Comparative Opinion Summarization via Collaborative Decoding

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Abstract

Opinion summarization focuses on generating summaries that reflect popular opinions of multiple reviews for a single entity (e.g., a hotel or a product.) While generated summaries offer general and concise information about a particular entity, the information may be insufficient to help the user compare multiple entities. Thus, the user may still struggle with the question “Which one should I pick?” In this paper, we propose a comparative opinion summarization task, which is to generate two contrastive summaries and one common summary from two given sets of reviews from different entities. We develop a comparative summarization framework CoCoSUM, which consists of two few-shot summarization models that are jointly used to generate contrastive and common summaries. Experimental results on a newly created benchmark CoCoTRIP show that CoCoSUM can produce high-quality contrastive and common summaries than state-of-the-art opinion summarization models.

1 Introduction

Widely available online customer reviews help the user with decisions in a variety of domains (e.g., hotel, restaurant, or company.) After creating a list of candidate entities based on initial conditions (e.g., area, price range, restaurant type), the user compares a few entities in depth by carefully reading the customer reviews to make a final decision (Payne et al., 1991). It is not only time-consuming but also difficult for the user to detect differences and similarities between the entities, as those pieces of information are often scattered in different reviews.

The recent success of neural summarization techniques (Rush et al., 2015) and the growth of online review platforms led to establishing the field of multi-document opinion summarization (Chu and Liu, 2019; Bražinskas et al., 2020b; Amplayo and Lapata, 2020; Iso et al., 2021), whose goal is to generate a summary that represents salient opinions in input reviews. However, existing opinion summarization techniques are designed to generate a single-entity opinion summary that reflects popular opinions for each entity, without taking into account contrastive and common opinions that are uniquely (commonly) mentioned in each entity (both entities) as depicted in Figure 1. Therefore, the user still needs to figure out which opinions are distinctive or common between the entities by carefully reading and comparing summaries generated by existing opinion summarization solutions.

Figure 1: Overview of the comparative opinion summarization task. The model takes two set of reviews about different entities to generate two contrastive opinion summaries, which contain distinctive opinions, and one common opinion summary, which describes common opinions between the two entities.
To this end, we take one step beyond the current scope of opinion summarization and propose a novel task of generating contrastive and common summaries by comparing multiple entities, which we refer to as comparative opinion summarization. In contrast to the conventional single-entity opinion summarization task that makes a general summary for each entity, the goal of comparative opinion summarization is to generate two contrastive summaries and one common summary from two sets of reviews about two entities. Thus, the user can easily understand distinctive and common opinions about multiple entities.

A key challenge of building a summarizer for the task is that the model has to correctly distinguish what are contrastive and common opinions from input reviews of two entities. Existing opinion summarization models do not implement this functionality as they are designed to summarize salient opinions for a single entity.

To address this issue, we develop a comparative opinion summarization framework CoCoSUM, which consists of two base summarization models for contrastive and common opinion summary generation. CoCoSUM employs a novel Collaborative Decoding (Co-decoding) that jointly uses the two models for contrastive and common summary generation. The main idea of Co-decoding is to jointly use two summarization models by aggregating the token probability distributions in the decoding step, so the models can generate more distinctive and entity-pair-specific summaries.

Experimental results on a newly created benchmark CoCoTRIP show that CoCoSUM with Co-decoding generate substantially high-quality contrastive and common summaries compared to baseline models including the state-of-the-art opinion summarization model.

Our contributions are as follows:

- We propose the novel task of comparative opinion summarization, which takes two review sets as input and outputs two contrastive summaries and one common summary.
- We develop CoCoSUM, which consists of two base summarization models and implements a novel Co-decoding algorithm that facilitates generating distinctive and entity-pair-specific summaries by aggregating the token probability distributions of the models.
- We create and release a comparative opinion summarization benchmark CoCoTRIP that contains manually written reference summaries for 50 entity pairs.\(^1\)

2 Comparative Opinion Summarization

2.1 Problem Formulation

Let \( \mathcal{C} \) be a corpus of reviews on entities from a single domain (e.g., hotels, restaurants.) For each entity \( e \), we define its review set \( \mathcal{R}_e = \{ r_{e,1}, r_{e,2}, \ldots, r_{e,|\mathcal{R}_e|} \} \).

