

# Multi-Review Fusion-in-Context

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## Abstract

Grounded text generation, encompassing tasks such as long-form question-answering and summarization, necessitates both content selection and content consolidation. Current end-to-end methods are difficult to control and interpret due to their opaqueness. Accordingly, recent works have proposed a modular approach, with separate components for each step. Specifically, we focus on the second subtask, of generating coherent text given pre-selected content in a multi-document setting. Concretely, we formalize *Fusion-in-Context* (FiC) as a standalone task, whose input consists of source texts with highlighted spans of targeted content. A model then needs to generate a coherent passage that includes all and only the target information. Our work includes the development of a curated dataset of 1000 instances in the reviews domain, alongside a novel evaluation framework for assessing the faithfulness and coverage of highlights, which strongly correlate to human judgment. Several baseline models exhibit promising outcomes and provide insightful analyses. This study lays the groundwork for further exploration of modular text generation in the multi-document setting, offering potential improvements in the quality and reliability of generated content.<sup>1</sup>

## 1 Introduction

Grounded text generation is the task of producing a passage from source texts, where the output is anchored around use-case-dependent spans within the source texts. Although such a task involves two distinct subtasks – identifying relevant spans and fusing them – it is commonly handled in an end-to-end approach, recently by using Large Language Models (LLMs) (Shuster et al., 2022; Su et al.,

2022; Zhang et al., 2023). While effective, this approach often lacks flexibility and control over the generation process, given its opaque nature.

Addressing this, Slobodkin et al. (2022) recently advocated splitting grounded generation tasks into their two subtasks, and particularly focused on the fusion step. They introduced *Controlled Text Reduction* (CTR), a task where pre-selected spans in a source document (‘highlights’) are fused into a coherent text that exclusively covers the spans. This approach enhances control and modularity in text generation, enabling a single CTR model to work with various content selection strategies and user preferences, applicable in different contexts like summarization or long-form question-answering. It could also support human-in-the-loop scenarios for tailored outputs based on user preferences, as explored in Slobodkin et al. (2023b). Further, the direct access to the highlights that contribute to the output facilitates attributed generation (Bohnet et al., 2023; Gao et al., 2023a,b), where models can cite source spans for generated text.

Despite its benefits, CTR’s focus on single-input scenarios limits its applicability to the broader, and more complex, multi-document setting. In this paper, we bridge this gap and extend the task to the multi-document setting. For that, we introduce the task of *Fusion-in-Context* (FiC), a generalized version of the CTR task, which processes multiple documents with pre-selected highlights, and aims to fuse them into a coherent, non-redundant text covering all and only the highlighted content, as demonstrated in Figure 1. In addition to the challenges of the single-input CTR task, including coreference resolution and proper discourse for coherence, the multi-document setting also requires handling repetitive, and sometimes conflicting information (Ma et al., 2020). Specifically, our work focuses on the business reviews domain, where contradicting opinions are more prevalent than in other more fact-oriented domains, such as news.

<sup>\*</sup> Work was done during an internship at Amazon.

<sup>1</sup>Our benchmark, FUSEREVIEW<sup>s</sup>, including the dataset, evaluation framework, and designated leaderboard, can be found at <https://fusereviews.github.io/>.

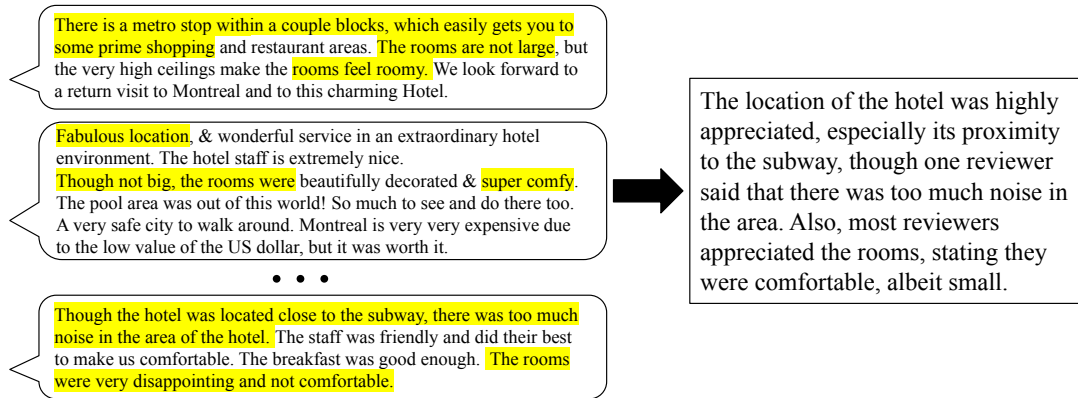


Figure 1: An example of an input, consisting of multiple reviews with highlights (left), and the generated text fusing the highlighted content while preserving coherence and non-redundancy (right). Such highlights in realistic use cases may be produced by different content-selection strategies.

To promote research on FiC, we start by formally defining the task (§3). We then introduce a dataset (§4), carefully constructed via controlled crowdsourcing (Roit et al., 2020). Each of its 1000 instances comprises a set of inputs with highlights, and a corresponding fused text. The dataset is created through an efficient procedure, adapted from Slobodkin et al. (2022), leveraging existing multi-document summarization datasets, specifically in the business reviews domain. We also develop an evaluation framework (§5) that assesses outputs’ faithfulness and coverage of highlights. The dataset and evaluation framework are released as a benchmark, called FUSEREVIEW<sup>s</sup>. We explore various baseline models on the benchmark and report their performance (§6). Our findings reveal that while these models show promising results, there is still room for further improvement in future research.

## 2 Background

Grounded text generation, an area focusing on generating text from source documents, requires identifying relevant task-specific details within the inputs, such as salient content for summarization, as well as their coherent fusion. This field includes tasks like long-form question-answering (Fan et al., 2019; Stelmakh et al., 2023), summarization (Nallapati et al., 2016a,b; Shapira and Levy, 2020; Bražinskas et al., 2020b; Zhao et al., 2022), and dialogue systems (Yan et al., 2017; Xu et al., 2019; Thopplian et al., 2022), with most related datasets aimed at end-to-end training (Fan et al., 2019; Bražinskas et al., 2020a; Liu et al., 2021; Iso et al., 2022a).

Despite the prevalence of end-to-end systems, there has been a growing trend towards decom-

posed pipeline approaches, particularly in summarization, with several recent studies focusing on content selection (Gehrmann et al., 2018; Lebanoff et al., 2020a; Ernst et al., 2021). Conversely, content fusion was largely explored at the full-sentence fusion level (Geva et al., 2019; Lebanoff et al., 2020b), with less emphasis on sub-sentence fusion.

Recently, Slobodkin et al. (2022, 2023a) have proposed a distinct separation of content selection from fusion, treating each as an independent task. They specifically concentrated on fusion, defining it as a standalone task termed *Controlled Text Reduction* (CTR). This task takes as input pre-selected spans, or ‘highlights’, within an input document, and requires a coherent merging of all the highlighted content, and nothing else. They also released a designated dataset and several CTR models showing strong adherence to these highlights.

While these studies acknowledged the benefits of decomposing grounded generation to subtasks, they mainly focused on single-document inputs. Our work builds on this decomposed approach, extending it to multi-document settings, which introduce new challenges such as managing longer inputs, handling redundant highlights (Suzuki and Nagata, 2017; Calvo et al., 2018), and dealing with potentially conflicting facts or opinions (Kim and Zhai, 2009; Ma et al., 2022).

Additionally, previous CTR studies assessed highlight adherence by comparing outputs with the concatenated highlights, using lexical metrics like ROUGE (Lin, 2004) and METEOR (Banerjee and Lavie, 2005), and semantic metrics like BERTScore (Zhang et al., 2020). These methods, while suitable for single-input scenarios, are less effective for multi-document contexts where redun-

dant and conflicting highlights are more prevalent. Additionally, these approaches did not distinctly evaluate faithfulness and coverage of highlights, typically assessing them jointly, with only manual evaluation for separate evaluation.

