

Hyperbolic Disentangled Representation for Fine-Grained Aspect Extraction

Chang-You Tai¹, Ming-Yao Li¹, Lun-Wei Ku¹

¹Academia Sinica, Taipei, Taiwan

johnnyjana730@gmail.com, xuauul@gmail.com, lwku@iis.sinica.edu.tw

Abstract

Automatic identification of salient aspects from user reviews is especially useful for opinion analysis. There has been significant progress in utilizing weakly supervised approaches, which require only a small set of seed words for training aspect classifiers. However, there is always room for improvement. First, no weakly supervised approaches fully utilize latent hierarchies between words. Second, each seed word’s representation should have different latent semantics and be distinct when it represents a different aspect. In this paper we propose HDAE, a hyperbolic disentangled aspect extractor in which a hyperbolic aspect classifier captures words’ latent hierarchies, and an aspect-disentangled representation models the distinct latent semantics of each seed word. Compared to previous baselines, HDAE achieves average F1 performance gains of 18.2% and 24.1% on Amazon product review and restaurant review datasets, respectively. In addition, the embedding visualization experience demonstrates that HDAE is a more effective approach to leveraging seed words. An ablation study and a case study further attest the effectiveness of the proposed components.

Introduction

Researchers have begun to focus on aspect extraction, the automatic detection of fine-grained segments with predefined aspects (Hu and Liu 2004; Liu 2012; Pontiki et al. 2016), due to its potential for downstream tasks. For example, aspect extraction benefits users and customers when searching through review segments for aspects of interest on the Internet. Aspect extraction is also crucial for document summarization (Angelidis and Lapata 2018), recommendation justification (Ni, Li, and McAuley 2019), and review-based recommendation (Chin et al. 2018).

Aspect extraction research can be divided into supervised approaches, unsupervised approaches, and weakly supervised approaches.¹ Among these, many studies have been conducted on weakly supervised approaches (Karamanolakis et al. 2019; Angelidis and Lapata 2018; Zhuang et al. 2020) since they allow the model to be trained without substantial human-labeled data. For example, Angelidis and Lapata (2018) initialize fine-grained aspect representations using

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¹We touch on unsupervised and supervised approaches in the related work section.

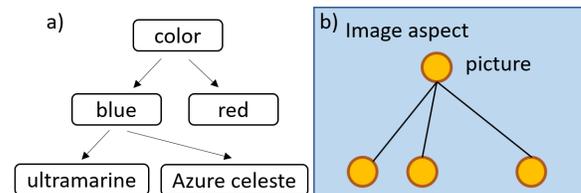


Figure 1: a) Seed word *color* and its hypernym pairs. b) An illustration of latent semantics under seed word *picture*. For example, in the TV domain’s *image* aspect, *pixel of picture* and *screen picture* exist.

only a small number of descriptive keywords, or seed words, to identify highly salient opinions in review segments. Also, Karamanolakis et al. (2019) propose a student-teacher framework that more effectively leverages seed words by using a bag-of-words classifier teacher.

However, there is room for improvement in such seed word based methods. First, they neglect to consider the latent hierarchies between words, and it is assumed that capturing latent hierarchies between words will further improve seed word based methods on aspect inference, for instance by better identifying and organizing seed words and their hypernym pairs (Huang et al. 2020; López, Heinzerling, and Strube 2019). For example, as shown in Fig. 1(a), the general seed word *color* near the top can be used to find the more specific words *blue* or *green* in the middle, after which even more specific words can be found such as *ultramarine* or *azure celeste*. If seed words or their hypernym pairs exist in one review segment, the model can infer that it is of the corresponding aspect.

To allow the model to fully capture latent hierarchies between words, we introduce hyperbolic space (Nickel and Kiela 2017; Murty et al. 2018; Xu and Barbosa 2018; López, Heinzerling, and Strube 2019; López and Strube 2020). Compared to Euclidean space, hyperbolic space effectively encodes hierarchical structure information (Nickel and Kiela 2017), the latent hierarchies between words in this paper. In particular, when embedding tree-like structures, compared to the volume in Euclidean space, which leads to high distortion embeddings (Sa et al. 2018; Sarkar 2011), volume in hyperbolic space grows exponentially and can embed trees

with arbitrarily low distortion (Sarkar 2011; Nickel and Kiela 2017). By virtue of such a hierarchy, a seed word based model can better identify and utilize seed words and their hypernym words and thus achieve better aspect inference in hyperbolic space.

Second, existing seed word-based approaches model each seed word representation in a uniform manner while neglecting the fact that each seed word should have different latent semantics when conducting aspect extraction. For example, for the Amazon product review dataset (Angelidis and Lapata 2018), in the TV domain’s *picture* aspect, the latent semantics under the seed word *picture* can be *pixel of the picture*, *screen picture*, or *HD picture*, as shown in Fig. 1(b). It is essential to select the most relevant latent semantics of the seed word when using the seed word *picture* to infer review aspects of segments. Furthermore, the latent semantics of the seed word should be different in different aspects: this is also neglected by the current uniform representation. Such a uniform approach to modeling seed words tends to result in sub-optimal representations.

