Building Robust Surrogates in Inertial Confinement Fusion with Cyclical Regularization

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Center for Applied Scientific Computing

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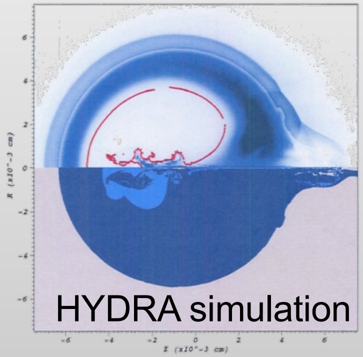
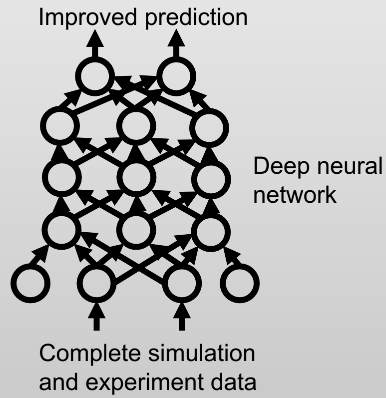
Modern machine learning can dramatically improve predictive modeling

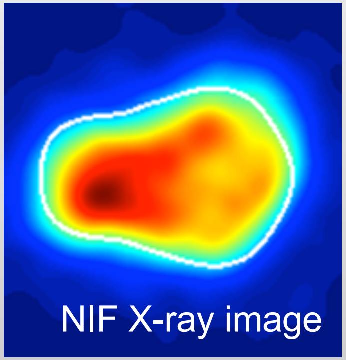
Traditional pillar
high-performance computing



New pillar
Machine learning to compare simulation and experiment



Traditional pillar
Large-scale experiments

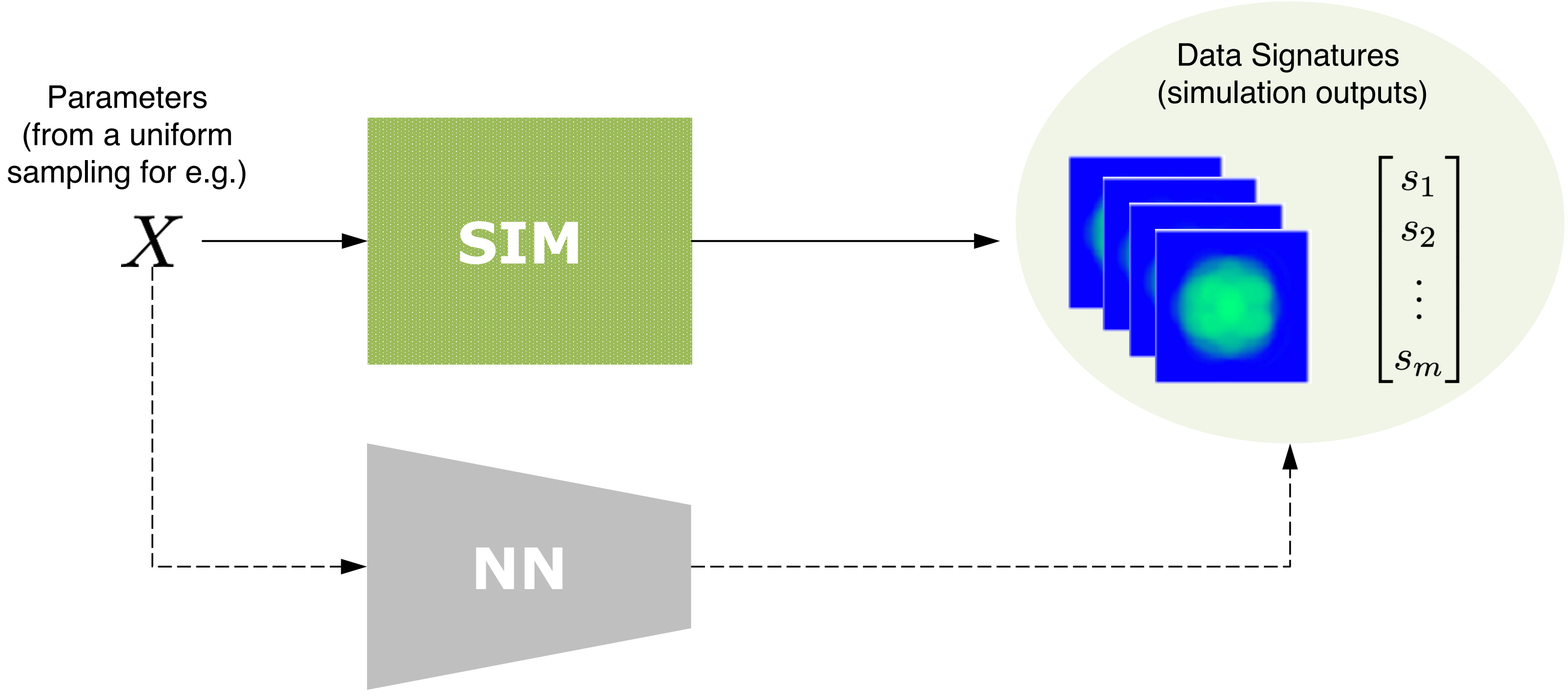


Machine learning will allow us to use our full data sets to make our models more predictive

Slide: Brian Spears

Surrogate modeling with Neural Networks

Traditional simulation workflow



Simulation is approximated as an inference step in the neural network

Requirements for NN surrogates

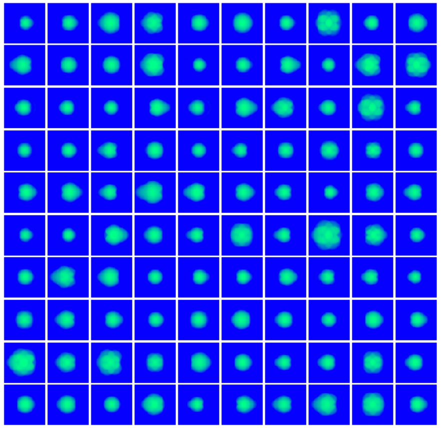
1. Use (and predict) all the data signatures: *replicate the simulator in all data modalities*

2. Be "physically consistent" : *predictions, errors should be meaningful*

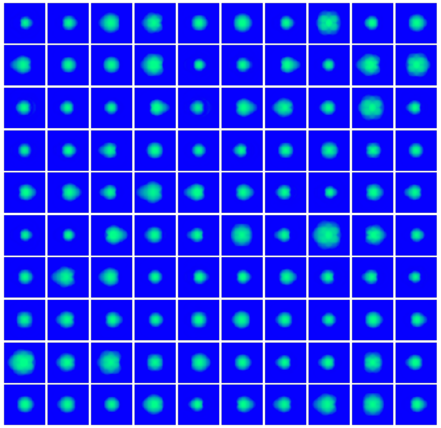
3. Be "self-consistent": *must be compatible with of pseudo-inverse models.*

