

Cross-modal Hallucination for Few-shot Fine-grained Recognition

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Abstract

State-of-the-art deep learning algorithms generally require large amounts of data for model training. Lack thereof can severely deteriorate the performance, particularly in scenarios with fine-grained boundaries between categories. To this end, we propose a multimodal approach that facilitates bridging the information gap by means of meaningful joint embeddings. Specifically, we present a benchmark that is multimodal during training (i.e. images and texts) and single-modal in testing time (i.e. images), with the associated task to utilize multimodal data in base classes (with many samples), to learn explicit visual classifiers for novel classes (with few samples). Next, we propose a framework built upon the idea of cross-modal data hallucination. In this regard, we introduce a discriminative text-conditional GAN for sample generation with a simple self-paced strategy for sample selection. We show the results of our proposed discriminative hallucinated method for 1-, 2-, and 5-shot learning on the CUB dataset, where the accuracy is improved by employing multimodal data.

1. Introduction

In recent years, deep learning techniques have achieved exceptional results in many domains such as computer vision (e.g. [9, 24]) and natural language processing (e.g. [11]). These advances can be explained by improvements to algorithms and model architecture along with increasing computational power, and growing availability of big data. The big data assumption is key for conventional deep learning applications but often also a limiting factor. Particularly for fine-grained recognition tasks, the existence of sufficient training samples is necessary [12]. However, for many applications, it is often too expensive or even impossible to acquire enough training samples in order to learn a

model at sufficient accuracy. Furthermore, the requirement for large amounts of training data is in stark contrast to human learning, which can quickly learn from few instances. This makes alternative learning approaches that require less training data an attractive research topic. For that reason, research in the domain of few-shot learning, i.e. learning and generalizing from few training samples, has gained more and more interest (e.g. [8, 16, 23, 25]). Specifically, most of the current works (e.g. [5]) have proposed meta-learning-based approaches. These assume the existence of some *base classes* with many training samples that can be used to learn powerful representations which, in turn, can be employed to perform classification on *novel classes* with only a few samples. However, research conducted has mainly focused on approaches with data coming from only one modality, primarily images. By overcoming the single-modality restriction and including data from additional modalities, limitations in the low data regime can be overcome, resulting in improved model performance. The key assumption is that incorporating multimodal data, i.e. images and fine-grained descriptions thereof, forces the model to identify highly discriminative features *across modalities*, facilitating training in few-shot scenarios. Specifically, pursuing multimodality suggests that novel concepts with low amount of training data in one modality can benefit from previously learned alignments between the two modalities, such that existing data in the additional modality (e.g. text) can compensate the lack of data in the other modality (e.g. image). This assumption leads to the proposed study of few-shot learning with multimodal data, more precisely images with fine-grained textual descriptions. The principal contribution of this paper is to extend few-shot learning to deal with multimodal data. Specifically, a scenario is assumed, that is multimodal during training (i.e. images and texts) and single-modal during testing time (i.e. images). Hence, the multimodal data is exploited during training, but the ultimate task remains to train an image classifier. We address this problem from a cross-modal generative perspective (e.g. [14, 15, 21, 30]), combining ideas from meta-

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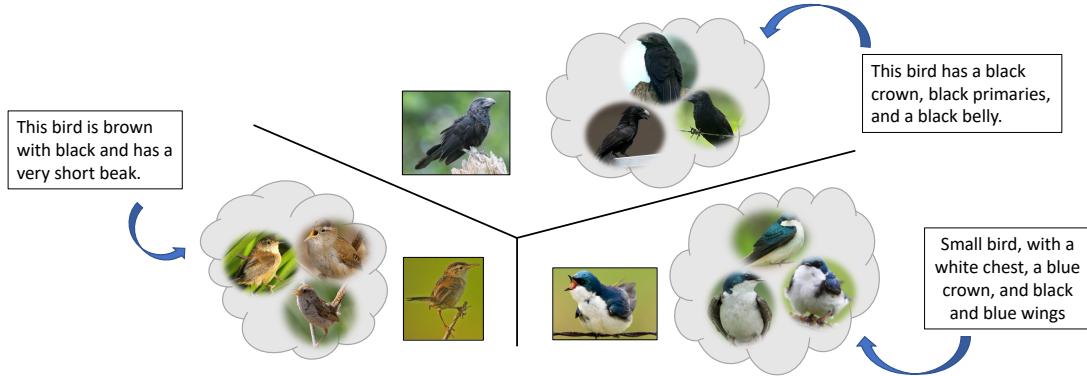


