Attribute Prototype Network for Any-Shot Learning

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Abstract Any-shot image classification allows to recognize novel classes with only a few or even zero samples. For the task of zero-shot learning, visual attributes have been shown to play an important role, while in the few-shot regime, the effect of attributes is under-explored. To better transfer attribute-based knowledge from seen to unseen classes, we argue that an image representation with integrated attribute localization ability would be beneficial for any-shot, i.e. zero-shot and few-shot, image classification tasks. To this end, we propose a novel representation learning framework that jointly learns discriminative global and local features using only class-level attributes. While a visual-semantic embedding layer learns global features, local features are learned through an attribute prototype network that simultaneously regresses and decorrelates attributes from intermediate features. Furthermore, we introduce a zoom-in module that localizes and crops the informative regions to encourage the network to learn informative features explicitly. We show that our locality augmented image representations achieve a new state-of-the-art on challenging benchmarks, i.e. CUB, AWA2, and SUN. As an additional benefit, our model points to the visual evidence of the attributes in an image, confirming the improved attribute localization ability of our image representation. The attribute localization is evaluated quantitatively with ground truth part annotations, qualitatively with visualizations, and through well-designed user studies.

Keywords Zero-shot learning · Few-shot learning · Attribute prototype · Attribute localization

1 Introduction

Visual attributes describe discriminative visual properties of objects shared among different classes. Attributes have been shown to be important for zero- and few-shot learning, i.e. any-shot learning, as they allow semantic knowledge transfer from known classes with abundant training samples to novel classes with only a handful of images. Most zero-shot learning (ZSL) methods (Romera-Paredes et al., 2015; Changpinyo et al., 2016; Akata et al., 2015a; Zhang et al., 2017)
rely on image representations extracted from a deep neural network pretrained on ImageNet, and essentially learn a compatibility function between the image representations and attributes. Early solutions for few-shot learning (FSL) are dominated by metric learning (Snell et al., 2017) or attribute classifiers (Sylvain et al., 2020). Zhu et al. (2019; Tang et al., 2020) scenarios where local attributes are critical to distinguish two similar categories. In this work, we refer to the ability of an image representation to localize and associate an image region with a visual attribute as locality. Our goal is to improve the locality of image representations for any-shot learning.

While modern deep neural networks (He et al., 2016) encode local information and some CNN neurons are linked to object parts (Zhou et al., 2018), the encoded local information is not necessarily best suited for any-shot learning. There have been attempts to improve the locality of image representations by learning visual attention (Li et al., 2018b) or attribute classifiers (Sylvain et al., 2020). Zhu et al. (2019c) propose to learn channel-wise attention for bird body parts. Similarly, Zhu et al. (2019a) apply the channel grouping model (Zheng et al., 2017) to learn part-based representations and part prototypes. However, the learned latent attentions/prototypes only localize a small number of object parts, and the semantic meaning of the attentions is induced by post-hoc observation.

Although visual attention accurately focuses on some object parts, the discovered parts and attributes are often biased towards training classes due to the learned correlations. For instance, the attributes yellow crown and yellow belly co-occur frequently (e.g., in Yellow Warbler). The model may learn such correlations as a shortcut to maximize the likelihood of training data and therefore fail to deal with unseen attributes configurations in novel classes, such as black crown and yellow belly (e.g., in Scott Oriole), as this attribute combination has not been observed before.

To improve locality and mitigate the above weaknesses of image representations, we develop a weakly supervised representation learning framework that localizes and decorrelates visual attributes. More specifically, we learn local features by injecting losses on intermediate layers of CNNs and enforcing these features to encode visual attributes defining visual characteristics of objects. To achieve this, we learn prototypes in the feature space which define the property for each attribute, at the same time, the local image features are encouraged to be similar to the corresponding attribute prototype. It is worth noting that we use only class-level attributes and semantic relatedness of them as supervisory signal, in other words, no human-annotated association between the local features and visual attributes is given during training. We propose to alleviate the impact of incidentally correlated attributes by leveraging their semantic relatedness while learning these local features. As an additional benefit, our model points to the visual evidence of the attributes in an image, confirming the improved attribute localization ability of our image representation. The attribute attention map is obtained by measuring the similarity between local image features and attribute prototypes. We evaluate the attribute localization ability quantitatively with the ground truth part annotations, and qualitatively with visualizations. For datasets without attribute location annotations, we propose two user studies to assess the accuracy and semantic consistency of attribute attention maps, and compare our APN model with the baseline visualized by two model explanation methods, Grad-CAM and CAM.

This paper extends our NeurIPS 2020 conference paper (Xu et al., 2020) with the following additional contributions. (1) We propose to apply the Attribute Prototype Network for the any-shot image classification task, where we improve the locality of image representations. In addition to zero-shot learning, our APN is extended to few-shot learning and the more realistic generalized few-shot learning setting. We evaluate our model under both N-way-K-shot and all-way scenarios and demonstrate that the local representations encoding semantic visual attributes are beneficial for the any-shot regime in discriminating categories with only a few training samples. (2) In addition to performing classification with the original image, we propose to highlight the informative image features discovered by the attribute prototypes, which helps the network to focus on informative attribute regions and discard the noisy background. (3) We verify the effectiveness of our locality-enhanced image representations on top of five generative models and demonstrate consistent improvement over the state-of-the-art on three challenging benchmark datasets. (4) Through qualitative analysis among three benchmark datasets and qualitative ablation study, we demonstrate that our proposed model helps to learn accurate attribute prototypes and produce compact attribute attention maps for each image. Quantitative evaluation indicates that our model outperforms other weakly
supervised attribute localization methods by a large margin. (5) We propose two well-designed user studies to evaluate the accuracy and semantic consistency of the attribute attention maps, which is an effective evaluation protocol in the absence of ground truth annotations.

2 Related work

**Zero-shot learning.** The aim of zero-shot learning is to classify the object classes that are not observed during training [Lampert et al., 2009]. The key insight is to transfer knowledge learned from seen classes to unseen classes with class embeddings that capture similarities between them. Many classical approaches [Romera-Paredes et al., 2015; Changpinyo et al., 2016; Akata et al., 2015a; Zhang et al., 2017; Xian et al., 2016; Wang and Chen, 2017] learn a compatibility function between image and class embedding spaces. Recent advances in zero-shot learning mainly focus on learning better visual-semantic embeddings [Liu et al., 2018; Zhang et al., 2017; Jiang et al., 2019; Cacheux et al., 2019; Wan et al., 2021; Li et al., 2020] or training generative models to synthesize features [Xian et al., 2018, 2019b; Zhu et al., 2019a, 2018; Kumar Verma et al., 2018; Schonfeld et al., 2019a; Changpinyo et al., 2019]. Those approaches are limited by their image representations, which are often extracted from ImageNet-pretrained CNNs or finetuned CNNs on the target dataset with a cross-entropy loss.

Despite its importance, image representation learning is relatively under-explored in ZSL. Recently, Yu et al. (2018) propose to weigh different local image regions by learning attentions from class embeddings. Zhu et al. (2019c) extend the attention idea to learn multiple channel-wise part attentions. Sylvain et al. (2020) show the importance of locality and compositionality of image representations for ZSL. In our work, instead of learning visual attention like Zhu et al. (2019c) and Yu et al. (2018), we propose to improve the locality of image features by learning a prototype network that is able to localize different attributes in an image.