We define a contrastive summary of a target entity \( A \) against a counterpart entity \( B \) as a summary that describes salient opinions in \( \mathcal{R}_A \) but not in \( \mathcal{R}_B \). Note that \( y_{A \setminus B} \) and \( y_{B \setminus A} \) are different unless \( \mathcal{R}_A \) and \( \mathcal{R}_B \) contain exactly same set of opinions. Similarly, we define a common summary \( y_{A \cap B} \) of entities \( A \) and \( B \) as a summary that describes common opinions in \( \mathcal{R}_A \) and \( \mathcal{R}_B \). For the

\(^1\)https://github.com/megagonlabs/cocosum
common summary, \( y^{A \cap B}_{Comm} \) and \( y^{B \cap A}_{Comm} \) are identical, thus we only consider a single common summary for an entity pair.

We formalize comparative opinion summarization as a task to generate two sets of contrastive summaries \( y^{A \setminus B}_{Cont} \cdot y^{B \setminus A}_{Cont} \), and a single common summary \( y^{A \cap B}_{Comm} \) from two sets of reviews \( R_A \) and \( R_B \) for a pair of entities \( A \) and \( B \).

Table 1 shows the task comparison against existing summarization tasks. Comparative opinion summarization is the first work that aims to generate abstractive summaries for contrastive and common opinions.

2.2 The CoCoTRIP Corpus

As the task requires three types of reference summaries for each entity pair, none of the existing benchmarks for opinion summarization can be used for evaluation. Therefore, we create a comparative opinion summarization corpus CoCoTRIP that contains human-written contrastive and common summaries for 50 pairs of entities. We sampled the entity pairs and reviews from the TripAdvisor corpus (Wang et al., 2010).

We sampled 16 reviews for each pair (i.e., 8 reviews for each entity.) For every entity pair, we collected 3 gold-standard summaries written by different annotators for two contrastive summaries and one common summary. Details of the corpus creation process are described in Appendix.

We summarize and compare the CoCoTRIP dataset with existing abstractive opinion summarization datasets in Table 2. Our dataset contains a similar scale of human-written summaries to existing abstractive opinion summarization datasets, and the input reviews are about three times longer than others.

3 CoCoSUM

For single-entity opinion summarization, input reviews can be used as pseudo summaries for training summarization models in a self-supervised fashion. This approach is not suitable for comparative opinion summarization as the task takes two sets of reviews for different entities to generate contrastive and common summaries, which have significantly different characteristics from the original review as supported by Table 2. In addition, recent studies have shown the effectiveness of pre-trained encoder-decoder models for summarization tasks (Zhang et al., 2020; Oved and Levy, 2021).

Therefore, we use a few-shot learning approach that fine-tunes a pre-trained language model using input reviews and corresponding reference summaries. However, while the few-shot learning approach helps the model acquire the writing style, we found that it was not sufficient to learn to generate summaries that contain distinctive and common opinions between two entities. This led us to design a “collaborative” decoding solution Co-decoding, which calculates the token probability distribution based on two summarization models trained for common and contrastive summary generation.

In this section, we first describe the base design of CoCoSUM; then, we introduce Co-decoding in §3.2.

3.1 Base Summarization Model

CoCoSUM consists of two summarization models that are separately fine-tuned using reference contrastive summaries and reference common summaries, respectively. Both summarization models take concatenated reviews of two entities as input. Specifically, for given two sets of reviews \( R_A = \{r_{A,1}, \ldots, r_{A,N}\} \) and \( R_B = \{r_{B,1}, \ldots, r_{B,M}\} \), the input to the model is a token sequence \( r_{A,1} \oplus \cdots \oplus r_{A,N} \oplus r_{B,1} \oplus \cdots \oplus r_{B,M} \), where each review \( r_{e,i} \) consists of a token sequence \( r_{e,i} = (x_{e,i}^{e_1}, \ldots, x_{e,i}^{e_t}) \), and \( \oplus \) denotes concatenation.

