Aspect-Oriented Summarization through Query-Focused Extraction

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Abstract

A reader interested in a particular topic might be interested in summarizing documents on that subject with a particular focus, rather than simply seeing generic summaries produced by most summarization systems. While query-focused summarization has been explored in prior work, this is often approached from the standpoint of document-specific questions or on synthetic data. Real users’ needs often fall more closely into aspects, broad topics in a dataset the user is interested in rather than specific queries. In this paper, we collect a dataset of realistic aspect-oriented test cases, ASPECTNEWS, which covers different subtopics about articles in news sub-domains. We then investigate how query-focused methods, for which we can construct synthetic data, can handle this aspect-oriented setting: we benchmark extractive query-focused training schemes, and propose a contrastive augmentation approach to train the model. We evaluate on two aspect-oriented datasets and find this approach yields (a) focused summaries, better than those from a generic summarization system, which go beyond simple keyword matching; (b) a system sensitive to the choice of keywords.\textsuperscript{1}

1 Introduction

Recent progress in text summarization (See et al., 2017; Liu and Lapata, 2019; Zhang et al., 2020a; Lewis et al., 2020) has been supported by the availability of large amounts of supervised data, such as the CNN/Daily Mail and XSum datasets (Hermann et al., 2015; Narayan et al., 2018), which provide a single, generic, topic-agnostic summary. However, a document often contains different aspects (Titov and McDonald, 2008; Woodsend and Lapata, 2012) that might be relevant to different users: for example, an article about an earthquake disaster contains information about geographic factors, recovery efforts, and broader social impacts, and a single generic summary of these factors may not be concise or what any user wants. Instead, systems should be able to produce summaries tailored to the diverse information needs of different users.

A large body of previous work focuses on query-focused summarization models (Baumel et al., 2014; Krishna and Srinivasan, 2018; Frermann and Klementiev, 2019; He et al., 2020; Xu and Lapata, 2020a) targeting example-specific queries or facts. A query like “What was the magnitude of the earthquake in Indonesia last Friday?” is a document-specific query, which could not be applied to other earthquake news articles and bears more resemblance to question answering (Fan et al., 2019). Our focus is closer to work on attribute extraction from opinions or reviews (Dong et al., 2017; Angelidis and Lapata, 2018), but particularly targets generalizing to domain-specific aspects in news. Factors like geographic details and recovery efforts are usually mentioned in many earthquake stories. Most crucially, previous work frequently adopts either synthetic settings (Frermann and Klementiev, 2019) or per-document keywords (Baumel et al., 2014) for evaluation.

In this work, we aim to build a system that can summarize a document conditioned on certain aspect-level queries when we do not have training data in our target domain.

To evaluate the model and compare it with other approaches, we present a new dataset for single-document aspect-oriented extractive summarization which we call ASPECTNEWS built around user information needs. We derive subsets of examples from CNN/DM following certain topics, namely earthquakes and fraud reports. These domains are special in that the articles within them have several aspects which are repeatedly mentioned across articles and form coherent topics, e.g., impact on human lives of an earthquake. We ask annotators to select sentences relevant to such an informa-
1. At least 42 people have died with hundreds more injured after a 6.2-magnitude earthquake hit Indonesia's Sulawesi Island early Friday, according to Indonesia's Disaster Management Agency.
2. The epicenter of the quake, which struck at 1:28 a.m. Jakarta time, was 6 kilometers (3.7 miles) northeast of the city of Majene, at a depth of 10 kilometers (6.2 miles), according to Indonesia's Meteorology, Climatology and Geophysics Agency.
3. Thirty-four people died in the city of Mamuju, to the north of the epicenter, while another eight died in Majene.
4. In Majene, at least 637 were injured and 15,000 residents have been displaced, according to […]
5. Many people are still trapped under collapsed buildings, according to local search and rescue teams.
6. Rescuers search for survivors at a collapsed building in Mamuju city in Indonesia.
7. “Our priority is saving victims who are still buried under the buildings,” Safaruddin Sanusi, head of West Sulawesi's Communications and Information Department, told CNN Friday. […]
8. “Most…of the people in Mamuju city are now displaced. They are afraid to stay at their houses.”
9. “We need more extrication equipment and more personnel to work fast on saving victims trapped under the building.”

