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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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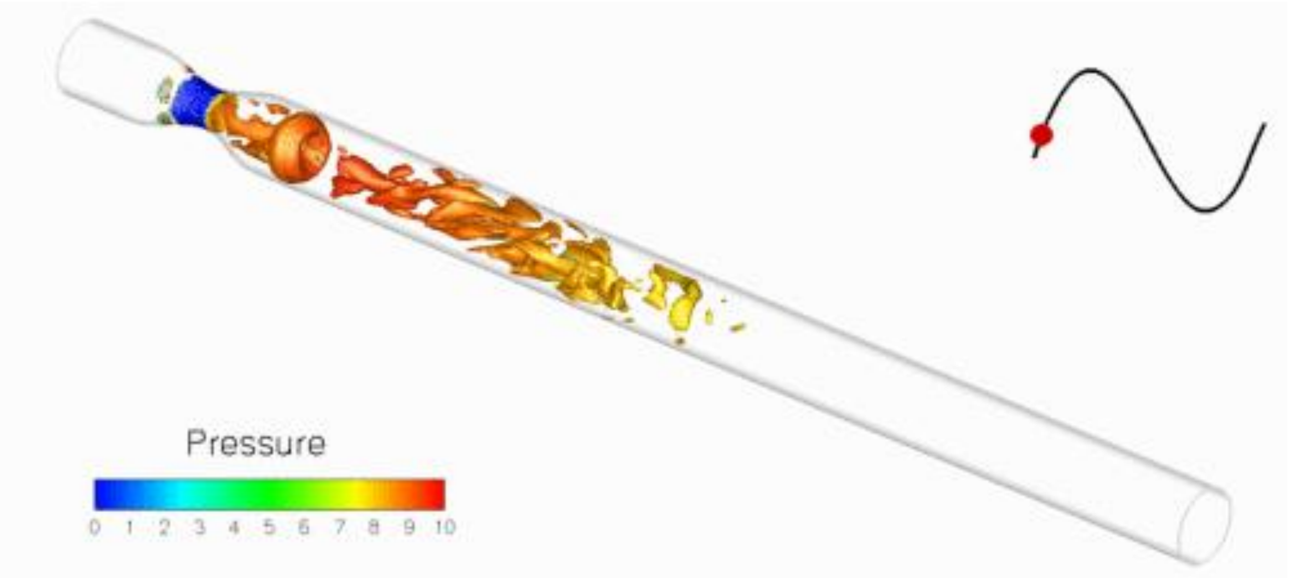
Motivation

- 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

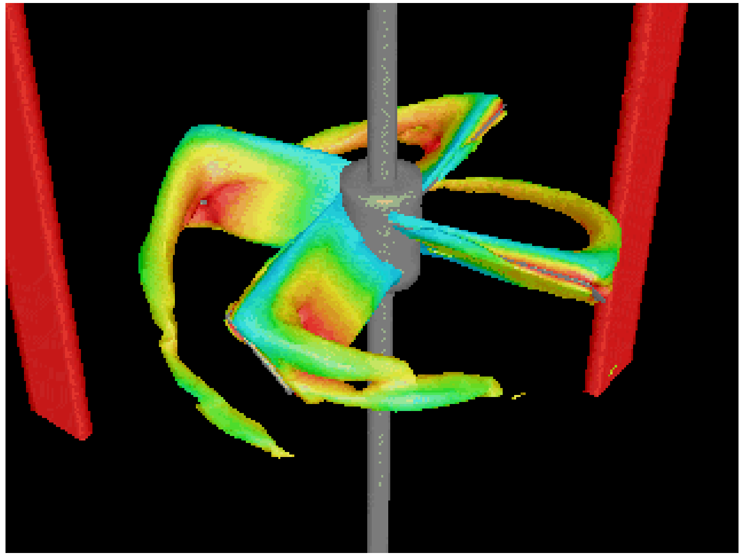


https://engineering.purdue.edu/CFDLAB/

Example

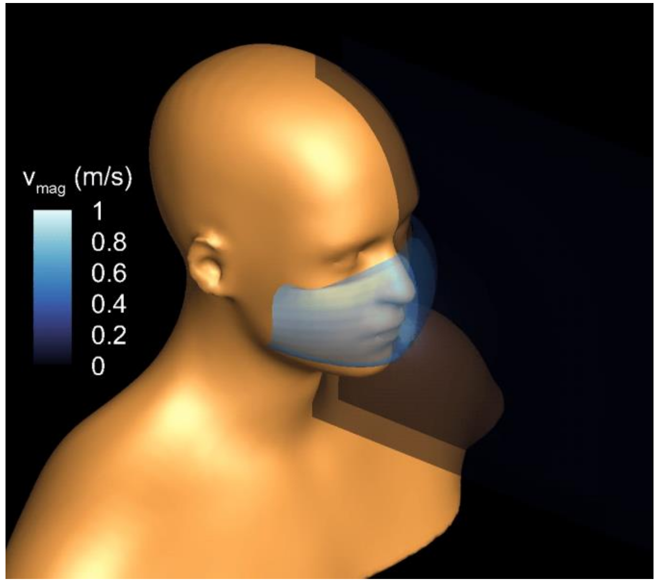
- Why fluid dynamic simulations?

Industrial turbines



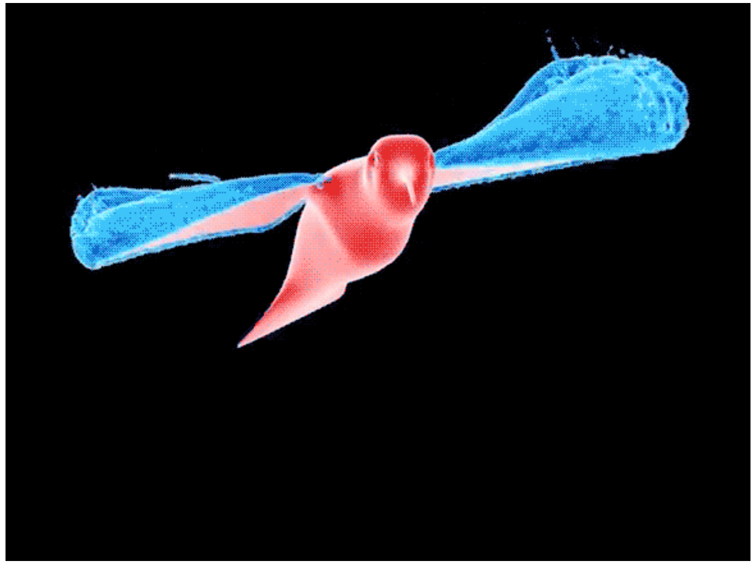
https://www.bakker.org/cfm/a5-3.gif

Coughing airflow



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

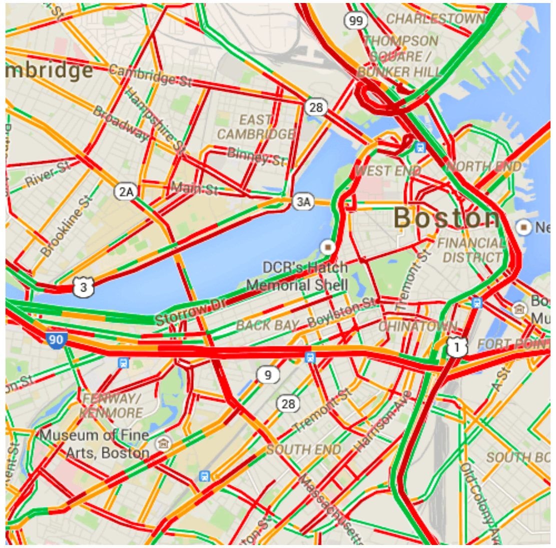
Bird wings



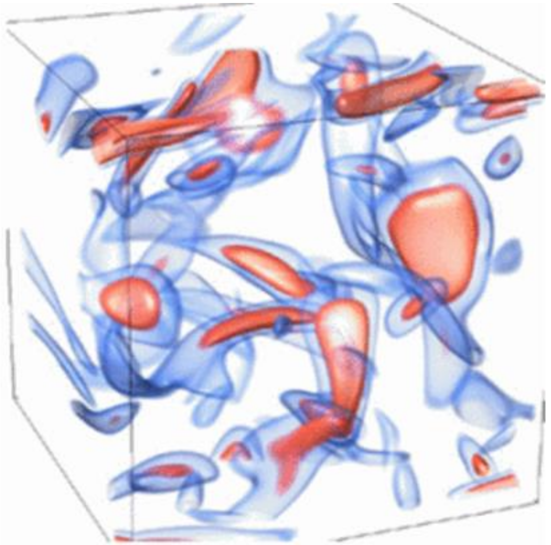
https://i.pinimg.com/originals/b5/28/c2/b5
28c22e8d18ed271bf4b8f3687a6e62.gif

Spatio-Temporal (ST) Data

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



3D Traffic Volume data [1]

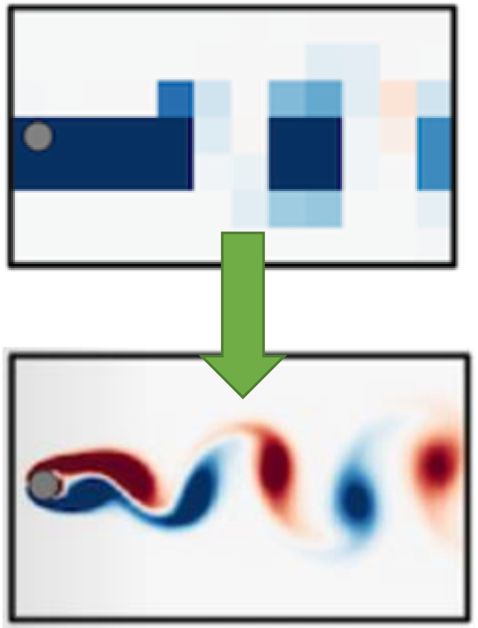


4D Particle Flow Field data [2]