In this way, the model cannot distinguish which reviews are about which entity. Thus, we introduce additional type embeddings into the input layer of the encoder to distinguish which reviews are about the target or counterpart entity, as shown in Figure 3.

Another challenge is that the input sequence of the model becomes longer after concatenation (i.e.,
Table 2: Statistics of CoCoTRIP and other benchmarks. CoCoTRIP has a comparable corpus size against the benchmarks, while offering unique characteristics (i.e., three types of reference summaries for a pair of entities.) The average input length in tokens is calculated using concatenated input reviews.

| Task                  | # of sEnt | Inp. Review | # of Summ. | Inp. len | Summ. len | Domain         |
|-----------------------|-----------|-------------|------------|----------|-----------|----------------|
| CoCoTRIP (This work)  | Contrastive | 100 | 16 | 300 | 1529.4 | 132.9 | Hotels        |
| Bražinskas et al. (2020a) | Single | 100 | 8 | 300 | 481.3 | 61.2 | Businesses    |
| Bražinskas et al. (2020a) | Single | 60 | 8 | 180 | 469.6 | 59.6 | Products      |
| Chu and Liu (2019)     | Single | 200 | 8 | 200 | 581.1 | 70.4 | Businesses    |
| Bražinskas et al. (2020b) | Single | 60 | 8 | 180 | 473.4 | 59.8 | Products      |

Figure 3: Encoder of the base summarization model has type embeddings to distinguish the original entity of each review. In this example, we consider Entity A (Entity B) as the target (counterpart) entity.

For contrastive summary generation (i.e., \( y^{A \setminus B} \neq y^{B \setminus A} \)), we keep the original order of the target entity and counterpart entity as the model should recognize which one is the target entity. Then, we fine-tune an LED model using reference summaries for entity pairs.

For common summary generation (i.e., \( y^{AB}_{\text{comm}} = y^{BA}_{\text{comm}} \)), the model should generate the same common summary for the same entity pair regardless of the input order of review sets. Thus, we augment training data by creating both concatenation orders for fine-tuning. For the inference time, we create two input sequences (i.e., \( A \cap B \) and \( B \cap A \)) and merge the token probability distributions of the two sequences for a summary generation.

### 3.2 Collaborative Decoding

Although few-shot learning is an effective solution for training summarization models, the model may not be sufficient to generate contrastive and common summaries as the model does not have the functionality to compare and contrast two summarization models for better contrastive and common summary generation. To incorporate direct interactions between models, we design a solution Co-decoding that uses two summarization models in the decoding phase, which would help generate better contrastive and common summaries than individual models.

We denote the token probability distribution of a model \( M \in \{ \text{cont}, \text{comm} \} \) at \( t \)-th step by \( P_M(Y_t \mid y_{<t}, R_A, R_B) \). The key idea of Co-decoding is to aggregate \( P_{\text{cont}}(\cdot) \) and \( P_{\text{comm}}(\cdot) \) at each step, so the two models can collaboratively generate (1) contrastive summaries that contain distinctive opinions that do not appear in the counterpart review set and (2) common summaries that only contain common opinions that appear in both target and counterpart review sets.

