

Prediction of Diffusion Coefficient using Machine Learning with Physical Formula Integration

[github](#)

Model Selection

1. Decision Tree Regressor
2. Random Forest Regressor

The models are trained and evaluated on three different target variables:

1. D
2. $D \cdot \rho$
3. $D \cdot \rho \cdot \sqrt{T}$

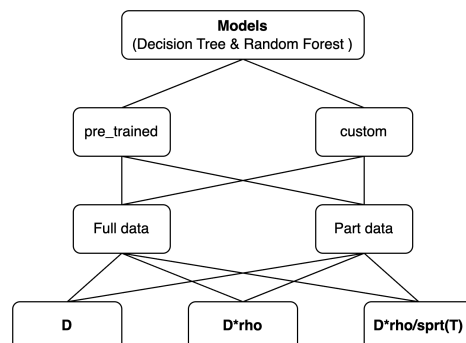
Data Splitting

- Training Set: $\rho^* \geq 0.1$
- Testing Set: $\rho^* < 0.1$

Performance Metrics

1. Mean Squared Error (**MSE**): Measures the average squared difference between actual and predicted values.
2. Mean Absolute Error (**MAE**): Measures the average absolute difference between actual and predicted values.
3. Relative Error (%): Measures the percentage deviation from actual values.

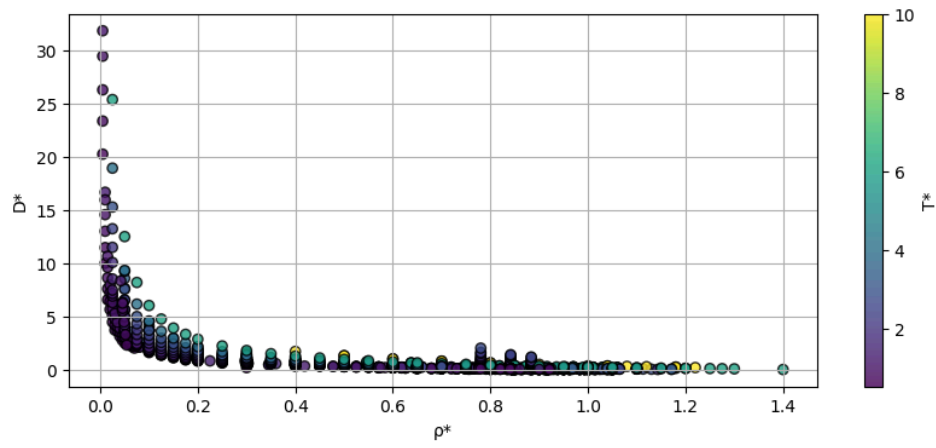
Experimental Design



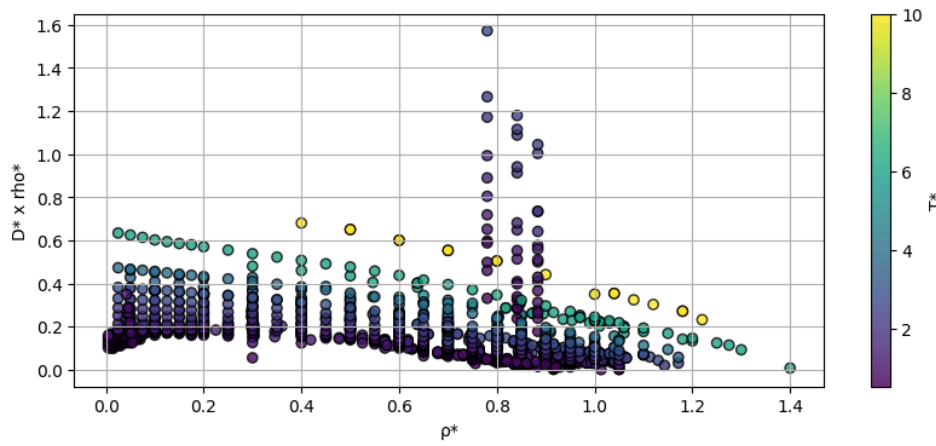
Dataset

1. Origin dataset

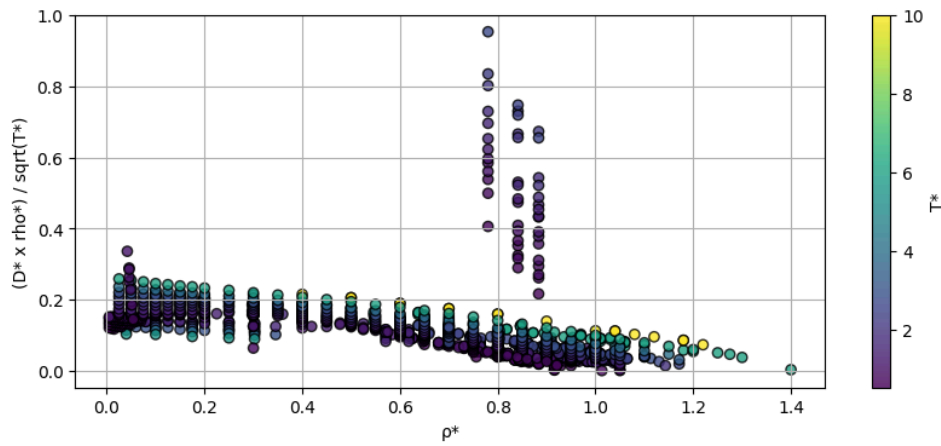
- D and ρ^*



- $D^*\rho$ and ρ^*



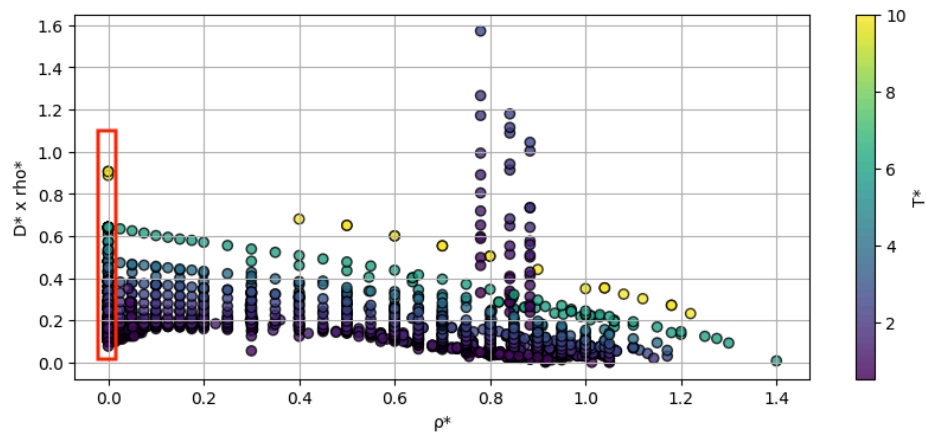
- $D^*\rho^*/\sqrt{T}$ and ρ^*



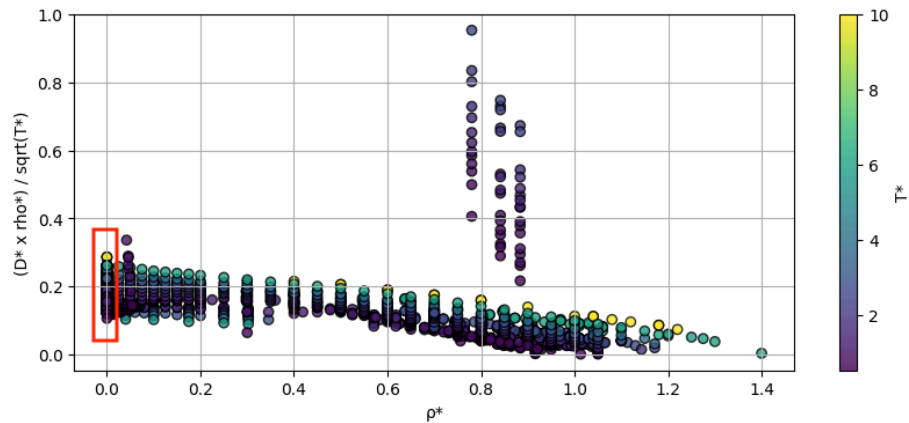
2. Augmented dataset

- New dataset added to train dataset ($\rho^* \geq 0.1$) with ρ^* is zero to help model enhance pattern where ρ^* is zero
- Original has **1251** samples with **566** unique values of T.
- New data created from **566** unique values of T with ρ^* is zero \rightarrow dataset with **566** samples.
- Merge original dataset and new data \rightarrow augmented dataset with **1817** samples.

