Vocabulary-informed Extreme Value Learning

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Abstract

The novel unseen classes can be formulated as the extreme values of known classes. This inspired the recent works on open-set recognition [32, 31, 28], which however can have no way of naming the novel unseen classes. To solve this problem, we propose the Extreme Value Learning (EVL) formulation to learn the mapping from visual feature to semantic space. To model the margin and coverage distributions of each class, the Vocabulary-informed Learning (ViL) is adopted by using vast open vocabulary in the semantic space. Essentially, by incorporating the EVL and ViL, we for the first time propose a novel semantic embedding paradigm – Vocabulary-informed Extreme Value Learning (ViEVL), which embeds the visual features into semantic space in a probabilistic way. The learned embedding can be directly used to solve supervised learning, zero-shot and open set recognition simultaneously. Experiments on two benchmark datasets demonstrate the effectiveness of proposed frameworks.

1 Introduction

Till now, object categorization algorithms are mostly solved in the form of “closed set” recognition in a supervised way, i.e., all testing classes should be known and have training instances at the training time. The main difficulty of “closed set” recognition is to generalize the classifiers to recognize the labels of testing instances that are mostly similar to what types of training instances (i.e. discriminative learning), or mostly likely belong to what kind of feature distribution of known classes (i.e. generative learning). These basic ideas had spawned research in supervised recognition and to an extent, semi-supervised learning.

Unfortunately, in the real-world scenarios, the recognition tasks have to be done in a form of “open set” recognition where the testing classes may not yet be observed in training time. The reasons are as follows. Firstly, in term of psychological theory [3] that human beings can distinguish beyond 30000 basic level categories as well as many subordinate ones (e.g. the breeds of birds), it may take prohibitive cost to collect enough training instances for each class. Secondly, humans have the ability of “learning to learn”; and thus we can dynamically create new categories purely from high-level semantic descriptions. The recognition models, if still works in the “closed set” recognition, must require increasing labelled instances for newly created categories. Nevertheless, the main challenge of open set recognition comes from generalizing the trained classifiers to categorize the training classes, and also be able to adaptively construct classifiers from trained classifier to identify the novel unseen classes.

Recently, there are huge efforts that have been made towards solving the challenges of generalization existing classifiers to novel unseen categories. We briefly summarize them here,
Class incremental learning. incrementally learned the concepts over time from data stream. However, such a learning only discriminatively augments the training classes but have no way for the name-ability of newly added classes.

**Extreme Value Machine (EVM).** As an early attempt towards open set recognition, systematically derived EVM from the extreme value theory and targeted at identifying images of known classes in the present of novel classes. The novel classes can thus be taken as extreme values of training classes. However the EVM can only tell the known labels apart from the unknowns rather than naming the novel classes.

**Zero shot learning (ZSL).** It aims at transferring semantic knowledge from the instances of (auxiliary) training classes, and recognizing the instances of unseen classes at test time. Semantic attributes or semantic word vectors are employed to transfer knowledge to name the novel unseen classes.

**Vocabulary-informed learning (ViL).** proposed utilizing the vocabulary of semantic space learned by word2vec to help learning the mapping from visual to semantic space. Most of the vocabulary belong to neither training nor testing classes and thus it is called “open set” vocabulary. Inspired by the extreme value theory that one object category can be naturally seen as extreme values of its similar object category, the novel unseen classes can be formulated as the extreme values of training classes, and thus better learning the mapping from visual feature space to semantic space. Thus the Extreme Value Learning (EVL) is formulated here to learn the semantic embedding space.