Figure 1. Learn classifier from dataset with a few samples per category extended by hallucinated data conditioned on textual descriptions

learning which have been put forward by Hariharan et al. [5] in conjunction with a simple self-paced learning strategy for sample selection. The intuition behind our method is that we generate additional training samples ([22, 32]) conditioned on textual descriptions that facilitate learning classification models in low data scenarios (see Fig. 1).

The most closely related work to the proposed approach is by Hariharan et al. [5] and Wang et al. [27], who similarly use hallucinated data for few-shot learning with the difference of the restriction to a single-modal image context. Analogously, Zhang et al. [30] and Reed et al. [18] proposed to use Generative Adversarial Networks (GANs) [4, 20] to generate images from textual descriptions. They, however, just employed it in a zero-shot fashion, ignoring a few number of samples available of novel classes.

Our contribution in this work is two-fold: **First**, we propose a benchmark for multimodal few-shot learning based on the challenging fine-grained visual recognition task that is multimodal during training and single-modal (i.e. images) during test time. **Second**, we develop a class-discriminative text-conditional generative adversarial network (tcGAN) that facilitates few-shot learning by hallucinating additional images conditioned on fine-grained textual descriptions. Our approach features robustness and outperforms the single-modality baseline in the challenging few-shot scenario on the fine-grained CUB dataset.

2. Related Work

Few-Shot Learning: For learning with limited amounts of data, Koch et al. [8] proposed a metric learning approach for which siamese convolutional networks were used in a one-shot learning scenario to rank the similarity of inputs. Other work seeks to avoid overfitting by modifications to the loss function or the regularization term. Yoo et al. [29] proposed a clustering of neurons on each layer of the network and calculated a single gradient for all members of a cluster during the training to prevent overfitting. A more

intuitive strategy is to approach few-shot learning on data-level, meaning that the performance of the model can be improved by finding strategies to enlarge the training data. For example, Douze et al. [1] proposed a semi-supervised approach in which a large unlabeled dataset containing similar images was included in addition to the original training set. Hariharan et al. [5] combined both strategies (data-level and algorithm-level) by defining the squared gradient magnitude (SGM) loss on the one hand and generating new images by hallucinating features on the other hand. Other recent approaches to few-shot learning have leveraged meta-learning strategies. Ravi et al. [16] trained a long short-term memory (LSTM) network as meta-learner that learns the exact optimization algorithm to train a learner neural network that performs the classification in a few-shot learning setting. Vinyals et al. [25] introduced matching networks for one-shot learning tasks. This network is able to apply an attention mechanism over embeddings of labeled samples in order to classify unlabeled samples. Snell et al. [23] proposed prototypical networks which can be interpreted as generalization for matching networks. Prototypical networks search for a non-linear embedding space in which classes can be represented as the mean of all corresponding samples, called a prototype and classification is performed by finding the closest prototype in the embedding.

Multi-modal Learning: By defining an encoder-decoder pipeline, Kiros et al. [7] proposed a method to align visual and semantic information in a joint embedding space. Faghri et al. [2] were able to improve this mixed representation by incorporated a triplet ranking loss. The work of Karpathy et al. [6] aims to generate image descriptions. Their model is able to infer latent alignments between regions of the image and segments of the sentences for the image description. Reed et al. [17] put their focus on fine-grained visual descriptions. They collected two datasets containing fine-grained visual descriptions and proposed a deep structured joint embedding that is end-to-end trainable.

