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# Reconstructing and Synthesizing Spatio-Temporal Super-Resolution Data Through Machine Learning

Shourya Verma

Fukami, K., Fukagata, K., & Taira, K. (2021). Machine-learning-based spatio-temporal super resolution reconstruction of turbulent flows. *Journal of Fluid Mechanics, 909*, A9. doi:10.1017/jfm.2020.948

J. Han, H. Zheng, D. Z. Chen and C. Wang, "STNet: An End-to-End Generative Framework for Synthesizing Spatiotemporal Super-Resolution Volumes," in *IEEE Transactions on Visualization and Computer Graphics*

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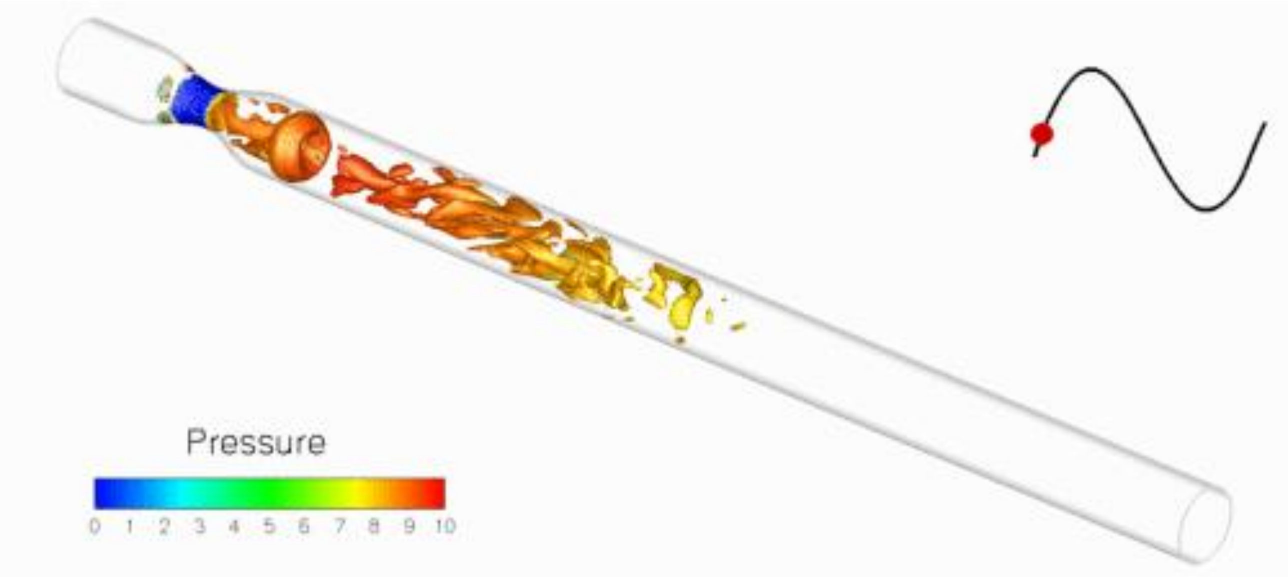
# Motivation

- 2D or 3D fluid dynamics simulations
- Problems:
  - Data storage – big data
  - Data sharing – between scientists
- Topic explores:
  - Data reduction and recovery
  - Turbulent vector and scalar data
  - Reconstructing and synthesizing data
  - Machine learning techniques
  - Super resolution spatio-temporal data

Fluid dynamic simulation

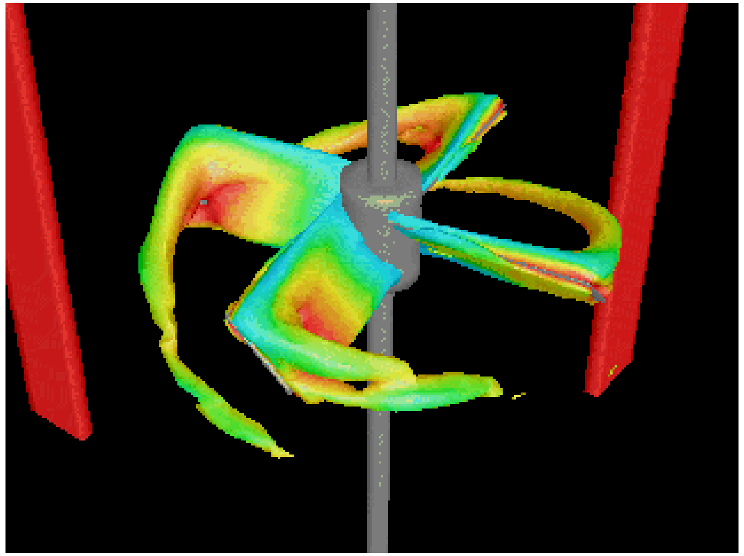



https://engineering.purdue.edu/CFDLAB/

# Example

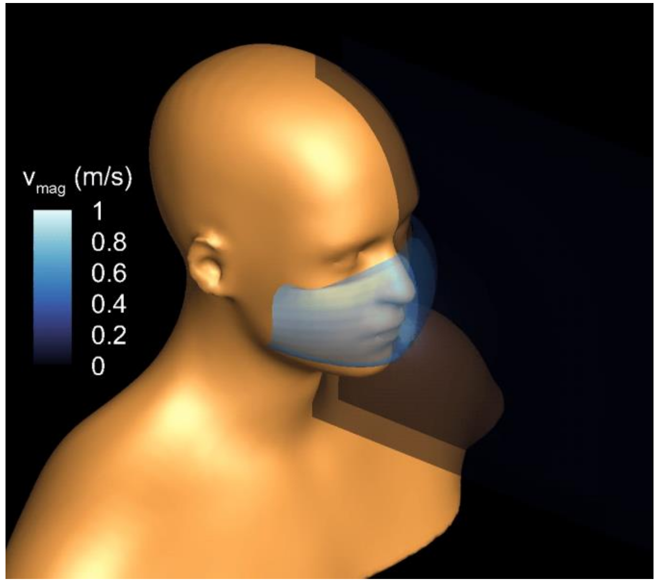
- Why fluid dynamic simulations?
  - Widely used in all areas
  - Spatio-temporal data

Industrial turbines



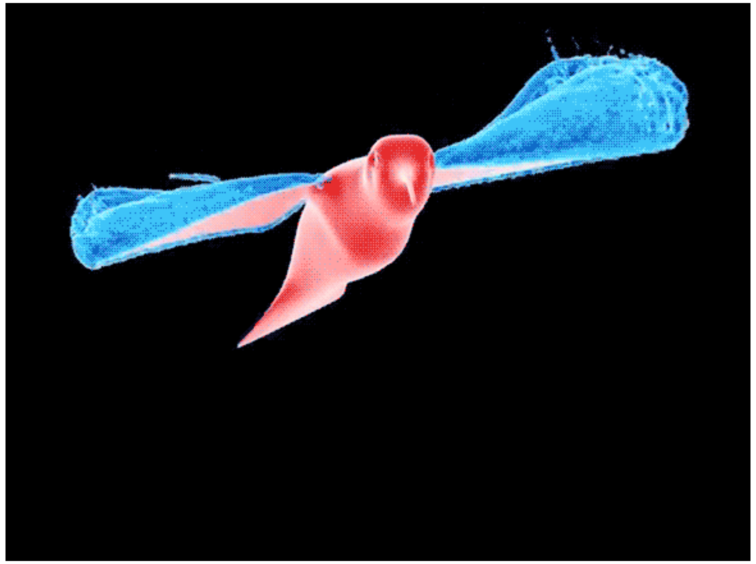
https://www.bakker.org/cfm/a5-3.gif

Coughing airflow




https://scx2.b-cdn.net/gfx/news/2020/whatfluiddyn.gif

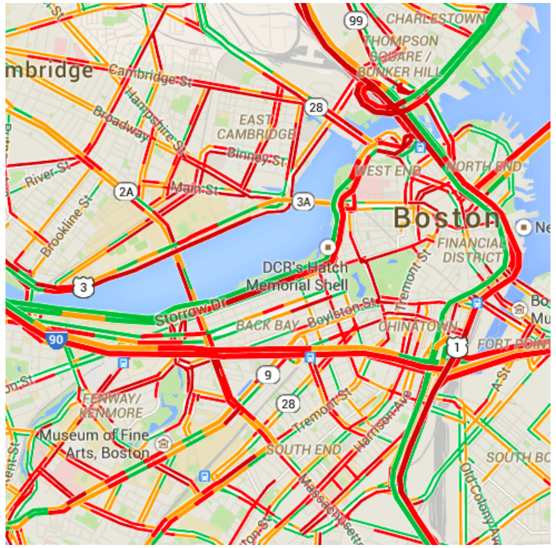
Bird wings



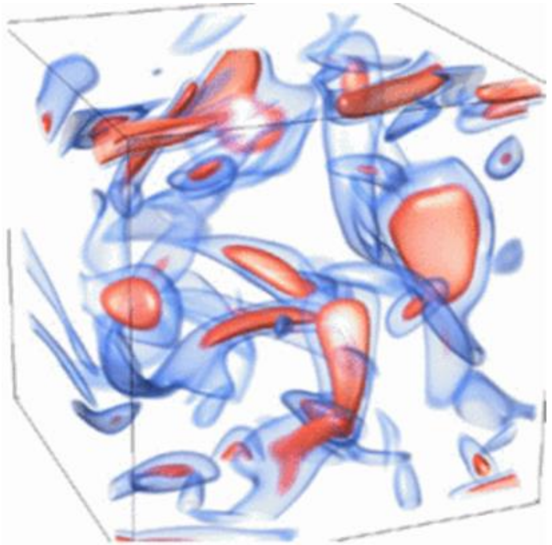
https://i.pinimg.com/originals/b5/28/c2/b5
28c22e8d18ed271bf4b8f3687a6e62.gif

# Spatio-Temporal (ST) Data

- Spatio-temporal data is data relating to both space and time, represented as vector $(\boldsymbol{x}, \boldsymbol{t})$
- Some examples:
  - *2D space + 1D time:* Traffic Volume data
  - *3D space + 1D time:* Particle Flow Field data




3D Traffic Volume data [1]

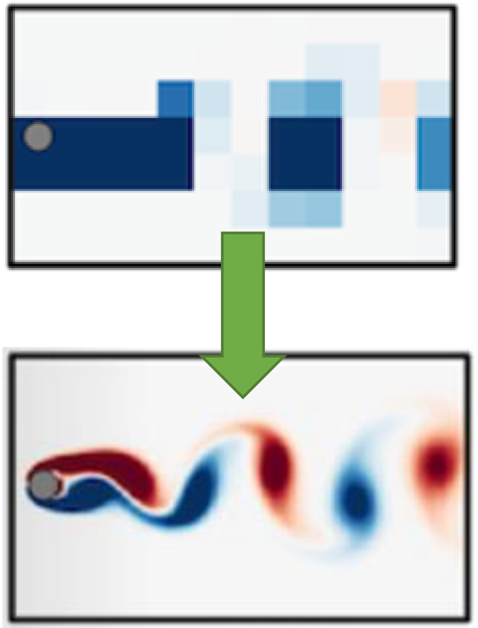


4D Particle Flow Field data [2]