Formally, in this paper, we propose a new type of learning paradigm – “Vocabulary-informed Extreme Value Learning” (ViEVL) to learn the feature mapping from feature space to semantic embedding space in a probabilistic way and be optimized for supervised learning, zero-shot and open set recognition. Particularly, in extreme value learning stage, the instances of training classes are used to construct the extreme value distribution and encode the extreme values of training classes as the constraints to learn the feature mapping. EVL will enable projected feature instances closer to the correct class prototypes than to incorrect ones. We also propose a ViL algorithm to generate the virtual instances of prototypes for the extreme distribution of prototypes. In the ViEVL stage, a jointly optimized strategy is utilized to efficiently solve the feature mapping. Classification is done through nearest-neighbor distance to class prototypes in the semantic embedding space.

**Contributions:** We highlight several contributions in this work. Firstly, extreme value learning (EVL) is introduced; and it employs the extreme values as the constraints to learn the semantic embedding from visual feature space to semantic space. Secondly, we propose a novel Vocabulary-informed Learning (ViL) algorithm to synthesize virtual samples in the embedding space and encode the extreme values for the training classes. Finally, to the best of our knowledge, a Vocabulary-informed Extreme Value Learning” (ViEVL) paradigm is proposed to combine the EVL and ViL. The ViEVL can solve in a probabilistic way the recognition tasks including one-shot, zero-shot and open-set classification. In open set recognition, our method can also give the names of novel unseen classes.

### 1.1 Related Work

In a broad sense, our ViEVL belongs to transfer learning, which is also called as meta-learning or learning to learn. The key idea of transfer learning is to transfer the knowledge from
We formulate our problems in a transfer learning setting. The source training dataset $D_s = \{x_i, z_i\}_{i=1}^{N_s}$ of $N_s$ samples: $x_i \in \mathbb{R}^p$ is the feature representation of image $i$ and $z_i \in \mathcal{W}_s$ is a class label taken from the vocabulary set $\mathcal{W}$. The target testing classes has the label set $\mathcal{W}_t$ ($\mathcal{W}_s \cap \mathcal{W}_t = \emptyset$) and potentially $|\mathcal{W}_t| \gg |\mathcal{W}_s|$. Given a testing image $x^*$, we aim at learning a function $z^* = f(x^*)$ to predict a class label $z^*$. The label $z^*$ changes depending on which label set assumed for $z^*$: (1) **Supervised learning**: $z^* \in \mathcal{W}_s$; (2) **Zero-shot learning**: $z^* \in \mathcal{W}_t$; (3) **Open set recognition**: $z^* \in \mathcal{W}$ ($\mathcal{W}_s \cup \mathcal{W}_t \subseteq \mathcal{W}$). Our ViEVL will learn a single unified $f(x^*)$ for all three cases. The vocabulary $\mathcal{W}$ is learned by word2vec [20] on large-scale corpus; each vocabulary entity $w \in \mathcal{W}$ is projected as a semantic vector $u \in \mathbb{R}^d$. To learn the function $f(x)$, one needs to establish the correspondence between visual feature space and semantic space. Particularly, on training step, each image sample $x_i$ is regressed towards its corresponding class prototype $u_{z_i}$ by minimizing

$$W = \arg \min_{W} \sum_{i=1}^{N_s} L(x_i, u_{z_i}) + \lambda \| W \|_F^2$$

(1)

where $L(x_i, u_{z_i}) = \| g(x_i) - u_{z_i} \|_2^2$; and $g : \mathbb{R}^p \rightarrow \mathbb{R}^d$ is the mapping from image features to semantic space. If $g(x) = W^T x$ is a linear mapping, we have the closed form solution of Eq (1). The loss function of Eq (1) can be taken as a variant of SVR embedding. The recognition step can thus be done by the nearest neighbor classifier, if given the testing instance $x^*$,

$$z^* = \arg \min_i \| W^T x^* - u_i \|_2^2$$

(2)

which basically measures the distance between predicted semantic vectors with the prototypes in semantic space. In terms of different label set, we can do supervise, zero-shot or open set recognition.

