Benchmarking Computer Science Survey Generation

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Abstract

Scientific survey articles play a vital role in summarizing research progress, yet their manual creation is becoming increasingly infeasible due to the rapid growth of academic literature. While large language models (LLMs) offer promising capabilities for automating this process, progress in this area is hindered by the absence of standardized benchmarks and evaluation protocols. To address this gap, we introduce SurGE (Survey Generation Evaluation), a new benchmark for evaluating scientific survey generation in the computer science domain. SurGE consists of (1) a collection of test instances, each including a topic description, an expert-written survey, and its full set of cited references, and (2) a large-scale academic corpus of over one million papers that serves as the retrieval pool. In addition, we propose an automated evaluation framework that measures generated surveys across four dimensions: information coverage, referencing accuracy, structural organization, and content quality. Our evaluation of diverse LLM-based approaches shows that survey generation remains highly challenging, even for advanced self-reflection frameworks. These findings highlight the complexity of the task and the necessity for continued research⁴.

1 Introduction

Large language models (LLMs) have shown impressive capabilities in scientific text generation [63, 12, 29], supporting various stages of academic writing from outlining to full-content generation. Among these applications, automated scientific survey generation stands out as a particularly valuable task. Scientific survey articles (also known as survey papers or literature reviews) synthesize knowledge from a broad collection of academic papers into a structured overview of a research area [23, 35, 4]. Traditionally, writing such surveys is highly labor-intensive: an expert in this field must gather dozens or even hundreds of relevant papers, understand their contributions, identify important themes and trends, and finally craft a well-structured survey paper. This labor-intensive process has become increasingly challenging due to the explosive growth of academic literature in recent years. For example, arXiv now receives over a thousand new computer science papers each day, and the annual volume of submissions has more than doubled from 2019 to 2024 [29]. Keeping pace with this scale of information is infeasible for individual researchers, prompting growing interest in automatic survey writing.

Despite the success of LLMs in various generation tasks, generating structured and comprehensive scientific surveys has received relatively little attention. A key reason is the lack of standardized benchmarks and evaluation protocols tailored to the unique demands of this task. Unlike general-purpose generation tasks, scientific survey writing remains difficult to evaluate in a quantitative and

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⁴We have open-sourced all the code, data, and models at: https://github.com/oneal2000/SurGE

standardized way, due to the lack of benchmarks that capture its unique requirements: synthesizing multiple sources, ensuring citation accuracy, and maintaining structural coherence. As a result, current systems are often assessed through manual expert reviews [56], which are costly, time-consuming, and hinder reproducibility and systematic progress.

To address these challenges and fill this research gap, we introduce **SurGE** (<u>Survey Generation E</u>valuation), a novel benchmark designed to facilitate reproducible research in scientific survey generation. We formalize the task as a two-stage process: given a topic description in the computer science domain (e.g., Machine Learning for Information Retrieval), the system should first collect a set of relevant papers from a large academic corpus and then synthesize a well-structured survey from them. To support this formulation, SurGE provides the necessary resources and a standardized evaluation framework for both the retrieval and generation stages. Each test instance in SurGE comprises a research topic and its corresponding *ground-truth survey*, which serves as a high-quality reference for evaluation. These ground-truth surveys are carefully selected from peer-reviewed, high-impact survey papers, based on citation statistics and topical relevance. SurGE dataset consists of two main components: (1) a set of test instances, where each instance includes a topic description, its ground-truth survey, and the full list of cited references in that survey; (2) a large-scale academic corpus containing over one million computer science papers, which serves as the retrieval pool for relevant document selection and coverage analysis.

Beyond dataset construction, we also propose an automated evaluation framework that enables reproducible and fine-grained assessment of generated surveys. This framework scores outputs across four key dimensions: information collection, referencing accuracy, structural organization, and content quality. Grounded in established academic writing guidelines [64, 4, 23, 35], this framework enables automatic, scalable evaluation without the need for human annotation, making it well-suited for benchmarking and driving systematic progress in this emerging task.

To validate the utility of SurGE, we evaluate a range of LLM-based baseline systems on the benchmark. These include standard retrieval-augmented generation approaches that first retrieve relevant documents and then generate a survey, as well as more advanced pipelines that incorporate explicit planning (e.g., outline generation) and iterative refinement of the draft. The results reveal that even the state-of-the-art systems struggle with the survey generation task, highlighting its difficulty. For example, models often miss important papers, produce fragmented or imbalanced coverage of subtopics, and sometimes generate hallucinations with irrelevant references. These findings indicate a significant gap between machine-generated surveys and expert-written ones, underscoring the need for further research. We hope that SurGE will spur the development of more effective techniques at the intersection of information retrieval and generative modeling to tackle this challenging task.

In summary, our contributions are threefold:

- 1. We introduce **SurGE**, the first comprehensive benchmark for scientific survey generation, featuring expert-written ground-truth surveys and a large-scale academic paper corpus.
- 2. We propose a fully automated evaluation framework that assesses survey quality across four crucial dimensions: information coverage, citation accuracy, structure, and content.
- 3. We provide extensive baseline results and analyses, offering reference points and highlighting key challenges in this emerging task.

2 Task Definition

We formalize scientific survey generation as a two-stage task. Given a topic description t and a large academic corpus $D = \{d_1, d_2, \dots, d_n\}$, the goal is to automatically generate a survey article S that provides a structured and comprehensive overview of the topic. The process consists of:

- **Document Collection:** A retrieval module or complex retrieval system identifies a topic-relevant paper set $\mathcal{R}_t \subseteq D$ containing papers relevant to t.
- Survey Generation: A generative model composes a well-structured survey S based on the topic t and the retrieved document set \mathcal{R}_t , including proper citations and a reference list.

