Graph Network Surrogate Model for Optimizing the Placement of Horizontal Wells for CO_2 Storage

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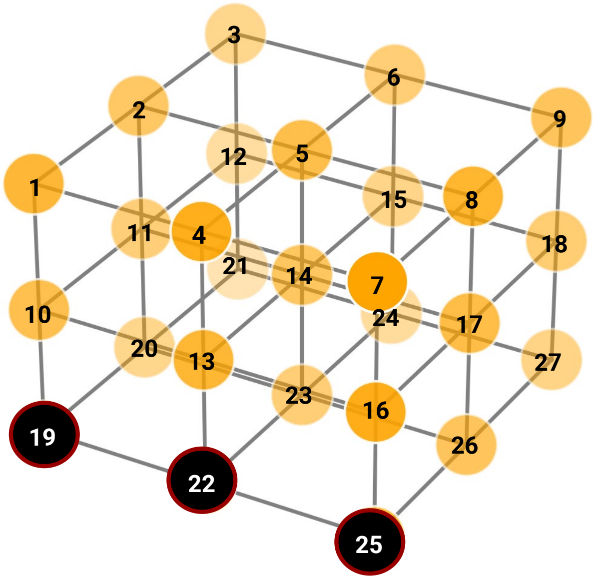
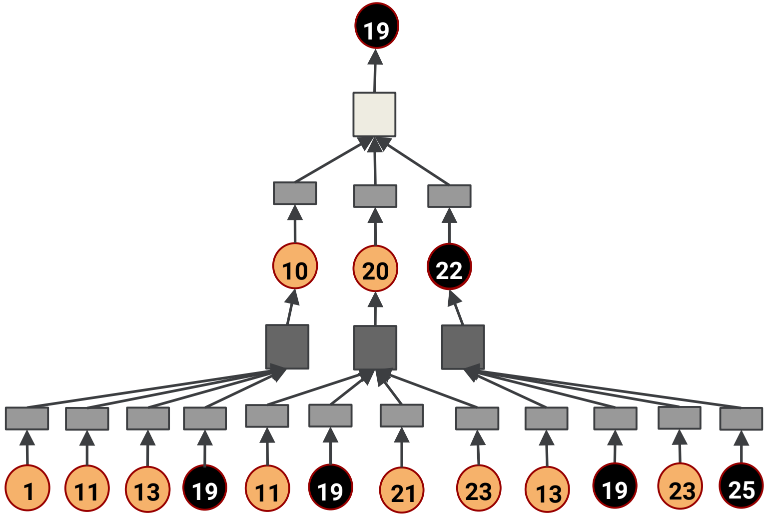
General Motivation

- Well placement optimization is often performed using population-based stochastic search algorithms (e.g., particle swarm optimization, genetic algorithms, differential evolution)
- These optimizations are computationally expensive due to the large number (~1000s) of simulation runs required
- Reduced-order/surrogate models can greatly improve optimization efficiency, but challenges exist for cases with changing well locations
- Here we use graph neural networks, with separate networks to predict global pressure and saturation, and a third network for bottom-hole pressure

