Multi-level Semantic Feature Augmentation for One-shot Learning

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Abstract-The ability to quickly recognize and learn new visual concepts from limited samples enables humans to quickly adapt to new tasks and environments. This ability is enabled by semantic association of novel concepts with those that have already been learned and stored in memory. Computers can start to ascertain similar abilities by utilizing a semantic concept space. A concept space is a high-dimensional semantic space in which similar abstract concepts appear close and dissimilar ones far apart. In this paper, we propose a novel approach to one-shot learning that builds on this core idea. Our approach learns to map a novel sample instance to a concept, relates that concept to the existing ones in the concept space and, using these relationships, generates new instances, by interpolating among the concepts, to help learning. Instead of synthesizing new image instance, we propose to directly synthesize instance features by leveraging semantics using a novel auto-encoder network we call dual TriNet. The encoder part of the TriNet learns to map multi-layer visual features from CNN to a semantic vector. In semantic space, we search for related concepts, which are then projected back into the image feature spaces by the decoder portion of the TriNet. Two strategies in the semantic space are explored. Notably, this seemingly simple strategy results in complex augmented feature distributions in the image feature space, leading to substantially better performance.

Index Terms—one-shot learning, feature augmentation.

I. INTRODUCTION

Recent successes in machine learning, especially deep learning, rely greatly on the training processes that operate on hundreds, if not thousands, of labeled training instances for each class. However, in practice, it might be extremely expensive or even infeasible to obtain many labelled samples, *e.g.* for rare objects or objects that may be hard to observe. In contrast, humans can easily learn to recognize a novel object category after seeing only few training examples [1]. Inspired by this ability, few-shot learning aims to build classifiers from few, or even a single, examples.

The major obstacle of learning good classifiers in a fewshot learning setting is the lack of training data. Thus a natural recipe for few-shot learning is to first augment the data in some way. A number of approaches for data augmentation have been explored. The dominant approach, adopted by the previous work, is to obtain more images [2] for each category and use them as training data. These additional augmented training images could be borrowed from unlabeled data [3] or other relevant categories [4], [5], [6], [7] in an unsupervised or semisupervised fashion. However, the augmented data that comes from related classes is often semantically noisy and can result in the negative transfer which leads to reduced (instead of improved) performance. On the other hand, synthetic images rendered from virtual examples [8], [9], [10], [11], [12], [13] are semantically correct but require careful domain adaptation to transfer the knowledge and features to the real image domain. To avoid the difficulty of generating the synthesized images directly, it is thus desirable to augment the samples in the feature space itself. For example, the state-of-the-art deep Convolutional Neural Networks (CNNs) stack multiple feature layers in a hierarchical structure; we hypothesize that feature augmentation can, in this case, be done in feature spaces produced by CNN layers.

Despite clear conceptual benefits, feature augmentation techniques have been relatively little explored. The few examples include [12], [13], [14]. Notably, [12] and [13] employed the feature patches (*e.g.* HOG) of the object parts and combined them to synthesize new feature representations. Dixit *et al.* [14], for the first time, considered attributes-guided augmentation to synthesize sample features. Their work, however, utilizes and relies on a set of pre-defined semantic attributes.

A straightforward approach to augment the image feature representation is to add random (vector) noise to a representation of each single training image. However, such simple augmentation procedure may not substantially inform/improve the decision boundary. Human learning inspires us to search for related information in the concept space. Our key idea is to leverage additional semantic knowledge, *e.g.* encapsulated by the semantic space pre-trained using the linguistic model such as Google's word2vec [15]. In such semantic manifold similar concepts tend to have similar semantic feature representations. The overall space demonstrates semantic continuity, which makes it ideal for feature augmentation.

To leverage such semantic space, we propose a dual TriNet architecture $(g(\mathbf{x}) = g_{Dec} \circ g_{Enc}(\mathbf{x}))$ to learn the transformation between the image features at multiple layers and the semantic space. The dual TriNet is paired with the 18-layer residual net (ResNet-18) [16]; it has encoder TriNet $(g_{Enc}(\mathbf{x}))$ and the decoder TriNet $(g_{Dec}(\mathbf{x}))$. Specifically, given one training instance, we can use the ResNet-18 to extract the features at different layers. The $g_{Enc}(\mathbf{x})$ efficiently maps these features into the semantic space. In the semantic space, the projected instance features can be corrupted by adding Gaussian noise,

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or replaced by its nearest semantic word vectors. We assume that slight changes of feature values in the semantic space will allow us to maintain semantic information while spanning the potential class variability. The decoder TriNet $(g_{Dec}(\mathbf{x}))$ is then adapted to map the perturbed semantic instance features back to multi-layer (ResNet-18) feature space. It is worth noting that Gaussian augmentations/perturbations in the semantic space ultimately result in highly non-Gaussian augmentations in the original feature space. This is the core benefit of the semantic space augmentation. Using three classical supervised classifiers, we show that the augmented features can boost the performance in few-shot classification.

Contributions. Our contributions are in several fold. First, we propose a simple and yet elegant deep learning architecture: ResNet-18+dual TriNet with an efficient end-to-end training for few-shot classification. Second, we illustrate that the proposed dual TriNet can effectively augment visual features produced by multiple layers of ResNet-18. Third, and interestingly, we show that we can utilize semantic spaces of various types, including semantic attribute space, semantic word vector space, or even subspace defined by the semantic relationship of classes. Finally, extensive experiments on four datasets validate the efficacy of the proposed approach in addressing the few-shot image recognition task.

II. RELATED WORK

A. Few-Shot Learning

Few-shot learning is inspired by human ability to learn new concepts from very few examples [17], [18]. Being able to recognize and generalize to new classes with only one, or few, examples [19] is beyond the capabilities of typical machine learning algorithms, which often rely on hundreds or thousands of training examples. Broadly speaking there are two categories of approaches for addressing such challenges:

Direct supervised learning-based approaches, directly learn a one-shot classifier via instance-based learning (such as Knearest neighbor), non-parametric methods [20], [21], [22], deep generative models [23], [24], or Bayesian auto-encoders [25]. Compared with our work, these methods employ a rich class of generative models to explain the observed data, rather than directly augmenting instance features as proposed.

