

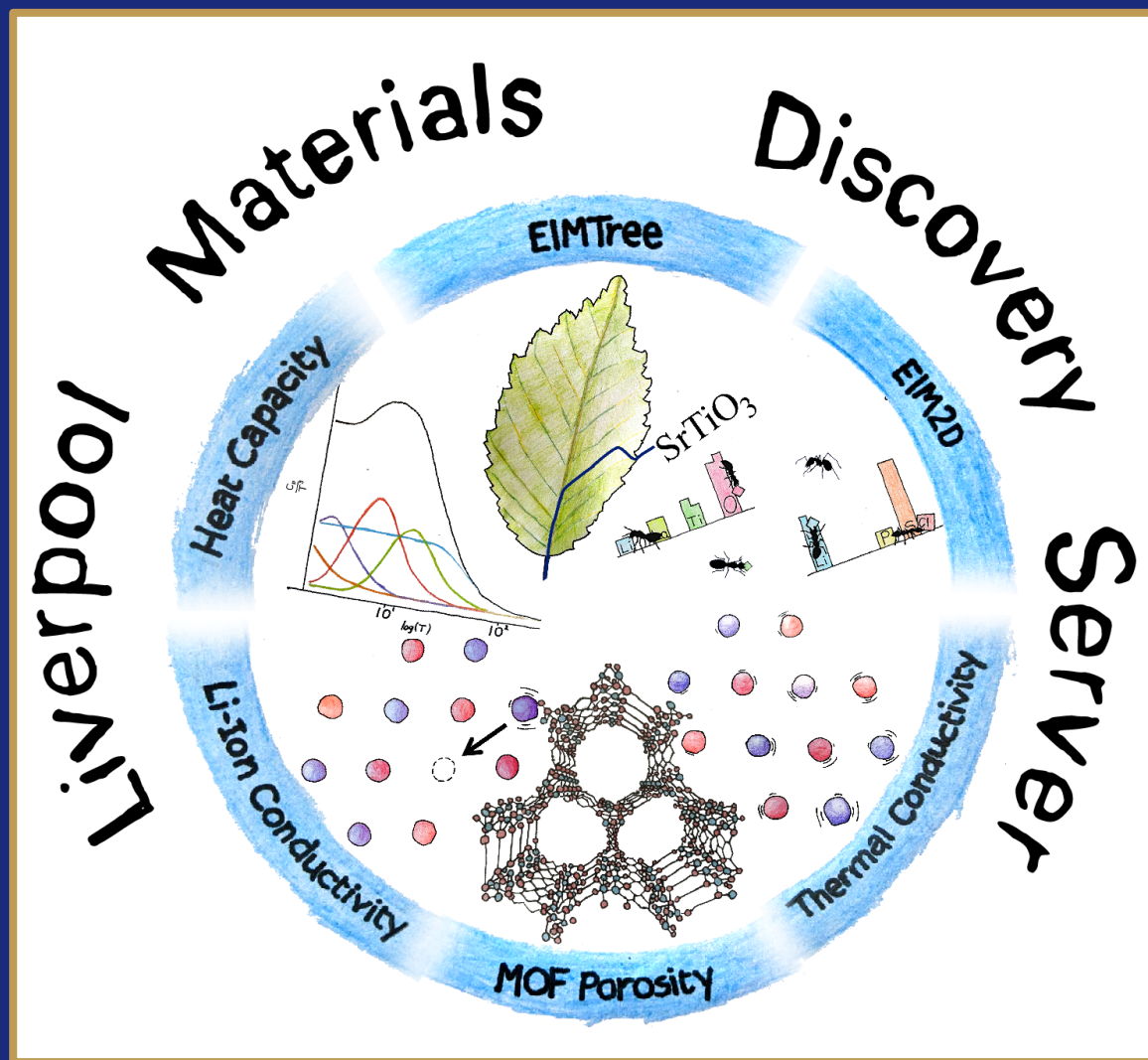
The Liverpool Materials Discovery Server: Background and Application

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<https://lmds.liverpool.ac.uk>

