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Generative Data Augmentation

Multi-Agent Diverse Generative Adversarial Networks for Generative Data Augmentation

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Abstract

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1 Introduction and Motivation

Generative Adversarial Networks (GANs) [GPAM+14] and their variants revolutionized the field of computer vision in the year of 2014, enabling advacements in multiple areas of generating data. From *Text to Image Synthesis* [RAY+16], *Image Translation* [IZZE18], *Super Resolution* [LTH+17], *Image Inpainting* [PKD+16], *Style Transfer* [WWR+23] to *Data Augmentation* [SK19], GANs have been used in a variety of applications.

The idea of using GANs for *Generative Data Augmentation* (GDA) has already been applied sucessfully, e.g.: in computer vision [JLR25], [BNI+23] or for creating music [JLY20]. Especially the former survey *A Comprehensive Survey of Image Generation Models Based on Deep Learning* has, along *Variational Auto Encoders* (VAEs), a dedicated focus on GANs. Despite these achievements, in practice, GANs suffer from several challenges, complicating the training and inference process:

- Mode Collapse
- Lack of inter-class Diversity
- Failure to Converge
- Vanishing Gradiants & Unstable Gradiants
- Imbalance between Generator- and Discriminator Model

This thesis investigates the potential of using GANs - specifically *Multi-Agent Diverse Generative Adversarial Networks* (MADGANs) [GKN+18] - for Generative Data Augmentation. MADGANs aim to aid the first two of the afore mentioned in particular: Mode Collapse and Loss of inter-class Diversity. They, along other modifications, "*propose to modify the objective function of the discriminator, in which, along with finding the real and the fake samples, the discriminator also has to correctly predict the generator that generated the given fake sample.*" [GKN+18]. The goal of this adjustment of the discriminator is, that the discriminator has to push the generators towards distinct identifiable modes. While various strategies have been proposed to addrese mode collapse and inter-class diversity MADGANs explicitly enfocre mode seperation by introduction of multiple generators and the adjusted discriminator objective. This makes them particularly promising for GDA, as diverse samples and clear distinction of modes is crucial for training robust classifiers. In their paper, they experimentally show, that their architectural adjustment of GANs is generally capable of giving providing assistance for the first two of the mentioned problems.

The experiments in this work are structured into three major parts.

Set 1: Training and Analysis of GANs The first set trains and analyses GANs, explicitly MADGANs and *Conditional GANs* (cGANs). Here, the quality of the resulting images during training will be scored by the *Fréchet Inception Distance* (FID) [HRU+18] and the *Inception Score* (IS) [SGZ+16].

Set 2: Generating and Classifying Unlabeled Images The second set uses the afore trained generative models to create images. Images without labels—images originating from MADGANs—will be classified using auxiliary classifiers trained with traditional data augmentation techniques.

Set 3: Training and Evaluating Classifiers The third and most significant set of experiments trains classifiers using the generated data. For this, stratified classifiers with differing numbers of real and fake images are trained and evaluated on the respective validation set. Their classification performance will be assessed using standard metrics. [1]

All of the above described is executed on the following datasets:

- MNIST [LCB10]
- Fashion MNIST [XRV17]
- CIFAR10 [Kri09]

Aim of the Thesis This thesis evaluates the effectiveness of Multi-Agent Diverse GANs for Generative Data Augmentation. First, the quality of their generated samples is compared to those produced by a Conditional GAN. Next, both sets of generated images are used to augment training datasets for classifiers, which are then assessed on their respective test sets. Classifiers trained on cGAN-augmented data and those trained with traditional augmentation techniques — such as flipping, rotation, and noise addition — serve as baselines for comparison. By doing so, this study examines the impact of MADGAN-based augmentation on classifier performance, highlighting its advantages and limitations relative to conventional methods and cGAN-based augmentation.

[1] The set of metrics used to assess the quality of the resulting classifiers is defined in chapter Experiments Setup 5.

2 Related Work

The effectiveness of deep learning models is instrinsically linked to the availability of large and diverse datasets for training. Models with deep and complex architectures require extensive exposure to a wide range of data to learn underlying patterns and generalize well to unseen instances. Insufficient training data can lead to a phenomena called *overfitting*, where a model becomes too specializied to the training data, failing to perfom accurately on previously unencountered data [Yin19].

To mitigate the problem of data scarcity and improve generalization capabilities of deep learning models, data augmentation techniques became indispensable. Data augmentation artificially expands the amounts and diversity of training datasets by creating modified versions of existing data or by generating entirely new instances.

