% The form of the entries in this file is \newacronym{label}{acronym}{phrase}
%                                      or \newacronym[options]{label}{acronym}{phrase}
% see "User Manual for glossaries.sty" for the  details about the options, one example is shown below
% note the specification of the long form plural in the line below
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% The following example also uses options
\newacronym[shortplural={OSes}, firstplural={operating systems (OSes)}]{OS}{OS}{operating system}

% note the use of a non-breaking dash in long text for the following acronym

\newacronym{KTH}{KTH}{KTH Royal Institute of Technology}

\newacronym{LMS}{LMS}{Learning Manegement System}
\newacronym{RAG}{RAG}{Retrieval Augmented Generation}
\newacronym{LLM}{LLM}{Large Language Models}
\newacronym{RNN}{RNN}{Recurrent Neural Network}
\newacronym{CNN}{CNN}{Convolutional Neural Networks}
\newacronym{LSTM}{LSTM}{Long Short-Term Memory}
\newacronym{GRU}{GRU}{Gated Recurrent Units}
\newacronym{BERT}{BERT}{Bidirectional Encoder Representations from Transformers}
\newacronym{GAN}{GAN}{Generative Adversarial Network}
\newacronym{NLP}{NLP}{Natural Language Processing}
\newacronym{GPT}{GPT}{Generative Pre-trained Transformers}
\newacronym{GQA}{GQA}{Grouped-Query Attention}
\newacronym{SWA}{SWA}{Sliding window attention}
\newacronym{SMoE}{SMoE}{Sparse Mixture of Experts}
\newacronym{IR}{IR}{Information Retrieval}
\newacronym{TF-IDF}{TF-IDF}{Term Frequency-Inverse Document Frequency}
\newacronym{CBOW}{CBOW}{Continuous Bag-of-Words}
\newacronym{MTEB}{MTEB}{Massive Text Embedding Benchmark}
\newacronym{seq2seq}{seq2seq}{Sequence-to-sequence}
\newacronym{TAM}{TAM}{Technology Acceptance Model}
\newacronym{ECM}{ECM}{Expectation-Confirmation Model}
\newacronym{RLHF}{RLHF}{Reinforcement learning from human feedback}
\newacronym{MMLU}{MMLU}{Massive Multitask Language Understanding}
\newacronym{GUI}{GUI}{Graphical user interface}
\newacronym{POC}{POC}{Proof-of-concept}
\newacronym{ORM}{ORM}{Object-relational mapping}
\newacronym{ECS}{ECS}{Amazon Elastic Container Service}
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\newacronym{ECR}{ECR}{Amazon Elastic Container Registry}
\newacronym{S3}{S3}{Amazon Simple Storage Service}
\newacronym{RDS}{RDS}{Amazon Relational Database Service}
\newacronym{SNS}{SNS}{Amazon Simple Notification Service}
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