Hochschule der Medien

Fakultät für Druck und Medien

Computer Science and Media

Generative Data Augmentation

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

**Dissertation submitted for the degree of
Master of Science**

Topic: Generative Data Aufmentation

Author: Nicolas Reinhart - nr063@hdm-stuttgart.de
                        MatNr. 44100

Version of Date: March 26, 2025

1. Advisor: Prof. Dr.-Ing. Johannes Maucher
2. Advisor: Prof. Dr.-Ing. Oliver Kretzschmar

Abstract

asdf

Contents

List of Figures

List of Tables

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
- Loss 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 Modifying the shape, position and perspective: Rotation, Scaling, Flipping, Cropping, Shearing, Perspective Transform.

Photometric Augmentation Altering the pixel values while keeping the spatial structure: Brightness, Contrast, Hue Shift, Noise Injection, Blurring.

Noise-Corruption Augmentation Imitating real-world degradations and distorions of cameras and sensors: Gaussion Noise, Speckle Noise, Salt-and-Pepper Noise.

The sucess of the above mentioned augmentation techniques is established in many papers [PW17], [KSH12], [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) 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

---

[2]More 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.

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.

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] .

3 Theoretical Background

4 Preliminary Remarks

5   Experiments Setup

6 Experiments Results

Motivation

7 Outlook

repair networks [TFNL22]

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 theoratival 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.

List of References

[BNI+23] BISWAS, Angona ; NASIM, MD Abdullah A. ; IMRAN, Al ; SEJUTY, Anika T. ; FAIROOZ, Fabliha ; PUPPALA, Sai ; TALUKDER, Sajedul: *Generative Adversarial Networks for Data Augmentation.* https://arxiv.org/abs/2306.02019. Version: 2023

[DHYY17] DONG, Hao-Wen ; HSIAO, Wen-Yi ; YANG, Li-Chia ; YANG, Yi-Hsuan: *MuseGAN: Multi-track Sequential Generative Adversarial Networks for Symbolic Music Generation and Accompaniment.* https://arxiv.org/abs/1709.06298. Version: 2017

[GKN+18] GHOSH, Arnab ; KULHARIA, Viveka ; NAMBOODIRI, Vinay ; TORR, Philip H. S. ; DOKANIA, Puneet K.: *Multi-Agent Diverse Generative Adversarial Networks.* https://arxiv.org/abs/1704.02906. Version: 2018

[GPAM+14] GOODFELLOW, Ian J. ; POUGET-ABADIE, Jean ; MIRZA, Mehdi ; XU, Bing ; WARDE-FARLEY, David ; OZAIR, Sherjil ; COURVILLE, Aaron ; BENGIO, Yoshua: *Generative Adversarial Networks.* https://arxiv.org/abs/1406.2661. Version: 2014

[HFM22] HUANG, Y. ; FIELDS, K. G. ; MA, Y.: A Tutorial on Generative Adversarial Networks with Application to Classification of Imbalanced Data. In: *Statistical Analysis and Data Mining* 15 (2022), Nr. 5, S. 543–552. http://dx.doi.org/10.1002/sam.11570. – DOI 10.1002/sam.11570

[HRU+18] HEUSEL, Martin ; RAMSAUER, Hubert ; UNTERTHINER, Thomas ; NESSLER, Bernhard ; HOCHREITER, Sepp: *GANs Trained by a Two Time-Scale Update Rule Converge to a Local Nash Equilibrium.* https://arxiv.org/abs/1706.08500. Version: 2018

[IZZE18] ISOLA, Phillip ; ZHU, Jun-Yan ; ZHOU, Tinghui ; EFROS, Alexei A.: *Image-to-Image Translation with Conditional Adversarial Networks.* https://arxiv.org/abs/1611.07004. Version: 2018

[JLR25] JUN LI, Wei Z. Chenyang Zhang Z. Chenyang Zhang ; REN, Yawei: A Comprehensive Survey of Image Generation Models Based on Deep Learning. In: *Annals of Data Science* 12 (2025), February, 141–170. http://dx.doi.org/10.1007/s40745-024-00544-1. – DOI 10.1007/s40745–024–00544–1

