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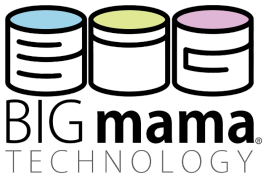

Graduation Thesis

To obtain the Industrial Engineering diploma

Option : Data Science & Artificial Intelligence

Unlocking Potential: Open Source LLMs in Rag Systems

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In the Name of God, Most Gracious, Most Merciful

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Abstract

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Glossary

Here are the main acronyms used in this document. The meaning of an acronym is usually indicated once, when it first appears in the text.

ABC	Asset Based Consulting
AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
NLP	Natural Language Processing
LLM	Large Language model
GPT	Generative Pre-trained Transformer
BERT	Bidirectional Encoder Representations from Transformers
RAG	Retrieval-Augmented Generation
NN	Neural Networks
ReLU	Rectified Linear Unit
RNN	Recurrent Neural Network
LSTM	Recurrent Neural Networks

Chapter 1

State of Play

"The true power of AI lies in its ability to augment human intelligence, not replace it."
Andrew Ng, Co-founder of Coursera and former Chief Scientist at Baidu

In this chapter, we embark on a journey through the landscape of existing literature and research pertinent to the convergence of open source Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG) systems, in collaboration with BIGmama Technology. Our objective is to establish a robust foundation for understanding the intricacies and potentials inherent in this symbiotic relationship. As we delve into the state of play, we aim to illuminate key theoretical underpinnings and empirical insights that underpin our study of open source LLMs and Rag systems within the context of BIGmama Technology. To initiate this exploration, we contextualize our inquiry within the broader discourse of natural language processing and information retrieval, elucidating the multifaceted challenges and opportunities presented by the integration of open source LLMs and Rag systems. Subsequently, we navigate through seminal concepts and methodologies, including the principles of LLM architecture, Rag framework components, and their applications in various domains. These foundational insights serve as pillars supporting our quest to explore the potential synergies and advancements offered by the convergence of open source LLMs and Rag systems within the framework of BIGmama Technology.

1.1 Presenting BIGmama Technology

BIGmama is an innovative startup founded in France with a subsidiary in Algeria, specializing in data science and artificial intelligence solutions. With over 9 years of experience as of 2024, the company has established itself as a leading provider of bespoke predictive applications tailored to meet the unique needs of its clients.

Guided by a distinguished board of directors comprising former CEOs of global conglomerates such as Danone and Safran, BIGmama boasts a team of highly skilled data scientists and software engineers. This multidisciplinary team, consisting of more than a dozen experts in their respective fields, brings a wealth of knowledge and expertise to the company's endeavors.

BIGmama's commitment to innovation and cutting-edge technologies has allowed them to deliver state-of-the-art solutions that leverage the power of data science and

artificial intelligence. With a strong focus on providing customized solutions, the company has consistently exceeded its clients' expectations, enabling them to gain valuable insights and make data-driven decisions.

Through its strategic partnerships and collaborations, BIGmama continues to push the boundaries of what is possible in the realms of data science and AI (Artificial Intelligence), positioning itself as a driving force in the ever-evolving technological landscape.

1.1.1 Mission

Beyond speeches, BIGmama's mission is to propose effective methodologies, action plans, and tools to:

- Solve problems with artificial intelligence tools.
- Put people at the heart of technology, i.e., the hybridization of AI.
- Make technology a common good, shareable, and accessible to the maximum number of people who can participate and contribute.

The company's commitment extends far beyond mere rhetoric; it is dedicated to developing practical solutions, methodologies, and actionable plans to leverage the power of artificial intelligence for problem-solving. BIGmama places a strong emphasis on ensuring that technology remains human-centric, fostering a harmonious integration and hybridization of AI with human intelligence.

Moreover, BIGmama recognizes the importance of democratizing access to technology, ensuring that it becomes a shared resource that can benefit society as a whole. The company aims to create an environment where the maximum number of individuals can actively participate and contribute to the advancement of technology.

Ultimately, BIGmama's mission is to position technology as a catalyst for freedom, empowering individuals and communities to unlock new possibilities and overcome barriers through innovative solutions.

1.1.2 Vision

"Standing on the Shoulders of Giants"

We find ourselves at a pivotal moment in human history, where the rapid advancements in artificial intelligence are poised to reshape our world in unprecedented ways. Groundbreaking technologies like ChatGPT, developed by industry giants, are at the forefront of this transformative wave, mobilizing vast resources to redefine the boundaries of what is possible.

However, BIGmama's approach is not to compete directly with these titans but rather to harness their innovations as a springboard for its own technological endeavors. By building upon the foundations laid by these industry leaders, BIGmama aims to leverage their advancements as a catalyst for its own visionary project.

Rather than reinventing the wheel, BIGmama recognizes the value in standing on the shoulders of giants, capitalizing on their groundbreaking work to propel its own unique solutions forward. This strategic approach not only allows for more efficient progress but also fosters an environment of collaboration and synergy within the broader technological ecosystem.

With a keen understanding of the rapidly evolving landscape, BIGmama remains agile and adaptable, poised to seize opportunities presented by the advancements of industry giants. By embracing a collaborative mindset and harnessing the collective wisdom of the technological community, BIGmama is well-positioned to contribute its own innovative solutions, shaping the future in alignment with its vision and mission.

1.1.3 BIGmama Specificities

One of the valuable heritages that BIGmama acquired during the 9 years of actively developing bespoke AI applications to its clients is its unique methodology of work. This methodology is centered around the following ideas :

- **Data science starts with problematization:**

  At BIGmama, the approach to data science does not begin with data science itself but rather with reframing and problematization. The company's clients often arrive with a subject or topic rather than a clearly defined problem. BIGmama has developed a methodology to convert these topics into well-defined problems that data scientists can effectively tackle.

- **The data scientist is a "maverick":**

  BIGmama recognizes that the data scientist is a "maverick" who cannot be restrained. The company understands that it cannot impose specific tools or methods on data scientists when it comes to solving problems.

- **Data science a tool to solve problems:**

  BIGmama views data science not as an end in itself but as a means to solve problems. Often, the solution to their clients' problems lies outside the realm of data science tools.

- **Hybridization:**

  BIGmama believes that the future of AI lies in what is commonly referred to as Hybrid AI (Hybrid Artificial Intelligence). This approach encompasses a set of

methodologies and techniques aimed at combining the potential of models with purely human knowledge. The company believes that this hybridization allows for putting humans at the heart of technological development and producing tools that are more efficient, easier to maintain, and less expensive.

