

Retrieval-Augmented Generation for AI-Generated Content: A Survey

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Abstract—The development of Artificial Intelligence Generated Content (AIGC) has been facilitated by advancements in model algorithms, the increasing scale of foundation models, and the availability of ample high-quality datasets. While AIGC has achieved remarkable performance, it still faces several challenges, such as the difficulty of maintaining up-to-date and long-tail knowledge, the risk of data leakage, and the high costs associated with training and inference. Retrieval-Augmented Generation (RAG) has recently emerged as a paradigm to address such challenges. In particular, RAG introduces the information retrieval process, which enhances the generation process by retrieving relevant objects from available data stores, leading to higher accuracy and better robustness. In this paper, we comprehensively review existing efforts that integrate RAG technique into AIGC scenarios. We first classify RAG foundations according to how the retriever augments the generator, distilling the fundamental abstractions of the augmentation methodologies for various retrievers and generators. This unified perspective encompasses all RAG scenarios, illuminating advancements and pivotal technologies that help with potential future progress. We also summarize additional enhancements methods for RAG, facilitating effective engineering and implementation of RAG systems. Then from another view, we survey on practical applications of RAG across different modalities and tasks, offering valuable references for researchers and practitioners. Furthermore, we introduce the benchmarks for RAG, discuss the limitations of current RAG systems, and suggest potential directions for future research. Project Repo: <https://github.com/hymie122/RAG-Survey>.

Index Terms—Retrieval-augmented generation, AI-generated content, generative models, information retrieval.

I. INTRODUCTION

A. Background

RECENT years have witnessed the surge in interests surrounding Artificial Intelligence Generated Content (AIGC). Various content generation tools have been meticulously crafted to produce diverse outputs across various modalities, such as Large Language Models (LLMs) including the GPT series [1]–[3] and the LLAMA series [4]–[6] for texts and codes, DALL-E [7]–[9] and Stable Diffusion [10] for images, and Sora [11] for videos. The word “AIGC” emphasizes that the contents are produced by advanced generative models other than human beings or rule-based approaches. These generative models have achieved remarkable

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performance due to the utilization of novel model algorithms, explosive scale of foundation models, and massive high-quality datasets. Specifically, sequence-to-sequence tasks have transitioned from utilizing Long Short-Term Memory (LSTM) networks [12] to Transformer-based models [13], and image-generation tasks have shifted from Generative Adversarial Networks (GANs) [14] to Latent Diffusion Models (LDMs) [10] as well. Notably, the architecture of foundation models, initially constituted by millions of parameters [15], [16], has now grown to billions or even trillions of parameters [1], [4], [17]. These advancements are further bolstered by the availability of rich, high-quality datasets [1], [18], which provide ample training samples to fully optimize model parameters.

Information retrieval is another pivotal application within the field of computer science. Different from generation, retrieval aims to locate relevant existing objects from a vast pool of resources. The most prevalent application of retrieval lies in web search engines, which primarily focus on the task of document retrieval [19], [20]. In the present era, efficient information retrieval systems can handle document collections on the order of billions [21], [22]. Besides documents, retrieval has also been applied for many other modalities [23]–[26].

Despite the remarkable progress made by advanced generative models, AIGC continues to face a number of well-known challenges, including the struggle to maintain up-to-date knowledge, the inability to incorporate long-tail knowledge [27], and the risk of leaking private training data [28]. Retrieval-Augmented Generation (RAG) is proposed to alleviate, if not completely address, the aforementioned challenges through its adaptable data repository. The knowledge stored for retrieval can be conceptualized as non-parametric memory. Such a form of memory is easily modifiable, capable of accommodating broad long-tail knowledge, and also able to encode confidential data. In addition, retrieval can also be employed to reduce the generation costs. For example, RAG can reduce the size of large generative models [29], provide support for long contexts [30], and eliminate certain generation steps [31].

A typical RAG process is shown in Fig. 1. Given an input query, the retriever locates and looks up relevant data sources, then the retrieved results interact with the generator to enhance the overall generation process. The retrieval results can interact with the generation process in different ways: they can serve as augmented input to the generator [32], [33]; they can join at the middle stage of generation as latent representations [34], [35]; they can contribute to the final generation results in the form of logits [36], [37]; they can even influence or omit

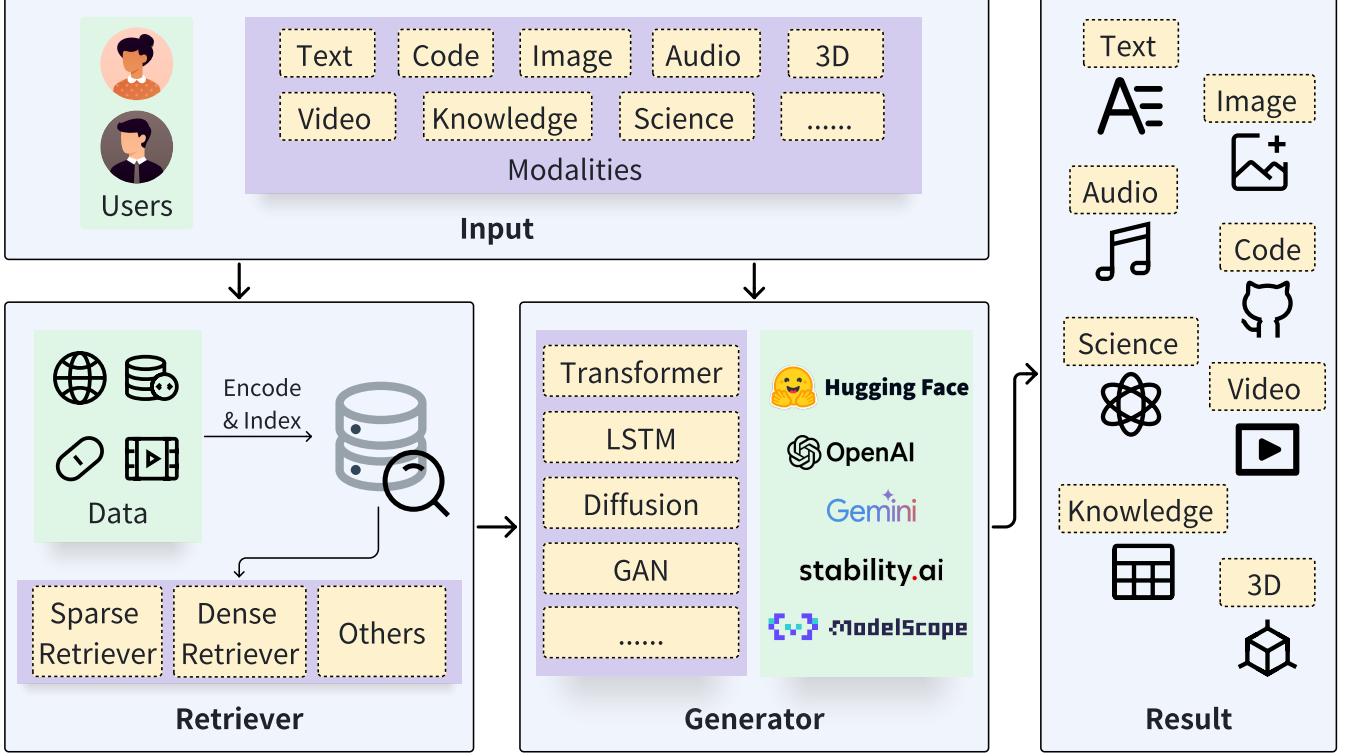


Fig. 1. A generic RAG architecture. The users’ queries, which may be different modality, serve as input to both the retriever and the generator. The retriever searches for relevant data sources in storage, while the generator interacts with the retrieval results and ultimately produces results of various modalities.

certain generation steps [31], [38]. Moreover, built upon the typical, foundational RAG process, numerous enhancements have also been proposed to improve the overall quality. These enhancements encompass methods for specific components as well as optimizations targeting the entire pipeline.

In addition, although the concept of RAG is initially emerged in text-to-text generation [33], it has also been adapted to various domains, including codes [39]–[41], audios [42], [43], images [44]–[46], videos [47], [48], 3D [49], [50], knowledge [51]–[53], and AI for science [54], [55]. In particular, the essential idea and process of RAG are largely consistent across modalities. However, it necessitates specific minor adjustments in augmentation techniques, and the selection of retrievers and generators varies depending on the specific modalities and/or applications.

Despite the rapid growth in recent research on RAG, a systematic review encompassing all foundations, enhancements, and applications is notably absent. The absence of discussion on RAG foundations significantly undermines the practical value of research in this domain, leaving the potential of RAG not fully explored. While the majority of research interest, particularly among LLM researchers, centers on query-based RAG in text-generation tasks, it is essential to acknowledge that other RAG foundation paradigms are also effective techniques with significant potential for usage and further development. The lack of an overview on RAG applications causes researchers and practitioners to overlook RAG’s progress across multiple modalities and remain un-

aware of how RAG can be effectively applied. Although text generation is typically considered as the main application of RAG, we emphasize that the development of RAG in other modalities also began at an early stage and has yielded promising advancements. Certain modalities have a rich historical connection to the retrieval technique, infusing RAG with distinctive characteristics. Despite that some surveys on RAG have already been proposed, they mainly focus on partial aspects, such as specific methodologies and tasks. In this paper, our objective is to present a comprehensive survey to provide a systematic overview of RAG.

B. Contribution

This survey offers a comprehensive overview of RAG, covering foundations, enhancements, applications, benchmarks, limitations, and potential future directions. While retrievers and generators exhibit variations across modalities and tasks, we distill the fundamental abstractions of RAG foundations, considering applications as adaptations stemming from these abstractions. We aim to offer references and guidelines to researchers and practitioners, providing valuable insights for advancing RAG methodologies and related applications. In summary, we list our contributions as follows:

- We conduct a comprehensive review of RAG, and distill the abstractions of RAG foundations for various retrievers and generators.

- We conclude the enhancements on existing RAG pipeline, elaborating the techniques leveraged to enable more effective RAG systems.
- For various modalities and tasks, we survey existing AIGC methods that incorporate RAG techniques, exhibiting how RAG contributes to current generative models.
- We discuss the limitations and promising research directions of RAG, shedding light on its potential future development.

C. Related Work

With the advancement of research on RAG, several survey papers focusing on RAG have been proposed. Li et al. [56] conducted survey on RAG for text generation. Since it reviews papers up to 2022, many new advancements of RAG for AIGC are not included. Asai et al. [57] delivered a tutorial on retrieval-based language models, introducing the architectures and training paradigms. Gao et al. [58] surveyed RAG for LLMs, especially investigating the enhancements on query-based RAG. The above surveys primarily consider RAG for text-related tasks that are facilitated by LLMs, leaving other modalities as potential extensions. However, the concept of RAG emerges across all modalities at an early stage, making it more suitable for discussion within the broader context of the entire AIGC. Zhao et al. [59] proposed a survey on RAG applications for multiple modalities, but ignoring the discussion on RAG foundations. These surveys either exclusively focus on a single RAG foundation paradigm or provide only a brief overview of RAG augmentation methodologies for limited scenarios. Consequently, while existing research has explored various aspects of RAG, there remains a need for a comprehensive overview that systematically covers RAG foundations, enhancements, and its applicability across different domains. In this paper, we aim to present a systematic overview of RAG that addresses these gaps.

D. Roadmap

The rest of the paper is organized as follows. Section II elaborates on the preliminary of RAG, introducing retrievers and generators. Section III presents the foundations of RAG and further enhancements on RAG. Section IV reviews existing research on RAG across various applications. Section V investigates the benchmark frameworks for RAG. Section VI discusses current limitations of RAG and potential future directions. Finally, Section VII concludes this paper.

II. PRELIMINARY

In this section, we first deliver an overview of the general RAG architecture. Subsequently, we delve into the details of the generators and retrievers employed in today's RAG-based AIGC.

A. Overview

As shown in Fig. 1, the entire RAG system consists of two core modules: the retriever and the generator. The retriever is responsible for searching relevant information from

a constructed data store, and the generator is responsible for producing generated contents. The RAG process unfolds as follows: firstly, the retriever receives the input query and searches for relevant information; then, the original query and the retrieval results are fed into the generator through a specific augmentation methodology; finally, the generator produces the desired outcomes. In Section III-A, we will introduce the RAG foundations. In Section III-B, we will introduce further enhancement methods based on a constructed RAG system.

B. Generator

The remarkable performance of generative AI across diverse tasks has ushered in the era of AIGC. Generative AI, powered by its robust generative module, has surpassed even the original expert systems in terms of effectiveness. Within the entire RAG system, the generation module holds significant importance. Different generative models are selected for different scenarios. For instance: transformer model for text-to-text task, VisualGPT [60] for image-to-text task, Stable Diffusion [10] for text-to-image task, and Codex [2] for text-to-code task.

Based on model structure, We categorize the generators into 4 main groups: transformer model, LSTM, diffusion model, and GAN. We will provide a detailed introduction to each category in the following sections.

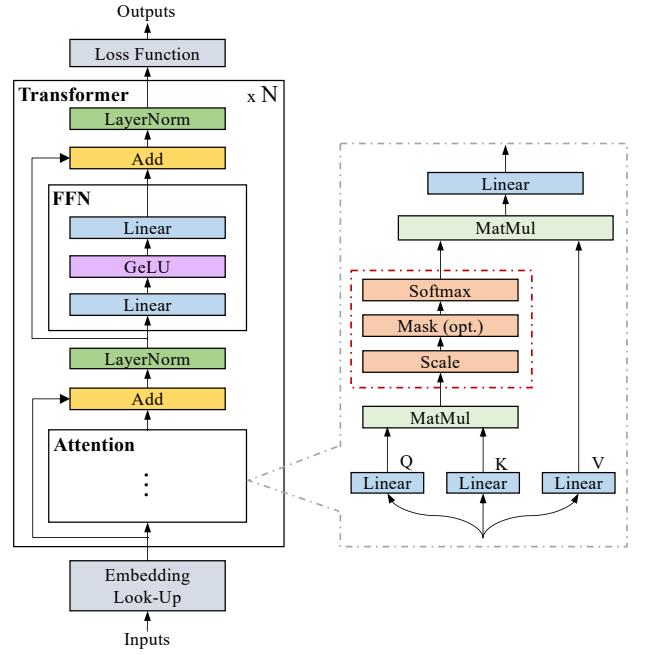


Fig. 2. Architecture of a traditional transformer model.

1) **Transformer Model:** The initial transformer was designed to solve problems in the Neural Language Process (NLP) field, consisting of self attention mechanism, feed forward network, layer normalization module, and residual network [61].

As shown in Fig. 2, the input of the transformer is mapped to a tensor x_{in} with a shape of (b, s, h) after the tokenization process and embedding model, where b represents batch size, s represents sequence length and h represents hidden dimension.

