Generalizable Generative Retrieval

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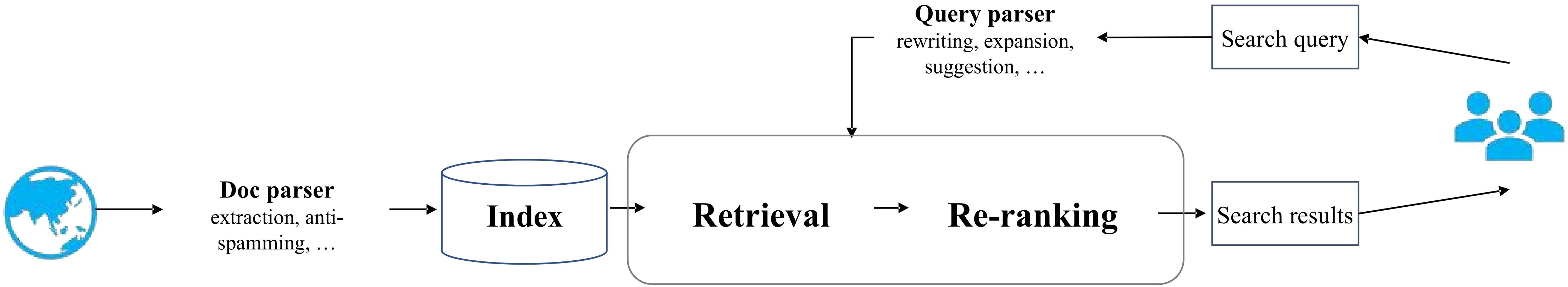
Pipeline of index-retrieval-ranking

- **Index**: Build an index for each document in the entire corpus
- **Retriever**: Find an initial set of candidate documents for a query
- **Re-ranker**: Determine the relevance degree of each candidate



Closed-book generative retrieval

Passage rank list

Query ---constrained generation---> Document identifiers (doc id)

Query: Who is the singer of *Does He Love You*?

→ **Autoregressive Model** →

Generated: recorded as a duet by American country music artists

Rank 1st passage:
Title: Does He Love You
Body: … recorded as a duet by American country music artists …
ID: 32 – 16 – 18

Rank 2nd passage:
Title: Does He Love You
Body: …
ID: 32 – 16 – 16

Other different designs of document identifiers:

Title: Does He Love You | **ID:** 32 – 16 – 18

[1] Recent advances in generative information retrieval, SIGIR 2024 tutorial

Components of existing GR models

- Document Identifiers design
- Corpus indexing
- Generative decoding from queries

Generative retrieval over dynamic corpora

- Generative Retrieval (GR) shows promise, but its effectiveness in dynamic corpora is largely unexplored.
- Systematically evaluated various current GR models and traditional IR models in dynamic settings.
  - Traditional IR: BM25, DPR, etc.
  - Numeric-based: DSI, GenRET, NCI, etc.
  - Text-based: SEAL, MINDER, etc.

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[1] Replication and Exploration of Generative Retrieval over Dynamic Corpora, SIGIR 2025

Experiments

Performance as documents are incrementally added:

Retrieval initial documents.

Method	DocID Type	NQ (Hit@10)						
		$\mathcal{D}_0$	$\mathcal{D}_1$	$\mathcal{D}_2$	$\mathcal{D}_3$	$\mathcal{D}_4$	$\mathcal{D}_5$	$F_n \downarrow$
Sparse retrieval								
BM25	Term Weight	0.647	0.625	0.611	0.598	0.573	0.573	0.051
Dense retrieval								
DPR	Dense Vector	0.725	0.704	0.696	0.686	0.670	0.660	0.042
DPR-HN	Dense Vector	0.826	0.801	0.797	0.776	0.773	0.768	0.043
Generative retrieval								
DSI-SE	Category Nums	0.718	0.710	0.706	0.702	0.699	0.696	**0.015**
Ultron-PQ	Category Nums	0.795	0.785	0.780	0.780	0.762	0.755	0.023
NCI	Category Nums	**0.871**	0.856	0.844	**0.839**	0.811	0.802	0.041
GenRET	Category Nums	0.858	0.853	0.836	0.829	0.812	0.796	0.033
Ultron-URL	URL Path	0.816	0.810	0.794	0.781	0.780	0.768	0.029
SEAL	N-gram	0.809	0.806	0.788	0.774	0.774	0.763	0.028
MINDER	Multi-text	0.838	0.828	0.813	0.811	0.801	0.773	0.033
LTRGR	Multi-text	0.862	**0.857**	**0.846**	0.827	**0.813**	**0.807**	0.032

Retrieval newly added documents.

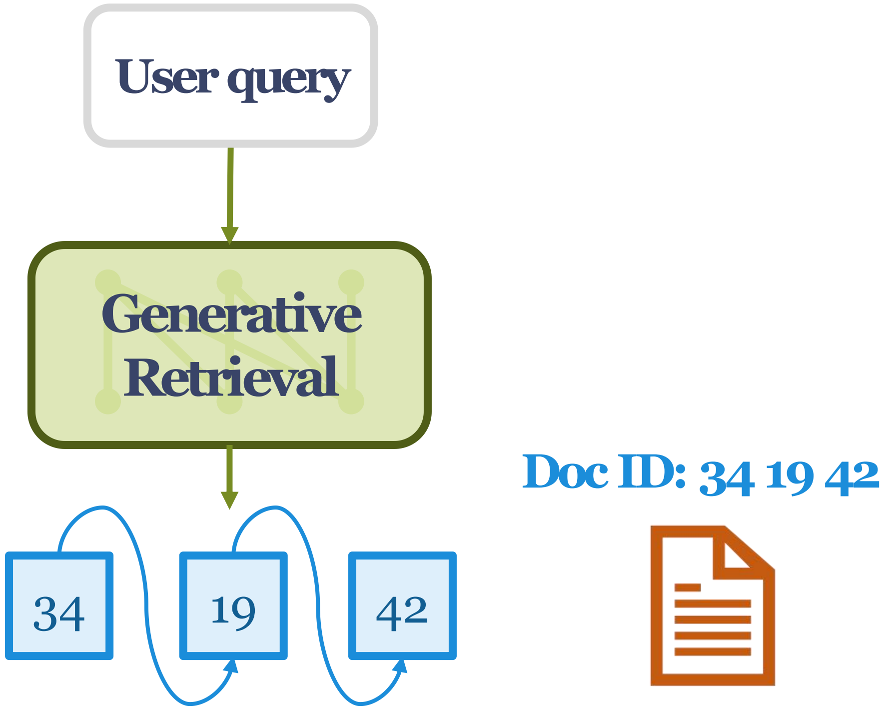
Method	DocID Type	NQ (Hit@10)						
		$\mathcal{D}_0$	$\mathcal{D}_1$	$\mathcal{D}_2$	$\mathcal{D}_3$	$\mathcal{D}_4$	$\mathcal{D}_5$	$GA_n \uparrow$
Sparse retrieval								
BM25	Term Weight	0.647	0.620	0.588	0.598	0.552	0.571	0.586
Dense retrieval								
DPR	Dense Vector	0.725	0.580	0.587	0.570	0.531	0.544	0.562
DPR-HN	Dense Vector	0.826	0.645	0.644	0.626	0.621	0.624	0.632
Generative retrieval								
DSI-SE	Category Nums	0.718	0.231	0.203	0.221	0.185	0.205	0.209
Ultron-PQ	Category Nums	0.795	0.548	0.549	0.542	0.539	0.532	0.542
NCI	Category Nums	**0.871**	0.464	0.437	0.433	0.358	0.323	0.403
GenRET	Category Nums	0.858	0.361	0.419	0.401	0.357	0.354	0.378
Ultron-URL	URL Path	0.816	0.553	0.545	0.543	0.541	0.532	0.543
SEAL	N-gram	0.809	0.744	0.736	0.727	0.727	0.725	0.732
MINDER	Multi-text	0.838	0.803	0.751	0.746	0.742	0.736	0.756
LTRGR	Multi-text	0.862	**0.831**	**0.803**	**0.811**	**0.779**	**0.773**	**0.799**

- Retrieving Initial Documents:
  - All Methods (BM25, DPR, GR) show stable performance and low forgetting.
  - GR often exhibits good resistance to forgetting, especially numeric-based ones.