1.1.4 Products

Historically, BIGmama is a startup specialized in the development of predictive applications for third parties. The company's approach is specific and based on the principles of hybridization between human and model capabilities. These specificities have led BIGmama to develop its own internal tools. These tools have evolved as the company's needs have changed, transitioning from Iko[1] to Hyko[2]. BIGmama is now willing to make these tools available to the broader technology ecosystem.

As a startup with a rich history in predictive application development, BIGmama has cultivated a unique approach that emphasizes the seamless integration of human expertise and model capabilities. This distinctive methodology, rooted in the principles of hybridization, has driven the company to develop its own suite of proprietary internal tools.

Over time, as BIGmama's requirements have evolved, these tools have undergone continuous refinement and adaptation. The company has transitioned from its initial Iko platform to the more advanced Hyko solution, ensuring that its tools remain aligned with its ever-changing needs and the dynamic technological landscape.

In recognition of the value these tools hold for the broader tech community, BIGmama has made the strategic decision to make them available to the larger ecosystem. By sharing its internally developed tools, the company aims to foster collaboration, knowledge exchange, and the collective advancement of technological solutions.

1.1.5 Service: Asset based consulting (ABC)

The evolving business landscape, driven by rapid technological advancements and heightened competition, necessitates innovative solutions for optimizing operations and fostering sustainable growth. Traditional consulting approaches, such as report writing, are no longer sufficient to meet the demand for specialized solutions tailored to individual client needs. This shift has led to the emergence of asset-based consulting (ABC), a specialized field focused on creating, leveraging, and maximizing the value of a company's assets. In ABC, consultants collaborate closely with clients to identify and harness tangible and intangible assets, including technology, intellectual property, and human capital, to drive operational efficiency and gain a competitive edge. Unlike traditional consulting, ABC takes a holistic and internal perspective,

[1] https://big-mama.io/en/iko
[2] https://www.hyko.ai

recognizing the unique assets and capabilities of each organization. Consultants draw on multidisciplinary expertise to assess, diagnose, and unlock hidden value through innovative asset management strategies. As industries become increasingly complex and competitive, the demand for asset-based consulting, particularly in leveraging AI assets, continues to grow across sectors. From optimizing supply chains to capitalizing on intellectual property, asset-based consulting offers a strategic framework and expertise to help organizations achieve their objectives in a dynamic business environment.

1.1.6 Hyko

Hyko is a platform that empowers you to become an AI toolmaker. It can be thought of as using "Lego" pieces from its vast toolbox, filled with AI models (over 130,000), APIs (such as Stability.ai, OpenAI, Cohere), web scraping tools, utility functions, and more.

Hyko is a powerful platform that puts the tools and resources necessary for building AI applications at your fingertips. By offering a comprehensive toolbox and streamlined workflow, Hyko empowers users to unleash their creativity and bring their AI-powered visions to life.

Many companies grapple with numerous manual tasks performed repetitively by employees, often numbering in the hundreds or thousands each month. Traditional automation tools struggled to automate these tasks fully due to their reliance on human reasoning. However, LLMs have revolutionized automation by exposing reasoning capabilities through an API.

In response to this advancement, Hyko emerged as an AI-first platform, designed not merely to streamline employee workflows but to entirely replace them from start to finish. The platform's automation builder offers unparalleled flexibility, enabling the automation of highly complex workflows with ease.

The future value of AI is anticipated to derive not solely from AI engineers or data scientists, but also from field experts who possess the capability to integrate their domain knowledge with AI technologies to address everyday challenges. This shift underscores the growing importance of domain-specific expertise in harnessing the potential of AI for practical applications.

This imperative is frequently encountered among Hyko users, who often find themselves in need of extracting vital insights from their diverse data repositories, which encompass web sources, PDF documents, and email archives. In response to this demand, Rag systems emerge as key facilitators, particularly when coupled with open-source LLMs such as Llama3, Phi3, and mixtral7B. Rag systems excel in the retrieval, aggregation, and generation of pertinent information, empowering users to distill valuable insights from their data reservoirs efficiently and effectively. This

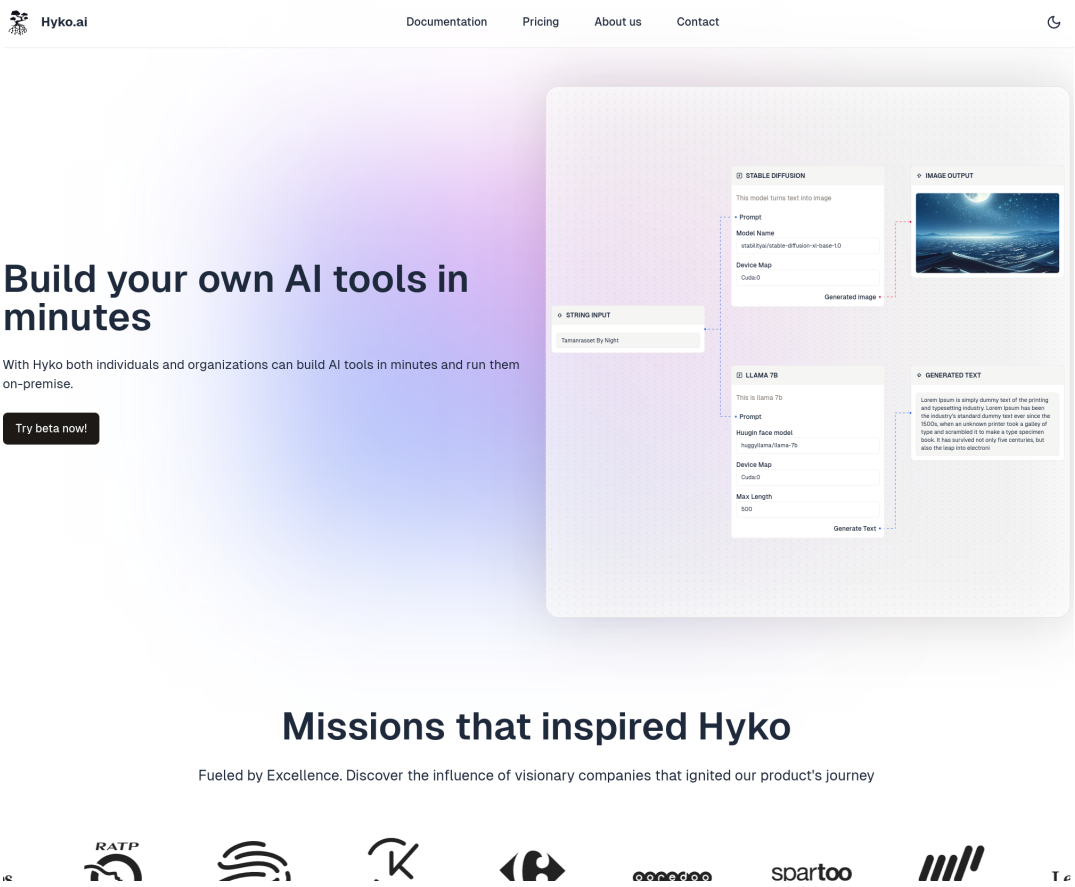

Figure 1.1: *Hyko's Landing page*

seamless integration enhances the capacity for nuanced understanding and actionable intelligence extraction, thereby augmenting the utility and versatility of Hyko across diverse information retrieval and analysis endeavors.