Next, the position encoding will be sent to the self attention layer along with this tensor. The input x_{in} and the output x_{out} of the self-attention module will be connected by the residual network and the layer normalization module. Finally, the output of the "Add & Norm" module x_{out} will be sent to the feed forward network. The entire process can be defined as follows:

$$Q = x_{in} * W_q + b_q$$

$$K = x_{in} * W_k + b_k$$

$$V = x_{in} * W_v + b_v$$

$$x_{out} = \text{LayerNorm1}(\text{Softmax}(\frac{Q * K^T}{\sqrt{h}}) * V * W_o + b_o) + x_{in}$$

$$y = \text{LayerNorm2}((x_{out} * W_1 + b_1) * W_2 + b_2) + x_{out}$$

It should be noted that w_q, w_k, w_v, w_o are learnable tensors with shape (h, h) ; b_q, b_k, b_v, b_o are learnable tensors with shape $(h,)$.

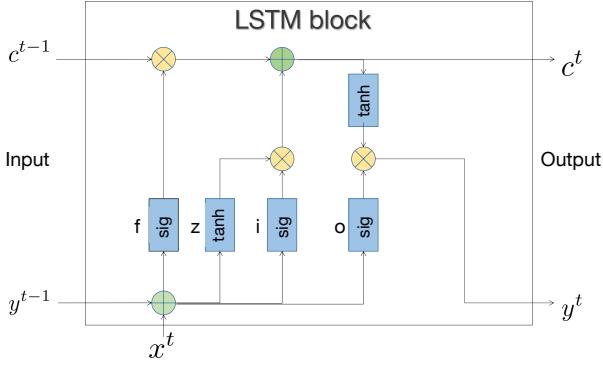


Fig. 3. Architecture of a typical LSTM block with forget gate.

2) **LSTM**: Long Short-Term Memory (LSTM) [62] is a special Recurrent Neural Network (RNN) model that overcomes the exploding/vanishing gradient problems of RNN in processing long-term dependency information by introducing cell state and gate mechanisms. The LSTM model consists of three gates: Input Gate, Forget Gate, and Output Gate. These gates update the cell state by controlling the information flow, enabling the model to remember long-term dependent information. Cell State is the core module of the LSTM model which can memorize and maintain information. The Input Gate decides which input data should be retained in the cell state. Forget Gate determines which cell state information should be discarded to avoid excessive memory. Output Gate determines how the information in the cell state affects the current output. The flow of data and the collaborative work process between components are shown in the Fig. 3. The entire process can be defined as follows:

$$f = \text{sigmoid}(W^f * x^t + U^f * y^{t-1} + b^f)$$

$$z = \tanh(W^z * x^t + U^z * y^{t-1} + b^z)$$

$$i = \text{sigmoid}(W^i * x^t + U^i * y^{t-1} + b^i)$$

$$o = \text{sigmoid}(W^o * x^t + U^o * y^{t-1} + b^o)$$

$$c^t = z \odot i + f \odot c^{t-1}$$

$$y^t = o \odot \tanh(c^t)$$

3) **Diffusion Model**: Diffusion models [63] are a family of deep generative models that can create realistic and diverse samples of data [64]–[71], such as images [72]–[78], texts [79]–[82], videos [83]–[87], and molecules [88]–[92]. As shown in Fig. 4, diffusion models work by gradually adding noise to data until it becomes random, then reversing the process to generate new data from noise. This process is based on probabilistic modeling and neural networks. Diffusion models mainly have three equivalent formulations: denoising diffusion probabilistic models [64]–[66], score-based generative models [67], [68], and stochastic differential equations [69], [70], with following improvements like DDIM [93], Rectified Flow [94], Consistency Model [95] and RPG-DiffusionMaster [78].

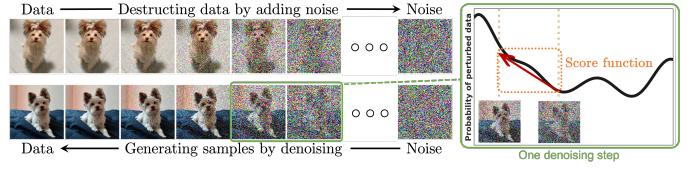


Fig. 4. Diffusion models smoothly perturb data by adding noise, then reverse this process to generate new data from noise. Each denoising step in the reverse process typically requires estimating the score function (see the illustrative figure on the right), which is a gradient pointing to the directions of data with higher likelihood and less noise, c.f. [63]

Especially, let x_0 be a random variable that follows the data distribution $q(x_0)$, and let x_t be a random variable that follows the distribution $q(x_t|x_0)$ after adding noise at time step t . Then, DDPM can be formulated as follows:

- **Forward Process** The forward process perturbs data with a sequence of Gaussian noise injections, transforming the data distribution $q(x_0)$ into a simple prior distribution $q(x_T) \approx N(0, I)$. The transition kernel at each time step is given by

$$q(x_t|x_{t-1}) = N(x_t; \sqrt{1 - \beta_t}x_{t-1}, \beta_t I),$$

where $\beta_t \in (0, 1)$ is a hyperparameter. The marginal distribution of x_t conditioned on x_0 is

$$q(x_t|x_0) = N(x_t; \sqrt{\bar{\alpha}_t}x_0, (1 - \bar{\alpha}_t)I),$$

where $\alpha_t = 1 - \beta_t$ and $\bar{\alpha}_t = \prod_{s=0}^t \alpha_s$.

- **Reverse Process** The reverse process generates new data samples by reversing the forward process with a learnable Markov chain. The prior distribution is $p(x_T) = N(x_T; 0, I)$ and the transition kernel is

$$\theta(x_{t-1}|x_t) = N(x_{t-1}; \mu_\theta(x_t, t), \Sigma_\theta(x_t, t)),$$

where θ denotes model parameters, and $\mu_\theta(x_t, t)$ and $\Sigma_\theta(x_t, t)$ are parameterized by deep neural networks. The reverse process starts from sampling $x_T \sim p(x_T)$ and iteratively samples $x_{t-1} \sim p_\theta(x_{t-1}|x_t)$ until $t = 0$.

- **Model Training** For each sample $x_0 \sim q(x_0)$, the model training objective is to maximizing the variational lower

bound (VLB) of the log-likelihood of the data x_0 . The simplified form $\mathcal{L}_{\text{VLB}}(x_0)$ is given by

$$\mathbb{E}_{q(x_{1:T}|x_0)} \left[-\log p(x_T) - \sum_{t=1}^T \log \frac{p_\theta(x_{t-1}|x_t)}{q(x_t|x_{t-1})} \right]$$

With simplification and reparameterization trick, the overall objective $\mathbb{E}_{q(x_0)} [\mathcal{L}_{\text{VLB}}(x_0)]$ can be simplified into the final form

$$\mathbb{E}_{t \sim U[1,T], x_0 \sim q(x_0), \epsilon \sim \mathcal{N}(0,I)} [\lambda(t) \|\epsilon - \epsilon_\theta(x_t, t)\|]$$

where $\lambda(t)$ is a positive weighting function, $U[1, T]$ is a uniform distribution over the set $\{1, 2, \dots, T\}$, and ϵ_θ is a deep neural network with parameter θ that predicts the noise vector ϵ given x_t and t . Note that, the overall objective is also equivalent to matching the joint distribution of the reverse process $p_\theta(x_0, x_1, \dots, x_T)$ to that of the forward process $q(x_0, x_1, \dots, x_T)$ by minimizing the KL divergence between them.

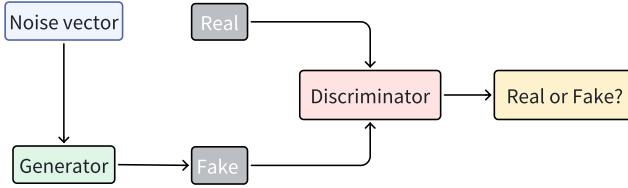


Fig. 5. Architecture of a typical Generative Adversarial Network (GAN).

4) GAN: Generative Adversarial Networks (GANs) [96] are highly anticipated deep learning models with amazing capabilities which can simulate and generate realistic images, audio, and other data. Due to its outstanding performance, GANs have achieved significant achievements in various fields [97]. The design inspiration of GANs comes from the zero-sum game in game theory.

As shown in Fig. 5, a typical GAN consists of two main components: a generator and a discriminator. These two parts compete with each other through adversarial learning, allowing the generator to continuously improve its ability to generate realistic samples, while the discriminator continuously improves its ability to distinguish between true and false samples.

C. Retriever

Retrieval is to identify and obtain information system resources that are relevant to an information need. Specifically, let's consider information resources that can be conceptualized as a key-value store $\{(k_i, v_i)\}_{i=1}^N$, where each key k_i corresponds to a value v_i (often, k_i and v_i are identical). Given a query q , the objective is to search for the top- k most similar keys using a similarity function s , and obtain the paired values. Based on different similarity functions, existing retrieval methods can be categorized into sparse retrieval, dense retrieval, and others. For widely used sparse and dense retrieval, the whole process can be divided into two distinct phases: in the first phase, each object is encoded into a specific representation; and in the second phase, an index is constructed to organize the data source for efficient search.

1) Sparse Retriever: Sparse retrieval methods are widely used in document retrieval, where the keys are actually documents to be searched (values are the same documents in this scenario). These methods leverage term matching metrics such as TF-IDF [98], query likelihood [99], and BM25 [19], which analyze word statistics from texts and construct inverted indices for efficient searching. Among them, BM25 is a hard-to-beat baseline in industrial-scale web search. For a query q containing keywords $\{q_i\}_{i=1}^n$, the BM25 score of a document D is:

$$s(q, D) = \sum_{i=1}^n IDF(q_i) \cdot \frac{f(q_i, D) \cdot (a + 1)}{f(q_i, D) + a \cdot (1 - b + b \cdot \frac{|D|}{avgdl})}$$

where IDF is the inverse document frequency weight, $f(q_i, D)$ is the number of times that q_i occurs in the document D , $|D|$ is the length of D , $avgdl$ is the average document length in the corpus collection, a and b are tunable parameters.

IDF is computed as:

$$IDF(q_i) = \ln(\frac{N - n(q_i) + 0.5}{n(q_i) + 0.5} + 1)$$

where N is the number of documents, and $n(q_i)$ is the number of documents containing q_i . IDF score is also used in TF-IDF.

To enable efficient search, sparse retrieval typically leverages an inverted index to organize documents. Concretely, each term from the query performs a lookup to obtain a list of candidate documents, which are subsequently ranked based on their statistical scores.

2) Dense Retriever: Different from sparse retrieval, dense retrieval methods represent queries and keys using dense embedding vectors, and build approximate nearest neighbor (ANN) index to speed up the search. This paradigm can be applied to all modalities. For text data, recent advancements in pre-trained models, including BERT [15] and RoBERTa [100], are employed as encoders to encode queries and keys separately [20], [101]–[104]. Similar to text, models have been proposed to encode code data [25], [105], [106], audio data [26], [107], image data [24], [108], and video data [109], [110]. The similarity score between dense representations can be computed using methods such as cosine, inner product, L2-distance.

During training, dense retrieval usually follows a contrastive learning paradigm, making positive samples more similar and negative samples less similar. Several hard negative techniques [101], [111] have been proposed to further improve the model quality. During inference, approximate nearest neighbor (ANN) methods are applied for efficient searching. Various indices are developed to serve ANN search, such as tree [112], [113], locality sensitive hashing [114], neighbor graph index (e.g., HNSW [115], DiskANN [116], HMANN [117]), the combination of graph index and inverted index (e.g., SPANN [118]).

3) Others: In addition to sparse retrieval and dense retrieval, there are alternative methods for retrieving relevant objects. Instead of calculating representations, some research works directly use the edit distance between natural language

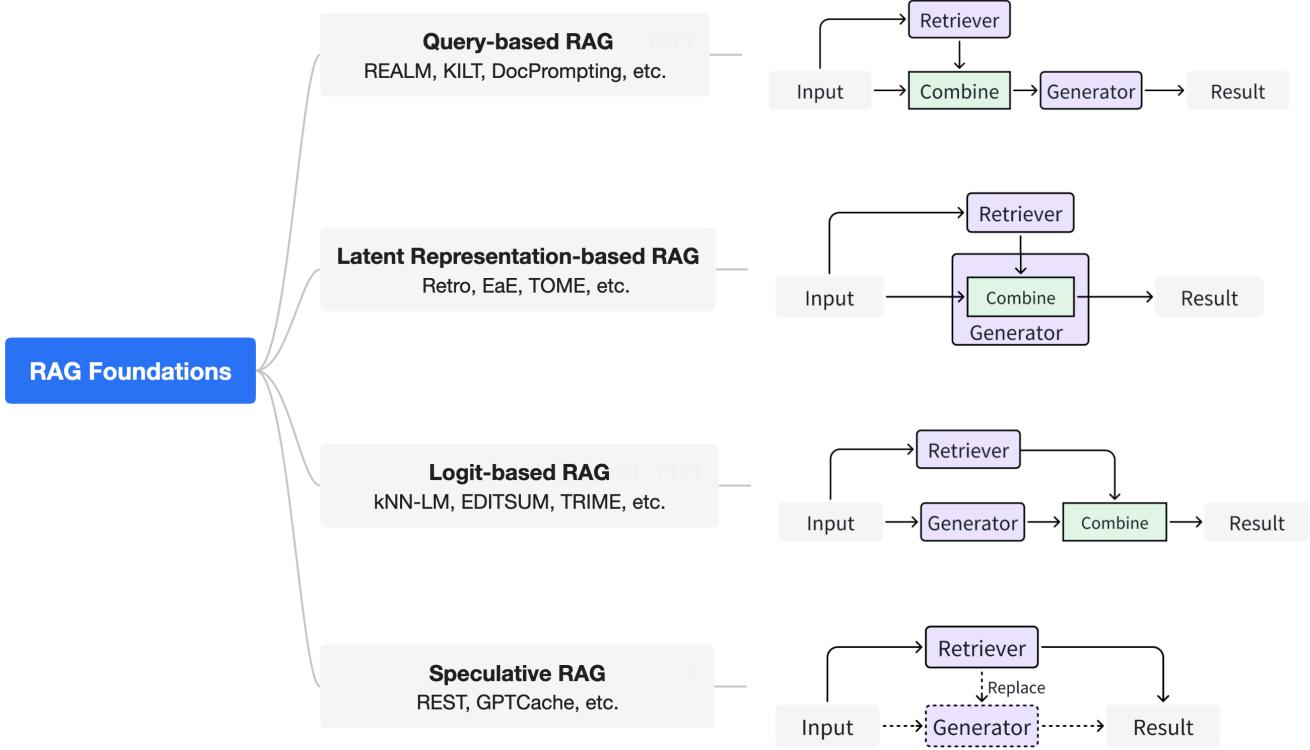


Fig. 6. Taxonomy of RAG foundations.

texts [119] or abstract syntax trees (AST) of code snippets [120], [121]. For knowledge graph, entities are linked with relations, which can be regarded as a pre-built index for retrieval searching. Therefore, RAG methods which involve knowledge graph can use k-hop neighbor search as retrieval process [122], [123]. Named entity recognition (NER) [124], [125] is another way of retrieval, where the input is the query and the entities are the keys.