### 3 Vocabulary-informed Extreme Value Learning

Directly employing Eq (1) is unsatisfied for several reasons. Firstly, Eq (1) as well as the SS-Voc of (13) is failed to encode the discriminative information of training classes in the embedding space. In general, the distances of any two instances of the same class should be closer than those of different classes. Secondly, the decision boundary of one class prototype learned in Eq (1) is simply the half distance to its nearest neighbor prototypes. More discriminative and compact decision boundary can be learned for the training classes, ideally in a probabilistic way. Thirdly, only the training source vocabulary $\mathcal{W}_s$ is used for the training in Eq (1); not the vast open set vocabulary $\mathcal{W}_S^C$ ($\mathcal{W}_S \cup \mathcal{W}_S^C = \mathcal{W}$), i.e. not in a Vocabulary-informed way. The learning setting of using complete vocabulary data ($\mathcal{W}$) during training is called Vocabulary-informed learning in [13]. To solve these limitations, we introduce the Vocabulary-informed Extreme Value Learning (ViEVL) framework.

#### 3.1 Extreme Value Learning in the Embedding Space

In this subsection, we introduce two types of distributions to describe the training classes, namely, margin distribution and coverage distribution.
**Margin distribution.** The margin is a fundamental concept to explain the behavior of discriminative classifiers, such as SVMs. In contrast to search a single large margin separator like SVMs, the margin distribution is more crucial for the generalization performance by the theoretical analysis in [30], Thus Sec. 3.1.1 models the margin distribution of instances among training classes.

**Coverage distribution.** We also need to measure the intra-class variations of training instances; and how the instances within the same class are scattered. Thus we introduce the coverage distribution to model such intra-class variations.

### 3.1.1 Margin distribution of instances and prototypes

By using the source training set $D_s$, we can construct the extreme value distribution of each training instance $\psi(x_i), i = 1, \ldots, N_s$ in the embedding space. We optimize the instance-wise margin distribution in the embedding space. Suppose we have a training instance $g(x_i)$ of class $z_i$, and sufficiently many samples $g(x_i)$, $z_i \neq z_j$ drawn from well-behaved class distributions; we can thus compute their Euclidean distance is $d_{ij} = \|g(x_i) - g(x_j)\|$. For instance $i$, we can thus obtain a set of distances $D_i = \{d_{ij}, z_j \neq z_i\}$. Thus we can fit the margin distribution of instance $i$ by computing the minimal values of the margin distance for $\bar{d}_i = \min D_i$, which can be given by a Weibull distribution [28].

$$\psi_M(x_i) = e^{-\left(\frac{d_{\bar{d}_i}}{\lambda_i}\right)^{\kappa_i}}$$

(3)

where $\kappa_i$ and $\lambda_i$ are Weibull shape and scale parameters individually and obtained from fitting to the smallest $d_{ij}$. Eq (3) aims at quantitatively describing the margin of one specific class by a probabilistic way in our semantic embedding space. Note that Eq (3) requires $\psi_M(\cdot)$ to be a non-degenerate margin distribution, which is essentially guaranteed by Extreme Value Theorem [18].

We also construct the margin distribution $\psi_M(u_{z_i})$ of the prototypes $u_{z_i}$, from open vocabulary in $\mathcal{W}$ in a vocabulary-informed way. Specifically, given a known prototype $u_{z_j}$ of training classes, suppose the label prototype $u_{z_j}$ is very near to $u_{z_i}$, where its corresponding class label $z_j \neq z_i$ and vocabulary $w_j \in \mathcal{W}^C$; and the label $z_j$ is the most likely be confused with the label $z_i$. The label class $z_j$ can be used to help construct the margin distribution of prototype $u_{z_j}$.