Table 1. Comparison of few-shot learning tasks

Task	Base Classes	Novel Classes	Multimodal Training Data	Examples
Classic One-shot Learning	no	yes	no	[3, 10, 8]
Few-shot Learning with Meta-Learning	yes	yes	no	[16, 5, 23]
Multi-modal Few-shot Learning	yes	yes	yes	Ours

Conditional GANs: After the introduction of GANs by Goodfellow et al. [4], the conditional generation of data was investigated by Mirza et al. [13]. Reed et al. [19] further studied image synthesis based on textual information. Using multiple stacked GANs on top of each other, Han et al. [31] pushed the quality of the generated images to photorealistic high-resolution level by stacking multiple GANs. Following that work, many improvements have been suggested. While in the optimization of StackGAN [31] all GANs are trained successively, the same authors have developed an end-to-end trainable version, which they named StackGAN++ [30]. Further improvements include the incorporation of an attention mechanism over the textual input (Xu et al. [28]) and the usage of additional dialog data (Sharma et al. [21]).

3. Multimodal Few-shot Learning Benchmark

The goal is to build a benchmark for multimodal few-shot fine-grained recognition that mimics situations that arise in practice. Therefore, we propose a few-shot learning benchmark inspired by Hariharan et al. [5] and extend it to work with multimodal training data. Following their work, the idea is to model a few-shot learning framework which consists of multiple phases. The first phase can be used to learn a meaningful representation on a large training set (*representation learning phase*). In a next phase the learned representation can be applied and finetuned for novel categories with few samples (*few-shot learning phase*). This is in contrast to classical one-shot learning settings (e.g. [3, 10]) in which no base classes with many samples were available (see Tab. 1). To this end, let \mathcal{I} denote the image space, \mathcal{T} the text space and $\mathcal{C} = \{1, \dots, Y\}$ be the discrete label space. Further, let $x_i \in \mathcal{I} \times \mathcal{T}$ be the i -th input data point and $y_i \in \mathcal{C}$ its label. Following [5], two disjunct subsets of the label space are considered in order to setup a few-shot learning setting: $\mathcal{C}_{\text{base}}$, that are labels for which a large amount of data samples is available; and novel classes $\mathcal{C}_{\text{novel}}$ which are underrepresented in the data and just a few instances per category are accessible. Note that both subsets exhaust the label space \mathcal{C} , i.e. $\mathcal{C} = \mathcal{C}_{\text{base}} \cup \mathcal{C}_{\text{novel}}$. It can further be assumed that in general $|\mathcal{C}_{\text{novel}}| < |\mathcal{C}_{\text{base}}|$. This is necessary in order for being able to learn powerful representations. Furthermore, the data set \mathcal{S} is organized as followed: Training data $\mathcal{S}_{\text{train}}$ consists of tuples $\{(x_i, y_i)\}_{i=1}^n$ taken from

the whole data set with $y_i \in \mathcal{C}_{\text{base}} \cup \mathcal{C}_{\text{novel}}$. Hence, the training data is composed of $\mathcal{S}_{\text{train}} = \mathcal{S}_{\text{train}}^{\text{novel}} \cup \mathcal{S}_{\text{train}}^{\text{base}}$, where $\mathcal{S}_{\text{train}}^{\text{novel}} = \{(x_i, y_i) : (x_i, y_i) \in \mathcal{S}_{\text{train}}, y_i \in \mathcal{C}_{\text{novel}}\}_{i=1}^k \subset \mathcal{S}_{\text{train}}$ and $\mathcal{S}_{\text{train}}^{\text{base}} = \{(x_i, y_i) : (x_i, y_i) \in \mathcal{S}_{\text{train}}, y_i \in \mathcal{C}_{\text{base}}\}_{i=1}^{n-k} \subset \mathcal{S}_{\text{train}}$. Furthermore, in accordance with a few-shot scenario let $|\mathcal{S}_{\text{train}}^{\text{novel}}| \ll |\mathcal{S}_{\text{train}}^{\text{base}}|$. Contrary to the benchmark defined by Hariharan et al. [5] and other popular few-shot learning tasks, our scenario is multimodal in training (see Tab. 1). However, the testing phase is single-modal on image data of $\mathcal{C}_{\text{novel}}$. That means, the classifier is evaluated on image data only to fulfill the ultimate goal to train a visual classifier.

