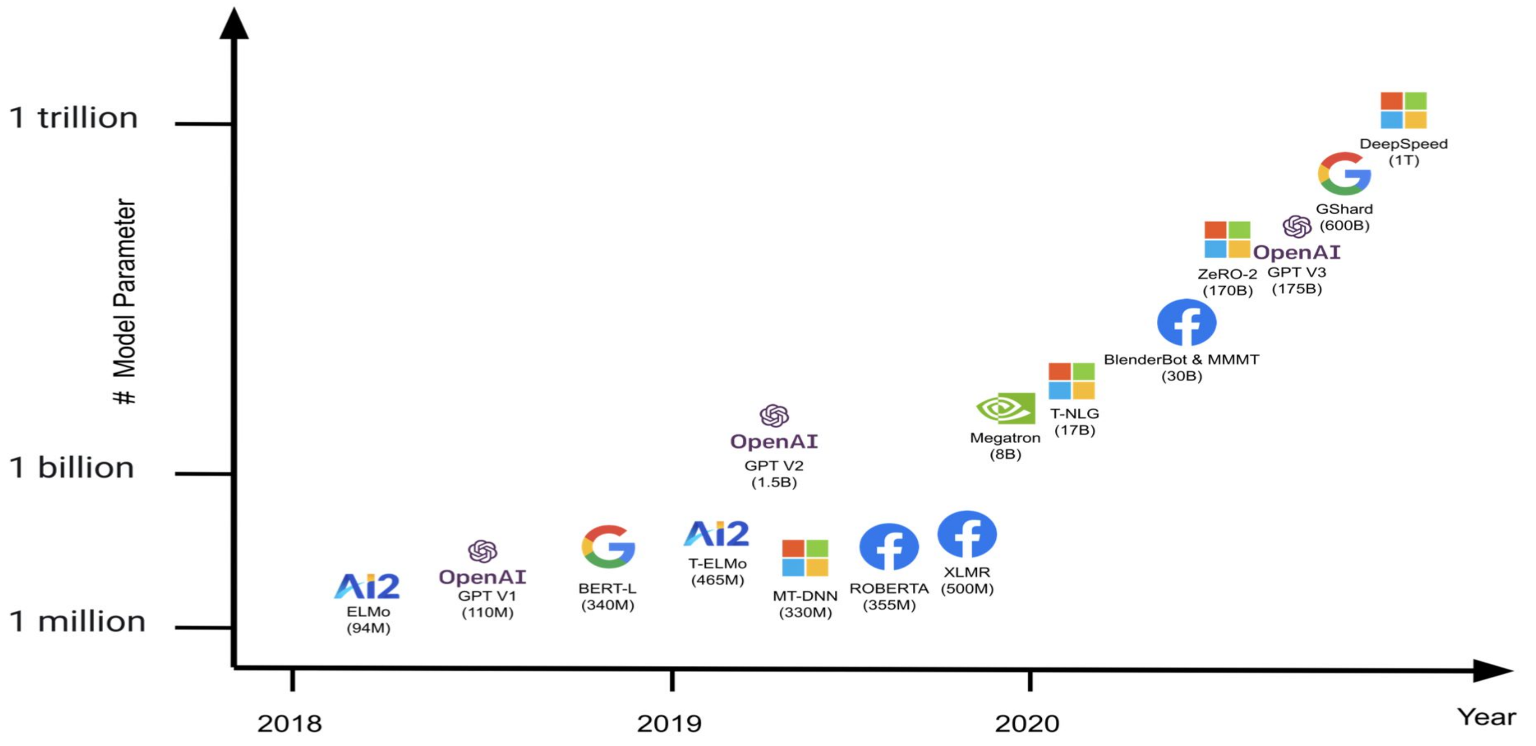
# Efficient & Scalable NLP through Retrieval-Augmented Language Models

Scott Wen-tau Yih

Meta AI - FAIR

# Language Model Pre-training: Ever bigger scale!




(slide from Luke Zettlemoyer, adapted from Myle Ott)

# What is a language model (LM)?

$$p(w_1, \ldots, w_n) = \prod_{i=1..n} p(w_i | w_1, \ldots, w_{i-1})$$

e.g. *p(ELMo and BERT are Sesame Street characters) =*

*p(ELMo) x p(and | ELMo) x p(BERT | ELMo, and) x ...*

$p(w_i | w_1, \ldots, w_{i-1})$ is often a (recurrent) neural network

(slide from Luke Zettlemoyer)

# Not just bigger... Zero-shot learner!

### Classification

Classification

Classify items into categories via example.

**Prompt**

The following is a list of companies and the categories they fall into

Facebook: Social media, Technology
LinkedIn: Social media, Technology, Enterprise, Careers
Uber: Transportation, Technology, Marketplace
Unilever: Conglomerate, Consumer Goods
Mcdonalds: Food, Fast Food, Logistics, Restaurants
FedEx:

**Sample response**

Logistics, Transportation

### TL;DR summarization

Transformation | Generation

This prompt summarizes text by adding a 'tl;dr:' to the end of a text passage. It shows that the API understands how to perform a number of tasks with no instructions.

**Prompt**

A neutron star is the collapsed core of a massive supergiant star, which had a total mass of between 10 and 25 solar masses, possibly more if the star was especially metal-rich.[1] Neutron stars are the smallest and densest stellar objects, excluding black holes and hypothetical white holes, quark stars, and strange stars.[2] Neutron stars have a radius on the order of 10 kilometres (6.2 mi) and a mass of about 1.4 solar masses.[3] They result from the supernova explosion of a massive star, combined with gravitational collapse, that compresses the core past white dwarf star density to that of atomic nuclei.

tl;dr:

**Sample response**

A neutron star is a star that is so dense that it has collapsed into a sphere the size of a city.

### Q&A

Answers | Generation | Conversation

This prompt creates a question + answer structure for answering questions based on existing knowledge.

**Prompt**

I am a highly intelligent question answering bot. If you ask me a question that is rooted in truth, I will give you the answer. If you ask me a question that is nonsense, trickery, or has no clear answer, I will respond with "Unknown".

Q: What is human life expectancy in the United States?
A: Human life expectancy in the United States is 78 years.

Q: Who was president of the United States in 1955?
A: Dwight D. Eisenhower was president of the United States in 1955.

Q: Which party did he belong to?
A: He belonged to the Republican Party.

Q: What is the square root of banana?
A: Unknown

Q: How does a telescope work?
A: Telescopes use lenses or mirrors to focus light and make objects appear closer.

Q: Where were the 1992 Olympics held?
A: The 1992 Olympics were held in Barcelona, Spain.

Q: How many squigs are in a bonk?
A: Unknown

Q: Where is the Valley of Kings?
A:

**Sample response**

The Valley of Kings is in Luxor, Egypt.

(slide from Luke Zettlemoyer)

# Not just bigger... Zero-shot learner!

**Q&A**

Answers | Generation | Conversation

This prompt creates a question + answer structure for answering questions based on existing knowledge.

**Prompt**

**Recipe generator**

Generation

Create a recipe from a list of ingredients.

**Prompt**

Write a recipe based on these ingredients and instructions:

Frito Pie

Ingredients:
Fritos
Chili
Shredded cheddar cheese
Sweet white or red onions, diced small
Sour cream

Directions:

**Sample response**

Preheat oven to 350 degrees. Spread fritos on an oven-safe dish. Top with chili and cover with cheese. Bake for 10 minutes. Garnish with onion and sour cream.

**SQL request**

Transformation | Generation | Translation

Create simple SQL requests.

**Prompt**

Create a SQL request to find all users who live in California and have over 1000 credits:

SELECT

**Sample response**

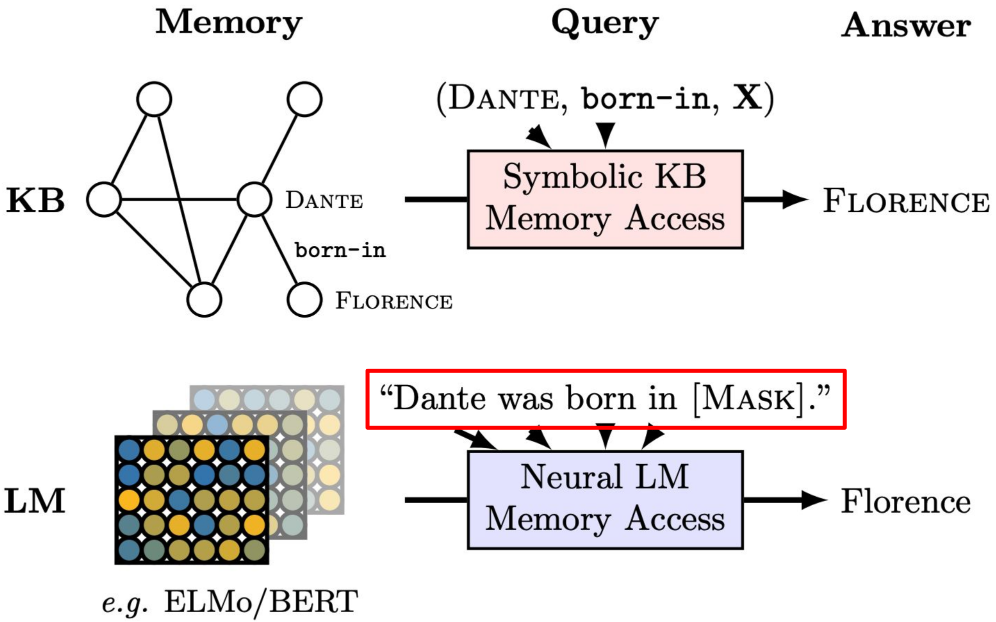
* FROM users WHERE state = 'CA' AND credits > 1000

The Valley of Kings is in Luxor, Egypt.

(slide from Luke Zettlemoyer)

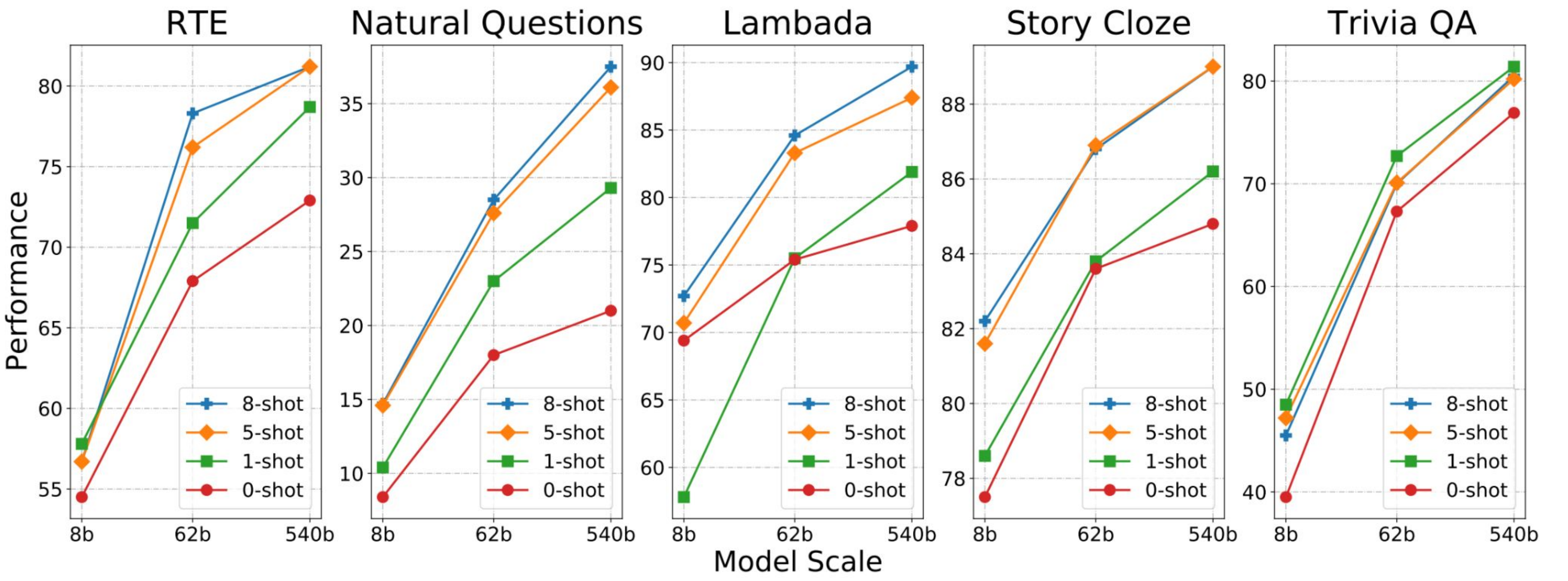
# Knowledge in LM's Parameter Space

Petroni et al., *Language Models as Knowledge Bases?* In EMNLP-2019




(figure from Petroni et al., 2019)

# More Parameters, More Knowledge?




(figure from PaLM; Chowdhery et al., 2022)

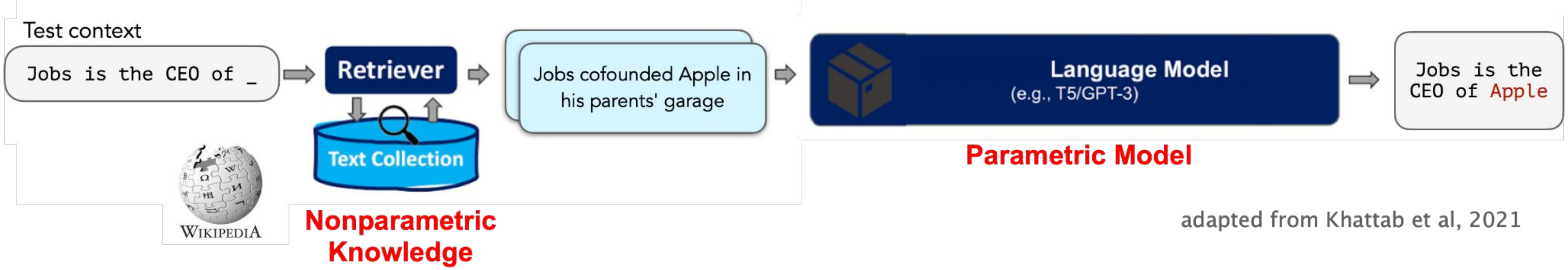
# Better Large Language Model Training?

