A Simple and Effective Self-Supervised Contrastive Learning Framework for Aspect Detection

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Abstract
Unsupervised aspect detection (UAD) aims at automatically extracting interpretable aspects and identifying aspect-specific segments (such as sentences) from online reviews. However, recent deep learning based topic models, specifically aspect-based autoencoder, suffer from several problems, such as extracting noisy aspects and poorly mapping aspects discovered by models to the aspects of interest. To tackle these challenges, in this paper, we first propose a self-supervised contrastive learning framework and an attention-based model equipped with a novel smooth self-attention (SSA) module for the UAD task in order to learn better representations for aspects and review segments. Secondly, we introduce a high-resolution selective mapping (HRSMap) method to efficiently assign aspects discovered by the model to aspects of interest. We also propose using a knowledge distilling technique to further improve the aspect detection performance. Our methods outperform several recent unsupervised and weakly supervised approaches on publicly available benchmark user review datasets. Aspect interpretation results show that extracted aspects are meaningful, have a good coverage, and can be easily mapped to aspects of interest. Ablation studies and attention weight visualization also demonstrate effectiveness of SSA and the knowledge distilling method.

Introduction
Aspect detection, which is a vital component of aspect-based sentiment analysis (Pontiki et al. 2014, 2015), aims at identifying predefined aspect categories (e.g., Price, Quality) discussed in segments (e.g., sentences) of online reviews. Table 1 shows an example from Amazon platform about a television from several different aspects, such as Image, Sound and Ease of Use. With a large number of reviews, automatic aspect detection allows people to efficiently retrieve review segments of aspects they are interested in. It also benefits many downstream tasks, such as review summarization (Angelidis and Lapata 2018) and recommendation justification (Ni, Li, and McAuley 2019).

There are several research directions for aspect detection. Supervised approaches (Zhang, Wang, and Liu 2018) can leverage annotated labels of aspect categories but suffer from domain adaptation problems (Rietzler et al. 2020). Another research direction consists of unsupervised approaches and

| Sentence | Aspect |
|----------|--------|
| Replaced my 27” jvc clunker with this one. | General |
| It fits perfectly inside our armoire. | General |
| Good picture. | Image |
| Easy to set up and program. | Ease of Use |
| Descent sound, not great... | Sound |
| We have the 42” version of this set downstair. | General |
| Also a solid set. | General |

Table 1: An example from Amazon product reviews about a television and aspect annotations for every sentence.
formulate UAD as a self-supervised representation learning problem and solve it using a contrastive learning algorithm, which is inspired by success of self-supervised contrastive learning in visual representations (Chen et al. 2020; He et al. 2020). In addition to the learning framework, we also resolve two problems that deteriorate the performance of ABAE, including its self-attention mechanism for segment representations and aspect mapping strategy (i.e., many-to-one mapping from aspects discovered by the model to aspects of interest). Finally, we discover that the quality of aspect detection can be further improved by knowledge distilling (Hinton, Vinyals, and Dean 2015). The contributions of this paper are summarized as follows:

- Propose a self-supervised contrastive learning framework for the unsupervised aspect detection task.
- Introduce a high-resolution selective mapping strategy to map model discovered aspects to aspects of interest.
- Utilize knowledge distilling to further improve the performance of aspect detection.
- Conduct systematic experiments on seven benchmark datasets, and demonstrate the effectiveness of our models, both quantitatively and qualitatively.

**Related Work**

Aspect detection is an important problem of aspect-based sentiment analysis (Zhang, Wang, and Liu 2018). Existing studies attempt to solve this problem in several different ways, including rule-based, supervised, unsupervised, and weakly supervised approaches. Rule-based approaches focus on lexicons and dependency relations, and utilize manually defined rules to identify patterns and extract aspects (Qiu et al. 2011; Liu et al. 2016), which require domain-specific knowledge or human expertise. Supervised approaches usually formulate aspect extraction as a sequence labeling problem that can be solved by hidden Markov models (HMM) (Jin, Ho, and Srihari 2009), conditional random fields (CRF) (Li et al. 2010; Mitchell et al. 2013; Yang and Cardie 2012), and recurrent neural networks (RNN) (Wang et al. 2016; Liu, Joty, and Meng 2015). These approaches have shown better performance compared to the rule-based ones, but require large amounts of labeled data for training. Unsupervised approaches do not need labeled data. Early unsupervised systems are dominated by Latent Dirichlet Allocation (LDA) based topic models (Brody and Elhadad 2010; Zhao et al. 2010; Chen, Mukherjee, and Liu 2014; García-Pablos, Cuadros, and Rigau 2018). Wang et al. (2015) proposed a restricted Boltzmann machine (RBM) model to jointly extract aspects and sentiments. Recently, deep learning based topic models (Srivastava and Sutton 2017; Luo et al. 2019; He et al. 2017) have shown strong performance in extracting coherent aspects. Specifically, Aspect-Based AutoEncoder (ABAE) (He et al. 2017) and its variants (Luo et al. 2019) have also achieved competitive results in detecting aspect-specific segments from reviews. The problem is that they need some human effort for aspect mapping. Tulkens and van Cranenburgh (2020) propose a simple heuristic model that can use nouns in the segment to identify and map aspects, however, it strongly depends on the quality of word embeddings, and its applications have so far been limited to restaurant reviews. Weakly-supervised approaches usually leverage aspect seed words as guidance for aspect detection (Angelidis and Lapata 2018; Karamanolakis, Hsu, and Gravano 2019; Zhuang et al. 2020) and achieve better performance than unsupervised approaches. However, most of them rely on human annotated data to extract high-quality seed words and are not flexible to discover new aspects from a new corpus. In this paper, we are interested in unsupervised approaches for aspect detection and dedicated to tackle challenges in aspect learning and mapping.

