

PEOPLE'S DEMOCRATIC REPUBLIC OF ALGERIA
MINISTRY OF HIGHER EDUCATION AND SCIENTIFIC RESEARCH
UNIVERSITY MUSTAPHA STAMBOULI OF MASCARA



Faculty of Exact Sciences
Department of Computer Science
Dissertation

Submitted in partial fulfilment of the requirements for Master degree in Computer Science

Option: Artificial Intelligence

Theme

Enhancing Legal Information Access and Reasoning with Retrieval-Augmented LLMs for Juridical Data

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Month 2025

Acknowledgements

First of all, praise and thanks to Allah Almighty for giving us all the patience, courage, will and motivation that allowed us to accomplish this work.

My deepest gratitude goes to my supervisor, **Mr Salem Mohamed** for his patient guidance, insightful feedback, and continuous encouragement throughout the course of this work .

I would like to acknowledge the members of the jury for their interest

I am also especially thankful to my parents, family, and friends for their unwavering support, love, and motivation at every step of this journey.

I would like to thank everyone who helps me to improve my work. and who gave me any remark that helped me to perfect this manuscript.

All the teachers of the University MUSTAPHA STAMBOULI DE LA WILAYA
MASCARA For the good contribution of this work.



Dedication

This work is dedicated with deep love and gratitude to:

My dear parents, whose unwavering support, sacrifices, and constant prayers have been the foundation of everything I've achieved. Your belief in me gave me the strength to persevere through every challenge.

My supervisor, Mr. [Mr Salem Mohamed], whose patient guidance, insightful feedback, and continuous encouragement made this journey not only possible but meaningful. Your dedication, expertise, and belief in my potential have left a lasting impact on me both academically and personally.

My beloved sister, for being my greatest cheerleader and my constant source of emotional support. Your encouragement and care during the toughest moments meant the world to me.

My wonderful friend [nial hadjer], for always being there with kind words, late-night conversations, and unshakable support.

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List of Abbreviations

LLM:	Large Language Models
RAG:	Retrieval-Augmented Generation
ANN	Artificial Neural Network
GPT:	Generative Pre-trained Transformer
BERT:	Bidirectional Encoder Representations from Transformers
T5:	Text-to-Text Transfer Transformer
FFN:	Feed-Forward Network
LSTM:	Long Short-Term Memory
MT:	Machine Translation
NLG:	Natural Language Generation
NLP:	Natural Language Processing
NLU:	Natural Language Understanding
RNN:	Recurrent Neural Network
Seq2Seq:	Sequence to Sequence
SASRec:	Self-Attentive Sequential Recommendation
TF-IDF:	(Term Frequency-Inverse Document Frequency)
QLM :	(Query Likelihood Model)

General introduction

Context :

In recent years, the legal domain has witnessed a growing interest in the application of advanced natural language processing techniques to improve access to legal information and automate reasoning over juridical data. Legal texts—such as statutes, court decisions, and regulatory documents—are often dense, context-dependent, and linguistically complex, making them challenging to interpret both for non-experts and legal professionals. This complexity is further amplified in multilingual and region-specific legal systems, such as Algeria’s[1], where access to structured and searchable legal data remains limited.

Large Language Models (LLMs) have emerged as powerful tools for understanding and generating human-like text, showing promise in tasks such as legal question answering, case summarization, and document classification[2]. However, their reliance on static training data and the inherent difficulty in capturing fine-grained, up-to-date legal knowledge limits their effectiveness in dynamic and high-stakes domains like law. To bridge this gap, Retrieval-Augmented Generation (RAG) architectures have been proposed, combining the linguistic capabilities of LLMs with external knowledge retrieval systems. This hybrid approach enables models to access and reason over relevant documents at inference time, offering a more grounded and contextually aware output [3].

Although these advances have been made, several challenges persist—particularly in the selection of the most relevant documents from large legal corpora. Poor retrieval quality can significantly degrade the performance and reliability of RAG-based systems. Therefore, refining the retrieval process remains a crucial area of research, especially in low-resource and domain-specific contexts [4] such as Arabic legal data in Algeria.

Problem Statement :

- Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG) architectures offer strong potential for legal AI applications. However, their performance is often constrained by weaknesses in the retrieval process.

- The selection of irrelevant or loosely related documents can result in hallucinated or misleading responses, which is especially critical in the legal domain.
- In the Algerian legal context[1], this problem is exacerbated due to:
 - The scarcity of structured and standardized legal resources.
 - The dominance of unstructured legal texts written in Arabic, often lacking annotations or metadata.

These limitations make the retrieval step a key bottleneck in the effectiveness of legal AI systems. This thesis aims to address this challenge by developing a more adaptive and context-sensitive retrieval mechanism tailored to the legal domain, specifically focusing on Arabic legal documents.

Objectives :

This research aims to explore and improve the integration of LLMs and retrieval systems in the legal field, with a focus on the Algerian legal context. The main objectives are as follows:

- To investigate the potential of LLMs and Retrieval-Augmented Generation models for processing Arabic legal texts .
- To identify and address challenges in document retrieval, particularly the issue of selecting the optimal number of candidate documents (the k-selection problem).
- To develop and share a curated dataset of Arabic legal case texts from Algeria, contributing to resources in low-resource legal NLP.

Contributions :

This thesis makes the following key contributions:

- A domain-specific chatbot designed to assist users in navigating Algerian legal case information using natural language queries.
- train a complete Retrieval-Augmented Generation (RAG) system fully tailored to Arabic, addressing both the retriever and generator components. This represents one of the first domain-specific implementations of a fully Arabic end-to-end RAG pipeline
- The creation of a new dataset of Arabic-language legal cases from Algeria, filling a gap in publicly available legal resources for this jurisdiction.
- A Dynamic Candidate Selection mechanism, which improves the retrieval phase of RAG by adaptively selecting relevant documents based on contextual thresholds.

Structure :

The thesis is organized into four main chapters:

- Chapter 1: Large Language Models – An overview of LLMs and their capabilities, with a focus on applications in legal NLP.
- Chapter 2: Retrieval-Augmented Generation – A detailed examination of RAG architectures, their strengths, and limitations in legal contexts.
- Chapter 3: Candidate Selection in Retrieval – The chapter reviews existing k selection methods, followed by a proposed dynamic selection method to improve retrieval efficiency and generation quality.
- Chapter 4: Experimental Results – Summarizes the dataset, experimental setup, and key findings, with analysis of hyperparameter effects and system performance.

Chapter 1

Large Language Models (LLMs)

1.1 Introduction

Large Language Models (LLMs) represent a transformative leap in Natural Language Processing (NLP), allowing machines to perform complex language tasks with remarkable accuracy. From generating coherent text to answering nuanced questions, LLMs have pushed the boundaries of what AI can achieve. This chapter delves into the architecture and principles behind LLMs, their development through scaling and training techniques, and the models that have defined this field. It also addresses the challenges these models face and their expanding role in various real-world applications.

1.2 Natural language processing (NLP)

Natural Language Processing (NLP) is a field within artificial intelligence (AI) that concentrates on the interaction between computers and human language. It involves the development of algorithms and models that allow machines to comprehend, interpret, and generate human language in a meaningful context. NLP is crucial for enabling computers to process and respond to human language effectively, as demonstrated by features like Google's predictive text in keyboards and language translation systems that manage multiple languages efficiently [5]

1.2.1 Historical development of (NLP)

The figure below presents a timeline outlining the key developments in Natural Language Processing (NLP) beginning with rule-based approaches in the 1950s and progressing through the rise of statistical methods and early neural networks in the late 1980s. It then highlights

the impact of deep learning from the 2000s onward, leading to the development of pre-trained models like BERT and GPT. The timeline concludes with the emergence of large language models (LLMs) from 2019 to the present, marking a significant shift in NLP research and applications.

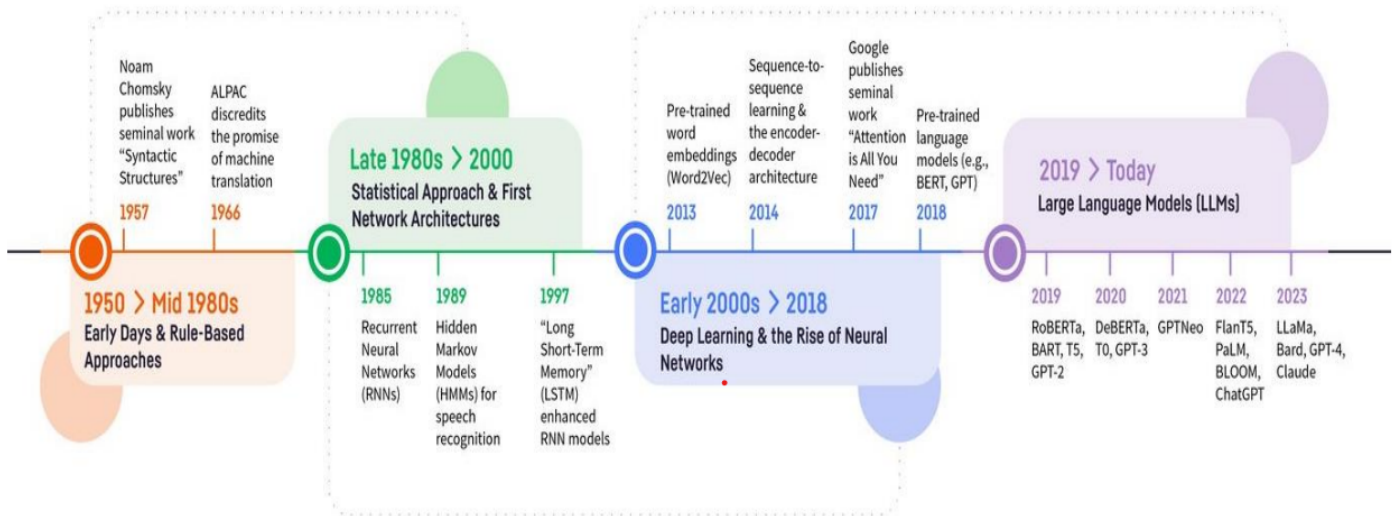


Figure 1.1: Historical development of (NLP)

1.2.2 Importance of natural language processing

1. **Efficient Data Processing:** NLP enables businesses to process and analyze large volumes of unstructured, text-heavy data that would be challenging to handle otherwise..
2. **Understanding Human Language:**NLP can interpret complex language elements, such as acronyms, abbreviations, and context, improving the accuracy of machine learning models..
3. **Advancements in Technology:**Improvements in deep learning and machine learning have made NLP more effective, expanding the types of data that can be analyzed.
4. **Natural Interactions:** NLP allows users to interact naturally with AI chatbots and voice assistants, like Siri, without needing to use specific,predefined[6].

1.3 Neural Networks in NLP

A neural network, or artificial neural network, is a machine learning algorithm inspired by the human brain. It is a key component of deep learning, a branch of machine learning

effective in solving complex problems like image recognition and language processing. Unlike traditional computer programs that use a step-by-step algorithmic approach, neural networks learn from examples, mimicking the way neurons in the human brain operate. They consist of interconnected nodes (processing elements) that work together in parallel to solve specific problems.

A neural network has three basic sections, or parts, each composed of "nodes."

The input layer is the first part, receiving raw data, with each node (or neuron) representing a feature of this data. The hidden layers, which form the intermediate section, perform various transformations and computations, enabling the network to learn complex patterns and relationships. Finally, the output layer, which is the last part, produces the network's output, with the number of nodes corresponding to the desired output classes or regression values [5].

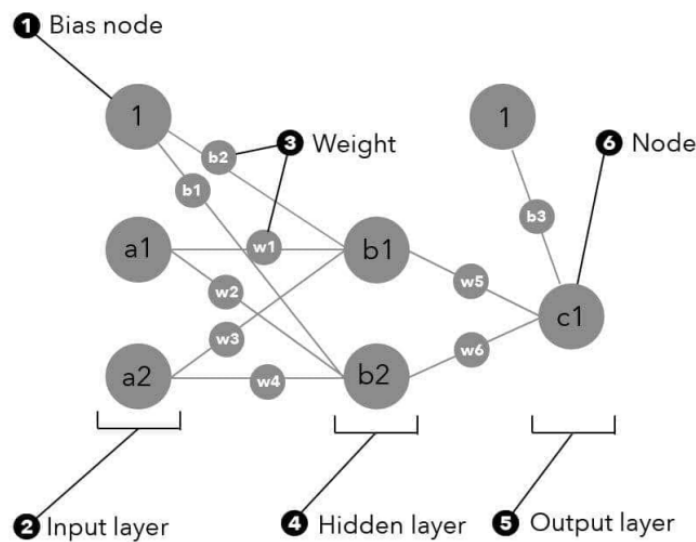


Figure 1.2: Artificial Neural Network (ANN).

1.3.1 Basics Concepts in Neural Networks

Weights

Variables on the edges between nodes that are multiplied with node outputs to form the input for the next layer. Weights are crucial for training and tuning a neural network and are often initialized within a range of -1 to 1.

Biases

Additional nodes in hidden and output layers that connect to every node within their respective layers but not to the previous layer. Biases add a constant value (typically 1 or -1) to the input of a layer, helping shift the activation function and aiding in effective learning.

Activation Functions

These functions introduce non-linearity to the network, enabling it to learn and model complex data patterns. Common activation functions include the sigmoid, hyperbolic tangent (tanh), and rectified linear unit (ReLU). [7].

1.3.2 Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs) are a type of neural networks specifically designed for modeling and processing sequential data, such as text or time series. They are particularly well-suited for handling inputs of variable length by maintaining a dynamic internal state. An RNN comprises a hidden state h and an optional output y , and operates over an input sequence $x = (x_1, x_2, \dots, x_t)$.

At each time step t , the hidden state $h^{(t)}$ is updated based on the previous hidden state $h^{(t-1)}$ and the current input x_t using a non-linear transition function f , as shown in Equation 1.1:

$$h^{(t)} = f(h^{(t-1)}, x_t) \quad (1.1)$$

The function f can be a simple non-linear activation such as the logistic sigmoid or hyperbolic tangent, or a more complex function such as a Long Short-Term Memory (LSTM) unit or a Gated Recurrent Unit (GRU).