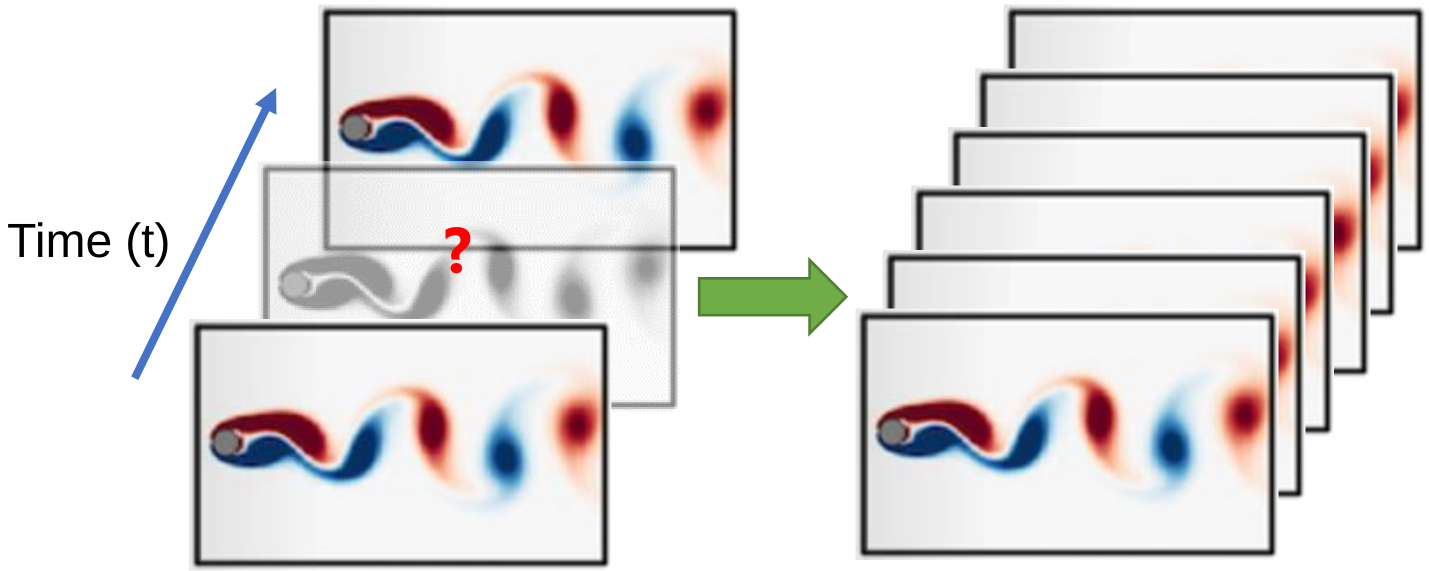
[1] https://medium.com/@imtechpros_87395/where-does-google-maps-get-its-traffic-data-from-2562f984d82f
[2] J. Han, H. Zheng, D. Z. Chen and C. Wang, "STNet: An End-to-End Generative Framework for Synthesizing Spatiotemporal Super-Resolution Volumes," in *IEEE Transactions on Visualization and Computer Graphics*

# Spatio Temporal Super Resolution (STSR) Data

- Low-resolution (128×128×50) → Super-resolution (512×512×200)  $(\boldsymbol{x} \times \boldsymbol{y} \times \boldsymbol{t})$
- *In space:* resolution is upscaled so visualizations appear at higher resolution
- *In time:* sequences are found between first and last frames of time-series



spatial super resolution

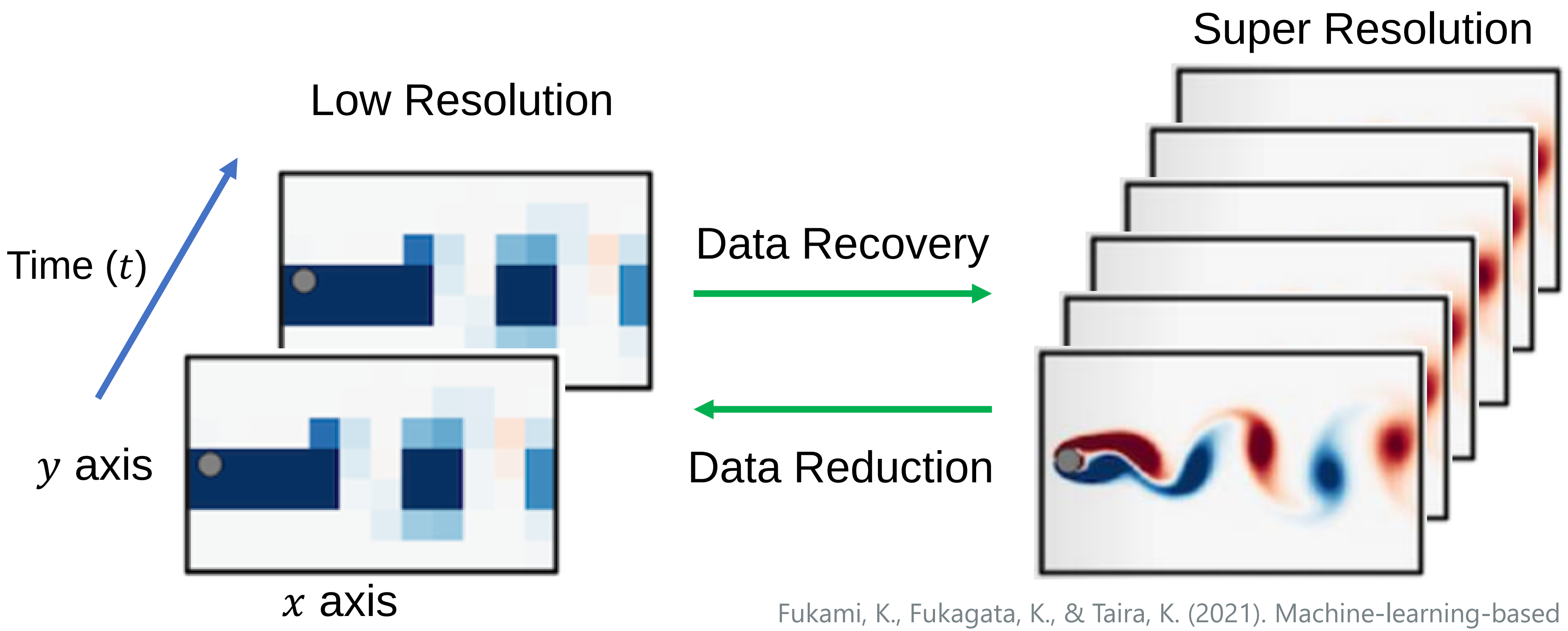



temporal inbetweening

Fukami, K., Fukagata, K., & Taira, K. (2021). Machine-learning-based spatio-temporal super resolution reconstruction of turbulent flows. *Journal of Fluid Mechanics, 909*, A9. doi:10.1017/jfm.2020.948

# Problem Setting

- How to reconstruct and synthesize spatio-temporal super-resolution data?
- Visual computing problem in *data reduction* and *data recovery*
- Dealing with spatio-temporal data → dimensions like 3D $(x, y, t)$ or 4D $(x, y, z, t)$
- Machine learning (ML) to create *super-resolution* output from *low-resolution* input

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# Machine Learning based Spatio-Temporal Super Resolution Reconstruction of Turbulent Flows

Fukami, K., Fukagata, K., and Taira, K.

*Journal of Fluid Mechanics, 909*, A9, 2021

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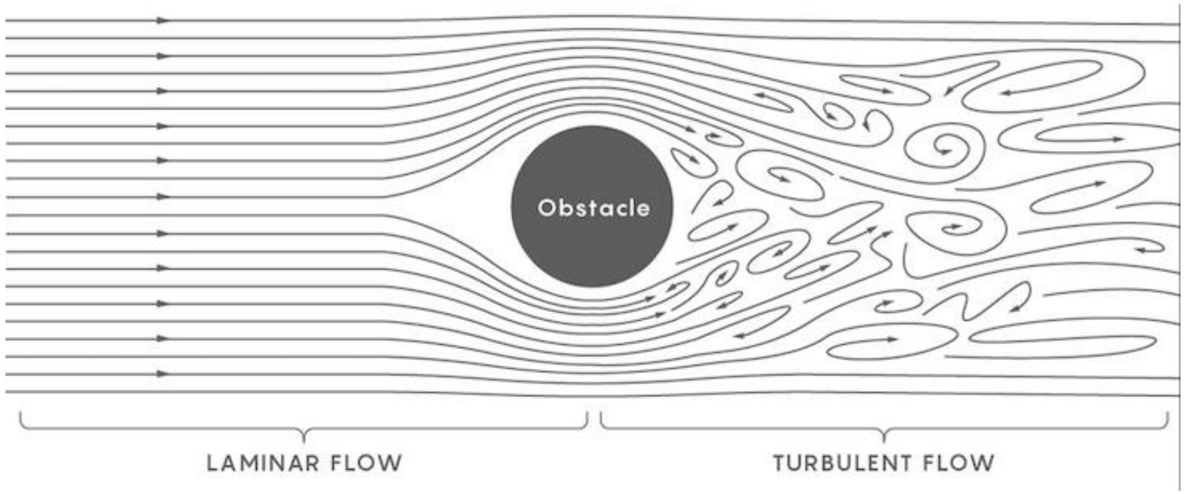
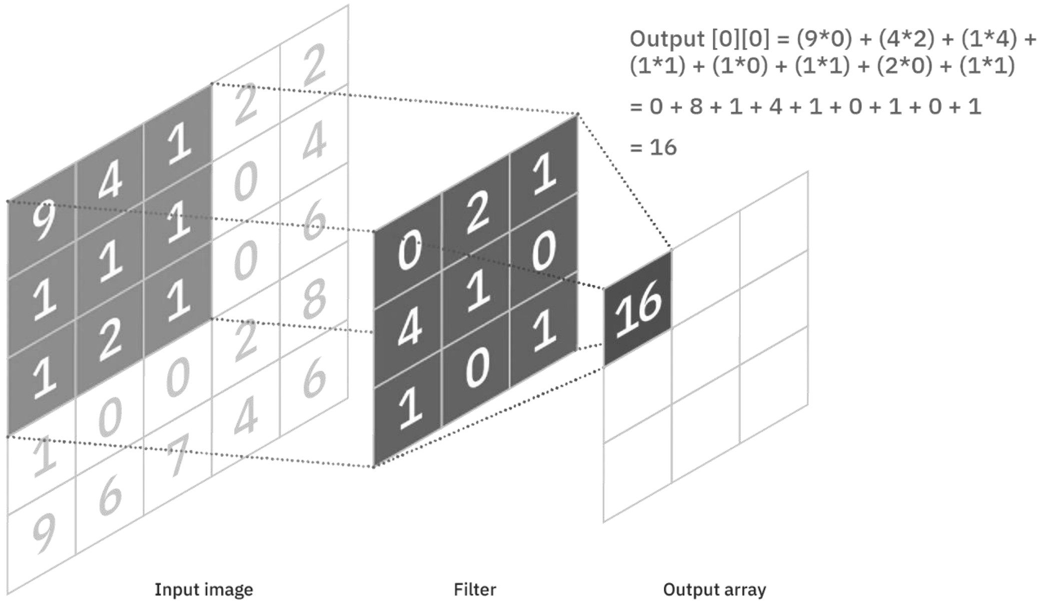
# ML based STSR Reconstruction of Turbulent Flows

- Why turbulent flows?
  - Large eddy simulations in fluid dynamics
  - Aerospace, automotive, and energy industries
  - Simulate airflow and atmospheric currents




https://nautil.us/what-makes-the-hardest-equations-in-physics-so-difficult-7006/

- Why machine learning for reconstruction?
  - Neural networks learn feature representations
  - Convolutional networks effective for 3D spatial data
  - Dot product of input and filter gives output array



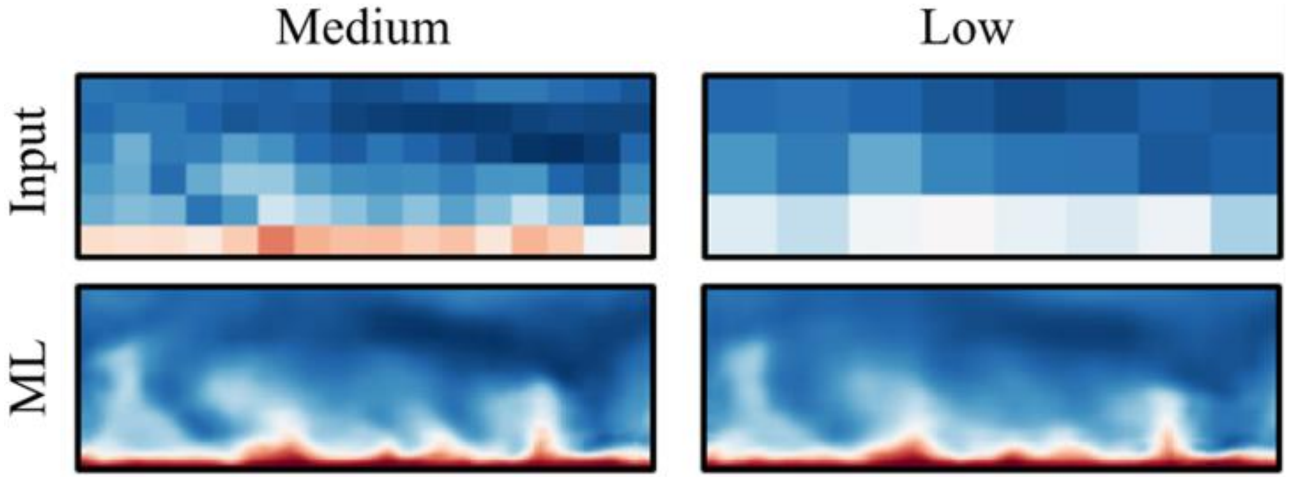

https://www.ibm.com/cloud/learn/convolutional-neural-networks

# ML based STSR Reconstruction of Turbulent Flows

- Turbulent flow data reconstruction task using ML.
- Reconstructs low resolution (LR) to high resolution (HR) flow field data

