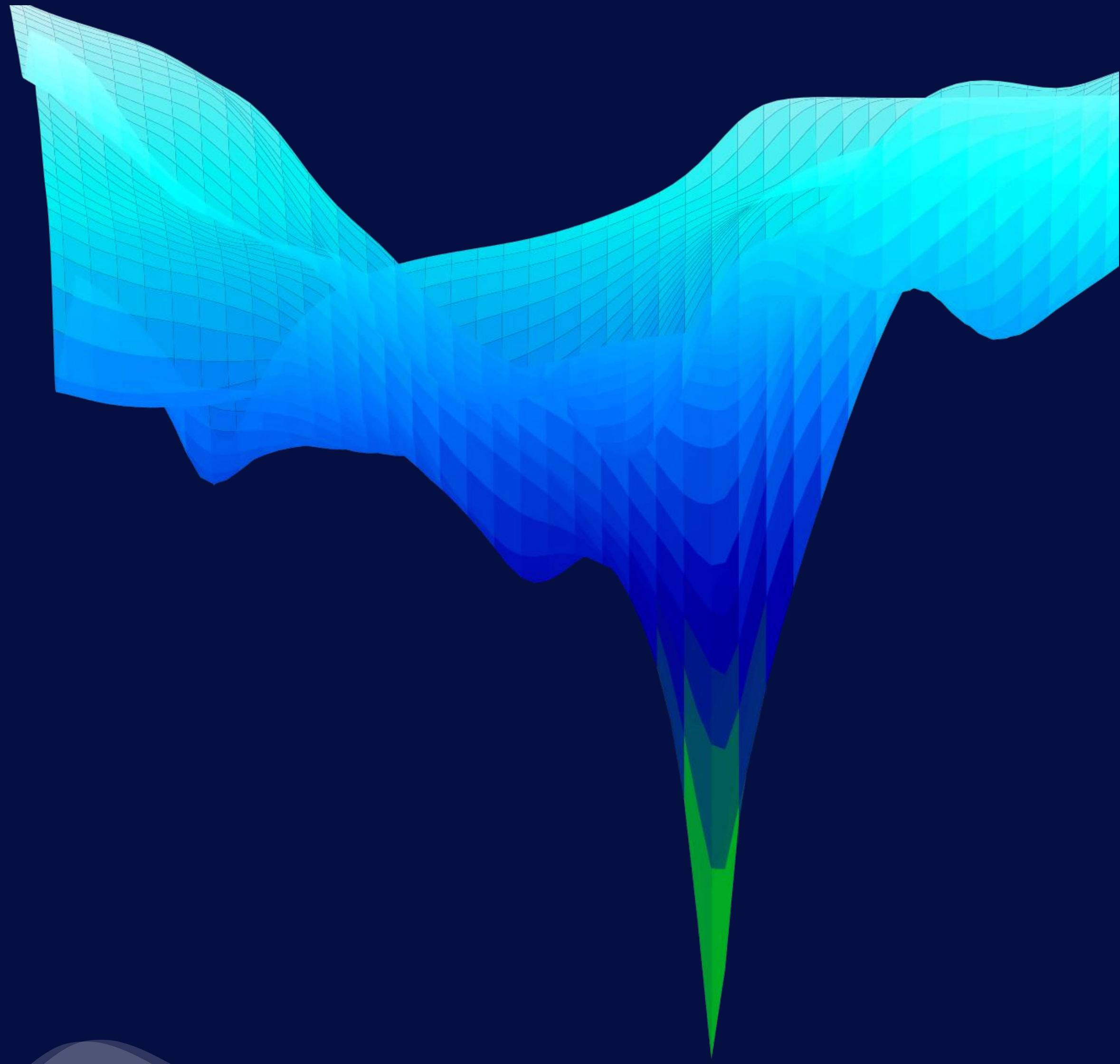
Scientific Machine Learning (SciML) for Solving PDEs

(Case Studies: two-phase flow in porous media)



University of Campinas (Nov. 2024)

A part of INTPART project, supported by NCS2030 - National Centre for Sustainable Subsurface Utilization of the Norwegian Continental Shelf.

NCS 2030 National Centre for Sustainable Subsurface Utilization of the Norwegian Continental Shelf

University of Stavanger

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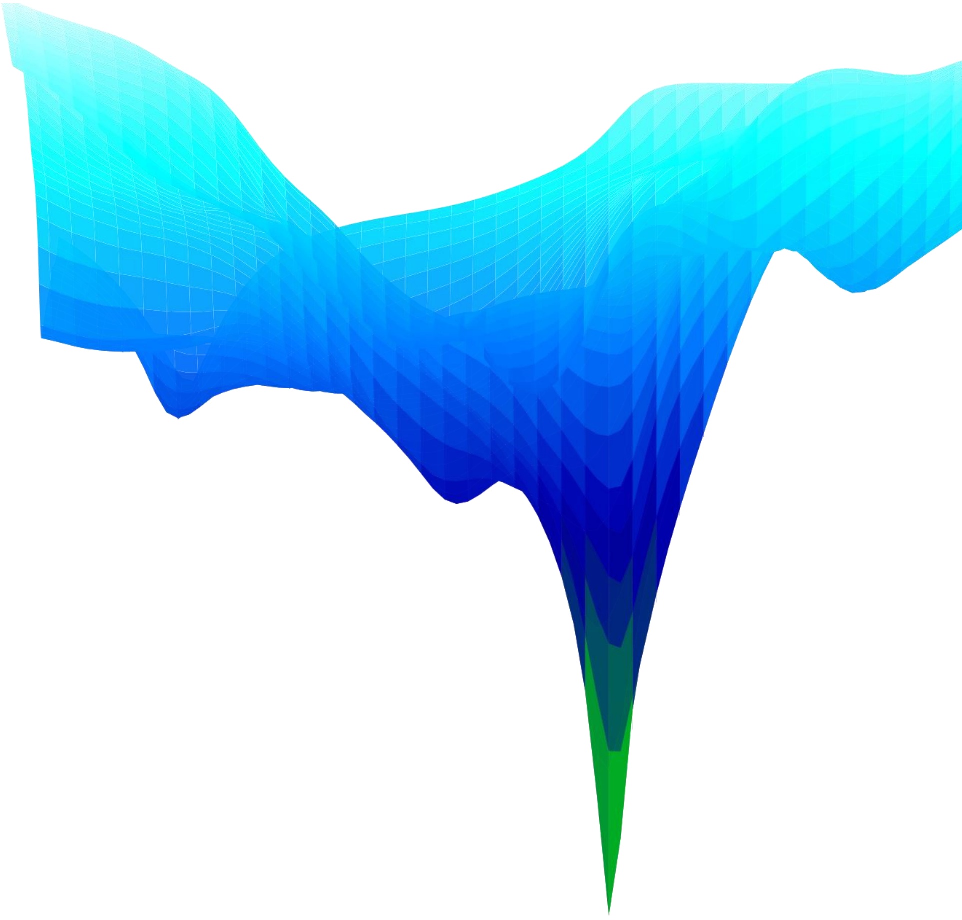
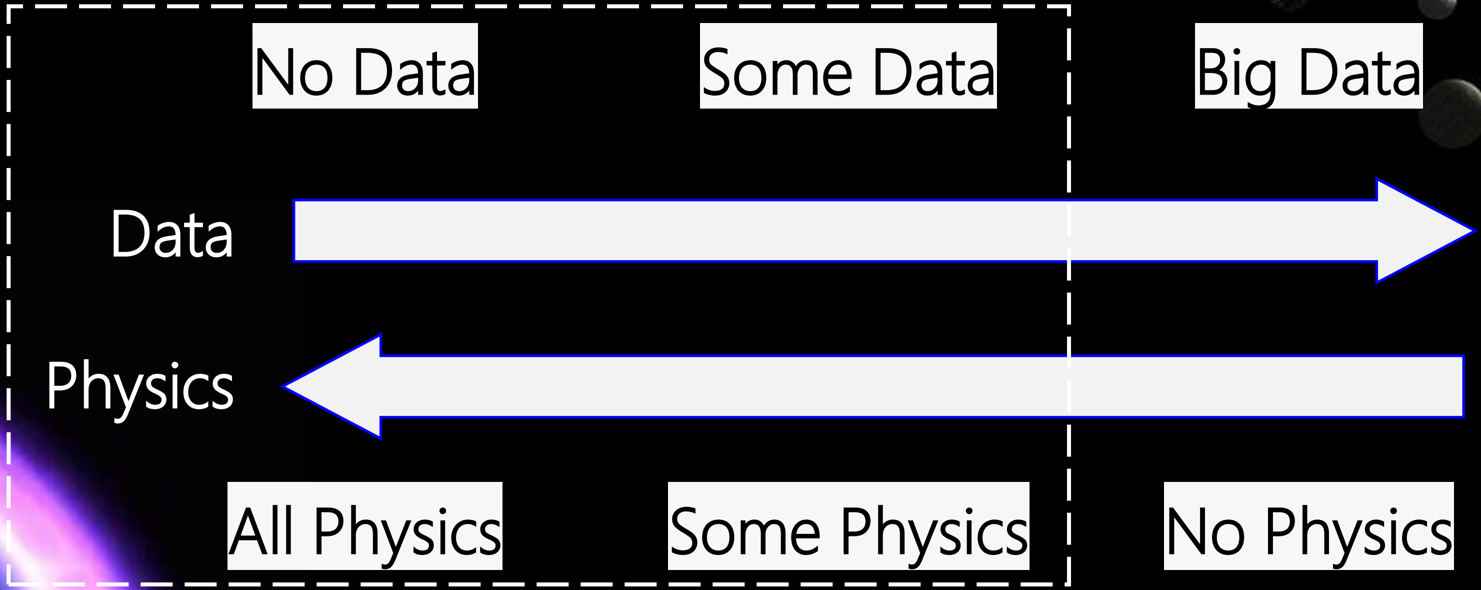
Part 4: Hands-on Experience with PINNs and Neural Operators



Data Driven Approaches

Physics-informed AI

Physics-informed Neural Networks (PINNs)

