nndraw is a LaTeXpackage which provides utilities to draw neural networks in an efficient way. Currently this package provides utilities to draw fully connected feedforward neural networks with an arbitrary number of layers described inside the 'fullyconnectednn' environment using the command 'nnlayer'. An example of usage is shown below, in this example, a fully connected feedforward deep neural network is provided with two inputs in the first layer, one hidden layer with four neurons and one output layer with one output. This example shows how easy it is to customize the presence/absence of biases in any layer as well as its position.

```
\begin{fullyconnectednn}[biasy = -4.5,
                         titley = 1,
                         inout = false]
    \nnlayer[title = Input layer]{2}
    \nnlayer[title = Hidden layer]{4}
    \nnlayer[title = Ouput layer, hasbias = false]{1}
\end{fullyconnectednn}
```

Which is drawn as

[biasy = -4.5, titley = 1, inout = false] [title = Input layer]2 [title = Hidden layer]4 [title = Ouput layer, hasbias = false]1

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OF TECHNOLOGY

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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

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Sammanfattning

Foobar

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
ECM	Expectation-Confirmation Model
GAN	Generative Adversarial Network
GPT	Generative Pre-trained Transformers
GQA	Grouped-Query Attention
GRU	Gated Recurrent Units
IR	Information Retrieval
LLM	Large Language Models
LMS	Learning Manegement System
LSTM	Long Short-Term Memory
MTEB	Massive Text Embedding Benchmark
NLP	Natural Language Processing
RAG	Retrieval Augmented Generation
RNN	Recurrent Neural Network
seq2seq	Sequence-to-sequence
SMoE	Sparse Mixture of Experts
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.

1.1.1 Where the research is taking place

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

Large Language Models (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 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 labelers 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. MMLU (*Measuring Massive Multitask Language Understanding*) [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. This dual purpose ensures the project not only addresses the immediate needs of KTH's digital learning environment but also enriches the scientific community's understanding of applied AI in education.[a]

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 benefit 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

The goals of this degree project are organised to comprehensively assess the deployment of AI-assistants within the educational framework of

KTH's Canvas LMS, focusing on technological effectiveness and user receptiveness:[b]

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.

2. **User Preference:** To ascertain the preferences of different user groups (students, faculty) regarding the usability, information quality, and overall experience of interacting with various AI-assistant models and retrieval techniques.

3. **Operational Feasibility:** To assess the feasibility of integrating a fully open-source AI-assistant 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 open-source and proprietary models concerning their deployment costs, maintenance needs, and infrastructure requirements.

Each goal is designed to address a specific aspect of AI technology integration within educational practices, ensuring that the project outcomes are relevant and useful for both academic research and educational administration.

1.5 Research Methodology

This project employs a hybrid research methodology combining empirical data collection with qualitative insights to evaluate the implementation of AI-assistants in an educational setting effectively:

1.5.1 System Design and Implementation

Model Selection Different models, including proprietary and open-source, with different training data/methods, will be evaluated to determine their performance in educational environments.

RAG Integration Various configurations of Retrieval Augmented Generation systems will be tested to identify the most effective method for enhancing the AI's responses with relevant information from KTH's course-specific data.

1.5.2 Evaluation Design

Study Participants The study will involve students using the AI-assistant and providing feedback on their experiences. There are various types of students participating in the study.

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 tools 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 LLMs 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. The findings might not be directly transferable to other institutions or countries without additional localization and adaptation.[c]

[d]

These delimitations are set to clarify the focus of the research and define what is outside the scope of this thesis project. They help in managing expectations and provide a clear framework within which the study operates.

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. ...

[a]formulera om [b]formulera om? [c]expand upon this [d]maybe add more here?

Chapter 2

Background

This chapter provides the necessary background for understanding the research conducted within this thesis. This chapter also showcase 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.

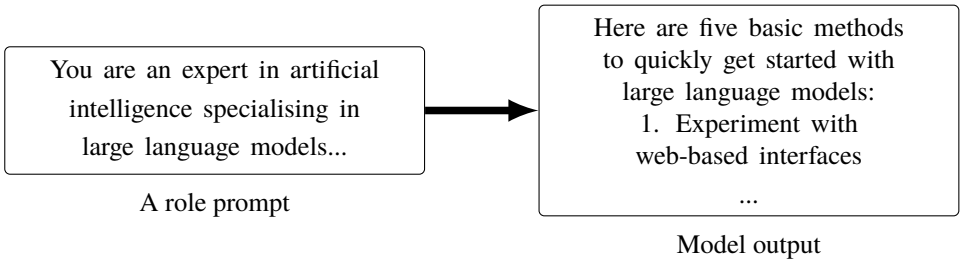

Figure 2.1: Role prompting example.

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.