**The Proposed Framework**

In this section, we describe our self-supervised contrastive learning framework for aspect detection; shown in Fig. 1. The goal is to first learn a set of interpretable aspects (named as model-inferred aspects), and then extract aspect-specific segments from reviews, so that they can be used in downstream tasks.

**Problem Statement** Aspect detection problem is defined as follows: given a review segment \( x = \{x_1, x_2, \ldots, x_T\} \) such as a sentence or an elementary discourse unit (EDU) (Mann and Thompson 1988), we target at predicting an aspect category \( y_k \in \{y_1, y_2, \ldots, y_K\} \), where \( x_i \) is the index of a word in the vocabulary, \( T \) is the total length of the segment, \( y_k \) is an aspect among all aspects that are of interest (named as gold-standard aspects), and \( K \) is the total number of gold-standard aspects. For instance, when reviewing restaurants, we may be interested in the following gold-standard aspects: Food, Service, Ambience, etc. Given a review segment, it most likely relates to one of the above aspects.

The first challenge in this problem is to learn model-inferred aspects from unlabeled review segments and map them to a set of gold-standard aspects. Another challenge is to accurately assign each segment in a review to an appropriate gold-standard aspect \( y_k \). For example, in restaurants reviews, “The food is very good, but not outstanding.” → Food. Therefore, we propose a series of modules in our framework, including segment representations, constrastive learning, aspect interpretation and mapping, and knowledge distilling, to overcome both challenges and achieve our goal.

**Self-Supervised Contrastive Learning (SSCL)**

To automatically extract interpretable aspects from a review corpus, a widely used strategy is to learn aspect embeddings in the word embedding space, so that aspects can be interpreted by their nearest words (He et al. 2017; Angelidis and Lapata 2018). Here, we formulate this learning process as a self-supervised representation learning problem.

**Segment Representations** For every review segment in a corpus, we construct two representations directly based on (i) word embeddings and (ii) aspect embeddings. Then, we develop a contrastive learning mechanism to map aspect embeddings to the word embedding space. Let us denote a word embedding matrix as \( E \in \mathbb{R}^{V \times M} \), where \( V \) represents the vocabulary size and \( M \) is the dimension of word vectors. The aspect embedding matrix is represented by \( A \in \mathbb{R}^{N \times M} \), where \( N \) is the number of model-inferred aspects.
Given a review segment $x = \{x_1, x_2, \ldots, x_T\}$, we construct a vector representation $s_{x,E}$ based on its word embeddings $\{E_{x_1}, E_{x_2}, \ldots, E_{x_T}\}$, along with a novel self-attention mechanism, i.e.,

$$s_{x,E} = \sum_{t=1}^{T} \alpha_t E_{x_t},$$

where $\alpha_t$ is an attention weight and is calculated as follows:

$$\alpha_t = \frac{\exp(u_t)}{\sum_{\tau=1}^{T} \exp(u_{\tau})}$$

Here, $u_t$ is an alignment score and $q = \frac{1}{T} \sum_{t=1}^{T} E_{x_t}$ is a query vector. $W_E \in \mathbb{R}^{M \times M}$, $b_E \in \mathbb{R}^M$ are trainable parameters, and the smooth factor $\lambda$ is a hyperparameter. More specifically, we call this attention mechanism as Smooth Self-Attention (SSA). It applies an activation function tanh to prevent the model from using a single word to represent the segment, thus increasing the robustness of our model. For example, for the segment “plenty of ports and settings”, SSA will attend both “ports” and “settings”, while regular self-attention may only concentrate on “settings”. Hereafter, we will use RSA to represent regular self-attention adopted in (Angelidis and Lapata 2018). In our experiments, we discover that the RSA without smoothness gets worse performance than a simple average pooling mechanism.

Further, we also construct a vector representation $s_{x,A}$ for the segment $x$ with global aspect embeddings $\{A_1, A_2, \ldots, A_N\}$ through another attention mechanism, i.e.,

$$s_{x,A} = \sum_{n=1}^{N} \beta_n A_n$$

The attention weight $\beta_n$ is obtained by

$$\beta_n = \frac{\exp(v_{n,A}^T s_{x,E} + b_{n,A})}{\sum_{\eta=1}^{N} \exp(v_{\eta,A}^T s_{x,E} + b_{\eta,A})},$$

where $v_{n,A} \in \mathbb{R}^M$ and $b_{n,A} \in \mathbb{R}$ are learnable parameters. $\beta = \{\beta_1, \beta_2, \ldots, \beta_N\}$ can be also interpreted as soft-labels (probability distribution) over model-inferred aspects for a review segment.