4. Be robust to sampling artifacts: *prediction function in the output space must be smooth*

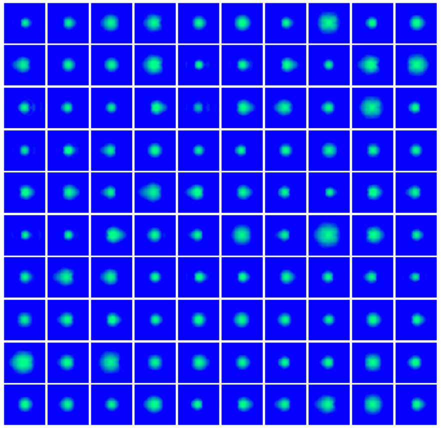
The JAG 1D simulator: semi-analytic model for inertial confinement fusion



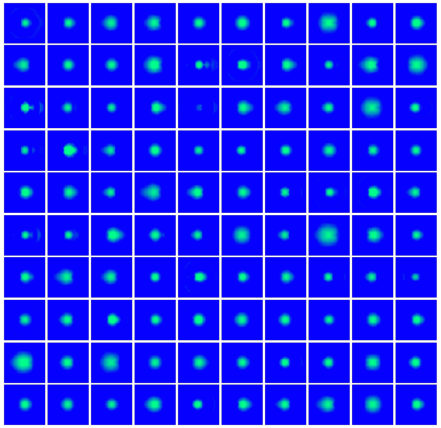
Channel 0



Channel 1



Channel 2



Channel 3

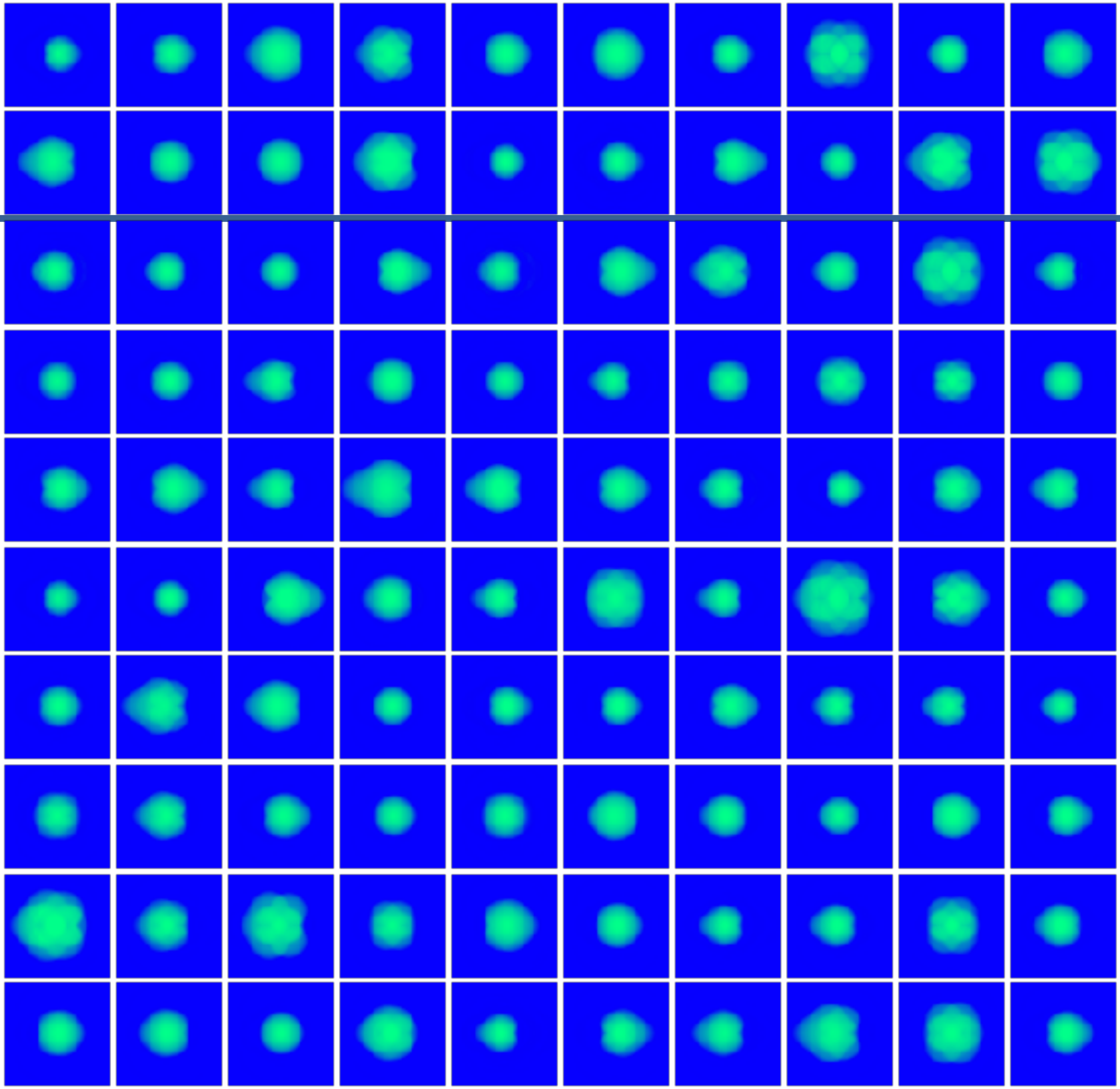
5 Input Parameters:

```
"shape_model_initial_modes:(4,3)"
"betti_prl15_trans_u”
"betti_prl15_trans_v”
"shape_model_initial_modes:(1,0)”
"shape_model_initial_modes:(2,1)"
```

15 Unique Scalars


```
"BWx": 0.0515213112511142,
"tMAXpressure": 1.79034984538632,
"BT": 1.79189354130192,
"tMAXt": 1.78628381635944,
"BWn": 0.0330097694604801,
"MAXpressure": 987070.653917313,
"BAt": 4.67056684976242,
"Yn": 6.03196569121564e+15,
"Ye": 13.6266468390836,
"Yx": 13.2147653631385,
"tMAXte": 1.78628381635944,
"BAtion": 4.67056684976242,
"iBT": 61,
"MAXte": 5.05740532321124,
"BAte": 4.67056684976242,
"tMAXtion": 1.78628381635944,
"BTx": 1.76320044937806,
"MAXt": 5.05740532321124,
"BTn": 1.79189354130192,
"BApressure": 801697.648687124,
"MAXtion": 5.05740532321124,
"tMINradius": 1.78141734691824,
"MINradius": 17.9333756055566
```