**Contrastive Summary Generation** To improve the distinctiveness of generated contrastive summaries that only contains entity-specific opinions, we consider penalizing the tokens that are likely to appear in the counterpart entity. That is, we use two token probability distributions and highlight tokens that are distinctive compared to the counterpart entity by using the token ratio distribution between them. We also introduce a trade-off hyperparameter \( \delta \) that controls the balance between the original token distribution and the token ratio distribution:

\[
\hat{p}_{\text{cont}}^{A \setminus B}(Y_t) \propto p_{\text{cont}}^{A \setminus B}(Y_t) \left( \frac{p_{\text{cont}}^{A \setminus B}(Y_t)}{p_{\text{cont}}^{B \setminus A}(Y_t)} \right)^{\delta}, \tag{1}
\]

where \( p_{\text{cont}}^{A \setminus B}(Y_t) := P_{\text{cont}}(Y_t \mid y_{<t}, R_A, R_B) \) is the token probability of CoCoSUM for a contrastive summary \( \hat{y}_{\text{cont}}^{A \setminus B} \). For the other contrastive summary \( \hat{y}_{\text{cont}}^{B \setminus A} \), the token probability can be obtained by simply swapping \( A \) and \( B \) in Eq. (1).
Co-decoding for contrastive summary generation is illustrated in Figure 2 (a). The intuition behind this approach is that the token ratio distribution \( p_{A \cap B}(Y_t) \) (i.e., \( A \land \neg B \)) highlights distinctive tokens that are relatively unique to the target entity, which are emphasized by combining with the original token distribution. This can be considered a variant of Product-of-Experts (Hinton, 2002; Liu et al., 2021), which models Logical AND with multiple probabilistic distributions.

Common Summary Generation

Common summaries should contain common opinions that are about a given pair of entities. However, we observe that simply fine-tuned summarization models tend to generate overly generic summaries that can be true for any entity pairs. The issue is more critical with common summaries as the target summary length is significantly shorter (20.3 tokens on avg.) than that of contrastive summaries (132.9 tokens on avg.), which we will discuss in §5.

To incorporate the entity-specific information into the common summary, we design Co-decoding to use the sum of the token probability distributions of the contrastive summarization model, which is then combined with the original token probability distribution using a trade-off hyperparameter \( \gamma \):

\[
p_{\text{comm}}(Y_t) \propto \frac{p_{\text{comm}}(Y_t)}{p_{\text{comm}}(Y_t) + \gamma \sum_{E \in \{A,\cap,B,\cap,A\}} p_{\text{cont}}(Y_t)},
\]

where \( p_{\text{comm}}(Y_t) := p_{\text{comm}}(Y_t \mid y < t, R_A, R_B) \) is the token probability distribution of the common summary model.

Co-decoding for common summary generation is illustrated in Figure 2 (b). The intuition behind this approach is that we first identify salient tokens for the input entity pair by adding the token probability distributions of contrastive summaries: \( p_A(Y_t) + p_B(Y_t) \) (i.e., \( A \lor B \)), which is then combined with the original distribution using the trade-off hyperparameter \( \gamma \). This can be considered a variant of Mixture-of-Experts (Jacobs et al., 1991), which models Logical OR with multiple probabilistic distributions and is suitable for interpolating the token probability distribution of models with different characteristics.

We would like to emphasize that Co-decoding is a token probability distribution calculation method for comparative opinion summarization based on two summarization models; thus, it is flexible of the choice of the base summarization model and the decoding algorithm. We verify the effectiveness of different configurations for Co-decoding in §5.

4 Evaluation

4.1 Experimental Settings

We used CoCoTRIP for the evaluation. For robust evaluation, we ran the training and evaluation process 5 times with different train/dev/test splits (40%/20%/40%) and report the average scores of the 5 trials.

For CoCoSUM, we used Hugging Face’s Transformers library (Wolf et al., 2020) for implementation and pre-trained models. For both contrastive and common opinion summarization models, we fine-tuned a pre-trained LED model allenai/led-base-16384\(^2\). We used Adam optimizer (Kingma and Ba, 2015) with a linear scheduler with an initial learning rate of 0.002 and a warm-up step of 1000. For Co-decoding, we used top-\(p\) vocabulary (Holtzman et al., 2020) with \( p = 0.9\), which is the smallest token set whose cumulative probability exceeds \( p \), for \( p_{A \cap B}(Y_t) \), \( p_{B \setminus A}(Y_t) \), and \( p_{\text{comm}}(Y_t) \). We used Beam Search with a width of 4. We chose \( \delta \) and \( \gamma \) using the dev set.