- Training large language models is expensive
  - GPT-3 175B: 355 years on one Tesla V100, ~$4.6M (2020 numbers; source)
  - PaLM 540B: 842 years on one TPU v4 chip, ~$17M (2022 numbers; source)

- Can we use an external knowledge store instead of cramming knowledge into parameters?
  - Smaller, core model has the basic capabilities
  - Retrieval component provides relevant knowledge at inference time

**Retrieval-Augmented Language Models**

# Retrieval-augmented Language Models




adapted from Khattab et al, 2021

Separating world knowledge information from LMs' parameters

(slide from Weijia Shi)

# Advantages of Retrieval-augmented LMs

- Parameter efficient
  - Knowledge is explicitly encoded in the datastore
  - Fewer model parameters are needed for memorization

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- Less opaque; more interpretable
  - Easier to trace the knowledge source of the predictions

# Advantages of Retrieval-augmented LMs

- Parameter efficient
  - Knowledge is explicitly encoded in the datastore
  - Fewer model parameters are needed for memorization
- Less opaque; more interpretable
  - Easier to trace the knowledge source of the predictions
- Easy to update knowledge
  - The datastore can be updated and expanded easily
  - No model retraining is needed

# This Talk

- REPLUG: Retrieval-Augmented Black-Box Language Models (arXiv Link)
  - Retrieval can help improve language models even in the “black-box” setting

- RA-CM3: Retrieval-Augmented Multimodal Language Modeling (arXiv Link)
  - Works on multimodal (text / image) as well

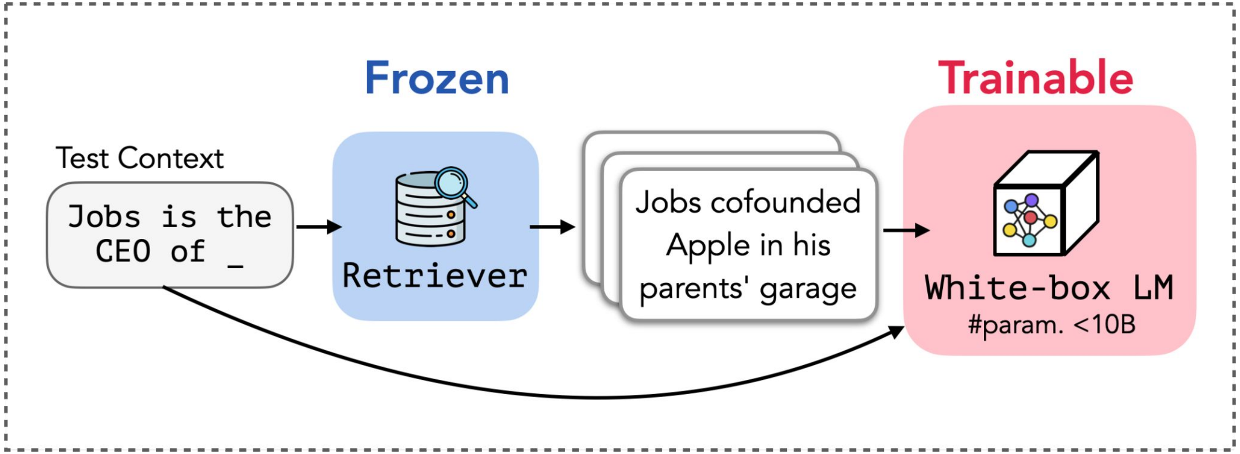
# REPLUG: Retrieval-Augmented Black-Box Language Models

Weijia Shi, Sewon Min, Minjoon Seo, Michihiro Yasunaga, Rich James, Mike Lewis, Luke Zettlemoyer, Scott Yih

(Slides from Weijia Shi)

# Previous Retrieval-Augmented LMs

Previous retrieval-augmented LMs
(e.g., RETRO (Borgeaud, et al. 2022), RAG (Lewis, et al. 2020))



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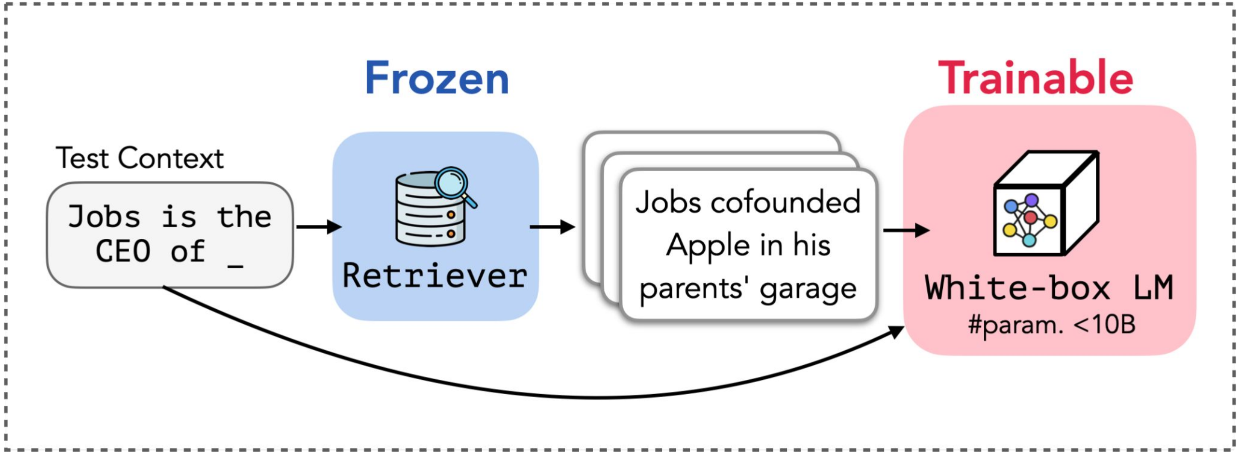
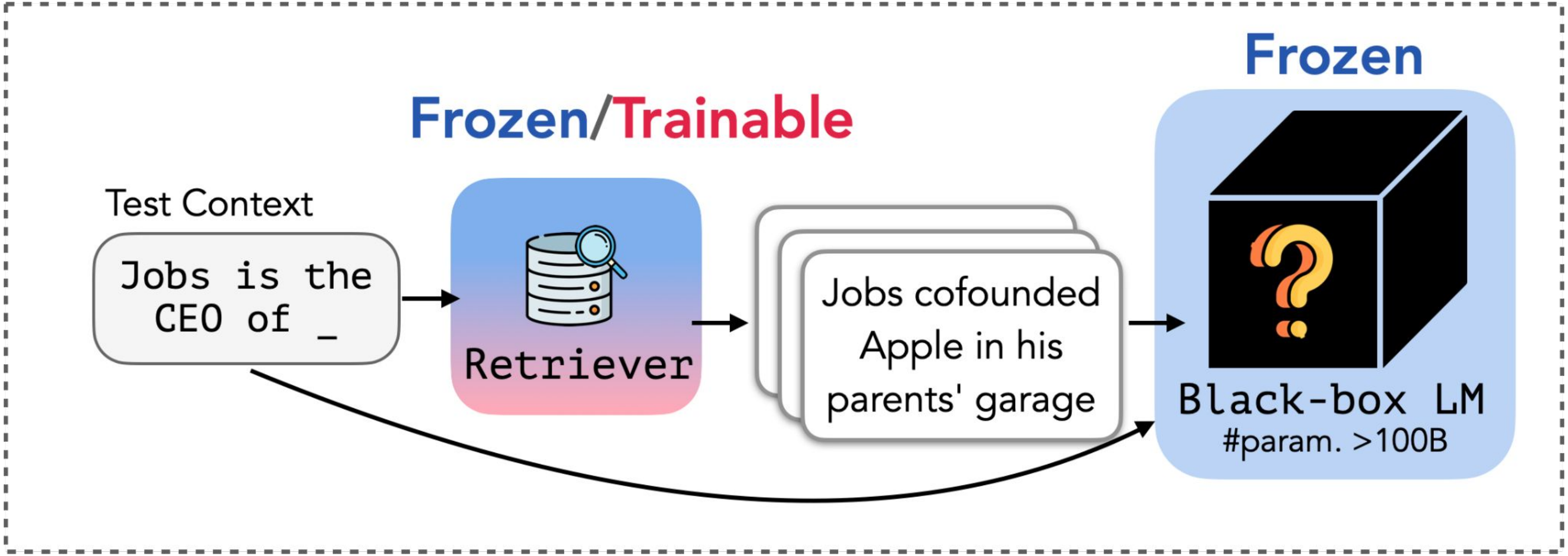



Not suitable for large language models

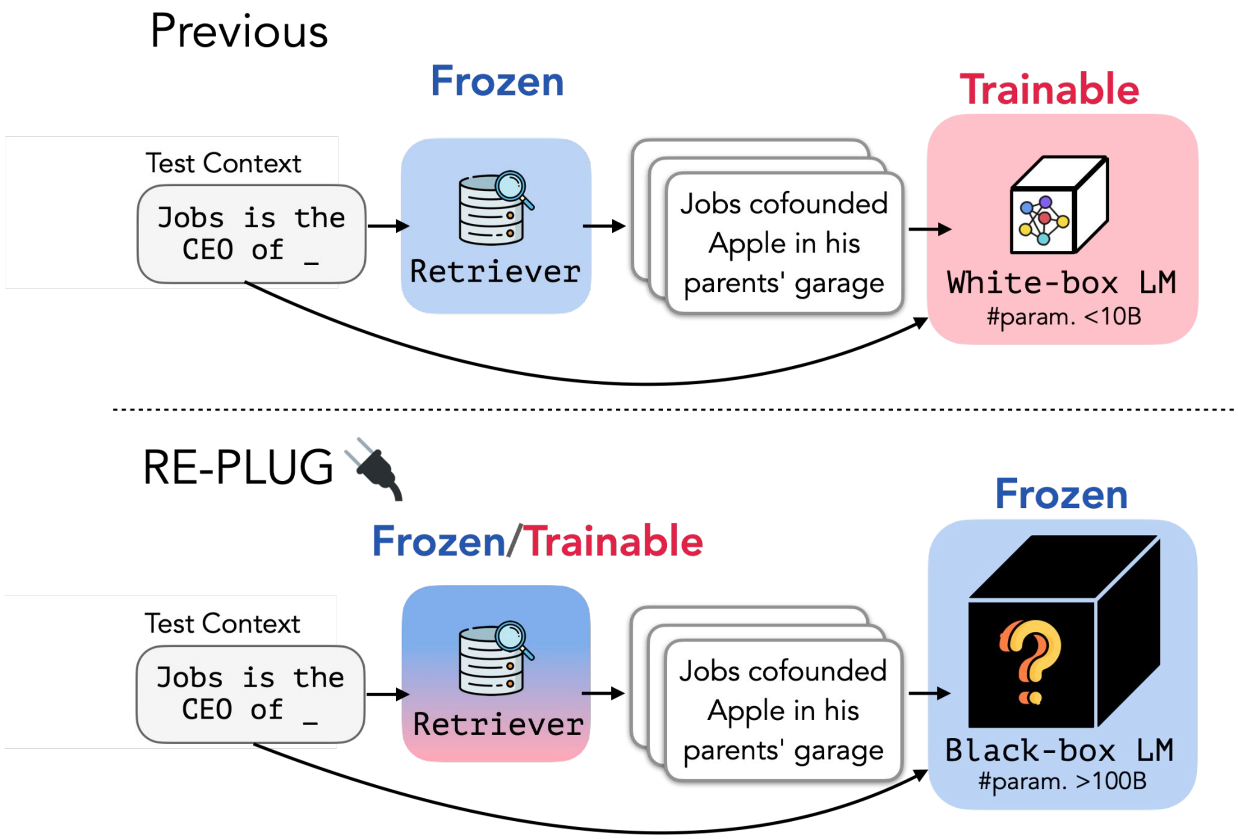
- e.g., expensive to finetune or only accessible by APIs

# Our Framework: RePlug




- How to incorporate retrieved texts?
- How to train a better dense retriever for language modeling and downstream tasks?

# Comparison: Previous vs. RePlug



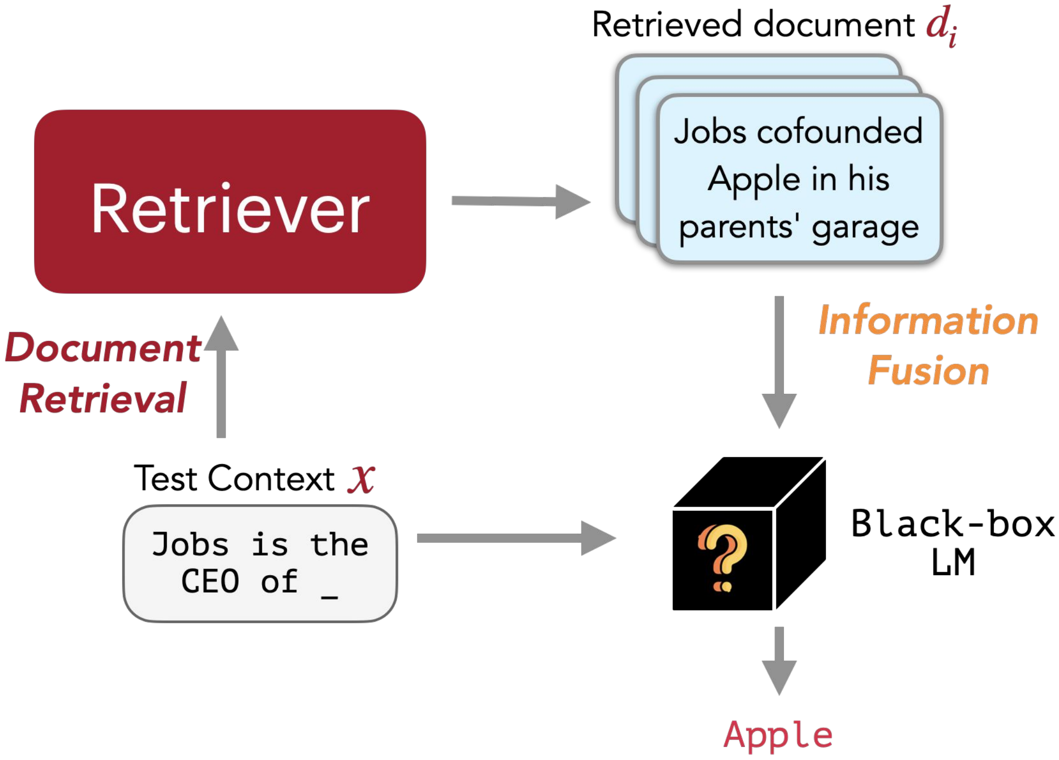
# Our Method

- REPLUG Inference
  1. Retrieves a small set of relevant documents from an external corpus
  2. Prepends each document separately to the input context
  3. Ensembles LM output probabilities