1.2 RAG: Enhancing LLMs with External Knowledge

LLMs showcase impressive capabilities but encounter challenges like hallucination [13], outdated knowledge, and non-transparent, untraceable reasoning processes. RAG has emerged as a promising solution by incorporating knowledge from external databases. This enhances the accuracy and credibility of the generation, particularly for knowledge-intensive tasks, and allows for continuous knowledge updates and integration of domain specific information. RAG synergistically merges LLMs' intrinsic knowledge with the vast, dynamic repositories of external databases [5].

General-purpose language models can be fine-tuned to achieve several common tasks such as sentiment analysis and named entity recognition. These tasks generally don't require additional background knowledge.

For more complex and knowledge-intensive tasks, it's possible to build a language model-based system that accesses external knowledge sources to complete tasks. This enables more factual consistency, improves reliability of the generated responses, and helps to mitigate the problem of "hallucination".

Meta AI researchers introduced a method called Retrieval Augmented Generation (RAG) [11] to address such knowledge-intensive tasks. RAG combines an information retrieval component with a text generator model. RAG can be fine-tuned and its internal knowledge can be modified in an efficient manner and without needing retraining of the entire model.

RAG takes an input and retrieves a set of relevant/supporting documents given a source (e.g., Wikipedia). The documents are concatenated as context with the original input prompt and fed to the text generator which produces the final output. This makes RAG adaptive for situations where facts could evolve over time. This is very useful as LLMs's parametric knowledge is static. RAG allows language models to bypass retraining, enabling access to the latest information for generating reliable outputs via retrieval-based generation.

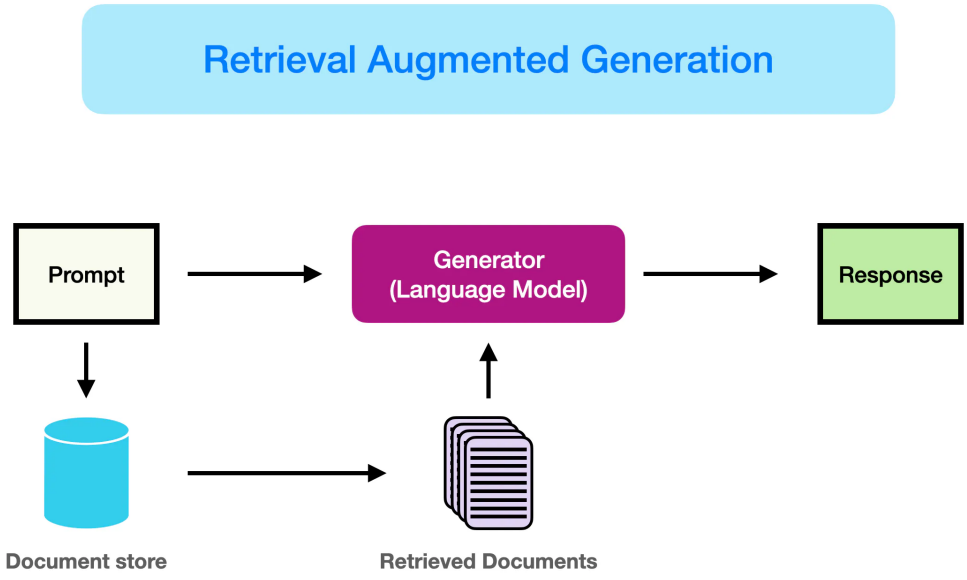

Figure 1.2: *Retrieval Augmented Generation.*

In short, the retrieved evidence obtained in RAG can serve as a way to enhance the accuracy, controllability, and relevancy of the LLM's response. This is why RAG can help reduce issues of hallucination or performance when addressing problems in a highly evolving environment.

1.3 Conclusion

In this chapter, we lay the foundation for the subsequent sections of this thesis. We introduce fundamental concepts in Retrieval-Augmented Generation (RAG) systems and Large Language Models (LLMs), along with a basic overview of the host company, BIGmama Technology.

Chapter 2

State of the Art

In recent years, the remarkable advancements in Natural Language Processing (NLP) have been primarily driven by the development of LLMs. These LLMs, such as GPT (Generative Pretrained Transformer) and BERT (Bidirectional Encoder Representations from Transformers), have demonstrated remarkable capabilities in understanding and generating human-like text. However, despite their impressive performance, LLMs still face challenges in effectively retrieving and incorporating relevant context for generating accurate and coherent responses.

Enter RAG systems, a novel approach that seeks to overcome the limitations of traditional LLMs by integrating retrieval mechanisms with generation models. RAG systems combine the strengths of both retrieval and generation techniques to enhance the quality and relevance of generated text.

This chapter provides a comprehensive exploration of RAG systems, delving into their architecture, components, training processes, applications, advantages, and challenges. We begin by establishing a foundational understanding of LLMs and their evolution, laying the groundwork for understanding the need for RAG systems. We then proceed to dissect the intricacies of RAG systems, discussing the role of retrieval in providing context and the role of generation in producing fluent responses.

Through detailed examination and analysis, we uncover the inner workings of RAG systems, exploring how retrieval and generation components interact within the architecture. Real-world applications and use cases of RAG systems across various domains are elucidated, demonstrating their potential to revolutionize tasks such as question answering, dialogue generation, and content creation.

Furthermore, we evaluate the advantages and limitations of RAG systems compared to traditional LLMs and other approaches in NLP. By examining performance metrics, challenges, and future directions, we gain insights into the transformative impact of RAG systems on the field of natural language processing.

