Bridging the Preference Gap between Retrievers and LLMs

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Abstract

Large Language Models (LLMs) have demonstrated superior results across a wide range of tasks, while retrieval has long been established as an effective means of obtaining task-relevant information for humans. Retrieval-augmented Generation (RAG) are known for their effectiveness in knowledge-intensive tasks by locating relevant information and placing it within the context window of the LLM. However, the relationship between retrievers and LLMs is still under-investigated. Most existing work treats the retriever and the LLM as independent components and leaves a gap between retrieving human-friendly information and assembling a LLM-friendly context. In this work, we examine a novel bridge model, validate the ranking and selection assumptions in retrievers in the context of RAG, and propose a training framework that chains together supervised and reinforcement learning to learn a bridge model. Empirical results demonstrate the effectiveness of our method in both question-answering and personalized generation tasks.

1 Introduction

Large language models (LLMs) such as GPT-3 (Brown et al., 2020) and PaLM2 (Anil et al., 2023), have demonstrated impressive performance on a wide range of language tasks. Alongside LLMs, retrieval-augmented generation (RAG), which can retrieve knowledge from an external dataset when needed, have also produced strong results in many knowledge intensive-tasks.

However, despite some extensive RAG studies (Khandelwal et al., 2020; Borgeaud et al., 2022; Izacard et al., 2022; Yasunaga et al., 2023), most of them study retrievers and LLMs **separately**. On one hand, considerable effort has been dedicated

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[*] The work was done during internship at Google Research.

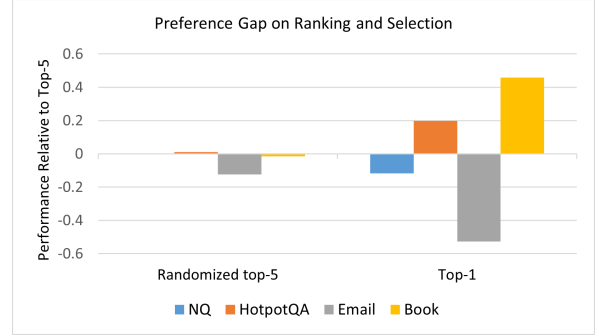[†] The work was done as a visiting researcher at Google Research.

Figure 1: We observe a preference gap when changing the ranking and selection within the LLM's input context. The experiments are conducted with GTR (Ni et al., 2021) as retriever and a fixed Palm2-S as the LLMs. "Top-K" means we select the top-k GTR retrieved passages. Different colors indicate different datasets. The selected passages are used as additional context. We see that selection (Top-1) significantly affects (either positively or negatively) the model's performance, while ranking (randomized top-5) does not have much impact (the metrics are detailed in Sec. 5.2).

to designing **user-friendly retrievers**, based on the **general belief** that ranking is paramount, as humans typically read from top to bottom. On the other hand, LLMs exhibit preferences different from humans and yield accurate predictions only when prompts align with these preferences. This discrepancy leads to sub-optimal design in current RAG systems, a phenomenon we term **preference gap**. This gap manifests in various aspects. For example, the general belief on **ranking** may not align with LLM's preferences due to the self-attention mechanism in Transformers, which can focus on any token regardless of its sequential position. Another aspect is **selection**; humans can disregard irrelevant passages, but it has been shown that LLMs are highly sensitive to irrelevant content (Shi et al., 2023a). There are likely more gaps that further diverge from human behavior, such as **repetition**, which is generally considered detrimental for retrieval systems (Xia et al., 2017), but maybe be

useful to LLMs for relevance weighting.

We empirically investigate this preference gap, focusing specifically on **ranking** and **selection**. As shown in Fig. 1, the performance varied by around 1% when we randomized the top-5 retrieved passages[1]. However, the variation exceeded 5% when selecting the top-1 passage. This indicates the general belief in the importance of ranking in retrieval does not apply to LLMs , indicating that selection could be more crucial. This finding confirms the existence of the preference gap between the retrievers and LLMs, and highlights the importance of **bridging this preference gap** to enhance RAG. This is a crucial insight that has not been revealed before, which can guide RAG designers towards what should be achieved in the model.

To design a RAG model, existing work has tried to finetune the LLMs to align with the retriever's preference, or to finetune the retriever to align with the LLM's preference. However, since they primarily focuses on ranking, their approaches are sub-optimal for bridging the preference gap. Finetuning retrievers can only achieve re-ranking, and fine-tuning LLMs is often impractical, as many are only accessible through APIs. To better bridge the gap beyond ranking, we propose a framework called **BGM** (**B**ridging the **G**ap between retrievers and LL**M**s). We propose to keep the retriever and LLM fixed, and train a bridge model in between. The bridge model aims to transform the retrieved information into a format that LLMs can work with effectively.

Since the preference gap is present in both ranking and selection, and potentially extends to aspects such as repetition, in contrast to the conventional scoring format, we structure the bridge model as a **sequence-to-sequence (seq2seq)** model. This approach allows it to not only rerank but also dynamically select passages for each query, and potentially employ more advanced strategies like repetition. In a typical RAG, there is no ground truth relevance label for what should be retrieved but only ground truth label for the downstream task. Existing supervised learning (SL) approaches use

the supervision provided by the LLM, such as the perplexity of downstream tasks. However, this is ineffective due to sparse supervision as it is nearly impossible to feed all possible retrieved sequences into the LLM to obtain supervision. Even worse, such SL relies on the intermediate relevance label and is not end-to-end training on the downstream tasks. To address these issues, we employed reinforcement learning (RL) on the SL trained bridge model, where the downstream performance metrics are used as the reward and the bridge model are regarded as a policy model. This framework, chaining SL and RL, provides increased supervision from the downstream task. It also offers the model the flexibility to explore more advanced strategies, such as repetition, in forming the optimal passage sequence.

Our experiments reveal that BGM can enhance the performance of various downstream tasks, such as Question Answering (QA) and personalized generation, across a spectrum of datasets, from public QA and amazon reviews to private email conversations. Notably, the modified passages retrieved by BGM surpass the performance of strong retrievers and reranking baseline models. This underscores the significance and promise of the bridging approach in the realm of RAG. In summary, our contributions can be summarized as follows:

- We empirically establish the existence of the preference gap between retrievers and LLMs, and introduce BGM, which designed to address this preference gap.

- We propose a seq2seq bridge model to jointly accomplish reranking and selection, adapting the retrieved information to be LLM-friendly. We employ a SL and RL training scheme to optimize this adaptation process.

- The evaluation of BGM comprises diverse datasets, including QA and text generation, including both publicly available and personal information sources. The comprehensive evaluation underscores the effectiveness of BGM in bridging the preference gap and improving performance in downstream tasks.

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[1]We note that this is different from (Liu et al., 2023), where a "loss in the middle" phenomenon is observed, meaning that the model are better at using the relevant information at the beginning or end of its input context. This is probably due to different number of passages used. In Liu et al. (2023), 20 total documents are employed, whereas we used 5 passages. Regardless, this does not affect the conclusion that there exists a preference gap between the retrievers and LLMs which needs to be bridged.

