Commonsense Retrieval-Augmented Generation for Large Language Models

CPSC 532V 2023W2 Project Proposal - 2024.03.06

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Background

Natural language generation has improved considerably owing to the rapid development of large language models (LLMs) [1, 2, 3].

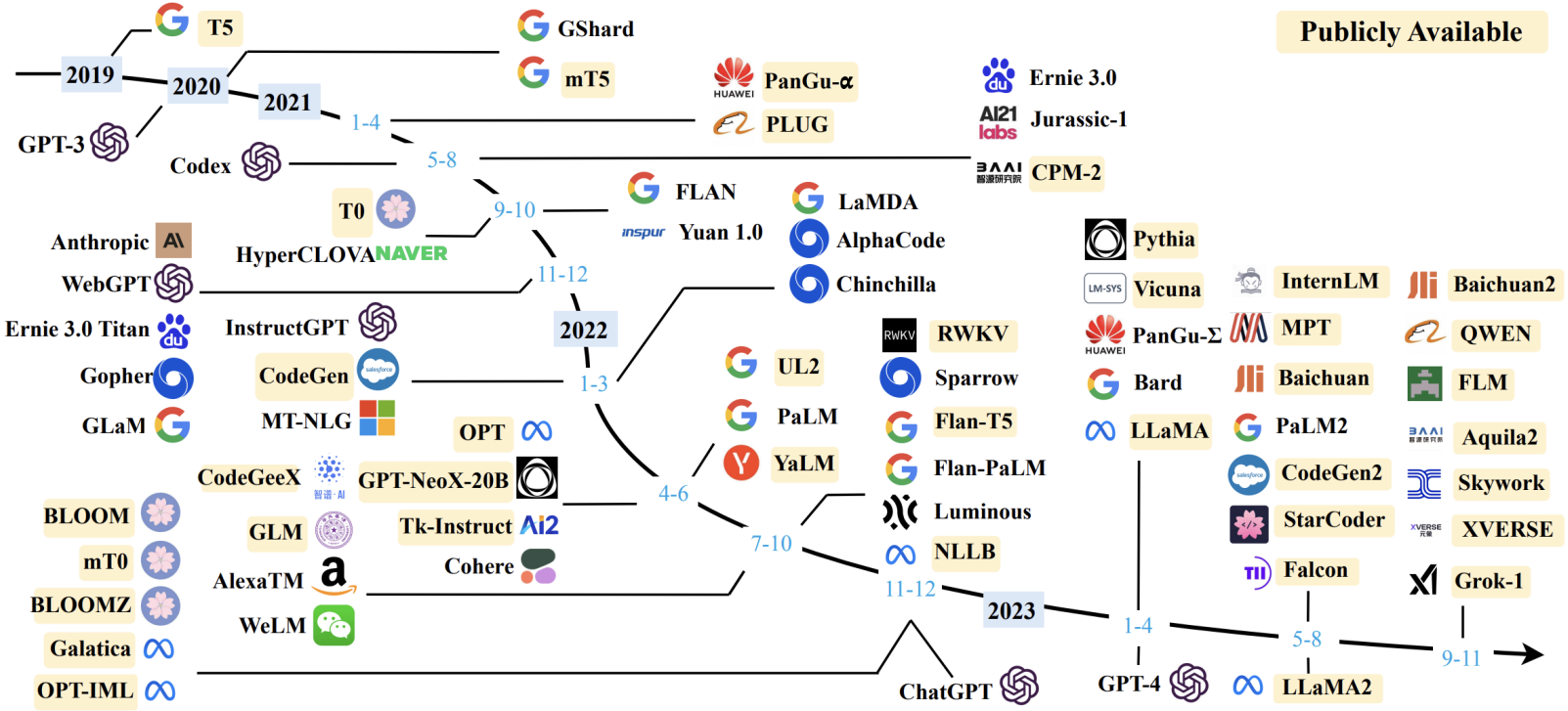

Figure 1: A timeline of existing LLMs (size > 10B) in recent years [3].