The output survey S is expected to (i) follow a logical hierarchical organization, (ii) cover key techniques and trends related to the topic, and (iii) provide accurate citations in the appropriate places using a consistent and correct format.

3 Dataset Construction

3.1 Ground-Truth Survey Collection and Annotation

To construct the SurGE benchmark, we began by collecting a diverse set of high-quality reference surveys (ground-truth surveys) from recent computer science literature. Candidate texts were drawn from the arXiv repository, focusing on publications between 2020 and 2024 that self-identified as survey articles or systematic reviews. To ensure the academic significance and reliability of each instance, we applied the following selection criteria: (i) the document must explicitly declare itself as a survey or review; (ii) it must have achieved a minimum citation count of 20, indicating scholarly impact [6]; and (iii) the publish date must be between 2020 and 2024.

Following the initial filtering process, we further refined the SurGE dataset through expert annotation to ensure the inclusion of only high-quality survey documents. This stage aimed to assess not only the citation-based impact of each candidate survey but also its quality from the perspective of experienced researchers. To this end, we recruited a team of four computer science Ph.D. students as annotators. Note that annotating a paper did not require a close reading of the entire document. Annotators could typically complete the task within 8–9 minutes per paper on average. Each candidate document was evaluated by two independent annotators along four key dimensions: (i) citation impact, reflecting the scholarly influence of the paper; (ii) content coverage, indicating how comprehensively the survey summarizes the literature within its scope; (iii) structural coherence, assessing the logical organization and clarity of the document's sections; and (iv) reference quality, which examines the relevance, diversity, and traceability of cited works.

Each annotator labeled the document as either "usable" or "not usable." A survey paper was included in the final dataset only if both annotators independently marked it as usable. In cases of disagreement, the paper was discarded to maintain a conservative quality threshold. To ensure fair and motivated participation, annotators were compensated based on working hours at an average rate of 60 CNY per hour, exceeding the local minimum wage in Beijing. Inter-annotator agreement was quantified using Cohen's Kappa, applied to 250 annotated instances. The resulting score of 0.792 indicates substantial agreement and reinforces the reliability of the quality control process. After this filtering stage, we finalized the dataset with 205 rigorously verified survey papers. The final set of 205 ground-truth surveys included in our benchmark is detailed in Appendix C.

3.2 Reference Extraction and Processing

For each of our selected ground-truth surveys, we extracted reference data from its LaTeX source and the associated BibTeX file. First, we parsed the LaTeX source files using custom regular expressions to extract all citation keys (e.g., \cite{...} commands). Next, we used these keys to look up the corresponding entries in the BibTeX files and retrieve their complete metadata, including titles, authors, and publication years. These metadata served as unique digital identifiers for each reference. Finally, to ensure data quality, we performed a cleaning step where we systematically removed duplicates and filtered out entries with inconsistencies, such as malformed or excessively long titles.

The core reason for extracting the full reference list from each ground-truth survey is to create a gold standard for evaluating the information collection stage. We operate on the premise that the citations in an expert-written survey represent a curated collection of the field's most foundational and relevant literature. By using this set as the ground truth, we can quantitatively measure the coverage and recall of a system-generated survey's references, providing a clear metric for its performance.

3.3 Academic Corpus Construction

A crucial component of the **SurGE** benchmark is a large-scale academic corpus designed to serve as the retrieval pool for the document collection stage. Our corpus is built entirely from scholarly metadata obtained from the arXiv repository. To ensure adherence to ethical and legal standards, we

Statistic	Number	Field	Description
Total Ground Truth Surveys	205	SurveyID	A unique identifier for the survey.
Average Tree Depth	3.073	Authors	List of contributing researchers.
Maximum Tree Depth	4	Title	The title of the survey paper.
Average Number of Tree Nodes	42.717	Year	The publication year of the survey.
Maximum Number of Tree Nodes	212	Date	The timestamp of publication.
Average Citations per Paper	65.78	Category	Subject classification following the arXiv taxonomy.
Average Citations per Section	1.577	Abstract	The abstract of the survey paper.
Corpus Size	1,086,992	Structure	Hierarchical representation of the survey.
Average Abstract Length (words)	156.57	All_Cites	List of document IDs cited in the survey.

Figure 1: Overview of the SurGE Benchmark. (a) Summary statistics of the curated survey dataset and its associated retrieval corpus. (b) Metadata of the pre-processed survey dataset used in SurGE.

exclusively collected metadata and did not include full-text PDFs, a practice permitted by arXiv's Terms of Use, which designates metadata as public domain under the CC0 license [2].

The corpus was constructed through a two-stage process. The initial stage involved seeding the corpus with the references from our 205 ground-truth surveys. We systematically retrieved the arXiv metadata for every cited paper that was publicly accessible. This process revealed that approximately 30% of the references were unavailable, primarily due to publication in closed-access journals or other restricted venues. In the second stage, we expanded the corpus to enhance its comprehensiveness. We queried the official arXiv search API, using keywords and titles from the ground-truth surveys to identify and collect metadata for other topically related papers. This methodology resulted in a final retrieval corpus of 1,086,992 unique papers. For each paper, the corpus provides rich metadata, including its title, authors, abstract, subject categories, publication date, and a direct link to its arXiv page for transparency and verification. To ensure high data quality, all collected metadata underwent a rigorous pre-processing pipeline involving text normalization, formatting removal, and deduplication.