Addressing this, we explore more suitable metrics focusing separately on faithfulness and coverage of fused texts, inspired by recent progress in this area. Several recent studies have used Natural Language Inference (NLI) models for faithfulness evaluation (Laban et al., 2022; Schuster et al., 2022). There have also been advances in utilizing LLMs to evaluate faithfulness in a zero-shot setting with NLI-style prompts (Chen et al., 2023; Kocmi and Federmann, 2023; Liu et al., 2023), or after fine-tuning on synthetic data for faithfulness evaluation (Kryscinski et al., 2020; Yin et al., 2021; Gekhman et al., 2023). Yet, these works mainly targeted overall source text faithfulness rather than to specific segments. Moreover, they have not been widely applied to assess coverage, which has traditionally been evaluated using lexical metrics (Grusky et al., 2018) or manual evaluation (Syed et al., 2021). In our work, we adapt these methods to our highlights-focused setting, both for faithfulness and coverage, and assess their effectiveness.

### 3 Task Definition

The *Fusion in Context* (FiC) task is defined as the process of synthesizing a coherent text from a given set of documents, specifically focusing on pre-selected spans within these documents, referred to as *highlights*. Formally, given a document set  $D$  with marked spans  $H = \{h_1, h_2, \dots, h_n\}$  (such that  $h_i$  may be non-contiguous), a coherent and non-redundant passage  $f$  is generated, adhering to the following two criteria: (1) *highlight faithfulness* –  $f$  must be collectively entailed by the content in  $H$ , adding only minimal non-highlighted content required for coherence; (2) *highlight coverage* – each  $h_i \in H$  must be represented in  $f$ , either explicitly, or via a generalized reference. For instance, if a highlight states “*the place serves great sushi*”, the output should either directly mention “*great sushi*” or refer to it in more general terms, such as “*great food*”. Moreover, the task permits the abstraction and aggregation of multiple highlights into a single, synthesized statement. For example, separate highlights noting “*the beds were clean*”, “*the bathrooms were spotless*”, and “*the windows were clean*” could be collectively abstracted to a

general statement like “*the rooms are clean*”. Overall, the goal is to produce a faithful, non-redundant and non-omissive, yet potentially abstractive and aggregated, fusion of the highlighted content.

Next, we describe a dataset (§4) and an evaluation framework (§5) that comply with the task definition. These are released as the FUSEREVIEW benchmark for the FiC task.

## 4 Dataset for FiC

To comply with the task definition, an instance in a FiC dataset is expected to be a document set  $D$  with marked spans  $H = \{h_1, h_2, \dots, h_n\}$ , and a corresponding fused text  $f$ . To compile such data, we leverage existing multi-document summarization datasets and extract high-quality FiC instances via controlled crowdsourcing (Roit et al., 2020), by adapting the method from Slobodkin et al. (2022) to the multi-text setting, and the business reviews domain.

### 4.1 Dataset Collection

Given a document set  $D$  and corresponding reference summary  $\hat{f}$  from an existing multi-document summarization dataset, the annotation process aims to identify the spans in the source texts  $\{h_1, h_2, \dots, h_n\}$  that cover all the information within  $\hat{f}$ . This approach simplifies the annotation process compared to annotating from scratch, i.e., reading documents, marking highlights according to some specifications, and writing a coherently-fused text, which is reminiscent of standard formation of multi-document summarization datasets. Conversely, our approach requires locating and aligning spans between the source text and the already available reference summary, essentially “reverse engineering” the original human summarization process.

**Source data.** For our dataset, we turn to the business reviews domain, and sample review-sets and corresponding summaries from the CocoTrip (Iso et al., 2022b) and the FewSum (Bražinskis et al., 2020a) datasets. CocoTrip is a dataset of comparative opinion summaries of hotel review-sets, and FewSum consists of summaries of review-sets on businesses. Each review-set in these datasets comprises 8 reviews and up to 6 (average 3.13) corresponding reference summaries.

**Annotation interface.** To facilitate the annotation of alignments between reviews and their corre-

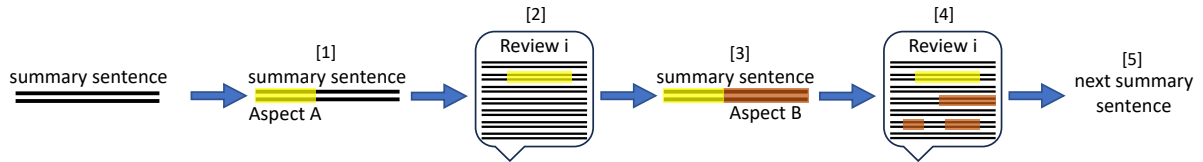


Figure 2: Illustration of the highlighting annotation process for a summary sentence, with reference to a specific review: [1] A *summary* aspect is identified and its statement highlighted; [2] Corresponding *review* spans are highlighted, and the alignment is saved; [3] Another *summary* aspect is identified and highlighted; [4] The matching *review* spans are highlighted, and the alignment is saved; [5] When all summary aspects that are alignable to the current review are highlighted, we proceed to the next sentence, and so on. In this example, the summary consists of two aspects, but steps 1 and 2 can be repeated as needed per sentence, until all alignable aspects are annotated. Borrowed and adapted from Slobodkin et al. (2022).

sponding summary, we adapt a web-based annotation tool from Slobodkin et al. (2022), and deploy it on Amazon Mechanical Turk<sup>2</sup> for crowdsourcing (§4.3 will explain the controlled crowdsourcing procedure). The application presents reviews and the respective summary side-by-side, and annotators are guided to highlight pairs of spans in the reviews and the summary that directly align. To reduce cognitive load, a summary is displayed alongside an individual review, and focus is placed on one summary sentence at a time. To further ease the process for annotators, lemmas in the review overlapping with lemmas in the currently focused summary sentence are emboldened.<sup>3</sup> This enables quick skimming through the review, however, workers are trained not to rely solely on exact matches for highlighting (as discussed in §4.2 and §4.3).

**Annotation procedure.** Annotators are guided to align statements dealing with a single aspect of a hotel or business (e.g., “room cleanliness”) from the summary with the most relevant spans in the reviews, and to do so for all summary aspects in order to cover the whole summary text (see §4.2 for the detailed annotation guidelines).<sup>4</sup> This, in turn, creates instances of highlighted spans within reviews, with a corresponding coherent fusion of those highlights (the summary). Each review-summary pair is annotated by a single trained annotator. To enhance quality, submissions are randomly sampled and reviewed, with feedback provided as necessary.

**Resulting dataset.** In total, we sampled 1000 instances of review-set/summary pairs (700 instances

from CocoTrip and 300 from FewSum). See Table 1 for full statistics.<sup>5</sup>

## 4.2 Annotation Guidelines and Data Traits

Figure 2 illustrates the annotation flow. When presented with a review of an entity (hotel or business) and a summary with a sentence in focus, an annotator first identifies aspects of the entity within the focused summary sentence. An aspect is not simply a facet of an entity, such as “rooms” or “staff”, but more specifically it is a characteristic, such as “room cleanliness”, “room style” or “staff helpfulness” (more on this in Appendix A.1).

Upon identifying an aspect in the summary sentence, annotators are tasked with locating corresponding spans in the review. These are the minimal spans that adequately cover the information as in the summary regarding the aspect, where omitting any content would miss out on some detail of that aspect in the summary. For example, omitting any mention of the room being ‘small’ from the review highlights in Figure 1, would overlook this characteristic of the room, which is mentioned in the second summary sentence.

As outlined in §3, alignments on aspects need to consider two entailment-related traits. Firstly, a summary may express a generalized phrasing of an aspect that is stated in the reviews. For instance, a review may say “*great sushi*” while the summary might just say “*great food*”. Annotators are hence directed to also mark review excerpts that are more specific than in the corresponding spans in the summary. Secondly, several spans in the reviews pertaining to the same aspect may yield an aggregated abstraction in the summary. Annotators must therefore also include review spans that exemplify the summary aspect. For example, aligning

<sup>5</sup>See Appendix F for more details.