Background

	Claude 3 Opus	Claude 3 Sonnet	Claude 3 Haiku	GPT-4	GPT-3.5	Gemini 1.0 Ultra	Gemini 1.0 Pro
Undergraduate level knowledge *MMLU*	86.8% 5 shot	79.0% 5-shot	75.2% 5-shot	86.4% 5-shot	70.0% 5-shot	83.7% 5-shot	71.8% 5-shot
Graduate level reasoning *GPQA, Diamond*	50.4% 0-shot CoT	40.4% 0-shot CoT	33.3% 0-shot CoT	35.7% 0-shot CoT	28.1% 0-shot CoT	–	–
Grade school math *GSM8K*	95.0% 0-shot CoT	92.3% 0-shot CoT	88.9% 0-shot CoT	92.0% 5-shot CoT	57.1% 5-shot	94.4% Maj1@32	86.5% Maj1@32
Math problem-solving *MATH*	60.1% 0-shot CoT	43.1% 0-shot CoT	38.9% 0-shot CoT	52.9% 4-shot	34.1% 4-shot	53.2% 4-shot	32.6% 4-shot
Multilingual math *MGSM*	90.7% 0-shot	83.5% 0-shot	75.1% 0-shot	74.5% 8-shot	–	79.0% 8-shot	63.5% 8-shot
Code *HumanEval*	84.9% 0-shot	73.0% 0-shot	75.9% 0-shot	67.0% 0-shot	48.1% 0-shot	74.4% 0-shot	67.7% 0-shot
Reasoning over text *DROP, F1 score*	83.1 3-shot	78.9 3-shot	78.4 3-shot	80.9 3-shot	64.1 3-shot	82.4 Variable shots	74.1 Variable shots
Mixed evaluations *BIG-Bench-Hard*	86.8% 3-shot CoT	82.9% 3-shot CoT	73.7% 3-shot CoT	83.1% 3-shot CoT	66.6% 3-shot CoT	83.6% 3-shot CoT	75.0% 3-shot CoT
Knowledge Q&A *ARC-Challenge*	96.4% 25-shot	93.2% 25-shot	89.2% 25-shot	96.3% 25-shot	85.2% 25-shot	–	–
Common Knowledge *HellaSwag*	95.4% 10-shot	89.0% 10-shot	85.9% 10-shot	95.3% 10-shot	85.5% 10-shot	87.8% 10-shot	84.7% 10-shot

Figure 2: Claude 3 – a new standard for intelligence [4] (Mar 4, 2024).

Motivation

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  "The president of US is" $\rightarrow$ "Biden" or "Trump" (Which year?)
- Hence, the models are supposed to produce better output if they are **conditioned on more relevant context**.
  "In 2020, the president of US is" $\rightarrow$ "Trump" (with context)

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  > training (planning, reinforcement learning, multi-task learning, controllable generation),
  > post-processing, etc.
- **Data-Related Methods**:
  > building a faithful dataset,
  > cleaning data automatically,
  > **information augmentation**, etc.

Research Problem

The focus of this project:

- ***How do we effectively incorporate contextual information to (MAIN) enhance problem-solving performance and (FUTURE) potentially mitigate hallucination in LLMs?***