2   Related Work

Retrieval-augmented Generation (RAG). Augmenting LLMs with relevant information retrieved
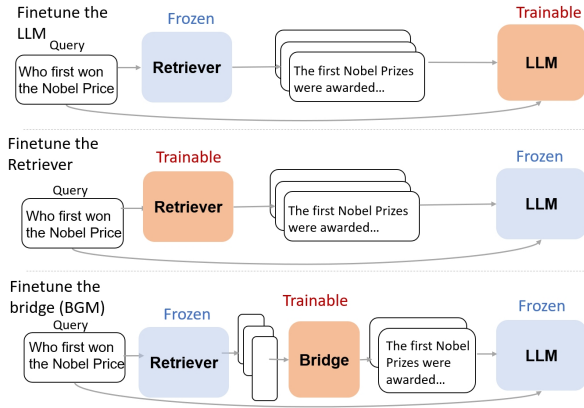
Figure 2: Differing from previous RAG that update either LLMs, retrievers, or both, BGM not only treats the LLM as a black box but also freezes the retrieval. Only a lightweight bridge model (a Seq2seq LM) is tunable in order to adapt the retrieved information to satisfy the LLM's preference. This makes BGM applicable to large LLMs, which are often served via APIs and also avoids expensive updates to the retriever.

from various knowledge sources has shown effective in improving performance across numerous NLP tasks, including language modeling (Borgeaud et al., 2022; Khandelwal et al., 2020; Shi et al., 2023b), question answering (Lewis et al., 2020; Izacard et al., 2022; de Jong et al., 2023; De Jong et al., 2023; Shi et al., 2023b; Guu et al., 2020; Izacard and Grave, 2020; Xu et al., 2023), fact versification (Lewis et al., 2020) and text generation (Lewis et al., 2020). Specifically, RAG utilizes input as a query and comprises two main components: (1) **retriever** retrieves a set of items from a large corpus. Note that the retrieval units vary across different works, including documents, passages, or even tokens. In this study, we focus on retrieving passages; and (2) **LLM** incorporate the retrieved passages as additional information, integrating them into the input context for making final predictions.

A fundamental question in this process arises regarding the differing preferences between LLMs and existing retrievers, with LLMs performing optimally only when their preferences are satisfied. Bridging the gap between these differing preferences is crucial. Depending on which components are subject to updates, this challenge can be categorized into three families

Finetuning retrievers and LLMs jointly. This is the most widely used and conventional setting of RAG (Izacard et al., 2022; Khandelwal et al., 2020; Wu et al., 2022; Guu et al., 2020; Lewis

et al., 2020). However, they are mostly less than 1B so may nor regard as "large" LM. For example, Altas (Izacard et al., 2022) finetunes LLM (T5 (Raffel et al., 2020a)) and retriever (Contriever (Izacard et al., 2021)) jointly by leveraging the LLM to provide supervisory signal to train the retriever. RAG (Lewis et al., 2020) uses a tunnable query encoder and DPR (Karpukhin et al., 2020) as retriever, BART as LLM, and design an end-to-end training and inference schema to train the query encoder and the LLM.

Finetuning LLMs only. Updating retrievers is not always desirable as it is costly and requires the document index to be periodically updated. To bridge the preference gap, it is also possible to only update the LLMs. Fid (Izacard and Grave, 2020) takes the retrieved documents and query as input, finetunes the LLM to adapt to the external information. Similarly, Lummen (De Jong et al., 2023) and Glimmer (de Jong et al., 2023) improve FiD via adding reranker and pre-encoding memeory.

Finetuning retrievers only. Although above systems have shown improves results, they are not always applicable in practice. Many LLMs such as GPT-3 and Codex are not open-sourced due to commercial considerations and are only available as black-box APIs. Through these APIs, users can send queries and receive responses. Given this constraint, a natural approach is to only update the retrievers to ensure they can retrieve passages that are more compatible with LLMs. REPLUG (Shi et al., 2023b) adapts a similar idea as Atlas but fix the LM. RECOMP (Xu et al., 2023) trains a compressors to summarize the retrieved document from retriever. However, this family of models is incapable of performing any sample-level selection and can only choose top passages by setting a fixed threshold.

Unlike the existing three families, BGM works on LLM (> 11B) and directly working on bridging the preference gap, without finetuning LLMs or retrievers but a bridge model in between (Fig. 2).

RL for information retrieval. Before the LLM era, RL has been used in information retrieval (IR) (Xia et al., 2017; Wei et al., 2017; Zeng et al., 2018; Xu et al., 2020). The core approach was to frame the IR problem as a Markov Decision Process and apply an RL algorithm to solve it. Typically, an IR task would be structured to determine which document to select for a ranking position, using ranking metrics such as DCG as the reward. This

approach had advantages, including using the ranking position directly as supervision and optimizing the IR measure directly. However, none of these existing works explored the application of RL in the context of RAG.

In the LLM era, RL has been used in query rewriting for retrieval (Wu et al., 2021; Nogueira and Cho, 2017; Adolphs et al., 2021), where a black-box retriever is assumed. This is a different problem from RAG. Bacciu et al. (2023) suggest using RL to fine-tune retriever in the RAG context in their opinion paper, but it does not conduct any experiments. More crucially, their work fails to recognize the importance of bridging the gap between retrievers and LLMs, nor does it specify what the bridge model should be.

3 Problem Formulation

Retriever. Given an input x, the retriever aims to retrieve a ranked list of passages from a corpus $D = \{d_i\}_{i=1}^m$ that are relevant to x. In this work, we assume a frozen dense retriever. Typically, a dual encoder architecture is applied, where an encoder is used to encode both the input context x and the passage d. Specifically, the encoder maps each passage to an embedding $\boldsymbol{E}(d)$. The similarity between input and passage embedding is computed by their cosine similarity,

$$s(d, x) = \cos(\boldsymbol{E}(d), \boldsymbol{E}(x)). \quad (1)$$

The top-k passages that have the highest similarity scores when compared with the input x are retrieved in this step.

$$(d_j^{\text{retr.}})_{j=1}^k = \text{Top-K}(\{s(d, x)\}_{i=1}^m). \quad (2)$$

Bridge Model for RAG. The retrieved top-K passages provide richer information about the original input x and can potentially help the LLM to make a better prediction on downstream tasks. However, since there is preference gap, we propose a bridge model $\boldsymbol{B}$ to adapt the retrieved passages to LLM-friendly passages. As mentioned in the Sec. 1, the bridge model is a seq2seq model. It takes as input all the retrieved passages $(d_j^{\text{retr.}})_{j=1}^k$ and output a subset of adapted passages $(d_j^{\text{bdr.}})_{j=1}^n$. This format is advantageous because the seq2seq model automatically considers ranking by generating the next token based on the preceding one and selection by placing the end-of-sentence token in the appropriate position. Note that n may or may not equal to k due to selection.

$$(d_j^{\text{bdr.}})_{j=1}^n = \boldsymbol{B}((d_j^{\text{retr.}})_{j=1}^k). \quad (3)$$

It is important to note that in practice, the bridge model's input includes the query, passage IDs, and passage content, while the output consists of passage IDs. We then convert the obtained passage IDs to their corresponding documents when we use them in RL (Sec. 4.2). Additionally, the passages in passage sequence (e.g., $(d_j^{\text{retr.}})_{j=1}^n$) are concatenated into a long sequence before being fed to the network.