**Few-shot learning.** Given a large number of training samples from the base classes, few-shot learning (FSL) aims to recognize novel classes with a handful of (typically 1–10) labeled examples. The data efficiency problem challenges the traditional classification task, and much effort has been devoted to overcome the data sparsity issue. Metric learning based methods tackle this problem by comparing the distance between images, i.e. Euclidean distance to class prototypes [Snell et al., 2017], cosine similarity [Vinyals et al., 2016], etc. Meta-learning based methods aim to learn a good model initialization [Finn et al., 2017, 2018; Rusu et al., 2019] or optimizer [Ravi and Larochelle, 2017; Munkhdalai and Yu, 2017], so that the classifiers for novel classes can be learned with a few labeled examples and a small number of gradient update steps. However, meta-learning may not sufficiently handle the domain shift between base and novel classes [Chen et al., 2019a], and has difficulty when scaling to a large number of training samples [Xian et al., 2019b]. This motivates data augmentation via feature synthesis which directly tackles the data deficiency problem by generating novel training examples [Guan et al., 2020; Xian et al., 2019b], e.g. Hariharan and Girshick (2017) and Qi et al. (2018) propose to hallucinate additional training examples for novel classes.

Existing FSL methods usually rely on prior knowledge from only visual modality, while in zero-shot learning, multi-modality data such as word embeddings [Xian et al., 2019a] and attributes [Lampert et al., 2009] have been adopted and achieve promising results. There are some attempts in applying multi-modality to aid representation learning in FSL (Sylvain et al., 2020; Tokmakov et al., 2019; Tang et al., 2020) or to train a feature generator with GANs [Xian et al., 2019a; Guan et al., 2020]. A few works have focused on enhancing the compositionality [Tokmakov et al., 2019] with the help of attributes or learning pose-normalized image representations [Tang et al., 2020], making the representation invariant to the spatial deformations and environmental changes. In this paper, we focus on learning locality-augmented image representations with the help of class attributes to aid the classification task under a low-data regime. We demonstrate that local information encoded in the image representation helps generative models to synthesize discriminative features.

**Prototype learning.** Prototype networks [Yang et al., 2018; Wang et al., 2019] learn a metric space where the labeling is done by calculating the distance between the test image and prototypes of each class. Prototype learning is considered to be more robust when handling open-set recognition [Yang et al., 2018; Shi et al., 2020] and few-shot learning [Snell et al., 2017; Gao et al., 2019; Oreshkin et al., 2018]. Some methods [Arik and Pfister, 2019; Yeh et al., 2018; Li et al., 2018a] base the network classification decision on learned prototypes. Instead of building sample-based prototypes, Chen et al. (2019a) dissect the image and find several prototypical parts for each object category, then classify images by combining evidences from prototypes. Similarly, Zhu et al. (2019a) use the channel grouping model [Zheng et al., 2017] to learn part-based representations and part prototypes.

In contrast, we treat each channel equally and use spatial features associated with input image patches
to learn attribute prototypes. Chen et al. (2019a) and Zhu et al. (2019c) learn latent attention or prototypes during training and induct the semantic meaning of the prototypes in a post-hoc manner. Their attribute or part localization ability is limited, e.g. Zhu et al. (2019c) can only localize two parts. To address those limitations, our method learns prototypes that represent the attributes/parts where each prototype corresponds to a specific attribute. The attribute prototypes are shared among different classes and encourage knowledge transfer from seen classes to unseen classes, yielding better image representation for zero-shot learning and few-shot learning.

**Locality and representation learning.** Here we define the local feature as the image feature encoded from a local image region. Local features have been extensively investigated for representation learning (Hjelm et al., 2019; Wei et al., 2019; Noroozi and Favaro, 2016), and are commonly used in person re-identification (Sun et al., 2018; Wang et al., 2018a). Image captioning (Anderson et al., 2018; Li et al., 2017) and fine-grained classification (Zheng et al., 2017; Fu et al., 2017; Zhang et al., 2016b). Hjelm et al. (2019) indicate that maximizing the mutual information between the representation and local regions of the image can significantly improve a representation’s suitability for downstream tasks. Thanks to its locality-aware architecture, CNNs (He et al., 2016) exploit local information intrinsically. Our work is related to methods that draw attention to local features (Kim et al., 2018; Sun et al., 2018; Zheng et al., 2017) generate the attention for discriminative bird parts by clustering spatially-correlated channels. Instead of operating on feature channels, we focus on the spatial configuration of image features and improve the locality of our representation. Besides, our work is supervised by the class attributes, and no part or bounding box annotation is required.

Our work is also related to the methods that localize the main object in a weakly supervised way and discard the irrelevant background for image classification (Zhang et al., 2021a; Wei et al., 2017). Wei et al. (2017) aggregate the activation map from the last CNN layer (before global average pooling) and select the highest activated location to filter the final representation for the target image. Zhang et al. (2021a) improve the localization accuracy by introducing multi-layer activation maps. While in our network, we aim to search for the informative image regions that contain important attributes for zero- and few-shot learning. Unlike previous pioneers utilizing intermediate activation maps to localize the informative area, we select the image regions highlighted by the attribute prototypes. Since most of the datasets lack ground truth attribute location annotation, e.g. AWA2 and SUN, we design two user studies to assess the accuracy and semantic consistency.

### 3 Attribute Prototype Network

In the following, we describe our end-to-end trained attribute prototype network (APN) that improves the attribute localization ability of the image representation, i.e. locality. We first define our zero-shot learning and few-shot learning problem. We then introduce in detail the three modules in our framework, the base module (BaseMod), the prototype module (ProtoMod), and the Zoom-In Module (ZoomInMod) as shown in Figure 1. At the end of the section, we describe how we perform ZSL and FSL and how the locality enables attribute localization.

**Problem Definition** The training set consists of labeled images and attributes from seen classes, i.e. $S = \{x, y, \phi(y)|x \in \mathcal{X}, y \in \mathcal{Y}_n\}$. Here, $x$ denotes an image in the RGB image space $\mathcal{X}$, $y$ is its class label, and $\phi(y) \in \mathbb{R}^K$ is the class embedding (i.e. a class-level attribute vector annotated with $K$ different visual attributes). Here we use $\mathcal{Y}_n$ to denote the unseen class label set in ZSL and the novel class in FSL for convenience. The class embeddings of unseen classes, i.e. $\{\phi(y)|y \in \mathcal{Y}_n\}$, are also known. The goal for ZSL is to predict the label of images from unseen classes, i.e. $\mathcal{X} \rightarrow \mathcal{Y}_n$, while for generalized ZSL (GZSL) (Xian et al., 2019a) the goal is to predict images from both seen and unseen classes, i.e. $\mathcal{X} \rightarrow \mathcal{Y}_n \cup \mathcal{Y}_u$. Few-shot learning (FSL) and generalized few-shot learning (GFSL) are defined similarly. The main difference lies that instead of only knowing the attributes of novel classes in ZSL, FSL also gets a few training samples from each novel class.

#### 3.1 Base Module (BaseMod) for global feature learning

The base module (BaseMod) learns discriminative visual features for classification. Given an input image $x$, the Image Encoder (a CNN backbone) learns a feature representation $f(x) \in \mathbb{R}^{H \times W \times C}$ where $H$, $W$ and $C$ denote the height, width, and channel respectively. BaseMod then applies global average pooling over the $H$ and $W$ to learn a global discriminative feature $g(x) \in \mathbb{R}^C$:

$$g(x) = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} f_{i,j}(x),$$

where $f_{i,j}(x) \in \mathbb{R}^C$ is extracted from the feature $f(x)$ at spatial location $(i, j)$ (blue box in Figure 1).

```latex
$$g(x) = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} f_{i,j}(x),$$
```
Fig. 1: Our attribute prototype network (APN) consists of an Image Encoder extracting image features $f(x)$, a BaseMod performing classification, a ProtoMod learning attribute prototypes $p_k$ and localizing them with similarity maps $M^k$, and a ZoomInMod cropping the informative image region $\tilde{x}$ covered by attribute similarity maps. The end-to-end training of APN encourages the image feature to contain both global information which is discriminative for classification and local information which is crucial to localize and predict attributes.