**Contrastive Learning**

Inspired by recent contrastive learning algorithms (Chen et al. 2020), SSCL learns aspect embeddings by introducing a contrastive loss to maximize the agreement between two representations of the same review segment. During training, we randomly sample a mini-batch of $X$ examples and define the contrastive prediction task on pairs of segment representations from the mini-batch, which is denoted as $(s_{1,E}, s_{1,A}), (s_{2,E}, s_{2,A}), \ldots, (s_{X,E}, s_{X,A})$. Similar to (Chen et al. 2017), we treat $(s_{i,E}, s_{i,A})$ as a positive pair and $(s_{j,E}, s_{i,A})_{j \neq i}$ as negative pairs within the mini-batch. The contrastive loss function for a positive pair of examples is defined as

$$l_i = -\log \frac{\exp(\text{sim}(s_{i,E}, s_{i,A})/\mu)}{\sum_{j=1}^{X} \mathbb{I}_{[j \neq i]} \exp(\text{sim}(s_{j,E}, s_{i,A})/\mu)},$$

where $\mathbb{I}_{[j \neq i]} \in \{0, 1\}$ is an indicator function that equals 1 iff $j \neq i$ and $\mu$ represents a temperature hyperparameter. We utilize cosine similarity to measure the similarity between $s_{j,E}$ and $s_{i,A}$, which is calculated as follows:

$$\text{sim}(s_{j,E}, s_{i,A}) = \frac{(s_{j,E})^T s_{i,A}}{\|s_{j,E}\| \|s_{i,A}\|},$$

where $\| \cdot \|$ denotes $L_2$-norm.

We summarize our SSCL framework in Algorithm 1. Specifically, in line 1, aspect embedding matrix $A$ is initialized with the centroids of clusters by running k-means on word embeddings. We follow (He et al. 2017) to penalize aspect embedding matrix and ensure diversity of different aspects. In line 13, the regularization term $\Omega$ is defined as

$$\Omega = \|AA^T - I\|,$$

where each row of matrix $A$, denoted as $A_j$, is obtained by normalizing corresponding row in $A$, i.e., $A_j = A_j/\|A_j\|$. 

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**Algorithm 1:** The SSCL Algorithm

**Input:** Batch size $X$; constant $\lambda$ and $\tau$; network structures;

**Output:** Aspect embedding matrix $A$; model parameters $W_E, b_E, v_A, b_A$;

1. **Initialize** Matrix $E$ with pre-trained word vectors; matrix $A$ with k-means centroids;

2. **for** sampled mini-batch of size $X$ **do**

3.   **for** $i=1, X$ **do**

4.     **Calculate** $s_{i,E}$ with Eq. (1);

5.   **Calculate** $s_{i,A}$ with Eq. (3);

6. **end**

7. **for** $i=1, X; j=1, X$ **do**

8.   **Calculate** $\text{sim}(s_{i,E}, s_{i,A})$ with Eq. (6);

9. **end**

10. **for** $i=1, X$ **do**

11.   **Calculate** $l_i$ with Eq. (5);

12. **end**

13. **Calculate** regularization term $\Omega$ with Eq. (7);

14. **Define** Loss function $L = \frac{1}{X} \sum_{i=1}^{X} l_i + \Omega$;

15. **Update** learnable parameters to minimize $L$.

16 **end**
where we can first calculate a similarity matrix $G$ which can be converted to a one-hot vector with length $K$.

Given soft-labels of model-inferred aspects $\gamma$, we calculate soft-labels $\gamma = \{\gamma_1, \gamma_2, ..., \gamma_K\}$ over gold-standard aspects for each review segment as follows:

$$\gamma_k = \sum_{n=1}^{N} I_{f(\beta_n) = \gamma_k} \beta_n,$$

where $f(\beta_n)$ is the aspect mapping for model-inferred aspect $n$. The hard-label $\hat{y}$ of gold-standard aspects for the segment is obtained by

$$\hat{y} = \text{argmax}\{\gamma_1, \gamma_2, ..., \gamma_K\},$$

which can be converted to a one-hot vector with length $K$.

### Knowledge Distilling

Given both soft- and hard-labels of gold-standard aspects for review segments, we utilize a simple knowledge distilling method, which can be viewed as classification on noisy labeled data. We construct a simple classification model, which consists of a segment encoder such as BERT encoder (Devlin et al. 2019), a smooth self-attention layer; see Eq. 2, and a classifier (i.e., a single-layer feed-forward network followed by a softmax activation). This model is denoted as SSCLS, where the last S represents student. SSCLS learns knowledge from the teacher model, i.e., SSCL. The loss function is defined as

$$\mathcal{L} = -\frac{1}{K} \sum_{k=1}^{K} I_{(H(\gamma) < \xi_k)} \cdot \hat{y}_k \log(y_k), \quad (10)$$

where $\hat{y}_k$ is the probability of aspect $k$ predicted by SSCLS. $y_k$ is hard-label given by SSCL. $H(\gamma)$ represents the Shannon entropy for the soft-labels and is calculated by $H = -\sum_{k=1}^{K} \gamma_k \log(\gamma_k)$. Here, the scalar $\xi_k = \chi_G$ if aspect $k$ is General, otherwise, $\xi_k = \chi_{NG}$. Both $\chi_G$ and $\chi_{NG}$ are hyperparameters. Hereafter, we will refer $I_{(H(\gamma) < \xi_k)}$ as an Entropy Filter.

Entropy scores have been used to evaluate the confidence of predictions (Mandelbaum and Weinshall 2017). In the training stage, we set thresholds to filter out training samples with less confident predictions by SSCL, so that the student model can focus on high confident training samples. Moreover, the student model also benefits from pre-trained encoders and overcomes the disadvantages of data preprocessing for SSCL, since we have removed out-of-vocabulary words and punctuation, and lemmatize tokens in SSCL. Therefore, SSCLS gets better performance in segment aspect predictions compared with SSCL.