- Retrieving Newly Added Documents:
  - BM25 & DPR demonstrate stable generalization ability.
  - GR performance varies Greatly:
    - Numeric-based DocIDs: Poor generalization on new documents (sharp performance drop).
    - Text-based DocIDs (Except Ultron-URL) : Strong generalization on new documents.

Generalization challenge for different corpora

- Related work:
  - Better modeling and training strategies
  - E.g., DSI++, GenRet
- Our work:
  - Impact of constrained generation



Can well-trained GR models generalize directly to different domains?

[1] Constrained Auto-Regressive Decoding Constrains Generative Retrieval, SIGIR 2025

Research problem

- *Can well-trained GR models generalize directly to different domains?*

Awareness of semantics

Can *constrained decoding* handle the domain variation?

We assume the model has perfect knowledge

This is what our work tries to explore

[1] Constrained Auto-Regressive Decoding Constrains Generative Retrieval, SIGIR 2025

Formulation – generative retrieval

- Numerical docID is a *sequence of numbers* from $[k]^m$
- Generative retrieval f is a mapping from user query $\rightarrow [k]^m$
- Let $f(\cdot)$ be the ground truth mapping → Perfect knowledge

[1] Constrained Auto-Regressive Decoding Constrains Generative Retrieval, SIGIR 2025

Formulation – domain-specific corpus

- $[k]^m$ is the ***complete code space*** including all possible docIDs

source

$\downarrow$

target

- $\mathcal{D} \subseteq [k]^m$ is the ***domain-specific corpus*** that is allowed to generate

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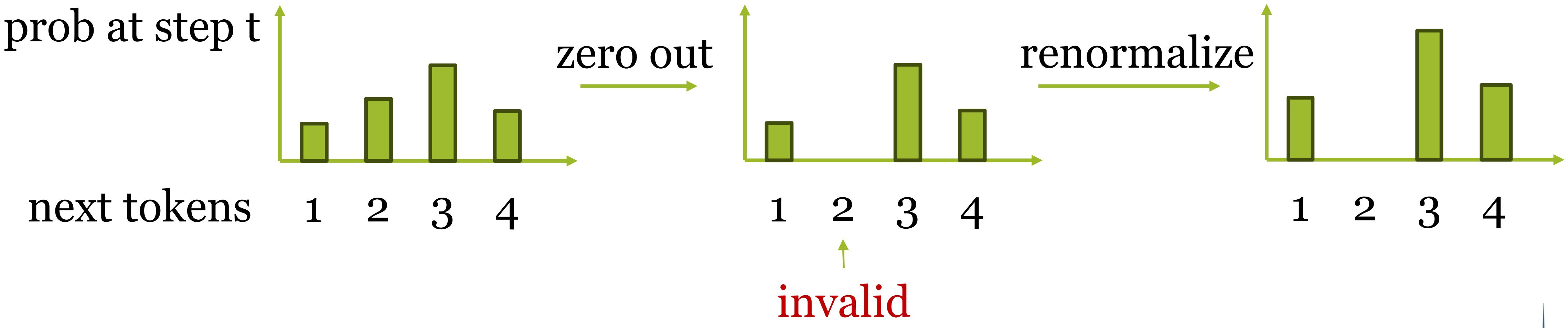
Formulation – generation

- ***Step-wise constraints*** are used to ensure generating in $\mathbb{D}$



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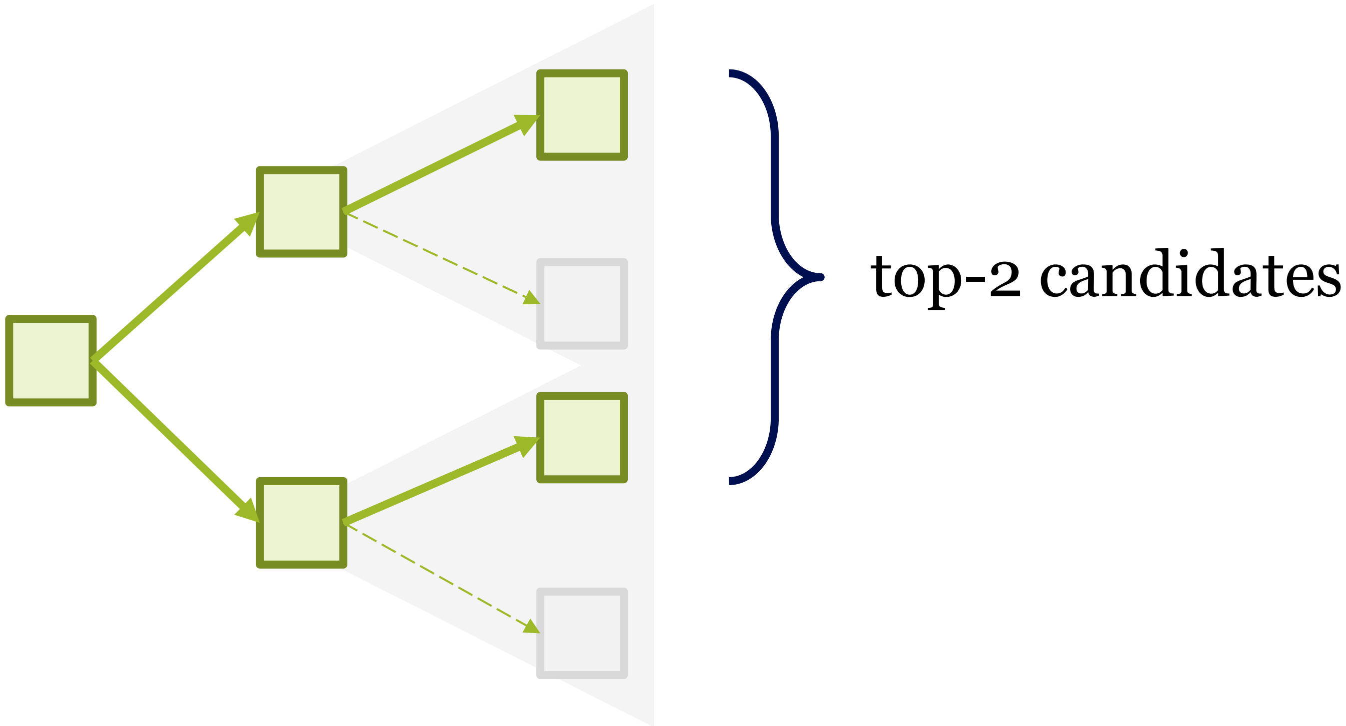
Formulation – generation

- ***Beam search*** is used for finding the top-*k* ranked docIDs



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Our results for research problem

Can a well-trained GR generalize to different domains directly?

RQ1

How does ***step-wise constraint*** affect prediction?

GR has error in prediction of each step

RQ2

How is ***beam search*** for top-k retrieval?