3.2 Prototype Module (ProtoMod) for local feature learning

The global features learned from BaseMod may be biased to seen classes because they mainly capture global context, shapes and other discriminative features that may be indicative of training classes. To improve the locality of the image representation, we propose a prototype module (ProtoMod) focusing on the local features that are often shared across seen and unseen classes.

Attribute prototypes. ProtoMod takes as input the feature $f(x) \in \mathbb{R}^{H \times W \times C}$ produced by the Image Encoder where the local feature $f_{i,j}(x) \in \mathbb{R}^C$ at spatial location $(i, j)$ encodes information of local image regions. Our main idea is to improve the locality of the image representation by enforcing those local features to encode visual attributes that are critical for ZSL. Specifically, we learn a set of attribute prototypes $P = \{p_k \in \mathbb{R}^C\}_{k=1}^K$ to predict attributes from those local features, where $p_k$ denotes the prototype for the $k$-th attribute. As a schematic illustration, $p_1$ and $p_2$ in Figure 1 correspond to the prototypes for black eye and blue crown respectively. For each attribute (e.g. $k$-th...
attribute), we produce a similarity map \( M^k \in \mathbb{R}^{H \times W} \) where each element is computed by a dot product between the attribute prototype \( p_k \) and each local feature, i.e. \( M^k_{i,j} = \langle p_k, f_{i,j}(x) \rangle \). Afterwards, we predict the \( k \)-th attribute \( \hat{a}_k \) by taking the maximum value in the similarity map \( M^k \):

\[
\hat{a}_k = \max_{i,j} M^k_{i,j}.
\]  

(3)

Other alternative operations such as average pooling and weighted average pooling are also performed for consideration, while max-pooling works the best, since it associates each visual attribute with its closest local feature and allows the network to efficiently localize attributes.

**Attribute regression loss.** The class-level attribute vectors supervise the learning of attribute prototypes. We consider the attribute prediction task as a regression problem and minimize the Mean Square Error (MSE) between the ground truth attributes \( \phi(y) \) and the predicted attributes \( \hat{a} \):

\[
\mathcal{L}_{Reg} = || \hat{a} - \phi(y) ||_2^2,
\]  

(4)

where \( y \) is the ground truth class. By optimizing the regression loss, we enforce the local features to encode semantic attributes, improving the locality of the image representation.

**Attribute decorrelation loss.** Visual attributes are often correlated with each other as they frequently co-occur, e.g. blue crown and blue back for Blue Jay birds. Consequently, the network may use those correlations as a useful signal and fails to recognize unknown combinations of attributes in novel classes. Therefore, we propose to constrain the attribute prototypes by encouraging feature competition among unrelated attributes and feature sharing among related attributes. To represent the semantic relation of attributes, we divide all \( K \) attributes into \( L \) disjoint groups, encoded as \( L \) sets of attribute indices \( S_1, \ldots, S_L \). We directly adopt the disjoint attribute groups defined by the datasets [Wah et al. 2011; Lampert et al. 2009; Patterson et al. 2014]. Two attributes are in the same group if they have some semantic tie, e.g. blue eye and black eye are in the same group as they describe the same body part, while blue back belongs to another group. For each attribute group \( S_l \), its attribute prototypes \( \{p_k | k \in S_l\} \) can be concatenated into a matrix \( P^S_l \in \mathbb{R}^{C \times |S_l|} \), and \( P^S_c \) is the \( c \)-th row of \( P^S \). We adopt the attribute decorrelation (AD) loss inspired from Jayaraman et al. (2014):

\[
\mathcal{L}_{AD} = \sum_{c=1}^{C} \sum_{l=1}^{L} \| P^S_l \|_2.
\]  

(5)

This regularizer enforces feature competition across attribute prototypes from different groups and feature sharing across prototypes within the same groups, which helps decorrelate unrelated attributes.

**Similarity map compactness regularizer.** In addition, we would like to constrain the similarity map such that it concentrates on its peak region rather than disperses on other locations. Therefore, we apply the following compactness regularizer [Zheng et al. 2017] on each similarity map \( M^k \),

\[
\mathcal{L}_{CPR} = \frac{1}{KHW} \sum_{k=1}^{K} \sum_{i=1}^{H} \sum_{j=1}^{W} M^k_{i,j} \left[ (i - \tilde{i})^2 + (j - \tilde{j})^2 \right],
\]  

(6)

where \( (\tilde{i}, \tilde{j}) = \arg \max_{i,j} M^k_{i,j} \) denotes the coordinate for the maximum value in \( M^k \). This objective enforces the attribute prototype to resemble only a small number of local features, resulting in a compact similarity map.

### 3.3 Zoom-In Module (ZoomInMod) for attribute prototype-informed feature learning

Previous works have shown that the informative attributes are critical to the knowledge transfer in zero-shot learning [Liu et al. 2019; Guo et al. 2018; Liu et al. 2014]. We propose a Zoom-In Module (ZoomInMod) to highlight the image regions covered by the informative attribute similarity maps and discard the irrelevant image regions. Instead of performing classification in BaseMod with the original image \( x \) (the orange pipeline in Figure [1]), the Zoom-In Module crops out the illuminating image region \( \hat{x} \) that are attended by informative attributes and feed the image into BaseMod (the green pipeline). As illustrated in Figure [1] (left), we sum up the attribute similarity maps for the most informative attribute in each attribute group to form the attention map \( \hat{M} \):

\[
\hat{M} = \sum_{l=1}^{L} M^{n_l} \text{, where } n_l = \arg \max_{k \in S_l} a_k.
\]  

(7)

\( M^{n_l} \) indicates the attribute similarity map, and \( n_l \) is the index of the highest predicted (most informative) attribute in the \( l \)-th attribute group (e.g. the attention maps for “white belly” in “belly” attribute group). We follow [Zhang et al. 2021a] to binarize the informative attention map \( \hat{M} \) with the average attention value to form a mask \( A \):

\[
A_{i,j} = \begin{cases} 
1 & \text{if } \hat{M}_{i,j} \geq \bar{m} \text{, where } \bar{m} = \frac{1}{HW} \sum_{i=1}^{H} \sum_{j=1}^{W} \hat{M}_{i,j} \\
0 & \text{if } \hat{M}_{i,j} < \bar{m}.
\end{cases}
\]
We upsample the binary mask \( A \) to the size of the input image, and use the smallest bounding box covering the non-zero area to crop the original image. Then we feed the cropped image \( \tilde{x} \) into the Image Encoder. Note that there are no parameters in the ZoomInMod. When ZoomInMod is working, the BaseMod takes into two inputs, i.e. the original image \( x \) and the Zoom-In image \( \tilde{x} \), and maps the visual feature \( g(x) \) and \( g(\tilde{x}) \) into the class embedding space with visual-semantic embedding layer \( V \). We sum up the class logits for each image to induct the predicted class. So the overall compatibility scores are as follows:

\[
s = g(x)^T V \phi(y) + g(\tilde{x})^T V \phi(y),
\]

used to optimize the classification loss in Equation (2).

**Joint global and local feature learning.** Our full model optimizes the CNN backbone, BaseMod and ProtoMod simultaneously with the following objective function,

\[
L_{APN} = L_{CLS} + \lambda_1 L_{reg} + \lambda_2 L_{AD} + \lambda_3 L_{CPF},
\]

where \( \lambda_1, \lambda_2, \) and \( \lambda_3 \) are hyper-parameters. The joint training improves the locality of the image representation that is critical for any-shot generalization as well as the discriminability of the features. In the following, we will explain how we perform any-shot inference and attribute localization.

