Can LLMs Generate Tabular Summaries of Science Papers? Rethinking the Evaluation Protocol

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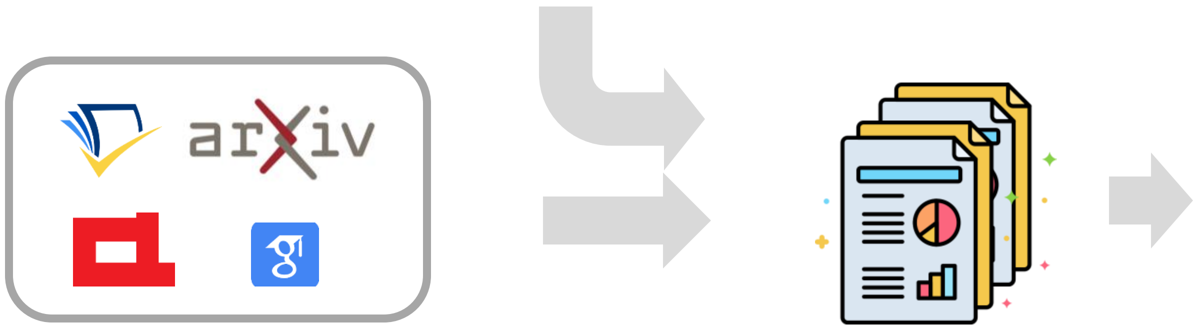
Task: Generating Tabular Summary for Scientific Content

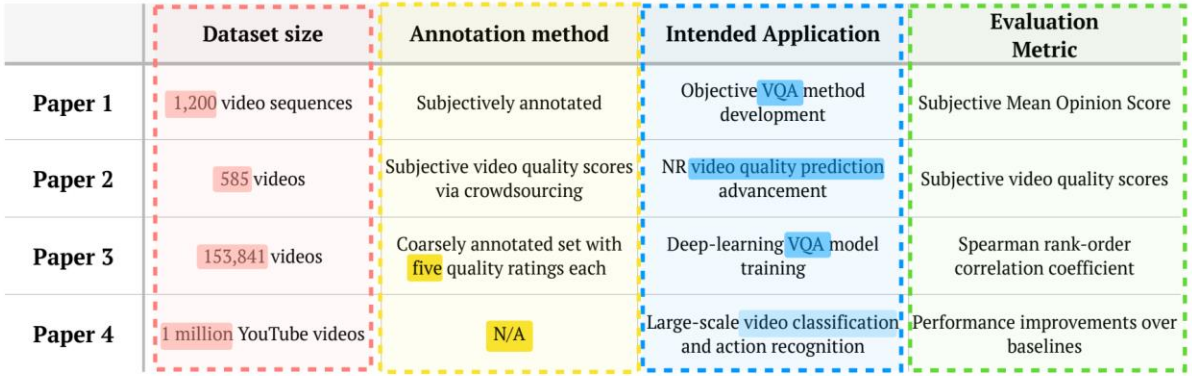
- **Input:** A user prompt seeking scientific information.
- **Output:** A table that summarizes the information/insights extracted from the relevant science papers.

Prompt: Generate a table comparing video dataset papers



Repositories of science: arXiv, Google Scholar, etc.

Potentially relevant papers



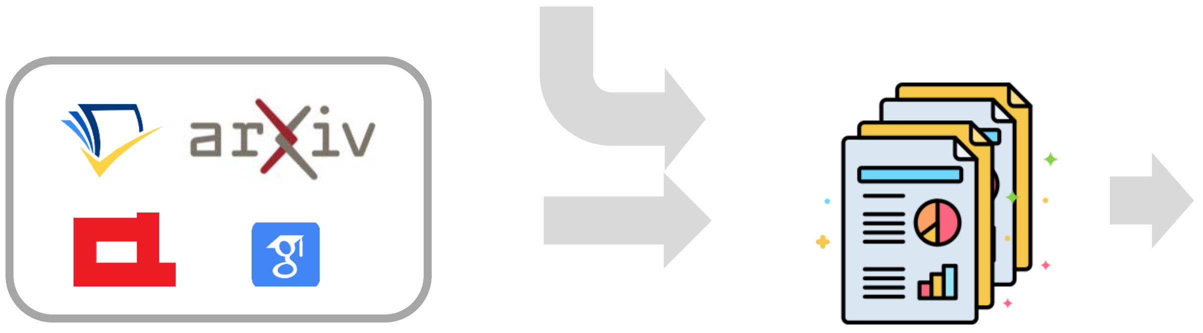
	Dataset size	Annotation method	Intended Application	Evaluation Metric
Paper 1	1,200 video sequences	Subjectively annotated	Objective VQA method development	Subjective Mean Opinion Score
Paper 2	585 videos	Subjective video quality scores via crowdsourcing	NR video quality prediction advancement	Subjective video quality scores
Paper 3	153,841 videos	Coarsely annotated set with five quality ratings each	Deep-learning VQA model training	Spearman rank-order correlation coefficient
Paper 4	1 million YouTube videos	N/A	Large-scale video classification and action recognition	Performance improvements over baselines

Tabular summary

Why solve this task?

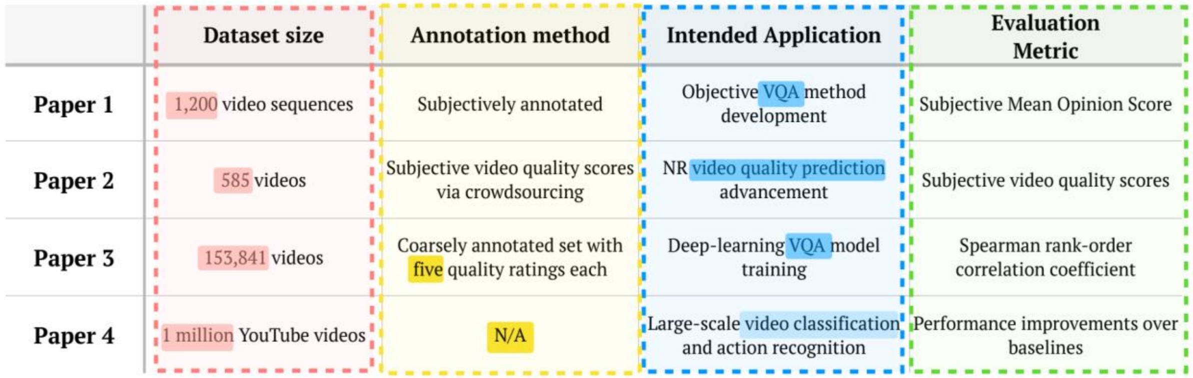
- Tables are widely accepted format for scientific content.
  - Improves clarity, enables comparisons
- Integrating it into our workflow will improve quality and interpretability.