(this also works with 3 views/4 channels)



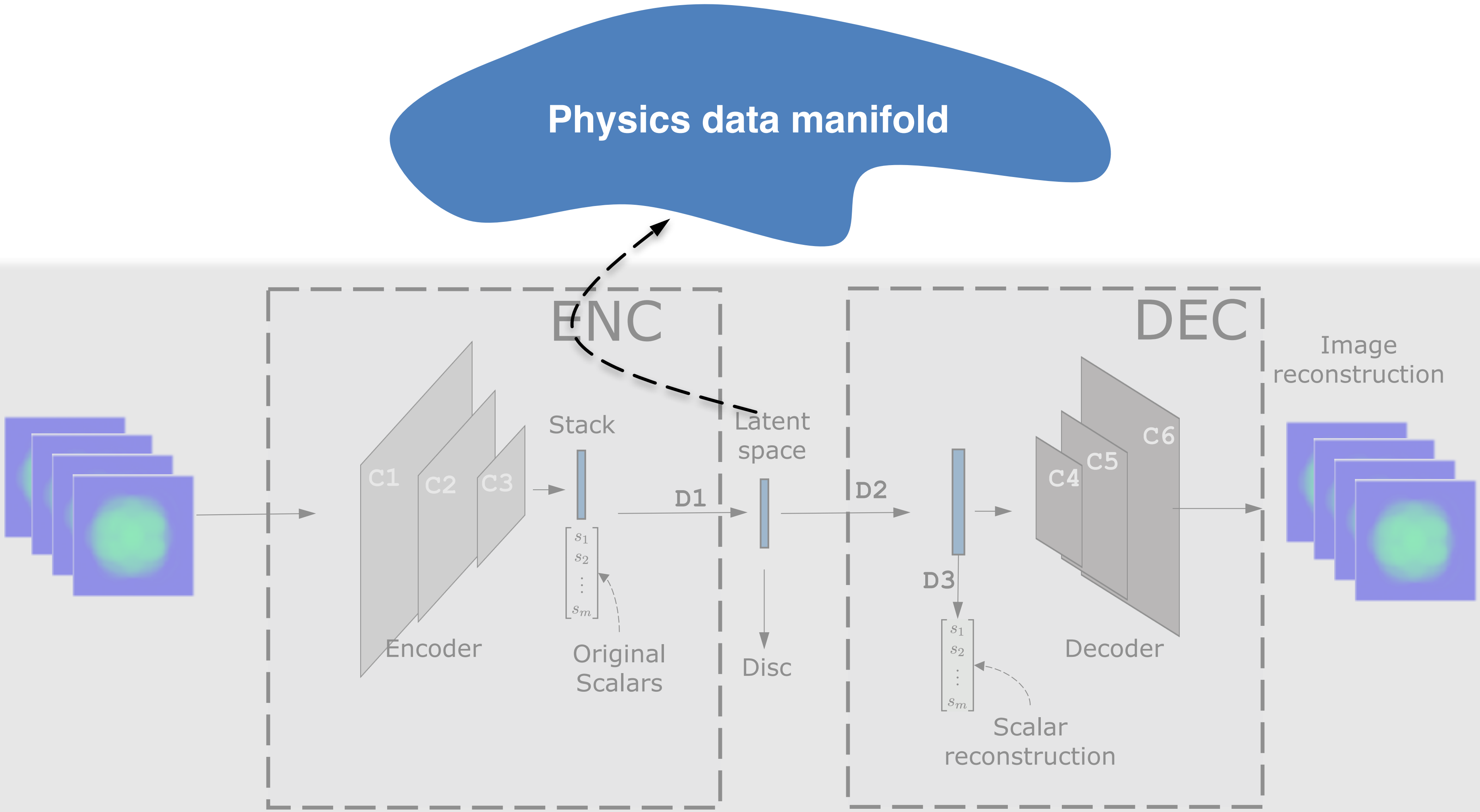
Three main components of our surrogate

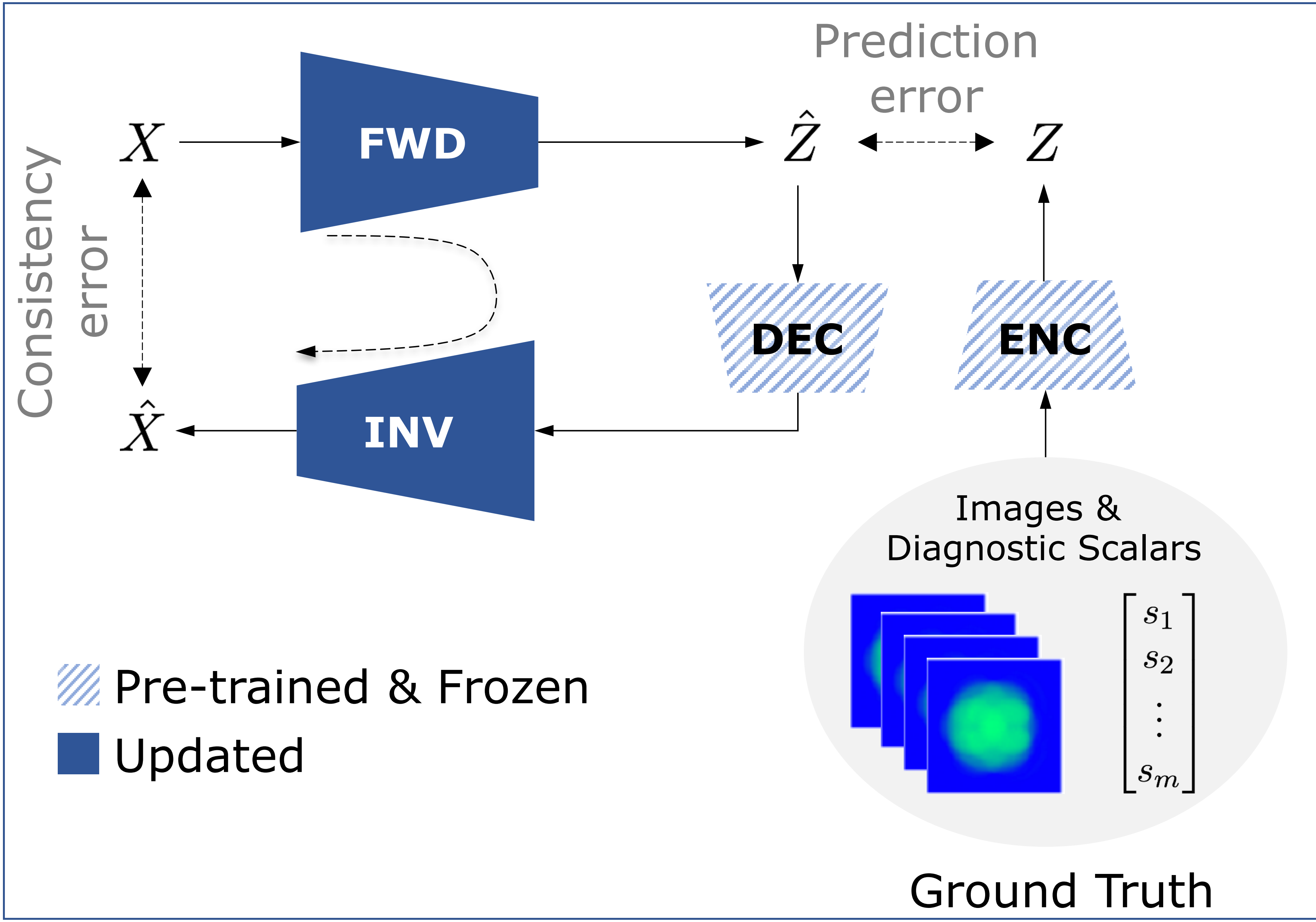
1. A joint **autoencoder** to approximate the physics manifold.