3D Graph & Computational Graph



Graph



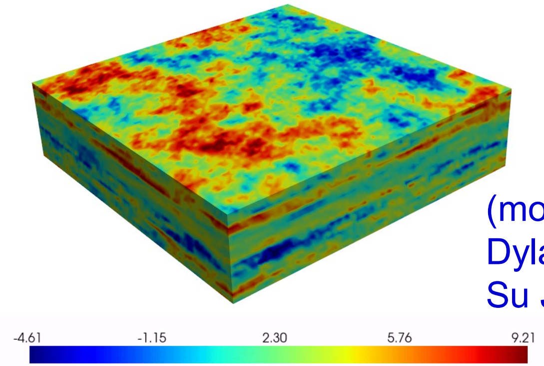
# of Message Passing Layers = 2

Input Features for GNN

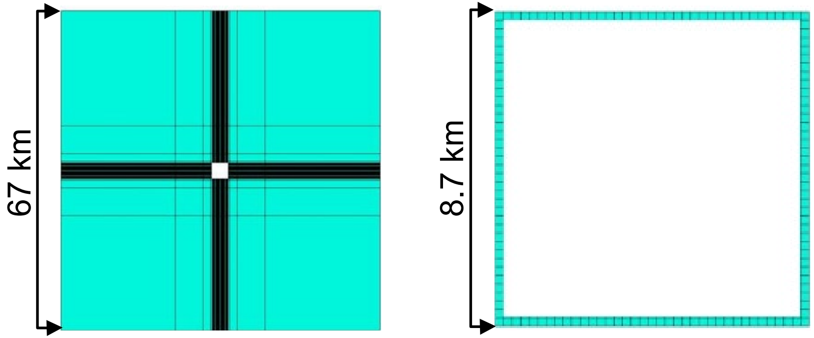
- Edge features: transmissibility and geometric quantities
- Node features
  - Current pressure & saturation (P_0 , S_0)
  - Permeability (k)
  - Depth (d)
  - Porosity (ϕ)
  - Well index of the cell (WI)
  - Injection mass rate by perforation (q_{inj})
  - One hot encoding for different types of nodes (e)
  - Current time step length (δt)

3D Geological Carbon Sequestration

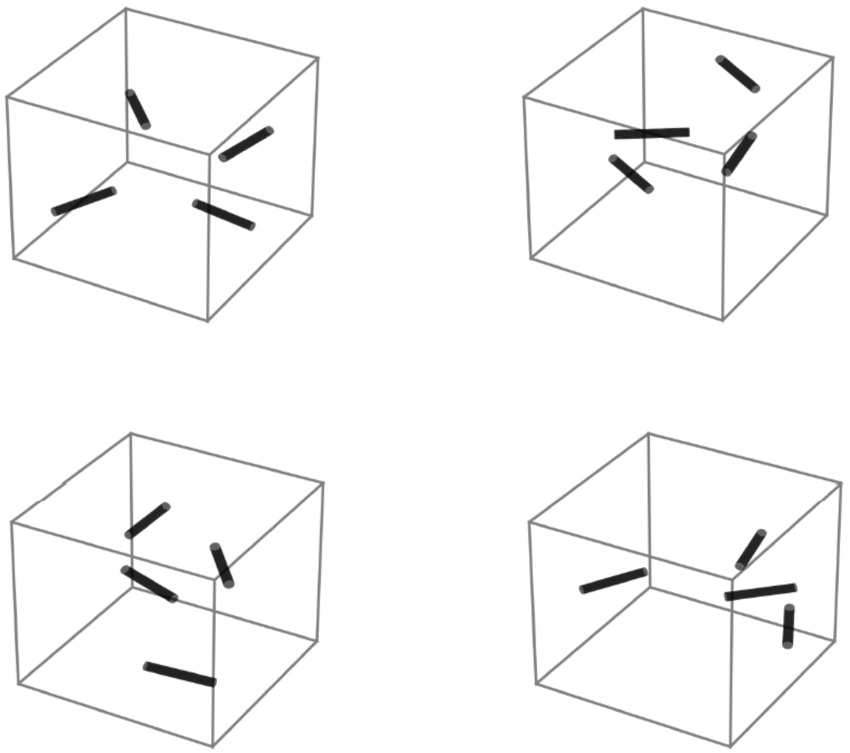
- Model parameters
  - Mt. Simon formation (Illinois Basin)
  - 82 x 82 x 20 grid (134,480 cells, structured grid)
  - 8.5 km x 8.5 km x 122 m
  - 4 horizontal injectors
  - Each well injects 0.5 Mt/year for 20 years
  - Using Eclipse 300 CO2STORE for training runs
- Deep-learning setup
  - 200 simulations with **random horizontal well configurations (4 wells in each case)**
  - 100 for training, 50 for validation, 50 for testing
  - Median errors for test set: 4% for pressure and 6% for saturation