We compare CoCoSUM with a variety of opinion summarization models as baselines, namely LexRank (Erkan and Radev, 2004; Reimers and Gurevych, 2019)\(^3\), MeanSum (Chu and Liu, 2019)\(^4\), OpinionDigest (Suhara et al., 2020)\(^5\), CopyCat (Bražinskas et al., 2020b)\(^6\), and BiMean-VAE (Iso et al., 2021)\(^7\).

Evaluation Metrics

For summarization quality, we use ROUGE 1/2/L F1 scores (Lin, 2004)\(^8\) as automatic evaluation based on reference summaries. To evaluate the distinctiveness of generated summaries, we calculate the average distinctiveness score (DS) between generated contrastive summaries and common summaries for all entity pairs.

\(^2\)https://huggingface.co/allenai/led-base-16384
\(^3\)https://github.com/UKPLab/sentence-transformers
\(^4\)https://github.com/sosuperic/MeanSum
\(^5\)https://github.com/megagonlabs/opiniondigest
\(^6\)https://github.com/abrazinskas/Copycat-abstractive-opinion-summarizer
\(^7\)https://github.com/megagonlabs/coop
\(^8\)https://github.com/Diego999/py-rouge
Table 3: ROUGE scores (summarization quality) for contrastive and common summaries on CCoTRIP and the distinctiveness score (DS) of generated summaries. Bold-faced and underlined denote the best and second-best scores, respectively.

| Unsupervised Extractive | Contrastive | Common | Pair |
|--------------------------|-------------|--------|------|
| LexRank (Takan and Radev, 2004) | R1 ↑ | 23.28 | 13.85 | 21.82 | 14.50 | 43.69 | R2 ↑ | 3.68 | 22.38 | 4.54 | 15.44 | 40.51 |
| LexRankBERT (Reimers and Gurevych, 2019) | RL ↑ | 27.64 | 15.89 | 23.01 | 4.02 | 14.87 | DS ↑ | 11.82 | 21.01 | 4.54 | 24.05 | 39.34 |

| Abstractive | Intra-ROUGE F1↓ | R1 | 68.23 | 50.52 | 71.61 | 54.81 |
|-------------|------------------|----|----------|---------|----------|---------|
| MeanSum (Chu and Liu, 2019) | BiMeanVAE (Iso et al., 2021) | 32.75 | 7.39 | 18.98 | 32.75 | 7.39 | 18.98 |
| OpinionDigest (Suhara et al., 2020) | Few-shot | 37.27 | 8.91 | 20.77 | 37.27 | 8.91 | 20.77 |
| CopyCat (Bražinskas et al., 2020b) | | 23.19 | 6.43 | 16.23 | 23.78 | 6.43 | 16.23 |
| BiMeanVAE (Iso et al., 2021) | | 37.87 | 9.82 | 22.20 | 37.87 | 9.82 | 22.20 |

| Few-shot | Inter-ROUGE F1↓ | R1 | 71.61 | 50.52 | 71.61 | 54.81 |
|-----------|------------------|----|----------|---------|----------|---------|
| CoCoSUM | Best Unsupervised | 68.23 | 49.12 | 54.81 |
| w/o Co-decoding | Few-shot | 32.75 | 7.39 | 18.98 |
| Human upper bound | | 38.07 | 7.94 | 20.17 |

| Common | Inter-ROUGE F1↓ | R1 | 55.69 | 37.93 | 55.69 | 50.35 |
|--------|------------------|----|----------|---------|----------|---------|
| CoCoSUM | Best Unsupervised | 71.61 | 50.52 | 59.84 |
| w/o Co-decoding | Few-shot | 55.69 | 37.93 | 50.35 |
| Human upper bound | | 38.18 | 16.72 | 30.11 |

Table 4: Intra-ROUGE scores for contrastive summary generation (above) and Inter-ROUGE scores for common summary generation (below.)