Figure 1: Examples of an earthquake-related article paired with extractive summaries from the CNN/DM dataset. “Generic” represents the selection of a general purpose summarization model. “Geo(graphy)” (colored in green) and “Recovery” (colored in orange) indicate our aspects of interest for the summary. We highlight aspect-relevant phrases in the document.

There are several key differences between ASPECTNEWS and existing aspect-oriented summarization datasets. Firstly, ASPECTNEWS focuses on evaluation of single-document summarization, while similar aspect-oriented datasets such as the SPACE dataset (Angelidis et al., 2021) focus on multi-document systems. Secondly, our model supports summarization of arbitrary aspects at test time, whereas SPACE and the associated model require approximately fifty scored seed words per aspect. Thirdly, compared to query-focused settings, our aspect-oriented dataset is closer to the actual information needs of users, since users are often interested in summaries about broad subtopics rather than specific queries.

Since there are no large-scale supervised training sets for targeting these sorts of aspects or broad topics in summarization, we explore what query-focused summarization techniques can do here. We devise a method to collect query-focused training data based on documents with generic summaries. We compare these with past approaches (Freermann and Klementiev, 2019) on their ability to adapt to our aspect-oriented setting, provide a system that can take generic query inputs (as opposed to specific entities or summary), and be sensitive to the input keywords.

Our experiments on our ASPECTNEWS dataset and the SPACE dataset yield several results. We find that a model trained on this query-focused training data produces summaries that score higher on agreement with human aspect-oriented annotations than generic summarization models, previous work on aspect-oriented summarization, and baselines such as keyword matching. Second, we find that the summaries our model generates are sensitive to the choice of query words. Thirdly, we find that our model performs competitively to leading models on the SPACE dataset in the multi-document setting. Finally, we find that an abstractive query-focused system hallucinates significantly in this setting (He et al., 2020), justifying our choice of an extractive framework here.

2 Related Work

Transformer-based text summarization models (Liu and Lapata, 2019; Lewis et al., 2020; Zhang et al., 2020a) have made great progress in the past few years, but little of this work is specifically on aspect-oriented or query-focused summarization. A lack of query-focused summarization datasets which simulate real users’ intent also poses a challenge for the field.

Methods Historically, most work on query-focused summarization has tackled the multi-document setting. You et al. (2011) apply regression models to this task, and Wei et al. (2008) approach the problem from the perspective of ranking sentences by their similarity to the query. These classic methods rely integrally on the multi-document setting, and so cannot be easily adapted to our task. More recently, Xu and Lapata (2020b) focus on multi-document summarization by modeling the applicability of candidate spans to both the query and their suitability in a summary. Angelidis et al. (2021) explore a method using quantized transformers for aspect-oriented summarization.
Datasets  The TAC 2010/2011 summarization dataset propose guided summarization tasks that involve similar aspects. However, each article cluster in TAC has a single, fixed set of aspects which don’t substantially differ from what a generic, non-query-focused summary should capture. The DUC 2005/2006 task (Dang, 2005) does not have aspects but rather can accept a “granularity” level at which to produce the summary. Christensen et al. (2014) produce a hierarchy of relatively short summaries among multiple documents, and allow for user tuning via navigation of this hierarchy. Angelidis and Lapata (2018) introduce the SPACE dataset, a multi-document summarization dataset comprised of general and aspect-specific summaries for hotel-related articles. We evaluate the performance of our model on this dataset.

Other previous work (He et al., 2020; Xu and Lapata, 2020a; Tan et al., 2020) proposes methods to construct synthetic training and test data for query-focused summarization by constructing keyword sets for each individual document. Krishna and Srinivasan (2018); Frermann and Klementiev (2019) condition on topic tokens referring to the topic tags in metadata. Compared to these approaches, we focus more on evaluation on particular aspects, as opposed to a purely keyword-and-query-driven view. Attribute extraction from opinion or review (Dong et al., 2017; Angelidis and Lapata, 2018) resembles a query-focused task. However, our dataset focuses on generalization to new aspect types, rather than assuming we’ve seen them during training.