Transfer learning-based approaches, are explored via the paradigm of learning to learn [1] or meta-learning [26]. Specifically, these approaches employ the knowledge from auxiliary data to recognize new categories with few examples by either sharing features [19], [27], [28], [29], [30], [31], semantic attributes [32], [33], [34], or contextual information [35]. Recently, the ideas of learning metric spaces from source data to support one-shot learning were quite extensively explored. Examples include matching networks [36] and prototypical networks [37]. Generally, these approaches can be roughly categorized as either meta-learning algorithms (including MAML [38], Meta-SGD [39], DEML+Meta-SGD [40], META-LEARN LSTM [41], Meta-Net [42], R2-D2[43], Reptile[44], WRN [45]) and metric-learning algorithms (including Matching Nets [36], PROTO-NET [37], RELATION NET [46], MACO [47], and Cos & Att. [48]). In [49], [50], they maintained external memory for continuous learning. MAML [51] can learn good initial neural network weights which can be easily fine-tuned for unseen categories. The [52] used graph neural network to perform message-passing inference from support images to test images. TPN [53] proposed a framework for transductive inference thus to solve the data-starved problem. Multi-Attention [54] utilized semantic information to generate attention map to help oneshot recognition, whereas we directly augment samples in the semantic space and then map them back to the visual space. With respect to these works, our framework is orthogonal but potentially useful – it is useful to augment instance features of novel classes before applying such methods.

B. Augmenting training instances

The standard augmentation techniques are often directly applied in the image domain, such as flipping, rotating, adding noise and randomly cropping images [2], [55], [56]. Recently, more advanced data augmentation techniques have been studied to train supervised classifiers. In particular, augmented training data can also be employed to alleviate the problem of instances scarcity and thus avoid overfitting in one-shot/fewshot learning settings. Previous approaches can be categorized into six classes of methods: (1) Learning one-shot models by utilizing the manifold information of a large amount of unlabelled data in a semi-supervised or transductive setting [3]; (2) Adaptively learning the one-shot classifiers from offshelf trained models [4], [5], [6]; (3) Borrowing examples from relevant categories [7], [57] or semantic vocabularies [58], [59] to augment the training set; (4) Synthesizing additional labelled training instances by rendering virtual examples [8], [9], [10], [11], [60] or composing synthesized representations [12], [13], [61], [62], [63], [64] or distorting existing training examples [2]; (5) Generating new examples using Generative Adversarial Networks (GANs) [65], [66], [67], [68], [69], [70], [71], [72], [73]; (6) Attribute-guided augmentation (AGA) and Feature Space Transfer [14], [74] to synthesize samples at desired values, poses or strength.

Despite the breadth of research, previous methods may suffer from several problems: (1) semi-supervised algorithms rely on the manifold assumption, which, however, cannot be effectively validated in practice. (2) transfer learning may suffer from the negative transfer when the off-shell models or relevant categories are very different from one-shot classes; (3) rendering, composing or distorting existing training examples may require domain expertise; (4) GAN-based approaches mostly focuse on learning good generators to synthesize "realistic" images to "cheat" the discriminators. Synthesized images may not necessarily preserve the discriminative information. This is in contrast to our network structure, where the discriminative instances are directly synthesized in visual feature domain. The AGA [14] mainly employed the attributes of 3D depth or pose information for augmentation; in contrast, our methods can additionally utilize semantic information to augment data. Additionally, the proposed dual TriNet networks can effectively augment multi-layer features.

C. Embedding Network structures

Learning of visual-semantic embeddings has been explored in various ways, including with neural networks, *e.g.*, Siamese network [75], [76], discriminative methods (*e.g.*, Support Vector Regressors (SVR) [32], [77], [78]), metric learning methods [36], [79], [80], or kernel embedding methods [27], [81]. One of the most common embedding approaches is to project visual features and semantic entities into a common *new* space. However, when dealing with the feature space of different layers in CNNs, previous methods have to learn an individual visual semantic embedding for each layer. In contrast, the proposed Dual TriNet can effectively learn a single visual-semantic embedding for multi-layer feature spaces.

Ladder Networks [82] utilize the lateral connections as auto-encoders for semi-supervised learning tasks. In [83], the authours fused different intermediate layers of different networks to improve the image classification performance. Deep Layer Aggregation [84] aggregated the layers and blocks across a network to better fuse the information across layers. Rather than learn a specific aggregation node to merge different layers, our dual TriNet directly transforms, rescales and concatenates the features of different layers in an encoderdecoder structure.

III. DUAL TRINET NETWORK FOR SEMANTIC DATA AUGMENTATION

A. Problem setup

In one-shot learning, we are given the base categories C_{base} , and novel categories $C_{novel}(C_{base} \cap C_{novel} = \emptyset)$ with the total class label set $\mathcal{C} = \mathcal{C}_{base} \cup \mathcal{C}_{novel}$. The base categories C_{base} have sufficient labeled image and we assume the base dataset $D_{base} = \{\mathbf{I}_{i}^{base}, z_{i}^{base}, \mathbf{u}_{z_{i}}^{base}\}_{i=1}^{N_{base}}$ of N_{base} samples. \mathbf{I}_{i}^{base} indicates the raw image $i; z_{i}^{base} \in \mathcal{C}_{base}$ is a class label from the base class set; $\mathbf{u}_{z_{i}}^{base}$ is the semantic vector of the instance i in terms of its class label. The semantic vector $\mathbf{u}_{z_{i}}^{base}$ can be either semantic attribute [32], semantic word vector [15] or any representation obtained in the subspace constructed or learned from semantic relationship of classes.