Traditional Data Augmentation

Traditional data augmentation on images typically involves applying various tranformations to existing data. For image based data, augmentations can take a variaty of forms such as [2] : *Geometric Augmentation*, *Photometric Augmentation*, *Noise-Corruption Augmentation* 3.2.1.

The sucess of the above mentioned augmentation techniques is established in many papers [PW17], [KSH12a], [Yin19], [SK19], [WZZ+13].

Generative Data Augmentation using Deep Convolutional GANs

The basic GAN framework introduced by Goodfellow and collegues offers a high degree of flexibility and can be adapted for specific augmentation tasks. It can be applied to generate music [DHYY17], speech [LMWN22], text [YZWY17], images [GPAM+14] or other instances of data, e.g. tabular data [XSCIV19].

Especially for image data, *Deep Convolutional GANs* (DCGANs) [RMC16] represent a significant advacement in applying GANs to iamge data augmentation [HFM22]. Their architecture specifically utilizes *Convolutional Neural Network* (CNNs) [LBD+89] in both, the generator and the discriminator. The use of CNNs allows DCGANs to learn hierarchical features from the input images and capture the spatial relationship and structure inherent in images. This leads to the generation of more realistic and coherent synthetic images. A study from Zhau et al. [ZCWD23] applied DCGANs, along their adjusted version of those on multiple dataset, including *Fashion MNIST* and *Cifar10*. With their experimental setup, they achieved consistent significant improvements over multiple datasets using the DCGAN-architechture, compared to their baseline.

[2] More categories of traditional data augmentation techniques exists, such as Occlusion-Based, Composition-Based, Domain-Specific or Adversarial Augmentation. For the purpose of this work, soley the afore mentioned are discussed in greater detail.

Inherently in the vanilla version of GANs or the DCGANs realization of using convoltional layers, the generators role is soley to learn the underlying data distribution of the training samples and produce instances of close resemblance to instances from the training data. This however results in unlabeled samples, not to be beneficial to expand data for a supervised classification task.

Generative Data Augmentation using Conditional GANs

The introduction of *Conditional Generative Adversarial Networks* (cGANs) [MO14] allows to condition the generative process by additional information, such as class labels or other modalities. The conditioning acts on both the generator and the discriminator, which means that both models have access to the same conditional information. The generator combines the random vector input and the conditioning information into a joint hidden representation. The discriminator, on the other hand, evaluates the created data from generator, given context of the conditining information, i.e. the class label passed. This approach enables the generator to create data that adheres to specific inputs, like creating specific digits from the MNIST dataset 1. Multiple papers were able to utilize the advantages of cGANs, to e.g. unify class distributions for a stratified classifier training or generatively increase the number of images and augmenting the training data[JPB22][ZCWD23][RCF25][WM21].

Generative Data Augmentation using MADGANs

Regardless of the mentioned sucesses using GANs (DCGANs or cGANs) for GDA 2 2, GANs in general have proven to be notoriously hard to train. "*Among them, mode collapse stands out as one of the most daunting ones.*" [DCLK20], which limits the GANs ability to generate diverse samples, able to be assigned to all classes trained on. Another prominent problem with GANs is the Lack of inter-class diversity between generated samples.

MADGANs [GKN+18] emphasis on diversity, achieved through its multi-agent architecture and the modified discriminator objective function, directly addresses these limitations. By encouraging multiple generators to specialize in different modes of the data distribution, MADGAN aims to generate a more comprehensive and diverse set of synthetic samples compared to traditional GANs and potentially other generative data augmentation techniques that might be susceptible to mode collapse. The ability of MADGAN to disentangle different modalities i.e. classes, as suggested by experiments involving diverse-class datasets, indicates its potential to generate augmented data that effectively covers both intra-class and inter-class variations. This comprehensive coverage is crucial for training robust image classifiers that can generalize well to a wide range of real-world scenarios.