2. The **surrogate** neural network that maps from the input parameters of the simulator to the desired outputs.

3. A **pseudo-inverse** neural network that takes the outputs and maps it back to the input parameters.

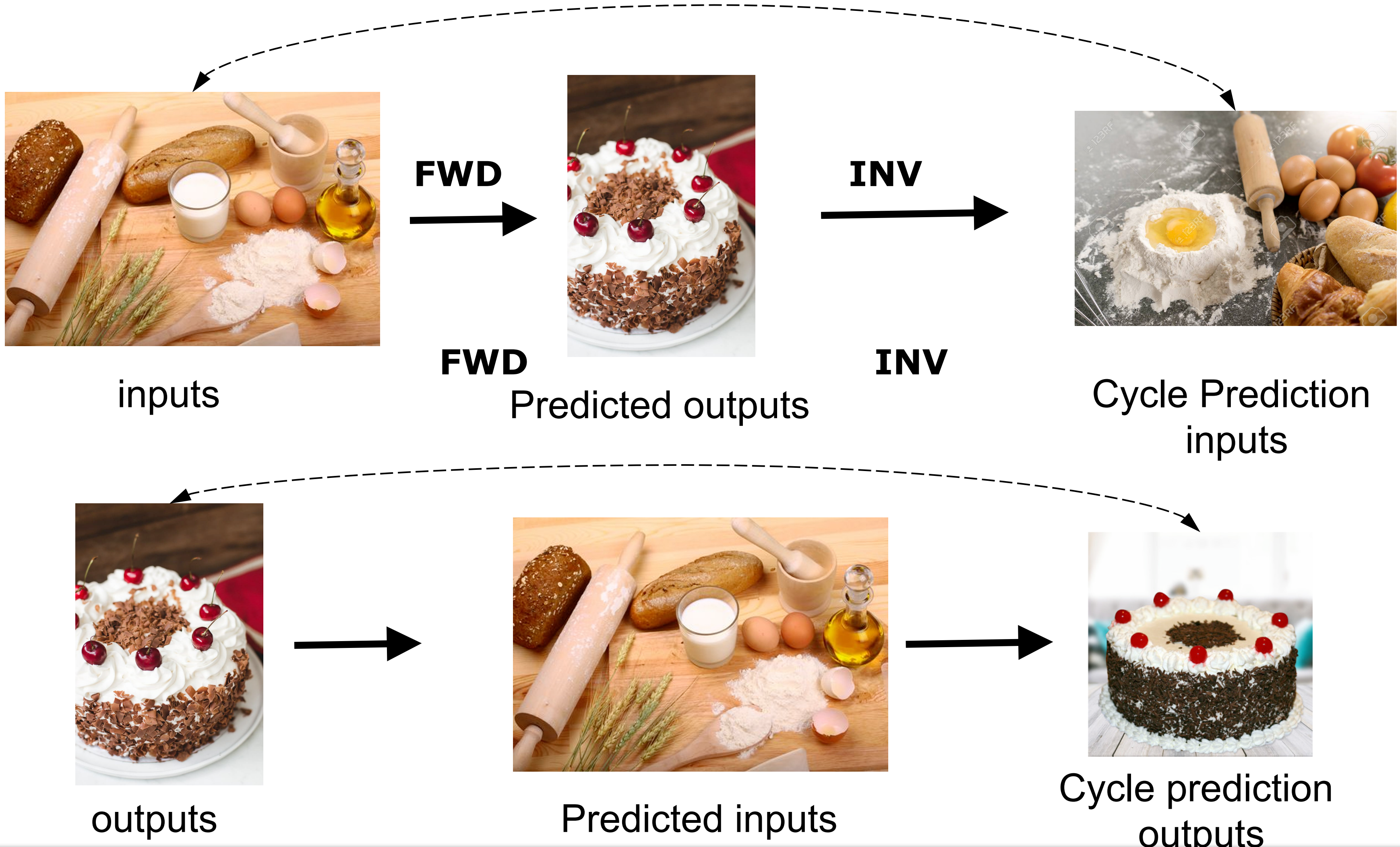
Joint latent space for image and scalars to learn the physics manifold





Prediction
error
X
FWD
$\hat{Z}$
Z
Consistency
error
DEC
ENC
$\hat{X}$
INV
Images &
Diagnostic Scalars
s_1
s_2
s_m
Pre-trained & Frozen
Updated
Ground Truth

Cyclical Consistency



Training Loss

$$\mathcal{L} = \|\mathcal{F}(\mathbf{x}) - \mathbf{z}\| + \lambda_{cyc}^{F}\|\mathbf{x} - \mathcal{G}(\mathcal{F}(\mathbf{x}))\| + \lambda_{cyc}^{I}\|\mathbf{z} - \mathcal{F}(\mathcal{G}(\mathbf{z}))\|$$

Surrogate fidelity

FWD Cycle

INV Cycle

Cyclical consistency as a powerful regularization strategy in many recent problems

Learning Dense Correspondence via 3D-guided Cycle Consistency

Tinghui Zhou, UC Berkeley
Philipp Krähenbühl, UC Berkeley
Mathieu Aubry, ENPC ParisTech
Qixing Huang, TTI-Chicago
Alexei A. Efros, UC Berkeley

Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks

Jun-Yan Zhu* Taesung Park* Phillip Isola Alexei A. Efros
Berkeley AI Research (BAIR) laboratory, UC Berkeley