$\boldsymbol{q(x_{LR}, t_{LR})}$ $\boldsymbol{q(x_{HR}, t_{HR})}$

- Sequential *spatial SR* and *temporal inbetweening* ML techniques




$\boldsymbol{q(x_{LR}, t_{LR})}$

$\boldsymbol{q(x_{HR}, t_{HR})}$

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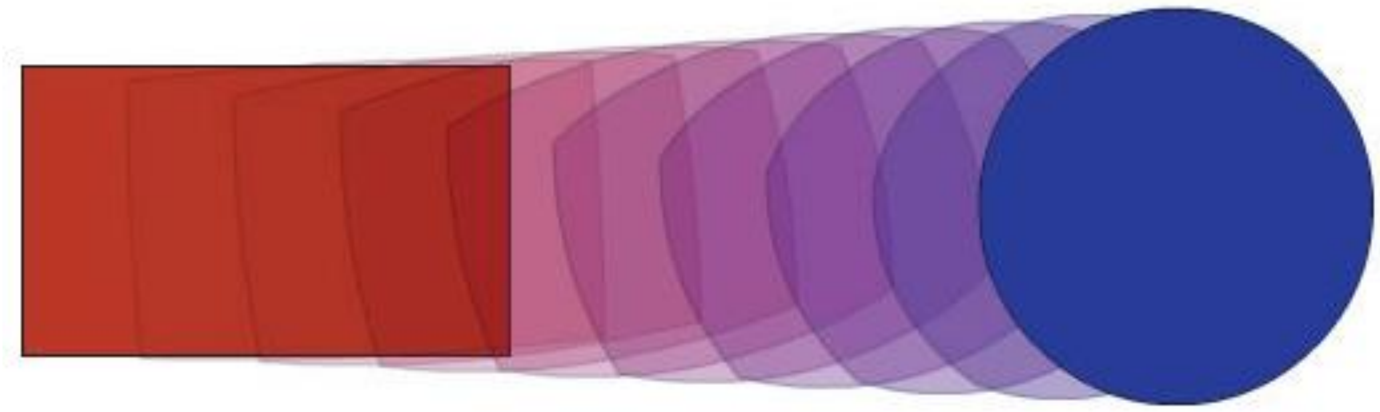
# Temporal Inbetweening

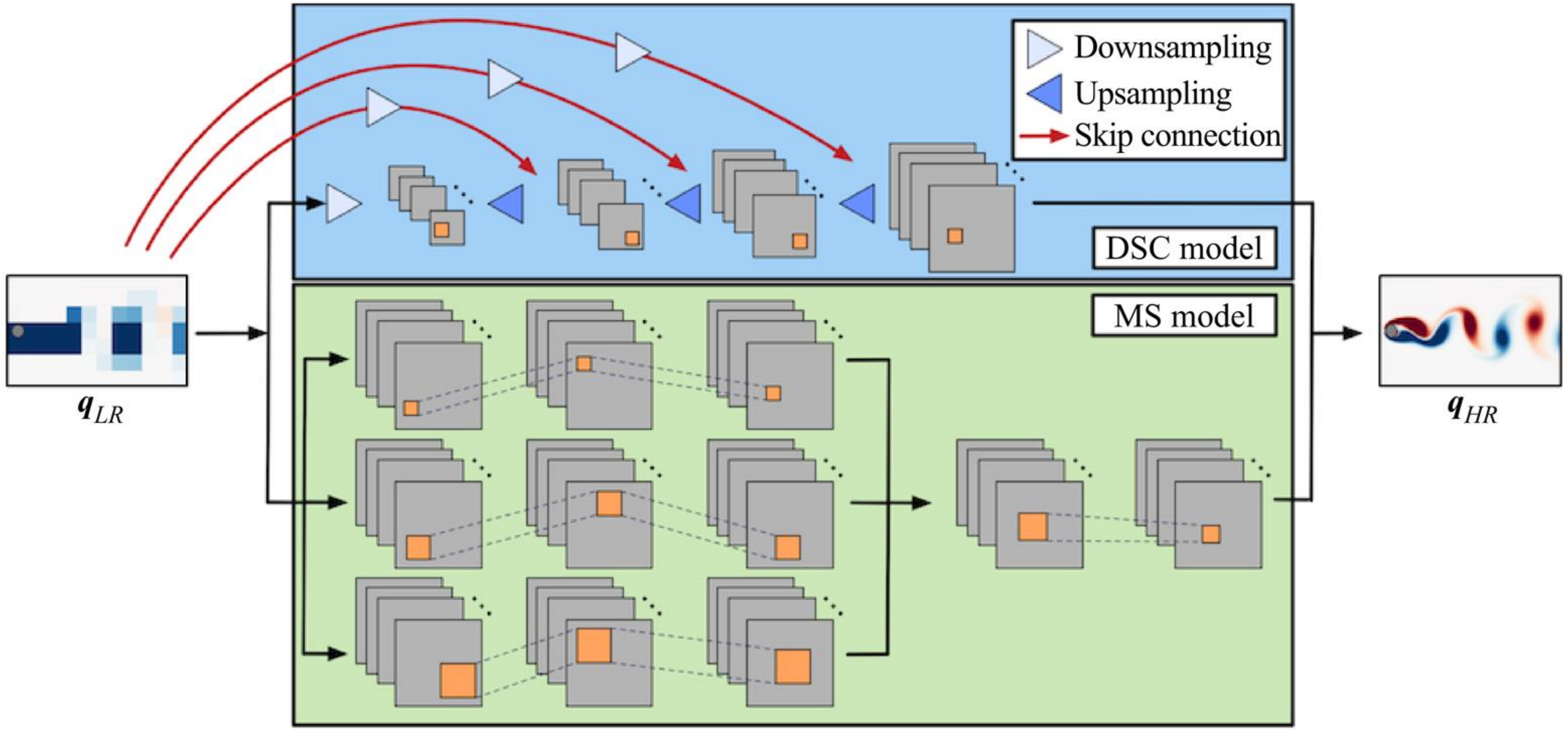
- Process of creating intermediate frames between two frames
- Creates the visualization of movement
- Smoothly transitioning one image into another at different time intervals
- Machine learning models generate as much as 14 frames between 2 given frames



https://www.slideshare.net/fatyalsaadi/lesson-4-shape-tween

# Hybrid Machine Learning Model

- The DSC model robust against rotation and translation
  - Combines compression procedures and skip-connection structures
- MS model useful for learning the property of flow field
  - It utilizes multiple channels of convolutional neural network layers

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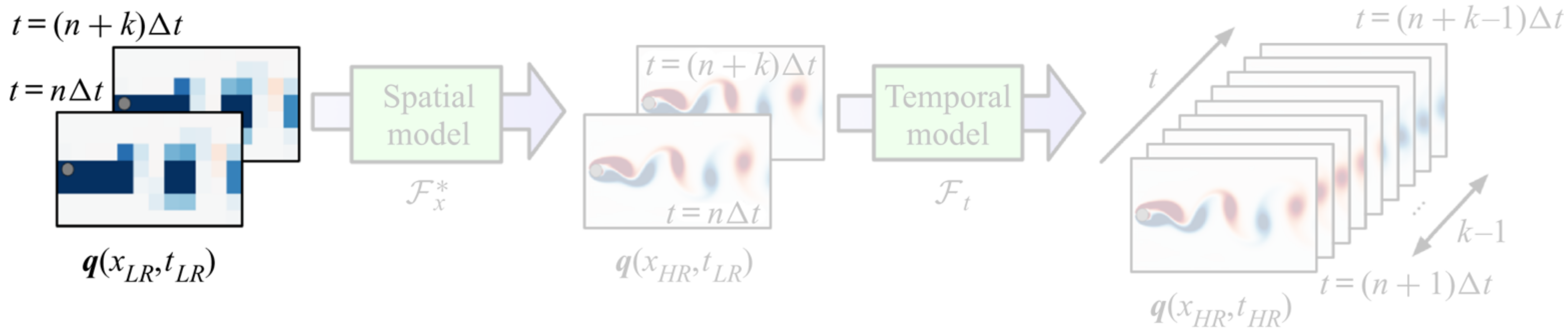
# Data Reconstruction Framework

- Reconstruction framework by applying *spatial SR* $\boldsymbol{Fx}$ then *temporal inbetweening* $\boldsymbol{Ft}$
- Two models were applied in sequence:
  - Error $\boldsymbol{\epsilon x}$ from $\boldsymbol{Fx}$ model accumulated into error $\boldsymbol{\epsilon t}$ from $\boldsymbol{Ft}$ model
  - $\boldsymbol{\epsilon tx}$ is the *total error*
- Spatio-temporal HR reconstruction:
  - $\boldsymbol{q(x_{HR}, t_{HR}) = Ft(Fx(q(x_{LR}, t_{LR}))) + \epsilon tx}$

$\boldsymbol{\Delta t}$ is time step between the first and last frames
$\boldsymbol{n}$ and $\boldsymbol{k}$ are number of snapshots

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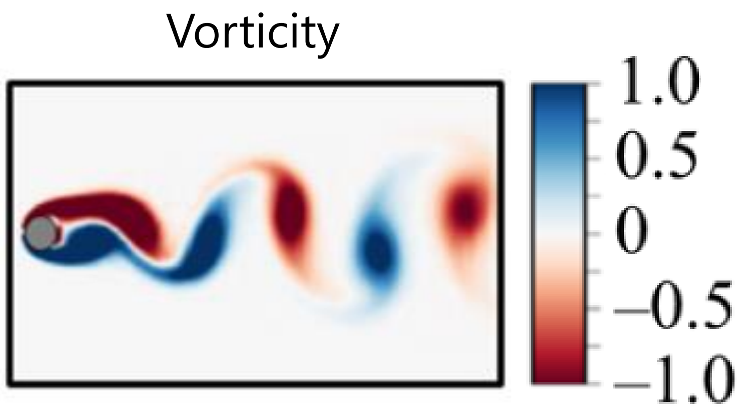
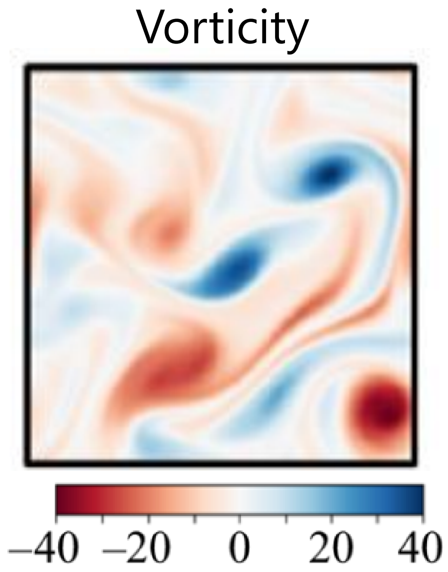
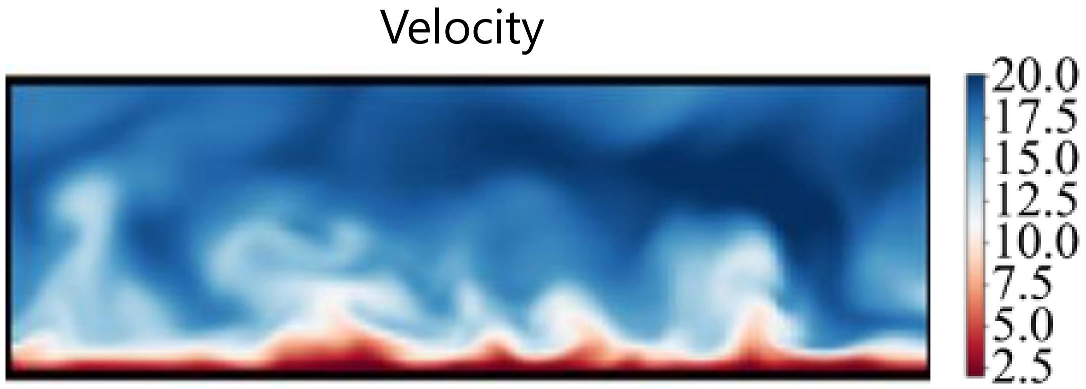
# Datasets