For novel categories C_{novel} , we consider the another dataset $D_{novel} = \{\mathbf{I}_i^{novel}, z_i^{novel}, \mathbf{u}_{z_i}^{novel}\}\$ and each class $z_i^{novel} \in C_{novel}$. For the novel dataset, we have a support set and test set. Support set $D_{support} = \{\mathbf{I}_i^{support}, z_i^{support}, \mathbf{u}_{z_i}^{support}\}\$ $(D_{support} \in D_{novel})$ is composed of a small number of training instances of each novel class. The test set $D_{test} = \{\mathbf{I}_i^{test}, z_i^{test}, \mathbf{u}_{z_i}^{test}\}\$ $(D_{test} \in D_{novel}, D_{support} \cap D_{test} = \emptyset)$ is not available for training, but is used for testing. In general, we only train on D_{base} and $D_{support}$, which contain adequate instances of base classes and a small number of instances of novel classes. We target learning a model that can generalize well to the novel categories, by using only a small support set $D_{support}$.

B. Overview

Objective. We seek to directly augment the features of the training instances of each target class. Given one training

instance $\mathbf{I}_{i}^{support}$ from the novel classes, the feature extractor network can output the instance feature $\{f_{l}(\mathbf{I}_{i}^{support})\}$ $(l = 1, \dots, L)$; and the augmentation network $g(\mathbf{x})$ can generate a set of synthesized features $g(\{f_{l}(\mathbf{I}_{i}^{support})\})$. Such synthesized features are used as additional training instances for one-shot learning. As illustrated in Fig. 1, we use the ResNet-18 [16] and propose a Dual TriNet network as the feature extractor network and the augmentation network respectively. The whole architecture is trained in an end-to-end manner by combining the loss functions of both networks,

$$\{\Omega, \Theta\} = \underset{\Omega, \Theta}{\operatorname{argmin}} J_1(\Omega) + \lambda \cdot J_2(\Theta) \tag{1}$$

where $J_1(\Omega)$ and $J_2(\Theta)$ are the loss functions for ResNet-18 [16] and dual TriNet network respectively; Ω and Θ represent corresponding parameters. The cross entropy loss is used for $J_1(\Omega)$ as in [16]. Eq. (1) is optimized using base dataset D_{base} .

Feature extractor network. We train ResNet-18 [16] to convert the raw images into feature vectors. ResNet-18 has 4 sequential residual layers, *i.e.*, layer1, layer2, layer3 and layer4 as illustrated in Fig. 1. Each residual layer outputs a corresponding feature map $f_l(\mathbf{I}_l)$, l = 1, ... 4. If we consider each feature map a different image representation, ResNet-18 actually learns a Multi-level Image Feature (M-IF) encoding. Generally, different layer features may be used for various one-shot learning tasks. For example, as in [2], the features of fully connected layers can be used for oneshot image classification; and the output features of fully convolutional layers may be preferred for one-shot image segmentation tasks [85], [86], [87]. By combining features from multiple levels, our method can be applied to a variety of different visual tasks.

Augmentation network. We propose an encoder-decoder architecture – dual TriNet $(g(\mathbf{x}) = g_{Dec} \circ g_{Enc}(\mathbf{x}))$. As illustrated in Fig. 1, our dual TriNet can be divided into encoder-TriNet $g_{Enc}(\mathbf{x})$ and decoder-TriNet sub-network $g_{Dec}(\mathbf{x})$. The encoder-TriNet maps visual feature space to a semantic space. This is where augmentation takes place. The decoder-TriNet projects the augmented semantic space representation back to the feature space. Since ResNet-18 has four layers, the visual feature spaces produced by different layers can use the same encoder-decoder TriNet for data augmentation.

C. Dual TriNet Network

The dual TriNet is paired with ResNet-18. Feature representations obtained from different layers of such a deep CNN architecture, are hierarchical, going from *general* (bottom layers) to more *specific* (top layers) [88]. For instance, the features produced by the first few layers are similar to Gabor filters [56] and thus agnostic to the tasks; in contrast, the high-level layers are specific to a particular task, *e.g.*, image classification. The feature representations produced by layers of ResNet-18 have different levels of abstract semantic information. Thus a natural question is whether we can augment features at different layers? Directly learning an encoder-decoder for each layer will not fully exploit the relationship of different

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Figure 1. **Overview of our framework.** We extract image features by ResNet-18 and augment features by dual TriNet. Encoder TriNet projects features to the semantic space. After augmenting data in semantic space, we use the decoder TriNet to obtain the corresponding augmented features. Both real and augmented data are used to train the classification model. Note that: (1) the small green arrow indicates the max pooling with 2×2 , and following by a "conv" layer which is the sequence Conv-BN-ReLU.

layers, and thus may not effectively learn the mapping between feature spaces and the semantic space. To this end, we propose the dual TriNet network.

Dual TriNet learns the mapping between the Multi-level Image Feature (M-IF) encoding and the Semantic space. The semantic space can be either semantic attribute space, or semantic word vector space introduced in Sec. III-A. Semantic attributes can be pre-defined by human experts [14]. Semantic word vector $\mathbf{u}_{z_i}^{base}$ is the projection of each vocabulary entity $w_i \in \mathcal{W}$, where vocabulary \mathcal{W} is learned by word2vec [15] on a large-scale corpus. Furthermore, the subspace $\mathbf{u}_{z_i}^{base}$ can be spanned by Singular Value Decomposition (SVD) of the semantic relationship of classes. Specifically, we can use $\left\{\mathbf{u}_{z_i}^{base}; \mathbf{u}_{z_j}^{novel}\right\}_{z_i \in C_{base}, z_j \in C_{novel}}$ to compute the semantic relationship M of classes using cosine similarity. We decompose $\mathbf{M} = \mathbf{U} \mathbf{\Sigma} \mathbf{V}$ by SVD algorithm. The U is a unitary matrix and defines a new semantic space. Each row of U is taken as a new semantic vector of one class.