3 Theoretical Background

This chapter serves as a reference for the theoretical background necessary to understand the insights gained in the following experimental chapters. Section 3.1 discusses classification models used to train on the extended dataset resulting from the generative augmentation process. In it, *Neural Networks* (NNs) for image classification are introduced and the baselines for later comparisons are examined. Sections 3.2 and 3.2.2 establish the foundation for data augmentation and generative data augmentation. Following sections 3.3, 3.4, 3.5, and 3.6 provide theoretical knowledge necessary to understand the GAN architectures and their differences. The narrative follows their increasing complexity, starting from vanilla GANs, moving through deep convolutional GANs and conditional GANs, before diving into the background of multi-agent diverse GANs. The final section (3.7) explains the theory behind the Inception Score and Fréchet Inception Distance, concluding with an examination of the state-of-the-art *InceptionV3* model used to compute them.

3.1 Image Classification Models

3.1.1 Neural Networks for Classification

Convolutional Neural Networks (CNNs) have become the dominant architecture for image classification tasks due to their inherent ability to automatically learn hierarchical features from raw pixel data. At their core, CNNs are build up by a sequence of convolutional-, pooling- and fully connected layers to extract hierarchical features, and funneling the information, typically into the N classes defined by the training data. Convolutional layers employ learnable filters to detect local patterns in the two-dimensional information - two dimensional in the case of images specifically. Pooling layers reduce the spatial dimensions to small translations. Fully connected layers then map the extracted information into class probabilities, utilizing the *Softmax* activation function. The afore mentioned layers are discussed in greater detail, in the following subsections.

Convolutional Layers TODO: here is a nice place for a ref to [DV18] These layers compute the output from the local regions of the input. Let $(r \times c)$ be the two-dimensional input, e.g., a grayscale image, where r represents the X-coordinate and c the Y-coordinate of a pixel. Thus, $r \cdot c$ denotes the size of the image. Furthermore, let $(a \times b)$ be a filter with kernel size $a \cdot b$, where the filter is smaller than the input. This filter is moved from the top-left to the bottom-right over the input.

In each iteration, the dot product between the respective coefficients of the input region and the coefficients of the filter is computed. This dot product is then processed by the activation function g, which determines how much of the feature is present. If

the activation function is ReLU, for example, only positive values are retained, meaning negative responses are set to zero. The result is written to the subsequent layer.

The stride determines how far the filter is moved after each operation. For a stride of $s = 1$, the filter can be placed in $(r-a+1)$ positions along the height and $(c-b+1)$ positions along the width, leading to an output size of $(r - a + 1) \times (c - b + 1)$. In general, the output size in the two-dimensional case is given by:

$$\left(\frac{r-a+s}{s}\right) \times \left(\frac{c-b+s}{s}\right).$$

An image of this process can be found in Figure X in the Appendix (7). This image shows an input of size $[10 \times 10]$ and a filter of size $[3 \times 3]$. With a stride of $s = 1$, the resulting layer has a size of $[8 \times 8]$ (computed as $(10 - 3 + 1) \times (10 - 3 + 1)$).

The stride of the filter can also be greater than 1. Additionally, there is the option to apply padding to the image. There are different ways to implement padding. When padding of size p is applied, the output size for a square input and filter is calculated as follows:

$$\textbf{Output size} = \left\lfloor \frac{r-a+2p}{s} \right\rfloor + 1$$

where $\lfloor \cdot \rfloor$ denotes the floor function, which ensures that the output size is an integer.

Pooling Layers A pooling layer compresses the data along the spatial axes to reduce its dimensionality. Similar to the convolutional layer, a pooling layer uses a filter that moves by the stride value. However, instead of summing the covered elements, the pooling operation applies the Max operator, selecting the maximum value within the filter's region.

For example, starting with an input of size $[32 \times 32 \times 10]$, applying a pooling operation with a $[2 \times 2]$ filter and a stride of 2 results in an output size of $[16 \times 16 \times 10]$. This operation reduces the spatial dimensions by half while keeping the depth unchanged.

Max pooling helps retain the most important features, providing some invariance to small translations or distortions in the input, which is crucial for tasks like object recognition in convolutional neural networks (CNNs).

Fully-Connected Layers Fully-Connected (FC), also called *Dense* layer, typically computes the scores for the respective classes. In the case of ten classes, the result is a volume of size $[1 \times 1 \times 10]$[3]. By this stage, all spatial information has been transformed, leaving a quasi-one-dimensional vector containing the ten class scores for the CIFAR-10 dataset.

In a FC layer, each input is connected to each output, meaning every neuron in the

[3]Typically, the output from the layer before the FC one is "flattened" into a one-dimensional vector, preserving all information but removing spatial structure. For example, a $[2 \times 2]$ layer would become a vector of size $[1 \times 4]$.

previous layer is connected to each neuron in the FC layer. The output is the weighted sum of all inputs, followed by an activation function, leading to the final classification scores that represent the likelihood of the input belonging to each class. The spatial dimensions are collapsed into a single vector of class scores, which are then used for classification.

