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Exploring the Impact of Table-to-Text Methods on Augmenting LLM-based Question Answering with Domain Hybrid Data

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Introduction

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- Enhancing LLMs in Domain-Specific Question Answering
  - ➢ Domain-Specific Fine-Tuning (DSFT)
  - ➢ Retrieval-Augmented Generation (RAG)

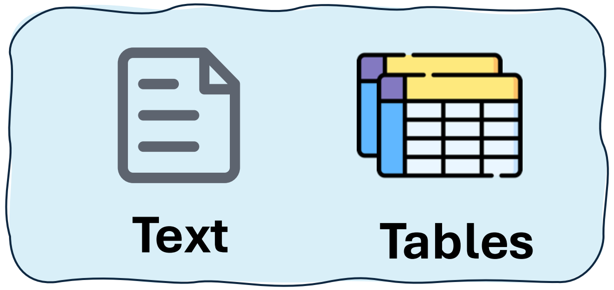
Both rely on domain-specific corpus

- Real-World Data Consists of Hybrid Data (Text and Tables)

Common in : Scientific Literature , Medical Reports, etc.

Tables alongside text provide :

- Supplementary or complementary information
- Enhancing the understanding of the content



Domain Documents

Current Methods and Their Drawbacks

- Method 1 : Flattening Tables (Concatenates table cells row by row)

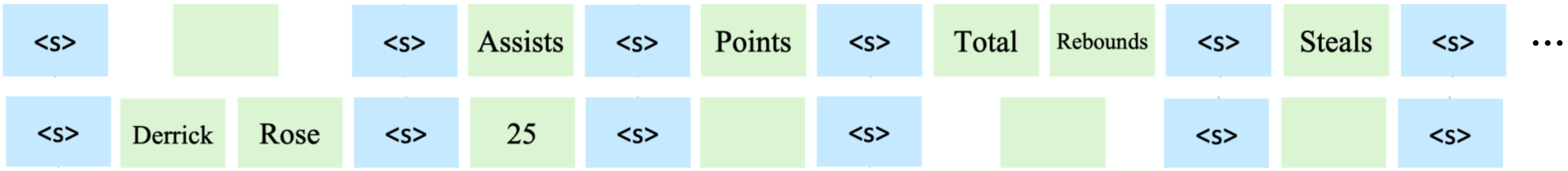
  Results in :

  ➢ The loss of structural information

  ➢ Disrupts the informational links between cells

  ➢ Introduces the non-natural language text

	Assists	Points	Total rebounds	Steals
Al Horford	5	15	7	3
Isaiah Thomas		27		
Marcus Smart	7	15		
Carmelo Anthony		29		
Kristaps Porzingis		22	12	
Derrick Rose		25		



Current Methods and Their Drawbacks

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- Method 2 : Mapping Text and Tables to Different Vector Spaces

  Results in :

  ➢ Increases the complexity of system (needs multimodal models or multiple models)

  ➢ Disrupts the semantic connection between the two types of data (Text and Tables)