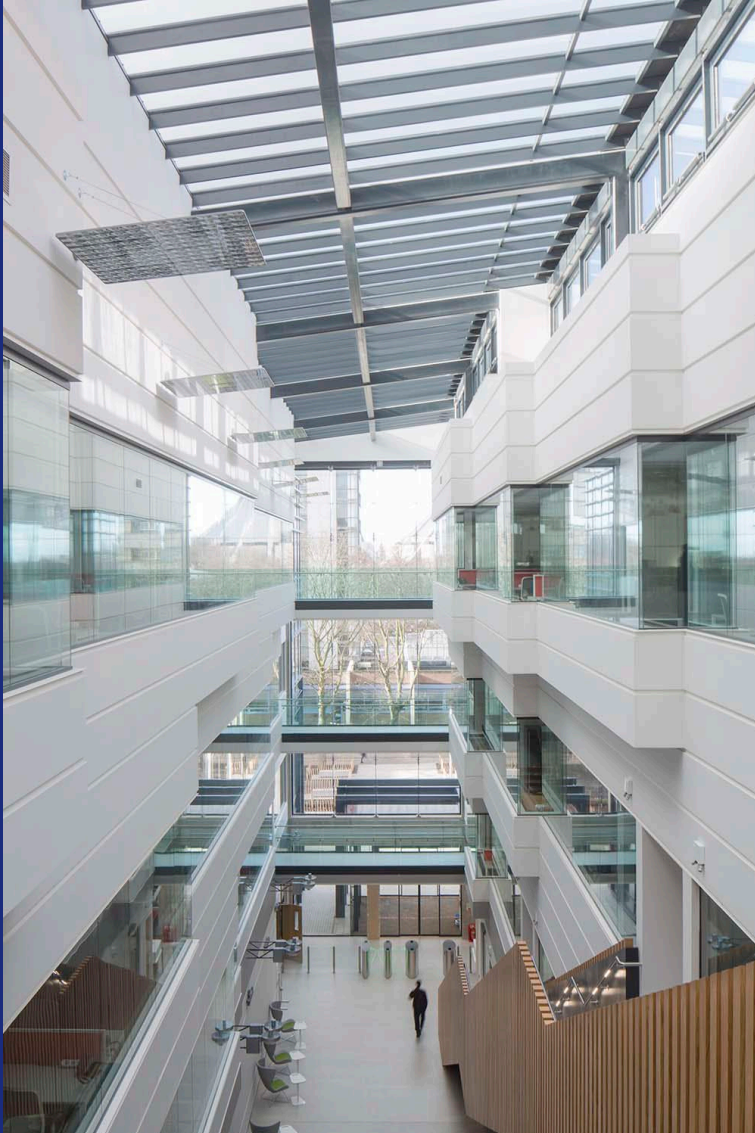


Sam
Durdy



Cameron
Hargreaves

S Durdy, C J Hargreaves, et al., *Digital Discovery* (2023) Accepted

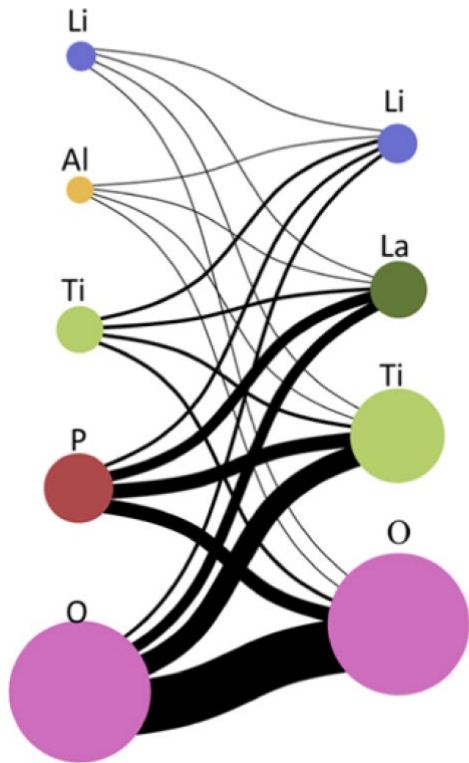
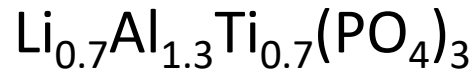


The Research Environment

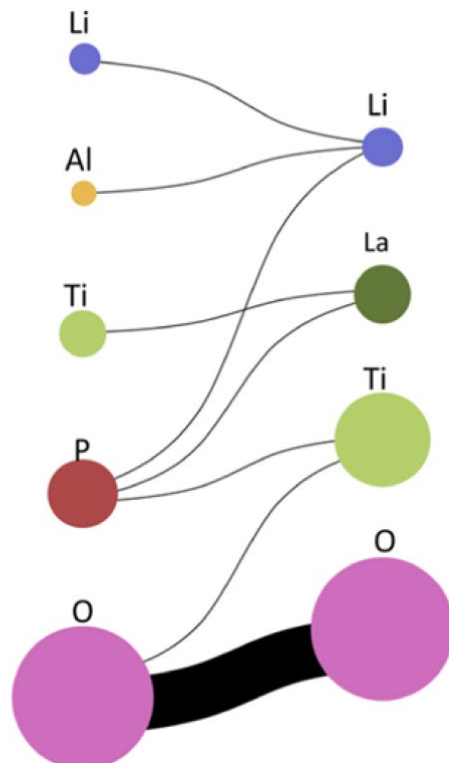
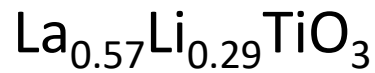
- The Materials Innovation Factory (MIF) enables chemists, physicists, mathematicians and computer scientists to work together on a single site.
- The Leverhulme Research Centre for Functional Materials Design funds researchers and PhD students to work in this interdisciplinary space.
- Resulting in new approaches to aid discovery of novel materials.



