Implementing Research Paper
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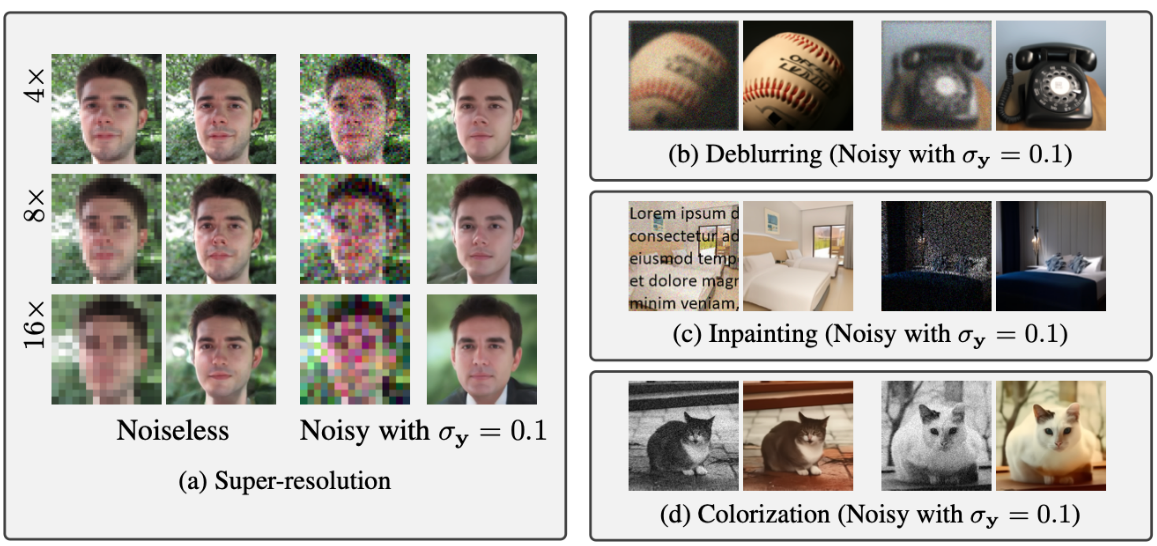
Denoising Diffusion Restoration Models

This paper discusses the use of diffusion models to restore a corrupted image [linear inverse problem]. Before we start, a small insight into why existing algorithms are not optimal - recent approaches use stochastic algorithms that sample from the posterior distribution of natural images given the degraded image, i.e, the probability distribution of original image given the degraded image.

However these methods come with two problems

- Efficient solutions require problem-specific supervised training model to model the posterior
- Unsupervised methods are generally not problem specific & rely on inefficient iterative methods

To overcome these limitations, this paper introduces an efficient, unsupervised posterior sampling method, called **Denoising Diffusion Restoration Models**. It takes advantage of a pre-trained denoising diffusion generative model for solving any linear inverse problem. Furthermore, the paper demonstrates the versatility of their approach on several images for **super-resolution, deblurring, inpainting, colorization, and compressive sensing** under different amounts of measurement noise. The paper also mentions on how **DDRM** approach outperforms the current leading unsupervised methods on the ImageNet dataset in reconstruction quality, perceptual quality and runtime [5 times faster than nearest competitor]



Some interesting results from DDRM paper

Key references :

- NeurIPS 2022 : DDRM – The supplemental section contains theoretical derivations & results
- NeurIPS 2022 : DDRM Paper – Link to the paper on which this project is based on
- Code – This repository by one of the authors of the paper, contains the code and instructions needed to reproduce the results of the paper

Relationship to team member's background :

- My interests lie along robotics and autonomous vehicles, currently I'm working with foundation models to generate optimal policies and use methods like conformal prediction to quantify the uncertainty in these predictions, so these methods can be used with confidence in real life
- With the recent advance in the generative ai community with Diffusion models, especially with applications like trajectory generation and motion planning, I felt the need to take this opportunity to explore them while being able to complete the project before the stipulated deadline.
- I had previously taken courses in Machine learning and Reinforcement learning in my undergraduate studies which involved lots of coding and training time. This experience has helped me in selecting a suitable project topic for this course.

Proposed Goals and Deadlines - *Assuming everything goes smoothly and ensuring adequate time for each step, while factoring in other courses and assignments *

Goals	**Deadlines**
Project Proposal	March 14
Literature Review and theoretical understanding	March 20
Start of Implementation	March 17 – March 20
Debugging Starts	March 30
Progress Update	April 15
Final Reports Starts	April 30
Final Deliverable	May 6