### Datasets

We train and evaluate our methods on seven datasets: Citysearch restaurant reviews (Gau, Elhadad, and Marian 2009) and Amazon product reviews (Angelidis and Lapata 2018) across six different domains, including Laptop Cases (Bags), Bluetooth Headsets (B/T), Boots, Keyboards (KBs), Televisions (TVs), and Vacuums (VCs).

The Citysearch dataset only has training and testing sets. To avoid optimizing any models on the testing set, we use restaurant subsets of SemEval 2014 (Pontiki et al. 2014) and SemEval 2015 (Pontiki et al. 2015) datasets as a development set, since they adopt the same aspect labels as Citysearch. Similar to previous work (He et al. 2017), we select sentences that only express one aspect, and disregard those with multiple and no aspect labels. We have also restricted ourselves to three labels (Food, Service, and Ambience), to form a fair comparison with prior work (Tulken and van Cranenburgh 2020). Amazon product reviews are obtained from the OPOSUM dataset (Angelidis and Lapata 2018). Different from Citysearch, EDUs (Mann and Thompson 1988) are used as segments and each domain has eight representative aspect labels as well as aspect General.
We compare our methods against five baselines on Citysearch.

**Comparison Methods**

We compare our methods against five baselines on Citysearch dataset. **SERBM** (Wang et al. 2015) is a sentiment-aspect extraction restricted Boltzmann machine, which jointly extracts aspect and sentiment polarities in an unsupervised manner. **W2VLDA** (Garcia-Pablos, Cuadros, and Rigau 2018) is a topic modeling based approach, which combines word embeddings (Mikolov et al. 2013) with Latent Dirichlet Allocation (Blei, Ng, and Jordan 2003). It automatically pairs discovered topics with pre-defined aspect names based on user-provided seed-words for different aspects. **ABAE** (He et al. 2017) is an auto-encoder that aims at learning highly coherent aspects by exploiting the distribution of word co-occurrences using neural word embeddings, and an attention mechanism that can put emphasis on aspect-related keywords in segments during training. **AE-CSA** (Luo et al. 2019) improves ABAE by leveraging sememes to enhance lexical semantics, where sememes are obtained via WordNet (Miller 1995). **CAT** (Tulkens and van Cranenburgh 2020) is a simple heuristic model that consists of a contrastive attention mechanism based on Radial Basis Function kernels and an automated aspect assignment method.

For Amazon reviews, we compare our methods with several weakly supervised baselines, which explicitly leverage seed words extracted from human annotated development sets. **Karanamolakis, Hsu, and Gravano** 2019 as supervision for aspect detection. **ABAEinit** (Angelidis and Lapata 2018) replaces each aspect embedding vector in ABAE with the corresponding centroid of seed word embeddings, and fixes aspect embedding vectors during training. **MATE** (Angelidis and Lapata 2018) uses the weighted average of seed word embeddings to initialize aspect embeddings. **MATE-MT** extends MATE by introducing an additional multi-task training objective. **TS*-** (Karanamolakis, Hsu, and Gravano 2019) is a weakly supervised student-teacher co-training framework, where **TS-Teacher** is a bag-of-words classifier (teacher) based on seed words. **TS-Stu-W2V** and **TS-Stu-BERT** are student networks that use word2vec embeddings and BERT model to encode text segments, respectively.

**Implementation Details**

We implemented all deep learning models using PyTorch (Paszke et al. 2017). For each dataset, the best parameters and hyperparameters are selected based on development set.

For our SSCL model, word embeddings are pre-loaded with 128-dimensional word vectors trained by skip-gram model [Mikolov et al. 2013] with negative sampling and fixed during training. For each dataset, we use gensim [1] to train word embeddings from scratch and set both window and negative sample size to 5. Aspect embedding matrix is initialized with the centroids of clusters by running k-means on word embeddings. We set the number of aspects to 30 for all datasets because the model can achieve competitive performance while it will still be relatively easier to map model-inferred aspects to gold-standard aspects. The smooth factor $\lambda$ is tuned in $\{0.5, 1.0, 2.0, 3.0, 4.0, 5.0\}$ and set to 0.5 for all datasets. The temperature $\mu$ is set to 1. For SSCLS, we have experimented with two pretrained encoders, i.e., BERT (Devlin et al. 2019) and DistilBERT (Sanh et al. 2019). We tune smooth factor $\lambda$ in $\{0.5, 1.0\}$, $\chi_G$ in $\{0.7, 0.8, 1.0, 1.2\}$, and $\chi_NG$ in $\{1.4, 1.6, 1.8\}$. We set $\chi_G < \chi_NG$ to alleviate label imbalance problem, since majority of the sentences in the corpus are labeled as General.

For both SSCL and SSCS, model parameters are optimized using Adam optimizer (Kingma and Ba 2014) with $\beta_1 = 0.9, \beta_2 = 0.999$, and $\epsilon = 10^{-9}$. Batch size is set to 50. For learning rates, we adopt a warmup schedule strategy proposed in (Vaswani et al. 2017), and set warmup step to 2000 and model size to $10^5$. Gradient clipping with a threshold of 2 has also been applied to prevent gradient explosion.

