Fine-Grained Opinion Summarization with Minimal Supervision

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Abstract

Opinion summarization aims to profile a target by extracting opinions from multiple documents. Most existing work approaches the task in a semi-supervised manner due to the difficulty of obtaining high-quality annotation from thousands of documents. Among them, some uses aspect and sentiment analysis as a proxy for identifying opinions. In this work, we propose a new framework, FineSum, which advances this frontier in three aspects: (1) minimal supervision, where only aspect names and a few aspect/sentiment keywords are available; (2) fine-grained opinion analysis, where sentiment analysis drills down to the sub-aspect level; and (3) phrase-based summarization, where opinion is summarized in the form of phrases. FineSum automatically identifies opinion phrases from the raw corpus, classifies them into different aspects and sentiments, and constructs multiple fine-grained opinion clusters under each aspect/sentiment. Each cluster consists of semantically coherent phrases, expressing uniform opinions towards certain sub-aspect or characteristics (e.g., positive feelings for “burgers” in the “food” aspect). An opinion-oriented spherical word embedding space is trained to provide weak supervision for the phrase classifier, and phrase clustering is performed using the aspect-aware contextualized embedding generated from the phrase classifier. Both automatic evaluation on the benchmark and quantitative human evaluation validate the effectiveness of our approach.

1 Introduction

Opinion summarization is the task of aggregating user opinions towards a single target from multiple documents (e.g., profiling a restaurant from online reviews). It benefits intelligent decision making by succinctly displaying diverse opinions to users and reducing the information overload.

Different from generic multi-document summarization, the large volumes of reviews and the inherent subjectivity within them pose challenges to curating golden annotation for this task, rendering end-to-end training infeasible. A majority of work focuses on developing weakly-supervised or unsupervised summarization approaches (Elsahar et al. 2021; Suhara et al. 2020). To further handle the diversity and conflicts in user opinions, some approaches perform aspect extraction and sentiment polarization at first, then generate summaries for different aspects and sentiments in either extractive or abstractive forms (Angelidis and Lapata 2018; Krishna and Srinivasan 2018).

Though previous methods partly consider the heterogeneity in user opinions, we argue that they still summarize at a coarse level for two reasons: (1) Opinions in the same aspect category may target at different subjects (e.g., in the {food, good} category of Fig. 1, one set of opinions can be about “burger” but the other about “fish”), and (2) different opinions may focus on different characteristics of the same subject (e.g., one may praise waiters for their kind service but the other may comment on their slowness). Motivated by this, we propose to drill down and aggregate similar opinions for each sub-aspect and characteristic.

Further, traditional extractive and abstractive methods may be sub-optimal for fine-grained summarization. It is common to see multiple fine-grained opinions entangled in the same sentence. In this scenario, extractive summarization will either bring outlier or cause information loss; whereas abstractive summarization usually suffers from hallucinations (Maynez et al. 2020) and text degeneration (Holtzman et al. 2019). Therefore, instead of extracting or generating sentences, we seek to extract and aggregate smaller semantic units, such as phrases, as our fine-grained summarization.

In this paper, we propose FineSum, a fine-grained opinion summarization approach, which leverages only aspect names and a few related keywords as supervision. It consists of the following three stages: (1) Extract meaningful candidate phrases by performing syntactic analysis towards the raw
corpus. (2) Classify each candidate phrase into a particular aspect and sentiment. We leverage two modules as phrase classifiers: (i) the opinion-oriented spherical embedding and (ii) the contextualized BERT classifier. The opinion-oriented embedding explicitly represents aspects/sentiments along with word semantics in a distinctive sphere space, and classifies phrases according to their directional similarities with the aspect/sentiment embedding. Meanwhile, it outputs aspect-related and sentiment-related sentences as weak supervision to train the BERT classifier. To enhance model performance, we additionally fine-tune BERT with jointly agreed phrases from the two classifiers. (3) Aggregate phrases within each aspect and sentiment to obtain fine-grained opinion clusters so that phrases in the same cluster convey coherent meanings.

We summarize our contributions as follows: (1) a minimally supervised approach is proposed for fine-grained opinion summarization, which relies only on aspect names and a few keywords; (2) extracted candidate phrases are classified by training an opinion-oriented spherical embedding and leveraging it to provide weak supervision for a contextualized classifier, and similar phrases are then aggregated within each aspect and sentiment to obtain fine-grained opinion clusters; and (3) Extensive automatic and human evaluations verify the superiority of this approach.