In summary, this chapter serves as a comprehensive guide to RAG systems, offering readers a deep dive into one of the most promising advancements in NLP. As we navigate through the complexities and potentials of RAG systems, we pave the way for understanding their role in shaping the future of human-computer interaction and language understanding.

2.1 Machine Learning

2.1.1 Definition

Machine Learning, often abbreviated as ML, is a subset of artificial intelligence (AI) that focuses on the development of computer algorithms that improve automatically through experience and by the use of data. In simpler terms, machine learning enables computers to learn from data and make decisions or predictions without being explicitly programmed to do so.

At its core, machine learning is all about creating and implementing algorithms that facilitate these decisions and predictions. These algorithms are designed to improve their performance over time, becoming more accurate and effective as they process more data.

In traditional programming, a computer follows a set of predefined instructions to perform a task. However, in machine learning, the computer is given a set of examples (data) and a task to perform, but it's up to the computer to figure out how to accomplish the task based on the examples it's given.

For instance, if we want a computer to recognize images of cats, we don't provide it with specific instructions on what a cat looks like. Instead, we give it thousands of images of cats and let the machine learning algorithm figure out the common patterns and features that define a cat. Over time, as the algorithm processes more images, it gets better at recognizing cats, even when presented with images it has never seen before.

This ability to learn from data and improve over time makes machine learning incredibly powerful and versatile. It's the driving force behind many of the technological advancements we see today, from voice assistants and recommendation systems to self-driving cars and predictive analytics [6].

2.1.2 Relationships to other fields

Artificial Intelligence (AI) encompasses the field of computer science dedicated to creating systems capable of emulating human-like intelligence, problem-solving, and decision-making. Machine Learning (ML) is a subset of AI focused on enabling computers to learn from data without being explicitly programmed. Within ML, Deep Learning stands out as a subfield that employs neural networks with multiple layers to learn complex representations of data, particularly effective in tasks like image and speech recognition. ML and Deep Learning are integral components of AI, providing the framework for developing intelligent systems capable of learning, reasoning, and adapting to new information, thereby advancing the capabilities of AI across various domains.

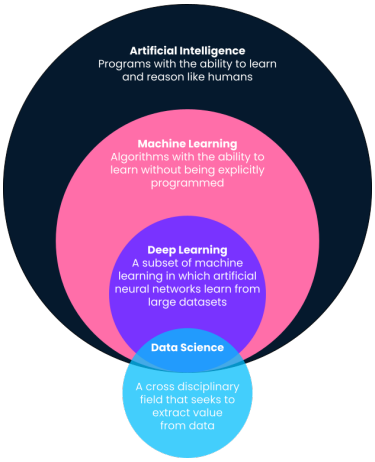

Figure 2.1: *Machine learning as subfield of AI [6].*

2.1.3 Types of Machine Learning

Machine Learning can be broadly categorized into several types based on the learning approach, the availability of labeled data, and the feedback mechanism. The main types of machine learning are:

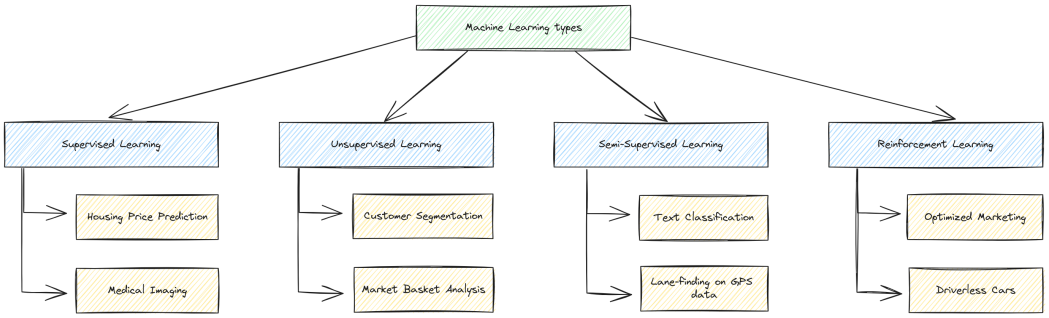

Figure 2.2: *Types of machine Learning.*

Supervised Learning

- In supervised learning, the algorithm learns from labeled data, where each input example is paired with the corresponding output label.
- The goal is to learn a mapping from inputs to outputs, allowing the algorithm to make predictions or classifications on unseen data.
- Common supervised learning tasks include regression (predicting continuous values) and classification (predicting discrete labels).

Unsupervised Learning:

- Unsupervised learning involves learning from unlabeled data, where the algorithm aims to find patterns, structures, or relationships in the data without explicit guidance.
- The algorithm discovers hidden structures or clusters within the data, facilitating tasks such as clustering, dimensionality reduction, and anomaly detection.

Semi-Supervised Learning:

- Semi-supervised learning lies between supervised and unsupervised learning, where the algorithm learns from a combination of labeled and unlabeled data.
- The presence of both labeled and unlabeled data allows the algorithm to leverage additional information and improve performance, particularly in scenarios where labeled data is scarce or expensive to obtain.

Reinforcement Learning:

- Reinforcement learning involves an agent learning to make decisions by interacting with an environment to achieve a specific goal.
- The agent receives feedback in the form of rewards or penalties based on its actions, enabling it to learn through trial and error.
- Reinforcement learning is commonly used in applications such as game playing, robotics, and autonomous systems.

2.1.4 Limitations of Machine Learning: Challenges and Considerations

Although machine learning is a powerful technique for extracting knowledge from data, it also has certain limitations that are important to consider:

- **Data dependency:** Machine learning heavily relies on the quality and quantity of training data. If the data is poorly labeled or unrepresentative, it can lead to errors in predictions.
- **Overfitting:** When the model is too complex compared to the training data, it can overfit and not generalize well to test data. This can also result in poor performance for new data.
- **Explainability:** Machine learning models can be very complex and difficult to understand. It can be challenging to understand how the model makes decisions and to explain these decisions to users.

- **Biased data:** Training data can be biased due to factors such as data selection, human biases, or measurement errors. This can lead to biased predictions for test data.
- **Lack of diversity:** Machine learning models may lack diversity in the types of data they can handle. For example, machine learning models may struggle to process unstructured data such as images, sounds, and texts.
- **Computational cost:** Machine learning algorithms may require high computational power and significant storage resources to process large amounts of data. This can be costly and time-consuming to train and implement models.

2.2 Deep Learning

2.2.1 Definition

Deep learning is a type of machine learning that teaches computers to perform tasks by learning from examples, much like humans do. Imagine teaching a computer to recognize cats: instead of telling it to look for whiskers, ears, and a tail, you show it thousands of pictures of cats. The computer finds the common patterns all by itself and learns how to identify a cat. This is the essence of deep learning.

