Bowtie Networks: Generative Modeling for Joint Few-Shot Recognition and Novel-View Synthesis

Zhipeng Bao  Yu-Xiong Wang  Martial Hebert  
Robotics Institute, Carnegie Mellon University  
{zbao, yuxiongw, hebert}@cs.cmu.edu

Abstract

Generative modeling has recently shown great promise in computer vision, but its success is often limited to separate tasks. In this paper, motivated by multi-task learning of shareable feature representations, we consider a novel problem of learning a shared generative model across various tasks. We instantiate it on the illustrative dual-task of joint few-shot recognition and novel-view synthesis: given only one or few images of a novel object from arbitrary views with only category annotation, we aim to simultaneously learn an object classifier and generate images of the object from new viewpoints. To this end, we propose bowtie networks that jointly learn 3D geometric and semantic representations with feedback in the loop. Experimental evaluation on challenging fine-grained recognition datasets demonstrates that our synthesized images are realistic from multiple viewpoints and significantly improve recognition performance as ways of data augmentation, especially in the low-data regime. We further show that our approach is flexible and can be easily extended to incorporate other tasks, such as style guided synthesis.

1 Introduction

Given a never-before-seen object (e.g., a gadwall in Fig. 1), humans are able to generalize even from a single image of this object in different ways, including recognizing new object instances and imagining what the object would look like from different viewpoints. Achieving similar levels of generalization for machines is a fundamental problem in computer vision, and has been actively explored in areas such as few-shot object recognition [6, 36, 29] and novel-view synthesis [21, 19, 28]. However, such exploration is often limited in separate areas but not jointly.

We argue that learning a shareable internal representation that is broadly useful for different tasks is a crucial element towards human-level generalization. While similar spirit has been widely studied as multi-task learning or meta-learning of a shared feature representation [6, 44], here we take a different perspective — learning a shared generative model across various tasks. Leveraging multiple tasks allows us to capture the underlying image generation mechanism for more comprehensive object understanding than it could be within individual tasks. Taking simultaneous recognition and view synthesis as an example, successful generative modeling requires understanding both the semantics and the 3D geometric structure of the input image. Meanwhile, a learned common generative model facilitates knowledge to flow across tasks, thus beneficial to each other. For example, the synthesized images provide viewpoint variations and could then be used as additional training data to build a better recognition model; meanwhile, the recognition model ensures the preservation of the desired category information and deals with partial occlusions during the synthesis process.

To this end, in this paper, we propose a novel task of joint few-shot recognition and novel-view synthesis. Given only one or few images of a novel object from arbitrary views with only category annotation, we aim to simultaneously learn an object classifier and generate images of the object from new viewpoints. This dual-task is challenging, because of its (i) weak supervision, where we
do not have access to any ground-truth 3D supervision, and (ii) few-shot setting, where we need to effectively learn both 3D geometric and semantic representations from minimal data.

We systematically address these challenges by proposing a feedback-based bowtie network (FBNet), as illustrated in Fig. 1. The network consists of a view synthesis module and a recognition module, which are linked through feedback connections in a bowtie fashion. This is a general architecture that can be used on top of any view synthesis model and any recognition model. The view synthesis module explicitly learns a 3D geometric representation from 2D images, which is transformed to target viewpoints, projected to 2D features, and rendered to generate images. The recognition module then leverages these synthesized images from multiple views together with the original images to learn a semantic feature representation and produce corresponding classifiers, leading to the feedback from the output of the view synthesis module to the input of the recognition module. The semantic features of real images extracted from the recognition module are further fed into the view synthesis module as conditional inputs, leading to the feedback from the output of the recognition module to the input of the view synthesis module.