High precision but low recall

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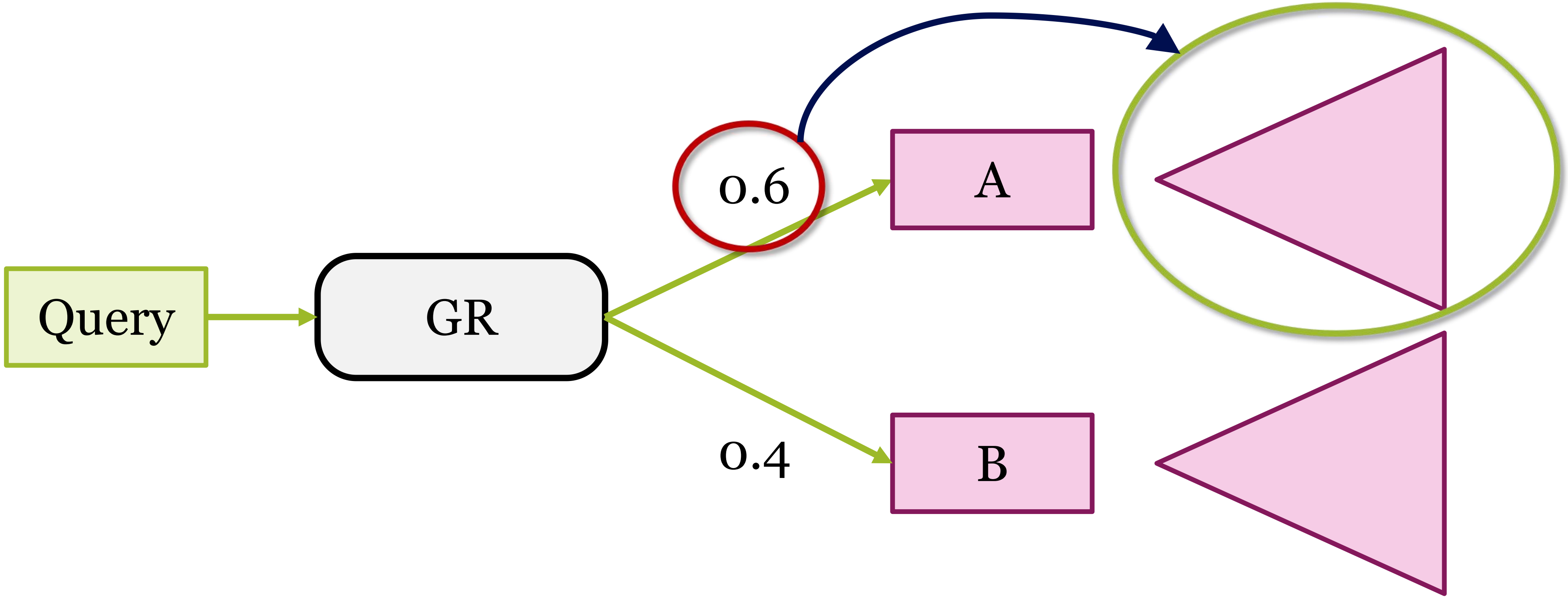
Step-wise constraints – intuition

Model knowledge → Overall estimation of a cluster of docs



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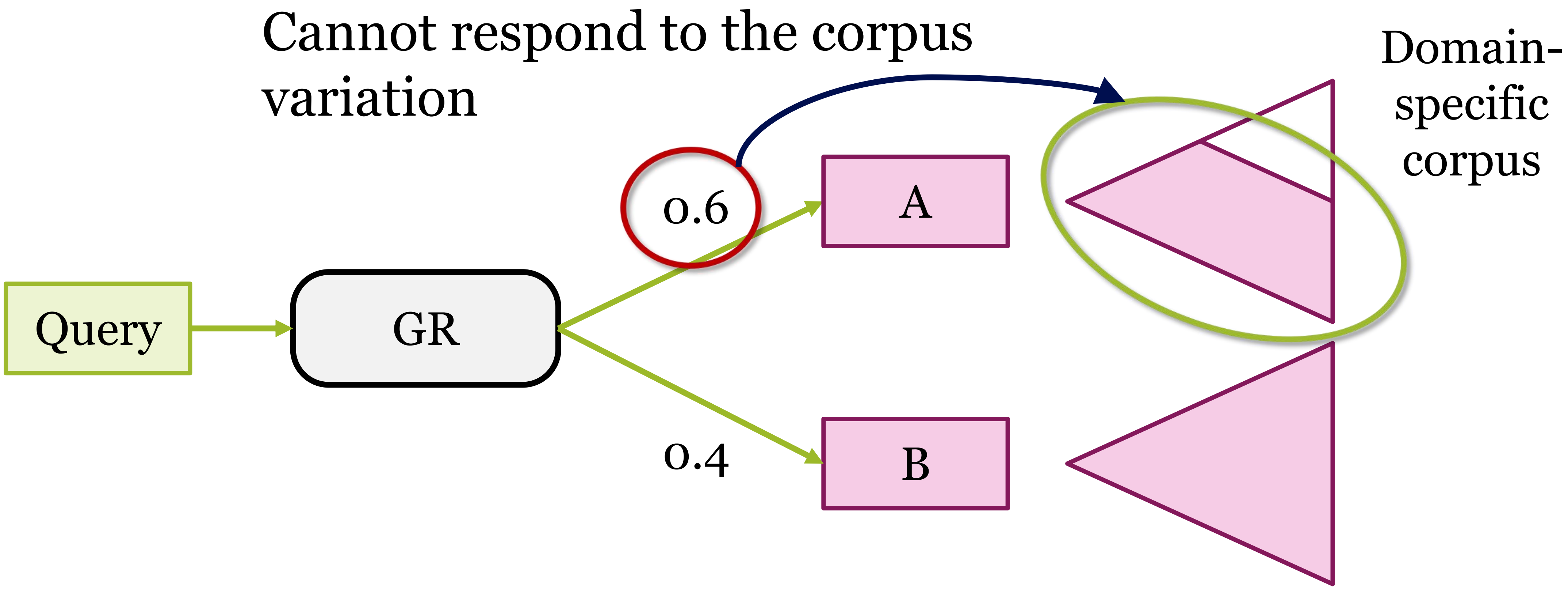
Step-wise constraints – intuition



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Step-wise constraints – formal result

Specific case:

uniformly sample domain-specific corpus Ɖ with ratio *p*

Our result:

lower-bound of error computed as KL divergence between model and real next-token distribution

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Step-wise constraints – formal result

- Formally, we have

$$\mathrm{KL}\left(\boxed{\Pr_c^1} \,\|\, \boxed{f_c^1}\right) \gtrsim \frac{A}{p}$$

A → Degree of concentration

p → Ratio of $\mathfrak{D}$ to $[k]^m$

$\Pr_c^1$ → **Real distribution**

f_c^1 → **Model estimation**

$$A = \mathbb{E}_{d_1}^2\left[\sqrt{\sum_d \Pr(d \mid d_1)^2}\right] \geq \frac{1}{k^{m-1}}$$

Measuring the sharpness of relevance distribution

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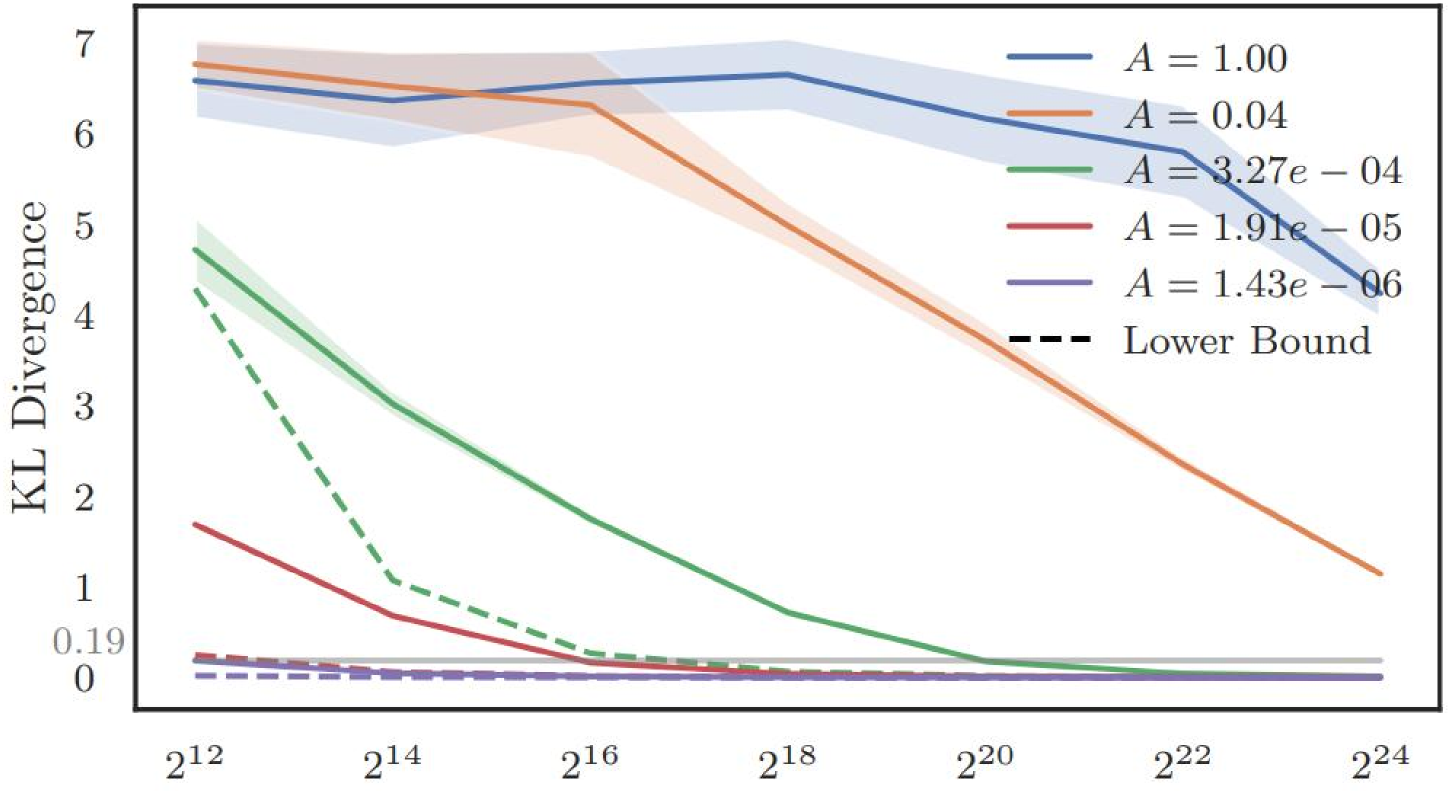
Step-wise constraints – simulation