Thus, we propose HDAE, a hyperbolic disentangled aspect extractor which captures words’ latent hierarchies and disentangles the latent semantics of each seed word. First, we propose a hyperbolic aspect classifier, using a hyperbolic distance function to calculate the relationship between the segment vector and the aspect representation generated from the seed word. Second, we introduce an aspect disentanglement module to model each seed word’s latent semantics and then generate an aspect-refined representation of each review segment by selecting the most relevant latent semantics. In addition, we propose aspect-aware regularization to model each latent semantic meaning under its aspect scope while encouraging the independence of different latent semantic meanings. We conduct experiments on two datasets, demonstrating that HDAE achieves better aspect inference, which is further substantiated by embedding visualizations. We also provide two case studies to investigate HDAE’s aspect inference ability compared with baselines without fully capturing words’ latent hierarchies and the interpretability of the seed words’ disentangled latent semantics.

We summarize our contributions: first, we propose a novel hyperbolic disentangled aspect extractor. To the best of our knowledge, this is the first work to investigate how to leverage hyperbolic components and disentangled representations for weakly supervised approaches to aspect extraction.² Second, we propose a hyperbolic aspect classifier which captures word’s latent hierarchies and generates associations between the review segment and aspects of interest. Third, we introduce the aspect disentanglement module and aspect-aware latent semantic regularization to model the latent semantic meaning of each seed word. Experiments and a case study demonstrate the effect of the proposed methods for aspect extraction.

Related Work

Aspect Extraction In addition to weakly supervised approaches, there are also supervised approaches and unsuper-

vised approaches. Supervised neural networks achieve better performance than traditional rule-based approaches by viewing aspect extraction as a sequence labeling problem which can be tackled with hidden Markov models (Jin, Ho, and Srihari 2009), conditional random fields (Yang and Cardie 2012; Mitchell et al. 2013), or recurrent neural networks (Wang et al. 2016; Liu, Joty, and Meng 2015). However, supervised approaches require large amounts of labeled data for training. Unsupervised approaches, in contrast, do not use annotated data. Early examples are latent Dirichlet allocation (LDA)-based methods (Chen, Mukherjee, and Liu 2014; García-Pablos, Cuadros, and Rigau 2018). Recently, neural network-based methods (Iyyer et al. 2016; Srivastava and Sutton 2017; He et al. 2017; Luo et al. 2019; Shi et al. 2020) have shown remarkable performance and have outperformed LDA-based methods. However, unsupervised approaches are not effective when used directly for aspect extraction (Karamanolakis et al. 2019; Angelidis and Lapata 2018; Tulkens and van Cranenburgh 2020). For example, many-to-one mapping or high-resolution selective mapping is required by He et al. (2017) and Shi et al. (2020) to manually associate the model-inferred aspect with gold-standard aspects.

Hyperbolic representations have been used to model complex networks (Krioukov et al. 2010; Nickel and Kiela 2017, 2018; Tay, Luu, and Hui 2017; Gülçehre et al. 2018; Huang et al. 2020) and have proven more suitable than Euclidean space in representing hierarchical data (Sala et al. 2018; Nickel and Kiela 2017). For example, López and Strube (2020) introduce hyperbolic representations to capture latent hierarchies arising from the class distribution for multi-class multi-label classification. Aly et al. (2019) use Poincaré embeddings to improve existing methods for domain-specific taxonomy induction. Le et al. (2019) propose utilizing hyperbolic representations to infer missing hypernymy relations. Sun et al. (2021) show that points in hyperbolic space can be more concentrated while maintaining the desired separation and revealing nuanced differences. To our knowledge, this is the first work to apply hyperbolic representations to weakly supervised approaches for aspect extraction.

Disentangled representations improve model performance by identifying and disentangling latent explanatory factors in the observed data (Yoshua Bengio and Vincent 2012) and have shown their success in the NLP domain (Shen et al. 2017; Zhao et al. 2018; Chen et al. 2019; Hu et al. 2017). For instance, Hu et al. (2017) propose disentangled representations with designated semantic structure, which generates sentences with dynamically specified attributes. Hou et al. (2021) derive disentangled representations which separate the distinct and informative factors of variations to improve content-based detection. Disentangled representation has been successively applied to the recommendation (Ma et al. 2019b,a; Hu et al. 2020) and computer vision (Liu et al. 2020; Dupont 2018) domains. For example, Wang et al. (2020) model diverse relationships and disentangle user intents to achieve better-performing representations. To our knowledge, this is the first work to apply disentangled representations to weakly supervised approaches for aspect extraction.

²The codes is at <https://github.com/johnnyjana730/HDAE/>

Preliminaries

Problem formulation The goal of aspect extraction is to predict an aspect category $a_i \in A_C = \{a_j\}_{j=1}^K$ given a review segment $x^s = \{x_1, x_2, \dots, x_T\}$ from a specific domain d_C , where the review segments are created by splitting each review in the corpus; x_i is the word index in the segment; a_i is an aspect and A_C refers to the aspect set pertaining to domain d_C ; K is the number of total aspects and T is the segment's length.

Hyperbolic Geometry We introduce two hyperbolic models:³ the Poincaré ball model and the Klein model.

