

# SUMIE: A Synthetic Benchmark for Incremental Entity Summarization

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## Abstract

No existing dataset adequately tests how well language models can incrementally update entity summaries – a crucial ability as these models rapidly advance. The Incremental Entity Summarization (IES) task is vital for maintaining accurate, up-to-date knowledge. To address this, we introduce SUMIE, a fully synthetic dataset designed to expose real-world IES challenges. This dataset effectively highlights problems like incorrect entity association and incomplete information presentation. Unlike common synthetic datasets, ours captures the complexity and nuances found in real-world data. We generate informative and diverse attributes, summaries, and unstructured paragraphs in sequence, ensuring high quality. The alignment between generated summaries and paragraphs exceeds 96%, confirming the dataset’s quality. Extensive experiments demonstrate the dataset’s difficulty – state-of-the-art LLMs struggle to update summaries with an F1 higher than 80.4%. We will open source the benchmark and the evaluation metrics to help the community make progress on IES tasks.<sup>1</sup>

## 1 Introduction

Entity Summarization (ES) distills key features of entities (e.g., people, places, organizations) from extensive unstructured data, essential for various NLP applications like question answering (Allam & Haggag, 2012), information retrieval (Kowalski, 2007), and entity comparison systems (Gunel et al., 2023). Traditional ES tasks focus on computing concise summaries for entities, drawing on a size-limited selection of triples (subject-predicate-object statements) within structured RDF data (Liu et al., 2020b; 2021). This work goes further, creating precise and comprehensive structured summaries for entities by leveraging the vast knowledge available in natural language on the web. This method tackles real-world issues, enhancing the utility for new entities mainly found online. For example, it streamlines gathering comprehensive summaries for hotels and restaurants, facilitating efficient destination research. Moreover, structured summaries simplify comparing detailed lodging options, aiding travelers in making choices that align with their preferences.

As the amount of information continues to grow, it is essential to be able to update these structured summaries automatically. Incremental Entity Summarization (IES) addresses this by enabling updates to entity summaries with new information (Chowdhury et al., 2024),

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<sup>†</sup>This work was completed while the author was working as an intern at Google Deepmind.

<sup>1</sup>We will release the SUMIE dataset at <https://github.com/google-research-datasets/sumie> soon.

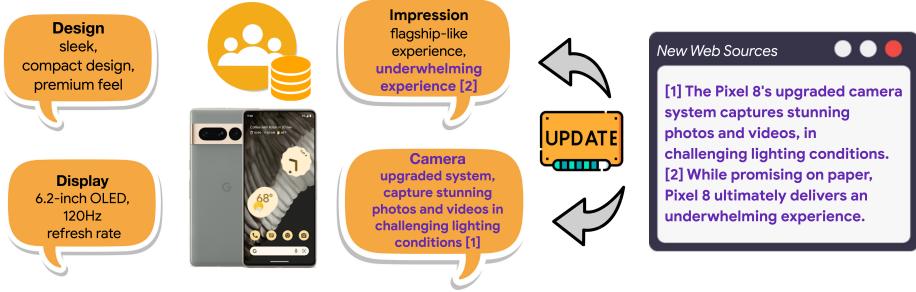


Figure 1: Overview of the Incremental Entity Summarization Task. Existing attribute (“Impression”) can be updated and new attribute (“Camera”) can be augmented.

ensuring entities in search engines, news aggregators, and knowledge bases are always accurately represented. IES removes the need for manual updates, efficiently managing vast and swiftly changing data. It allows for the addition of attributes and values to entity summaries from new web sources, enhancing entity representation comprehensiveness as depicted in Figure 1. Despite its critical importance, IES is underexplored. While some work (Goasdoué et al., 2019; Yang et al., 2021; Chowdhury et al., 2024) investigates updating entity summaries using abstractive or extractive techniques, these efforts often lack structured attribute-value organization or suffer from hallucination problems of LLMs. Crucially, there is no dataset specifically designed to test the ability of these models to maintain accurate, up-to-date entity knowledge. This is surprising given the vital role IES plays in organizing massive amounts of information.

To develop an effective dataset for IES systems, it needs a broad selection of entities with diverse and evolving attributes and values. This dataset should feature texts from varied writing styles to improve model adaptability and simulate the dynamic nature of entity information updates. Crucially, it requires accurate alignment between web documents and their structured summaries to trace attribute values to their sources. While diverse natural language web sources for various entities are readily available (Ganesan & Zhai, 2012; Asghar, 2016), creating well-maintained structured summaries from these sources remains both expensive and time-consuming. Even with the assistance of LLMs, achieving high accuracy and coverage in structured summary annotations is difficult and requires extensive human verification (Gunel et al., 2023). Further challenges arise in accurately representing how entity information evolves over time and maintaining a precise alignment between natural language and structured summaries (Chowdhury et al., 2024).

In this paper, we strategically generate a fully synthetic dataset using LLMs. This approach leverages the empirical finding that LLMs excel at expanding short phrases into descriptive, contextual paragraphs, rather than abstractly summarizing all important components from longer text. The dataset generation follows a structured approach: initially, LLMs use popular search topics to produce varied attributes and plausible entity names. To ensure the quality of attribute values, which vary in length and sentiment, a meticulous process is applied. Additionally, the dataset mimics real-world updates by including incremental changes, conflicts, and repetitions in the entity summaries. Corresponding paragraphs that reflect these summaries are then generated, showcasing a range of writing styles and tones. Overall, this synthetic dataset is carefully crafted to be both high-quality and complex, enabling it to effectively simulate real-world scenarios.

Our contributions are as follows:

- We present SUMIE, the first dataset built with high informativeness and diversity for rigorous evaluation of incremental entity summarization methods. We open-source SUMIE to accelerate research in this field, including metrics of evaluation.
- We propose simple but effective LLM-based solutions, **Update** and **Merge** for IES task. These methods provide valuable baselines for future advancements.
- We conduct insightful analyses to pinpoint the limitations of LLM-based entity summarization methods. State-of-the-art LLMs struggle to update summaries with an F1 score higher than 80.4%, highlighting the inherent complexity of this task.

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## 2 Dataset Desiderata

To build a dataset ideal for developing entity summarization systems with incremental generation capability, we outline the following key desiderata:

**Diversity of Entities.** The dataset should encompass a broad spectrum of entities across domains. This could include businesses (restaurants, hotels), products, events, and more. Diverse entities ensure the model encounters a wide choices of attributes and associated values, expanding its knowledge base.

**Complexity of Attributes and Values.** Values associated with attributes should demonstrate variation in length, sentiment and subjectivity. Even within the same entity category, attribute values should reflect high diversity to challenge the models' nuanced understanding. Likewise, attributes must range common (e.g. a restaurant's service) to niche and specific interests (e.g. a hiking trail's access to restrooms).

**Varied Information Sources.** The textual sources should exhibit a rich diversity of real-world styles and origins. Generate a mixture of editorial reviews (which often analyze with authority), user generated contents (informal and potentially biased, found in online forums or social media), and official product descriptions (which frequently use persuasive language focused on features and benefits). By exposing the model to these distinct writing styles and purposes, it will be compelled to adapt its understanding across different language patterns.

**Inclusion of Misleading Information** The dataset should contain subtly misleading details that requires contextual understanding for identification. The dataset can reference similar but distinct entities to create confusion. The goal is to challenge the model's ability to critically analyze information within the provided context rather than simply relying on basic fact-checking.