The Element Movers Distance



All solutions

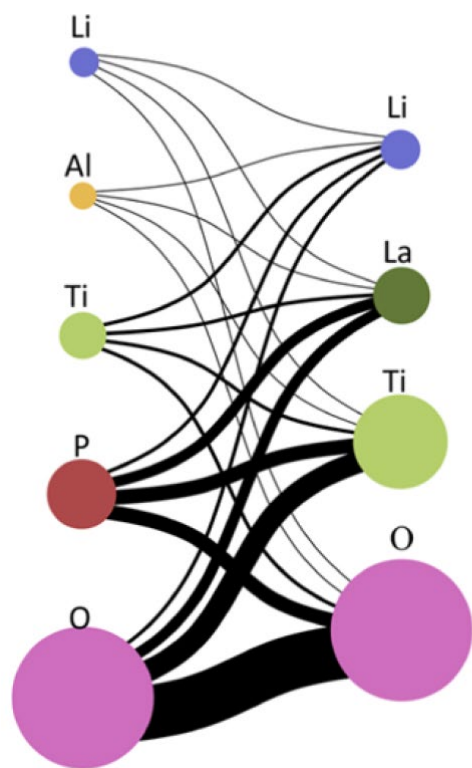


Optimal solution

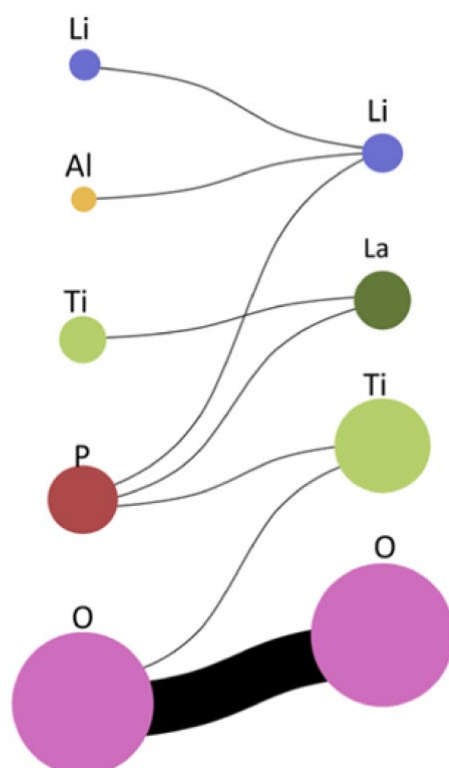
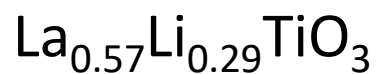
$EIMD = 12.7$

- We needed a quantitative measure of chemical similarity between two compositions
- We use the Earth Movers Distance
- Elements are labelled with their Pettifor number
- We seek the transfer elements from one to the other with the lowest total work done – the EIMD