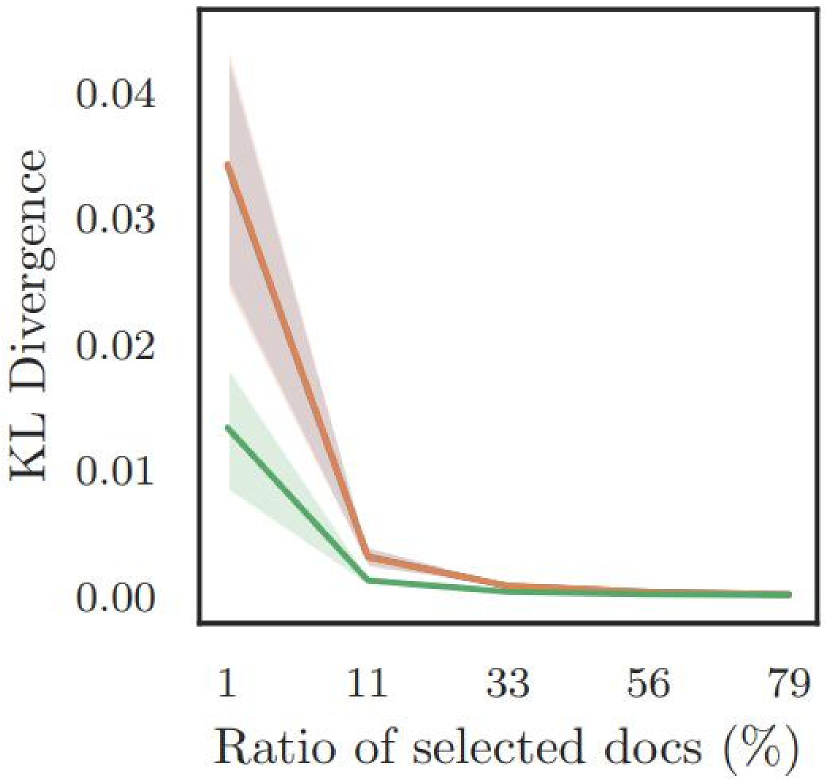
Size of domain-specific corpus

$k = 2^{10}$, $m = 3$

Synthetic distributions with different concentration

Step-wise Constraints – Real World Case

- MS MARCO as the whole corpus
- DocID from Zeng et al. 2024
- Relevance distribution from SLIM++



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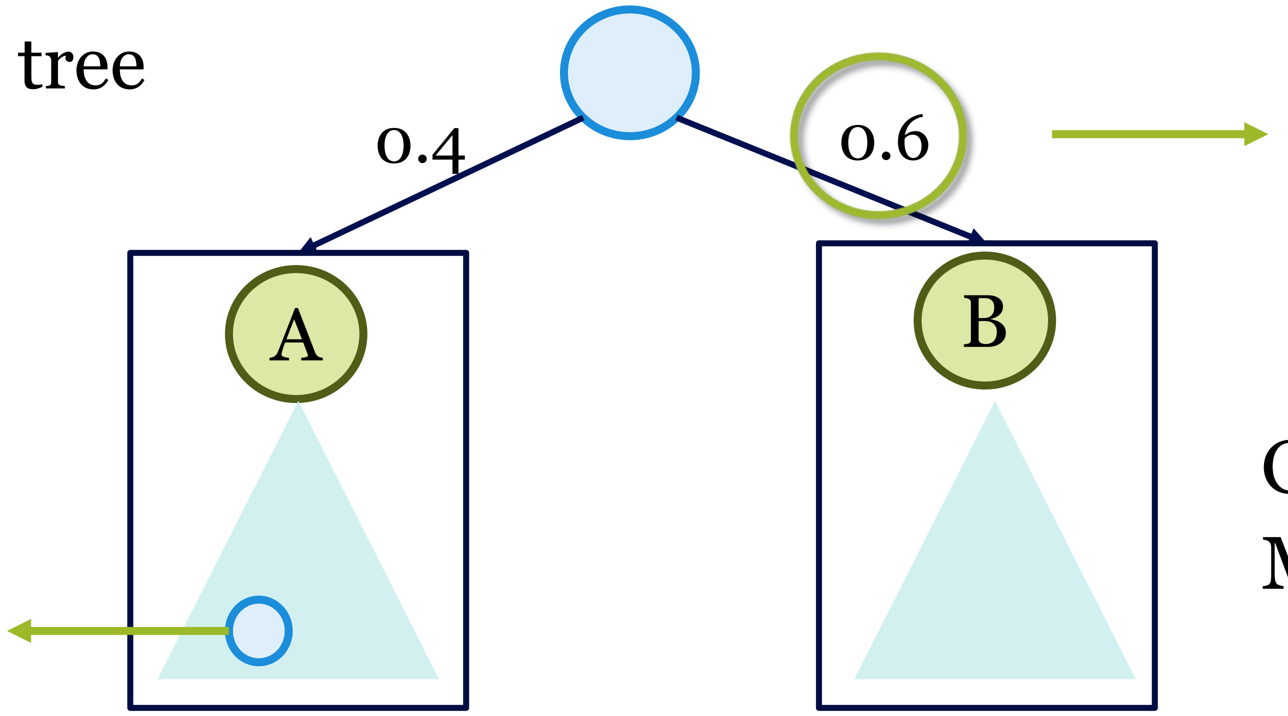
Beam search – intuition

Generation tree



$$\sum_{d \in B} \Pr(d)$$

Relevant doc

Goal: find top-*k*
More suitable: max

Relevant branch   Irrelevant branch

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Beam search – our result

Relevance distribution:

a. randomly select n docs as relevant

b. relevant score $O(k \log k)$, irrelevant score $o(1)$

Our result (for small n):

the recall of the top-n is upper-bounded by $0.5 + o(1)$ w.h.p.