3 Aspect-Oriented Data Collection

We begin by considering our target application: users who have specific information needs that they want to be satisfied. These broadly fall under the category of purpose factors defined by Jones (1998).

Our data collection process involves the following steps: (1) Identifying clusters of articles in our target domains from a large corpus of news summaries. (2) Manually specifying one or more user intents per target domain, representing the aspect of the summarization process. (3) Crowdsourcing annotation of extractive summaries in these domains based on the user intents.

3.1 Target Domains

We draw our datasets from the English-language CNN/Daily Mail summarization dataset (Hermann et al., 2015). We manually identified two domains, earthquakes and fraud, based on inspecting clusters of articles in these domains. These two domains are ideal for two reasons. First, they contain a significant number of low-noise articles (over 200) after careful filtering. Second, the articles in these domains are reasonably homogeneous: each article would often feature at least broadly similar information about an event, making aspect-based summarization well-defined in these cases. Although not completely universal, most earthquake articles refer to some information about each of two concepts here: geography (GEO) and recovery (RECV). Figure 1 shows an example of an earthquake-related article. Similarly, most fraud articles include information about the penalty (PEN) imposed for the fraud, and the nature (NATURE) of the fraud. While a generic summarization model like BERTSUM summarizes across all factors and entities, an aspect-oriented summarization model should summarize with a focus towards certain aspects.

To retrieve our examples from these two domains, we first encode each article in CNN/Daily Mail corpus C with a text encoder E. We adopt the Universal Sentence Encoder (Cer et al., 2018) for its efficiency and robustness. We create an exemplar sentence for each domain to serve as the target to retrieve the most relevant content. We describe the choice of exemplar sentences in Section A.2. We measure the similarity of each candidate article c and the exemplar sentence s as the average of the dot product’s cosine similarity between each of the candidate article’s sentences c_i and the exemplar, sim(c, s) = \frac{1}{D} \sum_{i=1}^{n} \cos(E(c_i), E(s)).

We find this procedure to be more robust than simple keyword matching for finding articles relevant to domains; for example, keyword matching for “earthquakes” resulted in returning articles primarily about tsunamis due to the imbalanced data distribution.

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3By contrast, other domains like legislation were too heterogeneous: articles about passing a bill may focus on different aspects of a bill’s journey, comments or quotes by elected officials, impact of the legislation, or other factors. We could not come up with a plausible unified information need for the sorts of articles available in this dataset.
Table 1: Prompts and keywords used for each of our two domains: Earthquake and Fraud. These represent prominent topics that users might be interested in.

| Domain | Aspect | Prompt | Keywords |
|--------|--------|--------|----------|
| Earthquake | GEO | geography, region, or location recovery and aid efforts (death toll and injuries, foreign/domestic government assistance, impact on survivors) | region, location, country, geography, miles recovery, aid, survivor, injury, death |
| |Recv | | |
| Fraud | PEN | penalty or consequences for the fraudster, or for others | penalty, consequences, jailed, fined, court amount, money, bank, stolen, time |
| | NATURE | nature of the fraud: the amount of money taken, benefits for the fraudster, and how the fraud worked | |

3.2 Specifying User Intents

With these two domains, we examine the dataset and come up with aspects which cover most articles and meet the realistic information needs of users. Table 1 describes the domain, aspect, annotation prompt and keywords used for evaluation. For each domain, we establish two aspects. Each aspect must be well-represented in the corpus and easy to understand by both readers and annotators. The authors annotated these aspects based on inspection of the articles and brainstorming about user intents based on scenarios. For example, the penalty scenario was motivated by a real use case derived from the authors’ colleagues investigating reporting of wrongdoing in news articles at scale, where summarization can be used to triage information.

3.3 Crowdsourcing

Finally, to construct actual extractive summaries for evaluation in these domains, we presented the user intents to annotators on Amazon Mechanical Turk. An annotator is shown a description of intent from Table 1 along with an article and is asked to identify a few sentences from the article that constitute a summary. They can rate each sentence on a scale from 0 to 3 to account for some sentences being more relevant than others. Their final summary, which they are shown to confirm before submitting, consists of all sentences rated with a score of at least 1. The exact prompt is shown in the Appendix.