**Incremental Information Updates.** The dataset should include examples where information about an entity evolves over time, simulating updates as new facets or perspectives are revealed. This forces the model to not only add new information but also potentially revise or re-prioritize existing facts. Introducing situations where initial information is incomplete or later contradicted by more supported sources. The model must learn to prioritize well-supported information over time, mirroring a common real-world scenario where our understanding of a subject develops.

**Rigorous Alignment between Structured Summaries and Natural Language Paragraphs.** Ensure a precise and traceable connection exists between a source paragraph and its corresponding structured summary (i.e. an attribute-value table). Focus on maintaining clear attributions, and ensure the origin of each value is precisely derived from the source paragraph. Avoid introducing information into the structured summary that isn't explicitly supported by the text for a rigorous alignment.

## 3 Dataset Generation Methodology

We create a synthetic dataset with generated attributes, entity names, and incrementally evolving summary tables (see Figure 2). Accompanying paragraphs mirror the tables, including distracting sentences. For LLM prompting instructions, see Appendix A.3.

### 3.1 Attribute and Entity Name Generation

We begin by selecting 20 popular categories (e.g. Hotels & Accommodations) (see Appendix A.2 for all category information). For each, we prompt an LLM to generate attributes (e.g. Room Quality) and entity names (e.g. The Whispering Canyon Hotel). To ensure attribute diversity, we retrieve up to 50 common (e.g. Room quality, Service) and 50 less-common attributes (e.g. Honeymoon packages) typically used to describe entities within that category. For entity names, we generate up to 40 plausible but fictitious names, randomly selecting 10. Each entity is then assigned 30 attributes, with an equal split between common and uncommon descriptors. This process results in a dataset containing 200 entities, which we consider *suitable* for evaluation. The use of random elements in the generation process

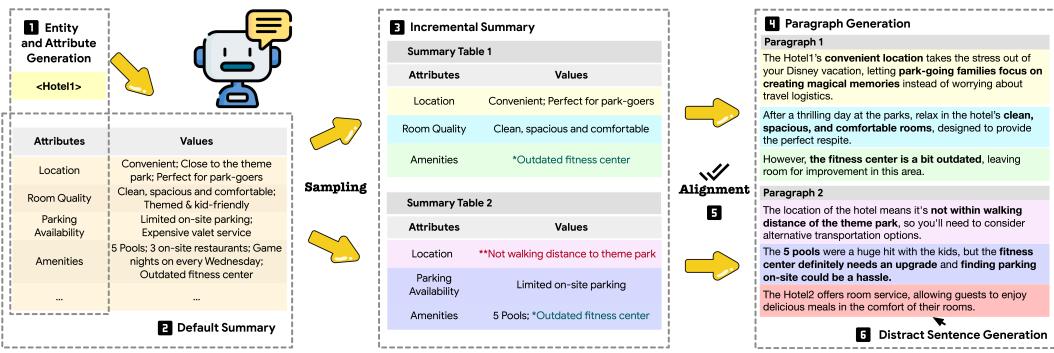


Figure 2: Dataset Generation Methodology Overview: (1) Generate entity names (masked for ethics consideration) and attributes. (2) Create default summary table with diverse values. (3) Sample attributes/values for incremental summaries (\* repeated sampling, \*\* conflicting values). (4) Generate paragraphs with varying tones based on attributes/values. (5) Verify summary table/paragraph alignment. (6) Add distractor sentence. Note that attribute values and sentences in the same color should be aligned and bold texts in paragraphs are the evidences for corresponding attribute values.

helps reduce the impact of LLM bias on the dataset. While we use specific entity names to promote contextual diversity in the models’ output until we generate paragraphs (Sec 3.3), in the final dataset, these names are replaced with generic ones (e.g., from The Whispering Canyon Hotel to Hotel1) to avoid any unintended claims related to real-world entities.

### 3.2 Summary Table Generation

**Default summary table generation.** Summary tables provide a structured representation of attributes associated with an entity in a given category. Each row details an attribute and its corresponding value. The goal in this stage is to generate values that meet three criteria: 1) Informative and meaningful, covering both subjective and objective aspects, 2) Diverse in length (one to 10 words), and 3) Varied in sentiment (positive, negative, and neutral). We generate at least three descriptive values per sentiment, resulting in three distinct summary tables for each entity. For instance, when the prompt specifies a positive sentiment, the model is directed to generate favorable descriptors such as “Spacious and comfortable” and “Clean” for a designated attribute like “Room Quality”. The final summary tables for each entity combine up to 10 attribute and value pairs, including varied sentiments derived from 3 separate summaries for each entity.

**Incremental summary table generation.** To assess the LLM’s incremental update capabilities, we generate multiple summary tables per entity. The initial summary is the basis from which we sample attributes and values for incremental versions. These incremental summaries simulate real-world scenarios where information evolves. We ensure two criteria are met: 1) Repetition of attributes and values across summaries, and 2) The presence of conflicting attribute information. Conflicting values can be generated by prompting an LLM to produce values that directly oppose the meanings of originally sampled values. This incremental summary generation iteratively creates K summaries. Each iteration combines half the attributes from a previous summary with half from the unused attribute pool, resulting in K summary tables per entity with diverse and potentially contradictory content.

### 3.3 Paragraphs

**Paragraph generation.** Building upon the K incrementally generated summary tables (Section 3.2), we craft aligned paragraphs for each. The fundamental goal is to seamlessly incorporate all attributes and values from a given table into the text. Additionally, we prioritize meaningful and diverse writing styles, avoiding overly simplistic language. To achieve this, we define 8 writing categories (user reviews by teenagers, user reviews by parents, user reviews by senior, user reviews, official product descriptions, editorial insights, posts on social media, discussions on online forums) and 6 tones (optimistic, neutral, pessimistic, sarcastic, humorous, analytic). Each paragraph is randomly assigned a category

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and a tone, which guide its generation. We also integrate citation numbers (e.g. 0, 1, 2, ...) that directly link each sentence to the attribute-value pair it reflects in the summary table. This process results in  $K$  paragraphs per entity (in our case,  $K=7$ ), showcasing a variety of styles, tones, and embedded citations for easy reference.

**Paragraph-Summary table alignment verification.** While the sentences in paragraphs are created based on summary tables, the generated paragraphs do not guarantee that all values are reflected in sentences. To make sure that sentences include the attribute-value pairs in the given summary table, we break paragraphs down into sentences and LLM verifies if the attribute-value pair (e.g. (Room quality, Clean)) is accurately represented in each sentence. If the value is correctly included and its meaning is not misrepresented (e.g. With its impeccable clean rooms...), no change is needed. If the value is missing or misrepresented (e.g. While its cleanliness of the rooms are debatable...), the sentence should be adjusted to accurately incorporate the value.

After the automated critique and revision step, we conduct human evaluation on 40 randomly sampled paragraphs and their corresponding summary tables. Three human annotators checked for misaligned attribute-value pairs in the paragraphs based on the summary tables. Our dataset achieved 96% of accuracy with 70% of agreement rate.<sup>2</sup>

### 3.4 Distracting Sentences

After ensuring paragraph-summary table alignment, where all sentences contain attribute-value pairs, we introduce distractor sentences to test the LLM’s focus. Since LLMs perform well in finding relevant contexts, we need to challenge their ability to identify and ignore incorrect entity associations. We do this in two ways: first, by generating sentences about irrelevant entities, explicitly including their generic names (e.g. HOTEL2 boasts a vibrant atmosphere, perfect for...), and second, by creating metaphorical sentences that describe a human using properties of the given entity’s category (always including the word “HUMAN”) (e.g. HUMAN’s empathy is a sprawling garden, teeming with vibrant blooms of compassion...). These distractors allow us to analyze two crucial aspects of LLM performance: entity focus (avoiding irrelevant information) and adjective sensitivity (understanding adjectives even in unrelated contexts).