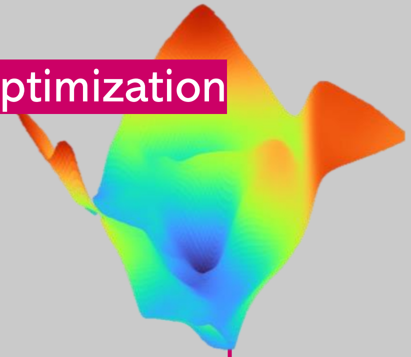


Karniadakis et al., 2021

Physics Informed Neural Networks

First Introduced by Raissi et al. (2019)

Optimization



- Reliable for mixed data types
- Flexible to noisy/incomplete data
- Quicker history matching
- More reliable sensitivity analysis
- Live interpretation with low supervision

Machine Learning

Physics

Numerical Methods

- Forward Simulation
- History Matching
- Uncertainty quantification
- Data-driven modeling

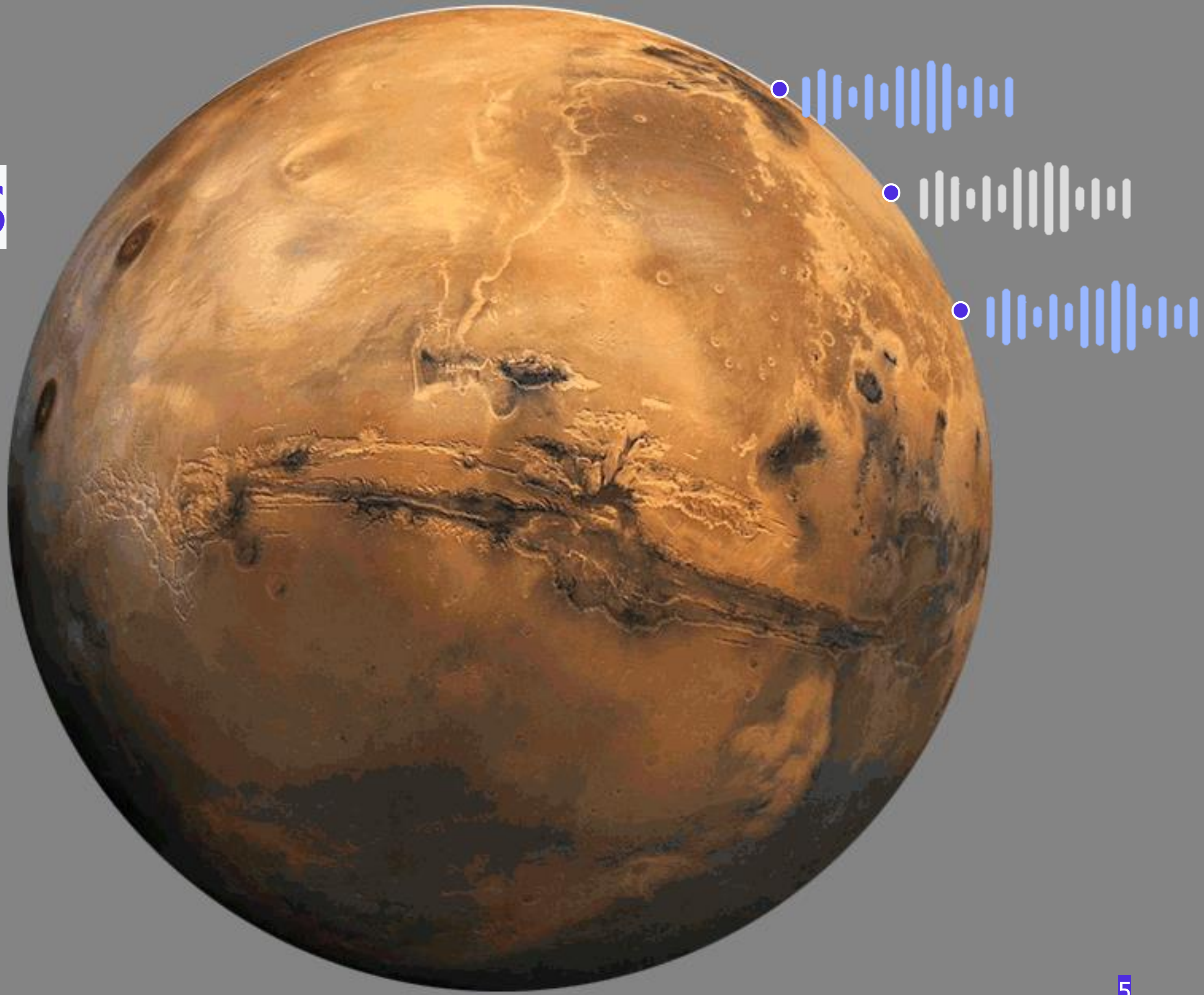
Inverse Problems

KEY CHARACTERISTICS

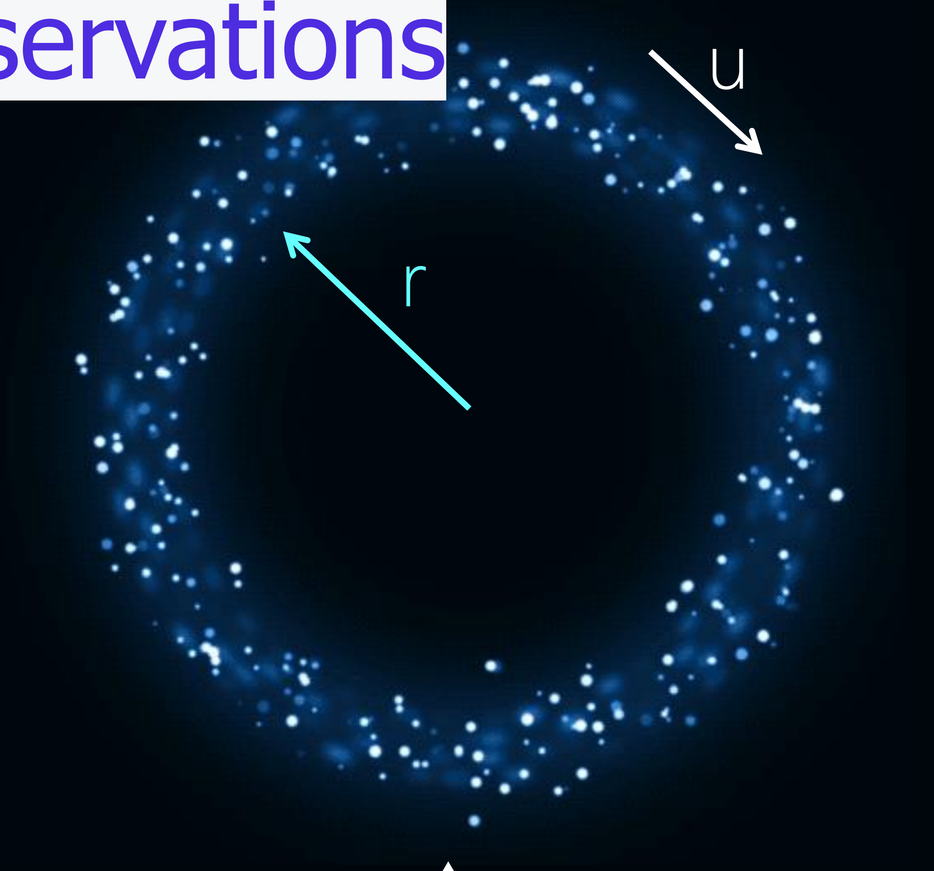
Ill-Posedness
Nonlinearity
Noisy Data

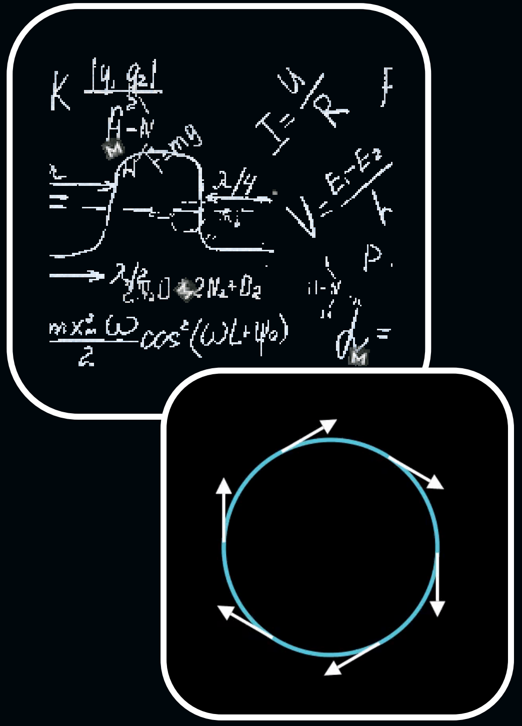
APPLICATIONS

Medical Imaging
Geophysics
Engineering



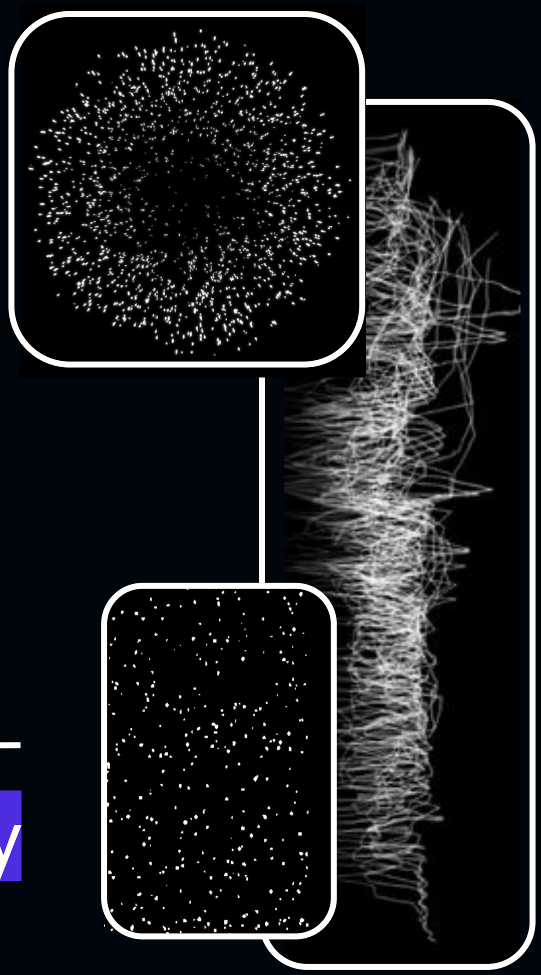
Multi-Fidelity Observations
Multi-Physics