2 Related Work
As the primary goal is to reduce redundancy, previous work on unsupervised or weakly-supervised opinion summarization mainly adopts a popularity-based approach (i.e., extract or generate sentences containing the most salient opinions in the original corpus) (Di Fabbrizio, Stent, and Gaizauskas 2014; Ganesan, Zhai, and Han 2010). A majority of early methods focus on extractive summarization. Ku et al. (2006) define popular opinions using TF-IDF and use pre-defined keyword sets to retrieve the most relevant and opinionated sentences. Paul, Zhai, and Girju (2010) extract opinions according to a variety of lexical and syntactic features, and calculate salience and contrastiveness of sentences using random walk. Recently, with the proliferation of end-to-end training, abstractive summarization receives much more attention. A typical practice is to encode salient information using an aggregated representation, then generate novel sentences by reconstructing this representation. A representative method is MeanSum (Chu and Liu 2019), which generates summaries by training an auto-decoder to reconstruct the averaged input representation. Similarly, Amplayo and Lapata (2021) condense review documents into multiple dense vectors and use a multi-source fusion module to generate summaries. Though effective, extractive and abstractive summarizations suffer from information loss since they only consider popular opinions. Moreover, they overlook the heterogeneity and conflicts in opinions by generating uniform summaries for all types of opinions.

Only a few unsupervised methods propose to summarize according to different aspects and sentiments (Krishna and Srinivasan 2018; Frermann and Klementiev 2019). Angelidis and Lapata (2018) first couple extractive opinion summarization with the tasks of aspect identification and sentiment polarization. It uses an aspect extractor trained under a multi-task objective and a sentiment predictor based on multiple instance learning. Following this, Angelidis et al. (2021) represent aspects as discrete latent codes in the quantized transformer space, and encode sentences to the aspect space using a variational autoencoder. However, the above methods remain coarse-grained because they are not designed to capture sub-aspects and specific characteristics within each aspect. On the contrary, we propose to generate fine-grained phrase clusters for sub-aspects. To our knowledge, this is the first work attempting to generate opinion summarization in the form of phrase clusters.

3 Problem Definition
Given a corpus $T$ containing reviews for targets $\{t_1, t_2, \ldots\}$ from a single domain (e.g., restaurants), we define a domain-related aspect set $A = \{a_1, a_2, \ldots\}$ and sentiment set $S = \{s_1, s_2, \ldots\}$ and input a keyword list as $L_a$ or $L_s$ for each $a$ or $s$. For every target $t$, we define its review sentence set as $R = \{r_1, r_2, \ldots\}$, where each review $r$ consists of multiple sentences $(x_1, x_2, \ldots)$. Each phrase $p$ is defined as a non-overlapped word sequence $(w_1, w_2, \ldots)$ in one sentence. For each target, our final model outputs are a set of clusters $C = \{c_1, c_2, \ldots\}$ for every aspect-sentiment pair $(a, s)$, where each cluster $c$ contains multiple semantically coherent phrases $(p_1, p_2, \ldots)$.

4 Approach
Fig. 2 illustrates the overall workflow of our approach, which decomposes the task of aspect-based fine-grained opinion summarization to three stages. The first stage, candidate phrase extraction, performs syntactic analysis to bring up consecutive and informative multi-word sequences from raw corpus as candidate phrases (Section 4.1). The following stage, opinion phrase classification, aims to classify extracted phrases into different aspects and sentiments (Section 4.2). The last stage, opinion phrase clustering, generates fine-grained clusters within each aspect and sentiment by gathering semantically coherent phrases into the same cluster (Section 4.3). We introduce them as follows.

4.1 Candidate Phrase Extraction
As phrases form concise but complete semantic units in the original review sentences, we propose to extract phrases as the basic component of summarization, instead of the whole sentences. However, existing phrase mining methods are usually designed to extract entity-like structures, which differs from our goal of extracting opinions.