- $D^*\rho$ and ρ^*



- $D^*\rho^*/\sqrt{T}$ and ρ^*



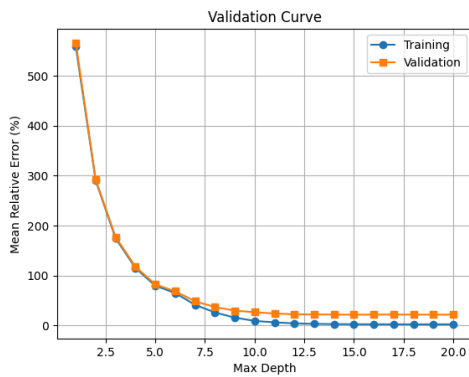
Balance trade-off

Purpose: Finding a best max depth to build custom decision model

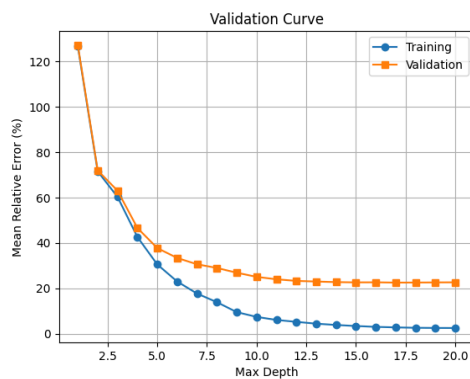
Steps: Finding max depth all targets on 2 datasets (original and augmented)