One potential difficulty, though, lies in the incompatibility of the operational resolutions when merging a view synthesis module with a recognition module. Deep recognition models can benefit from high-resolution images, and the recognition performance significantly improves with increased resolution [38, 19]. By contrast, it is still challenging for modern generative models to synthesize very high-resolution images [24, 18]. To address this issue, while operating on a resolution consistent with state-of-the-art view synthesis models [18], we further introduce resolution distillation to leverage additional knowledge in a recognition model that is learned from higher-resolution images.

Our contributions are three-folds. (1) We introduce a novel problem of multi-task oriented generative modeling, and instantiate it on the illustrative dual-task of few-shot recognition and novel-view synthesis. (2) We propose feedback-based bowtie networks that simultaneously learn 3D geometric and semantic representations with feedback in the loop. We further address the incompatibility issues between different modules by leveraging resolution distillation. (3) Our approach enables direct manipulation of view, shape, appearance, and semantics in generative image modeling, significantly improving both view synthesis and recognition performance, especially in the low-data regime. Our approach is flexible and can be easily extended to incorporate other tasks, e.g., style guided synthesis.

2 Related Work

Few-Shot Recognition is a classic problem in computer vision [32]. Many algorithms have been proposed to solve this problem [6, 36, 29], including the recent efforts on leveraging generative models [37, 35, 14, 33, 4]. A “hallucinator” was introduced to generate imaginary samples to help with low-shot classification [37]. MetaGAN improved few-shot recognition by producing fake images as a new category [45]. Generative versions of matching networks extended the capability and robustness of matching networks [14]. However, these methods either use pre-trained generative models or do not synthesize images directly. In comparison, our approach performs joint training of recognition and view synthesis and enable the two tasks to cooperate through feedback connections.

Novel-View Synthesis aims to generate a target image with an arbitrary camera pose from one given source image [34]. It is also addressed as “multiview synthesis” in literature. For this task, some approaches have synthesized lifelike images [21, 19, 28, 12, 45, 40]. However, they heavily rely...
on pose supervision or 3D annotation. Learning a view synthesis model in an unsupervised way is more challenging but useful. Pix2Shape proposed an unsupervised manner to learn an implicit 3D scene representation by generating a 2.5D surfel based reconstruction [23]. HoloGAN proposed an unsupervised approach to learn 3D feature representations and render 2D images accordingly [18]. Xiong et al. proposed a method that uses multiview images to help fine-grained recognition tasks [41]. However, their method needs pose supervision to train the view synthesis model, while we do not.

Multi-task Learning and Task Relationship: Many techniques have been proposed for multi-task learning, in which a collection of tasks are learned jointly [17][13][25]. In addition, task relationships among different tasks have been studied. Taskonomy exploited the relationships among various visual tasks to benefit the transfer or multi-task learning among them [44]. [29] proposed a meta-learning algorithm to adapt existing models to novel zero-shot learning tasks. Task cooperation and competition were also considered, and a method was proposed for assigning tasks to a few neural networks to best balance all the tasks [50]. Some recent work has investigated the connection between view synthesis and view recognition and has made some attempts to combine them together [31][32][27]. However, these approaches do not treat the two tasks of equal importance, i.e., one task as an auxiliary task to facilitate the other. On the contrary, our approach targets the joint learning of the two tasks and improves both of their performance. Importantly, we focus on learning a shared generative model rather than a shared feature representation, as is normally the case in multi-task learning.

3 Our Approach

3.1 Dual-Task of Few-Shot Recognition and Novel-View Synthesis

Problem Formulation: Given a dataset \( D = \{(x_i, y_i)\} \), where \( x_i \in X \) is an image of an object and \( y_i \in C \) is the corresponding category label (\( X \) and \( C \) are the image space and label space, respectively), we address the following two tasks simultaneously. (i) Object recognition: learning a discriminative model \( R : X \rightarrow C \) that takes as input an image \( x_i \) and predicts its category label. (ii) Novel-view synthesis: learning a generative model \( G : X \times \Theta \rightarrow X \) that, given an image \( x_i \) of category \( y_i \) and an arbitrary 3D viewpoint \( \theta_j \in \Theta \), synthesizes an image in category \( y_i \) viewed from \( \theta_j \). Notice that we are more interested in category-level consistency, for which \( G \) is able to generate images of not only the instance \( x_i \), but also other objects of the category \( y_i \) from different viewpoints. This dual-task scenario requires us to improve the performance of both 2D and 3D tasks under weak supervision without any ground-truth 3D annotations. Hence, we need to exploit the cooperation between them.