Encoder TriNet is composed of four layers corresponding to each layer of ResNet-18. It aims to learn the function $\hat{\mathbf{u}}_{z_i} = g_{Enc} \left(\{ f_l (\mathbf{I}_i) \} \right)$ to map all layer features $\{ f_l (\mathbf{I}_i) \}$ of instance *i* as close to the semantic vector \mathbf{u}_{z_i} of instance *i* as possible. The structure of subnetwork is inspired by the tower of Hanoi as shown in Fig. 1. Such a structure can efficiently exploit the differences and complementarity of information encoded in multiple layers. The encoder TriNet is trained to match the four layers of ResNet-18 by merging and combining the outputs of different layers. The decoder TriNet has inverse architecture to project the features $\hat{\mathbf{u}}_{z_i}$ from semantic space to the feature space $\hat{f}_l (\mathbf{I}_i) = g_{Dec} (g_{Enc} (\{ f_l (\mathbf{I}_i) \}))$. We learn TriNet by optimizing the following loss:

$$J_{2}(\Theta) = \mathbb{E}\left[\sum_{l=1}^{4} \left(f_{l}\left(\mathbf{I}_{i}\right) - \hat{f}_{l}\left(\mathbf{I}_{i}\right)\right)^{2} + \left(\hat{\mathbf{u}}_{z_{i}} - \mathbf{u}_{z_{i}}\right)^{2}\right] + \lambda P(\Theta)$$
(2)

where $\mathbf{I}_i \in D_{base}$ and Θ indicates the parameter set of dual TriNet network and $P(\cdot)$ is the L_2 -regularization term. The dual TriNet is trained on D_{base} and used to synthesize instances in the form of *l*-th layer feature perturbations with respect to a given training instance from $D_{support}$.

D. Feature Augmentation by Dual TriNet

With the learned dual TriNet, we have two ways to augment the features of training instances. Note that the augmentation method is only used to extend $D_{support}$.

Semantic Gaussian (SG). A natural way to augment features is by sampling instances from a Gaussian distribution. Specifically, for the feature set $\{f_l(\mathbf{I}_i^{support})\}(l = 1, \dots, L)$ extracted by ResNet-18, the encoder TriNet can project the $\{f_l(\mathbf{I}_i^{support})\}$ into the semantic space, $g_{Enc}(\{f_l(I_i^{support})\})$. In such a space, we assume that vectors can be corrupted by a random Gaussian noise without changing a semantic label. This can be used to augment the data. Specifically, we sample the k - th semantic vector $\mathbf{v}_i^{G_k}$ from $I_i^{support}$ using semantic Gaussian as follows,

$$\mathbf{v}_{i}^{G_{k}} \sim \mathcal{N}\left(g_{Enc}\left(\left\{f_{l}\left(\mathbf{I}_{i}^{support}\right)\right\}\right), \sigma \mathbf{E}\right)$$
(3)

where $\sigma \in \mathbb{R}$ is the variance of each dimension and **E** is the identity matrix; σ controls the standard deviation of the noise being added. To make the augmented semantic vector $\mathbf{v}_i^{G_k}$ still be representative of the class of $z_i^{support}$, we empirically

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set σ to 15% of the distance between $u_{z_i}^{support}$ and its nearest other class instance $\mathbf{u}_{z_j}^{support}$ ($z_i^{support} \neq z_j^{support}$) as this gives the best performance. The decoder TriNet generates the virtual synthesized sample g_{Dec} ($\mathbf{v}_i^{G_k}$) which shares the same class label $z_i^{support}$ with the original instance. By slightly corrupting the values of some dimensions of semantic vectors, we expect the sampled vectors $\mathbf{v}_i^{G_k}$ to still have the same semantic meaning.

Semantic Neighborhood (SN). Inspired by the recent work on vocabulary-informed learning [58], the large amount of vocabulary in the semantic word vector space (*e.g.*, word2vec [15]) can also be used for augmentation. The distribution of such vocabulary reflects the general semantic relationships in the linguistic corpora. For example, in word vector space, the vector of "truck" is closer to the vector of "car" than to the vector of "dog". Given the features $\{f_l(\mathbf{I}_i^{support})\}$ of training instance *i*, the *k*-th augmented data $\mathbf{v}_i^{N_k}$ can be sampled from the neighborhood of $g_{Enc}(\{f_l(\mathbf{I}_i^{support})\})$, *i.e.*,

$$\mathbf{v}_{i}^{N_{k}} \in Neigh\left(g_{Enc}\left(\left\{f_{l}\left(\mathbf{I}_{i}^{support}\right)\right\}\right)\right) \tag{4}$$

 $Neigh\left(g_{Enc}\left(\left\{f_l\left(\mathbf{I}_i^{support}\right)\right\}\right)\right) \subseteq \mathcal{W}$ indicates the nearest neighborhood vocabulary set of $g_{Enc}\left(\left\{f_l\left(\mathbf{I}_i^t\right)\right\}\right)$ and \mathcal{W} indicate vocabulary set learned by word2vec [15] on a large-scale corpus. These neighbors correspond to the most semantically similar examples to our training instance. The features of synthesized samples can again be decoded by $g_{Dec}\left(\mathbf{v}_i^{N_k}\right)$.

There are several points we want to highlight. (1) For one training instance $\mathbf{I}_i^{support}$, we use as the Gaussian mean in Eq (3) or neighborhood center in Eq (4), the $g_{Enc}\left(\left\{f_l\left(\mathbf{I}_i^{support}\right)\right\}\right)$ rather than its ground-truth word vector $\mathbf{u}_{z_i}^{support}$. This is due to the fact that $\mathbf{u}_{z_i}^{support}$ only represents the semantic center of class $z_i^{support}$, not the center for the instance i. Experimentally, on miniImageNet dataset, augmenting features using $\mathbf{u}_{z_i}^{support}$, rather than $g_{Enc}(\{f_l(\mathbf{I}_i^t)\})$, leads to $3 \sim 5\%$ performance drop (on average) in 1-shot/5shot classification. (2) Semantic space Gaussian noise added in Eq (3) or semantic neighborhood used in Eq (4) result in the synthesized training features that are highly nonlinear (non-Gaussian) for each class. This is the result of non-linear decoding provided by TriNet $g_{Dec}(\mathbf{x})$ and ResNet-18 ({ $f_l(\mathbf{I}_i^t)$ }). (3) Directly adding Gaussian noise to $\{f_l(\mathbf{I}_i^t)\}$ is another naive way to augment features. However, in miniImageNet dataset, such a strategy does not give any significant improvement in one-shot classification.