The Element Mover's Distance



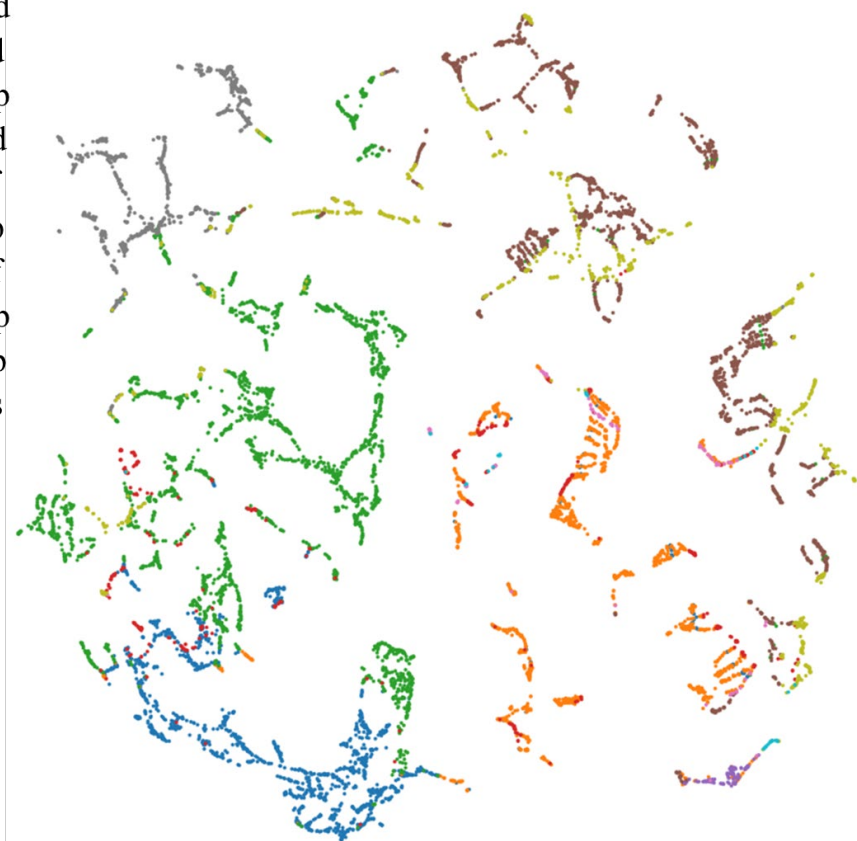
All solutions

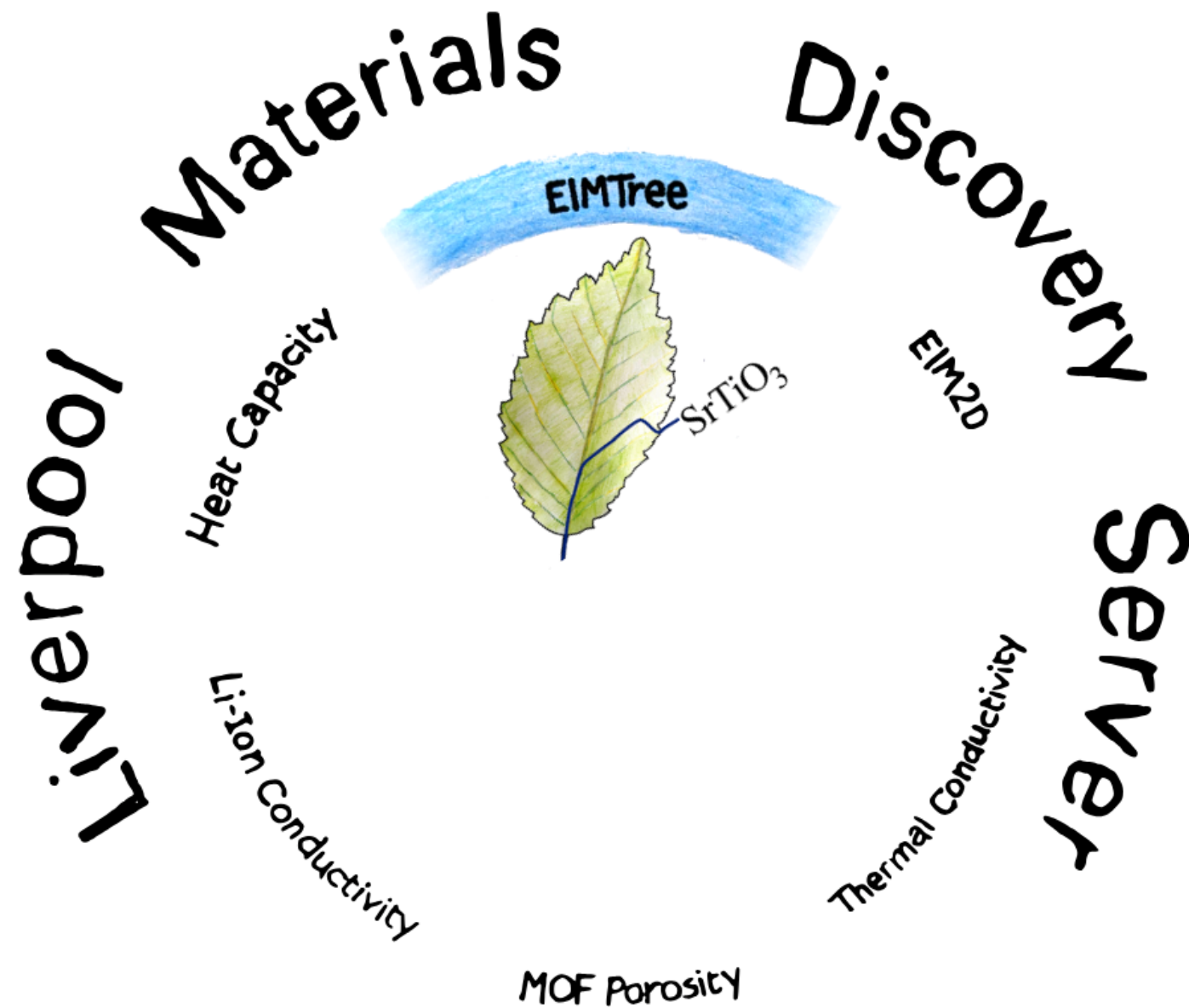


Optimal solution

$EIMD = 12.7$

- d-d
- f-d
- d-p
- s-d
- f-f
- f-p
- s-f
- p-p
- s-p
- s-s





Search the largest repositories of reported materials for compounds of interest using the chemical composition

EIMTree

Enter a chemical composition to see the 100 most similar EIMTree indexed compositions, the databases these are reported in with their associated IDs, and the EIMD distance to the query. This application was reported in [The Liverpool Materials Discovery Server: A suite of tools for the collaborative discovery of materials](#), and implements the process described in [The Earth Movers Distance as a Metric for the space of Inorganic Compositions](#). Please consider citing these papers if you use this in your work.