4.2 Results

As shown in Table 3, CoCoSUM outperforms the baseline methods for the ROUGE scores (summarization quality) and the distinctiveness score (DS), showing the effectiveness of few-shot learning and Co-decoding. Comparing the ROUGE scores by CoCoSUM and CoCoSUM w/o Co-decoding, we confirm that Co-decoding sacrifices the summarization performance as expected while significantly improving the distinctiveness, achieving the same quality level as the gold-standard summaries. We will further analyze and discuss the distinctiveness of generated contrastive and common summaries in §5.

Among the baseline methods, BiMeanVAE shows the highest ROUGE scores while performing poorly for the distinctiveness score. Although MeanSum and OpinionDigest show high distinctiveness score, those models show significantly worse performance on the common summary generation task. The results indicate it is challenging for existing opinion summarization models to improve the distinctiveness of generated summaries while keeping them high-quality for both of the tasks.

4.1 Distinctiveness in Generated Summaries

In addition to the summarization quality, distinctiveness is another important factor for comparative opinion summarization to help the user pick one against the other. Therefore, we conduct additional analysis to investigate the quality of distinctiveness in generated summaries.

How distinctive are generated contrastive summaries for each entity pair? Since we already confirm that CoCoSUM achieves the best performance for the distinctiveness score, we investigate pairs of generated contrastive summaries to verify
the intra-entity-pair distinctiveness of contrastive summaries generated by CoCoSUM. To this end, we measure the intra-entity-pair ROUGE (Intra-ROUGE) scores between a pair of generated contrastive summaries for each entity pair.

Table 4 (above) shows that CoCoSUM significantly outperforms the state-of-the-art opinion summarization model (BiMeanVAE) and the ablated version of CoCoSUM (i.e., w/o Co-decoding.) The results confirm that Co-decoding successfully generates contrastive summaries that contain distinctive opinions of each other.

**Does Co-decoding address the overly generic summary issue for common summaries?** As mentioned in §3.2, the simply fine-tuned model suffers from generating overly generic summaries that can be true for any entity pairs. We verify if CoCoSUM successfully addresses the issue by using Co-decoding, which takes into account salient tokens that are specific to a given entity pair from the contrastive summarization model. Thus, we measure inter-entity-pair ROUGE (Inter-ROUGE) scores as a distinctiveness metric in a similar manner as the Cross-Product Diversity proposed in (Oved and Levy, 2021).

Similar to the Intra-ROUGE scores, CoCoSUM also shows strong performance for the Inter-ROUGE scores as shown in Table 4 (below.) The results confirm that Co-decoding successfully addresses the overly generic summary issue, indicating that CoCoSUM generates a meaningful common summary for each entity pair.

### 5.2 Analysis on Co-decoding Design

Our design of Co-decoding uses different types of distribution aggregation methods for contrastive (Eq. (1)) and common summary generation (Eq. (2).) Although those designs are supported by the intuitions, we examine how the quality of generated summaries is affected when different configurations in Co-decoding are used for each task.

**Contrastive Summary Generation** First, we tested the Mixture-of-Experts style aggregation that is used for contrastive summary generation. Specifically, we use addition to combine the original distribution and the ratio distribution instead of multiplication: \( \frac{p^\text{cont}(Y_t)}{p^\text{comm}(Y_t)} \).

As shown in Table 5, this configuration does not generate contrastive summaries with an acceptable quality (thus, low Intra-ROUGE scores are not meaningful.)

We observe that this design causes a serious distribution collapse issue in the aggregated token probability distribution. This is mainly caused by the lack of the cancellation effect obtained by the Product-of-Experts style aggregation. That is, if the probability of a token were low in the ratio distribution, it would be canceled out via the multiplication operation.