III. METHODS

In this section, we first introduce the RAG foundations within the context of AIGC. Subsequently, we outline the enhancement methods that further improve the effectiveness of RAG.

A. RAG Foundations

Based on how the retriever augments the generator, we classify the RAG foundation paradigms into 4 distinct classes, as shown in Fig. 6.

1) **Query-based RAG**: Query-based RAG is also called prompt augmentation. It integrates the user's query with insights from documents fetched during the retrieval process, directly into the initial stage of the language model's input. This paradigm stands as a widely adopted approach within the applications of RAG. Once documents are retrieved, their content is merged with the original user query to create a composite input sequence. This enhanced sequence is subsequently fed into a pre-trained language model to generate responses.

REALM [32] employs a dual-BERT framework to streamline knowledge retrieval and integration, marrying pre-trained models with knowledge extractors. The initial BERT module processes the input question alongside documents to facilitate retrieval, utilizing MIPS for selecting the top-k documents with the highest probability and periodically updating the index. The document snippets obtained are then integrated with the query, feeding into the second BERT module to produce multiple outputs that are aggregated into a singular, comprehensive response. RAG [33] synergizes pre-trained language models with knowledge retrieval mechanisms, leveraging DPR and BART structures to accomplish retrieval-augmented generation tasks. DPR serves as the retrieval component, sourcing pertinent information from vast document databases, while BART uses this information for text generation. RAG-Token and RAG-Sequence differ in their retrieval timings, with the former retrieving information at each token generation and the latter conducting a single retrieval for the entire sequence. KILT [126] focuses on ensuring information accuracy and reliability by aligning Wikipedia pages with specific snapshots and pinpointing the most pertinent text ranges through BLEU score evaluations. It filters out lower-quality data to maintain a high standard of information mapping, offering a variety of retrieval system options like Tf-idf, DPR, RAG, and BLINK + flair to support evidence-based predictions or citations according to task requirements. SELF-RAG [127] enhances the accuracy and relevance of responses by integrating a retrieval and critique strategy. Initially, the model employs a retriever to

search for information paragraphs closely related to the input question. Subsequently, the critique model evaluates these paragraphs to determine their relevance and level of support of the retrieved text, assessing their impact on the generation of responses. Finally, the generator model constructs responses based on this information and evaluates the quality of these responses through critique marks.

Recently, some methods have proposed to implement RAG without modifying the language model architecture, which is particularly suitable for scenarios where language models are accessed through APIs. REPLUG [128] illustrates this methodology by treating the language model as a "black box," utilizing Contriever to seamlessly incorporate relevant external documents into the query. REPLUG LSR, a variant with LM-Supervised Retrieval, further refines this process by optimizing retrieval through language model-supervised insights, aiming to reduce perplexity scores and improve model performance by enriching its contextual understanding. In-Context RALM [129] uses the BM25 algorithm for document retrieval and predictive reranking to select pertinent documents for input integration.

In contemporary multimodal application research, integrating retrieved content into inputs has proven highly effective in enhancing the performance of various tasks. This strategy is applicable across several key fields, including code generation, audio generation, and Knowledge Base Question Answering (KBQA).

For text-to-code task, APICoder [130] and DocPrompting [41] demonstrate how effectively integrating retrieved information into language models can improve the accuracy and relevance of generated code. In automatic program repair task, CEDAR [131] and InferFix [132] utilize retrieved code snippets to aid the repair process, enhancing the model's understanding and application of repair strategies by combining them with the original input. For code completion task, ReACC [133] employs a prompting mechanism, leveraging retrieved code snippets as part of the new input to increase the accuracy and efficiency of code completion.

In the audio generation field, MakeAnAudio [43] leverages retrieval to construct captions of language-free audio, so as to mitigate the data sparsity for text-to-audio training.

Recent research in KBQA has shown significant effects of combining retrieval and language models. Uni-Parser [134], RNG-KBQA [122], and ECBRF [135] effectively improve the performance and accuracy of QA systems by merging queries and retrieved information into prompts. BLLM augmentation [136] represents an innovative attempt at zero-shot KBQA using black-box large language models. This method, by directly integrating retrieved information into the model input without the need for additional sample training, demonstrates the great potential of combining retrieval and language models to enhance the model's generalization ability in understanding and answering unseen questions.

In the scientific domain of RAG technology, Chat-Orthopedist [137] aims to provide support for shared decision-making among adolescents with idiopathic scoliosis. This approach enhances the application effectiveness and information accuracy of large language models by integrating retrieved

information into the prompts of the model.

In the task of image generation, RetrieveGAN [44] enhances the relevance and accuracy of generated images by integrating retrieved information, including selected image patches and their corresponding bounding boxes, into the input stage of the generator. IC-GAN [138] modulates the specific conditions and details of the generated images by concatenating noise vectors with instance features.

In the field of 3D generation, RetDream [49] initially utilizes CLIP to retrieve relevant 3D assets, effectively merging the retrieved content with the user input during the input phase.

2) Latent Representation-based RAG: In the framework of Latent Representation-based RAG, the generative models interact with latent representations of retrieved objects, thereby enhancing the model's comprehension abilities and the quality of the content generated.

The FiD [34] technique leverages both BM25 and DPR for sourcing supportive paragraphs. It concatenates each retrieved paragraph and its title with the query, processing them individually through the encoder. FiD reduces computational complexity and efficiently utilizes relevant information to generate answers by fusing information from multiple retrieved paragraphs in the decoder, rather than processing each paragraph in the encoder. The application of Fusion-in-Decoder methodologies transcends the realm of textual content processing, demonstrating substantial potential and adaptability in processing code, structured knowledge, and diverse multimodal datasets. Specifically within the code-related domain, technologies such as EDITSUM [139], BASH-EXPLAINER [140], and RetrieveNEdit [141] adopt the FiD approach, facilitating integration through encoder-processed fusion. Re2Com [142], and RACE [143], among other methods, also feature the design of multiple encoders for different types of inputs. In the field of Knowledge Base Question Answering (KBQA), the FiD method has been widely adopted, demonstrating significant effectiveness. UniK-QA [144], DECAF [145], SKP [146], KD-CoT [147], and ReSKGC [148] have effectively enhanced the performance of QA systems through the application of Fusion-in-Decoder technology. This illustrates that by integrating RAG for KBQA, the efficiency and accuracy of QA systems can be significantly improved. In the field of Science, RetMol [54] employ the Fusion-in-Decoder strategy, integrating information at the decoder stage to enhance the relevance and quality of the generated molecular structures.

Retro [35] pioneers the integration of retrieved text via "Chunked Cross-Attention," a novel mechanism that segments the input sequence into discrete chunks. Each chunk independently executes cross-attention operations, thereby mitigating computational burdens. This technique enables the model to selectively retrieve and assimilate distinct documents for varied sequence segments, fostering dynamic retrieval throughout the generation process. This enhances the model's adaptability and enriches the contextual backdrop of generated content. In the domain of image generation, cross-attention mechanisms have been widely adopted within RAG frameworks. Methods such as Re-imagen [149], KNN-Diffusion [150], RDM [151] and LAION-RDM & ImageNet-RDM [152] utilize cross-

attention to integrate multiple retrieval results, effectively enhancing the overall performance of the models. On the other hand, Li [153] introduces the ACM, a text-image affine combination module, which notably does not employ any form of attention mechanism.

Diverging from prior methods for knowledge, EaE [154] empowers language models to internalize explicit entity knowledge. EaE introduces an entity-specific parameterization, optimizing inference efficacy through an entity memory layer embedded within the transformer architecture. This layer directly acquires entity representations from textual data, utilizing a sparse retrieval strategy to fetch the nearest entities based on their embeddings, thus refining the model’s comprehension through a calculated aggregation of entity-specific information. Distinctly, TOME [155] shifts the focus towards comprehensive mention encodings, prioritizing the granularity of mention over mere entity representations. It meticulously generates encodings for each entity mention across Wikipedia, populating a repository with approximately 150 million entries. This repository, encompassing key and value encodings alongside entity IDs, empowers the retrieval of much more fine-grained information. TOME integrates an initial transformer block to process input texts, followed by TOME blocks with memory attention layers, facilitating the synthesis of multifaceted information sources and enhancing inferential reasoning capabilities, even for unencountered entities. Memorizing Transformers [30] revolutionize long document processing through the integration of a kNN-augmented attention mechanism within a Transformer layer. This innovation triggers a kNN search amidst input sequence processing, fetching data based on similarities between the sequence and stored key-value pairs, thereby elevating performance without necessitating complete retraining. This approach not only bolsters processing efficiency but also broadens the model’s memory span, enabling self-retrieval from its generated outputs and fine-tuning for extensive knowledge bases or code repositories. Unlimiformer [156], by embedding a k-nearest neighbors (kNN) index within a pre-trained encoder-decoder transformer framework, pioneers handling inputs of indefinite length. Storing hidden states of input tokens in the kNN index allows for the efficient retrieval of highly relevant tokens during decoding. This innovation extends the model’s capacity to manage prolonged sequences.

In the field of 3D generation, ReMoDiffuse [50] introduces a semantics-modulated attention mechanism. This technology enhances the accuracy of generating corresponding 3D motions based on textual descriptions. AMD [157] achieves efficient conversion from text to 3D motion by fusing the original diffusion process with the reference diffusion process.

In the audio domain, Koizumi [42] utilizes a pre-trained large-scale language model, incorporating dense features generated by VGGish and embedding networks in the attention module to guide the generation of audio captions. Re-AudioLDM [158] extracts deep features from text and audio using T5 and AudioMAE, and integrates these features within the attention mechanism of its Latent Diffusion Model (LDM).

In the field of video captioning, R-ConvED [47] employs a convolutional encoder-decoder network architecture, which

processes retrieved video-sentence pairs with the aid of an attention mechanism to generate hidden states and subsequently produce captions. CARE [159] introduces a concept detector as an input to the decoder and embeds concept representations within a hybrid attention mechanism. EgoInstructor [48] employs gated-cross attention to integrate these textual inputs with encoded video features, enhancing the relevance and coherence of the generated captions for egocentric video content.

3) Logit-based RAG: In Logit-based RAG, generative models combine retrieval information through logits during the decoding process. Typically, the logits are summed or combined through models to produce the probability for step-wise generation.

The kNN-LM [36] model integrates a pre-trained neural language model with the k-nearest neighbor search. It employs the pre-trained model to generate a list of candidate words and their probability distribution, while simultaneously performing retrieval from a data repository to find the k most relevant neighbors based on the current context, thus enhancing the output of the original language model. The innovation at the core of this model lies in its ability for dynamic retrieval of information from a broad text corpus, significantly improving the accuracy and relevance of its predictions, particularly in addressing rare patterns and adapting to various fields. He [37] introduces a new framework that is predicated on performing retrieval operations only when necessary, aimed at enhancing the inference efficiency of the kNN-LM model through an adaptive retrieval. This framework accelerates the model’s inference speed by training a retrieval adapter, which automatically identifies and eliminates unnecessary retrieval actions in certain scenarios. This method allows the model to dynamically decide on the necessity of retrieval based on the current context, thereby balancing the trade-off between performance and efficiency, and substantially increasing inference speed while maintaining model performance.

Unlike previous methods that only merge memories during the testing time, TRIME [160] achieves memory merging during both training and testing phases, treating in-batch examples as accessible memory. TRIME leverages new data batching and memory construction techniques to effectively utilize external memory. TRIME employs BM25 scores to pack paragraphs with high lexical overlap into the same batch, constructing the training memory to further optimize model performance. NPM [161] is a non-parametric masked language model comprised of an encoder and a reference corpus. Unlike traditional models that apply a softmax over a finite vocabulary, NPM models a non-parametric distribution over the corpus. The encoder’s role is to map phrases from the corpus into fixed-size vectors, filling in [MASK] by retrieving the phrase most similar to the masked position.

Beyond the text domain, other modalities such as code and image also utilize methods that integrate retrieved content with language models in the final output stage.

For code-to-text conversion task, Rencos [120] generates multiple summary candidates in parallel from the retrieved code. It then normalizes these candidates using edit distance and calculates the final probability to select the summary out-

put that best matches the original code. In code summarization task, EDITSUM [139] enhances the quality of summary generation by integrating prototype summaries at the probability level. For text-to-code tasks, the kNN-TRANX [162] model employs a combination of a confidence network and meta-knowledge to merge retrieved code fragments. It utilizes a seq2tree structure to generate target code that closely matches the input query, thereby increasing the accuracy and relevance of code generation.

In image captioning tasks, MA [163] combines an attention-based encoder-decoder, using the image encoder to extract visual features to construct the semantic part, and decodes it word by word with the information retrieved. MA interpolates between two distributions generated by the caption decoder and the memory-augmented module to determine the distribution of the next word.

4) Speculative RAG: Speculative RAG looks for opportunities to use retrieval instead of generation to save resources and accelerate response speed. REST [31] replaces the small models in speculative decoding [164] with retrieval, so as to generate drafts. GPTCache [38] tries to solve the problem of high latency when using the API of LLMs by building a semantic cache for storing LLM responses. COG [165] decomposes the process of text generation into a series of copy-and-paste operations, which retrieves words or phrases from the retrieved documents instead of generation. Cao et al. [166] proposes a new paradigm to eliminate the dependence of the final result on the quantity and quality of the first stage retrieve content, which replaces generation by directly retrieving phrase level content.

B. RAG Enhancements

In this section, we will introduce methods to enhance RAG performance. We categorize existing methods into 5 distinct groups based on their enhancement targets: input, retriever, generator, result, and the entire pipeline.

1) Input Enhancement: The input refers to the user's query, which is initially fed into the retriever. The quality of the input significantly impacts the final outcome of the retrieval stage. Consequently, enhancing the input becomes essential. In this section, we introduce two methods: query transformation and data augmentation.

a) Query Transformation: Query transformation can enhance the result of retrieval by modifying the input query. Query2doc [167] and HyDE [168] first use query to generate a pseudo document, and then use this document as a key for retrieval. The advantage of doing so is that the pseudo document will contain more rich relevant information, which helps to retrieve more accurate results. TOC [169] employs recursive retrieval augmented clarification on ambiguous questions to construct a tree of disambiguated questions, thereby generating comprehensive answers to these ambiguous questions. During the construction process of this tree structure, TOC utilizes a self-verification pruning method to ensure the factual relevance of each node.

b) Data Augmentation: Data augmentation refers to improving the data in advance before retrieval, such as removing irrelevant information, eliminating ambiguity, updating

outdated documents, synthesize new data, etc. which can effectively improve the performance of the final RAG system. MakeAnAudio [43] uses captioning and audio-text retrieval to generate caption for language-free audio to mitigate data sparsity, and adds random concept audio to improve the original audio. LESS [170] strategically selects an optimal dataset for downstream tasks by analyzing gradient information, with the aim of maximizing the dataset's impact on fine-tuning the model's performance in response to instructional prompts.