<sup>2</sup>[www.mturk.com](http://www.mturk.com)

<sup>3</sup>Lemmatizing with spaCy (Honnibal and Montani, 2017).

<sup>4</sup>We observed that instructing annotators to focus on one aspect at a time enhances the efficiency in locating the relevant review spans, particularly when a summary sentence includes content that is scattered across different parts of the review.



	#unique sets of reviews	#summaries/review-set (average)	#summary-review-set pairs	mean review/summary size (tokens)	max review/review-set/summary (tokens)	mean review/summary size (sentences)	summary sentences aligning to multiple reviews	summary sentences aligning to multiple review sentences
Train	237	2.71	643	87.6/75.18	239/1118/231	5.89/5.08	82.51%	53.20%
Dev	23	4.30	99	77.97/69.05	197/829/174	5.47/4.71	87.34%	57.73%
Test	60	4.30	258	77.33/67.62	279/881/266	5.39/4.68	83.28%	51.82%
Overall	320	3.13	1000	83.99/72.62	279/1118/266	5.72/4.94	83.15%	53.29%

Table 1: Statistics of our dataset, including the number of unique review-sets, the average number of summaries per review-set, the number of summary/review-set pairs (a unique review-set creates a pair with each of its summaries), the mean review/summary size (in tokens and in sentences), the maximum review/review-set/summary size (in tokens), the percentage of summary sentences whose alignments span across more than one review, and the percentage of summary sentences whose alignments span across more than one review sentence within one of its reviews (namely, within a single review, the alignments come from more than one sentence).

a review statement such as “*the beds were clean*” with a summary phrase “*the rooms were clean*”.

Additionally, reviews often express varying opinions about the same aspect, such as “*the service was great*” as opposed to “*the staff was unprofessional*”. When summarizing, all these varying opinions should be considered to reflect the overall sentiment. As a result, summary segments may range from statements like “*the staff was overall liked*” to “*some people liked the staff*”, depending on the spectrum of opinions. Hence, to properly capture this consolidation of differing viewpoints, annotators are also guided to align review mentions that either sentimentally entail *or* contradict the summary aspect. For example, the two aforementioned conflicting *review* spans should be aligned to the summary span “*the service was mostly good*”.

Finally, annotators may mark multiple spans in reviews that redundantly represent the same statement. The guidelines also address paraphrasing, non-consecutive highlights, and unalignable summary spans. A detailed explanation of these guidelines can be found in Appendix A.2.

### 4.3 Annotator Training

The requirements of the aforementioned annotation process call for proficient-level annotations, which we achieved by means of controlled crowdsourcing (Roit et al., 2020). We identified qualified annotators through three open qualification rounds, followed by three closed rounds for selected annotators, focusing on further training and refinement. Each open round involved annotators reading a brief task description and accordingly aligning information between a single summary sentence and a short review, on a simplified interface. After each open round, we reviewed the alignment and provided feedback. We then checked whether the annotators implemented our feedback in the following round (with a different sentence-review

instance). If the annotators satisfyingly cooperated throughout the open rounds, they moved on to the closed rounds. Before the closed rounds, the qualified workers were asked to watch a 25-minute tutorial on the full annotation tool and guidelines (§4.1 and §4.2). The closed rounds were conducted similarly to the open rounds, but with a whole summary and review, with all guidelines, and on the full interface. The qualification process was fully compensated with a customary wage, requiring up to 5 minutes per round. From this process, we were able to gather 8 trained annotators, who annotated the 1000 instances in our dataset.

### 4.4 Dataset Quality

To evaluate the quality of the compiled dataset, we compute the inter-annotator agreement. To this end, for every two annotators, we calculate intersection-over-union (*IoU*) of the tokens’ indices (considering only content words) between the highlighted review spans that are aligned to the same summary sentence, similarly to Ernst et al. (2021). The *IoU* scores are gathered on the sentence level across three review-set/summary pairs, annotated by six crowdworkers. The resulting *IoU* score is 61.8.

To better understand the sources of disagreements, we analyzed all cases when *IoU* < 90%. We found that the main cause of disagreement was related to our criteria for generalization and aggregation. Here, some annotators chose specific review spans they believed exemplified a summary characteristic, while others opted for different spans. This does not harm the quality of our data, as in all cases, the summary segment was indeed aligned with each of the corresponding review spans, according to our criteria. Another common source of disagreement involved annotators including additional phrases that provided only insignificant extra details on top of the summary. For detailed examples, refer to Appendix G.

Finally, an interesting aspect of our dataset is that 80% of the summary sentences align to spans from multiple reviews, and over 50% of the summary sentences align with non-consecutive spans from different sentences within a single review (see Table 1). We also find that on average, 25% of a review’s tokens were highlighted. These properties reflect the real-world challenges faced by FiC models, expected to coherently fuse disparate, and at times redundant, details.

## 5 Evaluation Framework

Consistent with the task definition in §3, a passage produced by a model as a fusion of highlights within source documents must uphold several criteria. (1) *Faithfulness*: it must only contain information from the highlights; (2) *Coverage*: it must cover all the information in the highlights, be it in an explicit, generalized, or aggregated form; (3) *Coherence and Redundancy*: it must convey the information in a well-structured and non-redundant form. In this section, we suggest several automatic metrics for faithfulness and coverage, and assess their effectiveness by correlating to human scores that we collected. Coherence and redundancy are measured using manual evaluation.

### 5.1 Limitations of Lexical and Semantic Matching

Output’s adherence to highlights was previously measured in Slobodkin et al. (2022, 2023a) by comparing the output passage and the concatenated highlights, using lexical metrics like **ROUGE** (n-gram matching) and **METEOR** (word matching with synonyms), and semantic metrics like **BERTScore** (probability of generating the output text). Our work, however, extends beyond the single-document scenario explored in these previous works, to also include multi-document contexts. This shift introduces additional complexities, such as managing redundancy and contradictions among highlights drawn from diverse sources, which may not be fully captured by standard lexical and semantic matching techniques. Further, our setting also enables highlights aggregation and generalization, which these metrics may not adequately address. Additionally, these automated approaches primarily measured overall adherence to the highlights without making a distinction between faithfulness and coverage. These latter aspects were evaluated manually, but only on a limited number of instances.

### 5.2 NLI-based Faithfulness Metric

Highlight-faithfulness requires the output passage to be entailed by the collective highlighted content. We employ the `flan-t5-xxl` model (Chung et al., 2022), shown to exhibit high performance on NLI tasks, for evaluating faithfulness to highlights in a zero-shot setting with a standard **NLI** prompt (see Appendix B). Previous research that used NLI models for faithfulness evaluation in summarization (Maynez et al., 2020; Laban et al., 2022; Honovich et al., 2022) typically set the grounding text as the premise, and the generated text as the hypothesis. Accordingly, we set the highlights concatenation to serve as the premise, since the outputs are expected to be entailed by all the highlighted content collectively (see §3). For the hypothesis, we segment the output passage into sentences, with each sentence serving as a separate hypothesis. The average of the sentence-level entailment scores is used as the overall entailment probability of the corresponding passage. This approach, inspired by (Laban et al., 2022), was found to be more effective than using the entire output as a single hypothesis.<sup>6</sup>

### 5.3 Trained Coverage Metric

Inspired by recent work that evaluates faithfulness and factuality using a dedicated **trained** model (Yin et al., 2021; Utama et al., 2022; Gekhman et al., 2023; Soleimani et al., 2023), we finetune an LLM that is tasked to assess whether the generated passage fully covers the highlights. In our methodology, each highlight is individually input along with the entire output, and the model outputs a binary answer for whether the highlight is contained in the passage.<sup>7</sup> We derive synthesized training data for this task from our FiC dataset, using highlights and their corresponding summaries. For negative samples, we remove the summary sentence that aligns with the highlight. For positive samples, a random non-aligning summary sentence is omitted (to avoid a potential bias caused by sentence exclusion in the negative samples). We finetune a `flan-t5-large` model (Chung et al., 2022) with the synthesized coverage data. The input to the model is the highlight and modified summary, and the output is ‘yes’ or ‘no’, for positive and negative samples, respectively. The final score is the average

<sup>6</sup>We also experimented with other methods for evaluating faithfulness and coverage, which exhibited lower correlation to human judgment. See Appendix E for more details.

