Probabilistic reconstruction of flow field with residual diffusion model

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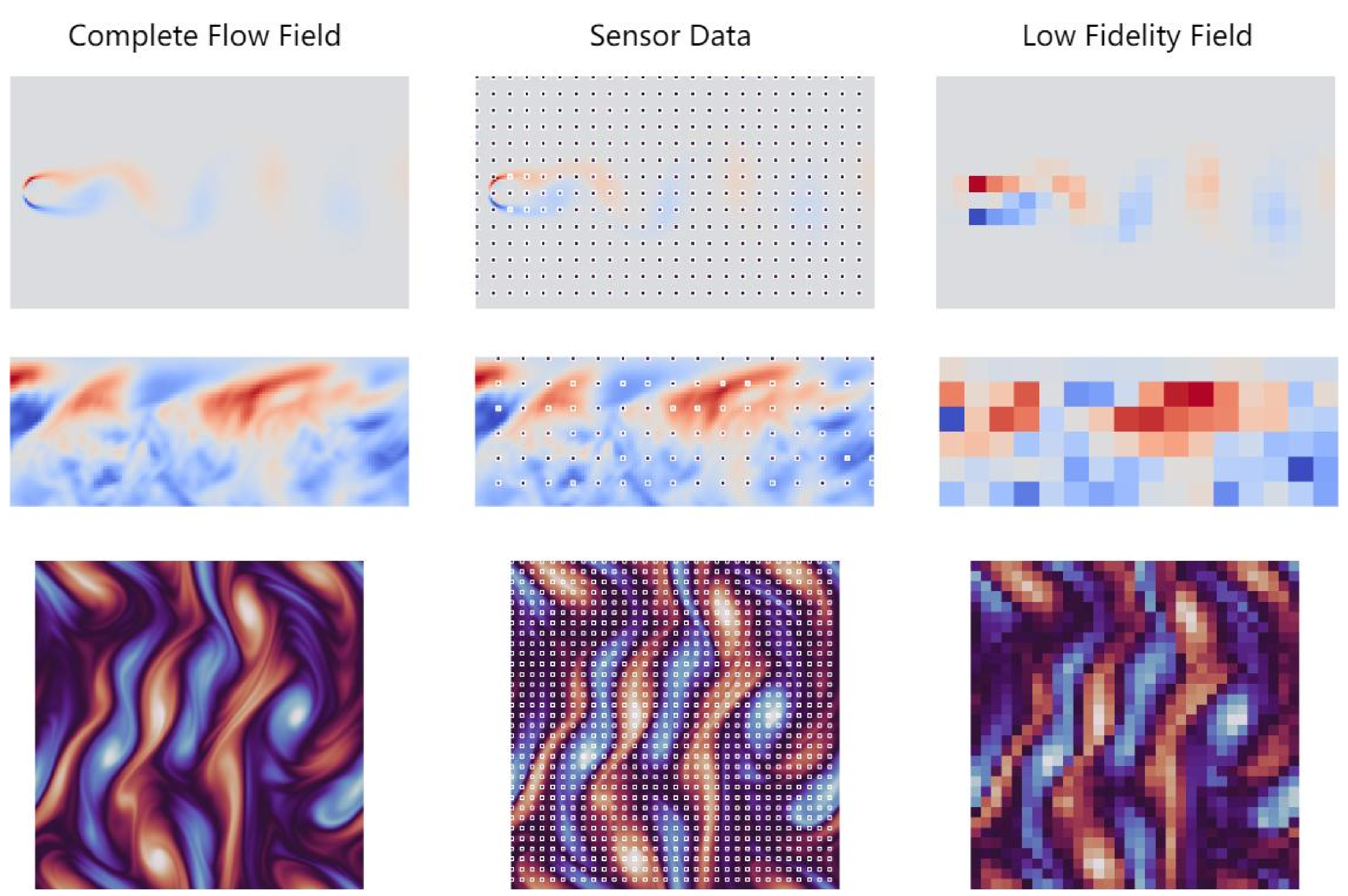
Motivation and problem setup

Flow field reconstruction is a critical challenge in fluid dynamics because it is impossible to observe the full field (e.g. 256 * 256) grid resolution in practical applications. Therefore, sensors are strategically placed at key locations to collect partial measurements, from which the complete flow field must be reconstructed using computational methods. This sparse sensing approach is necessary due to physical constraints, cost limitations, and measurement accessibility issues in real-world fluid systems. The ability to accurately reconstruct high-resolution flow fields from limited sensor data is essential for applications ranging from weather prediction and aerodynamic design to environmental monitoring and industrial process control, where understanding the complete flow behavior is crucial for analysis and decision-making.