Retrieval-augmented Generation with bridge model. Given the adapted passages from the bridge model as context, $(d_j^{\text{bdr.}})_{j=1}^n$, we concatenate them with the input x, and fed the resulting long sequence into the LLM to obtain the output for downstream tasks.

4 Training the Bridge Model

In Eq. 3, we format the bridge model as seq2seq model. However, it is challenging to effectively train it as there is no ground truth retrieved passages and LLM is assumed to be API without gradient. To address the issue, we propose to chain supervised learning (SL) and reinforcement learning (RL), where SL aims to reduce the search space of RL and provides a reasonably good initial model that does ranking and selection. Meanwhile, RL aims to optimize the policy model, i.e., bridge model, against the reward.

4.1 Supervised Learning

To conduct SL, the ground-truth sequence is required for each query. In a typical RAG, the ground truth relevance passage for the query is not provided, let alone the ground-truth sequence. To address this, we propose to synthesis silver passage sequence by selecting only the useful passage. This is done by **greedy search** that incrementally selects the next passage that can maximize the downstream task performance.

Synthesising silver passage sequence using greedy search. Assume that the downstream task performance for a given passage sequence of any length, used as context, is denoted as $R(\cdot)$. The empty passage sequence, i.e., no retrieved passage, denoted as $d_\varnothing^{\text{retr.}}$, has downstream task performance $R(d_\varnothing^{\text{retr.}})$. Starting from $d_\varnothing^{\text{retr.}}$ and empty silver passage sequence $d^{\text{silv.}}$, we try to add (i.e., concatenate) the candidate passage that can improve most to the silver passage sequence, until no improvement can
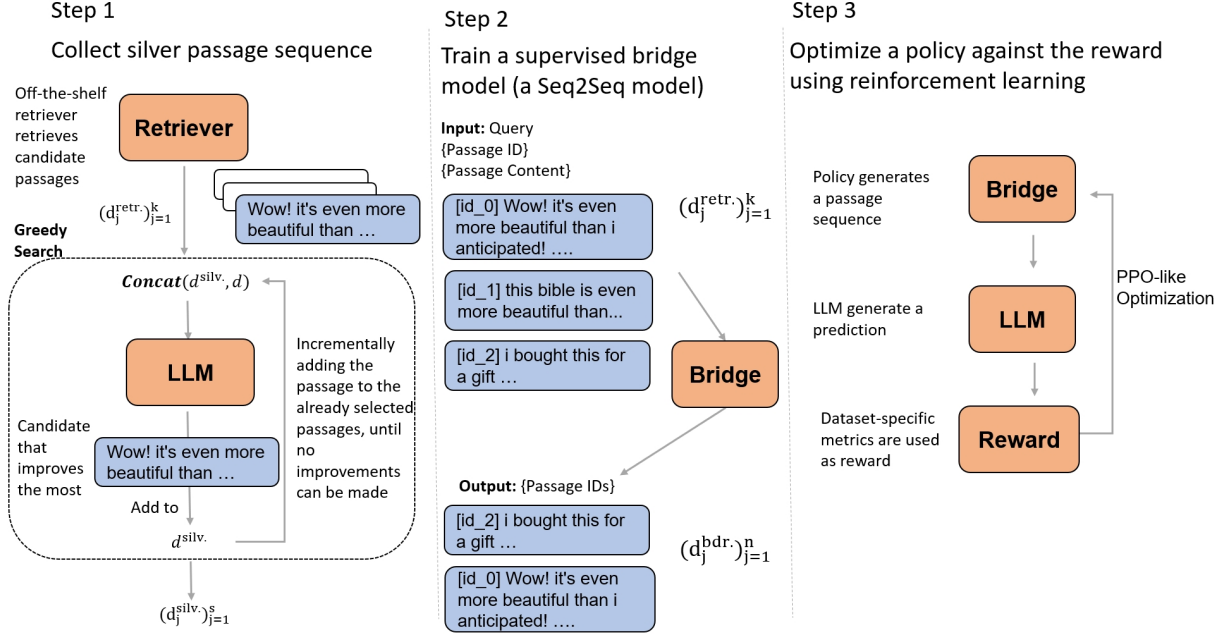
Figure 3: Illustrating the training of BGM: **Step 1:** First, we prepare the silver passage sequence for supervised learning (SL) through a greedy search on the retrieved passages. **Step 2:** This silver passage sequence is then used for the supervised training of the bridge model. The bridge model is a seq2seq model that takes the query, passage ID, and passage content as input and outputs the passage IDs. **Step 3:** Finally, the trained bridge model is treated as a policy model and is further trained using reinforcement learning

be made. Algorithm 1 shows the pseudo-code for synthesising silver passage sequence.

Training. Training with the silver passage sequence is straightforward, achieved by applying cross-entropy loss.

4.2 Reinforcement Learning

Although supervised learning can already help training the bridge model, it is still ineffective (we can see using SL alone results in mixed performance compared to using a retriever alone in Table 5). This is attributed to sparse supervision and the lack of end-to-end training on downstream results.

To address these issues, we apply RL to further train the bridge model. RL does not limit the possible passage sequences (we only consider permutations or deletions in the silver passage sequence in SL. However, the optimal passage sequence might require more complex manipulations, such as repetition, which RL can accommodate) and give more supervision to find the best passages sequence. Using the performance of downstream task as the reward, the bridge model is trained in an end-to-end manner on the downstream task. Specifically, our task can be formulated as a RL problem as follows:

Reward is the performance of tasks against their ground-truth labels as we focus on labeled downstream tasks.

Algorithm 1: Synthesis Silver Passage Sequence

Input: $(d_j^{\text{bdr.}})_{j=1}^n$, $R(\cdot)$
Output: $(d_j^{\text{silv.}})_{j=1}^s$

1 $d^{\text{silv.}} = ()$;
2 $silv = R(d_\varnothing^{\text{retr.}})$;
3 $prev = 0$;
4 $best = \varnothing$;
5 **while** *True* **do**
6   **for** $d \leftarrow d_1^{retr.}$ **to** $d_n^{retr.}$ *where d not in* $d^{silv.}$ **do**
7          $seq = \text{concat}(d, d^{\text{silv.}})$;
8          $cur = R(seq)$;
9   **if** *(cur > silv) and (cur > prev)* **then**
10             $best = d$;
11             $prev = cur$;
12   **if** $best \mathrel{!=} \varnothing$ **then**
13   add $best$ to the end of $d^{\text{silv.}}$;
14         $silv = prev$;
15         $prev = 0$;
16         $best = \varnothing$
17   **else**
18   Break;

Policy Model is the bridge model that need to be trained.