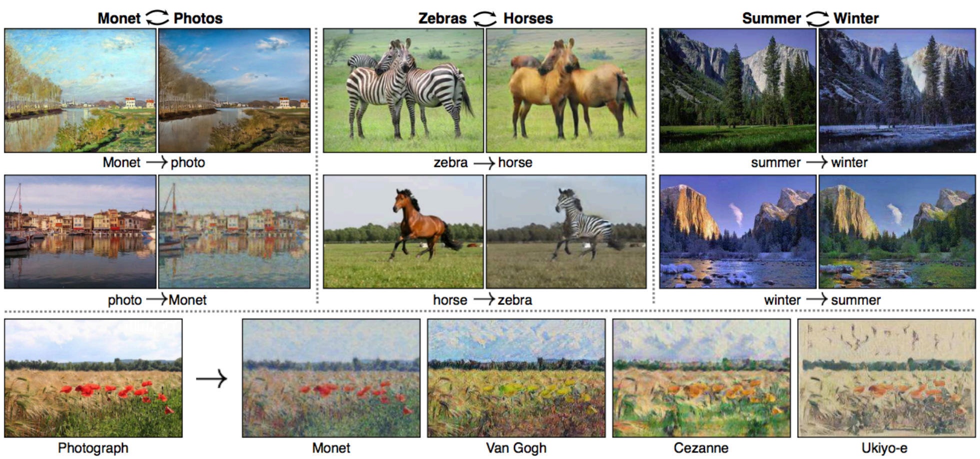


Figure 1: Given any two unordered image collections X and Y, our algorithm learns to automatically "translate" an image from one into the other and vice versa. Example application (*bottom*): using a collection of paintings of a famous artist, learn to render a user's photograph into their style.

Cycle-Consistency for Robust Visual Question Answering

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Learning to Sketch with Shortcut Cycle Consistency

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Semantically Tied Paired Cycle Consistency for Zero-Shot Sketch-based Image Retrieval

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Zeynep Akata
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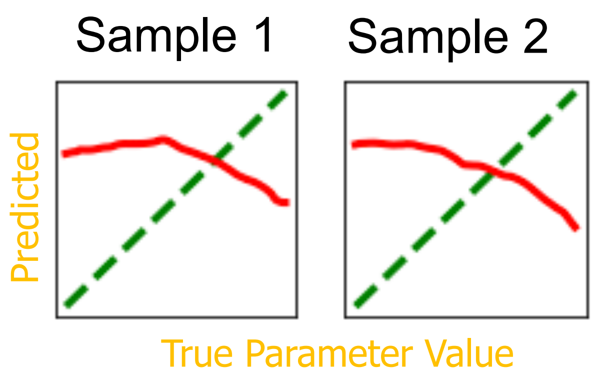
Translating and Segmenting Multimodal Medical Volumes with Cycle- and Shape-Consistency Generative Adversarial Network

Zizhao Zhang[+*], Lin Yang[+], Yefeng Zheng[*]
[+]University of Florida
[*]Medical Imaging Technologies, Siemens Healthcare

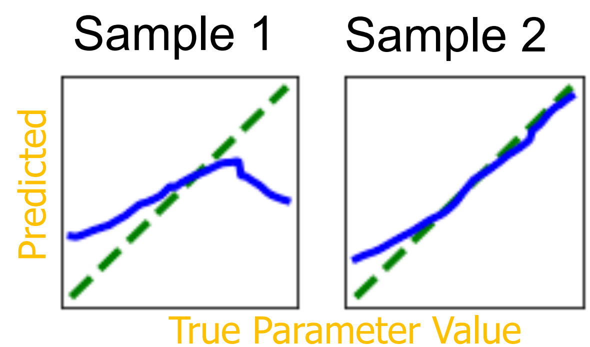
Results

A measure for cyclical consistency

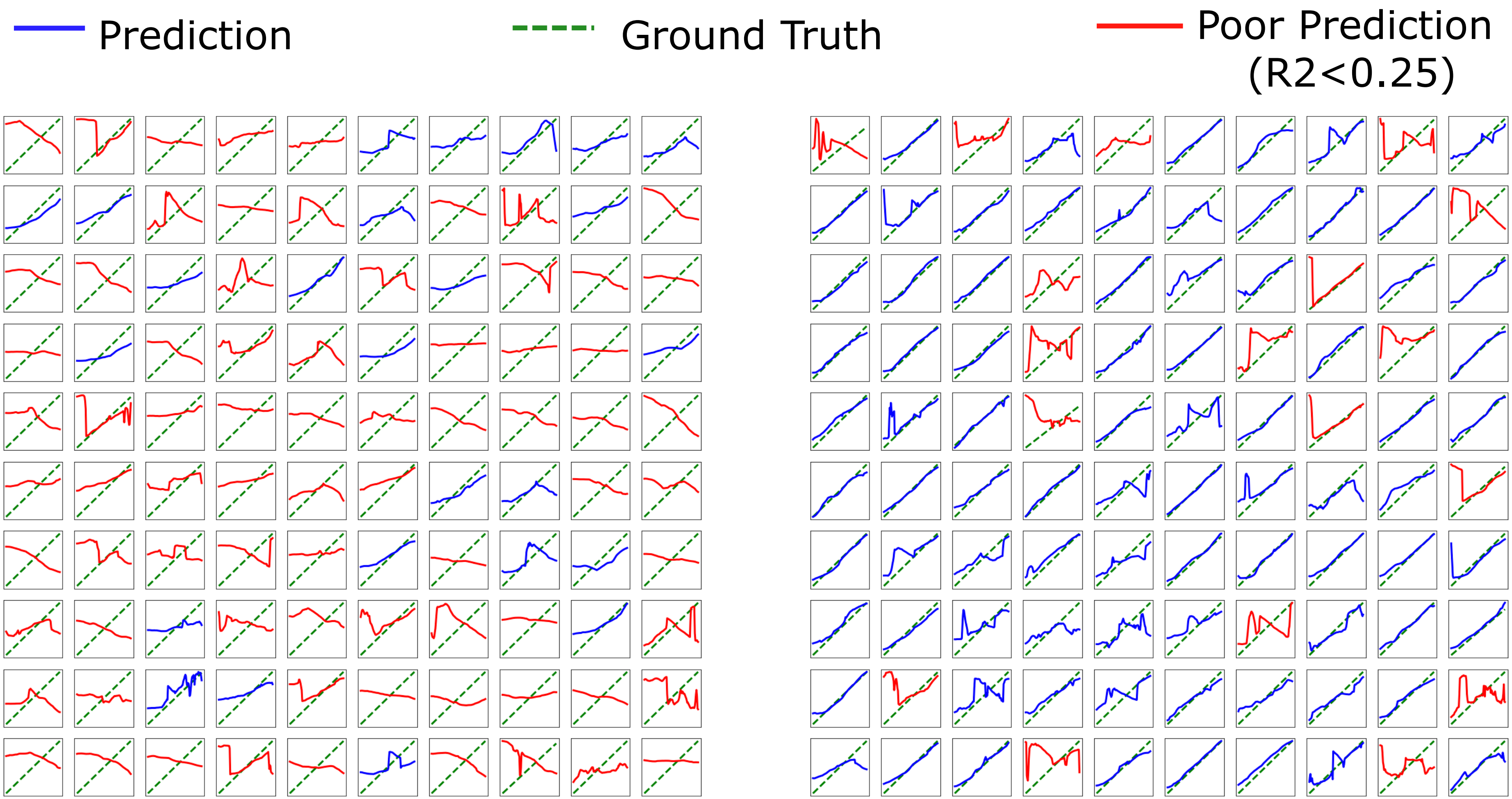
1. Run a linear parameter scan of a single parameter -- i.e. vary it from [min to max] while fixing all other parameters.
2. new parameters → forward model → (any) pseudo-inverse model.
3. How well is the linear variation recovered?



