Multi-Perspective Abstractive Answer Summarization

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Abstract

Community Question Answering (CQA) forums such as Stack Overflow and Yahoo! Answers contain a rich resource of answers to a wide range of questions. Each question thread can receive a large number of answers with different perspectives. The goal of multi-perspective answer summarization is to produce a summary that includes all perspectives of the answer. A major obstacle for multi-perspective, abstractive answer summarization is the absence of a dataset to provide supervision for producing such summaries. This work introduces a novel dataset creation method to automatically create multi-perspective, bullet-point abstractive summaries from an existing CQA forum. Supervision provided by this dataset trains models to inherently produce multi-perspective summaries. Additionally, to train models to output more diverse, faithful answer summaries while retaining multiple perspectives, we propose a multi-reward optimization technique coupled with a sentence-relevance prediction multi-task loss. Our methods demonstrate improved coverage of perspectives and faithfulness as measured by automatic and human evaluations compared to a strong baseline.

1 Introduction

In a world of information overload and the ubiquity of discussion forums, there is a need for text summarization as a means of distilling relevant information into a concise form. The problem is even more pertinent for question answering within the context of Community Question Answering (CQA) forums, where a person poses a question and can get an abundance of answers to sift through. Ideally, an answer summary should cover the multiple perspectives found in the answers, where available. For example, in Table 1, a person poses a question about finding a puppy and also provides context on the type of dog. We present a sample of the 14 answers to that question on Yahoo! Answers and an automatically-created summary consisting of bullet points covering the answers’ main perspectives. We introduce a novel pipeline to build such a multi-perspective, bullet-point summarization dataset and introduce models to generate faithful multi-perspective summaries.

To date, most CQA forums have a notion of a ’best answer,’ which is either manually chosen by the person who asked the question or by a moderator or obtained via community ratings. Work in this field typically makes use of this best answer as a proxy for summaries (Tomasoni and Huang, 2010; Chan et al., 2012; Pande et al., 2013; Wang et al., 2014; Song et al., 2017). However, the best answer only presents one person’s perspective and rarely

| Question: | i found a puppy that is less then six weeks old an no mother around what should i feed it? |
| Context:  | it a pit puppy i think |
| Answer 1: | Go to a vet and get some and a small feeding bottle. |
| Answer 2: | get a baby bottle warm milk best thing is to call a pet shop |
| Answer 3: | it needs a certain type of milk, dont feed it cows milk |
| Answer 4: | call a vet and ask them. if you cannot do that then give them alot of water and a little balloon a day, than go into dog food... |

Summary Bullet Points:

1. call the vet and tell them how old you think it is and what should you feed it...
2. the first thing you want to do if you plan to keep it is go to petsmart or pet co and ask anyone that specializes on dogs and get the pup a baby bottle and feed it milk but not cow milk try powder milk with water.
3. try and find something soft to eat (as in a soft dog food).
4. if it is not yet walking, then get a bottle

Table 1: An example bullet-point summary from our answer summarization dataset, illustrating the multiple viewpoints present in the summaries created through our pipeline, and a subset of the 14 user answers to which the target summary can be aligned.
captures the variety of perspectives discussed in the thread. Datasets such as WikiHowQA (Deng et al., 2020), which consists of a question, a long answer, and an answer summary, focus on answer selection and the summarization of a single answer. While CQASumm (Chowdhury and Chakraborty, 2019) uses the chosen best answer as the answer summary, they also apply heuristics to ensure token overlap with the remaining answers. However, we found that the heuristics applied generally promotes only long answers instead of multiple perspectives. To validate our hypothesis, we examine a set of 30 summaries from CQASumm and found that only 37% of the examples contained multi-perspective answers.

Although multi-perspective answer summarization is an important research topic with practical applications, there are no relevant datasets or techniques to address it effectively. This paper tries to close this gap by developing a dataset together with several modeling techniques for multi-perspective answer summarization. To generate a multi-perspective summarization dataset, we devise a pipeline to produce bullet point answer summaries. First, we select and cluster salient answer sentences. Then, we use the cluster centroids as our summary bullet points and remove them from the input to promote a more challenging, more abstractive task. We further filter the data to improve our dataset’s quality and promote desirable summary characteristics such as compression. We find that a strong baseline model trained on our data inherently outputs multi-perspective summaries. We focus our modeling efforts on generating content implied by the input text and being faithful to the underlying answers by covering multiple perspectives. To this end, we use a reinforcement learning (RL) framework with new rewards and a sentence-relevance multi-task loss, whereby the model learns to predict relevant sentences for the current decoding step to more closely align the source and generated output. Our models improve the coverage and faithfulness of generated summaries when compared to a state-of-the-art abstractive baseline.

The main contribution of this paper is to develop, for the first time, a method for multi-perspective abstractive answer summarization. To achieve this, 1) We introduce a dataset generation pipeline for answer summarization that goes beyond the best-answer summary, to create multi-perspective, bullet-point summaries for training and evaluation 2) We introduce and evaluate RL reward functions on answer summarization, including entailment as a measure of faithfulness and volume of semantic space as a way to increase coverage of multiple answer perspectives 3) We introduce a sentence-relevance prediction loss to increase the faithfulness and interpretability of the generated answer summaries. We will make our code available for reproducing our dataset pipeline and model results.

2 Related Work

Extractive Answer Summarization: Much work has focused on the extractive summarization setting as an answer-ranking problem (Chan et al., 2012; Pande et al., 2013; Wang et al., 2014). Liu et al. (2008) find that only 48% of the best answers on Yahoo! Answers are unique best answers; there are multiple correct ways to answer a question. Other recent work has focused on sentence extraction using metadata (Tomasoni and Huang, 2010) or sparse-coding frameworks (Song et al., 2017). Our focus is on representing multiple perspectives in an abstractive summarization framework.