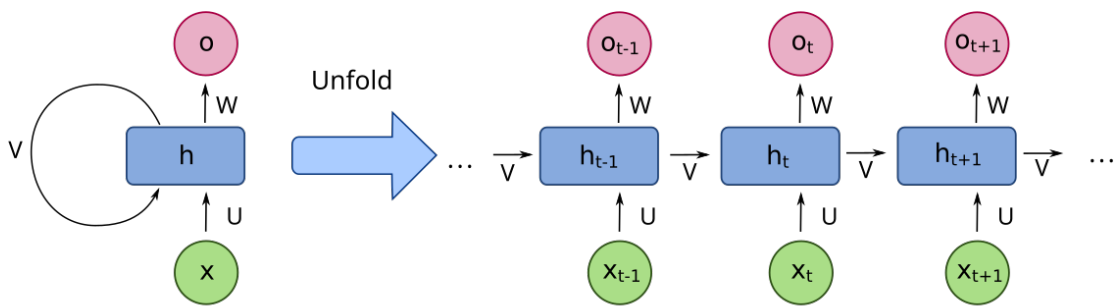


Figure 1.3: Recurrent Neural Networks (RNNs).

This architecture enables RNNs to retain information from previous time steps, allowing the model to capture temporal dependencies and patterns that span across various positions

in the sequence. Furthermore, the use of shared parameters across time steps facilitates generalization over sequences of different lengths and enhances the network's ability to learn long-range dependencies.

Despite known challenges, such as difficulties in capturing long-term dependencies due to issues like vanishing gradients, RNNs remain highly effective for tasks that require sequential reasoning or contextual awareness. As a result, they are widely used in applications ranging from time series forecasting to natural language processing. [8]

1.3.3 Long-Short Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks, designed by Hochreiter and Schmidhuber, are an improved version of recurrent neural networks (RNNs) designed to learn long-term dependencies in sequential data, making them suitable for tasks like time series forecasting and language translation. They address the limitations of traditional RNNs by introducing a memory cell that maintains information over extended periods. This memory cell is regulated by three gates—input, forget, and output gates—which control the flow of information in and out of the cell as shown in the fig [9]

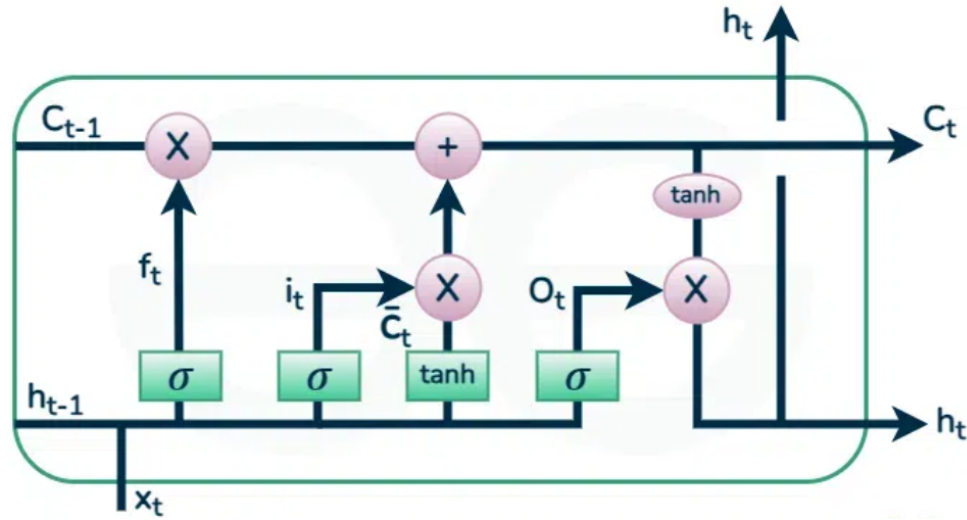


Figure 1.4: Long-Short Term Memory (LSTM).

Forget Gate: Decides what information to discard from the cell state

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1.2)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (1.3)$$

$$\tilde{c}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (1.4)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (1.5)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (1.6)$$

$$h_t = o_t \odot \tanh(C_t) \quad (1.7)$$

It is worth mentioning that Bidirectional LSTM networks extend the traditional LSTM architecture by processing data in both forward and backward directions. This approach enables the network to capture dependencies from both past and future contexts, improving its ability to resolve temporal dependencies.

Bidirectional LSTMs are particularly effective at handling multidimensional problems, encapsulating spatially and temporally distributed information, and dealing with incomplete data through flexible connection mechanisms [10].

1.4 Transformer Architecture

The Transformer architecture is a deep learning model introduced in June 2017 by Vaswani et al. from Google Brain. Their paper, titled "Attention Is All You Need," presented a groundbreaking approach to processing sequential data through the use of a self-attention mechanism. This innovative method allows the model to assign different levels of importance to various parts of the input, enabling it to capture long-range dependencies much more effectively than earlier models like RNNs and LSTMs. The original Transformer model is structured as a stack of six layers, where the output of each layer i serves as the input to the subsequent layer $i+1$, continuing this process until the final prediction is reached. It features a six-layer encoder on the left and a corresponding six-layer decoder on the right, both of which work together to transform input sequences into meaningful outputs. Each encoder and decoder consists of six identical layers that allow the model to process and generate language efficiently [11].

1.4.1 Encoder and Decoder Stacks

Encoder

Each layer in the encoder consists of two sub-layers:

Multi-head self-attention mechanism: This allows the model to focus on different parts of the input sequence.

Position-wise feed-forward network: A fully connected network applied to each position separately and identically.

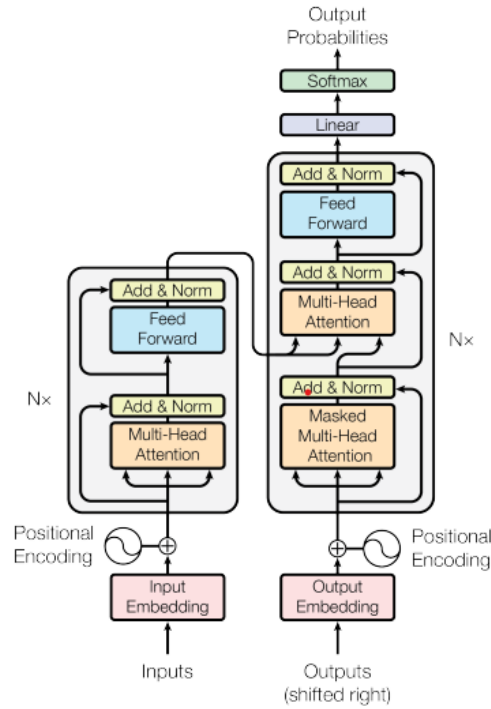


Figure 1.5: The Transformer - model architecture..

Residual Connections: Residual connections are applied around each sub-layer, followed by layer normalization. The output of each sub-layer is computed as $\text{Layer Norm}(x + \text{Sub-layer}(x))$.

Output Dimension: All sub-layers and embedding layers output vectors of dimension $d_{\text{model}} = 512$.

Decoder

Similar to the encoder, the decoder also has 6 identical layers, each containing the same two sub-layers: Multi-head self-attention mechanism, Position-wise feed-forward network.

Additional Sub-layer: The decoder includes a third sub-layer that performs multi-head attention over the output of the encoder stack.

Residual Connections and Normalization: Like the encoder, residual connections are applied around each sub-layer, followed by layer normalization.

Masked Self-Attention: The self-attention mechanism in the decoder is modified to prevent positions from attending to subsequent positions, ensuring that predictions for position i depend only on the known outputs at positions before i [12].

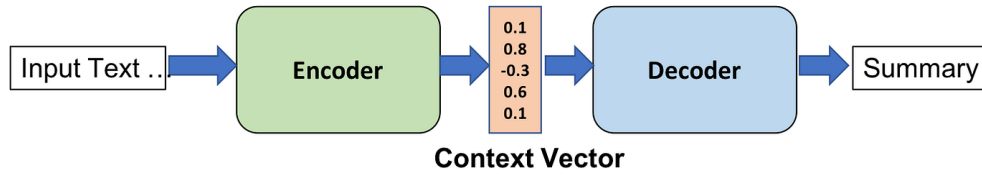


Figure 1.6: Encoder and Decoder Stacks

1.4.2 Self-Attention Mechanism in Transformers

Self-attention is a fundamental component of the Transformer architecture, enabling the model to dynamically assess the relevance of each token in a sequence relative to others. This mechanism facilitates the capture of contextual dependencies and semantic relationships among words.

The self-attention operation involves three key components derived from the input embeddings: the *Query* (Q), *Key* (K), and *Value* (V) matrices. The attention scores are computed by taking the dot product between the query vector of a token and the key vectors of all tokens in the sequence:

$$\text{Attention}(Q, K, V) = \text{softmax} \left(\frac{QK^\top}{\sqrt{d_k}} \right) V \quad (1.8)$$

Here, d_k denotes the dimension of the key vectors, which is used to scale the dot product to prevent excessively large values that could hinder gradient flow. The softmax function transforms the scaled scores into a probability distribution, which serves as the attention weights. These weights are then applied to the value vectors to compute a weighted sum, yielding the output representation for each token.

This mechanism allows each token to selectively focus on other relevant tokens, thereby enhancing the model's capacity to understand complex linguistic patterns [12].

1.4.3 Positional Encoding:

Since self-attention mechanisms do not inherently capture the order of words, positional encoding is added to the word embeddings to provide information about the relative position of each word in the sequence. These encodings are added directly to the input embeddings, allowing the model to consider both the position and the content of each word during processing[13].

1.4.4 Role of Multi-Head Attention

Multi-head attention is a key enhancement of the self-attention mechanism that significantly improves the model's representational capacity. Instead of relying on a single attention operation, the mechanism projects the input into multiple distinct sets of Query, Key, and Value vectors, referred to as attention heads. Each head independently performs self-attention, allowing the model to capture diverse contextual relationships from different subspaces of the input representation.

The outputs of all attention heads are then concatenated and linearly transformed, producing a unified representation that integrates the complementary information gathered by each head. This mechanism enhances the model's ability to capture complex patterns across different positions in the sequence, thereby improving overall performance in a variety of natural language understanding tasks[12].

1.4.5 The Rise of Transformers in Natural Language Processing

Transformers have revolutionized the field of Natural Language Processing (NLP) by introducing a powerful and efficient way to handle textual data. This advancement has led to the creation of highly effective models like BERT and GPT, with its deep bidirectional context, excels at understanding and improving performance across various NLP tasks. GPT, on the other hand, is renowned for generating coherent and contextually relevant text, significantly advancing applications such as text generation and translation[14].

Scalability: Transformers efficiently handle large datasets and long sequences, overcoming the limitations of RNNs. This scalability allows for training with billions of parameters, enhancing model capabilities.

Rich Contextual Understanding: The self-attention mechanism in transformers captures relationships between words across the entire sequence, enabling deep contextual understanding and more accurate language processing.

Model Efficiency: Transformers enable parallel processing, which speeds up training and makes them more efficient than sequential models like RNNs. This efficiency supports the rapid development and deployment of advanced language models[12].

1.5 Emergence of Large Language Models (LLMs)

Large Language Models (LLMs) are advanced artificial intelligence systems designed to process and generate human-like text. They are typically based on transformer architectures and are characterized by their enormous scale, with billions of parameters. LLMs are pre-

trained on vast amounts of text data in a self-supervised manner, enabling them to develop a broad understanding of language. They are capable of performing a wide range of tasks with minimal task-specific fine-tuning, often achieving significant performance improvements through few-shot or zero-shot learning[15].

1.5.1 Scaling in Large Language Models (LLMs)

Scaling is crucial in the evolution of large language models. The history of scaling shows that increasing both model size and dataset size leads to significant improvements in performance across various NLP tasks. For instance, early work by Brants et al. (2007) demonstrated the benefits of using language models trained on vast datasets, such as 2 trillion tokens, which led to significant advancements in machine translation quality. This was followed by efforts like those of Heafield et al. (2013), who scaled traditional models to Web-scale data, and Jozefowicz et al. (2016), who scaled LSTMs to 1 billion parameters, achieving state-of-the-art results on large benchmarks. The advent of transformer-based models marked a significant shift. Models like BERT, GPT-2, and GPT-3, with their enormous parameter counts—up to 175 billion for GPT-3—demonstrated that scaling up not only the model but also the dataset size yields substantial gains in performance. Researchers like Kaplan et al. (2020) and Hoffmann et al. (2022) studied how scaling affects model performance, proposing power laws that show a predictable relationship between model size, dataset size, and performance. These studies emphasized the importance of scaling for the continued progress of LLMs[16].

1.5.2 Pre-training

Pre-training is a crucial stage in developing Large Language Models (LLMs), where the model learns from extensive unlabeled datasets through a process called self-supervision. This stage allows the model to recognize and internalize a wide range of linguistic patterns, laying the groundwork for fine-tuning on specific tasks.

Several pre-training objectives have been implemented to maximize the effectiveness of this learning process, each offering distinct benefits to the model's performance .

Full Language Modeling: Used since GPT-2, this approach trains decoder-only models to predict the next token in a sequence based on previous tokens. This autoregressive method enables models like GPT-3 to generate coherent and contextually relevant text.

Prefix Language Modeling: Employed in encoder-decoder and non-causal decoder-only models, this technique uses a non-causal (considering both past and future tokens) prefix for predicting subsequent tokens, offering more flexibility and enhancing the model's adaptability across various language tasks.

Masked Language Modeling: Popularized by BERT, this method involves masking certain tokens in the input text and training the model to predict them, helping the model understand word context. An extension, span corruption, masks entire text spans for prediction, further improving contextual comprehension[17].

Unified Language Modeling refers to an approach that integrates multiple training objectives, including causal, non-causal, and masked language modeling. In this framework, masked language modeling differs from traditional bidirectional attention mechanisms by employing unidirectional attention—processing context either from left-to-right or right-to-left, rather than considering both directions simultaneously[18].

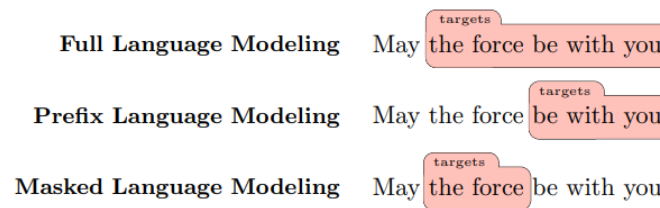


Figure 1.7: Training Tokenization in Full, Prefix, and Masked Language Modeling.

1.5.3 Fine-tuning

Fine-tuning is a key technique for adapting pre-trained large language models (LLMs) to specific downstream tasks. It encompasses several strategies, each serving different objectives.