4. Method

The overall framework of the proposed method can be split into two phases: 1) representation learning in which a discriminative text-conditional GAN is trained to hallucinate images given a textual description and 2) a finetuning phase in which we learn to pick the most discriminative images out of the generated data with a self-paced sample selection strategy. Finally, we train a generic classifier.

4.1. Discriminative Text-Conditional GAN

Inspired by Wang et al. [27], we follow a meta-learning framework and learn a generative model on the large amount of data available in $\mathcal{C}_{\text{base}}$, then utilize it to learn a classifier for the limited samples related to $\mathcal{C}_{\text{novel}}$. Therefore, we built a text-conditional GAN (tcGAN) (e.g. [13, 18, 30]) to learn the mapping $\mathcal{T} \rightarrow \mathcal{I}$, such that the generator G is trained to produce outputs that cannot be distinguished from “real” images by an adversarially trained discriminator D , which is trained to do as well as possible at detecting the generators “fakes”. This allows for cross-modal sample generation, which facilitates few-shot learning by compensating the lack of data in $\mathcal{C}_{\text{base}}$.

The objective of a tcGAN from observed text T and image I can concisely be expressed as:

$$\begin{aligned} \mathcal{L}_{\text{tcGAN}}(G, D) = & \mathbb{E}_{I, T} [\log D(I, T)] \\ & + \mathbb{E}_{I, z} [\log D(I, G(T, z))], \end{aligned} \quad (1)$$

where z denotes a random noise vector, and T and I the embeddings for observed text and image respectively. In practice, we built our method on top of the StackGAN

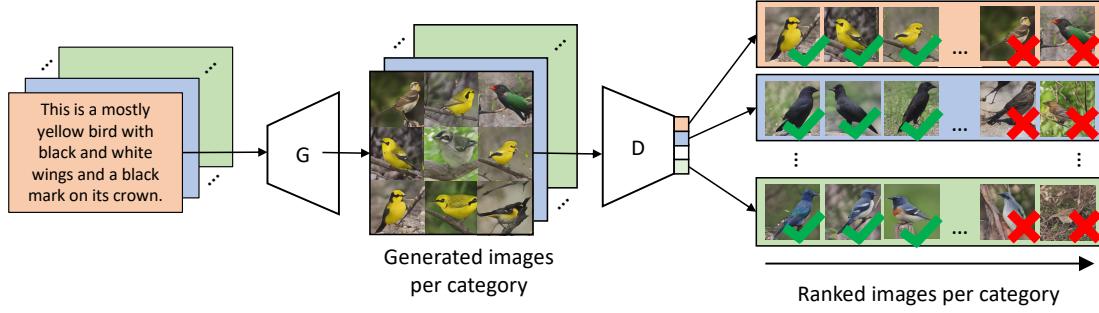


Figure 2. Selective image generation with tcGAN

framework proposed by Zhang et al. [30], which is a variant of tcGAN that features a robust pipeline for generating realistic images from fine-grained textual descriptions.

Optimization of the tcGAN loss \mathcal{L}_{tcGAN} alone, however, lacks class-discriminativeness. Therefore we augment \mathcal{L}_{tcGAN} by adding a class-discriminative term \mathcal{L}_{class} , which is defined as:

$$\mathcal{L}_{class}(D) = \mathbb{E}[P(C = c | I)], \quad (2)$$

where c denotes the class label. Furthermore, let

$$\mathcal{L}_{class}(D) = \mathcal{L}_{class}(G). \quad (3)$$

This leads to two loss terms:

$$\mathcal{L}(D) = \mathcal{L}_{tcGAN}(G, D) + \mathcal{L}_{class}(D) \quad (4)$$

and

$$\mathcal{L}(G) = \mathcal{L}_{tcGAN}(G) - \mathcal{L}_{class}(G), \quad (5)$$

which are optimized in alternative fashion, yielding D^* and G^* . It should be noted that whereas \mathcal{L}_{tcGAN} is trained on samples from \mathcal{C}_{base} , the compound loss is trained only on the (sub-)set of n training samples that are available within \mathcal{C}_{novel} . This provides us with the training of the tcGAN in a meta-learning fashion, where the cross-modal representation learned on the base classes, is later employed for the final class-discriminative few-shot learning task.

