QAFactEval: Improved QA-Based Factual Consistency Evaluation for Summarization

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Abstract

Factual consistency is an essential quality of text summarization models in practical settings. Existing work in evaluating this dimension can be broadly categorized into two lines of research, entailment-based metrics and question answering (QA)-based metrics. However, differing experimental setups presented in recent work lead to contrasting conclusions as to which paradigm performs best. In this work, we conduct an extensive comparison of entailment and QA-based metrics, demonstrating that carefully choosing the components of a QA-based metric is critical to performance. Building on those insights, we propose an optimized metric, which we call QAFACTELVAL, that leads to a 15% average improvement over previous QA-based metrics on the SummaC factual consistency benchmark. Our solution improves upon the best-performing entailment-based metric and achieves state-of-the-art performance on this benchmark. Furthermore, we find that QA-based and entailment-based metrics offer complementary signals and combine the two into a single, learned metric for further performance boost. Through qualitative and quantitative analyses, we point to question generation and answerability classification as two critical components for future work in QA-based metrics.

1 Introduction

Text summarization aims to compress long document(s) into a short and fluent form that preserves salient information. The field has benefited from the application of pretrained methods (Liu and Lapata, 2019; Lewis et al., 2020; Zhang et al., 2020a, inter alia). However, despite recent improvements, state-of-the-art models are not always factually consistent with the source documents they are conditioned on (Maynez et al., 2020; Fabbri et al., 2021, inter alia). Thus, determining the factual consistency of a summary remains an essential task.

| Document | Summary |
|-----------------|-----------------|
| The Knicks beat the Rockets. The fans were excited. | The Knicks beat the Bucks. |

Table 1: Toy example of a factual inconsistency between a summary and a source document. Left: The entailment-based metric computes the level of contradiction, neutrality, and support between the summary and each source document sentence. The final factual consistency metric is calculated as the maximum support score over all source sentences. Right: The QA-based metric first selects a noun-phrase answer from the summary. A QG model then generates an associated question that a QA model answers based on the source document. The answer overlap score of the QA-based metric measures the semantic overlap between the QA model output and the selected answer as the final metric score.

Recent metrics for summarization factual consistency can be broadly split into two categories 1) Entailment-based metrics that determine whether the content in the summary is entailed by the input document (Kryscinski et al., 2020; Koto et al., 2020, inter alia) and 2) QA-based metrics that compute a factual consistency score based on a QA model’s ability to answer, using the input document, questions generated from the summary (Wang et al., 2020a; Durmus et al., 2020, inter alia). We provide an illustrative example in Table 1 in which both metric types correctly identify a factual inconsistency and output a low score.

Quantitative comparisons among entailment-based and QA-based metrics, however, often differ in their choices of baseline model and input granularity, evaluating on single datasets and drawing dif-
fering conclusions as to the best paradigm. For example, some work reports entailment-based metrics as performing best (Koto et al., 2020; Maynez et al., 2020), while other work argues for QA metrics (Durmus et al., 2020; Wang et al., 2020b; Scialom et al., 2021). Recently, Laban et al. (2021) proposed a benchmark called SummaC to compare metrics across six factual consistency datasets for the task of binary factual consistency classification, whether a summary is entirely factually consistent or not. This work unifies prior work on entailment-based metrics by studying the effect of input granularity, pretrained entailment model, and other hyperparameter choices on downstream evaluation performance. However, it does not study the components of QA-based metrics.

In order to unify work in QA-based factual consistency evaluation, we do an extensive hyperparameter analysis of current metrics. We break down these metrics into four constituent components: 1) the selection of answers to ask questions about, 2) question generation (QG) conditioned upon these answers, 3) question answering based on the source document, and 4) answer overlap evaluation between QA model output and selected answers. We study the effect of each of these components on metric performance. Based on our insights, we propose an optimized metric, which we call QAFactEval, that outperforms the entailment-based metrics of Laban et al. (2021).

Our contributions are the following: 1) We analyze all components of the QA-based metric pipeline, and our proposed solution improves performance over prior QA-based metrics by over 15% on a factual consistency benchmark consisting of 6 individual datasets, achieving state-of-the-art results. 2) We show that QA-based metrics and NLI-based metrics offer complementary signals and combine them into a new metric via a simple learned network, further improving performance. 3) We report results for 10 additional metrics across classification and correlation analysis, providing the most comprehensive benchmark results for factual consistency metrics and highlighting areas for future work in QA-based metrics.