Few-Shot Setting: The few-shot dataset consists of one or only a few images per category, which makes our problem even more challenging. To this end, following the recent work on knowledge transfer and few-shot learning [8][2], we leverage a set of “base” classes \( C_{\text{base}} \) with a large-sample dataset \( D_{\text{base}} = \{(x_i, y_i) ; y_i \in C_{\text{base}}\} \) to train our initial model. We then fine-tune the pre-trained model on our target “novel” classes \( C_{\text{novel}} (C_{\text{base}} \cap C_{\text{novel}} = 0) \) with its small-sample dataset \( D_{\text{novel}} = \{(x_i, y_i) ; y_i \in C_{\text{novel}}\} \) (e.g., a \( k \)-shot setting corresponds to \( k \) images per class).

3.2 Feedback-Based Bowtie Networks

To address the dual-task, we are interested in learning a generative model that can synthesize realistic images of different viewpoints, which are also useful for building a strong recognition model. We propose a feedback-based bowtie network (FBNet) for this purpose. This model consists of a view synthesis module and a recognition module, trained in a joint, end-to-end fashion. Our key insight is to explicitly introduce feedback connections between the two modules, so that they cooperate with each other, thus enabling the entire model to simultaneously learn 3D geometric and semantic representations. This general architecture can be used on top of any view synthesis model and any recognition model. Here we focus on a state-of-the-art view synthesis model (HoloGAN [18]) and a widely adopted few-shot recognition model (prototypical network [29]), as shown in Fig. [2].

3.2.1 View Synthesis Module

The view synthesis module \( V \) is shown in the blue shaded region in Fig. [2]. It is adapted from HoloGAN [18], a state-of-the-art model for unsupervised view synthesis. This module consists of a generator \( G \) which first generates a 3D feature representation from a latent constant tensor (initial cube) through 3D convolutions. The feature representation is then transformed to a certain pose and projected to 2D with a projector. The final color image is then computed through 2D convolutions.
This module takes two inputs: a latent vector input $z$ and a view input $\theta$. $z$ characterizes the style of the generated image through adaptive instance normalization (AdaIN) [11] units. $\theta = [\theta^x, \theta^y, \theta^z]$ guides the transformation of the 3D feature representation. This module also contains a discriminator $D$ to detect whether an image is real or fake (not shown in Fig. 2). We use the standard GAN loss from DC-GAN [22], $L_{GAN}(G,D)$. We make the following important modifications to make the architecture applicable to our dual-task.

**Latent Vector Formulation:** To allow the synthesis module to get feedback from the recognition module (details are shown in Sec. 3.2.3), we first change HoloGAN from unconditional to conditional. To this end, we model the latent input $z$ as: $z_i = f_i \oplus n_i$, where $f_i$ is the conditional feature input derived from image $x_i$ and $n_i$ is a noise vector sampled from Gaussian distribution. $\oplus$ is the combination strategy (e.g., concatenation). By doing so, the synthesis module leverages additional semantic information, thus maintains the category-level consistency with target image and improves the diversity of the generated images.

**Identity Regularizer:** Inspired by [3], we introduce an identity regularizer to ensure the synthesis module to preserve two critical properties: (i) the identity for input $z$ with different $\theta$, and (ii) the correct viewpoint of the generated image. We simultaneously satisfy both properties by introducing an encoding network $H$ to predict the reconstructed latent vector $z'$ and view input $\theta'$: $H(G(z, \theta)) = [z', \theta']$, where $G(z, \theta)$ is the generated image. Then we minimize the difference between the real and the reconstructed input as

$$L_{identity}(G,H) = \mathbb{E}_z ||z - z'||^2 + \mathbb{E}_\theta ||\theta - \theta'||^2.$$  \hspace{1cm} (1)

Here $H$ shares the majority of the convolution layers of the discriminator $D$, but uses an additional fully-connected layer.