**Performance on Amazon Product Reviews**

Following previous work (Angelidis and Lapata 2018, Karanamolakis, Hsu, and Gravano 2019), we use micro-averaged F1 score as our evaluation metric to measure the aspect detection performance among different models on Amazon product reviews. All results are shown in Table 2, where we use bold font to highlight the best performance values. The results of the compared models are obtained from the corresponding published papers. From this table, we can observe that weakly supervised ABAEinit, MATE and MATE-MT perform significantly better than unsupervised ABAE since they leverage aspect representative words extracted from human-annotated datasets and thus leading to more accurate aspect predictions. TS-Teacher outperforms MATE and MATE-MT on most of the datasets, which further demonstrates that these words are highly correlated with gold-standard aspects. The better performance of both TS-Stu-W2V and TS-Stu-BERT over TS-Teacher demonstrates the effectiveness of their teacher-student co-training framework.

In our experiments, we conjecture that low-resolution many-to-one aspect mapping may be one of the reasons for low performance of traditional ABAE. Therefore, we have re-implemented ABAE and combined it with HRSMAP. The new model (i.e., ABAE + HRSMAP) gets significantly better results compared to the traditional ABAE on all datasets (performance improvement 51.7%), which shows HRSMAP is...
Table 3: Micro-averaged F1 scores for 9-class EDU-level aspect detection in Amazon reviews. AVG denotes the average of F1 scores across all domains.

| Methods          | Bags  | B/T   | Boots | KBs   | TVs   | VCs   | AVG  |
|------------------|-------|-------|-------|-------|-------|-------|------|
|                  |       |       |       |       |       |       |      |
| Unsupervised     |       |       |       |       |       |       |      |
| ABAE (2017)      | 38.1  | 37.6  | 35.2  | 38.6  | 39.5  | 38.1  | 37.9 |
| ABAE + HRSMap    | 54.9  | 62.2  | 54.7  | 58.9  | 59.9  | 54.1  | 57.5 |
| Weakly Supervised|       |       |       |       |       |       |      |
| ABAEinit (2018)  | 41.6  | 48.5  | 41.2  | 41.3  | 45.7  | 40.6  | 43.2 |
| MATE (2018)      | 46.2  | 52.2  | 45.6  | 43.5  | 48.8  | 42.3  | 46.4 |
| MATE-MT (2018)   | 48.6  | 54.5  | 46.4  | 53.1  | 51.8  | 47.7  | 49.1 |
| TS-Teacher (2019)| 55.1  | 60.2  | 54.5  | 52.0  | 60.8  | 57.0  | 58.7 |
| TS-Stu-W2V (2019)| 59.3  | 66.8  | 48.3  | 57.0  | 64.0  | 57.0  | 58.7 |
| TS-Stu-BERT (2019)| 61.4 | 66.5  | 52.0  | 57.5  | 63.0  | 60.4  | 60.2 |
| SSCL             | 61.0  | 65.2  | 57.3  | 60.6  | 64.6  | 57.2  | 61.0 |
| SSCLS-BERT       | 65.5  | 69.5  | 60.4  | 62.3  | 67.0  | 61.0  | 64.3 |
| SSCLS-DistilBERT |       |       |       |       |       |       |      |

Table 4: Aspect-level precision (P), recall (R), and F-scores (F) on the Citysearch testing set. For overall, we calculate weighted macro averages across all aspects.

| Methods          | Food | Staff | Ambience | Overall |
|------------------|------|-------|----------|---------|
|                  | P    | R     | F        | P       | R     | F     | P    | R     | F     |
| SERBM (2015)     | 89.1 | 85.4  | 87.2     | 81.9     | 58.2  | 68.0  | 80.5 | 59.2  | 68.2  | 86.0 | 74.6  | 79.5  |
| ABAE (2017)      | 95.3 | 74.1  | 82.8     | 80.2     | 72.8  | 75.7  | 81.5 | 69.8  | 74.0  | 89.4 | 73.0  | 79.6  |
| W2VLDA (2018)    | 96.0 | 69.0  | 81.0     | 61.0     | 86.0  | 71.0  | 55.0 | 75.0  | 64.0  | 80.8 | 70.0  | 75.8  |
| AE-CSA (2019)    | 90.3 | 92.6  | 91.4     | 92.6     | 75.6  | 77.3  | 91.4 | 77.9  | 77.0  | 85.6 | 86.0  | 85.8  |
| CAT (2020)       | 91.8 | 92.4  | 92.1     | 82.4     | 75.6  | 78.8  | 76.6 | 80.1  | 76.6  | 86.5 | 86.4  | 86.4  |
| ABAE + HRSMap    | 93.0 | 88.8  | 90.9     | 85.8     | 75.3  | 80.2  | 67.4 | 89.6  | 76.9  | 87.0 | 83.8  | 86.0  |
| SSCL             | 91.7 | 94.6  | 93.1     | 88.4     | 75.9  | 81.7  | 79.1 | 86.1  | 82.4  | 88.8 | 88.7  | 88.6  |
| SSCLS-BERT       | 89.6 | 97.3  | 93.3     | 95.5     | 71.9  | 82.0  | 84.0 | 87.6  | 85.8  | 90.0 | 89.7  | 89.4  |
| SSCLS-DistilBERT | 91.3 | 96.6  | 93.9     | 92.4     | 75.9  | 83.3  | 84.4 | 88.0  | 86.2  | 90.4 | 90.3  | 90.1  |

Table 5: Left: Gold-standard aspects for TVs reviews. Right: Model-inferred aspects presented by representative words.