3.4 Statistics and Analysis

The resulting SurGE benchmark comprises 205 ground-truth survey papers and a retrieval corpus of 1,086,992 documents. Table 1a presents the key statistics of our curated dataset. To quantitatively analyze the organizational complexity of the surveys, we model the hierarchical section headings (e.g., Section, Subsection) of each paper as a tree structure. Our analysis reveals that these surveys are structurally deep, with an average tree depth of 3.07 and a mean of 42.7 nodes (i.e., distinct sections) per document. This structural complexity presents a significant challenge for hierarchical text generation. Furthermore, the surveys are densely referenced, citing an average of 65.8 papers, which underscores the demand for high-recall information collection. Table 1b details the pre-processed fields for each survey instance, which include not only standard metadata but also the parsed structural tree and the ground-truth list of cited documents, enabling a fine-grained, multi-faceted evaluation of system-generated surveys.

3.5 Ethical Considerations and Licensing

Our corpus is constructed exclusively from arXiv-provided descriptive metadata (titles, authors, abstracts, identifiers, categories, and license URIs) harvested via the official API. We do not host or redistribute arXiv PDFs or source files. This design complies with arXiv's API Terms of Use, which place descriptive metadata under a CC0 public-domain dedication [2]. This design is also consistent with the arXiv Submittal Agreement's CC0 designation for metadata [1].

We have prioritized transparency, reproducibility, and ethical considerations throughout dataset construction. To support open science, we have publicly released the SurGE dataset, accompanying metadata, and all associated processing scripts on our official GitHub repository⁵. The dataset and codebase are distributed under the MIT license, granting researchers and developers unrestricted access and modification rights. Regular updates will ensure continued relevance and alignment with evolving research trends and standards.

⁵https://github.com/oneal2000/SurGE

4 Evaluation Framework

Developing a robust evaluation framework for automated scientific survey generation involves identifying critical dimensions that reflect a survey's overall accuracy, comprehensiveness, and quality. Through discussions with academic experts, peer reviewers, and experienced survey authors, we established four essential evaluation dimensions:Information Collection Quality, Referencing Accuracy, Structural Quality, and Content Quality. Each generated survey is systematically compared with an expert-written Ground Truth (GT) survey, ensuring alignment with high academic standards. In the following subsections, we deeply analyze each evaluation criterion and subsequently define the corresponding quantitative metrics.

4.1 Information Collection Quality

A fundamental requirement for scientific surveys is the comprehensive collection of relevant literature, covering key works that accurately represent the research field. Omissions or insufficient coverage can severely compromise a survey's credibility, causing readers to question its thoroughness. Therefore, this aspect is quantitatively assessed through the *Coverage Score*, measuring the extent to which a generated survey includes key literature identified by expert consensus in the GT survey.

Metric Definition. The coverage score C is defined as the recall of references included in the generated survey relative to the GT survey:

$$C = \frac{|R_{GT} \cap R_G|}{|R_{GT}|},\tag{1}$$

where R_{GT} denotes references in the GT survey, and R_{G} denotes references in the generated survey. A higher coverage score indicates more comprehensive inclusion of essential literature.

While the GT reference set is not assumed to be perfectly complete, it serves as the best available proxy for expert consensus on a topic's core literature, given that our GT surveys are highly cited, peer-reviewed publications. We therefore interpret the Coverage score not as a measure of absolute completeness, but as a pragmatic metric for evaluating a system's ability to identify the central body of work validated by the research community.

4.2 Referencing Accuracy

Referencing Accuracy evaluates how well the references cited in a generated survey align with its topic and content. This assessment is crucial for ensuring that the survey is well-supported and that citations are contextually appropriate. We propose a hierarchical evaluation framework that assesses referencing quality from three perspectives:

- **Document-level**: Determines if a cited paper is thematically relevant to the survey's overall topic.
- Section-level: Evaluates if a reference is placed within a semantically appropriate section of the survey.
- Sentence-level: Assesses if a reference directly supports the specific claim made in the sentence where it is cited.

4.2.1 Automated Relevance Judgment.

To automate this evaluation, we employ a Natural Language Inference (NLI) model (cross-encoder/nli-deberta-v3-base) to automatically assess relevance. For each reference, we form a premise-hypothesis pair and use the NLI model to predict the relationship between them. The premise is constructed from the reference's metadata, while the hypothesis is contextualized by its placement in the generated survey.

Specifically, a reference is judged based on the NLI model's output scores for "Entailment," "Neutral," and "Contradiction":

- It is deemed **relevant** if "Entailment" has the highest score.
- It is deemed partially relevant if "Neutral" is highest and "Entailment" is the second-highest.

• Otherwise, it is deemed **irrelevant**.

Since the survey generation process is grounded in our academic corpus, any reference cited by the model that is not found within this corpus is considered a hallucination. Such references are therefore automatically marked as irrelevant across all three hierarchical levels.

4.2.2 Hierarchical Evaluation Metrics.

- 1. Document-level Accuracy (R_d) . This metric assesses if each reference is relevant to the survey's main topic. For a cited reference r, we first apply a heuristic: if r is also cited in the ground-truth survey, it is automatically marked as relevant. For all other references, we use the NLI model with the following pair:
 - **Premise**: "There is a paper. Title: '{Reference Title}'. Abstract: {Reference Abstract}."
 - **Hypothesis**: "The paper titled '{Reference Title}' with the given abstract could be cited in the paper: '{Survey Title}'."
- **2. Section-level Accuracy** (R_s) . This metric evaluates the contextual appropriateness of a citation within a specific section. We assess each unique (reference, section) pair. If a citation marker in the text points to a non-existent entry in the bibliography, the pair is marked as irrelevant. Otherwise, we query the NLI model:
 - Premise: "There is a paper. Title: '{Reference Title}'. Abstract: {Reference Abstract}."
 - **Hypothesis**: "The paper titled '{Reference Title}' with the given abstract is relevant to the section: '{Section Title}'."
- 3. Sentence-level Accuracy (R_t) . For the most fine-grained evaluation, this metric measures if a reference directly supports the claim in its citing sentence. We assess each unique (reference, sentence) pair using the NLI model:
 - Premise: "There is a paper. Title: '{Reference Title}'. Abstract: {Reference Abstract}."
 - **Hypothesis**: "The paper titled '{Reference Title}' with the given abstract could be cited in the sentence: '{Sentence Text}'."