Prompt: Generate a table comparing video dataset papers



Repositories of science: arXiv, Google Scholar, etc.

Potentially relevant papers



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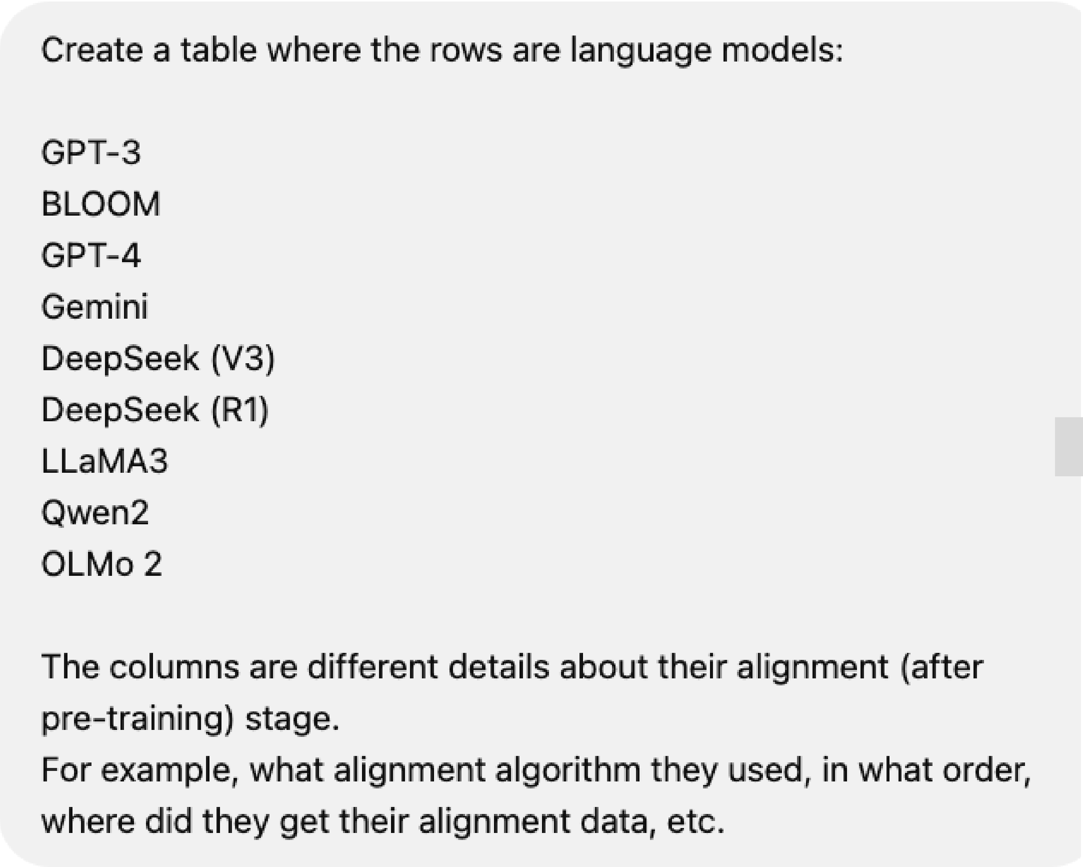
Tabular summary

How good is the state-of-the-art at this task?

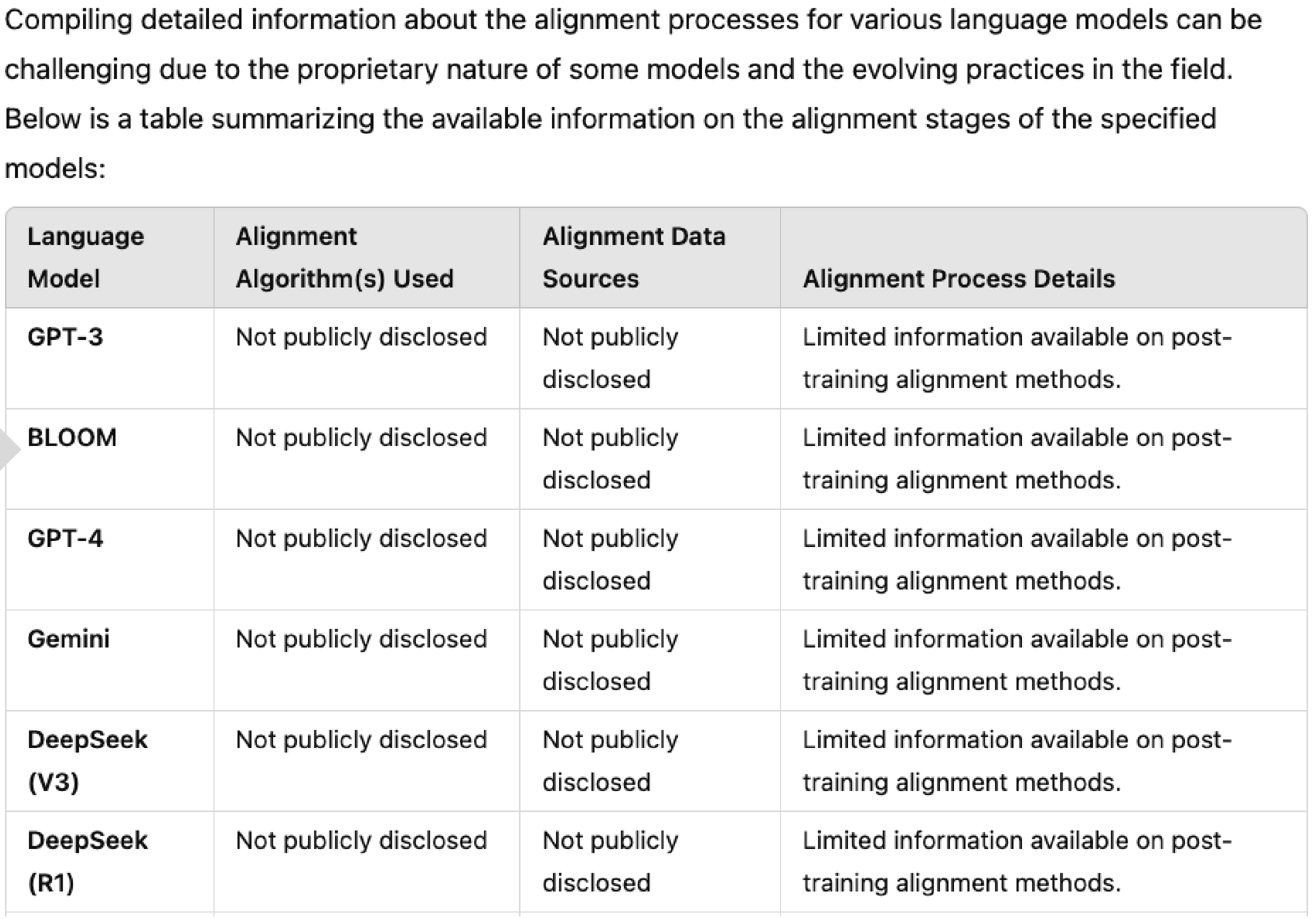


Create a table where the rows are language models:

GPT-3
BLOOM
GPT-4
Gemini
DeepSeek (V3)
DeepSeek (R1)
LLaMA3
Qwen2
OLMo 2

The columns are different details about their alignment (after pre-training) stage.
For example, what alignment algorithm they used, in what order, where did they get their alignment data, etc.

