Calibrating Likelihoods towards Consistency in Summarization Models

Anonymous ACL submission

Abstract

Despite the recent advances in abstractive text summarization, current summarization models still suffer from generating factually inconsistent summaries, reducing their utility for real-world application. We argue that the main reason for such behavior is that the summarization models trained with maximum likelihood objective do not accurately rank sequences by their consistency with the document. In this work, we solve this problem by calibrating the likelihood of model generated sequences to better align with a consistency metric measured by natural language inference (NLI) models. The human evaluation study and LLM-based evaluation show that the calibrated models generate more consistent and higher-quality summaries. We also show that the models trained using our method return probabilities that are better aligned with the NLI scores, which improves reliability of summarization models.

1 Introduction

Recent years have witnessed a huge leap forward in abstractive summarization (Zhang et al., 2019a; Liu et al., 2022), yet the wider adaptation of summarization models is limited by their tendency to generate *hallucinations* – outputs with contradicting or unsupported information to their input article (Falke et al., 2019; Maynez et al., 2020). Hallucinations in summarization models can be mostly attributed to two main reasons. First, most summarization systems are trained to maximize the log-likelihood of the reference summary, which does not necessarily reward models for being faithful. Moreover, models are usually agnostic to the noises or artifacts of the training data, such as reference divergence, making them vulnerable to hallucinations (Kryscinski et al., 2019; Dhingra et al., 2019). Thus, models can generate texts that are not consistent with the input, yet would likely have reasonable model log-likelihood. We refer to this phenomenon as models' sequence likelihood not being calibrated to their consistency.

Input: The man, from Aberdeen, was charged after "suspicious incidents" in the Aberdeen, Aberdeenshire and Montrose areas. A report has been submitted to the procurator fiscal. Sgt Andy Peerless, of Police Scotland, said: "The information provided to us from the public was vital."
Before: A 49-year-old man has been charged with a number of offences including rape and possession of a bladed article.
After: A man has been charged following "suspicious incidents" in Aberdeen, Aberdeenshire and Montrose.

Input: Violet D'Mello entered the enclosure for a photo next to the cats at the Kragga Kamma Game Park in Port Elizabeth earlier this year. She suffered injuries to her head, stomach and legs during the incident. The authorities in South Africa have ruled the park was not negligent. A party of visiting schoolboys and a cheetah in heat were said to have been factors in what happened. Mrs D'Mello, 60, said she survived by "playing dead". She had been on holiday with her husband Archie at the time.
Before: A woman who was mauled to death by a cheetah at a South African game park has been awarded a six-figure sum of money.
After: A woman who suffered injuries when she entered a cheetah enclosure at a South African game park has said she "played dead".

Figure 1: XSum inputs and system generated summaries before and after calibration. The text spans in amber are hallucinated.

The textual entailment score – the entailment probability of a summary (hypothesis) given its input (premise) – has been widely used to quantify the extent to which generated summaries are faithful or consistent to their input (Falke et al., 2019; Maynez et al., 2020; Narayan et al., 2022b; Honovich et al., 2022a). Unsurprisingly, several efforts aiming to calibrate summarization models towards consistency focus on textual entailment signals. Pasunuru et al. (2017) use the *multi-task learning* to jointly train their decoder as a summary generator as well as an entailment classifier. Pasunuru and Bansal (2018a) proposed to use *reinforcement learning* with sequence-level reward for entailment optimizing models to assign higher probability to logically-entailed summaries. *Reranking-based approach* (Falke et al., 2019) uses a two-stage reranking system that first generates candidate summaries and then uses textual entailment predictions to detect consistency errors and rerank alternative predicted summaries. Another trend proposes to leverage consistency signals via *controlled generation*

(Keskar et al., 2019; Rashkin et al., 2021) to calibrate summarization models. Specifically, training examples are supplemented by prepending special tokens to inputs to indicate/control whether the output should be entailed or not. This way model is better calibrated in differentiating inconsistent examples from consistent examples. Some have also relied on *data filtering* where we only train on examples whose summaries are predicted to be entailed by the input (Narayan et al., 2021; Aharoni et al., 2022).

Recently Liu et al. (2022) introduced calibration methods to align candidates' sequence likelihoods to their quality as measured by their similarities to the target sequence. First they decode candidates from a fine-tuned model on its own training dataset, and then continue training the model with a multi-task learning objective of sequence candidates with contrastive reranking and token-level generation. Liu et al. (2022) used metrics like Rouge (Lin, 2004) and BERTScore (Zhang et al., 2019b) to rank different decoded candidates with their similarities to the target sequence. Zhao et al. (2023b) generalizes Liu et al. (2022) and uses their similarities to the target sequence in the model's latent space, instead of relying on external metrics like Rouge and BERTScore. Both Zhao et al. (2023b) and Liu et al. (2022) demonstrate that their methods significantly improve the quality of generated summaries when evaluated against target sequences using Rouge or BERTScore. However, the improvements in the similarities to the target sequence doesn't necessarily lead to consistent summaries. Figure 1 presents few hallucinated (spans mark in amber) summaries generated using these methods.

In this paper we propose ***S**equence **Li**kelihood **C**alibration with **NLI** (or **SLiC-NLI**)* to calibrate summaries' sequence likelihood to their consistency. Our approach builds on (Zhao et al., 2023b) and (Liu et al., 2022) but uses textual entailment scores to rank candidate summaries, instead of Rouge or BERTScore. In particular, we decode candidates from a fine-tuned model on its own training dataset, estimate entailment probabilities of candidate summaries given their respective inputs, and then continue training the model with a multi-task learning objective of sequence candidates with contrastive reranking and token-level generation.

Unlike reinforcement learning, it is a one-time offline process that avoids costly online decoding processes. Also, when compared to two-stage reranking systems, it doesn't require a separate reranking model that incurs additional complexity and compute.

We experimented with five different abstractive summarization tasks: CNN/DailyMail (Hermann et al., 2015), ForumSum (Khalman et al., 2021), RedditTIFU-long (Kim et al., 2019a), SAMSum (Gliwa et al., 2019) and XSUM (Narayan et al., 2018), due to their diversity in domain, style, abstractiveness, and summary lengths. We show that using our approach models can generate better consistent summaries, without sacrificing their overall quality when evaluated automatically and by humans.

2 Related Work

2.1 Measuring Consistency

A large number of approaches have been proposed for automatic detection of factual inconsistencies. Most notably, Natural Language Inference (Bowman et al., 2015a) approaches has been shown to have a large correlation with human consistency ratings on generation tasks, including summarization (Maynez et al., 2020; Laban et al., 2022; Goyal et al., 2021; Goyal and Durrett, 2021). Other approaches based on question generation and answering have been also shown to perform well in detecting factual consistency (Scialom et al., 2021; Honovich et al., 2021; Deutsch et al., 2021), but usually require a pipeline of model inferences that makes them impractical for some applications. Many studies have investigated automatic detection of factual inconsistencies in a wider variety of tasks (Honovich et al., 2022a; Tang et al., 2022), and show that large-scale NLI models have among the highest agreement with human ratings.

2.2 Calibrating Consistency

Model calibration is commonly used in classification tasks, whereas in sequence generation it has not being well defined generally. In our context, model calibration refers to aligning the sequence likelihood to the target entailment probability.