E. One-shot Classification

Having trained feature extractor network and dual TriNet on base dataset D_{base} , we now discuss conducting one-shot classification on the target dataset D_{novel} . For the instance *i* in D_{novel} we can extract the M-IF representation $f_l (\mathbf{I}_i^{novel}) (l = 1, 2, ..., L)$ using the feature extractor network. We then use the encoder part of TriNet to map all layer features $\{f_l (\mathbf{I}_i)\}$ of instance *i* to semantic vector $g_{Enc} (\{f_l (\mathbf{I}_i^{support})\})$.

Our framework can augment the instance, producing multiple synthetic instances in addition to the original one $\left\{\mathbf{v}_{i}^{G_{k}}\right\} \cup \left\{\mathbf{v}_{i}^{N_{k}}\right\}$ using semantic Gaussian and/or semantic

neighborhood approaches discussed. For each new semantic vector $\mathbf{v}_i^k \in {\{\mathbf{v}_i^{\widehat{G}_k}\} \cup {\{\mathbf{v}_i^{N_k}\}}}$, we use decoder TriNet to map them from semantic space to all layer features $\{x_i^{augment_i}\} =$ $g_{Dec}(v_i^k)$ (l = 1, 2, ..., L). The features that are not at the final L-th layer are feed through from l+1-th layer to L-th layer of feature extractor network to obtain $\{\hat{x}_{l}^{augment}\}$. Technically, one new semantic vector \mathbf{v}_i^k can generate L instances: one from each of the L augmented layers. Consistent with previous work [2], [16], the features produced by the final layer are utilized for one-shot classification tasks. Hence the newly synthesized L-th layer features $\{\hat{x}_l^{augment_i}\}$ obtained from the instance i and original L-th layer feature $f_L(\mathbf{I}_i^{support})$ are used to train the one-shot classifier $g_{one-shot}(x)$ in a supervised manner. Note that all augmented feature vectors obtained from instance *i* are assumed to have the same class label as the original instance *i*.

In this work, we show that the augmented features can benefit various supervised classifiers. To this end three classical classifiers, *i.e.*, the K-nearest neighbors (KNN), Support Vector Machine (SVM) and Logistic Regression (LR), are utilized as one-shot classifier $g_{one-shot}(x)$. In particular, we use $g_{one-shot}(x)$ to classify the L-th layer feature $f_l(\mathbf{I}_i^{test})$ of test sample \mathbf{I}_i^{test} at the test time.

IV. EXPERIMENTS

A. Datasets

We conduct experiments on four datasets. Note that (1) on all datasets, ResNet-18 is only trained on the training set (equivalent to base dataset) in the specified splits of previous works. (2) The same networks and parameter settings (including the size of input images) are used for all the datasets; hence all images are resized to 224×224 .

*mini***ImageNet.** Originally proposed in [36], this dataset has 60,000 images from 100 classes; each class has around 600 examples. To make our results comparable to previous works, we use the splits in [41] by utilizing 64, 16 and 20 classes for training, validation and testing respectively.

Cifar-100. Cifar-100 contains 60,000 images from 100 finegrained and 20 coarse-level categories [89]. We use the same data split as in [90] to enable the comparison with previous methods. In particular, 64, 16 and 20 classes are used for training, validation and testing respectively.

Caltech-UCSD Birds 200-2011 (CUB-200). CUB-200 is a fine-grained dataset consisting of a total of 11,788 images from 200 categories of birds [91]. As the split in [47], we use 100, 50 and 50 classes for training, validation and testing. This dataset also provides 312 dimensional semantic attribute vectors on a per-class level.

Caltech-256. Caltech-256 has 30,607 images from 256 classes [92]. As in [90], we split the dataset into 150, 56 and 50 classes for training, validation and testing respectively.

B. Network structures and Settings

The same ResNet-18 and dual TriNet are used for all four datasets and experiments.

Methods	<i>mini</i> ImageNet	: (%)	CUB-200(%))
	1-shot	5-shot	1-shot	5-shot
META-LEARN LSTM [41]	43.44±0.77	60.60±0.71	40.43	49.65
MAML [38]	48.70±1.84	63.11±0.92	38.43	59.15
Meta-Net [42]	49.21±0.96	-	-	-
Reptile[44]	49.97	65.99	-	-
MAML* [38]	52.23±1.24	61.24±0.77	-	-
Meta-SGD* [39]	52.31±1.14	64.66±0.89	-	-
DEML+Meta-SGD [40]	58.49±0.91	71.28±0.69	-	-
MACO [47]	41.09±0.32	58.32±0.21	60.76	74.96
Matching Nets* [36]	47.89±0.86	60.12±0.68	-	-
PROTO-NET [37]	49.42±0.78	68.20±0.66	45.27	56.35
GNN [52]	50.33±0.36	66.41±0.63	-	-
R2-D2 [43]	51.5±0.2	68.8±0.1	-	-
MM-Net [50]	53.37±0.48	66.97±0.35	-	-
Cos & Att. [48]	55.45±0.89	70.13 ±0.68	-	-
TPN [53]	55.51	69.86	-	-
SNAIL [93]	55.71±0.99	68.88±0.92	-	-
RELATION NET [46]	57.02±0.92	71.07±0.69	-	-
Delta-encoder [57]	58.7	73.6	-	-
WRN [45]	59.60 ±0.41	73.74±0.19	-	-
ResNet-18	52.73±1.44	73.31±0.81	66.54±0.53	82.38±0.43
ResNet-18+Gaussian Noise	52.14±1.51	71.78±0.89	65.02±0.60	80.79±0.49
Ours: ResNet-18+Dual TriNet	58.12±1.37	76.92±0.69	69.61 ±0.46	84.10±0.35

Table I

Results on *mini*ImageNet and CUB-200. The "±" indicates 95% confidence intervals over tasks.*: indicates the corresponding baselines that are using ResNet-18. Note that "±" is not reported on CUB-200 in previous works.