One common method is **transfer learning**, where a pre-trained model is further trained on task-specific data to enhance its performance on targeted applications. This allows models to leverage general language understanding while adapting to more specialized domains.

Another approach is **instruction tuning**, which involves fine-tuning the model on datasets formatted as instruction-response pairs. These datasets typically include multiple tasks described in natural language, enabling the model to better understand prompts and generalize across various instructions. This method has been particularly effective in improving zero-shot and few-shot performance.

To address ethical and safety concerns, **alignment tuning** is employed. This involves adjusting the model's behavior based on human feedback to ensure outputs are helpful, honest, and harmless (the "HHH" criteria). A widely adopted framework for this is reinforcement learning with human feedback (RLHF). RLHF combines reward modeling—where human preferences guide the ranking of responses—with reinforcement learning techniques, such as proximal policy optimization (PPO), to iteratively align model behavior with human values.

These fine-tuning approaches, while powerful, come with trade-offs in terms of data requirements, computational cost, and generalization capabilities. Nonetheless, they remain essential for tailoring LLMs to both functional and ethical requirements across diverse applications.[16].

1.5.4 Few-Shot, One-Shot, and Zero-Shot Learning

Few-shot, one-shot, and zero-shot learning represent different paradigms of using LLMs without extensive fine-tuning. These methods involve using pre-trained models to perform tasks with minimal task-specific data.

Few-Shot Learning involves giving the model a few examples (typically 10-100) of the task during inference. This approach reduces the need for large, task-specific datasets and limits the risk of overfitting to narrow data distributions. However, few-shot results are generally not as strong as those from fully fine-tuned models.

One-Shot Learning is similar to few-shot learning but uses only a single example alongside a natural language description of the task. This method mirrors how humans are often instructed for tasks, making it an interesting approach for tasks where providing multiple examples is impractical.

Zero-Shot Learning requires the model to perform a task based solely on a natural language description, with no examples provided. While this method offers maximum flexibility and robustness, it is also the most challenging for models. Zero-shot performance is often weaker than few-shot or one-shot, but it represents a significant step towards task-agnostic AI, where models can generalize across a wide range of tasks with minimal human intervention[15].

1.5.5 Evaluation Datasets and Tasks

Evaluating Large Language Models (LLMs) is essential for determining their effectiveness and limitations in comprehending and generating human language. This evaluation typically falls into two primary categories:

- **Natural Language Understanding (NLU):** This measures the model's proficiency in comprehending language, encompassing tasks such as sentiment analysis, text classification, natural language inference (NLI), question answering (QA), commonsense reasoning (CR), mathematical reasoning (MR), and reading comprehension (RC).
- **Natural Language Generation (NLG):** This assesses the model's capability to produce text based on given context. It includes tasks like summarization, sentence completion, machine translation (MT), and dialogue generation.

Benchmarks play a critical role in evaluating LLMs, providing standardized tests to measure their performance across various tasks:

- MMLU: Measures model knowledge from pretraining and evaluates performance in zero-shot and few-shot scenarios across 57 subjects, testing world knowledge and problem-solving abilities.
- SuperGLUE: An advanced benchmark that builds on GLUE, assessing tasks like question answering and natural language inference. It is designed to test deeper aspects of language understanding and requires significant advancements in various learning methodologies.
- BIG-bench: A large-scale benchmark for evaluating LLMs across diverse tasks including reasoning, creativity, ethics, and domain-specific knowledge.
- GLUE: A foundational benchmark for evaluating and analyzing natural language understanding, offering a range of resources for model assessment[2].

1.6 Popular Models

Large Language Models (LLMs) like GPT-3, GPT-4, and BERT have revolutionized NLP by leveraging vast datasets such as Common Crawl and WebText. These datasets provide a diverse linguistic foundation, enabling models to perform a wide range of tasks with remarkable accuracy and contextual understanding.

1.6.1 GPT-N Models

GPT models are advanced autoregressive language models that generate substantial and complex machine-produced text from minimal input. They leverage deep learning techniques to mimic human text generation by predicting the current value based on preceding values. NLP models initially struggled with tasks outside their training sets due to data restrictions. OpenAI addressed this with GPT-1, introduced in 2018.

- GPT-1, trained on the BooksCorpus dataset, utilized a 12-layer transformer decoder with self-attention. Its pre-training allowed for zero-shot performance on various tasks, demonstrating the potential of generative language models.
- In 2019, GPT-2 improved upon GPT-1 by using a larger dataset and 1.5 billion parameters (compared to GPT-1's 117 million). It excelled in tasks like translation and summarization, enhancing accuracy in recognizing long-distance relationships.

- GPT-3, released later, featured around 175 billion parameters and was trained on the Common Crawl dataset. It could generate human-like text, perform basic math, and write code. Despite its capabilities, its size and cost made it challenging to implement.
- GPT-4, launched in March 2023, advanced further with multimodal capabilities and context windows of up to 32,768 tokens. It incorporates reinforcement learning for better alignment with human input and policy[19]

1.6.2 BERT

BERT (Bidirectional Encoder Representations from Transformers) is a language representation model that pretrains deep bidirectional representations from unlabeled text by jointly conditioning on both left and right contexts at every layer. This bidirectional strategy allows BERT to be fine-tuned for diverse downstream tasks, such as question answering and natural language inference, by simply appending a single output layer, thereby eliminating the need for extensive architectural modifications.

BERT has demonstrated exceptional performance, establishing new state-of-the-art results across eleven natural language processing benchmarks. Notably, it achieved a GLUE score of 80.5%, a MultiNLI accuracy of 86.7%, a SQuAD v1.1 F1 score of 93.2%, and a SQuAD v2.0 F1 score of 83.1%. The model's elegant design, coupled with its empirical success, underscores its versatility and efficacy as a powerful tool for a wide array of natural language processing applications. [14].

1.6.3 T5

The T5 (Text-To-Text Transfer Transformer) model represents a unified framework for natural language processing (NLP), designed to address various text processing tasks by treating them as "text-to-text" problems. This approach involves converting all tasks into a format where both input and output are text, allowing the same model, objective, and training procedure to be applied across different tasks. T5 leverages extensive pre-training on a large, unlabeled dataset, enabling it to develop general-purpose knowledge that enhances its performance on a range of NLP tasks, such as question answering, document summarization, and sentiment classification[20].

1.6.4 LLAMA2

Llama 2 introduces a new family of transformer-based language models available in both foundation and fine-tuned chat variants. These models incorporate architectural enhancements

through optimized training procedures, refined pretraining datasets, and advanced fine-tuning techniques including reinforcement learning from human feedback. Empirical evaluations reveal that Llama 2 outperforms its predecessors and other competitive benchmarks across a range of natural language processing tasks, demonstrating notable improvements in accuracy, safety, and generalization. Its open release not only promotes transparency and reproducibility but also fosters collaborative advancements in the field[21].

1.6.5 Jais

Jais and Jais-chat are advanced Arabic-centric large language models built on a GPT-3 decoder-only architecture. Pretrained on a diverse dataset of Arabic and English texts including programming language source code—these 13-billion-parameter models excel in Arabic knowledge and reasoning, outperforming existing open Arabic and multilingual models. Notably, they also remain competitive in English tasks despite limited English data. We detail their training, fine-tuning, safety alignment, and evaluation, and release both the foundational Jais and the instruction-tuned Jais-chat variants to foster further research on Arabic LLMs[22].

1.7 Limitations of Large Language Models

LLMs have greatly advanced NLP, but they also present challenges. As these models scale, they encounter new challenges in scalability, privacy, and real-time processing. Several studies have examined the inherent limitations of large language models (LLMs). Notably, [23] and [2] highlight critical challenges that affect the performance and reliability of these models applications.

1.7.1 Computational Cost

Training large language models (LLMs) demands significant computational resources, leading to higher production costs and environmental concerns due to the substantial energy used in large-scale training. Although enhancing computational resources can boost performance, the gains diminish over time when the size of the model and dataset stay constant, adhering to the power law of diminishing returns.

1.7.2 Bias and Ethical Concerns

The training data for LLMs often encapsulates various social, cultural, and linguistic biases, which the models can inadvertently learn and propagate. This bias can manifest in outputs that reinforce stereotypes or display partiality, raising significant ethical concerns. Addressing these issues is crucial for ensuring fairness and mitigating unintended consequences in real-world applications.

1.7.3 Hallucinations

LLMs sometimes produce "hallucinations," or responses that, despite appearing plausible, are incorrect or do not match the provided information. These hallucinations can be classified into three types:

- **Input-conflicting hallucination:** When the model generates responses that do not align with the user's input.
- **Context-conflicting hallucination:** When the model produces content that contradicts information it has previously generated.
- **Fact-conflicting hallucination:** When the model creates responses that conflict with established knowledge.

1.7.4 Overfitting

Despite their advanced learning abilities, they can overfit to noisy or unusual patterns in their large training datasets, which may result in generating nonsensical responses. The ongoing discussion about Memorization versus Generalization in LLMs revolves around finding an optimal balance. Memorization helps the model retain specific details from its training, allowing it to answer precise questions accurately. On the other hand, generalization enables the model to make predictions and generate responses for new, unseen inputs, which is crucial for handling diverse real-world tasks. The challenge is to find the right balance: excessive memorization can lead to overfitting, reducing the model's flexibility and ability to handle novel inputs.

1.8 Domains of Application

The use of Large Language Models (LLMs) in various downstream tasks has become increasingly prevalent in both AI research and industry, with new applications being identified and

explored regularly. These models, which excel at understanding and generating human-like text, are finding valuable applications across diverse fields.

1.8.1 Legal Information and Law

Large language models (LLMs) are increasingly influential in the legal sector, enhancing the analysis and processing of extensive legal texts. Their ability to manage and interpret large datasets supports tasks such as document classification, information retrieval, and even judicial outcome prediction. For instance, [24] presents Legal-BERT, adapts the BERT architecture specifically for legal applications, yielding notable improvements in handling legal documents. Similarly, [25] investigated the use of LLMs in forecasting Supreme Court decisions, demonstrating their potential to contribute to legal analytics and reasoning. These advancements underscore the transformative impact of LLMs on legal research, offering new tools to improve the efficiency and accuracy of legal practice.

1.8.2 Cybersecurity

Large Language Models (LLMs) have garnered significant attention in the field of cybersecurity. Recent research has highlighted their potential in addressing software bugs created by human developers and identifying cybersecurity threats. For example, Arora et al. have proposed methods for utilizing LLMs to evaluate cyber threats on social media through sentiment analysis. LLMs are also employed to detect cybersecurity-related information in Open Source Intelligence (OSINT), aiding in the identification of potential cyber threats. Additionally, LLMs have shown promise in detecting scams, such as phishing. Initial tests with models like GPT-3.5 and GPT-4 have demonstrated their ability to recognize common phishing indicators in emails. While LLMs exhibit considerable potential in cybersecurity, improving their reasoning abilities could enhance their effectiveness further, such as in uncovering zero-day vulnerabilities in open-source software by analyzing logic and source code[26].

1.8.3 Medicine

The integration of Large Language Models (LLMs) into medicine is transforming both health-care delivery and research. In clinical settings, LLMs are increasingly utilized in decision support systems to offer evidence-based treatment recommendations. By analyzing patient data and medical literature, these models can assist in diagnosing conditions, suggesting relevant tests, and proposing effective treatment options. Additionally, LLMs improve patient interactions through applications like chatbots that answer questions about symptoms and

medications, schedule appointments, and provide health advice.

In medical research, LLMs help sift through vast amounts of literature to extract, filter, and summarize relevant information, identify key studies, and predict future research directions. They also play a role in medical education by generating training materials, creating exam questions, explaining complex topics, and offering personalized feedback. Furthermore, LLMs simulate patient interactions, aiding students in honing their clinical skills [2].

1.8.4 journalism

Large Language Models (LLMs) offer valuable support to journalists, especially in fact-checking and news verification. They can process and cross-reference large volumes of data with established knowledge bases. Research has demonstrated that LLMs, such as GPT-3.5, can be used to detect fake news by providing rationales that enhance other models like BERT, which can then be fine-tuned for this purpose. In addition to fact-checking, LLMs are useful for analyzing political debates, helping journalists to identify key themes, monitor how discussions evolve, and evaluate sentiments. They can also assist in detecting logical fallacies and underlying motives in political discourse and propaganda. By enhancing their reasoning capabilities, LLMs can uncover deeper insights into propaganda and misinformation, making them a powerful tool for modern journalism[26].

1.9 Conclusion

This chapter has outlined the evolution and significance of Natural Language Processing (NLP), from early neural networks to advanced Large Language Models (LLMs). We covered key concepts in neural networks and the transformative impact of the Transformer architecture. We also discussed various challenges. Finally, the chapter reviewed the applications of LLMs in fields like Legal Information and Law, cybersecurity, medicine, and journalism, showcasing their potential and the ongoing need for further development.

Although LLMs have demonstrated promising applications in the legal sector, their influence is still constrained by practical limitations and contextual challenges. Recognizing these gaps, the next chapter explores Retrieval-Augmented Generation (RAG) as a novel approach to enhance legal information processing. This discussion will particularly focus on how RAG can be applied within the Algerian legal framework to address existing shortcomings and improve accessibility and accuracy in legal data management.

Chapter 2

Retrieval-Augmented Generation (RAG)

2.1 Introduction

Large language models (LLMs) have seen significant advancements but face challenges, particularly in tasks that demand extensive knowledge or deal with queries beyond their training data. These limitations often result in inaccuracies or “hallucinations.” To address this, Retrieval-Augmented Generation (RAG) supplements LLMs by retrieving relevant document chunks from external knowledge sources based on semantic similarity. By doing so, RAG helps reduce factual errors, allowing LLMs to produce more accurate content. This has led to the widespread adoption of RAG, particularly in chatbots and other real-world applications, making it a crucial technology in advancing the capabilities of LLMs.

2.2 Fundamentals of Retrieval-Augmented Generation

RAG represents a significant advancement in the capabilities of large language models (LLMs) by integrating external knowledge retrieval with the generation of text. Understanding the individual components of retrieval and generation is essential to appreciate how their synergy improves the overall performance of RAG systems.

2.2.1 Definition of (RAG)

Retrieval-Augmented Generation (RAG) is a technique that leverages the strengths of pre-trained large language models (LLMs) and external data sources. By merging the generative abilities of LLMs like GPT-3 or GPT-4 with the accuracy of specialized data search mecha-

nisms, RAG systems can generate more sophisticated and contextually relevant responses[27].