Domain Knowledge

Multi-Fidelity Data



Inverse Calculations on Spontaneous Imbibition Experiments

APPLICATIONS | APRIL 10 2024

Application of Physics-Informed Neural Networks for Estimation of Saturation Functions from Countercurrent Spontaneous Imbibition Tests

Journal Collections: Data Science & Engineering Analytics

Jassem Abbasi; Pål Østebø Andersen

SPE J. 29 (04): 1710–1729.
Paper Number: SPE-218402-PA

https://doi.org/10.2118/218402-PA

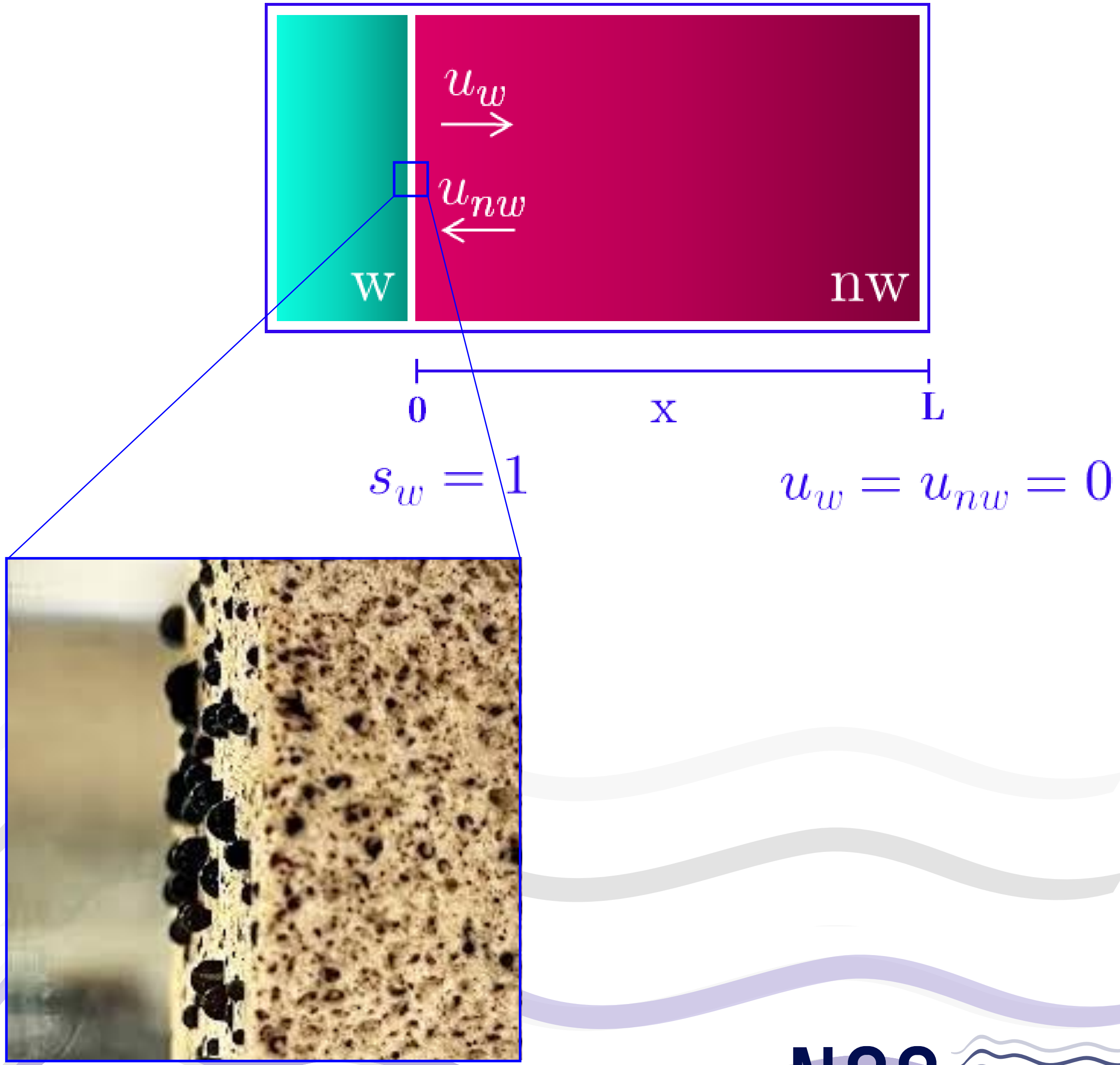
Spontaneous Imbibition

1D COUCSI

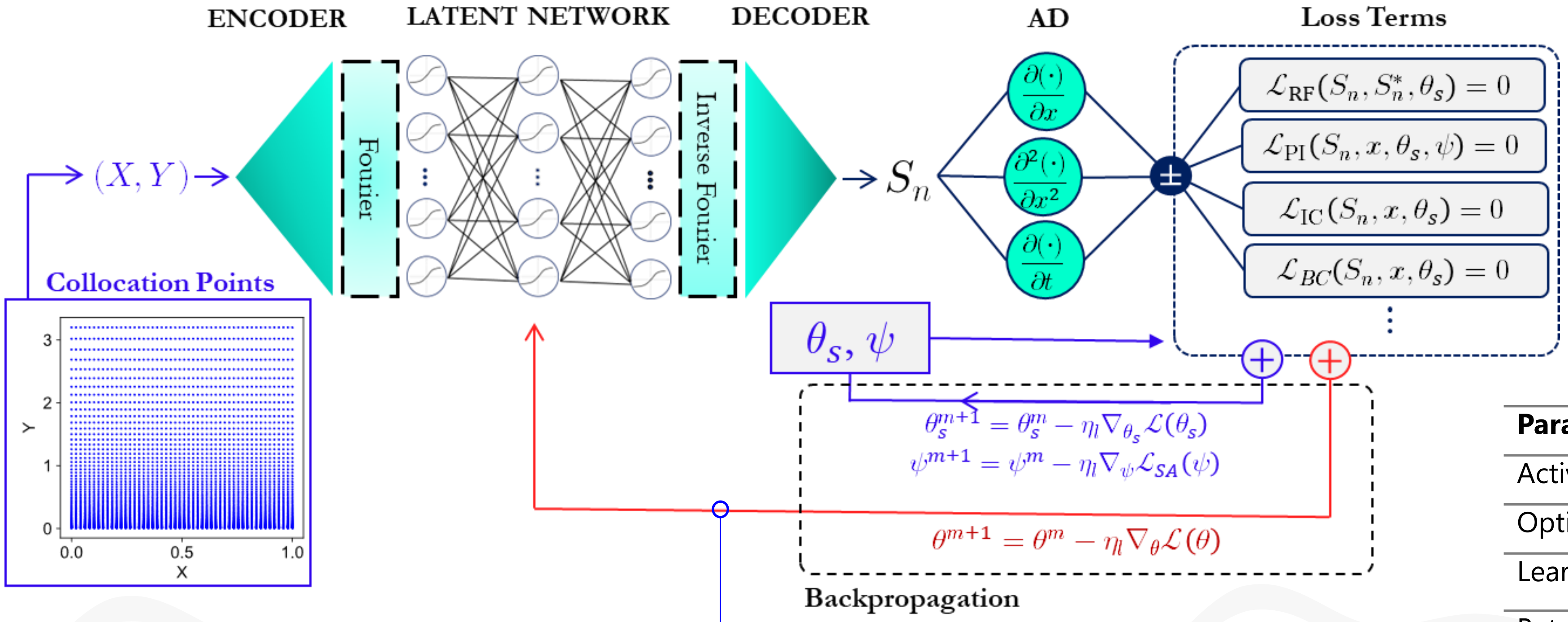
$$u_i = -\lambda_i[\partial_x p_i], \qquad \lambda_i = \frac{Kk_{ri}}{\mu_i}, \qquad (i = w, nw),$$

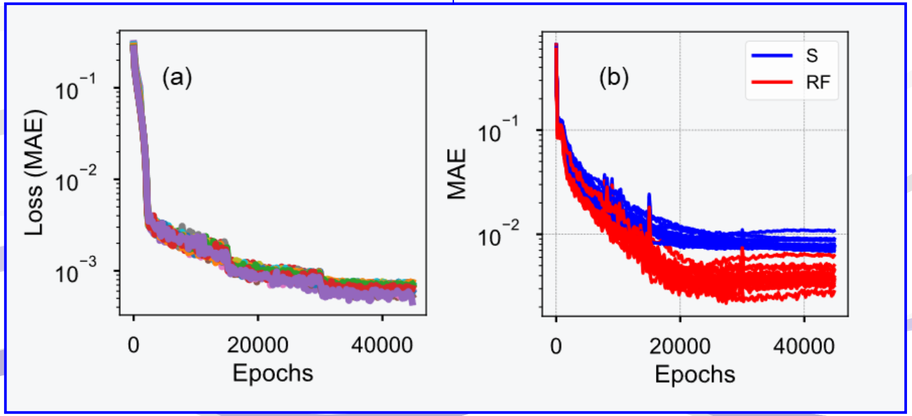
NEGLECT: Viscous and Capillary Forces

Known Parameters			
Parameters	Value	Parameters	Value
K	290 mD	μ_w	1.0 cP
ϕ	0.225	μ_{nw}	2.3 cP
s_{wr}	0.30	s_{nwr}	0.395
s_{wi}	0.395	S_{eq}	0.999
σ_{ow}	21 mN/m	L	0.1 m
Correct Values of Unknown Parameters			
Parameters	Value	Parameters	Value
k^*_{rw}	0.15	J_1	0.3
k^*_{rnw}	0.35	J_2	0.03
n_{w1}	6	n_{nw1}	2.0
n_{w2}	2.5	n_{nw2}	0.5