Parameters. The dropout rate and learning rate of the autoencoder network are set to 0.5 and $1e^{-3}$ respectively to prevent overfitting. The learning rate is divided by 2 every 10 epochs. The batch size is set to 64. The network is trained using Adam optimizer and usually converges in 100 epochs. To prevent randomness due to the small training set size, all experiments are repeated multiple times. The Top-1 accuracies are reported with 95% confidence interval and are averaged over multiple test episodes, the same as previous work [41].

Settings. We use the 100-dimensional semantic word vectors extracted from the vocabulary dictionary released by [58]. The class name is projected into the semantic space as a vector $\mathbf{u}_{z_i}^{base}$ or $\mathbf{u}_{z_i}^{novel}$. The semantic attribute space is pre-defined by experts [32], [91]. In all experiments, given one training instance the dual TriNet will generate 4 augmented instances in the semantic space. Thus we have 4 synthesized instances of each layer which results in 16 synthesized instances in the form of 4-th layer features. So one training instance becomes 17 training instances at the end.

C. Competitors and Classification models

Competitors. The previous methods we compare to are run using the same source/target and training/testing splits as used by our method. We compare to Matching Nets [36], MAML [38], Meta-SGD [39], DEML+Meta-SGD [40], PROTO-NET [37], RELATION NET [46], META-LEARN LSTM [41], Meta-Net [42], SNAIL [93], MACO [47], GNN [52], MM-Net[50], Reptile [44], TPN [53], WRN [45], Cos & Att. [48], Delta-encoder [57] and R2-D2[43]. To make a fair comparison, we implement some of the methods and use ResNet-18 as a commmon backbone architecture.

Classification model. KNN, SVM, and LR are used as the classification models to validate the effectiveness of our

augmentation technique. The hyperparameters of classification models are selected using cross-validation on a validation set.

D. Experimental results on miniImageNet and CUB-200

Settings. For *mini*ImageNet dataset we only have a semantic word space. Give one training instance, we can generate 16 augmented instances for Semantic Gaussian (SG) and Semantic Neighborhood (SN) each. On CUB-200 dataset, we use both the semantic word vector and semantic attribute spaces. Hence for one training instance, we generate 16 augmented instances for SG and SN each in semantic word vector space; and additionally, we generate 16 virtual instances (in all four layers) for Semantic Gaussian (SG) in semantic attribute space, which we denote Attribute Gaussian (AG).

Variants of the number of augmented samples. Varying the number of augmented samples does not significantly affect our performance. To show this, we provide 1-shot accuracy on CUB dataset with the different numbers of augmented samples (Table II). As shown, the improvements from increasing the number of augmented samples saturate at a certain point.

Results. As shown in Tab. I, the competitors can be divided into two categories: Meta-learning algorithms (including MAML, Meta-SGD, DEML+Meta-SGD, META-LEARN LSTM and Meta-Net) and Metric-learning algorithms (including Matching Nets, PROTO-NET, RELATION NET ,SNAIL and MACO). We also report the results of ResNet-18 (without data augmentation). The accuracy of our framework (ResNet-18+Dual TriNet) is also reported. The Dual TriNet synthesizes each layer features of ResNet-18 as described in Sec. III-D. ResNet18+Gaussian Noise is a simple baseline that synthesizes 16 samples of each test example by adding Gaussian noise to the 4 - th layer features. We use SVM classifiers for

	Semantic Neighbourhood						Sema	intic Gau	ıssian		Attribute Gaussian				
	0	2	4	10	50	0	2	4	10	50	0	2	4	10	50
L1	66.5	67.1	67.2	67.3	67.2	66.5	67.1	67.2	67.1	67.2	66.5	67.1	67.1	67.1	67.1
L2	66.5	67.0	67.1	67.1	67.0	66.5	67.1	67.1	67.1	67.0	66.5	67.1	67.3	67.3	67.2
L3	66.5	67.1	67.3	67.3	67.3	66.5	67.1	67.3	67.3	67.2	66.5	67.0	67.4	67.5	67.5
L4	66.5	67.4	67.5	67.4	67.4	66.5	67.1	67.3	67.2	67.3	66.5	67.1	67.6	67.6	67.5
M-L	66.5	68.0	68.1	68.1	68.1	66.5	67.9	68.0	68.0	68.0	66.5	68.2	68.3	68.4	68.3
Table II															

Ablation study of the number of augmented samples in semantic space on CUB. We report 5-way 1-shot accuracy. L1, L2, L3, and L4 indicate that we only use the augmented features of Layer 1, Layer 2, Layer 3 and Layer 4 respectively. M-L indicates that we use all augmented features from four layers;



Figure 2. One-shot Results of feature augmentation by different layers/classifiers on CUB-200 and *mini*ImageNet. "NoAug", "Layer1", "Layer2", "Layer3", "Layer4" indicate the one-shot learning results without any augmentation, with the feature augmentation by using layer 1, layer 2, layer 3, layer 4 of ResNet-18. "Multi-L" denotes the performance of using all augmented instances of one-shot learning. The X-axis represents the different supervised classifiers.

ResNet-18, ResNet18+Gaussian Noise and ResNet-18+Dual TriNet in Tab. I. In particular, we found that,

(1) Our baseline (ResNet-18) nearly beats all the other **baselines.** Greatly benefiting from learning the residuals, Resnet-18 is a very good feature extractor for one-shot learning tasks. Previous works [38][39][36] designed their own network architectures with fewer parameters and used different objective functions. As can be seen from Tab. I, after replacing their backbone architecture with ResNet-18, they still behave worse than our baseline (Resnet-18). We argue that this is because ResNet-18 is more adaptable to classification task and it can generate more discriminative space using Cross Entropy Loss than other objective functions used in metric learning. However, this topic is beyond our discussion. We want to clarify that since our augmentation method is capable of being combined with arbitrary approaches, we choose the strongest baseline to the best of our knowledge. This baseline can be enhanced by our approach, illustrate the universality of our augmentation.

