
End-to-end Generative Zero-shot Learning via Few-shot Learning

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Abstract

Contemporary state-of-the-art approaches to Zero-Shot Learning (ZSL) train generative nets to synthesize examples conditioned on the provided metadata. Thereafter, classifiers are trained on these synthetic data in a supervised manner. In this work, we introduce *Z2FSL*, an end-to-end generative ZSL framework that uses such an approach as a backbone and feeds its synthesized output to a Few-Shot Learning (FSL) algorithm. The two modules are trained jointly. *Z2FSL* solves the ZSL problem with a FSL algorithm, reducing, in effect, ZSL to FSL. A wide class of algorithms can be integrated within our framework. Our experimental results show consistent improvement over several baselines. The proposed method, evaluated across standard benchmarks, shows state-of-the-art or competitive performance in ZSL and Generalized ZSL tasks.

1. Introduction

Deep Learning has seen great success in various settings and disciplines, like Computer Vision (Krizhevsky et al., 2012; Zhou et al., 2017; Chen et al., 2019), Speech and Language Processing (Devlin et al., 2019; Brown et al., 2020), Computer Graphics (Starke et al., 2019; Park et al., 2019) and Medical Science (Ronneberger et al., 2015; Rajpurkar et al., 2017). Despite the variety of applications, there is a common denominator: resources. The overwhelming majority of applications not only benefit from but necessitate voluminous data along with the associated hardware resources to achieve their reported results. This is evident both from their unprecedented, “superhuman” performance in many narrow tasks compared to traditional algorithms (He et al., 2015; Silver et al., 2017) and their surprising deficiencies in low-data regimes. Consequently, resource requirements have skyrocketed. For instance, BERT’s (Devlin et al., 2019)

training requirements reach 256 TPU days.

A class of problems that deal with small and medium-sized data sets and distributions shifts are **Zero-Shot Learning (ZSL)** and **Few-Shot Learning (FSL)**. These can prove interesting testing grounds for efficient learning. In these problems, and particularly in ZSL for Computer Vision tasks, Deep Learning has failed to have an immediate impact. It has only been applied in indirect ways, most notably by replacing image features extracted with traditional Computer Vision algorithms, like Bag of Visual Words (Weston et al., 2010), with features extracted by deep nets such as ResNet (He et al., 2016). Further integration of Deep Learning techniques is important to advance these settings.

A step towards that direction has been made with the inclusion of generative models. For FSL, various forms of autoencoders have been leveraged to provide additional, synthetic examples given the actual support set (Antoniou et al., 2017; Wang et al., 2018; Xian et al., 2019). In ZSL, generative networks conditioned on some form of class descriptions are trained so as to generate synthetic samples of the test classes. In this way, the classification task is transformed into a standard supervised classification task. As a result, classifiers can be trained in a supervised manner (Xian et al., 2018b; Zhu et al., 2018). More elaborate training techniques have been proposed (Li et al., 2019b; Xian et al., 2019; Li et al., 2019a; Keshari et al., 2020; Narayan et al., 2020), yet without much progress on extending the basic approach.

In this work, we combine these two low-data regimes, namely ZSL and FSL. Specifically, we use the generative ZSL pipeline as a backbone and feed its synthesized output to a FSL classifier. The two modules can be trained jointly, rendering the overall process end-to-end. Formally, the FSL classifier’s loss is combined with the prior loss of the generative ZSL framework to form our proposed framework, *Z2FSL*. *Z2FSL* conceptually reduces ZSL to FSL by structuring the generator’s output as a support set for the FSL algorithm. Using the same FSL classifier during both training and testing is possible because of the flexibility of its output label space. This property holds because the FSL classifier can classify input patterns based on the examples and the classes present in its support set.

Our motivation and rationale for making the process end-to-

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end is threefold. First, the generative net gains access to the classification loss of the final classifier. This is beneficial because sample generation becomes more discriminative in a manner that explicitly helps the FSL classifier, since the latter’s loss drives the generation. Secondly, thanks to the aforementioned FSL property, the FSL classifier’s training is not reliant on the generated samples of the generator, so the former can be pre-trained on real examples. Additionally, this pre-training is not restricted to the corresponding training set of each task. For example, we can do so on ImageNet (Deng et al., 2009). Lastly, Few-shot learners perform favorably compared to other alternatives in low-shot classification tasks (Vinyals et al., 2016; Snell et al., 2017; Wang et al., 2018).

Our contributions to the study of ZSL are:

1. The coupling of two standard research benchmarks, ZSL and FSL, by our novel framework, Z2FSL, which makes generative ZSL approaches end-to-end by using a FSL classifier.
2. Formulating our framework in a manner that allows for a wide class of ZSL and FSL algorithms to be seamlessly integrated.
3. Achieving state-of-the-art or competitive performance on ZSL and Generalized ZSL benchmarks and analyzing the contributions of each component of our framework.

We have open-sourced our code¹.