Action Space is limitted to Passage IDs as we are interested in adapting the retrieved passages

Training. The reward objective can be optimized by any off-the-shelf RL algorithm, e.g., proximal policy optimization (PPO).

5 Experiments

5.1 Datasets and Baselines

Datasets. We consider four datasets, ranging from popular QA datasets to less investigated personalized ones. We also include one dataset that contains private email conversations (Avocado Email), which is unlikely to be included in the LLM's pretraining datasets. This will further help us investigate the effectiveness of our proposed BGM model, as the LLM will have to rely on the retrieved passages. The summary of statistics is given in Table 1.

Open-domain QA. We conduct evaluations on two open-domain QA: **Natural Questions (NQ)** (Kwiatkowski et al., 2019) and **HotpotQA** (Yang et al., 2018). They both consist of questions, answers collected from Wikipedia and the Web. HotpotQA is a multi-hop QA dataset which requires findings and reasoning over multiple passages to answer the question. The candidate passages are retrieved from WikiPedia pages

Personalized Generation. We follow (Li et al., 2023) to construct the personalized generation datasets. Specifically, suppose a user is writing a document, which we call the *current document*. Given the *immediate context* x and the user's *personal context*, we aim the finish the document as if the user had completed it. The immediate context x or the input to the personalized writing task, is defined as the title and the start of the current document. The candidate passages are retrieved from documents authored by this user in the past. This includes datasets from two domains: **Avocado Email (Email)** (Oard et al., 2015) and **Amazon Book (Book)** (Ni et al., 2019).

Baselines. We consider the state-of-the-art baselines: (1) **GTR** (Ni et al., 2021) a widely recognized retriever that operates independently of LLMs; (2) a variant of GTR, termed **Random**, in which the order of passages retrieved by GTR is randomized; (3) Point-wise score ranking **(PSR)** (Izacard et al., 2022). This is a variant from (Izacard et al., 2022) where we substitute the decoder with our LLM and apply point-wise scoring

> **Instruction**: Finish the passage in the user voice
> **Review title:** Perfect solution for long-range planning!
> **Review product:** 2018 - 2022 artwork five-year planner…
> **Review start:** Wow! I've been searching for something like this and was so pleased when it came in! the
>
> **Target:** Wow! I've been searching for something like this and was so pleased when it came in! the 2-page-per-month style works. The blocks on the calendar are big enough to write quite a bit….
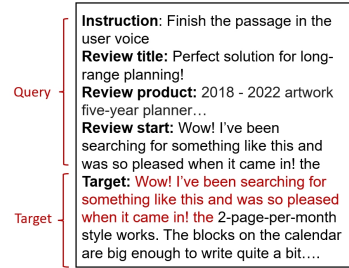
Figure 4: An example from the Book dataset. The query consists of the instruction, the document (i.e., review for Book) title, document product (there will be no product information for Email), document start. The target is to complete the text given the query.

reranking. This approach can be regarded as utilizing a reranker as a bridge model, but lacking the capability for dynamic selection; and (4) Additionally, we include a non-retrieval baseline, **Naive**, where no retrieval is conducted to aid in the generation process.

	#Training	#Val.	#Test	Avg. # words
NQ	79,168	8,757	3,610	517.82
HotpotQA	68,659	5,600	5,600	564.83
Email	13,305	764	1,227	173.85
Book	20,789	41,331	41,331	124.52

Table 1: Statistic of the 4 datasets.

5.2 LLM and Hyperparamters

We select the T5-XXL (11B) (Raffel et al., 2020b) model as our bridge model for most experiments. In the supervised learning stage, the T5-11B model is fine-tuned with a base learning rate of 0.001. A linear warmup scheduler is used for the first 1,000 training steps. Additionally, the square root normalized decay of the learning rate is applied. The model is trained until its performance converges on the validation set. Decoding is performed using beam search with a beam size of 4. We use the PaLM2 model (Anil et al., 2023), a new state-of-the-art LLM, as our LLM. It adopts temperature sampling as the decoding strategy. The parameters of PaLM2 are frozen, and we set the temperature to 0 to make the output deterministic. We use Exact-Match (EM) and BLEU as the metric to select the best prompt among prompt variants. It is also used as the reward to train the bridge model in the RL stage. The "Top-K" in Eq. 2 is set to 5.

5.3 Evaluation Results and Analysis

Superior of BGM. Table 2 reports the overall performance. We can see that

Model	NQ	HotpotQA	Email	Book
Metric	EM	EM	BLEU	BLEU
Naïve	33.07	28.01	5.57	11.5
Random	43.71	26.10	8.55	8.61
GTR	43.79	25.80	9.76	8.75
PSR	43.60	25.51	9.08	9.14
BGM	**45.37**	**35.64**	**10.42**	**12.07**

Table 2: Performance of all 4 datasets

Model	NQ	HotpotQA	Email	Book
Metric	EM	EM	BLEU	BLEU
Naive	33.07	28.01	5.57	11.5
PSR	43.6	25.51	9.08	9.14
PSR (Top1)	42.02	32.69	7.28	11.53
PSR (Top2)	42.54	31.05	7.77	10.11
PSR (Top3)	42.85	32.71	8.21	9.70
PSR (Top4)	43.71	32.37	8.26	9.11
BGM	**45.37**	**35.64**	**10.42**	**12.07**

Table 3: Ablation results - threshold the PSR

Silver Data	NQ	HotpotQA	Email	Book
Metric	EM	EM	BLEU	BLEU
GTR	43.79	25.8	9.76	8.75
PSR	43.68	29.73	10.1	10.35
Greedy (BGM)	**45.37**	**35.64**	**10.42**	**12.07**

Table 4: Ablation results - different silver passage sequence for SL

(1) **The proposed BGM outperforms all the 4 baselines in all 4 datasets.** This clearly indicates BGM is effective in adapting the retrieved passages.

(2) **Compared to the Naive approach, BGM shows significant improvement overall.** However, an exception is observed in the Book dataset, where BGM's improvement is more modest. This suggests that the LLM already possesses a substantial amount of relevant knowledge, likely due to the inclusion of Amazon reviews (which the Book dataset comprises) in the LLM's pre-training data. Consequently, retrieval is not always essential in this context. This also explains why the Naive approach outperforms other baselines (except BGM) on the Book dataset. It's important to note that BGM still manages to show improvement, albeit to a lesser extent, in this scenario

(3) **Compared to the GTR approach, BGM demonstrates substantial improvement.** The NQ dataset shows the least improvement, as most instances only require one retrieved passage, which both GTR and BGM can successfully include. On the other hand, the HotpotQA dataset shows the most significant improvement, indicating that HotpotQA may be more sensitive to irrelevant passages. It's noteworthy that Random and GTR perform similarly, while GTR shows improvement over Naive (with the exception of the Book dataset). This suggests that the ranking itself does not significantly impact performance, but the selection of passages does

(4) **Compared to the PSR approach, BGM once again demonstrates significant improvement.** This indicates that pure reranking alone is not sufficient for the bridge model. Selection must also be taken into account. It's notable that PSR performs similarly to GTR, further suggesting that reranking alone does not greatly affect performance

Understanding BGM. We are interested in what happen when we optimize the BGM, whether BGM's improvement is trival, and how some important setting affects the BGM.