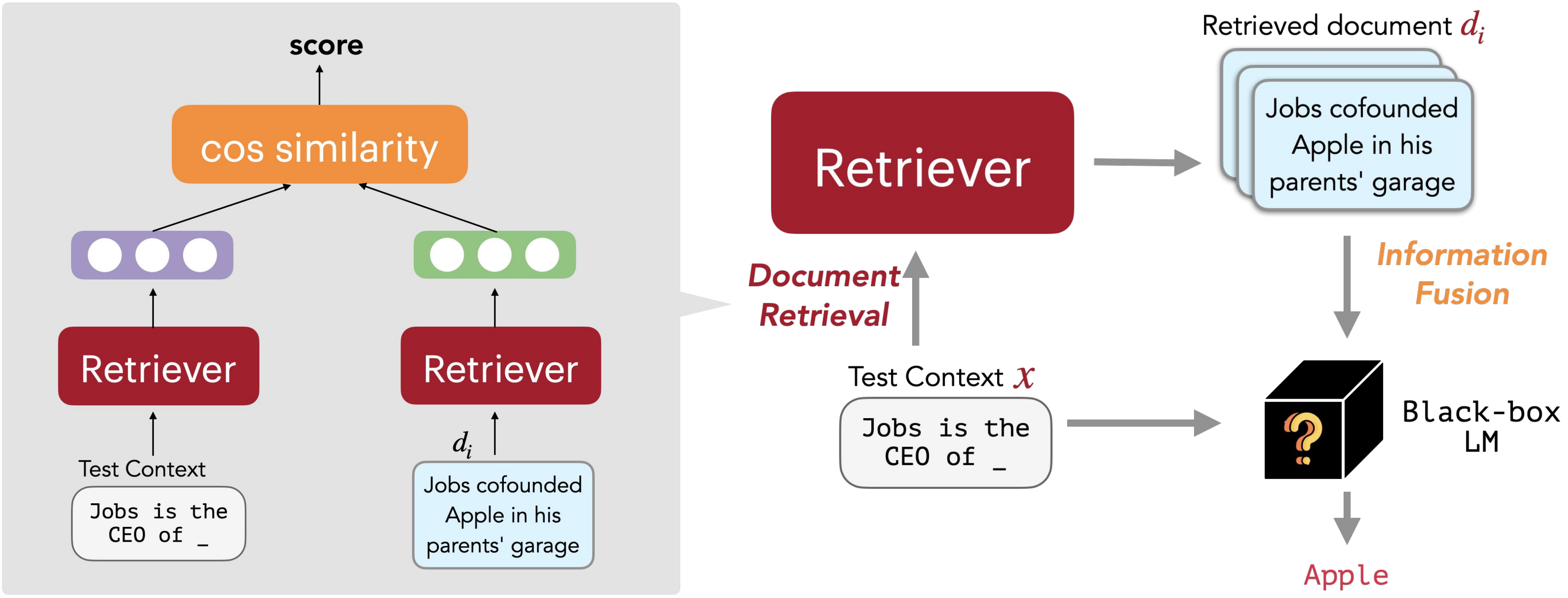
- REPLUG LSR (LM-Supervised Retrieval): Training the dense retriever

# RePlug Inference

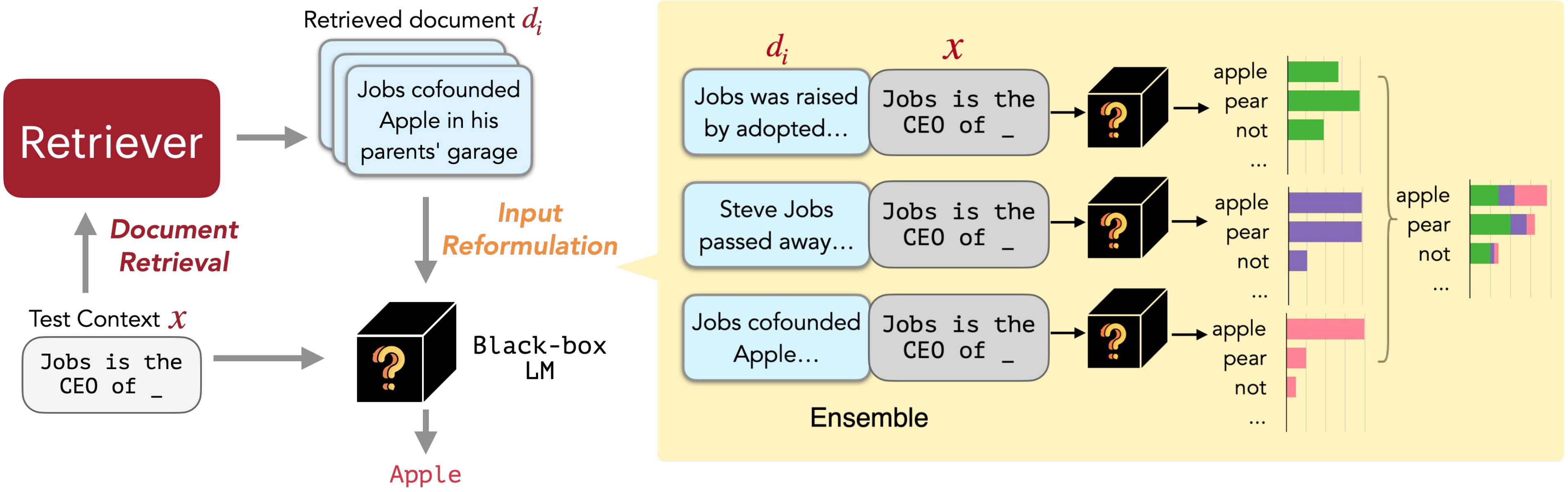
1. Document retrieval
2. Information fusion



# REPLUG Inference - Document Retrieval



# RePlug Inference - Information Fusion

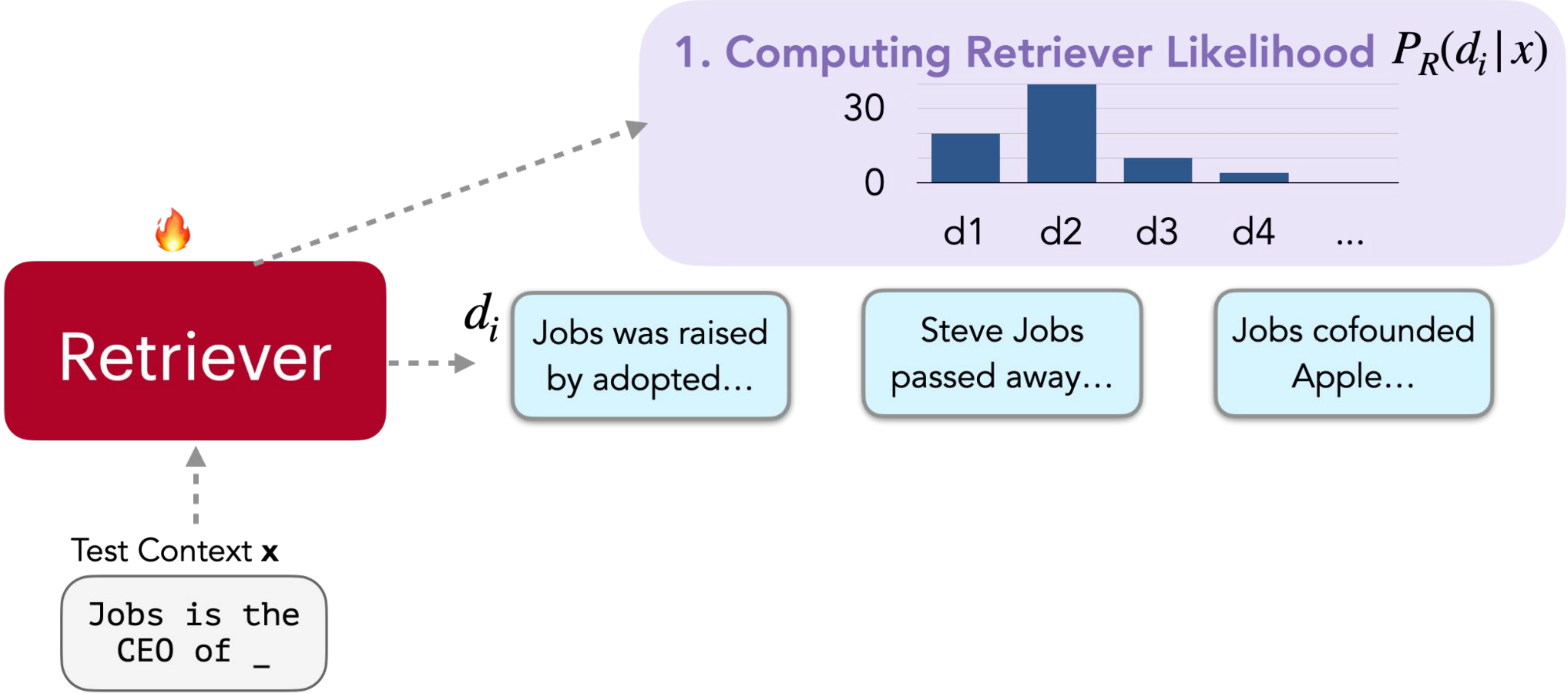


# Our Method

- REPLUG Inference
- REPLUG LSR (LM-Supervised Retrieval): Training the dense retriever
    - Use the LM output as supervision signals for different inputs (context + retrieved document)
    - Train the retriever using the “labeled” data

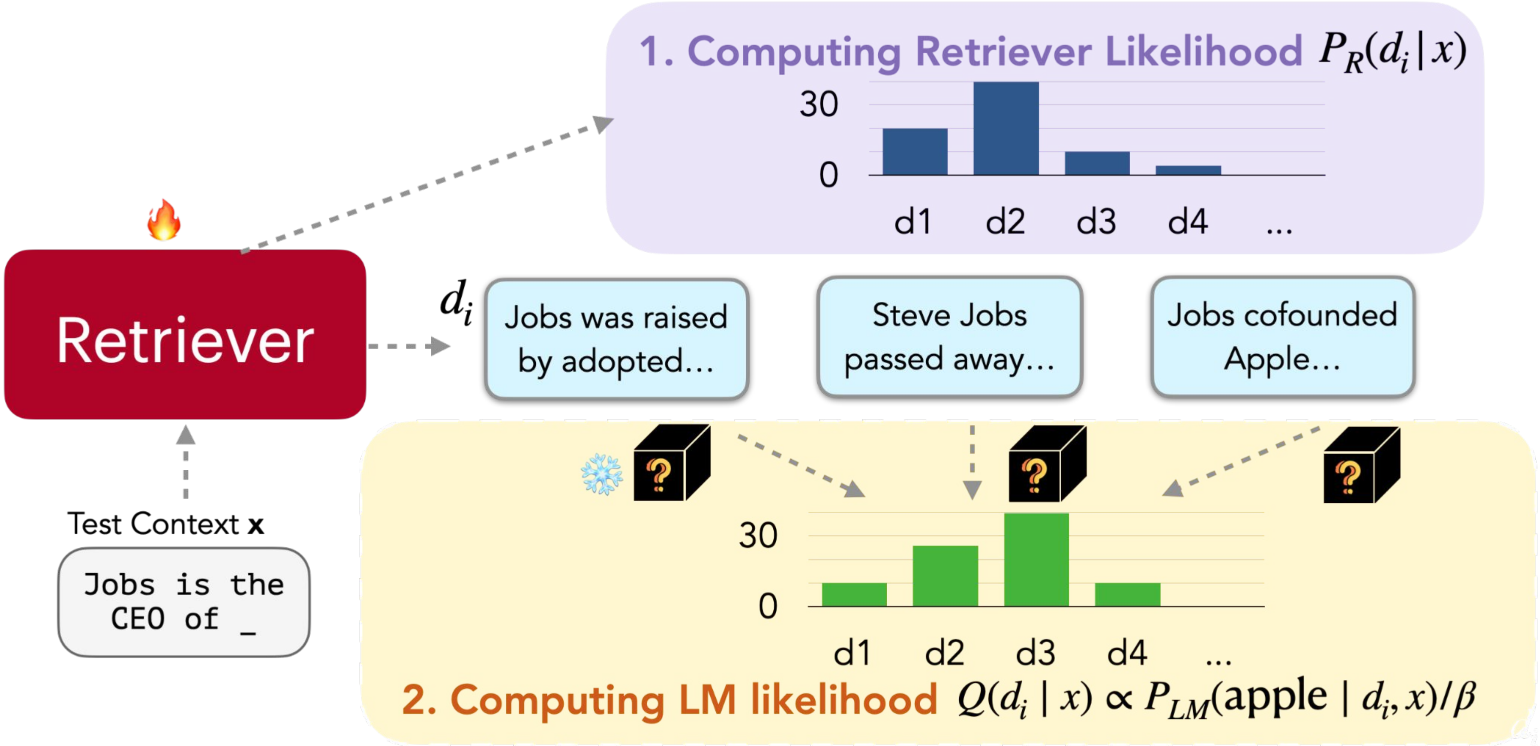
# RePlug LSR Training

Step 1: Compute retriever likelihood



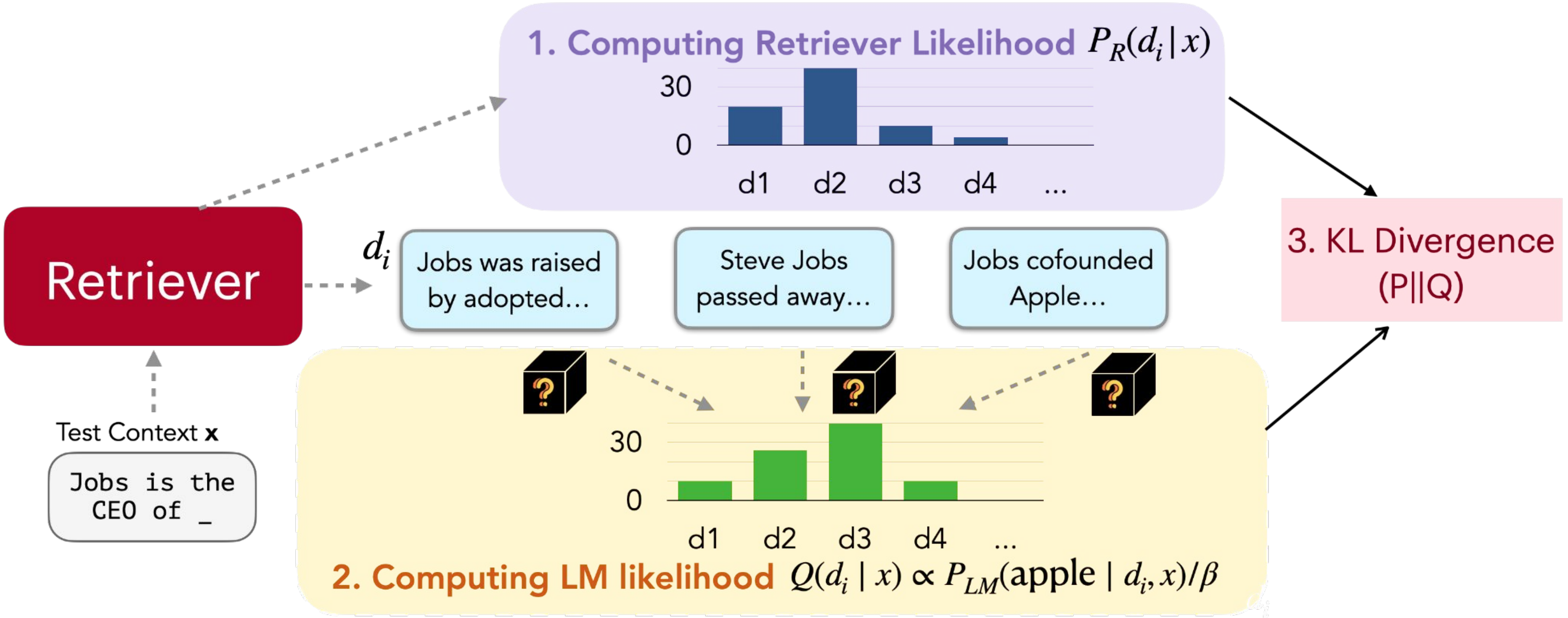
# RePlug LSR Training

Step 2: Compute LM likelihood



# RePlug LSR Training

Step 3: Minimize KL divergence (Update only the retriever parameters)