### 3.4 Zero- and few-shot learning

Once our full model is trained, the visual-semantic embedding layer of the BaseMod can be directly used for zero-shot learning inference, which is similar to ALE (Akata et al. 2015a). For ZSL, given an image \( x \), we generate the ZoomIn image \( \tilde{x} \) through the ProtoMod and ZoomInMod, and feed them into the BaseMod. The classifier searches for the class embedding with the highest compatibility via

\[
\hat{y} = \arg \max_{\tilde{y} \in Y^n} (g(x)^T V \phi(\tilde{y}) + g(\tilde{x})^T V \phi(\tilde{y})).
\]

For generalized zero-shot learning (GZSL), we need to predict both seen and unseen classes. The extreme data imbalance issue will result in predictions to be biased towards seen classes (Chao et al. 2016). To fix this issue, we apply Calibrated Stacking (CS) (Chao et al. 2016) to reduce the seen class scores by a constant factor. Specifically, the GZSL classifier is defined as,

\[
\hat{y} = \arg \max_{\tilde{y} \in Y^n \cup Y^s} (g(x)^T V \phi(\tilde{y}) + g(\tilde{x})^T V \phi(\tilde{y})) - \gamma \| \tilde{y} \in Y^s, \]

where the indicator \( \| \cdot \| = 1 \) if \( \tilde{y} \) is a seen class and 0 otherwise, \( \gamma \) is the calibration factor tuned on a held-out validation set.

Our model aims to improve the image representation for novel class generalization and is applicable to other ZSL methods (Zhu et al. 2019b; Xian et al. 2018; Changpinyo et al. 2016), i.e. once learned, our features can be applied to any ZSL model (Zhu et al. 2019b; Xian et al. 2018; Changpinyo et al. 2016). Therefore, in addition to the above classifiers, we use image features \( g(x) \) extracted from the Image Encoder, and train several state-of-the-art ZSL approaches on top of our features, e.g. ABP (Zhu et al. 2019b), f-VAEGAN-D2 (Xian et al. 2019b), and TF-VAEGAN (Narayan et al. 2020).

Our APN network can be adapted to the task of few-shot learning (FSL) by replacing the feature extraction network in FSL methods with our APN network. During the representation learning stage, we train the feature extractor \( f(\cdot) \) using the training examples in the base classes \( S = \{x, y, \phi(y) | x \in X, y \in Y^s\} \), and train the network with the original FSL training loss as well as our \( L_{APN} \) loss. With the help of the attribute prototype network, we can learn locality augmented representations that are discriminative for FSL models (Yang et al. 2020) and boost their performance. Besides, the locality augmented image representations in our model are applicable to the data synthesis based few-shot learning methods (Xian et al. 2019b; Guan et al. 2020). We use image features \( g(x) \) extracted from the Image Encoder to train several state-of-the-art generative FSL approaches (Narayan et al. 2020; Xian et al. 2019b) and improve their performance.

### 3.5 Attribute localization

As a benefit of the improved local features, our approach is capable of localizing different attributes in the image by inspecting the similarity maps produced by the attribute prototypes. More specifically, we upsample the similarity map \( M^k \) to the size of the input image with bilinear interpolation. The area with the maximum responses then encodes the image region that gets associated with the \( k \)-th attribute. Figure 4 illustrates the attribute regions of black eye, blue crown and solid belly from the learned similarity maps. It is worth noting that our model only relies on class-level attributes and semantic relatedness of them, i.e. attribute groups, as the auxiliary information and does not need any annotation of part locations.
Part localization on CUB

| Method          | ZSL       | Part localization on CUB |
|-----------------|-----------|--------------------------|
|                | CUB AWA2 SUN | breast belly back head wing leg | Mean |
| BaseMod         | 70.0 64.9 60.0 | 40.3 40.0 27.2 24.2 36.0 16.5 | 30.7 |
| + $L_\text{Reg}$ | 71.5 66.3 60.9 | 41.6 43.6 25.2 38.8 31.6 30.2 | 35.2 |
| + $L_\text{AD}$ | 71.8 67.7 61.4 | 60.4 52.7 25.9 60.2 52.1 42.4 | 49.0 |
| + $L_\text{CPT}$ | 72.0 68.4 61.6 | 63.1 54.6 30.5 64.1 55.9 50.5 | 52.8 |
| + ZoomInMod     | 75.0 69.9 61.5 | 67.8 55.9 29.4 68.7 49.2 49.1 | 53.4 |

Table 1: Ablation study of ZSL on CUB, AWA2, SUN (left, top-1 accuracy) and part localization on CUB (right, PCP). We train a single BaseMod with the original input $x$ as the baseline. Note that the last row represents our full model APN, which combines BaseMod and ProtoMod (trained with $L_\text{CLS}$, $L_\text{Reg}$, $L_\text{AD}$, $L_\text{CPT}$), and the ZoomInMod.

4 Experiments

In the following, we first introduce the datasets. Then we evaluate our attribute prototype network in both zero-shot learning as well as the attribute localization performance. We finally evaluate our network on few-shot learning.

Datasets. We conduct the experiments on three widely used benchmark datasets. CUB (Wah et al., 2011) is a fine-grained dataset containing 11,788 images from 200 bird classes with 312 attributes. Following SPDA-CNN (Zhang et al., 2016a), we define 7 body parts for all the birds in CUB dataset, i.e. belly, breast, back, wing, head, leg, tail. Part related attributes are divided into seven part groups. SUN (Patterson et al., 2014) is a fine-grained dataset consisting of 14,340 images from 717 scene classes, with 102 attributes divided into 4 groups, describing the functions, materials, surface properties and spatial envelope of scene images. AwA2 (Xian et al., 2019a) is a coarse-grained dataset containing 37,322 images of 50 animal classes with 85 attributes. We follow Lampert et al. (2009) to divide 85 attributes into 9 groups, describing various properties of animals, i.e. color, texture, shape, body parts, behaviour, nutrition, activity, habitat and character. For zero-shot learning, we split the seen/unseen classes following Xian et al. (2019a) to avoid overlap between novel images and ImageNet 1K images.

For few-shot learning, we follow two kinds of evaluation protocols. In the N-way-K-shot scenario, the task is to train a classifier with $K$ samples from $N$ classes, to correctly classify the query samples. Following Yang et al. (2020), we randomly split the CUB dataset into 100 base, 50 validation, and 50 novel classes. In addition to the widely used N-way-K-Shot benchmarks, we also focus on a more realistic setting, i.e. the all-way benchmark (Tang et al., 2020; Wang et al., 2018b; Hariharan and Girshick, 2017). The classifiers are supposed to recognize all the categories simultaneously, i.e. $X \rightarrow Y^n$ for FSL and $X \rightarrow Y^n \cup Y^s$ for generalized FSL. In the all-way scenario, we follow Xian et al. (2019b) to split three benchmark datasets, i.e. CUB, AwA2, and SUN.

Implementation. To train the attribute prototype network, we adopt ResNet101 (He et al., 2016) pre-trained on ImageNet (Deng et al., 2009) as the backbone, and jointly finetune the entire model in an end-to-end fashion to improve the image representation. We use the Adam optimizer (Kingma and Ba, 2015) with $\beta_1=0.5$ and $\beta_2=0.999$. The learning rate is initialized as $10^{-6}$ and decreased every ten epochs by a factor of 0.9. Hyperparameters in our model are obtained by grid search on the validation set (Xian et al., 2019a). We set $\lambda_1$ as ranges from 0.01 to 0.1 for three datasets, $\lambda_2$ as 0.01, and $\lambda_3$ as 0.2. The factor $\gamma$ for Calibrated Stacking is set to 0.7 for CUB, 0.85 for AwA2, and 0.4 for SUN.

Evaluation metrics. We follow the same evaluation protocol as demonstrated in Xian et al. (2019a) and Xian et al. (2019b). For ZSL/FSL, we report average top-1 accuracy for unseen (novel) classes; for GZSL, we report average top-1 accuracy for both seen (s) and unseen (u) classes, as well as their harmonic mean (H); for GFSL we report average top-1 accuracy for both seen and novel classes.