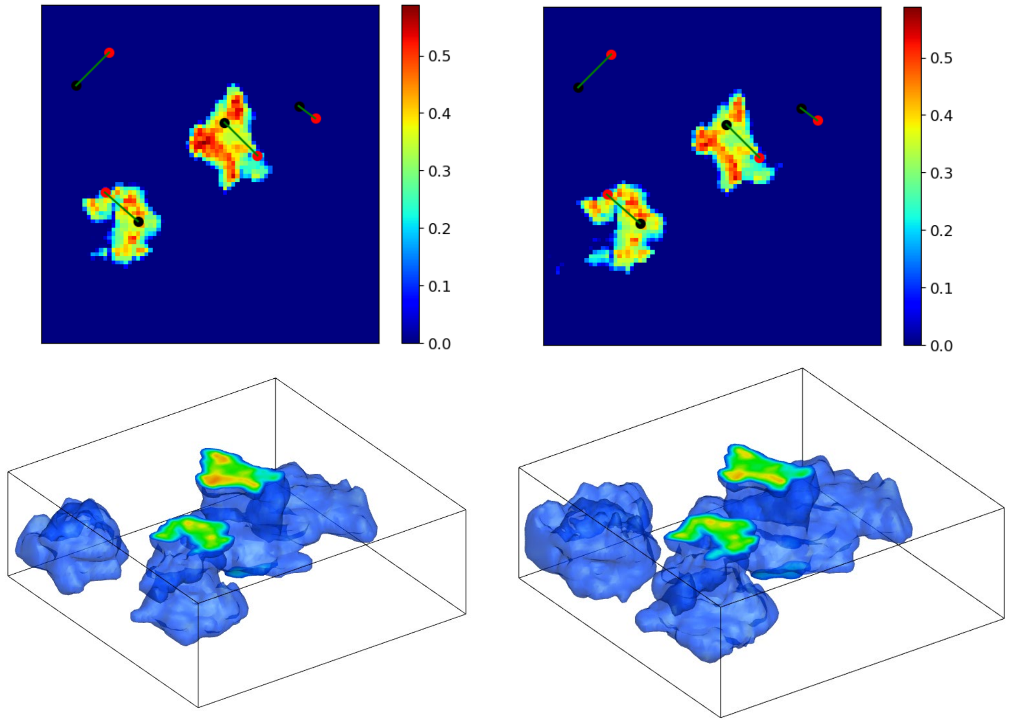
(model from Dylan Crain, Su Jiang)



Horizontal Well (Random) Configurations



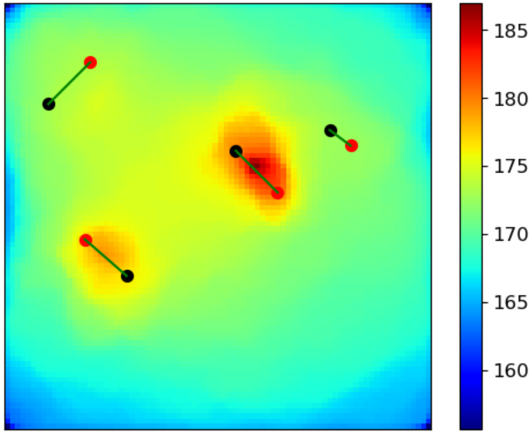
Test Case with P_{50} Error
Saturation at 20 years (10 Steps)



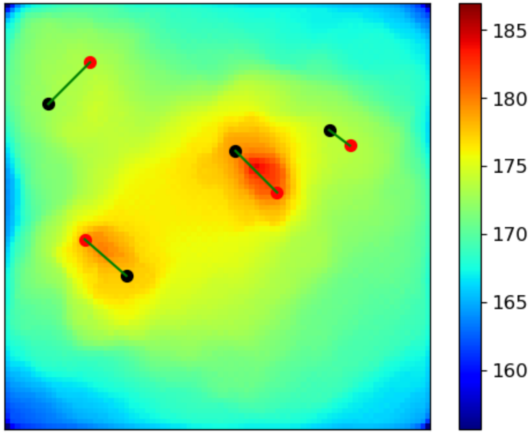
(wells projected onto top layer)

Simulation GNSM

Test Case with P_{50} Error
Pressure at 20 years (10 Steps)



