



# Data-driven Models of Adsorption Equilibria of Multi-component Mixtures in Porous Materials

Mohamed Mehana, EES16

September 13<sup>th</sup>, 2021

LA-UR-21-29091

# Adsorption & Confinement effects

## ❑ Adsorption Applications:

- ❑ CO<sub>2</sub> capture (e.g., power plant exhaust gases)
- ❑ Gas Masks
- ❑ Fuel Cells

## ❑ Nanopores

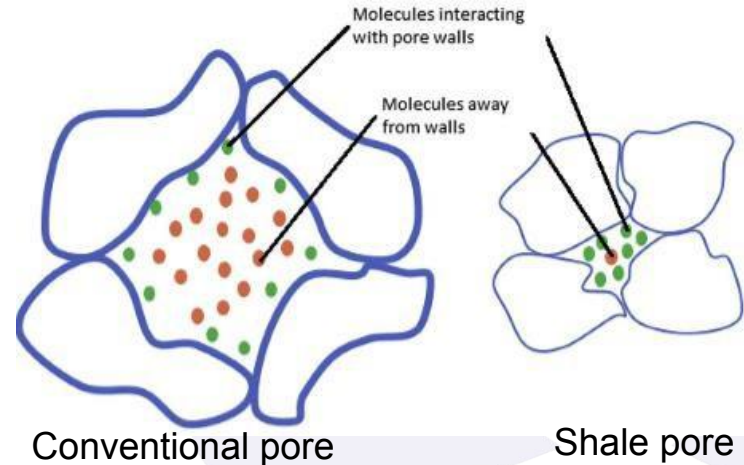
- ❑ ~80% of shale pores are less than 50 nm.
- ❑ Under confinement, fluid properties significantly deviate from bulk properties.
- ❑ Accumulated production can be drastically improved if matrix processes can be accelerated