2 Related Work

Evaluating Factual Consistency Within entailment-based factual consistency evaluation, Falke et al. (2019) propose the task of ranking summary pairs for factual consistency based on entailment models, while Kryscinski et al. (2020) explore factual consistency classification jointly with source support or contradiction span extraction. Other work on entailment-based metrics has examined input granularity (Goyal and Durrett, 2020), trained on adversarial datasets (Barrantes et al., 2020), and explored entailment-based models as the backbone of others metrics such as BERTScore (Zhang et al., 2020b) as in Koto et al. (2021). Metric comparisons, however, were often conducted on isolated datasets. Laban et al. (2021) unify work in entailment-based metrics for factual consistency, showing the effect of granularity, base models, and other hyperparameter choices. This work also proposes a learned metric built on top of the output of an entailment model, with parameters fine-tuned on synthetic data. While this work fills a gap in the use of entailment-based metrics for factual consistency, our work analogously unifies QA-based metrics for factual consistency and proposes to combine entailment and QA-based metrics in a single learned metric.

Another line of work in factual consistency evaluation centers around QA-based metrics (Scialom et al., 2019; Durmus et al., 2020; Wang et al., 2020b; Scialom et al., 2021; Deutsch et al., 2020). Recent work has shown that QA-based metrics better measure the overlap of information units for determining summary relevance over embedding-based metrics (Deutsch and Roth, 2021), further driving our study of QA-based metrics for factual consistency. While several QA-based models with similar structures have been applied for factual consistency, (Durmus et al., 2020; Wang et al., 2020b; Scialom et al., 2021), they differ in their underlying answer selection, question generation, question answering, and answer overlap components, reporting different performances. We perform a comprehensive evaluation of QA-based metric components and propose improved model components for the task of answer overlap and question consistency.

Summarization Benchmarking A recent line of work aims to take stock of the current state of summarization models and progress, both within factual consistency and across summarization more broadly. Kryscinski et al. (2019) note biases and failure modes of abstractive summarization models, while other work analyzes and collects annotations over the output of recent summarization models.

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1Code and metric outputs will be made publicly available: https://github.com/salesforce/QAFactEval
across multiple dimensions, including factual consist-
cency Fabbri et al. (2021); Bhandari et al. (2020); 
Huang et al. (2020). Lux et al. (2020) propose a
typology of errors found in summarization models, 
while Gabriel et al. (2021) propose a framework for 
meta-evaluation of faithfulness consistency metrics. 
Laban et al. (2021) propose to combine recent work 
in factual consistency evaluation for summarization 
through a single benchmark. Our work directly 
makes use of this benchmark while emphasizing 
QA-based metrics. We also include correlation 
analysis for a more comprehensive understanding 
of current factual consistency metrics.

3 Evaluation Metrics
In this section, we introduce the factual consistency 
metrics studied, which we divide into entailment 
metrics, QA-based metrics, and learned metrics

3.1 Entailment-based Metrics
The metrics below produce a score for each sum-
mary sentence which is then averaged to compute 
the final metric score.

MNLI applies a RoBERTa large (Liu et al., 2019) 
model trained on MNLI (Williams et al., 2018). 
The score of a summary sentence is the maximum 
entailment score over all input sentences.

ANLI Barrantes et al. (2020) uses the same 
method as the MNLI metric with a model trained 
on the ANLI (Nie et al., 2020) dataset consisting 
of adversarial datapoints.

SCZeroShot Laban et al. (2021) works analo-
gously to the above metrics with a base model 
trained on both MNLI and Vitamin-C data (Schus-
ter et al., 2021), consisting of closely-related con-
trastive entailment examples.

BertScore-FFCI Koto et al. (2021) applies 
BertScore (Zhang et al., 2020b) with an backbone 
RoBERTa-MNLI model, averaging the three high-
est BertScore F1 scores over the input sentences.

DAE Goyal and Durrett (2020) computes en-
tailment scores between a source document and 
summary dependency arcs, applying an entailment 
model trained on synthetic data.

FactCC Kryscinski et al. (2020) is a RoBERTa-
base model trained on FactCC synthetic data to 
calculate a document-level score, and thus the 
scores need not be aggregated over input sentences.

DocNLI Yin et al. (2021) train a document-level 
entailment model, similar to the FactCC metric.

3.2 QA Metric Components
We now describe the components that constitute 
the QA-based pipeline for factual consistency. We 
refer to our metric, consisting of the best combina-
tion of the below components, as QAFactEval.

Answer Selection QA-based metrics compare 
information units between the summary and source, 
so it is thus necessary to first extract such units, or 
answers, from the given summary. We follow the 
protocols from Deutsch et al. (2020) and compare 
extracting the following answer types: named enti-
ties (NER), noun phrase chunks (NP Chunks), max-
imally sized noun phrases (Max NP), whereby the 
dependency subtrees of nouns reached by travers-
ing a given sentence’s dependency parse from the 
root are chosen as answers, and All, which com-
bines answers from the above three techniques.