Note that the class $z_i$ has only one prototype vector $u_{z_i};$ and we have no way to sample sufficiently many samples drawn from class $z_j$. To solve this problem, a natural strategy is to synthesize virtual samples of class $z_j$ by assuming the Gaussian distribution of class $u_{z_j}$ with the mean as the prototype vector $u_{z_j}$, and the standard deviation as half of the distance between $u_{z_j}$ and the margin of class $z_i$,

$$\sigma_{z_j} = \frac{1}{2} \|u_{z_j} - g(x_{i^j})\|$$

(4)

where $x_{i^j} = \arg\max_{x_i \in z_j} \|g(x_i) - u_{z_i}\|$. The virtual instances can be sampled from the Gaussian distribution of class $z_j$. Thus, we can employ Eq (3) to construct the term $\psi_M(u_{z_i})$. Specifically, by sampling sufficiently many samples $x_{i^j} \sim N(u_{z_i}, \sigma_{z_j} I)$ from $z_j$; and $I$ is the identity matrix.

We can gain the distance set $D_{u_{z_i}} = \{d_{ij}, z_j \neq z_i\}$, $d_{ij} = \|g(x_i) - x_{i^j}\|$ , and $\bar{d}_{u_{z_i}} = \min D_{u_{z_i}}$.

The margin distribution of prototype $u_{z_i}$ is

$$\psi_M(u_{z_i}) = e^{-\left(\frac{\bar{d}_{u_{z_i}}}{\lambda_i}\right)^{\kappa_i}}$$

(5)

### 3.1.2 Coverage distribution of instances and prototypes

We can measure the coverage distribution of instances of one class in the embedding space. Specifically, assume for class $z_i$, we have the projected instance $g(x_i)$, and the nearest instance from another class $g(x_k)$ where $z_i \neq z_k$; with sufficient many instances $g(x_j)$ from class $z_i$, we have pairwise unique distance $c_{ij} = \|g(x_i) - g(x_j)\| \leq \|g(x_i) - g(x_k)\|$, $j \neq i$, and $C_i = \{c_{ij}\}$; then distribution of largest $c_{i*} = \max C_i$ will follow a reversed Weibull distribution as,

$$\psi_C(x_i) = 1 - e^{-\left(\frac{x_i}{\lambda_i}\right)^{\kappa_i}}$$

(6)
where \( \kappa_j \) and \( \lambda_j \) are reverse Weibull shape and scale parameters individually obtained from fitting the largest \( c_{ij} \). Eq (6) is supported by the Coverage Distribution Theorem [28]. Note that for coverage distribution, only one instance that is not in the class concerned is needed. A reversed Weibull PDF is a reflection of a Weibull PDF at the same scale and shape.

We can also construct the coverage distribution of prototype \( \psi(z_i) \). We have the training instances of class \( z_i \) and one nearest “negative” prototype \( u_{z_j} (z_i \neq z_j) \); and thus Eq (6) is directly utilized to construct \( \psi(z_i) \).

### 3.1.3 Extreme Value Learning by fusing distributions

The margin distribution \( \psi_M(x_i) \) and coverage distribution \( \psi_C(x_i) \) model different aspects of training instances and are both important for well-defining the boundaries of classes. Specifically, given the instance \( x_i \), maximum margin distance with distribution \( \psi_M(x_i) \) is measured by its distance to the closest training instance of another class; nevertheless, in a high dimension space, the classes may potentially be highly overlapped and \( \psi_M(x_i) \) may lead to overspecialized “spiky” regions of the support. In contrast, \( \psi_C(x_i) \) models the distribution that for instance \( i \), the distance to the farthest instances of class \( z_i \) is closer than the nearest instance of another class. Empirically, \( \psi_C(x_i) \) mainly uses the instance of the same class and allocates the support. In contrast, \( \psi_M(x_i) \) may potentially be highly overlapped and the closest training instance of another class; nevertheless, in a high dimension space, the classes are both important for well-defining the boundaries of classes.

