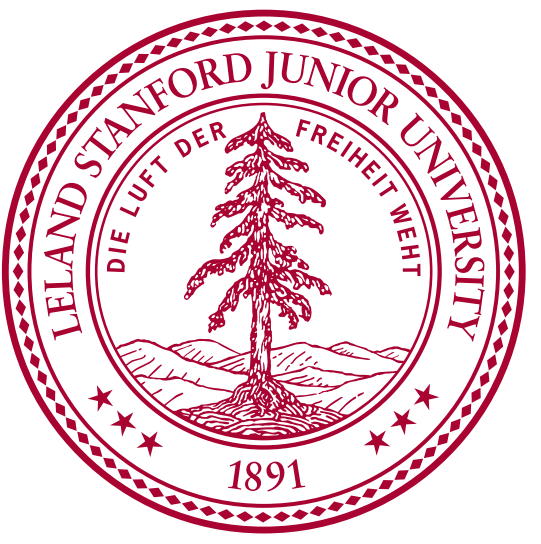




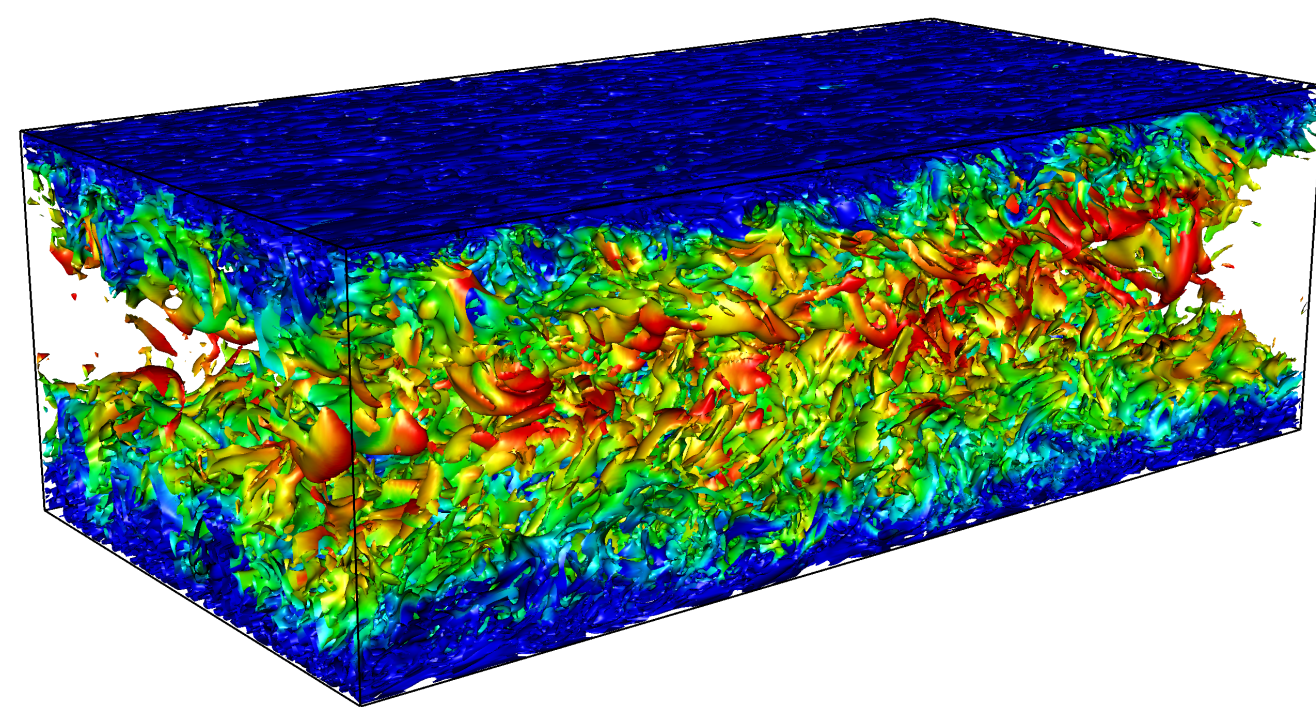
SYNTHETIC TURBULENT INFLOW GENERATION FOR SIMULATIONS OF TURBULENT WALL-BOUNDED FLOWS

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INTRODUCTION

Turbulent wall-bounded flows are the fundamental building blocks of most engineering flows of interest. Direct numerical simulations (DNS) of spatially-developing wall bounded turbulent flows at very high Reynolds number are limited by current high performance computing capabilities. The computational cost will be significantly reduced if a sufficiently realistic turbulent inflow can be provided simultaneously along with the simulation.