2) Retriever Enhancement: In the RAG system, the process of retrieval is crucial. Generally, the better the content quality, the easier it is to stimulate the ability of LLMs in-context learning as well as other generators and paradigms. The worse the content quality, the more likely it is to cause model hallucinations. Therefore, in this section, we will discuss how to efficiently improve the effectiveness of the retrieval process.

a) Recursive Retrieve: Recursive retrieve is the process of splitting a query before retrieval, and performing multiple searches to retrieve more and higher quality content. Jagerman et al. [171], RAT [172] and ReACT [173] all use Chain-of-Thought(COT) [174] to enable the model to break queries down gradually and provide more rich related knowledge. LLMCS [175] applies this technology to the conversational system and obtained better retrieval results by rewriting the conversation record. ACTIVERAG [176] employs the Cognition Nexus mechanism to skillfully merge retrieved knowledge with the language model's inherent cognitive system, thus optimizing the COT process and effectively aiding in answer generation. RATP [177] leverages Monte-Carlo Tree Search technique for multi-stage decision-making, where each node represents a thought. The system directs action choices based on scoring model feedback on these thoughts. In node expansion, it merges retrieved documents and thoughts via prompts into the language model to generate new thoughts. Kuratov et al. [178] integrates the Transformer with an RNN, utilizing the model's intermediate outcomes as the content for retrieval. This process was executed at each layer of the Transformer, thereby significantly extending the text window's length and effectively mitigating the issue of "Lost in the Middle" [179].

b) Chunk Optimization: Chunk optimization technique refers to adjusting the size of the chunk to achieve better retrieval results. Sentence-window retrieval [180] is an efficient approach that enhances retrieval by fetching small chunks of text and returning a window of relevant sentences surrounding the retrieved segment. This method ensures that the context before and after the targeted sentence is included, providing a more comprehensive understanding of the retrieved information. Auto-merge retrieval is another advanced RAG method of LlamaIndex [180] which organizes the document in a tree-like structure, with the parent node containing the content of all children nodes. For example, articles and paragraphs, as well as paragraphs and sentences, all follow a parent-child relationship. In the retrieve process, fine-grained search for children nodes ultimately returns the parent node, effectively providing richer information. To address the lack of contextual information, RAPTOR [181] employs recursive embedding, clustering, and summarization of text chunks until further

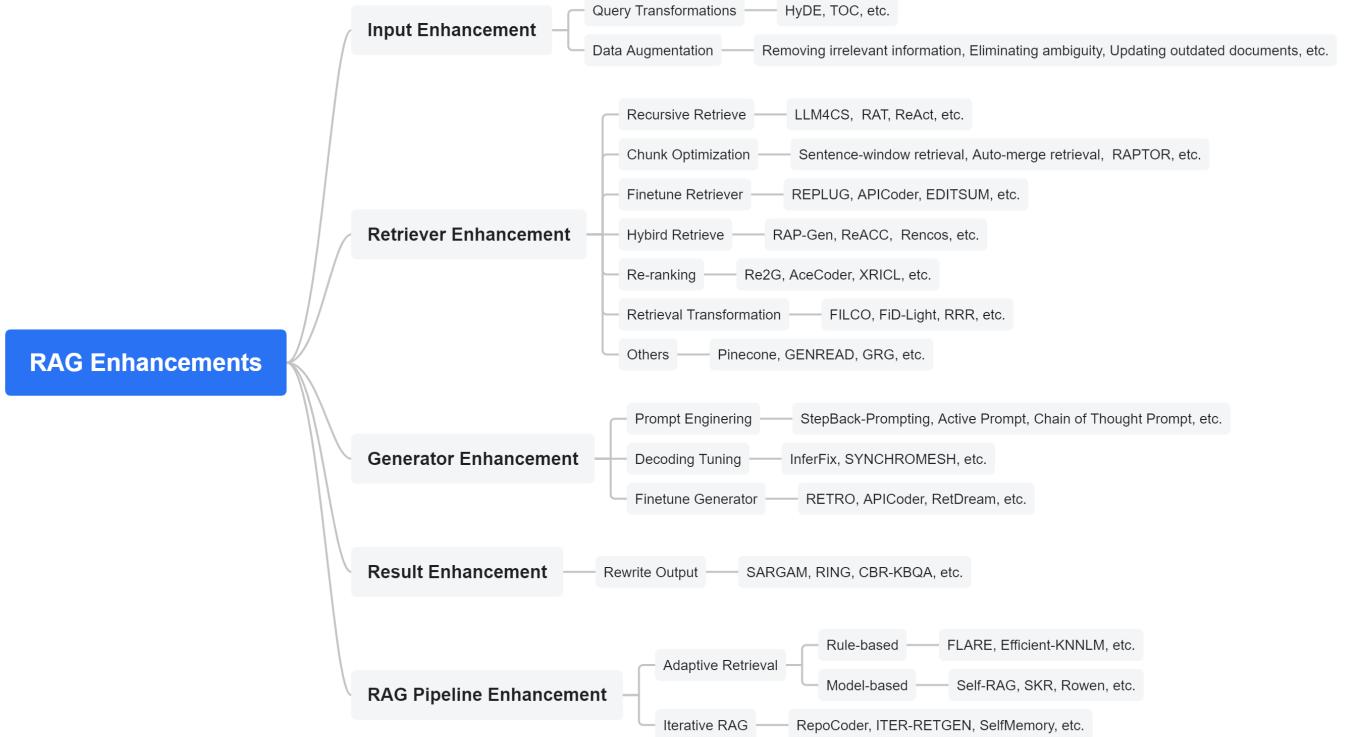


Fig. 7. Taxonomy of RAG Enhancements.

clustering becomes infeasible, thereby constructing a multi-level tree structure.

c) **Finetune Retriever:** As a core component in the RAG system, the retriever plays a crucial role in the entire system operation process. A good embedding model can bring semantically similar content closer together in vector space. The stronger the retriever's ability, the more useful information can be provided for the subsequent generator, thereby improving the effectiveness of the RAG system. Therefore, the ability of the embedding model [182]–[185] is crucial for the overall effectiveness of the RAG system.

In addition, for embedding models that already have good expression power, we can still finetune them using high-quality domain data or task related data to improve their performance in specific domains or tasks. REPLUG [128] treats LM as a black box and update the retriever model based on the final results. APICoder [130] finetunes the retriever with python files and api names, signature, description. EDITSUM [139] finetunes the retriever to decrease the jaccard distance between summaries after retrieval. SYNCHROMESH [121] adds tree distance os ASTs in the loss and uses Target Similarity Tuning to finetune the Retriever. R-Conved [47] finetunes the Retriever with the same data as generator. Kulkarni et al. [186] applies infoNCE loss to finetune the Retriever.

d) **Hybrid Retrieve:** Hybrid retrieve denotes the concurrent employment of a diverse array of retrieval methodologies or the extraction of information from multiple distinct sources. RAP-Gen [187] and ReACC [133] use both dense retriever and sparse retriever to improve the quality of retrieval. Rencos [120] uses sparse retriever to retrieve similar code snippets

on syntactic-level and usse dense retriever to retrieve similar code snippets on semantic-level. BASHEXPLAINER [140] first uses dense retriever to capture semantic information and then uses sparse retriever to acquire lexical information. RetDream [49] first retrieves with text and then retrieves with the image embedding. CRAG [188] has designed a retrieval evaluator to assess the relevance of retrieved documents to the input query, triggering three types of retrieval actions based on varying confidence levels: if deemed correct, it directly uses the retrieval results for Knowledge Refinement; if incorrect, it resorts to Web Search; and if ambiguous, it combines both approaches. To enhance performance in question-and-answer tasks, Huang et al. [189] introduces two metrics, DKS(Dense Knowledge Similarity) and RAC(Retriever as Answer Classifier), during the retrieval phase. These metrics account for both the pertinence of the answers and the applicability of the underlying knowledge. UniMS-RAG [190] introduces a novel kind of token, termed as the 'acting token', which determines the source from which to retrieve information.

e) **Re-ranking:** The Rerank technique refers to reordering the retrieved content in order to achieve greater diversity and better results. Re2G [191] applies a re-ranker [192] model after the traditional retriever. The effect of the re-ranker model is to re-rank retrieved documents, the purpose of which is to reduce the impact of information loss caused by compressing text into vectors on the quality of retrieval. AceCoder [193] rerank the retrieved programs with a selector. The purpose of introducing the selector is to reduce redundant programs and obtain diverse retrieved programs.

XRICL [194] uses a distillation-based exemplar reranker after retrieval. Rangan [195] employs the Quantized Influence Measure, assessing statistical biases between a query and a reference to evaluate the similarity of data subsets, and uses this assessment to rerank retrieval results. UDAPDR [196] utilizes large language models for the mass generation of synthetic queries at low cost, using these synthetic query sets to train domain-specific rerankers. These rerankers act as multiple teachers, and through multi-teacher knowledge distillation techniques, they create a single retriever. LLM-R [197] iteratively trains the retriever, using feedback from a frozen LLM to rank candidate documents and train the reward model. The retriever is further trained based on knowledge distillation. Each iteration of training builds upon the retriever trained in the previous cycle, facilitating iterative optimization in subsequent rounds.

f) Retrieval Transformation: FILCO [198] effectively filters out irrelevant content from the retrieved text chunk, leaving only the precise supporting content. This process simplifies the task for the generator, making it easier to predict the correct answer. FiD-Light [199] initially employs an encoder to convert the retrieved content into a vector, which it then compresses, resulting in a substantial reduction of latency time. RRR [200] integrates the current query with the top-k document in each round through a template, and subsequently restructures it via a pre-trained LLMs(GPT-3.5-Turbo et al.).

g) Others: In addition to the above optimization methods, there are also some other optimization methods for the retrieve process. For example, Meta-data filtering [201] is a method to help processing retrieved documents which uses metadata (such as time, purpose, etc.) to filter the retrieved documents for better results. GENREAD [202] and GRG [203] introduces a novel approach where the retrieval process is supplanted or improved by prompting a LLM to generate documents in response to a given question.

3) Generator Enhancement: In RAG systems, the quality of the generator often determines the quality of the final output results. Therefore, the ability of the generator determines the upper limit of the entire RAG system's effectiveness.

a) Prompt Engineering: Technologies in prompt engineering [204] that focus on improving the quality of LLMs' output, such as Prompt compression, Stepback Prompt [205], Active Prompt [206], Chain of Thought Prompt [174], etc., are all applicable to LLM generators in RAG systems. LLM-Lingua [207] applies a small model to compresses the overall length of the query to accelerate model inference, relieving the negative impact of irrelevant information on the model and alleviating the phenomenon of "Lost in the Middle" [179]. ReMoDiffuse [50] decomposes complex descriptions into anatomical text scripts by using ChatGPT. ASAP [208] add exemplar tuples to the prompt for better results. An exemplar tuple is composed of the input code, a function definition, the results of analyzing that definition and its associated comment. CEDAR [131] uses a designed prompt template to organize code demonstration, query, and natural language instructions into a prompt. XRICL [194] utilizes COT technology to add translation pairs as an intermediate step in cross linguistic

semantic parsing and inference. MakeAnAudio [43] is able to use other modalities as input which can provide much richer information for the following process.

b) Decoding Tuning: Decoding tuning refers to adding additional controls during the generator processing, which can be achieved by adjusting hyperparameters to achieve greater diversity, limiting the output vocabulary in some form, and so on. InferFix [132] balances the diversity and quality of results by adjusting the temperature in decoder. SYNCHROMESH [121] limits the output vocabulary of the decoder by implementing a completion engine to eliminate implementation errors.

c) Finetune Generator: The finetuning of the generator can enhance the model's ability to have more precise domain knowledge or better fit with the retriever. RETRO [35] fixes the parameters of the retriever and uses the chunked cross attention mechanism in the generator to combine the content of the query and retriever. APICoder [130] finetunes the generator CODEGEN-MONO 350M [209] with a shuffled new file combined with API information and code blocks. CARE [159] first uses image data, audio data and vedio-text pairs to train encoders and then finetune the decoder (generator) with the target of decreasing caption loss and concept detection loss together, during which the encoders and the retriever are frozen. Animate-A-Story [210] optimizes the video generator with image data, and then finetunes a LoRA [211] adapter to capture the appearance details of the given character. Ret-Dream [49] finetunes a LoRA adapter [211] with the rendered images.

4) Result Enhancement: In many scenarios, the final result of RAG may not achieve the expected effect, and some techniques of Result Enhancement can help alleviate this problem.

a) Rewrite Output: SARGAM [212] modifies the generated results in code-related task by classifying Deletion Classifier, Placeholder Classifier and Insertion Classifier with Levenshtein Transformer to better adapt to the actual code context. Ring [213] obtains diversity results by reranking candidates based on the average of per token log probabilities produced by the generator. CBR-KBQA [53] revises the result by aligning generated relations with those presented in the local neighborhood of the query entity in knowledge graph.

5) RAG Pipeline Enhancement:

a) Adaptive Retrieval: Some studies and practices on RAG have shown that retrieval is not always beneficial for the final generated results. When the parameterized knowledge of the model itself is sufficient to answer relevant questions, excessive retrieval will cause resource waste and may increase the model's confusion. Therefore, in this chapter, we will discuss two types of methods for determining whether to retrieve, named rule-based and model-based methods.

Rule-based: FLARE [214] actively decides whether and when to search through the probability in the generation process. Efficient-KNNLM [37] combines the generation probability of KNN-LM [36] and NPM [161] with a hyperparameter λ to determine the proportion of generation and retrieval. Mallen et al. [215] conducts statistical analysis on questions before generating answers, allowing the model

to directly answer high-frequent questions, and introducing RAG for low-frequent questions. Jiang et al. [216] studies Model Uncertainty, Input Uncertainty, and Input Statistics to comprehensively assess the confidence level of the model. Ultimately, based on the confidence level of the model, a decision is made whether to retrieve. Kandpal et al. [217] assists in determining whether a retrieval is needed by studying the relationship between the number of relevant documents in the training dataset and the degree to which the model masters relevant knowledge.