# REPLUG: **Retriever and Training Setup**

- REPLUG: using an off-the-shelf retriever, Contriever (Izacard et al., 2022)
- REPLUG LSR: a tuned retriever adapted to a black-box LM
    - Initialized with Contriever
    - Trained on the Pile with supervision signals provided by GPT-3 Curie

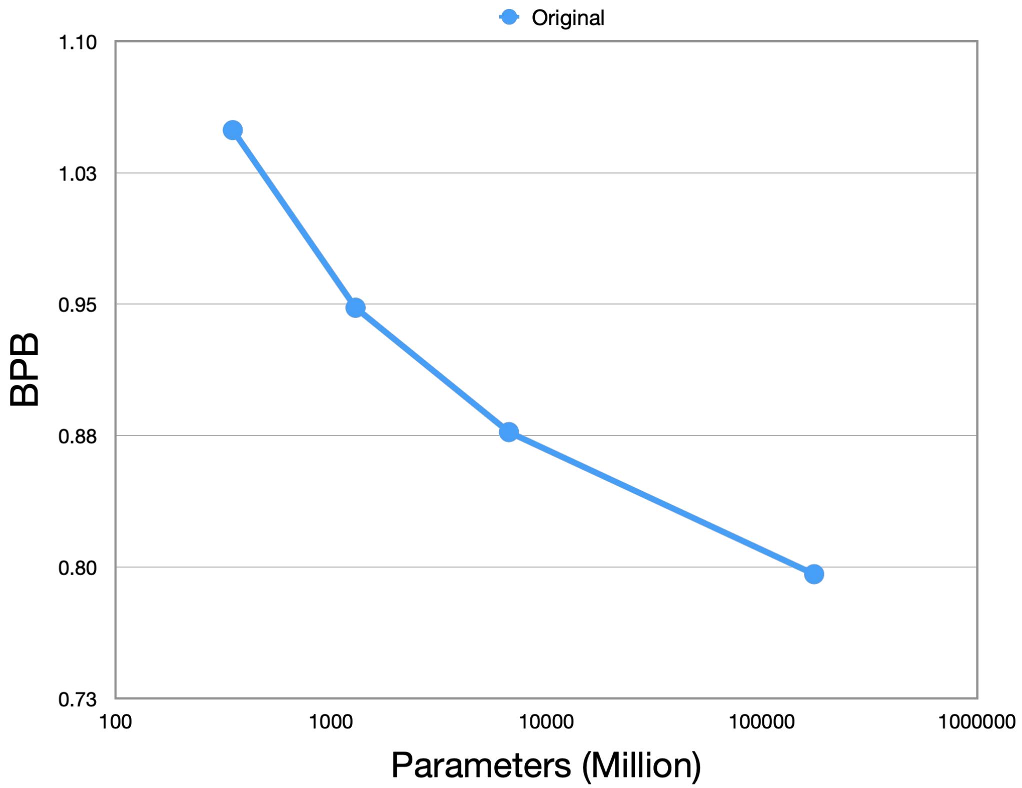
# Experiments

- Language Modeling
- MMLU (Massive Multitask Language Understanding)
- Open-domain Question Answering

# Language Modeling

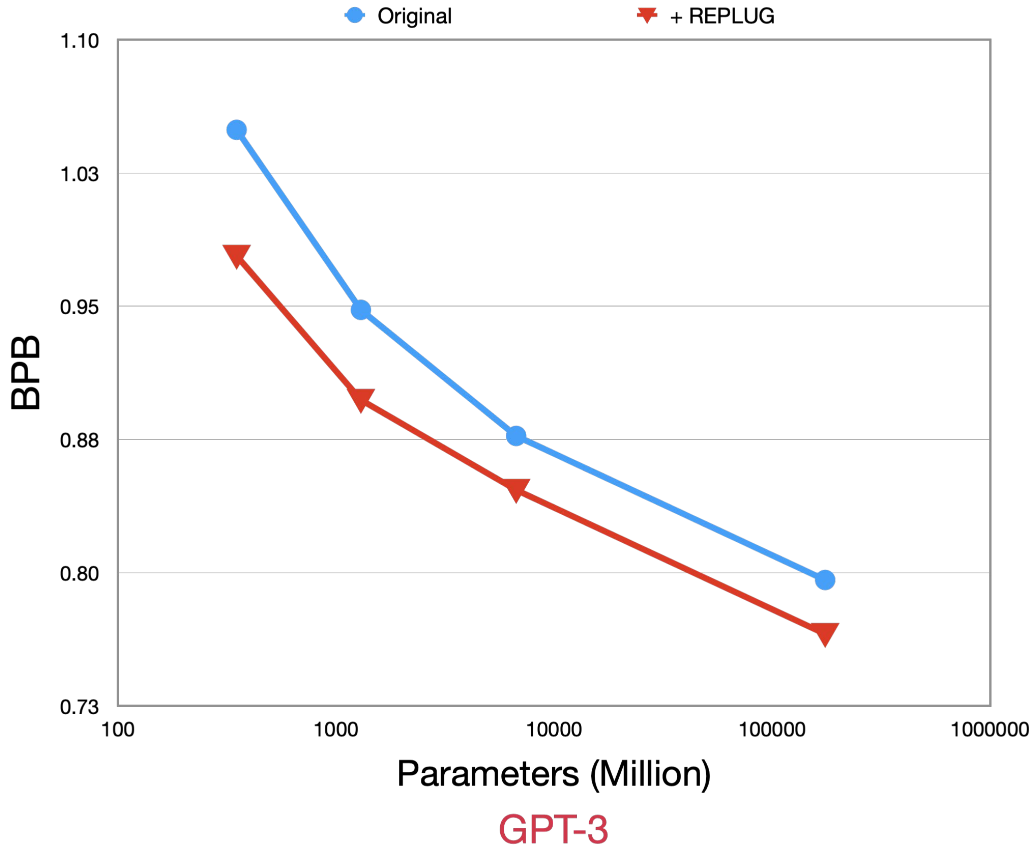
- Evaluation: the Pile test set
- Datastore: Subset of the Pile training data (367M documents of 128 tokens)

# Language Modeling

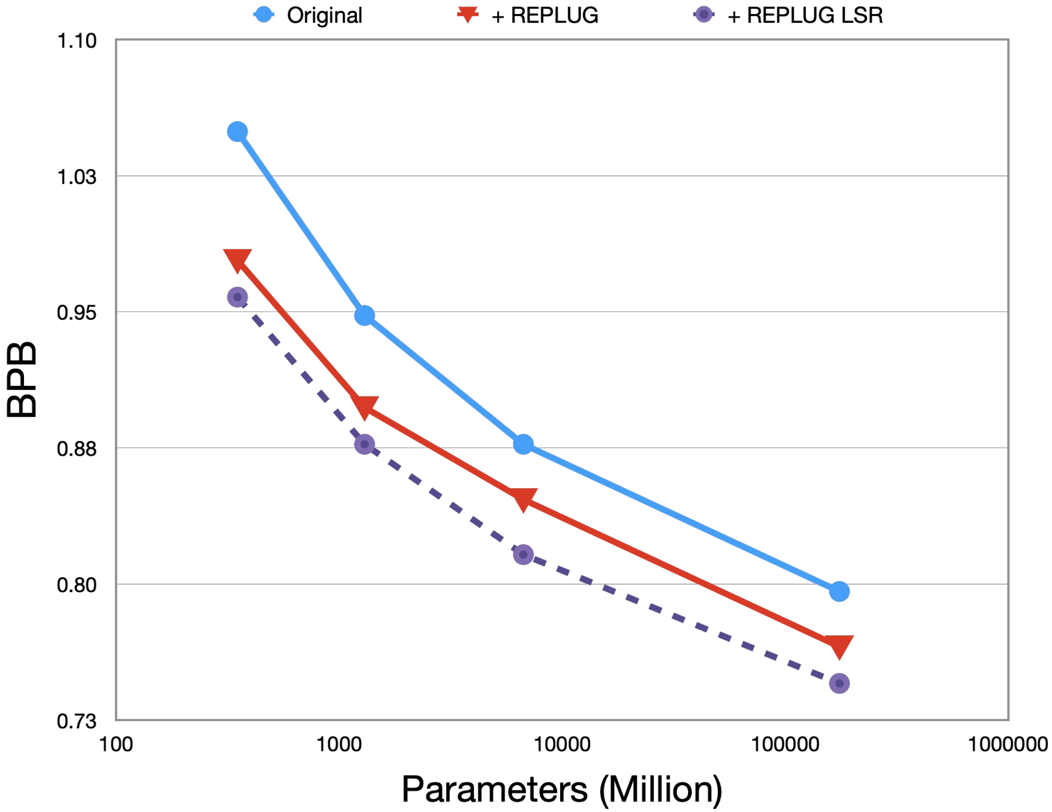



GPT-3

# Language Modeling



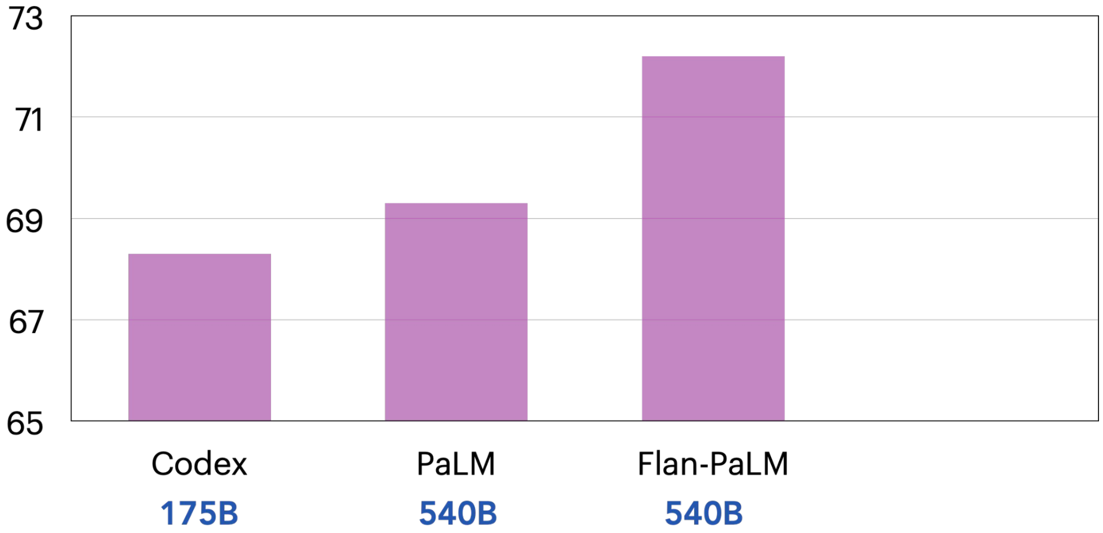
# Language Modeling




GPT-3

# MMLU (Massive Multitask Language Understanding)

- A multiple-choice QA dataset covering exam questions from 57 tasks (e.g., Math, CS, Law, Psychology, etc.)



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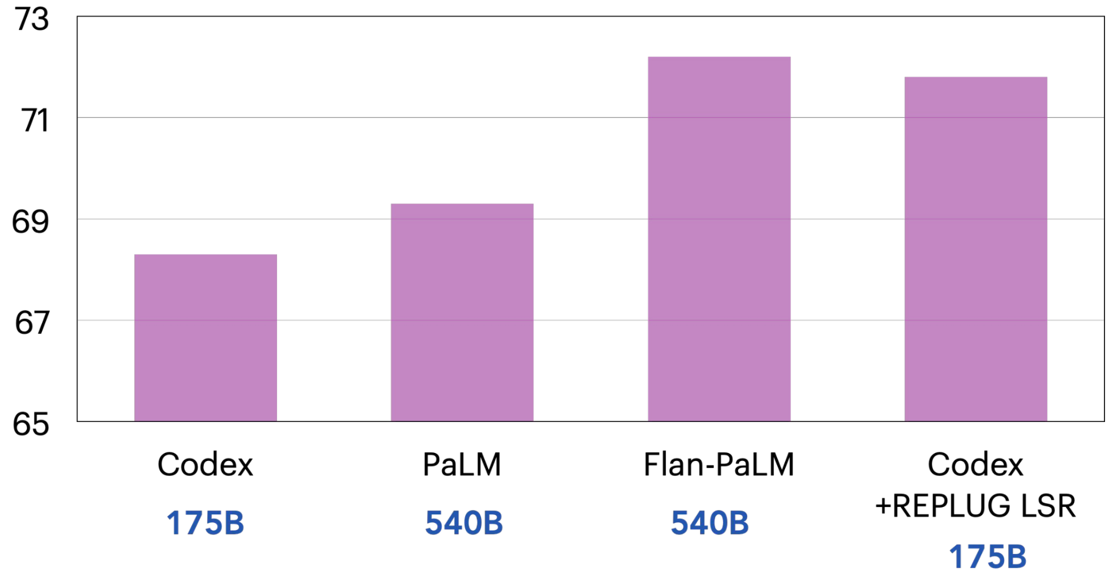
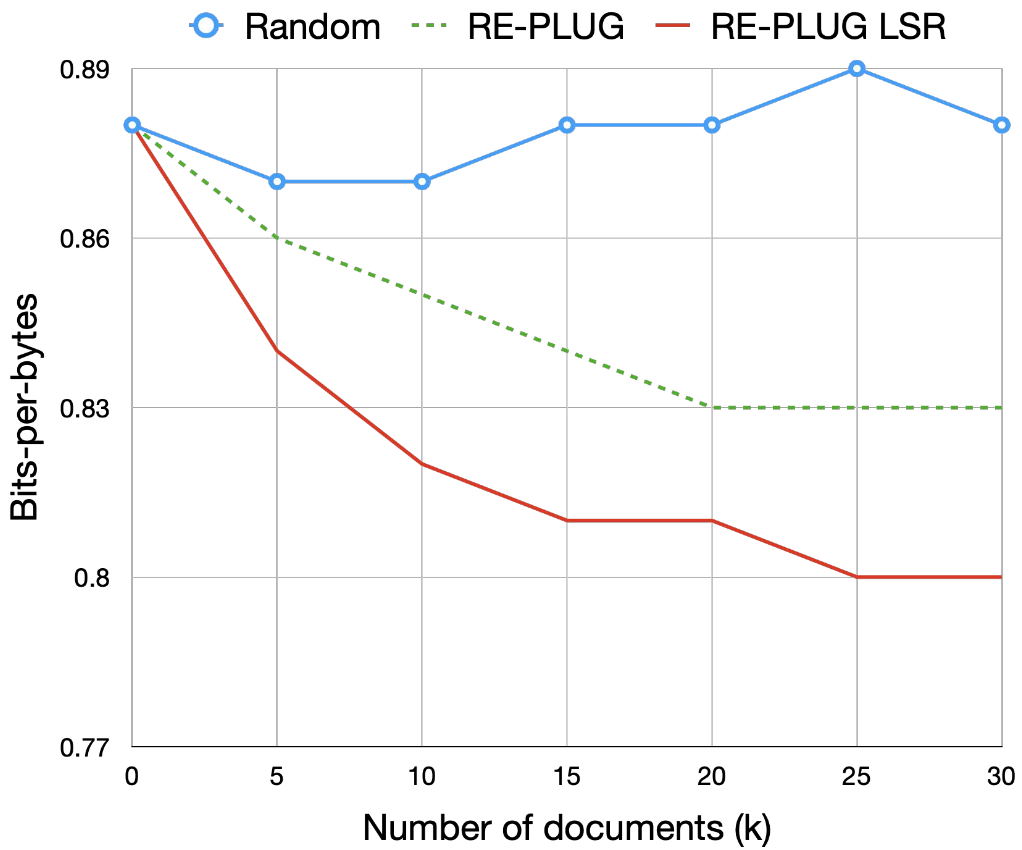
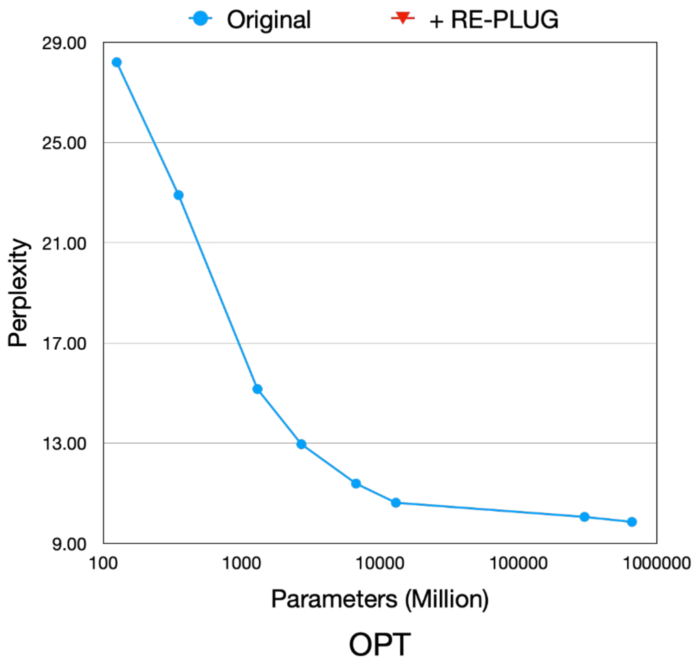