Abstractive Answer Summarization: Another line of work has attempted abstractive answer summarization by treating the tagged best answer as the gold summary of all the other answers (Chowdhury and Chakraborty, 2019; Chowdhury et al., 2020). Chowdhury and Chakraborty (2019) present CQA-Summ, a dataset of about 100k examples consisting of the best answer as the gold summary, which, however, often only contains one perspective.

Multi-document Summarization: Answer summarization can be viewed as a query-based multi-document summarization (MDS) problem. Several large-scale MDS datasets have been introduced in the news domain (Fabbri et al., 2019; Gu et al., 2020; Gholipour Ghalandari et al., 2020), for creating Wikipedia lead-paragraphs (Liu et al., 2018) and for long-form question answering (Fan et al., 2019). However, news-based MDS datasets are not query-based, Wikipedia summarization is topic-based and less granular than our setting, and the ELI5 dataset (Fan et al., 2019) summarizes web documents rather than direct query answers.

RL and Multi-task Learning for Summarization: Paulus et al. (2018) first apply the REINFORCE algorithm (Williams, 1992) in the context of summarization. RL has since been applied for both extractive (Narayan et al., 2018b; Dong et al., 2018), abstractive (Pasunuru and Bansal, 2018; Li
et al., 2018; Huang et al., 2020; Laban et al., 2020) and hybrid approaches (Chen and Bansal, 2018). Böhm et al. (2019) stress the role of using rewards that correlate well with human judgments on downstream performance. Our paper focuses on the selection of rewards applicable for promoting faithful and diverse, abstractive answer summaries. Previous work on entailment as an RL reward has focused on document-level entailment in the news domain (Li et al., 2018; Pasunuru and Bansal, 2018). In this work, we show the effect of the choice of entailment model on downstream faithfulness prediction and the importance of using sentence-level entailment. Recent work in multi-task learning with summarization consists of sharing parameters between an abstractive generator and auxiliary tasks such as entailment and question generation (Guo et al., 2018) and text classification and syntax-labeling tasks (Lu et al., 2019).

3 Dataset Creation
Previous CQA work lacks multi-perspective supervision. To address this research gap, we develop a system to create summaries covering multiple perspectives of answers to a given question.

3.1 Overview of Data Generation Pipeline
The input to our pipeline is a question and its answers. We use question threads from the Yahoo! Answers L6 corpus. Our pipeline operates on the sentence level of these answers versus the answer level, as we believe that this granularity allows us to capture additional perspectives. Our dataset pipeline consists of the following components: 1) a relevance model to remove irrelevant inputs, 2) a clustering model to cluster similar content, and 3) input and summary creation from centroids.

Relevance model: We first aim to determine whether a given sentence is relevant to answering a question and, therefore, to be considered as a potential summary sentence. We use the ANTIQUE (Hashemi et al., 2020) relevance data for training a query-sentence relevance model. The data consists of Yahoo! answers and relevance labels on a scale from 1-4, with 1-2 not relevant and 3-4 relevant. We use a RoBERTa-based (Liu et al., 2019) model fine-tuned on answer selection on the TREC-QA dataset (Wang et al., 2007) as a binary relevant/non-relevant classifier and further fine-tune it using the Tanda (Garg et al., 2020) method. We experimented with training the relevance classifier using Yahoo! Answers, treating the best answer as relevant and the other answers as not relevant, and analogously on the sentence level, although without improvements. The performance was measured using mean reciprocal rank on a held-out relevance set.

As input to the clustering stage, we remove sentences that our relevance model labels as irrelevant (our model tends to over-predict relevant sentences, as many answers contain relevant sentences, thus removing only 16% of sentences). Improving this relevance classifier to better filter irrelevant answer sentences is a very interesting research direction, although we leave this for future work.

Clustering: Most methods for short-text clustering (Hadifar et al., 2019; Xu et al., 2017) require a known value of k, the number of clusters, which is dynamic from question to question in our setting. In this work, we use the sentence-transformers library (Reimers and Gurevych, 2019a) to perform clustering. Specifically, we start with a RoBERTa-based model fine-tuned for sentence embeddings on an entailment dataset, which is further fine-tuned for semantic similarity. Clustering parameters were chosen based on a StackOverflow clustering dataset containing labeled clusters commonly used in short-text clustering. We used Agglomerative clustering with average linkage, cosine distance, and a maximum distance of .65.

To create the final summaries, we locate the centroid of clusters with at least two sentences and use these centroids as bullet-point summaries. Further, we remove the centroid sentences from the sentence-tokenized input answers to create a challenging abstractive summarization dataset analogous to the XSum dataset (Narayan et al., 2018a). Since each cluster contains at least two sentences, we assume that a perfect clustering algorithm, a related sentence can help generate the removed centroid sentence. While removing sentences naturally decreases coherence, we believe that this introduces a tolerable level of noise, considering the existing presence of noise through ungrammatical and occasionally incoherent answers. To further account for imperfections in the pipeline, we apply additional filtering techniques, described below.
3.2 Postprocessing and Quantitative Analysis

We obtained question threads from Yahoo! Answers and applied heuristics detailed in Tomasoni and Huang (2010) to find threads suitable for summarization. Threads were removed if 1) there were less than five answers, 2) the longest answer was over 400 words, 3) the sum of the length of all answers was outside of (100, 1000) words, and 4) the average length of answers was outside of the (50, 300) words interval. This filtering left us with about 350k of the approximately 4.4 million threads and included both factoid and non-factoid questions. Questions include the subject of the post as well as the content of the post when available.