To mine opinions, we need to simultaneously discover a subject, which is usually in the noun form, along with its associated descriptions, which are usually in the form of adjective, adverb, or verb. We achieve this by performing syntactic analysis towards each sentence using custom parsing tools. Specifically, we consider two types of syntactic structure: (1) dependency parsing which discovers a noun subject and its descriptive adjectives/adverbs; If a noun is in one-hop relation with any adjective or adverb, we count them together as a phrase; and (2) constituency analysis which
Dependency Parsing
We went there [last night]. [No allergic reactions]. The shrimp tacos and house fries are my standbys. The [fries are sometimes good and sometimes great], and the spicy dipping sauce they come with is to die for. [Full beer menu] and [long cocktail lists], all [reasonable prices].

Constituency Analysis
We went there last night. No allergic reactions. The [shrimp tacos and house fries are my standbys]. The [fries are sometimes good and sometimes great], and the [spicy dipping sauce they come with is to die for]. Full beer menu and long cocktail lists, all reasonable prices.

Figure 3: An illustration of phrases extracted by dependency parsing and constituency analysis. We highlight the subject and its associated descriptions inside each [phrase].

identifies a noun subject and its consecutive verb phrases: If a noun component and a verb component exist at the same level in the constituency parsing tree, they are considered as a phrase. We illustrate the results of both methods in Fig. 3. More technical details of it can be found in the Appendix. From the figure, dependency parsing usually mines concise phrases with similar structures, whereas constituency analysis can identify phrases in more diverse expression forms. We take the union of their results as our final candidate phrase set, resulting in a phrase extractor with high recall. According to our human evaluation on 50 reviews, the recall of this method reaches 0.92, suggesting it as an intuitive yet effective approach. Note that this semantic-agnostic method will inevitably introduce noisy phrases such as “last night”. However, this will be corrected by the subsequent classification stage. At this stage, our goal is to bring up as many candidates as possible.

4.2 Opinion Phrase Classification
Learning opinion-oriented embedding. Given the aspect/sentiment set and keyword lists, we leverage them as seeds to learn text embeddings tailored for aspects/sentiments. For simplicity, we take aspect categories as an example to introduce our phrase embedding learning and classification method, and sentiment categories follow the same procedure. To learn an aspect-distinctive embedding space, we jointly embed text and aspects in the spherical space, where directional similarity is used to effectively characterize semantic correlations among words, sentences, and aspects. Each aspect is surrounded by its representative keywords on the sphere. In this way, the aspect information of a word is explicitly measured by its directional similarity with different aspects.

The opinion-oriented spherical embedding is implemented via hierarchical topic mining (Meng et al. 2020). We simplify it to the flat case and the learning objectives are introduced as below:

\[
\mathcal{L} = \mathcal{L}_{\text{inter}} - \mathcal{L}_{\text{intra}} - \mathcal{L}_{\text{aspect}},
\]

where \(m_{\text{inter}}\) and \(m_{\text{intra}}\) are two learnable parameters, and \(h\) is the context window length. The first objective \(\mathcal{L}_{\text{inter}}\) encourages inter-aspect distinctiveness across different aspects by enforcing the cosine distance between any two aspects to be larger than \(m_{\text{inter}}\). The second objective \(\mathcal{L}_{\text{intra}}\) requires the embeddings of aspect keywords to be placed near the aspect center direction within a local region \(m_{\text{intra}}\). The third objective \(\mathcal{L}_{\text{aspect}}\) models the corpus generation process conditioned on the aspects in a three-step process: (1) \(p(x|a_z)\) conditions each sentence \(x\) on an aspect \(a_z\), (2) \(p(w_j|x)\) models the semantic coherence between a word \(w_j\) and the sentence \(x\) it appears, and (3) \(p(w_{i+j}|w_i)\) models co-occurring words within local contexts. Note that all three steps use directional similarity to model correlations. Namely, \(p(x|a_z) \propto x^T a_z\). More details on modeling and optimization can be found in the original topic mining paper.

Knowledge distillation to contextualized classifier. Context is crucial for phrase aspect classification. The context-free spherical embedding space mainly captures word-level
discriminative signals but is insufficient to model sequential information from ordering of words. Therefore, we propose to distill knowledge from the aspect-regularized embedding space by generating confident soft predictions for high-quality sentences, and fine-tune a pre-trained language model. Specifically, we leverage soft predictions given by the directional similarity between sentence embeddings and aspect embeddings as weak supervision to fine-tune the BERT-base model (Devlin et al. 2019) for aspect classification.