Question Generation Having selected answers, 
questions are generated conditioned upon these an-
swers using the summary as context. Typically, 
this is an encoder-decoder model which inputs the 
answer and context separated by a special token. 
On the modeling side, we examine BART (Lewis 
et al., 2020) and T5 (Raffel et al., 2019) as the un-
derlying generators. For T5 models, we study the 
effect of using the base and large models, which 
consist of 220 million and 770 million parameters, 
respectively. On the data side, we experiment with 
models trained for question generation on SQuAD 
(Rajpurkar et al., 2016), a standard QA dataset con-
sisting of questions on Wikipedia articles, and on 
QA2D (Demszky et al., 2018), a dataset of declar-
ative sentences with associated question/answer 
pairs derived from SQuAD. Furthermore, we ex-
periment with the recently-introduced MixQG mod-
els, which are trained on a combination of 9 QA 
datasets with diverse answer types and which out-
perform other QG models across several tasks.

Question Filtering Model-generated questions 
may contain noise from the QG model itself or 
from disfluencies in the summary the QG model 
conditions upon. Such noisy questions can skew 
the overall metric score, as the QA component may 
be unable to correctly answer the question, regard-
less of the summary’s factual consistency. We filter 
such questions through a step called QA Filter:

the QA model, described below, must be able to
correctly answer the question using the summary as context; this filters noisy questions while ensuring that the QA model has the capacity to locate this information in the summary.

**Question Answering** The QA component answers the questions from the previous steps using the input document as context. We experiment with both extractive QA models, which extract a span from the input as an answer, and abstractive QA models, which generate an answer. For extractive models, we ablate *Electra-large* (Clark et al., 2020), which achieves strong performance on the SQuAD 2.0 dataset, and *MADE*, which models multi-dataset QA with a collection of dataset-specific adapter modules (Houlsby et al., 2019) sharing the same underlying model. For abstractive QA, we experiment with *T5* fine-tuned on SQuAD and *UnifiedQA* (Khashabi et al., 2020), an approach which trains a T5 QA model on 8 diverse, seed datasets and was shown to generalize across 20 datasets and 4 input formats.

**Answer Overlap Evaluation** An answer overlap metric must be computed to determine the match between the initial answer selected in the first component and the QA model output. Typically, answer overlap in QA is measured through exact match *EM* score or word *F1* score. We also include a learned metric, the LERC score, proposed by Chen et al. (2020). This metric outputs a 1-5 answer overlap score conditioned on a question and context and is trained on the MOCHA dataset (Chen et al., 2020), consisting of 40k crowdsourced judgments on QA model outputs. We experiment with the BERT (Devlin et al., 2019) model from the original paper *LERC (orig)*, and a model trained from a RoBERTa-large checkpoint initialized for the task of jointly encoding passages and answers from Jia et al. (2021), which we call *LERC (ours)*.

All QA models except MADE are trained on data containing unanswerable questions. For the above metrics, we output a score of 0 if the QA model labels a given question as unanswerable with the input context. We experiment with the effect of this Answerability classifier by forcing the QA model to output an answer to all questions. We include this 0/1 score of whether the question is answerable as the *IsAnswered* answer overlap metric. The final factual consistency score is computed as the average of answer overlap metric scores over all questions remaining following QA Filtering.

### 3.3 Learned Metrics

**SCConv** is a model introduced by Laban et al. (2021) which learns to aggregate entailment-model output scores across input sentences into a single score. More concretely, for a document consisting of $M$ sentences and a summary consisting of $N$ sentences, the entailment-based model produces an $M \times N$ matrix of entailment scores. The $M \times N$ matrix is then transformed to an $H \times N$ matrix by binning the $M$ sentences to create a histogram, where $H$ is the number of bins. This matrix is input to a 1-D convolution layer to produce a score for each summary sentence, and the scores are averaged across summary sentences. The parameters of this model are fine-tuned on synthetic data that we describe below.

**QAFActEval-NLI** While SCConv captures sentence-level support, QAFActEval measures finer-grained answer overlap between the source and summary. We combine the two into a single factual consistency metric, QAFActEval-NLI. Assume that $K$ answers are extracted from the summary. The pipeline described above will then output a single score per answer for the entire summary, resulting in an array of length $K$. We convert this to a histogram of size $H$ in a similar manner as SCConv and pass this histogram through a 1-D convolution layer to produce a single QA score. This score is concatenated with the NLI score produced by SCConv and input to a linear layer to produce the final metric score. The linear layer can be trained in either *synthetic* or *supervised* ways.

### 3.4 Additional Metrics
For completeness, we also include the following metrics in our study.

**BARTScore** Yuan et al. (2021) calculates the log-likelihood from BART fine-tuned on CNN/DailyMail (Hermann et al., 2015; Nallapati et al., 2016) of the summary conditioned upon the source text as a metric for factual consistency.

**BLANC** Vasilyev et al. (2020) is a reference-less metric of summary quality that measures the difference in masked language modeling performance with and without access to the summary.

**QuestEval** (Scialom et al., 2021) is the prior state-of-the-art QA-based metric for factual consistency. The T5-SQuAD QG model and T5 QA
model pretrained models described above are applied from the QuestEval metric. QuestEval generates questions based on the input document and answers them using the summary in addition to following the above QA metric pipeline. QuestEval aggregates the score from these two pipelines. We believe that our described pipeline more closely measures factual consistency, while generating questions from the source may confound factual consistency with relevance.

