

SurveyGen: Quality-Aware Scientific Survey Generation with Large Language Models

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Motivation

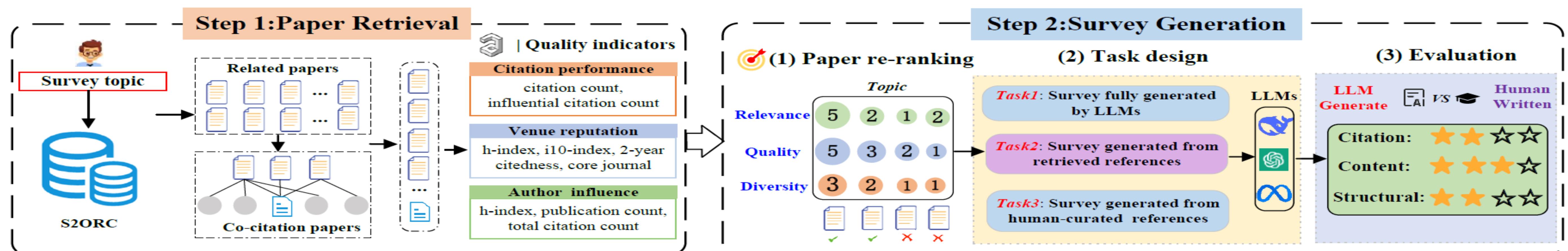
- Automatic survey generation has become a key task in the field of scientific document processing.
- RAG-based approaches overlook the assessment of academic quality during the paper retrieval stage.
- Missing large-scale datasets for evaluating generated surveys against human-written standards.

Dataset

We released **SurveyGen**, which includes over 4200 human-written surveys, 115,376 sections, 242,143 references directly cited within the surveys.

Dataset	Domains	#Docs	#Input Len	Target Len	#Input Docs	Structural Outline	Quality Indicators	Multi-level Citation	For Survey Generation
PubMed (2018)	Bio	133K	3016	203	1	✓	x	x	x
ArXiv (2018)	Mixed	215K	4938	220	1	✓	x	x	x
SciSummNet (2019)	CL	1K	4417	151	61.00	x	x	x	x
Multi-XScience (2020)	CS	40.5K	778	116	4.42	x	x	x	x
BigSurvey (2022)	Mixed	4.4K	11893	1051	76.30	x	x	x	x
SciReviewGen (2023)	CS	10.2K	12503	8082	68.00	✓	x	x	✓
SurveyGen(ours)	Mixed	4.2K	11423	5115	57.58	✓	✓	✓	✓

Our approach : QUAL-SG

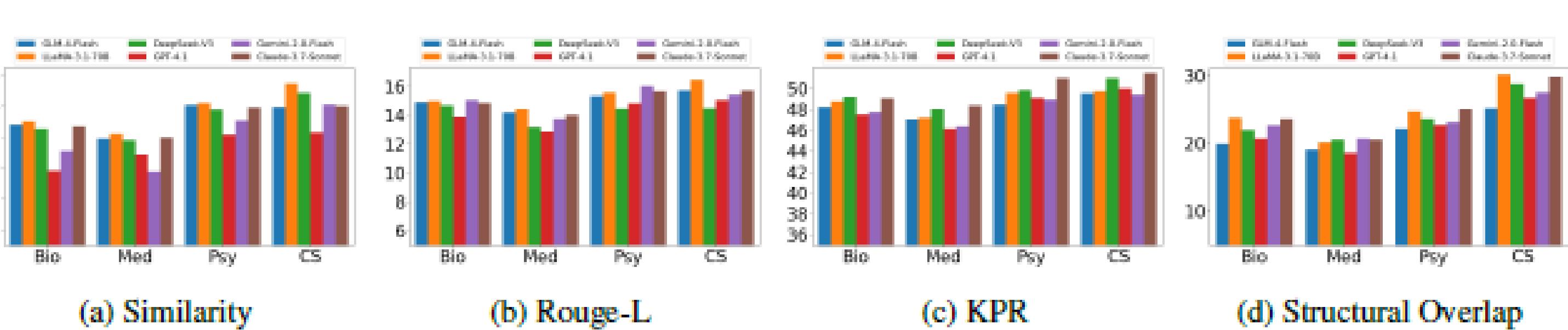


We build **QUAL-SG**, which includes two stages: **paper retrieval** and **survey generation**. The retrieval stage includes three steps: (1) retrieving topic-relevant papers, (2) expanding with frequently co-cited papers, and (3) enriching them with quality-related metadata. Based on the retrieved set, the generation stage first re-ranks the papers from three key aspects, then prompts LLMs to perform tasks under different input conditions. Finally, we evaluate the generated surveys against human-written ones across multiple dimensions.

Results

Model	Citation Quality			Content Quality			Structural Consistency		
	Acc. ↑	P ↑	R ↑	F1 ↑	Sim. ↑	R-L ↑	KPR ↑	Rel _{LLM}	Overlap (%)
🔓 Open-source LLMs									
GLM-4-Flash	9.27	9.03	3.26	4.79	81.27	15.04	41.71	2.44	10.62
LLaMA-3.1-70B	15.43	11.48	2.74	4.42	82.43	15.36	44.36	2.62	13.48
DeepSeek-V3	33.63	10.85	4.09	5.94	82.05	14.18	43.53	2.57	11.03
🔒 Closed-source LLMs									
GPT-4.1	21.07	12.31	3.72	5.71	79.51	13.48	39.21	2.39	10.95
Gemini-2.0-Flash	22.20	8.97	3.59	5.13	80.20	14.65	42.67	2.50	12.39
Claude-3.7-Sonnet	35.84	11.79	5.78	7.76	81.32	13.77	46.59	2.65	14.89

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Fully-LLMGen								
Fully-LLMGen	11.79	5.78	7.76	81.32	13.77	46.59	2.65	14.89
Naive-RAG	5.18	6.94	5.93	82.37	12.90	42.17	2.43	12.22
QUAL-SG (Ours)	15.87[†]	17.71[†]	16.73[†]	83.10[†]	15.17[†]	50.25[†]	2.81[†]	24.76[†]



- Only about 36% of the LLM-generated references are authentic, the RAG-retrieved references are real but largely **different from those selected by humans**, and the structural overlap with human-written surveys is only 14.89%.
- Our **QUAL-SG significantly improves** the reference matching, and further enhances performance at both the content and structural levels.
- The performance of LLM-generated surveys **varies across disciplines**, with better results observed in computer science.

Task	Comparison	Topic Relevance	Information Coverage	Critical Analysis	Overall Rating
Task 1	Comparable LLM-Generated > Human-written	33.3% 20.0%	33.3% 26.7%	26.7% 26.7%	20.0% 13.3%
Task 2	Comparable LLM-Generated > Human-written	33.3% 33.3%	46.7% 20.0%	40.0% 20.0%	26.7% 13.3%
Task 3	Comparable LLM-Generated > Human-written	40.0% 26.7%	53.3% 20.0%	46.7% 20.0%	26.7% 20.0%

- **Human evaluation results** show that human–AI collaboration—where humans refine the outline and select references, and then the LLM generates the survey content—achieves higher scores than fully LLM-generated surveys. However, they still fall short in terms of critical analysis and information coverage.

Discussions

- LLMs can assist in survey generation, they are still unable to independently craft surveys that meet academic standards at the current stage.
- Investigating human reference selection behavior is left for future work, and full-text access could further improve survey generation.



Code and data are available at:
<https://github.com/tongbao96/SurveyGen>