Model Architecture





$$\partial_T S_n = \partial_X\big(\Lambda_n(S_n)\partial_X S_n\big),$$

IC: $S_n(X=0, T) = 1,$

BC: $\partial_X S_n|_{X=1} = 0,$

BC: $S_n(X, T=0) = 0$

Parameter	**Value**
Activation function	Adaptive tanh
Optimizer	Adam
Learning rate (lr)	2e-4, 8e-5, and 1e-5
Batch size	Full batch
Length and width of the latent MLP layer	(4, 50)
Length and width of the encoder and decoder.	(2, 50)
Loss Weights	Self-adaptive loss-weight

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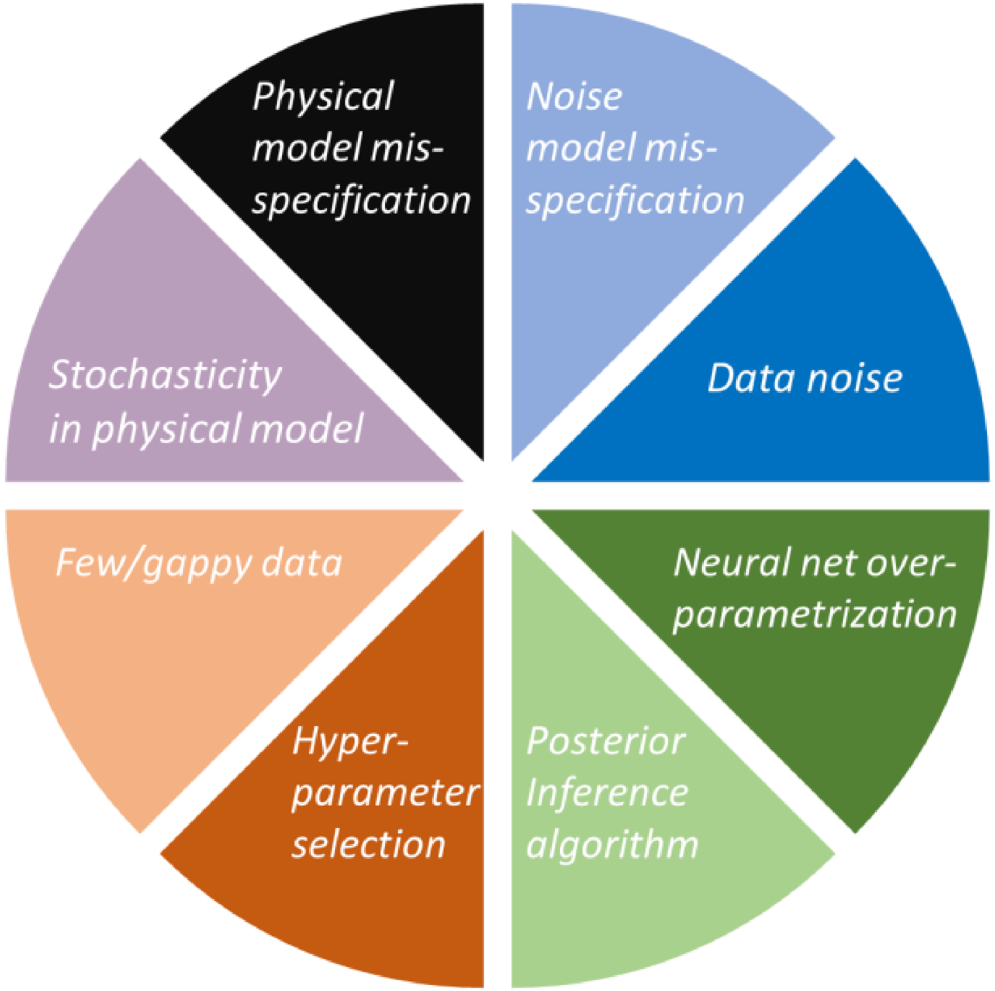
First of All: Types of Uncertainty

A qualitative breakdown of total uncertainty:

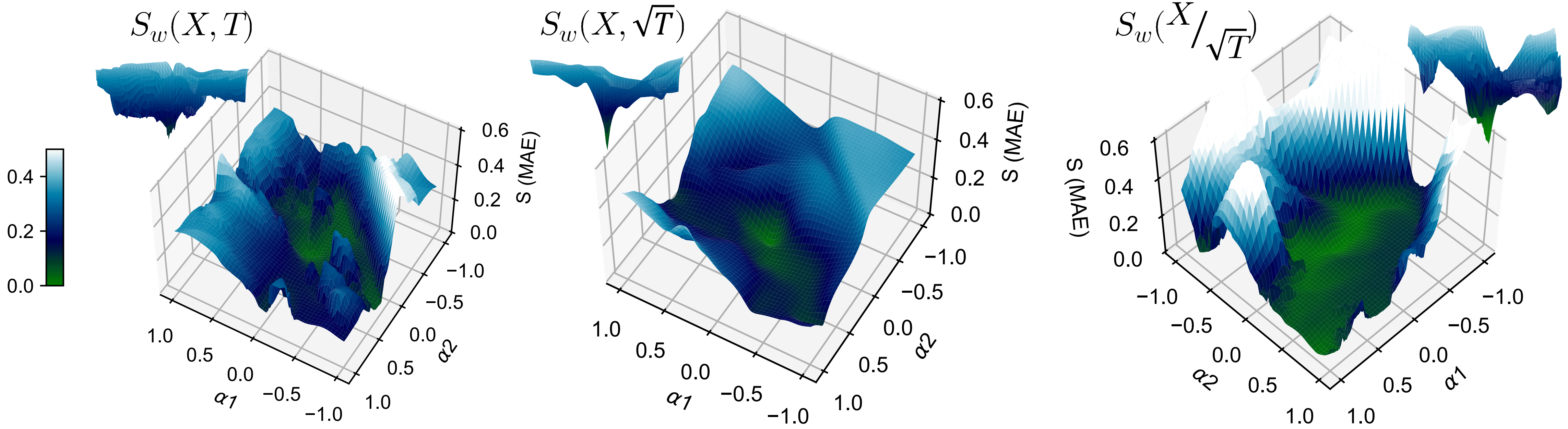
- Data (noisy, gappy);
- Physical models (misspecification, stochasticity),
- Neural networks (overparametrization),
- Hyperparameters,
- Posterior inference

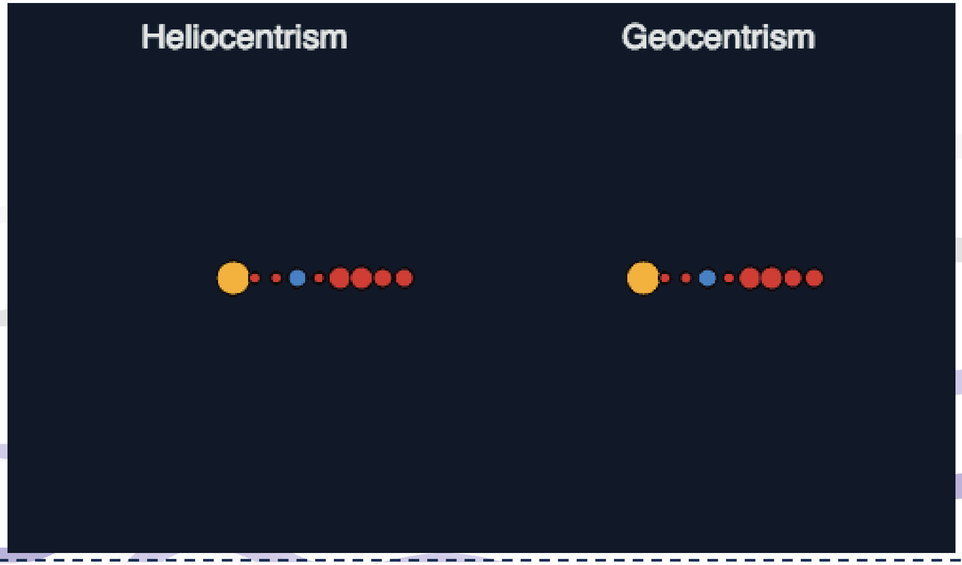


Note: Degree of freedom in the system

Apostolos F Psaros et al., 2022, Uncertainty Quantification in Scientific Machine Learning: Methods, Metrics, and Comparisons

A Comparison of Different Formulations





On the impact of data curation in Deep Learning

It tells us how to look at the problem!

Take advantage of Spectral Bias!

About Loss-landscapes:
www.losslandscape.com/

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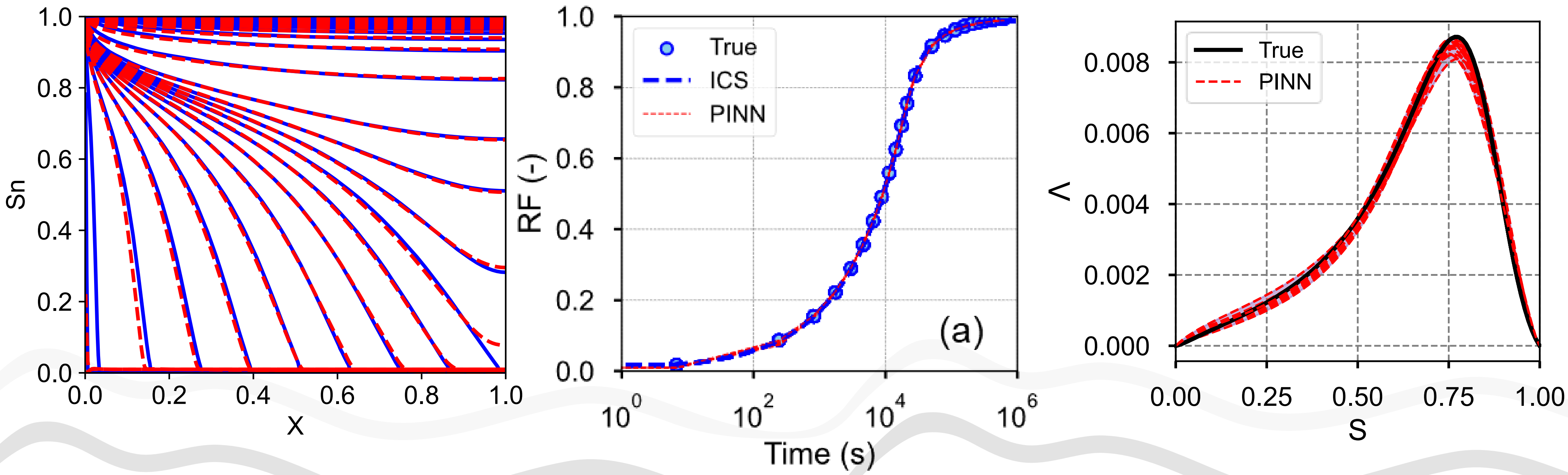
Results of Inverse Calculations