To provide high-quality supervision, for each aspect $a_i$, we select top-$K$ sentences from the entire corpus with the highest $x^T a_i$ score. We transform the directional similarity to pseudo training labels $l_x$ as below:

$$l_{xi} = \frac{\exp(\alpha \cdot x^T a_i)}{\sum_{a_i \in A} \exp(\alpha \cdot x^T a_i)}.$$  

(2)

where $l_{xi}$ is the probability of sentence $x$ belonging to the $i$th aspect. $\alpha$ is the temperature to control how greedy we want to learn from the embedding-based prediction. We then train BERT on the pseudo training sentences by minimizing the cross entropy $H$ between the embedding-based prediction $l$ and the output prediction $y$ of BERT, namely

$$H(x) = \sum_x \sum_i l_{xi} \log \frac{l_{xi}}{y_{xi}}.$$  

(3)

**Fine-tuning classifier on jointly agreed phrases.** To identify the aspect of candidate phrases, one direct method is to leverage the sentence-level classifier fine-tuned in previous stage. However, the sentence-level model may not perform as well on phrases because phrases are usually shorter, thus provide less context for accurate classification. Thus, we propose to further enhance the BERT model by fine-tuning it for phrase-level aspect classification. Note that the candidate phrase extraction stage may include phrases not belonging to any aspect. To exclude them, we additionally require the model to identify such “background” phrases by training BERT to output a uniform aspect distribution on them.

To generate high-quality pseudo training samples for BERT, we exploit the wisdom from both models (i.e., the opinion-oriented embedding and the weakly trained BERT). We select their jointly agreed predictions as pseudo training phrases, and generate pseudo labels $l'_s$ for phrase $s$ as:

$$l'_{si} = \begin{cases} \frac{\exp(\alpha y_{si})}{\sum_{s' \in [A]} \exp(\alpha y_{s'i})} & y_{si} \geq \theta_1, \bar{w}_s^T a_i \geq \theta_2, \\ \frac{1}{|A|} & y_{si} < \theta_1, \bar{w}_s^T a_i < \theta_2, \end{cases}.$$  

(4)

where $\bar{w}_s$ is the averaged embeddings of words in the phrase $s$, $y_{si}$ is the predicted probability from BERT, and $\bar{w}_s^T a_i$ is the directional similarity between phrase $s$ and the $i$th aspect in the embedding space. $\theta_1$ and $\theta_2$ are two probability thresholds. During inference, we also use $\theta_2$ for BERT to decide whether a phrase belongs to a certain aspect.

1Similar with aspect classification, we fine-tune another BERT-base model to classify sentiments.

### 4.3 Fine-Grained Opinion Clustering

Given predictions from the previous stage, we can organize all extracted phrases according to their aspects and sentiments. However, there are two problems with this practice: (1) Phrases located in the same aspect and sentiment may still cover diverse and heterogeneous opinions, varied by their subjects and targeted characteristics; and (2) some phrases express similar meanings using different words, which leads to unwanted semantic redundancy. To solve these problems, we propose to represent fine-grained opinions by automatically forming clusters under each aspect and sentiment. To guarantee that phrases belonging to the same cluster convey consistent and coherent meanings, we require them to locate near each other in the semantic space. We achieve this by clustering in the fine-tuned BERT embedding space, as it explicitly encodes aspect and sentiment information after training and fine-tuning in the previous stage.

Specifically, we use the bottom-up hierarchical agglomerative clustering (Dubitzky et al. 2013) which treats each phrase as a singleton cluster at the outset, and then successively merges pairs of phrases until the euclidean distance between phrases in the same cluster exceeds a pre-defined threshold $T_c$.

The final output of FineSum is the fine-grained clusters under each aspect and sentiment. Considering the semantic coherence in each cluster, one could further reduce redundancy by selecting salient phrase(s) to represent the whole cluster, or even selecting salient cluster(s) to represent each aspect-sentiment pair. In this work, we stay on the original complete clusters to offer comprehensive summarization. In real application, the best form of summarization should be adjusted according to user needs, which is beyond the scope of this paper.

### 5 Experiments

As no off-the-shelf evaluation framework exists, we evaluate model performance quantitatively and qualitatively on two major tasks in our approach: (i) opinion phrase classification and (ii) fine-grained opinion clustering. For each task, we create extra human annotation and use them for performance analysis. We will release the source code and test data together with human-curated annotations.