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Composition	Database: Matched IDs	Distance
$\text{Mg}_{0.2}\text{Si}_{0.2}\text{O}_{0.6}$ 	<p>MC : 355659, 286755, 197969, 288960, 286091, 121980, 92458, 443473, 287831, 67294, 299292, 356152,...</p> <p>3D</p> <p>ICSD: 290217, 68370, 290220, 34074, 31288, 37313, 171911, 30808, 31176, 137833, 80669, 64629, 290216,...</p> <p>Pearsons: 1247033, 1247034, 1247031, 1247036, 1247035, 1247032, 1213086, 1221853, 1247037, 1720923,...</p> <p>MPDS : S1247033, S1247034, S1247031, S1247036, S1247035, S1247032, S1213086, S1221853, S1247037,...</p> <p>Structural Database</p> <p>MPDS Property Database : P11803448, P11324227, P20004039, P1001007, P1800098, P1800348, P11324223,...</p> <p>Matbench Experimental Formation Enthalpy Kingsbury: 439</p> <p>Brgoch Superhard Dataset: 2107</p> <p>AFLOW: 0f52c618e87867cc, 1d7e4e940b42e292, 2ba30825feb0878, 8f13cdb0337ad6f5, 82d6b67054d0c51d,...</p> <p>Alexandria: agm003248137, agm002561439, agm003274640, agm003272733, agm003227041, agm003248089</p> <p>The Materials Project : mp-1180468, mp-657338, mp-644879, mp-1020125, mp-1182302, mp-603930, mp-554137, mp-...</p> <p>OMDB: 39549, 35</p> <p>2DMatpedia: 2dm-4459</p> <p>ICSD Theoretical : 5225, 159559, 159563, 159564, 680702, 5218, 163892, 5300, 674100, 163891, 151950, 159514,...</p> <p>Wolverton Oxides: 2251, 3626</p> <p>Jarvis ML: 11184, 11712, 12277, 12487, 15884, 20208, 24066, 24263</p> <p>Castelli Perovskites Dataset: 9276, 15213</p> <p>Matbench log gvrh v0.1: 7445, 8275, 8301, 8372, 10754</p> <p>Jarvis 3D: 11312, 11882, 12448, 12657, 16170, 20662, 24636, 24834</p> <p>Matbench log kvrh v0.1: 7445, 8275, 8301, 8372, 10754</p> <p>Matbench log gvrh v0.1: 9276, 15213</p> <p>Matbench Dielectric: 3427</p>	0.0
$\text{Mg}_{0.196}\text{Zn}_{0.004}\text{Si}_{0.2}\text{O}_{0.6}$	<p>MPDS Structural Database: S1047271, S1047268</p> <p>Pearsons: 1047271, 1047268</p>	0.004

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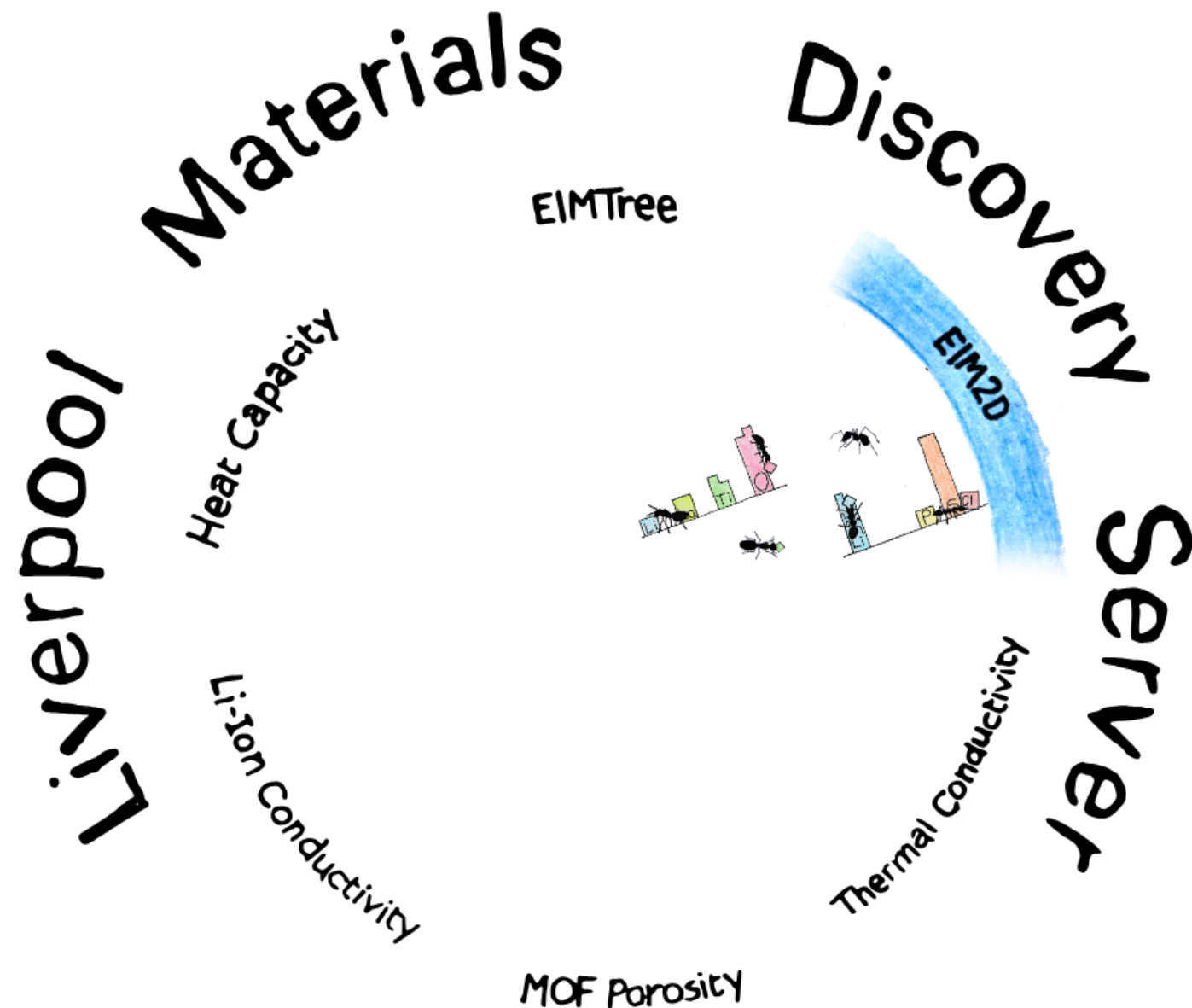