Reranking-based Approach Many works have proposed to reranking as approach to Many works have proposed approaches that first decode a number of outputs and re-rank them as a second stage. Liu and Liu (2021) decode outputs with diverse beam search and using a RoBERTa-based model to rank them next. Similarly in the neural machine translation (NMT), Fernandes et al. (2022) and Lee et al. (2021) train rerankers that mimic automatic metrics (BLEU, COMET and BLEURT) and rerank top-k decodes accordingly. SummaReRanker

(Ravaut et al., 2022) found that performance is improved by training generation and reranking models on exclusive halves of the training data instead of on the same data. BRIO (Liu et al., 2022) includes sequence-to-sequence generation models for both generation and reranking stages. They rank different candidates by their similarities to the target sequence using automatic metrics. Zhao et al. (2023b) generalizes this idea by computing the similarities to the target sequence in the model's latent space. Zhao et al. (2023a)

RL-based Approach Reinforcement learning has been proposed as an approach to optimize signals directly. Paulus et al. (2018) optimize the evaluation metric ROUGE via RL fine-tuning. The authors found that optimizing for single discrete evaluation metric such as ROUGE can be detrimental to the model quality and fluency. Ziegler et al. (2019) and Stiennon et al. (2020) trained reward models to learn human preference based on collected human judgments of competent fine-tuned models. Using PPO, the supervised policy is fine-tuned against the learned reward model. Roit et al. (2023) is optimizng entailment rewards while Pasunuru and Bansal (2018b) is combining ROUGE, saliency and entrailment-based rewards in their RL training. The authors found that this approach leads to better quality summaries than optimizing with respect to ROUGE.

Controllable Generation Controllable generation has been proposed as an approach to increase consistency. He and Yiu (2022) proposed the use of control codes to influence generated outputs to match desired characteristics such as style and length as they were observed in the training data. Rashkin et al. (2021) and Aharoni et al. (2022) extended this approach to increase consistency in grounded dialog and multilingual summarization, correspondingly, by adding a control feature based on inferred NLI scores given the summary and input document (Honovich et al., 2022a).

Summary Generation with Planning Narayan et al. (2021) proposed that intermediary plans, based on entities, are useful to increase grounding and consistency in summarization by avoiding common pitfalls seen in autoregressive generation. Moreover, sequence-to-sequence models can learn to produce those plans and the output summaries sequentially in an end-to-end manner. These plans are also controllable and models trained this way are able to produce summaries grounded to the modified plans. Further, Narayan et al. (2022a) showed that plans based on questions and answers provide anchoring for more complex tasks, for instance multi-document summarization, aiding further on consistency of longer summaries.

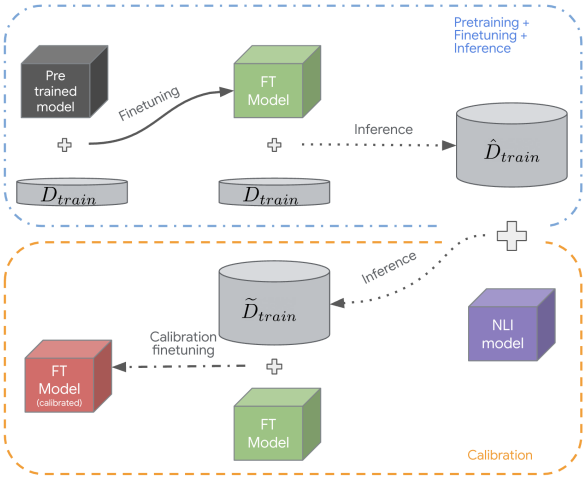

Figure 2: Our method consists of two parts: **top** (blue color) represents the usual finetuning and inference and **bottom** (orange color) represents the SLIC-NLI methods consisting of the inference using the NLI model and the SLIC calibration.

Data Filtering Approach Narayan et al. (2021) and Aharoni et al. (2022) additionally proposed a simple approach to filter the training data based on inferred NLI scores given the summary and input document. Using only a subset of the training data, inferred to be consistent with the input, model consistency by automatic metrics and human evaluations is improved.

3 Method

Following Zhao et al. (2023b) and Liu et al. (2022), we introduce a third *calibration stage* to the popular paradigm of pretraining and fine-tuning, as explained in Figure 2. Let D_{train} : $\{\mathbf{x}, \bar{\mathbf{y}}\}_n$ be the dataset used for fine-tuning. We first generate m candidates $\{\hat{\mathbf{y}}\}_m$ for each training instance in D_{train} from a fine-tuned model; we refer to this augmented dataset as $\hat{D}_{train}$ consisting of $\{\mathbf{x}, \{\hat{\mathbf{y}}\}_m, \bar{\mathbf{y}}\}_n$. We then calibrate the fine-tuned model by continuing training with the following loss:

$$\mathcal{L}(\theta) = \sum_n L^{\text{cal}}(\theta; \mathbf{x}, \{\hat{\mathbf{y}}\}_m, \bar{\mathbf{y}}) + \lambda L^{\text{reg}}(\theta, \theta_{ft}; \mathbf{x}, \bar{\mathbf{y}}), \quad (1)$$

where θ and θ_{ft} are the current and finetuned model weights, L^{cal} and L^{reg} are the calibration and regularization losses, respectively. The calibration loss

L^{cal} aims to align models' decoded candidates' sequence likelihood $P_\theta(\hat{\mathbf{y}}|\mathbf{x})$ according to their entailment scores, whereas the regularization loss L^{reg} prevents models from deviating significantly from their fine-tuned model parameters.

3.1 Calibrating towards Consistency

In order to calibrate the model towards the consistency we annotate $\{\hat{\mathbf{y}}\}_m$ with textual entailment scores (Natural Language Inference or NLI) (Bowman et al., 2015b), i.e. we estimate entailment probabilities of candidate summaries given their respective inputs. To esimate the entailment we follow Honovich et al. (2022a) and trained an NLI model by fine-tuning T5-11B (Raffel et al., 2020) on the Adversarial NLI (ANLI; Nie et al., 2020) dataset. In Figure 2 the dataset $\hat{D}_{train}$ annotated with entailment probabilities is represented as $\tilde{D}_{train} : \{\mathbf{x}, \{\hat{\mathbf{y}}, \hat{\mathbf{e}}\}_m, \bar{\mathbf{y}}\}_n$, where $\hat{\mathbf{e}}$ is the entailment score of the candidate $\hat{\mathbf{y}}$. Figure 3 shows how the NLI scores are distributed across different datasets, overall we found out that for every dataset except for CNN/DailyMail we have good representation of good and bad examples for effective calibration. The calibration loss

$$L^{\text{cal}} = \max(0, \beta - \log P_\theta(\hat{\mathbf{y}}_+|\mathbf{x}) + \log P_\theta(\hat{\mathbf{y}}_-|\mathbf{x})) \quad (2)$$

then trains the model to learn the ranking among candidates pairs $(\hat{\mathbf{y}}_+, \hat{\mathbf{y}}_-)$, uniformly sampled from $\{\hat{\mathbf{y}}\}_m$, according to their entailment scores. In this case, $\hat{\mathbf{y}}_+$ ranks highers than $\hat{\mathbf{y}}_-$ as $\hat{\mathbf{e}}_+ > \hat{\mathbf{e}}_-$.

Our approach differs from Zhao et al. (2023b) and Liu et al. (2022) where they proposed to use the similarity between the candidate $\hat{\mathbf{y}}$ and the target $\bar{\mathbf{y}}$ conditioned on the context $\mathbf{x}$ to get ranking among candidate pairs, instead of textual entailment scores.