Retrieval-Augmented Generation

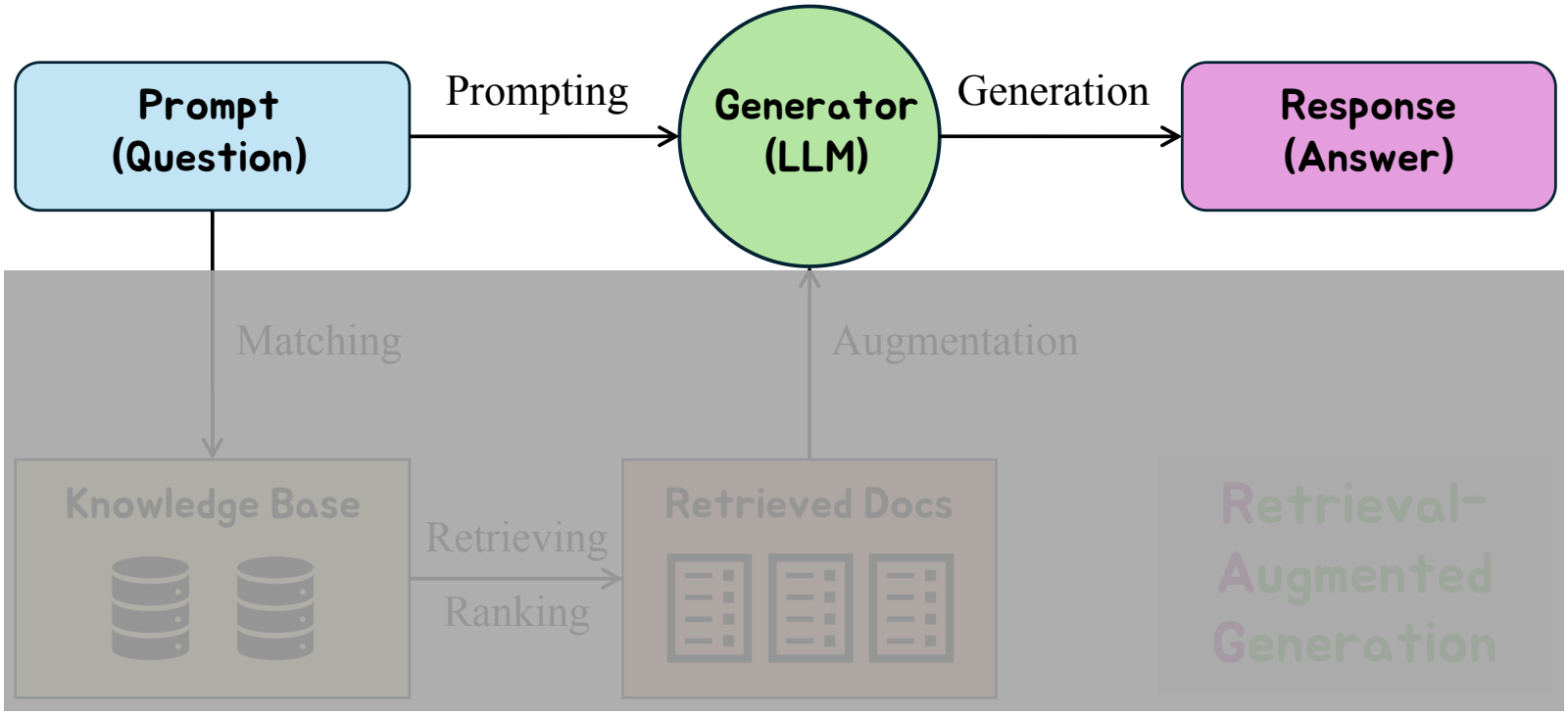

Figure 3: The overview of LLM generation.