precision@1 is perfect

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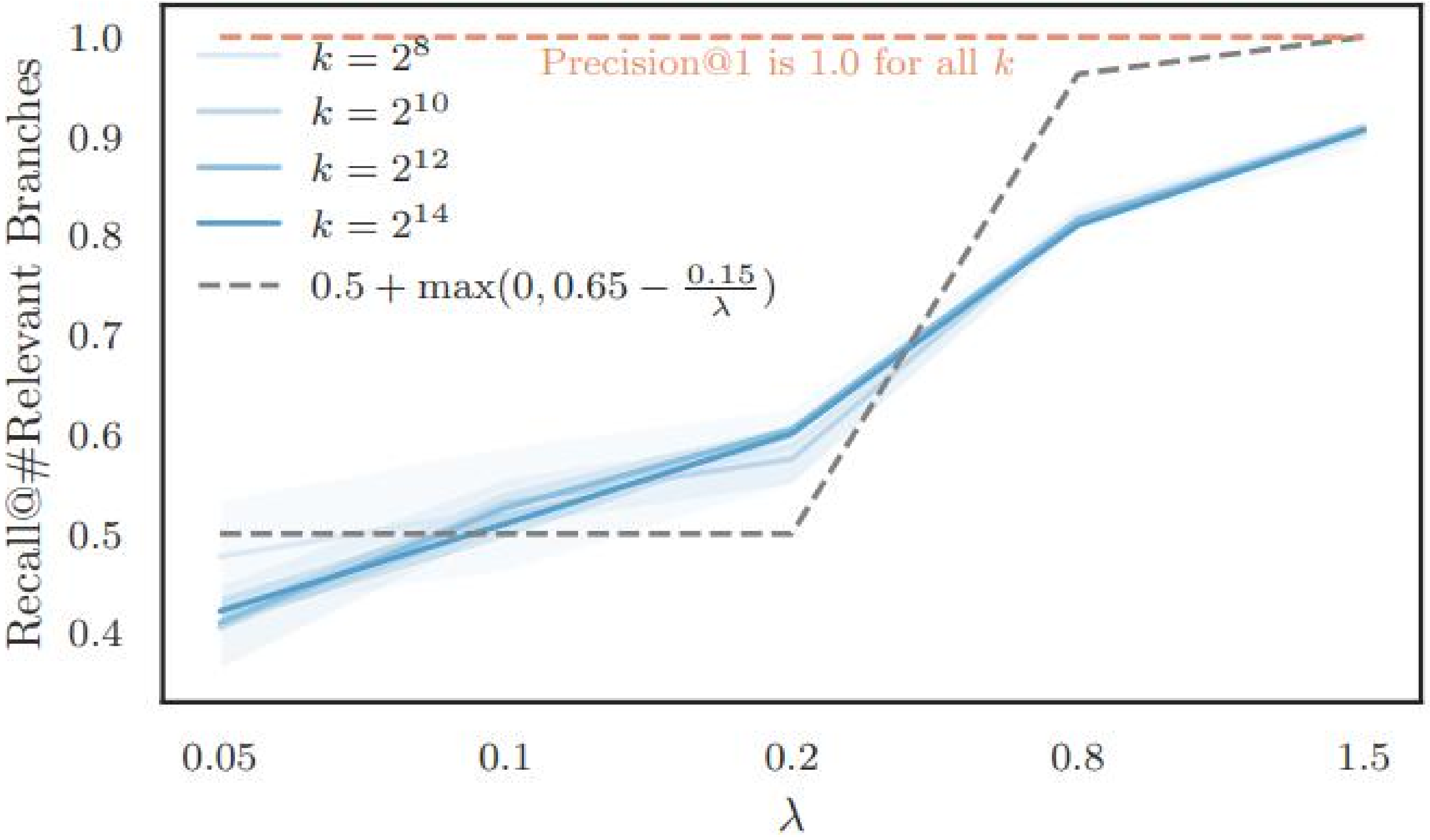
Beam Search – Simulation

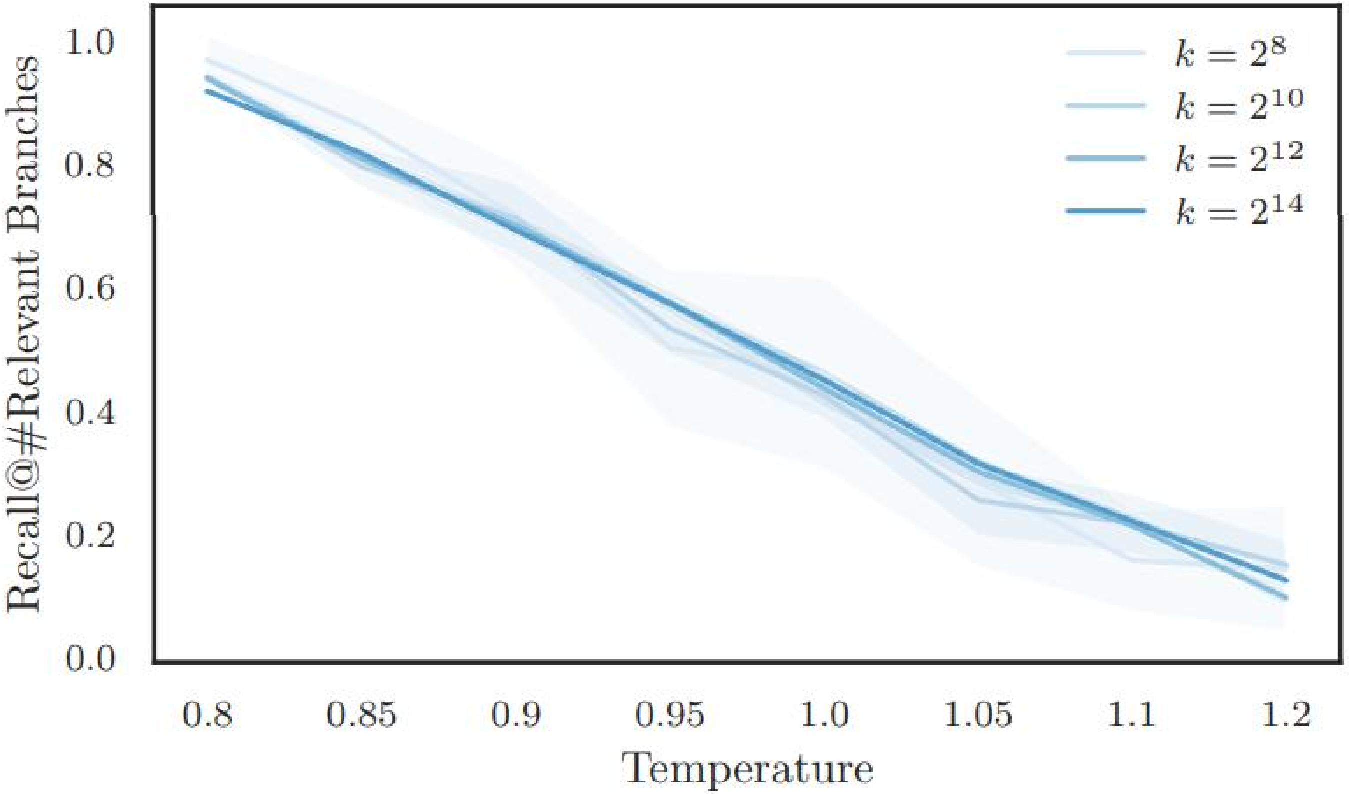
Consider corpus of size k^4, $n = \lambda k$



Number of relevant

Beam Search – control the sharpness

For the score s of a doc, we change it to $s^{\frac{1}{T}}$



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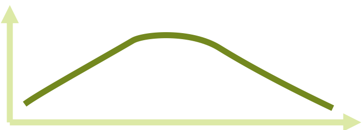
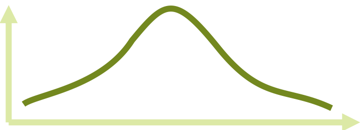
Trade-off factor – degree of concentration





low → high

Thick tail

Low recall during beam search

Larger variance

High discrepancy in each step

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Implication

A. Generation as retrieval
Model bias exists and can be interfering

B. Likelihood in retrieval
Generative modeling and retrieval task do not fit perfectly somewhere

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What does constraint GR?