3.2 Length regularization

As a result of our extensive experimentation with the various β's we have made curious observation about NLI scores. It appears that there is a slight positive correlation between the length of the generated summaries and NLI. However this phenomena could be seen as a way of the model to "cheat" and over-optimize in the direction of the higher NLI. Oftentimes a dramatic increase in the length can come out of the repetition of the same sentences over and over. Naturally we would like to avoid this behavior. In pursuit of containing the length of the generating summaries we experiment with an additional length regularization term. We have experimentally found out that it is best to compare the length of the generated sequence $\hat{\mathbf{y}}$ with the length of the target sequence $\bar{\mathbf{y}}$ via simple ratio:

$$f_{len}(\hat{\mathbf{y}}) = \left(1 - \left|1 - \frac{l(\hat{\mathbf{y}})}{l(\bar{\mathbf{y}})}\right|\right), \quad (3)$$

where $l(y)$ is the length of the sequence y. We subsequently update our calibration loss L^{cal} from (2) using f_{len} to scale the log-likelihoods, up-weighted with α:

$$L^{\text{cal}} = \max(0, \beta - \alpha \cdot f_{len}(\hat{\mathbf{y}}_+) \cdot \log P_\theta(\hat{\mathbf{y}}_+|\mathbf{x}) + \alpha \cdot f_{len}(\hat{\mathbf{y}}_-) \cdot \log P_\theta(\hat{\mathbf{y}}_-|\mathbf{x})) \quad (4)$$

Finally, for the regularization loss L^{reg} we follow Zhao et al. (2023b) and use the KL divergence loss minimizing the probability distribution distance between the calibrated model and the fine-tuned model at each token on the target sequence. Liu et al. (2022) proposed to use the cross-entropy loss as the regularization loss. Nevertheless, both losses have been shown to perform similarly for summarization (Zhao et al., 2023b).

4 Experimental Setup

4.1 Summarization Datasets

We have experimented with a diverse set of summarization datasets, with respect to different domains, styles, abstractivenesses, and summary lengths.

CNN/DailyMail (Hermann et al., 2015; See et al., 2017) summarization dataset contains 313k articles from the CNN and Daily Mail newspapers with bullet point summaries. The summaries are on average 3-4 sentences and relatively extractive.

ForumSum (Khalman et al., 2021) summarization dataset contains 4058 conversations from a wide variety of internet forums and their high-quality human written summaries.

RedditTIFU-long (Kim et al., 2019b) summarization dataset contains 42k posts of informal stories from sub-reddit TIFU from 2013-Jan to 2018-Mar with author written summaries. The style and length of the summaries are very diverse.

SAMSum (Gliwa et al., 2019) summarization dataset contains 16k high-quality chat-dialogues and their summaries written by linguists.

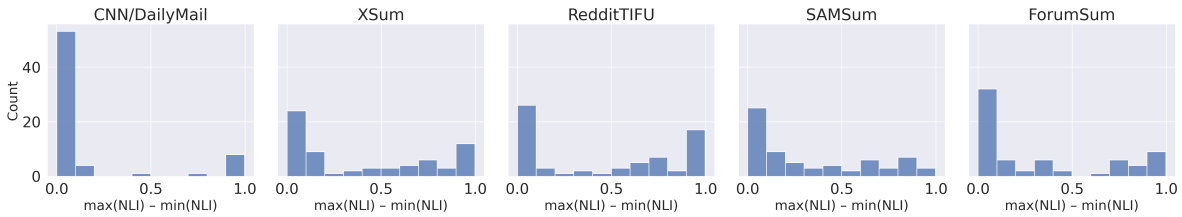

Figure 3: Distribution of the NLI scores over the inference outputs with beam size = 15. All dataset except for CNN/DailyMail have a diverse variety of generated summaries per document.

XSUM (Narayan et al., 2018) summarization dataset consists of 227k BBC articles from 2010 to 2017 with a single sentence highly abstractive summary. Sometimes the summary contains information not present in the article.

4.2 Automatic Evaluation

We report on ROUGE (Lin, 2004) which is commonly used to measure the informativeness and fluency of model generated summaries against gold-standard references.

We report on the reference-free NLI score as a proxy for faithfulness (Maynez et al., 2020; Honovich et al., 2022b). For NLI, we compute whether the summary is entailed by the input, and report the average over all examples. We use the same NLI model that we use for calibration as described in §3.1.

4.3 LLM Evaluation

We evaluate our model against the baselines by zero-shot prompting an LLM following the recipe in Guo et al. (2024). We adopt *Detailed 0-shot* prompt from Lee et al. (2023). You can find the exact prompt that was used in Figure 8. Just like in Guo et al. (2024) we use Gemini Pro (Gemini-Team et al., 2023) model to evaluate the results.

4.4 Human Evaluation

We conducted human evaluation of the generated summaries for all 5 datasets. We picked our 3 models: finetuned, best calibrated (Eq 2 for L^{cal}) and best calibrated with length regularization (Eq 4 for L^{cal}), along with other baselines. For each dataset we sampled 100 examples from its corresponding test set. For each example we generate summaries using different models and send to crowd-workers for side-by-side quality annotation. We present our raters a document and model generated summaries, and ask them to assess each summary individually for overall *quality* (on a scale of 1:Poor Summary to 5:Great summary) and *factuality* (a binary decision assessing whether everything in the summary can be verified in the document). Each assessment is replicated by three different crowd workers. For quality we average the annotated scores across all replicas of each task. For the factuality metric we aggregate the metric using majority vote. The models are anonymized and randomly shuffled to avoid biases in the annotation. For more details about the human evaluation template see Appendix D.

4.5 Implementation Details

We experimented with T5 (Large, 500M parameters) with a maximum input sequence length of 1,024 tokens and a maximum output length of 256 tokens. We trained all our models with a leaning rate of 0.001 and a batch size of 128, for 50K steps. We select best checkpoints using average Rouge performance on validation sets, unless specified otherwise. During inference, we use beam search with size 5 and alpha 0.8.

5 Results

Ablation on Calibration Weights and its Effect on Lengths We first ablate the effect of different calibration weights (β) in Eq 2 without applying the length regularization. Table 1 presents our results.

We achieve up to $\approx 30\%$ improvement in terms of the NLI scores on XSUM datasets, 10.47% on ForumSum, 9.41% on SAMSum, 8.23% on RedditTIFU-long, and, 2.12% on CNN/DailyMail. Using different values of β in L^{cal} allows to control the level of the calibration, i.e. the bold colors in Table 1 always correspond to the highest weight. We observe that higher calibration can often times affect the other metrics, for example ROUGE scores slightly decrease with the intensity of calibration, which can be non-desirable. A similar phenomenon can be seen with the increase in length and repetition which can be a symptom of the model trying to "cheat" the NLI metric. On Figure 4 we demonstrate the Pareto frontier that allows us to explore the optimal trade-off between the NLI scores and various metrics.

Ablation on Length Regularizer In order to prevent the model from overfitting to the NLI met-