<sup>7</sup>We also tried concatenating all the highlights together, and found it to be inferior.

Metric	Faithfulness		Coverage	
	$\tau$	CI	$\tau$	CI
ROUGE-1 (R)	0.2319	0.23-0.24	0.3467	0.34-0.35
ROUGE-1 (P)	0.5468	0.54-0.55	-0.0533	-0.06-0.05
ROUGE-2 (R)	0.3555	0.35-0.36	0.2731	0.27-0.28
ROUGE-2 (P)	0.5253	0.52-0.53	0.0071	0.00-0.01
ROUGE-L (R)	0.0958	0.09-0.10	0.3835	0.38-0.39
ROUGE-L (P)	0.4898	0.48-0.49	-0.0367	-0.04-0.03
METEOR	0.4017	0.40-0.41	0.2736	0.27-0.28
BERTScore (R)	0.2380	0.23-0.24	0.4165	0.41-0.42
BERTScore (P)	0.6004	0.59-0.60	0.0529	0.05-0.06
NLI (Faithfulness)	<b>0.6745</b>	<b>0.67-0.68</b>	0.0929	0.09-0.10
Trained (Coverage)	0.1771	0.17-0.18	<b>0.4992</b>	<b>0.49-0.50</b>

Table 2: Average Kendall-Tau rank correlations ( $\tau$ ) and their 95% confidence intervals (CI) for tested evaluation metrics against human judgment. Recall-based metrics (R) are more effective for coverage, and precision-based metrics (P) for faithfulness. Best correlations for each axis are in bold.

probability of the token ‘yes’ across all highlights.<sup>8</sup>

#### 5.4 Meta-Evaluation

**Setup.** To assess our evaluation metrics we follow the common practice (Fabbri et al., 2021) of correlating scores to human judgment. To that end, we gather faithfulness and coverage ratings for generated outputs from three co-authors of this paper. The outputs were produced by two models (see Flan-T5<sub>H</sub> and Flan-T5<sub>no-H</sub> in §6.1). A total of 50 review sets were randomly selected from our test set, leading to 100 scores for each of coverage and faithfulness. A 1-to-7 Likert scale was used to rate faithfulness and coverage separately for an output.

To ensure agreement among annotators, the three authors first evaluated a separate set of 10 outputs, and inter-annotator agreement was computed with Cohen’s Kappa coefficient (Cohen, 1960). The average Kappa coefficients were 0.49 and 0.42 for faithfulness and coverage, respectively, indicating a moderate level of agreement (Viera et al., 2005). For more details, see Appendix E.3.

After collecting scores for the 100 instances, we computed their correlation with human judgment using Kendall-Tau rank correlation, as suggested in (Deutsch et al., 2022).<sup>9</sup> We also apply bootstrapping (Efron, 1987) by performing 1000 samplings of 70 instances (with repetition) and calculating

<sup>8</sup>We also explored an NLI-based coverage metric, where the passage serves as the premise and the highlights function as the hypothesis. We found it to achieve comparable results, however it requires substantially more computation time and memory. For more details, see Appendix E.

<sup>9</sup>Spearman correlations were also calculated, showing similar trends. See Appendix E.4.

correlation scores for each such subset. We report the average correlation and 95% confidence intervals for each metric.

**Results.** Table 2 shows the average correlations with their 95% confidence intervals for faithfulness and coverage. We find that while certain lexical- and semantic-based metrics yield decent results, notably BERTScore-precision for faithfulness and BERTScore-recall for coverage, our proposed metrics demonstrate significantly higher correlations, with average values of 0.6745 and 0.4992 for faithfulness and coverage, respectively. In light of these findings, we employ our NLI-based and trained metrics for assessing model performance in terms of faithfulness and coverage, respectively (in §6.2).

#### 5.5 Human Evaluation of Coherence and Redundancy

We adopt the coherence assessment methodology from (Slobodkin et al., 2022). Crowdworkers judge the coherence of 100 randomly selected instances from the test set, for each examined model. A score between 1 and 5 is specified, and each passage is reviewed by three workers and averaged. Similarly, the redundancy of information in a passage is appraised. This approach follows standard practice, where coherence and redundancy are best evaluated manually (Fabbri et al., 2021; Steen and Markert, 2021). For more details see Appendix D.

## 6 Experiments

### 6.1 Experimental Setup

We examine several baseline models for solving the FiC task. The input to a model is a document set with spans marked within the documents (highlights), and the model is trained to generate a fused passage around the highlights.

**Models with full input.** Using the training set of our dataset, we finetune a large language model, marking the highlights in the input via designated mark-ups, following Slobodkin et al. (2022). Specifically, we finetune a flan-t5-large model (Chung et al., 2022), that exhibited enhanced performance in tasks requiring constrained generation (Sanh et al., 2022; Wei et al., 2022). We will refer to this model as **Flan-T5<sub>H</sub>** (‘H’ for ‘Highlights’). We develop an additional variant of Flan-T5<sub>H</sub>, which we further finetune using Reinforcement Learning (RL), following the method in Slobodkin et al. (2023a). It applies the Quark algorithm (Lu et al.,

Model	Faithfulness	Coverage	F-1	Coherence	Redundancy
Flan-T5 <sub>H</sub>	72.8	86.4	79.0	4.3	4.1
Flan-T5 <sub>H</sub> (RL)	54.0	82.0	65.1	4.1	4.0
Flan-T5 <sub>only-H</sub>	<b>84.6</b>	<b>87.8</b>	<b>86.2</b>	3.6	3.8
Flan-T5 <sub>no-H</sub>	53.7	76.9	63.2	4.1	3.9
GPT-4	81.6	85.6	83.6	<b>4.7</b>	<b>4.5</b>

Table 3: Results for the proposed models on our FiC dataset. Faithfulness is measured with our NLI-based metric, and Coverage with our trained metric. The F-1 is a harmonic mean of the two latter scores. Coherence and Redundancy are measured through manual assessment. For each metric, the best score is in bold.

2022) combined with a dual-reward policy (Pasunuru and Bansal, 2018), alternating between our NLI-based faithfulness and trained coverage metrics (§5) as rewards. We also examine the performance of a one-shot GPT-4 model (OpenAI, 2023), guided with an example of the task.<sup>10</sup>

**Models with highlights only.** To reveal the importance of the surrounding context, we also train a flan-t5-large model only with a concatenation of the highlights as the input (excluding surrounding context). We denote this variant **Flan-T5<sub>only-H</sub>**.

**Models without highlights.** Finally, we examine flan-t5-large in a standard summarization setting, where it is finetuned with the input review-set without the highlighted spans, denoting this variant **Flan-T5<sub>no-H</sub>**. It offers insights into the model’s ability to pick up on signals that point to highlights.


## 6.2 Results

We apply our evaluation metrics on the proposed systems, with results presented in Table 3. We first observe that the exclusion of context from the input (Flan-T5<sub>only-H</sub>) yields the strongest faithfulness and coverage scores, yet the lowest coherence and redundancy scores. This shows the importance of incorporating context for more seamless outputs. Meanwhile, the removal of highlights (Flan-T5<sub>no-H</sub>) leads to a substantial degradation in faithfulness and coverage. This indicates that the Flan-T5<sub>H</sub> model indeed succeeds in learning to adjust the output according to the highlights, underlining the highlights’ role in enhancing the model’s performance.