(1) **Whether the selection can be achieved naively by manually threshold the PSR?** We conducted an ablation experiment using various thresholds for PSR, as shown in Table 3. The term "Top-K" in rows 3 to 6 refers to the selection of only the Top-K passages from PSR reranked passages. The results are mixed, but consistently inferior to those of BGM. This suggests that a naive manual threshold applied to the reranking model is insufficient to meet our objectives. Therefore, it is necessary to consider both reranking and dynamic selection simultaneously

(2) **How different silver passage sequence will affect the final performance?** In Table 2, we employed greedy search passage sequences as silver passage sequence for SL (Sec. 4.1). However, lacking ground truth passage sequences, we also explored whether this approach is superior to others. Our ablation experiment in Table 4 involved using various types of silver passage sequence. The first row, labeled 'GTR', indicates the use of GTR's retrieved passages as silver passage sequence. Similarly, 'PSR' refers to using PSR reranked passages as silver passage sequence. In the final row, we used greedy search passage sequences, representing the current version of BGM. The results demonstrate that the quality of silver passage sequence significantly affects downstream task performance. While using PSR as silver passage sequence shows improvement over GTR on three datasets, Greedy (BGM) further enhances performance and achieves the best results. Identifying potentially better silver

Model	NQ	HotpotQA	Email	Book
Metric	EM	EM	BLEU	BLEU
GTR	43.79	25.8	9.76	8.75
BGM (SL only)	39.44	34.26	8.62	12.05
BGM	**45.37**	**35.64**	**10.42**	**12.07**

Table 5: Ablation results - SL only

Model	NQ	HotpotQA	Email	Book
Metric	EM	EM	BLEU	BLEU
GTR	43.79	25.8	9.76	8.75
FLAN-T5-Large	44.15	35.87	10.18	10.19
FLAN-T5-XL	44.87	35.41	9.64	10.7
FLAN-T5-XXL (BGM)	**45.37**	**35.64**	**10.42**	**12.07**

Table 6: Ablation results - different bridge model size

Model	Palm2-XXS		Palm2-S	
Data	NQ	HotpotQA	Email	Book
Metric	EM	EM	BLEU	BLEU
Naive	12.13	14.57	33.07	28.01
Random	31.19	24.41	43.71	26.1
GTR	31.91	23.17	43.79	25.8
PSR	32.04	22.53	43.60	25.51
BGM	**39.88**	**28.69**	**45.37**	**35.64**

Table 7: Ablation results - different LLM size

Model	NQ	HotpotQA	Email	Book
Metric	EM	EM	BLEU	BLEU
Test on Palm2-S				
BGM	**45.37**	**35.64**	**10.42**	**12.07**
BGM (Train on NQ)	—	33.42	5.66	11.22
BGM (Train on Email)	35.59	27.98	—	11.38
Test on Palm2-XXS				
BGM (Train on Palm2-XXS)	**39.88**	**28.69**	—	—
BGM (Train on Palm2-S)	30.63	24.55	—	—

Table 8: Ablation results - the generability of BGM across various datasets and LLM sizes.

passage sequence is left for future work.

(3) **How helpful RL is to the final performance?** BGM integrates SL and RL, and we aim to assess the effectiveness of each component. An ablation experiment is detailed in Table 5. We can observe that BGM, when operating with only SL, performs significantly worse than the full BGM model in NQ, HotpotQA, and Email, and in some cases, it even underperforms GTR. This suggests that SL alone is inadequate, highlighting the necessity of incorporating RL. It's important to note that removing SL is not feasible, as this would result in an excessively large search space for RL to effectively learn.

(4) **How different size of bridge model affect the final performance?** In Table 2, we utilized Flan-T5-XXL (11B) as the bridge model, which is already smaller than the LLM (24B). However, we are curious about the feasibility of using an even more lightweight language model (LM) as the bridge model. The ablation study shown in Table 6 presents the outcomes of employing bridge models of various sizes. It is evident that all three sizes (large, XL, and XXL) surpass the performance of the setup without a bridge model (i.e., GTR), with the largest size yielding the best results. This demonstrates that a bridge model is beneficial even at a smaller scale, and that larger sizes lead to further improvements.

(5) **How different size of LLMs affect the final performance?** In Table 2, Palm2-S was used as the LLM. We are interested in evaluating the effectiveness of the bridge model with different sizes of LLMs. We conducted experiments using Palm2-XXS, as detailed in Table 7. It is important to note that the smaller LLM struggles with personalized generation datasets (i.e., Email and Book), resulting in BLEU scores lower than 1%.

We opted not to report these results as they may not accurately reflect the trend. However, observations from NQ and HotpotQA suggest that BGM significantly outperforms all baselines by a large margin. This indicates that BGM is effective even with a smaller LLM.

(6) **Can a trained bridge model generalize to different datasets and LLMs?** The effectiveness of the bridge model across various datasets and LLMs has been demonstrated. A more ambitious objective is to extend this performance to new contexts without additional training. We conducted experiments to investigate the generalizability of the bridge model. The upper section of Table 8 presents the data on generalizability across different datasets. Row 2 shows the performance of BGM (i.e., the bridge model) when trained exclusively on the NQ dataset and then tested on three other unseen datasets. Similarly, row 3 describes training BGM solely on the Email dataset and testing it on the other three. In all cases, the performance is inferior to that of BGM when both training and testing are conducted on the same datasets. This result is expected, as no specific techniques have been developed for dataset generalization, a topic we leave for future work.

In the lower section of Table 8, we present the results of BGM when tested on Palm2-XXS, but

trained on Palm2-S. Comparing with results of BGM both trained and tested on Palm2-XXS (as shown in row 1 of the bottom section), the mismatch between LLM sizes leads to a significant decline in performance. This suggests that BGM's ability to generalize across different LLM sizes is currently limited. Addressing this limitation is considered an important direction for future research.