#### 5.1 Datasets and Experimental Settings

**Datasets.** We experiment on reviews from two domains: restaurant and laptop. Details of dataset statistics can be found in Table 1. We additionally provide four seed keywords for each aspect and sentiment as weak supervision, as listed in

| aspect-sentiment pair | # Training Sentences | # Training Phrases | # Test Reviews |
|-----------------------|----------------------|-------------------|---------------|
| Restaurant            | 16,000               | 297,210           | 917           |
|                      | location, drinks, food, ambiance, service | good, bad |
| Laptop                | 16,000               | 83,540            | 307           |
|                      | support, os, display, battery, company, mouse, software, keyboard | good, bad |

Table 1: Dataset Statistics.
We first evaluate the phrase classifier on sentence-level aspect identification and sentiment polarization tasks using the benchmark test set. However, a strong sentence-level classifier may not perform as well on phrase-level task, so we additionally evaluate the model on phrase-level aspect classification task. Due to the shortage of phrase-level annotation, we manually collect data by randomly sampling 500 extracted phrases from the Restaurant domain. We ask three human annotators to label their aspects and split them by half into validation and test sets. As the phrase extraction is aspect-agnostic, the collected set includes noisy phrases that do not belong to any aspect. To handle this, we allow multiple and none aspect assignment. Final labels were obtained using a majority vote among annotators. The three annotators provided the same labels on 85.60% phrases, guaranteeing the high quality of our annotation. More annotation and evaluation details can be found in the Appendix. We compare our approach with a series of weakly-supervised baselines and two variants of our own approach.

- **CosSim**: a Word2Vec embedding based model, which classifies according to the cosine similarity between the averaged word embedding and topic vectors. Topic vectors are calculated as the average of seed keywords.
- **W2VlDA** (García-Pablos, Cuadros, and Rigau 2018): an aspect-based sentiment analysis model, which leverages aspect and sentiment keywords as seeds to perform joint topic modeling.
- **BERT** (Devlin et al. 2019): a language model fine-tuning model. We incorporate sentences containing seed keywords as pseudo training samples to fine-tune BERT-base.
- **JASen** (Huang et al. 2020): a state-of-the-art aspect based sentiment analysis model. It first learns aspect-sentiment joint word embedding, then generalizes word knowledge to neural models through weakly-supervised training and iterative self-training.
- **FineSum w/o BERT**: A context-free ablation of our model. It uses the opinion-oriented spherical embedding as the only classifier.
- **FineSum w/o joint**: A BERT-based ablation without fine-tuning on the jointly agreed phrases (but trained on sentence-level classification).

### 5.2 Opinion Classification

The standard Accuracy, Precision, Recall and macro-F1 are used as evaluation metrics. We run experiments for 5 times and report average performances. For each method, we set a lowest threshold for their output classification probability. We classify phrases with a probability larger than the threshold

### Table 2: Quantitative evaluation of aspect identification and sentiment polarity on sentence level tasks. * denotes that the model learns aspect and sentiment jointly.

| Model          | Restaurant-phrase |  | Restaurant-phrase |  | Laptop-phrase |  | Laptop-phrase |
|----------------|-------------------|---|-------------------|---|---------------|---|---------------|
|                | Acc.   | Pre.   | Rec.   | Acc. | Pre. | Rec. | Acc. | Pre. | Rec. |
| CosSim         | 55.97  | 56.22  | 53.64  | 53.84 |     |      |      |      |      |
| W2VlDA*        | 63.34  | 61.64  | 61.37  | 60.93 |     |      |      |      |      |
| BERT           | 72.39  | 63.54  | 74.13  | 67.55 |     |      |      |      |      |
| JASen*         | 82.20  | 84.54  | 79.70  | 79.64 |     |      |      |      |      |
| FineSum w/o BERT| 84.10 | 82.76  | 60.19  | 58.21 |     |      |      |      |      |
| FineSum w/o joint| 76.82 | 66.41  | 78.98  | 70.43 |     |      |      |      |      |
| FineSum        | 88.60  | 85.44  | 86.98  | 84.57 |     |      |      |      |      |

