Supplementary Material for
VGSE: Visually-Grounded Semantic Embeddings for Zero-Shot Learning

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A. User Study

To evaluate if our VGSE embeddings convey consistent visual and semantic properties, we perform an user evaluation over the visual clusters. The illustration of user evaluation is shown in A.1. We randomly pick 50 clusters, each equipped with 30 images from the cluster center, and ask the users to observe the images and answer the following three questions.

Q1: Do images in this cluster contain consistent visual property? Q2: Do images in this cluster convey consistent semantic information? Q3: Please name the semantics you observed from the clusters, if your answer to Q2 is true.

We rate both the clusters learnt by our model for AWA2 dataset, and the clusters learnt by k-means. For each experiment, we employed 5 annotators, i.e., postgraduate students (2 female) aged between 20 and 30 and majoring in computer science. In total, we collect 500 ratings for each experiment. We treat the ratings higher than 3 as a hit. The results reveal that in 88.5% and 87.0% cases, users think our clusters convey consistent visual and semantic information. While for k-means clusters, the results are 71.5% and 71.0%, respectively.

In addition, we display some of the clusters and their semantics named by users in Figure A.2. As shown in the figure, images in each clusters show consistent visual properties that are human understandable, e.g., local properties such as the white fur, horns and stout legs, and global properties such as animals living near water and animals living near cage.

B. Additional Qualitative Results

We show additional qualitative results for SUN and CUB datasets in Figure B.2 and Figure B.1. Images shown in each cluster represent the cluster center. We have the following observations. First, the image patches in each cluster convey consistent visual properties, e.g., the slender bird legs (row 1, column 1) and white wing (row 2, column 1) in Figure B.1; the wheels (row 1, column 2) and the crowds (row 2, column 3) in Figure B.2. Moreover, our clusters convey fine-grained semantics that may be neglected by human-annotated attributes, e.g., the electrical screen (row 2, column 2) in Figure B.2. Though some clusters are consist of background patches, they still convey semantic information that is category related. For instance, some birds in the CUB dataset may live near Pine trees and Cypress trees (row 2, column 3), and some may live near water (row 1, column 3) in Figure B.1. However, we can still observe some clusters with semantically different patches, i.e., the cluster of grids contains patches of window and fence (row 2, column 3 in Figure B.2)

C. Ablation Study

In this section, we include the ablation study results on CUB and SUN dataset. To measure the influence of the cluster number $D_v$ on our semantic embeddings, we train the PC module with various $D_v$ (results shown in Figure C.1a and Figure C.2a). The observation is similar to that of the AWA2 dataset. When the unseen semantic embeddings are predicted under an oracle setting (predicted from the unseen class images), various dimension $D_v$ does not influence the classification accuracy on unseen classes (the orange curve). While under the ZSL setting where unseen semantic embeddings are predicted
Figure A.2. Qualitative results for AWA2 dataset. Each box represents one cluster, with images from the cluster center. The name above each image is the category. The phrase above each cluster is the semantic named during user evaluation.

from class relations (VGSE-SMO), the cluster numbers influence the ZSL performance. Before the cluster number increases up to a breaking point ($D_v = 200$ for CUB dataset and $D_v = 300$ for SUN dataset), the ability of the semantic embeddings is also improved (from 24.4% to 26.3% on CUB and from 35.0% to 36.1% on SUN), since the learned clusters contain visually similar patches from different classes, which can model the visual relation between classes. However, increasing the number of clusters leads to small pure clusters (patches coming from one single category), resulting in poor generalization between seen and unseen classes.

The influence of the patch numbers are shown in Figure C.1b, which reveals two observations. First, with the patch number increase from 1 (single image clustering) to 9, the ZSL performance increases as well, since the image patches used for semantic embedding learning contain semantic object parts and thus result in better knowledge transfer between seen and unseen classes. However, for a large $N_t$, the patches might be too tiny to contain consistent semantic, thus resulting in performance dropping, e.g., the ZSL accuracy on CUB drops from 26.1% ($N_t = 9$) to 23.9% ($N_t = 128$). We also compare the patches generated by watershed segmentation proposal with using $3 \times 3$ grid patches. By comparing $3 \times 3$ grid with the patches generated by watershed segmentation proposal ($N_t = 9$), we found that using watershed as the region proposal results in accuracy boost (1.9% on CUB and 1.4% on SUN) compared to the regular grid patch, since the former patches tend to cover more complete object parts rather than random cropped regions.