(8) **Case Studies.** We provided examples of GTR, PSR, and BGM in Table 9 in the Appendix for the NQ dataset. For **question I**, both GTR and PSR yield the same incorrect output, even though their contexts have different orders. Only BGM provides the correct answer, indicating that additional irrelevant context can be noisy and detrimental to RAG's performance. In **question II**, unlike question I, GTR and PSR produce different answers. This suggests that the ranking can sometimes influence the results. While the specific mechanism by which ranking affects outcomes remains unclear (we regard it as a valuable topic for future research), it is evident that we need to consider ranking, as it may or may not affect performance. Again, BGM selects the most relevant passage and delivers the correct answer. In **question III**, none of the candidate passages contain the answer (they discuss FaZe Clan and the number of subscribers, but do not identify who has the most subscribers). GTR and PSR provide incorrect answers, as their additional context is unhelpful. In contrast, BGM opts not to select any passages and answers the question using its own parameters, resulting in the correct answer. This demonstrates that retrieval-augmented processes are not always necessary, and BGM is capable of handling such cases

6 Conclusion

This paper highlights the importance of bridging the preference gap between retrievers and LLMs. It begins by demonstrating the existence of this gap, especially in terms of ranking and selection. This provides an important guidance about what should be achieved in a RAG system. It then suggests the development of a lightweight bridge model. This component is designed to adapt user-friendly passages retrieved by the retrievers into formats more suitable for LLMs. To accomplish these objectives, we introduce a novel system named BGM. BGM treats the bridging task as a seq2seq problem, allowing for simultaneous consideration of both ranking and selection. It is trained through a combination

of supervised learning and reinforcement learning, facilitating end-to-end training of the bridge model based on the performance in downstream tasks and is capble even when the LLM is black-box (i.e., API). Extensive experiments have demonstrated BGM's effectiveness.

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Question I
Where does new crust come from in sea floor spreading
Answer
"basaltic magma" or "volcanic activity"
GTR Context
Given the passage titles and contexts below:

Title: Seafloor spreading;

Context: Seafloor spreading Seafloor spreading is a process that occurs at mid-ocean ridges, where new oceanic crust is formed through volcanic activity and then gradually moves away from the ridge. Earlier theories (e.g. by Alfred Wegener and Alexander du Toit) of continental drift postulated that continents "ploughed" through the sea. The idea that the seafloor itself moves (and also carries the continents with it) as it expands from a central axis was proposed by Harry Hess from Princeton University in the 1960s. The theory is well accepted now, and the phenomenon is known to be caused by convection currents in the;

Title: Oceanic crust;

Context: frozen in the basalt. A symmetrical pattern of positive and negative magnetic lines emanates from the mid-ocean ridge. New rock is formed by magma at the mid-ocean ridges, and the ocean floor spreads out from this point. When the magma cools to form rock, its magnetic polarity is aligned with the then-current positions of the magnetic poles of the Earth. New magma then forces the older cooled magma away from the ridge. This process results in parallel sections of oceanic crust of alternating magnetic polarity. Oceanic crust Oceanic crust is the uppermost layer of the oceanic portion of a tectonic;

Title: Seafloor spreading;

Context: ~Tx/L, where L is the distance between the ridge to the continental shelf (roughly half the ocean width), and T is the ocean age. Seafloor spreading Seafloor spreading is a process that occurs at mid-ocean ridges, where new oceanic crust is formed through volcanic activity and then gradually moves away from the ridge. Earlier theories (e.g. by Alfred Wegener and Alexander du Toit) of continental drift postulated that continents "ploughed" through the sea. The idea that the seafloor itself moves (and also carries the continents with it) as it expands from a central axis was proposed by Harry Hess;

Title: Seafloor spreading;

Context: As new seafloor forms and spreads apart from the mid-ocean ridge it slowly cools over time. Older seafloor is therefore colder than new seafloor, and older oceanic basins deeper than new oceanic basins due to isostasy. If the diameter of the earth remains relatively constant despite the production of new crust, a mechanism must exist by which crust is also destroyed. The destruction of oceanic crust occurs at subduction zones where oceanic crust is forced under either continental crust or oceanic crust. Today, the Atlantic basin is actively spreading at the Mid-Atlantic Ridge. Only a small portion of the oceanic;

Title: Seafloor spreading;

Context: other areas), material from the upper mantle rises through the faults between oceanic plates to form new crust as the plates move away from each other, a phenomenon first observed as continental drift. When Alfred Wegener first presented a hypothesis of continental drift in 1912, he suggested that continents ploughed through the ocean crust. This was impossible: oceanic crust is both more dense and more rigid than continental crust. Accordingly, Wegener's theory wasn't taken very seriously, especially in the United States. Since then, it has been shown that the motion of the continents is linked to seafloor spreading by the;

What is the answer of the following question:

where does new crust come from in sea floor spreading

GTR Prediction
the upper mantle
PSR Context
Given the passage titles and contexts below:

Title: Seafloor spreading;

Context: Seafloor spreading Seafloor spreading is a process that occurs at mid-ocean ridges, where new oceanic crust is formed through volcanic activity and then gradually moves away from the ridge. Earlier theories (e.g. by Alfred Wegener and Alexander du Toit) of continental drift postulated that continents "ploughed" through the sea. The idea that the seafloor itself moves (and also carries the continents with it) as it expands from a central axis was proposed by Harry Hess from Princeton University in the 1960s. The theory is well accepted now, and the phenomenon is known to be caused by convection currents in the; **Title:** Seafloor spreading;

Context: $\sim$Tx/L, where L is the distance between the ridge to the continental shelf (roughly half the ocean width), and T is the ocean age. Seafloor spreading Seafloor spreading is a process that occurs at mid-ocean ridges, where new oceanic crust is formed through volcanic activity and then gradually moves away from the ridge. Earlier theories (e.g. by Alfred Wegener and Alexander du Toit) of continental drift postulated that continents "ploughed" through the sea. The idea that the seafloor itself moves (and also carries the continents with it) as it expands from a central axis was proposed by Harry Hess; **Title:** Seafloor spreading;

Context: other areas), material from the upper mantle rises through the faults between oceanic plates to form new crust as the plates move away from each other, a phenomenon first observed as continental drift. When Alfred Wegener first presented a hypothesis of continental drift in 1912, he suggested that continents ploughed through the ocean crust. This was impossible: oceanic crust is both more dense and more rigid than continental crust. Accordingly, Wegener's theory wasn't taken very seriously, especially in the United States. Since then, it has been shown that the motion of the continents is linked to seafloor spreading by the;

Title: Oceanic crust;

Context: frozen in the basalt. A symmetrical pattern of positive and negative magnetic lines emanates from the mid-ocean ridge. New rock is formed by magma at the mid-ocean ridges, and the ocean floor spreads out from this point. When the magma cools to form rock, its magnetic polarity is aligned with the then-current positions of the magnetic poles of the Earth. New magma then forces the older cooled magma away from the ridge. This process results in parallel sections of oceanic crust of alternating magnetic polarity. Oceanic crust Oceanic crust is the uppermost layer of the oceanic portion of a tectonic;

Title: Seafloor spreading;

Context: As new seafloor forms and spreads apart from the mid-ocean ridge it slowly cools over time. Older seafloor is therefore colder than new seafloor, and older oceanic basins deeper than new oceanic basins due to isostasy. If the diameter of the earth remains relatively constant despite the production of new crust, a mechanism must exist by which crust is also destroyed. The destruction of oceanic crust occurs at subduction zones where oceanic crust is forced under either continental crust or oceanic crust. Today, the Atlantic basin is actively spreading at the Mid-Atlantic Ridge. Only a small portion of the oceanic;