ChatGPT



Compiling detailed information about the alignment processes for various language models can be challenging due to the proprietary nature of some models and the evolving practices in the field. Below is a table summarizing the available information on the alignment stages of the specified models:

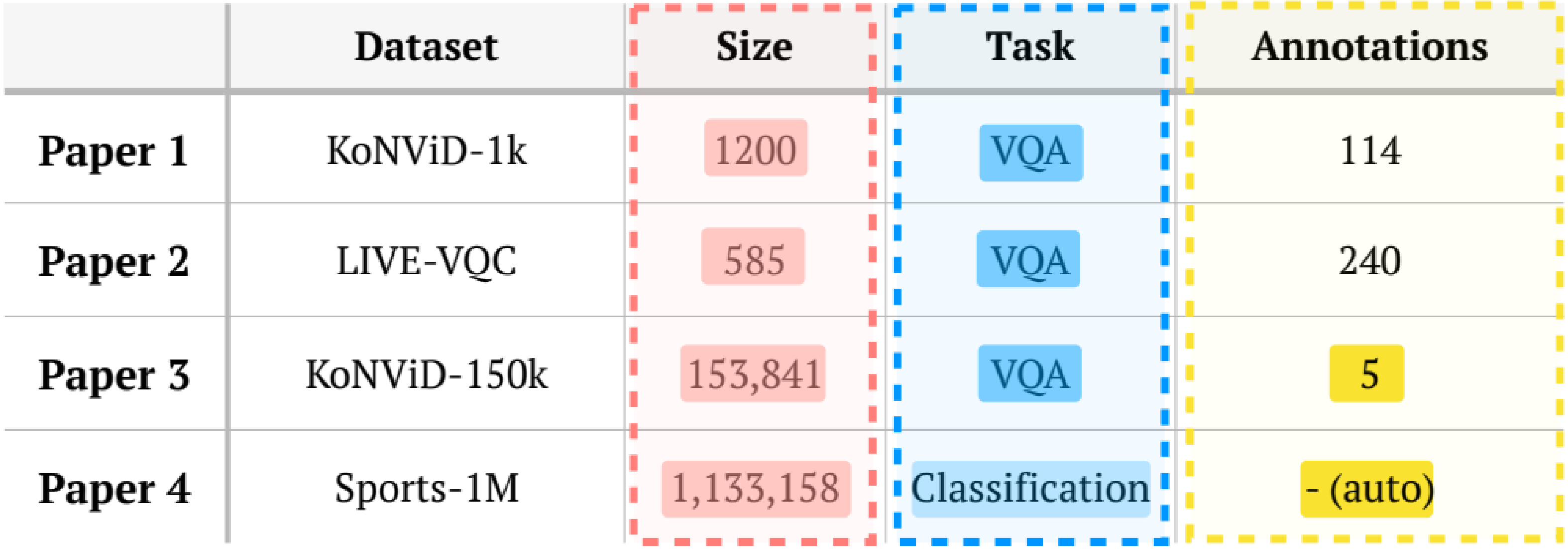
Language Model	Alignment Algorithm(s) Used	Alignment Data Sources	Alignment Process Details
GPT-3	Not publicly disclosed	Not publicly disclosed	Limited information available on post-training alignment methods.
BLOOM	Not publicly disclosed	Not publicly disclosed	Limited information available on post-training alignment methods.
GPT-4	Not publicly disclosed	Not publicly disclosed	Limited information available on post-training alignment methods.
Gemini	Not publicly disclosed	Not publicly disclosed	Limited information available on post-training alignment methods.
DeepSeek (V3)	Not publicly disclosed	Not publicly disclosed	Limited information available on post-training alignment methods.
DeepSeek (R1)	Not publicly disclosed	Not publicly disclosed	Limited information available on post-training alignment methods.

Example retrieved on 02/27/2025

Recent related work: ArxivDigesTables

Newman et al. ArxivDIGESTables: Synthesizing Scientific Literature into Tables using Language Models, EMNLP 2024

- Extracted 2.2K tables from existing papers.
- The table captions serve as the task prompts.
- Rows of the table correspond to individual papers (7K) papers.

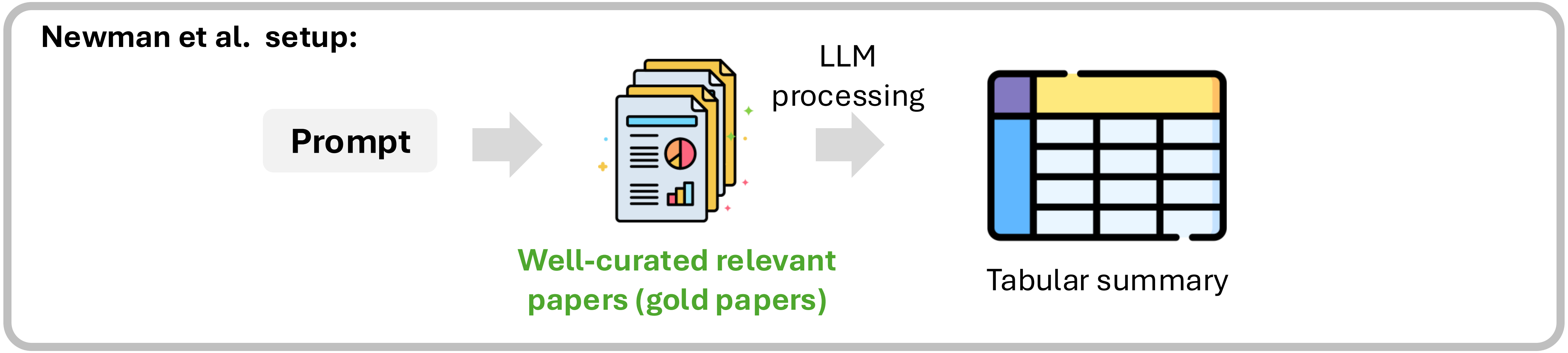


	Dataset	Size	Task	Annotations
Paper 1	KoNViD-1k	1200	VQA	114
Paper 2	LIVE-VQC	585	VQA	240
Paper 3	KoNViD-150k	153,841	VQA	5
Paper 4	Sports-1M	1,133,158	Classification	- (auto)

We build upon this work by addressing their weaknesses!