Method: Validation curve of scikit learn library

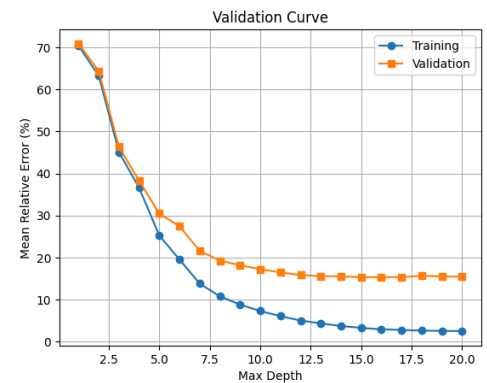
Original



D

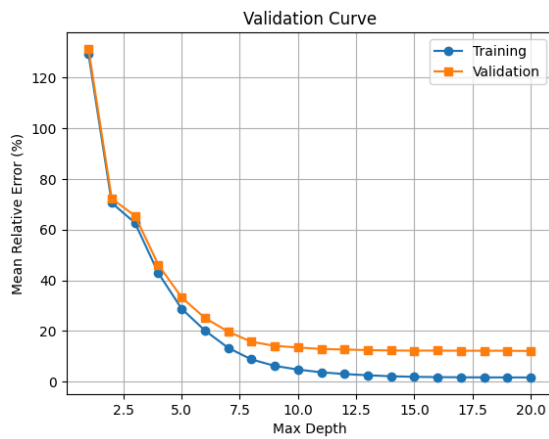


$D \cdot p$

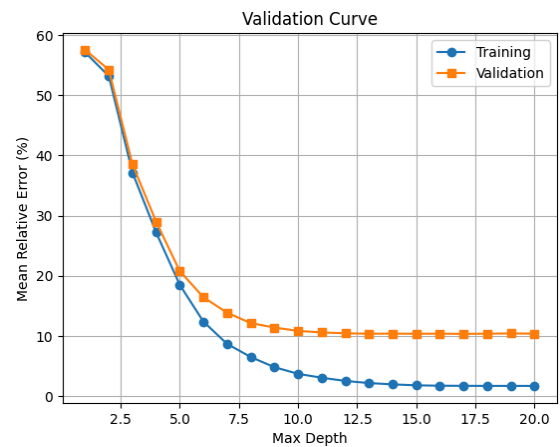


$D \cdot p \cdot \sqrt{1/T}$

Augmented



$D \cdot p$



$D \cdot p \cdot \sqrt{1/T}$

Max depth range	Training relative error	Validation relative error	Model behavior	Interpretation
1-4	high	high	underfitting	model is too simple to capture data pattern
5-10	sharply decreasing	sharply decreasing	well-fitting, balanced	model captures patterns well
11-20	very low	slightly decreasing	overfitting	Model memorizes training data and starts to lose generalization

Best max depth:

Optimal max_depth: **9 or 10**

A good trade-off between bias and variance

→ Building a Decision with max depth is **10** and min samples split is **2**

Results and Discussion

1. Decision Tree

Alias :

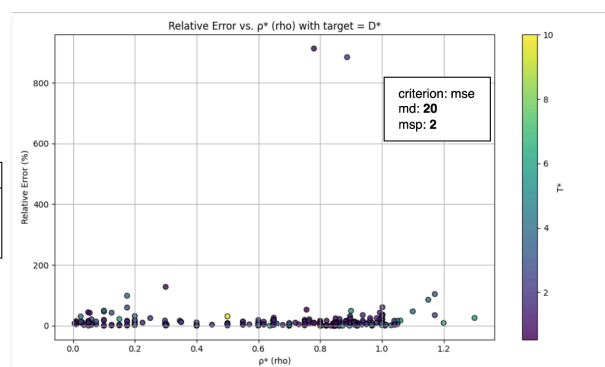
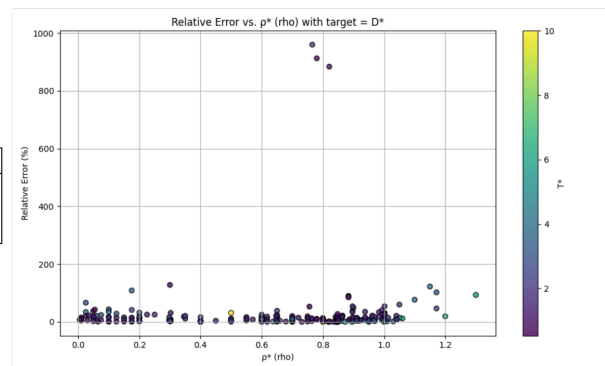
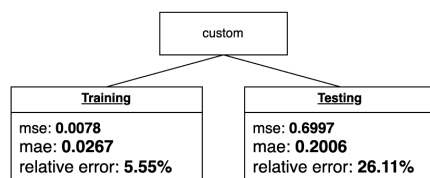
- max_depth = md
- min_samples_split = msp
- mean relative error = mre

Default params:

- criterion: mre
- max depth: **10**
- min samples split: **2**

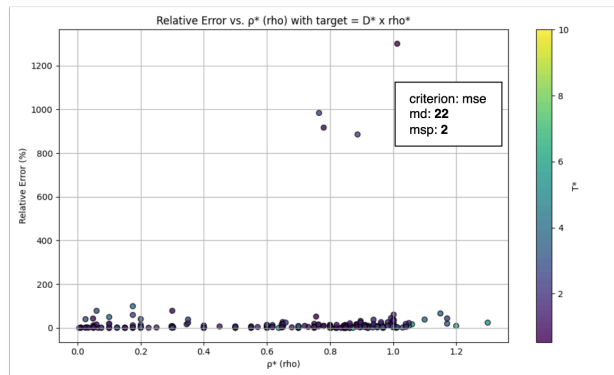
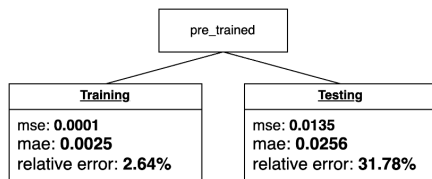
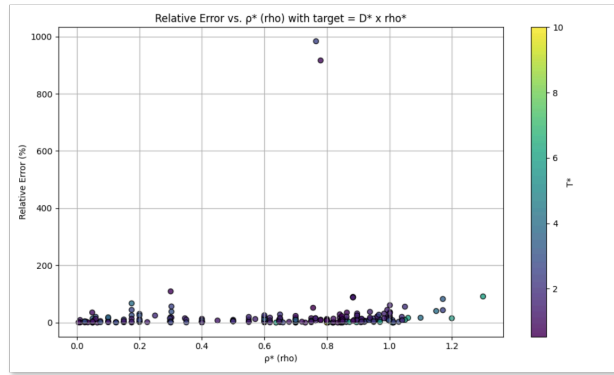
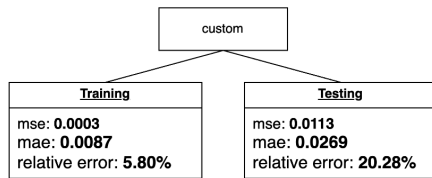
Full data