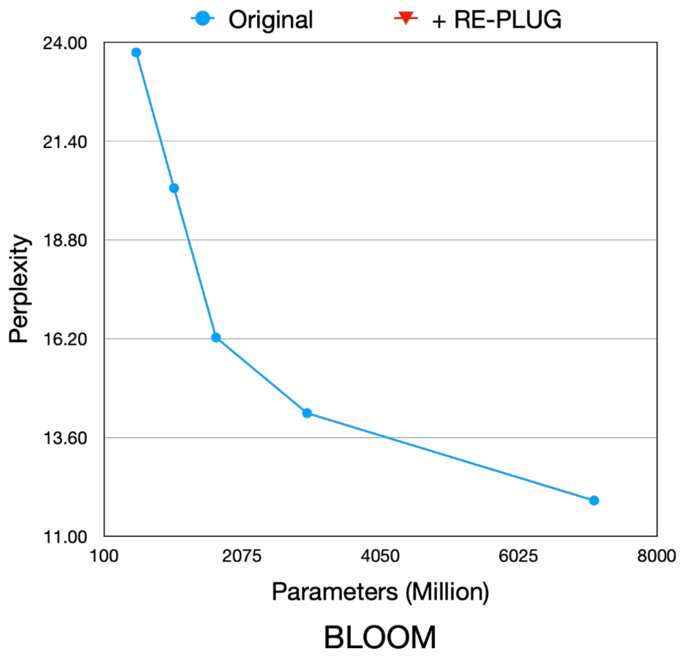
# Observation: Random Documents Don’t Help



# Observation: RePlug Works on other LMs too

- Evaluation: Wikitext-103 test set
- Datastore: Wikitext-103 training set



# Observation: REPLUG Works on other LMs too

- Evaluation: Wikitext-103 test set
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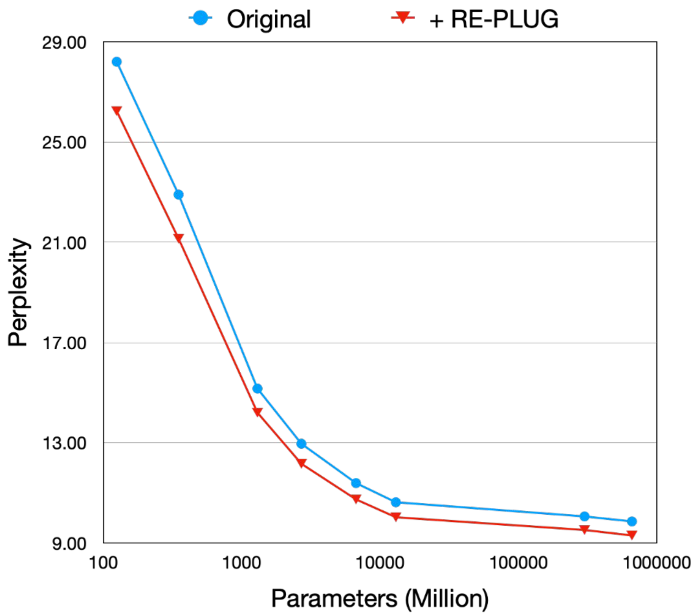
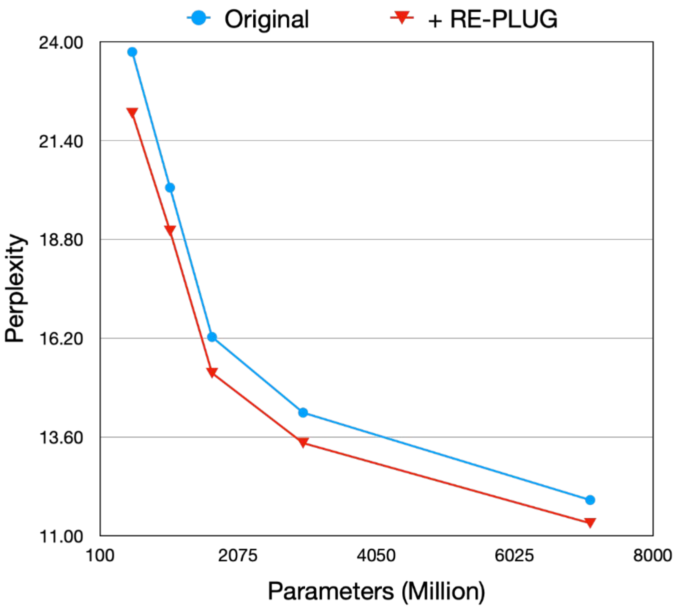



OPT




BLOOM

# Discussion / Questions

- What are other possible ways to incorporate retrieved data?
- Can there be a better query other than the input context?
- Does retrieval always help? If not, can we decide when to call retrieval?
- Any other ways to incorporate more retrieved data other than ensemble?
- What are other ways to use the LLM to provide supervision signals?
- If the LLM is not a complete blackbox, what will you do to improve this work?

# Retrieval Augmented Multimodal Model Training

Michihiro Yasunaga, Armen Aghajanyan, Weijia Shi, Rich James, Jure Leskovec, Percy Liang, Mike Lewis, Luke Zettlemoyer, Scott Yih

(Slides from Michihiro Yasunaga)

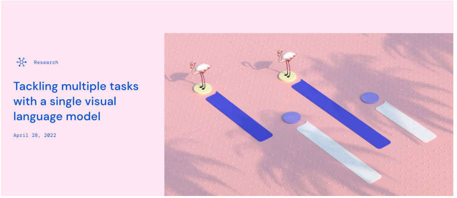
# Multimodal Models



TEXT PROMPT

an armchair in the shape of an avocado. . . .

AI-GENERATED IMAGES




**Parti-350M** | **Parti-750M** | **Parti-3B** | **Parti-20B**


A portrait photo of a kangaroo wearing an orange hoodie and blue sunglasses standing on the grass in front of the Sydney Opera House holding a sign on the chest that says Welcome Friends!

https://openai.com/blog/dall-e/, https://parti.research.google/

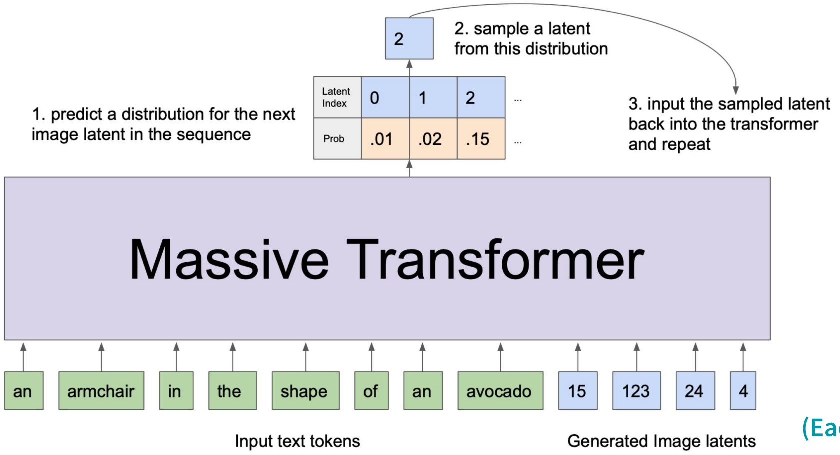
# Multimodal Models

DALL·E, Parti (text ⟶ image; autoregressive)

DALL·E 2, StableDiffusion (text ⟶ image; diffusion)

Flamingo (image ⟶ text; autoregressive)

CM3 (text ⇄ image; autoregressive) ⟵ We focus on this direction




(Each image = 1024 tokens)

https://ml.berkeley.edu/blog/posts/dalle2/

# Multimodal models need world knowledge

What does Bichon Frisé look like..?

A **Bichon Frisé** sitting on the bench.

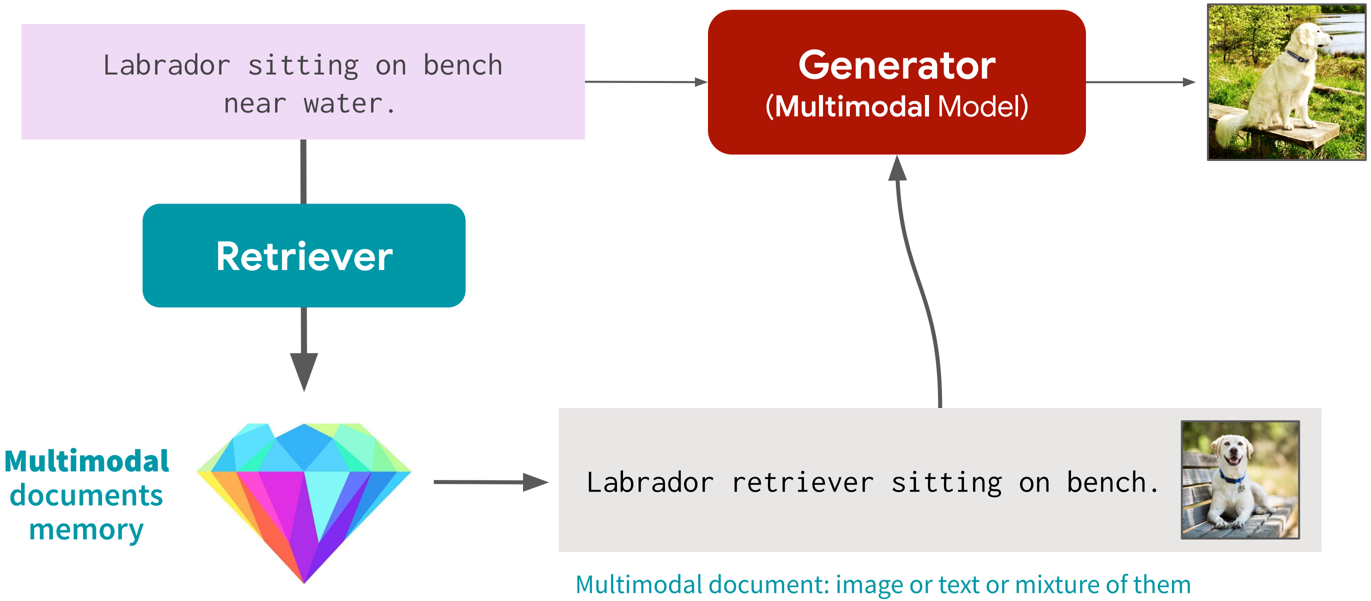
Text to image

What is the name of this place..?

Image to text

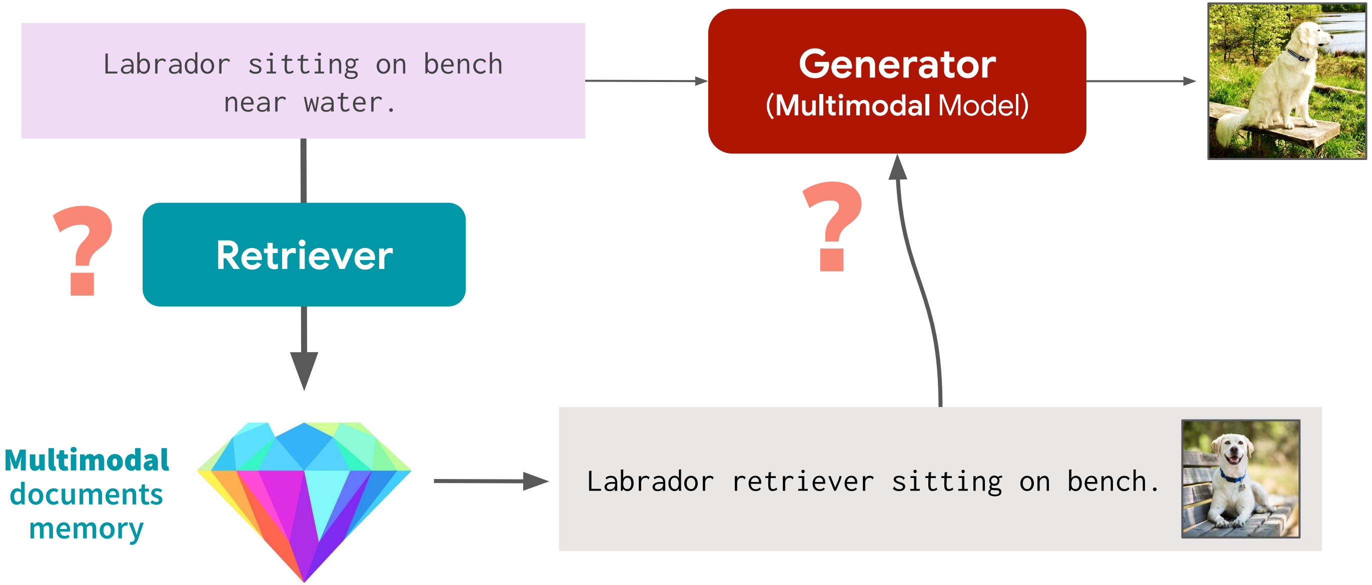
**The Dragon and Tiger Pagodas** next to fireworks.