Dataset	β	NLI %	NLI gain %	R1/R2/RL	Coverage %	Length	Repetition %
ForumSum	10^{-3}	**82.13**	**10.47**	38.51 / 18.08 / 31.16	88.5	43.25	19.10
	10^{-4}	78.15	6.50	**40.74 / 20.09 / 33.59**	86.9	32.28	13.10
	10^{-5}	75.05	3.39	40.50 / 19.39 / 32.97	84.5	27.17	7.20
	w/o	71.66	0.00	39.82 / 18.74 / 32.37	83.6	25.03	6.40
RedditTifu	10^{-3}	**89.43**	**8.23**	27.28 / 8.65 / 21.60	93.9	23.76	7.30
	10^{-4}	84.45	3.24	29.96 / 10.82 / 24.82	90.9	16.34	2.40
	10^{-5}	82.28	1.07	30.02 / **10.85 / 25.05**	89.2	15.27	1.30
	w/o	81.21	0.00	**30.22** / 10.70 / 24.63	88.9	16.28	1.80
SAMSum	10^{-2}	**96.14**	**9.41**	48.93 / 24.68 / 39.76	81.3	29.08	4.10
	$3 \cdot 10^{-4}$	91.51	4.78	**54.47 / 30.15** / 45.72	80.4	19.74	1.60
	10^{-4}	87.93	1.19	54.33 / 29.98 / **45.85**	79.6	17.92	1.50
	w/o	86.73	0.00	54.52 / 30.09 / 45.75	79.2	18.93	1.70
XSUM	10^{-2}	**81.21**	**28.19**	39.46 / 16.92 / 31.88	83.0	18.07	0.40
	$3 \cdot 10^{-4}$	77.46	24.44	41.32 /18.77 / 33.71	80.9	17.33	0.40
	10^{-3}	57.21	4.19	**44.80 / 21.93 / 36.99**	74.1	17.22	0.40
	w/o	53.02	0.00	44.73 / 21.88 / 36.94	73.4	16.94	0.40
CNN/ DailyMail	10^{-2}	**89.47**	**2.12**	42.41 / 20.25 / 29.78	99.4	68.68	18.50
	10^{-3}	89.08	1.72	42.96 / 20.79 / 30.28	99.4	70.42	17.60
	$3 \cdot 10^{-4}$	88.57	1.22	43.52 / 21.23 / 30.78	99.3	69.26	14.10
	w/o	87.36	0.0	**44.29 / 21.82 / 31.62**	99.2	57.13	3.90

Table 1: The effect of different calibration weights on the model performance in terms of NLI. We also report on other automatic measures: Rouge-1, Rouge-2 and Rouge-L scores (R1/R2/RL), Coverage (percentage of tokens in the generated summary that appeared in the input), Repetition (percentage of repeated tokens in the output summary) and the summary lengths. All the results are reported on respective validation sets.

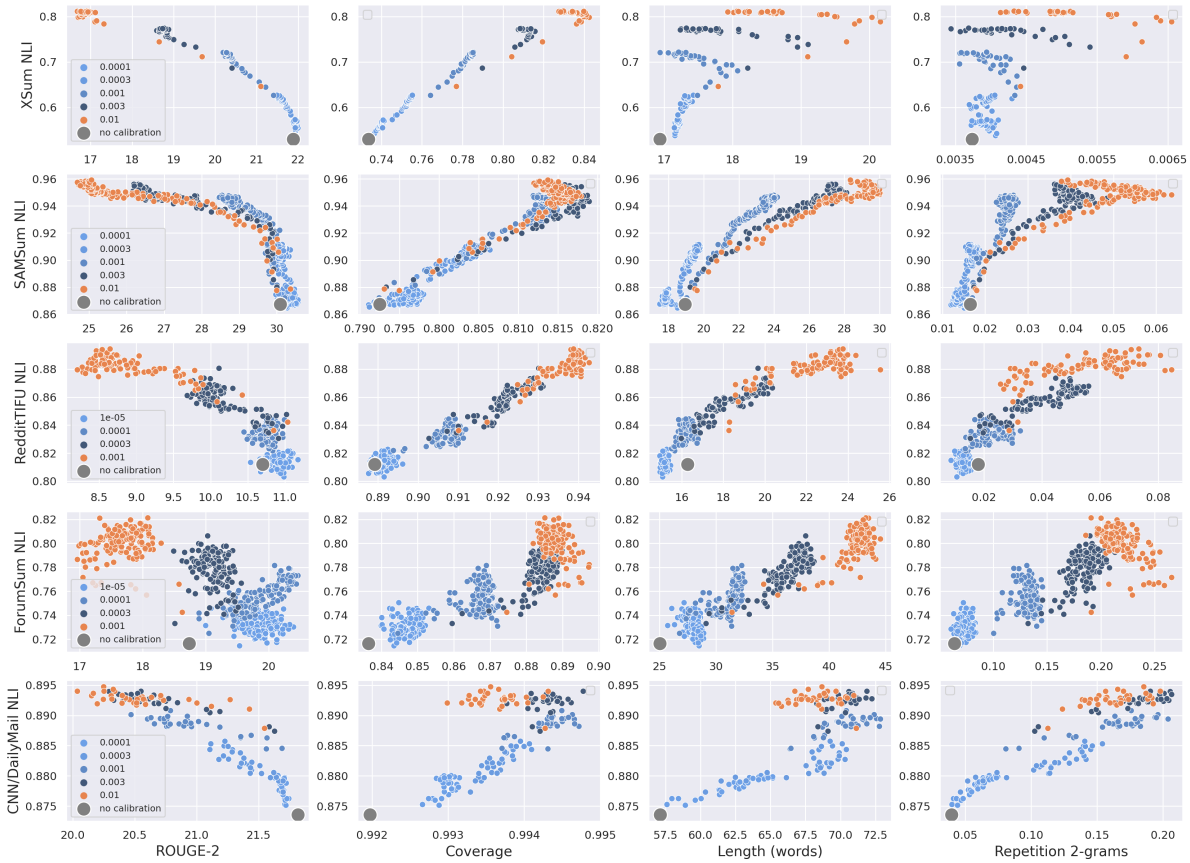

Figure 4: Pareto frontier that demonstrates the trade-offs between NLI and other metrics such as Rouge-2, Coverage, Length and Repetition on all datasets.

ric we conduct an extensive set of experiments to analyze the effect of the length regularization on the various metrics. As per Eq. 4 we choose various α in order to increase the effect of regularization. Results are presented in Table 2 and Figure 5. When α is very small, the model performs similar to its uncalibrated counterpart. But as we increase α, we start seeing the effect of joint consistency and length calibration. In order to pick the best configuration that equally optimizes for NLI and does

α	NLI %	NLI gain %	R1/R2/RL	Coverage %	Length	Avg
100	66.30	13.28	42.76/19.73/34.44	77.40	20.02	0.24
10	68.24	15.22	42.73/19.68/34.44	77.80	19.62	0.32
1	78.34	25.3	40.72/17.80/32.87	82.60	18.54	0.62
0.5	**78.87**	**25.85**	**40.17/17.64/32.80**	**82.20**	**16.82**	**0.81**
0.1	74.28	21.27	41.36/19.22/34.11	79.80	15.69	0.73
0.01	56.35	3.33	44.82/21.96/37.02	74.00	17.02	0.41
10^{-3}	53.62	0.60	44.89/21.99/37.06	73.30	17.16	0.34
10^{-4}	53.39	0.37	44.86/21.93/37.00	73.30	17.21	0.33
w/o f_{len}	81.21	28.19	39.46/16.92/31.88	83.00	18.07	0.73
w/o L^{cal}	53.02	0.00	44.73/21.88/36.94	73.40	16.94	0.36

Table 2: The effect of various length regularizer weights on the XSum dataset performance. We choose $\beta = 0.5$ with the highest NLI scores of 78.87% on the XSum validation set.

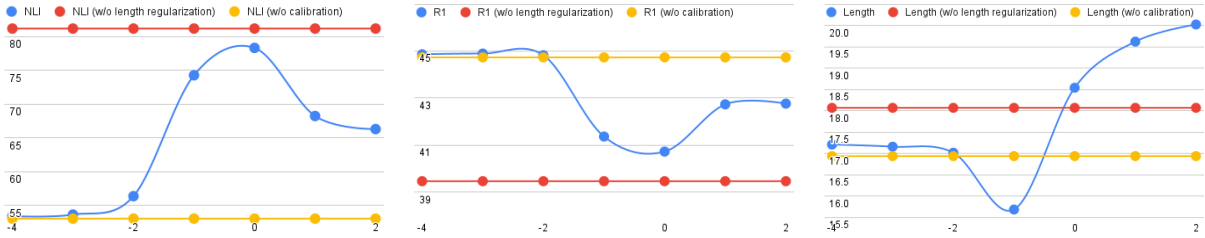

Figure 5: Plot of NLI, Rouge (R1) and Summary lengths with various length regularizer weights. See Table 2 for exact numbers.