4.2.3 Metric Calculation.

Based on the automated judgments, we define indicator functions for each reference r at a given level: $\mathbb{I}_{\text{rel}}(r) = 1$ if r is relevant, and 0 otherwise; $\mathbb{I}_{\text{half}}(r) = 1$ if r is partially relevant, and 0 otherwise. The final accuracy score for each level $x \in \{d, s, t\}$ is calculated as:

$$R_x = \frac{|\{r \in \mathcal{R}_x \mid r \text{ is relevant}\}| + 0.5 \cdot |\{r \in \mathcal{R}_x \mid r \text{ is partially relevant}\}|}{|\mathcal{R}_x|}, \tag{2}$$

where \mathcal{R}_d is the set of all unique references in the generated survey, while \mathcal{R}_s and \mathcal{R}_t are the sets of all unique (reference, section) and (reference, sentence) citation instances, respectively.

4.3 Structural Quality

A clear and logical structure is fundamental to a high-quality scientific survey, as it greatly enhances readability, coherence, and the ability to quickly navigate information. In contrast, poor structural organization can cause confusion, redundancy, and difficulty in following the paper's arguments. Therefore, a robust evaluation of structural quality is essential. We propose to assess structure from two complementary perspectives: coarse-grained, high-level organization and fine-grained, heading-level alignment.

To this end, we introduce two metrics for structural assessment:

- Structure Quality Score (SQS): Assesses the high-level structural alignment by comparing the list of generated headings with the ground-truth (GT) headings, focusing on their similarity in structure, meaning, and wording.
- Soft-Heading Recall (SHR): Measures the fine-grained alignment of headings and subheadings by
 using semantic embeddings to account for partial or paraphrased matches.

Structure Quality Score (SQS). SQS is designed to evaluate the overall quality of the generated survey's outline. For this evaluation, we define an outline as a hierarchical list of section and subsection headings extracted from a survey. SQS assesses the high-level structural alignment by comparing the generated outline against the ground-truth (GT) outline, focusing on aspects like topical coverage, logical flow, and hierarchical organization. To compute this score, we employ the "LLM-as-a-Judge" paradigm. Specifically, we prompt a powerful large language model, GPT-40, with both the generated and the GT outlines. The model is then instructed to provide a holistic quality score from 1 (poor) to 5 (excellent).

Soft-Heading Recall (SHR). To measure fine-grained alignment, SHR evaluates how well the generated outline covers the specific headings present in the ground-truth outline. Unlike metrics based on exact lexical matching, SHR leverages semantic similarity to robustly handle variations in wording and paraphrasing.

Formally, SHR is defined as the soft cardinality overlap between the predicted heading set (H_P) and the ground-truth heading set (H_{GT}) :

$$SHR = \frac{S(H_P \cap H_{GT})}{S(H_{GT})}$$
(3)

where S(A) denotes the soft cardinality of a heading set A. It is designed to down-weight redundant headings within the same set and is calculated as:

$$S(A) = \sum_{i=1}^{K} \frac{1}{\sum_{j=1}^{K} \sin(A_i, A_j)}$$
(4)

Here, $sim(A_i, A_j)$ is the cosine similarity between the embeddings of headings A_i and A_j :

$$sim(A_i, A_j) = cos(embed(A_i), embed(A_j))$$
(5)

Since a standard set intersection would be too strict for comparing paraphrased headings, we calculate the soft cardinality of the intersection $S(H_P \cap H_{GT})$ using the soft set inclusion-exclusion principle:

$$\mathcal{S}(H_P \cap H_{GT}) = \mathcal{S}(H_P) + \mathcal{S}(H_{GT}) - \mathcal{S}(H_P \cup H_{GT}) \tag{6}$$

This formulation ensures that semantically matched headings contribute positively to the recall, even with lexical variations. A higher SHR score indicates better structural alignment with the GT outline at a granular level.

4.4 Content Quality

Content quality evaluation is pivotal for ensuring surveys are not only comprehensive but also clear, coherent, and logically sound. Evaluating this dimension involves assessing the presence of essential information, accuracy, and fluency of expression. While traditional metrics such as ROUGE and BLEU effectively measure textual overlap and fidelity, they inadequately capture nuanced aspects of logical coherence and clarity. To address these limitations, we supplement these traditional metrics with a comprehensive logical coherence evaluation.

Metric Definitions. We apply ROUGE and BLEU at the section-level to effectively capture fidelity and precision in content representation without needing explicit mathematical formulations here. Logical coherence is evaluated using GPT-4o to assign readability and coherence scores (0–5) for each section. ⁷

5 Baseline Implementation

In this section, we detail the implementation of baseline methods. Each baseline follows a two-stage pipeline: (1) retrieving a set of potentially relevant papers for a given topic, and (2) organizing and

⁶The corresponding prompt templates are available in our official GitHub repository: https://github.com/oneal2000/SurgE.