### 3.5 Dataset Statistics

We present our dataset statistics for the entity level and paragraph level in Appendix A.2. Overall, the dataset contains 200 entities (20 for each of the 10 categories) and each entity contains an average of 22 attributes and 42 values across all paragraphs, which we believe, achieves *sufficient complexity* for evaluation. Entities within the same category display a significant amount of diversity. They have approximately 14 distinct attributes (64%) and 41 distinct values (97%) on average. This demonstrates a high degree of variation in their attributes and values. In paragraph statistics (in Appendix A.2), we find that number of “same”, “conflict”, and “new” attribute values in each paragraph are around 3.7, 3.5, and 2.3, respectively, meaning that same, conflict, and new attribute-value pairs are reasonably distributed across paragraphs. Average number of sentences in paragraphs is 12, with roughly 4 sentences acting as distractors. This indicates that our paragraphs offer sufficient length and incorporate a reasonable amount of distractor sentences.

We show 5 dataset examples in the Appendix from Figure 20 to 24 in categories of “Computer & Video Games”, “Vitamins & Supplements”, “Restaurants & Bars”, “Books & Literature”, and “Education”, respectively.

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<sup>2</sup>It means 70% of examples demonstrate full agreement among three annotators. Furthermore, 100% examples achieve at least two-annotator agreement.

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## 4 Experiments

### 4.1 Baseline Methods

Our dataset evaluation utilizes two prompt-based approaches, UPDATE and MERGE, designed to assess the LLM’s ability to handle new information and conflicts.

**Update.** LLMs struggle to create comprehensive, high-quality summary tables from large amounts of text due to limited recall (Gunel et al., 2023). We address information overload and reduce the LLM’s processing burden by feeding it one paragraph at a time. The first iteration involves generating a summary table from a single paragraph. Afterwards, the LLM receives a new paragraph (potentially containing overlapping, new, or conflicting information) and the previously generated summary table. Its goal is to produce an updated summary table, accurately incorporating relevant details from the new paragraph. Prompts for this method can be found in Appendix A.4.

**Merge.** This approach breaks down the UPDATE process into two steps, designed to enhance the LLM’s understanding. The first iteration remains the same as the UPDATE, with the model generating a summary table from a new paragraph. In later iterations, the model first creates a summary table solely from the new paragraph and then merges it with the existing table. This promotes a clear understanding of the two-step process of retrieving information and updating the summary, potentially reducing the LLM’s cognitive load. Prompts for this method can be found in Appendix A.4.

### 4.2 Evaluation Metrics

We evaluate the performance of the aforementioned approaches to the incremental entity summarization task using precision, recall, and F1. An extraction comprises three components – the attribute, its corresponding value, and the supporting evidence. A successful extraction is one that is also found in the set of goldens corresponding to the input paragraph.

We determine *true positives* via two methods. **Exact matching** checks for a direct match between the predicted value or evidence and the golden set.<sup>3</sup> **LLM-based evidence finding** leverages an LLM to detect if the predicted attribute and value find support within the larger golden set (see Appendix A.4 for prompt). Initially, we explored semantic similarity scores like BLEURT (Sellam et al., 2020). However, their limitations in handling paraphrases led us to adopt an LLM for this task, as it excels at identifying evidence even when phrased differently. If a predicted extraction fails to match exactly or through the LLM-based evidence prompt, it’s marked as a *false positive*. *False negatives* are tracked by noting goldens unmatched to any prediction. While exact matches are simple, LLM-based matches are trickier. The LLM outputs the matched golden row (attribute, value, evidence), but it may not precisely align with the table due to the LLM’s generative nature. To address this, we evaluate the cosine similarities between a sentence encoding (we use Universal Sentence Encoder (Cer et al., 2018)) of the response’s evidence to the sentence encodings of all the evidences in the golden set to find the highest likelihood golden.

To check its effectiveness in identifying evidence linking predicted and gold-standard attribute values, we manually checked up to 3 paragraphs under the 3 categories, which include more than 210 attribute-value pairs to evaluate. We count incorrectly classified pairs in true positive, false positive, and false negative sets. The Gemini-Pro model achieves 90.4% accuracy in evidence detection with a standard deviation of 1% across categories, proving its suitability as an evidence detector between predicted and gold values.

Redundancy and hallucination are crucial metrics requiring evaluation. Redundancy, where models repeatedly extract the same correct value, can artificially inflate F1 scores and hinder fair performance comparisons. Moreover, LLMs are prone to hallucinations, where they

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<sup>3</sup>But in tasks like structured entity summarization, it is rare that extractive techniques exactly match the gold truth sets, as such we need methods that can handle the nuance of language.

		Model	Metric	Turns							Avg.
				1	2	3	4	5	6	7	
UD	Gemini-Pro	Precision	80.0	81.9	82.6	82.5	83.8	84.1	84.3	82.8	
		Recall	82.5	76.2	73.2	70.4	69.7	68.4	67.3	72.5	
		F1	<b>80.7</b>	<b>78.4</b>	<b>77.2</b>	75.3	75.5	74.8	74.2	<b>76.6</b>	
	GPT3.5	Precision	78.7	78.2	79.3	79.4	79.8	79.7	80.0	79.3	
		Recall	81.6	78.1	75.7	74.8	74.8	74.9	75.1	76.4	
		F1	79.5	77.6	77.0	<b>76.7</b>	<b>76.8</b>	<b>76.9</b>	<b>77.1</b>	77.4	
	Gemini-Nano	Precision	58.7	52.6	49.0	47.0	46.1	46.0	45.9	49.3	
		Recall	65.4	43.5	31.0	25.0	21.1	18.6	16.2	31.5	
		F1	60.7	46.4	37.2	31.9	28.3	26.0	23.5	36.3	
MG	Gemini-Pro	Precision	79.4	79.7	80.4	80.6	80.8	81.8	83.1	80.8	
		Recall	82.1	84.0	83.2	82.0	81.1	78.7	74.8	80.8	
		F1	<b>80.1</b>	81.4	<b>81.4</b>	<b>80.9</b>	<b>80.5</b>	<b>79.9</b>	78.3	<b>80.4</b>	
	GPT3.5	Precision	75.7	76.4	76.1	77.4	76.4	76.2	77.7	76.6	
		Recall	83.3	88.3	87.8	85.3	84.2	82.9	82.5	84.9	
		F1	78.8	<b>81.6</b>	81.3	80.8	79.8	79.1	<b>79.8</b>	80.2	
	Gemini-Nano	Precision	60.0	51.0	53.7	54.0	56.7	57.9	57.1	55.8	
		Recall	66.5	47.4	37.0	32.0	29.6	25.5	22.0	37.1	
		F1	62.1	47.9	42.1	38.4	37.5	33.9	30.5	41.8	

Table 1: Performance with Gemini-Pro, GPT3.5, and Gemini-Nano models across different turns. UD denote UPDATE and MG denote MERGE. Best F1 scores are in **boldface**.

generate incorrect values from extracted evidences. Though these hallucinations negatively impact precision and F1 scores, we still want to explicitly measure its severity. For a thorough analysis, we employed two human experts to manually assess these issues within the predicted summary tables; their findings are discussed in the Section 4.4.