Batch Normalization Layers With their introduction in "*Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift*" by Ioffe et al. [IS15], Batch Normalization (batchnorm) is an integreal part of convolutional networks. These layers normalize the inputs to subsequent layers and theirby stability the distribution of activations throughout the training process. This reduces the internal covariate shift, allowing for higher learning rates and faster convergence. By normalization of activation, batchnorm helps prevent gradients from vanishing or exploding. Additionally, it can provide regularization benefits and eliminate the need for Dropout, in some cases. With the afore mentioned benefits, batchnorm layers are particularily beneficial for deep learning networks with many layers.

Typical Activation Functions for CNNs

- **ReLU (Rectified Linear Unit)**:

$$g(x) = \max(0, x) \tag{1}$$

  ReLU is the most widely used activation function in CNNs. It introduces nonlinearity while maintaining efficiency by outputting zero for negative values and passing positive values unchanged.

- **Leaky ReLU**:

$$f(x) = \begin{cases} 0 & \text{if } x < 0 \\ x & \text{otherwise} \end{cases} \tag{2}$$

  A variant of ReLU, Leaky ReLU allows small negative values to flow through, addressing the "dying ReLU" problem where neurons can become inactive.

- **Sigmoid (Logistic)**:

$$g(x) = \frac{1}{1 + e^{-x}} \tag{3}$$

  The sigmoid function squashes values between 0 and 1, commonly used for binary classification tasks. However, it can suffer from vanishing gradients for very large or small inputs.

- **Tanh (Hyperbolic Tangent)**:

$$g(x) = \frac{2}{1 + e^{-2x}} - 1 \tag{4}$$

Tanh outputs values between -1 and 1 and is similar to the sigmoid but with a wider output range, making it more effective in many scenarios compared to sigmoid.

- **Softmax**:

$$g(x_i) = \frac{e^{x_i}}{\sum_j e^{x_j}} \tag{5}$$

Softmax is typically used in the output layer of CNNs for multi-class classification. It converts logits into probabilities, ensuring that the sum of the outputs is 1.

3.1.2 Classification Models for augmented Training

The classification models, on which the data augmentation is tested, are simple CNN classifiers consisting of the described layers. For each dataset MNIST, Fashion MNIST and CIFAR10 1, a dedicated classifier architecture is created. The main differences between these architectures is the number of blocks, made of two-dimensional convolutional, batchnorm and pooling layers. All three models use a use the ReLU function for activation of the convolutional layers and the Softmax function for the activation at their respective output layer, resulting in probability distribution over the space of classes. More on the specifical model architectures can be found in chapter 4.

3.2 Data Augmentation

In this chapter, DA techiques in the context on images are discussed is greater detail. Starting with traditional augmentations e.g. rotating or cropping an image, ending on generative augmentations for which generative models are used to expand the training data of subsequent models.

3.2.1 Traditional Data Augmentation

The need for data augmentation to make classification algorithms more resilient has existed for decades. Early papers mentioning the augmentation of data for classification tasks date back to the 1970s [NS67]. For the context of deep learning, however, the augmentation of images was popularized by Krizhevsky et al. in 2012 [KSH12b], with the introduction of *AlexNet*—a deep CNN used to classify images from the *ImageNet* dataset [DDS+09], containing 1000 classes. This paper also referenced the earlier work of Simard et al. from 2003 [SSP03].

Generally speaking, traditional data augmentation techniques can be described as enlarging the initial training data by applying transformations that preserve the respective labels of individual instances. These techniques solely focus on modifying already existing data without creating entirely new instances (see: 3.2.2). Augmentations are categorized based on the type of transformations applied:

Geometric Augmentation This category modifies the shape, position, and perspective: Rotation, Scaling, Flipping, Cropping, Shearing, Perspective Transform.
Photometric Augmentation Alters pixel values while keeping the spatial structure: Brightness, Contrast, Hue Shift, Blurring.
Noise-Corruption Augmentation Imitates real-world degradations and distortions caused by cameras and sensors: Gaussian Noise, Speckle Noise, Salt-and-Pepper Noise.