4 Methodology

We present the datasets explored for binary classification and correlation analyses. We also describe settings for reporting ablation and final results.

4.1 Data

The SummaC benchmark (Laban et al., 2021) introduces a collection of datasets for binary factual consistency evaluation. A data point is labeled as positive if it contains no factual inconsistencies or is rated the highest possible score in the case of Likert scaling, and as negative otherwise. We now briefly describe the datasets found in the benchmark and any departures from the original benchmark, and additional datasets we use for correlation analysis. We refer the reader to Laban et al. (2021) for further details regarding the splits and benchmark creation.

- **CGS** Falke et al. (2019) consists of paired summary sentences from CNN/DailyMail (Hermann et al., 2015; Nallapati et al., 2016), one correct sentence and one containing an error. Laban et al. (2021) treats the correct summaries as positive examples and the others as negative examples.

- **XSF** Maynez et al. (2020) consists of summaries from the XSum dataset (Narayan et al., 2018) annotated for word-level factual consistency errors.

- **Polytope** Huang et al. (2020) propose a typology of eight summarization errors consisting of both content and stylistic errors and annotate model outputs from 10 systems on CNN/DailyMail data. The original SummaC benchmark included the Omission and Addition errors of this proposed typology as factual inconsistencies, but these are largely extractive sentences that should be considered factually consistent. We thus label these examples as factually consistency examples and report results on this modified dataset.

- **FactCC** Kryscinski et al. (2020) introduce a factual consistency dataset on CNN/DailyMail annotated by the authors of the paper to ensure the quality of the annotations.

- **SummEval** Fabbri et al. (2021) analyze summaries from 17 models on CNN/DailyMail across the dimensions of factual consistency, coherence, fluency, and relevance.

- **FRANK** Pagnoni et al. (2021) introduce an extensive typology of errors made by summarization systems across CNN/DailyMail and XSum.

- **QAGs** Wang et al. (2020b) crowdsource sentence-level summary annotations for factual consistency across CNN/DailyMail and XSum data. We only report correlation analysis for this dataset as it was not a part of SummaC.

4.2 Experiment Setup

**Metric Implementation** Metrics were applied directly from the original GitHub repository or by using the SacreRouge Library (Deutsch and Roth, 2020), which was also used in correlation analysis. The learned metrics make use of code released from Laban et al. (2021) for training, and all models are implemented in PyTorch (Li et al., 2020) and in the Transformers library (Wolf et al., 2019). The BART-QA2D QG and Electra-large QA models are applied from the QAEval relevance modeling metric (Deutsch et al., 2020).

**Ablation Settings** Following Laban et al. (2021), a metric threshold score for binary classification is determined from the validation set of SummaC and applied to the test set. For ablation studies, we both perform thresholding and evaluation on the validation set to preserve the integrity of the test set. For each benchmark dataset, we sample a random subset of 30% of the validation set to determine the threshold and evaluate on the remaining 70% of the validation set. The best performing combination of QA metric components constitutes our QAFACTEval metric. We take the best performing combination of QA metric components and vary a given component, such as answer selection, while holding all other components constant and consistent with the best component combination.

**Training Settings** To tune the parameters of the learned metrics, we train on a subset of 50k synthetic data points from FactCC, following Laban et al. (2021). We name these runs synthetic setting.
due to the lack of human-labeled data. We also experiment with a supervised setting by fine-tuning the parameters on the SummaC validation set for each individual dataset, choosing the threshold on this validation data, and applying the model to the test set. Training on such a small amount of data is feasible due to the small number of parameters of the learned metrics. Cross entropy loss with Adam (Kingma and Ba, 2015) optimizer is used, with a batch size of 32 and a learning rate of 1e-2.

5 Results

In this section, we first study the effects of model component choices on QAF\textsubscript{ACT}\textsubscript{EVAL}. We then compare metric results across both the SummaC binary classification task and correlation analysis.

5.1 Ablation Results

We provide the results of our ablation studies on the components of QA-based metrics in Table 2 and show two illustrative examples in Table 4.

Effect of Answer Selection Selecting NP Chunks performs best, aligning with Deutsch et al. (2020), who show that NP Chunks obtain the largest coverage of information units while retaining high precision. We find a large decrease in performance when selecting named entities and only a slight decrease in performance when choosing maximally sized noun phrases or all answers together. Named entity selection likely performs worse due to the scarcity of extracted answers; only three entities are extracted on average across the benchmark, while all other approaches extract over 10 answers per summary.