Each article was truncated to 10 sentences for ease of annotation. This assumption was reasonable for the two domains we considered, and the truncation approach has been used in See et al. (2017) without much performance degradation. We found that annotators were unlikely to read a full length article due to the inherent lead bias in news articles, so this was both cognitively simpler and also cheaper. In order to maintain a high quality of annotations, we discard annotations that do not have at least a single selected sentence in common with at least a single other annotator on that sample. In practice, this only discards a handful of isolated annotations.

3.4 Data Analysis & Annotator Agreement

In Table 2, we show the basic statistics of the collected dataset. We show the distribution of the number of sentences agreed upon by the annotators in Table 3. We see that annotators are likely to at least somewhat agree in most cases, but note that there is a substantial tail of disagreement. We view this disagreement as inherent to the task and evaluate on it accordingly.

We also compare the overlap between aspect based annotation and generic extractive oracle derived from reference summaries from CNN/DM. In Table 4, the similarity and exact match between generic oracle and annotated summaries are fairly low, which means the annotated aspect driven summaries significantly differ from the standard extractive oracle.

Table 2: Statistics for the collected datasets. For each aspect we collect 100 examples and with each example there are 5 turkers’ annotation. #sent and #words are the average number of sentences selected and average number of words in each sentence.

| Domain | # samples | # sent | # words |
|--------|-----------|--------|---------|
| PEN    | 100       | 2.90   | 30.5    |
| NATURE | 100       | 2.79   | 29.9    |
| GEO    | 100       | 2.53   | 28.4    |
|Recv    | 100       | 2.76   | 27.0    |

Table 3: Majority agreement distribution of 5 annotators on filtered collected data.

| Agreement | 1 | 2 | 3 | 4 | 5 |
|-----------|---|---|---|---|---|
| Freq (%)  | 19.61 | 29.26 | 25.16 | 19.16 | 6.80 |

The number of annotated examples for each aspect is 100, so the EM is an integer.
Table 4: Comparison of annotation labels and the non-query focused extractive oracle derived from reference summaries. We take the top-3 most common selected sentences from each aspect-oriented dataset and compute Jaccard similarity between the sets and the percentage of exact matches (EM).

| STDRef vs. | Jaccard Sim. | EM (%) |
|------------|--------------|--------|
| PEN        | 0.247        | 1.0    |
| NATURE     | 0.249        | 2.0    |
| GEO        | 0.265        | 2.0    |
| RECIV      | 0.201        | 1.0    |

Table 5: An example article from CNN/DM and keywords extracted. These keywords indicate both highly specific concepts and broad topic, but a model trained on data with appropriate reference summaries can learn to leverage either specific or generic keywords in the summarization process.

We experiment with two different criteria to select these sentences. Following Gillick and Favre (2009); Nallapati et al. (2017), we explore maximizing ROUGE-2 score of sentence combinations with respect to the abstractive summaries in the dataset.

However, one drawback of this method when used with query words is that it overly favors exact lexical overlap and ignores semantic similarity which requires “soft” match. To improve the quality and robustness of extractive labels, we also adopt BERTScore (Zhang et al., 2020b) to identify sentences that closely match the reference summary. BERTScore turns out to boost the evaluation performance by a large margin, as shown in Table 12, so we use BERTScore for oracle extraction for all our experiments.