- **Key Challenge – Generalization:**
  - GR models on unseen *out-of-distribution* corpora is not well.
  - The fundamental limitations imposed by GR's **constrained auto-regressive decoding** on generalization remain largely unexplored.
  - Two kinds of generalization challenges:

    Generalization challenge in newly added documents

    Generalization challenge in out-of-distribution IR tasks (unseen tasks)

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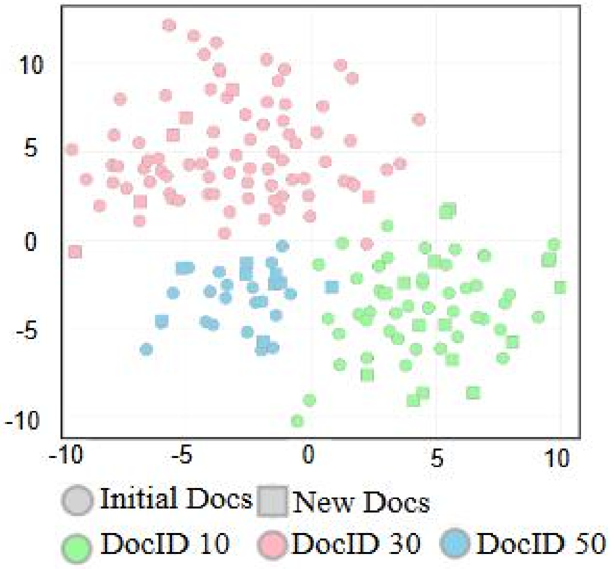
Generalization in newly added documents

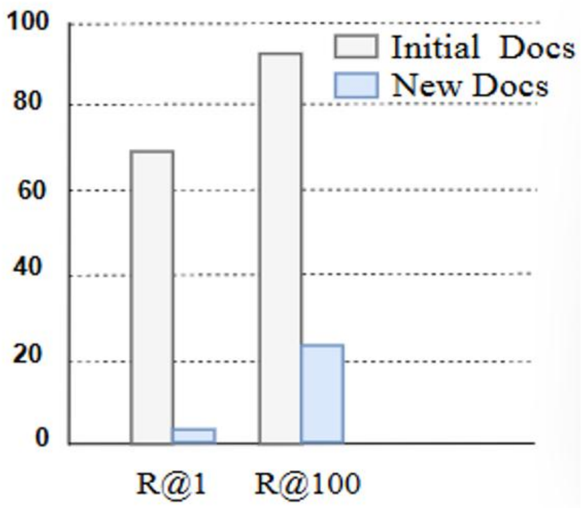
- **New problem framing:** Adapt GR to *new documents* by **editing the semantics→docID mapping**, not full model retraining **(DOME)**.
- **Targeted edit scope:** Use **patching analysis** to locate and edit only parameters responsible for mapping representations to docIDs.
- **GR-aware editing procedure:**
  - **Pseudo-query generation** per new doc to cover diverse intents (many-to-many q–d).
  - **Soft→hard label annealing** to preserve graded relevance patterns while learning unseen docIDs.
- **Forgetting-aware design:** Updates the new mappings **without degrading** existing ones.

DocID mapping bottleneck

- GR models successfully encode semantics of new documents (**a**).
- But fail to generate their correct docIDs (**b**).
- Traditional incremental training is costly and causes catastrophic forgetting.



(a) T-SNE Visualization



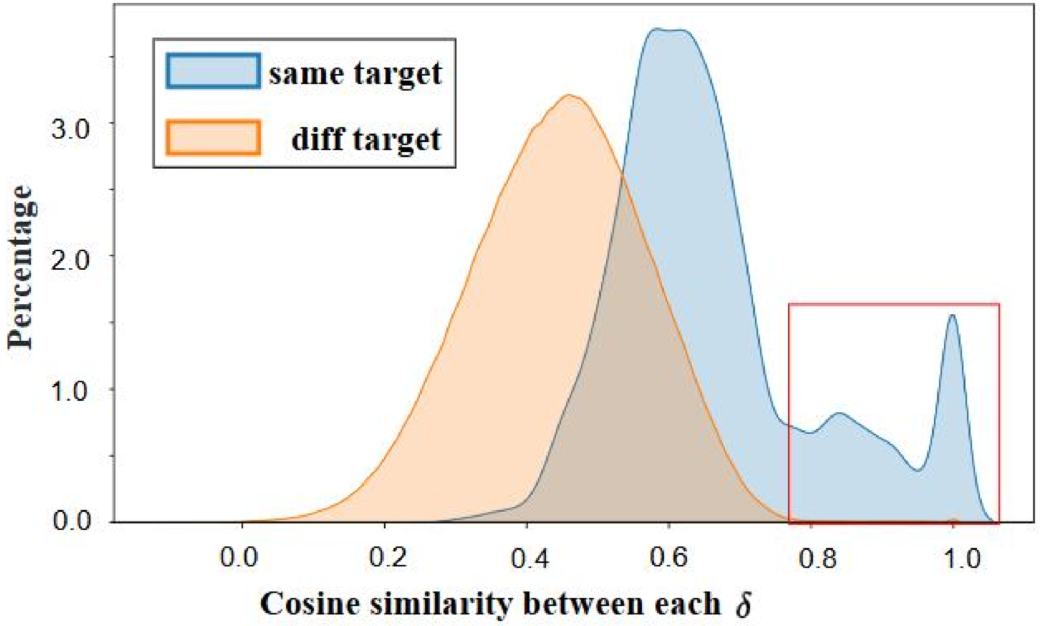
(b) Retrieval Performance

Updata docID mapping parameters

- **Bottleneck**: DocID mapping.
- **Goal**: Selectively updating only the mapping-relevant parameters.
- **Strategy**: Model editing for GR .

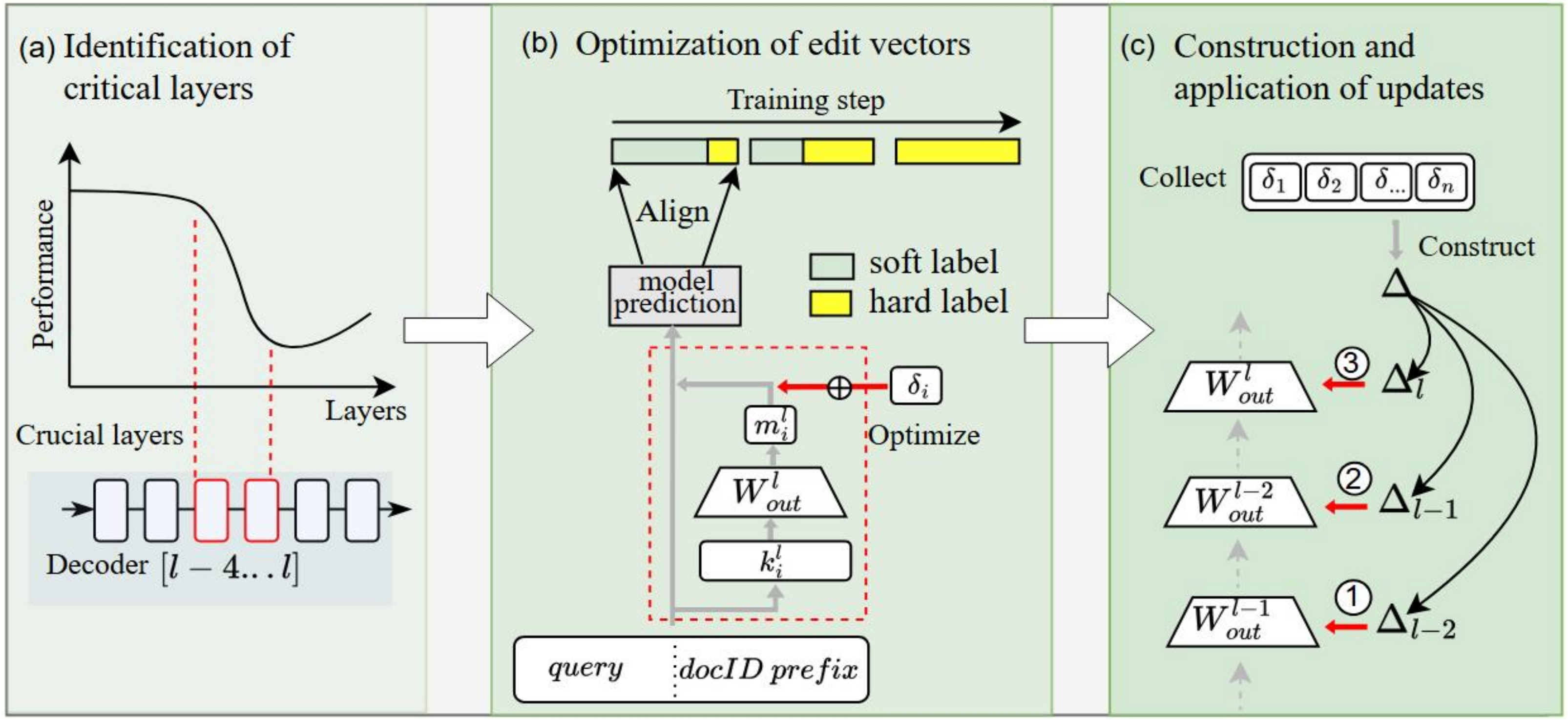
The effectiveness of editing in GR is limited by indistinguishable edit vectors.