Model-based: Self-RAG [127] uses a trained generator to determine whether to perform a retrieval based on the retrieve token under different instructions, and evaluates the relevance and level of support of the retrieved text through the Self-Reflection token. Finally, the quality of the final output result is evaluated based on the Critique token. Ren et al. [218] uses "Judgment Prompting" to determine whether LLMs can answer relevant questions and whether their answers are correct or not, thereby assisting in determining the necessity of a retrieval. SKR [219] uses the ability of LLMs themselves to judge in advance whether they can answer the question, and if they can answer, no retrieval is performed. Rowen [220] employs a model as a sophisticated multilingual detection system to evaluate the semantic coherence of answers to identical questions posed across various languages. In the event of detected inconsistencies, it decides to retrieve external information, thereby enhancing the reasoning process and rectifying inaccuracies. Conversely, when responses exhibit consistency, the system upholds the initially generated answer, which is derived from internal reasoning. AdaptiveRAG [221] dynamically decides whether to retrieve based on the query complexity by a classifier, which is a smaller LM.

b) **Iterative RAG:** RepoCoder [222] applies an iterative retrieval-generation pipeline to better utilize the useful information scattered in different files in the code completion tasks. It augments the retrieval query during the i -th iteration with previously generated code and obtain greater results. ITER-RETEGEN [223] synergizes retrieval and generation in an iterative manner. The current output of the generator can to some extent reflect the knowledge it still lacks, and the retrieve can retrieve the missing information as contextual information for the next round, which helps to improve the quality of the generated content in the next round. SelfMemory [224] employs a retrieval-augmented generator in an iterative manner to create an unlimited memory pool. Following this, a memory selector is used to choose one output, which then serves as the memory for the subsequent generation round.

IV. APPLICATIONS

In this chapter, we will introduce the popular RAG applications in different fields.

A. RAG for Text

In this section, we will introduce some popular work for text generation using RAG methods.

1) **Question Answering:** Question Answering involves the process of providing responses to posed questions by drawing from a vast and comprehensive collection of textual sources.

FID [34] and REALM [32] identify the top k most pertinent article snippets based on the query and forward each snippet along with the question to LLMs to generate k responses. These responses are then synthesized into a final answer. Toutanova et al. [225] substituted the text corpus in REALM with subgraphs from a knowledge graph, yielding impressive results. Atlas [29] demonstrated that leveraging RAG to assist LLMs in open-domain question answering tasks significantly enhances few-shot learning capabilities. As shown in Fig. 9, RETRO [35] employs attention mechanisms to integrate the question with relevant retrieved documents within the model to produce the final answer. SKR [219] observed that using RAG does not invariably benefit Question Answering and thus explored guiding the model to evaluate its grasp of pertinent knowledge, subsequently adapting its use of external resources for retrieval enhancement. TOG [226] introduced an innovative knowledge graph-augmented LLM framework, which excels by fostering interactions between LLMs and the Knowledge Graph and by expanding the inference path space with beam search. NPM [161] pioneered the use of nonparametric data distributions in lieu of the softmax layer, enabling models with fewer parameters to perform effectively. Self-RAG [127] improves answer quality by learning to discern when to retrieve, assess the retrieved content's relevance, and evaluate the final generated results using four types of reflective tokens. CL-ReLKT [227] employs a language-generalized encoder to bridge the gap between question-document pairs across languages, thus better leveraging multilingual data. CORE [228] mitigates language resource disparities by introducing a novel dense passage retrieval algorithm and a multilingual autoregressive generation model. Lastly, EAE [154] enhances answer quality by retrieving entity embeddings for query entities and integrating these with hidden states for further processing. UR-QA [229] found that when encountering unseen problems, retrieving QA pairs has a better final effect; When encountering problems that have not been seen before, the retrieve text chunk performs better. Therefore, it is proposed to simultaneously retrieve QA pairs and text chunks, and select the final answer by comparing the calibrated confidences. ARM-RAG [230] demonstrates exceptional performance in solving elementary mathematics problems by retrieving past successful reasoning steps. DISC-LawLLM [231] constructs a supervised fine-tuning dataset through a legal syllogism prompting strategy, enabling the model to receive support from the latest legal information. RAG-end2end [232] conducts simultaneous training of the retriever(DPR) and the generator(BART) to optimize performance for the end-to-end question-answering task and to facilitate domain adaptation. MultiHop-RAG [233] is designed to extract pertinent information from a variety of distinct documents, aggregating this knowledge to equip the generator with the necessary context for producing the definitive answer to the query.

2) **Fact Verification:** Fact Verification involves assessing the veracity of information, a critical function in disciplines such as Natural Language Processing (NLP), Information Re-



Fig. 8. Taxonomy of multiple applications in multimodality.

trieval, and Data Mining. In today’s digital era, characterized by an exponential increase in data, particularly across social media and online news platforms, there is a rapid proliferation of unchecked information. Fact verification plays an essential role in countering the spread of fake news, deceptive content, and rumors, thereby preserving the integrity of the information landscape and ensuring the public’s access to accurate knowledge. Consequently, automated fact verification systems are of immense importance, with broad applications and significant practical value.

CONCRETE [234] leverages cross-lingual retrieval mechanisms to tap into a wealth of multilingual evidence, effectively bridging the gap in resources for languages that are underrepresented in fact-checking datasets. Hagström et al. [235] proves on LLaMA [236] and Atlas [29] that search augmentation is more beneficial for solving inconsistency problems than increasing model size.

3) **Commonsense Reasoning:** Commonsense Reasoning entails the capability of machines to infer or make decisions on problems or tasks in a human-like manner, drawing upon their

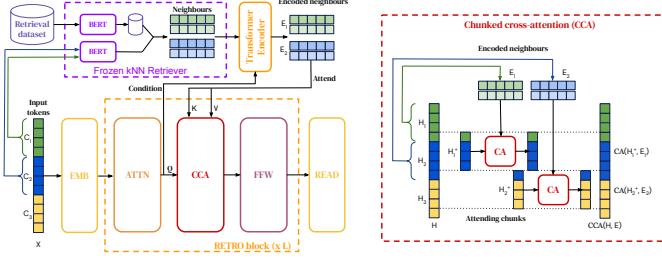


Fig. 9. Architecture of RETRO [35] model.

acquired external knowledge and its application. However, the vast scope of common sense knowledge and the intricacies of reasoning processes make Commonsense Reasoning a perennially challenging and prominent area of research within the field of NLP.

KG-BART [237] expands the conceptual landscape by incorporating intricate interrelations among diverse concepts within a knowledge graph. It employs graph attention mechanisms to aid LLMs in crafting more nuanced and logically coherent sentences. This approach not only improves the models' generalization capabilities but also significantly bolsters their Commonsense Reasoning proficiency. Wan et al. [238] constructs the CONFLICTINGQA dataset, comprising contentious questions and conflicting answer documents, to examine which textual features significantly influence LMs' ability to independently navigate controversial issues. The findings reveal that LMs often neglect the stylistic aspects of text that are typically valued by people.

4) Human-Machine Conversation: Human-Machine Conversation encompasses the ability of machines to comprehend natural language and adeptly employ this skill to engage with humans seamlessly. This capability represents a significant challenge within the realms of Artificial Intelligence and Natural Language Processing and offers a broad spectrum of practical applications. As such, Human-Machine Conversation continues to be a focal point of research for many scholars.

ConceptFlow [239] leverages a commonsense knowledge graph to structure conversations, directing the flow of dialogue based on attention scores, and propelling the conversation forward. This method achieves commendable results even with a substantial reduction in model parameters. Cai et al. [240] reimagines the text generation task as a cloze test by retrieving and distilling the essence of past conversational history, leading to notable outcomes. Komeili et al. [241] augments dialogue generation quality by harnessing advanced search engine technologies to source pertinent content from the internet. BlenderBot3 [242] broadens its search horizon, not only mining relevant internet content but also local dialogue history, and employs entity extraction among other techniques to refine the quality of the resulting dialogue. Kim et al. [243], PARC [244], and CREA-ICL [245] improve the caliber of non-English conversations by incorporating cross-lingual knowledge, effectively addressing the scarcity of non-English datasets and enhancing the quality of the generated dialogue. CEG [246] addresses hallucination issues through a post-processing mechanism, verifying LLM-generated an-

swers through retrieval. If the answer is correct, the retrieved document is added to the original answer as a reference; if the answer lacks reliable references, it guides the LLM to respond to the question anew.

5) Neural Machine Translation: Neural Machine Translation (NMT) is the automated process of translating text from a source language to a target language. It is a pivotal task in the domain of NLP and represents a significant objective in the pursuit of AI, boasting considerable scientific and practical significance.

Cai et al. [247] propose an innovative approach that utilizes monolingual corpora alongside multilingual learning techniques, challenging the traditional dependency on bilingual corpora in Neural Machine Translation. This approach ensures that the retrieval system provides ample information while simultaneously optimizing both the retrieval mechanism and the translation model, culminating in impressive performance. KNN-MT [248] executes translation tasks at the token level by computing vector space distances. TRIME [160] effectively minimizes the discrepancy between training and inference phases by jointly training the retrieval system and the generation model, thereby enhancing the precision of translations.

6) Event Extraction: Event Extraction is a specialized task within Natural Language Processing (NLP) that focuses on pinpointing and extracting instances of particular event types from unstructured textual data. An event is generally characterized by a central action or predicate and the related entities, which can include participants, temporal indicators, locations, and other relevant attributes. The objective of event extraction is to convert the nuanced details embedded within text into a structured format, thereby facilitating advanced analysis, efficient information retrieval, and practical downstream applications.

R-GQA [249] employs a retrieval-based approach to enhance the context of a given issue by identifying and utilizing the most closely aligned Question-Answer pair from a repository, thereby enriching the information available for processing the current query.

7) Summarization: In the realm of NLP, Summarization is a task aimed at distilling the essential information from lengthy texts and producing a concise, coherent summary that encapsulates the primary themes. Summarization enables users to quickly grasp the essence of a text, thereby conserving time that would otherwise be spent on reading extensive material. There are two main approaches to Summarization: Extractive and Abstractive.

Extractive Summarization involves the automatic selection and compilation of key phrases directly from the source text. A key phrase succinctly captures the main themes, content, or perspectives of the text and is typically composed of one or several words. The generation of key phrases is instrumental for understanding, categorizing, retrieving, and organizing textual information. It is extensively applied in fields such as search engine optimization, academic research, text summarization, and more. This technique refrains from creating new sentences, instead repurposing segments from the original text. Abstractive Summarization, on the other hand, entails comprehending the original text's meaning and

reformulating it into new sentences [156], [250]–[252]. This approach can convey the source’s intent more fluidly but poses greater challenges in terms of implementation due to its complexity.

RAMKG [250] effectively leverages a comprehensive English corpus to bolster the performance of Keyphrase Generation in non-English contexts. It does so by enhancing the alignment of keywords extracted from texts in different languages that share similar subject matter. Unlimiformer [156] addresses the issue of input length constraints in transformer-based models by retrieving and utilizing the top-k most relevant hidden states, thereby extending the model’s capacity to handle longer inputs.

RPRR [251] employs a Retrieve-Plan-Retrieve-Read approach to overcome the limited context window constraints faced by LLMs, utilizing retrieved information to generate high-quality Wikipedia documents for emerging events. RIGHT [252] chooses to use different types of retrievers in different datasets to enhance the generator, which can effectively improve the quality of automatically generated labels in simple deployment.

B. RAG for Code

Separate retrieval and generation approaches have historically been employed for code-related tasks. For retrieval, similar code snippets can be identified using Abstract Syntax Trees or text edit distances, while natural languages can be retrieved through sparse or dense retrieval. For generation, sequence-to-sequence models (such as LSTM and Transformers) are employed to generate code or natural language in sequential data form. Recent RAG research combines both retrieval and generation techniques to enhance the overall performance.

1) **Code Generation:** The goal of code generation is to transform natural language (NL) descriptions into code implementation, which can be seen a process of text-to-code. Therefore, LSTM and transformer models are widely used for generator. Whether to use code-specific retrieval or text-based retrieval depends on the contents to be searched.

Retrieval-based prompt engineering is one of the most prevalent scenarios of RAG in code generation. In-context learning includes training samples in prompts as the input for sequence-to-sequence generative models. Retrieval techniques are adopted to find similar training samples to the test input, so that the prompt can be more informative and related. REDCODER [39] retrieves similar NL descriptions using dense retriever CodeBert [25], then concatenates the NL texts, their paired codes, for downstream generator PLBART [40]. CodeT5Mix [253] adopts the paradigm of RECODER, proposing a model that functions dually as both the retriever and generator. APICoder [130] first train a Bert-based deep retriever to align the embeddings of NL descriptions and API documentation; then, it retrieves relevant API information to build prompt for the generator CODEGEN-MONO [254]. The following work [255] uses the same pipeline, renaming the retriever module as APIFinder. COCOGEN [256] aims at commonsense reasoning, which generates code-based reasoning graphs with Codex [2] given NL inputs; it adds an evaluation

setting of dynamic prompt selection, which actually retrieves relevant examples for prompts. In DocPrompting [41] given an NL intent, the retriever retrieves relevant documentations, then the generator generates codes based on the NL and retrieved documents. It evaluates both sparse retrievers and dense retrievers, and also tries different generators in experiments. CodeT5+ [257] adopts the CodeT5 [106] model for both the retriever and generator, leveraging only the encoder part in the retrieval process. AceCoder [193] fixes the retriever to BM25 [19], and tests several LLM generators for code generation. A3CodeGen [258] extracts local information, retrieves relevant global functions using embeddings, and incorporates third-party library information to construct the prompt for LLM-based code generation. SKCODER [259] employs BM25 to retrieve relevant code snippets, which are further processed to produce sketch template. The template and the original description are concatenated for final generation. CodeGen4Libs [260] uses RAG for both import statements and codes, employing BM25 as retriever and finetuned CodeT5 as generator. CODEAGENT [261] design agents to search on web, retrieve relevant documentation, generate programs, and test correctness. RRGCode [262] retrieves relevant code snippets using both sparse and dense retrieval, employs a cross-encoder to re-rank the retrieval results, then generates code using the concatenation of the query and the retrieved codes. A recent study [263] shows that retrieval-augmented framework for code suggestions, including code generation and code completion, can improve the performance by a large margin. ARKS [264] steps further upon prompt-based RAG, incorporating iterative RAG to re-formulate queries and update knowledge soup (containing documentation, execution feedback, generated code, etc.) for dense retrieval, improving final generation accuracy.

Retrieval results can be applied during the generation process as well. RECODE [119] retrieves similar NL descriptions using the edit distance, then extracts n-gram action subtrees from retrieved sentences’ corresponding target code abstract syntax trees (AST). During LSTM-based generation, the patterns of processed subtrees are leveraged to increase the corresponding word probability at each decoding step. kNN-TRANX [162] uses seq2tree model BertranX [265] to convert NL to code AST. It constructs a datastore for each code prefix and NL pair; i.e., for each NL-code pair, the context representation of the i-th context is obtained by encoding NL and the i-th prefix of code’s AST through the seq2tree model. During generation, at each decoding step the hidden representations are searched within the datastore to form a new probability, which is later combined with the seq2tree model’s output using a confidence network.

ToolCoder [266] performs normal code generation, and conducts online search or offline retrieval when encountering special $\langle \text{API} \rangle$ token. This paradigm makes the model learn to leverage API tools.

2) **Code Summary:** The goal of code summary is to transform code into natural language (NL) descriptions, which is a process of code-to-text. Same to code generation, many sequence-to-sequence models are applied as generator.