4.1 Zero-shot learning

In this section, we present an ablation study of our framework in the ZSL setting, and then we present a comparison with the state-of-the-art in ZSL and GZSL settings.

Ablation study. To measure the influence of each model component on the extracted image representation, we design an ablation study where we train a single BaseMod with cross-entropy loss as the baseline, and four variants of APN by adding the ProtoMod and the three loss functions, attribute regression loss $L_\text{Reg}$, attribute decorrelation loss $L_\text{AD}$, and compactness regularizer $L_\text{CPT}$ gradually, and finally we add the

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Evaluation metrics. We follow the same evaluation protocol as demonstrated in Xian et al. (2019a) and Xian et al. (2019b). For ZSL/FSL, we report average top-1 accuracy for unseen (novel) classes; for GZSL, we report average top-1 accuracy for both seen and unseen classes.
Fig. 2: The qualitative ablation study. We display the original image, the Zoom-In image from ZoomInMod in the first and second row. From the third to the fifth row, we show the attribute similarity maps from our APN model, our model trained without $L_{CPT}$, and our model trained without $L_{AD}$, respectively. The text above the attribute similarity maps indicates the attribute name. Green (purple) box outside the image indicates a correct (incorrect) localization by our model.

ZoomInMod to generate a ZoomIn image as the input for the BaseMod. Our results on CUB, AWA2 and SUN presented in Table 1 (left) demonstrate that the full APN model improve ZSL accuracy over BaseMod consistently, by 5.0% (CUB), 5.0%(AWA2), and 1.5% (SUN). The attribute regression loss supervises the learning of each attribute prototype and enforces the local image features to contain attribute information, which boosts the performance by 1.5% (CUB), 1.4% (AWA2), and 0.9% (SUN). This indicates that adding locality to the image representation can help the network to learn discriminative features and significantly improve the performance of unseen classes. The attribute decorrelation loss, which suppresses the unwanted attribute co-occurrence and helps to recognize unknown combinations of attributes in novel classes, provides accuracy gains on AWA2 (1.4%), CUB (0.3%), and SUN (0.5%). The compactness loss, which constrains the attribute attention maps, does not influence ZSL accuracy much. The ZoomInMod highlights the informative image region and provides significant performance gain for CUB (3.0%) and AWA2 (1.5%).

The accuracy improvement on SUN is not as great as that on CUB and AWA2 for the following reasons. First, APN aims to learn local image features by regressing and decorrelating attributes, which works well for local and visually-grounded attributes. Most attributes in CUB and AWA2 are related to the local visual properties of the birds and animals. However, the attributes of SUN are designed to be global and abstract [Patterson et al., 2014], thus sometimes can not help with learning locality image features. Second, the data distribution of SUN is quite different from CUB and AWA2. The datasets for bird (CUB) and animal (AWA2) classification contain main object and discriminative regions. However, dataset SUN is for scene classification, where each element in a scene is crucial in discriminating it from other categories. For instance, the “glacier” in Figure 4 (right, column 2) consists of mountains, snow, and sky, and the global feature of the whole scene can lead to good predictions. Emphasizing local features as APN and the ZoomInMod can not help much.

The qualitative ablation of our APN network is shown in Figure 2. We display the Zoom-In image $\tilde{x}$ generated by the ZoomInMod in the second row. The Zoom-In image $\tilde{x}$ accurately crops out the objects, e.g. the birds in the corner (row 2, column 3), and discards the noisy background. We qualitatively ablate the attribute decorrelation loss $L_{AD}$ and the compactness regularizer $L_{CPT}$ by visualizing the attribute similarity maps generated by different models.

Adding the ZoomInMod increases the model complexity by around two times, e.g. increasing FLOPs from...
7.9 GMac to 15.7 GMac, increasing memory from 5,216 MiB to 9,052 MiB. However, the training process is still efficient, which will finish in 48 minutes on CUB dataset with a single NVIDIA V100 GPU.

From Figure 2 (row 3-5), we have the following observations. First, the compactness regularizer $L_{crt}$ helps the model to generate compact attention maps that focus on the most salient attribute region. For instance, our APN model attends to the correct image area. This observation agrees with the quantitative results in Table 1 where $L_{crt}$ loss improves the part localization score.

Second, the decorrelation loss $L_{ad}$ helps the model to avoid attribute correlations and results in precise attention maps. For example, the model APN $- L_{ad}$ misunderstands “white throat” with “white belly” (row 5, column 2), and “green throat” with “green belly” (row 5, column 5). The reason might be the model APN $- L_{ad}$ learns similar prototypes for two attributes since they share often co-occurring color properties. While the model APN trained with attribute decorrelation loss forces attribute prototypes from different body parts to be different and correctly localizes the corresponding area.

### Comparing with the SOTA
We compare our attribute prototype network (APN) with two groups of state-of-the-art models: non-generative models, i.e. SGMA (Zhu et al., 2019c), AREN (Xie et al., 2019), LGFAA+Hybrid (Liu et al., 2019); and generative models, i.e. LisGAN (Li et al., 2019a), CLSWGAN (Xian et al., 2019), FREE (Chen et al., 2021), ABP (Zhu et al., 2019b), CVC (Li et al., 2019), GDAN$^*$ (Huang et al., 2019), and APN+f-VAEGAN-D2 (Xian et al., 2019b), APN+ABP (Ours), and APN+ZoomInMod (Ours) on CUB, AWA2 and SUN datasets. In the more challenging generalized ZSL setting, our APN achieves impressive gains over the state-of-the-art on ZSL and GZSL terms of ZSL accuracy. It indicates that our model learns an image representation that generalizes better to unseen classes. In the more challenging generalized ZSL setting, our APN achieves impressive gains over the state-of-the-art on ZSL and GZSL terms of ZSL accuracy. It indicates that our model learns an image representation that generalizes better to unseen classes.
state-of-the-art non-generative models for the harmonic mean (H): we achieve 69.4% on CUB and 37.5% on SUN. On AWA2, it obtains 69.6%, which is even better than other generative models, e.g. LisGAN with 62.3%, CLSWGAN with 59.6%, and FREE with 67.1%. This shows that our network is able to balance the performance of seen and unseen classes well, since our attribute prototypes enforce local features to encode visual attributes facilitating more effective knowledge transfer.

Image features extracted from our model also boosts the performance of generative models that synthesize CNN image features for unseen classes. We choose five SOTA methods ABP (Zhu et al., 2019b), GDAN (Huang et al., 2019), CVC (Li et al., 2019b), f-VAEGAN-D2 (Xian et al., 2019b), and TF-VAEGAN (Narayan et al., 2020) as generative models, and follow the same training and evaluation protocol as stated in these approaches. For fair comparison, we train these models with finetuned features \( g(x) \) (e.g. APN + TF-VAEGAN).

In the ZSL setting, we observe the following. First, for five generative models, our APN consistently boosts their performance on three datasets. For instance, for AWA2, we improve the accuracy of ABP from 68.5% to 73.8%, the performance of CVC from 64.6% to 71.2%. On the fine-grained datasets CUB and SUN, we also gain performance, e.g. the accuracy of ABP is improved from 70.7% to 73.3% on CUB, from 62.6% to 63.1% on SUN. This indicates that compared to standard finetuning with only cross-entropy loss, our APN features provide more local information helping the generative models to synthesize discriminative image features. In the GZSL setting, the model predicts both seen and unseen images. We observe that applying our feature to the generative models consistently boosts the harmonic mean, e.g. we improve ABP by 2.7% (CUB) and 2.3% (AWA2). Training with our APN feature achieves a more balanced accuracy with much better performance on unseen classes. Compared to CVC on AWA2, APN+CVC gains 5.8% on unseen while sacrificing only 2.1% on seen. These results demonstrate that our learned locality-enforced image representation lends itself better for knowledge transfer from seen to unseen classes, as the attribute decorrelation loss achieves de-biasing the label prediction.