Input: Police were alerted to the stabbing in Harehills Lane, Harehills, at about 15:40 GMT. The wounded teenager was taken to hospital for treatment, but died a short time later. A 15-year-old boy has been arrested on suspicion of murder, West Yorkshire Police said. He remains in custody for questioning. Det Supt Pat Twiggs, of West Yorkshire Police, said: This tragic incident happened in a busy area at a busy time of day with large numbers of people going about their daily business. I am appealing directly to anyone who witnessed the incident or has information that could help our inquiries to come forward. The force is hoping to speak to anyone who saw a person running in the area or those who have mobile phone footage. The scene remains cordoned off, with police forensic examinations expected to continue over the weekend.

Reference: A 16-year-old boy has died after he was stabbed in a busy Leeds street, prompting a murder inquiry.
Cliff: A 15-year-old boy has died after being stabbed in Leeds.
Frost (ECPP, Drop): A teenager has been stabbed to death in a "busy area" in a busy street.
Finetuned (w/o L^{cal}): A 16-year-old boy has died after being stabbed in a street in Leeds.
SLiC-NLI (w/o f_{len}): A teenage boy has been arrested after a teenager died following a stabbing in a busy area of West Yorkshire.
SLiC-NLI (with f_{len}): A teenage boy has died after being allegedly stabbed in a busy street in West Yorkshire.

Figure 6: An XSum inputs and various system generated summaries. The text spans in amber are hallucinated.

not deviate much on length we propose an average score $Avg_\alpha = \frac{\text{NLI}'_\alpha + (1 - \max(\text{L}'_\alpha, \text{L}'_{\text{w/o}})}{2}$, where $X'_\alpha = \frac{X_\alpha - \min(\mathbf{X})}{\max(\mathbf{X}) - \min(\mathbf{X})}$, i.e. simple min-max normalization. $\mathbf{X}$ is the set of values with different values of α. Table 2 highlights best scores that indicate the best results according to this metric. We follow the same recipe to select the best models for all datasets.

Final Results and Human Evaluations Table 3 present our final results on the corresponding test sets. We conducted human evaluation of the generated summaries. Table 5 shows that SLiC-NLI improves consistency of the summaries from 67% to 85% and the average quality scores from 2.96 to 3.43. The results of the experiments on all other datasets are summarized in Tables 8 (Appendix D). We also present summary lengths for comparison. The results show that calibration consistently improves the quality and factuality of all generated summaries.

Table 4 presents our LLM-based evaluations using Gemini Pro (Gemini-Team et al., 2023). We calculate the win ratio between the SLiC-NLI and the baselines against ground truth responses on XSum and CNN/DailyMail. On both datasets we outperform the finetuned baseline by a significant margin. Cliff seems to perform better on the CNN/DailyMail dataset, which can be explained by the Gemini Pro bias towards longer responses.

Humans consistently prefer the calibrated model over the non-calibrated model. See Figure 6 where we demonstrate one of the examples that was given to the raters, both SLIC version are the only two models that produced non-hallucinated summaries.

Correlation with probabilities We study how the log-probability of the calibrated model correlates with NLI (Table 6). For the beam search we either take the top-1 summary or the full beam outputs and compute the correlation across the whole datasets. The sentence log-probability as before computed as a sum of individual log-probabilities.

Dataset	Models	NLI %	R1/R2/RL	Length	Repetition %
XSUM	Pegasus	54.00	46.23 / 24.21 / 38.64	18.91	0.45
	Brio [1]	49.76	47.22 / 24.68 / 39.28	19.42	0.81
	SLiC	51.93	43.96 / 20.80 / 35.99 [2]	16.85	0.50
	Cliff	56.11	43.10 / 20.90 / 35.61	18.27	0.31
	FactPegasus	52.37	37.13 / 15.08 / 30.33	16.57	0.32
	Frost (Drop)	58.75	43.58 / 20.94 / 36.39	17.51	0.30
	Finetuned (w/o L^{cal})	48.52	44.02 / 22.07 / 36.64	17.75	0.35
	SLiC-NLI (w/o f_{len})	**80.01**	38.16 / 16.43 / 30.97	18.59	0.59
	SLiC-NLI (with f_{len}).	74.16	40.10 / 18.86 / 33.34	15.74	0.32
CNN/DailyMail	Pegasus	93.31	42.22 / 21.06 / 39.45	61.50	3.48
	Brio	88.75	46.30 / 23.25 / 31.93	63.09	3.27
	SLiC	93.38	43.86 / 21.18 / 30.88	52.59	3.80
	Cliff	91.08	33.91 / 14.29 / 24.27	51.43	1.45
	Frost (Drop)	93.49	43.50 / 21.56 / 40.83	57.54	3.46
	Finetuned (w/o L^{cal})	92.61	42.39 / 20.90 / 35.29	51.13	2.70
	SLiC-NLI (w/o f_{len})	**94.58**	40.84 / 19.54 / 38.30	66.48	15.68
	SLiC-NLI (with f_{len})	94.22	41.62 / 19.83 / 38.55	63.63	6.12
Forum Sum	SLiC	75.78	41.44 / 20.08 / 34.22	35.85	14.03
	Finetuned (w/o L^{cal})	72.97	40.34 / 19.29 / 32.66	31.66	7.88
	SLiC-NLI (w/o f_{len})	**78.26**	38.74 / 19.15 / 32.25	38.12	18.47
	SLiC-NLI (with f_{len})	77.82	40.82 / 20.22 / 34.07	30.61	8.59
SAMSum	SLiC	73.25	52.82 / 27.96 / 43.81	17.84	1.89
	Finetuned (w/o L^{cal})	73.00	51.01 / 26.36 / 42.54	18.62	2.04
	SLiC-NLI (w/o f_{len})	**86.57**	46.44 / 22.60 / 37.66	30.00	5.28
	SLiC-NLI (with f_{len})	84.63	49.79 / 25.39 / 41.51	20.59	1.65
Reddit TIFU-long	SLiC	75.61	27.51 / 7.98 / 21.71	16.22	1.20
	Finetuned (w/o L^{cal})	69.10	27.52 / 9.16 / 22.53	14.54	0.70
	SLiC-NLI (w/o f_{len})	**85.75**	27.40 / 9.01 / 22.33	18.92	3.81
	SLiC-NLI (with f_{len})	80.87	27.43 / 9.35 / 22.78	15.40	2.15

Table 3: Final results on various test sets. We include results from several state-of-the-art summarization models such as Pegasus (Zhang et al., 2019a), Brio (Liu et al., 2022), SLiC (Zhao et al., 2023b), Cliff (Cao and Wang, 2021), FactPegasus (Wan and Bansal, 2022) and Frost (Narayan et al., 2021). Cliff, FactPegasus and Frost are particularly trained or designed to generate factual summaries. For Frost, we report on Frost (Drop) which avoids hallucinated entities in summaries by dropping them form their entity plans. In each dataset we consistently show outstanding results on NLI. Having shorter sequence can be motivated by the generation latency or the risk of repetition in the summaries, in that case SLiC-NLI variant with length regularisation can be used and it surpasses other baselines as well.