# Our Idea: Retrieval Augmented Multimodal Model



# Challenges & Research Questions

- What is effective **retrieval** method in multimodal setting?
- How to incorporate multimodal docs into the **generator**?

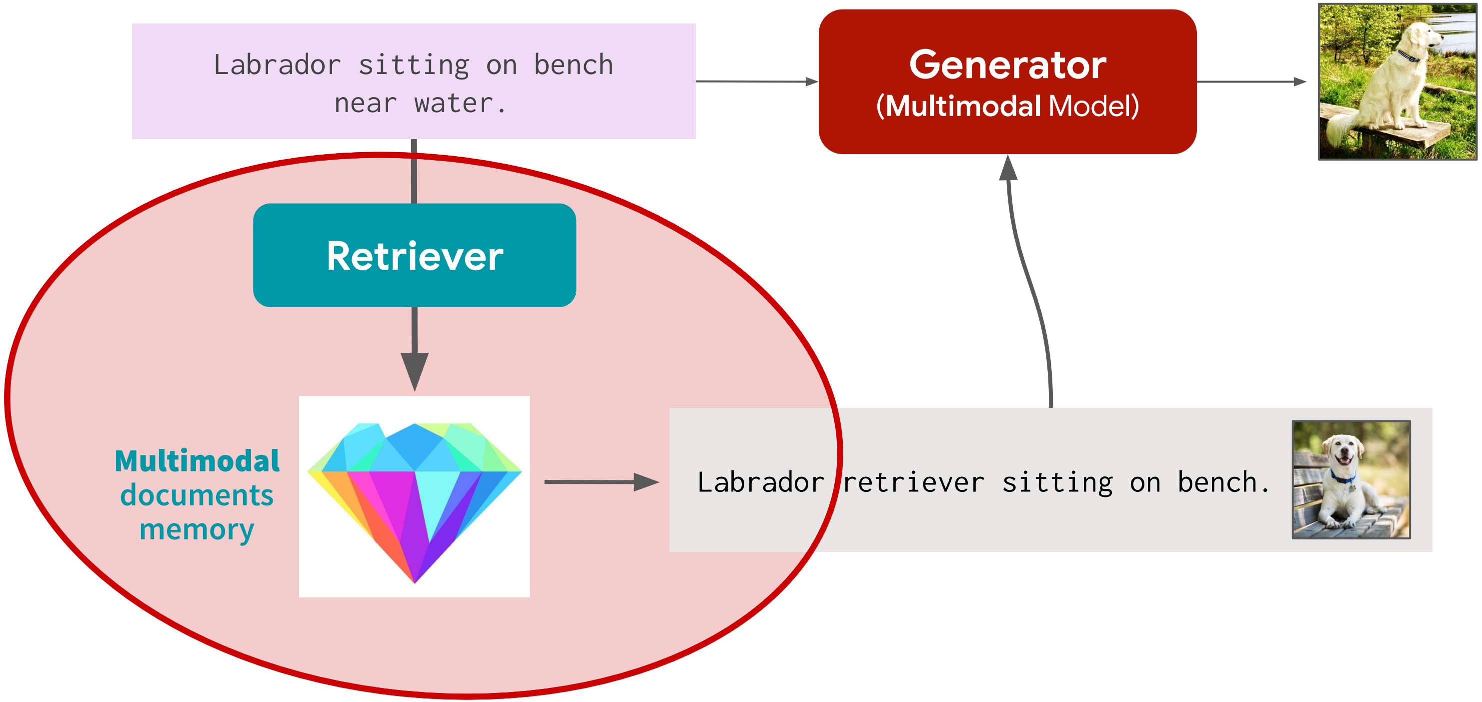


# Retrieval Augmented Multimodal Model

## Techniques

- Multimodal retrieval
  - Dense retriever with CLIP-based mix-modal encoder
  - Strategy for obtaining retrieved docs
- Multimodal retrieval-augmented generator
  - Prepend retrieved docs
  - Jointly train over retrieved docs and main doc

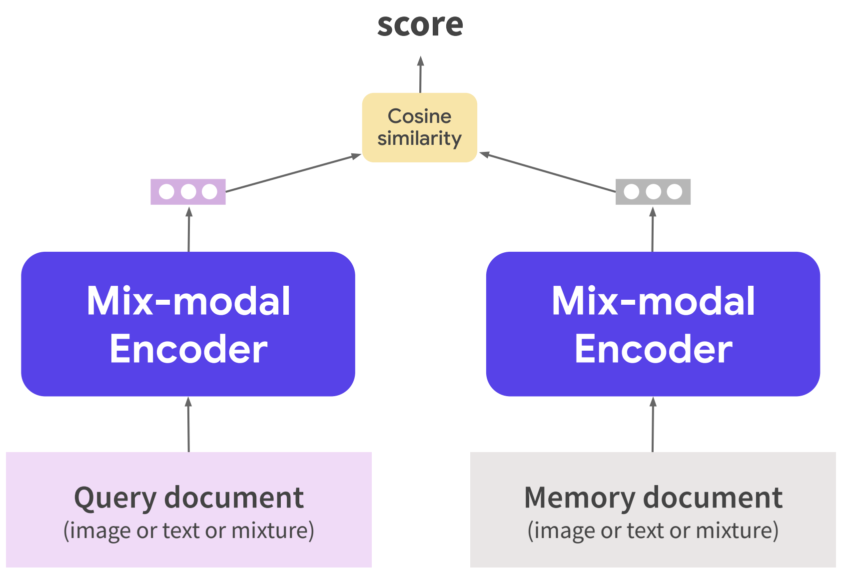
# Multimodal Retrieval



# Our Multimodal Retriever

## Dense Retriever with Mix-modal Encoder

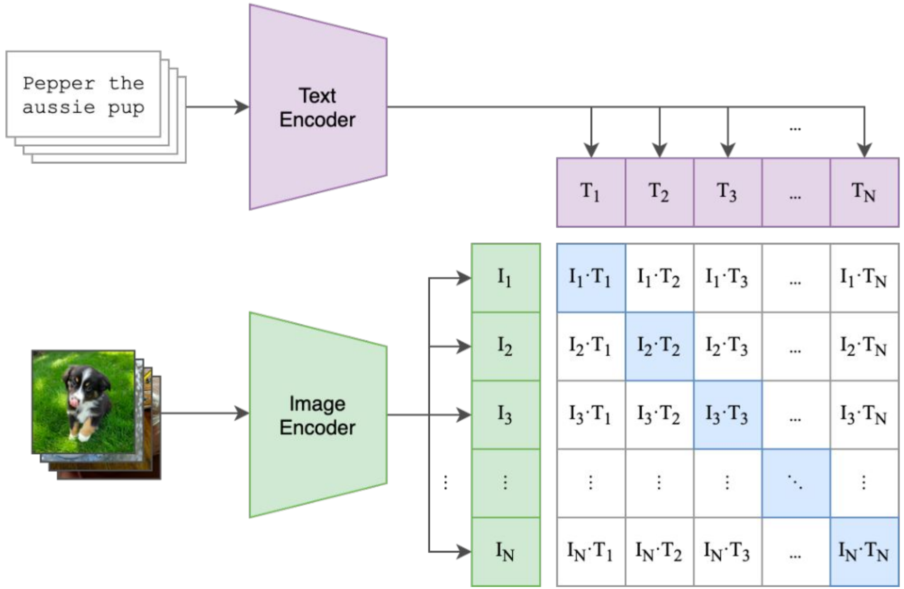
f(query, memory) ⟶ score



# Background: CLIP

CLIP produces text embeddings and image embeddings in shared vector space

(1) Contrastive pre-training

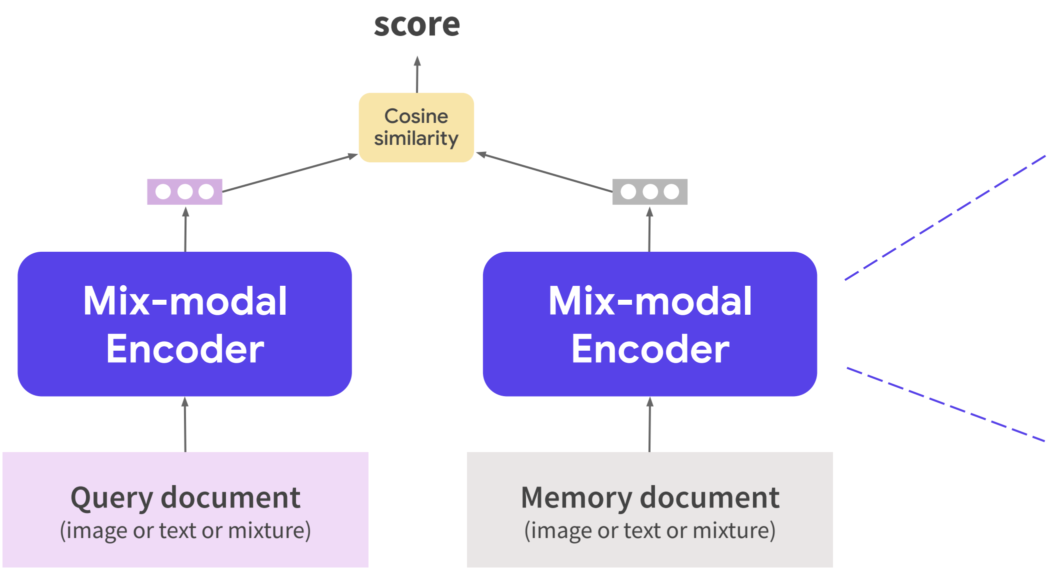



[Radford+2021]

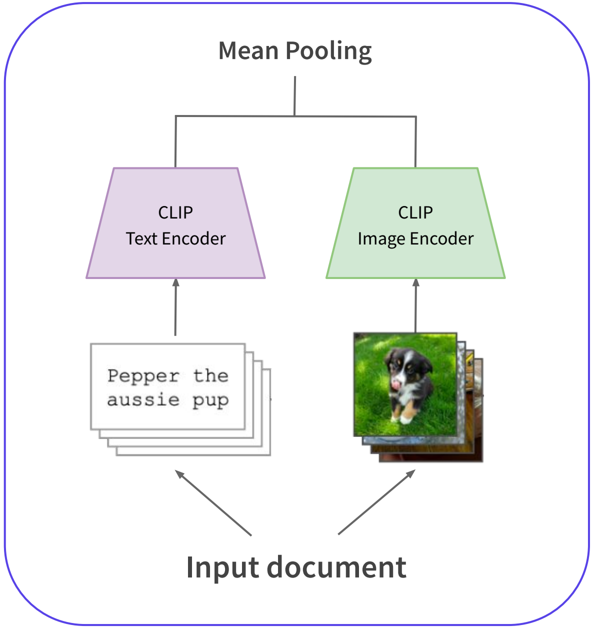
# Our Multimodal Retriever

## Dense Retriever with Mix-modal Encoder

`f(query, memory) ⟶ score`




E.g. Extension of CLIP



# Our Multimodal Retriever

## Example

Memory

Query

Labrador sitting on bench near water.

0.85

Labrador retriever sitting on bench.

0.81

Labrador retriever sitting by water.

0.35

⋮

# Strategy for Obtaining Retrieved Documents

## Relevance

The retrieved docs should be relevant to query

✅ **Cosine similarity score**

## Diversity (for training)

If simply take docs of top scores, may include duplicate images/text
This can cause model to overfit or pick up repetitive decoding

💡 **Avoid redundant docs**

- Skip candidate doc if it is too similar to query or docs already retrieved

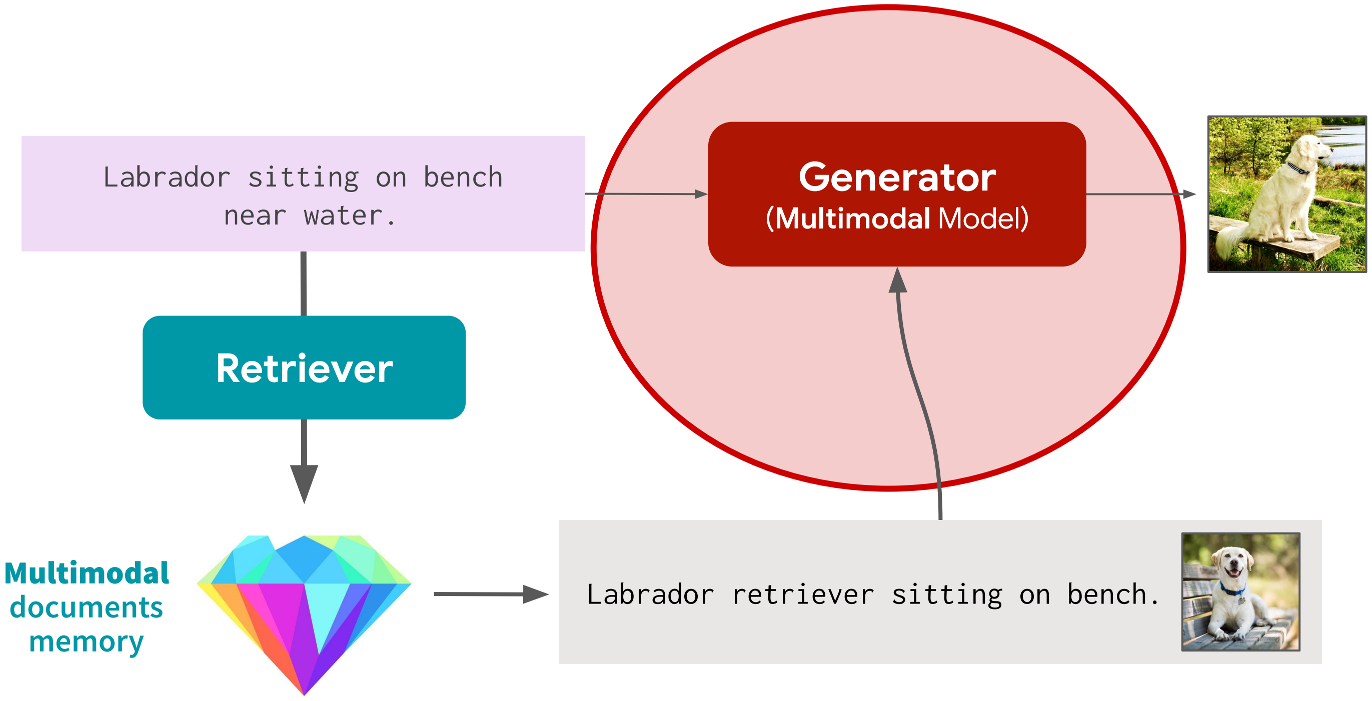
💡 **Query dropout**

- Drop some tokens of query used in retrieval (e.g., 20% of tokens)
- This further increases diversity and serves as regularization

