

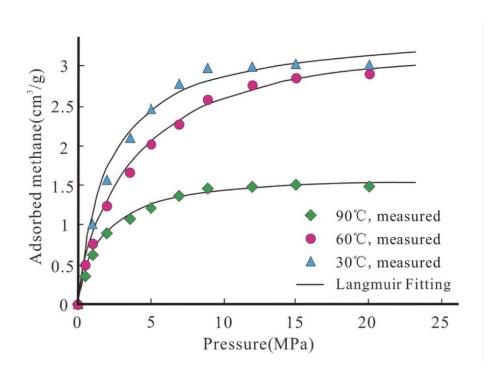


The prediction of Gas Isotherms by the Structures of Metal-Organic Frameworks

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Background: Gas Adsorption

- Adsorption is one of the most essential processes in chemical engineering.
- Adsorption isotherms = $\frac{\text{the amount of the adsorbate adsorbed}}{\text{mass adsorbent}}$
- Gas isotherms = f(Temp., Pres., Adsorbent, Adsorbate)





Background: Metal-Organic Frameworks

- MOFs are good candidates for gas adsorption:
 - High surface area, porosity, and functionality
- Applications for adsorptive separation:
 - Energy issue: CH₄ uptake
 - Global warming issue: CO₂ capture
 - Industrial example: C₂H₄/C₂H₆ separation

The search for the optimal MOF requires aggressive screening of a variety of MOFs



Motivation of the prediction of the isotherm

Experimental Measurement

- Measurement takes long time
- Synthesis of new MOFs: >12h
- Accuracy depends on exp. conditions

Grand canonical Monte Carlo(GCMC)

- Couple hours
- Require accurate force field

Prediction by machine learning

- A few seconds/minutes
- Rapid screening
- Advice for material design

Goal: Isotherm = f(structure info ...) without exp. or GCMC

Workflow for Data Cleaning and Retrieval

Isotherms in NIST adsorption database

- 1. Remove non-MOFs, such as Zeolites and AC
- 2. Convert pressure unit and adsorption unit

Structure information in computational-ready experimental (CoRE)
MOFs database

1. Remove MOFs with missing structure properties

NIST: 6000 adsorbents

MOFs not matched

124 MOFs have matched structure info.

Other adsorbents

Training/Test Examples

1

Workflow for CoRE MOFs Database

Define the feature vectors

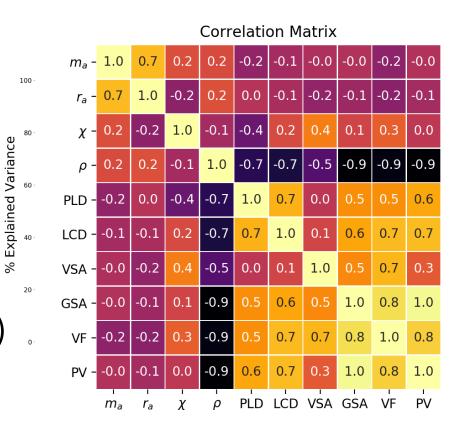
- Each MOF can be represented by PLD, LCD, SA, VF and density etc.
- Metals type as numerical variables

Principle Component Analysis

- Calculate the explained variance
- Minimum # of principle components

Metal type:

- Atomic mass (m_a)
- Atomic radius(r_a)
- Electronegativity(χ)
- Density (ρ)
- pore-limiting diameter (PLD)
- largest-cavity diameter (LCD)
- Volumetric Surface area (VSA)
- Gravimetric Surface area (GSA)
- Pore volume (PV)
- Void fraction (VF)

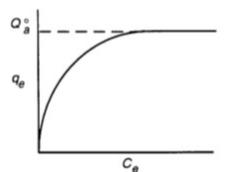


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Workflow for NIST Adsorption Database

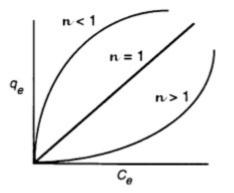
Linear Regression on Isotherms

Curve-fit isotherm data



Langmuir: $(Q_{0_i} b)$

$$n_{ad} = \frac{Q_0 b P}{1 + b P}$$

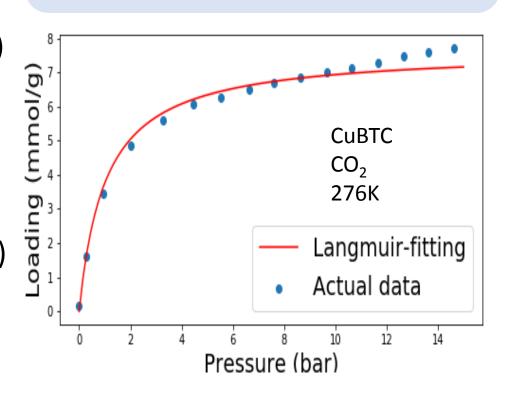


Freundlich: (K, n)

$$n_{ad} = KP^{\frac{1}{n}}$$

Isotherm Type Assignment

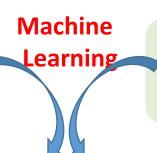
- Assign model based on R2 value
- Keep R2 higher than 0.95 (cutoff value)