In technical terms, deep learning uses something called "neural networks," which are inspired by the human brain. These networks consist of layers of interconnected nodes that process information. The more layers, the "deeper" the network, allowing it to learn more complex features and perform more sophisticated tasks [1].

2.2.2 Deep Learning vs. Machine Learning

Deep learning stands apart from traditional machine learning in its approach to data and learning methods. Machine learning algorithms typically rely on structured, labeled data for predictions, where specific features are defined and organized into tables. While machine learning can handle unstructured data, it often requires preprocessing to structure it. In contrast, deep learning streamlines this process by directly processing unstructured data such as text and images. It automates feature extraction, reducing reliance on human experts. For instance, in categorizing pet photos, deep learning algorithms autonomously identify key features, like ears, crucial for distinguishing between animals. In contrast, machine learning requires manual feature hierarchy establishment by human experts.

2.2.3 Deep Learning Applications

Deep learning has a wide range of applications across various domains due to its ability to learn complex patterns from large volumes of data. Some of the different

types of applications for deep learning include:

Image Recognition and Computer Vision:

- Deep learning is extensively used for tasks such as image classification, object detection, facial recognition, and image segmentation.
- Applications include self-driving cars, medical image analysis, surveillance systems, and augmented reality.

Natural Language Processing (NLP):

- Deep learning is employed for understanding and generating human language, enabling tasks such as sentiment analysis, machine translation, text summarization, and chatbots.
- Applications include virtual assistants, language translation services, social media sentiment analysis, and customer support chatbots.

These are just a few examples of the diverse applications of deep learning, demonstrating its versatility and impact across various industries and fields.

2.3 Natural Language Processing (NLP)

Natural Language Processing (NLP) serves as a crucial technology within artificial intelligence, facilitating communication between humans and computers. It represents a multidisciplinary field empowering machines to comprehend, analyze, and produce human language, thus facilitating seamless human-machine interaction. The importance of NLP manifests in its diverse applications, spanning automated customer support to instantaneous language translation, showcasing its pivotal role in modern computing.

2.3.1 What is Natural Language Processing?

NLP emerges as a vital component within artificial intelligence, dedicated to facilitating communication between computers and humans via natural language. Its core objective lies in programming computers to effectively process and analyze extensive volumes of natural language data.

NLP encompasses the task of enabling machines to comprehend, interpret, and generate human language in a manner that is not only valuable but also meaningful. OpenAI[1], renowned for pioneering sophisticated language models such as ChatGPT[2], underscores the significance of NLP in fostering the development of intelligent systems capable of comprehending, responding to, and generating text. This advancement in technology serves to enhance user-friendliness and accessibility across various applications.

2.3.2 How Does NLP Work?

NLP is a fascinating field that delves into the intricate mechanisms underlying human language comprehension and generation by machines. This section aims to unravel the complexities of NLP, shedding light on the fundamental principles and techniques that drive its functionality. By exploring the inner workings of NLP, we gain insight into how machines process and analyze natural language data, paving the way for groundbreaking applications in artificial intelligence and human-computer interaction. Through this exploration, we embark on a journey to discover the algorithms, models, and methodologies that empower machines to navigate the vast landscape of human language with precision and sophistication.

Components of NLP

Natural Language Processing is not a monolithic, singular approach, but rather, it is composed of several components, each contributing to the overall understanding

[1] https://openai.com/
[2] https://chat.openai.com

of language. The main components that NLP strives to understand are Syntax, Semantics, Pragmatics, and Discourse.

- **Syntax:** Syntax pertains to the arrangement of words and phrases to create well-structured sentences in a language.
- **Semantics:** Semantics is concerned with understanding the meaning of words and how they create meaning when combined in sentences.
- **Pragmatics:** Pragmatics deals with understanding language in various contexts, ensuring that the intended meaning is derived based on the situation, speaker's intent, and shared knowledge.
- **Discourse:** Discourse focuses on the analysis and interpretation of language beyond the sentence level, considering how sentences relate to each other in texts and conversations.

NLP techniques and methods

NLP employs a diverse array of techniques and methodologies to analyze and comprehend human language. Below are some foundational techniques utilized in NLP:

- **Tokenization:** This process involves segmenting text into individual units, such as words, phrases, or symbols, known as tokens.
- **Parsing:** Parsing entails examining the grammatical structure of a sentence to extract its meaning and syntactic relationships.
- **Lemmatization:** This technique involves reducing words to their base or root form, facilitating the grouping of different word forms with the same meaning.
- **Named Entity Recognition (NER):** NER is utilized to identify and classify entities within text, such as persons, organizations, locations, and other named items.
- **Sentiment Analysis:** This method enables the assessment of the sentiment or emotion expressed in a piece of text, aiding in understanding the underlying mood or opinion.

What is NLP Used For?

With some of the basic concepts now defined, one can explore how natural language processing is applied in the modern world.

- **Automatic Translation:** Automatic translation systems use NLP techniques to translate texts from one language to another.

- **Chatbots and Virtual Assistants:** Chatbots and virtual assistants use NLP to understand user's natural language and provide appropriate responses.
- **Automatic Summarization:** NLP algorithms can be employed to summarize lengthy documents into a few sentences.
- **Sentiment Analysis:** NLP is utilized to analyze sentiments expressed in text, which can be beneficial for businesses in assessing customer satisfaction.
- **Information Extraction:** NLP systems can extract important information such as names, locations, and dates from texts.
- **Speech Recognition:** Speech recognition systems utilize NLP techniques to convert speech into text.
- **Autocorrection:** NLP algorithms are utilized in autocorrection programs to suggest grammatical and spelling corrections.
- **Text Analysis:** NLP is used to analyze large volumes of text to detect trends, themes, and patterns.
- **Automatic Text Generation:** NLP enables the automatic generation of text for various applications, such as report writing or content creation.

2.4 Large language models (LLMS)

Large language models utilize deep neural networks to generate human-like language output by learning patterns from extensive text data. These models excel at various NLP tasks, including language generation, machine translation, question answering, and sentiment analysis.

The advent of transformer-based architectures, exemplified by GPT (Generative Pre-trained Transformer) and BERT (Bidirectional Encoder Representations from Transformers), marks a recent breakthrough in large language models. These models undergo pre-training on vast datasets, allowing them to learn from massive amounts of data. Subsequently, they can be fine-tuned for specific tasks.