In many research works, the retrieval results are processed

by additional encoders. Re2Com [142] and EditSum [139]

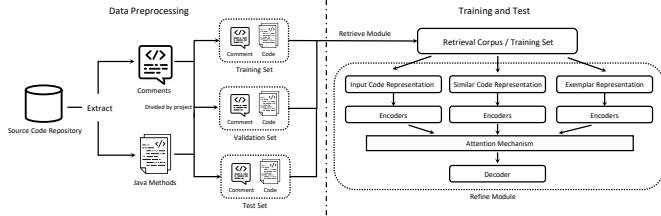


Fig. 10. Architecture of Re2Com [142] model.

both retrieve similar code using sparse retrieval BM25 and generate summary using LSTM. As shown in Fig. 10, they separately encode the input, the retrieved code, and the corresponding summary, then combine the middle representations or probabilities in the decoder. HGNN [267] instead uses code edit distance for retrieval, and substitutes the encoders for codes with hybrid GNN on their Code Property Graphs (CPG) [268]. RACE [143] aims at generating commit message for code difference. It leverages dense retrieval for similar examples and transformer model for generation. It also uses three encoders for the input, the retrieved code difference, and corresponding commit message, then combines the results before feeding into the decoder. BASHEXPLAINER [140] shares the similar idea. Its dense retrieval module is based on CodeBert [25], and for generation, the output representations of the input and the similar code from CodeBert are directly fused for transformer-based decoder. READSUM [269] retrieves similar code using Levenshtein distance, applies code encoder and summary encoder to retrieved pairs, and generates summary using a decoder where a fusion network combines the information.

RAG for in-context learning, which retrieves similar examples and build prompt for generation, also works in code summary. REDCODER [39] works for both code generation and summary, and it replaces the retriever with GraphCode-Bert [105] for code summary task. ASAP [208] retrieves similar code with BM25, and generates summary with GPT models. Similar to the paradigm described above, research on pseudocode generation [270] employs the retrieved code as input for generation and subsequently replaces the results with the original input. SCCLLM [271] retrieves relevant code snippets by semantic, syntactic, and lexical-based retrieval, then forms in-context prompts for smart contract comment generation via LLM. UniLog [272] retrieves similar code snippets paired with their log statements to conduct in-context learning for log statement generation.

Logit-based RAG also prevails in code summarization. Rencos [120] utilizes two different methods to retrieve similar code snippets, syntactic similarity between abstract syntax trees (AST) and cosine similarity between dense representations. For generator, it adopts attention-based LSTM. There are three encoder-decoder models for the code input and two retrieval results respectively, and the probabilities are combined for final generation. CoRec [273] generates commit message given code diff and retrieved similar code diff. Multiple LSTM generators handle the input code diff and the retrieved code

diff, then adds the probabilities for final generation. kNN-Transformer [274] obtains context vector by feeding code into an encoder-decoder generator, then gets three parts of logits: the first is from searching the vector, the second is from normal Transformer, and the third is the copy mechanism that reserve rare tokens from the input. Tram [275] involves retrieval in both token-level and sentence-level. It encodes source code and corresponding AST into hidden states representations; for token-level, it retrieves similar representations in the database to form next-token prediction logits; for sentence-level, it uses similar code for autoregressive generation logits; it also add the original autoregressive generation logits. CMR-Sum [276] uses encoder-decoder model to generate summaries. It conducts cross attention between representations of retrieved summary and generated summary, and add the logits to the original transformer logits for final distribution.

3) Code Completion: Code completion can be thought of as the coding equivalent of the “next sentence prediction” task. Early attempts on function completion [277] employs DPR to retrieve relevant template functions using function docstring, then concatenate the information as the input to the code generator BART. ReACC [133] retrieves similar codes to build prompts for generation. For retrieval, it uses hybrid retriever, which combines sparse and dense retrieval; for generation, it uses CodeGPT-adapted [278]. RepoCoder [222] steps further to perform iterative retrieval and generation to bridge the gap between the retrieval context and the intended completion target. In each iteration, for retrieval, the code query is augmented with previously generated code; for generation, the prompt is formed by combining the newest retrieved codes with the code query. Other than combining retrieval results in prompts, the retrieval-and-edit framework [141] first retrieves similar training examples using dense retrieval, then encodes the input and the retrieved result separately, finally combine them through attention for later LSTM decoder. CoCoMic [279] builds a project context graph for the whole code project, and retrieves top-k neighbors of the input source code. It generates representations of both source code and retrieved contexts, then jointly processes the embeddings to complete the code. RepoFusion [280] follows the idea of Fusion-in-Decoder; it employs multiple encoder to input the concatenation of the retrieved repo contexts and the unfinished code, then fuses them and generates the results through a decoder. KNMLM [281] uses the same model for retrieval encoding and generation, then combines the logits using bayes inference. EDITAS [282] aims at assertion generation. It retrieves similar queries and their assertions, encodes the edit sequence (from the retrieved query to the original query) and the retrieved assertion, then fuses the information for decoder generation. De-Hallucinator [283] first generates code snippets without retrieval, then retrieves relevant API references given generated contents. In the second pass, retrieved API references are combined in prompt for better generation. REPOFUSE [284] uses both rationale context and retrieved similar codes to construct prompt. To fit in the input length limit, it reserves the contexts that are most relevant to the query.

4) Automatic Program Repair: Buggy code can take a lot of effort to fix. Automatic program repair leverages generative

models to output the correct version. Query-based RAG technique is widely used in automatic program repair [131], [132], [187], [212], [213]. Among them, RING [213] retrieves similar error messages based on both sparse and dense vectors, then builds prompt for the generator Codex [2]. CEDAR [131] applies for both assertion generation and program repairs tasks; it uses sparse and dense retrieval to search for similar codes, then forms prompt for Codex to generate results. InferFix [132] crafts a prompt carrying the bug type, location, relevant syntax hierarchies, and similar fixes through dense retrieval. Then it also uses Codex for generation. RAP-Gen [187] also retrieves similar buggy codes and corresponding fixes through hybrid retriever (including both sparse and dense retriever). It finetunes CodeT5 [106] with this RAG paradigm. SARGAM [212] searches similar buggy code using dense retrieval, generates patches using augmented input, then applies another model to modify the final result. These research works also involve error localization, which is not our focus. RTLFixer [285] leverages ReAct and RAG to implement an agent fixing errors in Verilog codes. It iteratively retrieves relevant errors and corresponding solutions, and combines reasoning and action planning to form prompts for LLMs.

5) **Text-to-SQL and Code-based Semantic Parsing:** Semantic parsing is the task of translating natural language utterances to unambiguous structured meaning representations, where code language is often leveraged to augment this process. SQL is not only a programming language but can also be considered as a structured representation, so we place text-to-SQL (a special case of code generation) in this subsection. Related research works all apply query-based RAG. XRICL [194] focuses on the problem of translating non-English utterances into SQL queries. It searches and reranks English utterance using non-English ones by dense retrieval, then builds prompt for Codex to generate SQL queries. SYNCHROMESH [121] proposes constrained semantic decoding to enforce rich syntactic and semantic constraints during generation of SQL or other languages. It uses the similarity between abstract syntax trees (AST) to finetune the dense retriever S-Bert. During inference, similar NL and SQL are retrieved to form the prompt of GPT-3. CodeICL [286] uses Python for semantic parsing, and augments prompts with a structured domain description for GPT generation. In few-shot learning setting, it leverages BM25 sparse retrieval to find similar training examples. RES-DSQL [287] ranks schemas using cross-encoder, then includes ranked schemas into prompts to generate SQL skeleton and SQL query. ReFSQL [288] retrieves relevant questions and corresponding SQL to augment text-to-SQL generation. It involves structure-enhanced retriever with schema linking, and Mahalanobis contrastive learning to improve the retrieval performance. ODIS [289] retrieves in-domain and out-of-domain demonstrations using BM25, then includes them for in-context learning to generate SQL. Another work [290] retrieves both similar and diverse demonstrations, and then builds prompt for in-context learning to generate SQL. MURRE [291] conducts multi-hop retrieve-rewrite, where relevant tables are retrieved through dense retrieval and then re-written to generate new tabularized question. A rank module at last integrates the retrieval results and select the top tables for the text-to-SQL

module. CodeS [292] retrieves relevant information from table databases in a coarse-to-fine manner, then includes retrieved values to build prompts for both finetuning and inference.

6) **Others:** There are several other code-related tasks that adopt RAG paradigm. In [293] for numerical reasoning task, the Chain-of-Thought is replaced with the programs as the intermediate reasoning step, and dense retrieval-based similar examples are augmented in prompt for downstream LLMs. De-fine [294] tries to resolve intricate tasks using programs. It follows the paradigm in SKCODER, retrieves relevant pairs of query and code, then produces sketch template for real program generation. After generation, it combines the feedback to refine the answer with the same generator. The refined programs, regarded as optimal results, are added back to the codebase for subsequent serving. E&V [295] leverages an LLM-based agent for program static analysis. The agent uses source code retrieval, pseudo-code execution, execution specifications verification, and other tools to form intermediate results. The retrieval is implemented by AST pattern matching. Code4UIE [296] leverages code representation for information extraction tasks. It retrieves relevant examples through dense retrieval, and constructs in-context learning prompt using the retrieved queries and their corresponding codes. StackSpotAI [297] builds an AI coding assistant, which incorporates many code-related tasks. It implements an RAG component, identifying the most relevant pieces of information which serve as the context for GPT generation. InputBlaster [298] aims to generate unusual text input that could cause mobile app crash. It combines retrieved relevant buggy text with valid input to form the prompt for generation.

C. RAG for Audio

1) **Audio Generation:** The goal of audio generation is to generate audio with natural language input. Re-

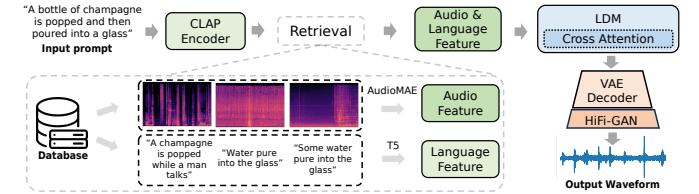


Fig. 11. Architecture of Re-AudioLDM [158] model.

AudioLDM [158] adopts dense retriever CLAP [26] to retrieve similar caption-audio pairs given input prompt. As shown in Fig. 11, the generator, latent diffusion model and VAE-based decoder, take the representations of input text and retrieved pairs as input and generate output audio. Make-An-Audio [43] uses dense retriever CLAP [26] to augment data, retrieving related audio given natural language text. It then constructs pseudo prompts for diffusion-based text-to-audio model training.

2) **Audio Captioning:** The goal of audio captioning is to generate natural language data with audio data, which is basically a sequence-to-sequence task. RECAP [299] leverages CLAP [26] to retrieve related captions given audio data. The retrieved captions are then included into the prompt input for

GPT-2 model, which interacts with audio embeddings through cross attention. In [42], dense retriever VGGish [107] is adopted to produce dense embedding of audio data, and GPT-2 is adopted to generate representations of the retrieved captions which are paired with similar audios. After obtaining the representations of audios and captions, an extra multi-head attention block and a linear layer fuses all the information and generates the output. Some research studies transform audio modality to text, in order to leverage advancements in LLMs [300]–[302]. They take advantage of deep retrieval models, aligning the modalities into the same latent space for downstream text generation.

D. RAG for Image

1) Image Generation: The retrieval process can not only help yield high-quality images even for rare or unseen subjects, but also reduces the parameter count and computational expense [44], [138], [149]–[151], [151]–[153], [303]. For GAN-based model, RetrieveGAN [44] employs a differentiable retrieval process to select compatible image patches for generation, with Gumbel-softmax trick and end-to-end training. ICGAN [138] models data as a mix of conditional distributions around each training instance, conditioning both the generator and discriminator on these instances, and can control the semantics and style by swapping class labels or conditional instances. Recently, diffusion models beat GANs on image generation [304]. KNN-Diffusion [150] trains a text-to-image diffusion model without text data, by conditions the model on CLIP joint embedding of the instance and k -nearest neighbors from image database. These k -NN embeddings bridge the text-image distribution gap and allow image generation from different domains by swapping the database. Similarly, RDM [151] conditions diffusion or autoregressive models on CLIP embeddings of external image databases. It enables post-hoc conditioning on class labels, text prompts and zero-shot stylization [152]. Beyond retrieving only images, Re-imagen [149] conditions on both text prompts and retrieved image-text pairs for text-to-image generation. Interleaved classifier-free guidance is also proposed to balance the alignment between text prompts and retrieval conditions. To avoid information loss of CLIP embeddings and access to all visual condition, Retrieve&Fuse [303] concatenates the retrieved conditional image and the noised image before each attention block in U-Net, and allowing interaction via self-attention. RPG [78] retrieves representative images to construct informative in-context examples (i.e., image-region pairs), and utilizes multimodal chain-of-thought reasoning [305] to plan out complementary subregions for compositional text-to-image diffusion.

2) Image Captioning: Retrieval-augmented image captioning typically synthesises description with a collection of retrieved captions, instead depending only on the input image. MA [163] augments via a memory bank, built with historical context and target word of image-text training set, and queried during inference with the current context. Vocabulary distribution is computed based on retrieved entries, and interpolated with the original prediction. In adversarial training, RAMP [306] employs retrieved captions as reference

for discriminator training, prompting the generator to make full use of retrieved captions. The memory-augmented attention and copying mechanism are also exploited to better use. The RA-Transformer [45] and EXTRA [307], both retrieval-augmented transformer-based captioning models, utilize cross-attention over encoded retrieved captions. EXTRA, as depicted

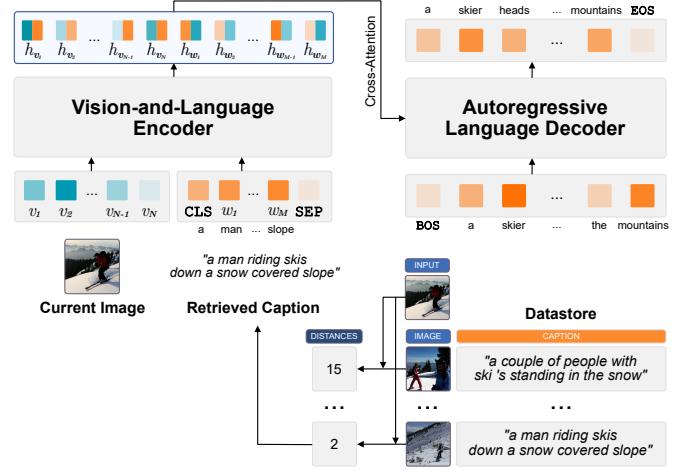


Fig. 12. Architecture of EXTRA [307] model.

in Fig. 12, jointly process the image and retrieved captions with V&L encoder, such that the decoder attends to both visual and linguistic contexts. Beyond retrieved captions, REVEAL [308] uniformly encodes and retrieves multi-modal world knowledge, including image-text pairs, question answering pairs, and knowledge graph triplets, which is then integrated with image features by retrieval score-aware attention module. Straightforwardly, SMALLCAP [46] employs a CLIP vision encoder and a LLM decoder, linked by trainable cross-attention layers, where retrieved captions serve as input-specific in-context examples for prompt for enhancement. For remote sensing image, CRSR [309] enhances retrieved captions with semantic refinement, i.e. filters out misleading details and emphasizes visually salient content. Besides, the visual features is also enriched by transformer network with learnable queries, capturing more intricate details within the images

3) Others: There also exist many retrieval augmented works for other image-related tasks. For visual question answering (VQA), PICa [310] leverages GPT-3's implicit knowledge retrieval and reasoning capabilities, which converts images into textual descriptions, and then prompts GPT-3 to predict answers based on these descriptions and the question. RA-VQA [311] identifies a limitation that the retrieval in previous work is trained separately from answer generation, and propose a joint training scheme that integrates differentiable retrieval with answer generation, enabling end-to-end training. For visually grounded dialogue, KNN-based Information Fetching (KIF) [312] enhances generative Transformer for dialog modeling. Each KIF module learns a read operation to access fixed external knowledge. Maria [313], a neural conversation agent, enhances dialog generation by leveraging visual experiences retrieved from a large-scale image index

as extra context. For multi-modal machine translation, which aims to improve NMT with multi-modal information, [314] incorporates visual information at the phrase level to address the sparsity of paired sentence-image, employing a conditional VAE to filters out redundant visual information from sentence-image datasets.

