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 22, 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 Netwrorks (GANs) [GPAM+14] and their variants revolution-ized 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 statigies have been proposed to adresse mode collapse and inter-class diversity MADGANs explicitly enfore 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 first two of the mentioned problems.

The experiments in this work are structured in to three major parts. 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]. The secoond set uses the afore trained generative models to create images. Images without

labels - images originating from MADGANs - will be classified using auxilary classifiers trained using classical data augmentation techniques. 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 and their classification performance will be assesed 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   The aim of the thesis is to investigate the potential use of MADGANs for GDA and compare their performance against traditional data augmentation techniques. Traditional techniques involve altering operation on the training images, such as flipping, rotating, cropping images, altering their contrasts and adding a small amount of noise to them.

---

[1]The set of metrics used to asses the quality of the resulting clasifiers 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:

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, Compression Artifacts, Salt-and-Pepper Noise.

[2]

The sucess of the above mentioned augmentation techniques is established in many papers [PW17], [KSH12], [Yin19], [SK19], [WZZ+13].

---

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

3 Preliminary Remarks

4 Theoretical Background

5 Experiments Setup

6 Experiments Results

Motivation

7 Outlook

repair networks [TFNL22]

8 Conclusion

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

[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

[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

[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

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

[LTH+17] LEDIG, Christian ; THEIS, Lucas ; HUSZAR, Ferenc ; CABALLERO, Jose
; CUNNINGHAM, Andrew ; ACOSTA, Alejandro ; AITKEN, Andrew ; TE-
JANI, 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

[PKD+16] PATHAK, Deepak ; KRAHENBUHL, Philipp ; DONAHUE, Jeff ; DARRELL,
Trevor ; EFROS, Alexei A.: *Context Encoders: Feature Learning by In-
painting.* 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, Lajanu-
gen ; SCHIELE, Bernt ; LEE, Honglak: *Generative Adversarial Text to
Image Synthesis.* https://arxiv.org/abs/1605.05396. Version: 2016.
– arXiv:1605.05396

[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

[WWR+23] WANG, Hanyu ; WU, Pengxiang ; ROSA, Kevin D. ; WANG, Chen ;
SHRIVASTAVA, Abhinav: *Multimodality-guided Image Style Transfer us-
ing 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

[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

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* :