This work explores the potential for a generative Variational Auto-Encoder (VAE) model to artificially provide a turbulent inflow velocity field.

PROBLEM STATEMENT

Objective:

Generate the three components of the velocity field of a turbulent channel flow in a 2D cross-sectional plane using a VAE model. The model should be able to capture the coherent turbulent structures and represent their multiscale statistics faithfully.

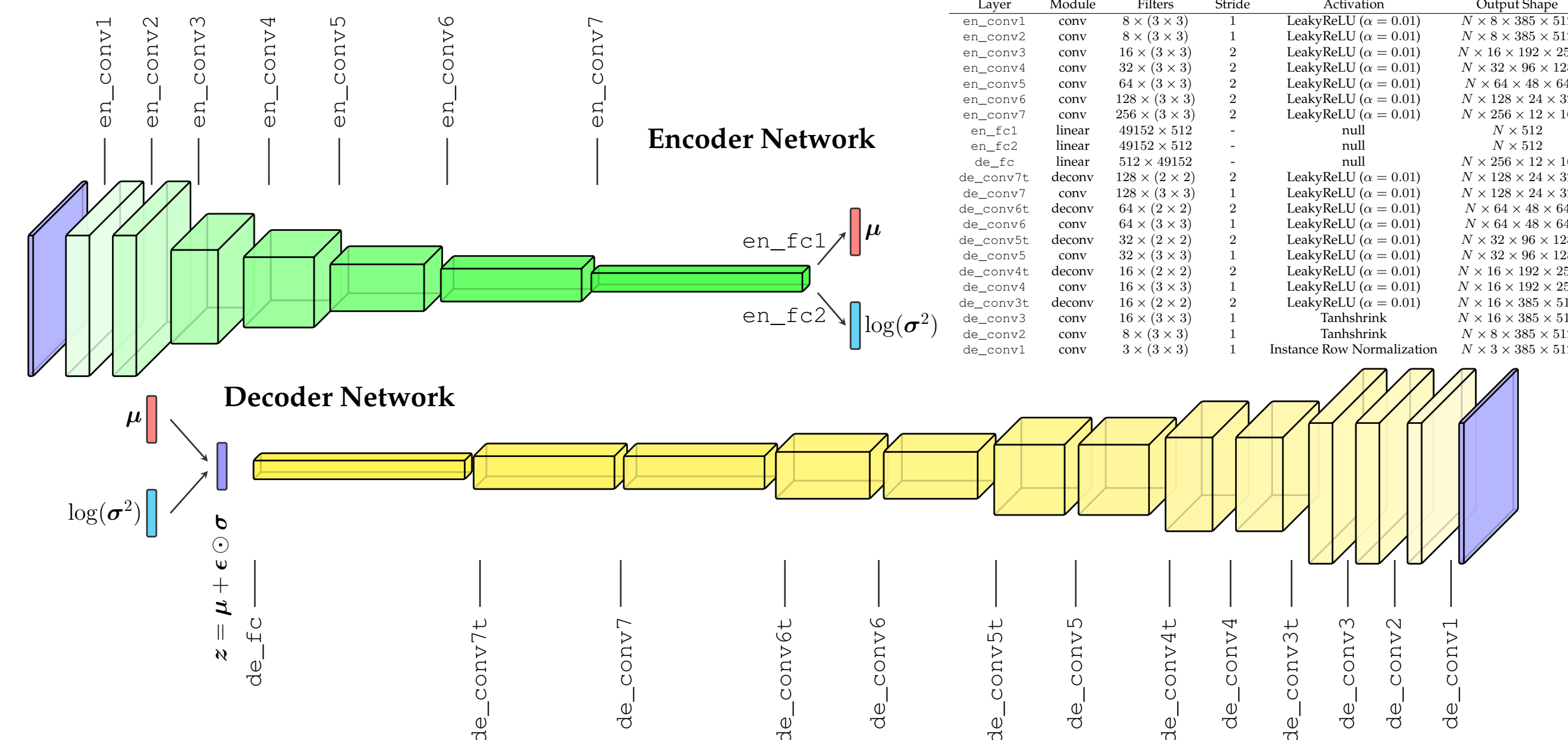
Inputs:

- Encoder: Three-component velocity field from DNS on a 2D computational mesh of resolution 385×512 .
- Decoder: Statistics for latent layer assembly.