**Diversity is crucial in multimodal setting**

- Multimodal dataset often contains duplicate images across docs
- Each image takes many tokens (1024), so can significantly hurt model training

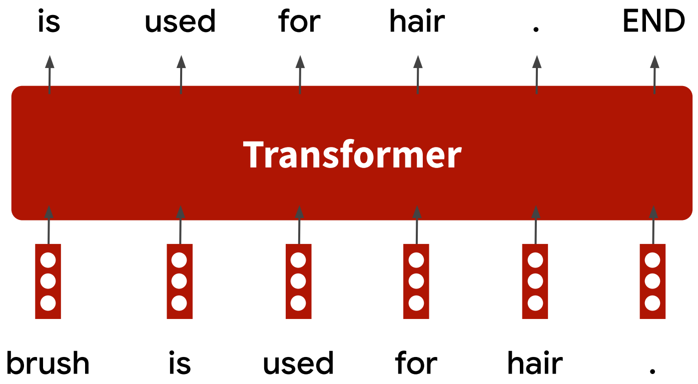
# Multimodal Generator



# Background: CLM and CM3

## Causal language model (CLM)

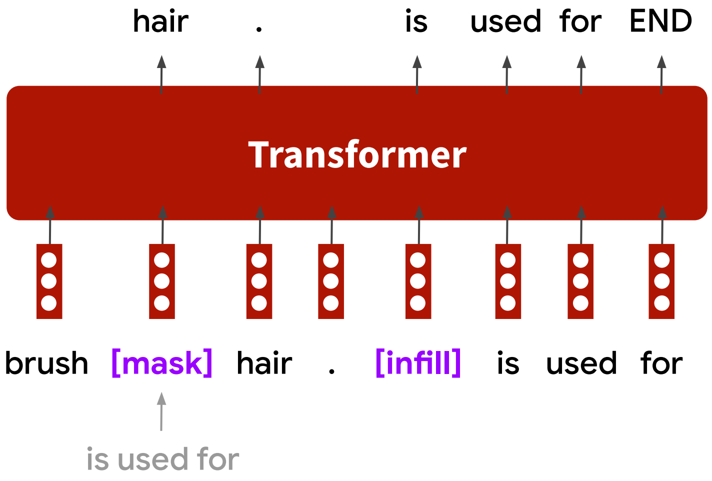
⇒ Inference: can do auto-regressive generation




## Causal masked language model (CM3)

⇒ Inference: can also do in-filling

If don't mask, same as CLM




[Aghajanyan+2022](#)

# Background: CM3 can do text ⇄ image

**Original doc**

Labrador sitting on bench near water. 

**Text to Image**

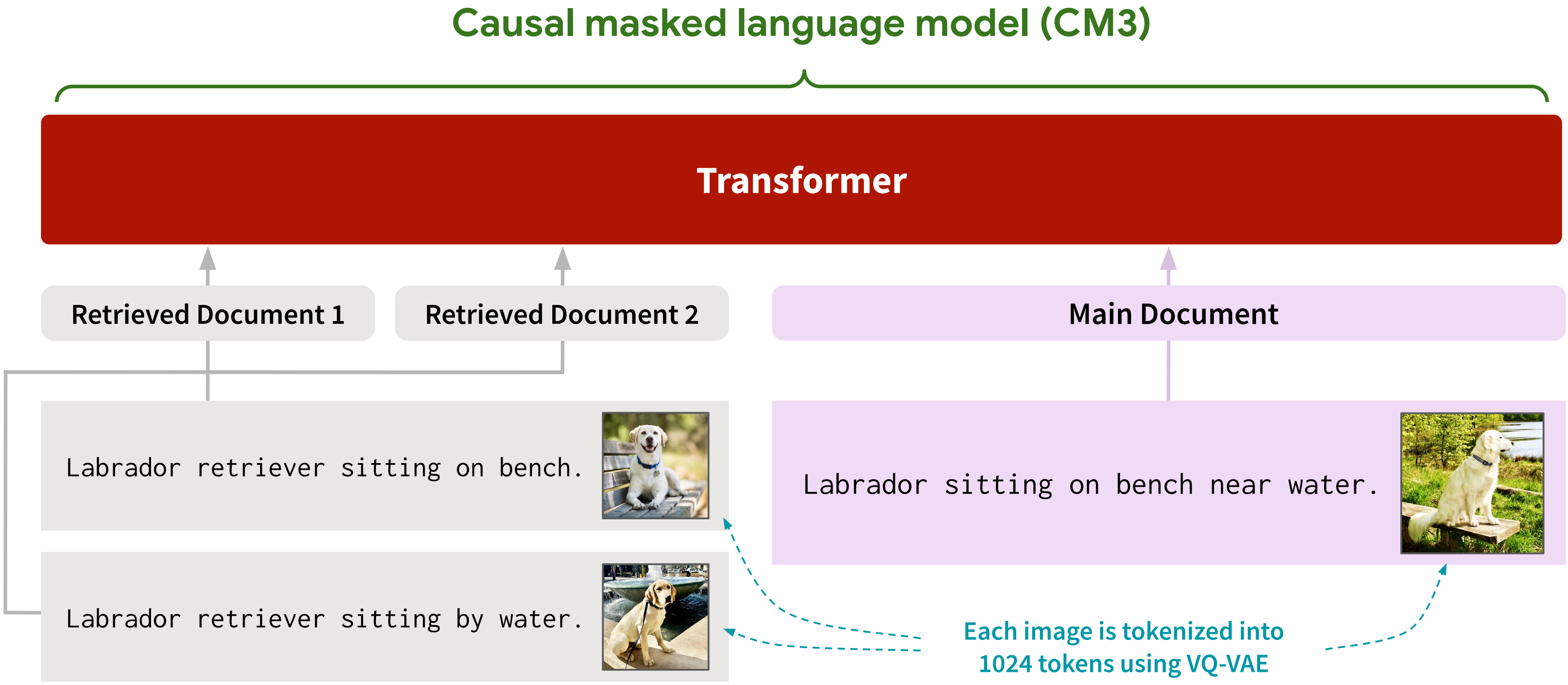
Labrador sitting on bench near water. → CM3 → 

**Image to text**

[mask]  [infill] → CM3 → Labrador sitting on bench near water.

Aghajanyan+2022

# Our Generator: Retrieval Augmented CM3



# How to Train the Generator

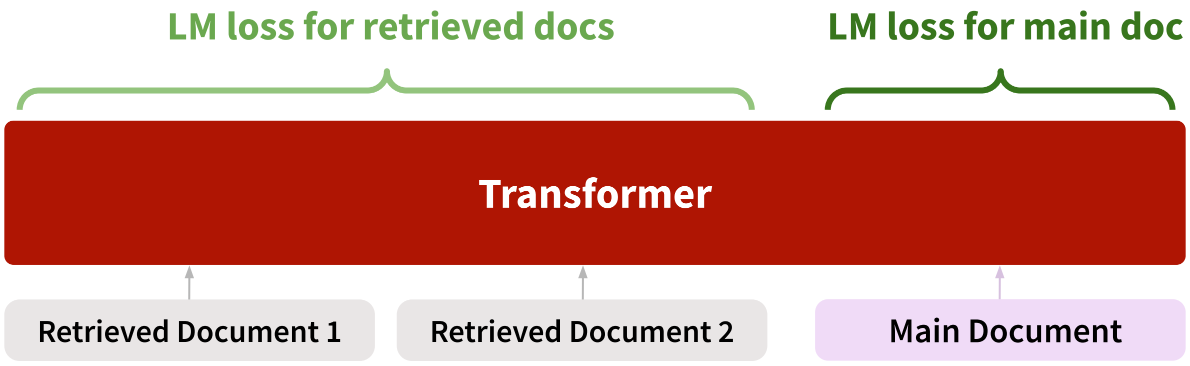
Loss = **(LM loss for main doc)** + α • **(LM loss for retrieved docs)**

- Existing retrieval augmented LMs: α = 0
- **Our method: α > 0 (α = 0.1 works the best)**

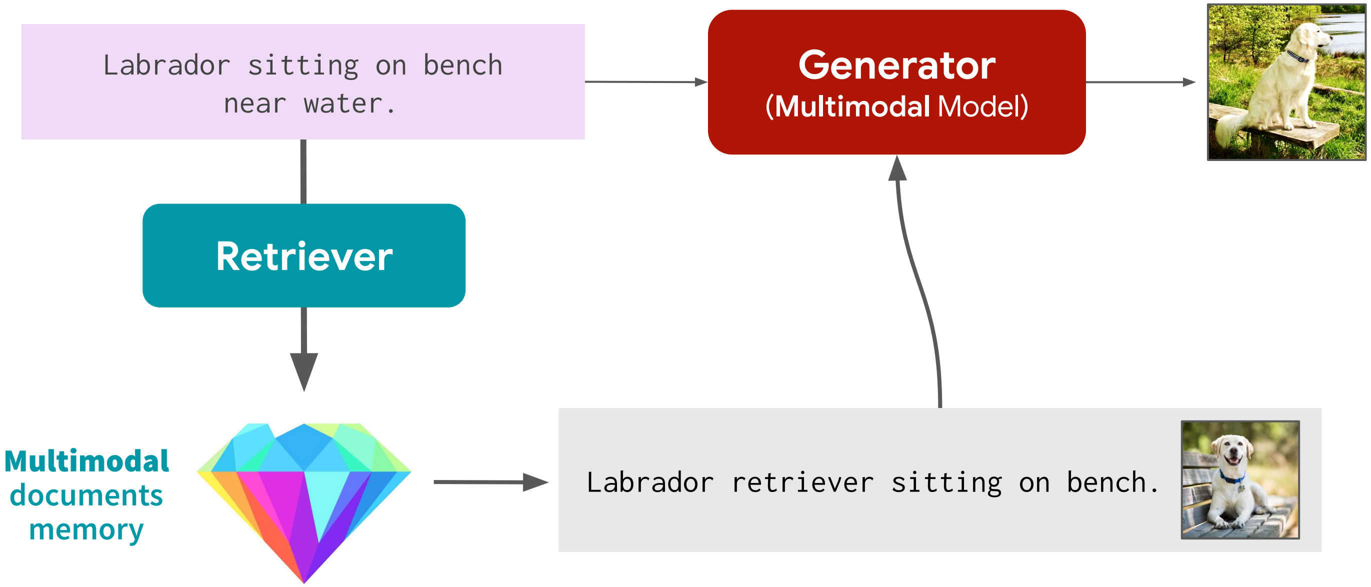
α > 0 has effect like increasing batch size without extra forward compute, increasing training efficiency

**α > 0 is crucial in multimodal setting**

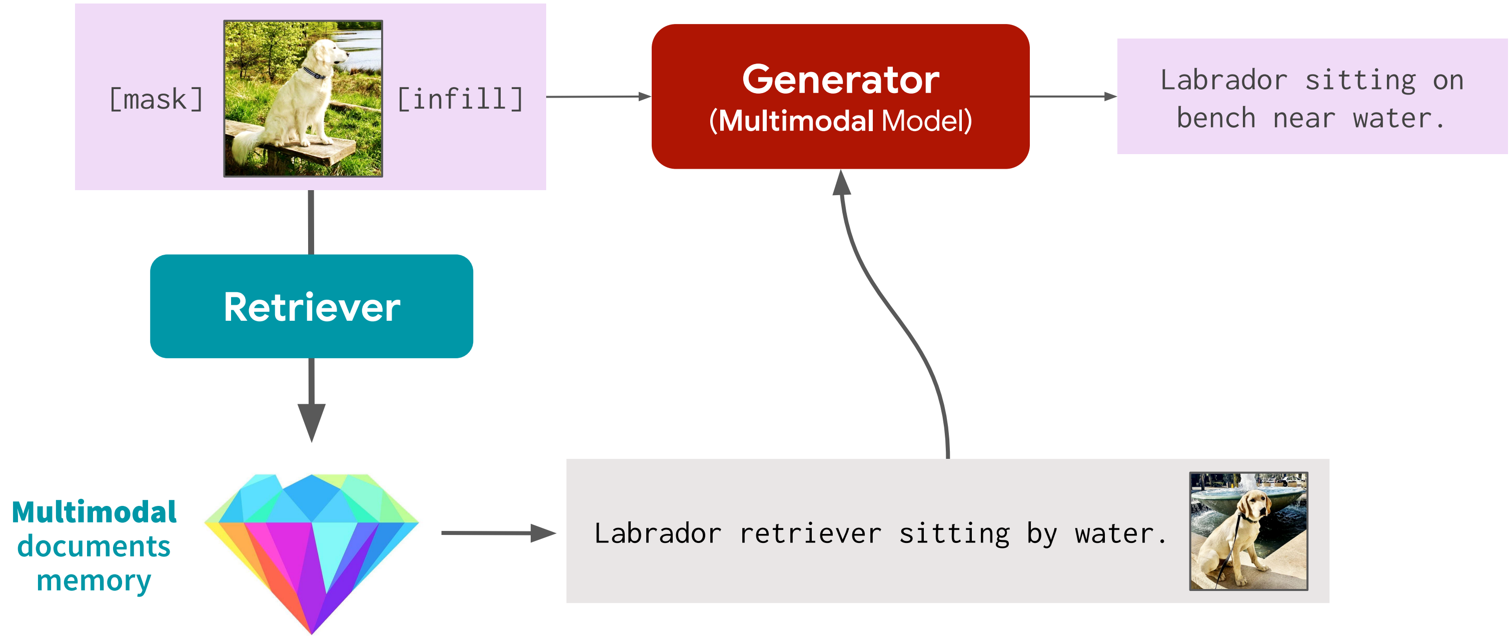
- Each image takes many tokens (1024)
- If α = 0, we are throwing away a lot of compute