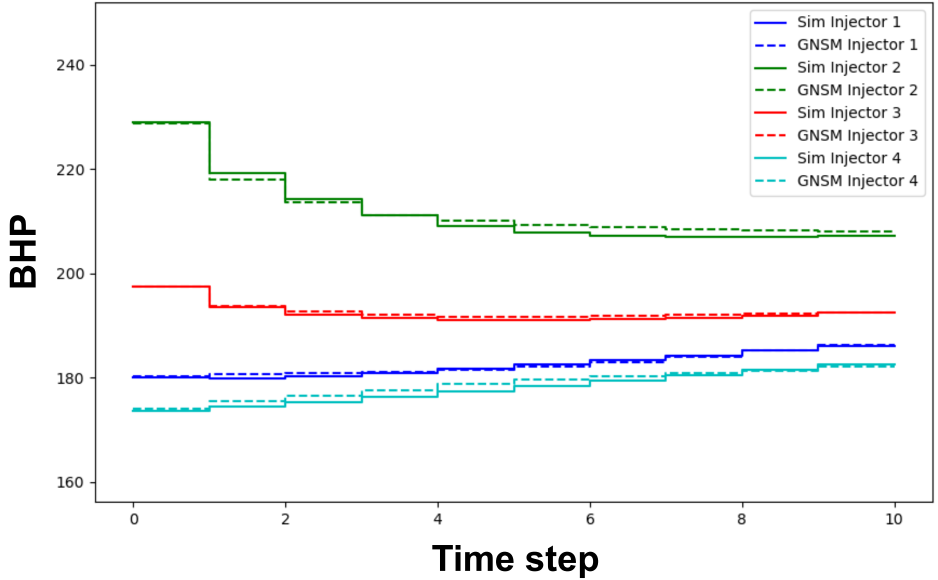
Simulation



GNSM

(wells projected onto top layer)