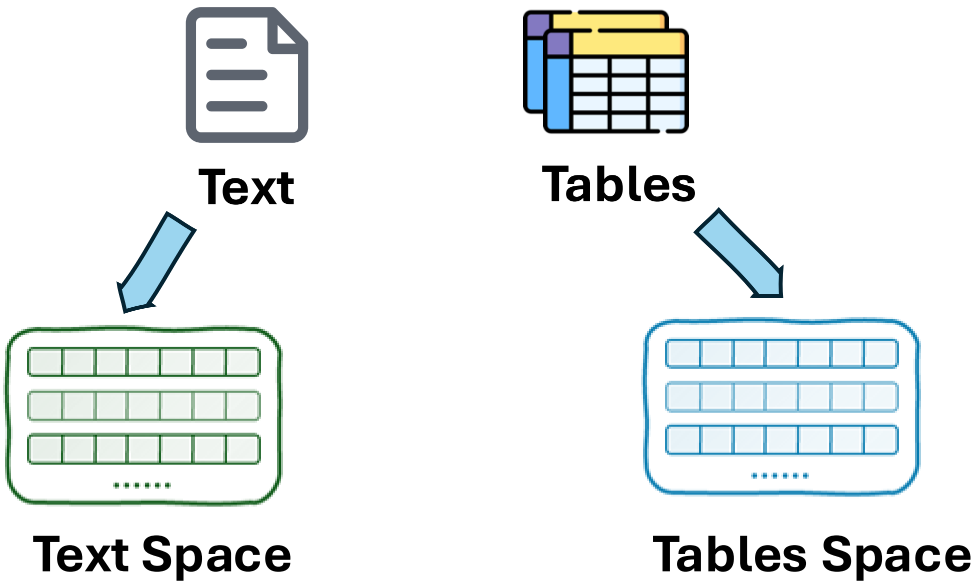

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Table-to-Text Generation

- Generates natural language statements that faithfully describe the information in the provided table
- Four representative table-to-text strategies:
  - ❑ 1. Markdown format.
  - ❑ 2. Template serialization: a set of templates designed.
  - ❑ 3. TPLM-based method: fine-tuning Traditional PLM, like BART, on specific task datasets
  - ❑ 4. LLM-based method: ChatGPT, one-shot in-context learning setting.

Frenquency Band	Channel Bandwidth	Peak Data Rate
6 GHz	320 MHz	11.53 Gbps
5 GHz	160 MHz	5.765 Gbps
2.4 GHz	40 MHz	1.376 Gbps
. . .		

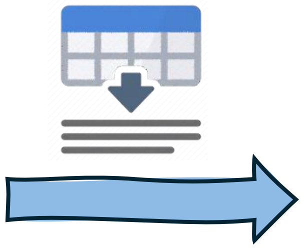

Table-to-Text Generation

The 6 GHz band offers a channel bandwidth of 320 MHz. It can reach a peak data rate of 11.53 Gbps (gigabits per second). The 5 GHz band has a channel bandwidth of 160 MHz. Its peak data rate is 5.765 Gbps ...

Advantages of Using Table-to-Text Generation

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- Transforms hybrid data into a unified natural language representation
  - 1. Simplifies hybrid data scenarios into pure text scenarios
  - 2. Seamlessly integrates with any SOTA LLMs (which typically focus on text understanding and processing)
  - 3. Pure text format is easy for training domain-specific LLMs

- Preserves the semantic connections between the data
  - 1. Preserves the integrity of document content

    → beneficial for the model to learn a complete knowledge by finetune
  - 2. Facilitates information retrieval in RAG systems

Research Gap

- The lack of comparative analysis on how different table-to-text methods affect the performance of domain-specific QA systems.

We address this research gap:

- Step 1: Innovatively integrates table-to-text generation into the LLM-based Domain QA framework
- Step 2: Conducts extensive experiments with different table-to-text methods on two types of QA systems