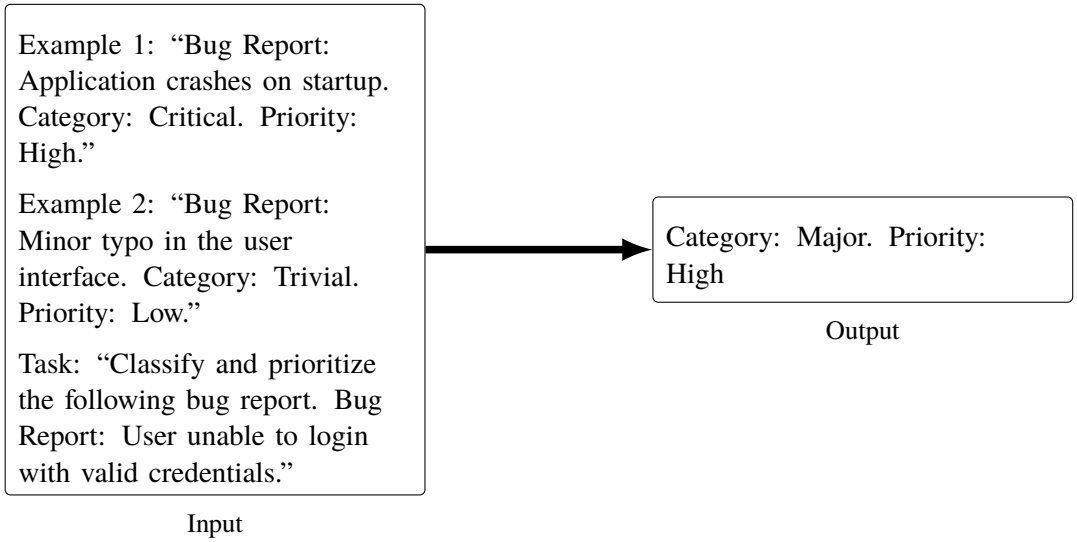

Figure 2.2: Few-shot prompting example.

2.5 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 [35, 36]. 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.

2.6 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 [37]. 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 [37].

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

2.6.1 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. [37].

2.6.2 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 [38].

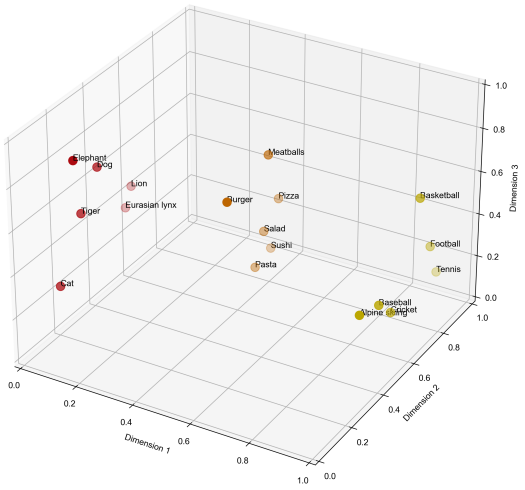

Figure 2.4: Simplified 3D space with simplified embeddings for various words

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. [38]. 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 [38, 39].

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 [40].

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. [41] 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 [42]. Similarly, OpenAI has developed several closed source embedding models that also rank highly on the MTEB leaderboard [43, 44].

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.

2.7 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.

*Massive Text Embedding Benchmark (MTEB) Leaderboard on Huggingface

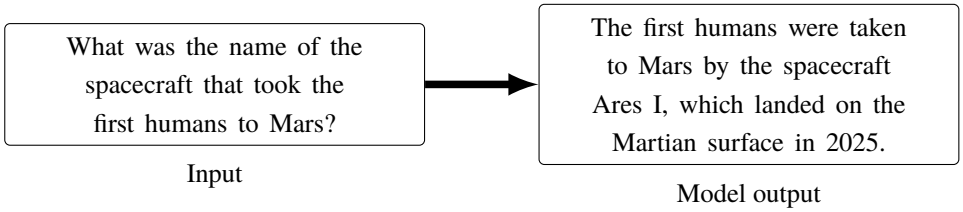

Figure 2.5: An example of how a model can hallucinate an answer to a question.

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 2.6.2) which enables efficient and effective search [45].

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, 46].

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.

2.8 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 [47].

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.

2.9 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" [48] 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 [49], 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 [50] 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 [51] 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 [52] 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.

2.10 Related work area

...

2.10.1 Major related work 1

Carrier clouds have been suggested as a way to reduce the delay between the users and the cloud server that is providing them with content. However, there is a question of how to find the available resources in such a carrier cloud. One approach has been to disseminate resource information using an extension to OSPF-TE, see Roozbeh, Sefidcon, and Maguire [**?**].

2.10.2 Major related work n

2.10.3 Minor related work 1

...

2.10.4 Minor related work n

2.11 Summary

Chapter 3

Method or Methods

3.1 Research Process

3.2 Research Paradigm

3.3 Data Collection

3.3.1 Sampling

3.3.2 Sample Size

3.3.3 Target Population

3.4 Experimental design and Planned Measurements

3.4.1 Test environment/test bed/model

3.4.2 Hardware/Software to be used

3.5 Assessing reliability and validity of the data collected

3.5.1 Validity of method

3.5.2 Reliability of method

3.5.3 Data validity

3.5.4 Reliability of data

3.6 Planned Data Analysis

3.6.1 Data Analysis Technique

3.6.2 Software Tools

Chapter 4

What you did

4.1 Hardware/Software design . . . /Model/Simulation model & parameters/. . .

4.2 Implementation . . . /Modeling/Simulation/. . .

4.2.1 Some examples of coding

4.2.2 Some examples of figures in tikz

4.2.2.1 Azure's Form Recognizer

Chapter 5

Results and Analysis

In this chapter, we present the results and discuss them.

5.1 Major results

Some statistics of the delay measurements are shown in table... The delay has been computed from the time the GET request is received until the response is sent.

5.2 Reliability Analysis

5.3 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

Supporting materials

Appendix B

Something Extra

TRITA-EECS-EX- 2023:0000

€€€€ For DIVA €€€€

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acronyms.tex

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%%% mode: latex
%%% TeX-master: t
%%% End:
% The following command is used with glossaries-extra
\setabbreviationstyle[acronym]{long-short}
% 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
\newacronym[longplural={Debugging Information Entities}]{DIE}{DIE}{Debugging Information Entity}
%
% 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}
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