Reference Summary Modification It is crucial for a query-focused model to learn a dependence between the query tokens and the generated summary. To accomplish this, when training we modify the generic gold summary to better reflect the query tokens. We concatenate the query tokens with the reference summary before computing the extractive oracle summary, thus incentivizing selection of sentences that relate to the query. Modifying the reference summary requires maintaining a balance between the influence of query words and of the original gold summary. Note that the extractive summary for training can change solely based on the query tokens, even if the document remains the same, and this is the intended behavior.
Keyword Intensity The constructed summaries for oracle derivation consists of concatenated keywords and the original summaries. To mediate the relative influence of the query tokens versus the original summary, we introduce a tunable parameter $k$, referring to the ratio of query tokens to original reference summary tokens. Higher values of $k$ lead to extracting sentences in a manner more closely approximating keyword matching, but yielding poor standalone summaries. On the other hand, lower values of $k$ may lead to generic summaries insensitive to the query tokens. In practice, the number of times a keyword $w$ is concatenated to the original summary $S$ is defined as $k \times \frac{\text{len}(S)}{\#(\text{keywords})}$, where $\text{len}(S)$ is the number of tokens in the original summaries and $\#(\text{keywords})$ is the total number of keywords available. When $k = 1$, the concatenated keywords have the same length of the original summary.

Contrastive Training When using contrastive training, we augment the training data with multiple variants of each original document from the dataset. Each document in the original dataset is mapped to two training samples, (1) a document without query tokens and an unmodified oracle extractive summary, (2) a document with query tokens and an oracle extractive summary using our modification procedure. We hypothesize that the contrastive approach allows the model to better recognize the intended impact of the query words on the generated summary. An added benefit of a contrastive model is that it can also produce reasonable generic summaries when so desired (not prompted with a query), since its training data is a strict superset of a generic model.

4.2 Query-Focused Model

Our model is trained to predict a summary $S$ from a document-query pair $(D, q)$. Following BERTSUM (Liu and Lapata, 2019), we fine-tune BERT (Devlin et al., 2019) for extractive summarization using our modified query-focused CNN/Daily Mail dataset. During training, we prepend a special query token followed by the query tokens to the original document, and use the modified oracle extractive summary as the gold outputs. During inference, the query words are user-defined.

5 Experiments

We evaluate our model on the ASPECTNEWS dataset, comparing performance on aspect-oriented summarization to several baselines. We additionally experiment on the SPACE multi-document dataset (Angelidis et al., 2021) to evaluate our performance in an abstractive setting.

5.1 Metrics

On ASPECTNEWS, we evaluate our model against the annotations using using $F_1$ score and ROUGE scores. Since the system summaries are extractive and the annotators labeled sentences to include in each summary, we can calculate $F_1$ score. Let the total number of annotators be denoted $a$, the number of annotators who selected sentence $i$ be denoted $a_i$, and the model’s predictions be denoted $P$. Then the precision of the model against the human annotations is $\frac{\sum_{i \in P} \alpha_i}{\sum_{i \in P} \alpha_i}$, the recall is $\frac{\sum_{i \in P} \alpha_i}{\sum_{i \in P} \alpha_i}$, and $F_1$ is the harmonic mean. Note that it is impossible to achieve 100 $F_1$ on this task due to disagreement between the annotators. We elected to preserve this disagreement to model human preferences on this task, as has been explored for NLI (Pavlick and Kwiatkowski, 2019; Nie et al., 2020).

One downside of $F_1$ evaluation is that the model may be penalized for selecting a different sentence from the human annotator, even when the predicted sentence is very similar to the annotation. To address this, we also calculate ROUGE-1, -2, and -L scores (Lin, 2004).

On the SPACE dataset, the gold summaries are abstractive, so we only calculate ROUGE scores.

5.2 Baselines & Competitor Models

For the ASPECTNEWS dataset, we benchmark our system against several other models and baselines, which we divide up by whether or not they are based on text summarization models.

On the SPACE corpus, we primarily focus on comparisons to quantized transformer (QT) (Angelidis et al., 2021) and CTRLSUM (He et al., 2020).

Non-model Baselines We first propose three non-model baselines which do not involve any summarization model. KEYWORD takes the keywords described in Table 1 and greedily finds the first occurrence of each keyword in the input document. STDREF stands for the extractive oracle given the original reference summaries from CNN/DM. QA is an ELMo-BiDAF Question Answering Model.
The input of the QA model includes the question and the input article. For each question, the output of the model is a span in the document. We select the sentence where the span is located as the extracted sentence. All these metrics are extractive baselines where top sentences are selected.