The Poincaré ball model is defined as a Riemannian manifold $\mathcal{P}^n = (\beta, g_{\mathbf{x}}^\beta)$, where $\beta^n = \{\mathbf{x} \in \mathbb{R}^n : \|\mathbf{x}\| < 1\}$ is an open unit ball, with the metric tensor $g_{\mathbf{x}}^\beta = \lambda_{\mathbf{x}}^2 g^E$, where $\lambda_{\mathbf{x}} = \frac{2}{1-\|\mathbf{x}\|^2}$; g^E is the Euclidean metric tensor. The distance on the manifold is defined as

$$d_{\mathcal{P}}(\mathbf{x}, \mathbf{y}) = \text{arcosh} \left(1 + 2 \frac{\|\mathbf{x}-\mathbf{y}\|^2}{(1-\|\mathbf{x}\|^2)(1-\|\mathbf{y}\|^2)} \right). \quad (1)$$

The Klein model is given by $\mathcal{K}^n = \{\mathbf{x} \in \mathbb{R}^n : \|\mathbf{x}\| < 1\}$ and is often used for aggregation since the Einstein midpoint (Gülçehre et al. 2018) can be easily computed in the Klein model. Formally, a point in the Klein model can be obtained from Poincaré coordinates by

$$\mathcal{P}^n \rightarrow \mathcal{K}^n : \pi_{\mathcal{P} \rightarrow \mathcal{K}}(\mathbf{x}_{\mathcal{P}}) = \frac{2\mathbf{x}_{\mathcal{P}}}{1 + \|\mathbf{x}_{\mathcal{P}}\|^2} \quad (2)$$

and the backward transition formulas

$$\mathcal{K}^n \rightarrow \mathcal{P}^n : \pi_{\mathcal{K} \rightarrow \mathcal{P}}(\mathbf{x}_{\mathcal{K}}) = \frac{\mathbf{x}_{\mathcal{K}}}{1 + \sqrt{1 - \|\mathbf{x}_{\mathcal{K}}\|^2}}. \quad (3)$$

For the Poincaré ball model, the exponential map, from tangent space to hyperboloid manifold, $\exp_{\mathbf{x}}: \mathcal{T}_{\mathbf{x}}\mathcal{P} \rightarrow \mathcal{P}$, and the logarithmic map, from hyperboloid manifold to tangent space, $\log_{\mathbf{x}}: \mathcal{P} \rightarrow \mathcal{T}_{\mathbf{x}}\mathcal{P}$, can be found in Liu, Nickel, and Kiela (2019). For simplicity, we denote $d_{\mathcal{P}}^{\text{exp}}$ as the hyperbolic distance of the tangent space vector after applying the exponential map:

$$d_{\mathcal{P}}^{\text{exp}}(\mathbf{x}, \mathbf{y}) = d_{\mathcal{P}}(\exp_0(\mathbf{x}), \exp_0(\mathbf{y})). \quad (4)$$

Methodology

Euclidean Aspect Extractor

Our work builds on the seed word based model developed by Angelidis and Lapata. We describe the method, including segment representation generation and the aspect classifier.

Segment Representation For each review segment $x^s = \{x_1, x_2, \dots, x_T\}$, the segment representation \mathbf{v}_s is generated by a weighted sum of an individual word:

$$\mathbf{v}_s = \sum_{i=1}^n c_i \mathbf{v}_{x_i} \quad (5)$$

$$c_i = \frac{\exp(u_i)}{\sum_{j=1}^n \exp(u_j)}; u_i = \mathbf{v}_{x_i}^\top \cdot \mathbf{M} \cdot \mathbf{v}'_s, \quad (6)$$

³For more details; see Robbin and Salamon (2011).

where \mathbf{v}_{x_i} is the vector of the i -th word x_i ; \mathbf{v}'_s is average of the segment's word vector; and $\mathbf{M} \in \mathbb{R}^{d \times d}$ denotes the attention matrix.

Euclidean Aspect Classifier To predict a probability distribution over K aspects, the vector \mathbf{v}_s is fed to a hidden classification layer followed by the softmax function:

$$p_s^a = \text{softmax}(\mathbf{W}\mathbf{v}_s + \mathbf{b}), \quad (7)$$

where \mathbf{W} and \mathbf{b} are trainable parameters. To focus on the aspect of interest, for each aspect a_i , which has seed words $[s_{i,1}, s_{i,2}, \dots, s_{i,N}]$, the model generates the aspect vector \mathbf{a}_i by using the labeled aspect seed words:

$$\mathbf{a}_i = \sum_j^N \mathbf{z}_{i,j} \mathbf{s}_{i,j}; \mathbf{A} = [\mathbf{a}_i^\top; \dots; \mathbf{a}_K^\top], \quad (8)$$

where $\mathbf{A} \in \mathbb{R}^{K \times d}$ denotes the aspect matrix; and $\mathbf{s}_{i,j}$ denotes the j -th seed word representation; the weight vectors $\mathbf{z}_{i,j}$ are determined by the method mentioned in Angelidis and Lapata (2018); and N is the number of seed words. Then, the segment reconstructed vector \mathbf{r}_s is generated based on the aspect vector:

$$\mathbf{r}_s = \mathbf{A}^\top p_s^{\text{asp}}. \quad (9)$$

To optimize the performance, the model is trained by reconstruction loss, which maximizes the distance between inner product $\mathbf{r}_s \mathbf{v}_s$ and $\mathbf{r}_s \mathbf{v}_n$, where \mathbf{v}_n is the vector of a randomly sampled negative segment.

$$J_r(\theta) = \sum_{x^s \in C} \sum_{i=1}^{k_n} \max(0, 1 - \mathbf{r}_s \mathbf{v}_s + \mathbf{r}_s \mathbf{v}_n), \quad (10)$$

Hyperbolic Disentangled Aspect Extractor

Here, we present HDAE, a hyperbolic aspect classifier with an aspect disentanglement module proposed to model multiple latent semantic meanings for each seed word according to its aspect category.