Example Filtering: We remove examples from the dataset based on desired summarization characteristics. A desirable trait in summarization datasets is compression, i.e., the ratio of the input size to the summary size (Grusky et al., 2018). We remove examples with a compression ratio under 4, examples for which the input length exceeded 1,100 tokens and for which the summary length exceeded 250 tokens, leaving us with 284,295 examples. We further remove target summaries labeled as contradictions from a RoBERTa-based entailment model following Matsumaru et al. (2020). Furthermore, we remove examples with more than 10 “+” or “=” signs (math queries), those with very long (>50 characters) tokens, and those with a link in the target or more than one link in the source. Finally, we filter to ensure that we have examples where the named entities found in the target are also found in the source document.

Quality Analysis: The filtering process yielded 96,701 examples, which we split into 88,512/4,032/4,157 training, validation, and testing examples. We annotated a subset of 400 summaries created by our pipeline to conduct quality checks. For each summary, the annotator reads the question, and if the answer coverage of the summary was determined as reasonable, the summary was marked as 1, otherwise 0. 370 of the 400 summaries were labeled as 1, showing that the pipeline creates largely relevant content. Additionally, on examining 30 summaries, we found that 80% contained multiple perspectives versus the 37% we found in CQASumm, showing the benefit of our dataset pipeline in encoding multiple viewpoints. To further analyze the types of questions present in our dataset, we trained a factoid/non-factoid question classifier using SQuAD (Rajpurkar et al., 2016) data as factoid examples and non-factoid Yahoo! Questions dataset as non-factoid examples. 8% of threads were labeled as factoid questions; the filtering steps based on answer size likely filter out examples with short, factoid answers.

3.3 Relation to Existing Datasets

CQASumm is the closest dataset with our desired answer summarization qualities, although it simply promotes answers as summaries rather than truly summarizing answers. As discussed above, this dataset lacks our desired multi-perspective summaries. A similar approach to dataset creation was taken by Shapira and Levy (2020) for review summarization by clustering reviews using pivot clustering, adding reviews to a cluster based on lexical overlap until a max length and min number of review requirements are met. There are significant differences to our approach in terms of granularity (reviews vs. sentence clustering), type of clustering (lexical vs. embedding-based), as well as the ultimate use of these clusters (they train a cluster summarizer while we combine cluster centroids for creating an abstractive bullet point combined with other cluster centroids). We present a comparison of dataset statistics between our dataset, which we
Table 2: Comparison between AnwerSumm and the XSum (Narayan et al., 2018a) and CNN-DailyMail (Nallapati et al., 2016) datasets. Oracle Extractive and Length refer to the maximum ROUGE (Lin, 2004) score achievable by an extractive model, and the average length of the summaries, respectively.

| Dataset       | % Novel unigrams | Oracle Extractive | Length |
|---------------|------------------|-------------------|--------|
| AnswerSumm (ours) | 32.2             | 40.02/11.16/33.70 | 67     |
| XSum          | 35.8             | 29.79/8.81/22.65  | 23     |
| CNN           | 16.8             | 50.38/28.55/46.58 | 46     |
| DailyMail     | 17.0             | 55.23/30.55/51.24 | 55     |

4 RL Rewards and Auxiliary Losses

Cross-entropy loss suffers from exposure bias and also does not directly optimize the evaluation metrics such as NLI and ROUGE-L (Ranzato et al., 2016). The REINFORCE algorithm (Williams, 1992), on the other hand, allows for optimizing the evaluation metrics using non-differentiable rewards. Therefore, we use an RL multi-reward objective to promote summaries with both high coverage of the input answers and faithfulness. Additionally, we also introduce an auxiliary loss function for more interpretable and faithful summaries.

4.1 Multi-Reward Optimization

We follow the settings of Pasunuru and Bansal (2018) for optimizing multiple rewards. In the equations which follow, $x = \{x_1, x_2, \ldots, x_{n'}\}$ refers to the input source tokens (e.g. a question and its answers), and $y^* = \{y_1^*, y_2^*, \ldots, y_N^*\}$ refers to the target summary which consists of $\{y_1^*, y_2^*, \ldots, y_N^*\}$ sentences. Standard training minimizes the negative log-likelihood (NLL) loss using teacher forcing (Williams and Zipser, 1989):

$$L_{ml} = - \sum_{t=1}^{N} \log p(y_t^*|y_1^*, \ldots, y_{t-1}^*, x)$$

(1)

For our RL optimization, we use self-critical policy gradient training as in Paulus et al. (2018); Rennie et al. (2017). At each time-step, we produce an output $y^*$ by sampling from the current decoding probability, $p(y_t^*|y_1^*, \ldots, y_{t-1}^*, x)$, as well as an output $\hat{y}$ obtained by greedily decoding from the current probability distribution. We define a reward function $r(y, x, y^*) \in [0, 1]$, i.e., the reward function compares $y$ with $x$ and $y^*$. The RL loss function $L_{rl}(x, y^*) =:

$$L_{rl} = \sum_{t=1}^{N} \log p(y_t^*|y_1^*, \ldots, y_{t-1}^*, x)$$

(2)

As in Paulus et al. (2018) and Pasunuru and Bansal (2018), we use a mixture of the above two losses:

$$L_{mixed} = \gamma_{rl}L_{rl} + \gamma_{ml}L_{ml},$$

(3)

where $\gamma_{rl}$ and $\gamma_{ml}$ are tunable hyperparameters used as scaling factors. Rather than applying weights to each reward, we follow Pasunuru and Bansal (2018) and optimize $L_{mixed}$ by alternating rewards in each minibatch.

4.2 Rewards

We now describe the three RL reward functions used: (1) ROUGE (Lin, 2004) as a proxy for content coverage, (2) entailment (NLI) for faithfulness, and (3) semantic area to measure the coverage of a summary in a semantic space.