### 4.3 Experimental Setup

We experiment with Gemini-Pro (Team et al., 2023), GPT3.5 (Ouyang et al., 2022), and Gemini-Nano (Team et al., 2023) models. The temperatures for all models are set to 0.7. With each entity having 7 paragraphs, we aggregate summary tables iteratively, reporting average precision, recall, and F1 scores across all entities.

### 4.4 Results and Discussion

**Overall performance, Table 1.** Table 1 shows an overall performance of Gemini-Pro, GPT3.5, and Gemini-Nano on our dataset. At first glance, all models have a large room for improvement, highlighting our dataset’s complexity. In particular, Gemini-Nano model performs significantly worse than Gemini-Pro and GPT3.5 in both UPDATE and MERGE methods, with an average F1 score gap of 40.3 for UPDATE and 38.6 for MERGE. The reason of this substantial performance gap between Gemini-Pro/GPT3.5 and Gemini-Nano models can be attributed to the differences across iterations. While the Gemini-Nano model performs reasonably well in the first iteration, its recall scores begin to rapidly decline from the second iteration, resulting in a decrease of more than 20 points. By the final iteration, the Gemini-Nano model produces significantly lower scores, reaching 23.5 for UPDATE and 30.5 for MERGE. This suggests that as the context becomes more complex, smaller LLMs struggle to identify and integrate new or relevant information effectively. Moreover, when the input context in the prompt becomes overly lengthy, Gemini-Nano model struggles to understand instructions correctly, leading to up to 13% of invalid answers, such as repeating the input prompt in the response. In contrast, Gemini-Pro and GPT3.5 generate substantially fewer invalid answers (around 0%) even with complex inputs.

Interestingly, while Gemini-Pro and GPT3.5 show comparable performance, Gemini-Pro tends to produce higher precision scores, suggesting that it prioritizes confident and accurate answers. On the other hand, GPT3.5 achieves better recall scores, indicating that it explores a broader range of answer choices. This becomes more evident in later iterations. While GPT3.5 model produces relatively stable performance in both precision and recall scores across all iterations, Gemini models exhibit a trade-off between precision and recall scores. This shows that Gemini models prioritize to keep the reliable results with the complex context. None of these advanced LLMs achieved higher F1 than 80.4%, supporting the

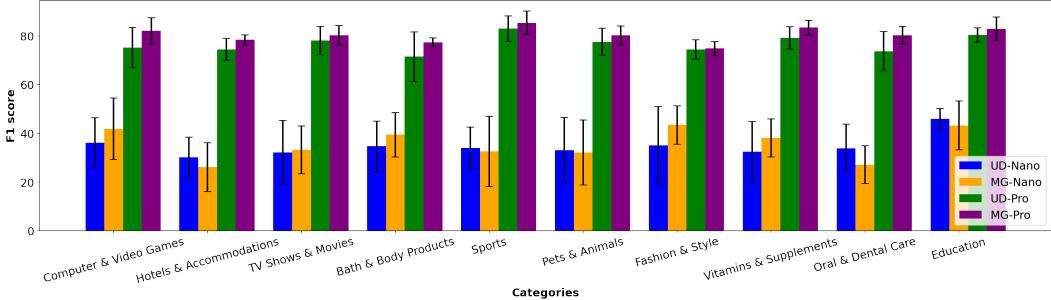


Figure 3: F1 scores across 10 categories (see Appendix A.5 for the rest.).

	Metric	0	1	2	3	4	5	6	Avg.
w/ distractor	Precision	80.0	81.9	82.6	82.5	83.8	84.1	84.3	82.8
	Recall	82.5	76.2	73.2	70.4	69.7	68.4	67.3	72.5
	F1	80.7	78.4	77.2	75.3	75.5	74.8	74.2	76.6
w/o distractor	Precision	97.2	96.5	96.6	96.6	97.0	96.7	96.8	96.8
	Recall	84.3	77.8	74.3	72.8	71.5	70.5	70.1	74.5
	F1	89.9	85.8	83.7	82.7	82.0	81.3	81.0	83.8

Table 2: Precision, Recall, and F1 score after removing distractor sentences.

empirical finding that LLMs excel at expanding short phrases into descriptive, contextual paragraphs, rather than abstractly summarizing all important components from longer text.

**Difference across methods, Table 1.** We observe that models perform better with MERGE method than UPDATE approach. This confirms our hypothesis that breaking down UPDATE method into two steps gives a better understanding of our task to LLMs. The MERGE method is particularly beneficial for maintaining recall scores. This is likely because it first extracts attributes and values from the given new paragraph, which are then presented to the model for merging with the existing knowledge. By making the information we want to add explicit in the prompt, the model can more easily make use of the given knowledge.

**Difference across categories and tones, Figure 3, 19.** Figure 3 presents the F1 scores achieved by the model across different categories, along with their standard deviations. As the figure shows, the model exhibits consistent performance across all categories. There are no significant outliers, implying that the performance of models on our dataset is not biased towards certain categories. Figure 19 in the Appendix shows the performance across paragraph tones and we observe the similar trends to the performance across categories. We also note that standard deviations of Gemini-Nano models are considerably larger than those of Gemini-Pro models in most cases, reconfirming the challenging nature of our dataset.

**Effect of distractor sentences, Table 2, Figure 4.** Table 2 shows the performance of Gemini-Pro model with UPDATE method after removing distractor sentences in paragraphs. We find that precision scores achieve up to 97 point when the distractor sentences are removed. This proves that our distractor sentences are effectively confusing LLMs and LLMs struggle in strictly focusing on the context relevant to the specific entity. Moreover, it further indicates that our evaluation method based on LLMs works reasonably well in detecting evidence between generated attribute and value pairs and gold attribute, value, and sentence pairs. Figure 4 shows an example of incorrect output from LLMs with distractor sentences. We find that LLMs can easily be misled by information that include several adjective words and also struggle in distinguishing context crucial to the specific entity.

**Human evaluation for checking value redundancy.** In addition to F1 scores, we perform two human evaluations to assess how well the model consolidates similar attribute-value pairs (redundancy checking) and to check how well the extracted evidence supports the values. For redundancy checking, two annotators are presented with 30 randomly selected attributes with more than two distinct values generated by Gemini-Pro. They indicate ‘yes’

<b>Entity:</b> RESTAURANT1
<b>Paragraph:</b>
...
P3: However, service can be a mixed bag, with some staff members exhibiting dismissive attitudes.
P4: RESTAURANT10's modern and elegant decor creates a sophisticated dining experience, ...
...
P6: Like a restaurant with a coveted reservation list, HUMAN's time is precious and highly sought after, ...
<b>Generated Summary Table:</b>
Attribute   Values
---   ---
Service   Dismissive staff ([P3, "...with some staff members exhibiting dismissive attitudes"])   <input checked="" type="checkbox"/>
Ambiance   Modern, elegant decor at RESTAURANT10 ([P4, "RESTAURANT10's...modern and elegant decor"])   <input type="checkbox"/>
Popularity   Highly sought after, requiring advance planning ([P6, "HUMAN's time is precious and highly sought after..."])   <input type="checkbox"/>

Figure 4: An example of an LLM distracted by irrelevant information.

if the values for each attribute are redundant (e.g., Attribute: Location, Values: [Walking distance from Downtown, easy access to Downtown]), and ‘no’ otherwise. This evaluation is crucial because an excessive number of similar values for the same attribute can inflate true positives, resulting in artificially high precision and recall scores. We find that, on average, 45% of values are deemed redundant with a 73% agreement rate, indicating that the LLM struggles with identifying and merging synonyms into a single value.