Hyperbolic Aspect Classifier To infer the review segment's aspect probability $p_s^{a_i}$ in hyperbolic space, we follow Balazevic, Allen, and Hospedales (2019) in using the hyperbolic distance function and biases to calculate the relationship between segment vector \mathbf{v}_s and aspect representation \mathbf{a}_i as

$$p_s^{a_i} = -d_{\mathcal{P}}^{\text{exp}}(\mathbf{v}_s, \mathbf{a}_i)^2 + b_v + b_{a_i}. \quad (11)$$

Then, to generate the reconstructed embedding \mathbf{r}_s , the Einstein midpoint is used to aggregate hyperbolic aspect weights, with a simple form in the Klein disk model:

$$\mathbf{r}_s = \log_0 \left(\pi_{\mathcal{K} \rightarrow \mathcal{P}} \left(\sum_{a_i \in A_C} \frac{k_i \gamma(\mathbf{a}_i^{\mathcal{K}})}{\sum_j k_j \gamma(\mathbf{a}_j^{\mathcal{K}})} \mathbf{a}_i^{\mathcal{K}} \right) \right) \quad (12)$$

$$k_i = \exp(\beta p_s^{a_i} - c), \quad (13)$$

where $\mathbf{a}_i^{\mathcal{K}} = \pi_{\mathcal{P} \rightarrow \mathcal{K}}(\mathbf{a}_i^{\mathcal{P}})$; $\mathbf{a}_i^{\mathcal{P}}$ denotes the Poincaré aspect embedding; $\mathbf{a}_i^{\mathcal{P}} = \exp_0(\mathbf{a}_i)$; β and c are set parameters; and Lorentz factors $\gamma(t) = \frac{1}{(1-|t|^2)^{1/2}}$.

Aspect Disentanglement Module To generate multiple latent semantic meanings for each seed word, we propose a disentangled semantic representation. Then, we present aspect-aware regularization, which models latent semantic vectors for each seed word, after which we discuss refined seed word representation.

Disentangled Semantic Representation For aspect a_i , we devise a representation function to output a disentangled semantic vector $\mathbf{s}_{i,j}^d$ for the j -th seed word $s_{i,j}$, which is composed of I independent components:

$$\mathbf{s}_{i,j}^d = (\mathbf{s}_{i,j}^{d_1}, \mathbf{s}_{i,j}^{d_2}, \mathbf{s}_{i,j}^{d_3}, \dots, \mathbf{s}_{i,j}^{d_I}), \quad (14)$$

where disentangled semantic vector $\mathbf{s}_{i,j}^{d_k}$ is generated by adding a standard Gaussian random variable to the original seed word representation $\mathbf{s}_{i,j}$.

Aspect-Aware Regularization This models the latent semantic representation of each seed word according to its aspect category and has three objectives, as shown in Fig. 2: (a) seed word dependence, (b) latent semantic independence, and (c) aspect scope confinement, which are controlled by latent semantic modeling distances d_1 , d_2 , and d_3 .

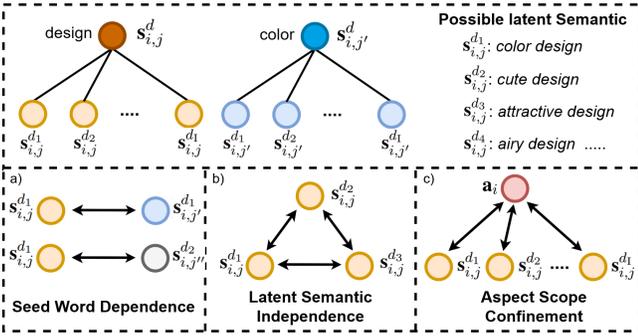


Figure 2: The proposed aspect disentanglement module generates disentangled semantic representations for each seed word and models latent semantics using (a) seed word dependence, (b) latent semantic independence, and (c) aspect scope confinement.

Seed Word Dependence The interdependence between seed word pairs sheds light on the modeling of the seed word’s latent semantics within the scope of its aspect. For example, for seed word *design* in the boot domain’s *look* aspect, the latent semantic meaning, which facilitates fine-grained aspect inference, can be *color design*, *design style*, *cute design*, and *attractive design*. The desired latent semantic meaning can be modeled by narrowing the gap between either the latent semantic meaning of *design* and the latent semantic meanings of other seed words, such as *color*, *style*, *cute*, and *attractive* in the same *look* aspect. Likewise, in the TV domain’s *service* aspect, latent semantic meanings *shipping service*, *replacement service*, and *delivery service* can be generated by minimizing the distance between either the latent semantic meaning of *service* and that of *shipping*, *replacement*, and *delivery*, which are seed words in the same aspect.