2. Related Work

Earlier works address ZSL by splitting inference into two stages, inferring the attributes – the auxiliary description – of an image and then assigning the image to the closest given attribute vector. Examples are DAP (Lampert et al., 2013) and the technique presented by Al-Halah et al. (2016). Alternatively, IAP (Lampert et al., 2013) predicts the class posteriors and these are used to calculate the attribute posteriors of any image. Word2Vec (Mikolov et al., 2013) descriptions have also been used instead of attributes, an example being CONSE (Norouzi et al., 2013).

More recent research concentrates on learning a linear mapping from the image-feature space to a semantic space. ALE (Akata et al., 2015a) learns a compatibility function between attributes and image features that is a bilinear form. SJE (Akata et al., 2015b), DEVISE (Frome et al., 2013), ESZSL (Romera-Paredes & Torr, 2015) and Qiao et al. (2016) learn a bilinear form as a compatibility function as well. SAE (Kodirov et al., 2017) tackles ZSL with a linear

autoencoder. Extending linear mappings, Xian et al. (2016) introduced LATEM, which is a piecewise-linear compatibility function.

Other recent approaches can be categorized as prototypical, because, at least conceptually, a prototype per class is computed. SYNC (Changpinyo et al., 2016) align graphs in semantic and image-feature space, calculating prototypes in the process. CVCZSL (Li et al., 2019b) learns a neural net that maps directly from attributes to image features, to class prototypes that is.

Currently, generative ZSL stands as the state of the art. The inaugural works of Xian et al. (2018b); Zhu et al. (2018) laid out the foundation, the basic generative approach, which can be broken down into three stages: first, a generative network is trained to generate instances of seen classes conditioned on the provided class descriptions. A differentiable classifier (*e.g.* pre-trained linear classifier, AC-GAN (Odena et al., 2017)) can also be used to drive discriminative generation. In the second stage, given the description of every test class, the generative net is used to create a synthetic data set, transforming the problem into a supervised one. Then, a supervised classifier (SVM, linear, *etc.*) is trained on this data set. In the last stage, the classifier is tasked with classifying the actual test samples.

This basic approach has been somewhat enriched to improve performance. CIZSL (Elhoseiny & Elfeki, 2019) uses creative generation during training. LisGAN (Li et al., 2019a) borrows from prototypical approaches and utilizes class representatives to anchor generation. f-VAEGAN (Xian et al., 2019) shares weights between the decoder of a VAE and the generator of a WGAN to leverage the better aspects of both. GDAN (Huang et al., 2019) uses cycle consistency. ZSML (Verma et al., 2020) introduces meta-learning techniques. OCD (Keshari et al., 2020) uses an over-complete distribution to generate hard examples and render the synthetic data set more informative. TF-VAEGAN (Narayan et al., 2020) uses feedback to augment the f-VAEGAN.

In all cases, the proposed algorithms deviate from the basic approach mainly in the training regime of the generative net. In this paper, we describe Z2FSL, a generative ZSL framework which, via FSL, allows for improvements to the whole pipeline. In the next section, we describe in detail how this is achieved.

3. Preliminaries

In this section, we give all the necessary definitions, introduce notation and briefly discuss the necessary background.

¹<https://github.com/gchochla/z2fsl>

3.1. Problem Definition

Let \mathcal{X}_{tr} be the training samples and \mathcal{X}_{ts} be the test samples. Let \mathcal{Y}_{tr} be the corresponding set of training labels and \mathcal{Y}_{ts} be the corresponding set of test labels.

In the **ZSL** setting, we have $\mathcal{Y}_{tr} \cap \mathcal{Y}_{ts} = \emptyset$, *i.e.* there are no common classes between training and testing, leading to the terms *seen* and *unseen* to describe the classes of the train and test setting respectively. In the **Generalized ZSL (GZSL)** setting, that restriction becomes $\mathcal{Y}_{tr} \subset \mathcal{Y}_{ts}$, meaning that there are samples from both unseen classes and every seen class during testing. Both in ZSL and GZSL, an auxiliary description of each class is provided to counterbalance the absence of training examples for unseen test classes. Such a description can be the Word2Vec representation of the class, an attribute vector or the Wikipedia article for the class.

In a **FSL** setting, it is sufficient to impose the restriction $\mathcal{Y}_{tr} \subset \mathcal{Y}_{ts}$, same as GZSL. However, no descriptions are provided. Rather, during testing, we are provided with a set of examples per test class, named *support set*. A support set essentially consists of labeled examples from all n_W test classes, with n_S examples each, where n_W and n_S are arbitrary natural numbers referred to as *way* and *shot* respectively. Also, let S_k denote the set of examples of class k in a support set. Given a support set, we are tasked with classifying a set of unlabeled samples of the same n_W classes called *query set*. For convenience, we consider query sets to contain n_Q samples per class, which is also an arbitrary natural number. Randomly sampling a support set and a corresponding query set from a (usually significantly) larger test data set constitutes an *episode*. The purpose of an episode is to test the ability of a model to generalize to possibly unseen classes given only a small number of examples of each class, seen or unseen, and its classification accuracy on the episode is naturally used as the metric of success. It is customary to report the average accuracy over many episodes to capture a more robust metric for a particular data set, where the way and the shot of the episodes remain constant. That is to say, a specific FSL setting is characterized by its way and shot and described as n_W -way n_S -shot, *e.g.* 25-way 4-shot refers to the regime where the support sets contain $n_W = 25$ classes, with $n_S = 4$ samples each.