**Human evaluation for hallucination between value and evidence.** Similarly to redundancy checking, two annotators are tasked with assessing the alignment between extracted evidence and attribute values. They are provided with 30 randomly selected attributes, along with their corresponding values and evidences. The annotators mark ‘yes’ if the attribute and values are supported by evidence, and ‘no’ otherwise. This allows us to assess the faithfulness of LLMs in extracting evidences to support attribute and values. We find that an average of 25% of the samples are marked as ‘no’, meaning that evidence does not support the values, with 90% of agreement ratio. An example where the value is not supported by evidence is the attribute-value pair “Guest Privileges” with the value “ability to earn points that can be redeemed for free nights,” and the evidence provided by the model is “Your loyalty will be rewarded,” where the evidence does not explicitly mention earning points or free nights. This suggests that LLMs often generate attributes and additional details that are not directly supported by the source information.

## 5 Related Work

Our review delves into incremental entity summarization (IES), analyzing approaches, methodologies, and datasets, with a particular emphasis on knowledge update techniques and conflict resolution.

### 5.1 Techniques for Incremental Entity Summarization

Current ES research has largely focused on summarizing entities from RDF data by selecting key triples (Wei et al., 2019; Liu et al., 2020a; 2021), aiming for compact summaries. Our approach, in contrast, seeks to harness unstructured web text for more comprehensive summaries. While Formal Concept Analysis shows promise in structured knowledge bases (Yang et al., 2021), it struggles with the complexity of web information. Existing datasets (Liu et al., 2020b; Gunaratna et al., 2015; 2016) fall short in testing LLMs’ capabilities for web-driven, incremental summary generation. The ENTSUM dataset (Maddela et al., 2022) aids in controllable summarization but is limited in assessing structured or incremental summary creation. Our work broadens the definition of IES, investigating the construction of comprehensive and precise structural summaries using advanced generation models such as LLMs, and introducing a dataset tailored for this innovative field.

### 5.2 Addressing Knowledge Updates and Conflicts

The main challenge in IES is enabling LLMs to handle knowledge updates and resolve information conflicts. Solutions like CoverSumm (Chowdhury et al., 2024) and the KNOWLEDGE CONFLICT dataset (Wang et al., 2023) offer ways to update summaries and test

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conflict resolution, albeit without the necessary complexity for IES. Similarly, the FreshQA benchmark (Vu et al., 2023) tests LLM factuality but doesn't cater specifically to evolving summaries. Our dataset fills this gap, demanding LLMs to identify and adjust to conflicts in entity summaries, with a focus on evidence-based claim reprioritization, aligning closely with the unique requirements of IES.

## 6 Conclusion and Future Work

In this paper, we introduce SUMIE, a novel benchmark, specifically created to assess the ability of LLMs to generate incremental summaries of entities. SUMIE's synthetic nature ensures data quality and diversity while minimizing the need for extensive human annotations. We also share our thoughts about paper's limitation in the Appendix A.1. While our initial baselines demonstrate the dataset's challenges, future work offers exciting avenues. We will focus on preventing knowledge loss during LLM updates, refining attribute and value recognition to minimize hallucinations, and extending the task to multi-entity comparison summaries. Overall, this paper aims to spark impactful research into the crucial task of maintaining up-to-date and comprehensive knowledge.

## 7 Ethics Statement

Our dataset is primarily meant to serve as a diagnostic tool to evaluate LLMs' ability of resolving knowledge conflicts incrementally and generating faithful responses. In addition, the LLMs we used for creating the dataset are trained on a large-scale web corpus and may also bring some bias when generating sentences.

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## A Appendix

### A.1 Limitations

Firstly, although the evaluation uses three LLMs (including Gemini and GPT-3.5), incorporating additional open-source models would strengthen the findings. Secondly, the chosen LLM-based evaluation metrics can be computationally expensive and time-consuming to execute. Finally, while the automated critique and revision module demonstrates high accuracy (96%) on a sample set, reviewing the entire dataset with human annotators could potentially achieve complete alignment (100%) between generated summary tables and paragraphs.

### A.2 Detailed Dataset Stats

We present our dataset statistics for the entity level and paragraph level in Table 3 and 4. Table 3 details the average number of attributes and values associated with individual entities. It also shows the average number of unique attributes and values observed across all entities, considering all paragraphs associated with each entity. Table 4 shows the average number of “same”, “conflict”, “new” attribute and value pairs, and an average number of sentences and distractor sentences in each paragraph.

Categories	# attr	# val	# diff attr	# diff val
Bath & Body Products	23.70	44.00	12.06	43.17
Bedding & Bed Linens	22.10	40.40	13.50	37.11
Books & Literature	22.30	43.80	16.78	43.00
Computer & Video Games	23.20	42.60	14.78	42.44
Computers & Electronics	22.50	43.80	15.72	42.22
Drugs & Medications	19.60	39.70	10.83	38.33
Education	23.20	45.20	14.56	44.50
Fashion & Style	23.50	45.60	15.17	45.11
Fruits & Vegetables	22.30	40.80	13.72	39.22
Hobbies & Leisure	22.80	44.50	16.06	44.22
Hotels & Accommodations	22.70	40.40	16.06	38.50
Household Supplies	21.60	40.90	13.50	38.39
Music Equipment & Technology	21.90	44.30	13.17	43.06
Oral & Dental Care	22.40	44.80	13.44	43.56
Pets & Animals	22.70	41.70	15.56	39.72
Restaurants & Bars	22.30	40.30	14.89	39.22
Skin & Nail Care	22.90	40.80	15.94	39.56
Sports	22.40	42.70	16.17	42.61
TV Shows & Movies	21.50	39.50	15.83	38.39
Vitamins & Supplements	20.80	39.70	13.44	38.89

Table 3: Entity level statistics. # attr: average number of attributes per entity, # val: average number of values per entity, # diff attr: average different number of attributes across entities, # diff val: average different number of values across entities.

Categories	# same attr-val	# conflict attr-val	# new attr-val	# sent	# dist
Bath & Body Products	3.45	3.58	2.43	12.28	4.00
Bedding & Bed Linens	3.50	3.87	2.23	12.33	4.00
Books & Literature	3.68	3.55	2.30	11.93	4.00
Computer & Video Games	3.57	3.35	2.48	12.13	4.00
Computers & Electronics	3.65	3.62	2.33	12.55	4.00
Drugs & Medications	4.17	3.22	1.95	12.12	4.00
Education	3.40	3.62	2.43	12.02	4.00
Fashion & Style	3.67	3.52	2.55	12.70	4.00
Fruits & Vegetables	3.93	3.02	2.38	11.88	4.00
Hobbies & Leisure	3.57	3.52	2.38	12.72	4.00
Hotels & Accommodations	3.45	3.67	2.38	12.33	4.00
Household Supplies	3.43	3.78	2.20	11.85	4.00
Music Equipment & Technology	3.58	3.72	2.28	12.25	4.00
Oral & Dental Care	3.40	3.88	2.20	11.80	4.00
Pets & Animals	4.00	3.30	2.32	12.18	4.00
Restaurants & Bars	4.02	3.45	2.18	12.23	4.00
Skin & Nail Care	3.77	3.55	2.42	12.42	4.00
Sports	3.87	3.27	2.32	12.35	4.00
TV Shows & Movies	3.55	3.42	2.22	11.97	4.00
Vitamins & Supplements	3.48	3.63	2.07	12.08	4.00

Table 4: Paragraph level statistics. # same attr-val: average number of same attribute-value pairs between paragraphs, # conflict attr-val: average number of conflicting attribute-value pairs between paragraphs, # new attr-val: average number of new attribute-value pairs between paragraphs, # sent: average number of sentences per paragraph, # dist: average number of distracting sentences per paragraph.