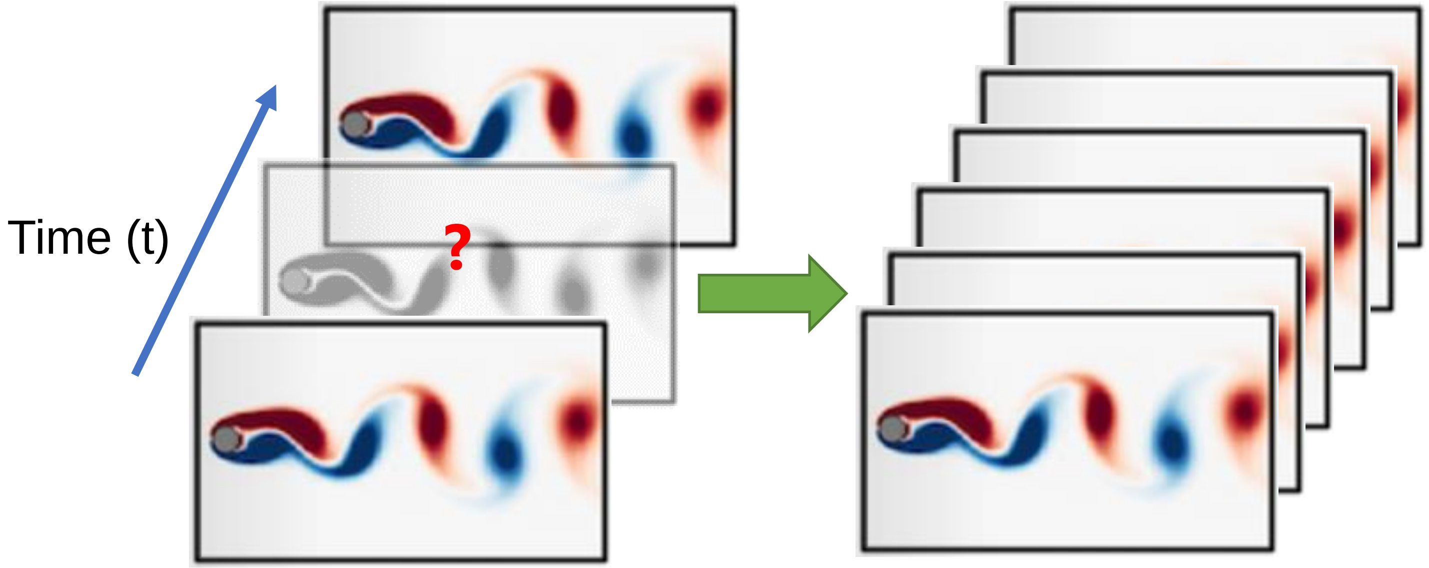
[1] https://medium.com/@imtechpros_87395/where-does-google-maps-get-its-traffic-data-from-2562f984d82f
[2] J. Han, H. Zheng, D. Z. Chen and C. Wang, "STNet: An End-to-End Generative Framework for Synthesizing Spatiotemporal Super-Resolution Volumes," in *IEEE Transactions on Visualization and Computer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

Spatio Temporal Super Resolution (STSR) Data

- Low-resolution (128×128×50) → Super-resolution (512×512×200) $(x \times y \times t)$
- *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

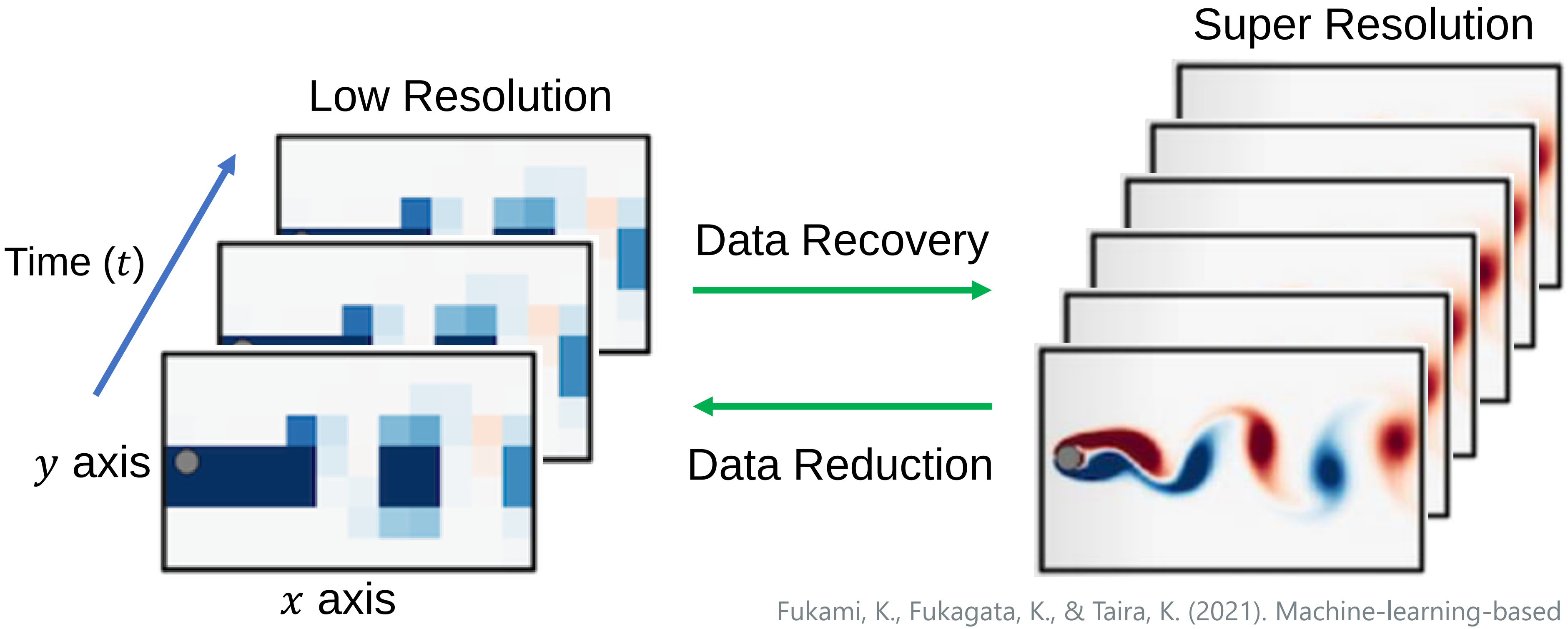


temporal inbetweening

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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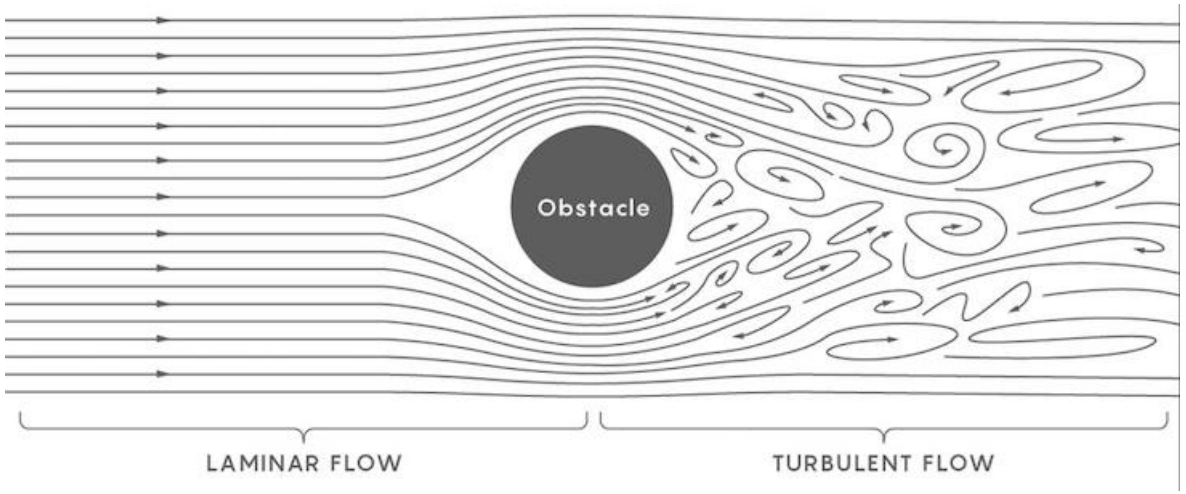
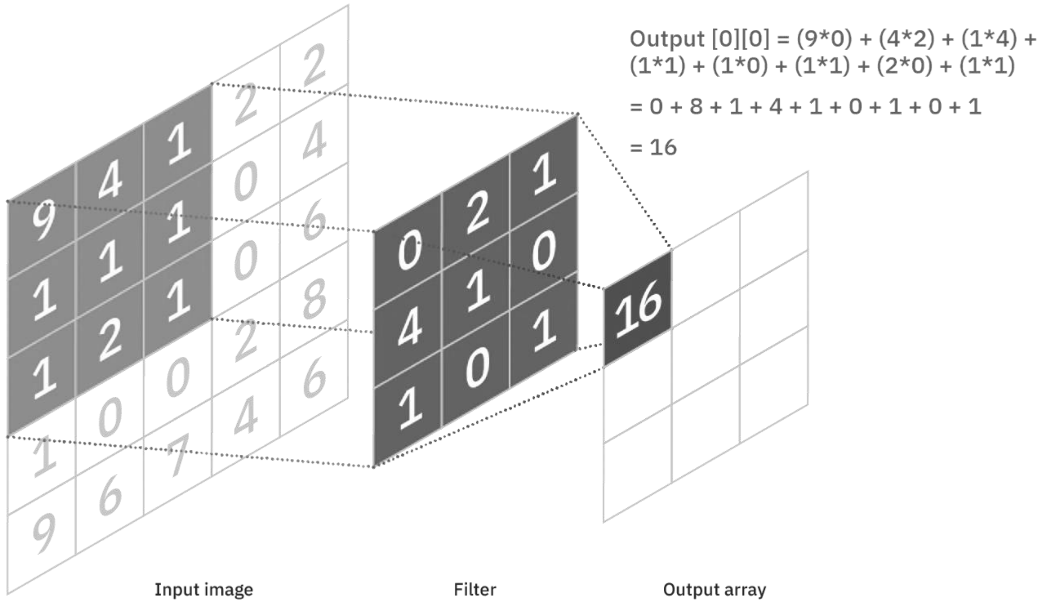
ML based STSR Reconstruction of Turbulent Flows

- 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



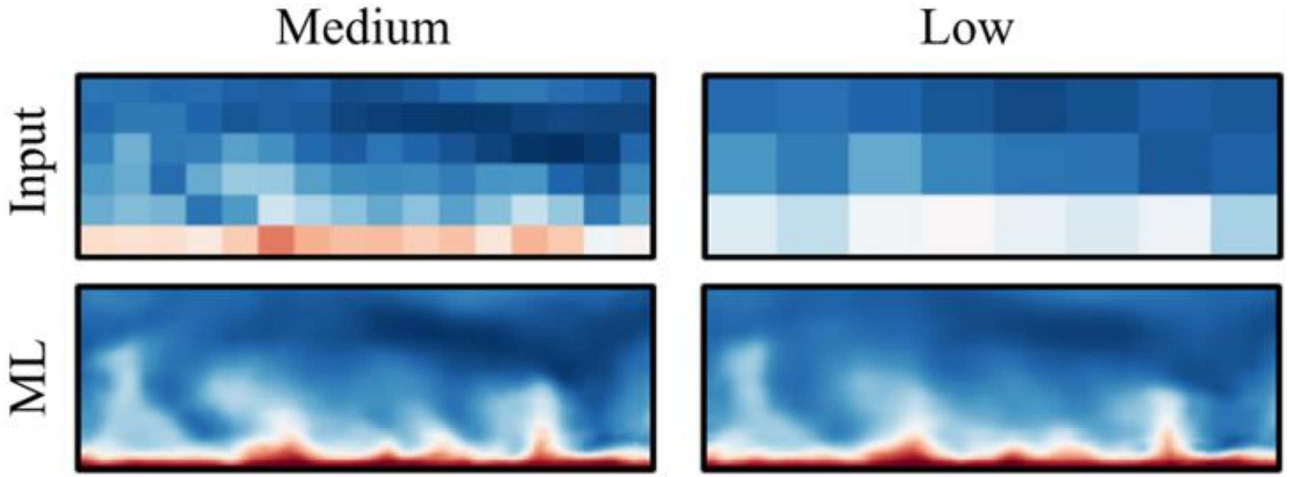
https://www.ibm.com/cloud/learn/convolutional-neural-networks