### Table 3: Quantitative evaluation of restaurant aspect identification on phrase level task.

| Model                | Restaurant-phrase |  | Restaurant-phrase |  | Laptop-phrase |  | Laptop-phrase |
|----------------------|-------------------|---|-------------------|---|---------------|---|---------------|
|                      | Acc.   | Pre.   | Rec.   | Acc. | Pre. | Rec. | Acc. | Pre. | Rec. |
| CosSim               | 55.97  | 56.22  | 53.64  | 53.84 |     |      |      |      |      |
| W2VlDA*              | 63.34  | 61.64  | 61.37  | 60.93 |     |      |      |      |      |
| BERT                 | 72.39  | 63.54  | 74.13  | 67.55 |     |      |      |      |      |
| JASen*               | 82.20  | 84.54  | 79.70  | 79.64 |     |      |      |      |      |
| FineSum w/o BERT     | 84.10  | 82.76  | 60.19  | 58.21 |     |      |      |      |      |
| FineSum w/o joint    | 76.82  | 66.41  | 78.98  | 70.43 |     |      |      |      |      |
| FineSum              | 88.60  | 85.44  | 86.98  | 84.57 |     |      |      |      |      |
Figure 4: Visualization of opinion clusters on Restaurant. Phrases assigned to the same cluster are denoted with the same color.

| Spherical Embedding | Vanilla BERT | BERT in FineSum |
|---------------------|--------------|-----------------|
| allergic reactions   | severe allergies | severe allergies |
| severe allergies     | broken leg     | intestinal/gastro issues |
| mild reactions       | severe food poisoning | severe food poisoning |
| no allergic reactions | suffer severe migraine | crazy allergies |

Table 4: Qualitative evaluation of fine-grained clustering on the restaurant dataset. We compare opinion clusters from different embeddings that show similar semantics. Conflicting and irrelevant phrases are denoted with red and blue.

We further visualize phrase distribution in Fig. 4 to intuitively understand how clusters distribute in the fine-tuned BERT embedding space. Compared with Spherical Embedding and Vanilla BERT, BERT in FineSum displays a clearer and better-separated cluster space.

5.3 Fine-Grained Opinion Clustering

We compare our fine-tuned BERT embedding with two ablations on clustering performance: (i) Opinion-oriented Spherical Embedding introduced in Section 4.2 and (ii) Last layer outputs from Vanilla BERT, which are not trained on the aspect classification task.

**Qualitative Evaluation.** To intuitively understand the difference between embedding methods, we display semantically similar clusters from them in Table 4. We observe that Spherical Embedding relies excessively on overlapped surface words. It tends to gather look-alike phrases even if their meanings are converse. For instance, “severe allergies” and “no allergic reactions” are in the same cluster. Besides, we also find that Vanilla BERT, although less reliant on overlapping words, sometimes suffers from semantic drifts. For example, “broken leg” and “severe migraine” are grouped together. On the contrary, BERT in FineSum forms clusters that are both coherent in meaning and diverse in expression. We further visualize phrase distribution in Fig. 4 to intuitively understand how clusters distribute in the fine-tuned BERT embedding space. Compared with Spherical Embedding and Vanilla BERT, BERT in FineSum displays a clearer and better-separated cluster space.

**Quantitative Evaluation.** We evaluate the coherence and diversity of generated clusters quantitatively. Coherence measures the semantic consistency of phrases within the same cluster, whereas diversity measures how their expressions differ from each other. In principle, a cluster of high quality should be in both high coherence and diversity, indicating that the model can gather phrases with similar semantic meanings regardless of their expression forms.

We define the two metrics as follows: (i) **Coherence:** Given an opinion cluster, we inject an intrusion phrase that is randomly chosen from another cluster. Then three human annotators are asked to identify the intruded phrase. Empirically, we observe that phrases within the same cluster usually share common words, making it easy to identify the intruded phrase. Hence, we require the intruded phrase to have at least one overlapped word with other phrases. We provide an example of this in the Appendix, along with other evaluation details. We compute the ratio of correctly identified
intrusion instances as the coherence score. (ii) Diversity: The percentage of unique words in each cluster. Fig. 5 showcases that BERT in FineSum significantly outperforms the other two ablations on coherence, validating that the fine-tuned BERT embeddings generate semantically coherent clusters. This finding indicates that fine-tuned BERT for aspect classification not only benefits the task itself, but also leads the model to better distinguish fine-grained sub-aspects within each aspect. Moreover, BERT in FineSum achieves slightly higher diversity score than the other two methods, indicating that the high coherence score of our approach is not brought by simply gathering phrases with similar words.