- **D**

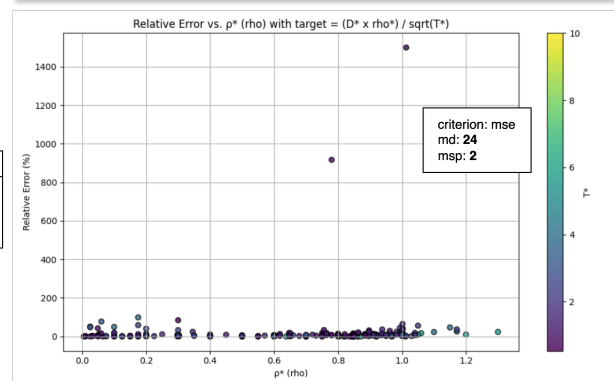
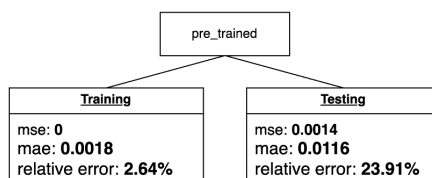
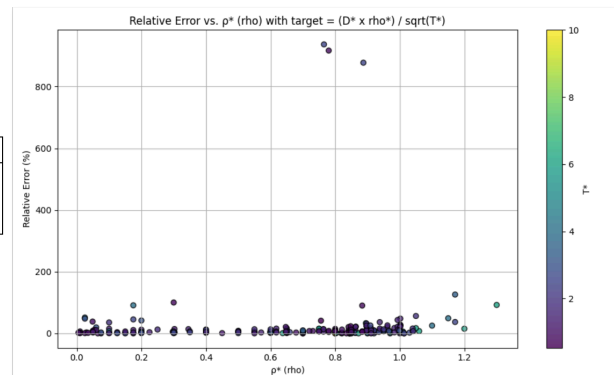
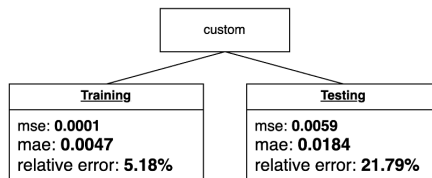


I realize that a custom model is worse than a pre-trained model in the training phase but is better in the testing phase. It proves that a pre-trained model is overfitting than a custom model. Show through a deeper tree (max-depth = 20).
→ Prefer to use a custom model .