Mathematically, let X be an original data sample drawn from the dataset distribution $P(X)$. Traditional data augmentation applies a transformation function $f : X \mapsto \tilde{X}$, where f is a function sampled from a predefined set of augmentation operations $\mathcal{F}$. The augmented data sample $\tilde{X}$ is then given by:

$$\tilde{X} = f(X), \quad f \sim \mathcal{F}.$$

Since TDA does not create entirely new data points but modifies existing ones, the distribution of augmented samples $P_{\tilde{X}}$ should ideally remain close to the original data distribution:

$$P_{\tilde{X}}(X) \approx P(X).$$

In the context of data augmentation pipelines, this can be generalized as:

$$\text{TDA} : (X, f) \mapsto \tilde{X}, \quad f \in \mathcal{F}.$$

When applying the augmentations shown in Figure 1, it is mandatory to consider domain-specific knowledge and constraints. For example, flipping images from the MNIST dataset to train a generative model may result in an image where a horizontally flipped "9" appears, which, in the domain of Arabic numerals, is semantically incorrect. Conversely, when classifying an airplane, which can have varying shapes, colors, three-dimensional orientations in space, and images taken through a dusted lens, applying all of the above augmentations could be beneficial.

3.2.2 Generative Data Augmentation

Differing from the previously mentioned TDA 3.2.1, GDA does not focus on altering existing data instances but rather on creating entirely new samples that match the underlying data distribution of the training data. These generated instances may or may not include labels.

The goal is to train a generative model G that produces instances X_1, for example, from a noise vector z, such that the distribution of the generated data approximates the true distribution $P(X)$ of the original dataset. In this context, G can be viewed as a function:

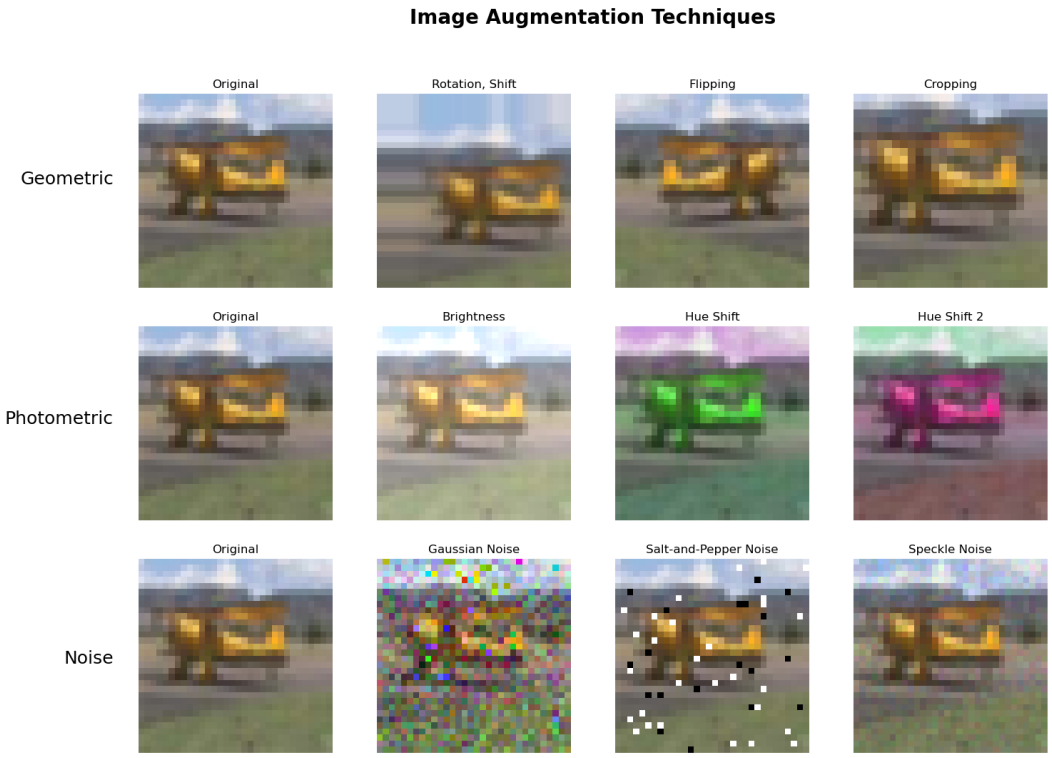

Figure 1: Exemplary use of traditional augmentation techniques from the categories *geometric* (first row), *photometric* (second row), and *noise-corruption* (third row).

$$G : z \mapsto X_1, \quad X_1 \sim P_G(X) \approx P(X),$$

where $P_G(X)$ is the learned distribution of the generative model, aiming to approximate the real data distribution $P(X)$.