What is the answer of the following question:
where does new crust come from in sea floor spreading

PSR Prediction
the upper mantle

BGM Context

Given the passage titles and contexts below:

Title: Seafloor spreading;

Context: Seafloor spreading Seafloor spreading is a process that occurs at mid-ocean ridges, where new oceanic crust is formed through volcanic activity and then gradually moves away from the ridge. Earlier theories (e.g. by Alfred Wegener and Alexander du Toit) of continental drift postulated that continents "ploughed" through the sea. The idea that the seafloor itself moves (and also carries the continents with it) as it expands from a central axis was proposed by Harry Hess from Princeton University in the 1960s. The theory is well accepted now, and the phenomenon is known to be caused by convection currents in the;

What is the answer of the following question:
where does new crust come from in sea floor spreading

BGM Prediction
volcanic activity

Question II
who sings i want to dance with you

Answer
"George Strait"

GTR Context

Given the passage titles and contexts below:

Title: I Just Want to Dance with You;

Context: I Just Want to Dance with You "I Just Want to Dance with You" is a song written by John Prine and Roger Cook, and performed by American country music singer George Strait. It was released in April 1998 as the first single to his album, "One Step at a Time", it is his 34th Number One single on the "Billboard" Hot Country Singles & Tracks chart, and his 42nd Number One single when all major trade charts are counted. Prine recorded it 12 years earlier, for his 1986 album "German Afternoons". It was also a hit for Daniel O'Donnell;

Title: Tony Caso;

Context: Tony Caso Tony Caso (Anthony Caso) is an American 1980s pop/dance music recording artist and, later, actor. Tony Caso began recording in the early 1980s, as "Tony Caso and Salvation". His first single, "I Want To Dance With You" (1981), was issued on Lam Records. A second single, 'Hot Blooded Woman', was also issued in 1981. Tony joined the Bobby O label in New York, recording in "One Two Three" and "Waterfont Home". He had a number of singles throughout the 1980s: All The Love In My Heart - 1983 (O Records) Take A Chance (On Me) - 1984 (O;

Title: Voglio ballare con te;

Context: Voglio ballare con te "Voglio ballare con te" (English: "I want to dance with you") is a song recorded by Italian rapper Baby K, with vocals by Spanish singer Andrés Dvicio, for her upcoming third studio album. The song was released on 2 June 2017, through Sony Music Italy. It was produced by Takagi and Mr Ketra, who also produced the singer's smash-hit "Roma Bangkok". In Italy, "Voglio ballare con te" debuted at number 51, and later peaked at number 2. The song reached the triple platinum certification in that territory for selling over 150,000 copies. It also peaked at;

Title: Voglio ballare con te;

Context: number 20 in Switzerland, marking Espósito's second entry and highest-charting song on the chart. "Locos Valientes", the Spanish-language version of the song, was released on September 8, 2017. The song became Baby K's second Spanish song, following "Roma-Bangkok" featuring Giusy Ferreri or Lali. Voglio ballare con te "Voglio ballare con te" (English: "I want to dance with you") is a song recorded by Italian rapper Baby K, with vocals by Spanish singer Andrés Dvicio, for her upcoming third studio album. The song was released on 2 June 2017, through Sony Music Italy. It was produced by Takagi and Mr Ketra,;

Title: Karen Brooks;

Context: Karen Brooks Karen Brooks (born April 30, 1954) is an American singer and writer who is best known for a series of singles recorded by Emmylou Harris, Rosanne Cash, Patty Loveless, Tanya Tucker, Russell Smith, David Allen Coe, Crystal Gayle and Exile. She won a Grammy for her contribution to the soundtrack for the Sesame Street movie "Follow That Bird". She sang a duet with Johnny Cash, "I Will Dance With You", and also with T. G. Sheppard, "Faking Love", which was a number-1 hit for three weeks on the "Billboard" country chart in February 1983. She also had a;

What is the answer of the following question:

who sings i want to dance with you

GTR Prediction
Tony Caso

PSR Context

Given the passage titles and contexts below:

Title: Pure Country;

Context: Pure Country Pure Country is a 1992 American dramatic musical western film directed by Christopher Cain and starring George Strait in his acting debut, with Lesley Ann Warren, Isabel Glasser and Kyle Chandler. The film was considered a box office bomb, but it grossed over $15 million against a 10 million budget, and the soundtrack was a critical success and, to date, is Strait's best selling album. It was followed by two direct-to-video sequels, "" (2010) and "" (2017). The film begins with various shots of the audience chanting "Dusty!", which is repeated throughout. Meanwhile, the band begins, as the;

Title: Pure Country;

Context: Worth, including North Side Coliseum. The bar scenes where Dusty meets Harley were filmed at Western Kountry Klub, located between Midlothian and Mansfield Tx. Despite Strait's super-star status in the music world, "Pure Country" only grossed just over $15 million at the box office. Although the expectations had been higher for Strait's first major film role, this did not stop the soundtrack album from becoming the best-selling of Strait's career to date. The film also received mainly negative reviews upon its release, but critics responded nicely to certain aspects of the film. It currently has a score of 38% on;

Title: Pure Country;

Context: Instead, it focuses on a young woman's struggles to become a country singer. George Strait appears as himself, but not as a central character of the film. A second sequel titled, "" was released for a direct-to-video on August 1, 2017. Pure Country Pure Country is a 1992 American dramatic musical western film directed by Christopher Cain and starring George Strait in his acting debut, with Lesley Ann Warren, Isabel Glasser and Kyle Chandler. The film was considered a box office bomb, but it grossed over $15 million against a $10 million budget, and the soundtrack was a critical success;

Title: Pure Country: Pure Heart;

Context: Pure Country: Pure Heart Pure Country: Pure Heart is a 2017 American direct-to-video country musical directed by Damon Santostefano. It's a story about teenage sisters who go to Nashville when they discover their late father was a country music singer. It is nominally a sequel to the 1992 film "Pure Country", but has a separate and unrelated plot. Ada Spencer and her younger sister, Piper, are high schoolers living in a rural Tennessee farmhouse with their widowed mother Elizabeth and their grandmother, Meemaw. When a water pipe bursts, the girls find a Silver Star and other information about their father,;

Title: Pure Country: Pure Heart;

Context: Elizabeth visits Marq, reconciling with her and leading to Ada and Piper singing one of their father's songs, on stage with Willie Nelson and Marq, at a fund raiser for veterans. Pure Country: Pure Heart Pure Country: Pure Heart is a 2017 American direct-to-video country musical directed by Damon Santostefano. It's a story about teenage sisters who go to Nashville when they discover their late father was a country music singer. It is nominally a sequel to the 1992 film "Pure Country", but has a separate and unrelated plot. Ada Spencer and her younger sister, Piper, are high schoolers living;