In recent years, large language models like GPT-3 and the more recent GPT-4 have witnessed a significant enhancement in performance and capabilities, achieving remarkable results across a diverse array of benchmarks.

LLMs use various NLP tasks to achieve their goals. For example, tokenization can be used for pricing the LLM usage when used tokens are counted [8], the models summarize texts, answer questions, etc. Different applications that use NLP are search engines,language translation services, chatbots, text summarization, and

question-answering. While LLMs can incorporate all these tasks and applications, their performance may differ from those designed for a specific task.

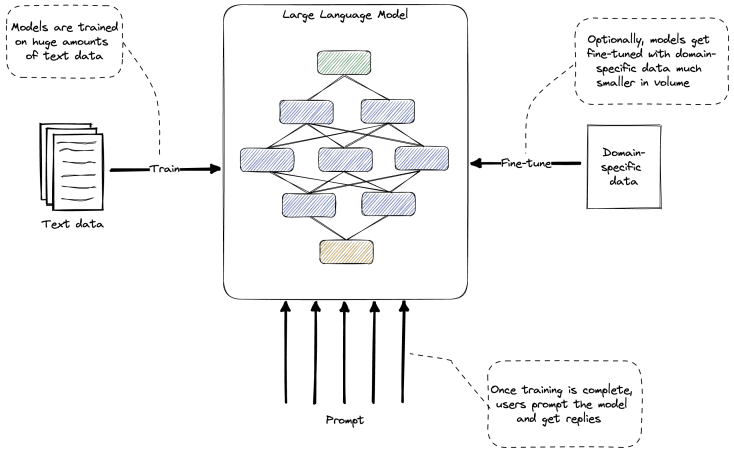

Figure 2.3: *Training, fine tuning, and prompting.*

2.4.1 History of Large Language Models

Over the years, the development of LLMs has been propelled by advancements in NLP, machine learning, and computing resources. This section offers a comprehensive overview of the significant milestones and breakthroughs that have shaped the evolution of LLMs.

Pre-Transformer Era

1. **Eliza (1964-1966):** One of the earliest NLP programs, Eliza was a simple chatbot developed by Joseph Weizenbaum, designed to mimic a Rogerian psychotherapist. It used pattern matching and substitution to generate responses, laying the foundation for future conversational AI systems.

2. **Statistical language models (1980s-2000s):** Statistical language models, such as n-grams, were developed to predict the probability of a word in a sequence based on the preceding words. These models were widely used in tasks like speech recognition and machine translation but struggled with capturing long-range dependencies in text.

3. **Neural language models (2003-2013):** Neural language models, such as feedforward and recurrent neural networks (RNNs), emerged as an alternative to statistical models. Bengio et al. (2003) introduced a feedforward neural network for language modeling, while Mikolov et al. (2010) popularized RNN-based models with the release of the RNNLM toolkit.

4. **Long Short-Term Memory (LSTM) models (1997-2014):** Hochreiter and Schmidhuber (1997) introduced LSTMs as a solution to the vanishing gradient problem faced by RNNs. LSTMs were later used in sequence-to-sequence models for tasks like machine translation (Sutskever et al., 2014) and formed the basis for several LLMs.

Transformer Era

1. **Attention is All You Need (2017) [12]:** Vaswani et al. introduced the transformer architecture, which replaced the recurrent layers in traditional models with self-attention mechanisms. This breakthrough enabled the development of more powerful and efficient LLMs, laying the foundation for GPT, BERT, and T5.

2. **GPT (2018) [2]:** OpenAI released the Generative Pre-trained Transformer (GPT), a unidirectional transformer model pre-trained on a large corpus of text. GPT showcased impressive language generation capabilities and marked the beginning of a new era of LLMs.

3. **BERT (2018) [4]:** Google introduced the Bidirectional Encoder Representations from Transformers (BERT) model, which used a masked language modeling objective to enable bidirectional context representation. BERT achieved state-of-the-art performance on numerous NLP tasks, revolutionizing the field.

4. **GPT-2 (2019) [9]** OpenAI released GPT-2, a significantly larger and more powerful version of the original GPT. GPT-2 demonstrated impressive text generation capabilities, generating coherent and contextually relevant text with minimal prompting.

5. **T5 (2019) [10]:** Google's Text-to-Text Transfer Transformer (T5) adopted a unified text-to-text framework for pre-training and fine-tuning, allowing it to be used for various NLP tasks by simply rephrasing the input and output as text. T5 demonstrated state-of-the-art performance across multiple benchmarks.

6. **GPT-3 (2020) [3]:** OpenAI unveiled GPT-3, an even larger and more advanced version of the GPT series, with 175 billion parameters. GPT-3's performance on various NLP tasks with minimal fine-tuning raised questions about the capabilities and potential risks associated with LLMs.

The history of large language models is marked by continuous innovation and progress in the field of natural language processing. As we move forward, LLMs are expected to grow in size, capability, and efficiency, enabling more complex and human-like language understanding and generation. However, the development of

these models also brings forth ethical and practical challenges that must be addressed, such as biases, misuse, and computational resource requirements. It is essential for researchers and practitioners to balance the potential benefits of LLMs with their limitations and risks, fostering responsible development and use of these powerful tools.

2.4.2 Neural networks

Neural Networks (NNs) are computational models composed of layers of neurons that can learn from data. They are versatile and robust models capable of learning directly from raw data, without the need for manually selected features. NNs employ a training algorithm known as backpropagation, which adjusts the model's parameters based on a loss function.

Feedforward networks

A feedforward neural network is characterized by its architecture, devoid of cycles, where the output of layer i can be computed using the outputs from layer $i-1$. The architecture of a neural network encompasses its structure, including the number of hidden layers and neurons, as well as the functions employed for computations. These selections, known as hyperparameters, are parameters whose values are not determined by the learning algorithm. Figure 2.4 shows a typical feedforward network architecture.