**Table 7: ROUGE-L scores on the SPACE dataset of our model, QFSUMM, versus baselines on the ASPECTNEWS dataset in both the earthquakes and fraud domains. For the earthquakes domain we have geography (GEO) and recovery (RECV) aspects, while for the fraud domain we compare on penalty (PENANNOT) and recovery (RECVANNOT) aspect annotations. The last row displays the maximum possible F1 score due to the disagreement of annotation.**

| Model      | PENANNOT | NATUREANNOT | GEOANNOT | RECVANNOT |
|------------|-----------|-------------|----------|-----------|
|            | F1 R-1 R-2 R-L | F1 R-1 R-2 R-L | F1 R-1 R-2 R-L | F1 R-1 R-2 R-L |
| STDREF     | 32.9 51.7 39.5 40.7 | 33.5 53.0 41.3 42.0 | 34.9 51.9 41.3 42.1 | 28.2 45.7 33.0 37.4 |
| KEYWORD    | 39.2 62.0 50.6 47.1 | 38.3 58.7 46.6 45.0 | 50.9 67.9 59.9 53.7 | 32.8 53.3 41.6 43.9 |
| QA         | 30.7 46.9 36.8 37.7 | 26.5 39.1 28.8 32.2 | 52.4 63.0 58.9 **56.8** | 32.9 46.6 36.5 38.5 |
| BERTSUM    | 40.1 60.1 47.8 46.5 | 41.6 63.5 51.7 **49.4** | 46.4 65.4 56.4 51.4 | 37.3 55.8 44.8 44.6 |
| BERT-FK    | 24.5 43.9 28.9 33.2 | 21.0 40.8 23.4 28.3 | 23.9 42.4 30.3 32.9 | 21.4 35.4 21.3 26.9 |
| CTRLSUM    | N/A 47.8 30.2 33.0 | N/A 51.7 35.3 35.4 | N/A 21.6 8.0 19.6 N/A | 32.3 11.6 19.2 |
| QFSUMM     | **44.8** 64.2 **54.1** **51.6** | **45.2** 64.4 **53.9** 48.0 | 49.9 **69.1** **61.2** 54.2 | **39.6** **59.5** **49.1** **46.7** |

Table 7: ROUGE-L scores on the SPACE dataset of our model, QFSUMM, versus BERTSUM, CTRLSUM, and quantized transformer (QT). Despite being an extractive model, our approach is competitive with strong query-focused or aspect-based models.

**Model Baselines** We also compare our QFSUMM model against text summarization models, and query-focused models from previous work (retrained or off-the-shelf). (i) BERTSUM is a bert-base-cased extractive summarization model fine-tuned on CNN/DM (Liu and Lapata, 2019). (ii) BERT-FK shares the similar model architecture as BERTSUM but the training data comes from Frermann and Klementiev (2019). This data is constructed by interleaving several articles from the CNN/DM dataset together, extracting a coarse aspect from the original URL of one of the article, and setting the new gold summary to match that article. (iii) CTRLSUM⁵ is an off-the-shelf abstractive summarization model with the capability of conditioning on certain queries or prompts (He et al., 2020). (iv) Our model QFSUMM is based on BERTSUM and trained with techniques described in Section 4.

5https://github.com_salesforce/cstrl-sum

### 5.3 Results

We assess our model performance on aspect-oriented datasets, compared to other models and baselines.

**ASPECTNEWS** The experimental results on ASPECTNEWS are shown in Table 6. We find that our model outperforms these baselines across the F1, ROUGE-1, ROUGE-2, and ROUGE-L scores. Significantly, our model generally outperforms keyword matching, demonstrating that semantic match information derived from BERTScore ranking may be more useful than pure lexical match information in tasks of this type. We note that our model’s performance falls behind keyword matching some baselines in the geography aspect; this may be because the aspect is relatively homogeneous and can be easily approximated by keyword matching.