2.2.2 Historical Development of (RAG)

The foundations of Retrieval-Augmented Generation (RAG) can be traced back to traditional information retrieval (IR) systems. Early models primarily relied on keyword matching and simple ranking mechanisms to retrieve relevant documents from databases, establishing a basic framework for information access. The landscape began to shift with the rise of neural networks in the 2010s. Notable innovations like Word2Vec and Transformer-based architectures enabled retrieval methods to incorporate deeper semantic understanding, paving the way for more sophisticated document retrieval processes. A significant advancement occurred with the introduction of dense passage retrieval (DPR) in 2020, which utilized bi-encoder architectures to map both queries and documents into dense vector spaces. The integration of these advanced retrieval techniques with large language models (LLMs) became a focal point as models like GPT-3 gained prominence. Researchers explored how LLMs could be augmented with retrieval capabilities, leading to the development of RAG systems that leverage the strengths of both retrieval and generative capabilities[28].

2.2.3 Differences between (RAG), fine-tuning and transfer learning

Recent advances in natural language processing have led to the development of three prominent methodologies for enhancing language models: Retrieval-Augmented Generation (RAG), fine-tuning, and transfer learning.

RAG, as described by Lewis et al. [3], integrates external retrieval mechanisms with generative models. This approach enables the model to dynamically access and incorporate relevant information from external knowledge bases during the generation process, thereby addressing limitations in its internal memory and providing more accurate responses for knowledge-intensive tasks.

Fine-tuning, detailed by Howard and Ruder [29], involves adapting a pre-trained model to a specific task by further training it on a targeted dataset. This process refines the model's parameters to better capture the nuances of the task at hand, leading to improved performance even when the available domain-specific data is relatively limited.

Transfer learning, as exemplified by Devlin et al. [30], refers to the broader strategy of leveraging a model that has been pre-trained on large, diverse datasets for use in various downstream tasks. This method capitalizes on the rich, generalized representations learned

during the pre-training phase, and then applies task-specific adaptations to achieve state-of-the-art results across a range of applications.

Collectively, these methodologies offer complementary strategies to enhance language model performance, each contributing unique advantages and addressing different challenges in the field of natural language processing.

2.3 Types of (RAG) Systems

As detailed in [28], the evolution of Retrieval-Augmented Generation (RAG) can be categorized into three distinct phases: Naive RAG, Advanced RAG, and Modular RAG .

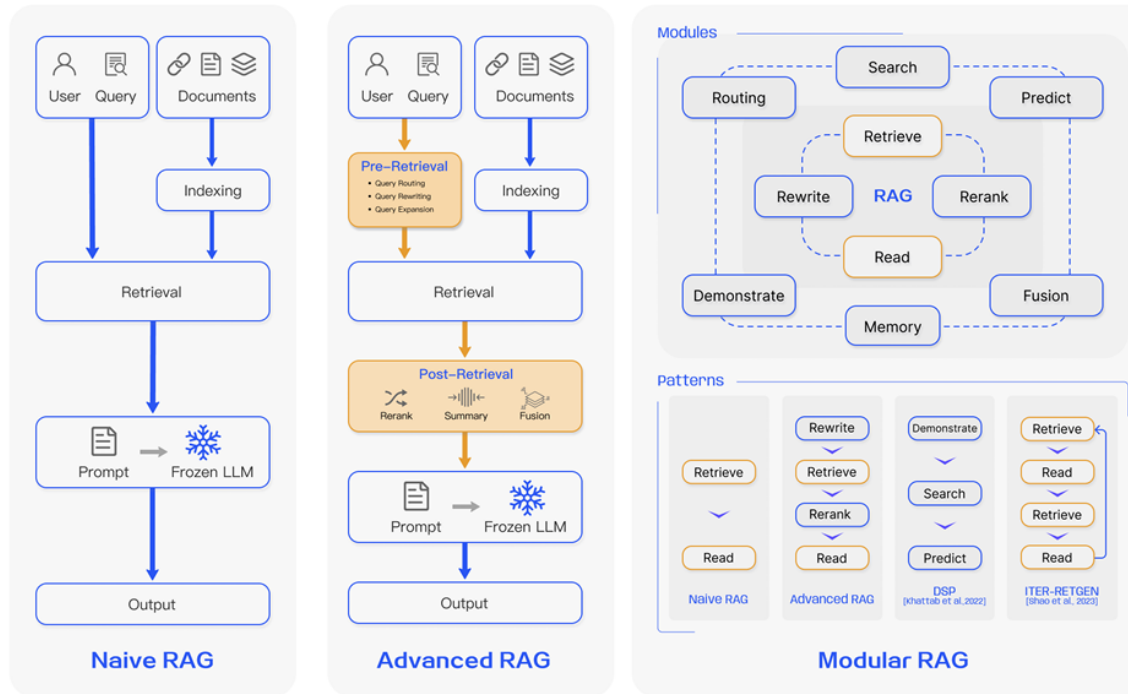


Figure 2.1: Types of RAG Systems

2.3.1 Naive (RAG)

Naive RAG, a foundational approach in Retrieval-Augmented Generation, operates on a straightforward "Retrieve-Read-Generate" paradigm. This method involves three primary steps:

- **Indexing:** Raw data is cleaned, extracted, and converted into a uniform text format. It's then segmented into smaller chunks and encoded into vector representations using an embedding model. These vectors are stored in a vector database for efficient similarity searches.

- **Retrieval:** When a user query is received, it's encoded into a vector and compared to the indexed chunks. The top K most similar chunks are retrieved and included in the prompt for the language model.
- **Generation:** The query and retrieved chunks are combined into a prompt, which is fed to a large language model. The model generates a response based on the provided context and its internal knowledge.

While Naive RAG offers a basic framework, it faces several challenges in

- **Retrieval Issues:** The retrieval process can be imprecise, leading to the selection of irrelevant or missing information.
- **Generation Challenges:** The language model may hallucinate, generating content not supported by the retrieved context. It may also produce irrelevant, toxic, or biased outputs.
- **Augmentation Difficulties:** Integrating retrieved information into the generation process can be challenging, leading to disjointed or redundant responses.

2.3.2 Advanced (RAG)

Taking aim at the shortcomings of Naive RAG, Advanced RAG introduces specific improvements to enhance retrieval quality. This approach utilizes pre-retrieval and post-retrieval strategies.

Pre-retrieval Strategies:

- **Enhanced Indexing:** Advanced RAG tackles indexing issues through a sliding window approach, finer segmentation of data, and inclusion of metadata. Additionally, it optimizes the retrieval process by employing various methods.
- **Query Optimization:** This stage focuses on refining the user's initial query to make it clearer and more suitable for retrieval. Techniques like query rewriting, transformation, and expansion are commonly used.

Post-Retrieval Strategies:

- **Re-ranking Chunks:** After relevant information is retrieved, Advanced RAG prioritizes the most relevant content by re-ranking the retrieved chunks and placing them strategically within the prompt.

- **Context Compression:** To avoid overwhelming the LLM with too much information, post-retrieval efforts focus on selecting the most essential parts of the retrieved context, highlighting critical sections, and compressing the data to be processed.

By addressing indexing issues and refining the query and retrieved information, Advanced RAG aims to improve the overall accuracy and relevance of the generated response.

2.3.3 Modular (RAG)

Modular RAG represents the latest evolution in RAG, offering greater adaptability. it introduces specialized modules and innovative patterns to enhance retrieval and processing capabilities.

New Modules

- **Search Module:** Adapts to specific scenarios by leveraging LLM-generated code and query languages to search across various data sources.
- **RAG Fusion:** Employs a multi-query strategy to expand user queries, uncover both explicit and implicit knowledge, and improve retrieval results.
- **Memory Module:** Leverages the LLM's memory to guide retrieval and create an unbounded memory pool, aligning the text more closely with data distribution.
- **Routing Module:** Navigates through diverse data sources, selecting the optimal pathway for a query based on its specific needs.
- **Predict Module:** Reduces redundancy and noise by generating relevant context directly through the LLM.
- **Task Adapter Module:** Tailors RAG to various downstream tasks by automating prompt retrieval and creating task-specific retrievers.

New Patterns

- **Flexible Module Arrangement:** Modular RAG allows for the substitution and reconfiguration of modules to address specific challenges, surpassing the fixed structures of previous RAG paradigms.
- **Innovative Retrieval Strategies:** Techniques like Rewrite-Retrieve-Read, Generate-Read, and Recite-Read leverage the LLM's capabilities to refine queries, generate content, and retrieve information from model weights.

- **Hybrid Retrieval:** Combines keyword, semantic, and vector searches to cater to diverse queries, improving retrieval relevance.
- **Dynamic Module Interaction:** Frameworks like Demonstrate-Search-Predict and ITER-RETGEN demonstrate the dynamic use of module outputs to enhance each other's functionality.
- **Adaptive Retrieval:** Techniques like FLARE and Self-RAG evaluate the necessity of retrieval based on different scenarios, allowing for a more flexible and efficient approach.

2.4 Core Components of RAG

The core components of Retrieval-Augmented Generation (RAG) systems consist of a retrieval mechanism, a generation process, and augmentation techniques. These elements work together to enhance the model's ability to access relevant external information, generate coherent and contextually appropriate responses, and improve overall performance in knowledge-intensive tasks.

2.4.1 Retrieval Mechanism

RAG systems combine parametric memory (a pre-trained language model) with non-parametric memory (a retrieval mechanism). The retrieval mechanism allows RAG models to access external information sources (e.g., Wikipedia), and this process is central to improving the model's ability to generate factual and accurate outputs [3].

- **Traditional Techniques:**
Classical retrieval methods include **TF-IDF** and **BM25**, which rely on sparse vector representations based on term frequencies. These methods use exact keyword matching, making them limited in semantic understanding.
- **Modern Retrieval Approaches:**
Dense Passage Retrieval (DPR): This approach utilizes dense vector representations learned by neural models like BERT to encode both the query and document. It allows for a more semantic understanding of the content, making retrieval more effective. DPR, for example, computes the similarity between the query and documents using Maximum Inner Product Search (MIPS), which finds the closest passages based on the dense vector space.

- Implementation in RAG:

In RAG, dense retrieval methods are often paired with techniques like **Maximum Inner Product Search** (MIPS), which efficiently matches query and document embeddings. This enables the system to return the most relevant documents for subsequent generation [31].

2.4.2 Generation Process

The generation in RAG occurs through a combination of retrieved passages and the input query.

Large Language Models (LLMs) like BART or T5 are utilized for this generation, leveraging their advanced capabilities in understanding and producing human-like text. The retrieval component supplies external context, which the generator conditions on to formulate a response. This context is crucial, as it enriches the LLM's understanding, enabling it to incorporate real-time, relevant information. Moreover, the generation process benefits from the LLM's ability to synthesize information, allowing it to create responses that are not only coherent but also informed by the latest data, thus improving accuracy and relevance in knowledge-intensive tasks [3].

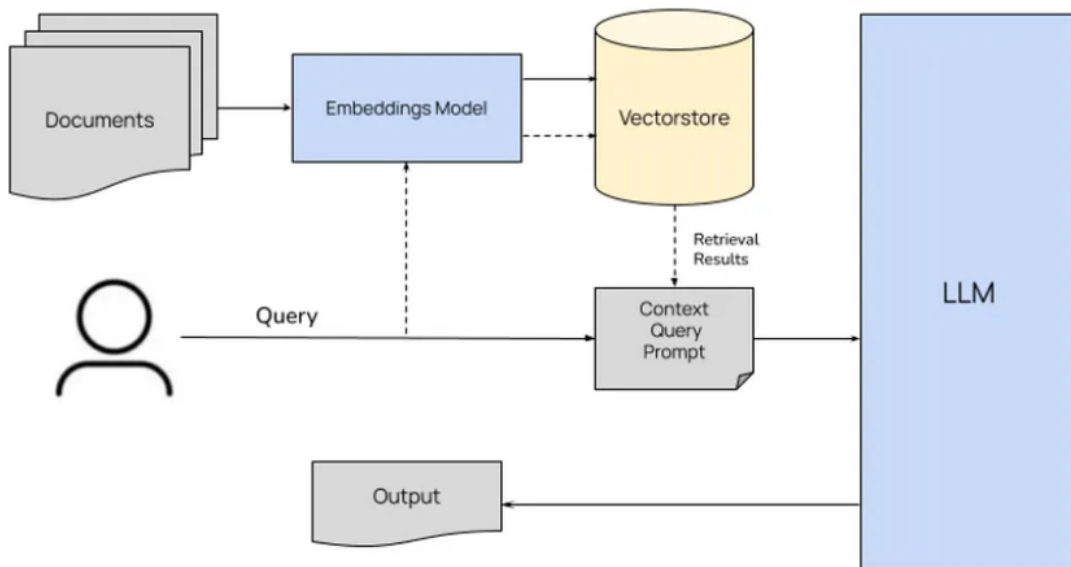


Figure 2.2: Rag architecture

2.4.3 Augmentation Techniques

The augmentation of the retrieval process in Retrieval-Augmented Generation (RAG) systems focuses on improving how queries are refined and how relevant information is retrieved for downstream generation tasks. Key augmentation methods include.

- **Query Augmentation:** In traditional retrieval pipelines, user queries are often under-specified or ambiguous, leading to poor retrieval performance. Query augmentation involves dynamically rewriting the user's query to better match the documents in the knowledge base. This can be done by leveraging large language models (LLMs) to generate tailored queries or synthetic questions and answers (QAs) that better align with the search objective
- **Synthetic QA Generation:** Instead of using raw document chunks, retrieval is enhanced by generating and embedding synthetic QA pairs from documents. This helps to capture the semantic essence of long texts more effectively, reducing noise and improving retrieval precision. These synthetic QAs can be used to rewrite the user query, making it more specific to the task at hand [32].

2.5 RAG for Legal Information Retrieval

Retrieval-Augmented Generation (RAG) holds significant promise for transforming the way legal information is accessed, processed, and utilized. In legal contexts, particularly where precision and comprehensiveness are critical, RAG enables the dynamic integration of relevant external knowledge into language models during inference. This is especially valuable for retrieving and synthesizing content from case law, legislative texts, legal commentaries, and scholarly analyses[33].

Unlike traditional keyword-based or Boolean legal search systems, which rely on exact matches and rigid query structures, RAG models operate by embedding both queries and documents into a shared vector space, allowing for more semantic and contextual retrieval. This enables users to pose natural language queries and obtain responses grounded in specific, retrieved legal documents. For instance, rather than retrieving a list of documents containing the keyword "contract termination," a RAG model can retrieve multiple relevant legal provisions, judgments, or commentaries and synthesize a coherent and accurate summary or answer.