### A.3 Dataset Generation Prompts

Figure 5 and 6 show prompts for generating attributes and fake entity names, respectively. Figure 7 presents a prompt for generating values as a summary table format. Figure 8 and

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[9](#) are prompts for generating paragraphs and for aligning summary tables to paragraphs, respectively.

TASK: List the top 50 attributes when people summarize entity of a given category. The attributes should be common or rare according to the request. Attributes should be separated by ' ; '.

Figure 5: Generate Attribute Instruction.

TASK: Generate 45 fake plausible entity names in the given category. Make sure that entity names are unique. Entities should be separated by ' ; '.

Figure 6: Generate Entity Name Instruction.

TASK: Create a descriptive summary table for a given entity focusing on the following attributes and the given type.  
For each attribute, generate at least three descriptive values that are:

1. Meaningful and informative.
2. Diverse in length, ranging from one word to a maximum of ten words.
3. Varied in style, offering a mix of user reviews, official product descriptions, and editorial insights.
4. Type: "Fact" should not contain any words that can be interpreted as positive or negative properties of the given entities (e.g. restrooms are well-maintained, family-friendly).

The summary table should have two columns: attributes and values. Ensure the values are separated by ' ; ' to clearly distinguish between them.

Figure 7: Generate Default Summary Instruction.

#### A.4 LLM-based Evaluation Prompts

Figure 17 shows a prompt used for LLM evidence finding (in Sec 4.2). In UPDATE method, we use prompts for GENERATE at 1st iteration, which are a combination of Figure 11 and 12. Afterwards, we use prompts for UPDATE in Figure 13 and 14 for the subsequent iterations. Similarly, in MERGE method, we use prompts for GENERATE at 1st iteration, which are a combined version of Figure 11 and 12. For the subsequent iterations, we employ two prompts for GENERATE (Figure 11 and 12) MERGE (Figure 15 and 16).

#### A.5 Performance across paragraph tones and categories

Figure 18 shows F1 scores across additional 10 categories. Figure 19 presents F1 scores across paragraph tones.

#### A.6 Example data points of SUMIE dataset

Figure 20, 21, 22, 23 and 24 show examples of (attribute, value, sentence) triples and distractor sentences exist in our dataset in 5 different categories.

---

TASK: Create a paragraph for a given entity focusing on the following attributes and values.

For each attribute and value, generate at least one sentence that is:

1. Meaningful and informative, including both subjective opinions and objective facts.
2. Writing style should follow the given paragraph writing style.
3. Make sure to cite index number in summary table when generating the sentence.
4. Make sure to include diverse sentiments and attribute and values in the summary table.
5. Make sure not to change the core meaning of attribute and value pair due to writing style and sentiment.

The paragraph should include all index numbers, attributes, and values in the summary table. Split sentences with a new line.

Figure 8: Generate Paragraph Instruction.

TASK: Verify whether the given attributes and values are described in the sentences and whether corresponding index number is cited correctly.

The inputs contain multiple lines, each of which starts with multiple (index, attribute, value) pairs, and a sentence can be followed or not.  
Please output True/False for each line.

These are two conditions of being False:

1. Given attribute and value pairs do not follow by a sentence.
2. The context around citation number does not match with the index number in the attribute and value pairs.
3. Sentiment of the given attribute and value pair is incorrectly reflected in the sentence.

If False is outputted, please provide an explanation and revise the original sentence or generate a new sentence to describe the attribute and value for an entity and its category.

Revised sentence should not include any new information other than provided attribute and value.

Ensure that all attribute and value pairs are completely mentioned.

Make sure to include the index number of the attribute and value pair using square braces (e.g. [index]).

Do not make up any citation numbers that are not provided in (index, attribute, value) pairs.

The format should be as follows: "[**(index1, attribute1, value1)**, (**index2, attribute2, value2**), ...];;**True**;;" or "[**(index1, attribute1, value1)**, (**index2, attribute2, value2**), ...];;**False**;;**Explanation**;;**Revised/New sentence**".

Figure 9: Critique for Summary-Paragraph Alignment Prompt.

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TASK: Generate 10-15 complicated sentences that describe the given entity and category using the given attributes.

Generated sentences should:

1. Be meaningful and informative, including both subjective opinions and objective facts.
2. Be varied in style, offering a mix of user reviews, official product descriptions, and editorial insights.
3. Make sure to include entity name in the sentence.

Split sentences with a new line.

Figure 10: Generate Irrelevant Sentence Instruction.

**Task Overview:**

Your task involves synthesizing information from detailed descriptive paragraphs about a specific entity into a summary table.

This table will highlight key attributes of the entity along with their detailed descriptions derived from the given texts.

**Instructions:**

- \* Extract Descriptive Values: Focus on extracting specific, detailed information rather than general or vague adjectives like "good" or "bad." Ensure that descriptions are precise and informative.
- \* Present a Balanced View: The table should reflect a balanced perspective, including positive, negative, and neutral attributes. For attributes with mixed reviews, indicate the sources supporting each viewpoint.

**Attribute Selection:**

- Commonly Interested Attributes: Include attributes that are generally of interest for the type of entity being described.
  - Unique Attributes: Also identify and include unique attributes that are specifically mentioned in the provided descriptions.
- \* Citations and Evidence: Each attribute listed in the table should be supported by citations from the source paragraphs. Keep evidence concise but ensure it substantiates the listed values.

**Structure of the Summary Table:**

- \* The table should be organized into two columns: Attribute and Value.
- \* List attributes with their corresponding values, including citations indicating the source paragraph and relevant excerpts for substantiation.
- \* Citation and evidence should be paired in a [] and separated by ';' . If an attribute has multiple values, then each value should be separated by '&&&' .

Figure 11: Instruction prompt for GENERATE.

---

**Example:**  
**Entity:** San Jose Marriott Hotel

**Paragraphs:**

P1. Great room and service, but breakfast was lacking. We loved the spacious room and friendly staff, but the breakfast options were limited. There are two pools.

P2. Poor customer service overshadowed the beautiful location. The beachfront view was amazing, but dealing with unhelpful staff was frustrating. Room is comfortable.

P3. Exceptional dining and comfortable beds, but noisy at night. The restaurant was five-star, and the beds were very cozy, but there was a lot of street noise.

**Summary Table:**

Attribute	Value
---	---
Room Quality	Spacious and comfortable rooms ([P1, "spacious room"]; [P2, "Room is comfortable"])
Amenities	Two pools ([P1, "There are two pools"])
Service	Friendly staff ([P1, "friendly staff"]) && overshadowed by unhelpful staff ([P2, "Poor customer service overshadowed the beautiful location"])
Location	Beautiful beachfront view ([P2, "The beachfront view was amazing"])
Food & Beverage	Exceptional dining experience ([P3, "Exceptional dining"]) && limited breakfast options ([P1, "but breakfast was lacking"])
Noise Level	Notable street noise at night ([P3, "but there was a lot of street noise"])

**Your Task:**  
Generate a similar table based on the following descriptions of the specified entity.  
**Entity:** < entity name >

**Paragraphs:**  
< paragraph >

Proceed to generate the summary table. Output summary table format should follow the above example of Summary Table.