Retrieval-Augmented Generation

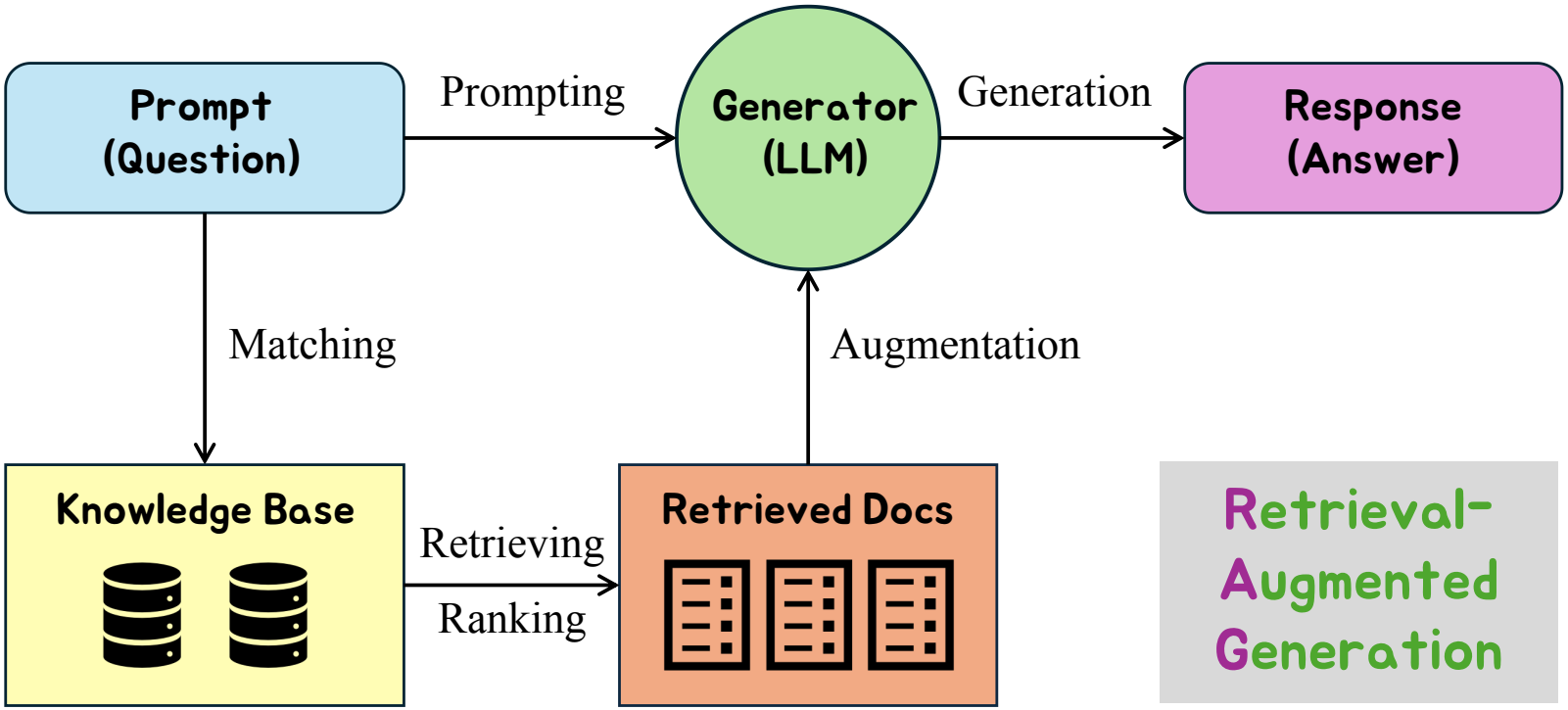

Figure 4: The overview of retrieval-augmented generation (RAG).

Retrieval-Augmented Generation

Key points and hardships of RAG:

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★ All points will be covered in our implementation.
Skip related work (in our proposal) for the sake of time

Implementation

Our project aims to develop an RAG system to examine and compare different RAG methods of integrating external knowledge into LLMs for solving commonsense NLP tasks.

Steps

1. Building knowledge base
2. Indexing
3. Retrieval
4. Augmentation
5. Generation
6. Advance RAG

Step 1 & 2: Building Knowledge Base and Indexing

- Encyclopedic and commonsense knowledge sources
  1. Atomic [10]
  2. ConceptNet [11]
  3. Wikipedia [1]
  4. NCLB [12]
  5. ...
- From individual KBs with different formats
  $\rightarrow$ a unified, structured KB.

[1] https://pypi.org/project/Wikipedia-API/

Step 3: Retrieval

The **retriever** module is responsible for *searching*, *semantic matching*, and *result ranking*.

Pre-retrieval

- Rewriting [13]
- Query routing [14]

Post-retrieval

- Re-ranking [15, 16]

Step 4: Augmentation

- Zero-shot generation [8, 9]
- In-context Learning (ICL) [17]
- Chain-of-Thought prompting (CoT) [18, 19]
- Supervised fine-tuning (SFT) with Instruction Tuning [20, 21, 22, 23, 24]

Step 5 & 6: Generation/Evaluation/Training and advanced RAG

- We will implement the language model evaluation scripts on selected commonsense benchmarks.
- If time allows, we will try to incorporate several advanced RAG methods like Robust RAG [25, 26], GAR (Generation Augmented Retrieval) [27, 28, 29], etc.

Tasks, Datasets, and Evaluation

- **Tasks**: Multi-choice Commonsense NLP Tasks (classification)
- **Datasets**: GLUE, SuperGLUE, WSC, WinoGrande, ANLI, ARC, PIQA, SWAG, HellaSwag, etc.
- **Evaluation**: Acc, F1, Mcc, EM, etc.
  Acc (Accuracy): for balanced classification
  F1: for unbalanced classification
  Mcc: Matthews correlation coefficient [30][2]
  EM (Exact Match): for multiple correct answers scenario

[2] The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation [31]

Tasks, Datasets, and Evaluation - GLUE

Dataset	Training	Validation	Test	# Class	Metric
GLUE [32]					
`cola` (The Corpus of Linguistic Acceptability)	8.55k	1.04k	1.06k	2	Mcc
`mnli` (MultiNLI Matched)	393k	9.82k	9.8k	3	Acc
`mnli` (MultiNLI Mismatched)	393k	9.83k	9.85k	3	Acc
`mrpc` (Microsoft Research Paraphrase Corpus)	3.67k	408	1.73k	2	Acc, F1
`qnli` (Question NLI)	105k	5.46k	5.46k	2	Acc
`qqp` (Quora Question Pairs)	364k	40.4k	391k	2	Acc, F1
`rte` (Recognizing Textual Entailment)	2.49k	277	3k	2	Acc
`sst2` (The Stanford Sentiment Treebank)	67.3k	872	1.82k	2	Acc
`wnli` (Winograd NLI)	635	71	146	2	Acc

Table 1: The statistics of datasets for evaluation. All of them are classification tasks, where the training and validation set have labels, while the test set does not. For the evaluation metrics, "Acc", "F1", "Mcc", and "EM" mean accuracy, f1 score, Matthews correlation coefficient, and exact match score, respectively.