Dataset	Finetuned	Frost	Cliff	SLiC-NLI
CNN/DailyMail	0.54	0.56	**0.63**	0.6
XSum	0.31	0.39	0.39	**0.52**

Table 4: Win rate of SLiC-NLI and the baselines against ground truth responses judged by Gemini Pro model for XSum and CNN/DailyMail datasets.

	quality	factual	length
Frost (ECPP, Drop)	3.18	.76	17.57
Cliff	3.10	.69	18.18
Finetuned (w/o L^{cal})	2.96	.67	17.77
SLIC-NLI (w/o f_{len})	**3.43**	**.85**	18.82
SLIC-NLI (with f_{len})	3.21	**.82**	15.54
Reference	2.94	.60	2.65

Table 5: Human Evaluation results on XSum dataset.

w	Decoding	P (all)	S (all)	P (top-1)	S (top-1)
		$\cdot 10^{-1}$			
w/o	Beam15	0.12	1.58	1.38	1.45
0.01		**3.05**	**3.12**	**2.83**	**2.94**
0.003		0.48	2.35	2.28	2.20
0.001		0.28	2.18	2.14	1.99
0.0003		0.14	1.85	1.70	1.71
0.0001		0.14	1.74	1.60	1.62

Table 6: Correlation between the log-probabilities of our model and NLI. We run inference with various decodings and compute the Pearson (**P**) and Spearman(**S**) correlations. For the **beam** decoding we either used all the outputs or top-1.

6 Conclusions

In this work we present ***SLiC-NLI*** — a new method for improving factuality of abstractive summarization models. The method calibrates the likelihood of the generative model with a consistency metric measured by NLI models. SLiC-NLI achieves state-of-the-art results on both human evaluation and automatic metrics while being simple, effective and straight-forward to implement. We show that SLiC-NLI achieves a 18% (from 67% to 85%) increase in consistency of the summaries according to humans and 31% (from 49% to 80%) according to automatic metrics on XSUM dataset. We hope that our work will contribute to the development of more reliable and accurate natural language generation systems.

[1] Metrics are computed using lowercase prediction and reference summaries available at https://github.com/yixinL7/BRIO/.

[2] We use our own implementation of SLiC so that these numbers don't match the ROUGE scores reported in the original paper

Limitations

While SLiC-NLI is a powerful and simple method for improving consistency of summarization models, it is important to acknowledge its limitations. For example, we haven't explored the capabilities of the method beyond summarization tasks, and since the field of LLMs is moving fast in the direction of single unified models, it is important to make sure that our method works well with instruction-tuning techniques. Additionally, improved consistency does not always lead to a high performance in terms of other metrics. There are no guarantees that creativity and helpfulness of a model outputs will not be affected by improved consistency. Finding a natural balance and control of these aspects is one of the topics we would like to explore in the future work. Finally, even though our method is exceptionally good at increasing the consistency between summaries and the documents, it doesn't guarantee that other types of hallucinations that are not covered by NLI metric will not be generated.

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A Length regularisation Pareto frontier

We compare how β weight of length regularizer affects the other properties of the generated summaries, such as NLI, ROUGE2, Length, Coverage and Repetition.

B Length regularisation ablation

See Figure 7 for the ablation study of how different length regularizers affect the model length, repetition, NLI and ROUGE metrics.

C Experimental set up

We run all experiments on T5 Large pre-trained checkpoints (770 million parameters), using open-sourced T5X framework[3]. For the infrastructure set up we used v3 TPU with 4×4 topology. Depending on the dataset the training can take from 5 hours (ForumSum) up to 7 days (CNN/DailyMail).

Reported metric results are collected from a single evaluation run on a test set, unless stated otherwise.

For each dataset we first train a finetuned checkpoint where we swept the hyperparameters(checkpoint step, leaning rate, number of training steps) such as to achieve the top scores on the selected metrics. We used the validation set to choose the best finetuning checkpoint. Later at the calibration step we swept over various calibration loss weights α and for the length regularization results we chose the best result based on the sweep over the β parameter. We used validation set again to pick the best checkpoint for the final results.

D Human Evals

Figure 10 presents our human evaluation template and instructions presented to our AMT workers who represent demographics from the USA. Table 8 shows our complete human evaluation results on all 5 datasets.

More examples of summaries before and after calibration can be found on Figure 9.

[3]https://github.com/google-research/t5x

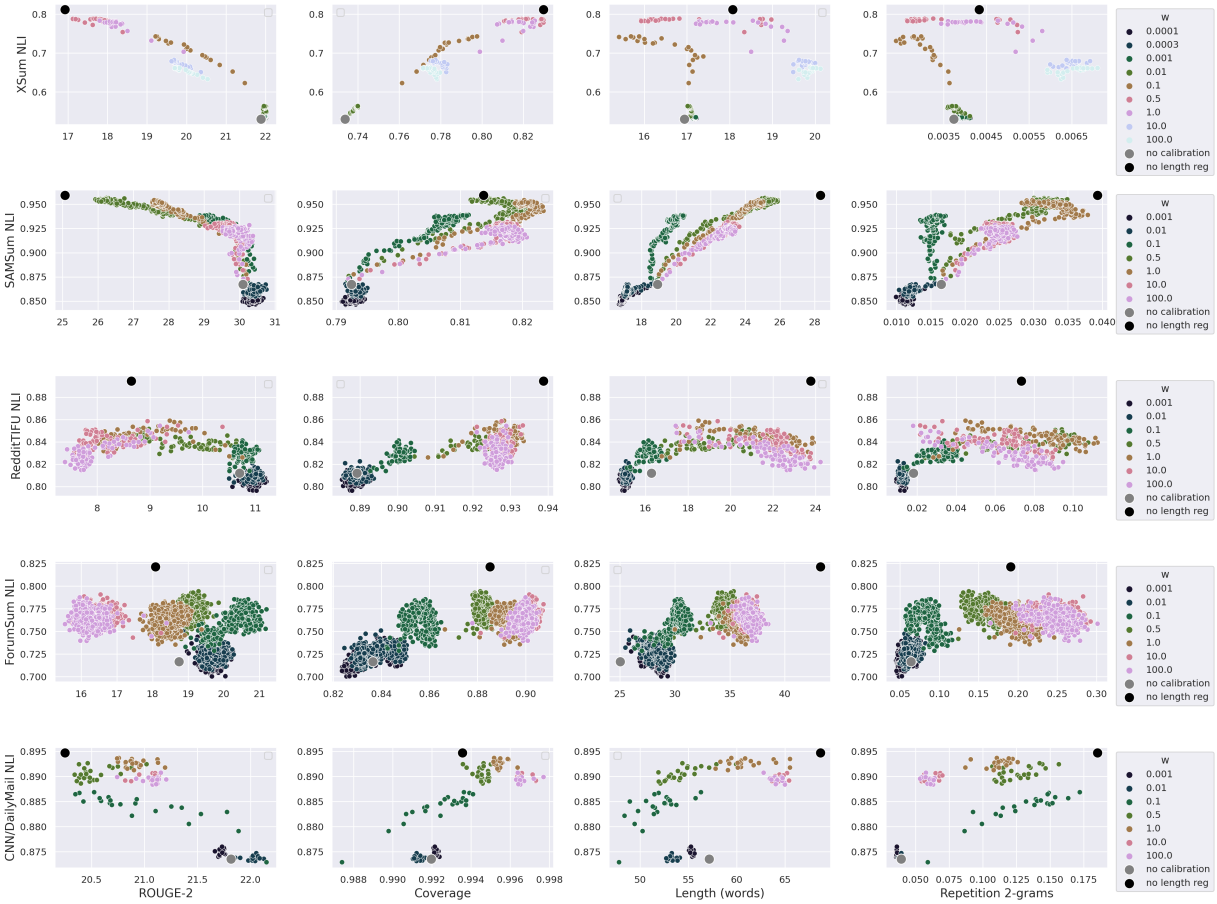

Figure 7: Pareto frontier for the length regularization weight. We compare the affect of the different length regularizes on metrics such as NLI, ROUGE2, Coverage, Length and Repetition.