E. RAG for Video

1) **Video Captioning:** Video captioning is to describe the visual content with a descriptive utterance. R-ConVED [47] introduces retrieval-augmented mechanism to facilitate the word prediction. It uses Dual Encoding [109] for video-text retrieval, and proposes a convolutional encoder-decoder network for generation. For a given input video, R-ConVED first retrieves top-k relevant sentences and their corresponding video from training set, then feeds these pairs and the input video into the generator separately. The obtained decoder hidden states are combined through attention-like read operation, so that the target word can be predicted using the final representation. CARE [159] utilizes visual encoder, audio encoder, and text encoder for frame, audio, and retrieved texts, respectively. It uses CLIP as retriever, and transformer decoder as generator. The embeddings of the three modalities are combined to augment the decoder, producing global semantic guidance which attends the input embedding, and local semantic guidance which attends the attention layer. EgoInstructor [48] generates captions for first-person view videos. It retrieves relevant exocentric videos and corresponding texts via dense retrieval, then encodes the input egocentric video and the retrieved exocentric videos through a CLIP-based visual encoder and a transformer-decoder-based bottleneck module. Then it generates captions through decoder-based LLM which takes the retrieved texts as input and interacts with encoded videos in gated cross-attention layer.

2) **Video Generation:** Text-to-video generation is to generate video given natural language descriptions. As shown in Fig. 13, Animate-A-Story [210] develops a framework which can generate high-quality storytelling videos based on texts. It first separates the text into individual plots, and decorates the description using LLM. It then retrieves relevant videos for each plot through a dense retriever [110]. It generates videos through a latent diffusion model, consisting of two branches: a text encoder CLIP, and a structure encoder which takes the estimated depth of the retrieved videos as structure control.

3) **Others:** There also exist many retrieval augmented works for other video-related tasks. For video question answering (VideoQA), MA-DRNN [315] leverages the differentiable neural computer (DNC) with an external memory, for storing and retrieving useful information in questions and videos, and modeling the long-term visual-textual dependence. Given the video input, R2A [316] retrieves semantically similar texts by multi-modal model, e.g. CLIP, and query LLM with both the question and the retrieved texts. For video-grounded dialogue, [317] proposes TVQA+ dataset which enables to retrieve relevant moments and visual concepts to answer questions about videos, and also proposes Spatio-Temporal Answerer with Grounded Evidence (STAGE) to exploit it.

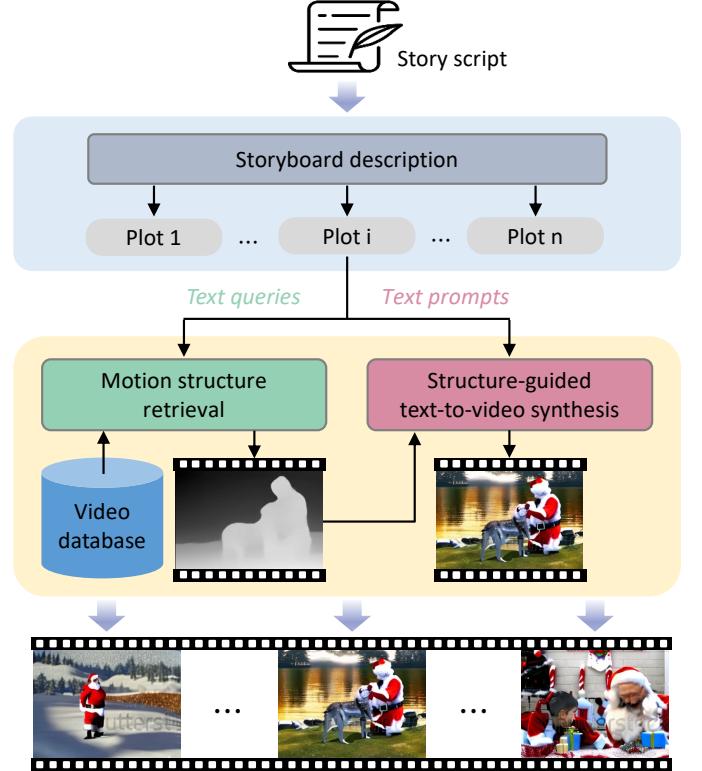


Fig. 13. Architecture of Animate-A-Story [210] model.

VGNMN [318] also extracts visual cues from videos, while the retrieval is carried out using neural module networks parameterized by entities and actions in previous dialogues. VidIL [319] exploits image-language models to translate video content into temporal-aware prompts with few-shot examples, for various video-language tasks including video captioning, video question answering, video caption retrieval, and video future event prediction. Notably, for trustworthy autonomous driving, RAG-Driver [320] grounds the MLLM in relevant expert demonstrations from a memory database, to produce driving action explanations, justifications, and control signal prediction.

F. RAG for 3D

1) **Text-to-3D:** Retrieval can be applied to augment the generation of 3D contents. ReMoDiffuse [50] aims at generating motions using diffusion models. It first retrieves relevant motion entites through CLIP given text input, then leverages the information of the text and the retrieved entities through a semantic-modulated attention layer. AMD [157] designs two branches of motion diffusion for fidelity and diversity. As shown in Fig. 14, the first branch inputs the original prompt text for diffusion; the second branch decomposes the input text into anatomical scripts and retrieve similar reference motions for diffusion. A transformer-based fusion module is further applied to adaptively balance the result from two branches. RetDream [49] targets general 3D generation, using retrieved 3D assets to augment the process of variational score distillation from 2D diffusion models. Given an input query,

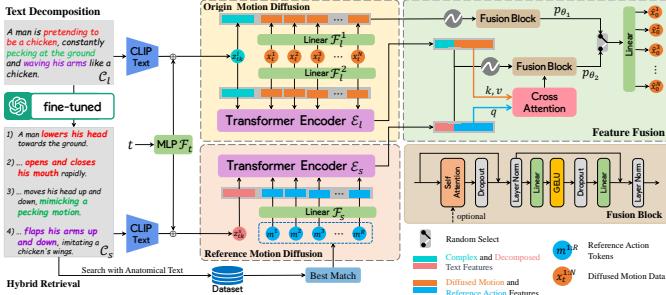


Fig. 14. Architecture of AMD [157] model.

it retrieves relevant 3D assets through CLIP, then utilizes the retrieved assets to provide geometric prior and adapted 2D prior. Concretely, retrieved assets not only impose an additional velocity on particles for distribution initialization, but also help optimize the 2D diffusion model through low-rank adaptation.

G. RAG for Knowledge

Structured knowledge, including knowledge graphs and tables, is widely used in language-related tasks. It usually serves as the retrieval source to augment generation. In addition to normal sparse retrieval and dense retrieval, NER (named-entity recognition) technique is applied to identify specific entities in queries, and graph-aware neighbor retrieval is leveraged to extract relevant entities and relations.

1) Knowledge Base Question Answering: KBQA (knowledge base question answering) typically leverages a knowledge base to identify the correct answer to a question. Many semantic parsing methods are proposed, which generate logical forms (e.g. SPARQL) given a question.

Query-based RAG is the mainstream approach. For a given query, Unseen Entity Handling [52] retrieves topic entities through FreeBase [321], and concatenates the query with the entity for an encoder-decoder to generate SPARQL output. CBR-KBQA [53] retrieves relevant questions and corresponding logical form answers with roberta-based deep retrieval, then concatenates the question and the retrieved pairs for encoder-decoder transformer model. It also revises the final generation result to align the generated relations with relations present in the local neighborhood of the query entity in the knowledge graph. GMT-KBQA [51] first retrieves relevant entities and relations through bert-based deep retrieval, then concatenates the information for T5 generation. To improve the retrieval result, it leverages cross-encoder to rerank the candidates, and uses the same T5 structure to conduct relation classification and entity disambiguation. RNG-KBQA [122] enumerates candidate logical forms in the knowledge graph, then ranks the candidates and concatenates them with query to form the prompt input to generate final logical form through a T5 model. Based on this idea, TIARA [123] also retrieve entity and schema besides logical forms, while a following work [322] retrieves top-k questions with BM25. UniParser [134] retrieves relevant entities from knowledge graph using mention detection, cross-encoder ranker, and 2-hop paths

extraction. It also considers enumerating tables and columns from databases. On obtaining the relevant information, it concatenates the top-k primitives with the query and generates logical forms through T5. BLLM augmentation [136] uses TIARA as the retrieval for relevant knowledge base elements, then performs in-context learning through black-box LLM such as GPT-4 for generating logical forms. ECBRF [135] follows the case-based reasoning paradigm [323], retrieving similar triplet with dense retriever and constructing prompt input for BART or GPT-2 in-context learning. FC-KBQA [324] extracts relevant class, relation, and entity given a question. For class and relation, it uses BM25 as retriever and a Bert-based cross-encoder as re-ranker. For entity, it follows the mention detection paradigm. To compose all the component candidates, it applies T5 model to generate logical expression. StructGPT [325] extracts relevant information, including triplets and nearest entities, to form prompt for subsequent LLM. KAPING [326] builds prompt including the user query and the retrieved relevant facts (through entity matching), then generates the answer through LLM. Another work [327] also follows the retrieve-then-generate paradigm, replacing the retrieval with a relation distribution generation model for weighted triplets. Retrieve-Rewrite-Answer [328] first retrieves subgraph using hop prediction, relation path prediction, and triplet sampling. It then performs KG-to-text and zero-shot generation with retrieved subgraphs as prompt. Keqing [329] first decomposes a complex question into simple sub-questions through finetuned LLM, then retrieves similar sub-question template by dense retriever RoBERTa to extract candidate entities from knowledge graph, and finally generates answer through ChatGPT given relevant entities as context input. To probe the deep understanding of natural language in LLMs with formal languages, a research work [330] explores the capability of formal language understanding and formal language generation. It leverages retrieved pairs to perform in-context learning. For understanding, it uses tree edit distance to retrieve similar logical forms, while for generation, it uses BM25 to retrieve similar natural language queries. Interactive-KBQA [331] treats LLM as agent and KG as environment. In each step, the LLM conducts entity-linking and one-hop retrieval on KG, then generates current thought and action, until obtaining the final answer.

Latent representation-based RAG is also employed in KBQA. ReTraCK [332] links entities using mention detection, and retrieves schema items using dense retriever Bert. It then generates logical forms by LSTM, incorporating retrieved items through knowledge-specific rules. SKP [146] concatenates triplets with the query and uses fusion-in-decoder technique in inference. It adds a pretraining stage with a knowledge-aware MLM loss on triplets and knowledge contrastive loss with respect to the retrieved items. DECAF [145] forms Resource Description Format knowledge base triplets into sentences, then concatenates sentences with the same head entity into documents. It retrieves relevant documents using BM25 sparse retrieval or Bert dense retrieval, then leverages Fusion-in-Decoder technique to generate logical form and direct answer given each (query, document) pair as input. It combines the output to obtain the final answer. KD-

CoT [147] uses the same dense retriever and fusion-in-decoder generator as DECAF. It follows a Chain-of-Thought paradigm, iteratively performing retrieval, generation, and verification until the CoT is finished.

2) Knowledge-augmented Open-domain Question Answering: Structured knowledge is often leveraged for open-domain question answering to achieve outstanding performance.

The use of latent representation-based RAG, particularly the fusion-in-decoder technique, is prevalent for knowledge-augmented open-domain question answering. UniK-QA [144] concatenates the text forms of the components in a triplet and build document pool for retrieval. For a given question, it leverages dense retriever for relevant documents, then performs fusion-in-decoder technique to incorporate the information for answer generation. KG-FiD [333] conducts the

KnowledgeGPT [338] uses generated code to retrieve from both public and personal knowledge bases, so as to build prompt for LLM question answering. EFSUM [339] generates evidence-focused summary with retrieved relevant facts, then optimizes the summary to align the QA-specific preference with another generator and the filters for helpfulness and faithfulness. GenTKGQA [340] conducts subgraph retrieval through relation ranking and time mining, then employs GNN to incorporate structural and temporal information into virtual token representations for subsequent LLM generation. KnowledgeNavigator [341] analyzes complex questions and performs retrieval on knowledge graph through iterative filtering of relations with respect to core entities, so as to obtain relevant triplets. It then includes the triplets into prompt for generation.

3) Table for Question Answering: Tables, as another form of structured knowledge, also facilitates question answering.

Fusion-in-decoder style RAG is often used for table QA. Many retrieval-reader systems are proposed on the EfficientQA competition in NeurIPS 2020 [342]. The systems retrieve from texts or tables, then leverage extractive or generative models as readers. Dual Reader-Parser [343] retrieves relevant textual and tabular information using BM25, then re-ranks using cross-encoder Bert. It leverages Fusion-in-Decoder to combine the retrieved results and generate the final answer. Convinse [344] first conducts question understanding, then retrieves relevant information from heterogeneous resources (including knowledge base, tables, and texts) by entity linking then sparse retrieval. It finally uses fusion-in-decoder to incorporate retrieved evidence and generate answers. CORE [345] retrieves relevant tables and passages through dense representation, then re-ranks the retrieved results using query-generation score from a T0 linker. It uses FiD for final generation. RINK [346] follows the retriever-reranker-reader paradigm for table-augmented question answering. It designs a set-level reader-inherited reranker to get the relevance score of blocks (table segments). TAG-QA [347] retrieves from both tables and texts: for tables, it converts tables to graphs then performs GNN to select relevant contents; for texts, it uses BM25 for retrieval. It then leverages FiD for answer generation.