We also tested another way to highlight contrastive opinions using the common summary generation model for the ratio distribution. That is, we replace the ratio distribution in Eq. (1) with \( \frac{p^\text{cont}(Y_t)}{p^\text{comm}(Y_t)} \). The result (\( p^\text{cont}/p^\text{comm} \) in Table 5) shows competitive performance as the original design with respect to the Intra-ROUGE scores. However, this configuration does not perform well in the summarization performance (i.e., the standard ROUGE scores.) This may be attributed to the fact that the contrastive and common summaries have significantly different characteristics, especially in the writing style and the summary length. Therefore, when the decoding step goes beyond the average length of common summaries, the common summary generation model might not provide a meaningful token probability distribution, which can harm summary generation by Co-decoding.

**Common Summary Generation** Similarly, we verified the effectiveness of the Product-of-Experts style configuration for common summary generation. That is, we use multiplication instead of addition: \( p^\text{cont}(Y_t) \prod_{E \in \{A, B, A, B\}} p^E_{\text{cont}}(Y_t) \).

The result in Table 5 shows that the configuration (Product-of-Experts) performs competitively with the original Co-decoding for the standard ROUGE scores while the Inter-ROUGE scores were significantly degraded. This indicates that Product-of-Experts focus too much on the tokens that are
likely to appear in both contrastive and common summaries, and thus it tends to generate overly generic summaries.

5.3 Qualitative Analysis

To further analyze the effect of Co-decoding in CoCoSUM, we conduct qualitative analysis on contrastive and common summaries generated by CoCoSUM and CoCoSUM without Co-decoding.

Contrastive Summary Generation Table 6 shows example generations by CoCoSUM with and w/o Co-decoding for contrastive summary generation. While both models generate summaries that are consistent with the target entity reviews, the summaries generated by CoCoSUM w/o Co-decoding tend to contain common opinions (highlighted in orange) that are true for both of the entities. This is not suitable for the comparative opinion summarization purpose, as the user would like to quickly understand the key difference from the contrastive summary. On the other hand, CoCoSUM successfully generates summaries that contain more entity-specific opinions (highlighted in blue), which help the user contrast the entities.

Common Opinion Summarization Table 7 shows examples of common summaries generated by CoCoSUM with and w/o Co-decoding for a couple of entity pairs. CoCoSUM w/o Co-decoding generates quite similar common summaries (highlighted in orange) even for different entity pairs. This is a limitation of the few-shot learning approach that is biased by the characteristics of reference common summaries in the training data. By getting feedback from the contrastive summarization model using Co-decoding, CoCoSUM can generate common summaries that contain entity-pair specific opinions (highlighted in blue) in addition to common opinions.
6 Related Work

Abstractive Opinion Summarization Abstractive opinion summarization aims to generate a fluent and concise summary that reflects salient opinions in input reviews. Due to the lack of sufficient amount of reference summaries, the most common solution is the unsupervised approach that trains a summarization model with the reconstruction objective (Chu and Liu, 2019; Bražinskas et al., 2020b; Amplayo et al., 2021b; Elsahar et al., 2021; Im et al., 2021; Wang and Wan, 2021; Isonuma et al., 2021; Iso et al., 2021).

Recent opinion summarization models use the few-shot learning approach that fine-tunes a pre-trained language model (Devlin et al., 2019; Lewis et al., 2020; Raffel et al., 2020) with a limited amount of pairs of input reviews and reference summaries. Bražinskas et al. (2020a) and Oved and Levy (2021) show that the few-shot learning approach substantially outperforms conventional unsupervised learning models.

All the existing methods listed above are designed for general opinion summarization and, thus, are not necessarily suitable for comparative opinion summarization, as shown in the experiments.

Controllable Summarization Controlling the summarization model is an important problem to satisfy various requirements (Fan et al., 2018), and conventional methods have used control tags (He et al., 2020), guidance signals (Dou et al., 2021), and classifiers (Cao and Wang, 2021).

For the opinion summarization, aspect-based control has gained much attention (Angelidis and Lapata, 2018; Suhara et al., 2020; Angelidis et al., 2021; Amplayo et al., 2021a). AceSum (Amplayo et al., 2021a), for example, uses an aspect controller to create aspect-specific pseudo-review-summary pairs, and train the aspect-specific summarizer.