Reference Solution : IORCoreSim (2023)

Abbasi and Andersen (2024) – SPE Journal

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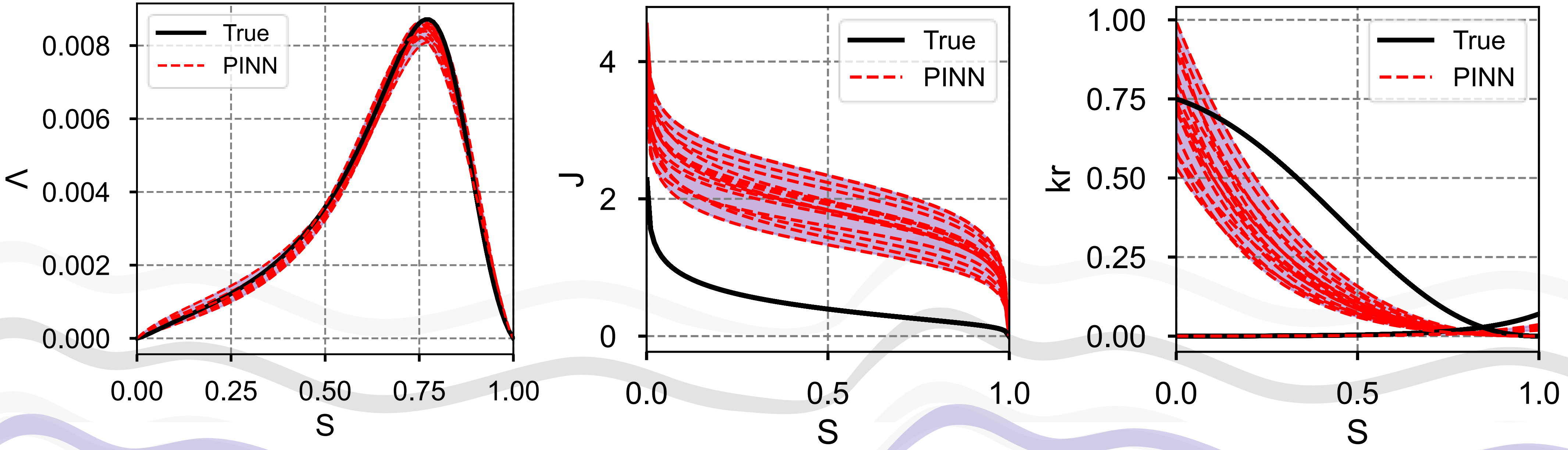
Unique Solution? Infinite Solutions?

- An ensemble with 20 members to explore the possible uncertainties in the calculations, with random initialization.

- There exists a wide range of k_r and J functions that can match the observed recovery data without coinciding with the correct curves



Abbasi and Andersen (2024) – SPE Journal

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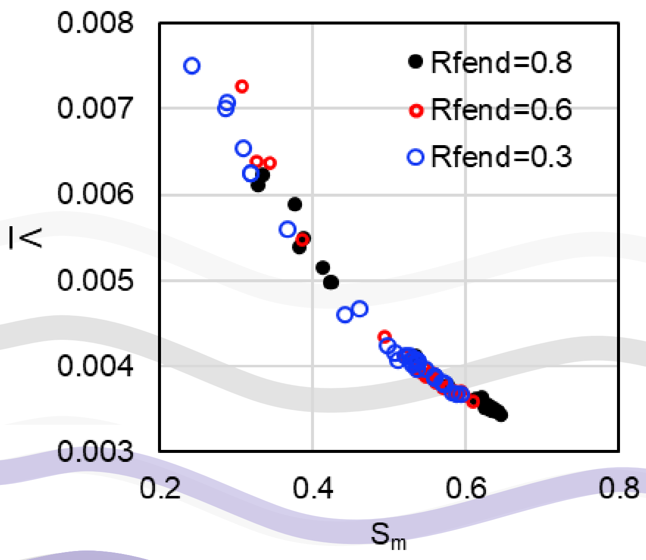
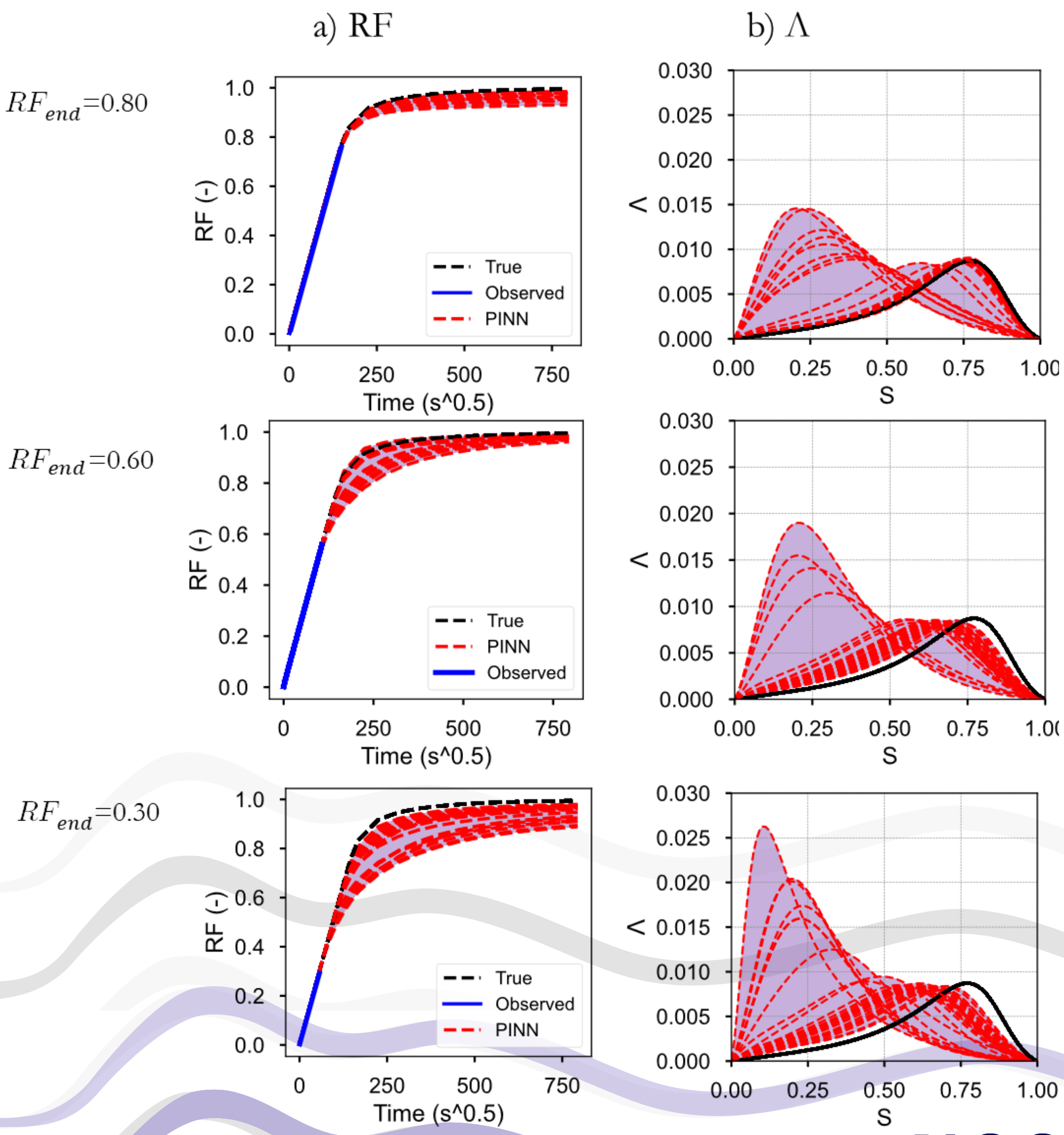
Incomplete Data (infinite-acting range)

- With more observational data (higher RF_{end}), the errors in the estimated curves reduced.
- If the observed recovery data are proportional with square root of time, there can be a large variation in CDCs explaining the observations.