**SPACE** The results on all the aspects of the SPACE dataset are shown in Table 7. All of the aspect-oriented models exceed the performance of the generic summaries produced by BERTSUM. We also find that our model’s capabilities generalize beyond the ASPECTNEWS dataset, and performance is largely competitive with quantized transformer (QT) (Angelidis et al., 2021) and CTRLSUM (He et al., 2017; Peters et al., 2018). Instead of searching for lexical exact matches in KEYWORD, we construct synthetic questions “What is [keyword]?” and feed the question to the QA model. The input of the QA model includes the question and the input article. For each question, the output of the model is a span in the document. We select the sentence where the span is located as the extracted sentence. All these metrics are extractive baselines where top sentences are selected.

| Model      | Service | Location | Food | Building | Cleanliness | Rooms |
|------------|---------|----------|------|----------|-------------|-------|
| BERTSUM    | 12.4    | 16.7     | 13.0 | 15.6     | 13.8        | 12.5  |
| CTRLSUM    | 20.1    | 18.6     | 17.4 | 18.9     | 23.3        | 19.7  |
| QT         | 26.0    | 23.6     | 17.7 | 16.0     | 23.1        | 21.6  |
| QFSUMM     | 26.9    | 20.3     | 17.4 | 16.4     | 22.8        | 21.6  |
This is somewhat surprising because the QFSUMM model is trained using out-of-domain synthetic data, without access to the aspects before test time. Additionally, our extractive model is being evaluated in an abstractive setting.

5.4 Ablations and Analysis

Keyword Sensitivity We evaluate the sensitivity of the model to different keywords. There is some overlap between the summaries returned by different keyword sets, as shown by the Jaccard similarity: some sentences may fit under both GEO and RECv, or both PEN and NATURE. In Table 9, we find that the model is more likely to return similar summaries across different queries in the Fraud domain. We also confirm that using the keywords “matched” to our setting outperforms using other keywords. The small Jaccard similarity suggests that our model is picking summaries with sentences that are dependent upon the keywords.

Keyword Intensity The number of times we append the keywords to the reference summary in order to generate the oracle extractive summary can be varied. We experiment with different level of intensity and show the result in Table 10. For most cases, \( k = 1 \) works fairly well among all the datasets.

Contrastive vs. Non-Contrastive We compare models trained using the contrastive technique against models trained without any augmentation, and find that the contrastive technique generally provides some benefit, but inconsistently. In Table 11, the Contrastive technique is effective on GEO, PEN, and NATURE, but not RECv. The small performance improvement from Contrastive training may result from the model more easily learning the relationship between the query tokens and the aspect-oriented summaries due to contrastive examples. Another benefit of this technique is that a single model is capable of producing both generic and aspect-oriented summaries.

Oracle Derivation: BERTScore vs. ROUGE

In Table 12 we show the performance improvement from replacing ROUGE-derived oracle labels with their BERTScore-derived counterparts. Using BERTScore (Zhang et al., 2020b) to obtain oracle extractive summaries for training data produces models that are significantly stronger than models trained on sentences selected by maximizing ROUGE score. We hypothesize this is because ROUGE score maximization essentially limits what the model learns to lexical matching, while BERTScore can score based on more abstract, semantic criteria.

6 Qualitative Evaluation & Comparison

Extractive vs. Abstractive Comparison It is difficult to directly compare the quality of summaries produced by an abstractive model (such as CTRLSUM) to those produced by an extractive model (such as QFSUMM). Abstractive models do not extract individual sentences from a summary so direct F1 evaluations cannot be compared in the manner of Table 6. ROUGE scores are a mislead-
Table 12: Comparison of using ROUGE (RS) or BERTScore (BS) as the scorer for oracle extraction. BS significantly surpasses the vanilla ROUGE score on all datasets.

|        | F1   | R-1  | R-2  | R-L  | F1   | R-1  | R-2  | R-L  |
|--------|------|------|------|------|------|------|------|------|
| **PEN** |      |      |      |      | **NATURE** |      |      |      |
| RS     | 36.3 | 55.8 | 42.1 | 43.0 | 38.0 | 57.6 | 44.8 | 43.3 |
| BS     | 44.8 | 64.2 | 54.1 | 51.6 | 45.2 | 64.4 | 53.9 | 48.0 |
| **GEO** |      |      |      |      | **RECV** |      |      |      |
| RS     | 39.5 | 59.2 | 49.1 | 47.2 | 34.9 | 54.9 | 44.3 | 45.2 |
| BS     | 49.9 | 69.1 | 61.2 | 54.2 | 39.6 | 59.5 | 49.1 | 46.7 |