Sparse flow field visualization

For complete flow field reconstruction, we evenly position sensors by sampling one data point every n grid points. We then interpolate this sparse sensor data back to the original dimensions to generate our low-fidelity input for reconstruction algorithms.



Residual shifting diffusion model for flow reconstruction

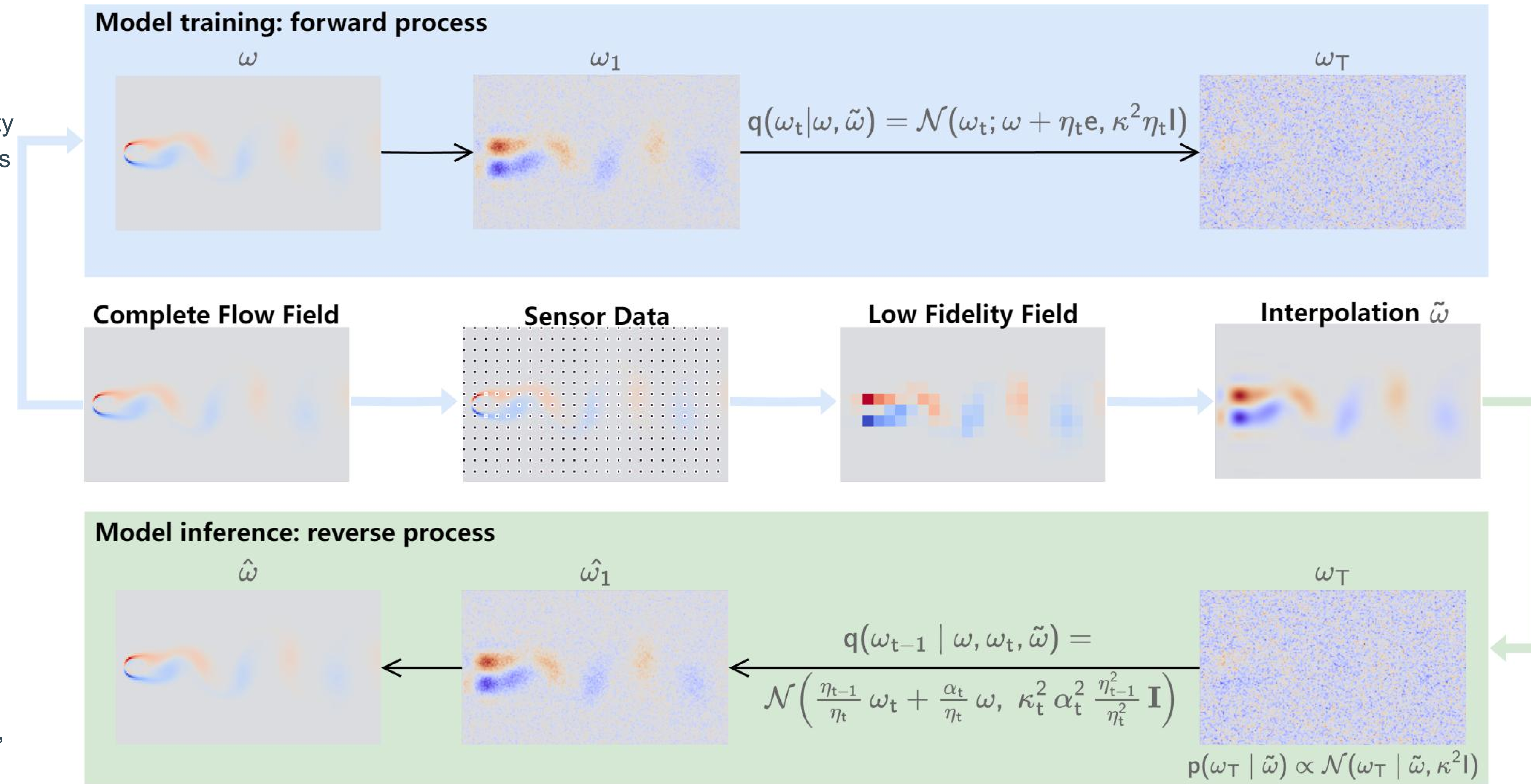
The Residual Shifting Diffusion Model (ResShift) is a sophisticated two-phase diffusion framework designed to establish a probabilistic linkage between high-fidelity and low-fidelity flow field distributions. This approach facilitates the robust reconstruction of detailed flow fields from degraded inputs, offering significant utility in fluid dynamics and related disciplines. Below, the two phases—the forward process and the reverse process—are briefly introduced.