(2) Our framework can achieve the best performance. As shown in Tab. I, the results of our framework, *i.e.*, ResNet-18+Dual TriNet can achieve the best performance and we can show a clear improvements over all the other baselines on both datasets. This validates the effectiveness of our framework in solving the one-shot learning task. Note, DEML+Meta-SGD [40] uses the ResNet-50 as the baseline model and hence has better one-shot learning results than our ResNet-

18. Nevertheless, with the augmented data produced by Dual TriNet we can observe a clear improvement over ResNet-18.

(3) Our framework can effectively augment multiple layer features. We analyze the effectiveness of augmented features in each layer as shown in Fig. 2. On CUB-200 and *mini*ImageNet, we report the results in 1-shot learning cases. We have several conclusions: (1) Only using the augmented features from one single layer (*e.g.*, Layer1 – Layer 4 in Fig. 2) can also help improve the performance of one-shot learning results. This validates the effectiveness of our dual TriNet of synthesizing features of different layers in a single framework. (2) The results of using synthesized instances from all layers (Multi-L) are even better than those of individual layers. This indicates that the augmented features at different layers are intrinsically complementary to each other.

(4) Augmented features can boost the performance of different supervised classifiers. Our augmented features are not designed for any one supervised classifier. To show this point and as illustrated in Fig. 2, three classical supervised classifiers (*i.e.*, KNN, SVM and LR) are tested along the X-axis of Fig. 2. Results show that our augmented features can boost the performance of three supervised classifiers on one-shot classification cases. This further validates the effectiveness of our augmentation framework.

(5) The augmented features by SG, SN and AG can also improve few-shot learning results. We compare different



Figure 3. One-shot results of feature augmentation by different types of semantic spaces on CUB-200 and *mini*ImageNet. "Single Layer" indicates the best one-shot performance augmented by using only single layer. "Multi-layer" represents the results of using synthesized instances from all layers.

types of feature augmentation methods of various semantic spaces in Fig. 3. Specifically, we compare the SG and SN in semantic word vector space; and AG in semantic attribute space. On CUB-200 dataset, the augmented results by SG, SN and AG are better than those without augmentation. The accuracy of combining the synthesized instance features generated by any two of SG, SN, and AG can be further improved over those of SG, SN or AG only. This means that the augmented feature instances of SG, SN and AG are complementary to each other. Finally, we observe that by combining augmented instances from all methods (SG, SN and AG), the accuracy of one-shot learning is the highest one.

(6) Even the semantic space inferred from the semantic relationships of classes can also work well with our framework. To show this point, we again compare the results in Fig. 3. Particularly, we compute the similarity matrix of classes in miniImageNet obtained using semantic word vectors. The SVD is employed to decompose the similarity matrix and the left singular vectors of SVD are assumed to span a new semantic space. Such a new space is hence utilized in learning the dual TriNet. We employ the Semantic Gaussian (SG) to augment the instance feature in the newly spanned space for one-shot classification. The results are denoted "SVD-G". We report the results of SVD-G augmentation in *mini*ImageNet dataset in Fig. 3. We highlight several interesting observations. (1) The results of SVD-G feature augmentation are still better than those without any augmentation. (2) The accuracy of SVD-G is actually slightly worse than that of SG, since the new spanned space is derived from the original semantic word space. (3) There is almost no complementary information in the augmented features between SVD-G and SG, still partly due to the new space spanned from the semantic and the word space. (4) The augmented features produced by SVD-G are also very complementary to those from SN as shown in the results of Fig. 3. This is due to the fact that additional neighborhood vocabulary information is not used in deriving the new semantic space. We have a similar experimental conclusion on CUB-200 as shown in Tab. IV.

E. Experimental results on Caltech-256 and CIFAR-100

Settings. On Caltech-256 and CIFAR-100 dataset we also use the semantic word vector space. For one training instance, we synthesize 16 sugmented features for SG and SN individually from all four layers of ResNet-18. On these two datasets, the results of competitors are implemented and reported in [40]. Our reported results are produced by using the augmented feature instances of all layers, both by SG and SN. The SVM classifier is used as the classification model.

Results. The results on Caltech-256 and CIFAR-100 are illustrated in Tab. III. We found that (1) our method can still achieve the best performance as compared to the state-of-the-art algorithms, thanks to the augmented feature instances obtained using the proposed framework. (2) The ResNet-18 is still a very strong baseline; and it can beat almost all the other baselines, except the DEML+Meta-SGD which uses ResNet-50 as the baseline structure. (3) There is a clear margin of improvement from using our augmented instance features over using ResNet-18 only. This further validates the efficacy of the proposed framework.

V. FURTHER ANALYSIS

A. Comparison with standard augmentation methods

Besides our feature augmentation method, we also compare the standard augmentation methods [2] in one-shot learning setting. These methods include cropping, rotation, flipping, and color transformations of training images of one-shot classes. Furthermore, we also try the methods of adding the Gaussian noise to the ResNet-18 features of training instances of one-shot classes as shown in Tab. I. However, none of these methods can improve the classification accuracy in oneshot learning. This is reasonable since the one-shot classes have only very few training examples. This is somewhat expected: such naive augmentation methods intrinsically just add noise/variance, but do not introduce extra information to help one-shot classification.

Methods	Caltech-256	(%)	CIFAR-100 (%)			
	1-shot	5-shot	1-shot	5-shot		
MAML [38]	45.59±0.77	54.61±0.73	49.28±0.90	58.30±0.80		
Meta-SGD [39]	48.65±0.82	64.74±0.75	53.83±0.89	70.40±0.74		
DEML+Meta-SGD [40]	62.25±1.00	79.52±0.63	61.62±1.01	77.94±0.74		
Matching Nets [36]	48.09±0.83	57.45±0.74	50.53±0.87	60.30±0.82		
ResNet-18	60.13±0.71	78.79±0.54	59.65±0.78	76.75±0.73		
ResNet-18+Dual TriNet	63.77 ±0.62	80.53 ±0.46	63.41 ±0.64	78.43±0.62		

Table III Results on Caltech-256 and CIFAR-100 datasets. The "±" INDICATES 95% CONFIDENCE INTERVALS OVER TASKS.