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

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

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



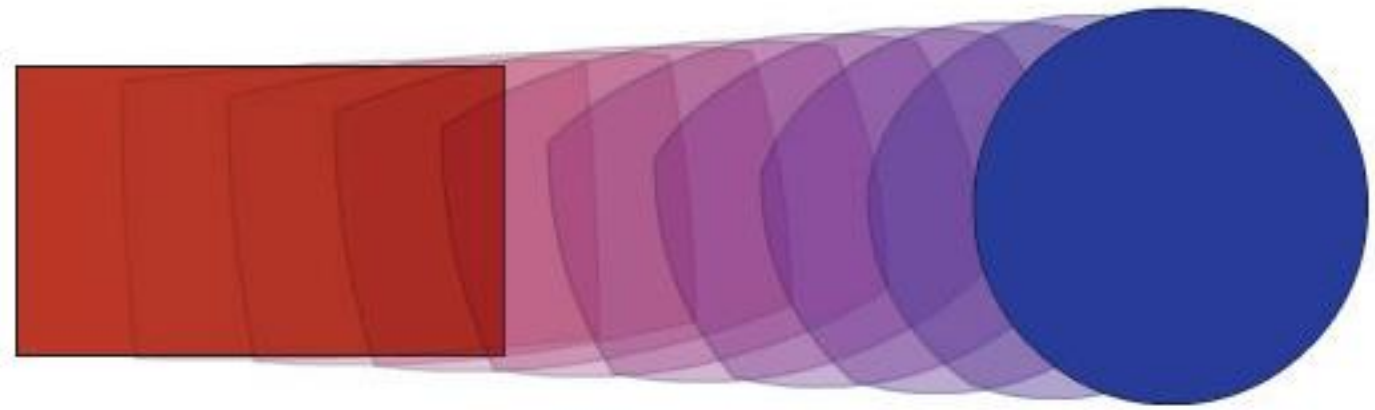
$q(x_{LR}, t_{LR})$

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

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

Temporal Inbetweening

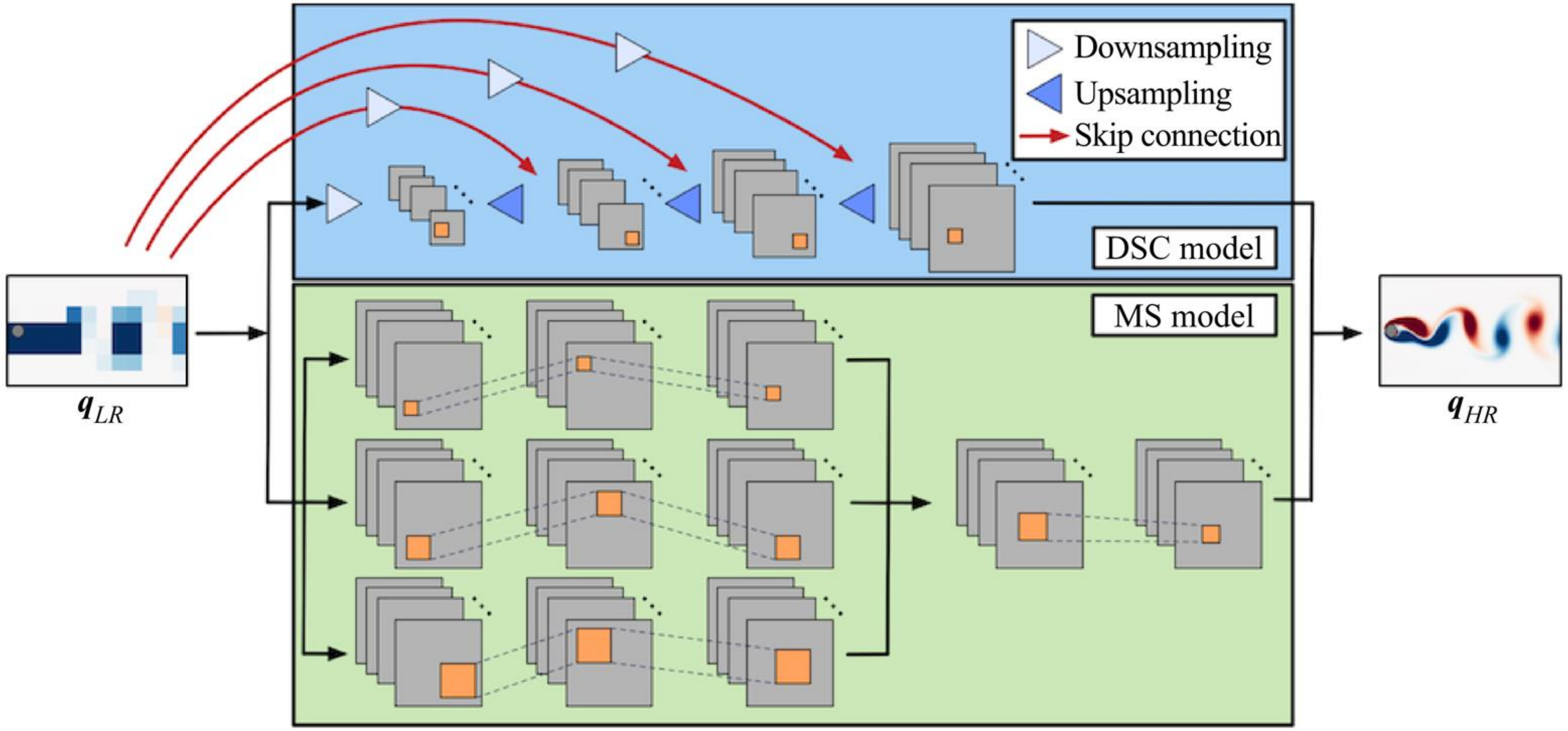
- Process of creating intermediate frames between two frames
- Creates the visualization of movement
- Smoothly transitioning one image into another at different time intervals
- Machine learning models generate as much as 14 frames between 2 given frames



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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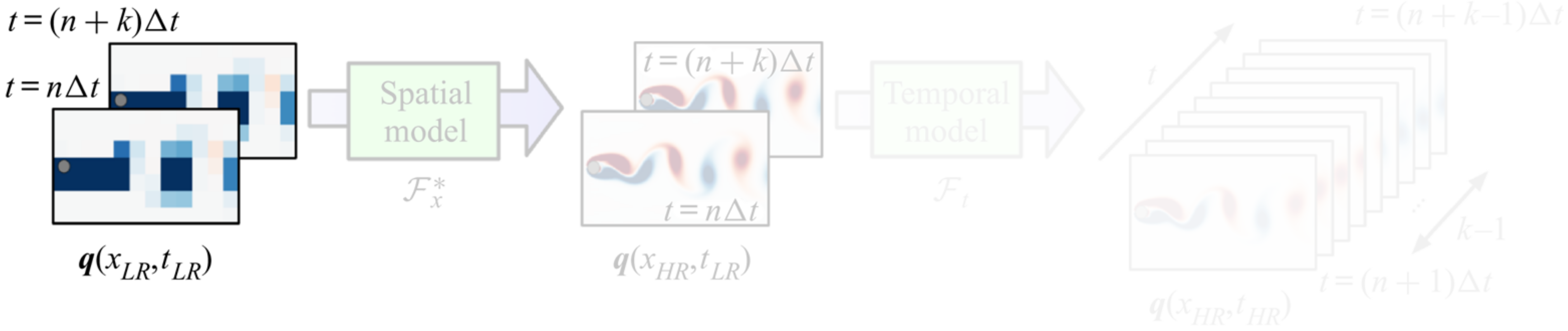
Data Reconstruction Framework

- 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:
  - $\boldsymbol{q}(\boldsymbol{x}_{HR}, \boldsymbol{t}_{HR}) = \boldsymbol{Ft}(\boldsymbol{Fx}(\boldsymbol{q}(\boldsymbol{x}_{LR}, \boldsymbol{t}_{LR}))) + \boldsymbol{\epsilon tx}$

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



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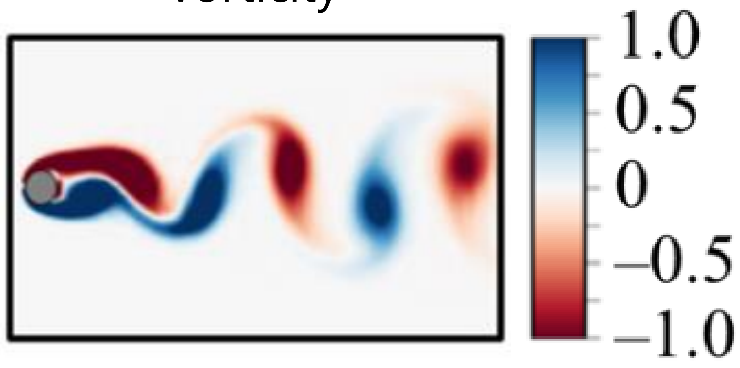
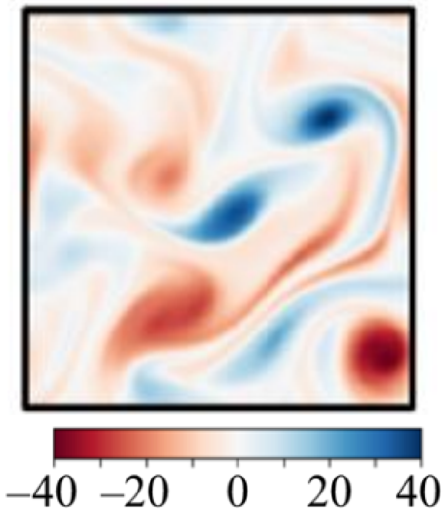
Datasets