Tasks, Datasets, and Evaluation - SuperGLUE

Dataset	Training	Validation	Test	# Class	Metric
SuperGLUE [33]					
`boolq` (BoolQ)	9.43k	3.27k	3.25k	2	Acc
`cb` (CommitmentBank)	250	56	250	3	Acc, F1
`copa` (Choice of Plausible Alternatives)	500	100	400	2	Acc
`multirc` (Multi-Sentence Reading Comprehension)	27.2k	4.85k	9.69k	2	Acc
`record` (Reading Comprehension w/ Commonsense Reasoning)	101k	10k	10k	N	F1, EM
`rte` (Recognizing Textual Entailment)	2.49k	277	3k	2	Acc
`wic` (Words in Context)	5.43k	638	1.4k	2	Acc
`wsc` (The Winograd Schema Challenge)	554	104	146	2	Acc

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Tasks, Datasets, and Evaluation - Other Commonsense Benchmark

Dataset	Training	Validation	Test	# Class	Metric
WSC273 [34]	-	-	273	2	Acc
WinoGrande [35]	9.25k	1.27k	1.77k	2	Acc
ANLI `r1` [36]	16.9k	1k	1k	3	Acc
ANLI `r2`	45.5k	1k	1k	3	Acc
ANLI `r3`	100k	1.2k	1.2k	3	Acc
ARC `Easy` [37]	2.25k	570	2.38k	4	Acc
ARC `Challenge`	1.12k	299	1.17k	4	Acc
PIQA [38]	16.1k	1.84k	3.08	2	Acc
SWAG [39]	73.5k	20k	20k	4	Acc
HellaSwag [40]	39.9k	10k	10k	4	Acc
Commonsense QA [41]	9.74k	1.22k	1.14k	5	Acc

Table 3: The statistics of datasets for evaluation. All of them are classification tasks, where the training and validation set have labels, while the test set does not. For the evaluation metrics, "Acc", "F1", "Mcc", and "EM" mean accuracy, f1 score, Matthews correlation coefficient, and exact match score, respectively.

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- **Analysis**:
  > Task performance (why better or worse);
  > Ablation study (effectiveness of each component);
  > Error analysis & Case study & Discussion → Research insights

Expected Contributions

Project focus: ***How do we effectively incorporate contextual information to (MAIN) enhance problem-solving performance and (FUTURE) potentially mitigate hallucination in LLMs?***

- We will systematically implement the RAG system emphasizing commonsense reasoning. The code, data, and results will be released on GitHub [3].

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- We will extensively examine the effectiveness of different RAG methods for multiple LLMs on various commonsense tasks. The results will bring findings & ideas for further improvement.
- We will conduct in-depth analyses and ablation studies to assess the efficacy of different RAG components. The analysis could shed light on future commonsense RAG research.

[3] `https://github.com/YuweiYin/UBC_CPSC_532V`

Task Division

We will work together on research idea discussion, result analysis, and paper writing. The main focus of each member is as follows:

- **Juntai Cao** & **Yilin Yang**:
  Step 1 Building knowledge base;
  Step 2 Indexing;
  Step 3 Retrieval;
  Step 6 Advanced RAG;
  Results analysis
- **Yuwei Yin**:
  Project leading;
  Step 3 Retrieval;
  Step 4 Augmentation;
  Step 5 Generation/Evaluation/Training;
  Step 6 Advanced RAG;
  Paper writing

Timeline

- Before Reading Week: Project planning & Literature review
- 02.19–02.25 (Reading Week) + 02.26–03.03:
  > Done: (Yuwei) Step 5 Generation/Evaluation/Training [4]
- 03.04–03.10:
  > Done: Proposal writing & presenting
  > Doing: collecting knowledge sources
- 03.11–03.17 Todo:
  > (Juntai & Yilin) Step 1 Building knowledge base
  > (Yuwei) Step 4 Augmentation (unify knowledge structure)

[4] The code and preliminary results: `https://github.com/YuweiYin/UBC_CPSC_532V/tree/master/Project#experimental-results`

Timeline

- 03.18–03.24 Todo:
  > (Juntai & Yilin) Step 1 Building KB & Step 2 Indexing
  > (Yuwei) Step 4 Augmentation (Zero-shot, ICL, CoT, SFT)
- 03.25–03.31 Todo:
  > (Juntai & Yilin) Step 2 Indexing & Step 3 Retrieval
  > (Yuwei) Experiment Pipeline: Step 4 + Step 5
- 04.01–04.07 Todo:
  > (Juntai & Yilin) Results analysis & Step 6 Advanced RAG
  > (Yuwei) Experiments (Step 1+2+3+4+5[+6])
- 04.08–04.12 Todo:
  > (Juntai & Yilin) Results analysis & Paper writing
  > (Yuwei) Experiments & Paper writing
  Project Presentation (due Apr 10) & Paper (ddl Apr 12)


Q&A

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Thanks