What is the answer of the following question:

who plays dusty in the movie pure country

PSR Prediction
George Strait

BGM Context

Given the passage titles and contexts below:

Title: I Just Want to Dance with You;

Context: I Just Want to Dance with You "I Just Want to Dance with You" is a song written by John Prine and Roger Cook, and performed by American country music singer George Strait. It was released in April 1998 as the first single to his album, "One Step at a Time", it is his 34th Number One single on the "Billboard" Hot Country Singles & Tracks chart, and his 42nd Number One single when all major trade charts are counted. Prine recorded it 12 years earlier, for his 1986 album "German Afternoons". It was also a hit for Daniel O'Donnell;

What is the answer of the following question: who sings i want to dance with you

BGM Prediction

Question III

who has the most subscribers in faze clan

Answer

"FaZe Rug"

GTR Context

Given the passage titles and contexts below:

Title: FaZe Clan;

Context: "FaZe 2.0" by FaZe members and fans. The FaZe "CS:GO" team went on to become one of the most successful rosters for the 2017/2018 seasons. FaZe Clan is the most popular esports organization in the world, based on the organization's social media following. As of November 28, 2018, FaZe Clan and its members together have 82 million YouTube subscribers, 11.2 billion YouTube views, 11.3 million Twitch followers, 130 million Twitch views, 43.1 million Twitter followers, 45.8 million Instagram followers, 2.8 million Facebook likes and followers. FaZe Clan has made $6,148,290.91 from esport tournament prize pools alone. FaZe Clan started on;

Title: FaZe Clan;

Context: February 18, 2018. FaZe Clan FaZe Clan (formerly FaZe Sniping) is an American esports and entertainment organization that competes in various video game tournaments. The organization was founded as a gaming clan on YouTube by players known as Housecat, ClipZ, and Resistance in 2010, who all created "trickshot" videos for the video game "". In 2012, with the release of "", the organization decided to expand into competitive play. In 2016, a new era for FaZe began when the organization bought a "" professional team. This moment marked the beginning of FaZe Clan expanding into various esports. This movement is;

Title: FaZe Clan;

Context: FaZe Clan FaZe Clan (formerly FaZe Sniping) is an American esports and entertainment organization that competes in various video game tournaments. The organization was founded as a gaming clan on YouTube by players known as Housecat, ClipZ, and Resistance in 2010, who all created "trickshot" videos for the video game "". In 2012, with the release of "", the organization decided to expand into competitive play. In 2016, a new era for FaZe began when the organization bought a "" professional team. This moment marked the beginning of FaZe Clan expanding into various esports. This movement is referred to as;

Title: FaZe Clan;

Context: Duty" community has been frustrated with the way FaZe Clan has been/not been involved in the game in which it was founded. Most of the other FaZe members have changed their video topics and mostly do vlog videos. This sparked FaZe Clan to organize the highly successful FaZe Bootcamp on the release of "". FaZe trickshotters known as Kitty, Dirty, Bloo, GwidT and Replays contributed to a week dedicated to creating "Call of Duty" content. FaZe's first roster—consisting of players named Heist, Folsom, Secretly, and Sham— was created to compete at the 2013 MLG Winter Championship. Their next roster—consisting of;

Title: F Is for Family;

Context: F Is for Family F is for Family is an American adult animated sitcom created by Bill Burr and Michael Price and produced by Gaumont International Television and Vince Vaughn's Wild West Television. The show premiered on December 18, 2015, to generally favorable reviews. Season 2 premiered May 30, 2017. On June 28, 2017, the show was renewed for a third season. On July 1, 2018, Burr confirmed season three. On November 30, the third season was released. The series was announced in October 2014 as part of a partnership between Netflix, Gaumont International Television, and Wild West Television.;

What is the answer of the following question:

who has the most subscribers in faze clan

GTR Prediction

Tfue

PSR Context

Given the passage titles and contexts below:

Title: FaZe Clan;

Context: Duty" community has been frustrated with the way FaZe Clan has been/not been involved in the game in which it was founded. Most of the other FaZe members have changed their video topics and mostly do vlog videos. This sparked FaZe Clan to organize the highly successful FaZe Bootcamp on the release of "". FaZe trickshotters known as Kitty, Dirty, Bloo, GwidT and Replays contributed to a week dedicated to creating "Call of Duty" content. FaZe's first roster—consisting of players named Heist, Folsom, Secretly, and Sham— was created to compete at the 2013 MLG Winter Championship. Their next roster—consisting of;

Title: FaZe Clan;

Context: "FaZe 2.0" by FaZe members and fans. The FaZe "CS:GO" team went on to become one of the most successful rosters for the 2017/2018 seasons. FaZe Clan is the most popular esports organization in the world, based on the organization's social media following. As of November 28, 2018, FaZe Clan and its members together have 82 million YouTube subscribers, 11.2 billion YouTube views, 11.3 million Twitch followers, 130 million Twitch views, 43.1 million Twitter followers, 45.8 million Instagram followers, 2.8 million Facebook likes and followers. FaZe Clan has made $6,148,290.91 from esport tournament prize pools alone. FaZe Clan started on;

Title: FaZe Clan;

Context: FaZe Clan FaZe Clan (formerly FaZe Sniping) is an American esports and entertainment organization that competes in various video game tournaments. The organization was founded as a gaming clan on YouTube by players known as Housecat, ClipZ, and Resistance in 2010, who all created "trickshot" videos for the video game "". In 2012, with the release of "", the organization decided to expand into competitive play. In 2016, a new era for FaZe began when the organization bought a "" professional team. This moment marked the beginning of FaZe Clan expanding into various esports. This movement is referred to as;

Title: F Is for Family;

Context: F Is for Family F is for Family is an American adult animated sitcom created by Bill Burr and Michael Price and produced by Gaumont International Television and Vince Vaughn's Wild West Television. The show premiered on December 18, 2015, to generally favorable reviews. Season 2 premiered May 30, 2017. On June 28, 2017, the show was renewed for a third season. On July 1, 2018, Burr confirmed season three. On November 30, the third season was released. The series was announced in October 2014 as part of a partnership between Netflix, Gaumont International Television, and Wild West Television.;

Title: FaZe Clan;

Context: February 18, 2018. FaZe Clan FaZe Clan (formerly FaZe Sniping) is an American esports and entertainment organization that competes in various video game tournaments. The organization was founded as a gaming clan on YouTube by players known as Housecat, ClipZ, and Resistance in 2010, who all created "trickshot" videos for the video game "". In 2012, with the release of "", the organization decided to expand into competitive play. In 2016, a new era for FaZe began when the organization bought a "" professional team. This moment marked the beginning of FaZe Clan expanding into various esports. This movement is;

What is the answer of the following question:

who has the most subscribers in faze clan

GTR Prediction

Tfue

BGM Context

What is the answer of the following question:

who has the most subscribers in faze clan

BGM Prediction
FaZe Rug

Table 9: Cases comparisons for GTR, PSR and BGM from NQ dataset.