Moreover, RAG is well-suited to handle the diversity and complexity of legal texts. It can retrieve from multiple sources—statutes, judicial rulings, legal doctrines—and present consolidated outputs that reduce the time and effort needed for legal research. In contexts

where laws are updated frequently or where legal reasoning requires multi-document understanding, such as in complex case analysis, RAG provides an efficient, scalable alternative to traditional systems.

The potential benefits are particularly evident when applied to under-resourced legal systems or multilingual environments, such as in Algeria, where legal texts exist in both Arabic and French, and digital legal resources remain fragmented. Here, RAG could offer a pathway toward more accessible, interpretable, and comprehensive legal information services[34].

2.6 Task and Evaluation

The rapid development and increasing use of Retrieval-Augmented Generation (RAG) models in NLP have made their evaluation a critical area of research within the LLM community. This section covers the primary downstream tasks associated with RAG, the datasets used, and the methods for evaluating RAG systems [35].

2.6.1 Factuality

- **Fact-Checking Benchmarks:** Using datasets like FEVER and SQuAD to evaluate the model's ability to identify and correct factual errors.
- **Adversarial Testing:** Creating adversarial examples to test the model's robustness against misleading information.
- **Contextual Understanding:** Assessing the model's ability to understand the context of a query and provide accurate answers.

2.6.2 Robustness

- **Noise Injection:** Introducing noise into the retrieved documents to test the model's ability to handle imperfect information.
- **Adversarial Attacks:** Evaluating the model's resilience to attacks that aim to manipulate its outputs.
- **Domain Adaptation:** Testing the model's ability to adapt to new domains and data distributions.

2.6.3 Fairness

- **Bias Detection:** Identifying and quantifying biases in the training data and model outputs.
- **Fairness Metrics:** Using metrics like demographic parity and equalized odds to evaluate the model's fairness.
- **Mitigation Techniques:** Implementing techniques like debiasing and fairness constraints to mitigate biases.

2.6.4 Objective Metrics:

- **Accuracy:** Precision, recall, and F1-score for evaluating the correctness of the generated responses.
- **Consistency:** Measuring the consistency of the model's outputs across different queries and contexts.
- **Coherence:** Assessing the coherence and fluency of the generated text.

2.6.5 Subjective Metrics

- **Human Evaluation:** Using human raters to evaluate the quality of the generated responses.
- **User Studies:** Conducting user studies to gather feedback on the user experience

2.7 Challenges and Limitations in (RAG)

While RAG has gained significant traction across diverse applications, it still faces certain limitations in terms of effectiveness and efficiency[36] [37].

2.7.1 Scalability and Efficiency

A major challenge for RAG models lies in their scalability. Since retrieval components depend on external databases, efficiently handling large and constantly expanding datasets demands robust retrieval algorithms. Additionally, the high computational and memory requirements pose difficulties for deploying RAG models in real-time or resource-limited environments

2.7.2 Noisy Retrieval Results

The quality of retrieval results can significantly impact the performance of Retrieval-Augmented Generation (RAG) models. Several factors contribute to noisy retrieval, including the methods used for indexing, the way queries are formulated, and the characteristics of the underlying datasets. When irrelevant or noisy information is retrieved, it may result in the generation of hallucinated or factually inaccurate responses, further compromising the reliability of the system. Additionally, the model's ability to correctly interpret the retrieved information can be hindered, particularly when the information lacks proper formatting or contains inconsistencies.

2.7.3 Bias and Fairness

Like other machine learning models, Retrieval-Augmented Generation (RAG) systems can inherit biases from the datasets they rely on for retrieval. These biases may be amplified during the generation process, potentially leading to biased or harmful outputs. Addressing this issue by developing effective techniques to mitigate bias in both the retrieval and generation phases remains an ongoing challenge.

2.7.4 Extra Overhead

- **Computational Cost:** Retrieval and processing additional information can increase computational costs, especially for large-scale models and complex queries.
- **Latency:** Retrieval and processing can introduce latency, impacting the real-time performance of RAG systems.
- **Complexity:** Implementing and deploying RAG systems requires careful consideration of various factors, including data preparation, model selection, and system architecture.

2.7.5 Long Context Generation:

- **Context Length Limits:** LLMs have limitations on the amount of context they can process at once.
- **Information Loss:** Long documents may be truncated or summarized, leading to loss of important information.
- **Computational Cost:** Processing long contexts can be computationally expensive.

2.8 Conclusion

In this chapter, we explored the core principles and mechanisms of Retrieval-Augmented Generation (RAG), emphasizing its potential to enhance language models through access to external knowledge sources during inference. We examined its general architecture, key stages, and its evolution from naive to more modular frameworks.

A particular focus was placed on the application of RAG in the legal domain, where we highlighted its potential for improving legal information retrieval by enabling more contextualized and semantically rich access to case law, statutes, and scholarly texts. We also outlined the main challenges and limitations facing RAG models, including noisy retrieval, bias, scalability.

Following this foundational understanding, the next chapter delves into a critical aspect of RAG performance: the problem of knowledge selection. Specifically, we explore how the effectiveness of retrieved documents directly influences the quality of generated responses, and we investigate strategies to improve relevance and ranking within RAG pipelines.

Chapter 3

k Selection in Retrieval

3.1 Introduction

Retrieval-Augmented Generation (RAG) systems enhance language models by grounding responses in externally retrieved documents. A critical challenge in these systems is determining the optimal number of documents (k) to retrieve for a given query. Current approaches fall into three categories: static k selection, which uses a fixed number of retrieved documents; dynamic k selection, which adjusts k based on query characteristics; and hybrid approaches, which combine both strategies. In this chapter, we first explore methods, highlighting their strengths and limitations. We then introduce our novel hybrid dynamic selection algorithm, provide a detailed description of its methodology, and present experimental results that demonstrate the effectiveness of its performance.

3.2 Defining k : The Number of Retrieved Documents

the parameter k denotes the number of documents or passages retrieved from an external knowledge base. This retrieval process is managed by the retriever component [38], which identifies the top k relevant documents based on similarity to the query typically using embedding-based search [39] (e.g., dense retrieval with FAISS, BM25, or hybrid methods). Subsequently, these documents are passed to the generator, typically a language model, which synthesizes the final response by integrating the retrieved

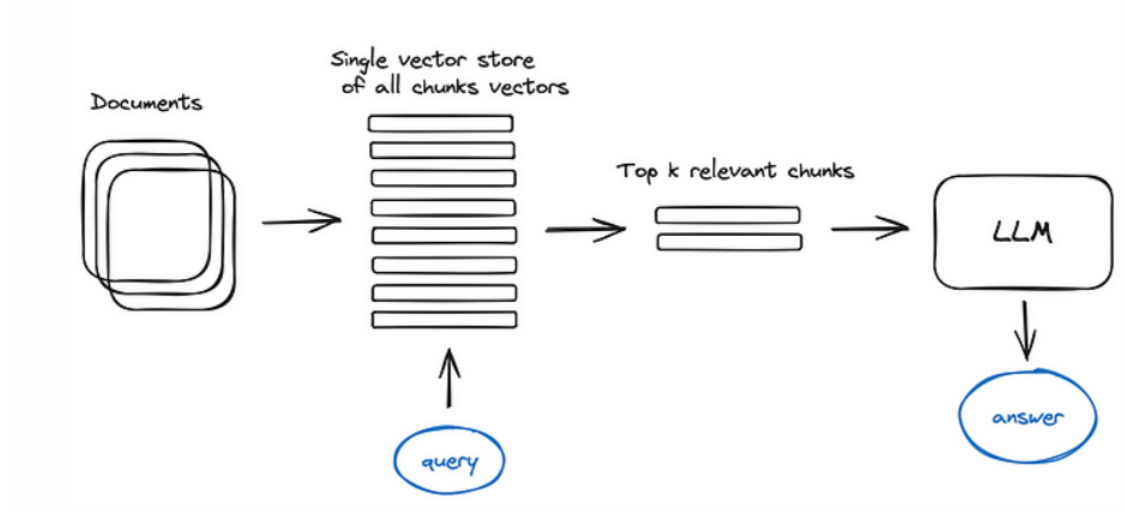


Figure 3.1: Basic retrieval

3.3 Impact of k on Retrieval Performance

The retriever's effectiveness in identifying relevant documents depends on k . Key impacts include :

3.3.1 Recall vs. Precision

When a user conducts a search query, the outcomes from the database can be grouped into four distinct types based on relevance and retrieval status [40]:

- Relevant and Retrieved: Documents that both address the user's query and appear in the search results.
- Relevant and Not Retrieved: Useful documents that answer the query but are not included in the results.
- Non-Relevant and Retrieved: Documents that appear in the results but lack meaningful value for the query.
- Non-Relevant and Not Retrieved: Irrelevant documents excluded from the results.

Precision@k: evaluates the proportion of relevant documents within the top k retrieved results. This metric is particularly valuable in scenarios where the focus is on delivering highly relevant information quickly, rather than ensuring complete coverage such as ,recommendation systems or search engines[41].

$$\text{Precision@k} = \frac{\text{Number of Relevant Items Retrieved in Top } k}{k}$$

Example Suppose we have a dataset of 10 documents. If we retrieve $k = 4$ documents and find that 3 of them are relevant to the query:

- **Dataset:** [doc1, doc2, doc3, doc4, doc5, doc6, doc7, doc8, doc9, doc10]
- **Retrieved:** [doc3, doc1, doc7, doc4]
- **Relevant:** [doc1, doc3, doc5, doc8]

The Precision@4 score would be:

$$\text{Precision@4} = \frac{3}{4} = 0.75$$

Recall@k :evaluates the proportion of relevant documents that are successfully retrieved within the top k results. This metric is particularly important in contexts where ensuring the completeness of information is crucial, such as in medical research or academic tools, where omitting relevant documents could result in incomplete or inaccurate conclusions[41].

$$\text{Recall@k} = \frac{\text{Number of Relevant Items Retrieved in Top k}}{\text{Total Number of Relevant Items}}$$

Example Consider a dataset of 10 documents. If we retrieve $k = 4$ documents and find that 2 of them are relevant, while the total number of relevant documents in the dataset is 4:

$$\text{Recall@4} = \frac{2}{4} = 0.5$$

Increasing k typically enhances recall by retrieving more relevant documents but may decrease precision due to the inclusion of irrelevant ones. Conversely, decreasing k can improve precision but at the cost of lower recall.

3.3.2 Retrieval Speed and Computational Cost

Retrieval speed and computational cost are two important areas where k has a big influence. Below is a detailed explanation of how higher k values affect these aspects.

Increased Computational Resources:

As the value of k expands, the retrieval system must handle a larger set of documents, leading to higher computational demands. Specifically, the system needs to perform additional operations like ranking, filtering, and similarity scoring to identify the most relevant documents. These tasks become increasingly resource-intensive, particularly in large-scale retrieval settings where the document corpus consists of millions or even billions of entries[42].

For instance, retrieving the top documents ($k=80$) requires significantly more computational resources compared to retrieving only the top 10 documents ($k=5$).

Higher Memory Usage: As the number of retrieved documents (k) increases, Storing and processing a larger set of retrieved documents requires more memory. This can become a significant bottleneck, especially in environments with constrained memory resources.

For large-scale retrieval tasks, where datasets may contain millions or even billions of documents, the memory demand grows proportionally with k . Each retrieved document needs to be stored temporarily, along with its associated metadata, such as embedding vectors, BM25 scores, or other relevance signals. Additionally, sorting and filtering operations further contribute to memory overhead.

3.3.3 Document Ranking Quality

Document ranking in information retrieval involves ordering documents by their relevance to a user's query. The objective is to prioritize the most relevant documents at the top of search results, making it easier for users to access useful information quickly. Different models, Vector Space, including Boolean, and Probabilistic models, are used to establish this ranking [43].

Increasing the number of retrieved documents, represented as k , may result in the addition of lower-ranked, less relevant documents, potentially diluting the overall quality of the retrieved information. This occurs because of the inherent balance between precision and recall in information retrieval systems.



Figure 3.2: Precision in Document Ranking



Figure 3.3: Recall in Document Ranking

As k grows, recall generally improves since a larger number of relevant documents are likely to be retrieved as shown in Figure 3.3. However, this often comes at the expense of precision, as the additional documents retrieved may include non-relevant ones, thereby lowering the overall precision as illustrated in Figure 3.2. This trade-off is a core principle in evaluating information retrieval systems.

3.4 Impact of k on Generation Quality

The impact of k (the number of retrieved documents or generated candidates) on generation quality is a crucial factor in many machine learning and information retrieval tasks, including text generation, recommendation systems, and search engines.

3.4.1 Trade-off Between Diversity and Relevance

Higher k : Increasing k often improves diversity in generated outputs or retrieved documents, as more candidates are considered. However, this can lead to a drop in relevance or quality, as lower-ranked candidates may be less accurate or coherent.

Lower k : A smaller k tends to prioritize high-quality, relevant outputs but may lack diversity, leading to repetitive or overly narrow results.

Research shows that the quality of retrieved documents plays a crucial role in the performance of Retrieval-Augmented Generation (RAG) systems. For example, one study demonstrated that the precision of retrieved documents directly affects the factual correctness of the generated responses [44]. Additionally, another study revealed that simply increasing the

number of documents does not necessarily improve generation quality, especially if the additional documents are not highly relevant[45]

3.4.2 Effect on Text Generation Models

In text generation tasks, such as machine translation and dialogue systems, The parameter k frequently refers to the beam width in beam search algorithms[46]. Beam search is a heuristic search algorithm that expands the most promising nodes in a graph to maximize the quality of the text that is produced. Adjusting the beam width (k) has significantly impacts how well text generation models function.

As the beam width is increased, the model must process and retain more candidate sequences concurrently, leading to higher computational and memory demands. Particularly in real-time applications where latency is crucial, this increase may have an effect on system performance and response time[47].

3.5 Existing Solutions for k Selection

Selecting an optimal k plays a crucial role in balancing retrieval effectiveness and generation quality. Over the years, various strategies have been proposed to determine k , ranging from static selection to dynamic and hybrid approaches.