Tables can be incorporated into prompts for query-based RAG. T-RAG [348] retrieves relevant tables given a user query, then concatenates the query with the tables as a prompt to generate the answer through BART. OmniTab [349] conducts multi-task training to improve the performance of table question answering model. It retrieves relevant tables given a query, then concatenates them for masked-token pre-training. CARP [350] retrieves relevant tables and passages using entity linking, then extracts hybrid chain of retrieved knowledge, which is later used to construct prompt for generation. StructGPT [325] extracts relevant information from knowledge graph, table, or database, to form prompt and generate answers through LLMs. cTBLs [351] retrieves relevant tables through dense retrieval, then for each query, it forms prompt with ranked tables for answer generation. A recent work [352] first uses table-to-text techniques to integrate tabular data into corpora, then conducts experiments on both finetuning and RAG for question answering.

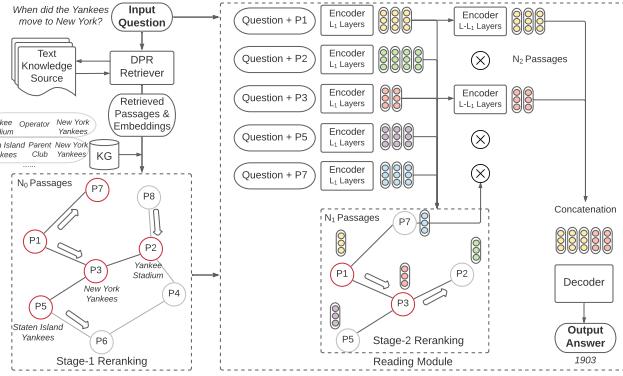


Fig. 15. Architecture of KG-FiD [333] model.

retrieval and generation as normal FiD. It add re-ranking in two ways: the first is to use a graph attention network on the graph formed by retrieved documents; the second is to use the hidden states in the generator. OREOLM [334] empowers LLM with knowledge reasoning paths. Concretely, it uses entity linking to determine the initial state, then conducts contextualized random walk on KG to get reasoning paths, whose entity value memory are combined into the hidden states of LLM for better generation. GRAPE [335] constructs bipartite graph for each pair of question and retrieved passage, then builds bipartite graph on entity for fusing knowledge. It leverages FiD as backbone model and generate answers. SKURG [336] forms a knowledge graph using text and image data, then updates each source's representation with their relevant sources. It then uses a specially designed decoder to iteratively retrieve and generate. It conducts cross-attention with all the sources, then retrieves the source with highest score and concatenates to the original input embedding; if a gate score does not exceed the threshold, it starts to generate the real answer, otherwise the retrieval stage re-starts.

With the rapid development of LLMs, query-based RAG is emerging as a new standard. DIVKNOWQA [337] develops a retrieval-augmentation tool, including sparse retrieval on structured knowledge, dense retrieval on texts, and sparql generation on KB. Through CoT-based LLM, it retrieves and re-ranks in each step, and generates the final answer.

4) Others: Prototype-KRG [353] retrieves knowledge facts and dialogue prototypes, then integrates them into the GRU-based generator by both hidden states and logits. SURGE [354] retrieves relevant subgraphs using dense retrieval, then adds them into the input of the generator for dialogue generation. RHO [355] fuses KG embedding of relevant entities and relations into textual embeddings during the generation of open-domain dialogue. K-LaMP [356] retrieves entity in history queries to construct prompt for query suggestion. ReSKGC [148] linearizes all training triplets into text by concatenation, then retrieves relevant triplets using BM25, and generates completed triplet using T5 with fusion-in-decoder. G-Retriever [357] retrieves relevant nodes and edges from graph-based data, then constructs subgraph and performs graph prompt tuning for question answering based on textual graphs.

H. RAG for Science

RAG has also emerged as a promising research direction for many interdisciplinary applications, such as strengthening molecular generation, guiding medical tasks and advancing computational research.

1) Drug Discovery: The goal of drug discovery is to generate molecules that concurrently fulfill diverse properties. RetMol [54] incorporates a lightweight retrieval mech-

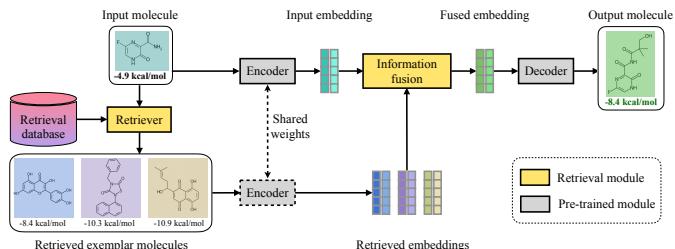


Fig. 16. Architecture of RetMol [54] model.

anism into a pre-trained encoder-decoder generative model. As shown in Fig. 16, this approach adopts the SMILES string [358] representation of molecules along with the ChemFormer model [359], involving the retrieval and fusion of exemplar molecules with the input molecule. PromptDiff [360] proposes an innovative interaction-based retrieval-augmented 3D molecular diffusion model to facilitate target-aware molecule generation. PromptDiff retrieves a curated set of ligand references, *i.e.*, those with desired properties such as high binding affinity, to steer the diffusion model towards synthesizing ligands that satisfy design criteria.

2) Biomedical Informatics Enhancement: Several recent studies have improved the expressiveness of LLM by retrieving information from biomedical domain-specific databases, thereby augmenting the model's capabilities to provide valuable guidance for tasks in the medical field. PoET [361] is an autoregressive generative model based on a variant of Transformer that integrates a retrieval mechanism to enable prompt augmentation, thereby expediting the prediction of fitness properties for protein variants. Chat-Orthopedist [137] creates a retrieval-augmented ChatGPT using an external

knowledge base on adolescent idiopathic scoliosis (AIS), enhancing LLMs with AIS-specific information to provide accurate responses to inquiries. BIOREADER [362] is the first retrieval-enhanced text-to-text transformer-based model for biomedical natural language processing, incorporating the retrieved literature evidence into the model using a chunked-cross attention mechanism. MedWriter [363] utilizes a hierarchical retrieval-augmented generation approach, where the Visual-Language Retrieval (VLR) module retrieves report-level templates, and the Language-Language Retrieval (LLR) module fetches sentence-level templates, to generate coherent and clinically accurate medical reports from images. QARAG [364], utilizing a dual-track RAG approach, leverages fine-tuned language model responses and user queries to accurately retrieve and synthesize regulatory guidelines, significantly improving task performance in pharmaceutical compliance.

3) Math Applications: Retrieval-augmented generation technology in mathematics streamlines problem-solving, boosts research innovation, and refines educational strategies. LeanDojo [365] enhances theorem proving with its ReProver model, utilizing retrieval-augmented techniques to efficiently select relevant premises from extensive mathematical libraries, thus improving automation and theorem generalization. RAG-for-math-QA [366] enhances math question-answering by leveraging retrieval-augmented generation to integrate content from a high-quality math textbook, aiming to improve the quality and educational relevance of LLM-generated responses for middle-school algebra and geometry queries.

V. BENCHMARK

Chen et al. [367] proposed an RAG benchmark, which evaluates RAG from four aspects: Noise Robustness, Negative Rejection, Information Integration, and Counterfactual Robustness, respectively. Noise Robustness evaluates whether LLMs could extract the necessary information from documents containing noisy information. The noisy information is relevant to the input query but useless for answering it. Negative Rejection measures whether LLMs would reject to respond the query when the retrieved content is not enough. Information Integration assesses whether LLMs could acquire knowledge and make responses by integrating multiple retrieved contents. Counterfactual Robustness refers to the ability of LLMs to identify counterfactual errors in the retrieved content.

Another three benchmarks, RAGAS [368], ARES [369] and TruLens [370], considers three different aspects: Faithfulness, Answer Relevance, and Context Relevance, respectively. Faithfulness focuses on the factual errors in the results when the correct answers can be inferred from the retrieved contents. Answer Relevance measures whether the generated results actually address the problems (*i.e.*, queries) or not. Context Relevance judges whether the retrieved contents contain as much knowledge as possible to answer the queries, and as little irrelevant information as possible.

CRUD-RAG [371] divides all RAG tasks into four categories, which are Create, Read, Update, and Delete, respectively, and also evaluates each category using text continuation,

question answering (with single- and multi-document questions), hallucination modification, and open-domain multi-document summary. MIRAGE [372] is a benchmark designed for assessing the application of RAG in the medical domain, focusing on the comparison and optimization of medical question-answering systems’ performance.

VI. DISCUSSION

A. Limitations

Despite the widespread adoption of RAG in various applications, there are indeed some limitations in terms of effectiveness and efficiency. In this paper, we summarize the limitations of RAG and deliver in-depth discussion.

1) **Noises in Retrieval Results:** Information retrieval cannot yield perfect results because information loss appears in representations generated by encoder models. Additionally, ANN search can also provide approximate results rather than exact ones. Consequently, certain degree of noise is inevitable in retrieval results, manifesting as irrelevant objects or misleading information, which may cause failure points in RAG systems [373]. Though the common sense is that increasing the accuracy of retrieval will contribute to the effectiveness of RAG, a recent study surprisingly shows that noisy retrieval results may conversely help improve the generation quality [374]. A possible explanation is that diversity in retrieval results may also be necessary for prompt construction [375]. As a result, the impact of noise in retrieval results remains uncertain, leading to confusion regarding which metric to employ for retrieval and how to facilitate the interaction between the retriever and the generator. Subsequent research on this topic is anticipated to demystify the confusion.

2) **Extra Overhead:** While retrieval can help mitigate the costs of generation in certain cases [29]–[31], the incorporation of retrieval sometimes introduces non-negligible overhead. Considering that RAG is primarily employed to improve the performance of existing generative models, the inclusion of additional retrieval and interaction processes leads to increased latency. Worse still, when combined with complex enhancement methods, such as recursive retrieval [171] and iterative RAG [222], the extra overhead will become even more significant. Furthermore, as the scale of retrieval expands, the storage and access complexity associated with data sources will also increase. In presence, RAG systems exhibit a trade-off between costs and benefits. Looking ahead, we anticipate further optimization to alleviate the associated overhead.

3) **Interaction of Retrieval and Generation:** Achieving seamless integration between the retrieval and generation components requires meticulous design and optimization. Given that the objectives of the retriever and generator are not aligned, and that the two models may not share the same latent space, designing and optimizing the interaction between these two components encounter challenges. As introduced in Section III, numerous approaches have been proposed to enable effective RAG, and these approaches either disentangle the retrieval and generation processes or integrate them at an intermediate stage. While the former is more modularized, the latter could potentially benefit from joint training. Till

not, there lacks a sufficient comparison of different ways of interaction across various scenarios.

The tuning of RAG systems is also challenging. A recent study on the trade-off between attribution and fluency in prompt-augmentation-style RAG demonstrates that using top-k retrieval for generation improves attribution, but hurts fluency in turns [376]. The counter effects of different aspects in RAG, such as metric selection and hyper-parameter tuning, remains unexplored. Therefore, further refinement of RAG systems, both in terms of algorithms and deployment, is necessary to fully unlock their potentials.

4) **Long Context Generation:** One of the primary challenges in early stage RAG, which leverages prompt augmentation, is the inherent context length limitation of the generators. The research advancements in prompt compression [207] and long-context support [377] have partially mitigated this challenge, albeit with a slight trade-off in accuracy or costs. Given this challenge, a recent notion appears that “long-context models like Gemini 1.5 will replace RAG”. Nevertheless, this assertion does not hold true — RAG exhibits greater flexibility in managing dynamic information, encompassing both up-to-date and long-tail knowledge [378]. We believe that RAG in the future will take advantage of long context generation to achieve even better performance, rather than simply being weeded out by it.

B. Potential Future Directions

Last but not least, we wish to identify a series of possible directions for the future research and applications of RAG.

1) **More Advanced Research on RAG Methodologies, Enhancements, and Applications:** A straight-forward research direction is to develop more advanced methodologies, enhancements, and applications of RAG.

As introduced in Section III-A, existing works have explored various interaction patterns between retrievers and generators. However, since the optimization target of these two components are distinct, the practical augmentation process has a large impact on the final generation results. Investigation of more advanced foundations for augmentation holds promise for fully unleashing the potential of RAG.

Based on a constructed RAG system, enhancements are helpful to improve the effectiveness of certain components or the entire pipeline. Given the inherent complexity of the system, there exists significant potential for RAG to improve, necessitating proper tuning and careful engineering. We look forward to further experimental analysis and in-depth exploration that will contribute to the development of more effective and more robust RAG systems.

As introduced in Section IV, RAG is a general technique that has been applied across diverse modalities and tasks. Yet most of existing works straightforwardly integrate external knowledge with the specific generation tasks, without thoroughly taking into account the key characteristics of the target domains. Therefore, for generation tasks that do not fully leverage the power of RAG, we are confident that designing proper RAG system will be beneficial.

2) Efficient Deployment and Processing: Currently, several deployment solutions of query-based RAG for LLMs have been proposed, such as LangChain [379], LLAMA-Index [180], and PipeRAG [380]. However, for other types of RAG and generation tasks, there lacks a plug-and-play solution. In addition, given the extra overhead introduced by retrieval, and considering that the complexities of both the retriever and generator will continue to grow, achieving efficient processing in RAG remains a challenge, necessitating targeted system optimization.

3) Incorporating Long-tail and Real-time Knowledge: While a key motivation of RAG is to harness real-time and long-tail knowledge, the pipeline for knowledge updating and expansion remains unexplored. Many existing works make up the retrieval sources with merely the training data of generators, thereby neglecting the dynamic and flexible information advantages that could have been offered by retrieval. As a consequence, designing a useful RAG system with continuously updated knowledge and/or flexible knowledge sources, along with corresponding system-level optimizations, is a growing research direction. With the capability of utilizing long-tail knowledge, we also expect RAG to leverage personalized information and features, so as to adapt to today's web service.

4) Combined with Other Techniques: In essential, RAG is orthogonal to other techniques that share the goal of improving AIGC effectiveness, including fine tuning, reinforcement learning, chain-of-thought, agent-based generation, and other potential optimizations. However, the exploration of simultaneously applying these techniques is still in its early stages, calling for further research to delve into algorithm design and fully leverage their potential.

VII. CONCLUSION

In this paper, we conduct a thorough and comprehensive survey on RAG in the scenarios related to AIGC, with a particular focus on augmentation foundations, enhancements, and practical applications. We first systematically organize and summarize the foundation paradigms in RAG, providing insights into the interaction between the retriever and the generator. Based on constructed RAG systems, we review the enhancements that further improve the effectiveness of RAG, including the enhancements on input, retriever, generator, and results. To facilitate researchers across diverse domains, we showcase practical applications of RAG in a range of modalities and tasks. Finally, we also present existing benchmarks for RAG, discuss current limitations of RAG, and shed light on promising future directions.

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