⁷Here, we employ the LLM-as-a-Judge paradigm for evaluation. The corresponding prompt templates are available on our official GitHub repository: https://github.com/oneal2000/SurGE.

summarizing the retrieved content to produce a structured survey. To ensure a fair comparison, all baselines rely on a shared dense retriever for the first stage. In the following subsections, we first describe the training procedure of the shared Paper Retriever, followed by the specific methodologies adopted by each baseline in generating the final survey.

5.1 Paper Retriever Training

We employ a dual-encoder architecture for document retrieval, initialized with roberta-base. For a query q and a paper abstract d, we first construct their input representations by prepending the special token [CLS] and appending [SEP]. Formally, let X(q) = [CLS] q [SEP] and X(d) = [CLS] d [SEP]. We then feed these tokens into the transformer encoder to obtain a hidden vector at the [CLS] position:

$$Emb(X) = transformer_{[CLS]}(X). \tag{7}$$

The similarity score between the query and the document is computed as the dot product of their embeddings:

$$S(q, d) = \operatorname{Emb}(X(q))^{\top} \cdot \operatorname{Emb}(X(d)). \tag{8}$$

During training, each query Q is paired with a relevant document d^+ to form a positive sample, while negative samples $d^- \in N$ are drawn from the corpus. The retriever is optimized via the softmax cross-entropy loss:

$$\mathcal{L}(Q, d^+, N) = -\log \frac{\exp(S(Q, d^+))}{\exp(S(Q, d^+)) + \sum_{d^- \in N} \exp(S(Q, d^-))}.$$
(9)

This objective encourages the model to assign higher scores to relevant papers while minimizing scores for irrelevant ones. We use the trained retriever to retrieve the top-ranked papers for each query, thereby providing a focused subset of literature for subsequent summarization.

5.2 Retrieval-Augmented Generation

In the first baseline, we combine retrieval with a direct generation approach. Given a topic t, we use the above retriever to collect the top 100 candidate papers. To manage lengthy inputs, these retrieved papers are split into smaller groups, each containing an approximately equal number of references. We then prompt a large language model (LLM) to summarize each group separately, guiding it to preserve references to the original papers. Formally, for each group of papers $G_k = \{d_1, d_2, \ldots, d_{n_k}\}$, the LLM is conditioned on the sequence of paper abstracts and instructed to produce a partial summary \hat{S}_k . Finally, we merge the partial summaries $\hat{S}_1, \hat{S}_2, \ldots$ into a unified survey. This merging step is performed by prompting the LLM once again with all partial summaries and asking for an integrated, logically coherent survey. Although this baseline follows a straightforward two-step approach, it provides a clear assessment of how effective retrieval-based summarization can be when coupled with an LLM's generative capabilities.

5.3 AutoSurvey

AutoSurvey [63] implements a multi-stage survey generation pipeline that starts with a high-level outline and proceeds through iterative expansions. We adapt it to use our fine-tuned retriever in place of its original retrieval mechanism and keep the number of retrieved references consistent for fairness. In the adapted workflow, we first issue a query based on the topic t to retrieve an initial collection of papers $P_{\rm init}$. The LLM is then prompted to create a structured outline, which includes main sections and subsections tailored to the subject matter. Next, each section is expanded by conditioning on the subset of papers most relevant to that specific section, producing a draft that includes references in a bracketed format (e.g., "[id]"). Once each section is drafted, the LLM refines it to address factual inconsistencies, stylistic mismatches, and reference-formatting issues. Finally, all refined sections are merged into a coherent final survey, with transitions and citation references carefully aligned. The workflow iterates over these stages, leading to incremental improvements in both thematic coverage and presentation quality.

5.4 StepSurvey

StepSurvey [25] is a more granular generation strategy that also begins with retrieving the top 100 candidate papers for a given topic t but proceeds through distinct planning and drafting phases in a

Table 1: Comparison of retrieval models on recalling ground-truth cited papers. The metric is Recall@k, where k is the number of top documents retrieved. Best results are in bold.

Model	Recall@20	Recall@30	Recall@100	Recall@200	Recall@500	Recall@1000
BM25	0.0548	0.0652	0.1193	0.1596	0.2213	0.2715
Paper Retriever	0.1706	0.2145	0.3665	0.4681	0.6011	0.6805

sequential manner. This baseline is proposed by a team named "ID" in the NLPCC2024 competition task 6 [57]. Rather than producing an overarching outline at once, it starts by proposing a survey title and a set of primary headings that collectively capture the central themes of the retrieved literature. Subsequently, it uses the primary headings to guide the selection of secondary or finer-grained topics, each mapped to a relevant subset of the retrieved papers. The LLM then produces a full draft by writing each subsection with explicit attention to references and academic conventions, thereby encouraging greater control and consistency across sections. Throughout this process, the system attempts to maintain a balanced level of detail, striving for a clear exposition of important subtopics while avoiding excessive verbosity or redundancy. By structuring the content in incremental steps, StepSurvey aims to achieve coherent organization and thorough coverage of the literature.

5.5 Implementation Details.

For the training of Paper Retriever, we randomly split the dataset into a training set and a test set at a ratio of 4:1. We adopt the AdamW optimizer for model optimization, the learning rate is set to 5×10^{-6} , the weight decay is set to 1×10^{-2} , and the epoch is set to 10. During the training process, we adopt mixed-precision (fp16) training for enhanced efficiency. At inference time, each query retrieves the top 100 most relevant papers according to the similarity score S(q,d). The retriever is initialized using the pre-trained RoBERTa model [30]. For the generation configuration of LLMs, all experiments are conducted using the publicly available implementations provided by Hugging Face. We utilize the default hyperparameters and the chat template as outlined in the official Hugging Face repository 8 . All experiments are conducted on a server with 1TB of RAM and eight NVIDIA A100 GPUs, each with 40GB of memory.