- 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

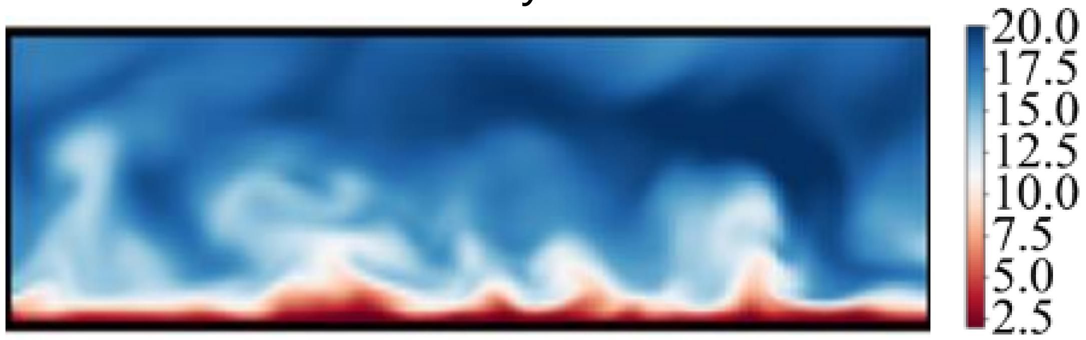
Vorticity



Vorticity



Velocity



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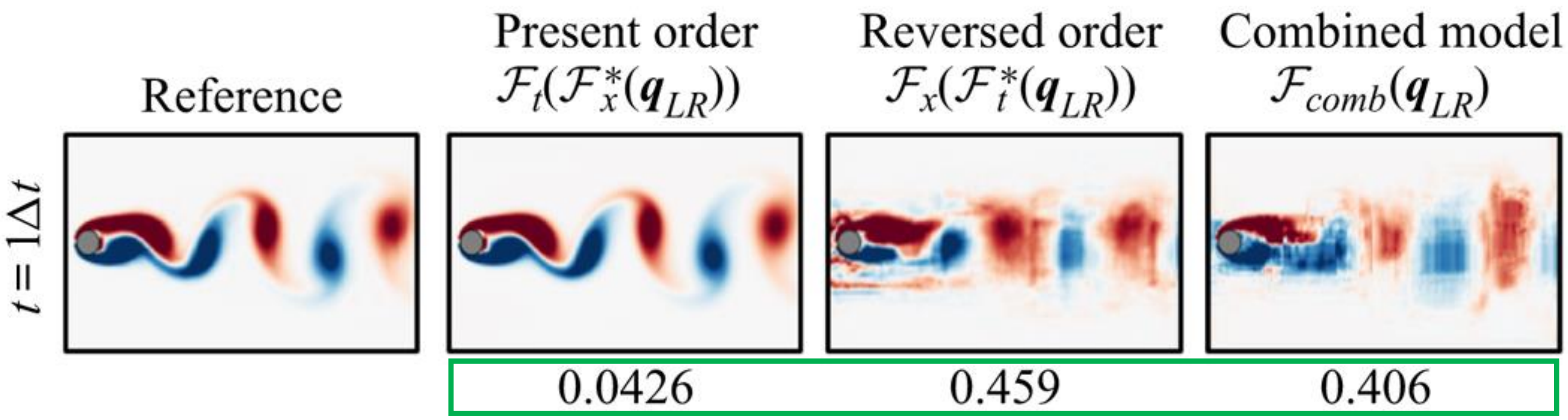
Sequential vs Combined Model



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

Root Mean Square Error Norm

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

optimized weights ω

- 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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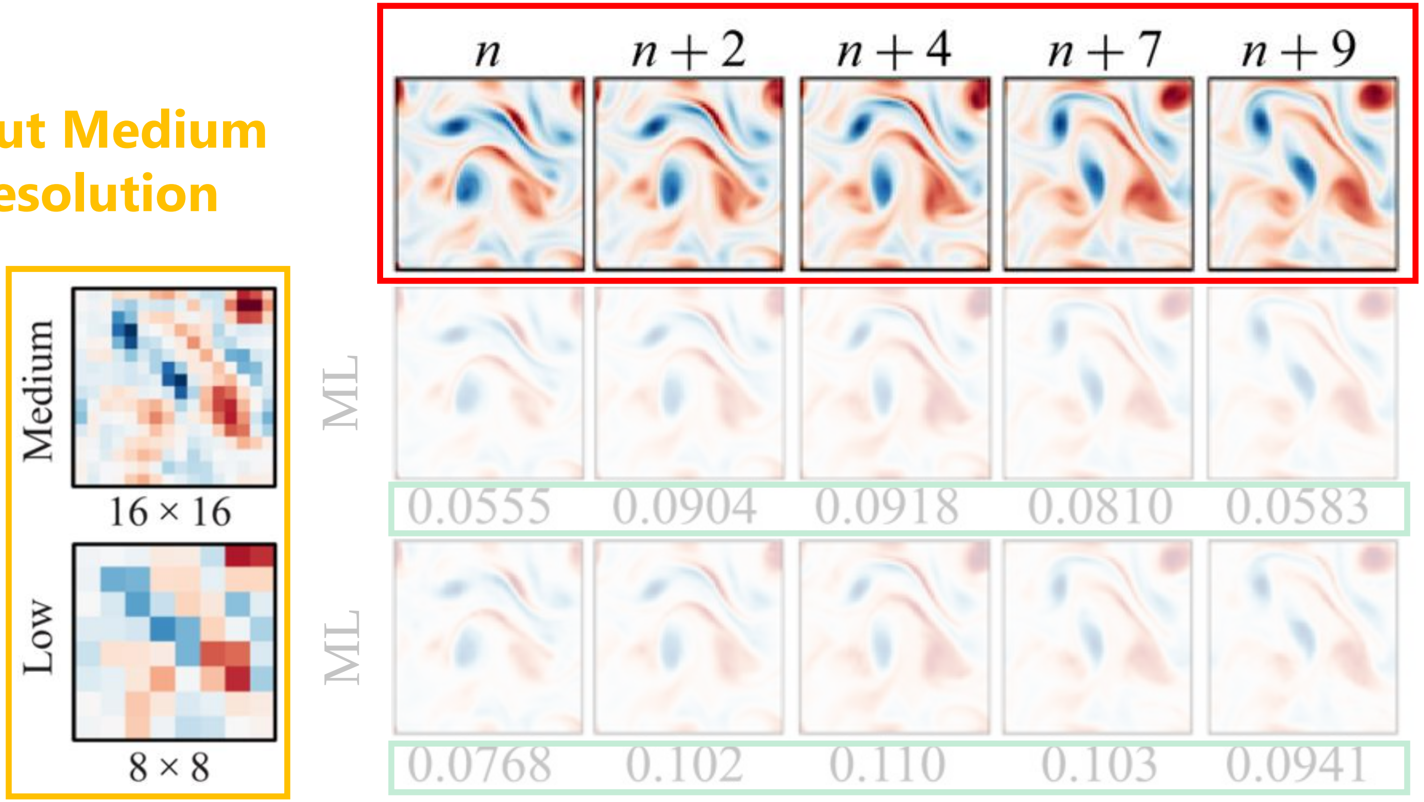
Results – Vorticity Contours

Coarse Input Medium and Low Resolution



Reference
128x128

Root Mean Square Error Norm

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

optimized weights ω

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

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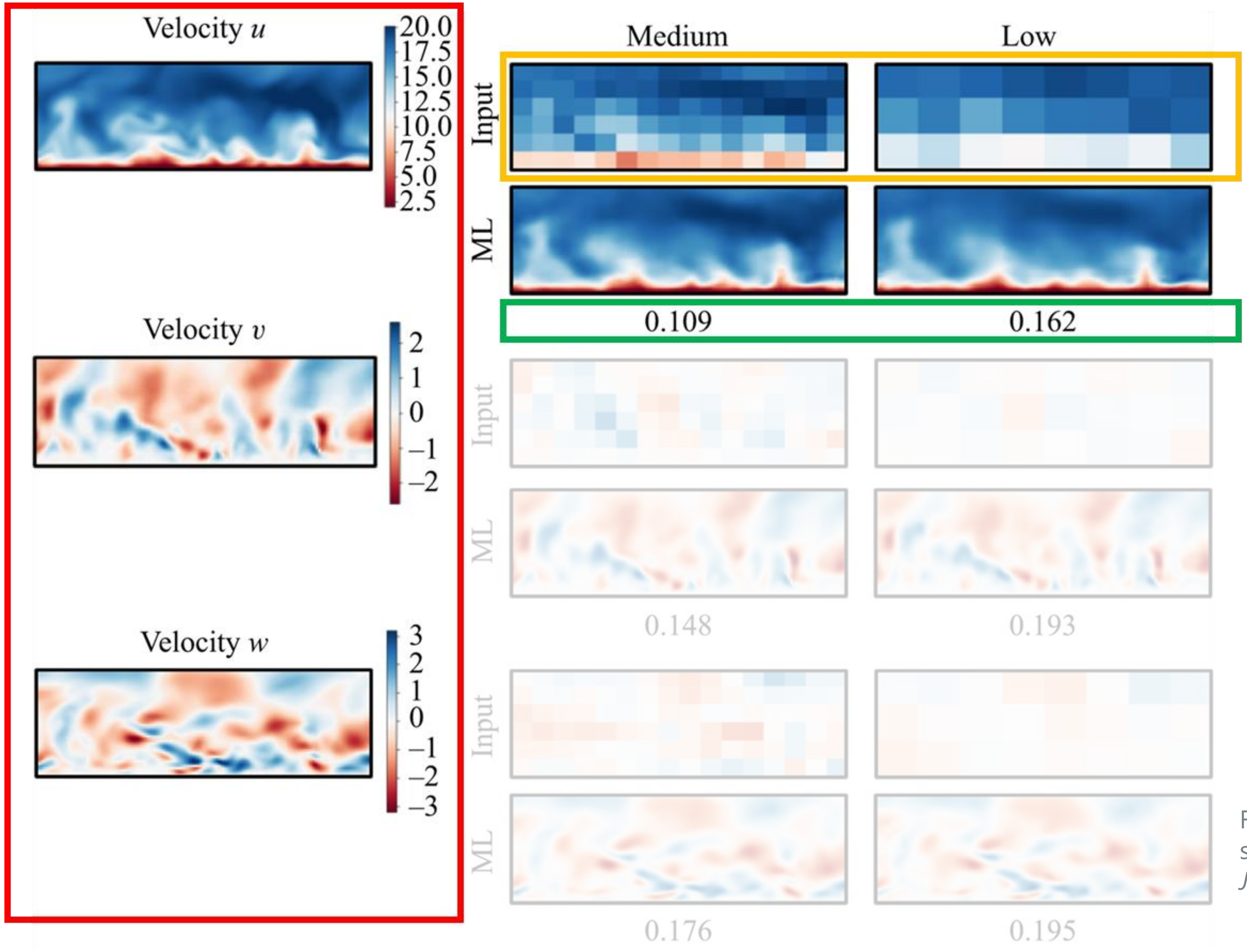
Results – Velocity Contours

Reference



Coarse Input Medium and Low Resolution

Root Mean Square Error Norm

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

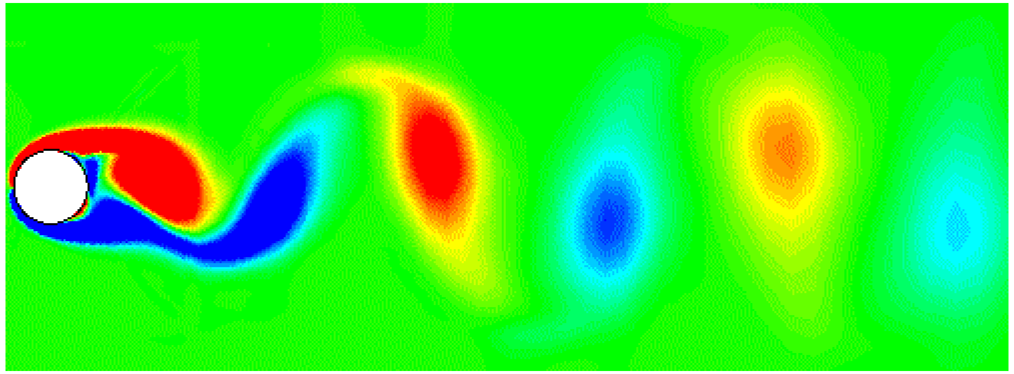
optimized weights $\boldsymbol{\omega}$

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

What can be improved?