**ROUGE (Lin, 2004):** Similar to Paulus et al. (2018) and Pasunuru and Bansal (2018), we use ROUGE-L as a reward to additionally promote important content beyond the cross-entropy loss.

**Natural Language Inference (NLI) for Faithful Summarization:** We use the degree of entailment, or the Importance of the NLI (Falke et al., 2019) score achievable by an extractive model, and the average length of the summaries, respectively.
of summaries given input answers as a reward to promote faithfulness of answer summarization. While entailment has been used as a reward as well as a summarization metric, we find several gaps in the current literature. Firstly, a discussion of the effect of the quality of the NLI evaluation model on downstream faithfulness metrics is incomplete. Also, summarization work typically uses NLI models with document-level input, while NLI models are generally trained on sentence-level data.

Falke et al. (2019) analyze NLI models for ranking summaries: given an input sentence and two summary sentences, one faithful and one unfaithful to the input, a model should rank the faithful summary higher than an unfaithful summary. They introduce a dataset of 377 examples and measure the rank accuracy of NLI models. They define NLI as a measure of faithfulness for ranking summaries in the following way: Let $N$ be an NLI model which, given a claim $c$ and a premise $p$, computes $N(p, c)$, the probability that the claim is entailed by the premise. We use this to calculate the NLI score for a summary $y$ consisting of $N_s$ sentences:

$$\text{NLI}(y, x) = \frac{1}{N_s} \sum_{i=1}^{N_s} \max_{s \in x} N(s, y_{i_s}) \quad (4)$$

For the original task introduced in Falke et al. (2019), $x$ consists of a single source sentence from the CNN-DailyMail corpus. We present our findings on this task in Table 3. We examine how the quality of the NLI model affects performance by comparing BART (Lewis et al., 2020) and RoBERTa fine-tuned on the MNLI corpus (Williams et al., 2018). Although the performance gap of these two models is very small on MNLI (90.2% for RoBERTa and 89.9% for BART), the performance gap is very large on ranking these sentences (89.8% for RoBERTa and 71.9% for BART).

We also address the effect of the granularity of the NLI model input. As discussed above, Falke et al. (2019) perform ranking based on sentence-level input and output. Recent work in entailment as a summarization metric, however, uses the entire input document as input to the NLI model for faithfulness calculations (Maynez et al., 2020), rather than computing the max over all the input sentences as in Equation (4). We locate the full source articles for the 377 examples and perform two experiments, one using Equation (4), and the other which uses the entire article to score the target sentence, $N(x, y_{i_s})$. Performance drops when using the entire article as the input versus using Equation (4). To ensure that the performance drop was not caused by content truncation due to the 512 input size limitation, we also experimented with using the article starting from the relevant source sentence, without improvements.

Furthermore, we find that the use of NLI is particularly suitable for AnswerSumm. We sampled six threads from our dataset. Then for each thread, we wrote sentences entailed by the source as well as sentences based on similar themes but not stated in the source, totaling 50 faithful and 50 hallucinated examples. We find that the RoBERTa MNLI model can correctly identify these examples with 96% accuracy. We believe that NLI is intuitively more suitable for our data, which is less entity-heavy when compared to the news domain.

Semantic Area for Multi-Perspective Summarization: We aim to reward summaries that include more of the perspectives found in the input answers. To achieve diverse extractive summarization, Yogatama et al. (2015) embed sentences in semantic space and select those whose convex hull maximizes the volume in that space. This idea of semantic volume is also used to measure the semantic overlap between summaries and references in Jung et al. (2019). We use semantic volume as a proxy for covering multiple perspectives; the summary with the larger semantic volume covers a wider range of views discussed in the input. We make use of sentence-transformers (Reimers and Gurevych, 2019b) to obtain sentence embeddings for each sentence. We project each embedding onto two dimensions using PCA, and thus, our volume calculation reduces to an area calculation, which we call Semantic Area. We use min-max normalization to keep the reward in the range of 0 to 1.

4.3 Relevant Sentence Prediction

We want to more closely align the decoded summary with the source text, as hallucinations may be caused by the decoder acting more as a language model rather than attending to the source text (Maynez et al., 2020). Aligning the source and generated output offers a potential interpretable output during inference, which goes beyond using attention for interpretation (Wiegreffe and Pinter, 2019). We introduce an auxiliary loss by which the model predicts, based on the decoder representation, a span of source text relevant to the current time-step, analogous to finding evidence to support...
We use the fairseq codebase (Ott et al., 2019) for our experiments. Our base abstractive text summarization model is BART (Lewis et al., 2020), a pretrained denoising autoencoder that builds off of the sequence-to-sequence transformer of Vaswani et al. (2017). Input to the model is the question concatenated with input answers. We fine-tune BART using a polynomial decay learning rate scheduler with learning rate $3e^{-5}$, using the Adam optimizer (Kingma and Ba, 2015). We train with 500 warmup steps and 20,000 total steps and pick the model with the best label-smoothed cross-entropy (Szegedy et al., 2016) validation loss. Cross-entropy loss is our main loss, while the RL rewards and sentence-relevance prediction can be viewed as auxiliary losses. In RL experiments, we train using BART from scratch, as opposed to using a model already fine-tuned on answer summarization, as we found that this model better learned to follow the given rewards. Following similar ratios as in Lu et al. (2019), we set $(\gamma_{rl}, \gamma_{ml}, \gamma_{span}) = (0.9, 0.1, 0.0)$ when experimenting without sentence-relevance loss, $(0.00, 1.0, 1.0)$ for experiments with just relevant sentence prediction and cross-entropy loss, and $(0.9, 0.5, 0.01)$ for experiments with all losses. Hyperparameters were tuned on the validation set; we found a larger $\gamma_{ml}$ necessary when combining rewards with sentence relevance prediction to ensure that the main negative log-likelihood loss was not drowned out by the auxiliary losses.