6 Experimental Results

This section demonstrates the utility of our proposed benchmark by presenting a detailed evaluation of three representative survey generation baselines: RAG, AutoSurvey, and StepSurvey. Our analysis is designed to showcase how the benchmark's multi-faceted metrics can be used to conduct a fine-grained analysis and pinpoint system bottlenecks. We first isolate and evaluate the performance of the shared Paper Retriever (§6.1). This analysis is crucial as it establishes the theoretical upper-bound performance for the reference coverage metric and highlights the challenges posed by the initial retrieval stage. Following this, we assess the complete end-to-end performance of the baselines (§6.2), leveraging our comprehensive evaluation suite to compare their architectural strengths and weaknesses and to shed light on the broader challenges facing automatic survey generation.

6.1 Analysis of Retrieval Performance

A crucial question in our two-stage pipeline is whether performance limitations stem from the retriever's inability to find relevant papers or the generator's inability to use them. To disentangle these factors and quantify the retrieval bottleneck, we first evaluate the performance of our fine-tuned dense retriever in isolation. This analysis establishes the theoretical upper bound for the reference coverage that our end-to-end systems can achieve.

We compare our dense retriever against a lexical baseline BM25 [38], using Recall@k as the evaluation metric. This metric measures the percentage of ground-truth papers from the reference survey that are present in the top-k retrieved documents. As shown in Table 1, our fine-tuned Paper Retriever substantially outperforms the BM25 baseline across all values of k. The performance gap underscores the inadequacy of lexical search, which struggles to find semantically relevant papers that

⁸https://huggingface.co/Qwen/Qwen2.5-14B-Instruct

Table 2: The experimental results combining Coverage, Referencing Accuracy (including Doc-Rel, Sec-Rel, and Sent-Rel), Structural Quality (including SQS and SHR), and Content Quality (as measured by ROUGE scores, BLEU, and Logic Score). Doc-Rel represents document-level relevance, Sec-Rel represents section-level relevance, Sent-Rel represents sentence-level relevance, SQS represents the structure quality score, and SHR represents soft-heading recall. R-L represents ROUGE-L. The best results are in **bold**, and the second-best results are <u>underlined</u>.

	Coverage	rerage Referencing Accuracy			Structural Quality		Content Quality		
Baseline	Recall	Doc-Rel	Sec-Rel	Sent-Rel	SQS	SHR	R-L	BLEU	Logic Score
RAG	0.0214	0.2857	0.2502	0.2500	0.6829	0.7900	0.1519	10.38	4.6723
AutoSurvey	0.0351	0.3617	0.4935	0.4870	1.3902	0.9697	0.1578	10.44	4.7390
StepSruvey	0.0630	0.4576	0.4571	0.4636	1.1951	0.9763	0.1590	12.02	4.8451

may not share overlapping keywords. Our dense retriever, by capturing deeper semantic relationships, is far more effective. However, the results also reveal a critical bottleneck in the survey generation pipeline. Even with a generous budget of k=1000, Paper Retriever recalls only 68.05% of the ground-truth papers. This finding is crucial as it establishes a hard upper-bound on the performance of the downstream generator. This finding suggests that achieving a breakthrough in survey quality may necessitate a shift towards more sophisticated retrieval paradigms, such as employing search agents powered by large language models [69].

6.2 Overall Performance of Survey Generation Baselines

The preceding analysis revealed that the retriever provides the generation models with over a third (36.65%) of the ground-truth references, setting a clear performance ceiling. We now demonstrate the full diagnostic power of our benchmark by applying its comprehensive suite of metrics to the end-to-end outputs of the three baselines: **RAG**, **AutoSurvey**, and **StepSurvey**. As detailed in Table 2, this multi-faceted evaluation allows us to pinpoint specific challenges in the generation stage. The key insights revealed by our benchmark are as follows:

- (1) Bottleneck of Existing Baselines. A striking observation across all methods is the significant gap between retrieval performance and final survey coverage. While our paper retriever makes 36.65% of the ground-truth references available (Recall@100), the best-performing baseline, StepSurvey, only achieves a final Coverage of 6.30%. The simpler RAG baseline is even lower at 2.14%. This disparity underscores that the primary limitation is the generation stage's inability to effectively identify and incorporate relevant information from the provided set of 100 papers. Nonetheless, the results also show that advanced, structured approaches like AutoSurvey (3.51%) and StepSurvey (6.30%) are substantially better at utilizing the retrieved context than a standard RAG pipeline.
- (2) Strengths of AutoSurvey. AutoSurvey exhibits excellent Section-Level Relevance (0.4935) and Sentence-Level Relevance (0.4870), surpassing both RAG and StepSurvey. This improvement appears to stem from AutoSurvey's iterative planning mechanism, where the system generates a high-level outline, retrieves relevant references for each section, and incrementally refines each subsection. By focusing on context-specific references and refining drafts section by section, AutoSurvey places citations more accurately at both the section and sentence levels. Moreover, AutoSurvey achieves the highest Structure Quality Score (SQS) of 1.3902, indicating that its top-down planning leads to well-organized hierarchical structures.
- (3) Strengths of StepSurvey. On the other hand, StepSurvey attains the best performance in several crucial dimensions: Coverage (6.30%) and Document-Level Relevance (0.4576). Its multi-phase workflow first generates major headings, then subtopics, and finally assigns references to each subsection. This step-by-step refinement appears particularly effective at broadening the coverage of included works and aligning the cited literature with the overarching survey theme. StepSurvey also achieves the highest Logic Score (4.8451) and excels in ROUGE and BLEU, reflecting strong content quality and coherent presentation. An interesting observation is that while StepSurvey's Section-Level Relevance is slightly lower than AutoSurvey's, the difference remains small (0.4571 vs. 0.4935), indicating that its primary strength lies in more holistic, document-wide alignment and consistent logical flow.