| Aspects          | Representative Keywords |
|------------------|-------------------------|
| Apps/Interface   | apps app netflix browser hulu youtube |
| Connectivity     | channel antenna broadcast signal station optical composite hdmi input component |
| Customer Serv.   | service process company contact support call email contacted rep phone repair |
| Ease of Use      | button remote keyboard control use qwerty |
| Image            | setting brightness mode contrast color motion scene blur action movement effect |
| Price            | dollar cost buck 00 tax pay |
| Size/Look        | 32 42 37 46 55 40 |
| Sound            | speaker bass surround volume sound stereo |
| General          | forum read reading review cnet posted recommend research buy purchase decision plastic glass screw piece metal base foot wall mount stand angle cabinet football watch movie kid night game pc xbox dvd ps3 file game series model projection plasma led sony |

Performance on Restaurant Review

We have conducted more detailed comparisons on the Citysearch dataset, which has been widely used to benchmark aspect detection models. Following previous work (Tulkens and van Cranenburgh 2020), we use weighted macro averaged precision, recall and F1 score as metrics to evaluate the overall performance. We also evaluate performance of different models for three major individual aspects by measuring aspect-level precision, recall, and F1 scores. Experimental results are presented in Table 4. Results of compared models are obtained from corresponding published papers.

From Table 4, we also observe that ABAE + HRSMap performs significantly better than traditional ABAE. Our SSCL outperforms all baselines in terms of weighted macro averaged F1 score. SSCLS-BERT and SSCLS-DistilBERT further improve the performance of SSCL, and SSCLS-DistilBERT achieves the best results. From aspect-level results, we can...
Figure 3: Ablation study on the Citysearch testing set. WMF represents weighted macro averaged F1-score.

Figure 4: Parameter sensitivity analysis on Citysearch.

which are able to capture high-quality aspects, effectively map model-inferred aspects to gold-standard aspects, and accurately predict aspect labels for given segments.

Aspect Interpretation
As SSCL achieves promising performance on aspect detection compared with baselines in the quantitative analysis, we further show some qualitative results to interpret extracted concepts. From Table 5, we notice that there is at least one model-inferred aspect corresponding to each of gold-standard aspects, which indicates model-inferred aspects based on HRSMap have good coverage. We also find that model-inferred concepts, which are mapped to non-general gold-standard aspects, are fine-grained, and their representative words are meaningful and coherent. For example, it is easy to map “app, netflix, browser, hulu, youtube” to Apps/Interface. Compared to weakly supervised methods (such as MATE), SSCL is also able to discover new concepts. For example, for aspects mapped to General, we may label “pc, xbox, dvd, ps3, file, game” as Connected Devices, and “plastic glass screw piece metal base” as Build Quality.

Ablation Study and Parameter Sensitivity
In addition to self-supervised contrastive learning framework and HRSMap, we also attribute the promising performance of our models to (i) Smooth self-attention mechanism, (ii) Entropy filters, and (iii) Appropriate batch size. Therefore, we systematically conduct ablation studies and parameter sensitivity analysis to demonstrate the effectiveness of them, and provide the results in Fig. 3 and Fig. 4.

First, we replace smooth self-attention (SSA) layer with a regular self-attention (RSA) layer used in (Angelidis and Lapata 2018) and an average pooling (AP) layer, respectively. The model with SSA performs better than the one with AP or RSA. Next, we examine the entropy filter for SSCLS-BERT, and observe that adding it has a positive impact on model performance. Then, we study the effect of smoothness factor \( \lambda \) in SSA and observe that our model achieves promising and stable results when \( \lambda \leq 1 \). Finally, we investigate the effect of batch size. F1 scores increase with batch size and become stable when batch size is greater than 20. However, very large batch size increases the computational complexity; see Algorithm 1. Therefore, we set batch size to 50 for all our experiments.

Case Study
Fig. 5 compares heat-maps of attention weights obtained from SSA and RSA on two segments from Amazon TVs testing set. In each example, RSA attempts to use a single word to represent the entire segment. However, the word may be either a representative word for another aspect (e.g., “scene” for Image in Table 5) or a word with no aspect tendency (e.g., “great” is not assigned to any aspect.). In contrast, SSA captures phrases and multiple words, e.g., “volume scenes” and “great value, 499”. Based on the results in Fig. 3 and Fig. 5, we argue SSA is more robust and intuitively meaningful than RSA for aspect detection.

Conclusion
In this paper, we propose a self-supervised contrastive learning framework for aspect detection. Our model is equipped with two attention modules, which allows us to represent every segment with word embeddings and aspect embeddings, so that we can map aspect embeddings to the word embedding space through a contrastive learning mechanism. In attention module over word embeddings, we introduce a SSA mechanism. Thus, our model can learn robust representations, since SSA encourages model to capture phrases and multiple keywords in the segments. In addition, we propose a HRSMap method for aspect mapping, which dramatically increases the accuracy of segment aspect predictions for both ABAE and our model. Finally, we further improve the performance of aspect detection through knowledge distilling. BERT-based student models can benefit from pretrained encoders and overcome disadvantages of data preprocessing for the teacher model. During training, we introduce entropy filters in the loss function to ensure student models concentrate on high confidence training samples. Our models have shown better performance compared with several recent unsupervised and weakly-supervised models on a restaurant review dataset and six Amazon reviews datasets across different domains. Aspect interpretation results show that extracted aspects are meaningful, have a good coverage, and can be easily mapped to gold-standard aspects. Ablation studies and visualization of attention weights further demonstrate the effectiveness of SSA and entropy filters.
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Supplementary Materials

Datasets
In this section, we provide more details about the datasets used in our experiments.