- Generated by 2D direct numerical simulation
- Incompressible Navier–Stokes equation simulate data
- Variables include velocity, vorticity, pressure and viscosity
  - Pressure: force per unit area
  - Vorticity: rotation of a fluid (curl of the velocity)
  - Viscosity: resistance to deformation at a given rate

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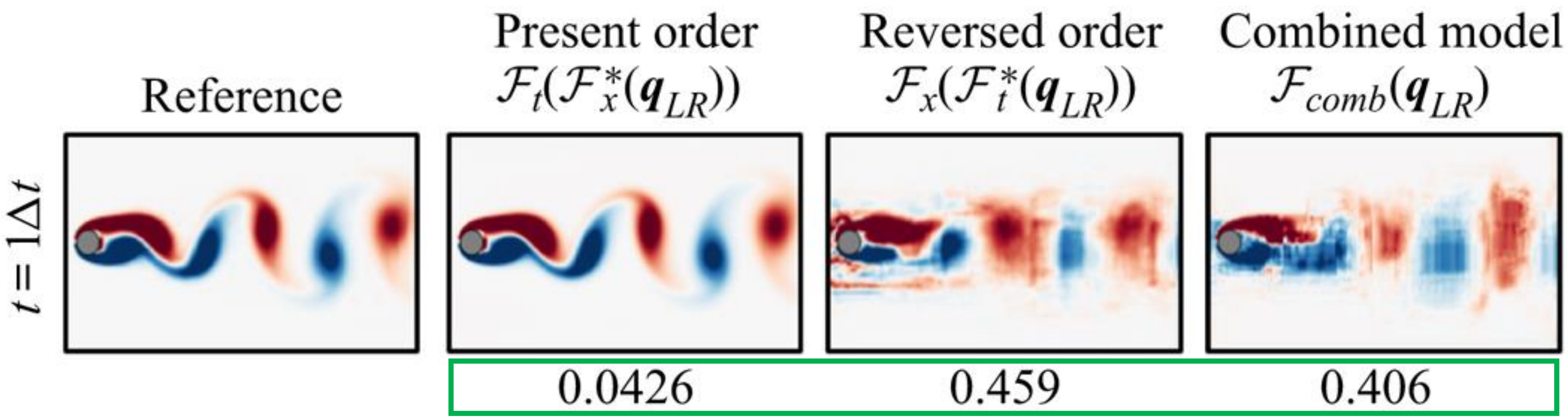
# Sequential vs Combined Model




$\boldsymbol{q(x_{HR}, t_{HR}) = F_{comb}\big(q(x_{LR}, t_{LR})\big)}$

**Root Mean Square Error Norm**

$\epsilon = |\omega_{DNS} - \omega_{ML}|_2 / |\omega_{DNS}|_2$

optimized weights $\boldsymbol{\omega}$

- Examine utilizing a single combined model
- The flow field cannot be reconstructed well
- This is caused by:
  - Difficulty in weight updates while training ML model
  - Error accumulation

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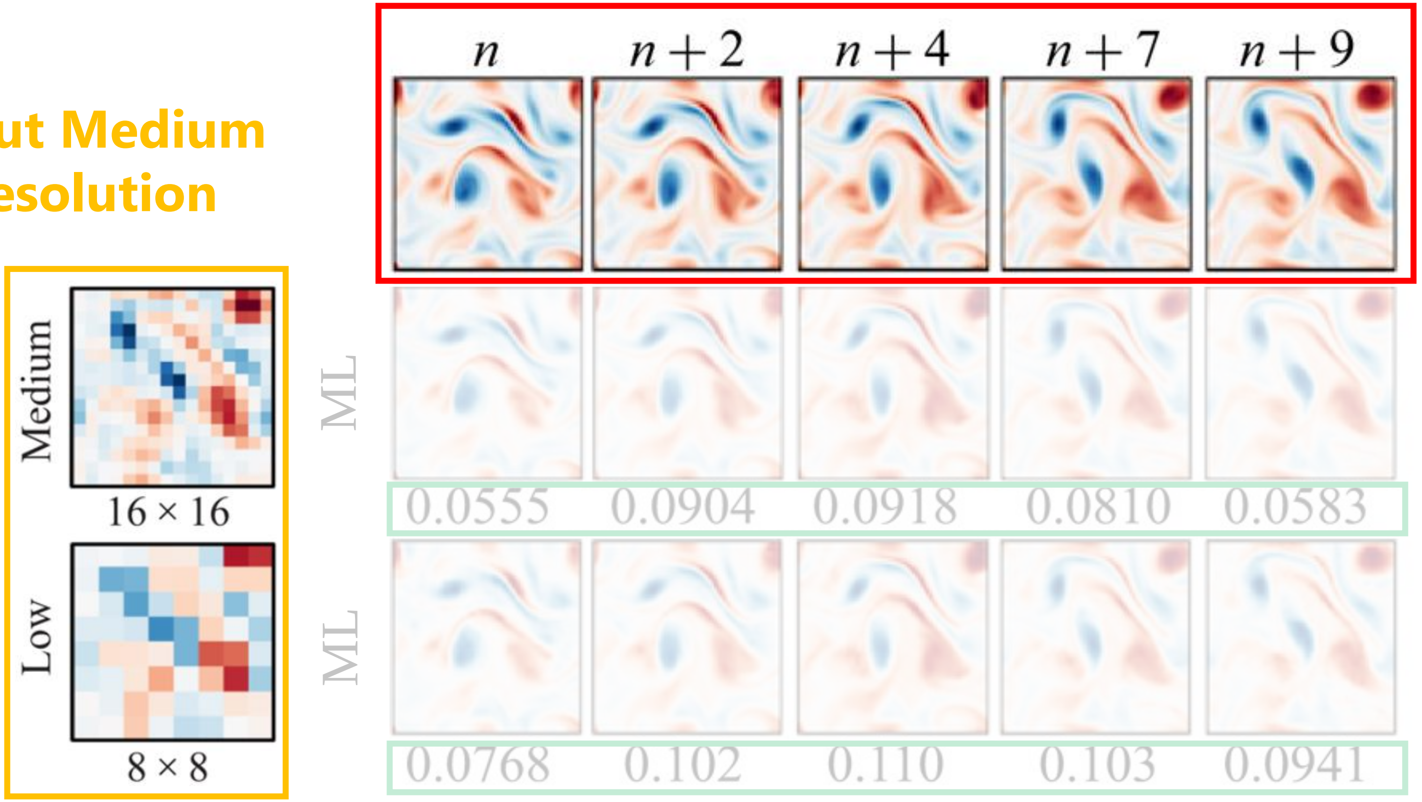
# Results – Vorticity Contours

**Coarse Input Medium and Low Resolution**




**Reference**
128x128

**Root Mean Square Error Norm**

$\epsilon = |\omega_{DNS} - \omega_{ML}|_2 / |\omega_{DNS}|_2$

optimized weights $\omega$

- Reconstructed from various coarse input
- Accurately reconstructed by ML models
- Reconstruction agreement with reference data.

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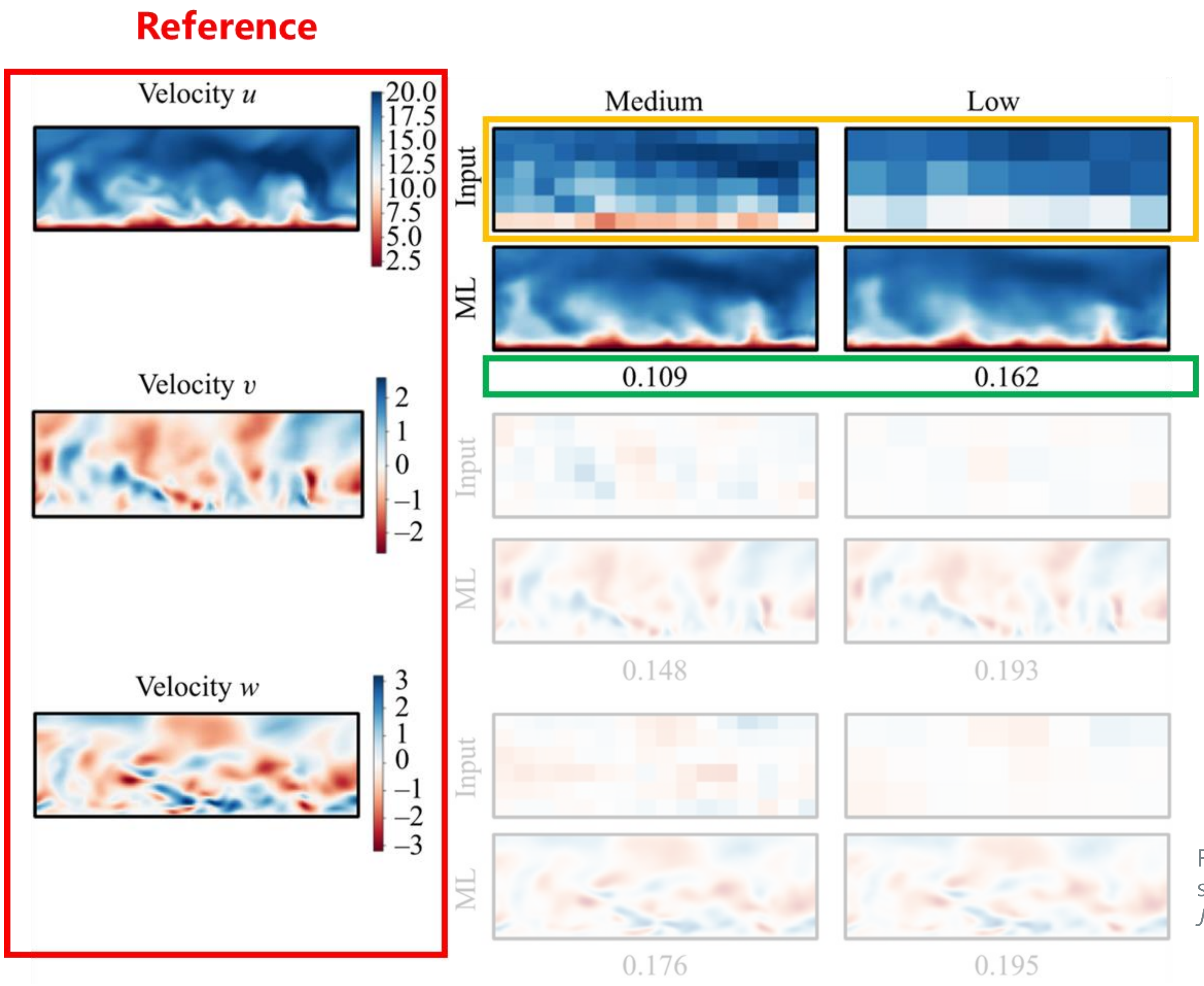
# Results – Velocity Contours




**Coarse Input Medium and Low Resolution**

**Root Mean Square Error Norm**

$$\epsilon = |\omega_{DNS} - \omega_{ML}|_2 / |\omega_{DNS}|_2$$

optimized weights $\omega$

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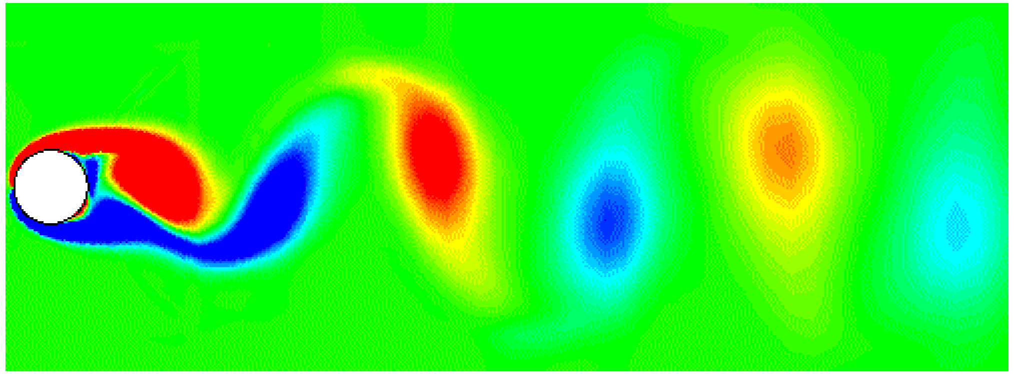
# What can be improved?