Desiccant



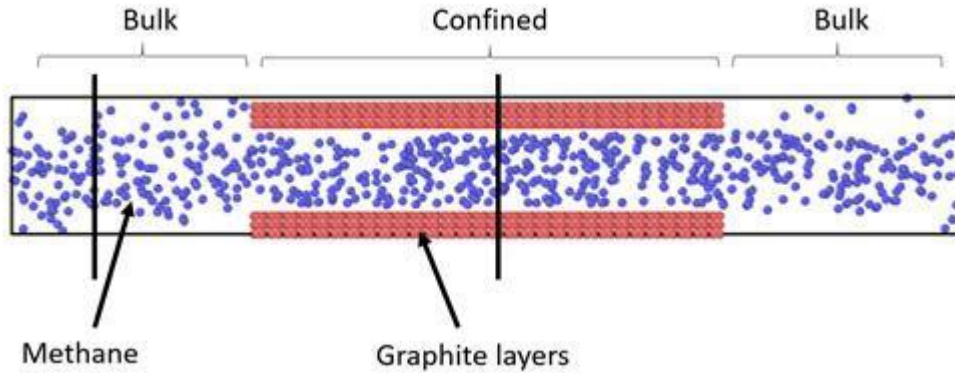
Shale Reservoirs



Conventional pore

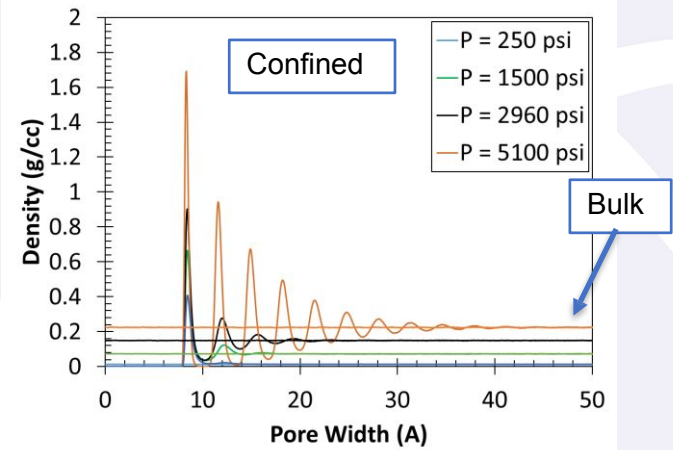
Shale pore

# Adsorption profile in shale pores



## Density profile of methane in a graphite slit pore

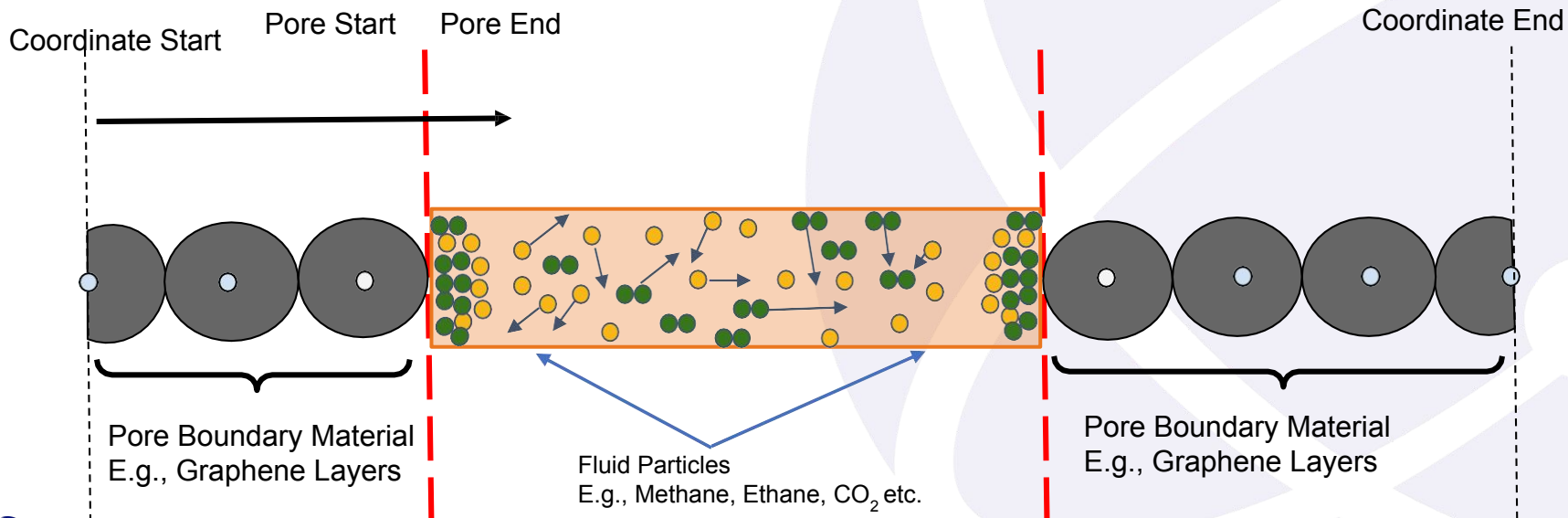
### Density Profile Cross-section



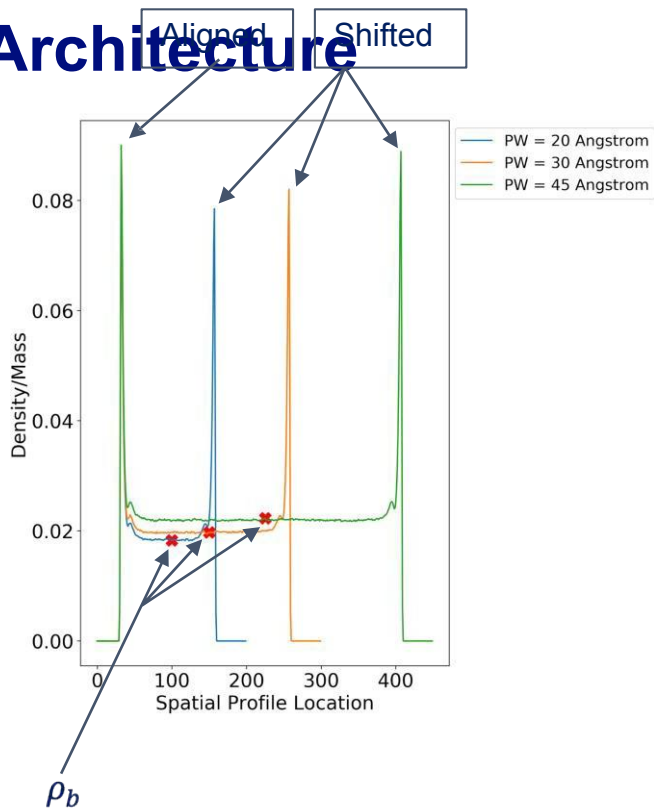
Adsorbed fluid density is ~ 4 times the bulk fluid density