Keyword Sensitivity Comparison  We find that although both CTRLSum and QFSUMM are sensitive to the choice of keywords and alter their summary in response to different keywords, CTRLSum often either hallucinates false information (Maynez et al., 2020) or simply rewords the prompt in the generated summary. We found that just under the Geo keywords in the earthquakes domain, out of 100 sample articles the bigram “not known” appears 27 times in relation to describing the location of the earthquake and “not immediately known” appears another 24 times. The CTRLSum model frequently rephrases the prompt rather than synthesizing information in the document related to the keywords into a cogent summary.

Comparison of Factuality of Output  Figure 13 shows one example of CTRLSum hallucination in the Geo case, where the location of the earthquake as Yucatán is incorrect. Here, the model also rewords the prompt and inserts it into the summary without adding new information. Although such behavior may possibly perform well on automated metrics, it does not serve the purpose of query-focused summarization.

Extractive summaries  Figure 13 shows that our model is able to successfully extract relevant parts of the document for our aspects under consideration. There are some features which may make these summaries hard to process in isolation, such as the quake in the first R sentence; our method could be extended with prior techniques to account for anaphora resolution (Durrett et al., 2016).

7 Conclusion  In this paper, we present aspect-oriented text summarization as a new task, along with realistic test set called AspectNews. Unlike query focused summarization which is mostly driven by document specific facts or knowledge, aspect summarization conditions on realistic domain-specific common user intents. We propose a query-focused system trained on synthetic data and show that it can address the aspect-oriented task better than a range of strong baseline methods, and that this generalizes to multiple datasets.
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A Appendices

A.1 Training Details

For all models, we split CNN/Daily Mail set into the standard 287,226 training pairs, 13,368 validation pairs and 11,490 test pairs following See et al. (2017).

We follow the training procedure for BERTSUM (Liu and Lapata, 2019) with modifications. We use the cased variant of bert-base-cased available through Wolf et al. (2019) instead of uncased and do not lowercase the dataset during preparation. Our learning rate schedule follows Vaswani et al. (2017) with

$$lr = 2e^{-3} \cdot \min(\text{step}^{-0.5}, \text{step} \cdot \text{warmup}^{-1.5})$$

where warmup = 10000.

For fine-tuning QFSUMM on the modified CNN/DM dataset, the training completes in 8 hours on a single NVIDIA Quadro RTX 8000.

A.2 Exemplar Sentences

In order to generate earthquake and fraud domain data we filter the CNN/DM dataset using similarity between latent representations of Universal Sentence Encoder (USE) (Cer et al., 2018). To find domain-related articles, we need to generate a sentence that is vague enough to match most in-domain articles but specific enough to exclude articles outside the domain. For earthquakes we found the sentence “An earthquake occurred.” to work well. We embedded this sentence with USE, and calculated distance in latent space to articles in CNN/DM. For the fraud dataset we use the similar sentence “A fraud occurred”. After inspecting the matches, we manually exclude articles that are outside the domain.

A.3 Crowdsourcing

To improve the quality of the data collected, we educate annotators with detailed instruction and user-friendly interface shown in Figure 2. We also manually sample and check the collected data.

A.4 SPACE Evaluation Details

Several adjustments were made in order to run our model on the SPACE dataset. Since there are multiple input documents per summary, we first concatenated all documents together and treated the result as a single article. In order to process this large “article” with our model, we processed it in 512-token chunks using BERT in order to obtain representations from the [CLS] token, and then concatenated those representations together before passing them through the classification layer. This allowed selection of any sentence from any part of the input. The following keywords were used for each of the aspects in the dataset: (i) service, customer, staff, employee, assistance; (ii) location, room, region, hotel, place; (iii) food, dining, restaurant, dinner, meal; (iv) building, establishment, room, property, site; (v) cleanliness, sanitary, polished, clean, washed; (vi) rooms, chair, table, bed, wall.