(4) Impact of Planning on Multi-Level Relevance. The multi-stage generation process adopted by AutoSurvey and StepSurvey benefits Document-Level and Section-Level Relevance in different ways. AutoSurvey's approach—outlining, drafting, and iteratively refining sections—yields highly relevant citations at the subsection and sentence granularity. In contrast, StepSurvey's method of organizing subtopics around central themes ensures strong document-wide alignment. This discrepancy suggests that carefully balancing local vs. global planning remains an open challenge: future work might explore hybrid strategies that combine AutoSurvey's fine-grained focus with StepSurvey's broad thematic coverage.

In conclusion, our results demonstrate that advanced, multi-stage planning approaches (AutoSurvey and StepSurvey) significantly outperform the standard RAG pipeline in nearly all metrics. While AutoSurvey excels in section- and sentence-level citation placement and high-level structural quality, StepSurvey provides superior document-level coverage, global relevance, and strong logical coherence. Nonetheless, all methods still struggle to capture the vast reference space fully. These findings underscore the importance of iterative refinement and structured planning in automated survey generation and suggest that there remains substantial room for further improvement, particularly in boosting coverage and refining the interplay between local and global survey organizations.

7 Related Work

7.1 Retrieval-Augmented Generation

Large Language Models (LLMs) are inherently limited by their static, pre-trained parametric knowledge. To address these limitations, Retrieval-Augmented Generation (RAG) has emerged as a key paradigm [13, 27, 7, 58, 46]. By grounding the model in external knowledge, RAG directly addresses several fundamental limitations of LLMs, offering a robust mechanism to mitigate hallucinations [18, 52, 49, 60], facilitate knowledge updating [9, 62, 59, 61], and enable effective domain adaptation [66, 54, 47, 53].

The conventional approach to traditional RAG is built upon the "Retrieval-then-Read" paradigm [5, 16, 27]. Within this framework, a user's query triggers a search module for relevant documents within a large-scale external corpus. This retrieval step is carried out by either an external retriever [68, 45, 38, 44, 31, 10] or a more sophisticated retrieval system [48, 41]. Building upon this foundation, recent work has proposed more advanced RAG architectures to improve efficiency and effectiveness. For instance, Dynamic RAG [19, 50, 67] moves beyond a single retrieval step by adaptively triggering the retriever during generation, specifically when the LLM is uncertain during the generation process. From another angle, GraphRAG [8] enhances the knowledge source by querying pre-constructed knowledge graphs instead of unstructured text, allowing it to retrieve interconnected facts and relationships. Furthermore, the Parametric RAG paradigm [51, 55, 11] alters the knowledge injection step by directly injecting retrieved knowledge into the LLM's parameters.

The scientific survey generation task, which is the focus of our SurGE benchmark, presents a significant challenge for even these advanced RAG systems. Unlike typical question-answering, survey generation demands the synthesis of a large, diverse set of documents into a coherent, well-structured survey paper. Therefore, while RAG provides the foundational technology, our SurGE benchmark is specifically designed to push the boundaries of current models by rigorously evaluating their capabilities in large-scale multi-document synthesis and structured content creation.

7.2 Long-Form Text Generation and Evaluation

Long-form text generation is substantially more challenging than short-text generation due to its inherent requirements for sustained coherence and rich contextual understanding. Early approaches mainly used generative adversarial networks and reinforcement learning to conduct long-sequence generation [15]. More recently, large language models have emerged as a strong tool for this task, offering advanced capabilities to handle long-text generation. For example, structured planning techniques and specialized inference mechanisms are proposed [42, 20] to generate consistent and high-quality clinical reports. Similarly, hierarchical planning frameworks have demonstrated that content control and multi-constraint instruction following can significantly enhance logical flow and topic coverage [17, 36]. Beyond medical or other task-specific applications, context-driven retrieval strategies, such as tree-structured retrieval, can support open-domain long-text generation by guiding

the model through extensive knowledge sources [39]. The effective evaluation framework is vital for measuring the quality, factualness, and user-centric utility of the long-form text generation task. Traditional metrics, designed for shorter texts, often fail to capture the intricacies of longer outputs. Recent work has introduced task-focused benchmarks that emphasize user-oriented objectives, such as personalized writing or domain-specific content generation [24, 40]. In parallel, factuality assessment has attracted growing interest, with methods proposed to evaluate both verifiable and unverifiable claims. Metrics such as VERISCORE and FACTSCORE break down generated text into atomic facts, checking each for consistency against reliable sources [43, 32]. Beyond factual correctness, coherence and structural quality have been studied extensively. Benchmarks like LongGenBench and HelloBench underscore the importance of evaluating a model's ability to maintain logical organization and clarity over extended passages [65, 37].

7.3 Survey Generation

In the domain of scientific writing, survey generation involves distilling extensive textual resources into a coherent and structured overview. Recent advances in AI-assisted systems have provided prompting-based approaches to expedite the drafting process while preserving content accuracy [14, 21]. One of the most commonly used approaches is retrieval-augmented generation, which combines large-scale knowledge retrieved from documents with language generation empowered by LLMs to yield factually comprehensive overviews [28]. Retrieval-augmented generation is often initiated with dense retrieval methods based on dual-encoder architectures to identify highly relevant documents [22]. Once these documents are retrieved, summarization techniques—spanning top-down, bottom-up, and graph-based ranking methods—play a pivotal role in producing concise yet faithful summaries [33, 34, 3]. Building on these retrieval and summarization-based methodologies, automated literature survey generation has garnered increasing attention [56, 26]. However, existing techniques depend on limited ground truths and employ coarse evaluation metrics, resulting in oversimplified assessments of survey quality [63]. To address these challenges, we present a refined ground truth and a multidimensional evaluation framework that emphasizes both accuracy and structural coherence. By evaluating quality through multiple dimensions, our proposed framework advances the capabilities of automated survey generation, offering a more comprehensive and rigorous approach to summarizing scientific literature.