# Problem Background & Formulation

- ❑ Molecular Dynamics (MD) Simulations can explicitly account for adsorption effects but are expensive
- ❑ **Goal:** *Given* an MD setting  
 $S = \{\text{Pore Width, (Angstrom), Pressure (Atmosphere), Temperature (K), Wall Material, Fluid Composition}\}$   
*Design* an ML solution capable of emulating the MD density profile for a particular experimental setting  $S$



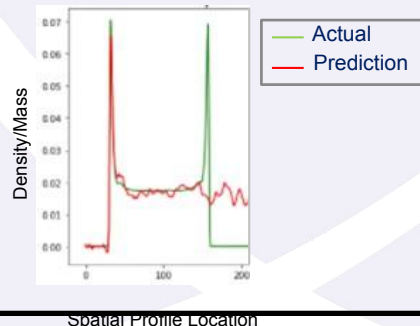
# Domain Informed Model Architecture



- ❑ Shift Invariant
- ❑ Decomposed Density Profile Prediction - Awareness of  $\rho_b$ , adsorption effect
- ❑ Fully Periodic
- ❑ Large Kernel size to capture scale of adsorption effects i.e., large receptive fields

## Learnings

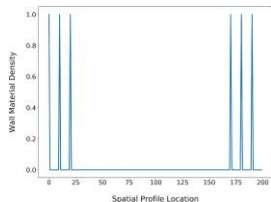
- Need for Shift Invariance
- Example Architecture with FCN and Striding
- Both adversely affect shift-invariance [Chaman et al. 2020]



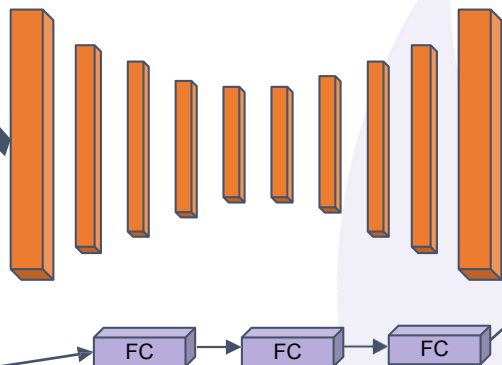
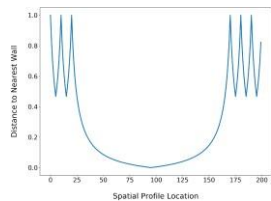
# Multi-Task Convolutional Model

## TRANSFORM SPATIAL LOCATION TO DENSITY PROFILE

Wall Material Density & Location



Relative Distance to Nearest Wall



Dimensions =  $\hat{\rho}_s \in \mathbb{R}^{1 \times l}$   
 $\hat{\rho}_b \in \mathbb{R}^{1 \times 1}$

$$\hat{\rho} = \hat{\rho}_s + \hat{\rho}_b$$

### Multi-Task Loss

$$L(\theta) = \|\hat{\rho} - \rho\|_2^2 + \|\hat{\rho}_b - \rho_b\|_2^2 + \lambda R(\theta)$$