Method	Shots	R-18	Layer	Data Augmentation							
Wiethou				SN	SG	SD	SN+SG	SG+SD	SN+SD	SN+SG+SD	
KNN	1	64.30	S.	65.12	65.21	65.38	66.82	65.50	67.21	67.23	
			M.	65.58	65.61	65.78	67.29	65.77	67.82	67.91	
	5	77.66	S.	78.34	78.42	78.62	79.01	78.66	79.12	79.36	
			M.	79.01	78.96	79.04	79.51	79.09	79.56	79.71	
SVR	1	66.54	S.	67.63	67.49	67.69	68.23	67.60	68.41	68.56	
			M.	68.10	68.03	68.22	68.71	67.98	68.89	69.01	
	5	82.38	S.	83.01	83.07	83.02	83.59	83.11	83.42	83.44	
			M.	83.47	83.51	83.60	83.82	83.49	83.99	84.10	
	1	64.22	S.	65.29	65.33	65.43	66.59	65.46	66.89	67.01	
LR			M.	65.71	65.92	65.89	67.12	65.74	67.63	67.55	
	5	82.51	S.	83.37	83.31	83.60	83.61	83.59	83.62	83.69	
			M.	83.82	83.83	83.90	84.21	83.71	84.23	84.17	
Table IV											

THE CLASSIFICATION ACCURACY OF ONE-SHOT LEARNING ON CALTECH-UCSD BIRDS IN 5-WAY. NOTE THAT: "S." AND "M." INDICATES THE SINGLE AND MULTIPLE LAYERS RESPECTIVELY. "SD" IS SHORT FOR "SVD-G". "R-18" IS SHORT FOR "RESNET-18".



Figure 4. Visualization of the original and augmented features.

Methods	MiniIm	agenet	CUB-200		Caltech	-256	CIFAR-100			
	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot		
ResNet-18	52.73	73.31	66.54	82.38	60.13	78.79	59.65	76.75		
ResNet-18+U-net	56.41	75.67	68.32	83.24	61.54	79.88	62.32	77.87		
ResNet-18+Auto-encoder	56.80	75.27	68.56	83.24	62.41	79.77	61.76	76.98		
Ours without encoder	50.69	70.79	64.15	80.06	58.78	76.45	57.46	75.12		
Ours without decoder	48.75	65.12	62.04	78.16	58.67	76.45	53.19	68.74		
Ours	58.12	76.92	69.61	84.10	63.77	80.53	63.41	78.43		
Table V										

Results of using alternative augmentation networks. Ours indicates ResNet-18+Dual-TriNet.

B. Dual TriNet structure

We propose the dual TriNet structure which intrinsically is derived from the encoder-decoder architecture. Thus we further analyze the other alternative network structures for feature augmentation. In particular, the alternative choices of augmentation network can be the auto-encoder [94] of each layer or U-net [95]. The results are compared in Tab. V. We show that our dual TriNet can best explore the complementary information of different layers, and hence our results are better than those without augmentation (ResNet-18), with U-net augmentation (ResNet-18+U-net) and with auto-encoder augmentation (ResNet-18+Auto-encoder). This validates that our dual TriNet can efficiently merge and exploit the information of multiple layers for feature augmentation. In addition, we conduct experiments to prove that the encoder part and decoder part is necessary. If we simply used the semantic vector of true label $\mathbf{u}_{z_i}^{base}$ instead of using encoder $g_{Enc}(\{f_l(\mathbf{I}_i^{support})\}), \text{ the augmented samples actually hurt}$ the performance. In the case where we do the classification in the semantic space, effectively disabling the decoder, the performance drops by over 5%. This is because of the loss of information during the mapping from visual space to semantic space, but in our approach, we keep original information and have additional information from semantic space.

C. Visualization

Using the technique in [96], we can visualize the image that can generate the augmented features $\hat{f}_l(\mathbf{I}_i) = g(f_l(\mathbf{I}_i))$ in ResNet-18. We first randomly generate an image \mathbf{I}_{i_0} . Then we optimize \mathbf{I}_{i_0} by reducing the distance betwen $f_l(\mathbf{I}_{i_0})$ and $\hat{f}_l(\mathbf{I}_i)$ (both are the output of ResNet-18):

$$\mathbf{I}_{i_0} = \underset{\mathbf{I}_{i_0}}{\operatorname{argmin}} \frac{1}{2} \left\| f_l \left(\mathbf{I}_{i_0} \right) - \hat{f}_l \left(\mathbf{I}_i \right) \right\|_2^2 + \lambda \cdot R \left(\mathbf{I}_{i_0} \right) \quad (5)$$

where $R(\cdot)$ is the Total Variation Regularizer for image smoothness; $\lambda = 1e-2$. When the difference is small enough, I_{i_0} should be representation of the image that can generate the corresponding augmented feature.

By using SN and the visualization algorithm above, we visualize the original and augmented features in Fig. 4. The top row shows the input images of two birds, one roof, and one dog. The blue circles and red circles indicate the visualization of original and augmented features of Layer 1 – Layer 4 respectively. The visualization of augmented features is similar, and yet different from that of original image. For example, the first two columns show that the visualization of augmented features of the bird. In the last two columns, the augmented features clearly visualize a dog which is similar have a different appearance from the input image. This intuitively shows why our framework works.

VI. CONCLUSIONS

This work purposes an end-to-end framework for feature augmentation. The proposed dual TriNet structure can efficiently and directly augment multi-layer visual features to boost the few-shot classification. We demonstrate our framework can efficiently solve the few-shot classification on four datasets. We mainly evaluate on classification tasks; it is also interesting and future work to extend augmented features to other related tasks, such as one-shot image/video segmentation [86], [87]. Additionally, though dual TriNet is paired with ResNet-18 here, we can easily extend it for other feature extractor networks, such as ResNet-50.

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