Limitations of prior work

1. **The assumption that papers a carefully curated relevant papers are available, is idealistic in realistic scenarios.**
2. Table captions are not appropriate task prompts.
3. Rely on static embedding and human annotation to evaluate generated tables.



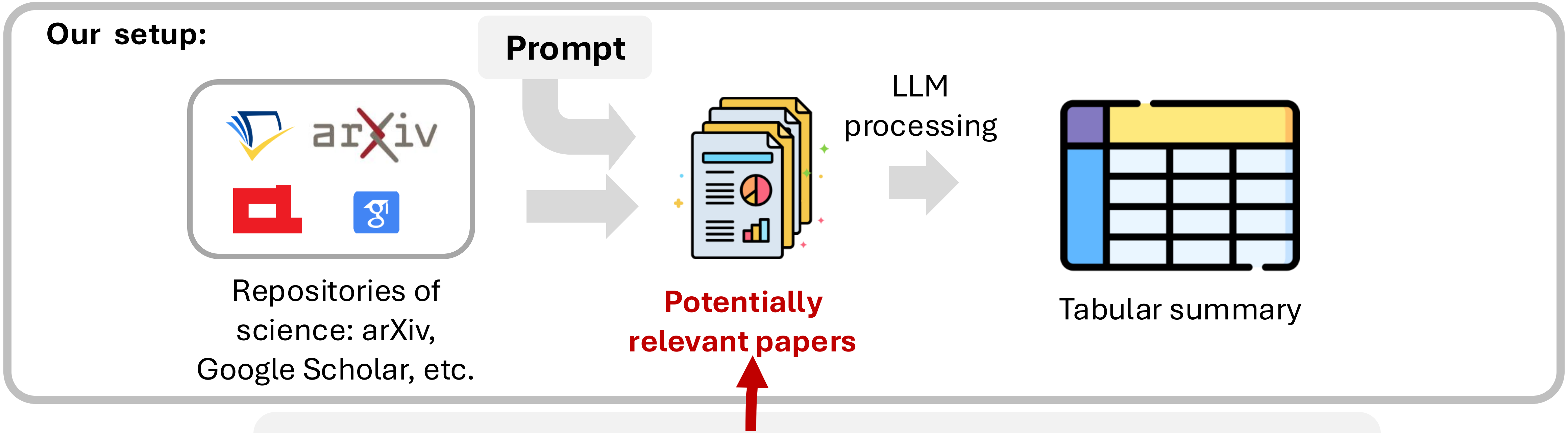
Newman et al. setup:

Prompt

LLM processing

Well-curated relevant papers (gold papers)

Tabular summary



Our setup:

Prompt

Repositories of science: arXiv, Google Scholar, etc.

LLM processing

Potentially relevant papers

Tabular summary

We build a retrieval engine over papers and identify hard negative candidate papers to make evaluation realistic.

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User Demand vs. Captions

- Prompts in prior work [Newman et al.] are table captions.

Comparison of Trajectory and Path Planning Approach

Brief and ambiguous

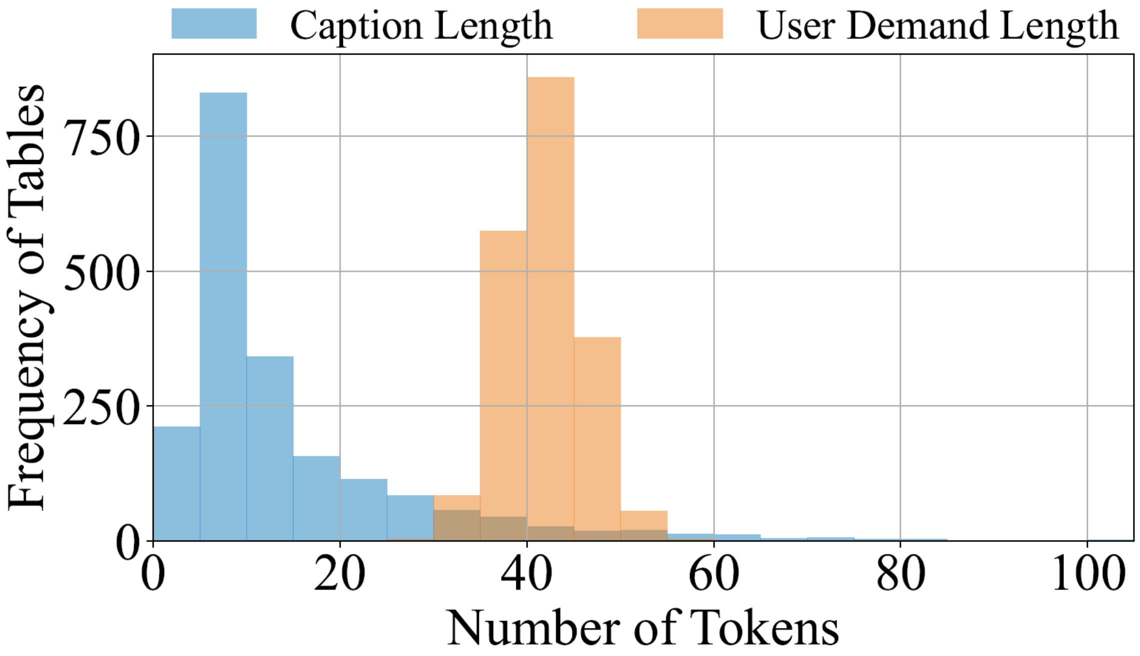
- We replace them with **user demand** prompts:

Generate a table that compares different trajectory and path planning approaches. You can focus on their collision avoidance techniques, benefits, limitations, and applicable scenarios.

Longer and more precise

  - We collect these by careful prompting of LLMs to:
    - (1) obtain a more complete prompt while
    - (2) avoiding leakage of table schema/values.

User Demand vs. Captions



Our collected user demands feature longer context, thus including better hints to curate the table.