[JLY20] JI, Shulei ; LUO, Jing ; YANG, Xinyu: *A Comprehensive Survey on Deep Music Generation: Multi-level Representations, Algorithms, Evaluations, and Future Directions.* https://arxiv.org/abs/2011.06801. Version: 2020

[JPB22] JEONG, Jason ; PATEL, B. ; BANERJEE, I.: GAN augmentation for multiclass image classification using hemorrhage detection as a case-study. In: *Journal of Medical Imaging (Bellingham, Wash.)* 9 (2022), Nr. 3, S. 035504. http://dx.doi.org/10.1117/1.JMI.9.3.035504. – DOI 10.1117/1.JMI.9.3.035504

[Kri09]   KRIZHEVSKY, Alex: *Learning Multiple Layers of Features from Tiny Images*. Technical Report, University of Toronto. `https://www.cs.toronto.edu/~kriz/learning-features-2009-TR.pdf`. Version: 2009

[KSH12]   KRIZHEVSKY, Alex ; SUTSKEVER, Ilya ; HINTON, Geoffrey E. ; PEREIRA, F. (Hrsg.) ; BURGES, C.J. (Hrsg.) ; BOTTOU, L. (Hrsg.) ; WEINBERGER, K.Q. (Hrsg.):   *ImageNet Classification with Deep Convolutional Neural Networks*.   `https://proceedings.neurips.cc/paper_files/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b-Paper.pdf`. Version: 2012

[LBD+89]   LECUN, Y. ; BOSER, B. ; DENKER, J. S. ; HENDERSON, D. ; HOWARD, R. E. ; HUBBARD, W. ; JACKEL, L. D.:   Backpropagation Applied to Handwritten Zip Code Recognition. In: *Neural Computation* 1 (1989), Nr. 4, S. 541–551. `http://dx.doi.org/10.1162/neco.1989.1.4.541`. – DOI 10.1162/neco.1989.1.4.541

[LCB10]   LECUN, Yann ; CORTES, Corinna ; BURGES, CJ: MNIST handwritten digit database. In: *ATT Labs [Online]. Available: http://yann.lecun.com/exdb/mnist* 2 (2010)

[LMWN22]   LI, Xiaomin ; METSIS, Vangelis ; WANG, Huangyingrui ; NGU, Anne Hee H.: *TTS-GAN: A Transformer-based Time-Series Generative Adversarial Network*. `https://arxiv.org/abs/2202.02691`. Version: 2022

[LTH+17]   LEDIG, Christian ; THEIS, Lucas ; HUSZAR, Ferenc ; CABALLERO, Jose ; CUNNINGHAM, Andrew ; ACOSTA, Alejandro ; AITKEN, Andrew ; TEJANI, Alykhan ; TOTZ, Johannes ; WANG, Zehan ; SHI, Wenzhe: *Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network*. `https://arxiv.org/abs/1609.04802`. Version: 2017

[MO14]   MIRZA, Mehdi ; OSINDERO, Simon: *Conditional Generative Adversarial Nets*. `https://arxiv.org/abs/1411.1784`. Version: 2014

[PKD+16]   PATHAK, Deepak ; KRAHENBUHL, Philipp ; DONAHUE, Jeff ; DARRELL, Trevor ; EFROS, Alexei A.: *Context Encoders: Feature Learning by Inpainting*. `https://arxiv.org/abs/1604.07379`. Version: 2016

[PW17]   PEREZ, Luis ; WANG, Jason: *The Effectiveness of Data Augmentation in Image Classification using Deep Learning*. `https://arxiv.org/abs/1712.04621`. Version: 2017

[RAY+16]   REED, Scott ; AKATA, Zeynep ; YAN, Xinchen ; LOGESWARAN, Lajanugen ; SCHIELE, Bernt ; LEE, Honglak: *Generative Adversarial Text to Image Synthesis*. `https://arxiv.org/abs/1605.05396`. Version: 2016. – arXiv:1605.05396