In the case of *conditional* generative data augmentation, additional information such as class labels y is incorporated into the generation process. This allows the model to generate samples corresponding to specific categories within the data. The conditional generative model G then follows:

$$G : (z, y) \mapsto X_1, \quad X_1 \sim P_G(X \mid y) \approx P(X \mid y),$$

where $P_G(X \mid y)$ represents the learned conditional distribution, aiming to approximate the real class-conditioned data distribution $P(X \mid y)$. This enables targeted data generation for specific categories, enhancing data diversity while maintaining class consistency.

3.3 Generative Adversarial Network

Generative Adversarial Network (GANs) have first been introduced by Goodfellow at al. in 2014 [GPAM+14] GANs are a type of generative models designed to learn the underlying data distribution of their training data and generate new, realistic instances.

The core idea of the framework is an adversarial training process between two NNs: the textitGenerator G and the *Discriminator* D, competing against one another in a minimax game [Neu28].

3.3.1 Mathematical Formulation

Let $X \sim P_{data}$ be samples drawn from the real data distribution, and let $z \sim P_z$ be random noise sampled from a known prior (e.g., a Gaussian or uniform distribution). The generator G is a function $G : \mathbb{R}^d \to \mathbb{R}^n$ that maps a noise vector z to a synthetic data instance $\tilde{X}$, attempting to approximate P_{data}:$\tilde{X} = G(z), \quad z \sim P_z$.

The discriminator D is a function $D : \mathbb{R}^n \to [0, 1]$ that outputs the probability that a given sample is real rather than generated. It is trained to distinguish between real samples $X \sim P_{data}$ and generated samples $\tilde{X} \sim P_G$, where P_G is the implicit distribution induced by G.

The training objective is formulated as the following minimax game:

$$\min_G \max_D \mathbb{E}_{X \sim P_{data}}[\log D(X)] + \mathbb{E}_{z \sim P_z}[\log(1 - D(G(z)))]. \tag{6}$$

Here, the discriminator D aims to maximize the probability of correctly classifying real and fake samples, while the generator G aims to generate samples that fool D, minimizing $\log(1 - D(G(z)))$. In an ideal scenario, the game converges to a Nash equilibrium where G produces samples indistinguishable from real data, i.e., $P_G \approx P_{data}$.

3.3.2 Training Process

GAN training follows an alternating optimization approach:

1. Update D: Given a batch of real samples from P_{data} and fake samples generated by G, update D to maximize its ability to discriminate real from fake data.

2. Update G: Generate new fake samples and update G to minimize $\log(1 - D(G(z)))$, effectively pushing G to generate more realistic samples.

3. Repeat the process iteratively, typically using stochastic gradient descent (SGD) or Adam optimization.

3.3.3 Challenges in GAN Training

Following, challenges that can occur during the training of gans are discussed. These have already been mentioned in the introductionary section 1. Here, they are described in greater detail.

Mode Collapse Mode collapse occurs when the generator produces only a small subset of the data distribution, leading to a lack of diversity. Instead of generating varied samples, it repeatedly produces similar ones that fool the discriminator. This happens when the generator finds an easy "shortcut" rather than learning the full distribution. More formally, G collapses many values of z to the same value of x [GPAM+14]. A common technique to mitigate this issue is minibatch discrimination [SGZ+16].

Lack of Inter-Class Diversity Even if mode collapse is avoided, GANs may struggle to generate samples that represent all data classes equally. This is a common issue in class-conditional GANs, where samples across different classes may overlap or lack distinct features. Causes include imbalanced datasets, poor class conditioning, or weak discriminator feedback [OOS17].

Failure to Converge Unlike traditional neural networks, GANs follow an adversarial training process, making optimization highly unstable. The loss functions of both the generator and discriminator change dynamically, often leading to non-convergent behavior. Methods like Wasserstein GANs (WGAN) [ACB17] and spectral normalization [MKKY18] improve stability and help achieve better convergence.

Vanishing & unstable Gradients When the discriminator becomes too strong, it perfectly distinguishes real from fake samples, leading to vanishing gradients for the generator. This prevents meaningful updates, stalling progress. On the other hand, unstable gradients cause erratic updates, preventing smooth learning. Alternative loss functions (e.g., LSGANs [MLX+17]) and spectral normalization help stabilize training.