Since \( \psi_M(x_i) \) and \( \psi_C(x_i) \) have similar function form, these two terms can be fused. Particularly, for every training class, we have the parameters \( (\kappa_i, \lambda_i, \kappa'_i, \lambda'_i) \), we can decide whether to use \( \psi_M \) or \( \psi_C \) via a comparison of the respective scale parameters and we can get the extreme value distribution of training data \( \psi(x_i) \) as [28].

\[
\psi(x_i) = \begin{cases} 
\psi_M(x_i) & \lambda_i \geq \lambda_i', \\
\psi_C(x_i) & \text{otherwise}.
\end{cases}
\]

Similarly, we can also fuse the margin distribution and coverage distribution of prototype \( u_i \) as vocabulary-informed extreme value distribution of prototypes \( \psi(u_i) \).

The higher probability of margin distribution implies well separated margins among training classes; and higher probability of coverage distribution means good support of instances for training classes. Interestingly, the fused extreme value distribution Eq (4) can also reflect such properties: the higher probability, the better quality of the boundaries/support among training classes.

As a result, the extreme value learning is to learn the \( W \) via maximizing the probability of extreme value distribution.

\[
W = \arg\min_W \sum_{i=1}^{N_i} L(x_i, u_{z_i}) - \alpha \sum_{i=1}^{N_i} \psi(x_i) - \beta \sum_{k=1}^{|W_z|} \psi(u_k) + \lambda \| W \|_F^2
\]

where \( \alpha \) and \( \beta \) are two weighting terms; \( \lambda \) is the regularization coefficient and \( \| \cdot \|_F^2 \) indicates the Frobenius Norm; and \( \sum_{i=1}^{N_i} \psi(x_i) \) as extreme values of data-term; and \( \sum_{k=1}^{|W_z|} \psi(u_k) \) as vocabulary-informed extreme values of prototypes.

### 3.2 Vocabulary-informed Extreme Value Learning

In Eq (8), we can further simplify extreme values of data-term since this term has the almost same goal as \( \sum_{k=1}^{|W_z|} \psi(u_k) \) to maintain good margin and coverage distribution for class \( z_i \). Additionally, as explained in Sec. 3.1.1, the term \( \sum_{k=1}^{|W_z|} \psi(u_k) \) utilizes the open vocabulary \( w_j \in W_S^C \) to better learn the embedding weight \( W \). Most importantly, the term \( \sum_{k=1}^{|W_z|} \psi(u_k) \) needs much less computations if comparing with computing \( \sum_{i=1}^{N_i} \psi(x_i) \). Then the Eq (8) can be turned into,

\[
W = \arg\min_W \sum_{i=1}^{N_i} (1 - \beta) L(x_i, u_{z_i}) - \beta \sum_{k=1}^{|W_z|} \psi(u_k)) + \lambda \| W \|_F^2
\]
where $\beta$ and $\lambda$ are coefficients of weighting each term.

Intrinsically the vocabulary-informed extreme value term $\sum_{k=1}^{W_S} |W_k| \psi(u_k)$ performs as a regularizer on $W$ by informed by the vast open set vocabulary. So we call our framework as vocabulary-informed extreme value learning.

4 Experiments

Dataset. We conduct our experiments on two benchmark datasets.

AwA-PCA dataset has 50 classes of animals (30, 475 images in total). We follow the zero-shot settings in [19] to split into 40 source/auxiliary classes ($W_S = 40$) and 10 target/test classes ($W_t = 10$). Overfeat features are used for AwA provided in [12]. For each class, we use 20 training instances. To further reduce the computational cost, we use PCA to reduce the feature dimension to 100-dim.

ImageNet-PCA 2012/2010 dataset includes 1000 ($W_S = 1000$) classes of ILSVRC 2012 as the source/auxiliary classes and 360 ($W_t = 360$) classes of ILSVRC 2010 that are not used in ILSVRC 2012 as target data. The VGG-19 features are extracted on this dataset. We sample 5 instances per source classes as the training data. Since this dataset has much much larger number of classes than AwA, the feature dimension is reduced to 1000-dim by performing PCA to save the computational cost in our experiments.