4.2 Attribute and part localization in ZSL setting

We first evaluate the part localization capability of our method quantitatively. We provide an ablation study and comparison with other methods in CUB (Wah et al., 2011). In addition, we provide qualitative results of attribute localization on three benchmark datasets. Two user studies are performed to evaluate the accuracy and semantic consistency of attribute similarity maps.

4.2.1 Body part localization

Given the attribute similarity maps related to six body parts of birds, we report the part localization accuracy by calculating the Percentage of Correctly Localized Parts (PCP) following SGMA (Zhu et al., 2019c). As shown in Figure 3 that the bounding box marks the image region with the highest attention in each attribute similarity map, then compared with the ground truth part annotation provided by the CUB (Wah et al., 2011) dataset.

Ablation study. We evaluates the effectiveness of our APN framework in terms of the influence of the attribute regression loss \( L_{\text{reg}} \), attribute decorrelation loss \( L_{\text{AD}} \), the similarity compactness loss \( L_{\text{CPT}} \), and the ZoomInMod.

Comparing with SOTA. We report PCP in Table 5. As the baseline, we train a single BaseMod with cross-entropy loss \( L_{\text{CLS}} \), and use gradient-based visual explanation method CAM (Zhou et al., 2016) to investigate the image area BaseMod used to predict each attribute. As state of the art, we report the part localization accuracy of a fine-grained classification model SPDA-CNN (Zhang et al., 2016a) which contains a bird part detection branch supervised by parts annotations. In the last two rows, we compare with the weakly supervised model (without part annotation) SGMA (Zhu et al., 2019c), which learns part attention for head and leg by clustering feature channels.

On average, our APN improves PCP over BaseMod by 22.7% (53.4% vs 30.7%). The majority of the improvements come from better leg and head localization, e.g. from 24.2% to 68.7% (head), and from 16.5% to 49.1% (leg). Compared to the supervised method SPDA-CNN, our method achieves comparable accuracy on breast and wing. Although there is still a gap to the
Table 3: Body part localization in CUB dataset. We compare our APN with detection model SPDA-CNN trained with part annotations (row 2), and a ZSL model SGMA. The baseline BaseMod takes the original image feature \( g(x) \) as input and is trained with \( L_{cls} \). For BB (bounding box) size, 1/4 means each part bounding box has the size \( \frac{1}{4}W_b \times \frac{1}{4}H_b \), where \( W_b \) and \( H_b \) are the width and height of the bird. We use gradient-based visual explanation method CAM to visualize the attribute attention map for the baseline BaseMod. For a fair comparison, we use the same evaluation protocol as SGMA in the last two rows.

| Method          | Parts Annotation | BB size | Breast | Belly | Back | Head | Wing | Leg | Mean  |
|-----------------|------------------|---------|--------|-------|------|------|------|-----|-------|
| SPDA-CNN (Zhang et al. 2016a) | ✓ | 1/4 | 67.5 | 63.2 | 75.9 | 90.9 | 64.8 | 79.7 | 73.6  |
| BaseMod (uses \( L_{cls} \)) | ✓ | 1/4 | 40.3 | 40.0 | 27.2 | 24.2 | 36.0 | 16.5 | 30.7  |
| APN (Ours)      |                  |         | 67.8 | 55.9 | 29.4 | 68.7 | 49.2 | 49.1 | 53.4  |
| SGMA (Zhu et al. 2019c) | ✓ | 1/\sqrt{2} | 88.1 | 81.3 | 71.6 | 91.4 | 76.2 | 70.8 | 79.9  |
| APN (Ours)      |                  |         | 81.3 | 81.3 | 71.6 | 91.4 | 76.2 | 70.8 | 79.9  |

Fig. 3: Part and attribute localization on CUB. Left: Attention maps for each body part of Mallard generated by our APN (first row) and the baseline model BaseMod visualized by CAM (BaseMod(C), second row). Boxes mark out the areas with the highest attention. Attention maps are min-max normalized for visualization. Right: Various attribute similarity maps generated by our model. Red, blue, yellow bounding boxes in the image represent the ground truth part bounding box, our results, and the results of BaseMod(C) respectively. Green (purple) box outside the image indicates a correct (incorrect) localization.

4.2.2 Qualitative results

Our model localizes attributes by inspecting the attention maps produced by the attribute prototypes. In this section, we qualitatively investigate the part localization ability on the CUB dataset, as well as the attribute localization results on three benchmark datasets.

Part localization in CUB. We first investigate the difference between our APN and the baseline BaseMod for localizing different body parts in CUB dataset. In Figure 3 (left), for each part of the bird Mallard, we display one attribute similarity map generated by our model APN, and the baseline model BaseMod visualized by CAM (BaseMod(C)). The baseline model tends to generate disperse attention maps covering the whole bird, as it utilizes more global information, e.g., correlated bird parts and context, to predict attributes. For instance, when predicting attributes of belly and back, the baseline model utilizes pixels scattered on the bird body. On the other hand, the similarity maps of our APN are more concentrated and diverse and therefore they localize different bird body parts more accurately. The improvement is lead by the attribute prototypes and compactness loss, which helps the model to focus on local image features when learning attributes.

Attribute localization in CUB. In addition, unlike other models (Zhang et al. 2016a; Uijlings et al. 2013; Zhu et al. 2019c) that can only localize body parts, our APN model can provide attribute-level localization for CUB dataset, as shown in Figure 3 (right). Our model can localize back with various shapes (row 1, column 1 and 2) and wings with different postures (row 2, column 1 and 2). We can also locate the pointed belly of the occluded bird (row 2, column 4). Compared
with BaseMod(C), our approach produces more accurate bounding boxes that localize the predicted attributes. For example, while BaseMod(C) wrongly learns the red leg from the image region of the belly (row 1, column 3), our model precisely localizes the red leg at the correct region. Specifically, when predicting the attributes for wings and legs, the model tends to focus on both two wings and legs even when they are physically separated (row 1, column 3 for red leg and row 2, column 2 for gray wing). These results are interesting because our model is trained on only class-level attributes without accessing any bounding box annotation.

As a side benefit, the attribute localization ability introduces a certain level of interpretability that supports the zero-shot inference with attribute-level visual evidence. The last two columns in Figure 3 (right) show some failure examples where our model makes wrong predictions. For example, when the yellow breast is wrongly predicted as black (row 1, column 4), the attention map tends to spread over the tail and background; when the black breast is recognized as multi-colored (row 1, column 5), the attention map points to the region of the black and white wing. Besides, although our attribute decorrelation loss in Equation 5 alleviates the correlation issue to some extent (as shown in the previous results in Table 1 and Figure 2), we observe that our APN seems to still confine the yellow belly and yellow breast (row 2, column 5) in some cases, indicating the attribute correlation issue as a challenging problem for future research.

Attribute localization in AWA2 and SUN. To show how these observations generalize in two other datasets, in Figure 4, we compare our APN model with two baseline models on AWA2 and SUN. The attribute attention maps of BaseMod is generated with two gradient-based visual explanation method CAM (Zhou et al., 2016) and Grad-CAM (Selvaraju et al., 2017).

In AWA2 dataset (Figure 4 left), our network produces precise similarity maps for visual attributes that describe texture and body parts, etc. We can localize visual attributes with diverse appearances, e.g. the white and black stripe of zebra, and the yellow and black stripe of tiger (row 2, column 3,4), while CAM and Grad-CAM fails in localizing the stripe on tigers. Our similarity maps for furry and longleg can precisely mask out the image regions of the ox and horse (row 2, column 3,4), while BaseMod only localizes part of the image (row 1, column 3,4). On AWA2 dataset we are interested in the visual attributes of animals, while our model in some cases highlights the attributes of the background, e.g. identifying the grid on the rat cage as stripes (row 2, column 5). This can be explained by the fact that our model only relies on weak supervision, i.e. class-level attributes and their semantic relatedness.