Effect of QG Models The choice of QG model notably affects downstream performance. BART-QA2D produces much longer questions, about 17 tokens on average, versus about 10 from the other models. Deutsch et al. (2020) note how humans tend to produce shorter questions. However, longer questions may be preferable for this task to facilitate the QA model’s ability to understand and answer the question. BART-QA2D also is the most extractive, with only about 20% novel unigrams in the question, while T5-SQuAd model is the most abstractive with about 47% novel unigrams, resulting in occasional hallucinations and questions that the QA model struggles to answer. As seen in Table 4, MixQG models do often produce highly-fluent questions, but the longer, highly-extractive output of BART-QA2D improves downstream factual consistency performance.

Effect of QA Model Surprisingly, we do not find a large difference in the QA model component, implying that QA ability is not the bottleneck of our task. In this setting, we keep the answerability classifier from Electra-large constant, as not all QA models are trained with unanswerable questions; thus the only differences are in the answers to questions marked as answerable by the classifier.

Effect of Answer Overlap Metric We observe a large difference between EM and other overlap metrics. We also see a notable gap between LERC (orig) and LERC (ours), showing the effect of the underlying model of the learned metric on factual consistency performance.

Effect of Question Filtering and Answerability Not filtering questions according to the ability of the QA model to answer them using the summary results in a decrease in performance. Furthermore, forcing the QA model to produce an answer for all questions, even those judged unanswerable by the model, leads to a sharp performance decrease. While the answer overlap metric should capture

| Component          | Model Choice | Benchmark |
|--------------------|--------------|-----------|
| Answer Selection   |              | 79.5      |
| NER                |              | 69.3      |
| ALL                |              | 78.3      |
| Question Generation| BART-QA2D    | 76.6      |
| T5-SQuAd           |              | 76.8      |
| MixQG-base         |              | 73.7      |
| MixQG-large        |              | 72.9      |
| Question Answering | Electra-large| 77.9      |
| T5                |              | 77.7      |
| UnifiedQA         |              | 78.5      |
| Answer Overlap     | LERC (ours)  | 72.2      |
| F1                |              | 76.5      |
| IsAnswered        |              | 75.9      |
| LERC (orig)       |              | 77.1      |
| Filtering/Answerability | Both Filters | 76.4      |
| No QG Filter       |              | 74.9      |
| No Answerability   |              | 71.6      |
| No Filters         |              |           |

Table 2: Results of ablation studies on the validation set of the SummaC benchmark showing the effect of the individual components of QAF\textsubscript{ACT}\textsubscript{EVAL}. The first row represents the performance of the best combination of components. For each component, the ablation is performed by swapping that component while holding all others consistent with the best overall model, and the best setting is bolded.
Paul Merson has restarted his row with Andros Townsend's call-up, he shouldn't have been in the squad. This example illustrates that the fluency of the QG model does not necessarily improve downstream factual consistency evaluation performance; the less fluent, more extractive BART-QA2D question is more-easily answerable by the QA model. Not shown in this table, the entailment-based SCConv metric incorrectly labels this entity-centric example, likely due the introduction of novel unigrams. The QA model incorrectly labels this question as unanswerable, perhaps due to the generality of the question or due to noise in the input document. The QA output and score if forced to extract an answer are in parenthesis. SCConv correctly labels this highly extractive example.

### 5.2 Overall Results

We present the results of the QAFACTEVAL along with other metrics on the test set of SummaC in Table 3. We show a substantial improvement over the previous state-of-the-art QA metric for factual consistency, QuestEval. Furthermore, our QA metric outperforms the learned metric SCConv and all other entailment-based metrics. Our combined QAFACTEVAL-NLI metric shows slight improvements on the synthetic data. Notable improvements, however, are seen in this synthetic setting on the FactCC dataset, likely as the synthetic FactCC data

| Model Type | Model Name                  | CGS | XSF | Polytope | FactCC | SummEval | FRANK | Benchmark |
|------------|-----------------------------|-----|-----|----------|--------|----------|-------|-----------|
| Misc       | BARTScore                   | 63.3| 53.3| 80.4     | 66.8   | 69.8     | 80.0  | 68.9      |
|            | BLANC                       | 51.5| 54.5| 72.2     | 53.0   | 63.0     | 76.2  | 61.8      |
| Entailment | FactCC                      | 64.8| 56.6| 80.2     | 71.1   | 73.6     | 70.3  | 70.4      |
|            | BertScore-FFCI              | 56.9| 68.8| 69.2     | 57.9   | 67.4     | 71.9  | 65.4      |
|            | DAE                         | 71.3| 49.7| 78.9     | 80.7   | 74.7     | 81.0  | 72.7      |
|            | ANLI                        | 74.9| 53.0| 77.6     | 85.8   | 75.9     | 78.9  | 74.4      |
|            | MNILI                       | 67.6| 61.5| 77.3     | 89.8   | 78.7     | 79.6  | 75.7      |
|            | DocNLI                      | 49.6| 57.0| 84.7     | 73.0   | 75.6     | 70.9  | 68.5      |
|            | SCZeroShot                  | 59.6| 56.1| 81.5     | 83.2   | 77.9     | 78.5  | 72.8      |
| QA         | QuestEval                  | 59.4| 61.9| 73.1     | 66.5   | 68.4     | 79.8  | 68.2      |
|            | QAFACTEVAL                  | 75.8| 63.1| 80.3     | 83.8   | 81.2     | 84.1  | 78.1      |
|            | (synthetic)                 | 60.8| 60.9| 76.0     | 81.1   | 81.6     | 74.3  |           |
| Learned    | SCConv                      | 74.2| 59.1| 82.1     | 91.1   | 80.2     | 83.4  | 78.3      |
|            | QAFACTEVAL-NLI              | 78.1| 60.9| 83.7     | 89.3   | 80.5     | 84.3  | 79.5      |
|            | (synthetic)                 |     |     |          |        |          |       |           |