Open set vocabulary. Google Word2vec [20] is adopted to train learn the semantic space from large text corpus of around 7 billion words including the UMBCWebBase, the latest Wikipedia articles. The resulting dictionary has more than 4 million vocabulary. As in [13], we further remove some rare (frequency $< 300$) words and high frequency stopping words (frequency $> 10$ million) words. Finally we can obtain a vocabulary set of around 300K words/phrases. According to the metrics of openness [32], we have openness $\approx 1$. To further reduce the computational cost, the 100 dimensional word vectors are used in our experiments.

Recognition tasks. In our tasks, we also consider three different types of settings:

Supervised Recognition: the model is learned on the source training dataset $D_S$ in order to predict the labels of test instances from the same class set $W_S$.

Zero-shot Recognition: the model learned from $D_S$ is applied to predict the labels of the testing instances from the target label set

Open-set Recognition: the entire open vocabulary $|W| \approx 300K$ is used as the candidate label set for testing instances.

Competitors. We compare our results with the state-of-the-art results.

Support Vector Regression (SVR) is used to learn $W$ in Eq (1) and the recognition is done via Eq (2). This is a generalization of DAP [19] to semantic word vectors.

Semi-Supervised Vocabulary-informed Learning (SS-Voc) is a maximum-margin learning framework to compute $W$ as in [13]: the vocabulary pairwise maximal margin term is constructed by comparing the training prototypes with nearest open-set vocabulary set in a vocabulary-informed way. Such a pairwise term is an alternative way of our vocabulary-informed extreme value term in Eq (9).

Settings and Evaluation. Our framework is solved by Stochastic Gradient Descent (SGD). The $\beta$ and $\lambda$ are set as 0.3 and 0.01 respectively. The neighborhood set has 10 prototypes in Eq (4). The results are averaged over 10 rounds repeated experiments to reduce the variance. For supervised and zero-shot learning, the mean accuracy (i.e. mean of the diagonal of the confusion matrix) is reported. The results of open-set recognition is reported by Hit@K which indicates the testing images is classified into a “correct label” if it is in the top-$K$ labels. The source codes will be released.

Running cost. Our experiments run on the machine with dual cores 2.7 GHz Intel Core i7 CPU and 8G memory. On AwA-PCA, it takes less than 5 minutes to compute the embedding weight $W$. On ImageNet-PCA dataset, it takes 6 ~ 7 hours to finish one round experiment.
Table 1: Results on AwA-PCA dataset. We compare the Top-1 results on SVR, SS-Voc and ViEVL methods under the settings of Supervised Learning (SL), and Zero-shot Learning (ZSL).

|                  | SVR  | SS-Voc | ViEVL | Chance |
|------------------|------|--------|-------|--------|
| Supervised Learning | 56.05 | 56.57  | 56.34 | 2.50   |
| Zero-shot Learning | 51.65 | 52.82  | 53.37 | 10.00  |

Table 2: The results of Open-set recognition on AwA-PCA dataset.

| Hit@K | 1   | 2   | 4  | 6  | 8  | 10 | 15 | 20   |
|-------|-----|-----|----|----|----|----|----|------|
| SVR   | 3.90| 5.50| 8.30|10.80|13.00|16.72|23.83|27.43 |
| SS-Voc| 3.81| 5.71| 8.50|10.60|13.10|16.42|23.32|26.62 |
| ViEVL | **4.11**| **5.81**| **8.80**|**11.30**|**13.80**|**17.64**|**23.94**|**27.21** |

4.1 Experiments on AwA-PCA dataset

We compare our ViEVL method with two competitors on AwA-PCA dataset. The results of supervised, zero-shot learning are summarized in Tab. 1. We examine the open-set recognition results in Tab. 2.