ELMTree

Searched 1,367,526 unique compositions across 5,410,119 records for $\text{Li}_{0.5} \text{Si}_{0.071} \text{O}_{0.357} \text{Cl}_{0.071}$ in 0.067s

[Refine Search](#)

Composition	Database: Matched IDs	Distance
$\text{Li}_{0.5} \text{Sn}_{0.083} \text{O}_{0.417}$ 	MPDS Structural Database: S1834891	0.595
$\text{Li}_{0.5} \text{B}_{0.1} \text{O}_{0.4}$ 	Alexandria: agm003225142, agm003281557 The Materials Project: mp-768960, mp-768966, mp-768967, mp-755346 Jarvis ML: 21977 Jarvis 3D: 22482	0.671
$\text{Li}_{0.5} \text{Bi}_{0.071} \text{O}_{0.429}$   	MC 3D: 426306 ICSD: 155950 Pearsons: 1818766, 1121989 MPDS Structural Database: S1818766, S1121989 MPDS Property Database: P1128474, P20057326, P1128479, P20103788 Alexandria: agm003215469, agm003215470 The Materials Project: mp-38487, mp-754060 Jarvis ML: 3407 Jarvis 3D: 3453	0.786
$\text{Li}_{0.496} \text{Ge}_{0.065} \text{P}_{0.007} \text{S}_{0.36}$ $\text{In}_{0.072}$	MPDS Structural Database: S1046127 Pearsons: 1046127	0.883



Enter a single composition to see it within the context of reported compositions or generate EIM2D plots and distance matrices from lists of comma separated compositions

EIM2D

Enter a composition to see the 100 most similar EIMTree indexed compositions, embedded to two dimensions via [UMAP](#). Enter up to 100 compositions, separated via commas, to plot their chemical similarity. Tap the distance matrix to view specific distances. This application was reported in [The Liverpool Materials Discovery Server: A suite of tools for the collaborative discovery of materials](#), and implements the process described in [The Earth Movers Distance as a Metric for the space of Inorganic Compositions](#). Please consider citing these papers if you use this in your work.