### 3.2.2 Recognition Module

The recognition module $R$ (green shaded region in Fig. 2) consists of a feature extraction network $F$ which transforms images to latent features, and a prototypical classification network $P$ [29] which makes the final classification. Below we explain the design of these two components, especially focusing on how to address the technical challenges faced by joint training with view synthesis.

**Resolution Distillation for Feature Extraction Network:** One of the main obstacles is that state-of-the-art synthesis models and recognition models operate on different resolutions. Concretely, to the best of our knowledge, current approaches to unsupervised novel-view synthesis still cannot generate satisfactory high-resolution images (e.g., $224 \times 224$) [18]. By contrast, the performance of current well-performing recognition models substantially degrades with low-resolution images [38][1]. To reconcile the resolution incompatibility, we introduce a simple distillation technique inspired by the general concept of knowledge distillation [10]. Specifically, we operate on the resolution of the...
synthesis module (e.g., 64 × 64). But we benefit from an additional auxiliary feature extraction network $F_{\text{highR}}$ that is trained on high-resolution images (e.g., 224 × 224). We first pre-train $F_{\text{highR}}$ following the standard practice with a cross-entropy softmax classifier [15]. We then train our feature extraction network $F_{\text{lowR}}$ (the one used in the recognition module), with the guidance of $F_{\text{highR}}$ through matching their features:

$$\mathcal{L}_{\text{feature}}(F_{\text{lowR}}) = \mathbb{E}_x \| F_{\text{highR}}(x) - F_{\text{lowR}}(x) \|^2,$$

where $x$ is the training image. With the help of resolution distillation, the feature extraction network re-captures information in high-resolution images but potentially missed in low-resolution images.

**Prototypical Classification Network:** We use the prototypical network $P$ [29] as our classifier. The network assigns class probabilities $\hat{p}$ based on distance of the input feature vector from class centers $\mu$; and $\mu$ is calculated by support images in the latent feature space:

$$\hat{p}_c(x) = \frac{e^{-d(P(F_{\text{lowR}}(x)), \mu_c)}}{\sum_j e^{-d(P(F_{\text{lowR}}(x)), \mu_j)}}, \quad \mu_c = \frac{\sum_{(x_i, y_i) \in S} P(F_{\text{lowR}}(x_i)) \mathbb{I}[y_i = c]}{\sum_{(x_i, y_i) \in S} \mathbb{I}[y_i = c]},$$

where $x$ is the real query image, $\hat{p}_c$ is the probability of category $c$, and $d$ is a distance metric (e.g., Euclidean distance). $S$ is the support dataset. $P$ operates on top of the feature extraction network $F$, and consists of 3 fully-connected layers as additional feature embedding (the classifier is non-parametric). Another benefit of using the prototypical network lies in that it enables the recognition module to explicitly leverage the generated images in a way of data augmentation, i.e., $S$ contains both real and generated images to compute the class mean. Notice that, though, the module parameters are updated based on the loss calculated on the real query images, which is a cross-entropy loss $\mathcal{L}_{\text{rec}}(R)$ between their predictions $\hat{p}$ and ground-truth labels.

### 3.2.3 Feedback-Based Bowtie Model

As shown in Fig. 2, we leverage a bowtie architecture for our full model, where the output of each module is fed into the other module as one of its inputs. Through joint training, such connections work as explicit feedback to facilitate the communication and cooperation between different modules.