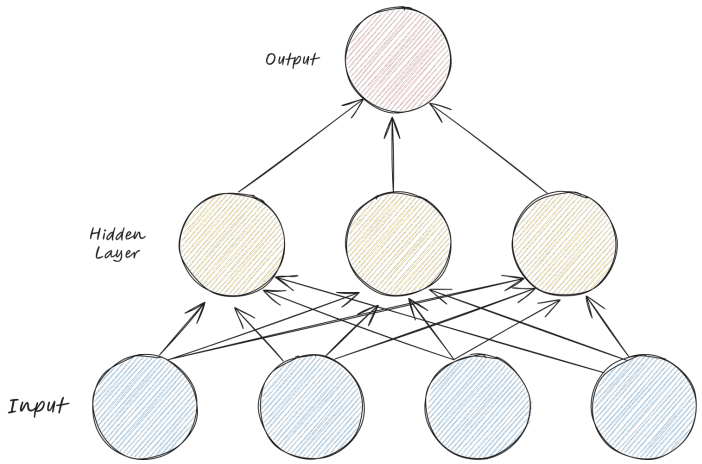

Figure 2.4: *Example of a feedforward neural network architecture. The network has an input layer with four neurons, one hidden layer with three neurons and an output layer with a single neuron.*

As depicted in Figure 2.4, neural networks comprise an input layer, n hidden layers, and an output layer. The input layer receives the data that the network needs

to process, which then traverses through the hidden layers before reaching the output layer. The output layer provides the model's result for the given input data. When a neural network contains multiple hidden layers, it qualifies as a deep neural network (DNN) and falls within the domain of deep learning [7]. Each layer consists of i neurons, with connections between each neuron in a layer and every neuron in the previous layer, except for the input layer.

Neurons serve as fundamental computational units and, as previously indicated, establish connections with all neurons in the preceding layer. Each connection is characterized by a numerical parameter referred to as a weight.

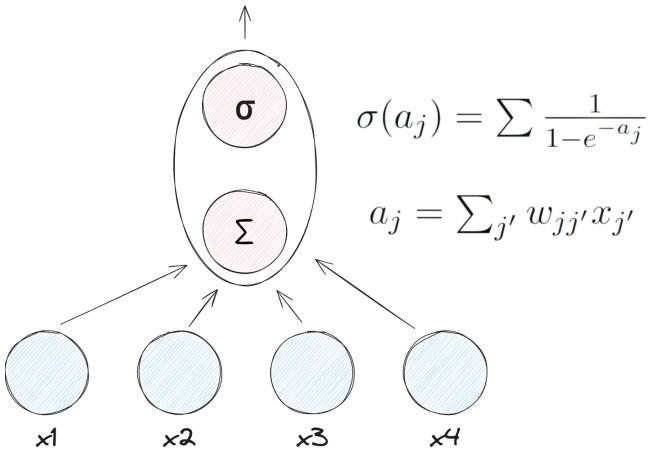

Figure 2.5: *Example of computation within a single neuron, where the weighted sum of inputs is passed through an activation function to get the output of the neuron.*

As show in Figure 2.5, the neuron receives inputs from neurons of the preceding layer, denoted as $x_1, x_2, ..., x_n$. Each neuron-to-neuron connection is assigned a weight, representing the strength of the connection. The output from a preceding neuron is multiplied by the weight of the connection and then summed for each connected neuron, yielding the weighted sum of values.

Although not visually represented in Figure 2.5, a bias parameter is introduced to the weighted sum, thereby altering a_j to

$$a_j = \sum_{j'} w_{jj'} x_{j'} + b \tag{2.1}$$

The bias serves to adjust the neuron's output independently of the input. This capability enables the model to alter the neuron's output during the learning process without necessitating adjustments to the weights, thereby facilitating finer control.

The weighted sum is subsequently forwarded to an activation function, which determines the neuron's output or its degree of "activation." An illustration of such an activation function is the sigmoid function denoted as σ, as depicted in Figure

2.5. The mathematical expression for the sigmoid function is:

$$\sigma(a_j) = \frac{1}{1 + e^{-a_j}} \tag{2.2}$$

According to Nielsen [19], two other common activation functions include $\tanh \phi$, which is defined as

$$\phi(a_j) = \tanh(a_j) = \frac{e^{a_j} - e^{-a_j}}{e^{a_j} + e^{-a_j}} \tag{2.3}$$

and Rectified Linear Unit (ReLU), which is defined by equation

$$R(a_j) = max(0, a_j) \tag{2.4}$$

Symbol a_j refers to the result of adding together the weighted sum and bias. The outputs of these functions are visualized in Figure 2.6.

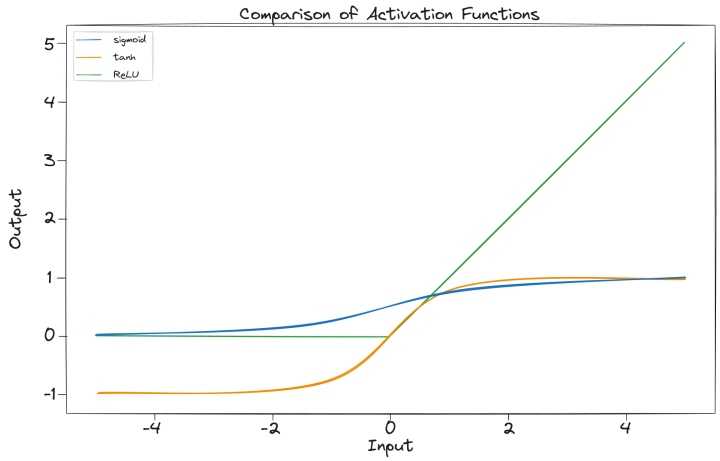

Figure 2.6: *Visualization of the sigmoid, tanh and ReLU activation function outputs.*

The outputs produced by these activation functions exhibit non-linearity, signifying that the input parameter does not linearly determine the output value, as evident from Figure 2.6. This concept holds significance in neural networks, enabling them to learn non-linear systems [20]. While several activation functions are commonly employed, ReLU has gained prominence in deep learning due to its demonstrated efficacy in enhancing the performance of numerous neural networks [18]. Typically, the same activation function is applied across all neurons, except for those in the output layer.

The choice of activation function for the output layer hinges on the specific task assigned to the neural network. In regression-based tasks, a linear activation function is employed to obtain the summed weighted output of the preceding neurons. Conversely, for classification problems involving k output neurons, a softmax function is

often utilized. The softmax function is defined as:

$$\hat{y} = \frac{e^{a_k}}{\sum_{j=1}^{J} e^{a_j}} \tag{2.5}$$

and ensures that all neuron outputs sum to one on the output layer.

Recurrent Neural Networks

Recurrent Neural Networks (RNNs) are specialized neural networks designed for processing sequential data. They operate by incorporating iterations that retain past states, enabling the network to leverage previous inputs as context for the current input [8]. Text serves as a prime example of sequential data, where individual words can be viewed as singular data points within the sequence. Consequently, RNNs can effectively process textual input by utilizing preceding words to predict the subsequent ones. Figure 5 provides an illustration of a basic RNN architecture.

