Integrating **Hard Data Consistency** with **Latent HMC** for Inverse Problems

Name: **Yujin Kim**

Background	Inverse problems aim to recover underlying signals from noisy measurements. **ReSample (ICLR 2024)** demonstrated the effectiveness of enforcing Hard Data Consistency through optimization. However, it relies on a heuristic mechanism called Stochastic Resampling to re-introduce noise, limiting its performance in complex nonlinear problems due to coupled noise. In contrast, **DAPS (CVPR 2025)** employs MCMC methods, enabling robust exploration via noise decoupling. However, LatentDAPS faces manifold mismatch, where sampled latents can deviate from the clean data distribution during the stochastic process.

Aim	The aim is to integrate **Hard Data Consistency** optimization into the **Latent HMC** framework to create a robust solver. This approach jointly mitigates the coupled noise of ReSample and the manifold mismatch of LatentDAPS. Additionally, we seek to identify the computational sweet spot, balancing optimization overhead with performance gains.

Methodology	**Algorithm Design:** We adopt ReSample objective, $\min_z \lVert y - A(D(z)) \rVert^2$, but replace the Stochastic Resampling step with Latent HMC updates. This substitutes heuristic noise injection with an HMC-based posterior sampling, allowing the model to escape local minima efficiently. Instead of vanilla ReSample's threshold-based iteration, we constrain the optimization to intermediate timesteps, (e.g., $t \in [15, 45)$ for $T = 50$) to target the most effective phase without parameter tuning. **Experimental Setup:** We utilize pre-trained LDMs on FFHQ and Image-Net (256x256, 100 validation images each). Robustness is tested on 8 linear and nonlinear inverse tasks, including SR (4x), inpainting (box/random), deblur(Gaussian/motion/nonlinear), phase retrieval, and HDR. **Comparative Evaluation:** We compare our method against Standard ReSample and LatentDAPS (ULA/HMC). Performance is evaluated using PSNR, SSIM, LPIPS, and runtime analysis to assess the optimization overhead.

Outcome, Significance, Rationale	**Rationale:** By utilizing HMC, we overcome the limitations of heuristic noise injection in ReSample. By enforcing data consistency via measurement error optimization, we resolve the issue in LatentDAPS where pixel-space dynamics deviate from the clean image manifold, leading to sub-optimal performance of the autoencoder, which is trained solely in pixel space. **Significance:** Our approach ensures efficiency by preventing early-stage waste and late-stage artifacts. By eliminating vanilla ReSample's ambiguous threshold tuning, we establish a robust, tuning-free framework applicable to diverse linear and nonlinear inverse tasks. **Outcome:** We anticipate that this hybrid integration will maximize robustness and computational efficiency compared to baselines. The results will demonstrate that high-fidelity reconstruction is achievable with minimal measurement error optimization overhead.