### 6 Results

#### Extractive Baselines

We use standard extractive summarization baselines such as Lexrank (Erkan and Radev, 2004) and TextRank (Mihalcea and Tarau, 2004), and a BERT-based extractive model, BertSum (Liu and Lapata, 2019). Results are presented in Table 4. We observe a large gap between these baselines and the extractive oracle, which is the upper bound for extractive model performance, showing potential for improvement. Since we focus on abstractive summarization, we leave improving extractive models for future work.

#### Abstractive Models

We present the results of the abstractive models in Table 5. We note that while the model with ROUGE reward outperforms the baseline in ROUGE-L (the ROUGE variant optimized), we do not see larger gains in ROUGE.

| Method          | ROUGE-1/2/L |
|-----------------|-------------|
| LexRank         | 26.86/5.05/22.68 |
| TextRank        | 27.44/5.05/22.13 |
| BertSum (Liu and Lapata, 2019) | 30.01/5.76/24.83 |

Table 4: ROUGE scores for baseline extractive models.
Table 5: ROUGE and NLI scores for proposed models, with the two highest scores for each metric highlighted due to the similarity between the ROUGE optimization and NLL on our datasets. For bullet-point summaries, minimizing the NLL is analogous to rephrasing relevant bullet-points from the source and increasing the ROUGE-L. The model that combines all the RL rewards achieves the highest ROUGE performance, while the model with all RL rewards and sentence-relevance loss achieves the highest NLI score. The faithfulness of the model with only sentence relevance loss is further improved by adding the RL rewards. In general, we see that the model with a single RL reward achieves the highest score of the target summaries for that metric, i.e., the highest NLI score is achieved using only the NLI-based reward. Additionally, we calculate the average semantic area of the resulting summaries. The baseline model, the model with just semantic reward, and the final model with all rewards have semantic areas of 39.7, 46.5, and 42. To further show the effect of our dataset on multi-perspective summarization, we train a BART model on the most related answer summarization dataset CQASumm and find that the semantic area of that model’s summaries is 31.54. This result shows the importance of supervision from our dataset pipeline for ensuring coverage of multiple perspectives in answer summarization.

As automatic metrics may not correlate perfectly with human judgments, we perform a human evaluation to determine the differences in model output qualities. We presented two annotators who are fluent in English with the question, answers, and summaries from three models and asked them to annotate the summaries along the following dimensions: 1) On a Likert scale from 1-5, label the ability to capture multiple perspectives, with points deducted for repetition 2) On a Likert scale from 1-5, label the extent of faithfulness of the summary, with 5 being a completely faithful summary and 1 being an entirely inaccurate summary.

We present results in Table 6. Annotations are averaged between each annotator and then across examples for 50 questions threads from three models. We choose to compare the BART baseline, the BART model with all RL rewards, and the BART model with span prediction to determine the effect of our rewards and the multi-task loss on output quality. Pearson correlations for faithfulness and multi-perspective scores among the annotators were 0.41 and 0.31, displaying moderate correlation. We find that most models can generate multiple perspective summaries. The baseline already generates multi-perspective output, likely because the dataset pipeline produces summaries that contain multiple perspectives, so the baseline learns to produce such output. Using a student’s t-test with a p-value of 0.05, we find that the improvement in faithfulness between the RL models and the baseline is statistically significant while the other differences are not. With the span-based model, this improvement comes at the cost of some level of abstraction, as the percentage of novel unigrams found in the summary is 10% vs. 13% found in the baseline and RL-only models. This reduction in abstraction likely results because the span loss more closely binds the decoder representation with the encoder representation, encouraging the model to copy more from the source. We demonstrate the added advantage of our span prediction model’s interpretability by using it to provide explanations for the generated summaries in the Appendix.

7 Conclusion and Future Work

We propose multi-perspective answer summarization by introducing a pipeline for creating a suitable dataset for the task and by introducing models to promote high-coverage, faithful answer summaries, as seen in automatic and human evaluations. We aim to refine this pipeline for future work by improving the relevance and clustering components and applying them to new data sources. We plan to study the abstractiveness-faithfulness tradeoff further, explore additional rewards for improved summary coherence, and move beyond bullet point summaries by building on work in sentence fusion.
8 Ethical Considerations

As we propose a novel conversation summarization dataset creation pipeline and modeling components, this section is divided into the following two parts.

8.1 New Dataset

**Intellectual Properties and Privacy Rights**  We will be providing scripts to run our dataset creation pipeline but will not be releasing the data itself. Access to the Yahoo! Answers dataset requires the submission of a user-agreement form through the webscope platform \(^3\). We do not do any crowdsourcing. All human annotations are done in-house. We manually reviewed our dataset output for quality and potential problems.

8.2 NLP Application

**Bias**  Biases may exist in the datasets, such as political bias and gender bias in Yahoo! Answers. Thus, models trained on these datasets may propagate these biases.

**Misuse Potential and Failure Mode**  When used as intended, applying the summarization models described in this paper can save people much time. However, the current models are still prone to producing hallucinated summaries, and in such a case, they may contribute to misinformation on the internet. We move the needle in faithful summarization in this paper, but further research is needed to ensure the faithfulness of abstractive summaries to address this issue, as this issue is present among all current abstractive summarization models.

**Environmental Cost**  The experiments described in the paper make use of V100 GPUs. We used up to 8 GPUs per experiment. The experiments may take several hours. Several dozen experiments were run due to parameter search, and future work should experiment with distilled models for more light-weight training. We note that while our work required extensive experiments to draw sound conclusions, future work will be able to draw on these insights and need not run as many large-scale comparisons. Models in production may be trained once for use using the most promising settings.