3.5.1 Static k Selection

In Retrieval-Augmented Generation (RAG) systems, "static k selection" means, refers to the process of setting a fixed number of top documents (k) to retrieve for every query, irrespective of how simple or complex the query might be. This approach simplifies the retrieval process by maintaining a consistent retrieval count across all queries

Sparse Retrieval with Fixed k

Sparse retrieval is a method of finding relevant documents from a large collection by representing both queries and documents as vectors where most values are zero. This focus on only the most important terms leads to faster, more accurate searches, especially useful when combining information from different sources [48].

Common approaches include **BM25**[49] where documents are scored for relevance by considering term frequency and inverse document frequency, it selects the ' k ' documents with the highest BM25 scores for each query, **TF-IDF** (Term Frequency-Inverse Document Frequency)[50] in this method the retrieved documents would be those with the highest

weighted term importance, Other methods like **QLM** (Query Likelihood Model)[51] use probabilistic models to evaluate the likelihood of a query and rank documents according to textual similarity.

Dense Retrieval with Fixed k

Dense retrieval [31] is a method for retrieving information that uses deep learning models to convert documents and queries into high-dimensional vector embeddings. A fixed number of top-k documents are selected based on similarity scores between the query embedding and document embeddings in a continuous vector space, the retrieval process allows the system to capture semantic relationships beyond exact term matches.

Methods such as dual-encoder architectures (e.g., DPR - Dense Passage Retrieval)[52] utilize separate neural networks (encoders) for queries and documents enable efficient retrieval, while Approximate Nearest Neighbor (ANN) search techniques (e.g., FAISS)[53] optimize search efficiency in large-scale datasets .

3.5.2 Dynamic k Selection

In retrieval, dynamic k selection is the process of varying the quantity of documents (k) that are retrieved according to the properties of the query, such as its ambiguity, complexity, or relevance score distribution. This approach is crucial for enhancing the effectiveness and efficiency of information retrieval systems.

Dynamic Trade-Off Prediction in Multi-Stage Retrieval Systems

This approach predicts the optimal number of documents (k) to retrieve. It uses pre-retrieval features to balance the trade-off between retrieval efficiency and effectiveness, ensuring that the system retrieves an appropriate number of documents for each query[54].

Dynamic Pruning Methods:

This approach addresses the challenge of balancing effectiveness and efficiency in large-scale Information Retrieval (IR) systems, particularly under temporal constraints. The goal is to process queries within a specified time limit while minimizing the loss in retrieval effectiveness. The authors propose and evaluate three techniques for temporally constrained top-K query processing [55].

3.5.3 Hybrid k Selection

hybrid methods aim to achieve optimal retrieval By merging static and dynamic k selection, These methods balance computational efficiency (from static k) with adaptive flexibility (from dynamic k) ensuring high-quality retrieval Below are some key hybrid strategies.

Blended RAG

An innovative method to improve Retrieval-Augmented Generation (RAG) systems, which integrate private document collections with Large Language Models (LLMs) for Generative Question-Answering (QA) it employs a hybrid retrieval approach, combining Dense Vector indexes and Sparse Encoder indexes with sophisticated query strategies, Blended RAG provides a scalable and efficient solution for enhancing RAG systems, showcasing the effectiveness of merging dense and sparse retrieval techniques[56].

STAYKATE (Static-Dynamic Hybrid Selection)

A new approach for selecting in-context examples to improve the performance of large language models (LLMs) in scientific information extraction. Scientific tasks often struggle with limited training data and expensive annotation processes. STAYKATE tackles these challenges by merging static and dynamic selection strategies, combining representativeness sampling from active learning with retrieval-based methods. This hybrid approach ensures the selection of high-quality, informative examples, enhancing in-context learning for LLMs[57].

3.6 Proposed Solution

While existing *k*-selection approaches—static, dynamic, and hybrid—offer distinct advantages, they also present notable limitations, such as lack of adaptability in static *k* selection, which fails to adjust for query complexity, leading to either missing relevant documents or retrieving irrelevant ones. Dynamic *k* selection, while more flexible, introduces higher computational costs and requires carefully tuned heuristics, making it challenging to scale. Hybrid approaches, attempt to balance both strategies but suffer from increased system complexity.

To address these challenges, we propose an enhanced *k*-selection strategy that optimally balances retrieval efficiency and relevance, leveraging adaptive mechanisms to improve performance across diverse query types

3.6.1 Mixture of Logits (MoL)

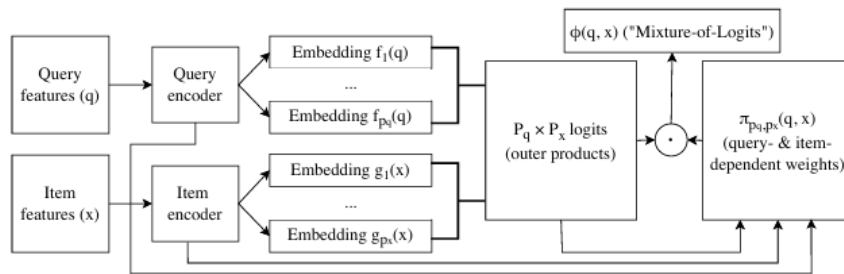


Figure 3.4: Mixture of Logits(MoL) learned similarity.

The **Mixture of Logits (MoL)**[58][59] approach is designed to enhance retrieval and ranking by leveraging multiple low-rank embeddings. It assumes that both the **query** (q) and **document/item** (x) are mapped into P groups of low-dimensional embeddings, denoted as $f_p(q)$ and $g_p(x)$, which are generated by neural networks based on their respective features.

To determine the similarity between a query and a document, MoL assigns **adaptive gating weights** $\pi_p(q, x)$ to the inner products of these low-rank embeddings[58]:

$$\phi(q, x) = \sum_{p=1}^P \pi_p(q, x) \langle f_p(q), g_p(x) \rangle \quad (3.1)$$

where $\pi_p(q, x)$ represents the learned weights for each component, ensuring that their sum equals one. These weights are typically parameterized using a neural network that takes embeddings and their inner products as input features.

To efficiently scale MoL for large datasets and hardware-optimized implementations, the formulation is extended by decomposing the dot products into **batched outer products** of query-side and document-side embeddings. This decomposition improves computational efficiency, particularly on accelerators like GPUs, by normalizing the embeddings using the l_2 -norm:[58]

$$\phi(q, x) = \sum_{pq=1}^{P_q} \sum_{px=1}^{P_x} \pi_{pq,px}(q, x) \frac{\langle f_{pq}(q), g_{px}(x) \rangle}{\|f_{pq}(q)\|_2 \|g_{px}(x)\|_2} \quad (3.2)$$

Since embedding normalization can be precomputed, both formulations remain interchangeable in practical applications. Furthermore, it is possible to **decompose any high-rank matrix** into a mixture of logits based on low-rank matrices, demonstrating the flexibility and scalability of this approach in large-scale information retrieval tasks.

3.6.2 Algorithm Design

we introduce an adaptive threshold mechanism (Dynamic Candidate Selection), the MoL framework is employed to refine the candidate retrieval process.

1. **Component-Level Embeddings:** Component-level embeddings are generated for all items in the dataset X . These embeddings facilitate efficient similarity computations during retrieval. Formally,

$$X_p \leftarrow \{g_p(x) \mid x \in X\}. \quad (3.3)$$

2. **Initial Candidate Retrieval:** This step involves computing similarity scores between a query representation and item representations for each feature component $p \in P$.

$$S_p \leftarrow \{\langle f_p(q), g_p(x) \rangle : x \in X_p\} \quad (3.4)$$

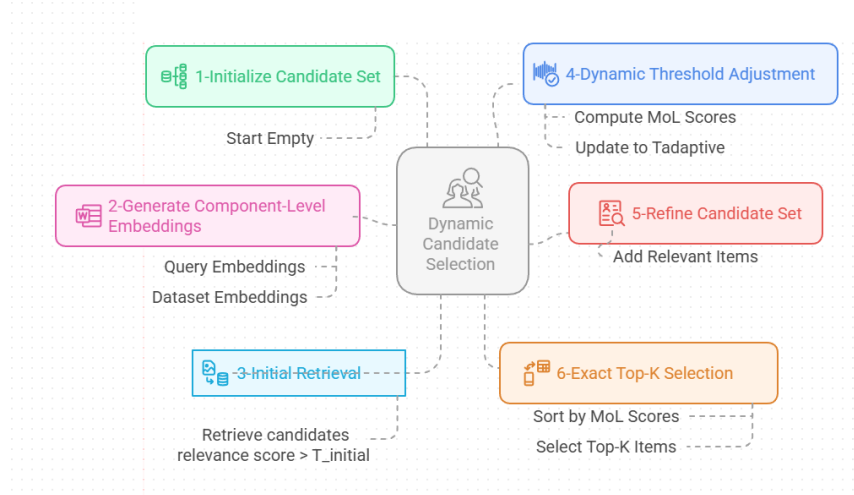


Figure 3.5: proposed solution steps

Here, $f_p(q)$ and $g_p(x)$ represent the feature embeddings of the query q and item x for the p -th component, respectively. The dot product $\langle f_p(q), g_p(x) \rangle$ measures the relevance of each item $x \in X_p$ with respect to q , producing a set of scores S_p .

3. Dynamic Threshold Adjustment: To improve retrieval quality, **Mixture of Logits (MoL)** scores are computed for each candidate $x \in G$. The adaptive gating weights $\pi_p(q, x)$ allow the algorithm to dynamically adjust the retrieval threshold T_{adaptive} based on the MoL scores. The scoring function is defined as:

$$\phi(q, x) = \sum_{p=1}^P \pi_p(q, x) \cdot \langle f_p(q), g_p(x) \rangle. \quad (3.5)$$

The adaptive threshold T_{adaptive} is set as the minimum score among the candidates:

$$T_{\text{adaptive}} = \min\{s \mid s \in G\}. \quad (3.6)$$

4. Refinement and Top-K Selection: Using the adaptive threshold T_{adaptive} , additional relevant candidates are retrieved, expanding the candidate set G' . This is achieved by including candidates whose scores exceed the threshold:

$$G' \leftarrow G \cup \{x \mid s_p \geq T_{\text{adaptive}}\}. \quad (3.7)$$

The algorithm then sorts G' based on MoL scores to select the most relevant top-k candidates.

4. Exact Top-K Selection: Finally, the candidates in G' are sorted by their MoL scores, and the exact top-k items are extracted:

$$G_{\text{final}} = \text{Top-k}(G', \phi(q, x)). \quad (3.8)$$

As shown in Algorithm 1, the retrieval process dynamically adjusts the threshold based on MoL scores. **Input:** Query q , Set of items X , Component-level embeddings: $f_p(q)$, $g_p(x)$ for

$p \in P, x \in X$, Initial threshold T_{init}

Output: Exact top k items based on dynamic threshold selection, G_{final}

3.6.3 Pseudocode

Algorithm 1: Hybrid Exact Top-k with Threshold-Based k Selection

```
1 Initialization  $G \leftarrow \emptyset$  // Initial candidate set
2 foreach component  $p \in P$  do
3    $X_p \leftarrow \{g_p(x) \mid x \in X\}$  // Precompute embeddings
4 end foreach
5
6 1. Initial Candidate Retrieval:
7 foreach component  $p \in P$  do
8   Compute dot product scores: with (eq(3.4)) Retrieve items with scores  $S_p \geq T_{\text{init}}$ 
9   Add these items to  $G$ 
10 end foreach
11 2. Adjust k Dynamically:
12 foreach  $x \in G$  do
13   Compute MoL scores  $s \leftarrow \phi(q, x)$  using : eq(3.5) Set  $T_{\text{adaptive}} = \min\{s : s \in G\}$ 
14 end foreach
15 3. Refine Candidate Set with Adaptive k:
16  $G' \leftarrow \emptyset$ 
17 foreach component  $p \in P$  do
18   Retrieve items from  $X_p$  with scores  $S_p \geq T_{\text{adaptive}}$ 
19   Add these items to  $G'$ 
20 end foreach
21 4. Select Exact Top-k Items:
22 foreach component  $p \in P$  do
23   Compute MoL scores for all items in  $G'$ 
24   Sort  $G'$  by MoL scores in descending order
25   Select the top  $k$  items from  $G'$  where  $k$  is the number of items in  $G'$  exceeding  $T_{\text{adaptive}}$ 
26 end foreach
27 Return:  $G_{\text{final}}$  // Retrieve Top  $k$  items from  $G'$ 
```

3.7 Recommendation System Overview

Modern technology and online services have enabled unprecedented access to vast amounts of data. However, this abundance of information creates an overload, making it harder for users to find relevant content efficiently. Recommender systems address this by filtering information and delivering personalized suggestions, saving users time and effort[60]. These systems are now integral to platforms like e-commerce, television programs[61], e-learning[62], tourism, and more, though further improvements are needed to enhance their versatility and accuracy.

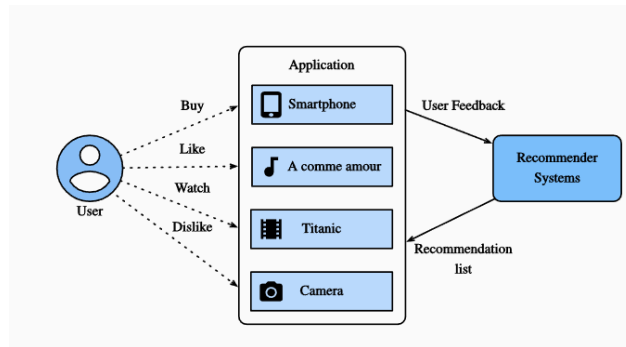


Figure 3.6: Recommendation System Process

3.7.1 SASRec: Self-Attentive Sequential Recommendation

Sequential recommendation systems aim to predict a user's next interaction based on their historical behavior while incorporating contextual information from recent actions. However, effectively capturing patterns in sequential data is challenging due to the exponential growth of the input space as more past interactions are considered.[63]

3.7.2 SASRec Model Architecture

SASRec leverages self-attention to assign adaptive weights to past items at each time step. The key components include:

Embedding Layer: Converts user interactions into dense vector representations.

Self-Attention Layer: Captures dependencies between different interactions in the sequence, allowing for long-range modeling.

Point-Wise Feed Forward Network (FFN): Enhances feature extraction for better predictions.

Prediction Layer: Computes the likelihood of the next interaction based on learned patterns.