Interestingly, even though the RL reward functions used in the RL-enriched model are the faithfulness and coverage metrics themselves, the outputs are eventually negatively affected when eval-

uating with these metrics. This result calls for a more in-depth investigation of enhanced reward functions that can leverage the benefits of RL training, as was shown to be helpful in Slobodkin et al. (2023a) for the single-input setup. We also find that single-shot GPT-4 yields the most coherent and least redundant texts. While it ranks highly in faithfulness and coverage, it is still overtaken by the finetuned Flan-T5<sub>only-H</sub>. Overall, our findings invite for further research on the FiC task, to develop fusion strategies that ensure comprehensive coverage and faithfulness to highlighted content, with coherent and low-redundancy outputs.

## 7 Conclusion

In this paper, we further promote the decomposition of grounded text generation as presented in (Slobodkin et al., 2022), extending it to the multi-document setting. To that end, we introduce the Fusion-in-Context (FiC) task, an extension of the task from (Slobodkin et al., 2022) which focuses on the content fusion step, to the multi-document setting. The FiC setting facilitates employing a single general-purpose fusion model for diverse content selection needs, capturing the challenges of repetitiveness and contradictions in source documents. It also supports interactive, user-driven generation, by allowing users to choose personalized content for the FiC module to merge into a customized passage. Moreover, direct access to the pre-selected “highlights” can facilitate attributed generation, where the pre-selected segments also serve as supporting cited content for the fused text. To advance the task, we introduce the FUSEREVIEWS  benchmark, which includes a high-quality dataset, an evaluation framework for faithfulness and coverage of selected spans, and several baseline models to stimulate further research and exploration.

Future work may include expanding the FiC task to other multi-input contexts, e.g., the news do-

<sup>10</sup>Preliminary experiments on a separate development set, with varying numbers of in-context examples, indicated that a single exemplar yields the best results. See Appendix C.



main. We also plan to investigate ways to leverage the built-in traceability of the output text’s origin, namely the highlights, for facilitating attributed generation.

## 8 Limitations

In this work, we construct the first FiC dataset, developed by instructing crowdworkers to identify relevant spans within reviews that align with the content of corresponding summaries. To reduce cognitive load, each summary was displayed alongside individual reviews. While this approach streamlined the annotation process, there are instances where viewing the complete set of input reviews is advantageous, particularly for aggregative summary segments. In such segments, multiple review spans are combined into a single summary span, necessitating a broader understanding of the entire input set for accurate highlighting.

Moreover, the focus of our dataset on the business reviews domain may constrain its generalizability to other contexts with distinct textual structures, like news articles. This limitation extends to our trained evaluation metrics, which were developed using a derivative of our crowdsourced dataset and, therefore, are tailored to the specific characteristics of business reviews.

## 9 Ethics Statement

The proposed Fusion-in-Context (FiC) task, despite offering enhanced control over the content generated, is not expected to achieve complete resolution. Therefore, integrating FiC modules in modular generative systems should be done so with caution, since there is a possibility that these modules may overlook certain highlighted content or inadvertently include content that was not highlighted. This concern is particularly relevant for future endeavors that aim to use FiC for attributed generation. In such cases, there is a risk that some portions of the generated content may not be directly traceable to the pre-defined highlighted segments, leading to potential inaccuracies, or incompleteness, in attribution.

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## A Annotation Full Guidelines

In this section, we provide the full annotation guidelines, presented to our workers.

### A.1 Summary-related Guidelines

As mentioned in §4.2, we guide annotators to segment summary sentences into the different aspects of hotels or businesses. The annotation guidelines distinguish between two classifications of aspects:

- **DIFFERENT ASPECTS:** This refers to independent facets of the business, e.g., location and room quality.
- **DIFFERENT CHARACTERISTICS OF THE SAME ASPECT:** This pertains to addressing varied characteristics within the same aspect, for example, the cleanliness and size of a room.



## A.2 Review-related Guidelines

This section provides a detailed overview of the review-related guidelines presented to our crowdworkers during their training:

- ANY MENTION OF THE ASPECT: Annotators are trained to align all review mentions of a summary aspect, encompassing both similar and contrasting sentiments. For instance, if the summary aspect is “*The staff was friendly*”, both positive and negative mentions regarding staff friendliness are to be aligned.
- SPECIFICITY IN REVIEWS: Crowdworkers are advised to align review mentions that offer more specificity than the summary aspects. For example, a general summary statement like “*The staff was helpful*”, should be aligned with a more specific review comment, such as “*the concierge was very helpful*”. We also emphasize that the other way around, namely, that the summary is more specific than the reviews, should not be aligned.
- EXEMPLIFICATION IN REVIEWS: In line with the previous point, annotators are guided to focus on identifying review segments that provide examples of the summary statements. An example would be aligning the summary span “*The hotel is well-maintained*” with a review segment that exemplifies it, such as “*the pool area is very clean*”. As in the previous point, we discourage our crowdworkers from considering the reverse cases, when the summaries exemplify the reviews.
- PARAPHRASING: Annotators are instructed to align paraphrased mentions in reviews with the summary content, such as aligning “*the hotel is overpriced*” with “*you can stay at lovely B&B in the old town that is actually cheaper than this*”.
- CONSECUTIVENESS: We guide our workers to avoid highlighting unnecessary details, i.e., that did not appear in the summary span, and keep the highlights inconsecutive if needed.
- UNALIGNABLE SPANS: Recognizing that each summary is derived from multiple reviews, but reviewers assess only one review at a time, it is often the case that not all summary details will be present in the reviewed content. In such instances, annotators are instructed to leave such summary spans unhighlighted.

## B NLI Zero-Shot Prompt

Figure 3 demonstrates the structure of the zero-shot prompt used for the nli-based evaluation frameworks of highlights coverage and faithfulness.

Number of Exemplars	Faithfulness	Coverage	F-1
1	<b>80.1</b>	85.0	<b>82.5</b>
2	72.1	<b>86.1</b>	78.5
3	73.6	84.0	78.5
4	72.8	82.2	77.2

Table 4: Faithfulness, coverage, and F-1 scores of the zero-shot GPT-4 model on 30 instances for the FiC development set, for varying numbers of in-context examples in the prompt. For each metric, the best scores are in bold.

## C GPT-4 Prompting

Table 4 presents the faithfulness, coverage, and F-1 scores of the zero-shot GPT-4 model across 30 instances from the FiC development set, for varying numbers of in-context examples in the prompt. Based on these outcomes, we chose to proceed with a single in-context example.

## D Fluency and Redundancy Human Annotation Protocol

We ask crowd-workers to assess the fluency and redundancy of the texts produced by all models under examination. We employ annotators who have demonstrated proficiency in semantic tasks, including summarization, in previous experiments. For evaluation purposes, 100 instances are randomly selected from our test set, and the texts generated by each model for these instances are evaluated, resulting in 500 total samples. Each sample is reviewed by three different annotators, and their scores are averaged to obtain a final assessment. The evaluation is facilitated through two Amazon Mechanical Turk interfaces, specifically designed for this study. One interface focuses on evaluating coherence, while the other assesses redundancy, with each interface presenting the annotators with one of the 500 samples (as depicted in Figure 4). Consistent with the methodology of (Slobodkin et al., 2022), a 5-point Likert scale is employed to rate the fluency and redundancy of the generated summaries. To minimize ambiguity and promote consistent ratings, each score on the scale is accompanied by explicit criteria (also illustrated in Figure 4). Taking into account an average response time of 30 seconds for each evaluation, we set the compensation for each response at 10 ¢.

```

1   ### Instruction: Read the following and determine if the hypothesis can be inferred from
   the premise.
2   Options: Entailment, Contradiction, or Neutral
3
4   ### Input:
5   Premise: {Premise}
6   Hypothesis: {Hypothesis}
7
8   ### Response (choose only one of the options from above):

```

Figure 3: The prompt structure employed in zero-shot configurations as a basis for evaluating the frameworks of faithfulness and coverage.