baseline



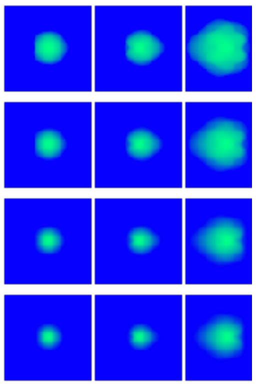
proposed surrogate

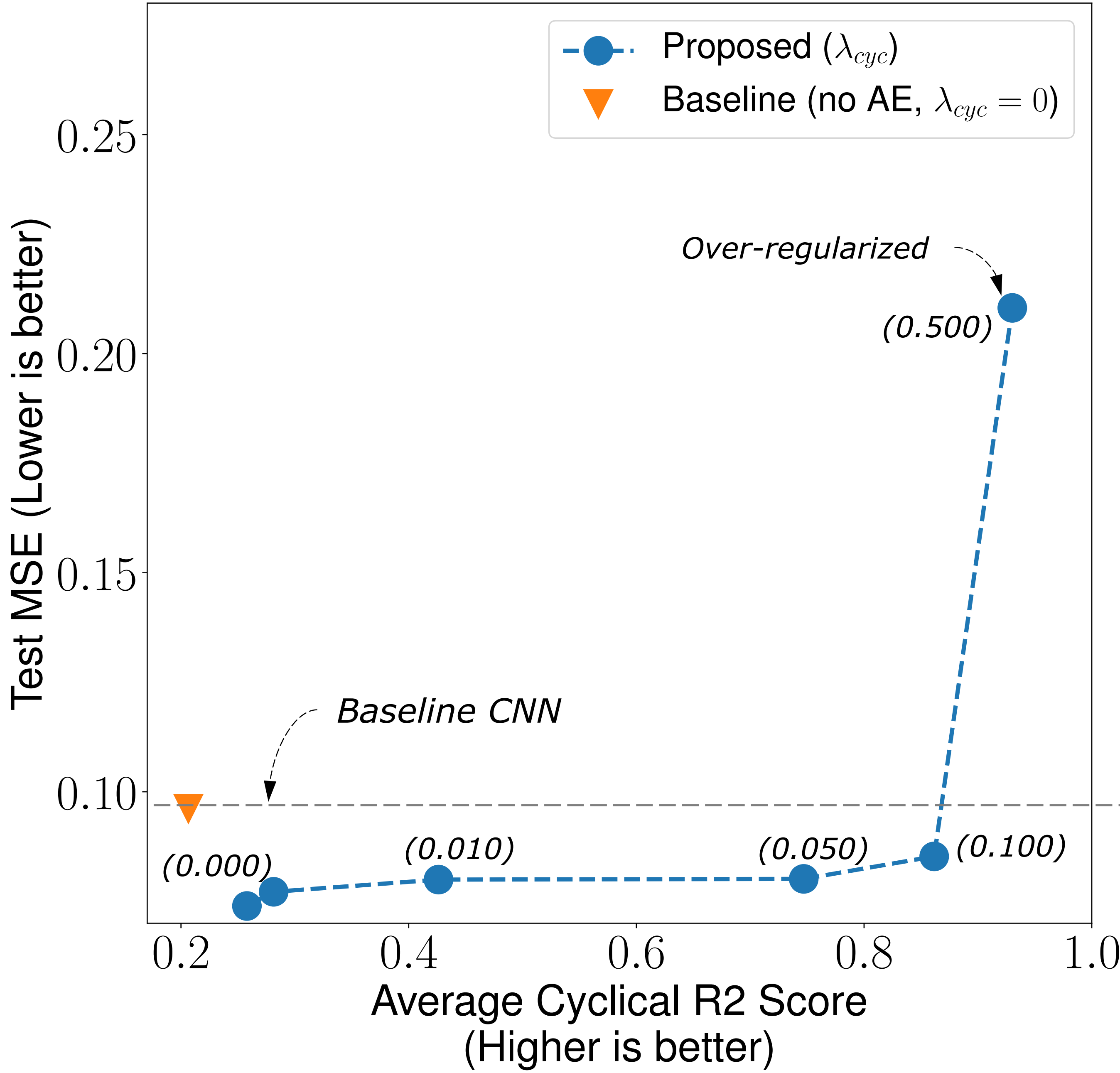


Baseline