Amazon Reviews  We obtain Amazon product reviews from the OPOSUM dataset (Angelidis and Lapata 2018), which has six subsets across different domains, including Laptop Cases, Bluetooth Headsets, Boots, Keyboards, Televisions, and Vacuums. For each subset, reviews are segmented into elementary discourse units (EDUs) through a Rhetorical Structure Theory parser (Feng and Hirst 2014). Then, each segment in development and test sets is manually annotated with eight representative aspect labels as well as aspect General. We show the annotated aspect labels in Table A1. In our experiments, we use exactly the same segments and aspect labels as Angelidis and Lapata (2018).

| Domains  | Aspects                                                                 |
|----------|--------------------------------------------------------------------------|
| Bags     | Compartments, Customer Service, Handles, Looks, Price, Quality, Protection, Size/Fit, General. |
| Bluetooth| Battery, Comfort, Connectivity, Durability, Ease of Use, Look, Price, Sound, General |
| Boots    | Color, Comfort, Durability, Look, Materials, Price, Size, Weather Resistance, General |
| Keyboards| Build Quality, Connectivity, Extra Function, Feel Comfort, Layout, Looks, Noise, Price, General |
| TVs      | Apps/Interface, Connectivity, Customer Service, Ease of Use, Image, Price, Size/Look, Sound, General |
| Vacuums  | Accessories, Build Quality, Customer Service, Ease of Use, Noise, Price, Suction Power, Weight, General |

Table A1: The annotated aspects for Amazon reviews across different domains.

Restaurant Reviews  For restaurant reviews, training and testing sets are from the Citysearch dataset (He et al. 2017), while the development set is a combination of restaurant subsets of SemEval 2014 and SemEval 2015 Aspect-Based Sentiment Analysis datasets (Pontiki et al. 2014, 2015). Similar to previous work (He et al. 2017), sentences are treated as segments. In the development and testing sets, we select sentences that only express one aspect, and disregard those with multiple and no aspect labels. We have also restricted ourselves to three labels (i.e., Food, Service, and Ambience), to form a fair comparison with prior work (He et al. 2017; Tulkens and van Cranenburgh 2020).

In our experiments, we have also exploited the English restaurant review dataset from SemEval-2016 Aspect-based Sentiment Analysis task (Pontiki et al. 2016) containing reviews for multiple domains and languages, which has been used in prior work (Karamanolakis, Hsu, and Gravano 2019) for aspect detection. However, we find that the dataset suffers from severe label-imbalance problem. For example, there are only 3 and 13 out of 676 sentences labeled as drinks#prices and location#general, respectively.

Aspect Mapping
In this section, we provide more details of high-resolution selective mapping (HRSMap). High-resolution refers to the fact that the number of model-inferred aspects (MIAs) should be at least 3 times more than the number of gold-standard aspects (GSAs), so that model-inferred aspects have a better coverage. Selective mapping implies that noisy or meaningless aspects will not be mapped to gold-standard aspects.

In our experiments, we set the number of MIAs to 30, considering the balance between aspect coverage and human-effort to manually map them to gold-standard aspects. Usually, it takes less than 15 minutes to assign 30 MIAs to GSAs. First, we automatically generate keywords of MIAs and dump them into a text file, where the number of the most relevant keywords for each aspect is 10. Second, we create several rules for aspect mapping: (i) If keywords of a MIA are clearly related to one specific GSA (not General), we map this MIA to the GSA. For example, we map “apps, app, netflix, browser, hulu, youtube, stream” to Apps/Interface. (ii) If keywords are coherent but not related to any specific GSA, we map this MIA to General. For instance, we map “football, watch, movie, kid, night, family” to General. (iii) If keywords are related to more than one GSA, we treat this MIA as a noisy aspect and it will not be mapped. For example, “excellent, amazing, good, great, outstanding, fantastic, impressed, superior” may be related to several different GSAs. (iv) If keywords are not quite meaningful, their corresponding MIA will not be mapped. For instance, “ugo, within, last 30, later, took, couple, pet, every” is a meaningless MIA. Third, we further verify the quality of aspect mapping using development sets.

We provide more qualitative results to demonstrate: (i) MIAs are meaningful and interpretable. (ii) MIAs based on HRSMap have good coverage. (iii) Our model is able to discover new aspects. All results are summarized in Tables A2-A7.

| Aspects                        | Representative Keywords |
|-------------------------------|-------------------------|
| Compartments                  | zipper, velcro flap, main, zipper, front |
| Customer Serv.                | service, customer, warranty, shipping, contacted, email |
| Handles                       | shipping, arrived, return, shipped, sent, amazon |
| Looks                         | color, blue, pink, purple, green, bright |
| Price                         | $0, cost, spend, paid, dollar, price |
| Protection                    | protect, protection, protects, protecting, protected, safe |
| Quality                       | scratch, drop, damage, scratched, bump |
| Size/Fit                      | inch, perfectly, snug, tight, dell, nicely |
| General                       | plenty, lot, amount, enough, ton, extra |
|                              | 1, 7, 15, 13, 14, 11, 16 |
| General                       | purchased, bought, ordered, buying, buy, owned |
|                              | review, read, people, mentioned, reviewer, reading |
|                              | airport, security, tsa, friendly, checkpoint, luggage |
|                              | trip, travel, carry, seat, traveling, school |

Table A2: Left: GSAs for Laptop Cases reviews. Right: MIAs presented by representative words.
Ablation Study and Parameter Sensitivity