- $D^* \rho^*$



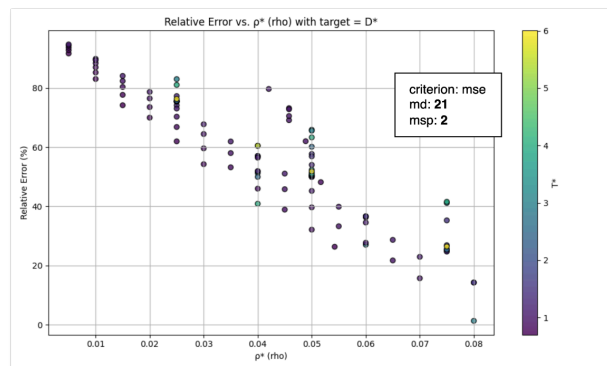
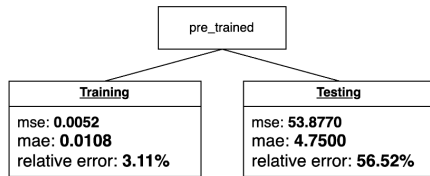
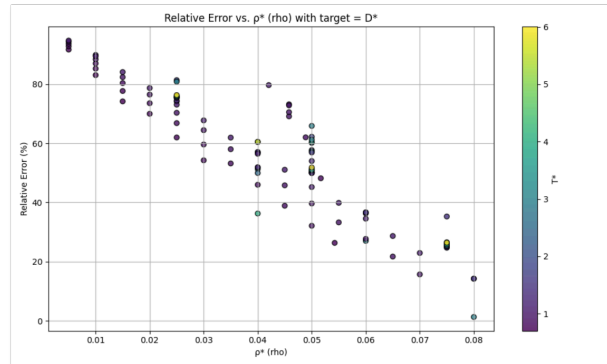
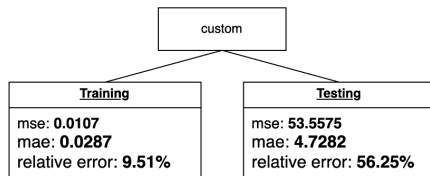
- $D^* \rho^* / \sqrt{T}$ and ρ^*



When change target from D to $D^* \rho^*$ or $D^* \rho^* / \sqrt{T}$ and ρ^* then have better result (about 5 - 6 %)

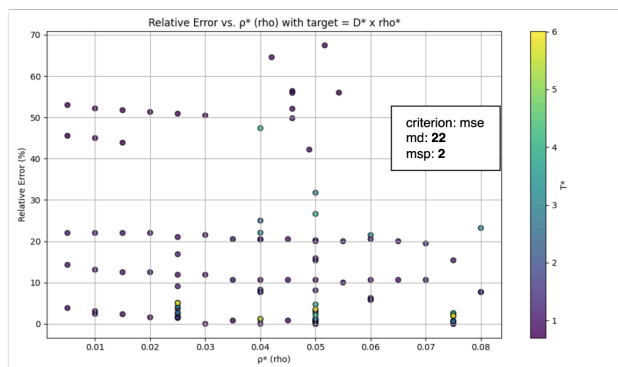
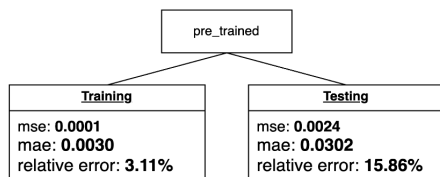
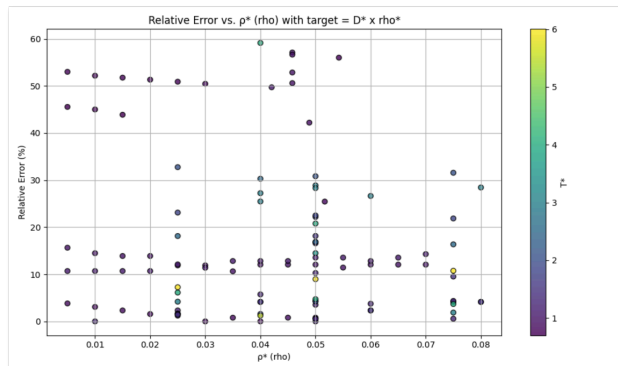
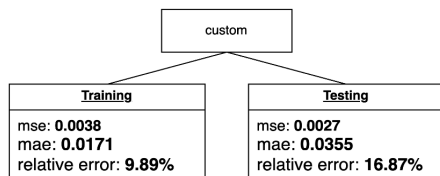
Part data