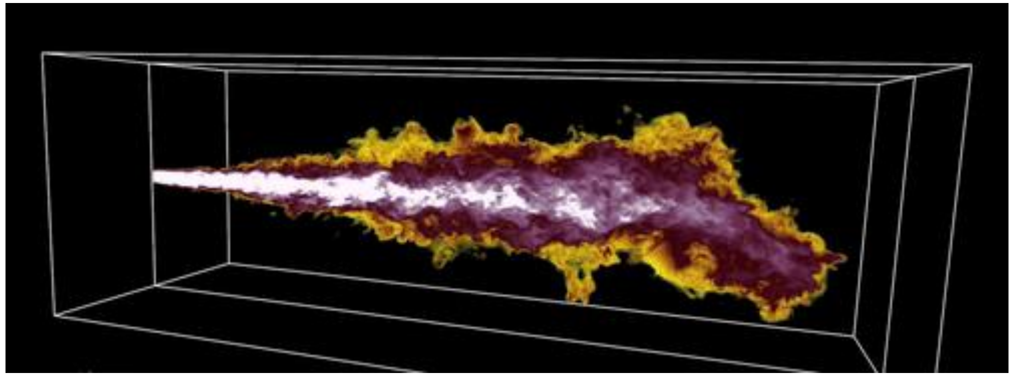
- Sequential model does not provide high fidelity results
  - Due to error accumulation
- Data space interpolation computationally heavy
  - Inbetweening of high resolution
- Turbulent vector data difficult for volumes
  - Computationally heavy

2D turbulent flow



https://engineering.purdue.edu/CFDLAB/

3D turbulent flow



https://thumbs.gfycat.com/UnsungDistinctHochstettersfrog-max-1mb.gif

# STNet: End to End Generative Framework for Spatio Temporal Super Resolution Volumes

J. Han, H. Zheng, D. Z. Chen and C. Wang

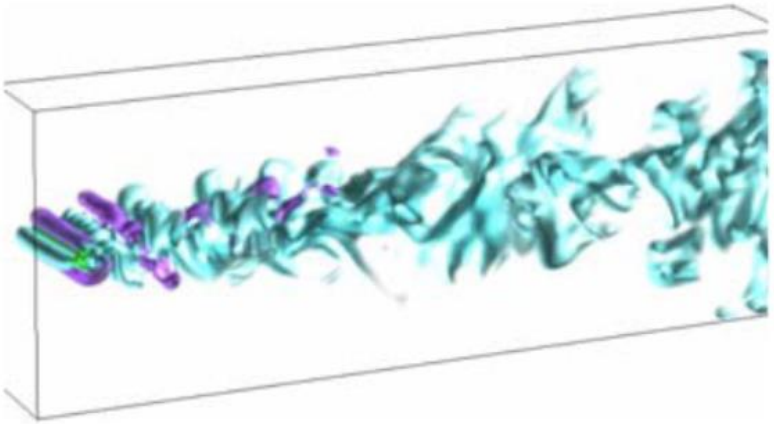
*IEEE Transactions on Visualization and Computer Graphics*, vol. 28, no. 1, pp. 270-280, Jan. 2022

Shourya Verma

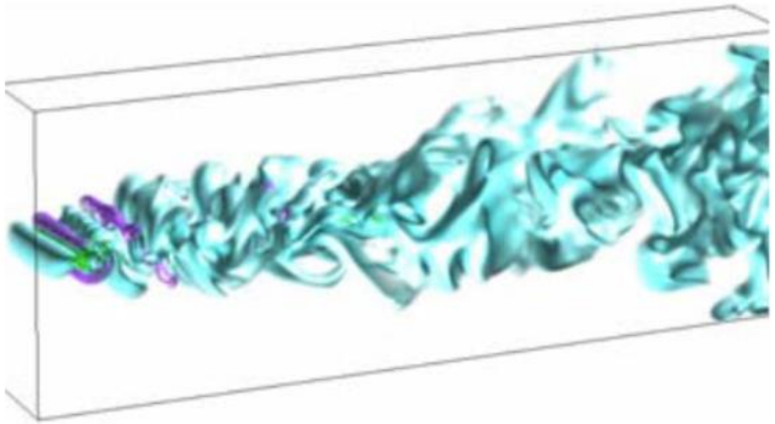
# STNet: End to End Generative Framework for STSR Volumes

- Synthesizing STSR volumes using end-to-end ML
- *End-to-end* generative architecture critical for avoiding error accumulation
- Leverages *feature interpolation* instead of data interpolation
- Network uses *fine-tuning* stage for better generalizability

STNet



Ground Truth



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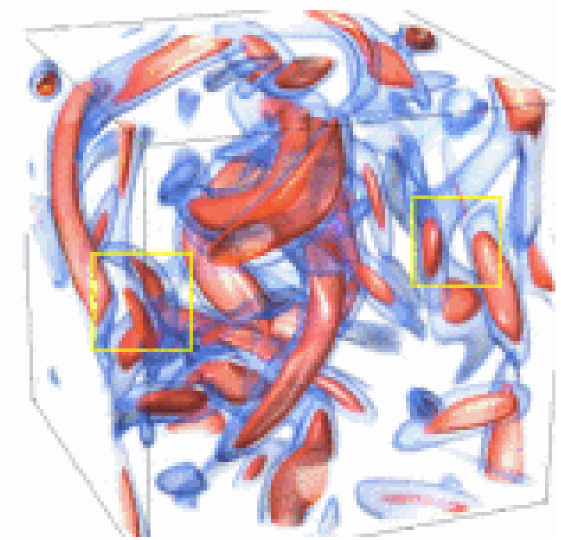
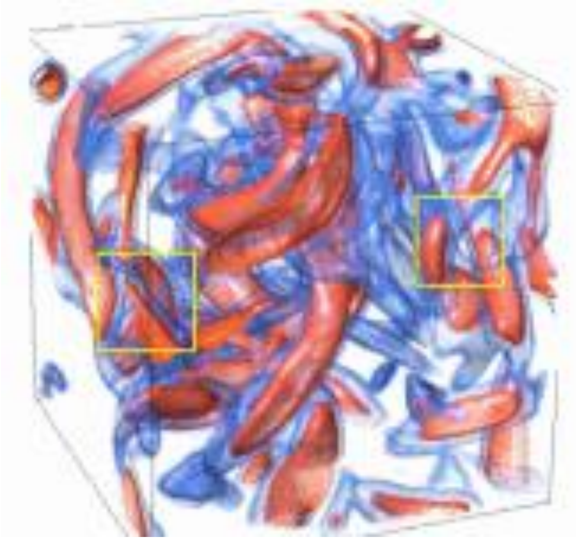
# End to End Network

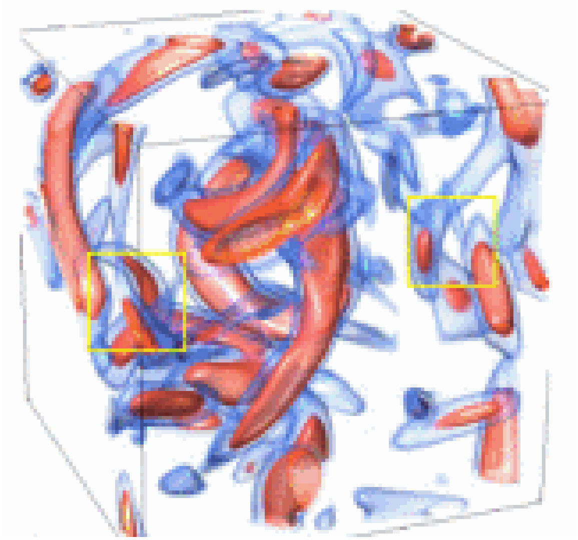
- *Single training phase*, instead of building sequential spatial and temporal models
- Errors do not accumulate from different sequential stages
- Yields much higher quality results
- STNet upscale volumes at both spatial and temporal dimensions simultaneously



Ground Truth



Spatial + Temporal



STNet

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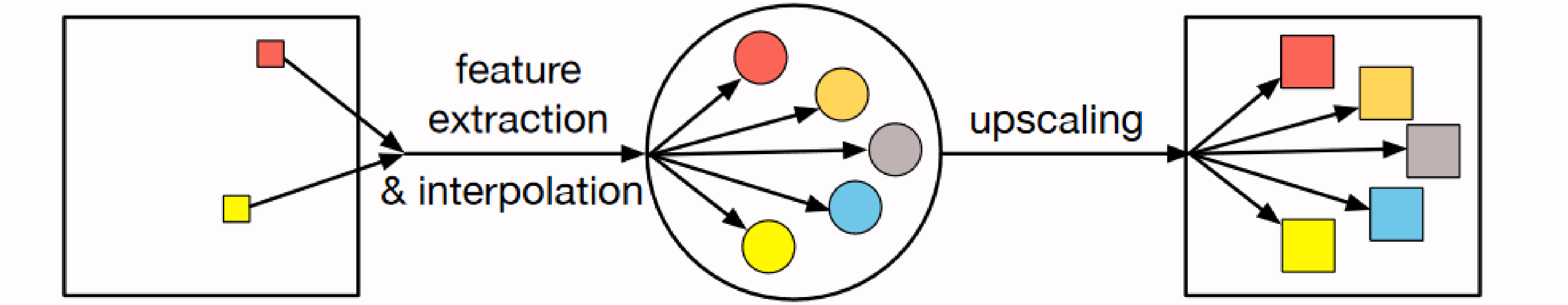
# Feature Interpolation

- Feature-space interpolation:
  - Feature extraction and interpolation through ML
  - Generates feature of each intermediate time step individually
  - Upscales all time steps to super resolution after feature generation
- Post-upsampling brings two benefits:
  - *Speed*: Low computation cost, fewer operations occur in high-dimensional space
  - *Performance*: No issue in upscaling, convolutions occur in low-dimensional space

Feature Space

Low Resolution Space




Super Resolution Space

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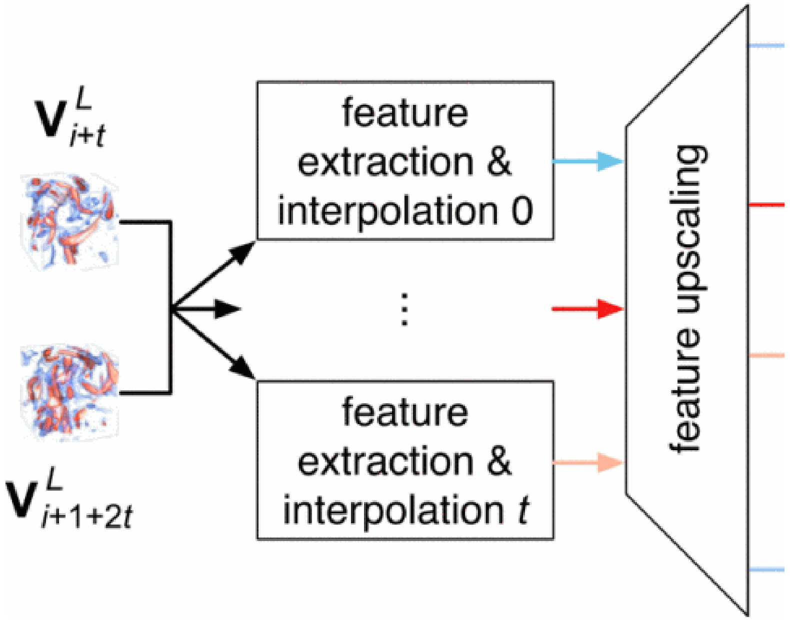
# Data Synthesizing Framework