P_{50} Error Test Case Bottom-hole Pressures

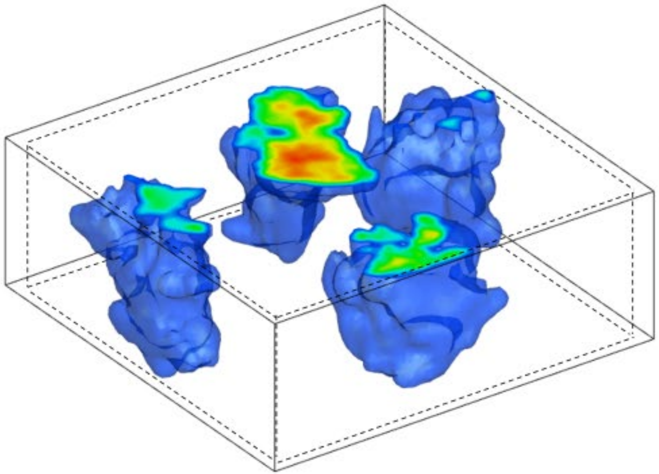


Footprint Ratio Calculation

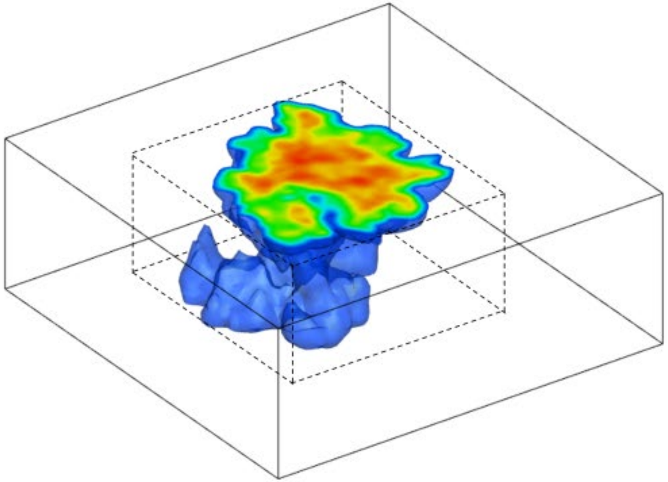
$$R^i_{fp} = V^i_{fp}/V_{tot}$$

V^i_{fp} : CO_2 footprint (at 20 years) for test case *i*

V_{tot} : total bulk volume of storage aquifer



Example 1



Example 2

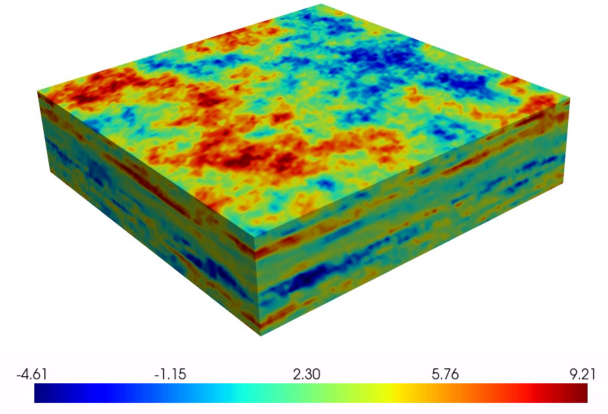
Optimization Setup

❑ Simulation parameters

- Optimize locations of four horizontal injectors to minimize the CO_2 footprint ratio
- Well geometric constraints (in table)
- Maximum BHP (276 bar) and CO_2 retention constraints
- Run for 20 years (ECLIPSE CO2STORE)

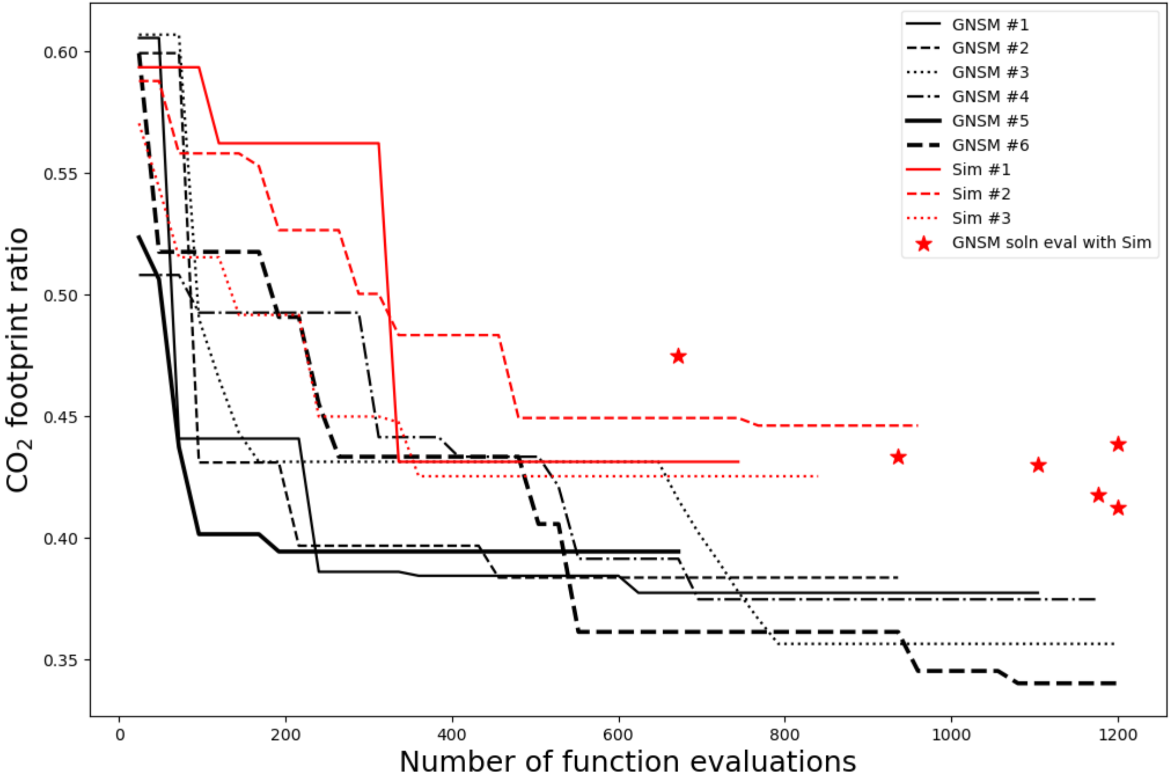
❑ Optimization setup

- Optimization method: differential evolution
- Population size: 24
- Terminate when obj. fcn. change is less than 1% over 20 iterations, or after 50 iterations