To model the interdependence of seed word pairs, we use the hyperbolic distance function $d_{\mathcal{P}}()$ to achieve fine-

grained relationship modeling, since hyperbolic space offers the ability to not only preserve hierarchical (tree-like) information (Nickel and Kiela 2017; Zhang and Gao 2020; Gülçehre et al. 2018; Chami et al. 2019) but also nuanced differences (to better group them) (Sun et al. 2021; Tai et al. 2021) and outperforms Euclidean counterparts in various kinds of data (Zhang and Gao 2020; Gülçehre et al. 2018; Chami et al. 2019, 2020; Sun et al. 2021; Tai et al. 2021). Thus, it is assumed that with more space (hyperbolic space) to organize points, the model can divide disentangled representations and better group them. Given seed word pairs such as *design* $s_{i,j}$ and *color* $s_{i,j'}$ in the specific aspect, we require at least one latent semantic pair distance to be close enough:

$$\text{sim}(s_{i,j}, s_{i,j'}) = \text{argmin}\{d_{\mathcal{P}}^{\text{exp}}(\mathbf{s}_{i,j}^{d_k}, \mathbf{s}_{i,j'}^{d_{k'}}) | \mathbf{s}_{i,j}^{d_k} \in \mathbf{s}_{i,j}^d, \mathbf{s}_{i,j'}^{d_{k'}} \in \mathbf{s}_{i,j'}^d\} \quad (15)$$

$$J_{d_1}(\theta) = \sum_{a_i \in A_C} \sum_{j=1}^N \sum_{j'=j+1}^N \max(0, \text{sim}(s_{i,j}, s_{i,j'}) - d_1), \quad (16)$$

where sim outputs the minimal distance from all possible seed word latent semantic meaning pairs; d_1 is the inter seed word alignment distance, which maintains two latent semantic meanings within a certain distance. Intuitively, for different aspect word pairs, the alignment score should be different, as in Wang et al. (2020). For example, in the boot domain’s *look* aspect, the seed word dependence between *design* and *color* should be more significant than *design* and *going*. We leave this to future work.

Latent Semantic Independence Latent semantic meanings should be distinct from each other. Independent latent semantic meanings reduce redundancy and confusion in aspect inference. To achieve this, we maintain the distance between the seed word’s latent semantic meanings.

$$J_{d_2}(\theta) = \sum_{a_i \in A_C} \sum_j \sum_{k=1}^I \sum_{k'=k+1}^I \max(0, d_2 - d_{\mathcal{P}}^{\text{exp}}(\mathbf{s}_{i,j}^{d_k}, \mathbf{s}_{i,j}^{d_{k'}})), \quad (17)$$

where d_2 is the latent semantic distance.

Aspect Scope Confinement For each seed word, all latent semantic meanings should be limited in terms of aspect scope. For example, in the boot domain’s *color* aspect, all latent semantic meanings of seed word *style* should refer to *color’s style*. However, in the *look* aspect, all latent semantic meanings of the same seed word *style* should refer to *outlook style*. To thus limit all latent meanings of a seed word to its aspect scope, we introduce another regularization:

$$J_{d_3}(\theta) = \sum_{a_i \in A_C} \sum_j \sum_{k=1}^I \max(0, d_{\mathcal{P}}^{\text{exp}}(\mathbf{s}_{i,j}^{d_k}, \mathbf{a}_i) - d_3), \quad (18)$$

where d_3 is the aspect scope confinement distance and \mathbf{a}_i is the aspect representation from Eq. 8. Note compared to seed word dependence and Eq. 16, which focuses on dependence between seed word pairs, Eq. 18 ensures all latent semantic meanings are modeled within the specific aspect scope.

Refined Seed Word Representation This constructs refined seed representations based on its latent semantics. For each seed word, the latent semantics should be independent from each other; only one latent semantic meaning should be used to find the aspect relevant content. For example, for the boot domain’s *look* aspect, possible latent semantics of seed word *style* include *cute style*, *casual style*, or *attractive style*; as we can see these latent semantics are of different meanings, and combining them together may led to a sub-optimal seed word representation. Also, according to each review segment, the most relevant latent semantic meaning should be selected when predicting its aspect distribution. Thus, we introduce the Gumbel softmax, a differentiable softmax function for generating discrete variables, and use this to generate the desired refined seed word representation $\mathbf{s}_{i,j}^r$ according to each segment \mathbf{v}_s :

$$\mathbf{s}_{i,j}^r = \sum_{k=1}^I g_k \mathbf{s}_{i,j}^{d_k}, \quad g_k = \frac{c_k}{\sum_{k'} c_{k'}}, \quad (19)$$

$$c_k = \exp\left(\frac{-d_p(\mathbf{v}_s, \mathbf{s}_{i,j}^{d_k})}{\tau}\right) \quad (20)$$

where τ , the temperature parameter, controls the extent to which the output becomes a one-hot vector. With the refined seed word representation $\mathbf{s}_{i,j}^r$, the aspect representation can be generated by Eq. 8.