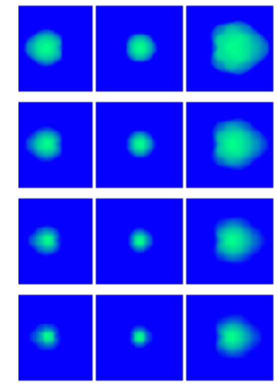
Proposed

10 Random S

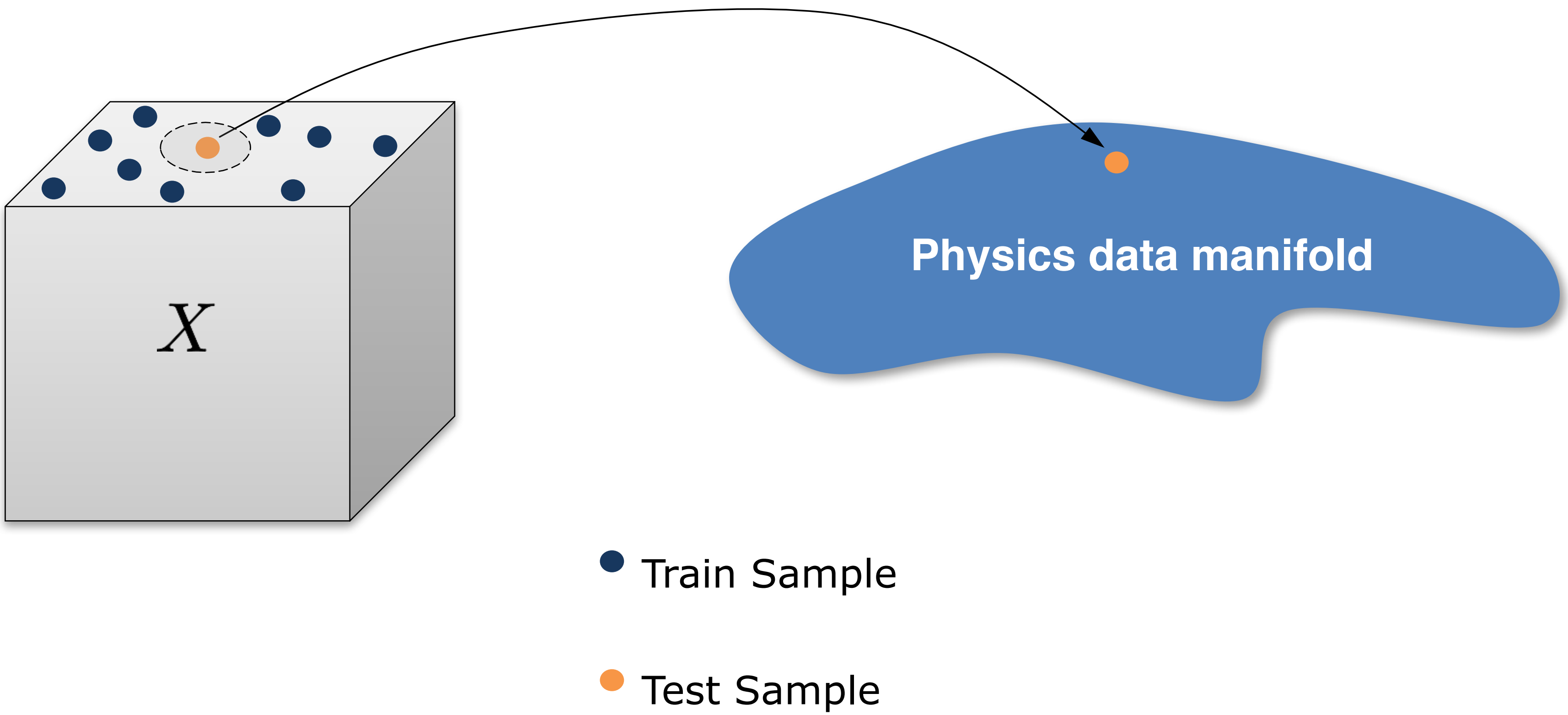




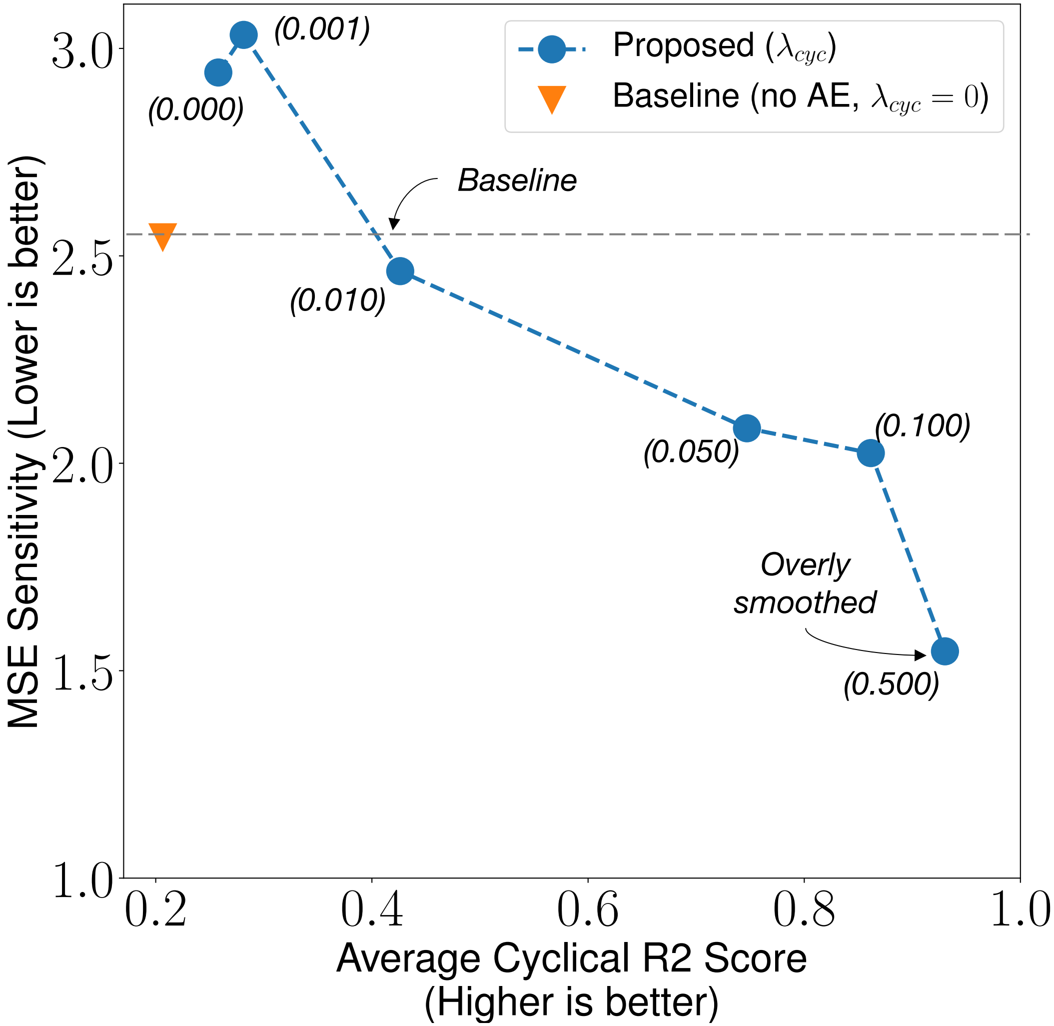
Normalized)