Our proposed method, Co-decoding, can be seen as a method to control the summarization model. In Co-decoding, the target summarization model is controlled by using the counterpart summarization model.

Comparative Summarization There is a line of work on extracting comparative information from single/multiple documents. Lerman and McDonald (2009) defined the contrastive summarization problem and presented early work on the problem. Their method selects sentences so that two sets of summaries can highlight differences. Wang et al. (2013) developed an extractive summarization method for a problem of Comparative Document Summarization, which is to select the most discriminative sentences from a given set of documents. Bista et al. (2019) tackled a similar problem by selecting documents that represent in-cluster documents while they are useful to distinguish from other clusters.

Other studies (Kim and Zhai, 2009; Huang et al., 2011; Sipos and Joachims, 2013; Ren et al., 2017) tackled similar tasks by developing extracting sentences/phrases from given sets of documents for comparative document analysis. Topic models have been also used to capture comparative topics for better understanding text corpora but they do not generate textual summaries (Ren and De Rijke, 2015; He et al., 2016; Ibeke et al., 2017).

Our work differs from them in two points, as shown in Table 1: First, none of the work focuses on generating common summaries. Second, all of the previous studies for contrastive summary generation use the extractive approach. To the best of our knowledge, we are the first to develop an opinion summarization model and a benchmark for abstractive contrastive and common summary generation tasks.

7 Conclusions

In this paper, we propose a new comparative opinion summarization task, which aims to generate contrastive and common summaries from reviews of a pair of entities, to help the user answer the question “Which one should I pick?” To this end, we
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A The CoCoTRIP Corpus

A.1 Entity-Pair Selection

For comparative opinion summarization, each of the selected entity pairs should always be comparable. To achieve this goal, we leverage the meta information of hotels in the TripAdvisor corpus to make sure that the selected entity pairs always locate in the same region (e.g., Key West of Florida.)

A.2 Annotation

The input for each entity pair includes 16 reviews, which may be too difficult for human writers to write summaries from. Thus, we used a two-stage annotation method to ensure the quality of reference summaries.

Sentence Annotation Our first annotation task focuses on obtaining a set of sentences that contain contrastive and common opinions. Since the average number of sentences in each entity pair (90 in CoCoTRIP) was too many to annotate at once, we grouped sentences based on their aspect category to further simplify the annotation task. In particular, we first split input reviews into sentences. Then, we grouped sentences into 6 aspect categories (i.e., general, staff, food, location, room, and others) using a BERT-based aspect category classifier trained with 3K labeled sentences. By doing so, we ensure that the number of sentences annotators need to review each time is no more than 20. For every sentence from entity $e_A (e_B)$, we asked human annotators to compare it against a group of reference sentences of the same aspect category from entity $e_B (e_A)$ and to distinguish whether it contains any
common opinions that also appear in the reference sentences.

We collected 3 annotations and finalized the label through a majority vote. We obtained labels suggesting whether it contains contrastive or common opinions for every sentence in the entity pairs with the sentence annotation task.

**Summary Collection**  In the second annotation task, we first asked human writers to write aspect-based summaries. To exclude unreliable labels obtained in the previous step, we displayed two sets of sentences, one from each entity, to human writers for the summary collection task. This helps human writers ignore irrelevant or incorrectly labeled sentences. For example, to obtain the contrastive summary for aspect location, we first show two corresponding sets of contrastive sentences from both $e_A$ and $e_B$ based on the labels we collected in the previous annotation step. Then, we asked human writers to write two contrastive summaries for $e_A$ and $e_B$, respectively. Similarly, we asked human writers to write a single common summary by showing two corresponding sets of common sentences. By doing so, we obtained aspect-based summaries for each entity pair, which are then concatenated into a reference summary. For every entity pair, we collected 3 reference summaries for each of two contrastive summary generation and one common summary generation tasks.