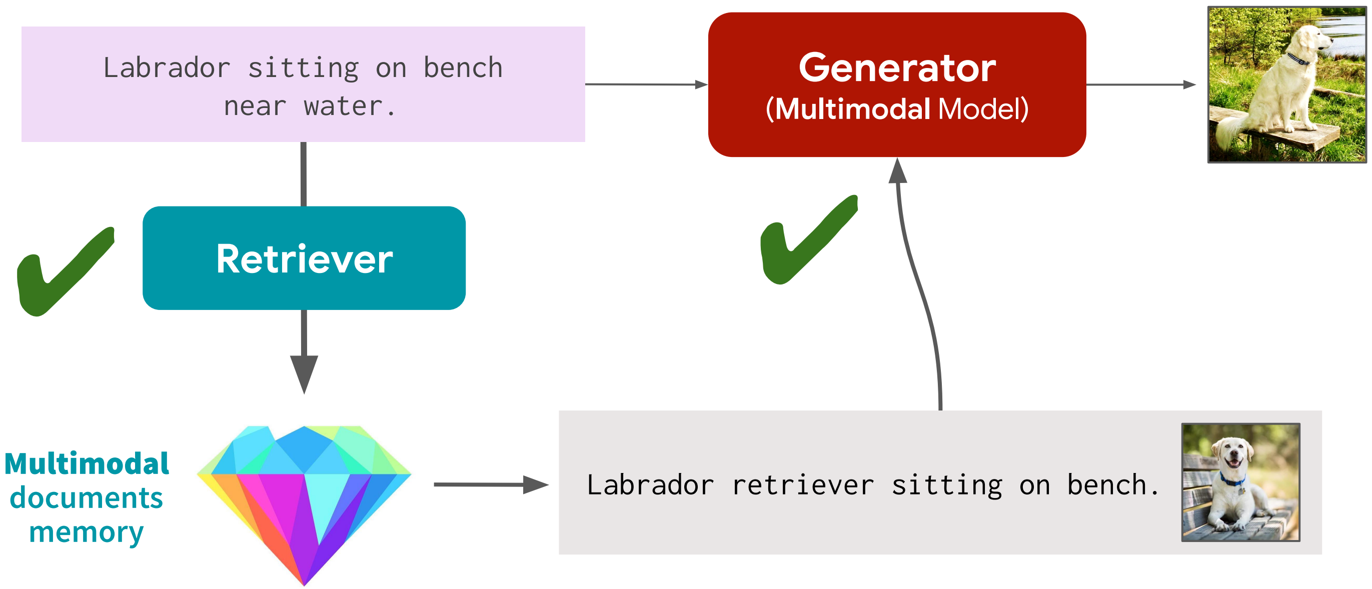
# Text to Image



# Image to Text



# Retrieval Augmented Multimodal Model



# Experiments

## Train data

- **LAION** (cleaned 150M image-text pairs)
  External memory: LAION

## Evaluation

- **MSCOCO** caption2image, image2caption.
  External memory: MSCOCO train set

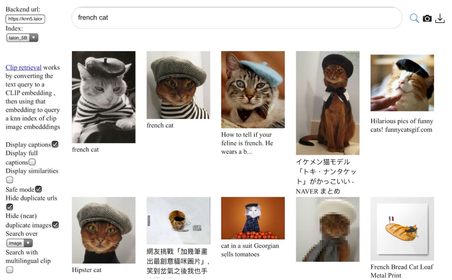
## Model

- Transformer with seq_length 4096 (up to 2 retrieved documents)
- 2.7B parameters trained for 5 days on 256 GPUs
- **“Retrieval Augmented CM3 (RA-CM3)”**

## Baseline

- Vanilla CM3 with no retrieval, same size, trained using the same amount of compute

LAION
Large-scale Artificial Intelligence Open Network



# Performance

## MSCOCO caption to image generation

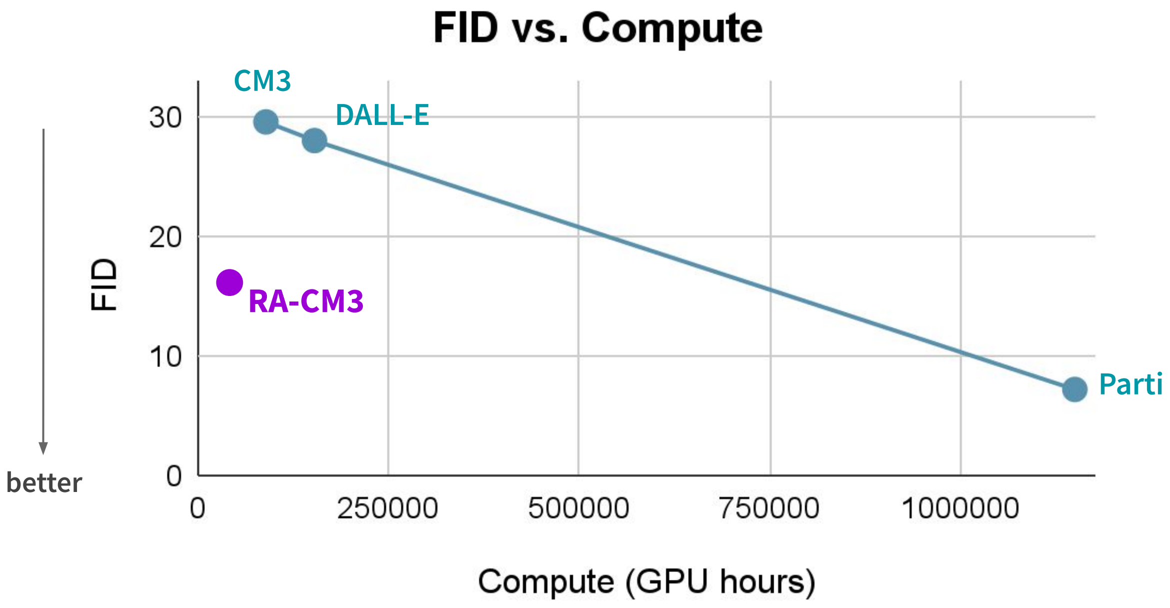
- RA-CM3 outperforms vanilla CM3 as well as DALL-E (which uses more params and images)

| Model | Model type | #Train images | FID score (↓) |
|---|---|---|---|
| DALL-E (12B) | Autoregressive | 250M | 28 |
| Parti (20B) | Autoregressive | 6B | 7.2 |
| Stable Diffusion | Diffusion | 1B | ~12 |
| DALL-E 2 | Diffusion | 650M | 10.3 |
| Vanilla CM3 | Autoregressive | 150M | 25.8 |
| **RA-CM3** | Autoregressive | 150M | **16.9** |

# Performance

## MSCOCO caption to image generation

- RA-CM3 is more compute efficient than non-retrieval models like DALL-E, CM3, Parti



# Performance

## MSCOCO image to caption generation

- RA-CM3 outperforms vanilla CM3 and Flamingo (equivalent size); competitive with Parti

| Model | #Train images | CIDEr score (↑) |
|---|---|---|
| Parti (20B) | 6B | 0.89 |
| Flamingo (3B) 4-shot | 2.5B | 0.85 |
| Flamingo (80B) 4-shot | 2.5B | 1.03 |
| PaLI (17B) | 10B | ~1.4 |
| Vanilla CM3 | 150M | 0.72 |
| **RA-CM3** | 150M | **0.89** |

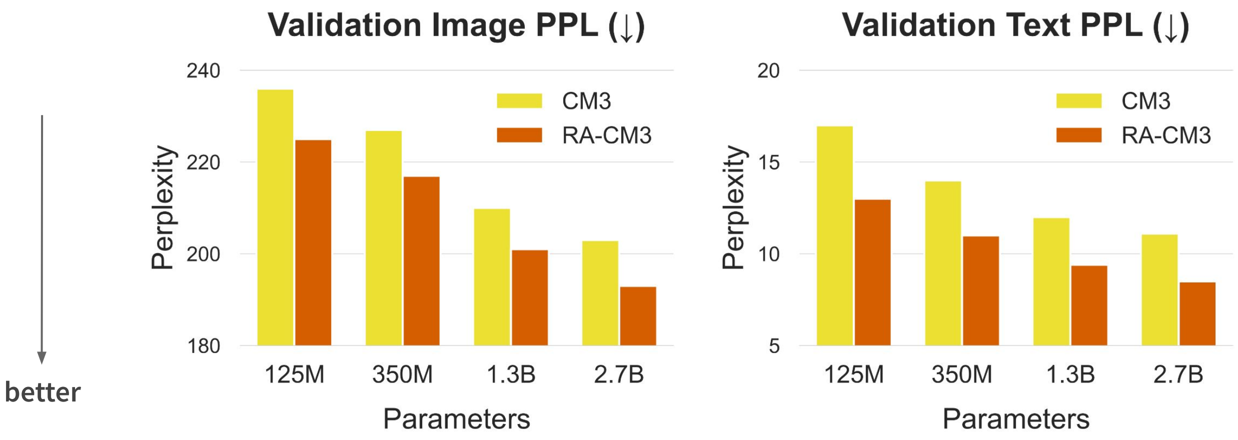
# Scaling Laws

## Setup

- All models are trained for 2 days on 256 GPUs. Evaluation metric is validation perplexity

## Observation

- Retrieval augmentation is consistently helpful across scales
- Larger models perform better (even under the same compute budget)



# Ablation Study

## **Key factors in obtaining retrieved docs** (relevance, diversity)

| Ablation: Relevance | Val PPL (↓) |
|---|---|
| Random | 130 |
| **CLIP-based retrieval (Final)** | **121** |

| Ablation: Diversity | Val PPL (↓) |
|---|---|
| Simply take top docs | 131 |
| Avoid redundant docs | 125 |
| **Avoid redundant docs + Query dropout (Final)** | **121** |

## Comment

- Diversity is important in the multimodal setting, because each image takes many tokens. Redundant image can significantly hurt model training (model learns to repeat stuff)

# Ablation Study

## Training objective

- Loss = (LM loss for main doc) + α • (LM loss for retrieved docs)

| Loss function | Val PPL (↓) |
|---|---|
| $\alpha = 0$ | 127 |
| $\alpha = 1$ | 126 |
| $\alpha = 0.3$ | 123 |
| **$\alpha = 0.1$ (Final)** | **121** |

$\alpha > 0$ has effect like increasing batch size without extra forward compute, increasing training efficiency.

But $\alpha = 1$ puts too much weight in modeling retrieved docs, hurting the PPL of the main doc.

## Comment

- $\alpha > 0$ is especially effective in the multimodal setting, because each image takes many tokens. If $\alpha = 0$, we are throwing away a lot of compute that could be leveraged

# Capabilities

- Knowledge-intensive image generation
- Image infilling & editing
- Controlled image generation
- One/few-shot image classification

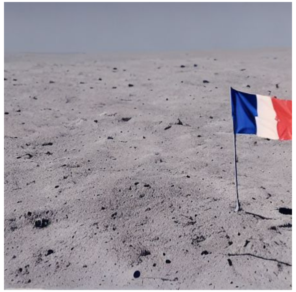
# Capability: Knowledge-intensive Generation

**RA-CM3 In-context** | **RA-CM3 outputs** | **Baseline outputs** (Vanilla CM3) (Stable Diffusion)

Ming Dynasty vase

A **Ming Dynasty vase** with orange flowers painted.

French flag



**French flag** waving on the moon's surface.

# Capability: Knowledge-intensive Generation

**RA-CM3 In-context** | **RA-CM3 outputs** | **Baseline outputs** (Vanilla CM3) (Stable Diffusion)

Armenian church

An **Armenian church** during a sunny day.

Mount Rainier

People standing in front of the **Mount Rainier**.

# Capability: Knowledge-intensive Generation

**RA-CM3 In-context**

**RA-CM3 outputs**

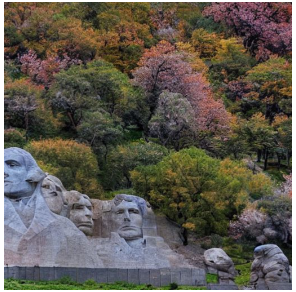
**Baseline outputs**

(Vanilla CM3)

(Stable Diffusion)

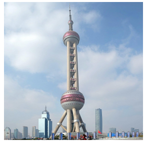
Mount Rushmore

Japanese cherry



The **Mount Rushmore** with **Japanese cherry** trees in the front.

Oriental Pearl tower



**The Oriental Pearl tower** in oil painting.

# Capability: Knowledge-intensive Generation

**RA-CM3 In-context**

**RA-CM3 outputs**

**Baseline outputs**

(Vanilla CM3) (Stable Diffusion)

Callanish standing stones

Photo of the **Callanish standing stones**, fireworks in the sky.

Dragon and Tiger Pagodas

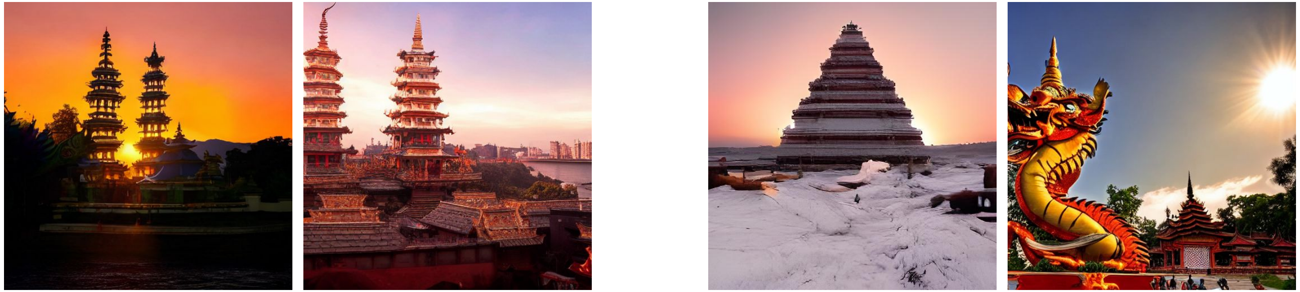
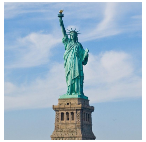


Photo of **the Dragon and Tiger Pagodas**, the sun is setting behind.

# Capability: Knowledge-intensive Generation

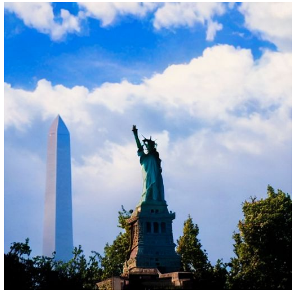
**RA-CM3 In-context**

Statue of Liberty



Washington monument

**RA-CM3 outputs**



**Baseline outputs**

(Vanilla CM3)

(Stable Diffusion)

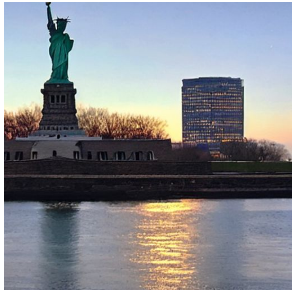


Photo of **the Statue of Liberty** standing next to **the Washington monument**.

# Discussion / Questions

- What are other possible ways to incorporate retrieved data?
- Any ways to incorporate more retrieved data?
- Can there be a better query other than the input context?
- Does retrieval always help? If not, can we decide when to call retrieval?
- How do we reduce the retrieval data/index size?

# Conclusion

Aspirational goal: A core model that fits in a single GPU, but can

- easily access additional, task-related knowledge via retrieval, and
- perform comparably to the largest language models available today

Key to success:

- Large quality data
- Efficient retrieval infrastructure
- Effective communication channels between retrieval and core LM models

**Thank you!**

**Questions?**