Limitations of prior work

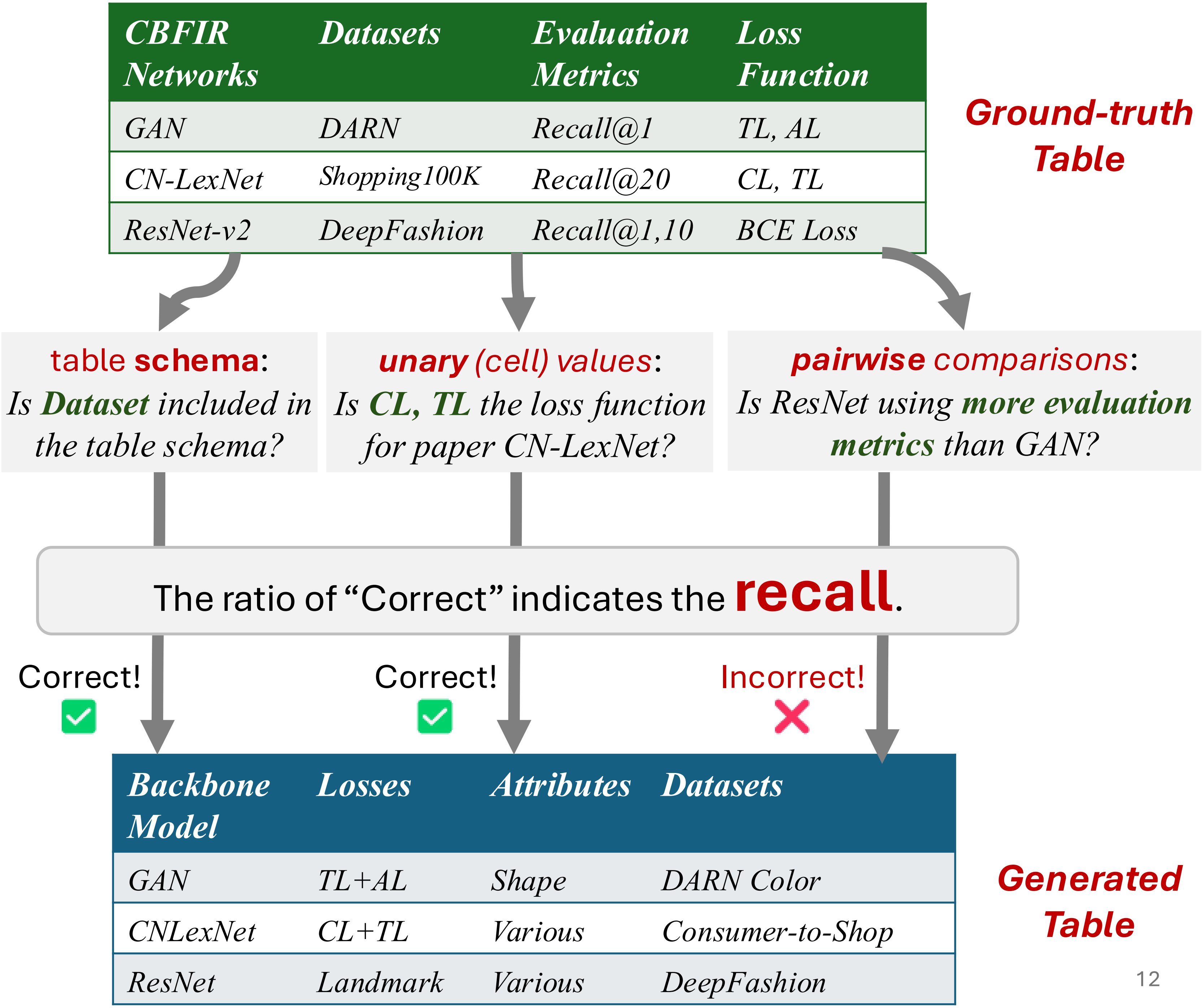
1. The assumption that papers a carefully curated relevant papers are available, is idealistic in realistic scenarios.
2. Table captions are not appropriate as task prompts.
3. **Rely on static embedding and human annotation to evaluate generated tables.**

Originally, we have a ground-truth table extracted from a paper

We synthesize QA pairs from the ground-truth table about schema and values

Then, we ask an LLM to answer these QAs based on the generated table

Then, we have a table that is generated by an LLM



Ground-truth Table

CBFIR Networks	*Datasets*	*Evaluation Metrics*	*Loss Function*
GAN	*DARN*	*Recall@1*	*TL, AL*
CN-LexNet	*Shopping100K*	*Recall@20*	*CL, TL*
ResNet-v2	*DeepFashion*	*Recall@1,10*	*BCE Loss*

table **schema**:
*Is **Dataset** included in the table schema?*

unary *(cell) values*:
*Is **CL, TL** the loss function for paper CN-LexNet?*

pairwise comparisons:
*Is ResNet using **more evaluation metrics** than GAN?*

The ratio of "Correct" indicates the **recall**.

Correct! ✓

Correct! ✓

Incorrect! ✗

Backbone Model	*Losses*	*Attributes*	*Datasets*
GAN	*TL+AL*	*Shape*	*DARN Color*
CNLexNet	*CL+TL*	*Various*	*Consumer-to-Shop*
ResNet	*Landmark*	*Various*	*DeepFashion*