A visual representation of SASRec's training process (Figure 3.7) illustrates how the model uses self-attention to focus on relevant past interactions when making predictions

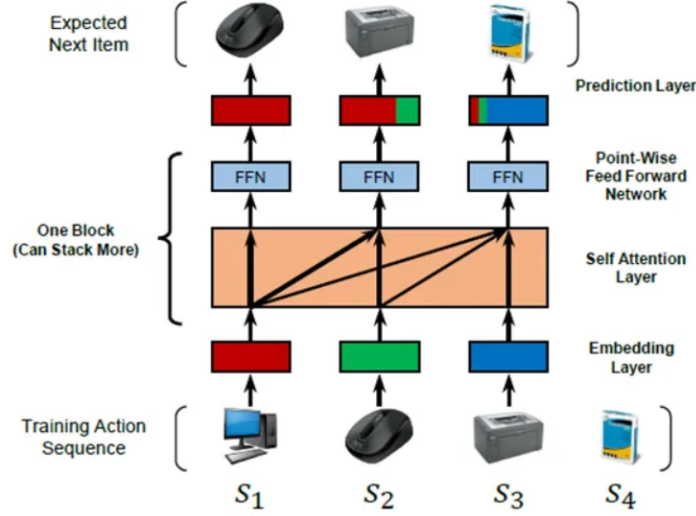


Figure 3.7: the training process of SASRec

3.8 Evaluation Metrics

We employ standard ranking metrics widely used in sequential recommendation:

- **Hit Rate at k (HR@ k):** Measures the proportion of cases where the target item appears in the top- k recommendations. The HR@ k is computed as:[64]

$$\text{HR@}k = \frac{1}{|U|} \sum_{u=1}^{|U|} \mathbb{I}(\text{rank}_u \leq k), \quad (3.9)$$

where $|U|$ is the number of users, rank_u is the rank of the target item for user u , and $\mathbb{I}(\cdot)$ is the indicator function that returns 1 if the condition is true and 0 otherwise.

- **Mean Reciprocal Rank (MRR):** is a ranking quality metric that measures how quickly a system retrieves the first relevant item. It is calculated as the average of reciprocal ranks across all users or queries, MRR ranges from 0 to 1, with higher values indicating better performance [65].

$$\text{MRR} = \frac{1}{|U|} \sum_{u=1}^{|U|} \frac{1}{\text{rank}_u}, \quad (3.10)$$

where rank_u is the position of the first relevant item for user u within the top- K results. U represents the total number of users (for recommendation systems) or queries (for information retrieval tasks) in the dataset.

- **Normalized Discounted Cumulative Gain (NDCG)**: Assesses the ranking quality while accounting for position importance. The $\text{NDCG}@k$ is computed as:[64]

$$\text{NDCG}@k = \frac{1}{|U|} \sum_{u=1}^{|U|} \frac{\text{DCG}@k}{\text{IDCG}@k}, \quad (3.11)$$

where $\text{DCG}@k$ is the Discounted Cumulative Gain at position k :

$$\text{DCG}@k = \sum_{i=1}^k \frac{2^{\text{rel}_i} - 1}{\log_2(i + 1)}, \quad (3.12)$$

and $\text{IDCG}@k$ is the Ideal $\text{DCG}@k$, computed by sorting the items by their true relevance scores.

Table ?? summarizes the performance of our hybrid algorithm compared to the MoL-based approach on the MovieLens 100K and 1M datasets, both tested using a Max Sequence Length of 50, an Embedding Dimension of 128, 2 Attention Heads, a Feedforward Dimension of 128, a Batch Size of 128, and trained for 10 epochs

3.9 Conclusion

The selection of k in retrieval plays a pivotal role in balancing relevance, efficiency, and computational cost. Throughout this chapter, we explored how different approaches—static, dynamic, and hybrid—impact retrieval performance and generation quality. While static selection provides consistency, it lacks adaptability to varying query complexities. Dynamic methods introduce flexibility but come with computational overhead, whereas hybrid strategies aim to balance both. The Hybrid Exact Top- k with Threshold-Based k Selection method offers an advanced solution by leveraging adaptive weighting to enhance ranking effectiveness. Ultimately, an effective k -selection strategy is essential for optimizing retrieval systems, ensuring both efficiency and high-quality results in knowledge-augmented applications.

Chapter 4

Experimental Results

4.1 Introduction

In this chapter, we present the experimental results of applying our novel algorithm to SASRec and compare its performance with SASRec tested using MOL. The goal of these experiments is to assess the effectiveness of our approach in improving recommendation accuracy, model efficiency, and overall performance metrics.

4.2 Experimental Results

In order to measure the effectiveness of our proposed method, we perform a comprehensive evaluation of both the retrieval algorithm and the Mixture-of-Logits (MoL) approach. This assessment focuses on the next-item prediction task, a fundamental challenge in recommendation systems[63], where the goal is to predict the most relevant item a user will interact with next based on their past interactions.

4.2.1 Dataset

We conducted experiments using two MovieLens datasets : ML-100K and ML-1M [66] which are widely used benchmarks for evaluating sequential recommendation models as detailed in Table4.1.

4.2.2 Setup

For both datasets, We utilize the SASRec architecture as our sequential user encoder, a model renowned for achieving state-of-the-art performance in next-item prediction tasks.

Dataset	Description
MovieLens-100K	100,000 ratings (1-5 scale) from 943 users on 1,682 movies. Each user has rated at least 20 movies. Includes user demographic information (age, gender, occupation, zip code).
MovieLens-1M	1,000,209 ratings from 6,040 users on approximately 3,900 movies. Data collected from users who joined MovieLens in 2000. Represents a larger-scale recommendation scenario.

Table 4.1: Summary of MovieLens datasets

This architecture processes the user’s historical interaction sequence, generating embeddings that encapsulate the user’s preferences at each time step. These embeddings serve as the foundation for predicting the next item in the sequence.

The query q represents the user’s state at a specific time step, derived from their interaction history. In the MoL (Mixture of Logits) framework, q is transformed into Pq embeddings through a multi-layer perceptron (MLP).

4.2.3 Impact of Hyperparameters

For fair comparison, we maintained consistent architectural choices and training conditions across all experiments. We conducted an extensive hyperparameter analysis comparing both approaches (Hybrid+SAS and MoL+SAS) across different architectural configurations. All experiments were Implemented in TensorFlow and trained on a Google Colab environment with a T4 GPU. We use the Adam optimizer with a learning rate of 0.001. For the hybrid algorithm, we initialize the threshold (Tinit) to 0.3 and adaptively adjust it during training. We discuss detailed hyperparameter settings in table 4.2, table 4.3

Model	Max Sequence Length	Embedding Dimension	Number of Heads	Feedforward Dimension	Batch Size	Epochs	Val Loss	Val Accuracy
Hybrid+SAS	50	128	2	128	128	12	5.3036	0.1584
MoL+SAS	50	128	2	128	128	12	5.3152	0.1582
Hybrid+SAS	128	256	4	256	128	10	3.6364	0.4301
MoL+SAS	128	256	4	256	128	10	3.6374	0.4299
Hybrid+SAS	512	512	4	512	128	10	1.2808	0.8120
MoL+SAS	512	512	4	512	128	10	1.3050	0.8016

Table 4.2: Results on 100kMovies dataset

Model	Max Sequence Length	Embedding Dimension	Number of Heads	Feedforward Dimension	Batch Size	Epochs	Val Loss	Val Accuracy
Hybrid+SAS	50	128	2	128	128	10	4.5721	0.1530
MoL+SAS	50	128	2	128	128	10	4.5733	0.1526
Hybrid+SAS	128	256	4	256	128	10	3.4152	0.3680
MoL+SAS	128	256	4	256	128	10	3.4671	0.3627
Hybrid+SAS	512	512	4	512	128	10	1.0275	0.8350
MoL+SAS	512	512	4	512	128	10	1.0350	0.8276

Table 4.3: Results on 1M Movies dataset

Both approaches demonstrate significant performance improvements as model capacity increases, with larger configurations consistently delivering better results. For instance, when increasing the model’s capacity such as expanding the (Max Sequence Length: 512, Embedding Dimension: 512, Number of Heads: 4, Feed-Forward Dimension: 512) the hybrid algorithm combined with SASRec (Hybrid+SAS) achieves notable gains, particularly in the most resource-intensive setup. On the ML-100K dataset, Hybrid+SAS reaches a score of **0.8120** compared to the baseline’s **0.8016**, while on ML-1M, it achieves **0.8350** versus **0.8276**. The ML-1M dataset generally benefits more from increased capacity, with the performance gap between datasets narrowing as the model scales. While smaller configurations provide a balance of efficiency and performance, the largest configuration, despite its higher computational

demands, yields the best results, making it suitable for scenarios where resources are not a constraint. Both approaches show similar benefits from scaling, but Hybrid+SAS maintains a consistent edge in performance.

4.2.4 Impact of Adaptive k-Variations on Model Performance

As shown in Figures 4.1a and 4.1b, the value of k fluctuates across epochs for both MovieLens 100K and MovieLens 1M datasets. These variations indicate the adaptive nature of k in response to the dataset characteristics and training progress. In the following section, we analyze how these changes influence model performance.

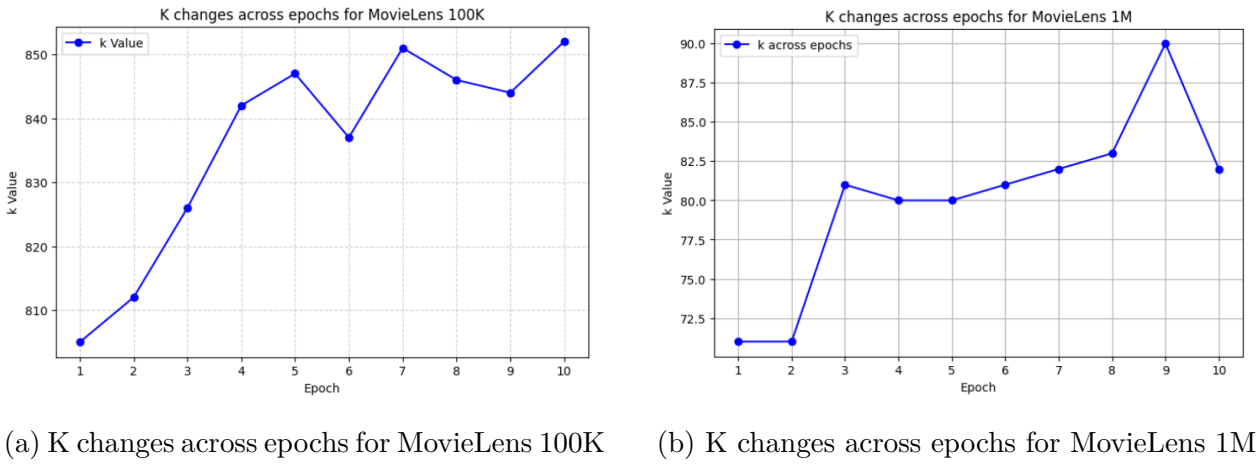


Figure 4.1: Comparison of K changes across epochs for different datasets

the value of K changed dynamically during training, with different behaviors. For the MovieLens 100K dataset, K showed a steady increase across epochs, whereas for the MovieLens 1M dataset, K began at a lower value, experienced fluctuations, peaked, and then stabilized. This indicates that the larger dataset necessitated more adaptive adjustments in retrieval compared to the smaller dataset.

Figure 4.2 summarizes the performance of our hybrid algorithm compared to the MoL-based approach on the MovieLens 100K and 1M datasets, both tested using a Max Sequence Length of 50, an Embedding Dimension of 128, 2 Attention Heads, a Feedforward Dimension of 128, a Batch Size of 128, and trained for 10 epochs .

The variations in K help explain the performance differences seen in the fig 4.2. The Hybrid+SAS model applied to the MovieLens 1M dataset, which exhibited more dynamic changes in K achieved higher HR@50(0.3631) and HR@200(0.6170) scores, reflecting better long-range recommendation quality. The fluctuations in K in the 1M dataset likely allowed the model to balance exploration and precision, improving its overall ranking performance.

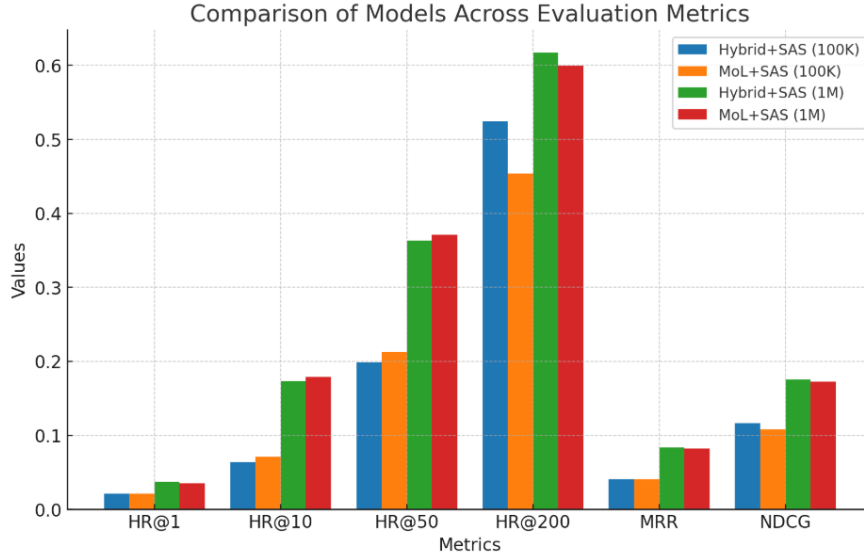


Figure 4.2: Comparison of Models Across Evaluation Metrics

On the other hand, the more gradual K increase in the 100K dataset resulted in relatively lower scores, suggesting that a static or overly conservative K selection might limit retrieval effectiveness.

Additionally, the MoL+SAS model achieved better performance than Hybrid+SAS in HR@10 for both datasets. This aligns with the observation that MoL+SAS tended to retrieve fewer but more relevant items at shorter ranking positions. This behavior can be attributed to how K evolved during training?smaller K values in earlier epochs likely enabled MoL+SAS to maintain higher precision at shorter ranks. These findings highlight the importance of dynamically tuning K based on dataset characteristics to optimize recommendation effectiveness.

The results demonstrate that the Hybrid Exact Top-k algorithm effectively leverages both sequential user behavior and item metadata to improve recommendation quality. The adaptive MoL threshold allows the model to dynamically refine candidate items during training, leading to better performance. The improvements are consistent across both datasets, highlighting the robustness of our approach.