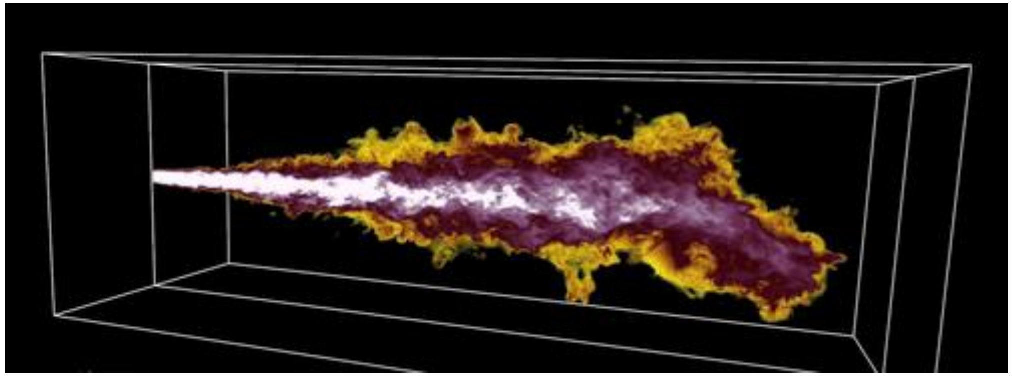
- Sequential model does not provide high fidelity results
  - Due to error accumulation
- Data space interpolation computationally heavy
  - Inbetweening of high resolution
- Turbulent vector data difficult for volumes
  - Computationally heavy

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

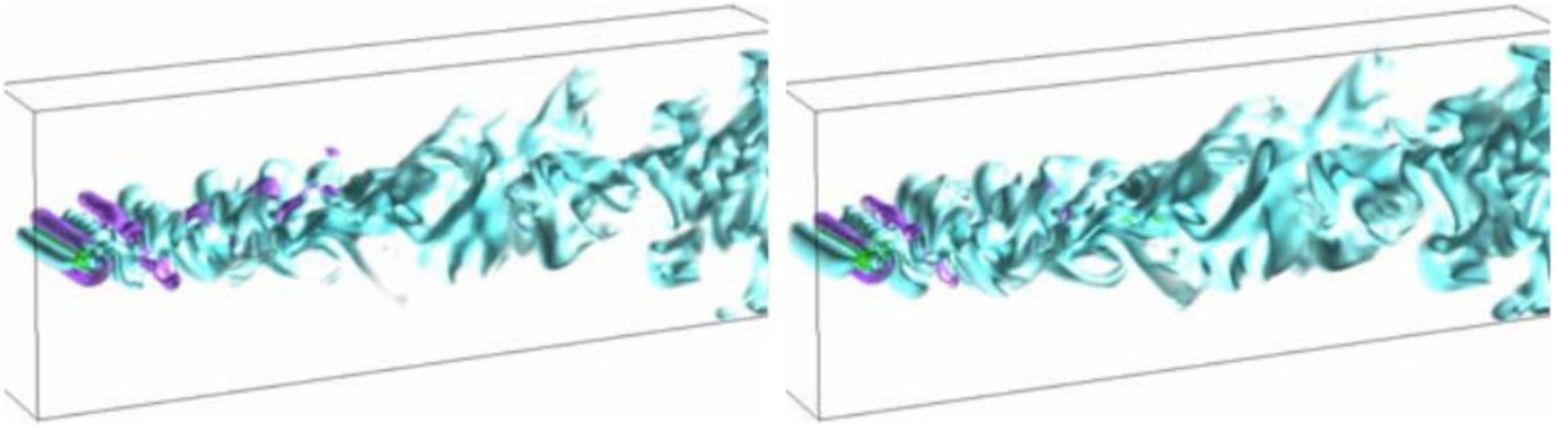
IEEE Transactions on Visualization and Computer Graphics, vol. 28, no. 1, pp. 270-280, Jan. 2022

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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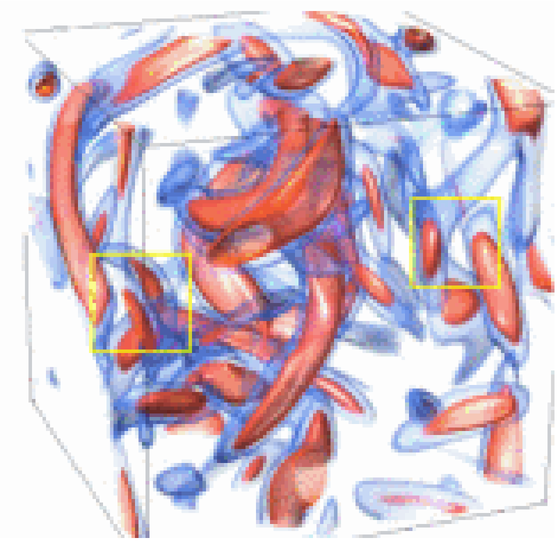
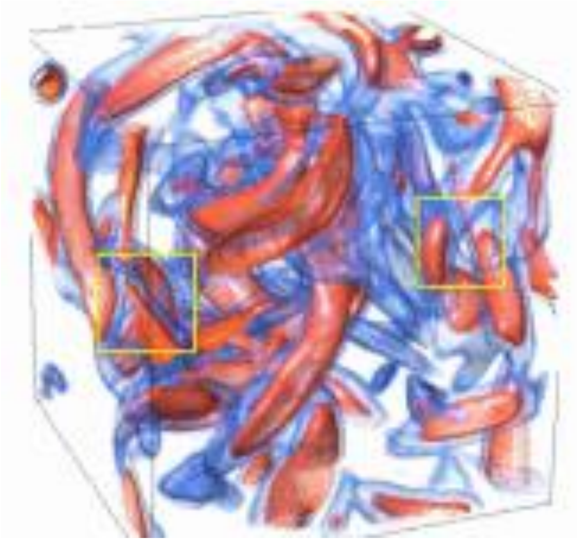
End to End Network

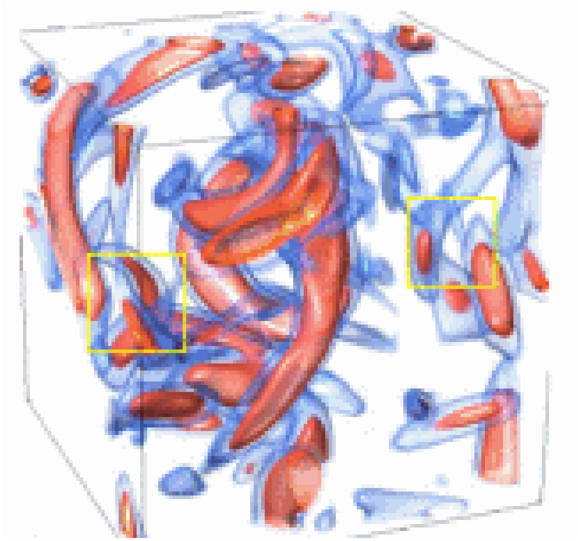
- *Single training phase*, instead of building sequential spatial and temporal models
- Errors do not accumulate from different sequential stages
- Yields much higher quality results
- STNet upscale volumes at both spatial and temporal dimensions simultaneously



Ground Truth



Spatial + Temporal



STNet

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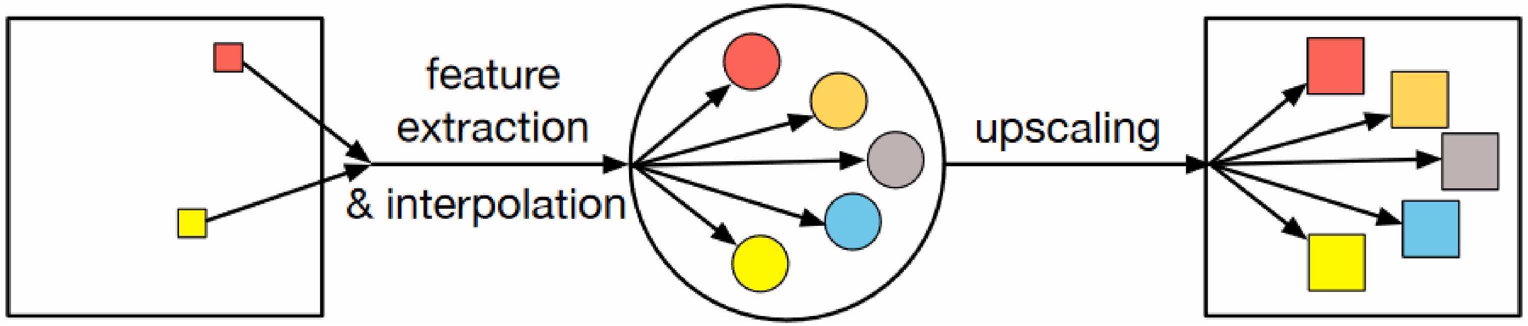
Feature Interpolation