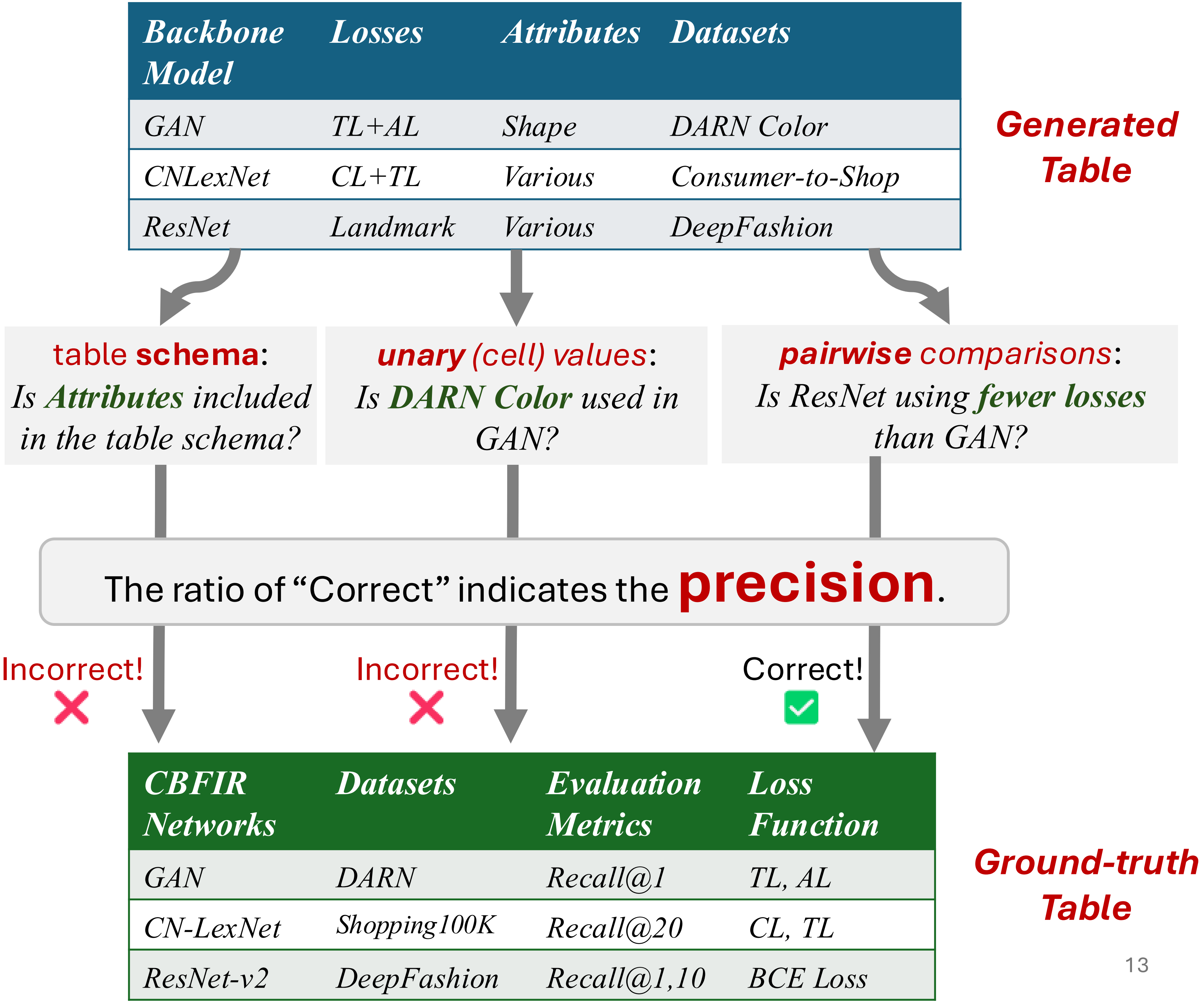
Generated Table

Similarly, we can reverse the process by starting with the generated table.

Again, we synthesize QAs based on the generated table.

But answer them using the ground-truth table.

And answer QAs using our ground-truth table.



Generated Table

Backbone Model	*Losses*	*Attributes*	*Datasets*
GAN	*TL+AL*	*Shape*	*DARN Color*
CNLexNet	*CL+TL*	*Various*	*Consumer-to-Shop*
ResNet	*Landmark*	*Various*	*DeepFashion*

table **schema**: *Is* ***Attributes*** *included in the table schema?*

unary *(cell) values*: *Is* ***DARN Color*** *used in GAN?*

pairwise *comparisons*: *Is ResNet using* ***fewer losses*** *than GAN?*

The ratio of “Correct” indicates the **precision**.

Incorrect! ✗

Incorrect! ✗

Correct! ✓

Ground-truth Table

CBFIR Networks	*Datasets*	*Evaluation Metrics*	*Loss Function*
GAN	*DARN*	*Recall@1*	*TL, AL*
CN-LexNet	*Shopping100K*	*Recall@20*	*CL, TL*
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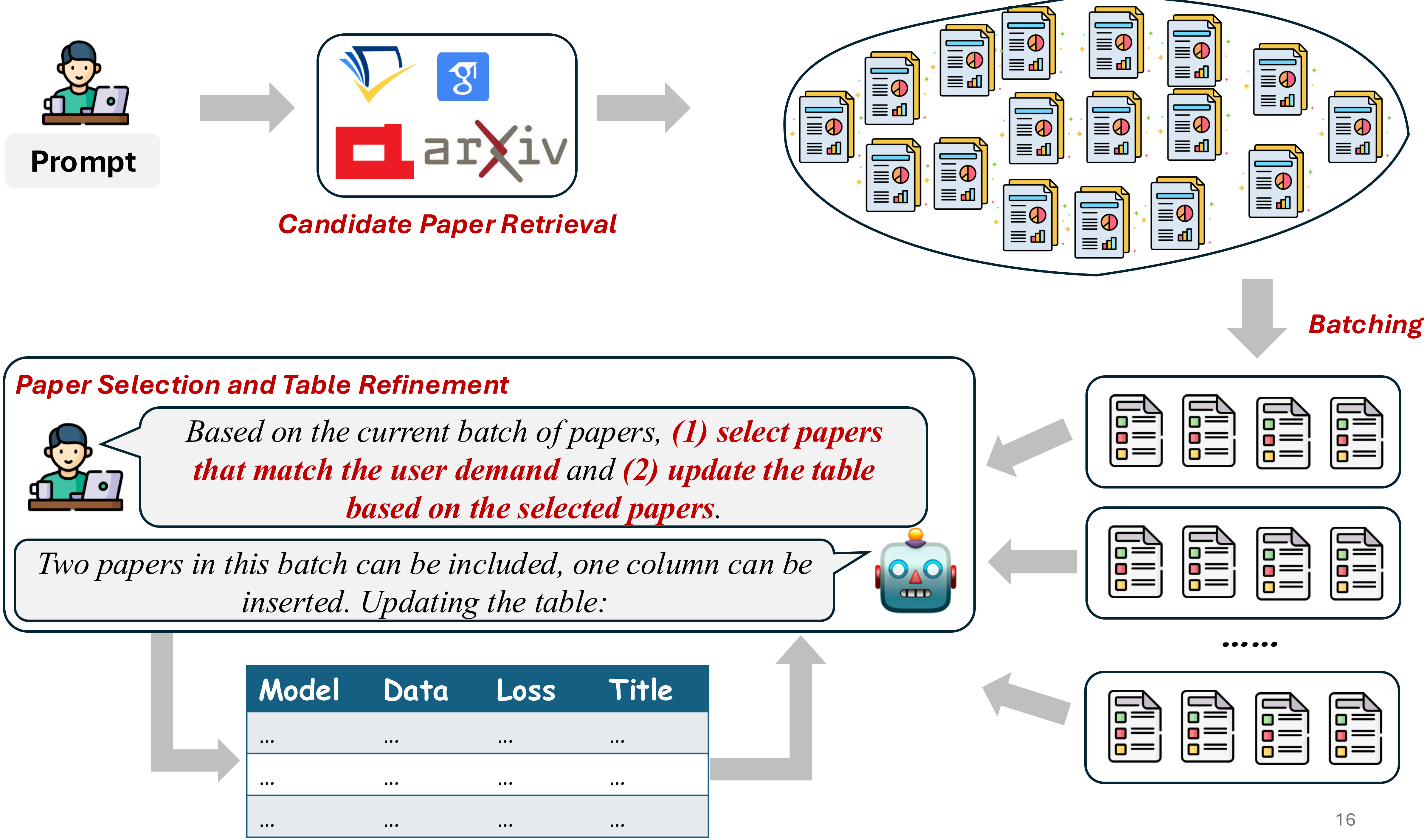
Our released data: **arXiv2Table**