Algorithm 1: HDAE Learning

Input: review segments $S = \{s \mid s \in C\}$, aspect seed words

- 1 **Initialize** HDAE parameter with pre-trained word vector
- 2 **foreach** $epoch$ **do**
- 3 **for** $x^s \in S$ **do**
- 4 Generate segment embedding \mathbf{v}_s (Eq 5)
- 5 **for** $i \leftarrow 1$ **to** K **do**
- 6 Generate refined aspect seed word vector $\mathbf{s}_{i,j}^r$ (Eq 19)
- 7 Calculate aspect embedding \mathbf{a}_i (Eq 8)
- 8 Generate aspect probability $p_s^{a_i}$ (Eq 11)
- 9 Generate reconstructed embedding \mathbf{r}_s (Eq 12)
- 10 Calculate objective J (Eq 21)
- 11 Update parameters by Adam optimizer

Learning Algorithm

The formal description of the above aspect inference process is presented in Algorithm 1. To train HDAE, we rely on the previously introduced reconstruction loss J_r (Eq. 10). Since the reconstruction objective only provides a weak training signal (Angelidis and Lapata 2018), the distillation objective J_d from the teacher (Karamanolakis et al. 2019) is used to provide an additional training signal. Also, the disentangled

modeling objectives J_{d_1} , J_{d_2} , and J_{d_3} are used to model each latent semantic meaning according to its aspect category. Thus, the overall objective is

$$J(\theta) = J_r(\theta) + \lambda J_d(\theta) + J_{d_1}(\theta) + J_{d_2}(\theta) + J_{d_3}(\theta). \quad (21)$$

The λ controls the influence of the distillation objective loss.

Experiments and Results

Datasets We used Amazon product reviews from the OPO-SUM dataset (Angelidis and Lapata 2018) and restaurant reviews from the SemEval-2016 Aspect-based Sentiment Analysis task (Pontiki et al. 2016). The Amazon product reviews cover six domains, ranging from laptop bags (Bags), bluetooth headsets (B/T), boots, keyboards (KBs), and televisions (TVs) to vacuums (VCs). The restaurant reviews dataset covers six languages: English (En), Spanish (Sp), French (Fr), Russian (Ru), Dutch (Du), and Turkish (Tur). During training, seed words are provided but not segment aspect labels. Details are provided in the appendix.

Baseline LDA-Anchors (Lund et al. 2017), an interactive topic model which utilizes seed words as “anchors” to identify the segment aspect. **ABAE** (He and Chua 2017), an unsupervised method which adopts reconstruction loss to make the reconstructed embedding similar to a segment vector. This requires a manual mapping between the model-inferred aspect and gold-standard aspects. **SSCL** (Shi et al. 2020), an unsupervised method that uses a contrastive learning algorithm and knowledge distillation for aspect inference. For manual mapping, the high-resolution selective mapping (HRSSMap) is used. **MATE*** (Angelidis and Lapata 2018), a seed-based weakly supervised method which generates pre-defined aspect representations by seed word vector. This can be trained by an extra multitask training objective (MT).⁴ **TS*** (Karamanolakis et al. 2019), a seed based weakly supervised method which adopts a teacher-student iterative co-training framework, where the teacher (TS-Teacher) is a bag-of-words classifier based on seed words and the student uses the attention-weighted average of word2vec embeddings (TS-ATT). **Gold***, supervised models trained using ground truth aspect labels, only available for restaurant reviews, and not directly comparable with other weakly supervised baselines (Karamanolakis et al. 2019).

Note that for SSCL and TS, the BERT model also can be used as the encoder (SSCL-BT, TS-BT). The results of the compared models are obtained from the corresponding published papers. We also report our re-implemented version of SSCL-BT*. We do not provide the ABAE and SSCL results for restaurant reviews for non-English datasets, since this requires domain knowledge for manual aspect mapping.⁵

Experimental Results

Overall Inference Performance Tables 1 and 2 show the results for aspect extraction on both datasets. We observe that

⁴MT cannot be applied in restaurant reviews since it requires datasets from different domains but the same language.

⁵We report ABAE and SSCL results for EN restaurant reviews in the appendix in our arxiv version.

Model	Product review domain					
	Bags	KBs	Boots	B/T	TVs	VCs
LDA-Anchors	33.5	34.7	31.7	38.4	29.8	30.1
ABAE	38.1	38.6	35.2	37.6	39.5	38.1
SSCL	61.0	60.6	57.3	65.2	64.6	57.2
SSCL-BT	65.5	62.3	60.4	69.5	67.0	61.0
SSCL-BT*	56.5	61.7	41.5	51.4	58.2	52.4
MATE	46.2	43.5	45.6	52.2	48.8	42.3
MATE-MT	48.6	45.3	46.4	54.5	51.8	47.7
TS-Teacher	59.3	58.2	50.6	63.3	61.0	58.4
TS-ATT	58.7	57.0	52.6	67.6	63.2	58.8
TS-BT	59.1	59.0	53.9	65.8	66.1	61.0
HDAE	68.8	72.2	64.0	72.0	71.2	66.9

Table 1: Micro-averaged F1 for 9-class EDU-level aspect detection in product reviews