**Instructions**

In this task, you will evaluate the quality of a summary.  
To correctly solve this task, please follow these steps:

1. Read the summary.
2. Rate it on a scale from 1 (worst) to 5 (best) by its fluency/coherency.

**Definition of Fluency**

This rating measures the quality of the text - are the sentences well written and grammatically correct, do they fit together and sound natural.  
Consider how legible, grammatical and coherent the summaries are.  
The scale should be:

- 1 - The summary is incoherent, contains multiple grammatical errors and doesn't sound natural.
- 2 - Only small parts of the summary are coherent, containing many grammatical errors and its sentences fit together poorly.
- 3 - The summary is somewhat coherent, but it either contains several grammatical errors or its sentences don't fit very well.
- 4 - The summary is mostly coherent, contains little to no grammatical errors and sounds natural enough.
- 5 - The summary is very coherent, contains no grammatical errors and sounds natural.

Instructions | Shortcuts | How fluent is this summary?

The staff at the hotel were very helpful and friendly. The location of the hotel is great and the view of the canal was really nice. The hotel is in a great location and the staff were very friendly and efficient. The rooms were clean and comfortable and the location was great. The staff were friendly and helpful and the breakfast was adequate. This hotel is definitely recommended and we will definitely stay again. The room was overlooking the canal and had a view of boats as they plied their way down the canal. The shower was great but there was no bath, but this wasn't important to ourselves. The breakfast was standard and there were hot options available but they were gone by the time we went down.

Select an option

not fluent	1
mostly not fluent	2
partially fluent	3
mostly fluent	4
fluent	5

(a) Fluency Evaluation Interface

**Instructions**

In this task, you will evaluate a summary's level of redundancy.  
To correctly solve this task, please follow these steps:

1. Read the summary.
2. Rate it on a scale from 1 (worst) to 5 (best) by its redundancy.

**Definition of Redundancy**

This rating measures the level of redundancy of the text - to what extent is the text repetitive. The scale should be:

- 1 - The summary is redundant and repeats the same content.
- 2 - The summary is mostly redundant.
- 3 - The summary is partially redundant, with half of the content being repeated.
- 4 - The summary is mostly **non**-redundant, with very little repeated content.
- 5 - The summary is **non**-redundant, with no repeated content.

Instructions | Shortcuts | How fluent is this summary?

This is a great hotel with great views. The rooms are very nice and the suites are amazing. The food is really good, but not all of the dishes served there are to be considered as real Mexican. The staff is very friendly and helpful. There are several pools, as well as plenty of lounge chairs, at this hotel. If you can deal with driving in Mexico, I would recommend renting a car if you want to leave the hotel frequently. The hotel has a children's club.

Select an option

redundant	1
mostly redundant	2
partially redundant	3
mostly non-redundant	4
non-redundant	5

(b) Redundancy Evaluation Interface

Figure 4: Example of the data collection interfaces used by the crowd-workers to evaluate the fluency (4a) and redundancy (4b) of summaries.

## E Additional Evaluation Framework Details

### E.1 Trained Faithfulness Metric

In a similar fashion to the trained coverage metric, we use our crowdsourced dataset to generate training data for evaluating highlights faithfulness. This approach mirrors the NLI-based metric we proposed, wherein a model is trained to individu-

ally evaluate the faithfulness of each output sentence, subsequently averaging the scores across all sentences.

For the positive training instances, we separate each summary from our crowdsourced dataset into sentences, and pair each sentence with all the instance's highlights. In contrast, for the creation of negative instances, we remove all highlights that were aligned with any segment of the cor-

Judges	Faithfulness	Coverage
1-2	0.37	0.31
2-3	0.71	0.67
1-3	0.39	0.27

Table 5: The individual Cohen’s Kappa coefficients for each pair of judges, on the faithfulness and coverage axes.

responding summary sentence. The training process involves fine-tuning a `flan-t5-large` model (Chung et al., 2022). In this setup, the input comprises the highlights and the summary sentence, while the output is either the token ‘yes’ for positive instances, or ‘no’ for negative ones. The final score is calculated based on the probability assigned to the token ‘yes’ by the model.

## E.2 NLI-based Coverage Metric

For the evaluation of highlight-coverage using Natural Language Inference (NLI), our approach mirrors the one implemented for assessing faithfulness using NLI (see §5.2), albeit with a role reversal, where the output serves as the premise and the highlights function as the hypothesis. Rather than treating all highlights collectively as the hypothesis, we calculate the coverage of each highlight separately and then average across all highlights.<sup>11</sup>

## E.3 Additional Meta Evaluation Setup Details

**Pairwise Cohen Kappa Coefficients** Table 5 shows the pairwise Cohen’s Kappa coefficients for each pair of judges.

**Reconciliation Process** To achieve further agreement between the three authors, an additional reconciliation procedure was undertaken for the ten instances annotated by all three authors. This procedure entailed discussions for each instance where the annotations diverged by more than one point, separately for the faithfulness and coverage scores. During these discussions, each author explained the rationale behind their assigned score. Subsequently, the authors endeavored to reach a unanimous agreement on each instance, thereby further aligning their scoring criteria.

## E.4 Additional Meta Evaluation Results

Tables 6 and 7 present the full correlations with human judgments using the Kendall-Tau rank correlations and Spearman’s rank correlations, respec-

<sup>11</sup>We consider each individual alignment in our crowd-sourced dataset as a distinct highlight.

Metric	Faithfulness		Coverage	
	$\tau$	CI	$\tau$	CI
ROUGE-1 (R)	0.2319	0.23-0.24	0.3467	0.34-0.35
ROUGE-1 (P)	0.5468	0.54-0.55	-0.0533	-0.06-0.05
ROUGE-1 (F1)	0.5587	0.55-0.56	0.1497	0.14-0.16
ROUGE-2 (R)	0.3555	0.35-0.36	0.2731	0.27-0.28
ROUGE-2 (P)	0.5253	0.52-0.53	0.0071	0.00-0.01
ROUGE-2 (F1)	0.4964	0.49-0.50	0.1477	0.14-0.15
ROUGE-L (R)	0.0958	0.09-0.10	0.3835	0.38-0.39
ROUGE-L (P)	0.4898	0.48-0.49	-0.0367	-0.04-0.03
ROUGE-L (F1)	0.3880	0.38-0.39	0.1950	0.19-0.20
METEOR	0.4017	0.40-0.41	0.2736	0.27-0.28
BERTScore (R)	0.2380	0.23-0.24	0.4165	0.41-0.42
BERTScore (P)	0.6004	0.59-0.60	0.0529	0.05-0.06
BERTScore (F1)	0.4958	0.49-0.50	0.2555	0.25-0.26
NLI (Faithfulness)	<b>0.6745</b>	<b>0.67-0.68</b>	0.0929	0.09-0.10
NLI (Coverage)	0.2255	0.22-0.23	<b>0.5084</b>	<b>0.50-0.51</b>
Trained (Faithfulness)	0.5836	0.58-0.59	0.2495	0.24-0.25
Trained (Coverage)	0.1771	0.17-0.18	0.4992	0.49-0.50

Table 6: Average Kendall-Tau rank correlations ( $\tau$ ) and their 95% confidence intervals (CI) for tested evaluation metrics against human judgment. Recall-based metrics (R) are more effective for coverage, and precision-based metrics (P) for faithfulness. Best correlations for each axis are in bold.