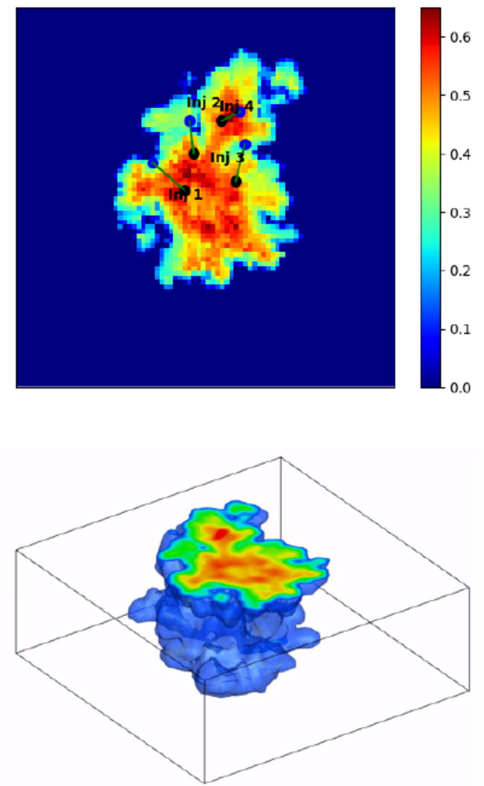
No.	Constraint type	Number
1.	Maximum well length	1200 m
2.	Minimum well length	480 m
3.	Minimum interwell distance	720 m
4.	Minimum well-to-boundary distance	424 m
5.	Maximum heel-to-toe difference in depth	0 m

Progress of Optimizations

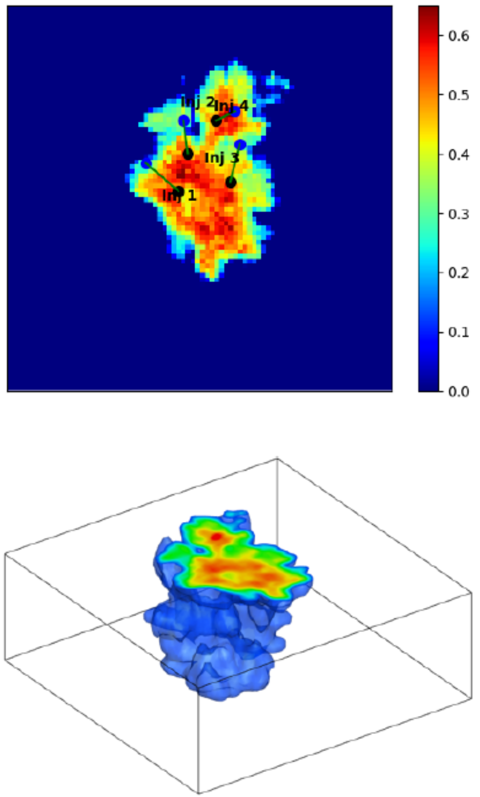


- GNSM speedup ~120x
- 6 GNSM runs versus 3 sim-based opt runs
- Best GNSM run outperforms best simulation-based run

Optimized CO_2 Footprint



Simulation (w/ opt well locations from GNSM run)