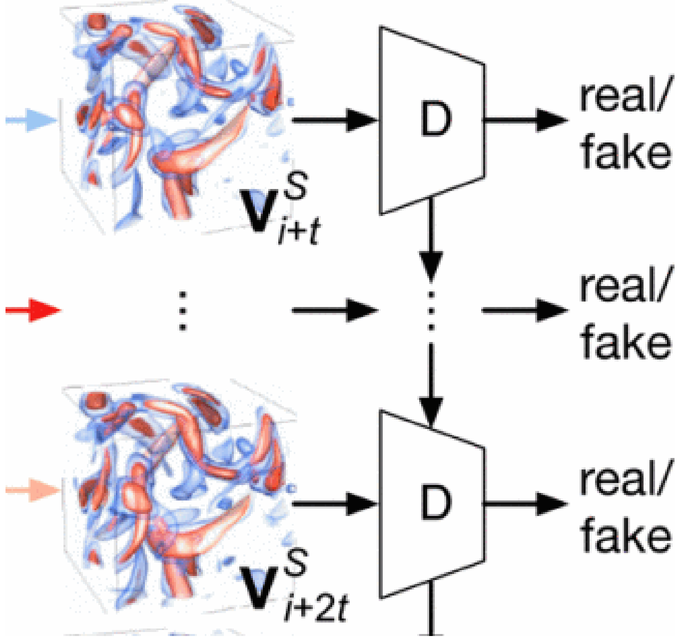
**Generator**

- Feature extraction interpolation module
  - Takes low resolution input
  - Performs interpolation in feature space
  - Convolutional layers extract features
- Feature upscaling module
  - Upscales all intermediate frames




**Discriminator**

- Judge closeness and realness of volumes
  - Convolutional layers extract features
  - Features compressed to single value
- Scores assigned to each value
  - Closeness to original volume
  - Real or Fake



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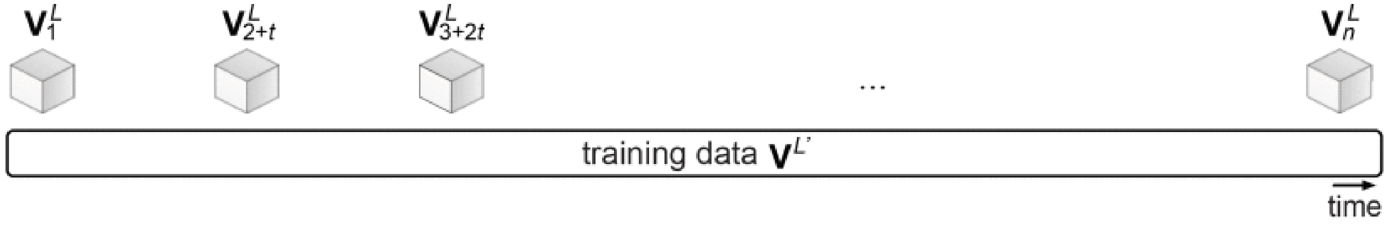
# Pre-training and Fine-tuning

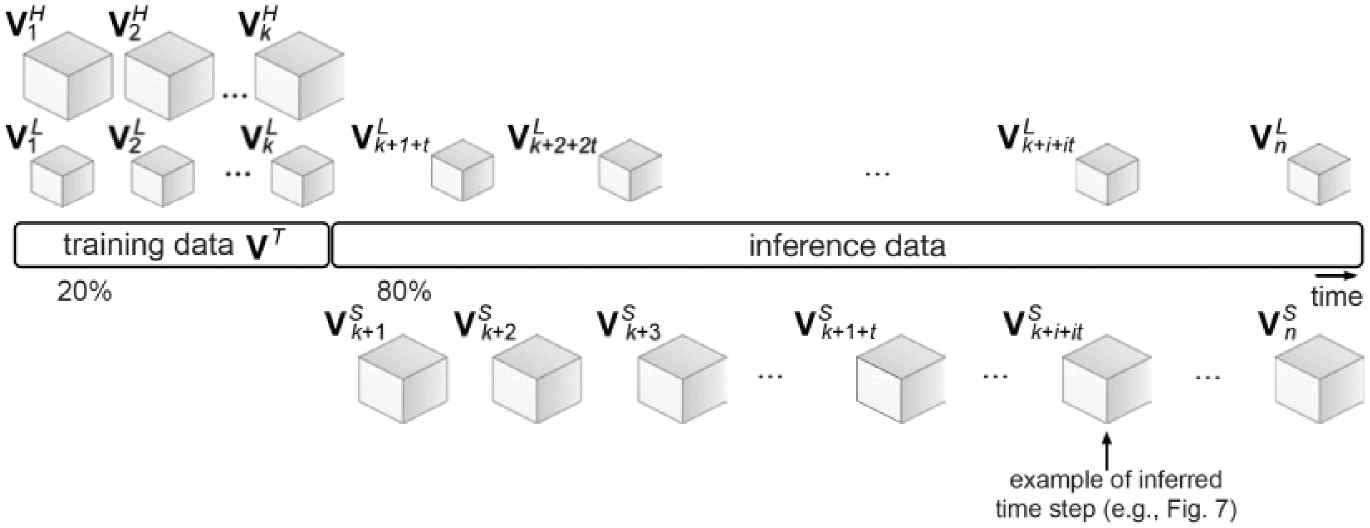
## Pre-training

- Avoids model to be stuck in a local minimum
- Avoids overfitting of training data
- *Cycle loss* to optimize model




## Fine-tuning

- Enhances network fit
- Improves generalizability of the model
- *Volumetric loss* to measure closeness
- *Adversarial loss* to measure realness

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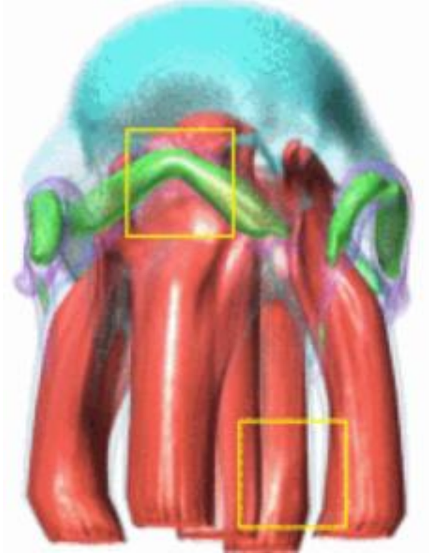
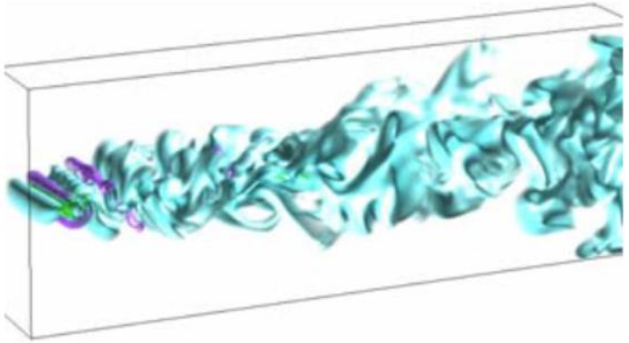
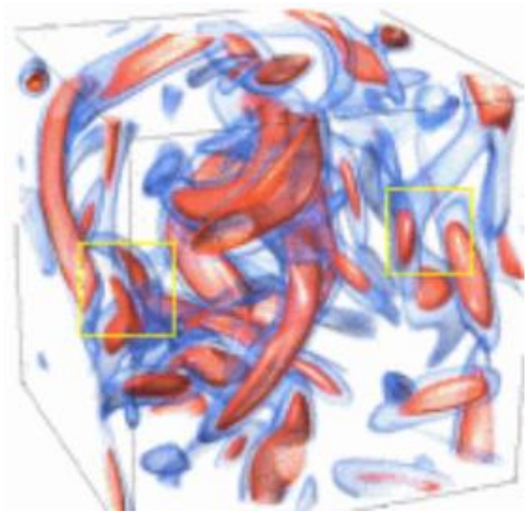
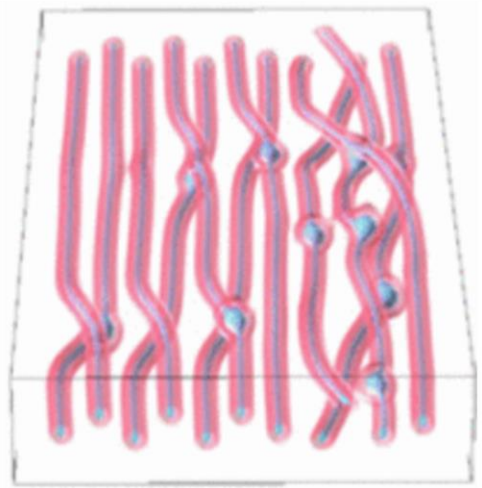
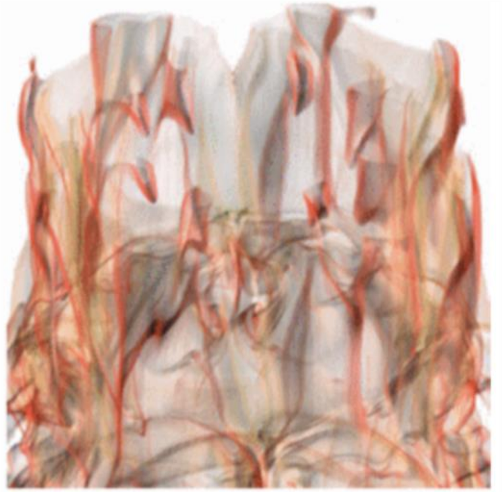
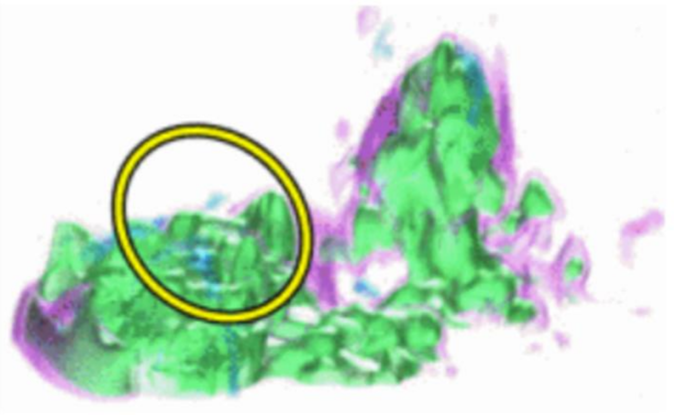
# Datasets

| Dataset | Five Jets | Half Cylinder | Vortex |
|---|---|---|---|
| Variable | Intensity | Velocity Magnitude | Vorticity Magnitude |

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| Dataset | Supercurrent | Ionization (H) | Tangaroa |
|---|---|---|---|
| Variable | Rho | H | Velocity Magnitude |

# Results – Volume Rendering

- Peak signal-to-noise (PSNR)
  - Ratio of signal power and corrupting noise
- Image-level structural similarity index (SSIM)
  - Quantifies image quality degradation

| Dataset | PSNR | SSIM |
|---|---|---|
| Five Jets | **39.63** | 0.901 |
| Half Cylinder | 36.84 | **0.944** |
| Vortex | 32.73 | 0.720 |