Metric	Faithfulness		Coverage	
	$\tau$	CI	$\tau$	CI
ROUGE-1 (R)	0.3124	0.31-0.32	0.4440	0.44-0.45
ROUGE-1 (P)	0.6892	0.68-0.69	-0.0861	-0.09-0.08
ROUGE-1 (F1)	0.7172	0.71-0.72	0.1654	0.16-0.17
ROUGE-2 (R)	0.4842	0.48-0.49	0.3537	0.35-0.36
ROUGE-2 (P)	0.6807	0.68-0.69	0.0005	-0.01-0.01
ROUGE-2 (F1)	0.6590	0.65-0.66	0.1885	0.18-0.20
ROUGE-L (R)	0.1237	0.12-0.13	0.4902	0.48-0.50
ROUGE-L (P)	0.6420	0.64-0.65	-0.0596	-0.07-0.05
ROUGE-L (F1)	0.5160	0.51-0.52	0.2531	0.25-0.26
METEOR	0.5412	0.54-0.55	0.3487	0.34-0.36
BERTScore (R)	0.3141	0.31-0.32	0.5237	0.52-0.53
BERTScore (P)	0.7450	0.74-0.75	0.0485	0.04-0.06
BERTScore (F1)	0.6516	0.65-0.66	0.3267	0.32-0.33
NLI (Faithfulness)	<b>0.8257</b>	<b>0.82-0.83</b>	0.1088	0.10-0.12
NLI (Coverage)	0.2831	0.28-0.29	<b>0.6355</b>	<b>0.63-0.64</b>
Trained (Faithfulness)	0.7268	0.72-0.73	0.3271	0.32-0.33
Trained (Coverage)	0.2315	0.22-0.24	0.6178	0.61-0.62

Table 7: Average Spearman’s rank correlations ( $\tau$ ) and their 95% confidence intervals (CI) for tested evaluation metrics against human judgment. Recall-based metrics (R) are more effective for coverage, and precision-based metrics (P) for faithfulness. Best correlations for each axis are in bold.

tively, including the additional evaluation frameworks we explored (see Appendices E.1 and E.2), and the F-1 scores for the ROUGE and BERTScore metrics.

	#unique sets of reviews	#summaries/review-set (average)	#summary-review-set pairs	mean review/summary size (tkns)	max review/review-set/summary (tkns)	mean review/summary size (sents)	summary sents aligning to multiple reviews	summary sents aligning to multiple review sents
Train								
CocoTrip	184	2.63	484	97.56/80.15	239/1118/231	6.22/5.32	80.74%	50.02%
FewSum	53	3.00	159	57.27/60.06	75/497/104	4.87/4.34	89.13%	65.07%
Total	237	2.71	643	87.6/75.18	239/1118/231	5.89/5.08	82.51%	53.20%
Dev								
CocoTrip	10	6.00	60	91.24/75.93	197/829/174	5.64/5.07	85.53%	46.05%
FewSum	13	3.00	39	57.55/58.46	78/493/102	5.21/4.15	90.74%	79.63%
Total	23	4.30	99	77.97/69.05	197/829/174	5.47/4.71	87.34%	57.73%
Test								
CocoTrip	26	6.00	156	90.34/74.28	279/881/266	5.64/4.86	79.95%	42.74%
FewSum	34	3.00	102	57.43/57.44	74/509/105	5.0/4.41	88.89%	67.11%
Total	60	4.30	258	77.33/67.62	279/881/266	5.39/4.68	83.28%	51.82%
Overall								
CocoTrip	220	3.18	700	95.41/78.48	279/1118/266	6.04/5.2	80.97%	48.17%
FewSum	100	3.00	300	57.36/58.96	78/509/105	4.96/4.34	89.25%	67.59%
Total	320	3.13	1000	83.99/72.62	279/1118/266	5.72/4.94	83.15%	53.29%

Table 8: Full statistics of our dataset, including the number of unique review-sets, the average number of summaries per review-set, the number of summary/review-set pairs (a unique review-set creates a pair with each of its summaries), the mean review/summary size (in tokens and in sentences), the maximum review/review-set/summary size (in tokens), the percentage of summary sentences whose alignments span across more than one review, and the percentage of summary sentences whose alignments span across more than one review sentence within one of its reviews (namely, within a single review, the alignments come from more than one sentence).

## F Additional Dataset Details

### F.1 Full FiC Dataset Statistics

Table 8 presents the full FiC dataset statistics, including specific statistics for each of the dataset’s splits and instances origin, i.e., CocoTrip or FewSum.

### F.2 Annotation Cost

Each annotation instance, averaging 4 minutes, is priced at 70¢. Annotators also receive compensation for training activities, including a 5\$ bonus for taking the 25-minute tutorial and an additional 2\$ for reviewing feedback. The total cost for the dataset amounted to approximately 5700\$.

### F.3 Additional Details about the Annotators Recruitment

For our crowdsourcing project, we hired annotators from English-speaking countries who had over 5000 approved HITs as well as an approval rate higher than 98% on Amazon Mechanical Turk. During the recruitment process, in addition to explaining the annotation guidelines, we also explained to the crowdworkers the purpose of the dataset, in order to rationalize different aspects of the annotation protocol.

## G IAA disagreement Examples

Figure 5 demonstrates two instances of disagreements between our annotators.

## H Additional Experimental Details

To incorporate the highlighting signal in the baseline Flan-T5<sub>H</sub>, `<extra_token_1>` and `<extra_token_2>` tokens were added to the input, before and after each highlight. For all trained models, we set the maximum input length to 2048, to accommodate the input length of the language model.

We also set the maximum target length to 200, which we found works best, as well as setting the batch size to 1. The other parameters are similar to Slobodkin et al. (2022, 2023a). The model is trained for 10k steps. Training is performed on two A100-SXM4-80GB GPUs, and costs about 12 GPU hours for the supervised models (Flan-T5<sub>H</sub>, Flan-T5<sub>no-H</sub>, and Flan-T5<sub>only-H</sub>) and about 36 GPU hours for the RL-tuned variant of Flan-T5<sub>H</sub>.

Additionally, to train the trained faithfulness and coverage evaluators, we concatenate the highlights concatenation and the output’s sentence (for faithfulness) and the generated output with each of the highlights (for coverage), and use the special token `<extra_token_4>` as a delimiter. For both evaluators, we set the maximum input length to 1024, the maximum target length to 4, and the batch size to 1. We train the models for 10 epochs. Training is



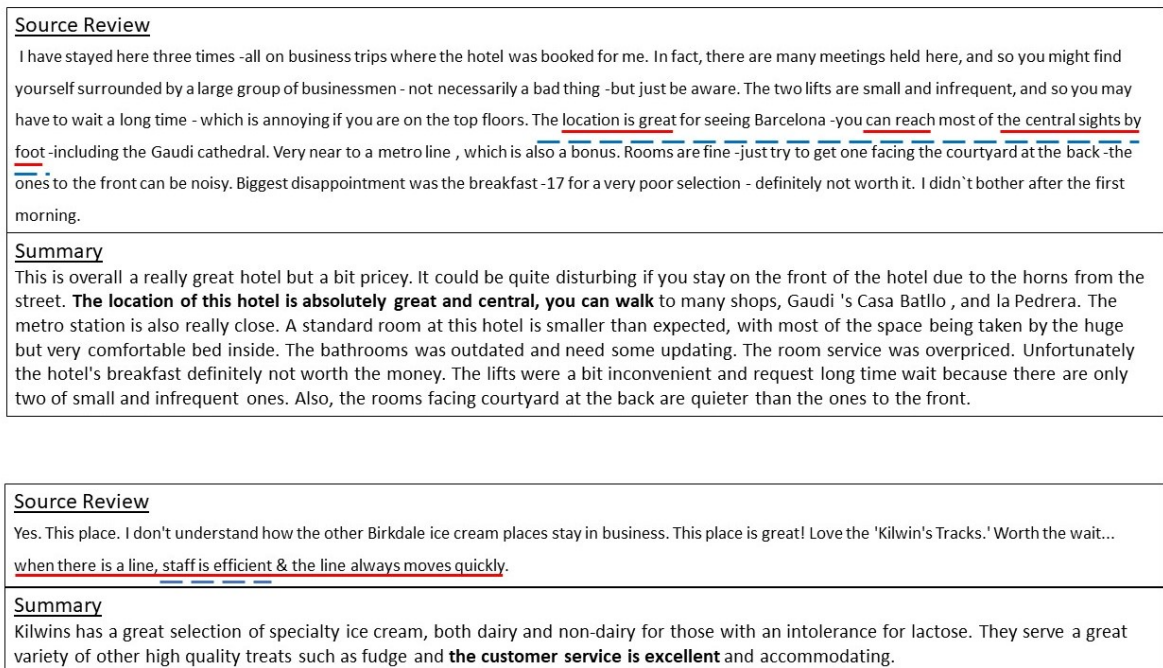


Figure 5: Two examples of disagreement between annotators. For each example, the bottom part is the summary (with the summary span over which there was disagreement in bold) and the top part is a review with both the annotators’ highlights (marked with a red solid line and a blue dashed line to indicate each highlight).