Outputs:

- Encoder: Encoded statistics from DNS data for latent layer assembly.
- Decoder: Synthetic velocity field on a 2D computational mesh of resolution 385×512 .

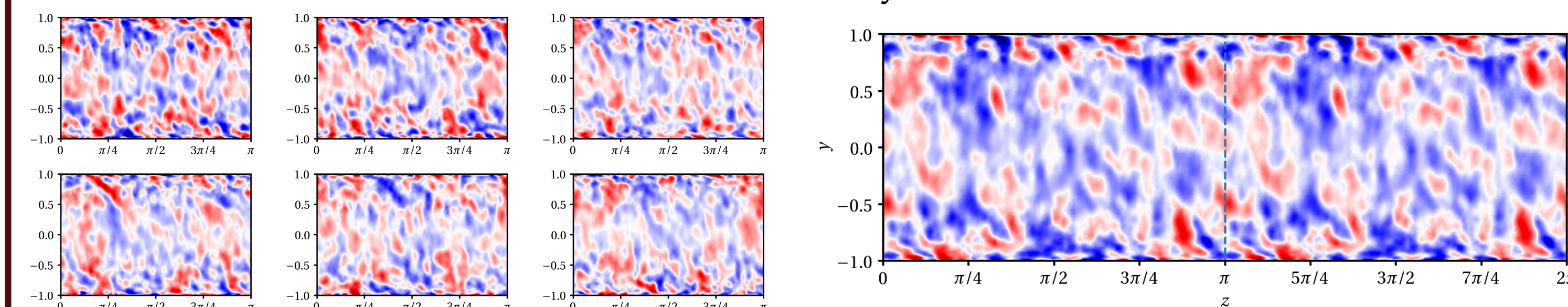
METHODOLOGIES



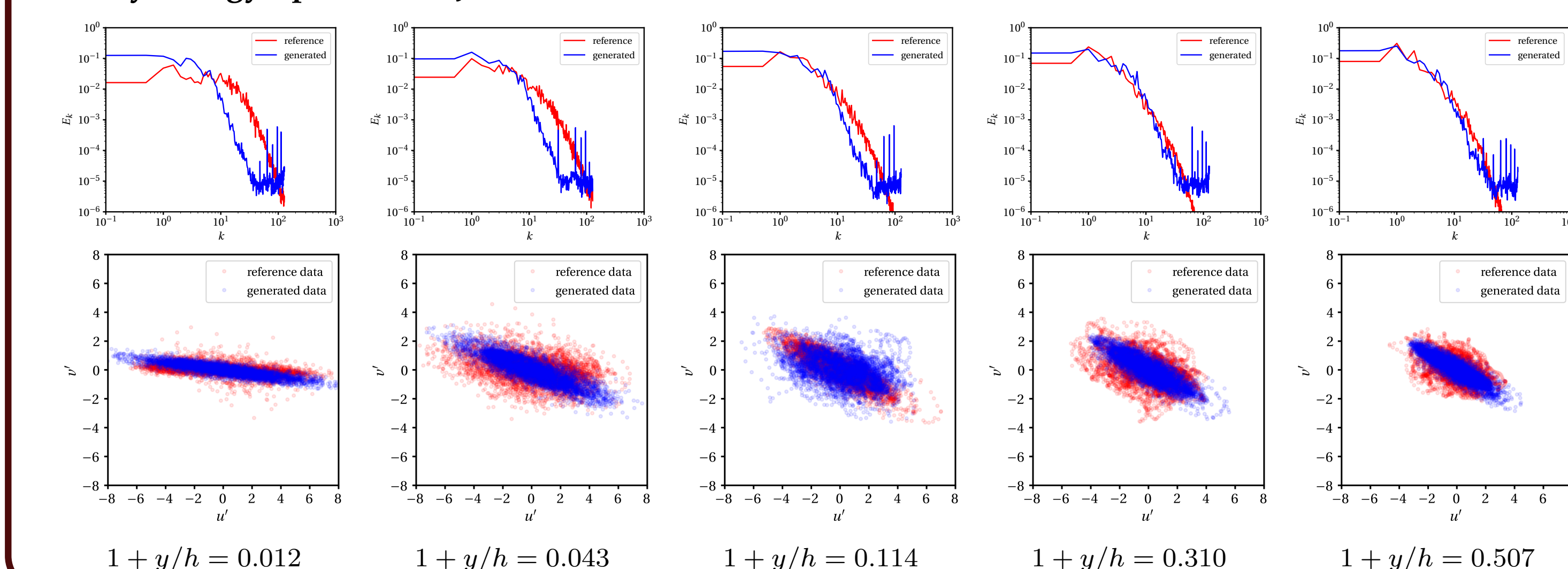
Padding: Circular padding in the periodic direction and zero padding in the wall-normal direction.