9 Appendix

We show the model-generated summaries for the model "BART + Sent Relevance + RL (ALL)" as well as the sources sentences the model predicts as relevant at the end of each sentence generated during decoding. In the example below, the model can correctly abstract meaning from the source sentences and formulate summary bullet points. Occasionally the model will output a point which is not coherent by itself (e.g. 'It’s a great book') or may output related but not supported text. We believe this is due to the BM25 relevance function used for determining relevant sentences for training. Examining this mechanism sentence relevance prediction as a model probing task as well as improving coherence in summaries, to go beyond bullet point summaries via methods such as sentence fusion, are valuable areas of future work.

We show model outputs from the three models examined in human evaluation in Table 8. We see that the baseline hallucinates several times. We also notice how the hallucinations, as opposed to typical hallucinations in the news domain which may replace entities, are often plausible responses. For example, although the baseline generates an output saying that it is not a good idea to lose weight, which is not directly stated in the source, such an answer is very plausible. We also found that there was occasionally a fine line between what was a hallucination and what was a plausible generated text which is not entirely implied in the source. For example, the text stating it is not a good idea to lose weight echoes the sentiment that the user asking the question should make the choice for themselves, although this is not stated in this fashion. We believe that more precisely defining the degrees of hallucination and plausibility to be an important direction for future work.

\(^3\)https://webscope.sandbox.yahoo.com/catalog.php?datatype=l&did=11
Question: What is the secret to work/life balance?

Summary Sentences:

| You have to find the right balance between work and life. |
| I mean you keep looking outside of work for happiness, and you want a balance, so why not be happy everywhere |
| If you don’t try something new, you’ll never know what you’re doing. |
| Only then will they matter equally |
| It’s a great book, and you can get it at any book store. |
| It’s absolutely possible, and in my sources is a book that you can get as cheap as $1.62 |
| I think the trick is to go to work with the right attitude. |
| It seems to me that people just go to work with the wrong attitude actually |

Table 7: An example of the predicted sentences from our span-based model with all rewards. On the left side are the generated summary sentences and on the right side are the sentences predicted to be relevant at the end of sentence timestep during generation.

References

Florian Böhm, Yang Gao, Christian M. Meyer, Ori Shapira, Ido Dagan, and Iryna Gurevych. 2019. Better rewards yield better summaries: Learning to summarise without references. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3110–3120, Hong Kong, China. Association for Computational Linguistics.

Wen Chan, Xiangdong Zhou, Wei Wang, and Tat-Seng Chua. 2012. Community answer summarization for multi-sentence question with group L1 regularization. In Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 582–591, Jeju Island, Korea. Association for Computational Linguistics.

Yen-Chun Chen and Mohit Bansal. 2018. Fast abstractive summarization with reinforce-selected sentence rewriting. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 675–686, Melbourne, Australia. Association for Computational Linguistics.

Table 8: Example question and answers along with bullet-point answer summaries from three models. Possible hallucinations are shown in red.

| Question: average 14 year old girls weight? |
| Context: im 14 years old, 145 pounds, 5’5” and 1/2, need to know if i need to lose weight. my brother and his friend(who is also my friend) have told me i do, but i dont know. is this a normal weight? |
| Answer 1: be comfortable in your own body, don’t worry what others think of you! If you feel like you need to lose weight then exercise and make that choice for yourself. |
| Answer 2: your bro and his friend are retards who cares what they say??!! and if you think you weigh alot it probably doesn’t show |
| Answer 3: First off, that is not very nice for your brother and his friends to be telling you to loose weight ... It is actually more healthy to be about 10% over what is normal for your age. Remember that muscle weights more than fat but it takes up less room than fat does. If you eat well and exercise daily you have nothing to worry about. |
| Answer 4: I’m 5’8” and wrestled at 126 lbs when i was a freshman and sophomore. |
| Answer 5: Your BMI (Body Mass Index) is 24.1 Based on this number and your age you are not overweight, but are considered “at risk for overweight.” |

BART Baseline Summary: You are not overweight if you are eating healthy and exercising. (S) Your weight will change as you get older. (S) If you are overweight, it is because you have too much muscle and not enough fat. (S) I’m not sure how old you are, but I’m assuming you are 14. (S) It is not a good idea to lose weight.

BART + RL (ALL) Summary: You feel like you need to lose weight then exercise and make that choice for yourself. (S) You are not overweight, and you are not at risk for overweight. (S) It is normal for a fourteen year old to be a little over weight, but not overweight. (S) If you are a wrestler, you will know how much muscle you have.

BART + Sent Relevance + RL (ALL) Summary: If you feel like you need to lose weight then do so, but don’t listen to your brother and his friend. (S) You are not overweight, but you are at risk for being overweight. (S) You should be comfortable with your weight. (S) If you have muscle, you will be able to lose more weight than if you had fat.

Tanya Chowdhury and Tamnay Chakraborty. 2019. Cqasumm: Building references for community question answering summarization corpora. In Proceedings of the ACM India Joint International Conference on Data Science and Management of Data, pages 18–26.

Tanya Chowdhury, Sachin Kumar, and Tamnay Chakraborty. 2020. Neural abstractive summarization with structural attention. In Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence, IJCAI 2020, pages 3716–3722. ijcai.org.

Yang Deng, Wai Lam, Yuexiang Xie, Daoyuan Chen, Yaliang Li, Min Yang, and Ying Shen. 2020. Joint learning of answer selection and answer summary generation in community question answering. In The Thirty-Fourth AAAI Conference on Artificial Intelligence, AAAI 2020, The Thirty-Second Innova-
Yue Dong, Yikang Shen, Eric Crawford, Herke van Hoof, and Jackie Chi Kit Cheung. 2018. BanditSum: Extractive summarization as a contextual bandit. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 3739–3748, Brussels, Belgium. Association for Computational Linguistics.