Predicted Density Profile

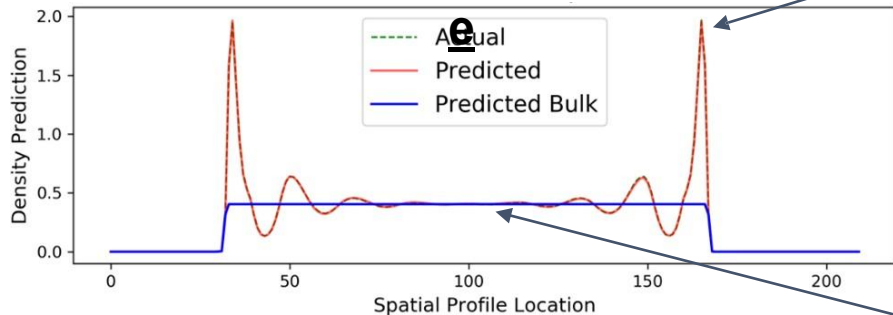
Predicted Bulk Density

[Pressure, Temperature]

# Qualitative Prediction Characterization

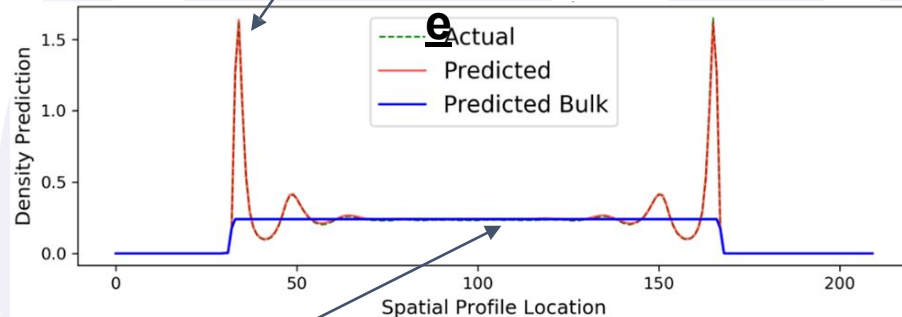
**Pore Width:  
21 Angstrom**

**Ethan**



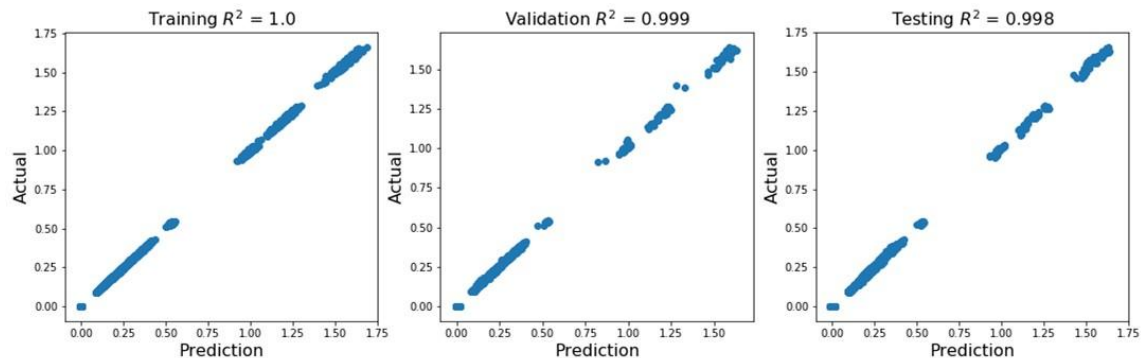
Different Peak Scales

**Methan**



Different Bulk Scales

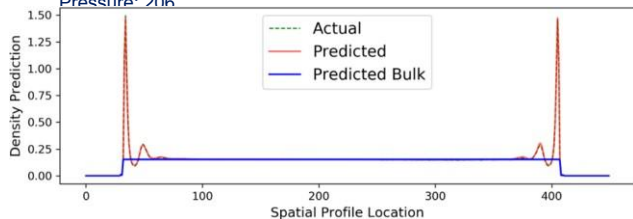
# Performance Characterization (Methane)