4.2. Self-paced Sample Selection

Training the text-conditioned GAN allows for the generation of a potentially infinite number of samples given textual descriptions using G^* . However, the challenge is to pick adequate samples out of the pool of generated samples that allow for building a better classifier within the fine-grained few-shot scenario. Such a subset of images should not only be realistic but also class-discriminative. To this end, we follow the *self-paced strategy* and select a subset of images corresponding to ones in which the generator is most confident about their “reality” and the discriminator is the most confident about their “class discriminativeness”.

Specifically, we use the score computed using D^* per category and sort generated images in a descending order using these scores. Then we select the first m top-most elements. Intuitively, we select a subset of the generated samples that the classifier trained on the real data is most confident about, as illustrated in Fig. 2. Finally, a convolutional neural network (CNN) is trained on the concatenated set of real images and those ones selected as the best generated class-discriminative images.

5. Experimental Results

For our experiments we use the CUB dataset [26], which contains 11,788 images of 200 different bird species. The data is split equally in training and test data, resulting in roughly 30 training and 30 test images per category. 10 short textual descriptions per image are provided by Reed et al. [17]. Following Zhang et al. [30] we use a pre-trained text-encoder [17] and split the data such that $|\mathcal{C}_{base}| = 150$, $|\mathcal{C}_{novel}| = 50$. To perform few-shot learning $n = \{1, 2, 5, 10, 20\}$ images of \mathcal{C}_{novel} are used for training, as proposed by Hariharan et al. [5]. For the sake of simplicity, a CNN with basic architecture is employed for classification, although any other classifier is applicable. It consists of two convolutional layers paired with max-pooling, followed by two linear layers that are connected with dropout completed with a softmax of $|\mathcal{C}_{Novel}|$ units. For training SGD is used for 800 epochs with a learning rate of 0.01 and momentum of 0.5. The experiments are composed of: **1) Single modality baseline (Baseline):** a baseline is evaluated, in which the classifier is trained exclusively on real samples. Thus, in the n -shot scenario, only n images are available per category. **2) Few-shot StackGAN baseline (StackGAN):** the generator G is obtained from the representation learning phase in which a StackGAN was trained. Then, G is employed to generate additional training images conditioned on one caption randomly chosen (out of 10) for the missing $m = 30 - n$ images of \mathcal{C}_{novel} . Following the notion of image generation conditioned on the chosen descriptions, the classifier is trained on an extended dataset that contains the few real images and the generated



Figure 3. Images for two different bird categories: a) real image data, b) data generated with StackGAN, c) data generated with StackGAN and ranked with D , d) data generated with StackGAN and ranked with D^* .

samples. **3) StGD baseline:** To show the importance of our proposed discriminative tcGAN, we generated a large amount of images for captions using the G of StackGAN and then rank these samples by the score of D (real vs. fake discriminative). To this end, samples with a low visual appearance are ranked low. Note that this experiment slightly differs from our method, as we proposed to employ D^* (class-discriminative) instead of D (real vs. fake) for the ranking. **4) Our proposed method (StGD *):** Similar to the previous baseline with the difference of employing the class-discriminative D^* for ranking generated images. Doing that, images are not picked based on their realistic appearance but on how class-discriminative they are. The top-5 accuracy of the classifier for our different experiments is reported in Tab. 2.

We observe that the proposed approach outperforms the baseline in the particular challenging few-shot scenarios with $n = 1, 2, 5$ by 4.9 to 8.6 percentage points, respectively. Additionally to commonly reported top-5 accuracy, we evaluated the experiments with top-1 and top-3 accuracy, observing a similar performance results. Using the score of D as measure to rank the generated images alone has shown not to be sufficient. However, enforcing class-discriminativeness within the discriminator leads to significantly higher accuracies. Our experiments confirm that multimodality allows to close the information gap in few-shot scenarios, yielding more robust classifiers.