The attribute similarity maps on SUN dataset are shown in figure 4 (right). Our model can discriminate between different attributes with similar color or texture, e.g. correctly locating snow and cloud in one image (row 2, column 2,3). The baseline models, on the other hand, cannot distinguish between cloud and snow. Although the appearance of one visual attribute may vary significantly, we can still locate them correctly, e.g. the fencing with different colors, location, and shape (row 2, column 4,5). Overall, those results indicate that we can perform attribute localization in a weakly supervised manner and provide visual evidence for the inference process of ZSL.

| Methods       | Results       |
|---------------|---------------|
| Accuracy      | APN vs CAM    | 76.0% vs 24.0% (±5.1%) |
|               | APN vs Grad-CAM | 74.4% vs 25.6% (±2.9%) |
| Semantic consistency | Grad-CAM    | 55.0% (±3.2%) |
|               | APN           | 60.0% (±5.5%) |
|               | APN           | 89.0% (±3.7%) |

Table 4: User study results. Top: the percentage of time that one method is marked as more accurate than the other one by users. Bottom: the percentage of attention maps that can be correctly associated with the target attribute by users. APN, CAM, and Grad-CAM denote our model, baseline model visualized by CAM (Zhou et al., 2016), and Grad-CAM (Selvaraju et al., 2017) respectively.

4.2.3 User study

Since the CUB dataset is the only one among the datasets considered here that contains ground truth parts, we design two user studies to assess the accuracy and semantic consistency of attribute attention maps from SUN and AWA2 datasets. We compare the performance of our APN model and the baseline BaseMod visualized by two model explanation methods, Grad-CAM and CAM, respectively.

Accuracy of attribute localization. The goal is to evaluate whether the attribute attention maps precisely attend to the related image area. As shown in Figure 5 (left), each test is a tuple (M_{APN}^{a_i}, M_{BaseMod}^{a_i}) for attribute a_i, where M_{APN} is the attribute attention maps generated by our APN model, and M_{BaseMod} by the BaseMod. The human annotators are presented with the tuple and they are asked to choose the attention map that more accurately covers the attribute region. We randomly sample 50 attention maps from our APN model for 20 visual attributes, then generate the corresponding
Grad-CAM and CAM attention maps for BaseMod, and create 100 tuples in total. Two separate experiments are performed to compare our APN model with the BaseMod visualized by Grad-CAM and CAM. For each experiment, we employed 5 annotators, i.e. in total 10 students (4 female) aged between 20 and 30 and majoring in computer science participated in the experiment.

We average the responses from each participant and report the standard deviation between each participant as well as the overall accuracy in Table 4 (top). As for the result, our APN attribute attention maps outperform the BaseMod by a large margin. When comparing the attribute attention maps generated by our APN model and the BaseMod visualized by CAM, in 76.0% cases, APN are marked as more accurately covers the attribute-related area than CAM. And in 74.4% cases, APN are more accurate than Grad-CAM. The user study results agree with the qualitative results in Figure 4 that APN demonstrates more accurate attribute attention maps than the baseline model.

**Semantic consistency.** Here, our aim is to measure whether the attention maps on different images for one attribute is semantically consistent and can be understood by human. Each test is a tuple \((M^i, a_i, a_j)\), where \(a_i\) is the target attribute, and \(a_j\) is a distractor attribute that is semantically similar to \(a_i\). \(M^i = \{M_1^i, M_2^i, M_3^i\}\) is a random subset of attribute attention maps for the target attribute \(a_i\). As shown in Figure 5 (right), the human annotators are presented with the tuple via a user interface, and their task is to identify which of the attributes does the attention map refer to. The performance is defined as the average accuracy of solving such tasks correctly. We sample 20 tuples for three methods (APN, BaseMod+CAM and

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**Fig. 4:** Attribute attention maps for AWA2 (left) and SUN (right) from our APN model (row 2), BaseMod visualized with CAM (row 3), and BaseMod with Grad-CAM (row 4). The attribute similarity maps are min-max normalized for visualization. We cover the upsampled attention map on the original image, to show the corresponding location of the highlighted area. Green (purple) box outside the image indicates a correct (incorrect) localization.

**Fig. 5:** User Study. Left: User study interface to evaluate the accuracy. Participants are required to choose the attention map that more accurately covers the area related to the attribute:          A              B

Following are attention maps for attribute Long leg
Please choose which attention map more accurately covers the area related to the attribute:          A              B

Following are attention maps for one attribute.
Please choose which attribute do they refer to:            Grass        Tree

Fig. 5: User Study. Left: User study interface to evaluate the accuracy. Participants are required to choose the attention map that more accurately covers the attribute related region from two attention maps generated by our APN model and the BaseMod (in random position). Right: User study interface for the semantic consistency. Given three attention maps generated for an attribute, the user selects from two candidate attributes which one is the target of the attention maps.
4.3 Few-shot learning

In the few-shot learning (FSL) scenario, the images are divided into base classes where plenty of training samples can be obtained and novel classes with only a handful of training samples. The goal of FSL is to learn a classifier to recognize novel classes with limited labeled examples. In the generalized few-shot learning (GFSL) setting, the classifier is trained to recognize images from both base and novel classes.

**Compared methods.** In this section, we evaluate our attribute prototype network under two evaluation protocols, i.e. the all-way evaluation and N-way-K-shot evaluation. In the all-way evaluation, our model is compared with several state-of-the-art generative FSL methods. **Analogy** (Hariharan and Girshick, 2017), **f-VAEGAN-D2** (Xian et al., 2019b) and **TF-VAEGAN** (Narayan et al., 2020) are data synthesis methods that augment image features for novel classes. **Imprinted** (Qi et al., 2018) directly uses the normalized activation of novel images as the classifier weight. For a fair comparison, these models are trained with finetuned feature extracted from ResNet101, and under the same dataset split (Xian et al., 2019b). In the FSL setting, we report the averaged top-1 accuracy for novel classes with the model that only predicts novel classes. In the GFSL setting, we report the averaged top-1 accuracy of test samples of all classes, where the model predicts both base and novel classes labels.

In the N-way-K-shot evaluation, we build our attribute prototype network over the ResNet12 (He et al., 2016) backbone in DPGN (Yang et al., 2020), and train the network with both the FSL training losses (Yang et al., 2020) and our $L_{APN}$ loss. Our model is compared with state-of-the-art FSL methods under the N-way-K-shot evaluation. **MatchingNet** (Vinyals et al., 2016), **ProtoNet** (Snell et al., 2017) and **CloserLook** (Fu et al., 2017) propose to optimize the representation learning model with metric learning methods. **MAML** (Finn et al., 2017) learns to initialize the model weight so that it can adapt to novel classes efficiently. Two latest methods further enhance the meta-learning approach with graph network (Yang et al., 2020) and attention agent trained with reinforcement learning (Hong et al., 2021). We report the top-1 accuracy in the 5-way-1-shot and 5-way-5-shot setting following (Yang et al., 2020).

**Comparing with the SOTA.** We display the few-shot learning accuracy in Table 5. Under the all-way evaluation setting, our model yields consistent improvement on three datasets, i.e. CUB, AWA2, and SUN. On AWA2 dataset, compared to **TF-VAEGAN** trained with finetuned feature, our model **APN+TF-VAEGAN** improve the FSL accuracy of by a large margin, especially in the low-shot scenario where only a small number of samples from novel classes are available, i.e. we gain 9.9% (1-shot), 8.4% (2-shot), 7.0% (5-shot), and 6.2% (10-shot). On fine-grained dataset CUB, our **APN feature** yields consistent improvement over the finetuned feature. Compared to **f-VAEGAN-D2** trained with finetuned feature, our model **APN+f-VAEGAN-D2** gain 1.7% (1-shot), 1.5% (2-shot), 1.4% (5-shot), and 1.2% (10-shot) on FSL. The same trend is observed on SUN dataset. Though the accuracy for the 1-shot and 2-shot regime are comparable to other methods, we manage to improve a lot when training samples increase, e.g. our model **APN+TF-VAEGAN** achieves 74.1% (5-shot) and 76.0% (10-shot), compared to **TF-VAEGAN** with 68.9% (5-shot) and 74.0% (10-shot).