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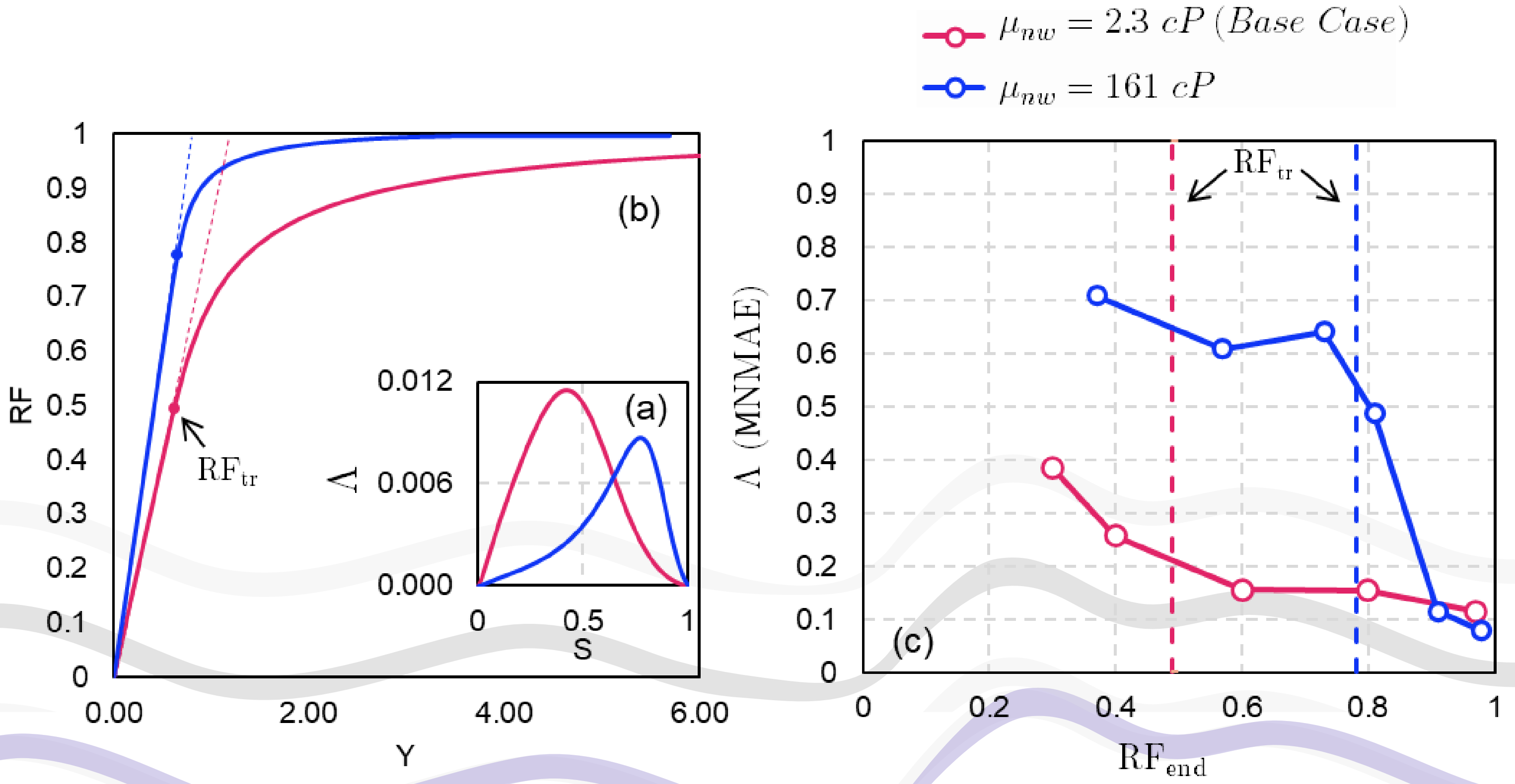
Incomplete Data (finite-acting range)

- We recommend to measure recovery at least until the data are visibly deviating from the initial square root of time profile.



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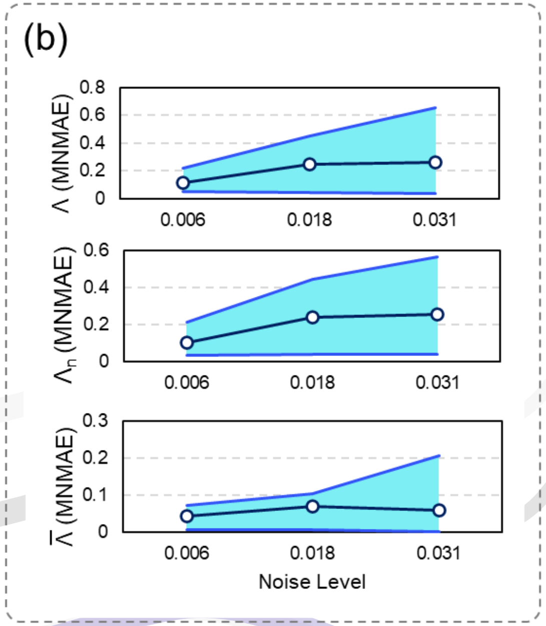
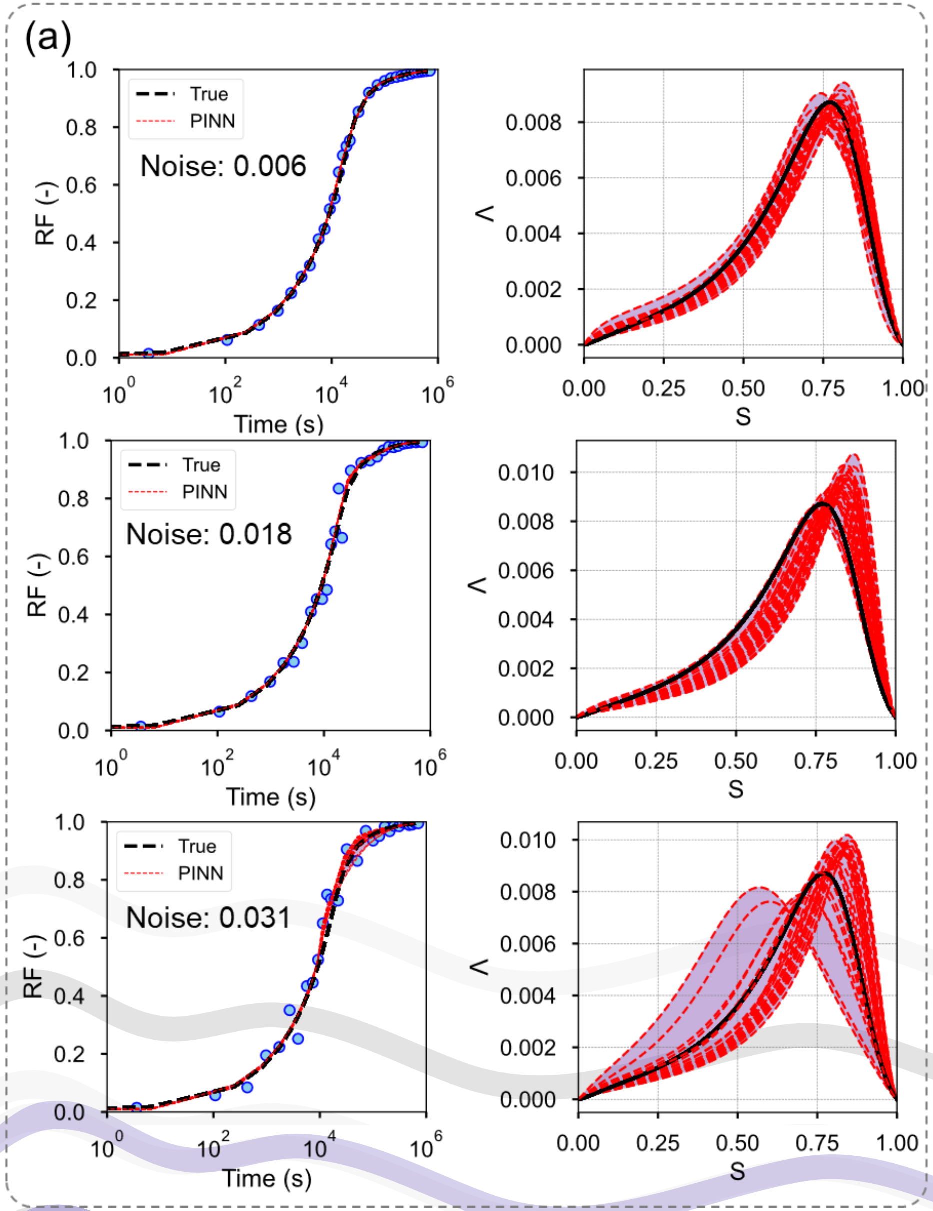
Impact of Noisy Data

- An increased uncertainty in the inverse calculation from increasing the measurement noises.





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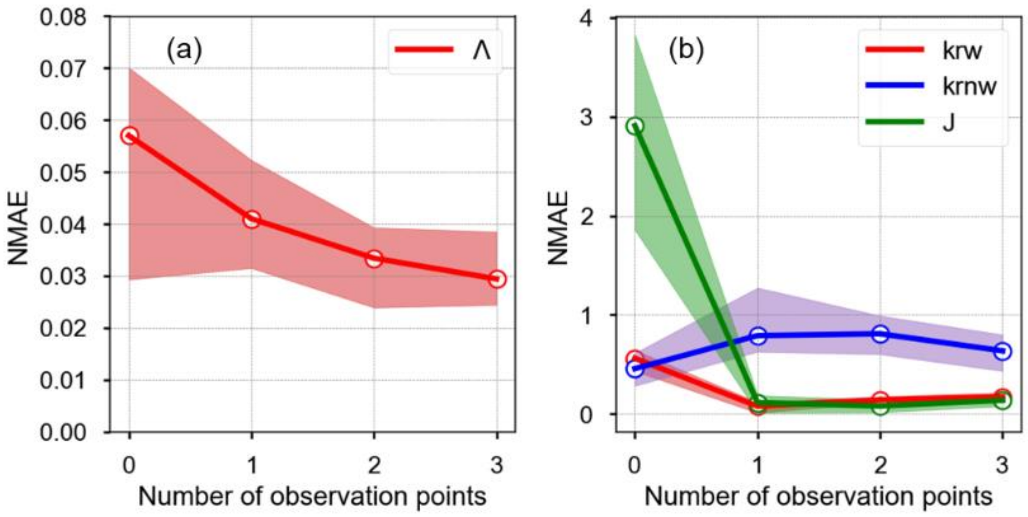
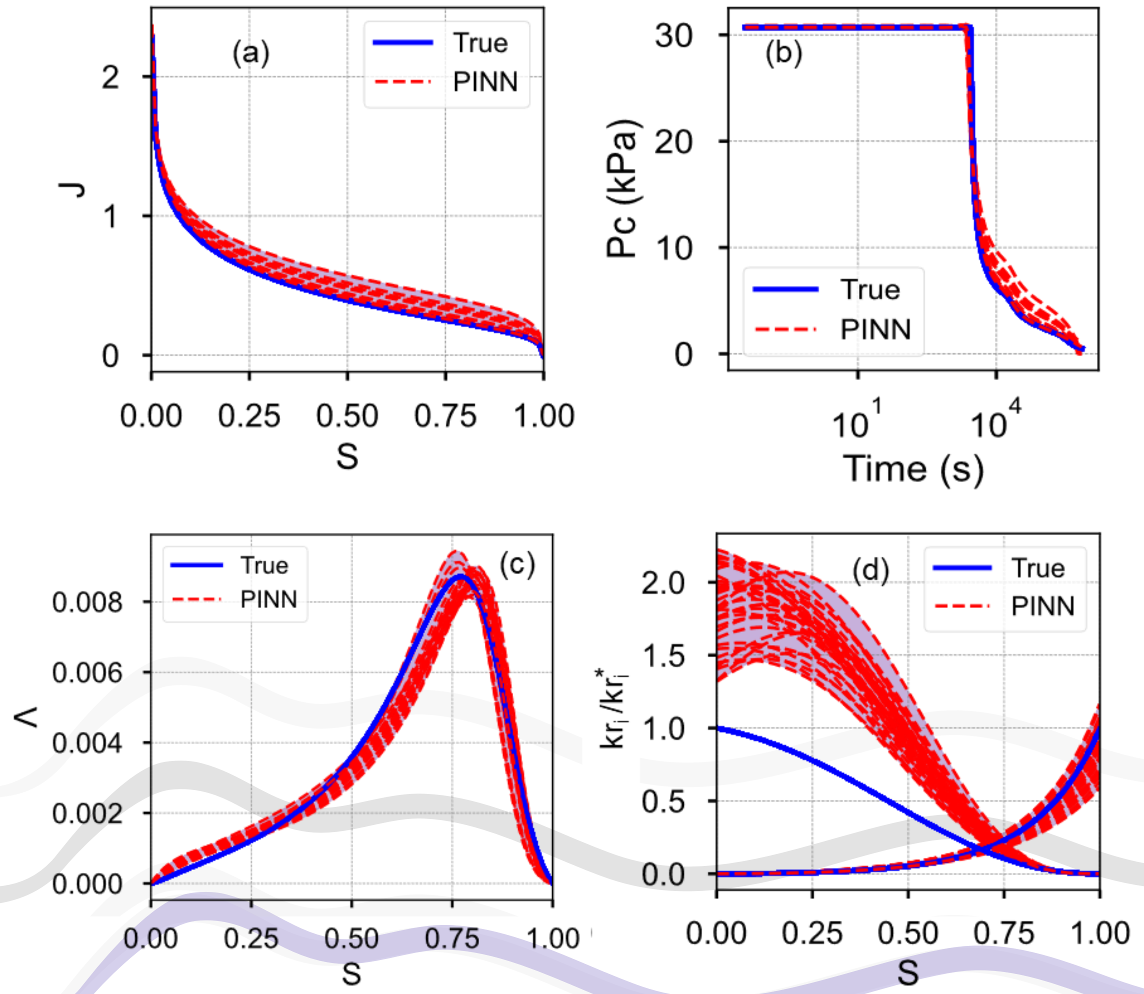
Multi-Fidelity Data (in-situ pressure)