Figure 12: Prompt that describes GENERATE task with one example.

---

**Task Overview:**

You are tasked with refining and expanding an existing summary table based on new descriptive paragraphs about an entity.

This involves updating the table to include new information, modify existing details without removing any, and ensuring all entries are supported by evidence from the text.

**Instructions:**

\* Update Descriptive Values: Carefully read the new paragraph(s) and identify any information that should be added to the current table entries or modify them. Focus on specific, descriptive details, avoiding vague adjectives.

\*\*Do not remove any existing attributes or values\*\*, but rather add to or revise them as necessary.

\* Maintain a Balanced View: Ensure the updated table continues to present a balanced perspective, incorporating positive, negative, and neutral values. For any attribute with mixed evidence, update the count of sources supporting each view.

\* Maintain a Balanced View: Ensure the updated table continues to present a balanced perspective, incorporating positive, negative, and neutral values. For any attribute with mixed evidence, update the count of sources supporting each view. All original attributes and values must be preserved in the table, with modifications only to reflect new insights or corrections based on the latest information.

\* Attribute Revision and Addition:

- Commonly Interested Attributes: Update or add attributes that are of general interest for the type of entity being described, based on the new information.

- Unique Attributes: Identify and incorporate any unique attributes mentioned in the new paragraphs that were not previously included in the table.

\* Evidence and Citations: For each updated or new attribute entry, provide citations from the new paragraphs. Strive for concise evidence that directly supports the attribute values.

**Structure of the Updated Summary Table:**

\* Retain the two-column format: Attribute and Value.

\* For each attribute, list the updated or new values along with citations indicating the source paragraph and relevant excerpts. Original attributes and values should remain listed, with additional information appended as necessary.

\* Citation and evidence should be paired in a [] and separated by ';''. If an attribute has multiple values, then each value should be separated by '&&&'.

Figure 13: Instruction prompt for UPDATE.

---

**Example**

Entity: San Jose Marriott Hotel

New Paragraph:

"P4. The hotel has recently renovated its lobby, which now features a modern design. Guests have also noted improvements in breakfast variety and quality."

Given Existing Summary Table:

Attribute	Value
---	---
Room Quality	Spacious and comfortable rooms ([P1, "spacious room"]; [P2, "Room is comfortable"])
Amenities	Two pools ([P1, "There are two pools"])
Service	Friendly staff ([P1, "friendly staff"]) && overshadowed by unhelpful staff ([P2, "Poor customer service overshadowed the beautiful location"])

Updated Summary Table:

Attribute	Value
---	---
Room Quality	Spacious and comfortable rooms ([P1, "spacious room"]; [P2, "Room is comfortable"])
Amenities	Two pools ([P1, "There are two pools"])
Food & Beverage	Exceptional dining experience ([P3, "Exceptional dining"]) && limited breakfast options ([P1, "but breakfast was lacking"]) && improved breakfast variety and quality ([P4, "improvements in breakfast variety and quality"])
Lobby Design	Modern design ([P4, "recently renovated its lobby, which now features a modern design"])

Your Task:

Update the summary table with the given new descriptions of the specified entity.

Entity: < entity name >

New Paragraph:

< paragraph >

Given Existing Summary Table:

< existing summary table >

Proceed to update the summary table. Output summary table format should follow the above example of Summary Table.

Figure 14: Prompt that describes UPDATE task with one example.

---

**Task Overview:**

You are tasked with combining two summary tables based on existing and new descriptive paragraphs about an entity and generating an updated summary table that contains information from both tables (existing summary table and new summary table). This involves updating the table to include new information, modify existing details without removing any, and ensuring all entries are supported by evidence from the text.

**Instructions:**

- \* Update Descriptive Values: Carefully read the new paragraph(s) and identify any information that should be added to the current table entries or modify them. Focus on specific, descriptive details, avoiding vague adjectives.
- \*\*Do not remove any existing attributes or values\*\*, but rather add to or revise them as necessary.
- \* Maintain a Balanced View: Ensure the updated table continues to present a balanced perspective, incorporating positive, negative, and neutral values. For any attribute with mixed evidence, update the count of sources supporting each view.
- \* Maintain a Balanced View: Ensure the updated table continues to present a balanced perspective, incorporating positive, negative, and neutral values. For any attribute with mixed evidence, update the count of sources supporting each view. All original attributes and values must be preserved in the table, with modifications only to reflect new insights or corrections based on the latest information.
- \* Attribute Revision and Addition:
  - Commonly Interested Attributes: Update or add attributes that are of general interest for the type of entity being described, based on the new information.
  - Unique Attributes: Identify and incorporate any unique attributes mentioned in the new paragraphs that were not previously included in the table.
- \* Evidence and Citations: For each updated or new attribute entry, provide citations from the new paragraphs. Strive for concise evidence that directly supports the attribute values.

**Structure of the Updated Summary Table:**

- \* Retain the two-column format: Attribute and Value.
- \* For each attribute, list the updated or new values along with citations indicating the source paragraph and relevant excerpts. Original attributes and values should remain listed, with additional information appended as necessary.
- \* Citation and evidence should be paired in a [] and separated by ';'. If an attribute has multiple values, then each value should be separated by '&&&'.

Figure 15: Instruction prompt for MERGE.

---

Example  
Entity: San Jose Marriott Hotel

Given Existing Summary Table:

Attribute	Value
---	---
Room Quality	Spacious and comfortable rooms ([P1, "spacious room"]; [P2, "Room is comfortable"])
Amenities	Two pools ([P1, "There are two pools"])
Service	Friendly staff ([P1, "friendly staff"]) && overshadowed by unhelpful staff ([P2, "Poor customer service overshadowed the beautiful location"])
Food & Beverage	Exceptional dining experience ([P3, "Exceptional dining"]) && limited breakfast options ([P1, "but breakfast was lacking"])

New Summary Table:

Attribute	Value
---	---
Food & Beverage	improved breakfast variety and quality ([P4, "improvements in breakfast variety and quality"])
Lobby Design	Modern design ([P4, "recently renovated its lobby, which now features a modern design"])

Combined Summary Table:

Attribute	Value
---	---
Room Quality	Spacious and comfortable rooms ([P1, "spacious room"]; [P2, "Room is comfortable"])
Amenities	Two pools ([P1, "There are two pools"])
Food & Beverage	Exceptional dining experience ([P3, "Exceptional dining"]) && limited breakfast options ([P1, "but breakfast was lacking"]) && improved breakfast variety and quality ([P4, "improvements in breakfast variety and quality"])
Lobby Design	Modern design ([P4, "recently renovated its lobby, which now features a modern design"])

Your Task:  
Combine existing and new summary tables of the specified entity and generate a new output summary table.  
Entity: < entity name >

Given Existing Summary Table:  
< existing summary table >

New Summary Table:  
< new summary table >

Proceed to combine the two summary tables and generate a new output summary table. Output summary table format should follow the above example of Summary Table.

Figure 16: Prompt that describes MERGE task along with one example.

You will be given two summaries: a reference summary table (gold standard) and a generated summary table. Your task is to check if the gold standard contains the information in the generated summary.

