MSc Project - Reflective Essay

Project Title:	Class Conditioned Data Augmentation for FashionMNIST Dataset using Conditional DCGAN
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Introduction:

My motivation to obtain first-hand experience and a deeper knowledge of generative adversarial networks drove my decision to pursue the research project on "class-conditional data augmentation using DCGANs". I wanted to acquire practical knowledge about leveraging AI to synthesize images, which I saw as an emerging technology with a multitude of promising applications. The FashionMNIST dataset available online fitted perfectly with the project as it was not complex and had greyscale images with low tensor shape, which allowed me to test the conditional DCGAN effectively with requiring less time to train.

By creating, training, and testing my own image-generating Generative Adversarial Network (GAN) architecture from the bottom up, I knew I would acquire essential direct knowledge of the intricacies and complexity of using this technique. The process of designing the entire augmentation pipeline required me to engage intimately with several important difficulties. To improve the quality and diversity of the GAN's generated outputs, I had to experiment with optimisation tactics, thorough hyperparameter tuning, and iterative architecture alterations.

During training, I encountered typical GAN issue of unstable oscillation loss values, which provided insights into the delicate balance required for stable adversarial training dynamics. Dealing with these difficulties helped me better comprehend the finely tuned interplay between the generator and discriminator models that underlie GANs. Rather than employing a pre-trained GAN off the shelf, I built my own architecture from scratch, involving myself in the practical complexities of training generative adversarial networks. The first-hand experience shed light on the inner workings of GANs, common issues, and best practices for synthesising customised synthetic image data.

Another important motivator for my participation in this project was enhancing the augmentation of imbalanced classes within datasets, which leads to the creation of biased models. These biases not only reduce the model's prediction accuracy but also its ability to capture properties for underrepresented groups. With a resolve to confront this challenge head-on, my objective was to leverage augmentation techniques to effectively amplify class labels that were underrepresented. This pursuit naturally led me to further delve into the topic of conditional Generative Adversarial Networks (cGANs), which emerged as a viable option for creating targeted and balanced data augmentations of specific class labels in a dataset.

Analysis of relation between theory and practical implementation:

The implementation of a conditional DCGAN for class-based data augmentation necessitated a close integration of theoretical knowledge and practical experimentation on my part. Theoretical research laid the groundwork for a development of a conditional GAN architecture, but the practical implementation of these approaches revealed critical details that went beyond the principles reported in the research studies. Despite the fact that studies mentioned the general issue of training instability with GANs, I had no idea how tough it would be to achieve convergence and image quality with my GAN model design. To guide the extensive hyperparameter tuning necessary, I drew significantly on theoretical studies of strategies used to improve GANs.

In addition to instability, hands-on experimentation uncovered diversity flaws that weren't apparent from theory alone. The conditional augmented images lacked variation throughout each class, it became clear after I started building the model and qualitatively analysing the results. For instance, instead of displaying variety, the generated shoes always had the same design pattern. I would not have been inspired to look into these extra ideas if I had not witnessed how the lack of diversity showed up in practice. The practical experience demonstrated that multimodal diversity could not be achieved by conditioning alone, inspiring additional theoretical investigation and hyperparameter tuning.

The back-and-forth between theoretical study and actual troubleshooting was critical in this project. Simply said, theory gave guidance, but it was through practical application that I learnt the complexities of training DCGAN's conditional adversarial network. This experience amply illustrated the limitations of textbook knowledge when not supplemented by hands-on practice.

Analysis of strengths and weaknesses:

The use of Conditional DCGANs for image data augmentation was an exciting approach to try that displayed creativity and innovativeness in image synthesis. This approach generated diverse and class-specific images, which could improve the robustness and generalisation capabilities of machine learning models trained on this enriched data.

Furthermore, the project's use case can be to overcome the difficulty of insufficient dataset diversity by creating extra fake images that varied in comparison to the original dataset. This variety is critical for training machine learning models that may be able to correctly categorise a wide range of labels, resulting in improved model performance.
In the context of classification problems, there may be an imbalance in the class labels within the dataset, with certain labels being more frequent than others, resulting in the creation of a biased model. Conditional DCGAN's customised nature promptly solves this by creating class-specific images, effectively supplementing our dataset with images that capture the particular traits of each fashion item class. By directing the augmentation towards specific classes, we can improve not only the accuracy of models trained on our augmented dataset but also their capacity to generalise to different items in the dataset. This augmentation strategy can reduce the risks associated with challenging classes being overlooked or incorrectly classified, improving our model's ability to recognise even the most underrepresented classes.