3.2. Background

Wasserstein Generative Adversarial Net: Wasserstein Generative Neural Nets (WGAN) (Arjovsky et al., 2017), an evolution of Generative Adversarial Nets (Goodfellow et al., 2014), are a framework to train a generator G , formulating $p(x|z)$ of real samples x with noise inputs z , in a minimax fashion with another network, a discriminator D . Gulrajani et al. (2017) added a regularization term to improve performance. We present the formulation of $p(x|a, z)$, which

includes a conditioning variable a , namely

$$\begin{aligned} \mathcal{L}_{WGAN}(G, D; p_R, p_Z) = & \\ & \mathbb{E}_{(x,a) \sim p_R, z \sim p_Z} [D(x, a) - D(G(a, z), a)] \\ & - \lambda \mathbb{E}_{(\hat{x}, a) \sim p_{\hat{X}}} [(\|\nabla_{\hat{x}} D(\hat{x}, a)\|_2 - 1)^2], \end{aligned} \quad (1)$$

where p_R is the distribution of the real data, p_Z a “noise” distribution, $p_{\hat{X}}$ the joint distribution of the conditioning variable and the uniform distribution on the line between x and $G(a, z)$, $(x, a) \sim p_R, z \sim p_Z$ (intuitively $\hat{x} = ux + (1 - u)G(a, z)$, $u \sim U(0, 1)$) and λ is a hyperparameter. The minimax game is defined as:

$$\min_G \max_D \mathcal{L}_{WGAN}(G, D; p_R, p_Z). \quad (2)$$

We use *generator* and *generative net* interchangeably.

Variational Autoencoder: The Variational Autoencoder (VAE), introduced by Kingma & Welling (2014), is an autoencoder that maximizes the variational lower bound of the marginal likelihood. An autoencoder consists of an encoder E , which compresses its input to a “latent” variable z , and a decoder D , which reconstructs the original input of E based on z . We present the formulation of the VAE with a conditioning variable a ,

$$\begin{aligned} \mathcal{L}_{VAE}(E, D; p_R, p_{\theta}) = & \\ & - \mathbb{E}_{(x,a) \sim p_R} [x \cdot \log D(E(x, a), a) \\ & + (1 - x) \log (1 - D(E(x, a), a))] \\ & + \mathbb{E}_{(x,a) \sim p_R} [D_{KL}(p_E(z|x, a) || p_{\theta}(z))], \end{aligned} \quad (3)$$

where D_{KL} is the Kullback-Leibler (KL) divergence, p_R the distribution of the real data, p_E the output distribution of E , which is a Gaussian Feedforward Neural Network (FFNN), *i.e.* it outputs the mean and the diagonal elements of the covariance of a Gaussian distribution, which makes the KL divergence analytical, and p_{θ} is the prior distribution of the “latent” variable. For practical purposes, the prior is set to $\mathcal{N}(\cdot; 0, I)$, and the reparameterization trick (Bengio et al., 2013) is used to sample from the encoder as $z = \mu(x, a) + \epsilon \odot \sigma(x, a)$, $\epsilon \sim \mathcal{N}(\epsilon; 0, I)$, where \odot is the Hadamard product and μ, σ the encoder’s outputs.

f-VAEGAN: f-VAEGAN (Xian et al., 2019) is a generative ZSL approach that deploys both a WGAN and a VAE to train the generator, by sharing its weights between the VAE’s decoder and the WGAN’s generator. The overall loss function of the approach is

$$\begin{aligned} \mathcal{L}_{VAEGAN}(G, E, D; p_R, p_Z, \beta) = & \\ & \mathcal{L}_{VAE}(E, G; p_R, p_Z) \\ & + \beta \cdot \mathcal{L}_{WGAN}(G, D; p_R, p_Z), \end{aligned} \quad (4)$$

where E is the encoder of the VAE, D the discriminator of the WGAN, G the generator of the WGAN and the decoder of the VAE and β a hyperparameter.

Prototypical Network: Prototypical Networks (PN) (Snell et al., 2017) present a simple, differentiable framework for FSL. A neural network, f_ϕ , is used to map the input samples to a metric space. The support set is mapped and the embeddings are averaged per class so as to get a prototype c_k for each. Then, each sample in the query set is mapped to the metric space and classified to the nearest prototype based on the Euclidean distance $d(\cdot, \cdot)$. The formulation is

$$\begin{aligned} c_k &= \frac{1}{|S_k|} \sum_{x_i \in S_k} f_\phi(x_i), \\ p_\phi(y = k|x) &= \frac{\exp(-d(f_\phi(x), c_k))}{\sum_{k'} \exp(-d(f_\phi(x), c_{k'}))}, \\ \mathcal{L}_{PN}(f_\phi; S, Q) &= \frac{1}{|Q|} \sum_{(x_i, y_i) \in Q} \log p_\phi(y = y_i|x), \end{aligned} \quad (5)$$

where $p_\phi(y|x)$ is the softmax output distribution of x belonging to some class. To compute \mathcal{L}_{PN} , we have to sample episodes instead of batches. In this manner, training resembles testing. We refer to that manner of training as *episodic*.