Model	Restaurant review domain					
	En	Sp	Fr	Ru	Du	Tur
W2V-Gold	58.8	50.4	50.4	69.3	51.4	55.7
BERT-Gold	63.1	51.6	50.6	64.6	53.5	55.3
HDAE-Gold	70.5	72.5	65.4	67.9	73.8	65.4
LDA-Anchors	28.5	17.7	13.1	14.8	25.9	27.7
MATE	41.0	24.9	25.8	18.4	36.1	39.0
MATE-UW	40.3	18.3	27.8	21.8	31.5	25.2
TS-Teacher	44.9	41.8	34.1	54.4	40.7	30.2
TS-ATT	47.8	41.7	32.4	59.0	42.1	42.3
TS-BT	51.8	42.0	39.2	58.0	43.0	45.0
HDAE	57.9	65.7	48.6	62.9	57.2	50.8

Table 2: Micro-averaged F1 for 12-class sentence-level aspect detection in restaurant reviews

HDAE achieves superior performance. For example, in Amazon product reviews, compared to TS-W2V, HDAE yields F1 performance gains of 16.0%, 8.1%, 31.9%, 24.7%, 11.3%, and 17.4% on Bags, KBs, Boots, B/T, TVs, and VCs, respectively; similar trends are observed in the restaurant review dataset. Moreover, the reduction in the parameter size of HDAE is also remarkable: 97.8% versus TS-BT.⁶ These results demonstrate the effectiveness of the proposed hyperbolic disentangled aspect extractor (HDAE).

We also observe the weakly unsupervised approaches MATE* and TS-* significantly outperform the unsupervised approaches LDA-Anchors and ABAE, suggesting the effectiveness of seed words. Note our reproduced SSCL-BT* does not consistently outperform MATE, perhaps because SSCL-BT relies heavily on the quality of initial k-means centroids since poorly initialized centroids may cause model-inferred aspects after training to lack good coverage for gold-standard aspects, and thus make manual mapping more difficult.

Compared to fully supervised (*-Gold) models, HDAE dramatically reduces the performance gap between weakly supervised approaches and fully supervised approaches and even outperforms in Spanish and Dutch restaurant reviews. Moreover, we investigate HDAE’s performance when given ground-truth aspect labels denoted by HDAE-Gold in Table 2. The result shows that HDAE-Gold outperforms both W2V-Gold and BERT-Gold, showing the effectiveness of the proposed hyperbolic disentangled based approach. Note that

⁶The parameter sizes of HDAE and TS-BT are 2.5M and 109.5M.

Ablation	Bag	KBs	B/T	Boots	TV	VCs
HDAE	68.8	72.2	72.0	64.0	71.2	66.9
HDAE ($\lambda = 0$)	67.3	65.6	70.1	60.5	54.1	59.1
MATE	46.2	43.5	52.2	45.6	48.8	42.3

Table 3: HDAE ablation study. The λ is the ratio of distillation objective loss. When λ is 0, the distillation objective J_d is not used.

we vary the ratio of ground-truth aspect labels and compare model performance for different label ratios; these result are provided in the appendix.

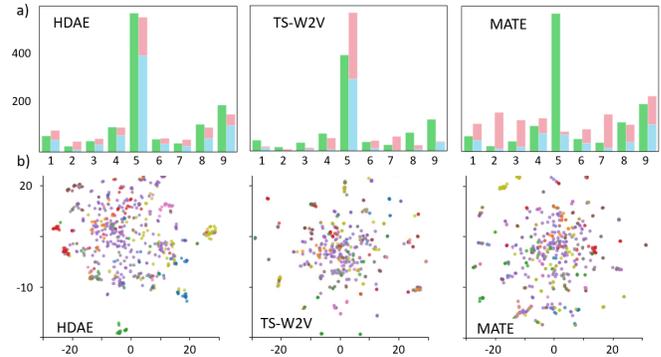


Figure 3: Inference performance per aspect of HDAE, TS-W2V, and MATE on the a) Bags dataset. On Bags, we use t-SNE to compare b) the embedding of each model, where the different colors represent different aspects.

Inference Performance per Aspect Here we investigate the abilities that seed word based approaches infer on different aspects, shown in Fig. 3(a). First, we observe that TS-W2V puts a greater focus on the general aspect, possibly because the teacher always predicts review segments as general aspect if no seed word appears. Second, compared to MATE and TS-W2V, HDAE yields better inference performance in almost all aspects without putting excessive bias on certain predictions, showing better aspect inference ability. To further investigate the performance on Bags, we compared sentence vectors \mathbf{v}_s of each model⁷ by using t-SNE to visualize vectors, as shown in Fig. 3(b). We find that a well-differentiated sentence vector benefits the model’s aspect inference ability. First, compared to HDAE and MATE, less-separated vectors are found for TS-W2V, which correlates to the fact that TS-W2V performs poorly in every aspect except the general aspect. Second, we observe for both the *looks* (red) and *size fit* (yellow) aspects, differentiated vector clusters are found in HDAE and MATE, which correlates to the good accuracy in both aspects. Third, compared to MATE, the differentiated vector clusters of the *handles* (green), *protection* (pink), *price* (brown), and *compartments* (blue) aspects explain HDAE’s better inference ability in those aspects.