Model	Faithfulness	Coverage	F-1
flan-t5-small	66.9	83.4	74.2
flan-t5-base	70.1	85.5	77.0
flan-t5-large	72.8	86.4	79.0

Table 9: Faithfulness, coverage, and F-1 results on the FiC testset, for different sizes of flan-t5 (all finetuned on the FiC trainset).

performed on a single A100-SXM4-80GB GPU, and costs about 4 GPU hours.

Overall, our trained models, both for faithfulness and coverage evaluation and for the FiC task, use flan-t5-large as their backbone model, which consists of 780 million parameters, and our zero-shot NLI-based evaluation frameworks use flan-t5-xxl as the backbone model, consisting of 11 billion parameters.

## I Generation Examples

Figure 6 and Figure 7 demonstrate two examples of highlighted reviews and the corresponding output generated by Flan-T5<sub>H</sub>.

## J Impact of Model Size

Table 9 illustrates the performance on the test set of flan-t5 with different model sizes, finetuned

on the FiC trainset.

## K List of Data and Software Licenses Employed in this Paper

Our framework dependencies are:

1. CocoTrip dataset: <https://github.com/megagonlabs/cocosum/blob/main/LICENSE>, under an Apache License 2.0.
2. FewSum dataset: <https://github.com/abrazinskas/FewSum/blob/master/LICENSE.txt>, under the MIT License.
3. Quark: <https://github.com/GXimingLu/Quark>, Misc.
4. Baseline model for the zero-shot NLI-based evaluation frameworks: <https://huggingface.co/google/flan-t5-xxl/tree/main>, under an Apache License 2.0.
5. Baseline model for the trained evaluation frameworks and models: <https://huggingface.co/google/flan-t5-large/tree/main>, under an Apache License 2.0.

**Review 1:** I recently travelled to Singapore and ended up to the Grand Hall City Park as booking late on a busy weekend, the rest was either sold out or too expensive. I had a corporate rate, and must say it was good value for money, given the **quite central location**. The service was good and **the hotel staff very friendly**. On the negative side, the hotel is a bit outdated and lacking style. I got a room close to the elevator, which turned out to be very noisy, and got waken up in the middle of the night by people spekaing loud (isolation is really bad, and that is the main reason why i would not recommend this hotel). Also breakfast was disappointing with very limited choices and no fresh fruit apart from apples and bananas. There is a pool, which is ok, but very very small. Perhaps a better room would make me change my opinion, but still it was lacking style and personality.

**Review 2:** I am a first time traveller overseas with my husband, therefore we are comparing to 5 star accomodation in Australia. We read the reviews on all the hotels in Singapore and decided this was the hotel for us. The hotel was very clean, although the furnishings are getting old and need updating in the rooms and eating areas. **We found the staff very accomodating** and the buffet breakfast and dinner meals changed all the time. **The hotel was central for all our travelling**. The only bad comment, we were on a non smoking floor, yet the wardrobes smelt smoky. There was a cross section of travellers. When we go back to Singapore, we would stay again as good value for the price Over 50s from Adelaide

**Review 3:** We were very impressed by the standard of service we received from all the staff, especially Ms Kripa at the club floor. **The staff were friendly** and keen to ensure we enjoyed our stay at the hotel. **The location is great, close to MRT, Clarke Quay, the National Museum etc - all walking distances**. Our king size bed was very comfortable but the bathroom was a little small and only one person at a time can fit, but having a full size bath was very nice to relax in. We would stay at this Hotel again.

**Review 4:** for the last 3 years have been staying 3to 4times a year for periods of up to 2 weeks in this hotel. plusses: **great location with short walk to mrt, staff very friendly** and helpfull.minus is no wifi in rooms.rooms at floor which are not yet removed are run down.

**Review 5:** Went to Singapore for the Grand Prix and **this hotel was just 2 minutes away from Gate 4**. The **hotel staff were** very **helpful and** the whole hotel we found to be very **pleasant** and would definitely go back again to stay.

**Review 6:** This is my first time in the hotel. **I found it conveniently located, very nice and friendly staff**, excellend dining and a very nice fitness Center. I look forward to returning.

**Review 7:** **This is a very central, large good value hotel in Singapore**. Maybe the rooms are not as grand as the reception area, but overall I would recommend it to most travellers

**Review 8:** **Great location, excellent service, beautiful view, nice staffs**. The price is quite high but worth it.



**Generated Summary :** This hotel is in a great location and the staff is very friendly and helpful. Besides this the hotel is very pleasant and the view from the hotel was really good too. The Grand Prix of Singapore was only 2 minutes away from this hotel and it is very close to the MRT, Clarke Quay and the National Museum too. Overall this hotel is a very pleasant place to stay and the price is quite high but it is worth the money because it is in such a central location and there are lots of attractions nearby.

Figure 6: Example of generated output by Flan-T5<sub>H</sub>.

**Review 1:** Very nice staff! It's always packed in here & I'm not surprised! Quality food! Lots of options! I absolutely love the vegan options as well as the GMO-free foods (all Trader Joe's brand is GMO-free). I have to say the prices are great as well! Love TJ's!!

**Review 2:** I love getting my Pirate Booty from here (the puffs people) and the ready made pizzas, pretty much everything that they have ready made is really good. The store can get pretty crowded, especially during the dinner hour rush. Employees are friendly and I recommend you take advantage of the samples throughout the store. Come hungry!

**Review 3:** This store gives me a nice and warm feeling. The feeling that I didn't and won't have with Walmart Market. Trader Joe's has a lot of eye-catching snacks and healthy food. Therefore, I have no idea which items I should buy. If I can, I want to try everything. Absolutely, comeback

**Review 4:** Checked out this location. Smaller than the Albuquerque NM store that we frequently visit but found the items we were needing but noticed selection was different or maybe I just wasn't finding what I needed. I didn't find the selection of jelly and jams that I wanted but that is okay.

**Review 5:** Love this store... can't get enough of it. I have been going to Trader Joe's for years. This store always makes me happy. From great recipes idea to great selections of groceries. Staff is really friendly as well. Thumbs up Trader Joe on Camelback Rd!

**Review 6:** This is a big TJ's. What else is there to say? It's a Trader Joe's. Awesome food, great employees. I don't know what I could complain about. Skip Fry's and shop here. The food is healthier and taste better.

**Review 7:** The parking for this location can be a madhouse because it's located in a very busy strip mall and largely due to the construction surrounding it. But in TJ fashion, it won't disappoint with all the usual goodies that make you feel so adult and domesticated shopping here. Staff is always awesomely happy and helpful.

**Review 8:** This is my favorite Joe's. From SF to SD to Scottsdale, the T & C location is the best. Everyone here genuinely knows me and my son. They interact with you like a friend. Products are always great and when they're not they exchange with no hassle. Thanks to the whole staff for always being so welcoming.



**Generated Summary :** This Trader Joe's is a great place to shop for groceries. The store is located in a busy strip mall, so it can get crowded, especially during the dinner hour rush. However, the store is well-stocked with healthy food options, as well as vegan and GMO-free options. The staff is friendly and helpful, and there are samples available to take advantage of. Overall, this store is highly recommended for its quality food, friendly staff, and warm, welcoming atmosphere.

Figure 7: Example of generated output by Flan-T5<sub>H</sub>.