## Qualitative Predictions

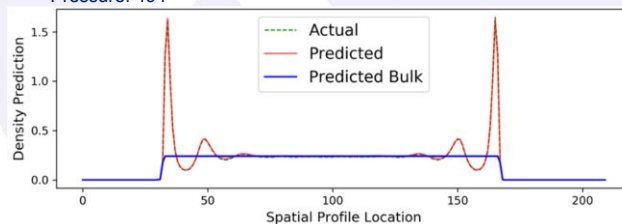
### Experimental Setup:

Pore Width: 45  
Angstrom  
Temperature: 334 K  
Pressure: 206



### Experimental Setup:

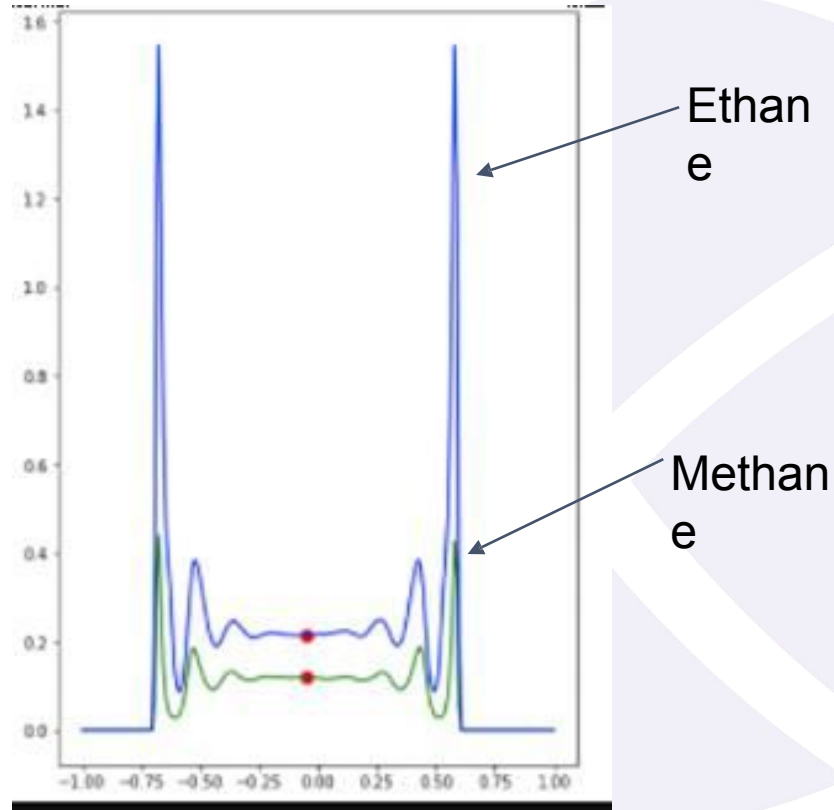
Pore Width: 21  
Angstrom  
Temperature: 336 K  
Pressure: 494