Table 3: Balanced accuracy for each model on the test set of the six datasets in the SummaC benchmark, and the average over the benchmark. Metrics are divided into entailment-based, QA-based, and learned metrics which fine-tune additional parameters based on synthetic data from Laban et al. (2021).

| Document | Paul Merson has restarted his row with Andros Townsend, ... ’... it was a great goal,’ Merson said. ‘It’s just a matter of opinion, and ... he got pulled off after half an hour .... in front of Roy Hodgson, so he shouldn’t have been in the squad. ...’ ... Sky Sports pundit Merson (centre) criticised Townsend’s call-up to the England squad last week .... | They’re not gonna take it anymore. Really. Twisted Sister says that its 2016 tour will be its last, according to a press release. ... The band will also perform two shows in Pero’s honor: one at Las Vegas Hard Rock Hotel and Casino, the other at the Starland Ballroom in Sayreville, New Jersey. |
| Summary  | Paul Merson is not happy with Andros Townsend’s call-up to the England squad last week | The band will perform two shows. |
| Selected Answer | Andros Townsend’s call-up | the band |
| **Question Generation** | **BART-QA2D** | **MixQG-large** | **BART-QA2D** |
| What is Paul Merson not happy with to the England squad last week? | What is Paul Merson not happy with? | Who will perform two shows? |
| **QA Output** | Townsend’s call-up | he shouldn’t have been in the squad | Unanswerable (Twisted Sister) |
| **Answer Overlap** | 1.00 | 0.30 | 0.00 (0.80) |

Table 4: Example source documents and summaries along with component outputs from the QA-based metric. Left: This example illustrates that the fluency of the QG model does not necessarily improve downstream factual consistency evaluation performance; the less fluent, more extractive BART-QA2D question is more-easily answerable by the QA model. Not shown in this table, the entailment-based SCConv metric incorrectly labels this entity-centric example, likely due the introduction of novel unigrams. Right: The QA model incorrectly labels this question as unanswerable, perhaps due to the generality of the question or due to noise in the input document. The QA output and score if forced to extract an answer are in parenthesis. SCConv correctly labels this highly extractive example.
the model is trained on was designed to mirror the errors captured in annotations. This performance boost on FactCC motivated our use of supervised data for fine-tuning our learned metric combination. We find that supervised fine-tuning on validation data helps in most cases and leads to an overall benchmark improvement. The reason for the performance drop on FactCC could be the proximity of the synthetic data to the labeled data and the data size difference. Similarly, we believe that BertScore-FFCI performs best on XSF due to the closeness between BertScore’s token-level metric and XSF’s word-level annotations.

We find that QAFACTEVAL and SCConv do offer complementary signals that can be learned from supervised data. Individually fine-tuning the learned SCConv or a learned variation of QAFACTEVAL on supervised data did not improve results over the non-supervised metrics; this result suggests the necessity of combining the two for further improvements. Training on the validation sets combined, rather than on each individual dataset separately, did not give an improvement, likely due to the learnable combination of NLI and QAFACTEVAL being dataset dependent.

5.3 Correlation Analysis

We provide instance-level Pearson correlation between aggregated human judgments and metric scores for each model to compare to previous work in factual consistency that reports correlation analysis. We split FRANK into CNN/DailyMail and XSum subsets for finer-grained analysis, as substantial differences have been noted in correlation performance across the two datasets (Durmus et al., 2020). We exclude the Polytope, FactCC, and CGS datasets here as prior work has only studied these datasets in the binary classification setting. Results are shown in Table 5.

We find that QAFACTEVAL performs well across most datasets. As in the classification results, BertScore-FFCI’s performs well on XSF, and we note that QuestEval’s answerability classifier correlates more so with these fine-grained annotations than on other datasets. QAFACTEVAL-NLI performs well on most datasets except XSF. Fine-tuning on FactCC synthetic data for binary classification likely does not capture the aggregated, word-level factuality scores of XSF. We leave a study of fine-tuning this model on supervised data with a regression loss for future work.