8 Conclusion

In this paper, we introduce SurGE, a benchmark for end-to-end scientific survey generation in computer science. We construct a high-quality dataset and develop a multi-dimensional evaluation framework that assesses the coverage, coherence, factual accuracy, and writing quality of automatically generated surveys. Extensive experiments with various baselines highlight the challenges in producing high-quality surveys. SurGE is expected to serve as a valuable resource for future research in information retrieval, fostering advancements in both retrieval methodologies and generative AI techniques. Several limitations guide future work, including: (1) The benchmark is limited in the domain of computer science but could be extended to broader domains. (2) Integration with more advanced retrieval and generation methods could further enhance automated scientific survey generation for computer science.

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A Details of the Academic Corpus

Table 3 provides an overview of the metadata schema used in our academic corpus. Each entry is structured to support efficient retrieval and interpretability.

Table 3: Fields and Descriptions for the Literature Knowledge Base.

Key	Description
Title	The title of the research paper.
Authors	A list of contributing researchers.
Year	The publication year of the paper.
Date	The exact timestamp of the paper's release.
Abstract	The abstract of the paper.
Category	The subject classification following the arXiv taxonomy.
doc_id	A unique identifier assigned for reference and retrieval.

B Social Impact

Automated scientific survey writing brings two-sided social impacts. On the one hand, automated survey generation can save significant time and resources for researchers. This efficiency allows for quick data collection and analysis, enabling more rapid responses to a research domain. Automated survey generation could even provide innovation and lead to discoveries and insights with the help of LLMs. On the other hand, we have shown that the current method for automated survey generation is limited. Such a low-quality survey could poison the academic environment and bring ethical concerns, such as biased content generated by LLMs. Therefore, surveys generated by LLMs should be noted and published in different tracks. Such research direction should be carefully supervised by the collaboration of researchers.

C Selected Ground Truth Survey

The following three tables provide the complete list of the ground-truth surveys that comprise the SurGE benchmark. In line with our selection methodology outlined in Section 3, these surveys represent high-impact, peer-reviewed works. For each entry, we list its full title, publication year, primary arXiv category, and its citation count. The provided citation counts represent a snapshot taken from Google Scholar on May 10, 2025.

Survey Title	Year	Category	Citation Count
A Survey on Edge Computing Systems and Tools	2019	cs.DC	384
A Survey on Graph-Based Deep Learning for Computational Histopathology	2021	cs.LG	141
A Survey of Uncertainty in Deep Neural Networks	2021	cs.LG	1547
A Survey on Explainability in Machine Reading Comprehension MAC Protocols for Terahertz Communication: A Comprehensive Survey	2020 2019	cs.CL cs.NI	50 154
Event Prediction in the Big Data Era: A Systematic Survey	2019	cs.AI	175
A Survey on Deep Neural Network Compression: Challenges, Overview, and Solutions	2020	cs.AI	142
Analysis of the hands in egocentric vision: A survey	2019	cs.CV	113
Neural Machine Translation for Low-Resource Languages: A Survey	2021	cs.CL	321
Physics-Guided Deep Learning for Dynamical Systems: A Survey	2021	cs.LG	115
A Survey on Bias and Fairness in Machine Learning	2019	cs.LG	6292
Generative Adversarial Networks for Spatio-Temporal Data: A Survey	2020	cs.LG	136
Ubiquitous Acoustic Sensing on Commodity IoT Devices: A Survey	2019	cs.SD	82
A Survey of Black-Box Adversarial Attacks on Computer Vision Models	2019	cs.LG	120
A Comprehensive Survey on Pretrained Foundation Models: A History from BERT to ChatGPT	2023	cs.AI	726
A Survey on Dynamic Network Embedding	2020	cs.SI	49
A Survey of Moving Target Defenses forNetwork Security	2019	cs.CR	295
A Survey on the Evolution of Stream Processing Systems	2020	cs.DC	111
Deep Gait Recognition: A Survey	2021	cs.CV	264
Transformers in Vision: A Survey	2021	cs.CV	3276
Image Classification with Deep Learning in the Presence of Noisy Labels: A Survey	2019	cs.LG	433
Change Detection and Notification of Web Pages: A Survey	2019	cs.IR	26
A Survey on Deep Learning-based Architecturesfor Semantic Segmentation on 2D images	2019 2019	cs.CV cs.AR	276 28
A Survey on Tiering and Caching in High-Performance Storage Systems Multimodal Learning with Transformers: A Survey	2022	cs.CV	766
Attention, please! A survey of Neural Attention Models in Deep Learning	2022	cs.LG	251
Explanation-Based Human Debugging of NLP Models: A Survey	2021	cs.CL	80
Federated Learning in Mobile Edge Networks: A Comprehensive Survey	2019	cs.NI	2488
Deep Learning for Image Super-resolution: A Survey	2019	cs.CV	2036
Deep Learning for Weakly-Supervised Object Detection and Object Localization: A Survey	2021	cs.CV	25
Survey of Transient Execution Attacks	2020	cs.CR	23
A Survey of Syntactic-Semantic Parsing Based on Constituent and Dependency Structures	2020	cs.CL	47
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