# Science-informed Machine Learning for Accelerating Real-Time Decisions in Subsurface Applications

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### **Problems and motivations**

Carbon Storage

- Bring AI and machine learning (ML) capabilities to
  - Inform pre-injection permitting
    - Class VI permit ( characterization, uncertain quantification, plume assessment)
  - Site development
    - History matching
    - Operation optimization
    - Induced seismicity
- Visualization (real-time)
- Idea is to use AI and ML to speed up these simulations by orders of magnitude







### **Task 5 Motivation**

Can we rapidly develop experience among CCS stakeholders to facilitate rapid & safe deployment of largescale geologic CO<sub>2</sub> storage?

<u>Vision:</u> Enable a Virtual Learning Environment (VLE) for exploring and testing strategies to optimize reservoir development, management & monitoring prior to field activities

<u>Phase 1 Goal:</u> Demonstrate the proof-of-concept with a prototype





# Deep-learning-based surrogate model for fast forward simulation

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#### **Definitions**

• Capture the relationship between the input data and output data and use neural networks as mapping function.

State variables (2D slice for visualization):

**Pressure/CO2 saturation/Production rate** 

- Faster, more flexible, scalable, and efficient.
- Forward simulation and inverse problem (history matching).

Geological parameter: Porosity/Permeability



#### **Table of contents**

- 1. Convolutional neural network/Multilayer perceptron model
  - Dataset: The Illinois Basin Decatur Project (IBDP) simulations
  - Data size: 126, 126, 110
  - Time step: 50 (Months)

- 2. Reduced-order Model
  - Dataset: GoM simulations
  - Data size: 54, 48, 92
  - Time step: 720 (Months)



#### **CNN/MLP on IBDP**

• Model architecture: CNN-MLP

• Input and output overview

• Results: Pressure

• Results: Saturation



#### **Model architecture: CNN-MLP**





#### **CNN/MLP on IBDP**

• Model architecture: CNN-MLP

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• Results: Saturation



### Input and output overview

- Training, validation, and test split
  - Training (80 realizations): [1, 2, 3, 4, 6, 7, 8, 9, 11,..., 99];
  - Validation (10 realizations): [5, 15, 25, 35, 45, 55, 65, 75, 85, 95];
  - Testing (10 realizations): [10, 20, 30, 40, 50, 60, 70, 80, 90, 100].
- Origin of tartan Input data 9.7 mile grid, [1,1,1] on Injection time: (100, 50,); the top surface • Injection rate: (100, 50,); • Permeability: (100, 126, 125, 110, 3); Porosity: (100, 126, 125, 110, 1). - 117500 - 116500 Output data  $\bullet$ • Pressure: (100, 50, 126, 125, 110, 1); Saturation: (100, 50, 126, 125, 110, 1). 114500



Figure 67. Dynamic model domain and tartan grid.

### **Pre-processing: Input data**

• Injection rate and time

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#### Scaled cumulative injection rate



#### Scaled injection time

### **Pre-processing: Input data**

• Permeability (X, Y, and Z): scaled logK to [-1, 1];

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### **Pre-processing: Input data**

• Porosity





# Pre-processing: Output data Pressure: Scaled to [0, 1]





### **Pre-processing: Output data**

Saturation





#### **CNN/MLP on IBDP**

• Model architecture: CNN-MLP

• Input and output overview

• Results: Pressure

• Results: Saturation



#### **Pressure: Good results**

#### Training curve



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#### Cropped Pressure comparison (mse: 6.2715e-5)



#### Pressure comparison (mse: 0.001885)



### **Pressure: injection and monitoring well**

#### Injection well

Monitoring well



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#### **CNN/MLP on IBDP**

• Model architecture: CNN-MLP

• Input and output overview

• Results: Pressure

• Results: Saturation



#### **Saturation: Not good**

#### Training curve



#### Testing (scaled permeability) mse: 0.0001711



#### Saturation comparison



#### **ROM on GoM**

• Problems and motivations

• Dimension reduction and workflow

• Results: Pressure and saturation

• Future work



### **Problems and motivations**

- ML and DL model training:
  - Massive feature numbers: hundreds of thousands or million grid cells;
  - Strong feature correlations;
  - Limited realizations;
  - High computational cost and time for model training.

- Any solutions to improve model performance?
- Can we implement model training with fewer but more representative features?





#### **ROM on GoM**

• Problems and motivations

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• Future work



#### **Dimension reductions**

- What can DR do?
  - Reduce feature numbers;
  - Retain important information.





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#### **Dimension reductions**



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#### **Workflow diagram**

- Step 1: Dimension reduction models for Geological Parameters and State Variables;
- Step 2: Construct mapping function in latent spaces with less features;
- Step 3: Apply to new realizations or new datasets.



#### **ROM on GoM**

• Problems and motivations

• Dimension reduction and workflow

• Results: Pressure and saturation

• Future work



### **Preliminary results: GoM datasets**

#### • 3D Pressure: Good with less than 1% errors.



Comparison between Ground Truth and Model Predicted PCA reconstruction

• 3D Saturation: Bad with more than 20% errors.

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Comparison between Ground Truth and Model Predicted PCA reconstruction



#### **ROM on GoM**

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• Future work



#### **Future works**

- Pressure prediction: from good to better
  - Improve the accuracy on the large-scale domain
  - Coarsened input data for higher model efficiency
  - ...
- Saturation prediction: from bad to good
  - Custom loss function
  - Attention mechanism
  - More powerful models
  - ...







### Thank you!