6 Conclusion

In this work, we demonstrated that QA-based metrics, when its components are properly optimized, outperform entailment-based metrics on a comprehensive factual consistency evaluation benchmark. We identify question generation and answerability detection as key components for improving QA-based metrics in future work. Furthermore, we show that entailment and QA-based metrics offer complementary signals through a combined metric that achieves state-of-the-art performance on this benchmark. We believe that our work lays the foundation for future work in QA-based metrics for factual consistency by offering a fairer comparison to other metrics across datasets and settings.

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A Appendix

We provide additional correlation coefficients as a point of reference for future work. Summary-level correlations are excluded for QAGS as this dataset does not contain annotations for multiple models, which is necessary to compute this score.
### Table 6: Instance-level Spearman correlation coefficients across factual consistency evaluation datasets. Metrics are divided into entailment-based, QA-based, and learned metrics which fine-tune additional parameters based on synthetic data from Laban et al. (2021). The two highest-correlated metrics for each dataset are shown in bold.

| Model Type | Model Name | XSF | SummEval | FRANK-CNNDM | FRANK-XSum | QAGs-CNNDM | QAGs-XSum |
|------------|------------|-----|----------|-------------|-------------|-------------|-------------|
| Misc       | BARTScore  | 0.25 | 0.14     | 0.54        | 0.14        | 0.68        | 0.17        |
|            | BLANC      | 0.07 | 0.20     | 0.33        | 0.06        | 0.30        | 0.03        |
| Entailment | FactCC     | 0.05 | 0.37     | 0.41        | 0.05        | 0.49        | 0.26        |
|            | BertScore-FFCI | 0.45 | 0.26 | 0.34        | 0.15        | 0.50        | 0.20        |
|            | DAE        | 0.00 | 0.40     | 0.49        | 0.20        | 0.58        | -0.14       |
|            | ANLI       | 0.18 | 0.35     | 0.46        | 0.08        | 0.60        | 0.36        |
|            | DocNLI     | 0.16 | 0.39     | 0.49        | 0.11        | 0.61        | 0.35        |
|            | SCZeroShot | 0.01 | 0.34     | 0.11        | 0.21        | 0.21        | -0.38       |
| QA         | QuestEval  | 0.43 | 0.33     | 0.47        | 0.24        | 0.45        | 0.24        |
|            | QAFAC• EVAL | 0.30 | 0.43 | 0.54        | 0.26        | 0.64        | 0.44        |
| Learned    | SCConv (synthetic) | 0.19 | 0.41 | 0.54        | 0.22        | 0.04        | 0.04        |
|            | QAFAC• EVAL-NLI (synthetic) | 0.16 | 0.47 | 0.60        | 0.21        | 0.64        | 0.47        |

### Table 7: Instance-level Kendall correlation coefficients across factual consistency evaluation datasets. Metrics are divided into entailment-based, QA-based, and learned metrics which fine-tune additional parameters based on synthetic data from Laban et al. (2021). The two highest-correlated metrics for each dataset are shown in bold.

| Model Type | Model Name | XSF | SummEval | FRANK-CNNDM | FRANK-XSum | QAGs-CNNDM | QAGs-XSum |
|------------|------------|-----|----------|-------------|-------------|-------------|-------------|
| Misc       | BARTScore  | 0.17 | 0.27     | 0.42        | 0.12        | 0.55        | 0.14        |
|            | BLANC      | 0.05 | 0.15     | 0.25        | 0.05        | 0.24        | 0.02        |
| Entailment | FactCC     | 0.03 | 0.29     | 0.31        | 0.04        | 0.38        | 0.21        |
|            | BertScore-FFCI | 0.31 | 0.20 | 0.25        | 0.12        | 0.39        | 0.16        |
|            | DAE        | 0.00 | 0.32     | 0.38        | 0.16        | 0.47        | -0.11       |
|            | ANLI       | 0.12 | 0.28     | 0.36        | 0.07        | 0.48        | 0.30        |
|            | MNLI       | 0.11 | 0.31     | 0.38        | 0.09        | 0.49        | 0.28        |
|            | DocNLI     | 0.01 | 0.27     | 0.08        | 0.17        | 0.17        | -0.31       |
|            | SCZeroShot | 0.04 | 0.31     | 0.37        | 0.18        | 0.41        | 0.36        |
| QA         | QuestEval  | 0.30 | 0.26     | 0.36        | 0.20        | 0.35        | 0.20        |
|            | QAFAC• EVAL | 0.22 | 0.34 | 0.43        | 0.23        | 0.51        | 0.36        |
| Learned    | SCConv (synthetic) | 0.13 | 0.33 | 0.42        | 0.18        | 0.03        | 0.03        |
|            | QAFAC• EVAL-NLI (synthetic) | 0.11 | 0.37 | 0.47        | 0.17        | 0.51        | 0.38        |