**Feedback Connections:** We introduce two complementary feedback connections between the view synthesis module and the recognition module: (1) recognition output → synthesis input (green arrow in Fig. 2), where the features of the real images extracted from the recognition module are fed into the synthesis module as conditional inputs to generate images from different views; (2) synthesis output → recognition input (blue arrow in Fig. 2), where the generated images are used to produce an augmented set to train the recognition module.

**Categorical Loss for Feedback:** To further encourage the generated images to benefit the recognition, the view synthesis module needs to capture the categorical semantics. Therefore, we introduce a categorical loss to update the synthesis module with the prediction results of the generated images:

$$\mathcal{L}_{\text{cat}}(G) = \mathbb{E}_{y_i} \| - \log(R(G(z_i, \theta_i))) \|,$$

where $y_i$ is the category label for the generated image $G(z_i, \theta_i)$. This loss also implicitly increases the diversity and quality of the generated images.

**Final Loss Function:** The final loss function is:

$$\mathcal{L}_\text{Total} = \mathcal{L}_{\text{GAN}} + \mathcal{L}_{\text{rec}} + \mathcal{L}_{\text{feature}} + \lambda_{\text{id}} \mathcal{L}_{\text{identity}} + \lambda_{\text{cat}} \mathcal{L}_{\text{cat}},$$

where $\lambda_{\text{id}}$ and $\lambda_{\text{cat}}$ are trade-off hyper-parameters.

**Training Procedure:** We first pre-train $F_{\text{highR}}$ on the high-resolution dataset and save the computed features. These features are used to help train the feature extraction network $F$ through $\mathcal{L}_{\text{feature}}$. Then the entire model is first trained on $\mathcal{L}_\text{base}$ and then fine-tuned on $\mathcal{L}_\text{novel}$. The training on the two sets are similar. During each iteration, we randomly sample some images per class as support set and one image per class as query set. The images in the support set, together with their computed features via the entire recognition module, are fed into the view synthesis module to generate multiple images from different viewpoints. These synthesized images are used to augment the original support set to compute the prototypes. Then, the query images are used to update the parameters of the recognition module through $\mathcal{L}_{\text{rec}}$; the view-synthesis module is updated through $\mathcal{L}_{\text{GAN}}$, $\mathcal{L}_{\text{identity}}$ and $\mathcal{L}_{\text{cat}}$. The entire model is trained in an end-to-end fasion.
For the novel classes, we run five trials for each setting of \(k\). Matching Net (MN) is essentially a prototypical network \([36]\). We investigate the novel-view synthesis results under two metrics. The best few-shot recognition performance on the two datasets.

| Model      | Base     | Novel-\(k=1\) | Novel-\(k=5\) |
|------------|----------|---------------|---------------|
| MN \([36]\) | 58.04    | 47.31 ± 0.11  | 71.53 ± 0.15  |
| PMN \([37]\) | 57.99    | 48.02 ± 0.09  | 71.42 ± 0.17  |
| FBNet-rec  | 57.91    | 47.53 ± 0.14  | 71.26 ± 0.26  |
| FBNet-aug  | 58.03    | 47.20 ± 0.19  | 71.51 ± 0.33  |
| FBNet      | 59.43    | 48.39 ± 0.19  | 72.76 ± 0.24  |

| Model      | Base     | Novel-\(k=1\) | Novel-\(k=5\) |
|------------|----------|---------------|---------------|
| MN          | 44.79    | 23.62 ± 0.08  | 58.21 ± 0.05  |
| PMN         | 44.68    | 23.88 ± 0.06  | 58.39 ± 0.07  |
| FBNet-rec   | 44.56    | 23.97 ± 0.05  | 58.09 ± 0.19  |
| FBNet-aug   | 44.85    | 23.69 ± 0.08  | 58.40 ± 0.26  |
| FBNet       | 45.63    | 24.15 ± 0.07  | 58.98 ± 0.15  |

Table 1: Top-1 (%) recognition accuracy on the CUB and NAB datasets. Our FBNet consistently achieves the best performance for both base and novel classes.