- Utilizing the in-situ measurements helps in reducing the uncertainties in the predictions!

Full recovery curve with local capillary pressure data





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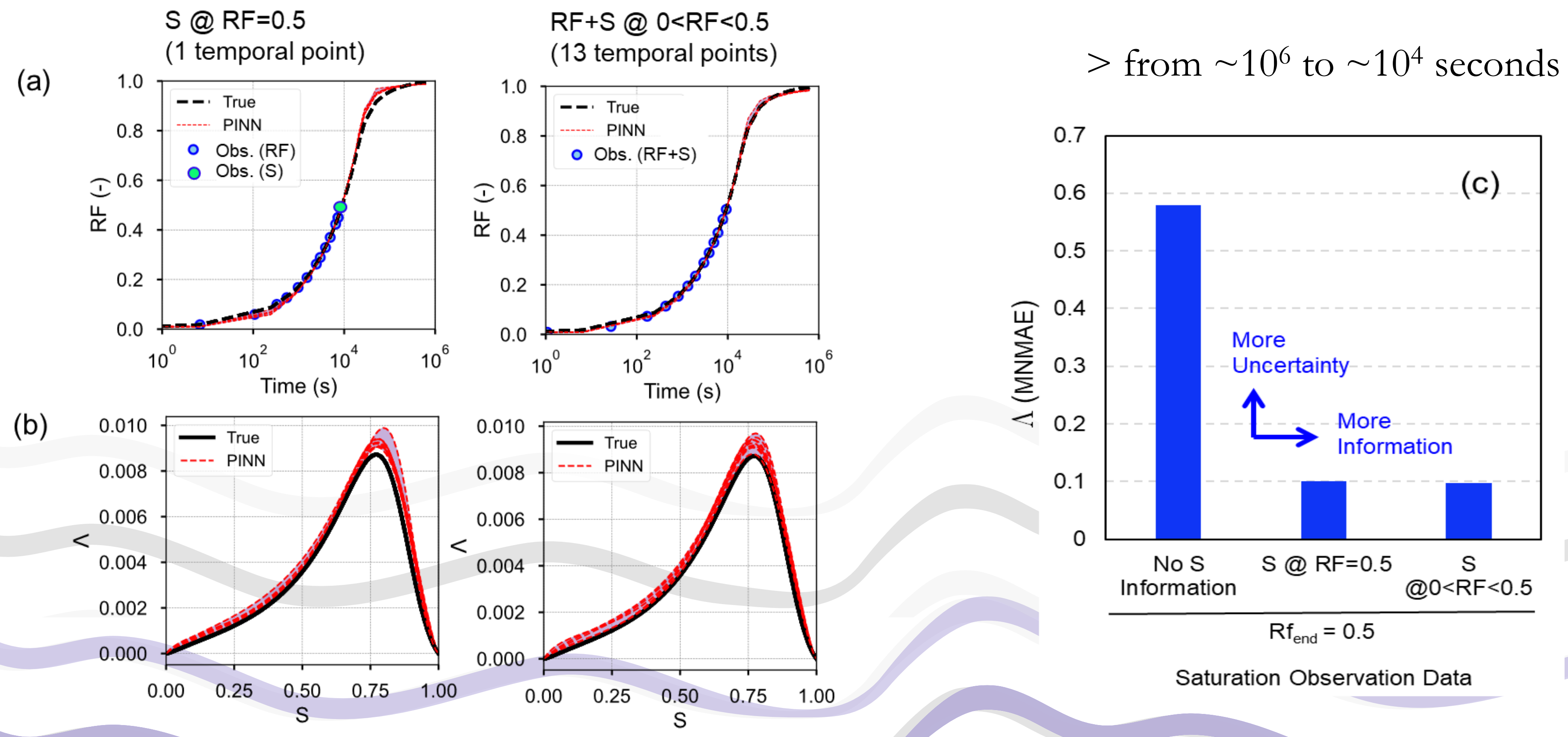
Incomplete + In-situ Data

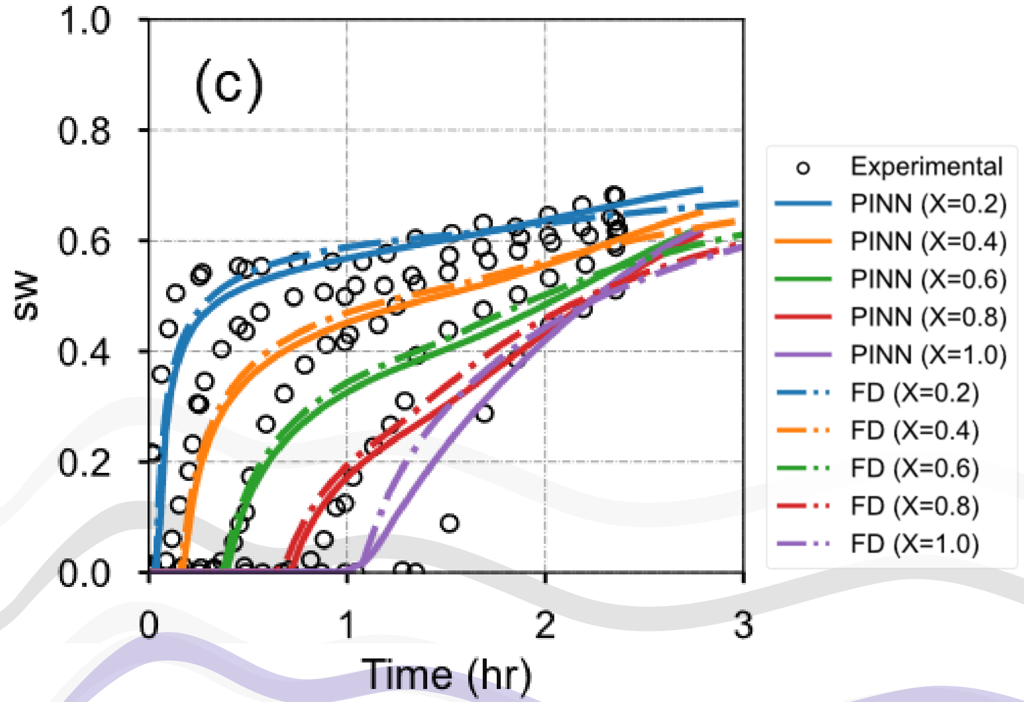
> combined utilization of RF and in-situ saturation data provide enough information within short time to accurately estimate the CDC curve (allows to significantly reduce laboratory test duration)



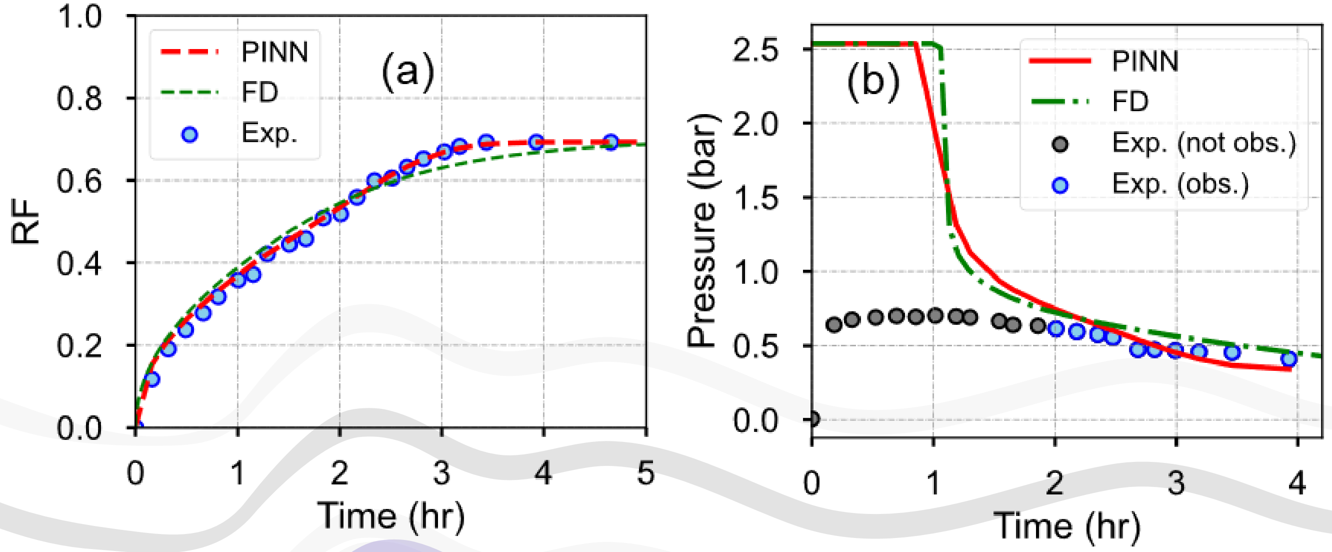
> from ~10^6 to ~10^4 seconds

Real Experimental Data

1. The produced volume of non-wetting phase (oil) versus time,
2. Pressure versus time at $X = 1.0$,
3. The local saturation versus time, at positions $X = \{0.2, 0.4, 0.6, 0.8, 1.0\}$.