- **D**

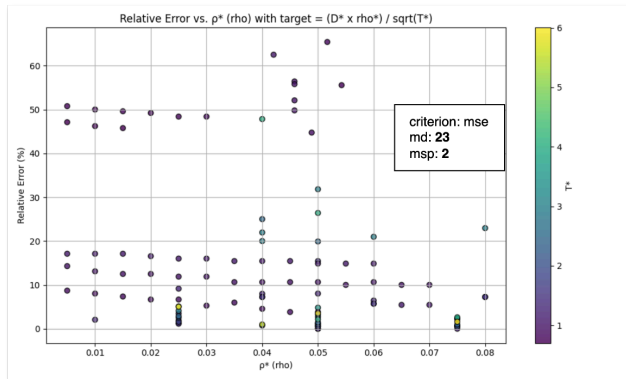
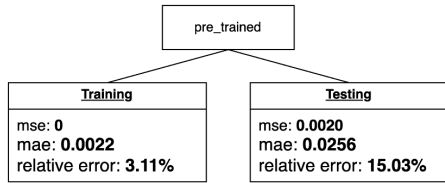
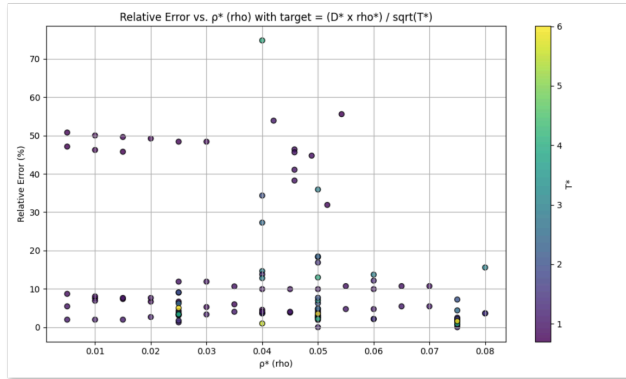
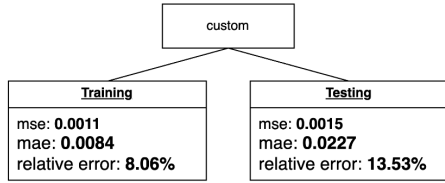


We can see that when we only take part data to train and test a different part. Relative error is significant higher than full data from **26%** to **56%**

- **D*p***



- $D^* \rho^* / \sqrt{T}$ and ρ^*



Amazing! we observe that when we change target from D to $D^* \rho^*$ or $D^* \rho^* / T$ and ρ^* , the result improve dramatically better than full data, reducing relative error from **56%** to **13%** (more **40%**). Custom model still prefers to be selected to pre_trained model.

Part data with augmented data (at $\rho = 0$)

New dataset is calculated by formula ($\rho = 0$): here's formula to calculate $D^* \rho^*$ at $\rho = 0$

$$(D\rho)_0(T) = \frac{3}{8} \sqrt{\frac{kT}{m\pi}} \frac{f_{D\rho}}{\sigma^2 \Omega^{(1,1)*}}$$

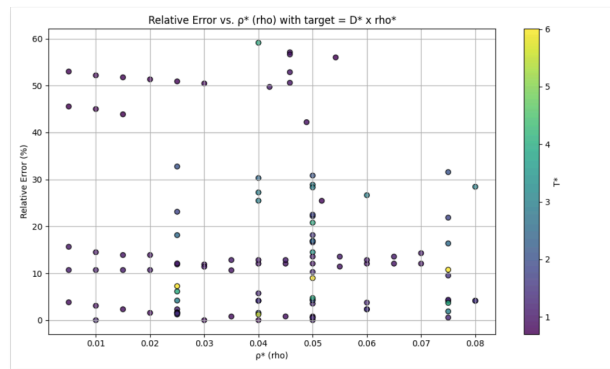
Note: Using custom model

- $D^* \rho^*$

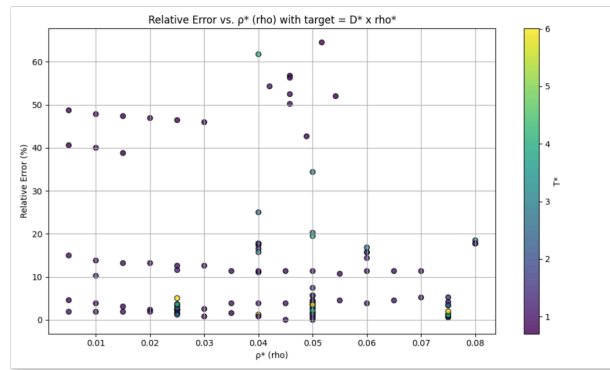
I observe that when adding a new dataset to train model then result improve better (about **3%**). But both adding a new dataset and adding weight (8) in training phase then result even better.