[RCF25]   RIBAS, Lucas C. ; CASACA, Wallace ; FARES, Ricardo T.: Conditional Generative Adversarial Networks and Deep Learning Data Augmentation: A Multi-Perspective Data-Driven Survey Across Multiple Application Fields and Classification Architectures. In: *AI* 6 (2025), Nr. 2. `http://dx.doi.org/10.3390/ai6020032`. – DOI 10.3390/ai6020032. – ISSN 2673–2688

[SGZ+16] SALIMANS, Tim ; GOODFELLOW, Ian ; ZAREMBA, Wojciech ; CHEUNG, Vicki ; RADFORD, Alec ; CHEN, Xi: *Improved Techniques for Training GANs.* https://arxiv.org/abs/1606.03498. Version: 2016

[SK19] SHORTEN, Connor ; KHOSHGOFTAAR, Taghi M.: A survey on Image Data Augmentation for Deep Learning. In: *Journal of Big Data* 6 (2019), July, Nr. 1, 60. http://dx.doi.org/10.1186/s40537-019-0197-0. – DOI 10.1186/s40537–019–0197–0. – ISSN 2196–1115

[TFNL22] TANNO, Ryutaro ; F.PRADIER, Melanie ; NORI, Aditya ; LI, Yingzhen: Repairing Neural Networks by Leaving the Right Past Behind. (2022), 07, S. 19. http://dx.doi.org/10.48550/arXiv.2207.04806. – DOI 10.48550/arXiv.2207.04806

[WM21] WICKRAMARATNE, S. D. ; MAHMUD, M. S.: Conditional-GAN Based Data Augmentation for Deep Learning Task Classifier Improvement Using fNIRS Data. In: *Frontiers in Big Data* 4 (2021), S. 659146. http://dx.doi.org/10.3389/fdata.2021.659146. – DOI 10.3389/fdata.2021.659146

[WWR+23] WANG, Hanyu ; WU, Pengxiang ; ROSA, Kevin D. ; WANG, Chen ; SHRIVASTAVA, Abhinav: *Multimodality-guided Image Style Transfer using Cross-modal GAN Inversion.* https://arxiv.org/abs/2312.01671. Version: 2023

[WZZ+13] WAN, Li ; ZEILER, Matthew ; ZHANG, Sixin ; LE CUN, Yann ; FERGUS, Rob ; DASGUPTA, Sanjoy (Hrsg.) ; MCALLESTER, David (Hrsg.): *Regularization of Neural Networks using DropConnect.* https://proceedings.mlr.press/v28/wan13.html. Version: 17–19 Jun 2013 (Proceedings of Machine Learning Research)

[XRV17] XIAO, Han ; RASUL, Kashif ; VOLLGRAF, Roland: *Fashion-MNIST: a Novel Image Dataset for Benchmarking Machine Learning Algorithms.* 2017

[XSCIV19] XU, Lei ; SKOULARIDOU, Maria ; CUESTA-INFANTE, Alfredo ; VEERAMACHANENI, Kalyan: *Modeling Tabular data using Conditional GAN.* https://arxiv.org/abs/1907.00503. Version: 2019

[Yin19] YING, Xue: An Overview of Overfitting and its Solutions. In: *Journal of Physics: Conference Series* 1168 (2019), feb, Nr. 2, 022022. http://dx.doi.org/10.1088/1742-6596/1168/2/022022. – DOI 10.1088/1742–6596/1168/2/022022

[YZWY17] YU, Lantao ; ZHANG, Weinan ; WANG, Jun ; YU, Yong: *SeqGAN: Sequence Generative Adversarial Nets with Policy Gradient.* https://arxiv.org/abs/1609.05473. Version: 2017

[ZCWD23] ZHAO, Gaochang ; CAI, Zhao ; WANG, Xin ; DANG, Xiaohu: GAN Data Augmentation Methods in Rock Classification. In: *Applied Sciences* 13 (2023), Nr. 9, S. 5316. http://dx.doi.org/10.3390/app13095316. – DOI 10.3390/app13095316

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* :