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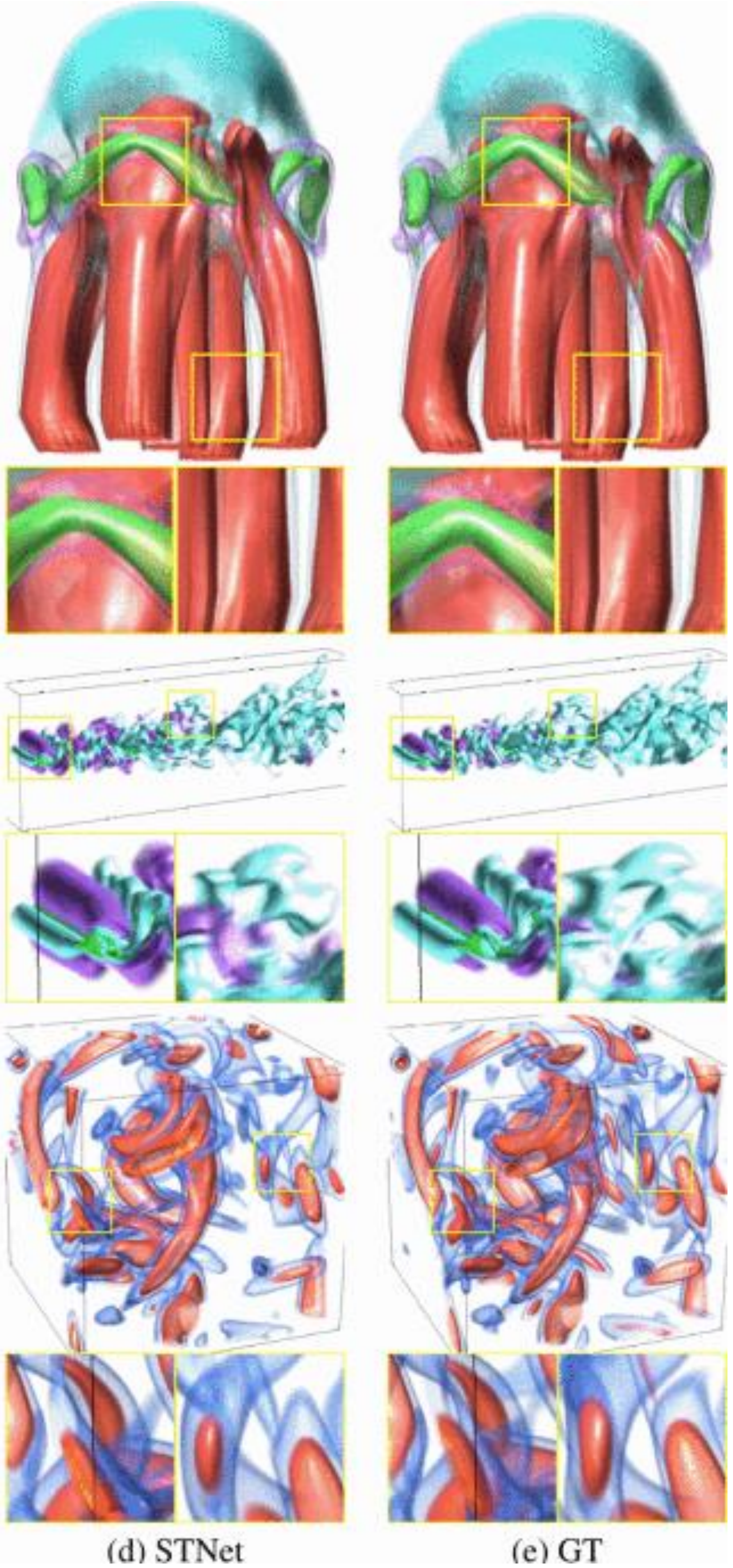
Five Jets

Half Cylinder

Vortex

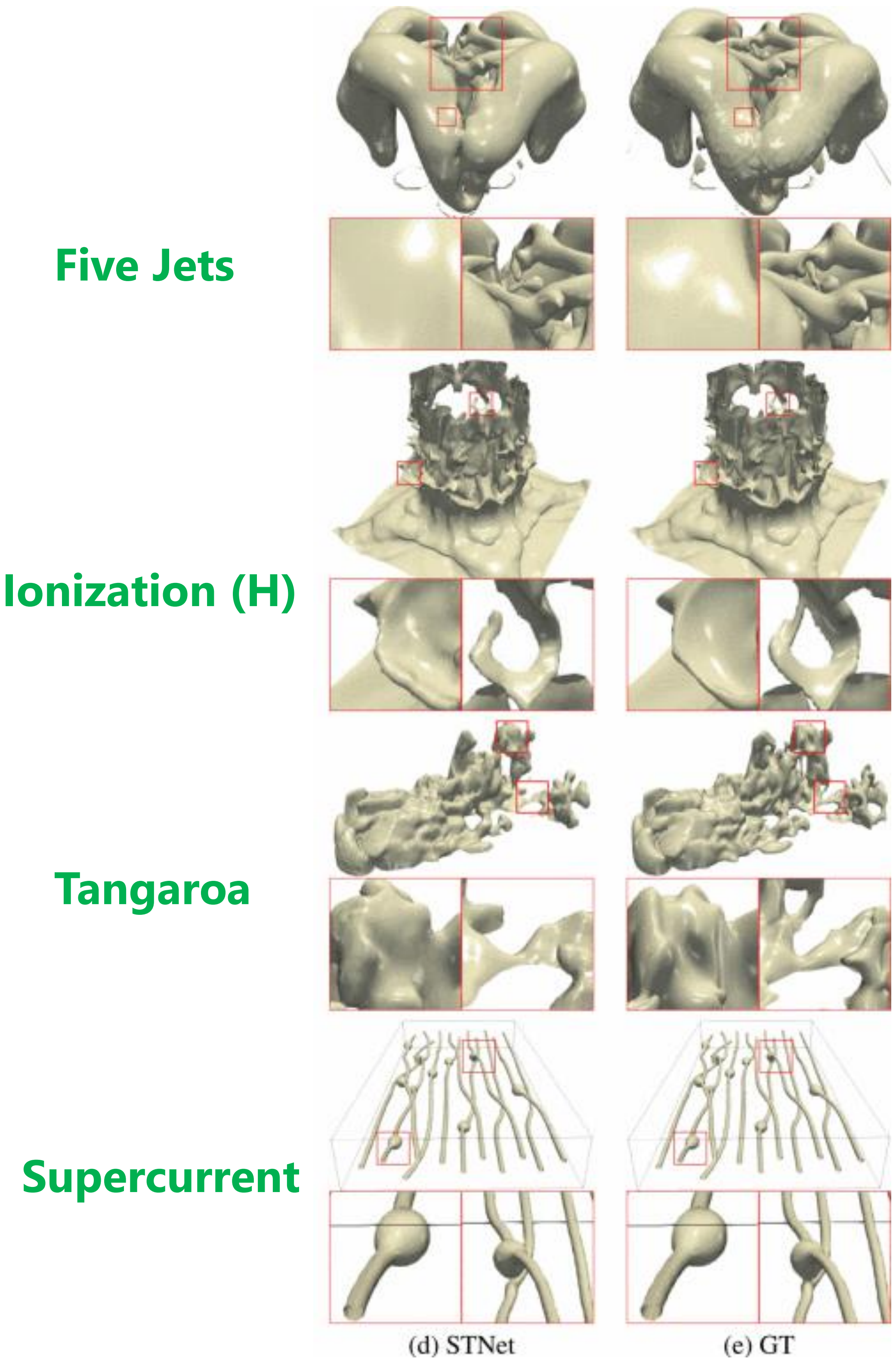


# Results – Iso-surface Rendering

- Iso-surface similarity index (IS)
  - Quantifies image quality degradation

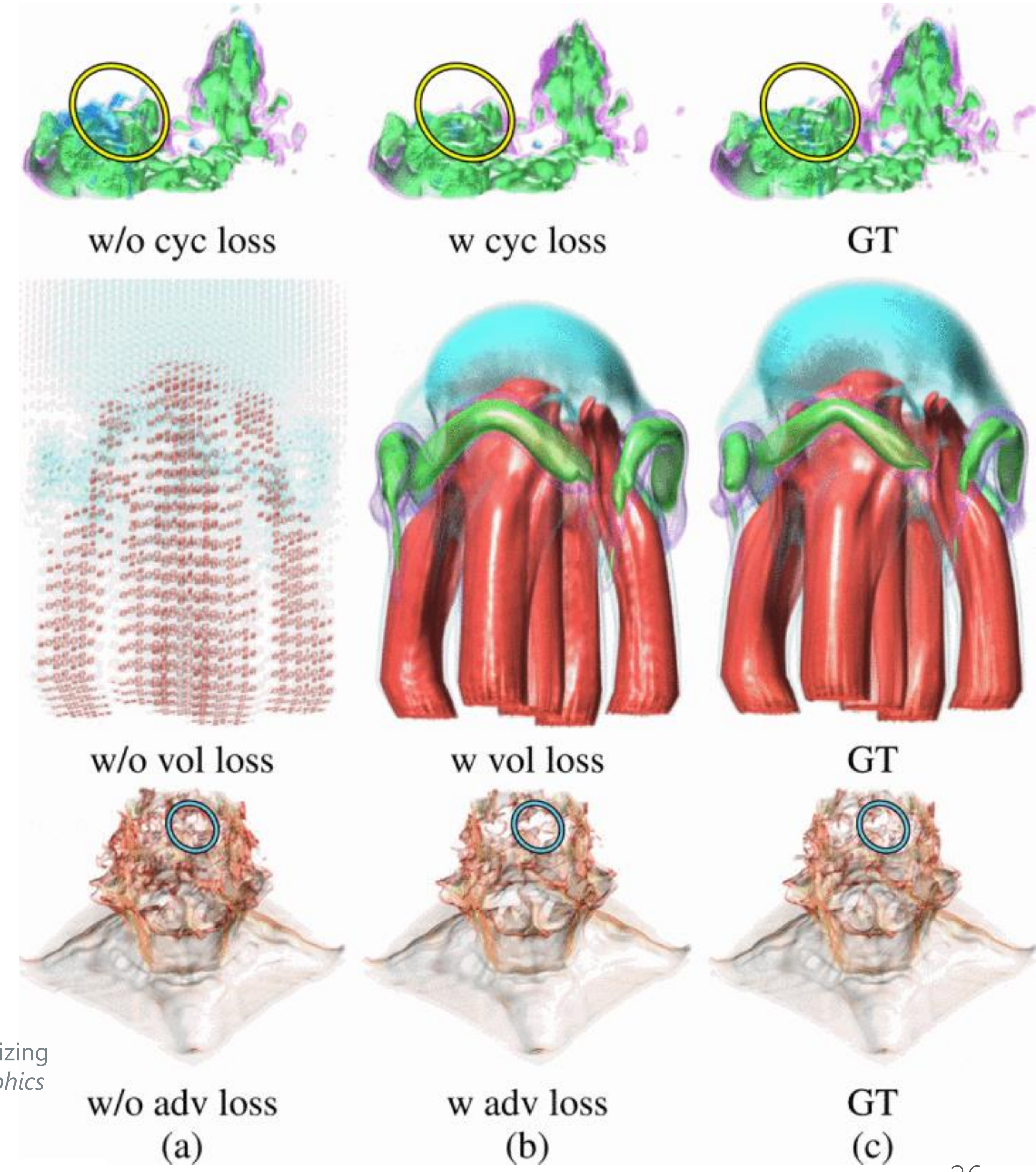
| Dataset | IS |
|---|---|
| Five Jets | 0.88 |
| Ionization (H) | 0.81 |
| Tangaroa | 0.75 |
| Supercurrent | **0.96** |

J. Han, H. Zheng, D. Z. Chen and C. Wang, "STNet: An End-to-End Generative Framework for Synthesizing Spatiotemporal Super-Resolution Volumes," in *IEEE Transactions on Visualization and Computer Graphics*