4.3 Conclusion

The experimental results demonstrate the effectiveness of our proposed algorithm when applied to SASRec. Through extensive evaluation on the MovieLens-100K and MovieLens-1M datasets, we observe that our method consistently outperforms the baseline models, including

SASRec with MOL. Our approach shows improvements in key evaluation metrics, particularly in Hit Rate (HR@k) and Normalized Discounted Cumulative Gain (NDCG@k), indicating better recommendation relevance. Furthermore, the results highlight the importance of hyperparameter tuning, as different configurations significantly impact model performance. Overall, the findings confirm that incorporating our algorithm enhances sequential recommendation capabilities, making it a promising approach for future research and real-world applications. Future work will focus on further optimizing the model and testing on additional datasets to validate its generalizability.

Conclusion

Bibliography

- [1] Abdellah Hamouda Sidhoum, Mataoui M'hamed, Sebbak Faouzi, Ouazene Aymen, Hus-sine Fedoua, Amrani Mohamed Chakib, and Boumediri Takieddine. Transforming legal documents into knowledge goldmines: Application on the algerian official journal. pages 1–7, 09 2024.
- [2] Humza Naveed, Asad Ullah Khan, Shi Qiu, Muhammad Saqib, Saeed Anwar, Muham-mad Usman, Naveed Akhtar, Nick Barnes, and Ajmal Mian. A comprehensive overview of large language models, 2024. <https://arxiv.org/abs/2307.06435>.
- [3] Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, Sebastian Riedel, and Douwe Kiela. Retrieval-augmented generation for knowledge-intensive nlp tasks.
- [4] Imen Bouaziz Mezghanni and Faiez Gargouri. Information retrieval from unstructured arabic legal data. In Richard Booth and Min-Ling Zhang, editors, *PRICAI 2016: Trends in Artificial Intelligence*, pages 44–54, Cham, 2016. Springer International Publishing.
- [5] Mohana Murugan. *Natural Language Processing (NLP)*, 2024.
- [6] Alexander S. Gillis, Ben Lutkevich, and Ed Burn. Natural language processing (nlp), 2024. Accessed: 2024-08-22.
- [7] Michael Taylor. *Make Your Own Neural Network: An In-depth Visual Introduction For Beginners*. CreateSpace Independent Publishing Platform, Scotts Valley, CA, 2017. Paperback edition, October 4, 2017.
- [8] Kyunghyun Cho, Bart Van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. Learning phrase representations using rnn encoder-decoder for statistical machine translation. *arXiv preprint arXiv:1406.1078*, 2014.

- [9] GeeksforGeeks. Deep learning - introduction to long short term memory, 2024. Accessed: August 2024.
- [10] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural Computation*, 9(8):1735–1780, November 1997.
- [11] Denis Rothman. *Transformers for Natural Language Processing: Build innovative deep neural network architectures for NLP with Python, PyTorch, TensorFlow, BERT, RoBERTa, and more*. Packt Publishing Ltd, 2021.
- [12] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in neural information processing systems*, pages 5998–6008, 2017.
- [13] Jay Alammar. The illustrated transformer. <https://jalammar.github.io/illustrated-transformer/>, 2018. Accessed: 2024-08-28.
- [14] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186. Association for Computational Linguistics, 2019.
- [15] Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901, 2020.
- [16] Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*, 2023.
- [17] Thomas Wang, Adam Roberts, Daniel Hesslow, Teven Le Scao, Hyung Won Chung, Iz Beltagy, Julien Launay, and Colin Raffel. What language model architecture and pretraining objective work best for zero-shot generalization? *arXiv preprint arXiv:2302.03072*, 2023.
- [18] Li Dong, Nan Yang, Wenhui Wang, Furu Wei, Xiaodong Liu, Yu Wang, Jianfeng Gao, Ming Zhou, and Hsiao-Wuen Hon. Unified language model pre-training for natural

- language understanding and generation. In *Advances in Neural Information Processing Systems (NeurIPS)*, volume 32, 2019.
- [19] Gokul Yenduri, M Ramalingam, Chemmalar G Selvi, Y Supriya, Gautam Srivastava, Praveen Kumar Reddy Maddikunta, Deepti Raj, Rutvij H Jhaveri, B Prabadevi, Weizheng Wang, Athanasios V Vasilakos, and Thippa Reddy Gadekallu. Gpt (generative pre-trained transformer) – a comprehensive review on enabling technologies, potential applications, emerging challenges, and future directions. *Journal of Artificial Intelligence Research*, 82:123–157, 2023.
 - [20] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *arXiv preprint arXiv:1910.10683v4*, September 2023. Editor: Ivan Titov.
 - [21] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, et al. Llama 2: Open foundation and fine-tuned chat models, 2023.
 - [22] Neha Sengupta, Sunil Kumar Sahu, Bokang Jia, Satheesh Katipomu, et al. Jais and jais-chat: Arabic-centric foundation and instruction-tuned open generative large language models, 2023.
 - [23] Emily M Bender, Timnit Gebru, Angelina McMillan-Major, and Shmargaret Shmitchell. On the dangers of stochastic parrots: Can language models be too big? In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, 2021.
 - [24] Matthew Chalk et al. Legal-bert: The muppets meet the supreme court. *arXiv preprint arXiv:2010.02010*, 2020.
 - [25] Michael Bommarito and Daniel Martin Katz. Predicting the behavior of the supreme court of the united states: A general approach. *arXiv preprint arXiv:1807.09850*, 2018.
 - [26] Chadi Helwe. *Evaluating and Improving the Reasoning Abilities of Language Models*. PhD thesis, Institut Polytechnique de Paris, Palaiseau, France, July 2024. Thèse de doctorat préparée à Télécom Paris, École doctorale n°626, École doctorale de l’Institut Polytechnique de Paris (ED IP Paris), Spécialité de doctorat: Informatique, Données, IA.
 - [27] Natassha Selvaraj. What is retrieval augmented generation (rag)?, 2024. Updated Jan 30, 2024.

- [28] Yunfan Gao, Yun Xiong, Xinyu Gao, Kangxiang Jia, Jinliu Pan, Yuxi Bi, Yi Dai, Jiawei Sun, Meng Wang, and Haofen Wang. Retrieval-augmented generation for large language models: A survey. 2024.
- [29] Jeremy Howard and Sebastian Ruder. Universal language model fine-tuning for text classification. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics*, 2018.
- [30] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.
- [31] Vladimir Karpukhin, Barlas Oguz, Sewon Min, Patrick Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. Dense passage retrieval for open-domain question answering. *arXiv preprint arXiv:2004.04906*, 2020.
- [32] Laurent Mombaerts, Terry Ding, Florian Felice, Jonathan Taws, Adi Banerjee, and Tarik Borogovac. Meta knowledge for retrieval augmented large language models. *arXiv preprint arXiv:2408.09017v1*, 2024. <https://arxiv.org/abs/2408.09017v1>.
- [33] Lexemo. Retrieval-augmented generation (rag) in legal research. [Online; accessed April 2025].
- [34] Astera. Legal document data extraction with rag: A new era for law firms. <https://www.astera.com/type/blog/rag-driven-legal-data-extraction-for-faster-case-management/>.
- [35] Yujia Zhou, Yan Liu, Xiaoxi Li, Jiajie Jin, Hongjin Qian, Zheng Liu, Chaozhuo Li, Zhicheng Dou, Tsung-Yi Ho, and Philip S. Yu. Trustworthiness in retrieval-augmented generation systems: A survey. *arXiv preprint arXiv:2409.10102*, September 2020. <https://arxiv.org/abs/2409.10102v1>.
- [36] Penghao Zhao, Hailin Zhang, Qinhan Yu, Zhengren Wang, Yunteng Geng, Fangcheng Fu, Ling Yang, Wentao Zhang, and Bin Cui. Retrieval-augmented generation for ai-generated content: A survey. *arXiv preprint arXiv:2402.19473*, February 2024. <https://arxiv.org/abs/2402.19473v1>.
- [37] Shailja Gupta, Rajesh Ranjan, and Surya Narayan Singh. A comprehensive survey of retrieval-augmented generation (rag): Evolution, current landscape and future directions, 2024. <https://arxiv.org/abs/2410.12837>.

- [38] Pareto AI. The ultimate guide to retrieval-augmented generation (rag), 2024. <https://pareto.ai/blog/retrieval-augmented-generation>.
- [39] Nicholas Rossi, Juexin Lin, Feng Liu, Zhen Yang, Tony Lee, Alessandro Magnani, and Ciya Liao. Relevance filtering for embedding-based retrieval. In *Proceedings of the 33rd ACM International Conference on Information and Knowledge Management*, CIKM '24, page 4828–4835. ACM, October 2024.
- [40] GeeksforGeeks. Precision and recall in information retrieval, 2022. <https://www.geeksforgeeks.org/precision-and-recall-in-information-retrieval/>.
- [41] David Kirchhoff. Metrics for evaluation of retrieval in retrieval-augmented generation, 2024. <https://deconvoluteai.com/blog/rag/metrics-retrieval>.
- [42] Christopher D. Manning, Prabhakar Raghavan, and Hinrich Schütze. *Introduction to Information Retrieval*. Cambridge University Press, 2008. <https://nlp.stanford.edu/IR-book/>.
- [43] Wikipedia contributors. Ranking (information retrieval) — Wikipedia, the free encyclopedia. [https://en.wikipedia.org/w/index.php?title=Ranking_\(information_retrieval\)&oldid=1262179867](https://en.wikipedia.org/w/index.php?title=Ranking_(information_retrieval)&oldid=1262179867), 2024. [Online; accessed 7-March-2025].
- [44] Alireza Salemi and Hamed Zamani. Evaluating retrieval quality in retrieval-augmented generation. Amherst, MA, United States, 2023. ACM. Accessed via https://dl.acm.org/doi/pdf/10.1145/3626772.3657957?utm_source=chatgpt.com.
- [45] Bingyu Wan, Fuxi Zhang, Zhongpeng Qi, Jiayi Ding, Jijun Li, Baoshi Fan, Yijia Zhang, and Jun Zhang. Cognitive-aligned document selection for retrieval-augmented generation, 2025.
- [46] Markus Freitag and Yaser Al-Onaizan. Beam search strategies for neural machine translation. In Thang Luong, Alexandra Birch, Graham Neubig, and Andrew Finch, editors, *Proceedings of the First Workshop on Neural Machine Translation*, pages 56–60, Vancouver, August 2017. Association for Computational Linguistics.
- [47] NVIDIA. Best practices for tuning the performance of TensorRT-LLM beam search, 2023. [Accessed: 7-March-2025].
- [48] Buqian Zheng. Enhancing information retrieval with learned sparse retrieval, 2024. Accessed: 2025-03-09.

- [49] Stephen Robertson and Zaragoza. The probabilistic relevance framework: Bm25 and beyond. *Found. Trends Inf. Retr.*, 3(4):333–389, April 2009.
- [50] GeeksforGeeks. Understanding tf-idf (term frequency-inverse document frequency), 2025. Last Updated: 07 Feb, 2025. Accessed: 2025-03-09.
- [51] Shengyao Zhuang, Hang Li, and Guido Zuccon. Deep query likelihood model for information retrieval. In *Advances in Information Retrieval: 43rd European Conference on IR Research, ECIR 2021, Virtual Event, March 28 – April 1, 2021, Proceedings, Part II*, page 463–470, Berlin, Heidelberg, 2021. Springer-Verlag.
- [52] Tong Chen, Hongwei Wang, Sihao Chen, Wenhao Yu, Kaixin Ma, Xinran, Hongming Zhang, and Dong Yu. Dense X retrieval: What retrieval granularity should we use? In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen, editors, *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 15159–15177, Miami, Florida, USA, November 2024. Association for Computational Linguistics.
- [53] Wikipedia contributors. Faiss — Wikipedia, the free encyclopedia, 2025. [Online; accessed 9-March-2025].
- [54] J. Shane Culpepper, Charles L. A. Clarke, and Jimmy Lin. Dynamic trade-off prediction in multi-stage retrieval systems, 2016.
- [55] Hao Wu, Kuang Lu, Xiaoming Li, and Hui Fang. Improving retrieval effectiveness for temporal-constrained top-k query processing. In Won-Kyung Sung, Hanmin Jung, Shuo Xu, Krisana Chinnasarn, Kazutoshi Sumiya, Jeonghoon Lee, Zhicheng Dou, Grace Hui Yang, Young-Guk Ha, and Seungbock Lee, editors, *Information Retrieval Technology*, pages 3–15, Cham, 2017. Springer International Publishing.
- [56] Kunal Sawarkar, Abhilasha Mangal, and Shivam Raj Solanki. Blended rag: Improving rag (retriever-augmented generation) accuracy with semantic search and hybrid query-based retrievers, 2024.
- [57] Chencheng Zhu, Kazutaka Shimada, Tomoki Taniguchi, and Tomoko Ohkuma. Staykate: Hybrid in-context example selection combining representativeness sampling and retrieval-based approach – a case study on science domains, 2024.
- [58] Jiaqi Zhai, Zhaojie Gong, Yueming Wang, Xiao Sun, Zheng Yan, Fu Li, and Xing Liu. Revisiting neural retrieval on accelerators. In *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, KDD '23*, pages 5520–5531, New York, NY, USA, 2023. Association for Computing Machinery.

- [59] Bailu Ding and Jiaqi Zhai. Efficient retrieval with learned similarities. In *THE WEB CONFERENCE 2025*, 2025. <https://openreview.net/forum?id=eHF4pDRWjT>.
- [60] Deepjyoti Roy and Mala Dutta. A systematic review and research perspective on recommender systems. *Journal of Big Data*, 9(1):59, 2022.
- [61] Choonsung Shin and Woontack Woo. Socially aware tv program recommender for multiple viewers. *IEEE Transactions on Consumer Electronics*, 55(2):927–932, 2009.
- [62] Shu-Lin Wang and Chun-Yi Wu. Application of context-aware and personalized recommendation to implement an adaptive ubiquitous learning system. *Expert Systems with Applications*, 38(9):10831–10838, 2011.
- [63] Wang-Cheng Kang and Julian McAuley. Self-attentive sequential recommendation, 2018.
- [64] Yan-Martin Tamm, Rinchin Damdinov, and Alexey Vasilev. Quality metrics in recommender systems: Do we calculate metrics consistently? In *Fifteenth ACM Conference on Recommender Systems*, RecSys '21, page 708–713. ACM, September 2021.
- [65] Evidently AI. Mean reciprocal rank (mrr) explained, 2025. Last accessed: March 13, 2025.
- [66] F. Maxwell Harper and Joseph A. Konstan. The movielens datasets: History and context. *ACM Transactions on Interactive Intelligent Systems*, 5(4), dec 2015.