Forward Process

The forward process transforms a high-fidelity flow field into a low-fidelity approximation by adding Gaussian noise and shifting the residual

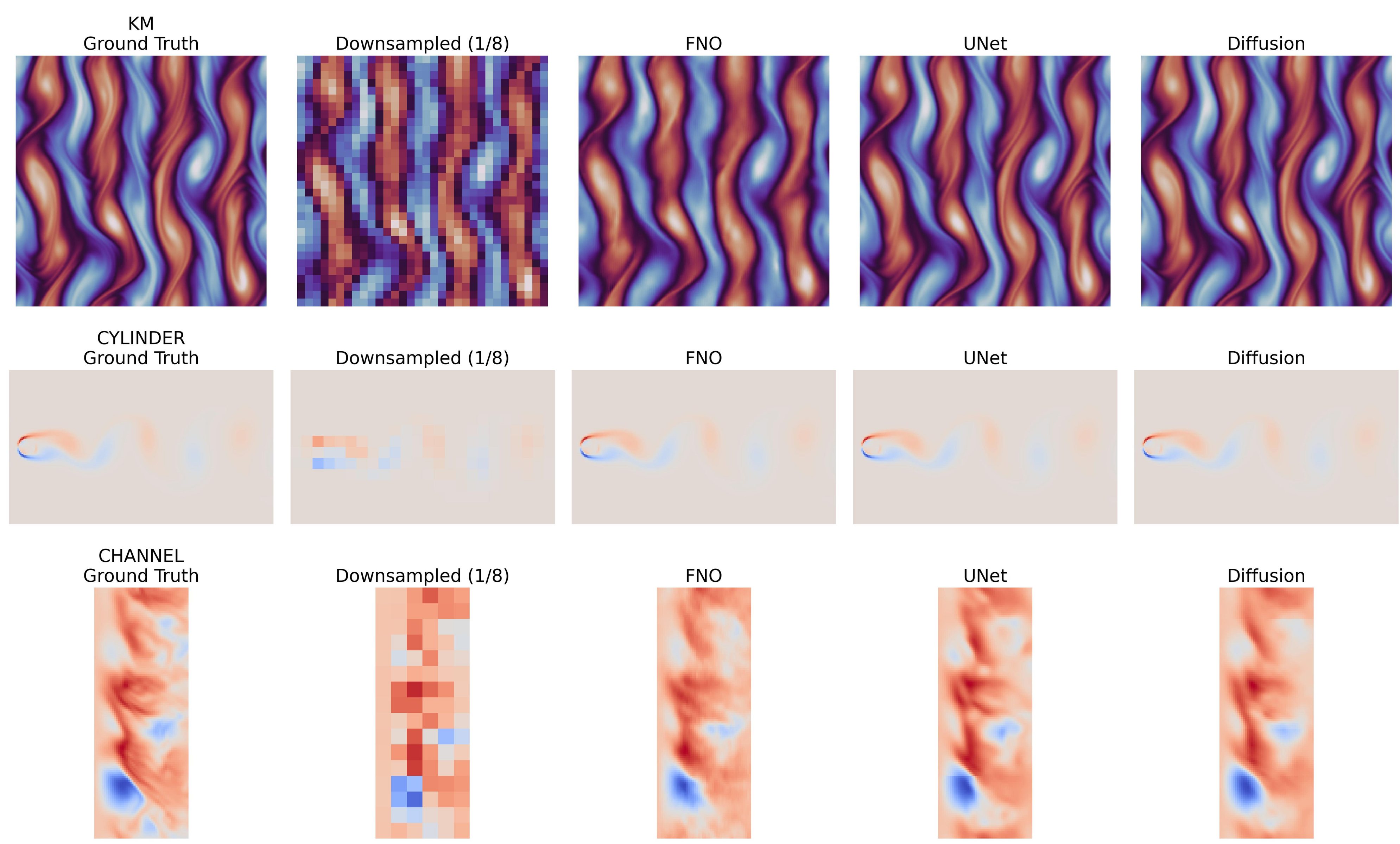
Reverse Process

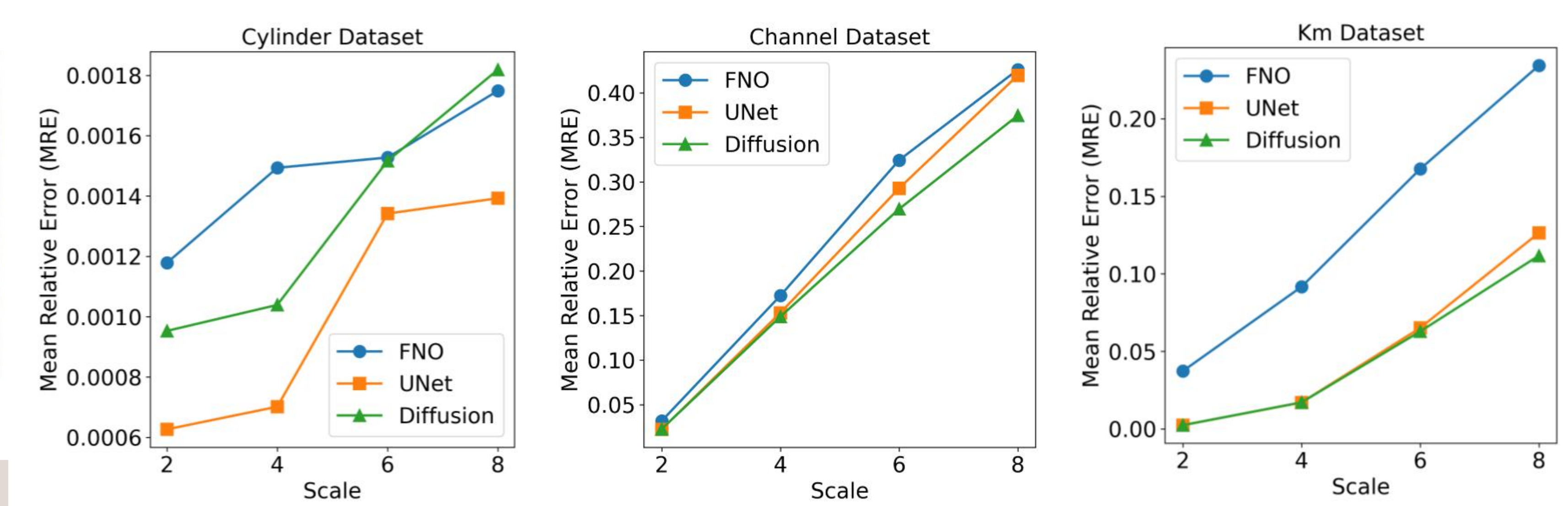
The reverse process reconstructs the original high-fidelity flow field from the degraded output using iterative denoising, guided by a learned statistical mapping



Performance comparison among methods

Each model is trained seperately for each reconstructions task





The diffusion model outperforms two state-of-the-art (SOTA) models, UNet and FNO, in reconstructing both Channel Flow and Kolmogorov Flow across all evaluated reconstruction tasks. Notably, it excels in more challenging scenarios, such as higher upsampling scales (e.g., 6x or 8x), where recovering fine details becomes increasingly difficult. However, for simpler tasks, such as reconstructing Cylinder Flow, the diffusion model does not surpass UNet, though it still demonstrates superior performance compared to FNO.

References

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