Tobias Falke, Leonardo F. R. Ribeiro, Prasetya Ajie Utama, Ido Dagan, and Iryna Gurevych. 2019. Ranking generated summaries by correctness: An interesting but challenging application for natural language inference. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 2214–2220, Florence, Italy. Association for Computational Linguistics.

Angela Fan, Yacine Jernite, Ethan Perez, David Granger, Jason Weston, and Michael Auli. 2019. ELI5: Long form question answering. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 3558–3567, Florence, Italy. Association for Computational Linguistics.

Siddhant Garg, Thuy Vu, and Alessandro Moschitti. 2020. TANDA: transfer and adapt pre-trained transformer models for answer sentence selection. In The Thirty-Fourth AAAI Conference on Artificial Intelligence, AAAI 2020, The Thirty-Second Innovative Applications of Artificial Intelligence Conference, IAAI 2020, The Tenth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2020, New York, NY, USA, February 7-12, 2020, pages 7651–7658. AAAI Press.

Demian Gholipour Ghalandari, Chris Hokamp, Nghia The Pham, John Glover, and Georgiana Ifrim. 2020. A large-scale multi-document summarization dataset from the Wikipedia current events portal. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 1302–1308, Online. Association for Computational Linguistics.

Max Grusky, Mor Naaman, and Yoav Artzi. 2018. Newsroom: A dataset of 1.3 million summaries with diverse extractive strategies. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 708–719, New Orleans, Louisiana. Association for Computational Linguistics.

Han Guo, Ramakanth Pasunuru, and Mohit Bansal. 2018. Soft layer-specific multi-task summarization with entailment and question generation. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 687–697, Melbourne, Australia. Association for Computational Linguistics.

Amir Hadifar, Lucas Sterckx, Thomas Demeester, and Chris Develder. 2019. A self-training approach for short text clustering. In Proceedings of the 4th Workshop on Representation Learning for NLP (RepL4NLP-2019), pages 194–199, Florence, Italy. Association for Computational Linguistics.

Helia Hashemi, Mohammad Aliannejadi, Hamed Zamani, and W Bruce Croft. 2020. Antique: A non-factoid question answering benchmark. In European Conference on Information Retrieval, pages 166–173. Springer.

Luyang Huang, Lingfei Wu, and Lu Wang. 2020. Knowledge graph-augmented abstractive summarization with semantic-driven cloze reward. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 5094–5107, Online. Association for Computational Linguistics.

Taehee Jung, Dongyeop Kang, Lucas Mentch, and Eduard Hovy. 2019. Earlier isn’t always better: Sub-aspect analysis on corpus and system biases in summarization. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3324–3335, Hong Kong, China. Association for Computational Linguistics.

Diederik P. Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings.

Wojciech Kryscinski, Bryan McCann, Caiming Xiong, and Richard Socher. 2020. Evaluating the factual consistency of abstractive text summarization. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 9332–9346, Online. Association for Computational Linguistics.
Philippe Laban, Andrew Hsi, John Canny, and Marti A. Hearst. 2020. The summary loop: Learning to write abstractive summaries without examples. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 5135–5150, Online. Association for Computational Linguistics.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising sequence-to-sequence pretraining for natural language generation, translation, and comprehension. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7871–7880, Online. Association for Computational Linguistics.

Haoran Li, Junnan Zhu, Jiajun Zhang, and Chengqing Zong. 2018. Ensure the correctness of the summary: Incorporate entailment knowledge into abstractive sentence summarization. In Proceedings of the 27th International Conference on Computational Linguistics, pages 1430–1441, Santa Fe, New Mexico, USA. Association for Computational Linguistics.

Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In Text Summarization Branches Out, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.

Peter J. Liu, Mohammad Saleh, Etienne Pot, Ben Goodrich, Ryan Sepassi, Lukasz Kaiser, and Noam Shazeer. 2018. Generating wikipedia by summarizing long sequences. In 6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 - May 3, 2018, Conference Track Proceedings. OpenReview.net.

Yang Liu and Mirella Lapata. 2019. Text summarization with pretrained encoders. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3730–3740, Hong Kong, China. Association for Computational Linguistics.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.

Yuanjie Liu, Shasha Li, Yunbo Cao, Chin-Yew Lin, Dingyi Han, and Yong Yu. 2008. Understanding and summarizing answers in community-based question answering services. In Proceedings of the 22nd International Conference on Computational Linguistics (Coling 2008), pages 497–504, Manchester, UK. Coling 2008 Organizing Committee.

Yao Lu, Linqing Liu, Zhile Jiang, Min Yang, and Randy Goebel. 2019. A multi-task learning framework for abstractive text summarization. In The Thirty-Third AAAI Conference on Artificial Intelligence, AAAI 2019, The Thirty-First Innovative Applications of Artificial Intelligence Conference, IAAI 2019, The Ninth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2019, Honolulu, Hawaii, USA, January 27 - February 1, 2019, pages 9987–9988. AAAI Press.

Kazuki Matsumaru, Sho Takase, and Naoaki Okazaki. 2020. Improving truthfulness of headline generation. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 1335–1346, Online. Association for Computational Linguistics.

Joshua Maynez, Shashi Narayan, Bernd Bohnet, and Ryan McDonald. 2020. On faithfulness and factuality in abstractive summarization. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 1906–1919, Online. Association for Computational Linguistics.

Rada Mihalcea and Paul Tarau. 2004. TextRank: Bringing order into text. In Proceedings of the 2004 Conference on Empirical Methods in Natural Language Processing, pages 404–411, Barcelona, Spain. Association for Computational Linguistics.