- Expanded version of Newman et al. 2024.
- Contains
  - 2.1K user demand prompts
  - 2.1K tables (inherited from arXivDigestable).
    - Dropped few low-quality tables.
  - Each prompt comes with it a set of candidate (distractor + gold) papers.
  - Evaluation framework based on utilization.

Dataset will be on arXiv on coming weeks!

We also proposed a new approach

- An inference-time algorithm that iteratively digests and organizes papers in tabular form.



Prompt

Candidate Paper Retrieval

Batching

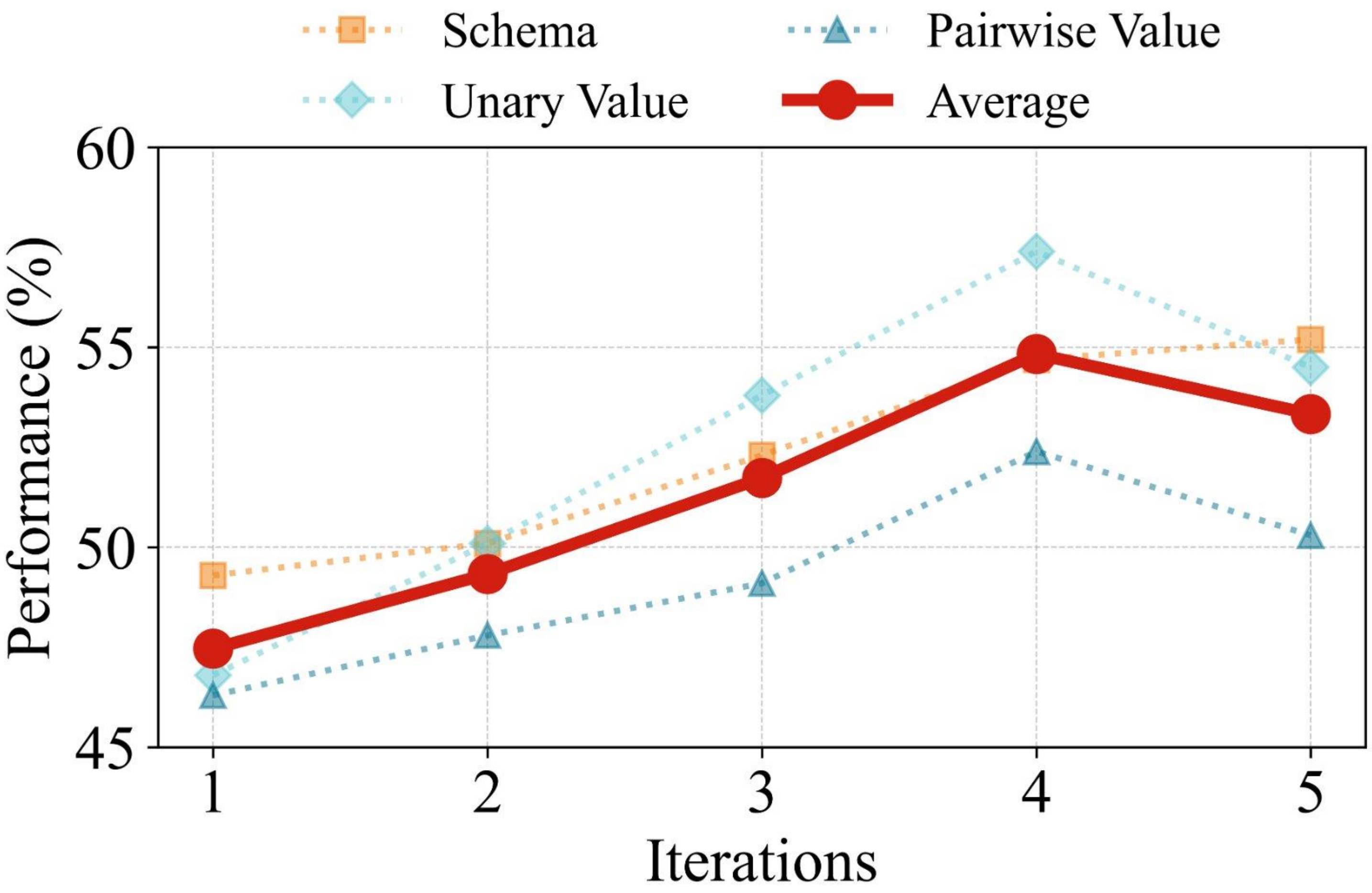
Paper Selection and Table Refinement

*Based on the current batch of papers, **(1) select papers that match the user demand** and **(2) update the table based on the selected papers**.*

Two papers in this batch can be included, one column can be inserted. Updating the table:

Model	Data	Loss	Title
...	...	...	...
...	...	...	...
...	...	...	...