Small local perturbations

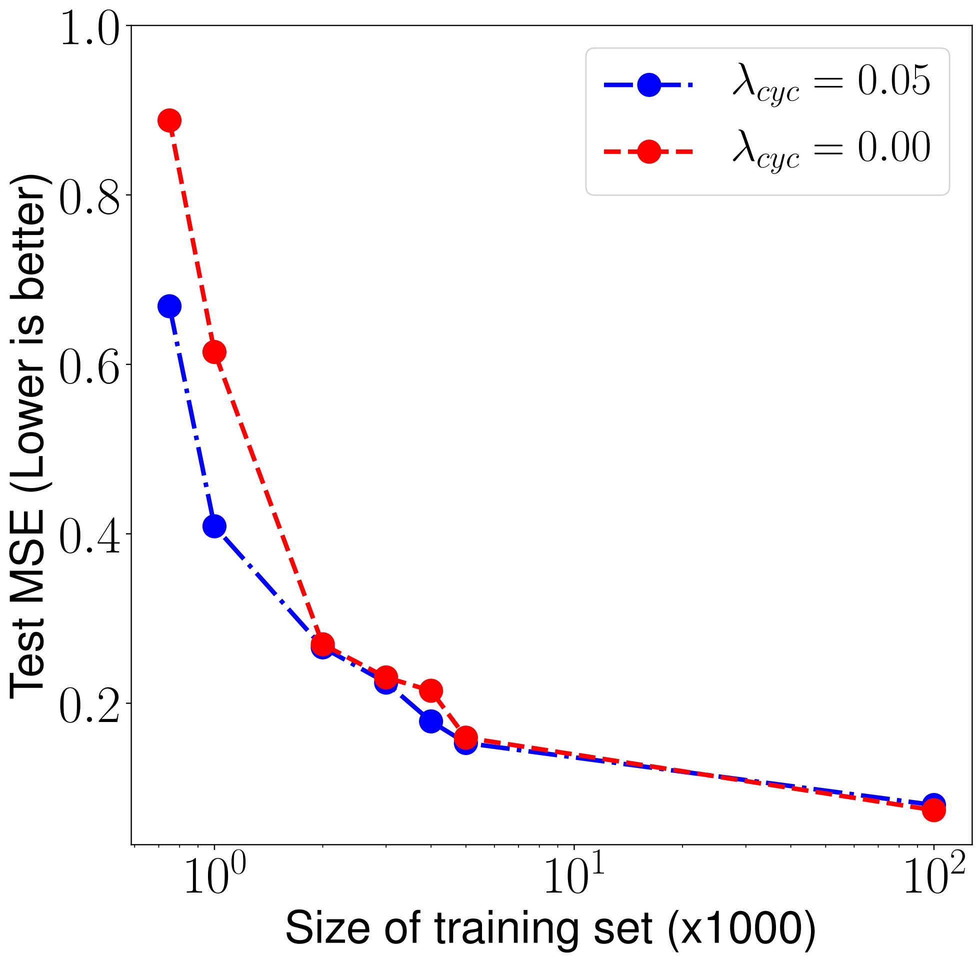


Finding #2: Cyclical regularization results in surrogates robust to small local perturbations



For the approx. same MSE performance, these models have very different sensitivities to small local perturbations.

Finding #3: Cyclical regularization results in better generalization over smaller training sets



The autoencoder is fixed in both cases here. Performance shown on the same 10K test set.

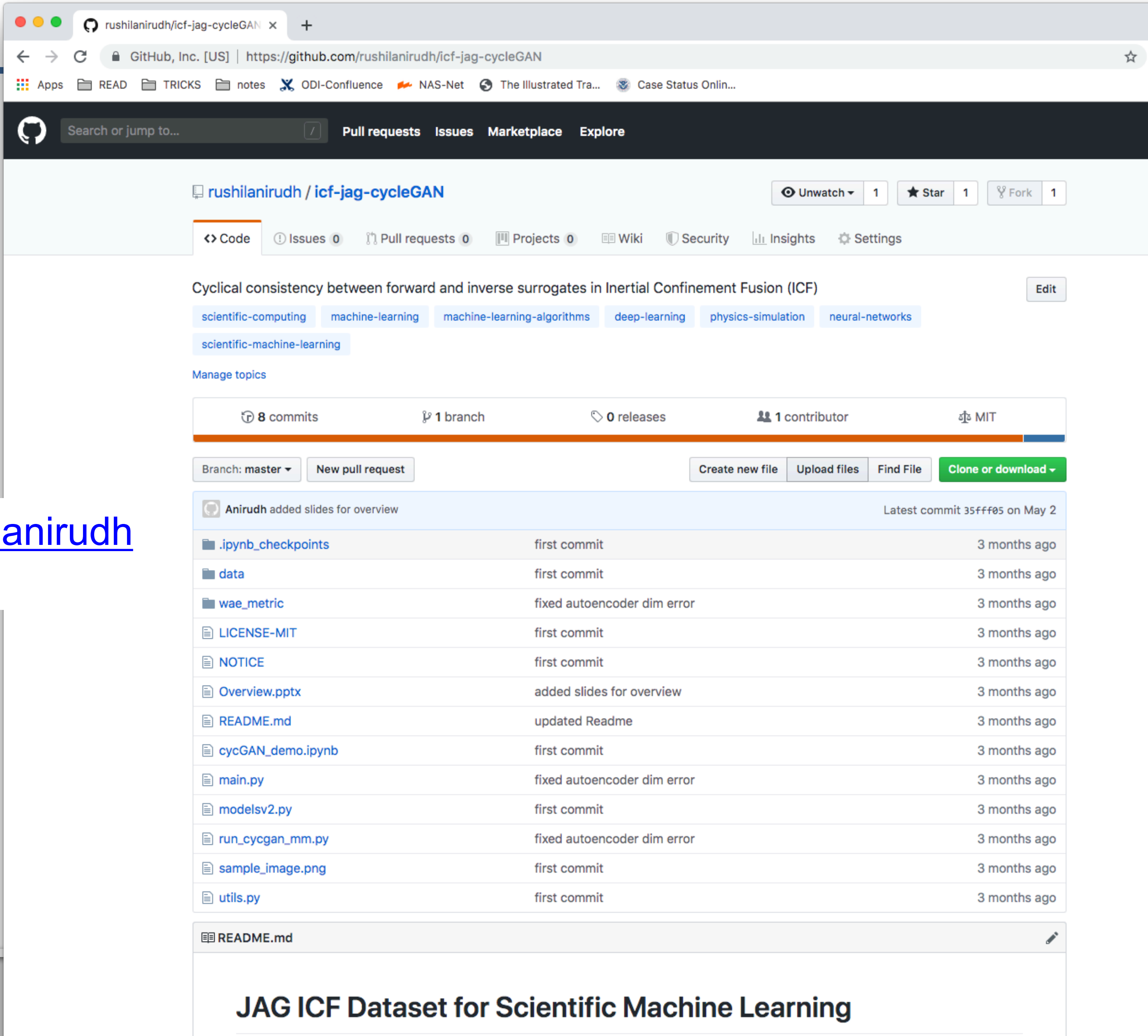
Conclusion

1. When you have a complex set of data signatures, use an autoencoder for surrogate modeling.

2. Cyclical regularization gives you self-consistent, robust surrogates. It encourages the high dimensional output space to be smooth

3. Cyclical regularization results in better generalization in small data regimes.

JAG 10K dataset public release: Python + TensorFlow scripts for architecture, data and models!



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https://github.com/rushilanirudh/icf-jag-cycleGAN

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