5.4 Parameter Study
To investigate whether FineSum is sensitive to different choices of seed keywords, we initiate the opinion-oriented embedding with different numbers of seeds. Figure 6 shows sentence-level classification results on the Restaurant dataset. As can be observed from the figure, the classification accuracy and macro-F1 remain relatively stable when we alter the number of seeds. This result indicates that the opinion-oriented embedding can learn well-separated semantic space with little human guidance, which validates the robustness of FineSum and opens up possibilities to apply it to diverse domains in the future.

5.5 Case Study
Table 5 shows an example of our system output. We observe that different opinion phrase clusters are well-separated by their aspects and sentiments, which is guaranteed by the opinion phrase classification stage. Probing into each aspect and sentiment, we discover that the model automatically forms clusters which represent concrete sub-aspects or describes particular traits. For example, under the aspect-sentiment pair ‘food, bad’, we find one cluster expressing overall disappointment for their food and two clusters complaining about specific food types. The coherent and meaningful clusters under each aspect validate the effectiveness of clustering with fine-tuned BERT embedding.

6 Conclusion
In this paper we propose FineSum, a minimally supervised approach for fine-grained opinion summarization. FineSum works by first extracting candidate phrases, then classifying them into aspects and sentiments using the opinion-oriented spherical embedding and the weakly-supervised BERT. We further propose to aggregate similar phrases using the fine-tuned BERT embedding to obtain fine-grained opinion clusters. Comprehensive automatic and human evaluation demonstrate that our approach generates high-quality phrase-level summarization.
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A Appendix

A.1 Details on Candidate Phrase Extraction

We introduce technical details of two modules in the candidate phrase extraction stage, i.e., dependency parsing and constituency analysis.

Dependency Parsing. This module aims to discover a noun subject and its descriptive adjectives/adverbs together as a phrase. Given a review sentence, it first recognizes all nouns, adjectives, and adverbs according to their pos-tags. For instance, in Figure 1, the pos-tag “NN” corresponds to noun, so “beer menu” and “price” are recognized as noun (or compound noun). Similarly, “full” and “reasonable” are adjectives. The next step is to investigate the dependency relationship between noun subject and adjectives/adverbs. This can be achieved by directly examining the results of our dependency parser. As illustrated in Figure 1, the “amod” relation indicates the adjective “full” is used to modify the noun “menu”, and the “nsubj” relation indicates the noun “price” is the subject of the adjective “reasonable”. Empirically, we use the “amod” and “nsubj” relation to decide whether a noun and an adjective is dependent. If a noun and an adjectives/adverb are connected by a one-hop “amod” or “nsubj” relation, we count them as one candidate phrase.

Constituency Analysis. Dependency parsing can only recognize phrases when adjectives or adverbs are present. However, not all opinion phrases contain adjectives, such as the sentence “the dipping sauce is my favorite”. Therefore, we additionally propose the constituency analysis module to make up the shortage. This module identifies a noun subject and its consecutive verb phrases as a candidate phrase. The constituency parser outputs consecutive multi-word sequences as different components of a sentence, which is illustrated in Fig 2. The whole sentence is a parsing tree, where “the dipping sauce” is a root-level noun phrase (NP), “is my favourite” is labeled as its root-level consecutive verb phrase (VP). The shorter sequence “my favourite” is a leaf-level noun phrase. To obtain a complete opinion phrase, we take all root-level noun phrases and their consecutive verb phrases as candidate opinion phrases.

A.2 Datasets and Experimental Settings

Datasets Table 1 displays seed keywords for each aspect and sentiment. The seed keywords along with aspect names are used as the only supervision for FineSum. We also display the number of samples under each aspect and sentiment.