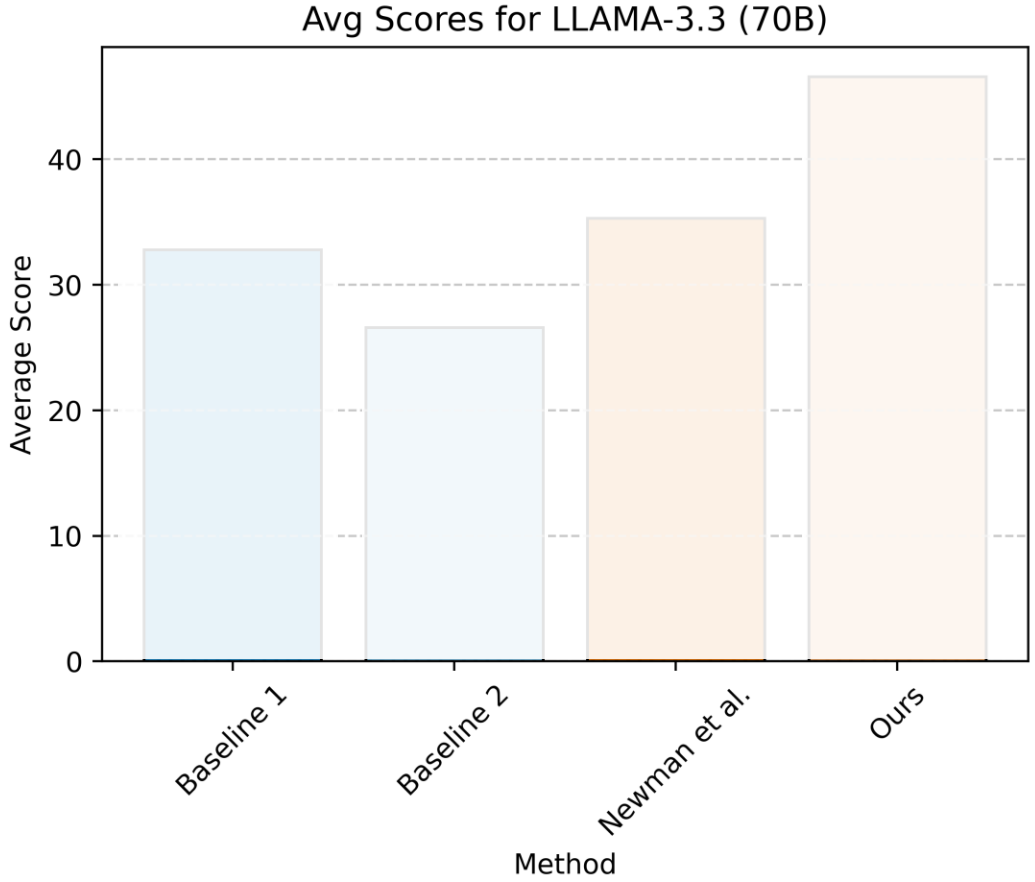
Evaluation vs Number of Iterations



With more iterations, all aspects of the generated tables improves (up to iter ~4).

Evaluation of the end-to-end pipeline

- **Model:** Llama 3.3 (70B)
- **Baseline 1:** All papers processed in one conversation round.
- **Baseline 2:** One-conversation round per paper.
- **Newman et al.:** Two stages; define schema in the first round, then fill in the values.

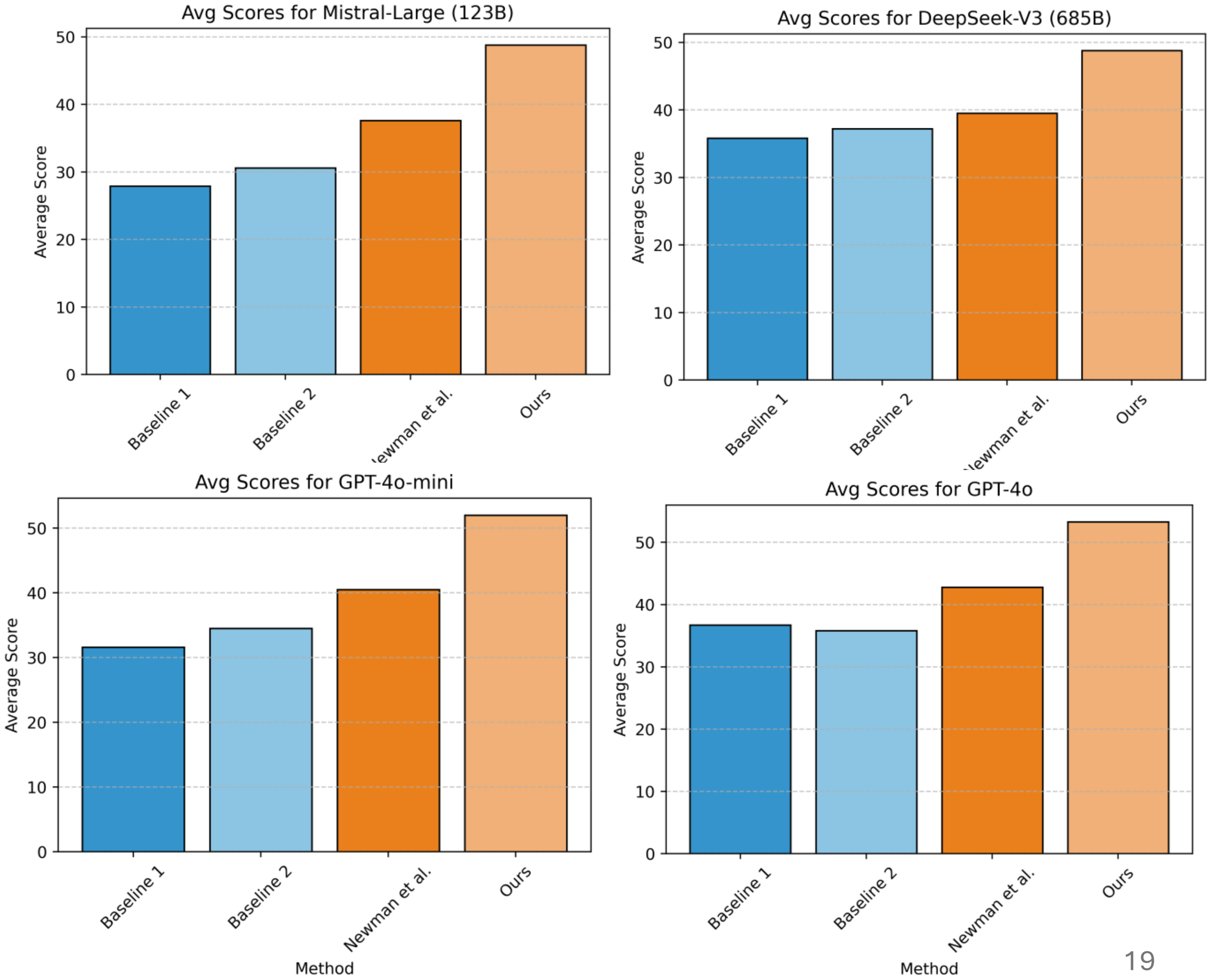


Our proposed approach outperforms existing results.

Evaluation of the end-to-end pipeline (other models)

The gains of our approach is consistent across different models.

The task remains challenging for all these approaches.



Summary and Conclusion

- **Motivation:** A more realistic pipeline for evaluating tabular summarization of science literature.
  - **Why?** Tabular summaries are crucial framework for quickly aggregating and understanding the progress in science.
- We introduce arXiv2Table, a framework for evaluating systems for tabular summarization.
- We also develop a system to address the challenge posed.
- Our benchmark is challenging! Give it a try!! 🚀