GNSM

Summary & Current Work

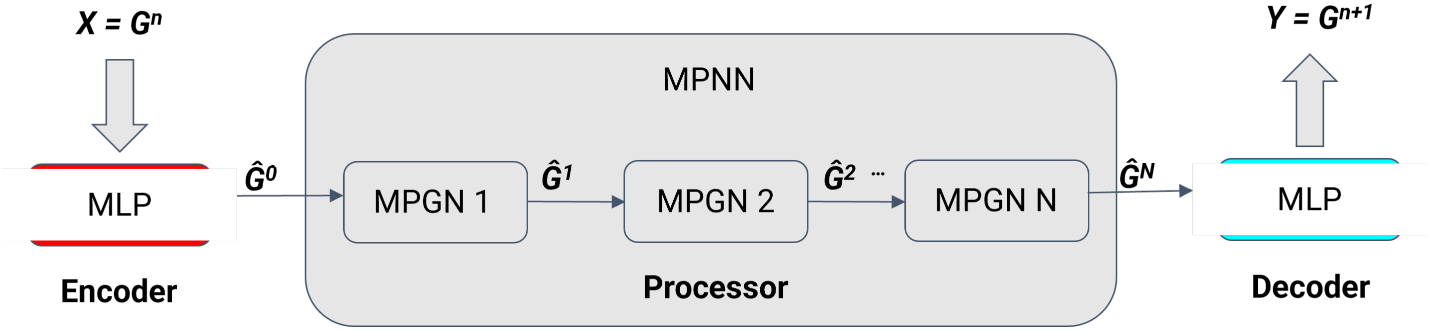
- Developed a graph network surrogate model for 3D CCS problem with changing horizontal well locations
- Achieved reasonable accuracy for global pressure and saturation states and for well bottom-hole pressures
- Applied the GNSM for well placement optimization with constraints; achieved ~120x speedup in DE optimization runs
- *Currently investigating extrapolation to new geomodels, considering other network architectures like graph transformers and graph U-Net*

Acknowledgements

- BHP (through GeoCquest II), Stanford Smart Fields Consortium, Stanford Center for Carbon Storage
- Oleg Volkov, Su Jiang, Dylan Crain, Amy Zou
- SDSS Center for Computation

Backup Slides

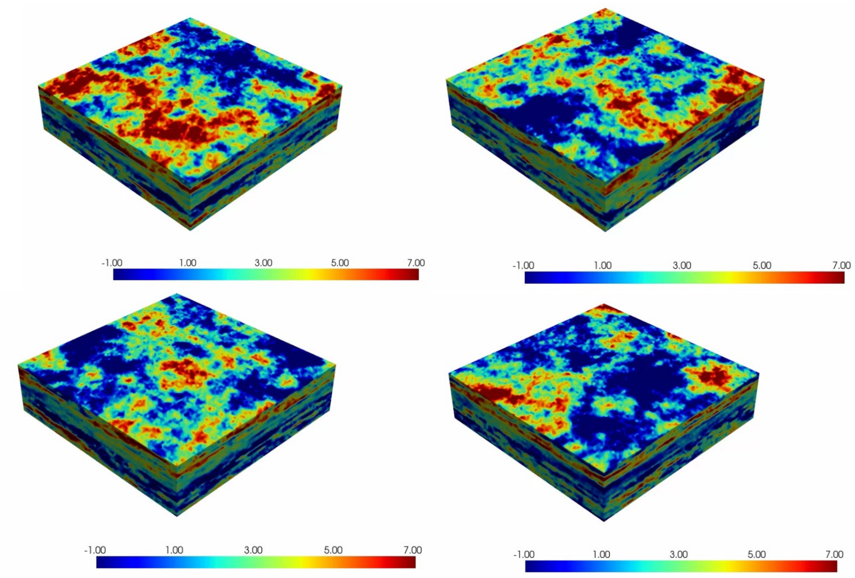
GNN Model Architecture



- ***X*** : input to the **encoder** (multilayer perceptron, MLP)
  $\boldsymbol{G^n}$: current state graph (including node and edge features)
- $\boldsymbol{\hat{G}^0}$: current encoded graph and input to the **processor**
  $\boldsymbol{\hat{G}^i}$: output of message passing graph network *i* (MPGN)
- ***Y*** : output of the **decoder** (MLP)
  $\boldsymbol{G^{n+1}}$: predicted future state graph (pressure/saturation at next time step)

New Realizations – Extrapolation Test

- ❑ Different permeability & porosity fields
- ❑ Deep-learning setup
  - **No retraining**
  - 100 test case configurations each



Errors for State Variables New Realizations (1–3)