Further, qualitative analysis by means of visualization of generated data (see Fig. 3) in our experiments confirms that images ranked high by D^* contain the most class-discriminative features (d). In contrast to that, only picking random descriptions as input for the tcGAN leads to

Table 2. Top-5 accuracy of our classifier for different training set-ups

Method	n				
	1	2	5	10	20
<i>Baseline</i>	19.9	24.8	36.8	49.2	70.6
<i>StackGAN [30]</i>	27.3	30.7	37.4	45.3	69.0
<i>Our (StGD)</i>	25.7	30.1	36.8	50.5	68.6
<i>Our (StGD*)</i>	28.5	31.6	41.7	52.2	68.5

an undesirable large variety of birds because many descriptions do not include sufficient class-discriminative information (b). Further, ranking on D produces realistic looking images, however, mixing categories (c).

6. Conclusion

In this paper, we proposed to extend few-shot learning for fine-grained recognition to deal with multimodal data and introduced a discriminative tcGAN for sample generation along with a self-paced strategy for sample selection. Experiments on our proposed benchmark demonstrate that learning generative models in a cross-modal fashion facilitates few-shot learning for fine-grained categories by compensating the lack of data in novel categories. For future work we plan to investigate the use of D^* as the final classifier. Furthermore, we seek to incorporate class-discriminativeness property at the representation learning stage jointly with the ranking loss of the self-paced stage.