Dataset	α	NLI %	NLI gain %	R1/R2/RL	Coverage %	Length	Avg
CNN/DailyMail	100	89.07%	1.72%	43.96 / 21.15 / 30.72	62.78	99.6%	0.60
	10	89.07%	1.71%	43.88 / 21.10 / 30.60	65.21	99.7%	0.52
	1	89.37%	2.01%	43.14 / 20.76 / 30.36	59.44	99.5%	0.77
	0.5	89.26%	1.91%	42.42 / 20.46 / 30.15	54.37	99.5%	**0.83**
	0.1	88.69%	1.33%	42.41 / 20.52 / 30.36	56.30	99.4%	0.69
	0.01	87.47%	0.11%	44.42 / 22.06 / 32.00	53.27	99.1%	0.40
	0.001	87.60%	0.24%	44.08 / 21.73 / 31.57	55.26	99.2%	0.43
	SLIC-NLI (w/o f_{len})	89.47%	2.12%	42.41 / 20.25 / 29.78	68.68	99.4%	0.50
	Finetuned (w/o L^{cal})	87.36%	0.00	44.29 / 21.82 / 31.62	57.13	99.2%	0.37
ForumSum	100	78.76%	7.10%	35.86 / 15.96 / 28.52	36.71	90.0%	0.52
	10	79.07%	7.41%	36.10 / 16.54 / 29.14	36.52	90.2%	0.54
	1	78.27%	6.61%	37.65 / 18.34 / 30.94	35.28	89.5%	0.53
	0.5	79.43%	7.77%	39.80 / 19.29 / 32.56	35.35	88.1%	0.59
	0.1	78.54%	6.89%	41.23 / 20.29 / 33.99	30.52	85.8%	**0.68**
	0.01	75.09%	3.43%	40.12 / 18.91 / 32.70	25.92	84.0%	0.64
	0.001	74.40%	2.74%	40.21 / 19.26 / 32.86	26.21	83.8%	0.60
	SLIC-NLI (w/o f_{len})	82.13%	10.47%	38.51 / 18.08 / 31.16	43.25	88.5%	0.50
	Finetuned (w/o L^{cal})	71.66%	0.00	39.82 / 18.74 / 32.37	25.03	83.6%	0.50
RedditTIFU-long	100	85.43%	4.22%	28.21 / 9.19 / 22.50	17.42	92.9%	**0.62**
	10	85.85%	4.64%	27.87 / 8.96 / 22.16	19.40	92.8%	0.53
	1	85.89%	4.69%	27.68 / 9.38 / 22.59	18.50	92.8%	0.59
	0.5	85.15%	3.95%	26.41 / 8.98 / 21.53	19.67	92.8%	0.48
	0.1	84.11%	2.91%	29.82 / 10.76 / 24.69	16.14	90.0%	0.61
	0.01	82.25%	1.05%	30.26 / 10.96 / 25.13	15.09	89.0%	0.49
	0.001	81.59%	0.38%	30.39 / 10.79 / 24.96	15.37	89.1%	0.45
	SLIC-NLI (w/o f_{len})	89.43%	8.23%	27.28 / 8.65 / 21.60	23.76	93.9%	0.50
	Finetuned (w/o L^{cal})	81.21%	0.00	30.22 / 10.70 / 24.63	16.28	88.9%	0.43
SAMSum	100	92.84%	6.10%	54.80 / 30.28 / 45.24	22.88	81.7%	0.62
	10	93.15%	6.41%	54.13 / 29.65 / 44.87	22.98	81.8%	0.63
	1	95.41%	8.68%	52.16 / 27.59 / 42.92	24.77	82.0%	0.67
	0.5	95.63%	8.90%	51.02 / 26.23 / 41.86	25.13	81.5%	0.66
	0.1	93.89%	7.15%	53.47 / 29.15 / 44.76	20.46	81.0%	**0.80**
	0.01	86.90%	0.17%	54.60 / 30.10 / 45.84	18.72	79.2%	0.50
	0.001	86.73%	0.00%	54.52 / 30.09 / 45.75	18.93	79.2%	0.49
	SLIC-NLI (w/o f_{len})	96.14%	9.41%	48.93 / 24.68 / 39.76	29.08	81.3%	0.50
	Finetuned (w/o L^{cal})	86.73%	0.00	54.52 / 30.09 / 45.75	18.93	79.2%	0.49
XSUM	100	66.30%	13.28%	42.76 / 19.73 / 34.44	20.02	77.4%	0.24
	10	68.24%	15.22%	42.73 / 19.68 / 34.44	19.62	77.8%	0.32
	1	78.34%	25.32%	40.72 / 17.80 / 32.87	18.54	82.6%	0.62
	0.5	78.87%	25.85%	40.17 / 17.64 / 32.80	16.82	82.2%	**0.81**
	0.1	74.28%	21.27%	41.36 / 19.22 / 34.11	15.69	79.8%	0.73
	0.01	56.35%	3.33%	44.82 / 21.96 / 37.02	17.02	74.0%	0.41
	0.001	53.62%	0.60%	44.89 / 21.99 / 37.06	17.16	73.3%	0.34
	0.0003	53.54%	0.53%	44.88 / 21.97 / 37.02	17.20	73.3%	0.33
	0.0001	53.39%	0.37%	44.86 / 21.93 / 37.00	17.21	73.3%	0.33
	SLIC-NLI (w/o f_{len})	81.21%	28.19%	39.46 / 16.92 / 31.88	18.07	83.0%	0.73
	Finetuned (w/o L^{cal})	53.02%	0.00%	44.73 / 21.88 / 36.94	16.94	73.4%	0.36

Table 7: The effect of various length regularizer weights on performance on all 5 datasets.

		SAMSum	ForumSum	RedditTIFU-long	XSUM	CNN/DailyMail
factual	Cliff	—	—	—	.69	**.99**
	Frost (ECPP, Drop)	—	—	—	.76	**.99**
	Finetuned (w/o L^{cal})	**.88**	**.92**	**.88**	.67	**.98**
	SLIC-NLI (w/o f_{len})	**.93**	**.89**	**.91**	**.85**	**.98**
	SLIC-NLI (with f_{len})	**.91**	**.94**	**.89**	**.82**	**.98**
	Reference	*.94*	*.97*	*.79*	*.60*	*.97*
quality	Cliff	—	—	—	3.10	3.75
	Frost (ECPP, Drop)	—	—	—	3.18	3.60
	Finetuned (w/o L^{cal})	3.41	3.46	3.19	2.96	3.62
	SLIC-NLI (w/o f_{len})	3.94	3.44	3.18	3.43	3.70
	SLIC-NLI (with f_{len})	3.54	3.48	3.11	3.21	3.78
	Reference	3.63	3.81	3.18	2.94	3.48
length	Cliff	—	—	—	18.18	59.85
	Frost (ECPP, Drop)	—	—	—	17.57	56.10
	Finetuned (w/o L^{cal})	18.99	31.37	14.37	17.77	49.85
	SLIC-NLI (w/o f_{len})	31.17	37.05	18.53	18.82	66.56
	SLIC-NLI (with f_{len})	21.04	28.65	15.07	15.54	63.24
	Reference	20.47	34.32	19.77	20.65	53.86

Table 8: Human Evaluation results on all 5 datasets.

A good summary is a shorter piece of text that has the essence of the original. It tries to accomplish the same purpose and conveys the key information from the original post. Below we define four evaluation axes for summary quality: coherence, accuracy, coverage, and overall quality.