- 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



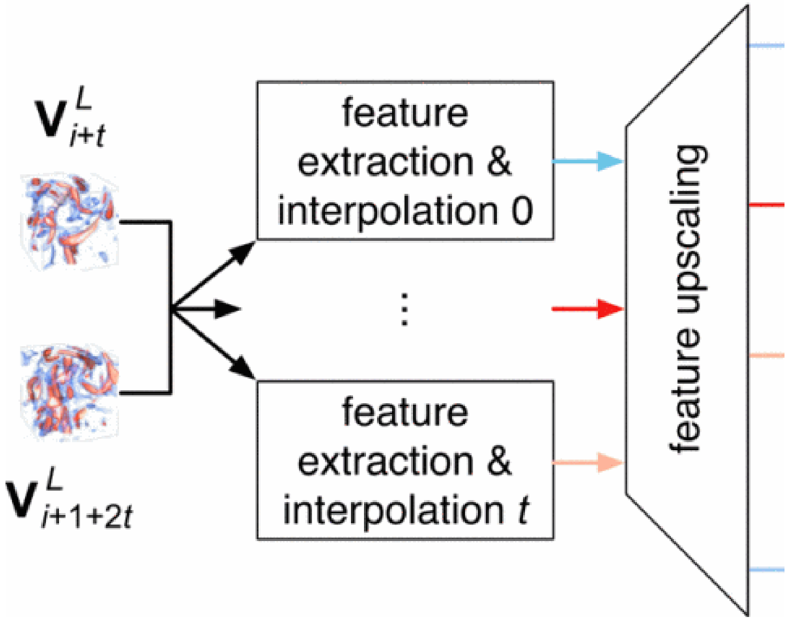
Super Resolution Space

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*

Data Synthesizing Framework

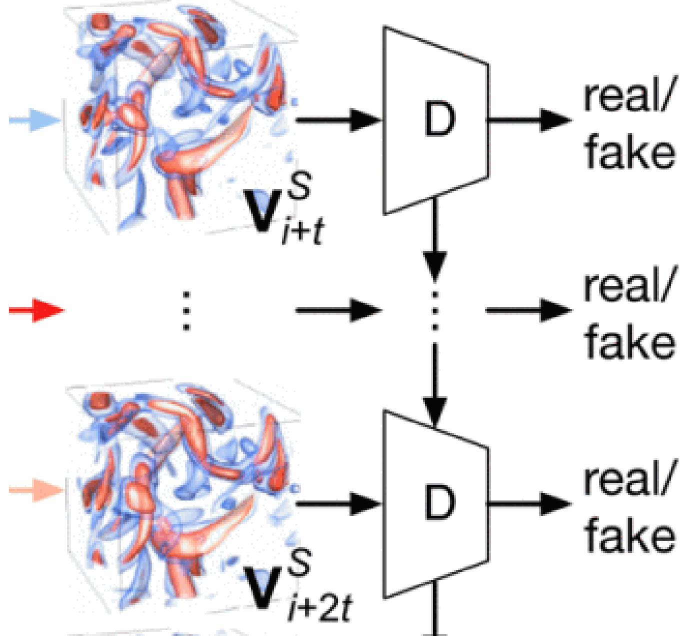
Generator

- 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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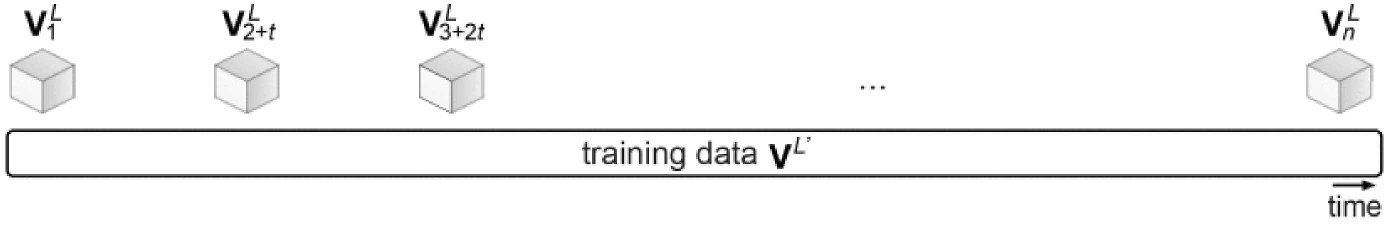
Pre-training and Fine-tuning

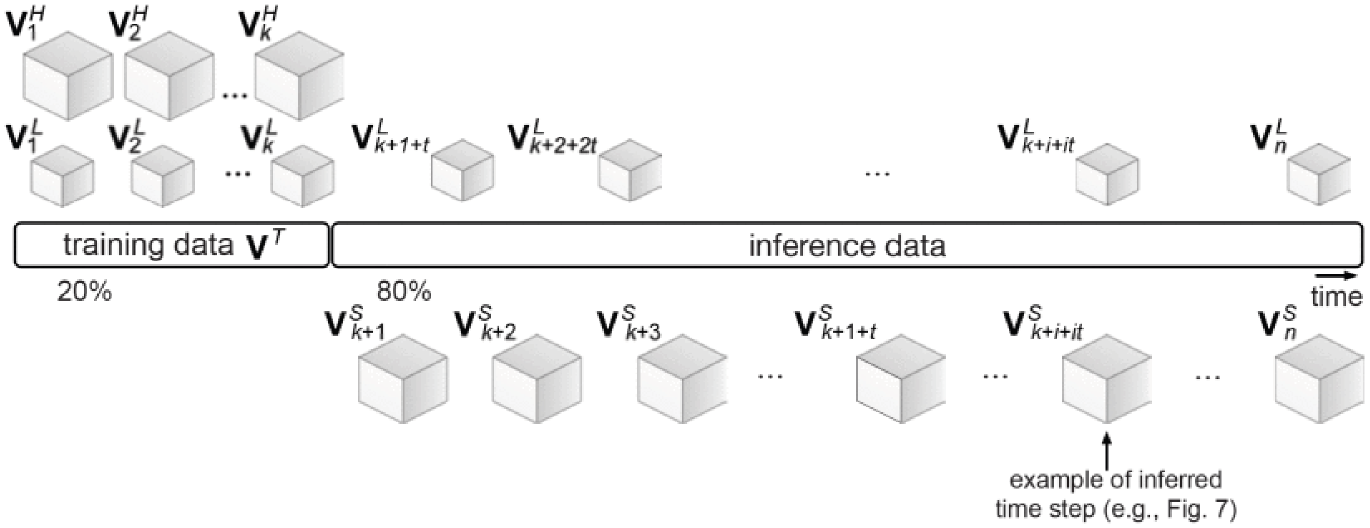
Pre-training

- 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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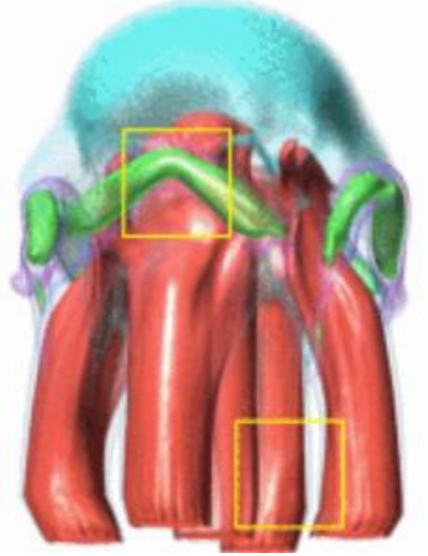
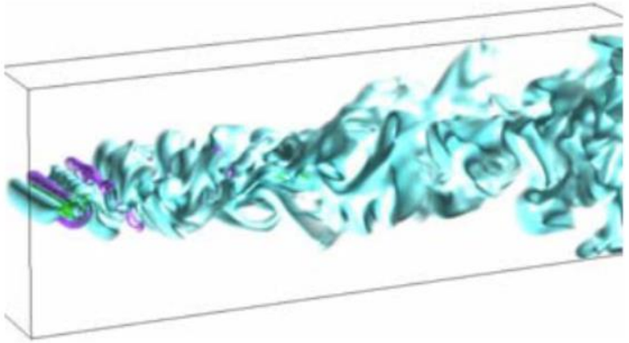
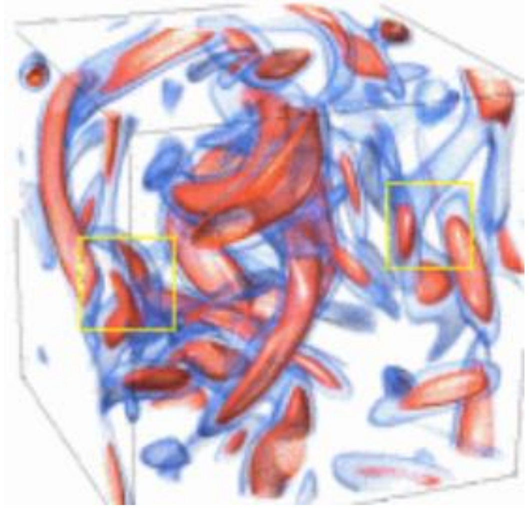
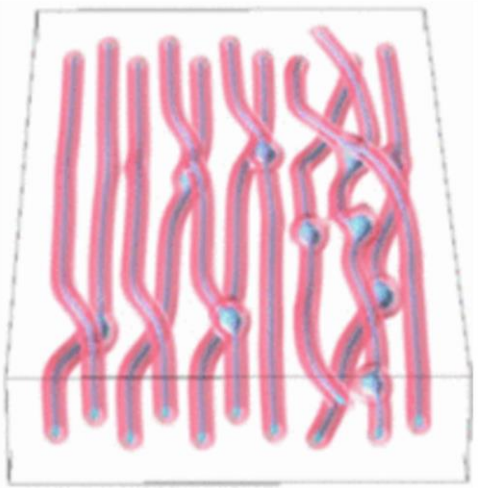
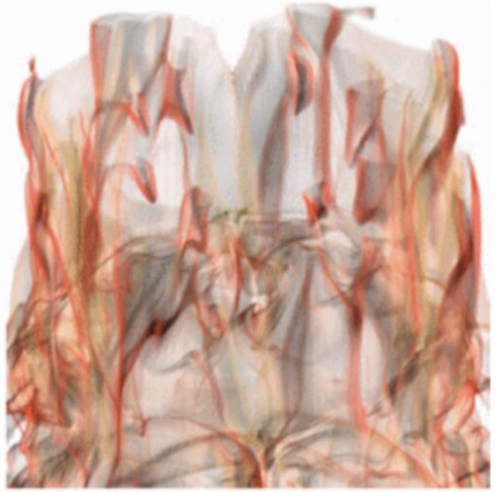
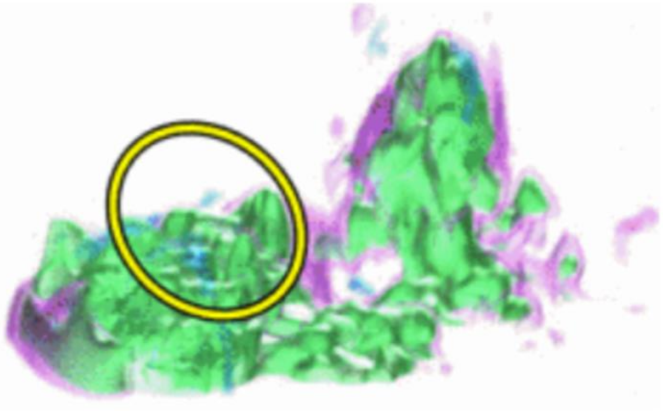
Datasets