Please output with Yes/No.

Requirements for Yes:

- Meaningful Correspondence: Each attribute-value pair in the generated table should capture the core meaning of its corresponding pair in the reference table, even if worded differently.
- Partially relevant evidence is okay: While the evidence in the generated table does not have to be exactly match with its corresponding attribute-value pair's evidence, it should not be completely off base.

Figure 17: LLM-based redundancy checking prompt.

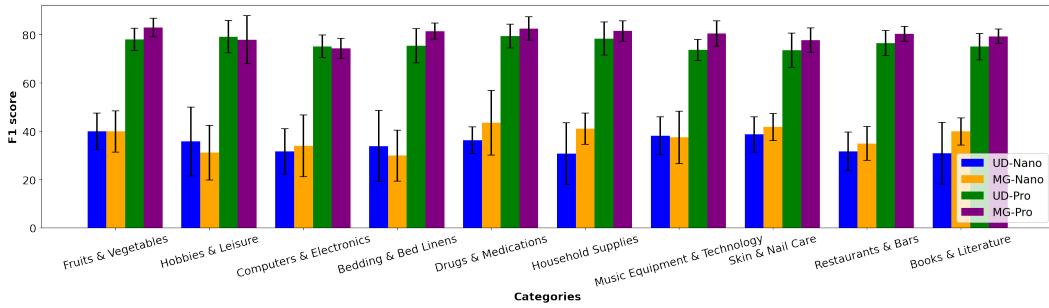


Figure 18: F1 scores across 10 paragraph categories.

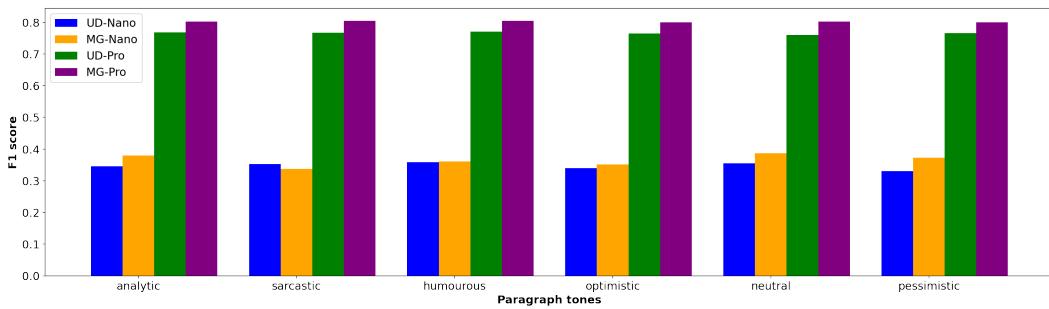


Figure 19: F1 scores across paragraph tones.

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**Category:** Computer & Video Games

**Examples of (Attribute, Value, Sentence):**

**Attribute:** Memorability of characters  
**Value:** Limited  
**Sentence:** GAME1 offers limited memorable characters , making it a forgettable gaming experience.

**Attribute:** Story  
**Value:** Lackluster and predictable storyline  
**Sentence:** And don't even get me started on the story - it's so predictable, I could write it in my sleep!

**Attribute:** Microtransactions and in-game purchases  
**Value:** Optional microtransactions  
**Sentence:** The game features optional microtransactions , so you can choose not to spend any additional money.

**Examples of distractor sentences:**

- HUMAN's empathy is a healing potion, allowing them to connect with others and understand their virtual and real-life struggles.
- GAME10's characters are complex and relatable, drawing players into the game's world and making them care about the fate of Aloy and her companions.

Figure 20: Examples of (attribute, value, sentence) triples and distractor sentences in Computer & Video Games category.

**Category:** Vitamins & Supplements

**Examples of (Attribute, Value, Sentence):**

**Attribute:** Brand  
**Value:** Longstanding history in the industry  
**Sentence:** Vitamin Company1 boasts a long-standing history in the industry , ensuring credibility and trust for their products.

**Attribute:** Price  
**Value:** Not covered by insurance  
**Sentence:** But hey, at least it's not covered by insurance .

**Attribute:** Side Effects  
**Value:** May cause mild gas or bloating  
**Sentence:** But be warned, this fiber party comes with a side of gas and bloating.

**Examples of distractor sentences:**

- HUMAN's optimism is a probiotic, maintaining a healthy balance in their outlook and promoting a positive gut feeling about the future.
- The technology-enabled tracking feature of Vitamin Company10 allows users to monitor their caffeine intake conveniently.

Figure 21: Examples of (attribute, value, sentence) triples and distractor sentences in Vitamins & Supplements category.

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**Category:** Restaurants & Bars

**Examples of (Attribute, Value, Sentence):**

**Attribute:** WiFi Access  
**Value:** Convenient for business meetings or working lunches  
**Sentence:** This spot offers convenient WiFi access, making it perfect for business meetings or working lunches.

**Attribute:** Catering Services  
**Value:** Delicious and customizable menus  
**Sentence:** And if you're feeling fancy, hit up their catering service.

**Attribute:** Noise Level  
**Value:** Excessively loud and distracting  
**Sentence:** Just be warned, it can get loud AF , so if you're trying to have a deep convo, forget about it.

**Examples of distractor sentences:**

- HUMAN's determination is a bustling coffee shop, where the aroma of ambition permeates the air.
- RESTAURANT10's edible garden on-site provides fresh, seasonal ingredients that add a touch of vibrancy to their dishes.

Figure 22: Examples of (attribute, value, sentence) triples and distractor sentences in Restaurants & Bars category.

**Category:** Books & Literature

**Examples of (Attribute, Value, Sentence):**

**Attribute:** Overall Quality  
**Value:** A masterpiece of literature  
**Sentence:** Step into BOOK1, a literary masterpiece that will transport you to another realm.

**Attribute:** Language  
**Value:** Written in prose  
**Sentence:** AndImmerse yourself in the author's exquisite prose , which paints vivid imagery on the canvas of your mind.

**Attribute:** Binding  
**Value:** Unattractive and unappealing  
**Sentence:** While the binding may not be its strong suit , the power of the story within far outweighs its aesthetic shortcomings.

**Examples of distractor sentences:**

- HUMAN's life is a masterpiece, a unique and captivating story that is still being written with every passing day.
- BOOK10's books are not only visually stunning but also intellectually stimulating, inviting readers to engage with complex themes and ideas.

Figure 23: Examples of (attribute, value, sentence) triples and distractor sentences in Books & Literature category.

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**Category:** Education

**Examples of (Attribute, Value, Sentence):**

**Attribute:** School Culture

**Value:** Lack of support and camaraderie among students

**Sentence:** Welcome to The Evergreen School, where the competition is fierce and the support is scarce .

**Attribute:** Learning Environment

**Value:** Innovative teaching methods

**Sentence:** But hey, at least they'll be exposed to innovative teaching methods (if they can keep up with the breakneck pace).

**Attribute:** Study Abroad Opportunities

**Value:** Immersive experiences in diverse cultures

**Sentence:** If you're looking for immersive experiences in diverse cultures, this school offers study abroad programs that will expand your horizons.

**Examples of distractor sentences:**

- HUMAN's mind is a fertile ground where ideas bloom and take root, transforming into a thriving garden of understanding.
- EDUCATION10's strong industry partnerships provide students with valuable internships and networking opportunities, preparing them for successful careers.

Figure 24: Examples of (attribute, value, sentence) triples and distractor sentences in Education category.