Experimental Settings We first explain how we select hyperparameters: We set the probability thresholds $\theta_1 = 0.35$, $\theta_2 = 0.30$ because it shows the best performances on our self-annotated phrase validation set. We set the context window length $h=5$, embedding dimension= 100 by following the settings in the hierarchical topic mining paper (?). We adopt the default learning rate $1e-5$ in the Hugging Face transformer package3, and set batch size= 64 according to the maximum capacity of our computing facilities. When selecting the top-K sentences as training data, we initially set $K=2000$ and observed promising results, so we did not try a larger value of $K$. We conducted all model training using a single NVIDIA GTX 1080 Ti.

A.3 Evaluation on Phrase Classification

Evaluation Details In the phrase annotation process, we ask three human annotators to assign aspect labels to 500 randomly extracted restaurant phrases. Annotators consist of two graduates and one undergraduate, all with CS background (as labeling restaurant aspects requires little domain knowledge). Considering there exist non- and multi-aspects, we define the agreement among annotators as: Given a phrase, all three annotators provide the same number(s) and categor(ies) of aspect(s).

Qualitative Evaluation We qualitatively compare FineSum with its two variants and show results in Table 2. From the first two rows, we observe that FineSum is able to correct the false prediction from either opinion-oriented embedding.

3https://huggingface.co/transformers/
Table 2: Comparison of predictions on sample phrases between FineSum and its variants.

| Phrase                        | FineSum w/o BERT | FineSum w/o joint | FineSum | Truth |
|-------------------------------|-------------------|-------------------|---------|-------|
| hot tucson dog place          | location          | food              | food    | food  |
| bloody delicious maryl's      | drink             | food              | drink   | drink |
| find everything ok            | food              | service           | none    | none  |
| we went yesterday on taco     | food              | location          | none    | none  |
| tuesday to meet friends       |                   |                   |         |       |
| wrong food order              | food              | food              | food    | none  |
| friendly environment          | none              | service           | none    | ambience |

(FineSum w/o BERT) and sentence-level BERT classifier (FineSum w/o joint). The third and fourth rows show that FineSum can distinguish non-aspect phrases better than its variants, as it is fine-tuned to output uniform aspect distribution on non-aspect phrases. The last two rows showcase the false prediction of FineSum. It wrongly predicts the phrase “wrong food order” into the food aspect, suggesting that FineSum may rely excessively on aspect-indicative words to make prediction. Future work may focus on improving its performance on these ambiguous and hard phrases.

A.4 Evaluation on Phrase Clustering

In this section, we introduce evaluation details of phrase clustering. We employ intrusion test to evaluate the coherence of opinion clusters. Table 3 shows three sample intrusion sets. During human evaluation, we shuffle the intrusion phrase with its corresponding in-cluster phrases and ask human annotators to identify the intrusion one. We employ the same annotators as in Section A.3. For each embedding method, we generate 40 intrusion sets and randomly shuffle sets from different methods during human evaluation. In total, annotators are asked to work on 3*40 clusters, each containing 6 phrases.
the bread basket was also something that stood out; pretty nice bread basket; the best thing i can say about the restaurant is the bread basket; the bread basket was a unique and unexpected touch; bread basket is also a lovely touch

it ranged from jalapeno corn bread to a sweet dessert bread

delicious pear margarita; the lime margarita tasted like pure lime; the white peach margarita is tasty; skinny delicious and thankfully overly sweet margarita; delicious pear margarita; the margarita that i had was tasty too

everyone had the cactus pear margarita

recommend this place for lunch; love this restaurant though; i love this restaurant; this was perfect lol; this one is a definite miss for dinner

we visit this one twice

| Cluster | Intrusion Phrase |
|---------|------------------|
| the bread basket was also something that stood out; pretty nice bread basket; the best thing i can say about the restaurant is the bread basket; the bread basket was a unique and unexpected touch; bread basket is also a lovely touch | it ranged from jalapeno corn bread to a sweet dessert bread |
| the lime margarita tasted like pure lime; the white peach margarita is tasty; skinny delicious and thankfully overly sweet margarita; delicious pear margarita; the margarita that i had was tasty too | everyone had the cactus pear margarita |
| recommend this place for lunch; love this restaurant though; i love this restaurant; this was perfect lol; this one is a definite miss for dinner | we visit this one twice |

Table 3: Examples of the intrusion test on fine-grained clustering. For each opinion cluster, we randomly sample an intrusion phrase from outside the cluster. To evaluate the distinctiveness of clusters, we require all in-cluster phrases and the intrusion phrase to share at least one common word, which is italicized and in bold.