Compared to other FSL models, we gain significant improvements. For instance, we achieve 77.8% (1-shot) on FSL for CUB dataset, compared to 48.5% (Analogy) and 56.5% (Imprinted). For AWA2 dataset, we gain 87.2% on FSL, compared to 66.9% (Analogy) and 62.5% (Imprinted). Specifically, our model using one labeled image per class approaches the accuracy of Analogy and Imprinted trained with five samples. It indicates that improving the locality of image features can better help the feature generators to mimic the real data distribution. When increasing the number of training samples (i.e. in the 10-shot scenario), the...
distance between the other three methods shrinks as we are going towards the fully supervised setting. However, our model still manages to improve the performance, which denotes that even with abundant training samples, locality enhanced image features will train a more discriminative classifier than ordinary features.

The locality augmented model generates discriminative features for novel classes, especially when applied to the generalized setting where the model should predict both base and novel classes. As shown in Table [6] on AWA2 dataset, our model APN+TF-VAEGAN gains accuracy improvement for 5.4% (1-shot), 4.8% (2-shot), 2.6% (5-shot), and 3.2% (10-shot). The results demonstrate that our model generates highly discriminative image features by leveraging attribute information. In CUB dataset, we gain 1.0% (1-shot), 1.6% (2-shot), 1.7% (5-shot), and 1.1% (10-shot). In SUN dataset, we also manage to improve the accuracy consistently, e.g. we gain 1.0% (1-shot), 0.7% (2-shot) and 3.2% (5-shot), and 1.3% (10-shot) on GFSL.

As shown in Table [7] in the N-way-K-shot scenario where we train DPGN (Yang et al., 2020) with our attribute prototype network, we yield improvement over the baseline DPGN on CUB and achieve new state-of-the-art accuracy. We achieve 77.4% (5-way-1-shot), compared to 68.4% (CloseLook), 74.1% (RAP+ProtoNet) and 75.7% (DPGN). In the 5-way-5-shot setting, we also improve over CloseLook, RAP+ProtoNet and DPGN by 12.9%, 3.6% and 0.7% respectively. The results indicate that integrating attribute prototype network into the representation learning process helps the network to learn locality enhanced features and benefit the FSL performance.
We study the flexibility of our APN model with other state-of-the-art models in Table 8. In this work, we develop a representation learning framework for zero-shot learning and few-shot learning, i.e. attribute prototype network (APN), to jointly learn global and local features. Our model improves the locality of image representations by regressing attributes with local features and decorrelating prototypes with regularisation. We explicitly encourage the network to learn from informative attribute related image regions and discard noisy backgrounds by cropping the original image with attribute similarity maps. We demonstrate consistent improvement over the state-of-the-art on three benchmarks. And our representations improve over finetuned ResNet representations when used in conjunction with feature generating models. We qualitatively verify that our network is able to localize 300-dim word2vec embeddings as the class embedding for ImageNet since there is no attribute annotation. Our APN model is trained with only w2v learns better representations and further boosts the few-shot learning performance on the large-scale ImageNet dataset. Notably, we gain 1.6% (1-shot) on FSL and 1.2% (1-shot) on GFSL.

### 5 Conclusion

In this work, we develop a representation learning framework for zero-shot learning and few-shot learning, i.e. attribute prototype network (APN), to jointly learn global and local features. Our model improves the locality of image representations by regressing attributes with local features and decorrelating prototypes with regularisation. We explicitly encourage the network to learn from informative attribute related image regions and discard noisy backgrounds by cropping the original image with attribute similarity maps. We demonstrate consistent improvement over the state-of-the-art on three benchmarks. And our representations improve over finetuned ResNet representations when used in conjunction with feature generating models. We qualitatively verify that our network is able to localize 300-dim word2vec embeddings as the class embedding for ImageNet since there is no attribute annotation. Our APN model is trained with only w2v learns better representations and further boosts the few-shot learning performance on the large-scale ImageNet dataset. Notably, we gain 1.6% (1-shot) on FSL and 1.2% (1-shot) on GFSL.

### Table 8: Zero-Shot Learning results from our APN model and other state-of-the-art on CUB, AWA2, and SUN datasets. All the models are trained with unsupervised class embedding, i.e. w2v. SJE [Akata et al. 2015b], GEM-ZSL [Liu et al. 2021], and our model APN are non-generative models, while CADA-VAE [Schonfeld et al. 2019b] is feature generation model. We measure top-1 accuracy (T1) in ZSL, top-1 accuracy on seen/unseen (s/u) classes and their harmonic mean (H) in GZSL.

| Method            | Few-Shot Learning | Generalized Few-Shot Learning |
|-------------------|-------------------|-------------------------------|
|                   | AWA2   | CUB   | SUN   | AWA2   | CUB   | SUN   | AWA2   | CUB   | SUN   |
|                   | T1     | T1    | T1    | u     | s     | H     | u     | s     | H     |
| CADA-VAE (Schonfeld et al. 2019b) | 49.0   | 22.5  | 37.8  | 38.6  | 60.1  | 47.0  | 16.3  | 39.7  | 23.1  |
| SJE (Akata et al. 2015b) | 53.7   | 14.4  | 26.3  | 39.7  | 65.3  | 48.8  | 13.2  | 28.6  | 18.0  |
| GEM-ZSL (Liu et al. 2021) | 50.2   | 25.7  | –     | 40.1  | 80.0  | 53.4  | 11.2  | 48.8  | 18.2  |
| APN(w2v) (Ours)    | 59.6   | 27.7  | 32.1  | 41.8  | 75.0  | 53.7  | 20.6  | 26.4  | 23.4  |

### Table 9: Few-Shot Learning results on ImageNet with increasing number of training samples per novel class (top-5 accuracy). Our APN(w2v) model is trained with w2v class embeddings. We apply our APN features to feature generation model (i.e. APN(w2v) + f-VAEGAN-D2).

```latex
| Method           | Few-Shot Learning | Generalized Few-Shot Learning |
|------------------|-------------------|-------------------------------|
|                  | 1                 | 2                 | 5                 | 1             | 2             | 5             |
| softmax          | 49.3              | 64.5              | 76.7              | 81.0          | 84.2          | 81.0          |
| Analogy Harihara and Girshick [2017] | 40.5 | 50.7 | 61.6 | 69.5 | 76.0 | 51.5 | 59.8 | 67.4 | 72.0 | 77.3 |
| f-VAEGAN-D2-ind Xian et al. [2019b] | 54.4 | 64.4 | 74.6 | 79.9 | 84.0 | 60.3 | 65.7 | 73.5 | 78.8 | 79.5 |
| f-VAEGAN-D2 Xian et al. [2019b] | 60.1 | 70.0 | 79.0 | 81.5 | 84.5 | 66.3 | 72.6 | 78.6 | 81.5 | 83.2 |
| APN(w2v)+f-VAEGAN-D2 | 61.7 | 70.9 | 79.5 | 83.4 | 85.5 | 67.5 | 73.8 | 79.6 | 82.5 | 84.3 |
```
attributes in images accurately. Two well-designed user studies indicate that our network can generate semantically consistent and accurate attribute attention maps. The part localization accuracy significantly outperforms a weakly supervised localization model designed for zero-shot learning. We further show that our model can be extended to the FSL scenario, and we consistently improve the classification accuracy in any-shot regimes on three datasets.

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