Workflow for machine learning

Results from NIST:

MOFs labeled with model, and corresponding parameters



Results from CoRE MOFs

MOFs and their structure properties after PCA

Final Model

Classification:

$$Model = f(PLD, LCD, SA, VF ...)$$

• Regression:

Langmuir:

$$Q_0 = f(PLD, LCD, SA, VF \dots)$$

$$b = f(PLD, LCD, SA, VF \dots)$$

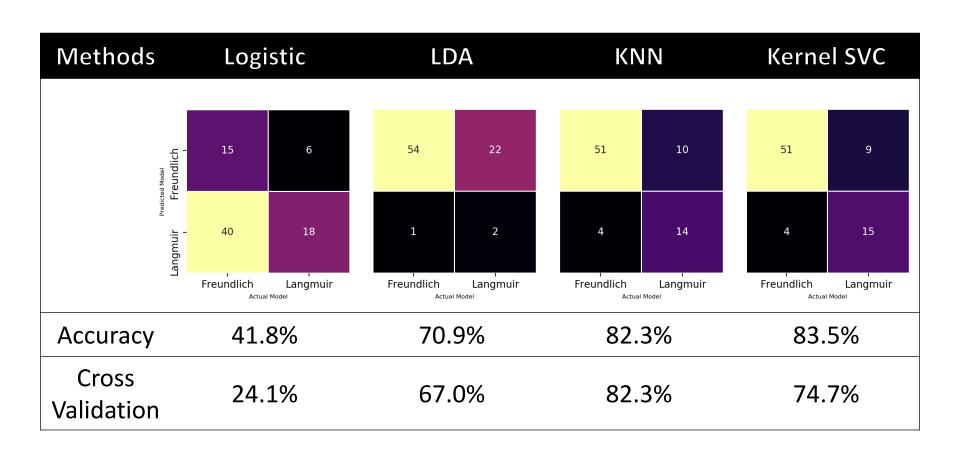
Freundlich:

$$K = f(PLD, LCD, SA, VF \dots)$$

$$n = f(PLD, LCD, SA, VF \dots)$$

Result 1: Isotherm classification for N₂

 $Isotherm\ Model = f(PLD, LCD, SA, VF...)$



Result 2: Regression of N₂ by Linear Regression

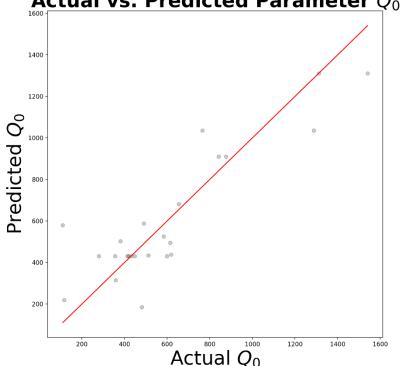
Langmuir:

$$Q_0 = f(PLD, LCD, SA, VF ...)$$

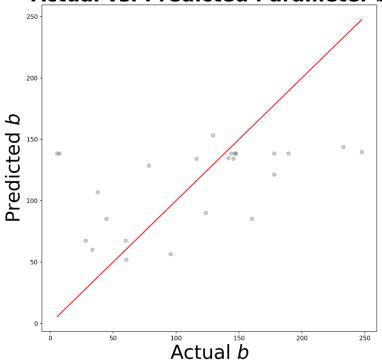
$$b = f(PLD, LCD, SA, VF ...)$$

Parameters by LR	R2	CV mean relative error
Q_0	0.78	1.02
b	0.24	3.02





Linear Regression Actual vs. Predicted Parameter b



Result 2: Regression of N₂ by Linear Regression

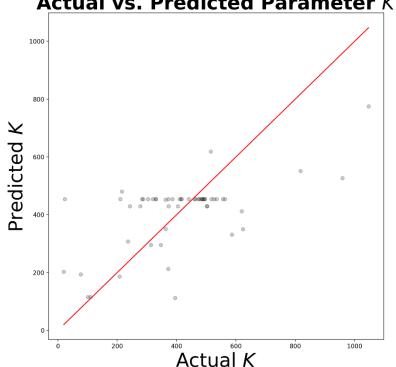
Freundlich:

$$K = f(PLD, LCD, SA, VF \dots)$$

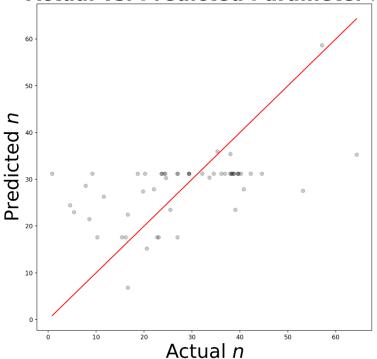
$$n = f(PLD, LCD, SA, VF \dots)$$

Parameters by LR	R2	CV mean relative error
K	0.38	0.85
n	0.29	1.22

Linear Regression Actual vs. Predicted Parameter K



Linear Regression Actual vs. Predicted Parameter *n*



Result 3: Regression of N₂ by Kernel SVR, RBF

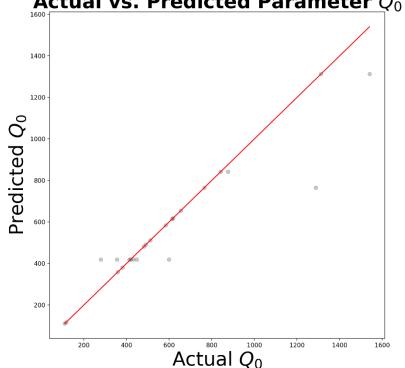
Langmuir:

$$Q_0 = f(PLD, LCD, SA, VF ...)$$

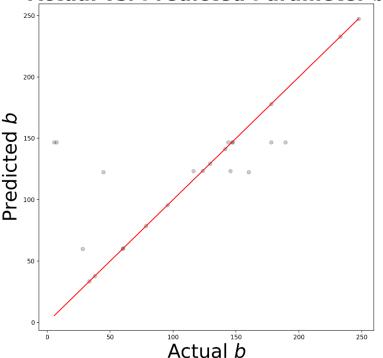
$$b = f(PLD, LCD, SA, VF ...)$$

Parameters by SVR	R2	CV mean relative error
Q_0	0.87	0.53
b	0.53	2.44

Support Vector Regression Actual vs. Predicted Parameter Q_0



Support Vector Regression Actual vs. Predicted Parameter *b*



Result 3: Regression of N₂ by Kernel SVR, RBF

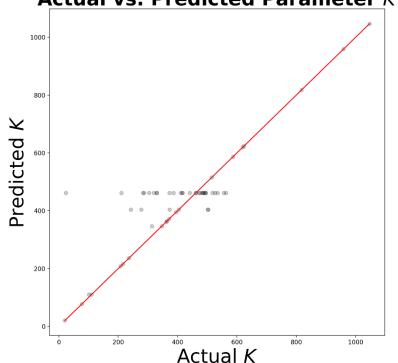
Freundlich:

$$K = f(PLD, LCD, SA, VF \dots)$$

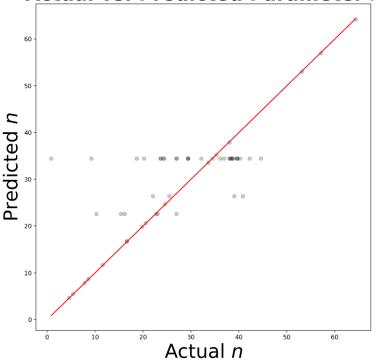
$$n = f(PLD, LCD, SA, VF \dots)$$

Parameters by SVR	R2	CV mean relative error
K	0.75	1.10
n	0.60	1.35

Support Vector Regression Actual vs. Predicted Parameter K



Support Vector Regression Actual vs. Predicted Parameter n



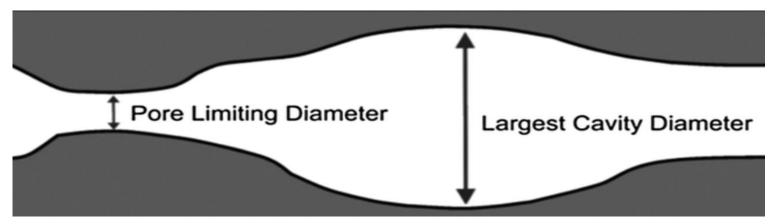
Discussion and Conclusions

- Classification of isotherm models:
 - Tried Logistic, LDA, KNN, SVC method to classify
 - Both KNN and SVC work well. (KNN:82.3% mean accuracy, CV)
- Regression of isotherm parameters for each model:
 - Tried linear regression and support vector regression with RBF
 - SVR works well with higher R2 and lower CV mean relative error
- Analysis on Data source :
 - Same MOF has different isotherm results
 - Training examples are not large enough (124 matched MOFs)
- Future plan:
 - Adding more isotherm types during the model assignment
 - Gather more matched MOFs manually to increase the training set
 - Consider the chemical information of MOFs as the feature vector: use more variables to describe metals and organic linkers





Backup: Adsorbent Structural Descriptors



- Density (ρ) g/cm3
- Volumetric Surface area (VSA) m2/cm3
- Gravimetric Surface area (GSA) m2/g
- Pore volume (PV): cm3/g
- Void fraction (VF)
- pore-limiting diameter (PLD): Å
- largest-cavity diameter (LCD): Å
- Metal type:
 - Atomic mass (m_a)
 - Atomic radius(r_a)
 - Electronegativity(χ)

Backup: These authors also explored the trade-off between volumetric capacity and gravimetric capacity. The results show a concave downward relationship between volumetric and gravimetric storage capacities.