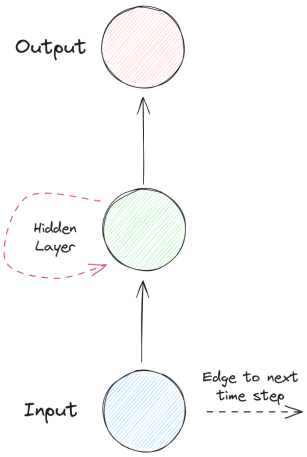

Figure 2.7: *Visualization of an RNN with one input neuron, one hidden neuron and one output neuron.*

The neuron on the hidden layer stores the hidden state, as visualized by the dashed line. The activation of the hidden state can be defined as

$$H_t = \phi(X_t W_{xh} + H_{t-1} W_{hh} + b_h) \tag{2.6}$$

where H_t is the hidden state at time step t, ϕ_t is the activation function of the neuron, X_t is the neuron input at time step t, W_{xh} is a weight matrix, W_{hh} is the weight matrix of the hidden state and b_h is bias.

RNNs are trained utilizing the backpropagation through time (BPTT) algorithm, which is an adaptation of the standard backpropagation algorithm tailored for networks with a sequential order of computations. In this setup, the output at time

step t depends on the states from preceding steps [21]. During training, the forward pass computes through all time steps, and the resultant loss is utilized to update the parameters across all time steps. One way to conceptualize this process is by envisioning an unrolled RNN, where the recurrent loops are eliminated, resulting in a network structure akin to a feedforward neural network. However, due to the nature of the hidden state dynamics, RNNs are notorious for encountering gradient-related issues during training. As illustrated in Figure 2.8, if the weight associated with the dotted line is less than one, future values may decrease exponentially [18]. Conversely, weights that start to grow can lead to the exploding gradient problem [8]. When gradients become too small or too large, it can impede the training process of the model.

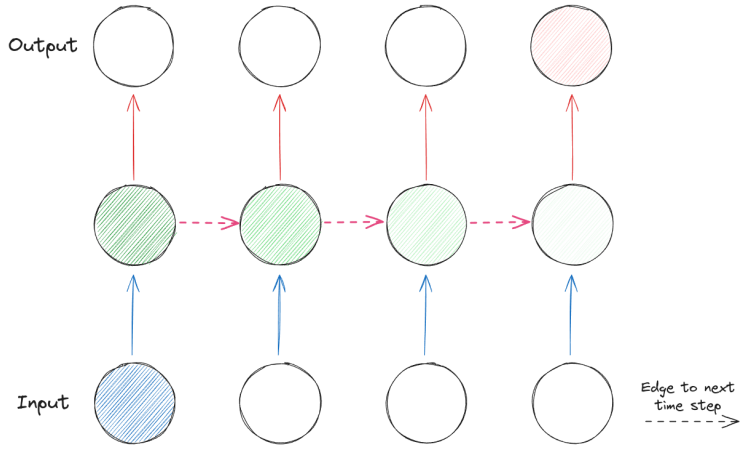

Figure 2.8: *Visualization of the vanishing gradient problem, which is indicated by the hidden neuron color fading away.*

Despite offering a robust framework for sequential learning, RNNs are hindered by significant limitations arising from the aforementioned issues. One critical limitation stems from the gradient problem encountered during training, which can constrain the effective handling of lengthy sequences. Consequently, RNNs may struggle to capture dependencies between inputs across extended sequences. To address these challenges, numerous techniques and alternative architectures have been proposed. Among these, the Long Short-Term Memory (LSTM) architecture stands out as one of the most prominent examples, and its discussion follows.

Long Short-Term Memory

The Long Short-Term Memory (LSTM) [9] architecture addresses the gradient-related challenges inherent in RNNs by incorporating constant error, memory cells, and gate units. This design enables the network to effectively handle sequences spanning over 1000 time steps. The memory cells employ three gate units: an input gate I_t, an

output gate O_t, and a forget gate F_t, which regulate the flow of information. Specifically, the input gate facilitates the addition of information to the memory cell, the output gate facilitates information retrieval from the cell, and the forget gate facilitates cell resetting [8]. Moreover, the memory cells possess an internal state with a self-connected recurrent edge featuring a constant weight, ensuring consistent error propagation across time steps and mitigating previously discussed gradient-related issues [18]. Additionally, a candidate memory cell $\tilde{C}$, utilized for proposing new information, is integrated with the old memory content C_{t-1} through the gates to govern the preservation of old memory in the new memory C_t [8]. Figure 7 illustrates the complete architecture of the LSTM memory cell.

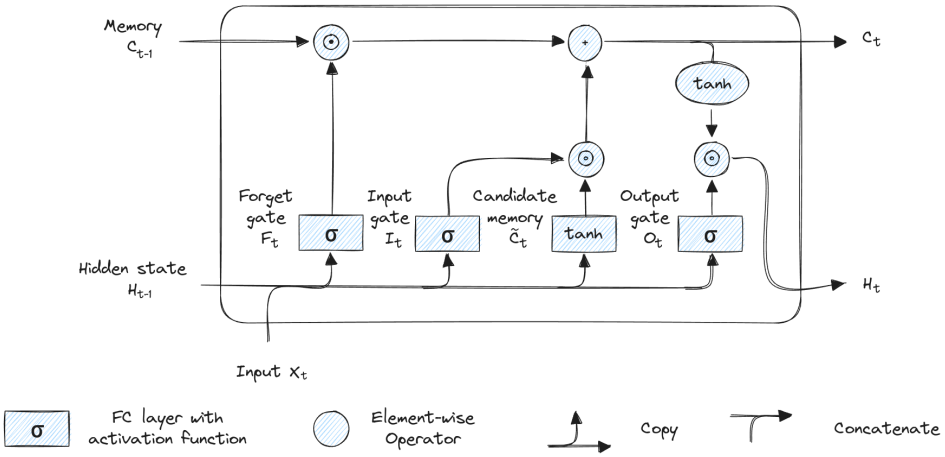

Figure 2.9: *Visualization of an LSTM memory cell.*

Although the LSTM architecture enhances performance compared to the RNN architecture discussed in section 2.4.2, it still possesses limitations. Like the RNN architecture, models utilizing LSTM must process the previous time step before computing the next, rendering them computationally intensive and impeding parallelization. Additionally, LSTM typically lacks an explicit attention mechanism and tends to prioritize the most recent words. These constraints are addressed by the Transformer model, which will be introduced next.

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