References

- [1] M. Douze, A. Szelam, B. Hariharan, and H. Jgou. Low-shot learning with large-scale diffusion. *CVPR*, 2018. 2
- [2] F. Faghri, D. J. Fleet, J. R. Kiros, and S. Fidler. VSE++: Improving Visual-Semantic Embeddings with Hard Negatives. *arXiv:1707.05612 [cs]*, July 2017. 2
- [3] L. Fei-Fei, R. Fergus, and P. Perona. One-shot learning of object categories. *IEEE transactions on pattern analysis and machine intelligence*, 28(4):594–611, 2006. 3
- [4] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio. Generative adversarial nets. In *Advances in neural information processing systems*, pages 2672–2680, 2014. 2, 3
- [5] B. Hariharan and R. Girshick. Low-shot Visual Recognition by Shrinking and Hallucinating Features. In *ICCV*, 2017. 1, 2, 3, 4
- [6] A. Karpathy and L. Fei-Fei. Deep visual-semantic alignments for generating image descriptions. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3128–3137, 2015. 2
- [7] R. Kiros, R. Salakhutdinov, and R. S. Zemel. Unifying Visual-Semantic Embeddings with Multimodal Neural Language Models. *arXiv:1411.2539 [cs]*, Nov. 2014. arXiv: 1411.2539. 2
- [8] G. Koch, R. Zemel, and R. Salakhutdinov. Siamese neural networks for one-shot image recognition. In *ICML Deep Learning Workshop*, volume 2, 2015. 1, 2, 3
- [9] A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, pages 1097–1105, 2012. 1
- [10] B. Lake, R. Salakhutdinov, J. Gross, and J. Tenenbaum. One shot learning of simple visual concepts. In *Proceedings of the Cognitive Science Society*, volume 33, 2011. 3
- [11] G. Lample, M. Ballesteros, K. Kawakami, S. Subramanian, and C. Dyer. Neural architectures for named entity recognition. In *Proc. NAACL-HLT*, 2016. 1
- [12] A. Li, Z. Lu, L. Wang, T. Xiang, X. Li, and J.-R. Wen. Zero-shot fine-grained classification by deep feature learning with semantics. *arXiv preprint arXiv:1707.00785*, 2017. 1
- [13] M. Mirza and S. Osindero. Conditional generative adversarial nets. *arXiv preprint arXiv:1411.1784*, 2014. 3
- [14] A. Mishra, M. S. K. Reddy, A. Mittal, and H. A. Murthy. A generative model for zero shot learning using conditional variational autoencoders. *CoRR*, abs/1709.00663, 2017. 1
- [15] A. Mishra, V. K. Verma, M. S. K. Reddy, A. Subramaniam, P. Rai, and A. Mittal. A generative approach to zero-shot and few-shot action recognition. *2018 IEEE Winter Conference on Applications of Computer Vision (WACV 2018)*, pages 372–380, 2018. 1
- [16] S. Ravi and H. Larochelle. Optimization as a model for few-shot learning. In *International Conference on Learning Representations (ICLR)*, 2017. 1, 2, 3
- [17] S. Reed, Z. Akata, H. Lee, and B. Schiele. Learning deep representations of fine-grained visual descriptions. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 49–58, 2016. 2, 4
- [18] S. Reed, Z. Akata, X. Yan, L. Logeswaran, B. Schiele, and H. Lee. Generative adversarial text to image synthesis. In M. F. Balcan and K. Q. Weinberger, editors, *Proceedings of The 33rd International Conference on Machine Learning*, volume 48 of *Proceedings of Machine Learning Research*, pages 1060–1069. PMLR, 2016. 2, 3
- [19] S. Reed, Z. Akata, X. Yan, L. Logeswaran, B. Schiele, and H. Lee. Generative adversarial text to image synthesis. In *Proceedings of The 33rd International Conference on Machine Learning*, pages 1060–1069, 2016. 3
- [20] T. Salimans, I. Goodfellow, W. Zaremba, V. Cheung, A. Radford, and X. Chen. Improved techniques for training gans. In *Advances in Neural Information Processing Systems*, pages 2234–2242, 2016. 2
- [21] S. Sharma, D. Suhubdy, V. Michalski, S. E. Kahou, and Y. Bengio. Chatpainter: Improving text to image generation using dialogue. *ICLR Workshop*, 2018. 1, 3
- [22] L. Sixt, B. Wild, and T. Landgraf. Rendergan: Generating realistic labeled data. *arXiv preprint arXiv:1611.01331*, 2016. 2
- [23] J. Snell, K. Swersky, and R. Zemel. Prototypical Networks for Few-shot Learning. In *Advances in Neural Information Processing Systems 30*, pages 4080–4090. 2017. 1, 2, 3
- [24] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, A. Rabinovich, J.-H. Rick Chang, et al. Going deeper with convolutions. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015. 1
- [25] O. Vinyals, C. Blundell, T. Lillicrap, D. Wierstra, et al. Matching networks for one shot learning. In *Advances in Neural Information Processing Systems*, pages 3630–3638, 2016. 1, 2
- [26] C. Wah, S. Branson, P. Welinder, P. Perona, and S. Belongie. The Caltech-UCSD Birds-200-2011 Dataset. Technical Report CNS-TR-2011-001, California Institute of Technology, 2011. 4
- [27] Y.-X. Wang, R. Girshick, M. Hebert, and B. Hariharan. Low-Shot Learning from Imaginary Data. In *CVPR*, 2018. 2, 3
- [28] T. Xu, P. Zhang, Q. Huang, H. Zhang, Z. Gan, X. Huang, and X. He. AttnGAN: Fine-grained text to image generation with attentional generative adversarial networks. *CVPR*, 2018. 3
- [29] D. Yoo, H. Fan, V. N. Boddeti, and K. M. Kitani. Efficient K-Shot Learning with Regularized Deep Networks. In *Association for the Advancement of Artificial Intelligence (AAAI) 2018*. 2
- [30] H. Zhang, T. Xu, H. Li, S. Zhang, X. Wang, X. Huang, and D. Metaxas. Stackgan++: Realistic image synthesis with stacked generative adversarial networks. *arXiv: 1710.10916*, 2017. 1, 2, 3, 4, 5
- [31] H. Zhang, T. Xu, H. Li, S. Zhang, X. Wang, X. Huang, and D. Metaxas. Stackgan: Text to photo-realistic image synthesis with stacked generative adversarial networks. In *ICCV*, 2017. 3
- [32] X. Zhu, Y. Liu, Z. Qin, and J. Li. Data augmentation in emotion classification using generative adversarial networks. *CoRR*, 2017. 2