4 Experimental Evaluation

Datasets: We use two datasets for our experiments: the Caltech-UCSD Birds (CUB) dataset which contains 202 classes with 11,788 images \([39]\), and the North American Birds (NAB) dataset which consists of 555 classes with 48,527 images \([35]\). These are challenging fine-grained recognition datasets for our dual-task. All the images are square-cropped using the given bounding boxes and resized to \(64 \times 64\). We randomly split the entire dataset into 75% as the training set and 25% as the test set. For CUB, 150 classes are selected as base classes and 50 as novel classes. For NAB, 350 classes are selected as base classes and 205 as novel classes. Note that we focus on simultaneous recognition and synthesis over all base or novel classes, which is significantly more challenging than typical 5-way classification over sampled classes in most of few-shot classification work \([29, 2]\).

Implementation Details: We set \(\lambda_{id} = 10\) and \(\lambda_{cat} = 1\) via cross-validation. We sample 5 images per class for \(C_{base}\) and 1 image for \(C_{novel}\). We use ResNet-18 as the feature extraction network, unless otherwise specified. To match the resolution of our data, we change the kernel size of the first convolution layer of ResNet from 7 to 5. Since the training process requires hundreds of examples at each iteration, which may not fit in the memory of our device, we made a trade-off to first train the feature extraction network through resolution distillation. Then we froze the parameters of it and train the other parts of the framework.

Compared Methods: Our feedback connections enable the two modules to leverage shared representations through joint training. Therefore, to verify the effect of the feedback connections, we focus on the following comparisons. For the novel-view image synthesis task, we compare our approach FBNet with the state-of-the-art method HoloGAN \([18]\). We also consider a variant of our approach FBNet-view, which has the same architecture of our novel-view synthesis module but takes the constant features extracted by a pre-trained ResNet-18 \([9]\) as latent input. FBNet-view can also be viewed as a conditional version of HoloGAN. For the few-shot recognition task, we compare our full model with its two variants: FBNet-rec inherits the architecture of our recognition module, which is essentially a prototypical network \([29]\); FBNet-aug trains the two modules individually, and uses the synthesized images as data augmentation for the recognition module. To have a better understanding of the improvements of the feedback connections, we also compare our approach with two effective few-shot recognition models: Matching Net (MN) \([36]\) and Proto-Matching Net (PMN) \([37]\). Note that while conducting comparisons with other view synthesis models (such as \([32, 34, 19, 28, 12, 43, 49]\)) and few-shot recognition models (such as \([2, 16, 6]\)) are interesting, this is not the main focus of our paper. We aim to validate that the bowtie architecture outperforms the single-task models upon which it builds. All the models are trained following the same few-shot setting described in Sec. 3.1.

4.1 Quantitative Results

Recognition: We present the top-1 accuracy for the base classes and the novel classes, respectively. Following \([37]\), we focus on the 1, 5-shot settings, where the number of examples per novel class \(k\) is 1 or 5. For the novel classes, we run five trials for each setting of \(k\), and report the average accuracy and standard deviation for all the approaches. Table 1 shows that our FBNet consistently achieves the best few-shot recognition performance on the two datasets.

Novel-View Synthesis: We investigate the novel-view synthesis results under two metrics. The FID score is calculated by computing the Fréchet distance between two Gaussians fitted to feature...
Table 2: Quantitative results of novel-view synthesis under the FID and IS metrics. ↑ indicates that higher is better, and ↓ indicates that lower is better. FBNet brings up to 18% improvement for FID and 19% for IS and consistently outperforms the baselines.