Coherence: This axis answers the question "how coherent is the summary on its own?" A summary is coherent if it's easy to understand when read on its own and free of English errors. A summary is not coherent if it's difficult to understand what the summary is trying to say. Generally, it's more important that the summary is understandable than it being free of grammar errors. Accuracy: This axis answers the question "does the factual information in the summary accurately match the post?" A summary is accurate if it doesn't say things that aren't in the article, it doesn't mix up people, and generally is not misleading.

Coverage: This axis answers the question "how well does the summary cover the important information in the post?" A summary has good coverage if it mentions the main information from the post that's important to understand the situation described in the post. A summary has poor coverage if someone reading only the summary would be missing several important pieces of information about the situation in the post. A summary with good coverage should also match the purpose of the original post (e.g. to ask for advice).

Overall quality: This axis answers the question "how good is the summary overall at representing the post?" This can encompass all of the above axes of quality, as well as others you feel are important. If it's hard to find ways to make the summary better, the overall quality is good. If there are lots of different ways the summary can be made better, the overall quality is bad.

You are an expert summary rater. Given a piece of text and two of its possible summaries, output 1 or 2 to indicate which summary best adheres to coherence, accuracy, coverage, and overall quality as defined above.

Text - text
Summary 1 - summary1
Summary 2 - summary2

Preferred Summary=

Figure 8: Prompt for LLM-based summarization ratings. {text} is the unlabeled input context, {summary1} and {summary2} are generated or ground truth summaries.

Input: (SAMSum)
Raymond: Charlotte! Help!
Charlotte: What's up bro??
Raymond: What do I want to eat, pizza or pasta?
Charlotte: Hmm.. What kind of pizza and what kind of pasta?
Raymond: So I have a regular cheese and pepperoni pizza and I was thinking some pesto pennes.
Charlotte: Oo, those both sound good.
Raymond: That's not helpful.
Charlotte: Have the pizza!
Raymond: But pasta sounds so good.
Charlotte: Then have the pasta silly.
Raymond: But the pizza sounds delicious too.
Charlotte: Omg Raymond, make up your mind.
Raymond: I can't! Please help me.
Charlotte: Why not have both?
Raymond: Well, that's just unreasonable no?
Charlotte: How about this. I come over and we have both!
Raymond: That could work. That way I would eat the same amount but of the two things I want to eat.
Charlotte: Alright, so I'm going to head over in like 10 minutes. That sound good?
Raymond: For sure. Oh, and bring wine!
Charlotte: Yes sir. See you in 15.
Before: Raymond wants to eat pizza and pasta. Charlotte will come over in 10 minutes and they will have both. Raymond will bring wine.
After: Raymond wants to eat pizza or pasta. He has a regular cheese and pepperoni pizza and pesto pennes. Charlotte wants to come over in 10 minutes and they have both. Raymond wants Charlotte to bring wine. They'll see each other in 15.

Input: (SAMSum)
Amal: hey, did you see what Beyonce tweeted?
Amir: haha. yeah, i did. isnt she wonderful?
Amal: yeah, shes great.
Before: Amal and Amir are laughing at Beyonce's tweet.
After: Amir saw what Beyonce tweeted. Amal thinks Beyonce is wonderful.

Figure 9: Inputs and system generated summaries before and after calibration for different datasets. The text spans in amber are hallucinated.

Instructions:

1. Carefully read the document and the summaries below.
2. Determine for each summary whether **everything said in the summary**factually consistent with respect to the document.
3. Determine for each summary whether **the summary hallucinates facts or details** meaning **mention any details, not specified in the document.**
4. Rate the summaries for quality on a scale of 1-5. (1 = Poor summary, 5 = Great summary)
5. Select the summary that better summarizes the document.

Document:

```
David Brown became ill in Maghaberry Prison in December 2012 and died later in hospital from a brain haemorrhage.
The Prisoner Ombudsman said staff left him unattended for five minutes in an unresponsive state and did not raise the alarm immediately.
The watchdog has concluded the response of the Prison Service was "inadequate".
The report by Prisoner Ombudsman Tom McGonigle also found that a nurse treating the inmate was not made aware that it was an emergency situation
and other prisoners were not locked in their cells during the incident.
However, Mr McGonigle, said: "While some things could have been done better, a key finding of this independent investigation is that there was no
possibility to achieve an alternative outcome for Mr Brown."
The Prisoner Ombudsman's office is required to investigate all deaths in custody in Northern Ireland, including deaths due to natural causes.
The report into David Brown's death said painkilling drugs were found in the 46-year-old's system during toxicology tests, but added that the
drugs had been prescribed to him.
It said the medication was found at "concentrations that lay within their respective therapeutic ranges".
"This is important as there was speculation about a white powdery substance that was found around Mr Brown's nose at the time of his death," a
statement from the ombudsman said.
Despite criticising prison staff for their immediate reaction to finding the prisoner unconscious in his cell, the report did not find fault with
the inmate's medical management during his time in the jail.
A clinical reviewer who investigated the case "did not feel that an opportunity to achieve an earlier diagnosis existed, or that there would have
been a possibility to achieve an alternative outcome for Mr Brown".
The ombudsman's report into the handling of the prison's case identified four matters that required improvement.
Two of the four areas related to record-keeping and post-incident support for staff.
The need for improvement in these two areas had already been highlighted to the prison authorities and the South-Eastern Health and Social Care
Trust, which treated the inmate.
The Northern Ireland Prison Service (NIPS) has accepted the ombudman's four recommendations and said they have already been implemented.
The health trust has also accepted their recommendation, and told the ombudsman it has been reiterated to their staff and will be considered at a
"Lessons Learned" forum.
Mr McGonigle has expressed sympathy to the prisoner's family.
```

Summary 0:

```
A watchdog has criticised prison staff in Northern Ireland for their
reaction when an inmate, who later died, was found "unresponsive" in
his cell.
```

Summary 0 is **factually consistent** with respect to the document:
○ **Yes** ○ **No**

Summary 0 **hallucinates facts or details**:
○ **Yes** ○ **No**

Summary 0 Quality:

Summary 1:

```
Staff at a Northern Ireland prison left a man unconscious in his
cell before he died, a report has found.
```

Summary 1 is **factually consistent** with respect to the document:
○ **Yes** ○ **No**

Summary 1 **hallucinates facts or details**:
○ **Yes** ○ **No**

Summary 1 Quality:

Summary 2:

```
Northern Ireland's Prisoner Ombudsman has criticised the response of
staff to a man who died after being left unattended in his cell.
```

Summary 2 is **factually consistent** with respect to the document:
○ **Yes** ○ **No**

Summary 2 **hallucinates facts or details**:
○ **Yes** ○ **No**

Summary 2 Quality:

Summary 3:

```
There was "no possibility to achieve an alternative outcome" in the
case of a prisoner who died in prison, a report has found.
```

Summary 3 is **factually consistent** with respect to the document:
○ **Yes** ○ **No**

Summary 3 **hallucinates facts or details**:
○ **Yes** ○ **No**

Summary 3 Quality:

Summary 4:

```
A report into the death of a prisoner in Northern Ireland has
criticised the response of prison staff.
```

Summary 4 is **factually consistent** with respect to the document:
○ **Yes** ○ **No**

Summary 4 **hallucinates facts or details**:
○ **Yes** ○ **No**

Summary 4 Quality:

Summary 5:

```
A report into the death of an inmate in Northern Ireland has
criticised prison staff for leaving him alone in his cell for minutes
after he collapsed.
```

Summary 5 is **factually consistent** with respect to the document:
○ **Yes** ○ **No**

Summary 5 **hallucinates facts or details**:
○ **Yes** ○ **No**

Summary 5 Quality:

Figure 10: An example of the task template that was offered to Amazon Mechanical Turk workers.