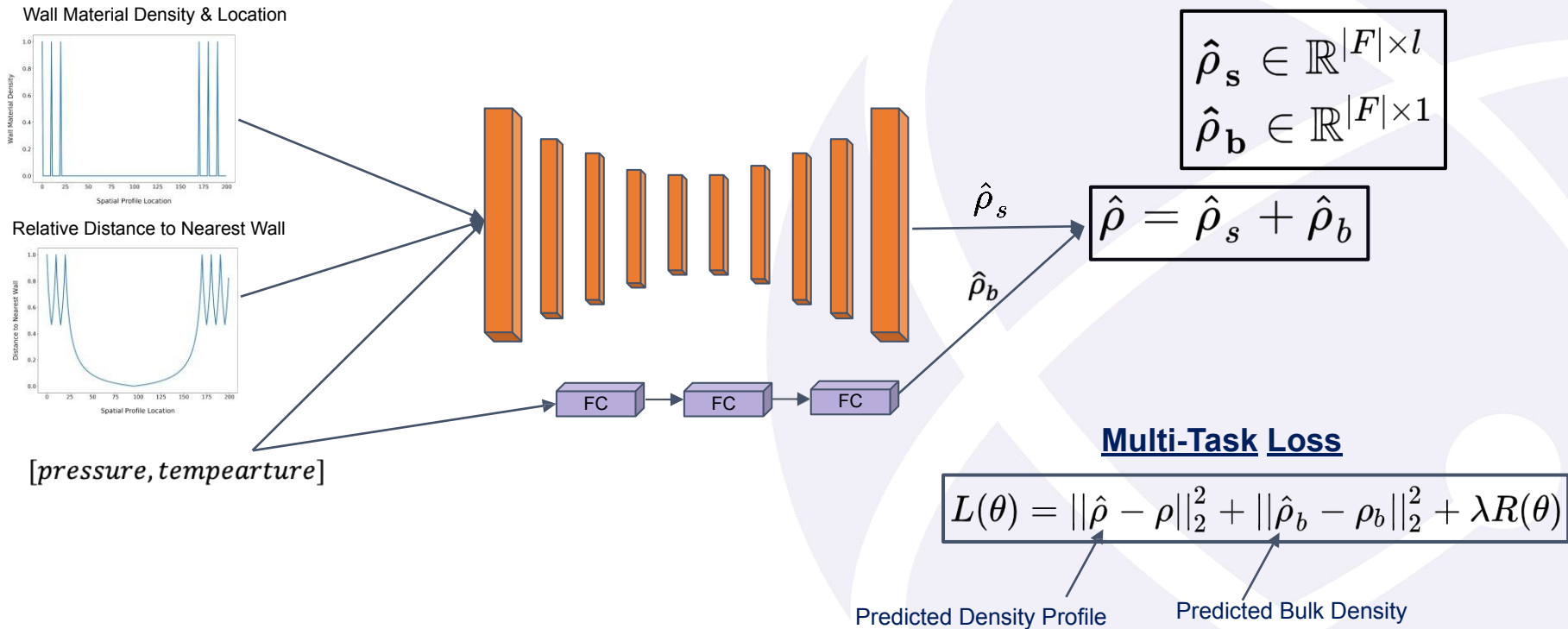
# Fluid Mixtures

# Sample Density Profile Characterization



# Multi-Task Convolutional Model (Fluid Mixture)

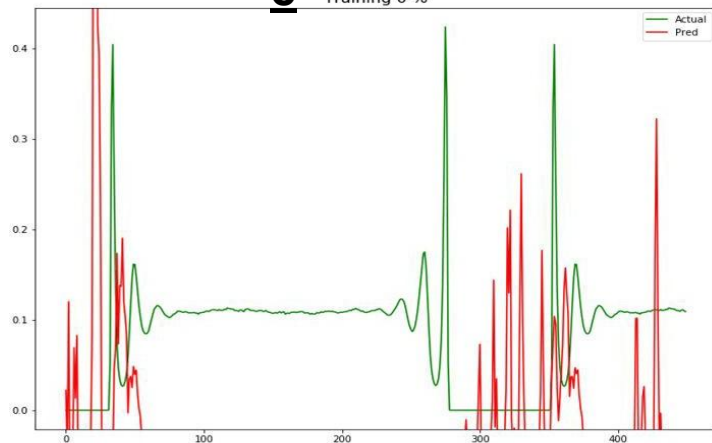
## TRANSFORM SPATIAL LOCATION TO DENSITY PROFILE



# Learning Dynamics

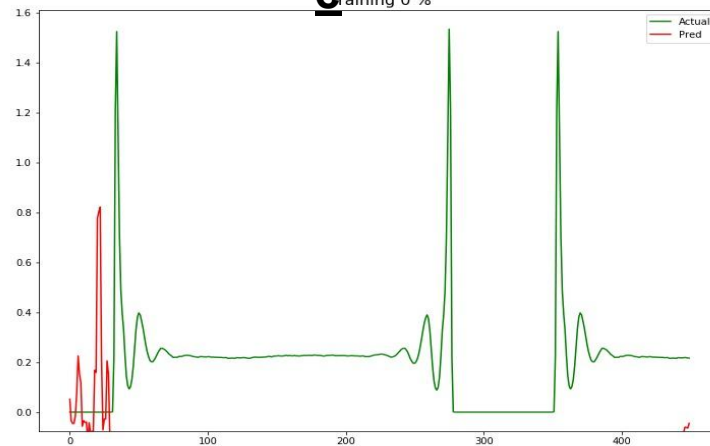
## Methan

**e** Training 0 %



## Ethan

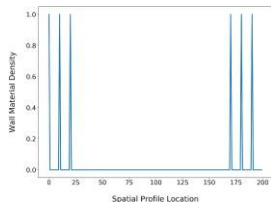
**e** Training 0 %



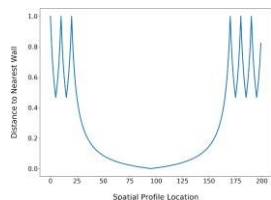
# Weighted Multi-Task Convolutional Model (Fluid Mixture)

## TRANSFORM SPATIAL LOCATION TO DENSITY PROFILE

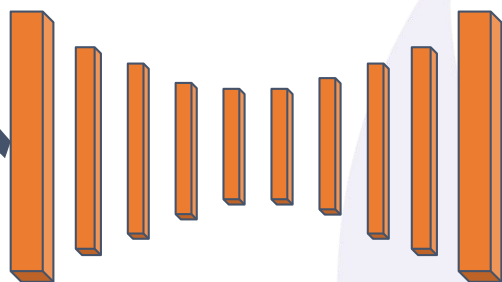