4. Method

We now describe the proposed Z2FSL framework in detail. In Z2FSL, a generative ZSL pipeline, used as a backbone, is coupled with a FSL classifier. We can train the two modules jointly by conceptually reducing ZSL to FSL, which simply means that the backbone generates the classifier’s support set. To get an episode, real examples of the classes that are present in this support set can be used as the query set. During testing, the test samples become the query and the support is again provided by the backbone. The framework is also presented in Figure 1, where a graphical representation of how the novel component of our framework, the FSL classifier, affects the pipeline can be seen. The backbone provides the support set of the FSL classifier in all settings. During training, this allows the back-propagation of the FSL loss to the generator. During testing, synthesized examples of the test classes are provided in order to enable the classification of unseen classes.

This is possible because the FSL algorithm can classify its input dynamically, in the sense that its output distribution is based on the classes present in the support set. This allows us to train the classifier on classes other than the unseen classes and simply provide the necessary synthetic support set during testing. Another advantage is that the FSL algorithm can actually be pre-trained before the joint training with the backbone and/or fine-tuned afterwards, or even trained completely separately of the backbone.

4.1. Training

We train all the components for multiple iterations. As an example, the components in this work, other than the

generator and the FSL classifier, which are also visible in Figure 1, include the discriminator of a WGAN and the encoder of a VAE. In each iteration, we take steps training the components: training the FSL classifier, training the generator and training all the other components as necessary.

First, when training the FSL algorithm, we randomly sample query sets from the training set and support sets are generated by the backbone, conditioned on the metadata of the classes that appear in the query set. The FSL loss, denoted \mathcal{L}_{FSL} , remains intact (e.g. Equation 5 for PNs). This is a slightly modified version of the episodic training we defined in Section 3.1, since the support set is now synthetic. Episodes during training, n_W , n_S and n_Q in particular, can be set arbitrarily, similar to batches. The process can be seen indirectly in Figure 1. For this step, we would have to simply back-propagate \mathcal{L}_{FSL} only to the FSL classifier.

Second, when training the generator of the ZSL backbone, we use the loss within the generative framework of the backbone, which we denote as \mathcal{L}_{ZSL} (e.g. Equation 4 if the backbone is the f-VAEGAN). By feeding the generated samples to the FSL algorithm, we can back-propagate \mathcal{L}_{FSL} to the generator. This also requires sampling a query set based on the classes the generator provides. The overall objective of the ZSL generator is then described as:

$$\mathcal{L}_{Z2FSL} = \mathcal{L}_{ZSL} + \gamma \mathcal{L}_{FSL}, \quad (6)$$

where γ is a hyperparameter. This is the step depicted in Figure 1 if we take into account all arrows.

The rest of the components can be trained before or after the two aforementioned steps. In this work, for example, we update the discriminator multiple times before each generator update, as suggested by Goodfellow et al. (2014); Arjovsky et al. (2017).

However, components of the backbone can even be trained along with the generator. A component that does not affect the generation of the support set in the forward pass can be trained along with the generator, but it remains unaffected by \mathcal{L}_{FSL} . Such a component is the encoder of a VAE, which we also use in our work, or a regressor for cycle consistency (Huang et al., 2019). A component that affects generation in the forward pass, such as a feedback module (Narayan et al., 2020), can be trained along with the generator and updated based on the objective in Equation 6 rather than \mathcal{L}_{ZSL} alone.

In Figure 1, we can more generally see that both real examples and corresponding descriptions are provided to the backbone, while only real and generated examples to the classifier. Real samples are useful to the backbone only during training, e.g. to compute the VAE reconstruction loss.

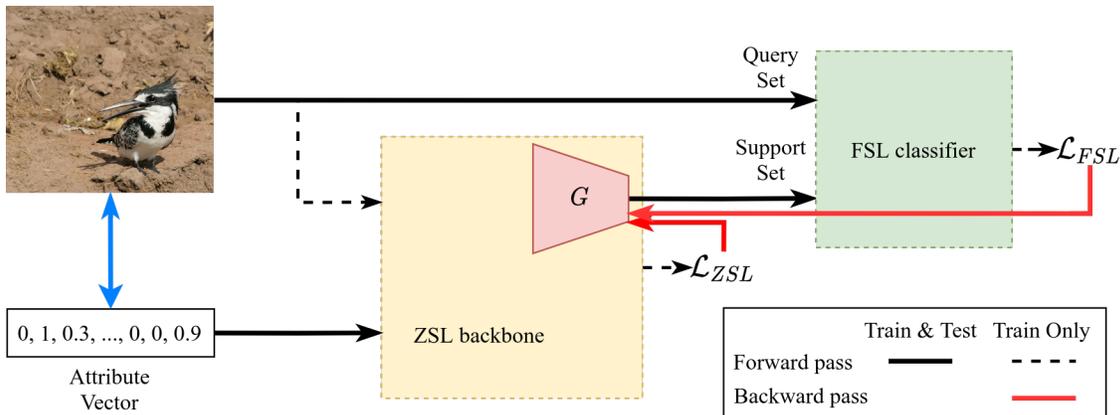


Figure 1. Graphical representation of the Z2FSL framework and pipeline. We use a generative Zero-shot Learning backbone with a Few-shot Learning classifier. During training, we train the generator G with a combination of its training within the backbone and the Few-shot Learning classification task. During testing, the forward pass is only altered in that real examples are not provided to the backbone and no backward pass is performed.