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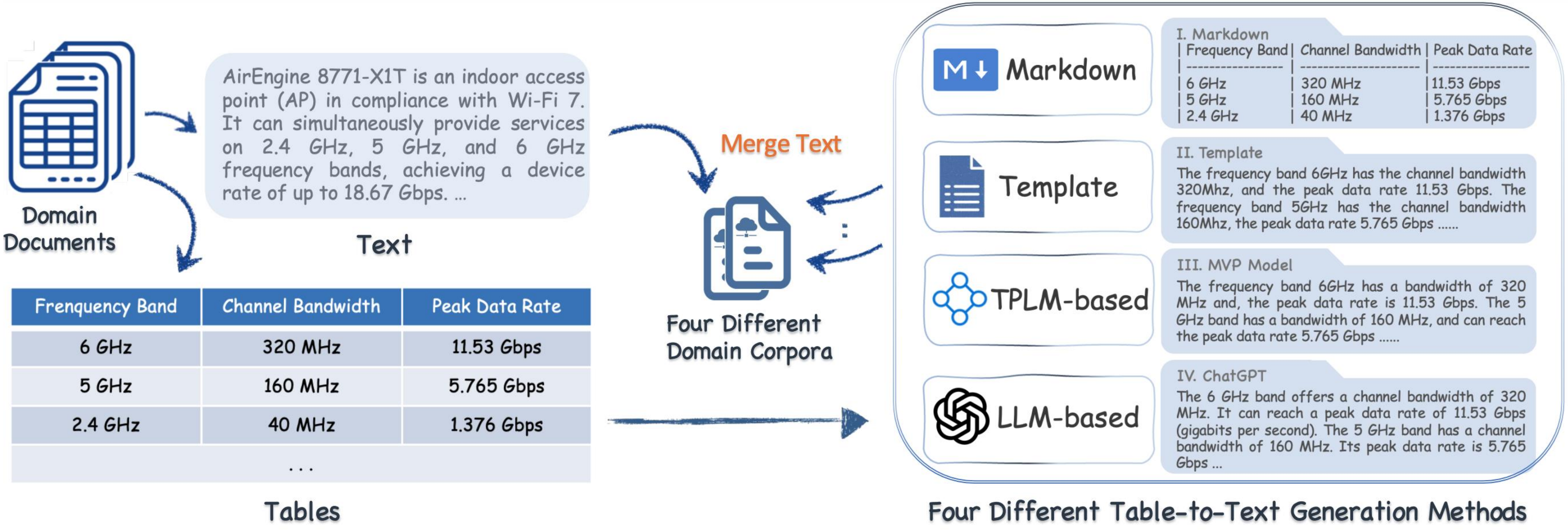
Building Domain Corpora with Table-to-text



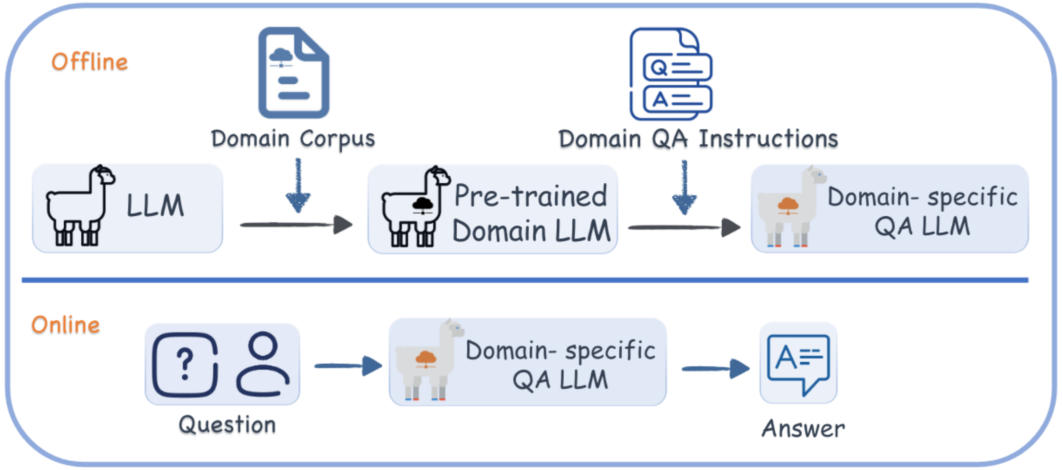
Building LLM-based QA Systems with Domain Corpora

System1 - DSFT:

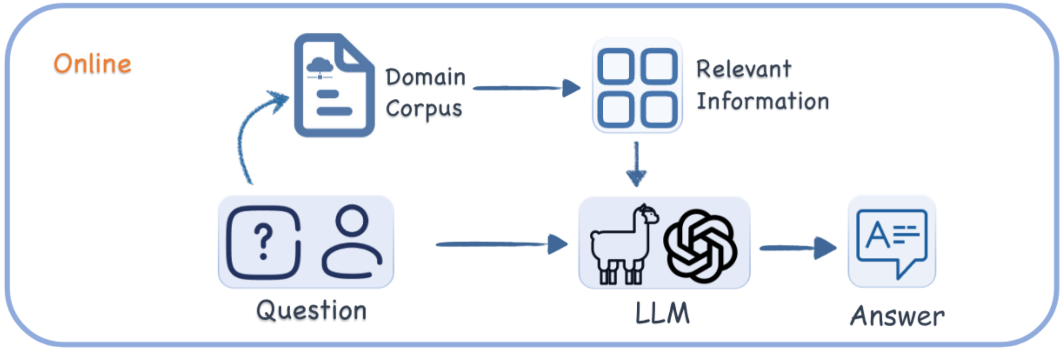
- Step 1: Incrementally pre-train the LLM on the domain corpus
- Step 2: Instruction tuning on the QA task

System 2 - RAG:

- LangChain framework
- Dense Passage Retriever (DPR) method for information retrieval



(a) Domain-Specific Fine-Tuning QA system



(b) Retrieval-Augmented Generation QA system

Dataset

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ICT-DATA:

- Real-world industry hybrid dataset, English.
- Based on 170 technical documents related to ICT products
- 178 million words, 6GB text storage size
- Table data accounts for about 18% of the total word count

ICTQA:

- 9k questions with long-form answers
- Test set: 500 questions, whose answers involve knowledge from both tables and text.

ICT: Information and Communication Technology

Evaluation Metrics

Automated Evaluation:

- GPT-4 as an evaluator
- In-context learning: one demonstration
- Range: 0 to 5, discrete values. larger denotes better
- Based on helpfulness and similarity to the golden answer

Human Evaluation:

- 3 evaluators with domain knowledge
- Same scoring criteria with GPT-4

Experimental Setup

DSFT Paradigm:

- Meta's OPT (1.3B to 13B)
- Llama2-base (7B, 13B)
- QLoRA for pre-training and instruction fine-tuning

RAG Paradigm:

- Llama2-chat (7B, 13B, and 70B)
- GPT-3.5-turbo
- BGE model for DPR embedding
- Top-3 relevant text chunks based on similarity

Fair Comparison: the same settings on four different corpora.

Results and Analysis

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Metrics	Table-to-Text Method	Domain-Specific Fine-Tuning OPT-1.3B	OPT-2.7B	OPT-6.7B	OPT-13B	Llama2-7B	Llama2-13B	Retrieval-Augmented Generation GPT-3.5-turbo	Llama2-7B	Llama2-13B	Llama2-70B
Human Eval.	Markdown	2.05	2.41	2.38	2.51	2.82	3.05	3.29	**3.72**	3.98	3.94
	Template	2.04	2.40	2.26	2.47	2.82	3.04	3.36	3.44	3.96	3.76
	TPLM-based	2.12	2.43	2.43	2.58	**3.20**	3.13	3.26	3.27	3.92	3.64
	LLM-based	**2.18**	**2.57**	**2.51**	**2.62**	2.96	**3.19**	**3.62**	3.71	**4.26**	**4.09**
	RSD(%)	2.80	3.40	5.00	3.00	7.60	3.00	7.20	9.00	6.80	9.00
GPT-4 Eval.	Markdown	1.74	2.16	2.27	2.25	2.7	3.06	3.28	**3.66**	3.67	**3.74**
	Template	1.81	2.22	2.39	2.34	2.84	3.08	3.27	3.06	3.38	3.37
	TPLM-based	2.33	2.46	2.45	2.53	**3.20**	3.19	3.28	2.9	3.41	3.30
	LLM-based	**2.57**	**2.69**	**2.73**	**2.86**	3.06	**3.30**	**3.64**	3.59	**3.69**	3.54
	RSD(%)	16.60	10.60	9.20	12.20	10.00	4.80	7.40	15.20	6.20	8.80

Relative Score Differences (RSD):

- 2.8% to 9.0% in human evaluation
- 4.8% to 16% in GPT4 evaluation

significantly impact the performance of systems

Performs well in DSFT paradigm:

- LLM-based method
- TPLM-based method

Performs well in RAG paradigm:

- LLM-based method
- Markdown format (surprise!)