# Results – Different Settings

| Dataset | PSNR | SSIM | Method |
|---|---|---|---|
| Tangaroa | 32.26 | 0.883 | w/o cycle loss |
| | **33.26** | **0.892** | w cycle loss |
| Five Jets | 22.11 | 0.621 | w/o volumetric loss |
| | **39.63** | **0.892** | w volumetric loss |
| Ionization (H) | **43.80** | 0.904 | w/o adversarial loss |
| | 43.19 | **0.913** | w adversarial loss |

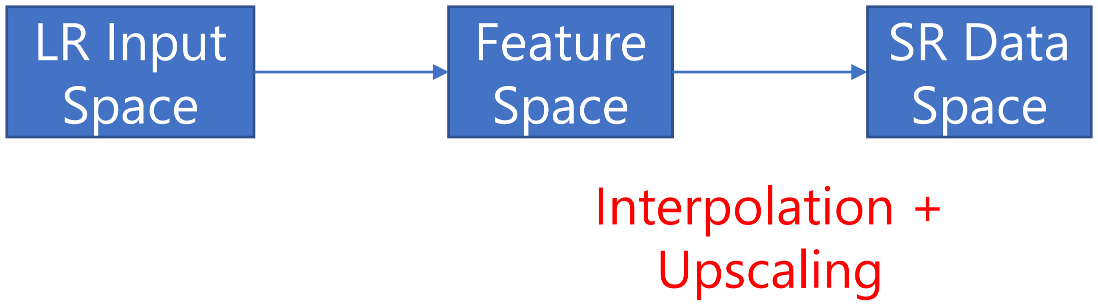



J. Han, H. Zheng, D. Z. Chen and C. Wang, "STNet: An End-to-End Generative Framework for Synthesizing Spatiotemporal Super-Resolution Volumes," in *IEEE Transactions on Visualization and Computer Graphics*

# Reconstruction Task vs Synthesizing Task

**Reconstruction Task**

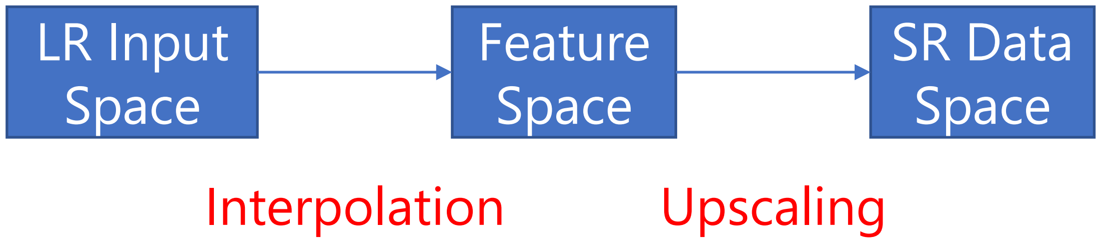
- From medium / low resolution data
- Interpolates in the data space




- Sequential model
- Data variables magnitude and direction

**Synthesizing Task**

- From low + high resolution data
- Interpolates in the feature space

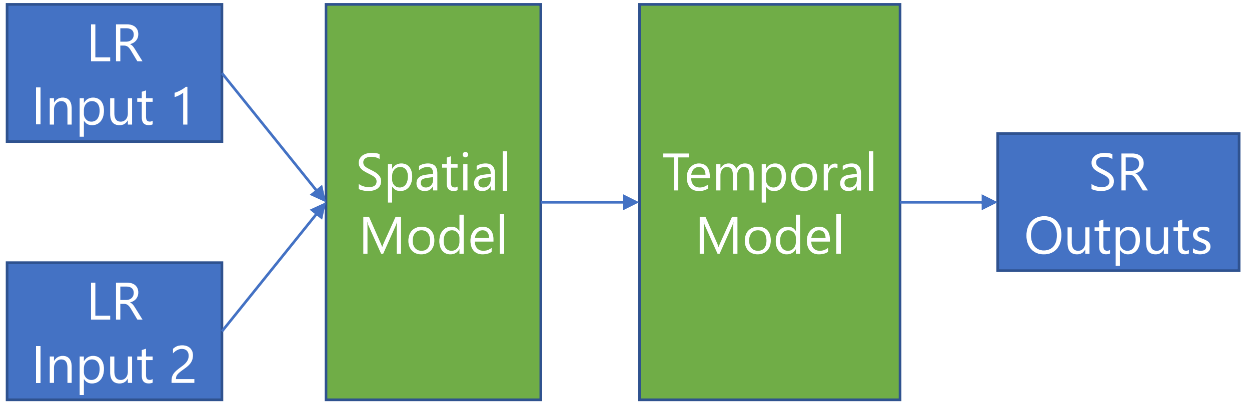



- End to end model
- Data variables magnitude only

# Sequential Model vs End to End Model

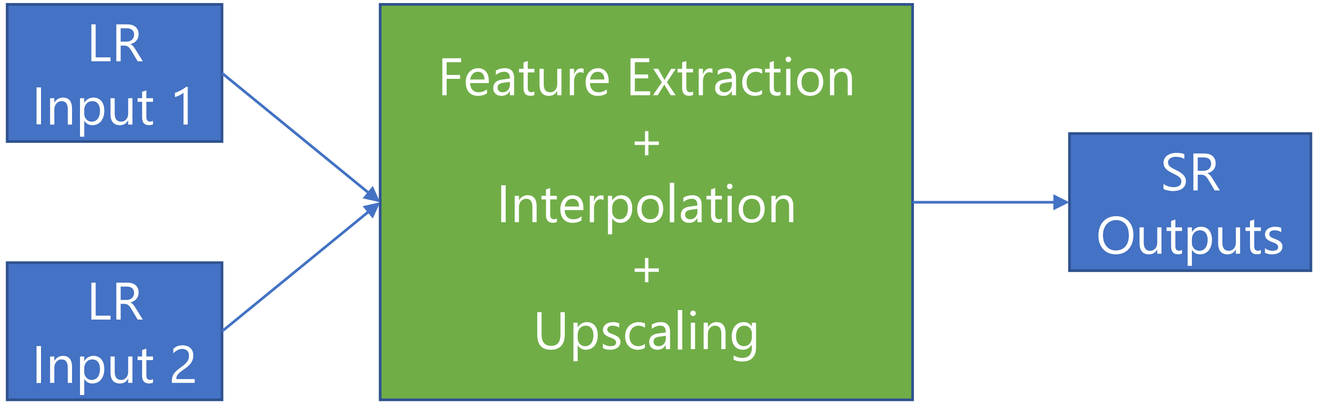
## Sequential Model

- Upscales spatial data then temporal data
- Model accumulates errors and amplifies them




## End to End Model

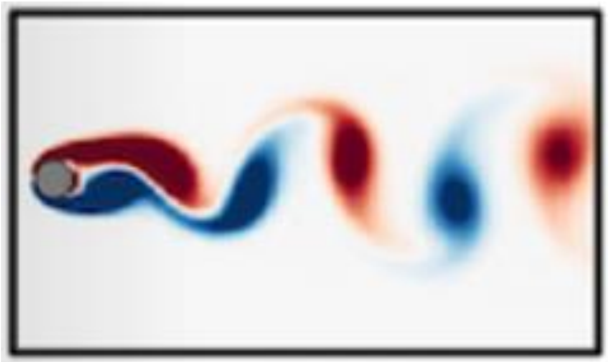
- Upscales spatio-temporal data simultaneously
- No accumulation and amplification of errors



# Vector Data vs Scalar Data

**Vector Data**

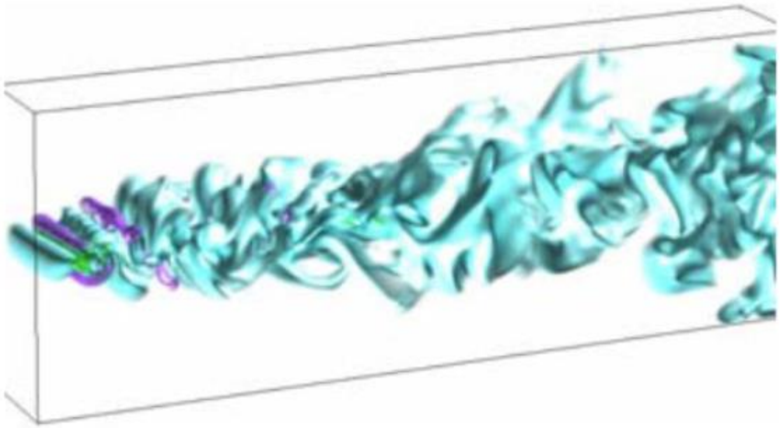
- Velocity, pressure and vorticity
  - direction and magnitude
- 2D and 3D data *plus time*
- Computation heavy



Fukami, K., Fukagata, K., & Taira, K. (2021). Machine-learning-based spatio-temporal super resolution reconstruction of turbulent flows. *Journal of Fluid Mechanics, 909*, A9. doi:10.1017/jfm.2020.948

**Scalar Data**

- Velocity, pressure, intensity and vorticity
  - magnitude only
- 3D volume data only *plus time*
- Computation lighter

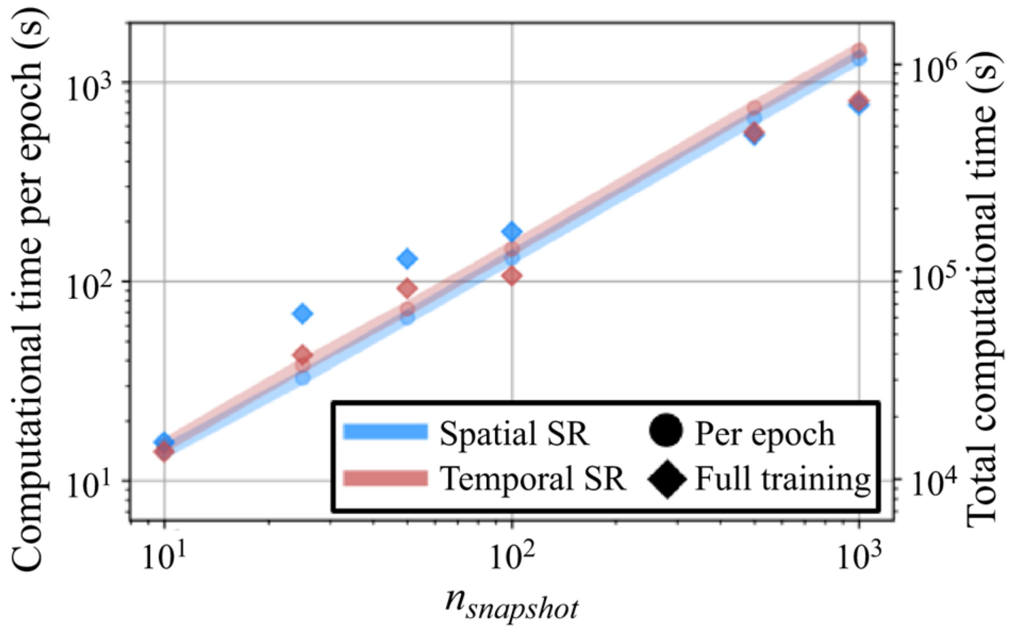


J. Han, H. Zheng, D. Z. Chen and C. Wang, "STNet: An End-to-End Generative Framework for Synthesizing Spatiotemporal Super-Resolution Volumes," in *IEEE Transactions on Visualization and Computer Graphics*

# Limitations

**Reconstruction Task**

- Could not minimize loss well
  - At higher wave-number regions
- High computational time
  - 15 days for training 1000 snapshots




**Synthesizing Task**

- Temporal sampling uses uniform sampling
  - May not capture dynamic pattern well
- Framework not powerful enough
  - Only upscaled data 4 times each dimension

**Future Work**

- STNet will explore fully unsupervised techniques to generate STSR data


Fukami, K., Fukagata, K., & Taira, K. (2021). Machine-learning-based spatio-temporal super resolution reconstruction of turbulent flows. *Journal of Fluid Mechanics, 909*, A9. doi:10.1017/jfm.2020.948

# Conclusions

- Spatio temporal super resolution data can be reduced and recovered using ML
- End to end models work better than sequential models
- Interpolation in feature space more efficient compared to data space
- Turbulent vector data is much harder to work with compared to laminar or scalar data

# Thank you for your attention!

# Any Questions?

Shourya Verma