EXPERIMENTS & ANALYSIS

Visualization of Generated Fields and Enforced Periodicity



Velocity Energy Spectra and Joint Distributions



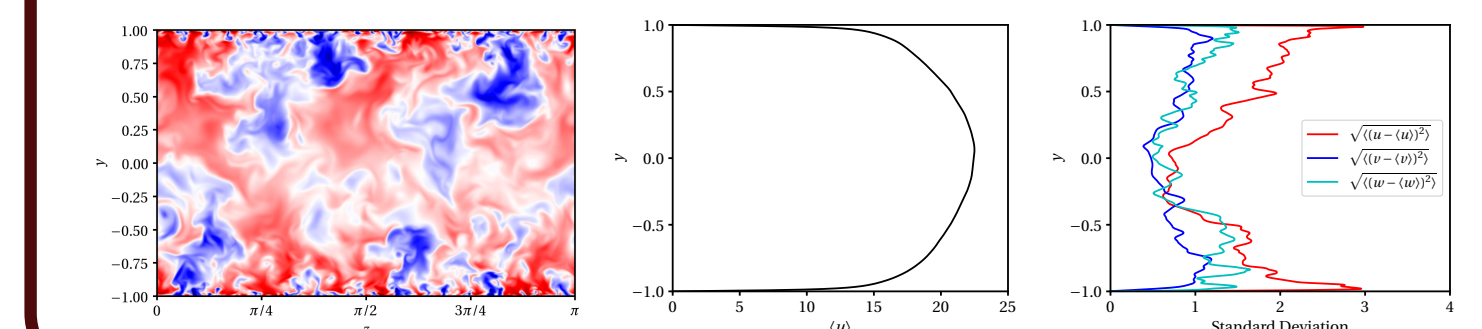
DATASET

Description:

1264 planes of DNS data, each with three velocity components are used. Only 8 planes were extracted from each snapshot (there are 512 per snapshot) to ensure that some spatial decorrelation is present between them. Similarly, the snapshots extracted were spaced 100 timesteps apart for temporal decorrelation. The channel flow was in equilibrium at $Re_\tau \approx 950$.

Pre-processing:

The wall-normal dependent mean is removed and the velocity fields are normalized by their wall-normal dependent standard deviation.



CONCLUSIONS & FUTURE WORK

Key Takeaways:

- The large scales of the flow in the center of the domain are well represented.
- Qualitative observations are verified using both energy spectra and joint probability density functions at various wall-normal heights.
- Deeper VAE models, with larger latent vector sizes and larger batch sizes performed better.

Limitations:

- The flow field sizes were much larger than what is currently considered state-of-the-art; 385×512 versus 256×256 .
- The model is incapable of representing the finer scales and the cross-correlations are incorrect in the center of the domain.

Next Steps:

- A scale-based hierarchical generative model, where structures are generated scale-by-scale, then assembled in space.
- Using GANs, and in particular, Style-GANs, which have been shown to generate extremely fine-scale features by using the latent space distribution to influence each convolutional layer.