Results and analysis

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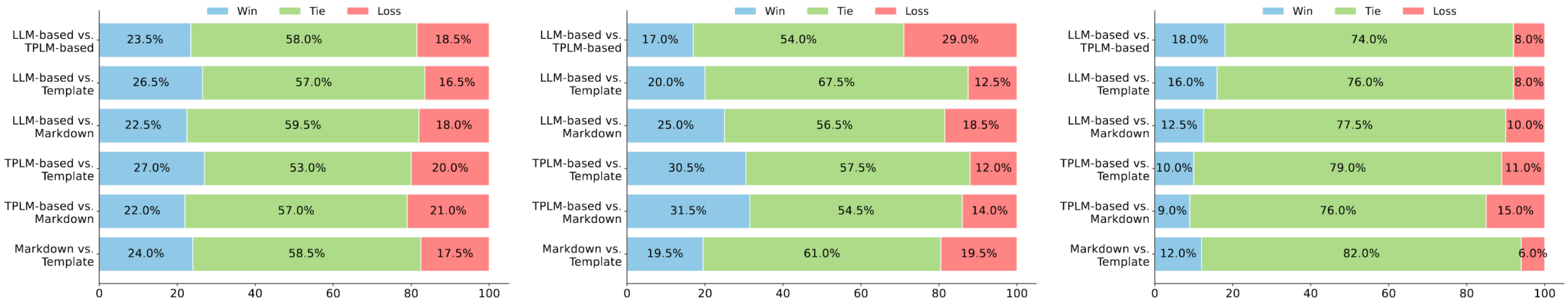

(a) OPT-6.7B in DSFT Paradigm (b) Llama2-7B in DSFT Paradigm (c) Llama2-70B in RAG Paradigm

Comparison of human evaluation scores between QA models using different Table-to-Text methods.

‘A vs. B win’ indicates the percentage of test set instances where Model A’s score surpasses Model B’s.

Results and analysis

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RQ: What are the potential reasons for their different performances?

In DSFT Paradigm:

Freq (k)	$C_1\cdot$ Markdown	$C_2\cdot$ Template	$C_3\cdot$ TPLM-based	$C_4\cdot$ LLM-based
Term	821	1040	2358	2254
Verbs	313	315	682	1207

Absolute frequency of verbs and terms contained in the corpora C_i generated by different methods.

higher frequency of domain-specific terms and verbs leads to better system performance.

- *LM-based methods tend to supplement the domain entities as subjects/objects.
- Template methods use more pronouns, and monotonous predicates.
- Markdown format only retains the original content in the tables.

Results and analysis

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RQ: What are the potential reasons for their different performances?

In RAG Paradigm:

Under the same LLM reader setup:

Semantic representations quality

↓

Retrieval accuracy

↓

RAG performance

A t-SNE visualization of chunk clusters in the embedding space.

Retrieval-friendly method: LLM-based | Markdown format

Results and analysis

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Some practical suggestions for choosing table-to-text methods

Ready-to-use tips

DSFT Paradigm:

- LLM-based method (Pros: best performance; Cons: GPU/API cost, Data leakage risks)
- TPLM-based(Can well-tuned on this task. A good alternative for LLM)

RAG Paradigm:

- LLM-based method
  - best performance
- Markdown format (viable substitute)
  - ✓ easy-to-use
  - ✓ GPU-Free

Freq (Avg.)	Markdown	Template	TPLM-based	LLM-based
Text Len	998	1259	1138	897

The average length of text generated by different methods for each table.

More Concise Text → Less Memory Costs
Less GPU Costs

Thank You

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