Figure 3: Synthesized images from multiple viewpoints for all the compared methods. Our approach captures the shape and attributes well even in the extremely low-data regime (1-shot).

representations of the Inception network [5]. The Inception Score (IS) seeks to capture both the quality and diversity of a collection of generated images [26]. A higher IS or a lower FID value indicates better realism of the generated images. A larger variance of IS indicates more diversity of the generated images. We generated images of random views in one-to-one correspondence with the training examples for all the models, and compute the IS and FID values based on these images. The results are reported in Table 2. Our FBNet consistently achieves the best performance among all the competing models under both metrics. Compared with HoloGAN, our method brings up to 18% improvement for FID and 19% for IS. However, IS and FID only measure the similarity between the synthesized images and the real images, they cannot effectively evaluate whether the generated images maintain the category-level identity and capture different viewpoints. To have a full understanding of the synthesized images, we also provide qualitative analysis in the next section.

4.3 Ablation Study

Categorical Loss: Our synthesis and recognition modules are connected partially through the categorical loss. To analyze its effect, we vary $\lambda_{cat}$ among 0 (without the categorical loss), 0.1, 1, and 5. Fig. 4 shows the quantitative and qualitative results on CUB. With $\lambda_{cat}$ increasing, the few-shot
recognition performance improves gradually. Meanwhile, a too large $\lambda_{cat}$ reduces the visual quality of the generated images: checkerboard noise appears. While these images are not visually appealing, they still benefit the recognition task. This shows that the categorical loss trades off the performance between the view synthesis and recognition, and there is a “sweet spot” between them.

View Synthesis Facilities Recognition: The comparison among FBNet-rec, FBNet-aug, and FBNet in Table 1 shows that our full FBNet equipped with the synthesis module outperforms the pure recognition model under ResNet-18 [9], and that the joint training of the two tasks is the key to improve the recognition performance. In fact, our approach is applicable to different recognition models. Table 3 shows the recognition performance with different feature extraction networks on CUB, where the performance of all the networks get improved.

Recognition Facilities View Synthesis: Comparing the quantitative and qualitative results among HoloGAN, FBNet-view, and FBNet in Table 1 and Fig. 3, we have the following observations. The synthesis results almost remain, when only changing the view synthesis model from unconditional to conditional versions. However, when we introduce the joint training with recognition through feedback connections, the quality and diversity of the generated images significantly improve. These results reflect the help of recognition to view synthesis and the effect of our feedback connections.

Resolution Distillation and Prototypical Classification: Our proposed resolution distillation reconciles the resolution inconsistency between the synthesis and recognition modules, and further benefits
from recognition models trained on high-resolution images. The prototypical network leverages the synthesized images and provided another feedback connection. We evaluate their effect by building two variants of our model without these techniques: ‘FBNet w/o Dist’ trains the feature extraction network directly from low-resolution images; ‘FBNet w/o Proto’ uses regular classification network instead of prototypical network. The result in the first two lines of Table 4 shows that the performance of full FBNet significantly outperforms these variants, verifying the importance of our techniques.

Comparison with Multi-task Learning of Shared Feature Representation: We also compare with the standard multi-task learning that learns shared feature representation across the dual-task. We achieve this by treating the feature extraction network as a component of view synthesis, and thus perform two tasks with the shareable feature extraction network without feedback connections. The last row in Table 4 shows that our generative modeling level sharing outperforms feature level sharing.

Extension–From Dual-Task to Triple-Task: The proposed bowtie network could also be extended to more than two tasks by introducing more feedback connections. For example, we add an image style transfer task combined with the novel-view synthesis task (Fig. 5). Note that slightly different from general style transfer tasks [7, 11, 46], our “styles” are manifested in attributes and the “content” keeps category-level consistency. We achieve it by arranging different latent inputs for 3D AdaIn modules and 2D AdaIN modules in the view synthesis module.

5 Conclusion

This paper proposed a feedback-based bowtie network for dual-task of few-shot recognition and novel-view synthesis. Our model consistently improves performance for both tasks, especially with extremely limited data. The proposed framework could be potentially extended to address more tasks, leading to a generative model useful and shareable across a wide range of tasks. As future work, we will explore broad application of multi-task oriented generative modeling for more visual tasks.

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