4.2. Evaluation

For the evaluation, the pipeline is modified in two ways. First, as shown in Figure 1, we stop providing real samples to the backbone. Only the descriptions are necessary so as to generate the test support set. Second, episodes are restricted by the test setting. The number of classes in each set, n_W , is fixed and equal to the number of test classes. n_Q is equal, for each test class, to the number of test samples available. n_S remains a hyperparameter, as we can choose the number of samples to generate per class. In this manner, the query set contains all test samples and the FSL classification accuracy is exactly the final ZSL accuracy.

4.3. Assumptions

We make three assumptions about the backbone and the classifier altogether. First, the backbone is a generative ZSL approach. Second, the classifier is trained through a differentiable process. Third, the classifier can classify its input dynamically, by matching support and query classes (Vinyals et al., 2016; Snell et al., 2017; Wang et al., 2018). This fact allows the usage of the classifier during testing without any training on unseen classes as long as corresponding supporting examples are provided at that time. This means that the classifier is not reliant on the generator and, consequently, the modules can be trained separately or jointly.

As a result, our framework is suitable for a wide class of ZSL and FSL algorithms. We formulate our framework as agnostic to the generative ZSL and the FSL algorithm, and refer to a specific implementation of it by the following macro: $Z2FSL(z, \mathcal{f})$, where z is the generative ZSL backbone and \mathcal{f} the FSL classifier.

5. Experiments

We first present the datasets, followed by implementation details and finally present our experimental results along with comparison to state of the art.

5.1. Data sets

We use the Caltech UCSD Bird 200 (CUB, Wah et al. 2011), which consists of 11788 images of birds belonging to 200 species. One 312-dimensional attribute vector per class is provided as well. We also use Animals with Attributes 2 (AwA2, Xian et al. 2018a). It contains 37322 images from 50 categories and 85-dimensional attributes. Our last data set is the SUN Scene Classification (SUN, Patterson & Hays 2012) data set, with 14340 images of 717 categories and 102-dimensional attributes.

We use the provided attributes as our auxiliary descriptions, and in particular the continuous attributes after normalizing them w.r.t. their L2 norm. We use 10 crops per image (original image, top-right, top-left, bottom-right, bottom-left and their horizontally flipped counterparts) as augmentation. We use the original image for testing. Instead of images, we use features extracted by the ResNet-101 (He et al., 2016) trained on ImageNet (Deng et al., 2009). We choose the 2048-dimensional output of its adaptive average pooling layer. Additionally, we perform min-max normalization of the features to $[0, 1]$ and use the train-test and seen-unseen splits proposed by Xian et al. (2018a).

5.2. Implementation Details

Since we present the results of $Z2FSL(f\text{-VAEGAN}, \text{PN})$ in comparison to the state of the art, we present details for that

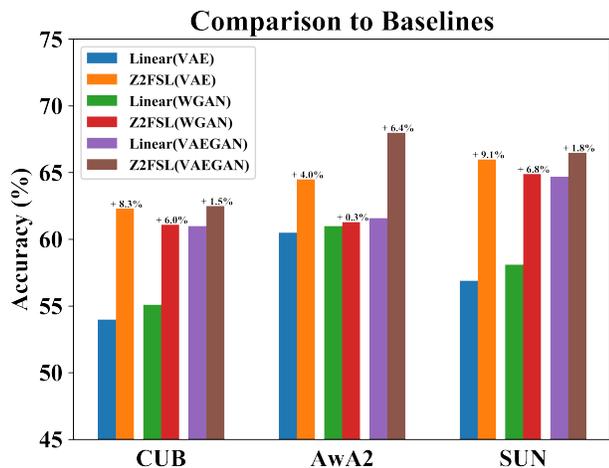


Figure 2. Comparison of Z2FSL to baseline generative ZSL backbones. Linear(z) describes the setting where the generative ZSL approach z is used with a linear classifier trained on the generated data. We skip the second argument of the Z2FSL macro for convenience, since it is the PN in all cases. Linear(VAEGAN) results for CUB and SUN reported from Xian et al. (2019). The metric presented is the average per class top-1 accuracy. Performance gains denote absolute improvement compared to the corresponding baseline.

specific architecture in this section.

We pre-train the PN in an episodic manner as suggested by Snell et al. (2017), where support and query sets are sampled from the real training data of the corresponding data set. The PN is implemented as a FFNN with n_h hidden layers with square weight matrices and ReLU activations. The FSL classifier’s learning rate is kept the same in pre-training and the joint training with the generator.

The generator and the encoder are FFNNs with 2 hidden layers each, 4096 followed by 8192 units for the generator and the reverse for the encoder, Leaky ReLU hidden activations (0.2 slope), linear output for the encoder and sigmoid for the generator. The noise dimension is chosen to be equal to the dimension of the attributes. The discriminator is a FFNN with one hidden layer of 4096 neurons and Leaky ReLU hidden activations (0.2 slope). We set the coefficient of the regularization term of WGAN $\lambda = 10$ and the training updates of the discriminator per generator update equal to 5.