Many docIDs share the same target docID
 (e.g., “13-14-17" and "32-16-17" share "-17"),
making their editing vectors indistinguishable.



DOME – DocID-oriented model editing

- (a) Identification of critical layers
- (b) Optimization of edit vectors
- (c) Construct and application of updates

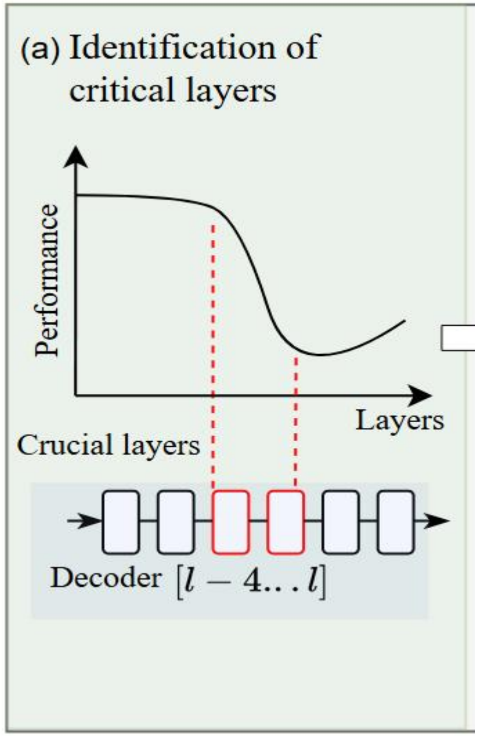


DOME – Identification of critical layers

Pinpoint the decoder layers responsible for DocID mapping.

- Replace a layer's output with its pre-computed average representation.
- Measure the resulting drop in retrieval accuracy.
- Layers causing the largest performance drop are identified as "critical".

All subsequent edits are focused only on these key layers for efficiency and effectiveness.



DOME – Optimization of edit vectors

Generate diverse and effective update vectors δ for new documents.
Challenge: Standard training creates indistinguishable edit vectors for different queries and documents.

Hybrid-Label Adaptive Training

- Create hybrid target label ($\boldsymbol{p_{target}}$)

Blend soft and hard label with an adaptive weight λ:

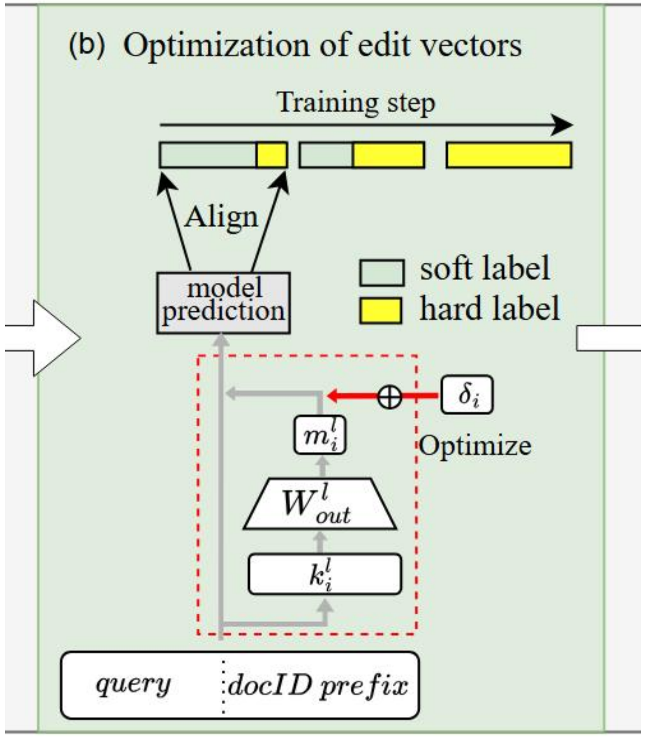
$$p_{target} = (1-\lambda)\underbrace{p_{orig}}_{\text{Soft label (preserves diversity)}} + \lambda \underbrace{\mathbb{1}[v = y_t]}_{\text{Hard label (ensure accuracy)}}$$

λ from 0.3 to 1

- Optimize the edit vector (δ)

$$\delta = \underset{\delta}{\operatorname{argmin}} \left(-\sum_v p_{target}(v) \log p_{edit}(v \mid m_i + \delta)\right)$$

Minimize the cross-entropy loss between the model's new prediction and the hybrid target.



DOME – Construct and application of updates

Precisely inject the new docID mappings into the model's critical layers while preserving its existing retrieval knowledge.

1. Gather key-value pairs

New knowledge (to learn):

- Keys: K_1(FFN inputs from new docs)
- Values: $V_1 = m_1 + \delta$ (FFN outputs with edit vectors)

Old knowledge (to preserve):

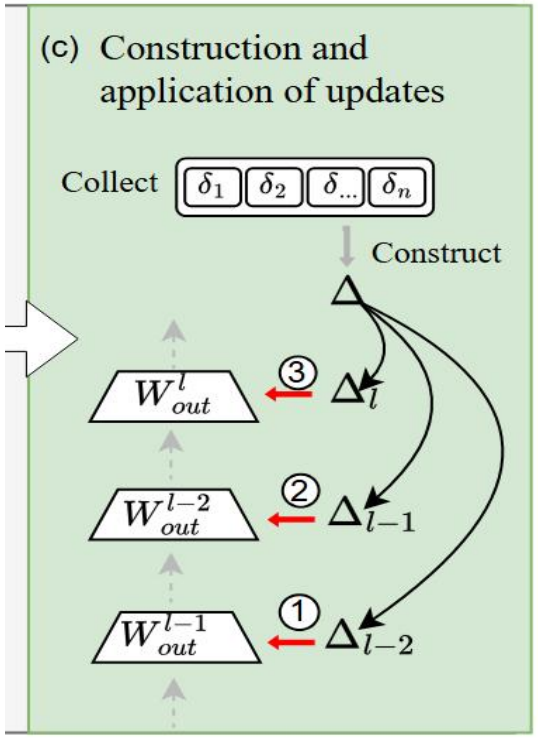
- Keys: K_0(FFN inputs from original docs)
- Values: $V_1 = m_0$(FFN output)

2. Compute update metrix (Δ)

Solve for Δ that maps $K_1 \rightarrow V_1$ while preserving $K_0 \rightarrow V_0$ using a constrained, closed-form solution in model editing.

3. Apply Sequentially Across Layers

Distribute the update based on layer distance: $\Delta_j \propto \frac{1}{dist(j,l)} \Delta$



Main results

New documents.

Method	NQ	MS-MARCO	Time/Doc
	R@1 / R@100	R@10 / MRR@10	(s)
No Training			
DSI	0.07 / 0.25	0.06 / 0.03	-
Incremental			
DSI++	0.67 / 0.92	0.76 / 0.52	3.54
Model Editing			
MEMIT	0.61 / 0.76	0.67 / 0.50	12.62
DOME	**0.69 / 0.93**	**0.76 / 0.52**	**2.14**

Initial documents.

Method	R@1 / R@100	Fn
Base model	0.696 / 0.931	-
Baselines		
New-Doc FT	0.544 / 0.805	0.125
DSI++	0.674 / 0. 926	0.007
Model Editing		
ROME	0.285 / 0.774	0.317
MEMIT	0.647 / 0.904	0.020
DOME	**0.692 / 0.928**	**0.003**

- **Efficiency:** Dramatically **reduces adaptation time** vs. incremental retraining—no full corpus re-indexing or large-scale fine-tuning.
- **Accuracy on new docs:** Significant **Recall@10 / Acc gains** on **NQ** and **MS-MARCO** for newly added items.
- **Robustness: Strong resistance to catastrophic forgetting** on original corpus.

Ablation study

Pseudo Queries

More queries → Richer context → Higher recall. (R@1: .506 → .652)

DocID Assignment

Works with any scheme (RQ, BM25, PQ) → Highly generalizable.

Edited Layer Range

Optimal at layers 14-18 → Confirms our localization is critical.

Hybrid-Label Training

- Hard-Label Only: Lacks diversity (vectors collapse).
- Soft-Label Only: Lacks accuracy (no precise target).
- Hybrid (Both): Achieves diverse and accurate updates.