Wall Material Density & Location



Relative Distance to Nearest Wall



[pressure, temperature]



$$\hat{\rho}_s \in \mathbb{R}^{|F| \times l}$$

$$\hat{\rho}_b \in \mathbb{R}^{|F| \times 1}$$

$$\hat{\rho} = \hat{\rho}_s \odot \hat{\rho}_b$$

## Weighted

## Multi-Task

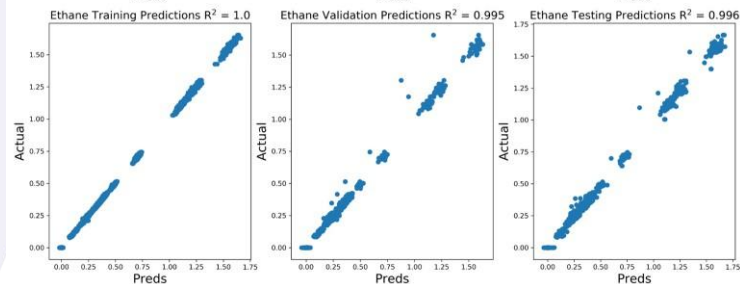
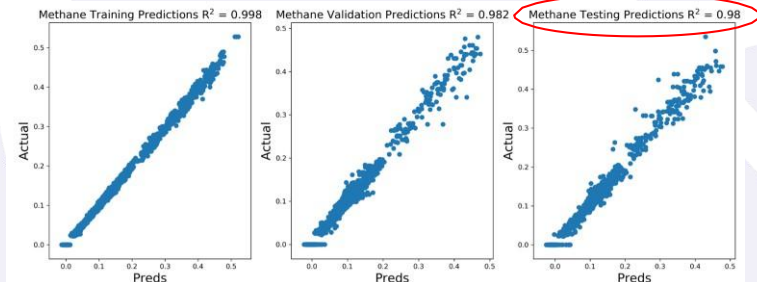
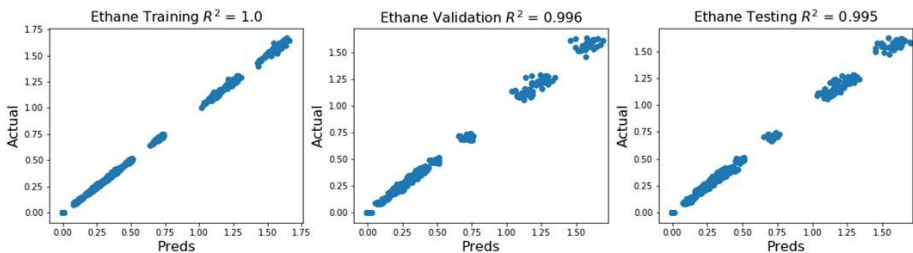
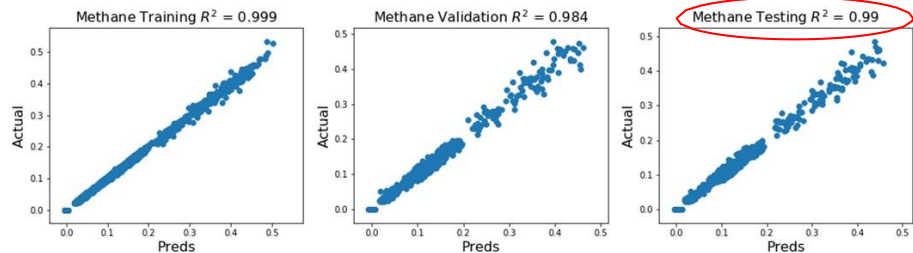
$$L(\theta) = \sum_{i=1}^{|F|} \frac{1}{w_i} \|\hat{\rho}_i - \rho_i\|_2^2 + \frac{1}{w_i} \|\hat{\rho}_{bi} - \rho_{bi}\|_2^2 + \lambda R(\theta)$$