When we sample support sets from the generative net, we set $n_S = 5$ during training. During testing, we set it to $n_S = 1800$ for unseen classes. For seen classes in the GZSL test setting, we experiment with both seen and unseen support and select the better alternative for each benchmark. We also consider the shot of the test support set for seen classes a different hyperparameter m_S .

Table 1. Comparison of our approach, Z2FSL(f-VAEGAN, PN), to previous work. The metric presented is the average per class top-1 accuracy.

APPROACH	ZERO-SHOT LEARNING		
	CUB	Awa2	SUN
CVCZSL (LI ET AL., 2019B)	54.4	71.1	62.6
F-CLSWGAN (XIAN ET AL., 2018B)	57.3	-	60.8
LISGAN (LI ET AL., 2019A)	58.8	-	61.7
F-VAEGAN (XIAN ET AL., 2019)	61.0	-	64.7
OCD (KESHARI ET AL., 2020)	60.3	71.3	63.5
TF-VAEGAN (NARAYAN ET AL., 2020)	64.9	72.2	66.0
Z2FSL(F-VAEGAN, PN)	62.5	68.0	66.5

The optimizer in all cases is Adam (Kingma & Ba, 2015) with $\beta_1 = 0.5$ and $\beta_2 = 0.999$. We apply gradient clipping, restricting the gradient for each parameter within $[-5, 5]$. Our implementation is in PyTorch (Paszke et al., 2019).

The tunable hyperparameters that we either search for or vary by data set are presented in the Supplementary Material.

5.3. Backbone Baselines

In this section, we present the performance of our framework using various generative ZSL approaches as backbones and compare that with the plain generative ZSL approaches, *i.e.* without the FSL algorithm, as baselines. The comparison can be seen in Figure 2. The baselines we have chosen are a VAE, a WGAN and a f-VAEGAN. Z2FSL improves the performance of all baselines consistently across all benchmarks. It is interesting to see that, in most cases, the simple backbones, the VAE and the WGAN, enhanced by our framework, exceed the performance of the more elaborate and superior – on its own – plain f-VAEGAN.

5.4. State of the art

In this section, we present our results in comparison with the current state-of-the-art approaches that use the same test setting as our approach (feature extractor, dimensionality of features, splits, *etc.* described in Sections 5.1 and 5.2).

5.4.1. ZERO-SHOT LEARNING

For ZSL, our experimental evaluation in Section 5.3 shows that Z2FSL(f-VAEGAN, PN) outperforms the f-VAEGAN. This performance compares favorably to the rest of the state-of-the-art approaches as well, as can be seen in Table 1. In particular, even though the TF-VAEGAN itself builds on top of the f-VAEGAN and improves performance, our approach outperforms that on SUN, where it achieves state-of-the-art performance, improving the previous one by an absolute

Table 2. Comparison of our approach, Z2FSL(f-VAEGAN, PN), to previous work. The metrics presented are: \mathbf{u} is the average per class top-1 accuracy of unseen classes, \mathbf{s} is the average per class top-1 accuracy of seen class and \mathbf{H} their harmonic mean. \mathbf{H} is considered the main metric of this setting.

APPROACH	GENERALIZED ZERO-SHOT LEARNING								
	CUB			AWA2			SUN		
	U	S	H	U	S	H	U	S	H
CVCZSL (LI ET AL., 2019B)	47.4	47.6	47.5	56.4	81.4	66.7	36.3	42.8	39.3
F-CLSWGAN (XIAN ET AL., 2018B)	43.7	57.7	49.7	-	-	-	42.6	36.6	39.4
LISGAN (LI ET AL., 2019A)	46.5	57.9	51.6	-	-	-	42.9	37.8	40.2
F-VAEGAN (XIAN ET AL., 2019)	48.4	60.1	53.6	-	-	-	45.1	38.0	41.3
OCD (KESHARI ET AL., 2020)	44.8	59.9	51.3	59.5	73.4	65.7	44.8	42.9	43.8
TF-VAEGAN (NARAYAN ET AL., 2020)	52.8	64.7	58.1	59.8	75.1	66.6	45.6	40.7	43.0
Z2FSL(F-VAEGAN, PN)	47.2	61.2	53.3	57.4	80.0	66.8	44.0	32.9	37.6

margin of 0.5%.

5.4.2. GENERALIZED ZERO-SHOT LEARNING

For GZSL, results can be seen in Table 2. Performance in AWA2 is marginally better than the previous state of the art, CVCZSL and TF-VAEGAN. In contrast, in CUB and SUN it is harder to balance seen and unseen accuracies, as decreasing the s metric, which is partly controlled by m_S , is required to achieve the best H possible. This leads to inferior performance compared to our specific backbone in SUN and marginally worse accuracy in CUB. The state-of-the-art results in AWA2 can be partly explained by the small number of classes, which are 50 in total, only 10 of which are unseen.