Ramesh Nallapati, Bowen Zhou, Caglar Gulcehre, and Bing Xiang. 2016. Abstractive text summarization using sequence-to-sequence RNNs and beyond. In Proceedings of The 20th SIGNLL Conference on Computational Natural Language Learning, pages 280–290, Berlin, Germany. Association for Computational Linguistics.

Shashi Narayan, Shay B. Cohen, and Mirella Lapata. 2018a. Don’t give me the details, just the summary! topic-aware convolutional neural networks for extreme summarization. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 1797–1807, Brussels, Belgium. Association for Computational Linguistics.

Shashi Narayan, Shay B. Cohen, and Mirella Lapata. 2018b. Ranking sentences for extractive summarization with reinforcement learning. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 1747–1759, New Orleans, Louisiana. Association for Computational Linguistics.

Myle Ott, Sergey Edunov, Alexei Baevski, Angela Fan, Sam Gross, Nathan Ng, David Grangier, and Michael Auli. 2019. fairseq: A fast, extensible toolkit for sequence modeling. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics (Demonstrations), pages 48–53, Minneapolis, Minnesota. Association for Computational Linguistics.

Vinay Pande, Tanmoy Mukherjee, and Vasudeva Varma. 2013. Summarizing answers for community question answer services. In Language Pro-
cessing and Knowledge in the Web, pages 151–161. Springer.

Ramakanth Pasunuru and Mohit Bansal. 2018. Multi-reward reinforced summarization with saliency and entailment. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers), pages 646–653, New Orleans, Louisiana. Association for Computational Linguistics.

Romain Paulus, Caiming Xiong, and Richard Socher. 2018. A deep reinforced model for abstractive summarization. In 6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 - May 3, 2018, Conference Track Proceedings. OpenReview.net.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. SQuAD: 100,000+ questions for machine comprehension of text. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 2383–2392, Austin, Texas. Association for Computational Linguistics.

Marc’Aurelio Ranzato, Sumit Chopra, Michael Auli, and Wojciech Zaremba. 2016. Sequence level training with recurrent neural networks. In 4th International Conference on Learning Representations, ICLR 2016, San Juan, Puerto Rico, May 2-4, 2016, Conference Track Proceedings.

Nils Reimers and Iryna Gurevych. 2019a. Sentence-BERT: Sentence embeddings using Siamese BERT-networks. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3982–3992, Hong Kong, China. Association for Computational Linguistics.

Nils Reimers and Iryna Gurevych. 2019b. Sentence-BERT: Sentence embeddings using Siamese BERT-networks. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3982–3992, Hong Kong, China. Association for Computational Linguistics.

Steven J. Rennie, Etienne Marcheret, Youssef Mroueh, Jerret Ross, and Vaibhava Goel. 2017. Self-critical sequence training for image captioning. In 2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017, pages 1179–1195. IEEE Computer Society.

Ori Shapira and Ran Levy. 2020. Massive multi-document summarization of product reviews with weak supervision.

Hongya Song, Zhaochun Ren, Shangsong Liang, Piji Li, Jun Ma, and Maarten de Rijke. 2017. Summa-

rizing answers in non-factoid community question-

answering. In Proceedings of the Tenth ACM International Conference on Web Search and Data Mining, WSDM 2017, Cambridge, United Kingdom, February 6-10, 2017, pages 405–414. ACM.

Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jonathon Shlens, and Zbigniew Wojna. 2016. Re-thinking the inception architecture for computer vi-

sion. In 2016 IEEE Conference on Computer Vi-

sion and Pattern Recognition, CVPR 2016, Las Ve-

gas, NV, USA, June 27-30, 2016, pages 2818–2826. IEEE Computer Society.

Mattia Tomasoni and Minlie Huang. 2010. Metadata-

aware measures for answer summarization in community question answering. In Proceedings of the 48th Annual Meeting of the Association for Computational Linguistics, pages 760–769, Uppsala, Sweden. Association for Computational Linguistics.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Ilya Polosukhin. 2017. Attention is all you need. In Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA, pages 5998–6008.

Alex Wang, Kyunghyun Cho, and Mike Lewis. 2020. Asking and answering questions to evaluate the factual consistency of summaries. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 5008–5020, Online. Association for Computational Linguistics.

Lu Wang, Hema Raghavan, Claire Cardie, and Vittorio Castelli. 2014. Query-focused opinion summarization for user-generated content. In Proceedings of COLING 2014, the 25th International Conference on Computational Linguistics: Technical Papers, pages 1660–1669, Dublin, Ireland. Dublin City University and Association for Computational Linguistics.

Mengqiu Wang, Noah A. Smith, and Teruko Mitamura. 2007. What is the Jeopardy model? a quasi-synchronous grammar for QA. In Proceedings of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL), pages 22–32, Prague, Czech Republic. Association for Computational Linguistics.

Sarah Wiegreffe and Yuval Pinter. 2019. Attention is not not explanation. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 11–20, Hong Kong, China. Association for Computational Linguistics.

Adina Williams, Nikita Nangia, and Samuel Bowman. 2018. A broad-coverage challenge corpus for sentence understanding through inference. In Proceedings of the 2018 Conference of the North American
R. J. Williams. 1992. Simple statistical gradient-following algorithms for connectionist reinforcement learning. *Machine Learning*, 8:229–256.

Ronald J Williams and David Zipser. 1989. A learning algorithm for continually running fully recurrent neural networks. *Neural computation*, 1(2):270–280.

Jiaming Xu, Bo Xu, Peng Wang, Suncong Zheng, Guanhua Tian, and Jun Zhao. 2017. Self-taught convolutional neural networks for short text clustering. *Neural Networks*, 88:22–31.

Dani Yogatama, Fei Liu, and Noah A. Smith. 2015. Extractive summarization by maximizing semantic volume. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 1961–1966, Lisbon, Portugal. Association for Computational Linguistics.