PINNs vs. IORCoreSim



Source of Data: Ruth et al. (2016)

Abbasi and Andersen (2024) – SPE Journal

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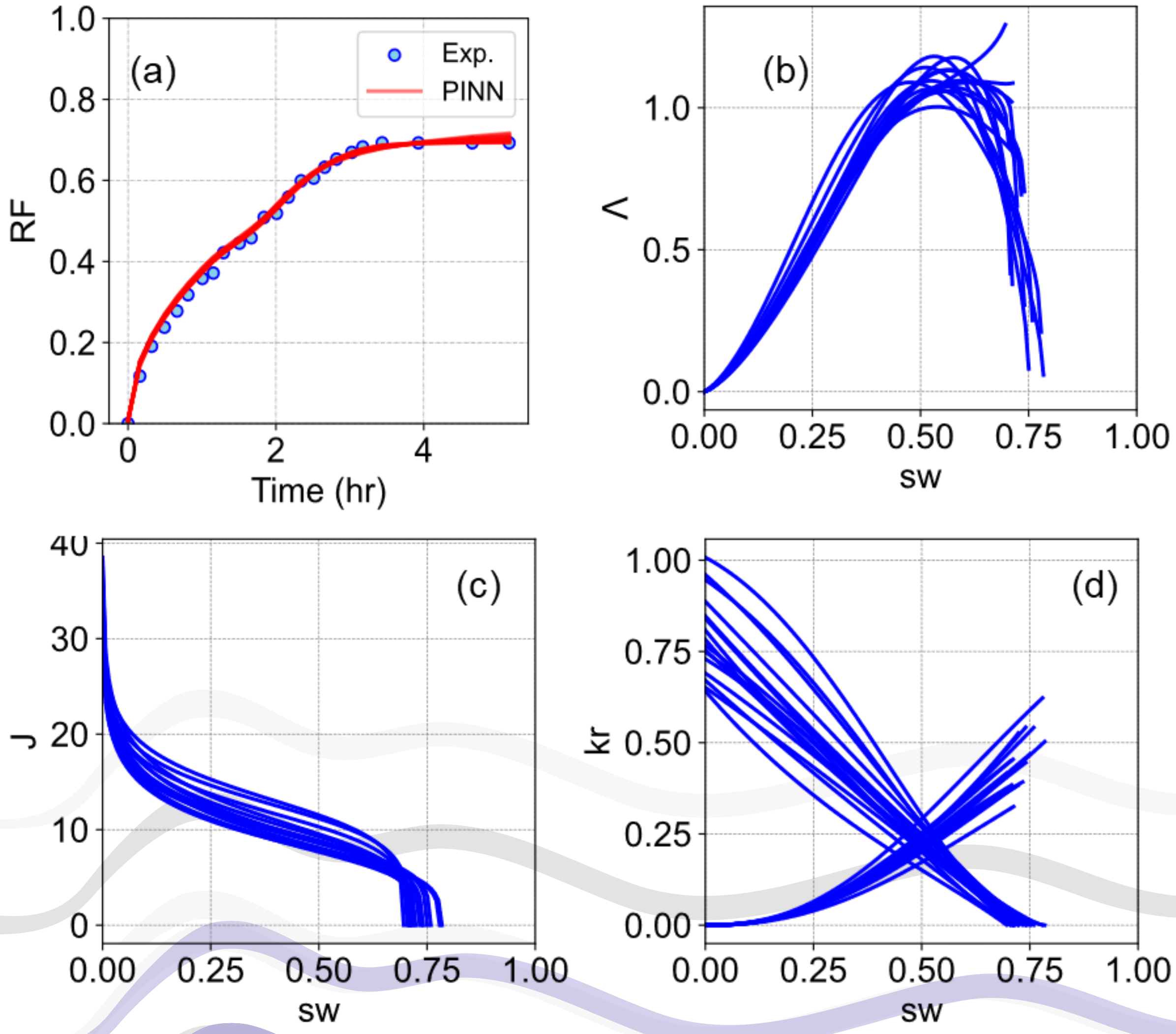
Real Experimental Data

> Access to a full recovery profile and detailed in situ saturation profiles can yield accurate predictions of the CDC

> Noise/uncertainty in the data can be reflected in uncertainty in the estimated CDC function.

Observation Data	MNAAD in Λ	
	Experimental Case	Synthetic Case
RF	0.062	0.042
RF + S + P_c	0.087	0.028



It is time for hand on experience

We will have three exercises.

> Computations on Google Colab:
https://colab.research.google.com/

> All the materials are available on:
https://github.com/jcabbasi/SCIML2024workshop

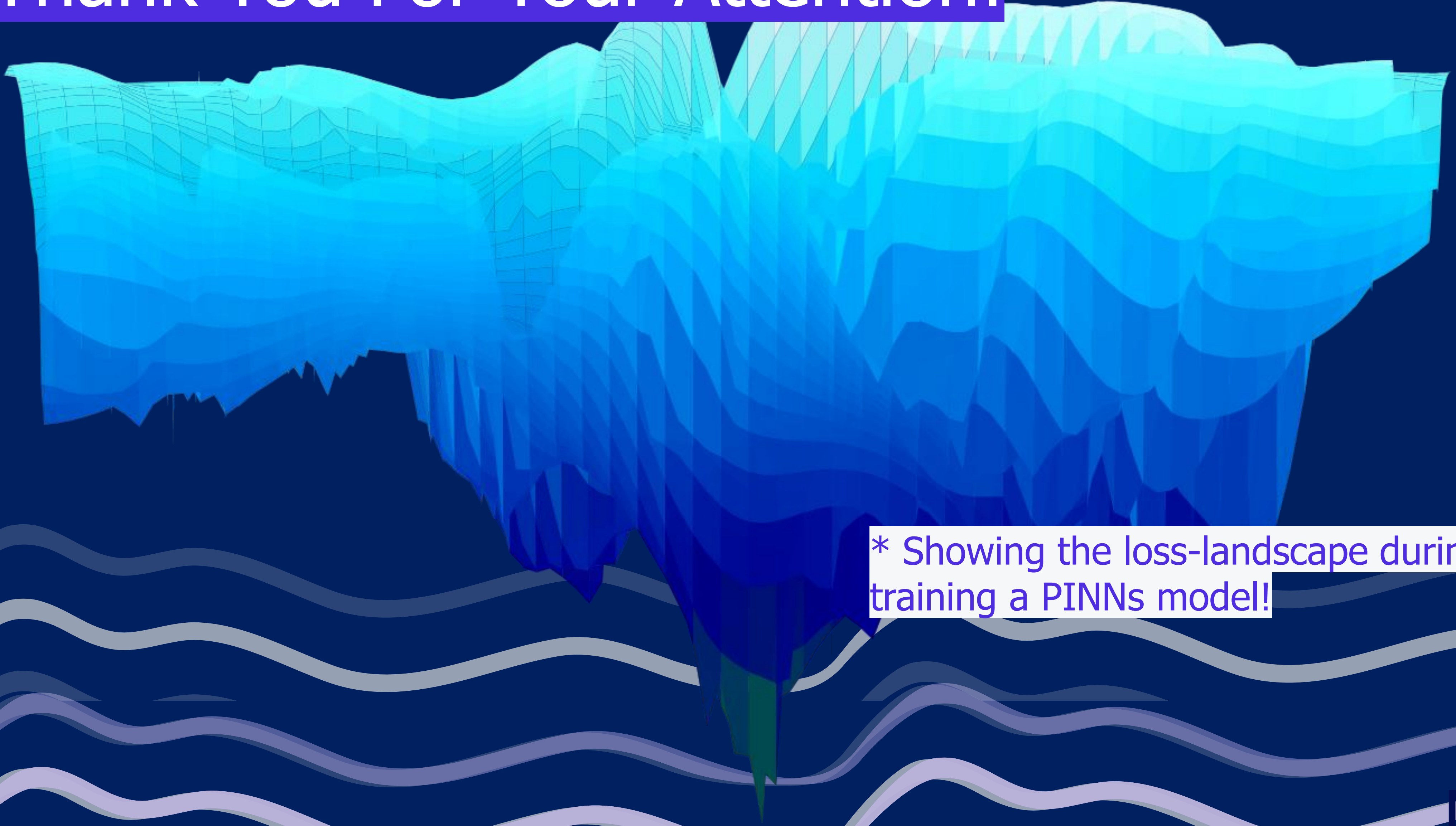
Exercises:

A Beginner's Introduction to PINNs (Case of Harmonic Oscillator)

A Beginner's Introduction to PINNs (Buckley-Leverett Problem)

A Beginner's Introduction to Neural Operators (Integral Operator)

Thank You For Your Attention!



* Showing the loss-landscape during training a PINNs model!