Project Proposal
Image Restoration

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Abstract

In this project, we aim to explore the potential of alternative sampling techniques to enhance the diversity and quality of image generation in diffusion models. By applying strategically designed masks and altering the underlying data distributions, we intend to investigate how sampling diversity impacts the generative process. Our hypothesis is that incorporating more diverse and tailored sampling strategies will lead to better representations and more nuanced image outputs. This study will evaluate the proposed methods using quantitative metrics of diversity and quality, as well as qualitative analysis, to validate their effectiveness in improving the capabilities of diffusion-based image generation networks.

Introduction

Image generation has emerged as a pivotal application in machine learning, with generative models achieving remarkable success in tasks spanning art, design, and medical imaging. Diffusion networks, in particular, have gained prominence for their ability to produce high-quality and detailed images by modeling the iterative denoising process. However, the sampling strategies employed during training and generation phases often fail to capture the full diversity of the underlying data distribution. This limitation constrains the generative model's ability to produce truly representative and creative outputs. This project proposes to address this gap by implementing alternative sampling techniques that leverage masked distributions to encourage more meaningful diversity in the generated images.

Background, Related Work, and Motivation

Recent advancements in diffusion models, such as Denoising Diffusion Probabilistic Models (DDPM) and Denoising Score Matching (DSM), have demonstrated their efficacy in image synthesis. Most of these methods rely on standard sampling approaches that, while effective, do not adequately account for diversity or the nuances of specific data characteristics. Prior studies have suggested that data augmentation and tailored sampling can improve generative performance, but few have explored how alterations to the data distribution or masking strategies might influence outcomes.

Motivated by the success of approaches that prioritize diversity, such as Diverse Data Augmentation (DDA) and Subpopulation Modeling, we wish to propose a systematic or unsystematic exploration of sampling strategies that apply dynamic masks to the data distribution. By explicitly incorporating diversity into the sampling process, we aim to enhance the diffusion network's ability to generalize and produce more varied image outputs. This work will build upon existing methodologies while contributing new insights into the intersection of masked data processing and generative image modeling.

Furthermore, the idea behind all these came from a paper named "From Posterior Sampling to Meaningful Diversity in Image Restoration". Moreover, we will use the already coded material in their github repository at: `https://github.com/noa-cohen/MeaningfulDiversityInIR` which is in line with its corresponding paper[1].

Methodology

The proposed methodology involves the following key steps:

1. **Mask Design and Distribution Alteration:** We will design various types of masks to selectively highlight or suppress certain regions of the data distribution. These masks will be crafted to amplify underrepresented features and reduce redundancy in the sampling process.

2. **Integration with Diffusion Networks:** The diffusion model's sampling procedure will be adapted to integrate masked data inputs. Modifications to the network's training loop will ensure the model can effectively learn from the altered distributions.

3. **Evaluation Metrics:** At the end we must come up with a metric ti validate the diversity of our modified diffusion model such as Fréchet Inception Distance (FID) and Inception Score (IS) that are used in GANs, as well as metrics that capture diversity, such as Pairwise Similarity and Coverage Rate.

4. **LoRA**: if we had time we would also take our time to investigate ways to fine tune the saved diffusion model that we are using for sampling tasks in order to get better results.

Requirements

To accomplish this project, we will require computational resources capable of handling deep learning tasks, such as GPUs with sufficient memory for training large diffusion models. Additionally, access to diverse datasets, such as ImageNet or CIFAR-10(presumably CIFAR-10 for the sake of less parameters and less computations), will be essential for validating our methods.

References

[1] Noa Cohen, Hila Manor, Yuval Bahat, and Tomer Michaeli. *From posterior sampling to meaningful diversity in image restoration*. Published as a conference paper at ICLR 2024. Available at: arXiv:2310.16047.

[2] Yuyang Hu, Mauricio Delbracio, Peyman Milanfar, and Ulugbek S. Kamilov. *A Restoration Network as an Implicit Prior*. Available at: arXiv:2310.01391.