⁷For HDAE, the hyperbolic sentence vector $\text{exp}_0(\mathbf{v}_s)$ is used.

a) The keyboard works very well. GT: General		
Seed Words: think, recommend, purchase, using, unit, star, microsoft		
HDAE: General ✓	MATE: General ✓	TS-W2V: General ✓
b) The color is nice, more light blue. GT: Color		
Seed Words: color, love, style, unbelievably, gorgeous, blue		
HDAE: Color ✓	MATE: Color ✓	TS-W2V: Color ✓
c) What I received is a grayish brown shoe. GT: Color		
Seed Words: color, love, style, unbelievably, gorgeous, blue		
HDAE: Color ✓	MATE: General ✗	TS-W2V: Price ✗
d) It's not leather. GT: Quality		
Seed Words: quality, material, handle, poor, broke, durable, month		
HDAE: Quality ✓	MATE: Handles ✗	TS-W2V: General ✗
e) On the other hand, find it to be too stiff. GT: Comfort		
Seed Words: feel, comfortable, mushy, key, like, difficult		
HDAE: Comfort ✓	MATE: Function ✗	TS-W2V: General ✗

Table 4: Comparison of predictions on sample Product review segments between HDAE, MATE, and MATE. For each review segment, the ground truth (GT) aspect and its corresponding seed words are provided.

Ablation Study

To verify the effectiveness of the proposed components, we conducted an ablation study for HDAE, as shown in Table 3. After removing the hyperbolic aspect classifier (3) and aspect disentangle module (4), we observe drops in performance, indicating the effect of the proposed components. Note that (4), which only contains the hyperbolic aspect classifier, outperforms the MATE-* and TS-* models, showing that the proposed hyperbolic aspect classifier effectively leverages the seed words. Furthermore, removing the hyperbolic distance function for the disentangled aspect representation, shown by (2), degrades performance, suggesting that the hyperbolic distance function is indispensable for modeling the latent semantic meanings of seed words.⁸

Case study

To more closely investigate the aspect inference ability of HDAE, we compare the predictions made by HDAE, MATE, and TS-W2V, the results of which are shown in Table 4. For the example in Table 4(b), we see that the review segment contains keywords such as *color* and *blue* which are explicitly captured in aspect seed words. All models correctly infer and review the segment's aspect. However, for cases in Table 4(c,d,e), the reviews' segments do not explicitly match their aspect seed words but instead match the hyponymic relations (is-a) present between seed words and review segments. For example, there are hierarchical relations such as *grayish brown* is a *color*, *leather* is a *material*, and *stiff* is a type of *difficult* for cases in Table 4(c,d,e). We find only HDAE correctly recognizes the review segments' aspects. We thus conclude HDAE captures and utilizes hyponymic relations (is-a) present between seed words and review segments, deriving reasonable aspect inference for each review segment and thus achieving better performance.

To explore the interpretability of the seed words' latent semantic meanings, we conducted a case study in which we

⁸we also conduct parameters sensitivity study, please refer to the appendix in our arxiv version.

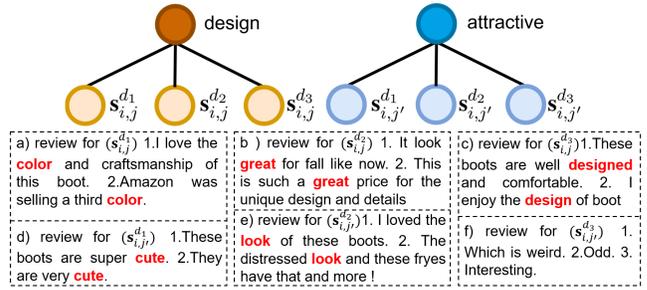


Figure 4: Interpretability of latent semantic meanings of seed words. Best viewed in color.

randomly selected review segments from the boot domain's *look* aspect and investigated its association with each aspect of latent semantic meaning. Figure 4 shows the review segments captured by each seed word's latent semantic meaning; we find that each aspect's latent semantics focus on a distinct type of review segment. For example, for the seed word *design*, the latent semantic meaning $s_{i,j}^{d1}$ focuses on segments with *color* information, whereas $s_{i,j}^{d2}$ focuses on segments with the *great* keyword. Likewise, for the seed word *attractive*, the latent semantic meaning $s_{i,j'}^{d1}$ focuses on segments with *cute* information, whereas $s_{i,j'}^{d3}$ focuses on segments with *unattractive* information. These results demonstrate that the proposed aspect disentanglement module assists HDAE in modeling different latent semantics for each seed word. Also, HDAE finds the most relevant latent semantic meanings for each review segment, explaining the improvements in the aspect inference ability.

Conclusions and Future Work

We present HDAE, which includes a hyperbolic aspect classifier and an aspect disentanglement module. On two datasets, HDAE, with its 97.8% reductions in parameter size versus TS-BT, shows superior aspect inference ability, further substantiated by an embedding visualization. The effect of the proposed components is proved by an ablation study, a parameter sensitivity study, and a case study. In the future, we plan to explore the proposed module on other aspect-based sentiment analysis (ABSA) subtasks. We would also like to further improve the performance of the proposed components, for instance by setting up alignment scores for different aspect word pairs when modeling seed word dependence.

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