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

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

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Results – Volume Rendering

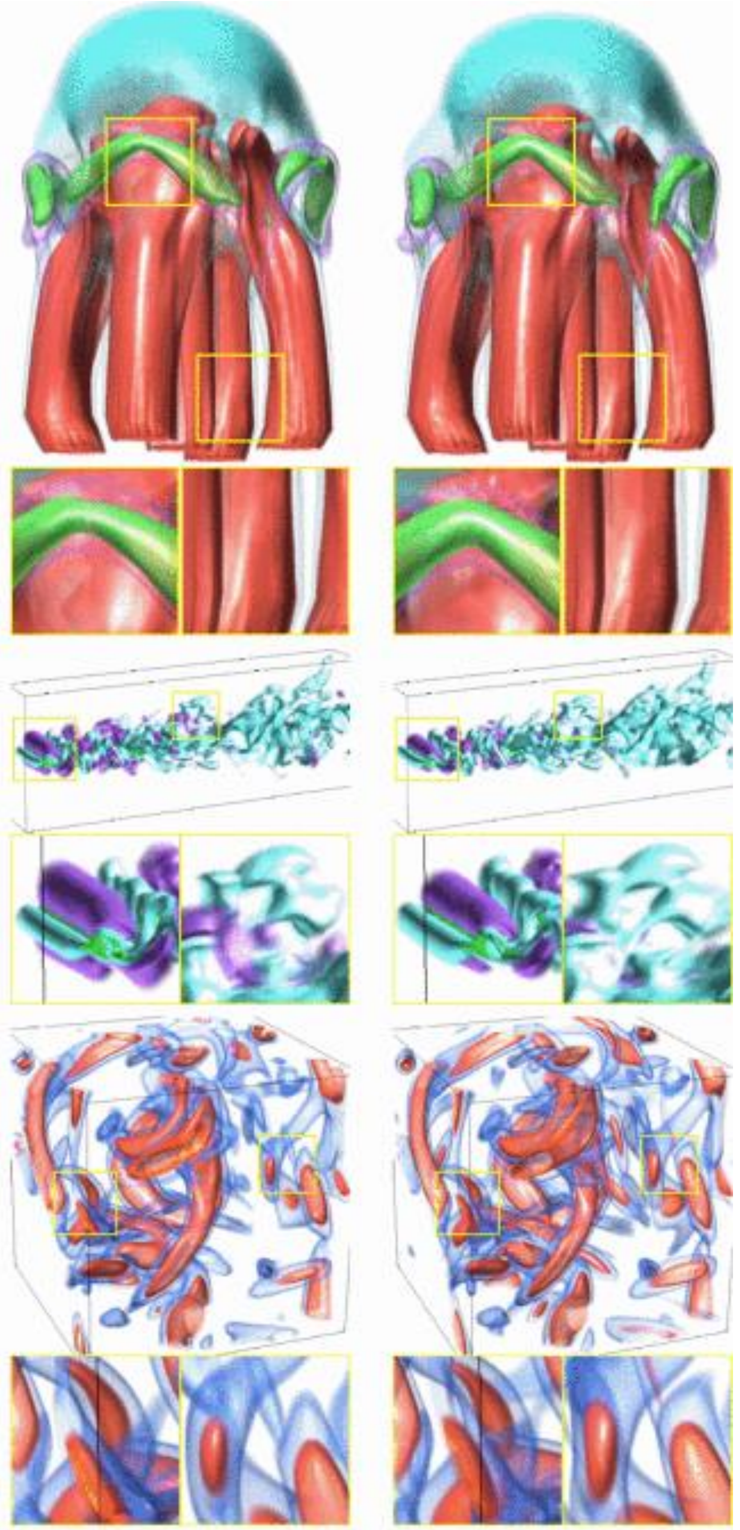
- Peak signal-to-noise (PSNR)
  - Ratio of signal power and corrupting noise
- Image-level structural similarity index (SSIM)
  - Quantifies image quality degradation

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

Five Jets

Half Cylinder

Vortex



(d) STNet (e) GT

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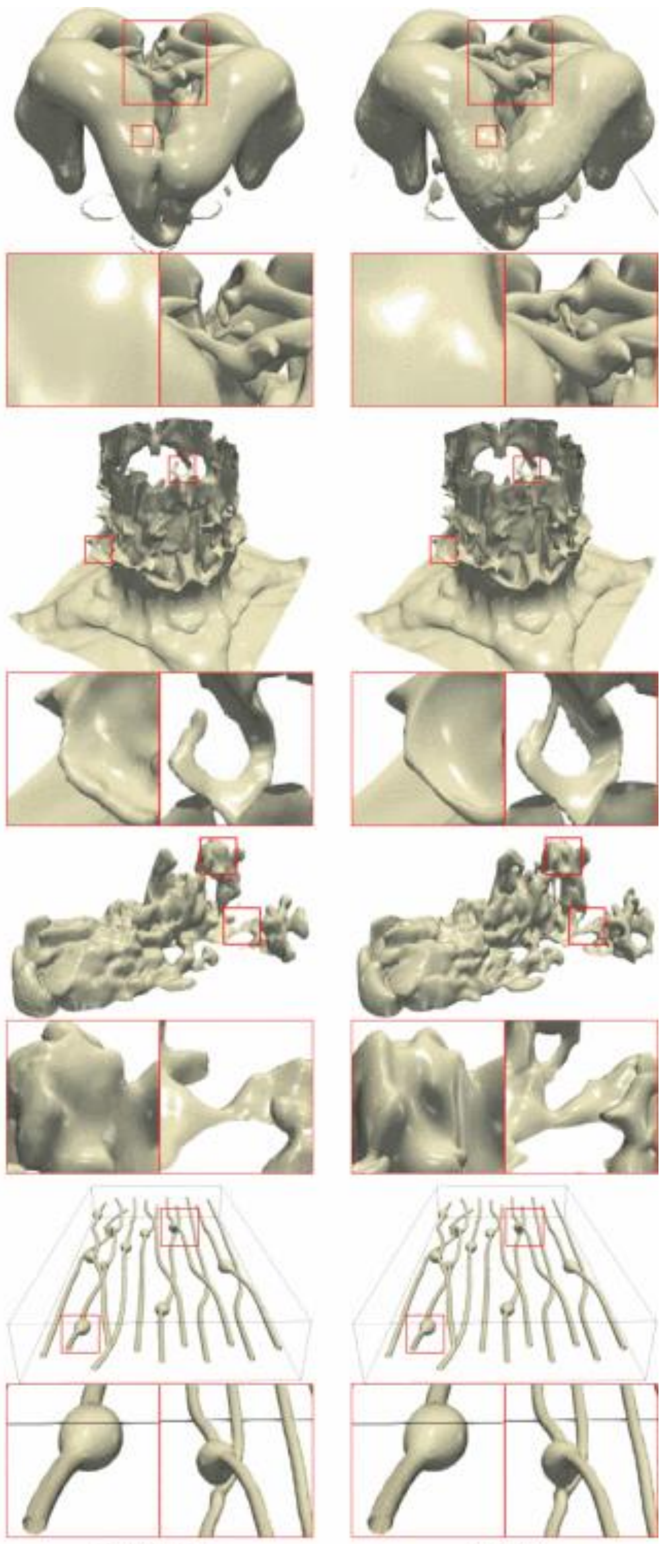
Results – Iso-surface Rendering

- 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**



Five Jets

Ionization (H)