5.5. Ablation studies

5.5.1. COMPONENT ANALYSIS

We perform a more detailed analysis of how the usage of the novel component of our approach, the FSL classifier, affects performance. We experiment with using the FSL classifier solely during the training of the backbone. During testing, we follow the standard practise of training a linear classifier on the synthetic data. We also experiment with using the FSL classifier only during testing, *i.e.* simply setting $\gamma = 0$ in Equation 6. Results are presented in Figure 3. We can observe that both regimes yield improvement compared to the plain backbone. Additionally, regarding the gains in performance compared to the backbone, the gain of Z2FSL is greater than the sum of the gains of the two ablation studies. This shows that end-to-end training yields a significant improvement and validates that this process renders the generation discriminative in a manner that explicitly helps the classifier.

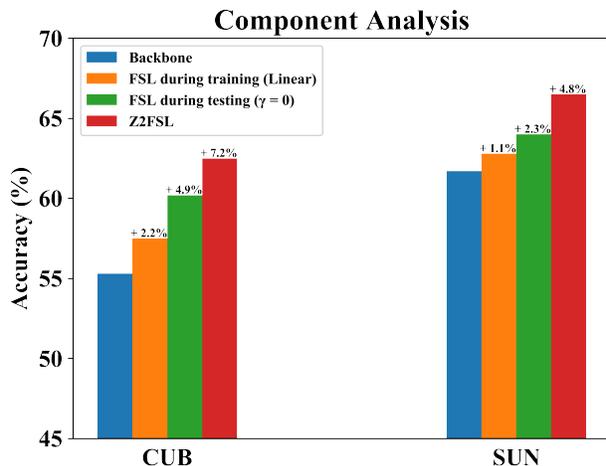


Figure 3. FSL classifier’s effects on performance. We compare the performance of the f-VAEGAN, the backbone generative ZSL approach, to the performance of Z2FSL(f-VAEGAN, PN) when we discard the FSL classifier during the evaluation and use a linear classifier instead, the performance of Z2FSL(f-VAEGAN, PN) when $\gamma = 0$ (Equation 6), *i.e.* discarding the FSL classifier during training only, and the complete Z2FSL(f-VAEGAN, PN) (with the FSL classifier in both settings). The metric presented is the average per class top-1 accuracy. Performance gains denote absolute improvement compared to the backbone.

5.5.2. SYNTHETIC VS. REAL SUPPORT SET

We also examine the performance of Z2FSL when using real supporting examples of seen classes compared to performance with synthetic ones. Results are presented in Table 3. In AWA2 and SUN, the synthetic support results in a better harmonic mean. On the other hand, in CUB, real support leads to an increase in performance. Moreover, as we noted in Section 5.2, the shot for seen classes in the test support set is controlled by a different hyperparameter than that of un-

Table 3. Comparison of our approach, Z2FSL(f-VAEGAN, PN) with real and synthetic support for seen classes. The metrics presented are: \mathbf{u} is the average per class top-1 accuracy of unseen classes, \mathbf{s} is the average per class top-1 accuracy of seen class and \mathbf{H} their harmonic mean.

APPROACH	GENERALIZED ZERO-SHOT LEARNING								
	CUB			AWA2			SUN		
	U	S	H	U	S	H	U	S	H
Z2FSL(F-VAEGAN, PN) (WITH REAL SUPPORT)	47.2	61.2	53.3	49.4	77.7	60.4	48.1	27.4	34.9
Z2FSL(F-VAEGAN, PN)	44.4	58.0	50.3	57.4	80.0	66.8	44.0	32.9	37.6

Table 4. Comparison of our approach, Z2FSL(f-VAEGAN, PN), with and without pre-training the FSL classifier. The metric presented is the average per class top-1 accuracy.

APPROACH	ZSL	
	CUB	SUN
Z2FSL (NO PRE-TRAINING)	58.0	61.3
Z2FSL	62.5	66.5

seen classes, m_S and n_S (for testing) respectively². These facts clearly demonstrate the bias towards seen classes the naive approaches of using all the available training data in the support set or too many synthetic ones could lead to.

5.5.3. PRE-TRAINING

We also test the effects of pre-training the FSL classifier of our framework. It makes sense, intuitively, to pre-train it in an actual FSL setting before the joint training with the generator, where we choose to train it with a combination of real and synthetic data. Table 4 shows a decrease in performance without pre-training, 5.2% absolute decrease in SUN and 4.5% in CUB to be exact. This illustrates that training in the FSL setting is essential to avoid overfitting.

6. Conclusions

In this paper, we introduce a novel, end-to-end generative ZSL framework, Z2FSL. Z2FSL uses the same supervised classifier during both training and testing. We choose a FSL algorithm to fill that role, since the choice of classifier is restricted by the ZSL setting. In this manner, we also couple the two low-data regimes. We formulate our framework so as to allow a broad class of generative ZSL approaches and FSL classifiers to be integrated. Empirically, we show that our framework improves upon the results of the plain generative approach. Extensive ablation studies reveal that the improvement originates from the fact that the generated samples of the generative net are rendered more discrimina-

²The results in Table 3 are achieved with a n_S that is roughly two orders of magnitude greater than m_S

tive in a way that explicitly helps the classifier. In addition, these studies demonstrate the advantages of being able to use a pre-trained classifier. Our results are state of the art or competitive across all benchmarks. We also show that using synthetic samples for seen classes as well as decreasing the number of samples of these classes compared to unseen ones can improve performance in GZSL.