In this section, we provide more results for ablation study and parameter sensitivity. Tables A8 and A9 show models with SSA achieve better performance than those with RSA and AVGP. Tables A10 and A11 show effects of the smoothness factor on the performance of our SSCL model. We find that our model achieves promising and stable results when $\lambda \leq 1.0$ and $\lambda$ is fixed to 0.5 for all datasets. From Table A12 and A13, we can see that F1 scores increase with batch size and become stable when batch size is greater than 20. According to Algorithm 1 line 7-8, we calculate similarities for $X^2$ times at each training step, where $X$ is the batch size. Since large batch size requires extra computations, we set batch size to 50 for all our experiments as a trade-off between performance and computational complexity.
### Aspects

| **Representative Keywords** | **Ambience** | **Food** | **Staff** | **General** |
|-----------------------------|--------------|----------|-----------|-------------|
| room wall ceiling wood floor window | music dj bar fun crowd band | atmosphere romantic cozy feel decor intimate | wall ceiling wood high black lit | steak medium cooked try dry tender | pork chicken potato goat rib roast | tuna shrimp pork lamb salmon duck | chocolate coffee cake cream tea dessert | large small big three four huge | tomato sauce cheese onion oil crust | american menu variety japanese italian cuisine |
| **Staff** | staff waiter server waitress waitstaff manager | friendly attentive helpful prompt knowledgeable courteous | per tip bill 20 fixe dollar | sunday night saturday friday weekend evening | ago birthday anniversary recently last celebrate | overpriced worth average quality bit pretty | street west east park manhattan village | minute year month min hour week | review say heard believe read reading |
| **General** | | | | | | | | | |

Table A7: Left: GSAs for Restaurant reviews. Right: MIAs presented by representative words.

| **Smooth** | **Bags** | **Food** | **Staff** | **Ambience** | **WMF** |
|------------|---------|---------|---------|-----------|---------|
| SSA | 61.0 | 93.1 | 81.7 | 82.4 | 88.6 |
| RSA | 55.9 | 92.6 | 79.6 | 80.5 | 87.5 |
| AVGP | 61.6 | 91.5 | 79.8 | 79.2 | 86.6 |
| **B/T** | 59.5 | 92.0 | 79.9 | 77.8 | 86.7 |
| **Boots** | 59.5 | 89.4 | 75.4 | 73.4 | 83.4 |
| **KBs** | 60.6 | 91.7 | 79.0 | 76.2 | 86.1 |
| **TVs** | 64.6 | 64.6 | 75.3 | 73.4 | 83.4 |
| **VCs** | 57.2 | 74.6 | 73.4 | 83.4 | 86.1 |
| **AVG** | 61.0 | 87.5 | 80.5 | 86.6 | 87.5 |

Table A8: Effects of SSA on micro-averaged F1 scores for Amazon review datasets. SSA, RSA, AVGP represent smooth self-attention, regular self-attention and average-pooling, respectively.

| **Smooth** | **λ** | **Bags** | **Food** | **Staff** | **Ambience** | **WMF** |
|------------|-------|---------|---------|---------|-----------|---------|
| SSA | 0.5 | 61.0 | 65.2 | 57.3 | 60.6 | 64.6 | 57.2 | 61.0 |
| RSA | 1.0 | 61.6 | 65.1 | 58.3 | 61.8 | 66.4 | 55.6 | 61.5 |
| AVGP | 2.0 | 60.7 | 63.9 | 57.3 | 59.8 | 67.0 | 55.0 | 60.6 |
| **B/T** | 3.0 | 61.8 | 64.6 | 57.6 | 59.9 | 63.0 | 55.3 | 60.4 |
| **Boots** | 4.0 | 58.2 | 64.2 | 54.0 | 59.9 | 64.3 | 56.1 | 59.4 |
| **KBs** | 5.0 | 57.4 | 63.0 | 54.2 | 59.3 | 66.4 | 54.9 | 59.2 |

Table A9: Effects of SSA on aspect-level F1 scores and weighted macro-averaged F1 scores for the Citysearch dataset. WMF represents weighted macro averaged F1-score.

| **Bsize** | **Bags** | **Food** | **Staff** | **Ambience** | **WMF** |
|-----------|---------|---------|---------|-----------|---------|
| 20 | 60.2 | 66.9 | 56.0 | 60.4 | 66.7 | 56.3 | 61.1 |
| 50 | 61.0 | 65.2 | 57.3 | 60.6 | 64.6 | 57.2 | 61.0 |
| 100 | 61.8 | 66.0 | 55.8 | 61.4 | 63.4 | 57.4 | 61.0 |
| 200 | 59.4 | 64.6 | 56.3 | 60.8 | 64.6 | 56.6 | 60.4 |

Table A12: Effects of batch size on micro-averaged F1 scores for Amazon review datasets.

| **Bsize** | **Bags** | **Food** | **Staff** | **Ambience** | **WMF** |
|-----------|---------|---------|---------|-----------|---------|
| 10 | 92.3 | 80.4 | 79.5 | 81.4 | 88.5 |
| 20 | 93.3 | 81.3 | 81.4 | 88.5 |
| 50 | 93.1 | 81.7 | 82.4 | 88.6 |
| 100 | 92.9 | 81.7 | 80.9 | 88.2 |
| 200 | 93.0 | 82.6 | 82.9 | 88.9 |

Table A13: Effects of batch size on aspect-level F1 scores and weighted macro-averaged F1 scores for the Citysearch dataset.