Tangaroa

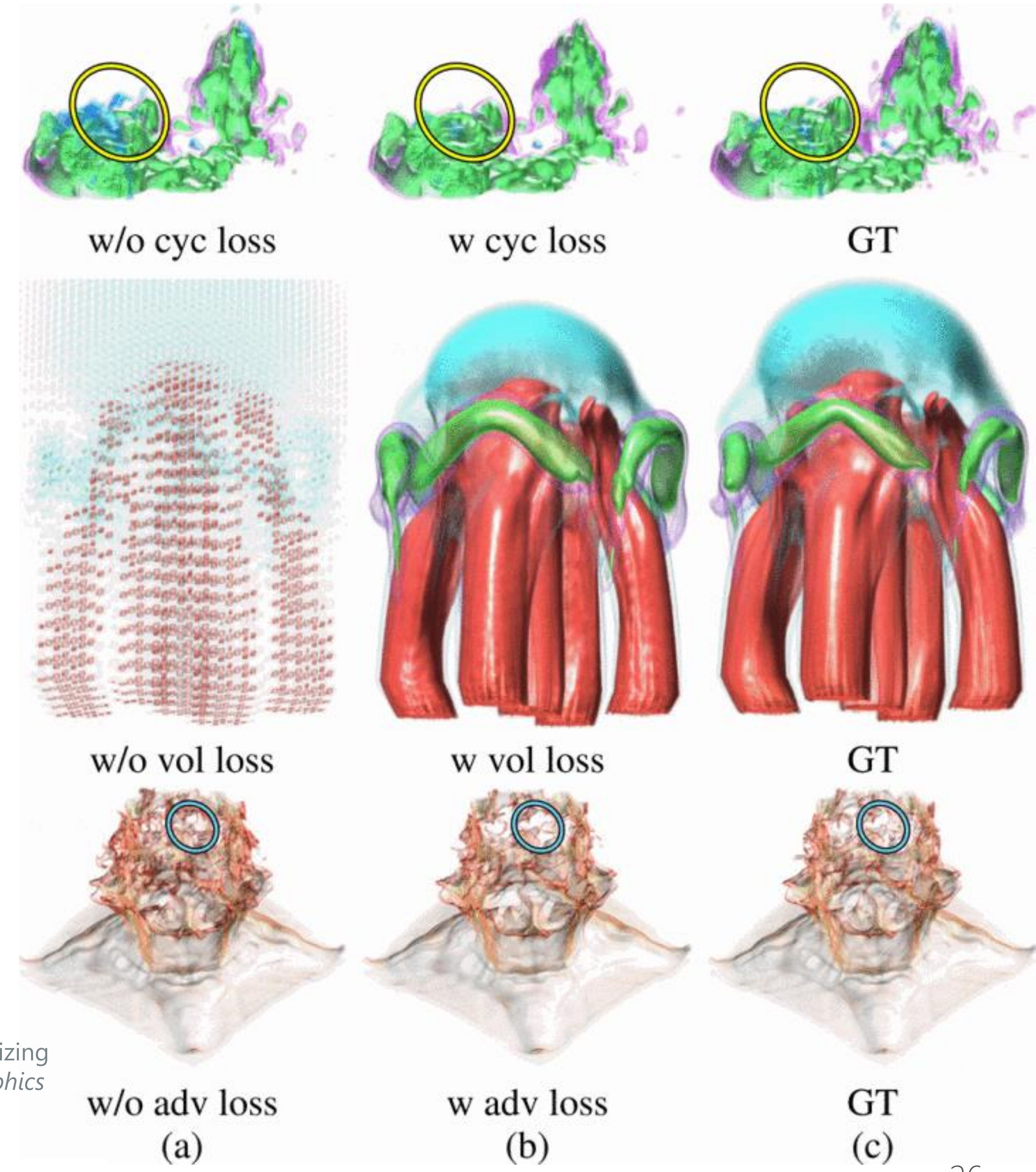
Supercurrent

(d) STNet (e) GT

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

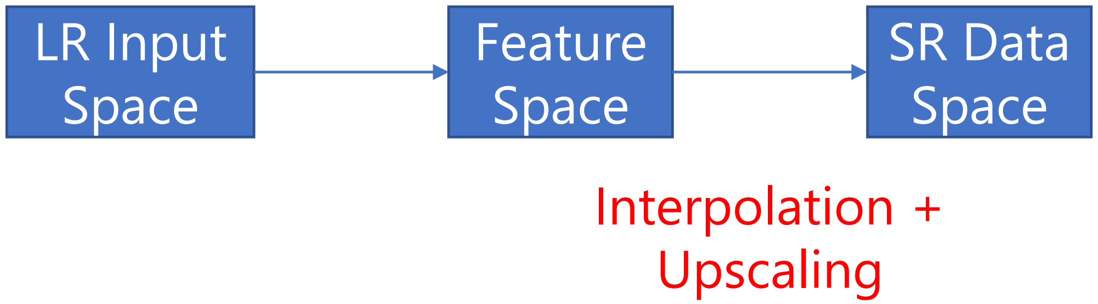


J. Han, H. Zheng, D. Z. Chen and C. Wang, "STNet: An End-to-End Generative Framework for Synthesizing Spatiotemporal Super-Resolution Volumes," in *IEEE Transactions on Visualization and Computer Graphics*

Reconstruction Task vs Synthesizing Task

Reconstruction Task

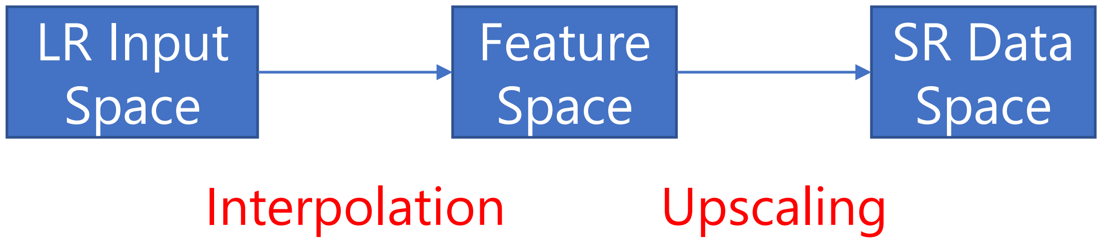
- From medium / low resolution data
- Interpolates in the data space



- Sequential model
- Data variables magnitude and direction

Synthesizing Task

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

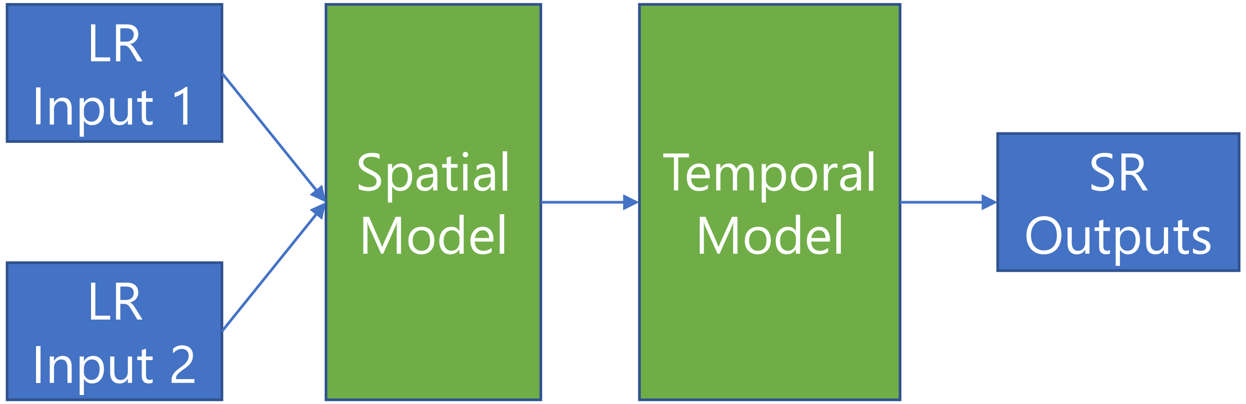


- End to end model
- Data variables magnitude only

Sequential Model vs End to End Model

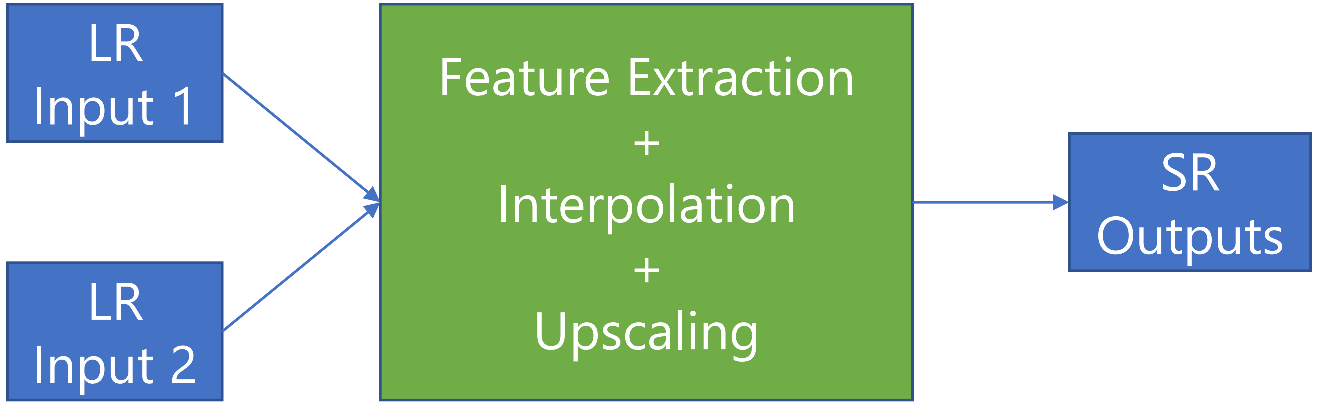
Sequential Model

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



End to End Model

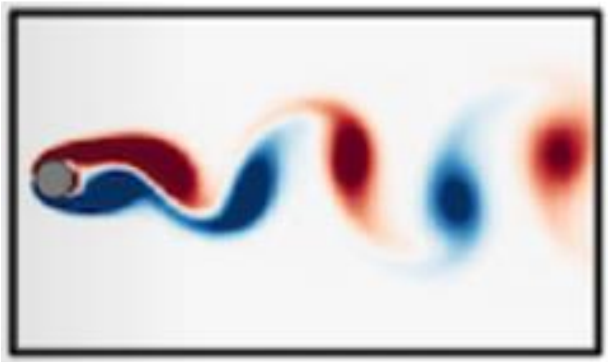
- Upscales spatio-temporal data simultaneously
- No accumulation and amplification of errors



Vector Data vs Scalar Data

Vector Data

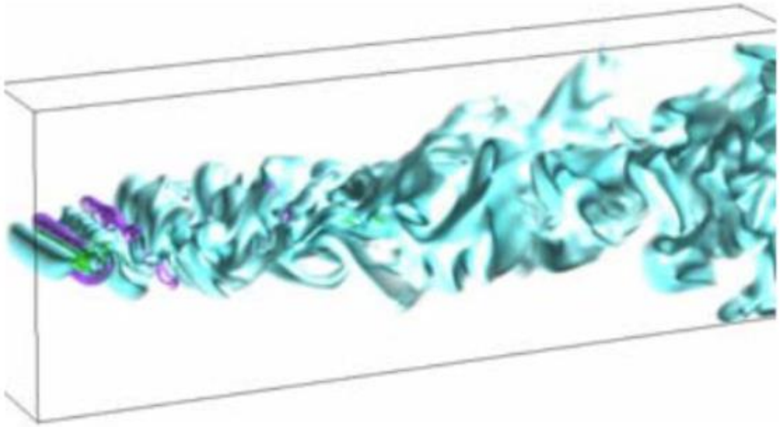
- Velocity, pressure and vorticity
  - direction and magnitude
- 2D and 3D data *plus time*
- Computation heavy



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

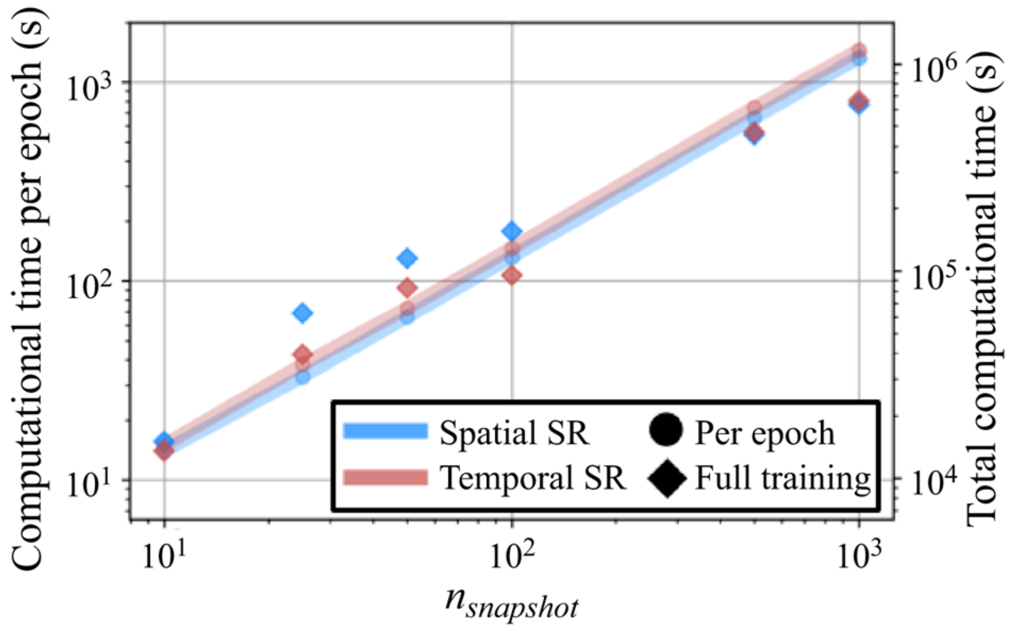


J. Han, H. Zheng, D. Z. Chen and C. Wang, "STNet: An End-to-End Generative Framework for Synthesizing Spatiotemporal Super-Resolution Volumes," in *IEEE Transactions on Visualization and Computer Graphics*

Limitations

Reconstruction Task

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



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

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

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