Our future plans include further investigating and mitigating the bias towards seen classes in the GZSL. Another research direction we plan to investigate are techniques to better train the FSL classifier separately of the generator. Initial thoughts include consistent fine-tuning on generated samples of unseen classes after the joint training and extensive pre-training on other data sets. Since we now have an end-to-end process to train the generative net, it is possible to completely dispose of the generative framework and, therefore, we also plan to investigate this training regime.

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A. Evaluation Metrics

For the sake of completeness, we formally define the the Zero-Shot Learning (ZSL) and Generalized Zero-Shot Learning (GZSL) metrics we use. We evaluate our framework with the *average per-class [top-1] accuracy* for ZSL, defined as

$$acc_{\mathcal{Y}} = \frac{1}{\|\mathcal{Y}\|} \sum_{y \in \mathcal{Y}} \frac{\# \text{ correct predictions in } y}{\# \text{ samples in } y}, \quad (7)$$

where in the case of ZSL \mathcal{Y} are the unseen classes. For GZSL, we use the *harmonic mean* of the average per-class accuracy of seen classes and that of unseen classes, defined as

$$H = 2 \frac{u \cdot s}{u + s}, \quad (8)$$

where we define $u = acc_{\mathcal{Y}}$ for unseen classes and $s = acc_{\mathcal{X}}$ for seen classes for convenience and adherence to established notation.

B. Hyperparameters

We present the rest of the hyperparameters for the pre-training of the **Few-Shot Learning (FSL)** algorithm, the Prototypical Network (PN), in Table 5 and for the training within our framework, Z2FSL(f-VAEGAN, PN), in Table 6, both for **Zero-Shot Learning (ZSL)** and **Generalized Zero-shot Learning (GZSL)**.

C. Classifier Fine-tuning

After the joint training of the FSL classifier and the generator of the backbone, we fine-tune the FSL classifier on samples generated by the generator conditioned on attributes of the unseen classes. This basically means that the generator provides both the support and the query set. We train for 25 episodes, using the same learning rate as in the other two settings the classifier is trained. We also retain the hyperparameters of the episode in this training regime the same as in the joint training of the FSL classifier and the generator. This process provides marginal improvement, if any, and is generally inconsistent. Further work is required to stabilize it.

D. Prototypical Network initialization

We initialize the weight matrices of the PN by setting all the diagonal elements equal to 1, while the rest are randomly sampled i.i.d. from $\mathcal{N}(\cdot; 0, 0.01)$. We do so to bias the PN to preserve its input space structure as much as possible, which we expect to be somewhat discriminative due to ResNet-101. Notice that we can do so because ResNet-101 yields non-negative values and we use ReLU activations.

This structure can be thought of as similar to a residual layer (He et al., 2016) routinely used in Convolutional Neural nets. It is for this reason that all weight matrices in the PN are square. We observed an increase in validation accuracy in all settings using this clever initialization trick. We are unaware of another similar approach in the literature, so further investigation may be warranted.

E. Data Augmentation

For the extra crops besides the original image, we crop the original image starting from the desired corner and extending up to 80% of each dimension and finally resize the crop to match the original image’s dimensions.

Table 5. Hyperparameter configuration per setting and data set for the Prototypical Network’s pre-training. From top to bottom, the hyperparameters presented are the learning rate of the FSL algorithm α_h , the number of episodes N_h , the number of hidden layers n_h , the number of classes in an episode n_W , the number of support examples per class n_S , and the number of queries per class n_Q .

HYPERPARAMETER	ZSL			GZSL		
	CUB	AWA2	SUN	CUB	AWA2	SUN
α_h	$5 \cdot 10^{-5}$	10^{-5}	10^{-5}	10^{-3}	10^{-5}	$5 \cdot 10^{-5}$
N_h	12000	15000	10000	10000	12000	8000
n_h	0	1	1	0	1	1
n_W	25	10	40	25	10	50
n_S	5	5	5	5	5	5
n_Q	10	15	5	10	15	2

Table 6. Hyperparameter configuration per setting and data set for our main experiments. We have the ZSL learning rate α_f , the coefficient of the WGAN loss β , the coefficient of the FSL loss γ , the number of classes in a training episode n_W , the number of generations per class in during training n_S , the number of generations per seen class during testing m_S , the number of “queries” per class in a training episode n_Q , and the number of episodes N .

HYPERPARAMETER	ZSL			GZSL		
	CUB	AWA2	SUN	CUB	AWA2	SUN
α_f	10^{-4}	10^{-4}	10^{-4}	10^{-4}	10^{-4}	10^{-4}
β	100	100	100	100	100	100
γ	100	100	100	10	10	10
n_W	25	10	80	25	10	80
n_S	5	5	5	5	5	5
m_S	-	-	-	5	2	5
n_Q	10	15	5	10	15	5
N	8000	8000	6500	6500	8500	8000