Imbalance between Generator and Discriminator A well-balanced GAN requires both models to improve at a similar pace. If the discriminator overpowers the generator, training halts. If it's too weak, the generator receives poor feedback and produces low-quality outputs [GPAM+14]. Balancing techniques include adaptive learning rates, gradient penalties, and label smoothing [RMC16].

3.4 Deep Convolutional Generative Adversarial Network

Deep Convolutional Generative Adversarial Networks (DCGANs) were introduced by Radford et al. in 2015 [RMC16] as an improvement over vanilla GANs. While the

fundamental adversarial framework remains the same (see 3.3 Mathematical Formulation, 3.3 Training Procecss), DCGANs leverage deep convolutional neural networks to enhance stability and generate higher-quality images.

3.4.1 Architectural Improvements

To improve training stability and image quality, DCGANs implement the use of convolutional layers.

- **Convolutional Architecture:** Fully connected layers in both G and D are replaced with deep convolutional layers, enabling better spatial feature extraction.
- **Strided Convolutions:** In the discriminator, pooling layers are removed in favor of strided convolutions, reducing the risk of information loss.
- **Transposed Convolutions:** The generator employs transposed convolutions (also known as fractionally-strided convolutions) instead of upsampling layers to improve the quality of generated images.
- **Batch Normalization:** Applied to both G and D, batchnorm helps stabilize training by reducing internal covariate shift 3.1.1. Batchnorm is omitted in the generator's final layer to allow unrestricted output variability and in the discriminator's input layer to preserve the original data distribution.
- **LeakyReLU Activation:** The discriminator uses LeakyReLU instead of standard ReLU to prevent dying neurons and allow gradients to flow through negative inputs 3.1.1.
- **No Fully Connected Layers:** Fully connected layers are removed to maintain spatial coherence in generated images, as they discard spatial information by flattening feature maps. Instead, convolutional layers preserve local structures, enabling more realistic image synthesis 3.1.1.

3.5 Conditional Generative Adversarial Network

3.6 Multi-Agent Diverse Generative Adversarial Network

3.7 Image Scores

3.7.1 Inception Score

3.7.2 Fréchet Inception Distance

3.7.3 InceptionV3 for Image Evaluation

4 Preliminary Remarks

5 Experiments Setup

6 Experiments Results

Motivation

7 Outlook

repair networks [TFNL22]

Measure the resulting diversity between the generatoed samples using the MS-SSIM scores [OOS17]; they did that as well

8 Conclusion

Data generated by a GAN, may it be a cGAN or a MADGAN, may not fully capturethe distribution characteristics of its training data. Though, generated images do visually appear realistic, they may only partially reflect the statistical characteristics of the original data. This can lead to synthetic images that appear *good* to a human inspector, but may contain amounts of noice that may interfere with a subsequent classifier.

from an information theorativa l standpoint, a generative model G trained on data X, distilling knowledge into a classifier C should not offer more information that what was already present in X.

Future research could focus on directly evaluating the impact of using MAD-GAN generated samples for augmenting various image classification datasets across different domains and comparing the resulting performance gains with those achieved by traditional and other generative augmentation techniques. Exploring methods to exert more control over the types of variations generated by MAD-GAN to specifically target weaknesses or improve the robustness of classifiers against particular types of noise or adversarial attacks would also be a valuable direction. Additionally, investigating the computational efficiency and scalability of training MAD-GAN for very large and complex datasets in the context of practical data augmentation pipelines would be crucial for its wider adoption. Finally, exploring the applicability of the MAD-GAN framework to generate diverse augmented data for other computer vision tasks beyond image classification, as well as for other data modalities such as natural language processing or audio processing, could further broaden its impact. The work by Ghosh et al. on Multi-Agent Diverse GANs represents a promising step towards leveraging the power of generative models for more effective and robust data augmentation in image classification and beyond.

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Appendix

Declaration of Academic Integrity

Generative Data Augmentation

Multi-Agent Diverse Generative Adversarial Networks for Generative Data Augmentation.

I hereby declare that I have written this thesis independently. I have properly cited all passages that are taken verbatim or in essence from published or unpublished works of others. All sources and aids used in the preparation of this thesis have been fully acknowledged. Furthermore, this thesis has not been submitted, in whole or in substantial part, to any other examination authority for academic credit.

Signiture :

Place, *Date* :