D. SOTA results for VGSE-WAvg

In this section, we extend Table 1 in the main paper with the SOTA results of VGSE-WAvg embeddings. As shown in Table D.1, the VGSE-WAvg embeddings outperform the w2v embeddings by a large margin. In particular, when coupled with
APN, our $\text{VGSE-WAvg}$ boosts the ZSL performance of w2v from 59.6% to 63.7% on AWA2 dataset and from 23.6% to 35.8% on SUN dataset. We compare our two class relation functions $\text{VGSE-WAvg}$ and $\text{VGSE-SMO}$ in Table D.1. The results demonstrate that $\text{VGSE-WAvg}$ works on par with $\text{VGSE-SMO}$ on SUN and CUB datasets, i.e., when coupled with f–VAEGAN–D2, $\text{VGSE-WAvg}$ achieves 34.8% on CUB comparing to $\text{VGSE-SMO}$ with 35.0%. While on AWA2 dataset, $\text{VGSE-SMO}$ yields slightly better ZSL performance than $\text{VGSE-WAvg}$. In particular, when coupled with GEM-ZSL, $\text{VGSE-SMO}$ (with 58.0%)
improves over VGSE-WAvg (with 53.3%) by 4.7%. The results indicate that predicting the unseen semantic embeddings with the weighted average of a few seen classes semantic embeddings (VGSE-WAvg) is working well for fine-grained datasets such as SUN and CUB, since the visual discrepancy between classes is small. However, for coarse-grained dataset AWA2, the class relation function considering all the seen classes embeddings (VGSE-SMO) works better.

E. Implementation Details

Image regions. To discover the clusters of image patches, we crop the image $x_n$ into $N_t$ patches $\{x_{nt}\}_{t=1}^{N_t}$. Previous works [9, 10] obtain 1,000 regions for each image with Selective Search [11], resulting in large amount of overlapped patches. To avoid that, we crop the segments generated by unsupervised compact watershed segmentation algorithm [7] into image patches. In detail, for each image $x_n$, we find the smallest bounding box that fully covers each segment and crop $x$ into $N_t$ rectangular patches $\{x_{nt}\}_{t=1}^{N_t}$ that cover different parts of the image. In our experiment, the patch number $N_t$ is set to 9, and the tiny patches with $w < W/20$ or $h < H/20$ are removed, where $w$ and $W$ represents the width of the patch $x_{nt}$ and the original image $x_n$ respectively; $h$ and $H$ represents the height of the patch $x_{nt}$ and the original image $x_n$.

Figure C.1. Ablation study on CUB dataset. (a) Influence of the cluster number $D_v = 50, \ldots, 3000$. In the oracle setting, we feed unseen classes images to the $PC$ module to predict unseen semantic embeddings. (b) Influence of the patch number $N_t$ we used per image with the watershed segmentation for obtaining our VGSE-SMO class embeddings. $N_t = 1$ uses the whole image (no patches). “3×3 grid” crops the image into 9 square patches. Both plots report ZSL accuracy with SJE model trained on CUB dataset (mean and std over 5 runs).

Figure C.2. Ablation study on SUN dataset. (a) Influence of the cluster number $D_v = 50, \ldots, 3000$. In the oracle setting, we feed unseen classes images to the $PC$ module to predict unseen semantic embeddings. (b) Influence of the patch number $N_t$ we used per image with the watershed segmentation for obtaining our VGSE-SMO class embeddings. $N_t = 1$ uses the whole image (no patches). “3×3 grid” crops the image into 9 square patches. Both plots report ZSL accuracy with SJE model trained on SUN dataset (mean and std over 5 runs).
Training details. In the patch clustering (PC) module, we learn seen-semantic embeddings with train set (seen classes) proposed by [13]. We adopt ResNet50 [3] pretrained on ImageNet1K [2] as the backbone. We use ADAM optimizer [4] by setting weight decay of $10^{-4}$ and learning rate of $10^{-4}$. The cluster number $D_v$ is set as 150 for three datasets. We set $\lambda$ as 5 following [12]. The unseen-class embeddings are predicted in the class relation (CR) module without seeing unseen images. For the Weighted Average module, we set $\gamma$ as 5 for all datasets, and use 5 neighbors for all datasets. For the similarity matrix optimization, we set $\alpha$ as -1 for AWA2 and CUB, and as 0 for SUN. All hyperparameters are selected over the validation set. We set $\lambda$ to 5 following [12]; $\beta$ and $\gamma$ to 1 for all datasets.

F. Limitations and Broader Impact

The generalization ability of our VGSE class embeddings depends to a great extent on the external knowledge used to model the seen and unseen class relations. External knowledge that can well capture the visual relation between classes will lead to higher ZSL accuracy. This motivates us to discover better external knowledge that captures both the semantic and visual relation between classes in future work. Broadly speaking, the prediction accuracy of current zero-shot learning models is still lower than models trained with both seen and unseen classes. To this end, ZSL models might not be applicable to situations that require high confidence and precision, e.g., medical auxiliary diagnosis and self-driving cars.

References


Table D.1. Comparing our VGSE-SMO, VGSE-WAvg, with the w2v semantic embedding over state-of-the-art ZSL models. In ZSL, we measure Top-1 accuracy (T1) on unseen classes, in GZSL on seen/unseen (s/u) classes and their harmonic mean (H). Feature Generating Methods, i.e., f-VAEGAN-D2, and CADA-VAE synthesizing training samples, and SJE, APN, GEM-ZSL using only real image features.