Firstly, in supervised learning, both the results of ViEVL and SS-Voc are higher than that of SVR. We argue that this improvement is largely due to the vocabulary-informed term which is directly optimized in the supervised learning setting. This vocabulary-informed term is referring to “the vocabulary pairwise maximal margin term” in SS-Voc or “the vocabulary-informed extreme value term” in Eq (9). This suggests the effectiveness of vocabulary-informed learning since in supervised learning, the vast open set vocabulary is directly optimized to build the margin boundary and coverage of training classes. We also note that the supervised result of our ViEVL is slightly inferior to that of SS-Voc by 0.23 percent. Since AwA only has 40 training classes, the vocabulary pairwise maximal margin term in SS-Voc is better at learning the discriminative information from relative small number of training classes, if compared with our extreme value term, which probabilistically models the margin distribution and coverage distribution of classes.

Secondly, we evaluate these three methods in the zero-shot setting. Our ViEVL achieves 53.37 percent, outperforming the SVR and SS-Voc baselines by 1.72 and 0.55 percent. This shows the effectiveness of our ViEVL. We believe the improvement comes from the good generalization ability of our vocabulary-informed extreme value term. Critically, our ViEVL effectively learns the embedding weight $W$ by constraining the training classes with its corresponding the margin and coverage distributions. As a result, the novel unseen zero-shot classes will have good coverage (which has much less overlapping with the other known classes than that in SS-Voc) and well separated margins.

Thirdly, we use the testing instances from source classes $W_S$ to conduct open-set recognition and compared the results in Tab. 2. On the results of Hit@K ($K \leq 10$), we still observe that our ViEVL consistently have better results than all SVR and SS-Voc, again thanks to the vocabulary-informed extreme value term which can robustly models the coverage and margin of training classes. Nevertheless, for the results of Hit@K ($K > 10$), all these three methods have similar performance due to constraints from the open-vocabulary getting less pronounced in top-$K$ ($K > 10$). On the other hand, we note that the performance has dropped from 56.34 percent (Supervised) to 4.11 percent (Open-set) since open set recognition tasks are intrinsically much difficulty for our 100-dimensional AwA-PCA dataset.

4.2 Results on ImageNet-PCA 2012/2010 dataset

This is a large-scale dataset to validate our ViEVL algorithm. The supervised and zero-shot learning results are compared in Tab. 3 the open-set results are listed in Tab. 4. For zero-shot learning, we also compare several recent zero-shot learning on large-scale dataset, including DeVise [11], ConSE [21] and AMP [14]. We discuss our results on different settings accordingly.

In supervised learning and zero-shot learning settings, our ViEVL achieves 16.27 percent classification accuracy which is 0.9 percent higher than SS-Voc, still thanks to vocabulary-informed extreme value term in Eq (9). Essentially, such a term probabilistically models the data distribution of train-
The testing instances from source classes $W_s$ are employed to conduct the open-set recognition; and the results are listed in Tab. 4. Our ViEVL still outperforms the other baselines when $Hit@K$ ($K \leq 15$). On Imagenet-PCA, the performance has dropped by 3.05 percent from 16.27 percent (Supervised) to 13.22 percent (Open-set). Interestingly, the dropped percentage on Imagenet-PCA is much less significant than that of AWA-PCA dataset, largely due to the 1000-dimensional feature used on ImageNet-PCA dataset.

### 5 Conclusion

In this paper, we investigate using margin distribution and coverage distribution to measure the data distribution of training classes. Build upon the extreme value theory, we propose the idea of extreme value learning to utilize the extreme values as the constraints of learning the visual-semantic embedding. In particularly, we further propose the Vocabulary-informed Extreme Value Learning (ViEVL) by incorporating the vocabulary-informed learning into the extreme value learning. Our ViEVL can encode the extreme values for training classes in a probabilistic way and thus facilitates a wide range of recognition tasks including supervised learning, zero-shot learning and open-set recognition. The experiments on two benchmark datasets validate our proposed framework.

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