$$w_i = \rho_{bi}^2 + \sum_{j \in F \setminus f_i} \rho_{bj} \rho_{bi}$$

# Fluid Mixture Prediction Performance

## Methane-Ethane Fluid Mixture

### Weighted Multi-Task CNN Multi-Task CNN



# Summary

- Machine Learning based **MD emulator** capable of generating density profiles for unseen conditions

  - Domain informed fully convolutional solution

- (Weighted) Multi-Task CNN Model to handle **Single Fluids & Mixtures**  
Results on Single & Multiple fluids indicate **promising initial results**



## Future Work





  - Fully Periodic Convolutional Network  
Smoother Adsorption Isotherm







    - Few-shot generalization









      - Novel Mixtures (i.e., unseen fluids)
      - Novel Wall-Material (affects adsorption properties)
      - Method: Meta-learning

# Data-driven Models of Adsorption Equilibria of Multi-component Mixtures in Porous Materials

## ***Project Description***

We propose building machine learning capabilities to develop adsorption models for multi-component systems of interests to subsurface applications using a molecular- simulation-generated database.

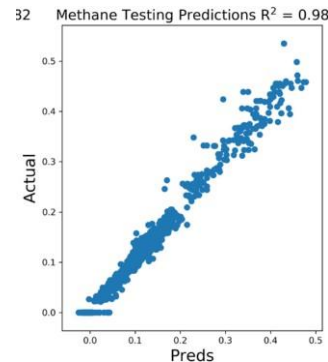
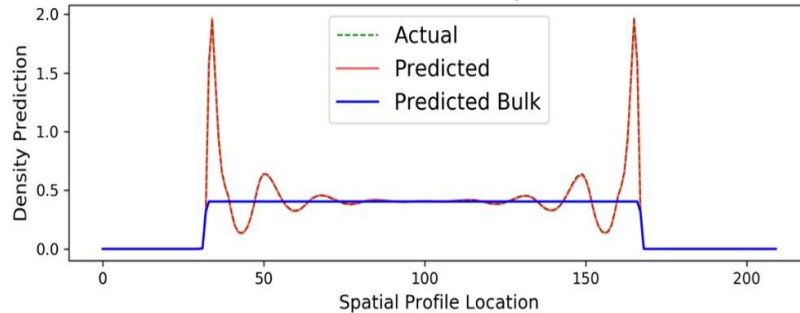
## ***Project Outcomes:***

Develop fast and reliable data-driven models to predict the adsorption characteristics of multi- component mixtures of interest to subsurface applications.

***PI: Mohamed Mehana***

***Total Project Budget: \$40k***

***ISTI Focus Area: Data Science and Artificial Intelligence***



Machine learning vs molecular simulations predictions for single and multi-component systems



END