My interest on adopting cutting-edge AI approach in my project is highlighted by my foray into the field of Generative Networks. Immersing myself in GAN technology provided me with significant insights into the architecture, training complexities, and adversarial learning issues inherent in GANs. This endeavour was about more than just learning GANs; it was about developing a deeper grasp of how GANs deal with the generation of realistic data. The expertise I gained goes beyond this project, enhancing my ability to contribute to a wide range of future AI projects.

While the conditional DCGAN I implemented had the potential to generate fashion item images, their quality was not always on par with the original dataset. I noticed blurriness and discrepancies in image information, which may limit the utility of these enhanced images in training high-quality models.

The resource-intensive aspect of training Deep Convolutional Generative Adversarial Networks (DCGANs) was also one of the limitation in the project, limiting evaluation of overall project strategy. Mitigating this obstacle needs improvements to model training efficiency, where more powerful GPUs can offer a viable option for relieving computational restrictions. By optimising training methods and leveraging sophisticated hardware capabilities, the project can overcome resource consumption constraints and accelerate its potential for significant outcomes.

Apart from that, my project's impact on downstream tasks, such as the performance of a fashion item classification model, was quite limited. A more thorough evaluation would have given me a better grasp of how the generated dataset from the GAN may affect model accuracy and generalisation. While my experiment highlighted the promise of conditional DCGANs for data augmentation, I discovered several areas for development, particularly in improving generated image quality, lowering resource needs, and conducting a comprehensive evaluation on the influence on downstream activities. Resolving these issues would increase the feasibility and benefit of employing DCGANs for dataset augmentation in production scenario.

Possibilities for further work:

If I had more time to continue research on conditional GANs, there are several directions I would pursue to try to improve the quality and diversity of generated images.

Firstly, to promote convergence and reduce instability over time, I would try training the GAN model for significantly more epochs. Due to resource limitations, the model was only trained for 200 epochs. As the generator and discriminator have more time to evenly match in competence, operating for numerous more epochs may produce more stable training dynamics and higher-quality outputs.

Secondly, I would look into more sophisticated GAN architectures that have the potential to produce high-fidelity images. For instance, self-Attention GANs (SAGANs) employ attention processes to more accurately simulate the global context and remote dependencies in images (Zhang et al.,2018). Similar to this, BigGANs has shown a remarkable ability to produce realistic photos using deep models (Brock et al.,2019). The potential use of these cutting-edge methods may push the limits and possibly improve image quality while training.

Finally, in order to enhance the stability and convergence of the training process, I would have experimented with many adversarial loss functions and regularization techniques. The utilization of Wasserstein GANs in conjunction with an Earth Mover distance measure offers a potential approach to mitigate issues such as mode collapse and vanishing gradients (Arjoskyet al.,2017). Moreover, the incorporation of consistency regularization terms into CT-GANs (Drakopoulos al.,2020) has demonstrated the capability to enhance the stability of adversarial training, which is a technique that I might consider implementing in my project as well.

Social Ethical Issues pertaining to use of GANs:

In recent years, there has been a significant growth in the field of Generative AI models, resulting in notable improvements. The advancements in artificial intelligence (AI) technology have resulted in a wide range of applications that encompass several sectors. Significantly, the field of generative models specifically designed for images has had a similar increase in popularity, proving to be useful in several industries.

Within the scope of this research project, the primary focus is on the use of Generative Adversarial Networks (GANs) for the purpose of image generation. However, it is important to note that this endeavour is limited by the employment of a very small dataset, namely the 'FashionMNIST' dataset, which only consists of grayscale images. Notwithstanding these constraints, the fundamental model used in this project has the possibility for expansion in order to generate more complex and realistic RGB images, hence indicating its capacity for wider creative outcomes.

The breakthroughs in generative technology have revealed encouraging progress; yet, it is crucial to realize the possible consequences. In addition to their ability to optimize and improve the processes, these innovations also present a paradoxical nature. The power to generate new and advantageous products is accompanied by the potential to unintentionally produce detrimental and ethically complex things. Therefore, it is crucial to adopt a well-rounded strategy that incorporates moral and ethical issues in both the creation and implementation of these technologies. The deliberate approach employed in this project guarantees that the potential of modern technologies to bring about significant changes is effectively utilized for the betterment of society, while simultaneously advising and mitigating any negative implications on societal and ethical aspects.

Conclusion:

This essay offered a concise summary of the research project's learning process and its underlying motivations. It provided a thorough analysis of the interaction between theoretical constructs and their application. It also analysed the project's inherent strengths and shortcomings, casting light on potential future research avenues. In addition, the essay delves into the social and ethical implications of Generative Adversarial Networks (GAN) application.

References:

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