### Table 8: Summary-level Pearson correlation coefficients across factual consistency evaluation datasets. Metrics are divided into entailment-based, QA-based, and learned metrics which fine-tune additional parameters based on synthetic data from Laban et al. (2021). The two highest-correlated metrics for each dataset are shown in bold.

| Model Type | Model Name | XSF | SummEval | FRANK-CNNDM | FRANK-XSum |
|------------|------------|-----|----------|-------------|-------------|
| Misc       | BARTScore  | 0.18 | 0.40     | 0.65        | 0.29        |
|            | BLANC      | 0.12 | 0.27     | 0.47        | 0.01        |
| Entailment | FactCC     | -0.02 | 0.39    | 0.40        | -0.07       |
|            | BertScore-FFCI | 0.21 | 0.37 | 0.44        | 0.19        |
|            | DAE        | 0.01 | 0.51     | 0.54        | 0.32        |
|            | ANLI       | 0.09 | 0.49     | 0.53        | 0.18        |
|            | MNLI       | 0.10 | 0.48     | 0.51        | 0.17        |
|            | DocNLI     | 0.00 | 0.52     | 0.21        | 0.47        |
|            | SCZeroShot | 0.11 | 0.57     | 0.60        | 0.52        |
| QA         | QuestEval  | 0.30 | 0.45     | 0.54        | 0.44        |
|            | QAFAC• EVAL | 0.24 | 0.64 | 0.68        | 0.53        |
| Learned    | SCConv (synthetic) | 0.17 | 0.54 | 0.60        | 0.46        |
|            | QAFAC• EVAL-NLI (synthetic) | 0.16 | 0.64 | 0.70        | 0.48        |
Table 9: Summary-level Spearman correlation coefficients across factual consistency evaluation datasets. Metrics are divided into entailment-based, QA-based, and learned metrics which fine-tune additional parameters based on synthetic data from Laban et al. (2021). The two highest-correlated metrics for each dataset are shown in bold.

| Model Type | Model Name       | XSF | SummEval | FRANK-CNNDM | FRANK-XSum |
|------------|------------------|-----|----------|-------------|------------|
| Misc       | BARTScore        | 0.18| 0.38     | **0.59**    | 0.28       |
|            | BLANC            | 0.12| 0.25     | 0.43        | 0.06       |
| Entailment | FactCC           | 0.00| 0.37     | 0.42        | -0.01      |
|           | BertScore-FFCI   | 0.21| 0.34     | 0.40        | 0.20       |
|           | DAE              | 0.00| 0.40     | 0.47        | 0.30       |
|           | ANLI             | 0.10| 0.39     | 0.47        | 0.17       |
|           | MNLI             | 0.08| 0.38     | 0.48        | 0.15       |
|           | DocNLI           | -0.02| 0.39    | 0.19        | 0.41       |
|           | SCZeroShot       | 0.11| 0.41     | 0.51        | **0.50**   |
| QA         | QuestEval        | **0.27**| 0.35 | 0.47     | 0.45       |
|           | QAFACTEVAL       | **0.22**| **0.45**| **0.59** | 0.47       |
| Learned    | SCConv (synthetic) | 0.16| 0.43     | 0.55        | 0.44       |
|           | QAFACTEVAL-NLI(synthetic) | 0.17| **0.47**| **0.63**  | **0.49**   |

Table 10: Summary-level Kendall correlation coefficients across factual consistency evaluation datasets. Metrics are divided into entailment-based, QA-based, and learned metrics which fine-tune additional parameters based on synthetic data from Laban et al. (2021). The two highest-correlated metrics for each dataset are shown in bold.

| Model Type | Model Name       | XSF | SummEval | FRANK-CNNDM | FRANK-XSum |
|------------|------------------|-----|----------|-------------|------------|
| Misc       | BARTScore        | 0.15| 0.32     | **0.51**    | 0.25       |
|            | BLANC            | 0.11| 0.21     | 0.38        | 0.05       |
| Entailment | FactCC           | 0.00| 0.30     | 0.35        | -0.01      |
|           | BertScore-FFCI   | 0.17| 0.28     | 0.34        | 0.18       |
|           | DAE              | 0.00| 0.33     | 0.41        | 0.27       |
|           | ANLI             | 0.08| 0.32     | 0.41        | 0.16       |
|           | MNLI             | 0.07| 0.31     | 0.41        | 0.14       |
|           | DocNLI           | -0.01| 0.32   | 0.17        | 0.37       |
|           | SCZeroShot       | 0.10| 0.34     | 0.44        | **0.45**   |
| QA         | QuestEval        | **0.23**| 0.29 | 0.41     | 0.41       |
|           | QAFACTEVAL       | **0.19**| **0.37**| **0.51** | **0.45**   |
| Learned    | SCConv (synthetic) | 0.14| 0.36     | 0.49        | 0.41       |
|           | QAFACTEVAL-NLI(synthetic) | 0.14| **0.39**| **0.55**  | 0.44       |