Variant	R@1	R@10	R@100	MRR@100
DOME (full)	**0.686**	**0.880**	**0.927**	**0.740**
Number of pseudo queries per new doc				
Pseudo = 1	0.506	0.760	0.875	0.592
Pseudo = 4	0.615	0.832	0.898	0.678
Pseudo = 7	0.652	0.866	0.918	0.698
DocID type				
BM25-based docIDs	0.683	0.860	0.921	0.722
PQ-based docIDs	0.675	0.877	0.933	0.719
Edited decoder layer range				
Layers 11–15	0.659	0.857	0.904	0.704
Layers 18–22	0.536	0.717	0.836	0.624
soft-to-hard label strategy				
w/o soft label	0.646	0.805	0.901	0.697
w/o hard label	0.325	0.556	0.711	0.436

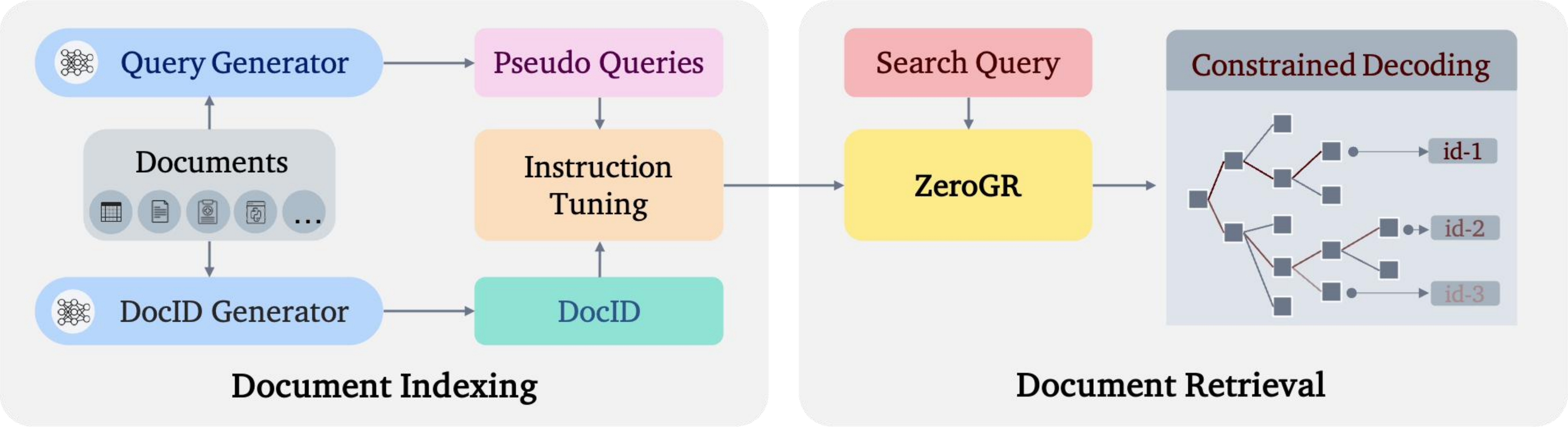
Generalization to unseen tasks

- Generative Retrieval (GR) encodes corpus in parameters → generate docids at query time.
- **Gap:** GR trained in-domain struggles to generalize to *unseen* tasks (zero-shot, heterogeneous corpora, task-specific relevance).

- **Question: How to make GR *generalize* across tasks with no supervision?**

ZeroGR at a glance

- Leverages **natural-language task instructions** to adapt GR without labels.
- Three components:
  - **Unified DocID generator** G_{ψ} → short, keyword-rich docids for any modality (text/tables/code).
  - **Instructed query generator** GF_{θ} → diverse pseudo-queries from task instruction.
  - **Reverse-annealed decoding** → balanced precision/recall when generating ranked docids.



Unified DocID representation

- **Problem:**
  - Titles/URLs/spans don't generalize to custom corpora;
  - RQ-VAE can be unstable.
- **Design:** LM-based generator maps a document to a short (6–8 words) *keyword-centric* sentence ranked by coverage.
- Train data: prompt a powerful LM for ⟨doc, docid⟩ pairs → fine-tune a compact Llama-1B-Instruct.
- **Benefits: Natural language priors, fewer conflicts, faster convergence.**

DocID

Token sequence

Instructed corpus indexing

- **Goal:** Close pseudo-query vs real-query distribution gap in heterogeneous IR.
- Using Instruction-tune Llama-1B on diverse IR tasks verbalized via instructions.
- For each doc d_i & instruction *instr*, sample B pseudo-queries $\{q_{i,1..B}\}$.

Pseudo query

- Train GR index (*LLM*) with cross-entropy on ⟨instr $\oplus$ q, docid⟩.

Reverse-Annealed DocID decoding

- Problem:
  - Beam search collapses diversity → low recall;
  - nucleus sampling improves recall but hurts precision.
- **Reverse annealing:** Sample docids *without replacement* while **increasing temperature** across iterations.
- Constrained by a prefix tree of valid docids; remove leaves after sampling.

- **Effect:** Early high-precision picks, later broader exploration → better overall ranking.

Experimental setups

- Datasets: curated from MAIR training splits + additional instruction-tuning data.
  - **Coverage:** 69 tasks across 6 domains; ~41M query–doc pairs with instructions.
  - **Domain stats (illustrative):** Medical (5), Finance (8), Academic (16), Code (13), Legal (7), Web (17).

MAIR dataset

[1] MAIR: A Massive Benchmark for Evaluating Instructed Retrieval, EMNLP 2024

Experimental setups

- **Evaluation benchmarks:** BEIR (12 tasks) and MAIR (seen vs. **unseen** subsets).
- **Metrics:** Acc@1, nDCG@10, Recall@100.
- **Implementation:**
  - Llama-based models for docid gen, query gen, and GR index;
  - fixed LR 5e-5; 5 epochs for 1B components.
- **Baselines:**
  - **Sparse:** BM25 (BM25S).
  - **Single-task dense:** Contriever-MARCO, GTR-base/large.
  - **Multi-task dense:** E5-Base/Large, BGE-Base/Large, OpenAI-Embed-v3-Small.
  - **Instruction-tuned dense:** E5-Mistral-7B-instr, GritLM-7B.
  - **GR competitors (for BEIR table):** GENRE, GENRET, GLEN, TIGER.

Research questions in the experiments

- **How does ZeroGR compare with state-of-the-art retrieval methods?**
  - We evaluate ZeroGR against leading models on the MAIR benchmark and conduct additional analysis on the BEIR datasets
- **How do model design and training strategies influence the performance of ZeroGR on unseen IR tasks?**
  - a systematic study on the development set, investigating key factors in generative retrieval.

Main results on MAIR and BEIR

- ZeroGR Average **Acc@1 = 41.1** on MAIR
  - above BM25, Contriever/GTR/E5/BGE, and OpenAI-Embed-v3-Small.
- **Unseen subsets:** State-of-the-art on Apple, MB, PM.A, DD, NCL (examples) → robust transfer.
- **Efficiency:** 3B-param GR rivaling/ surpassing 7B instruction-tuned dense retrievers.

- **Average:** ZeroGR **44.9** vs GENRET **41.1**; outperforms on SciFact, FiQA, Covid, etc.
- Per-dataset highlights: best on ArguAna, SciFact, FiQA, Covid; competitive on NFCorpus.

Scaling instruction fine-Tuning

- Increase *task diversity* in instruction-tuning → consistent gains on MAIR-unseen.
- Data ramps: MS MARCO → +OpenQA → +BEIR-Train → +MTEB-Train → +ZeroGR-Train.
- Effects:
  - Longer & more diverse queries (task-aware).
  - Lower docid conflict rate.
  - Higher Acc@1 on unseen tasks.

Scaling query numbers and model size

Takeaways

Takeaways

- **DOME**: docID-oriented model editing that effectively and efficiently adapts GR models to unseen documents.
- **ZeroGR**: instruction-driven GR that generalizes in zero-shot settings across heterogeneous tasks.
- Unified docids + instructed pseudo-queries + reverse-annealed decoding → SOTA GR on BEIR/MAIR.
- Positive scaling trends: task diversity, query count, model size.

Limitations / Future

- multimodal docids;
- decoding theory;
- safety & bias auditing.

Thanks for your attention!

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