without_augmentation	→	with_augmentation	→	with_augmentation_weight
16.87 %		13.82 %		9.54 %

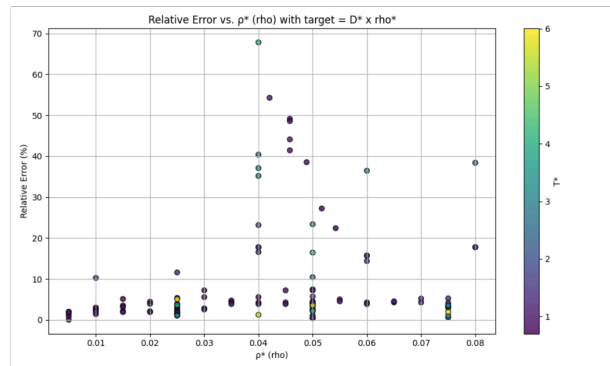
without augmentation	
Training	Testing
mse: 0.0038 mae: 0.0171 relative error: 9.89%	mse: 0.0027 mae: 0.0355 relative error: 16.87%



with augmentation	
Training	Testing
mse: 0.0001 mae: 0.0055 relative error: 4.21%	mse: 0.0022 mae: 0.0269 relative error: 13.82%



with augmentation weight (8)	
Training	Testing
mse: 0.0002 mae: 0.0059 relative error: 4.39%	mse: 0.0017 mae: 0.0215 relative error: 9.54%

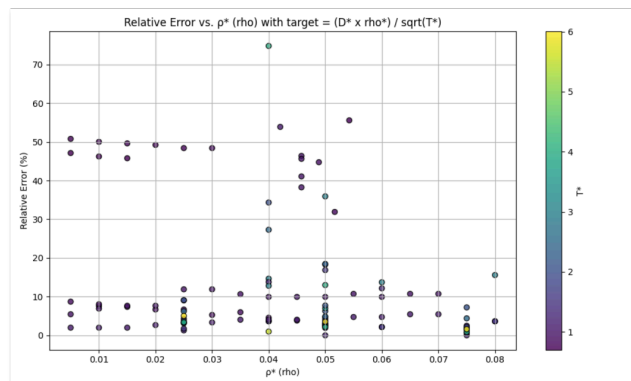


- D^*p^*/T and p^*

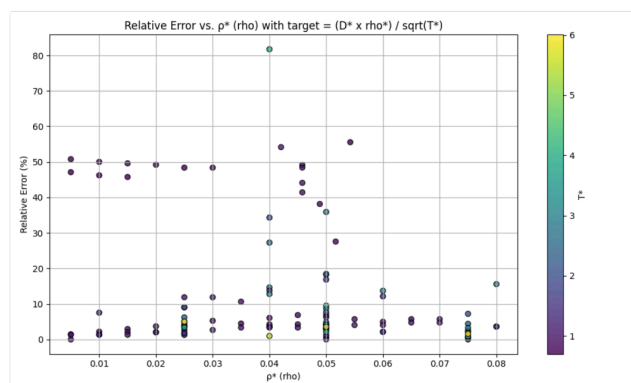
I observe that when change target from D^*p^* to D^*p^*/T and p^* then the result improve better (about 3%). Afterward adding a new dataset and adding weight (8) in training phase then results even better.

without_augmentation → with_augmentation → with_augmentation_weight
13.53 % 12.78 % 8.74 %

without augmentation	
Training	Testing
mse: 0.0011 mae: 0.0084 relative error: 8.06%	mse: 0.0015 mae: 0.0227 relative error: 13.53%



with augmentation	
Training	Testing
mse: 0.0001 mae: 0.0031 relative error: 3.72%	mse: 0.0015 mae: 0.0217 relative error: 12.78%



with augmentation weight (8)	
Training	Testing
mse: 0.0001 mae: 0.0033 relative error: 3.83%	mse: 0.0012 mae: 0.0163 relative error: 8.74%