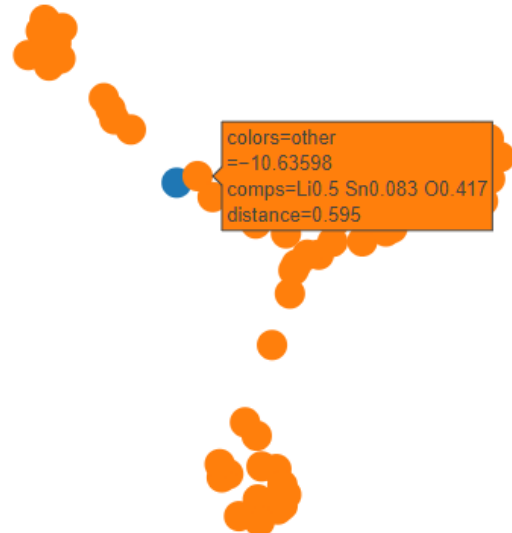


EIM2D

Q Li7SiO5Cl

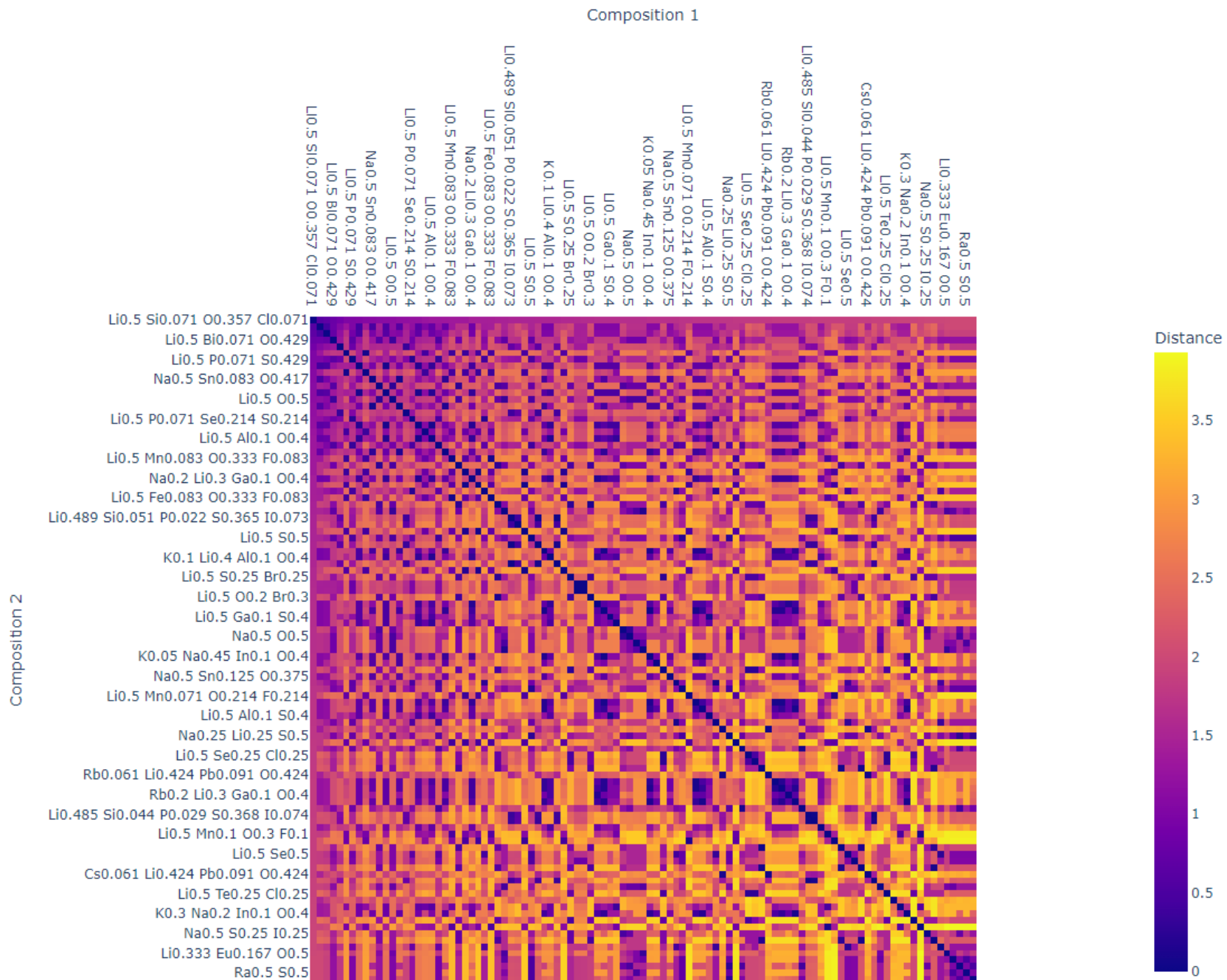


colors
● query
● other



colors=other
=-10.63598
comps=Li0.5 Sn0.083 O0.417
distance=0.595



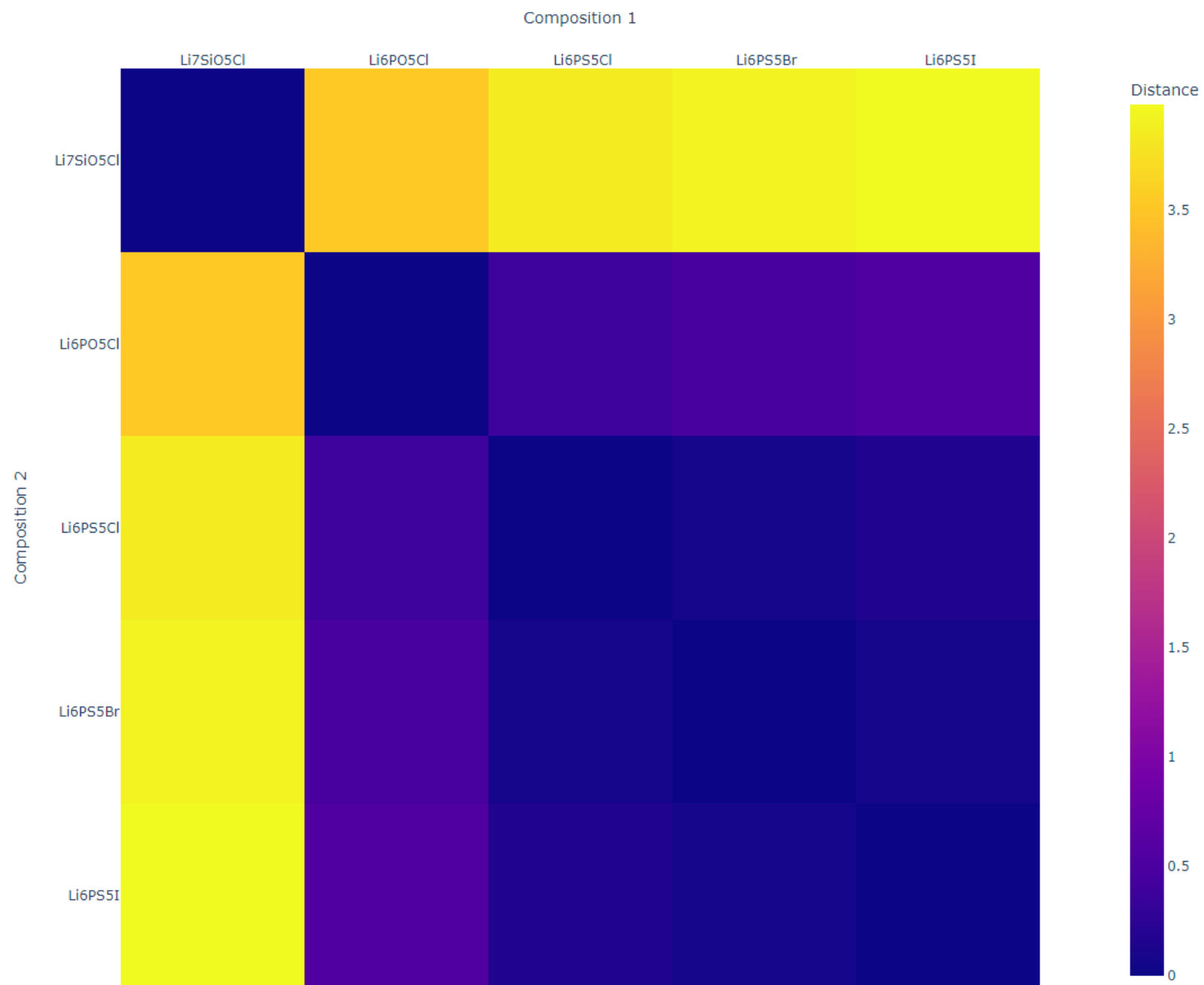


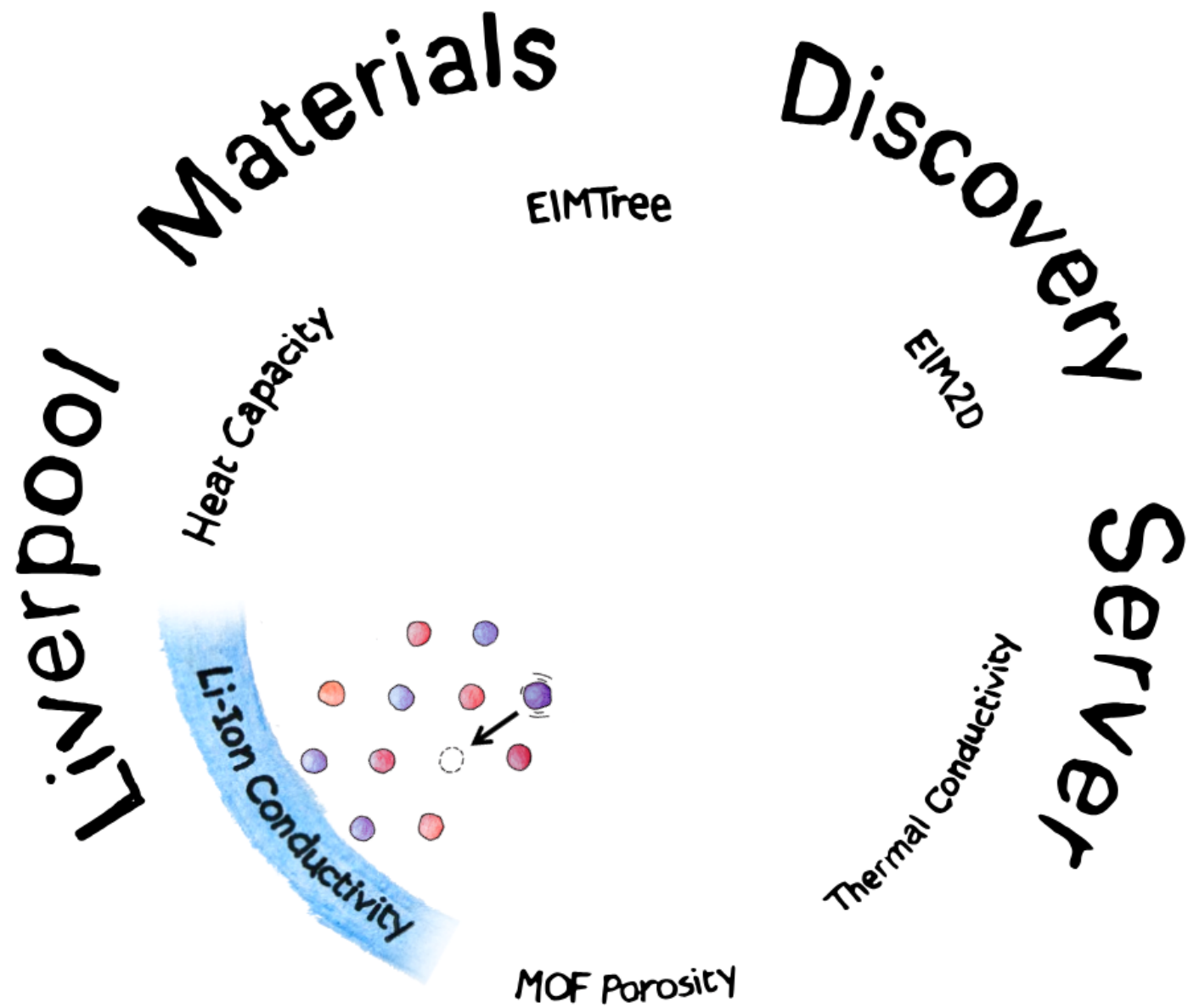
EIM2D

Q Li₇SiO₅Cl, Li₆PO₅Cl, Li₆P:

Enter a composition to see the 100 most similar EIMTree indexed compositions, embedded to two dimensions via [UMAP](#). Enter up to 100 compositions, separated via commas, to plot their chemical similarity. Tap the distance matrix to view specific distances. This application was reported in [The Liverpool Materials Discovery Server: A suite of tools for the collaborative discovery of materials](#), and implements the process described in [The Earth Movers Distance as a Metric for the space of Inorganic Compositions](#). Please consider citing these papers if you use this in your work.

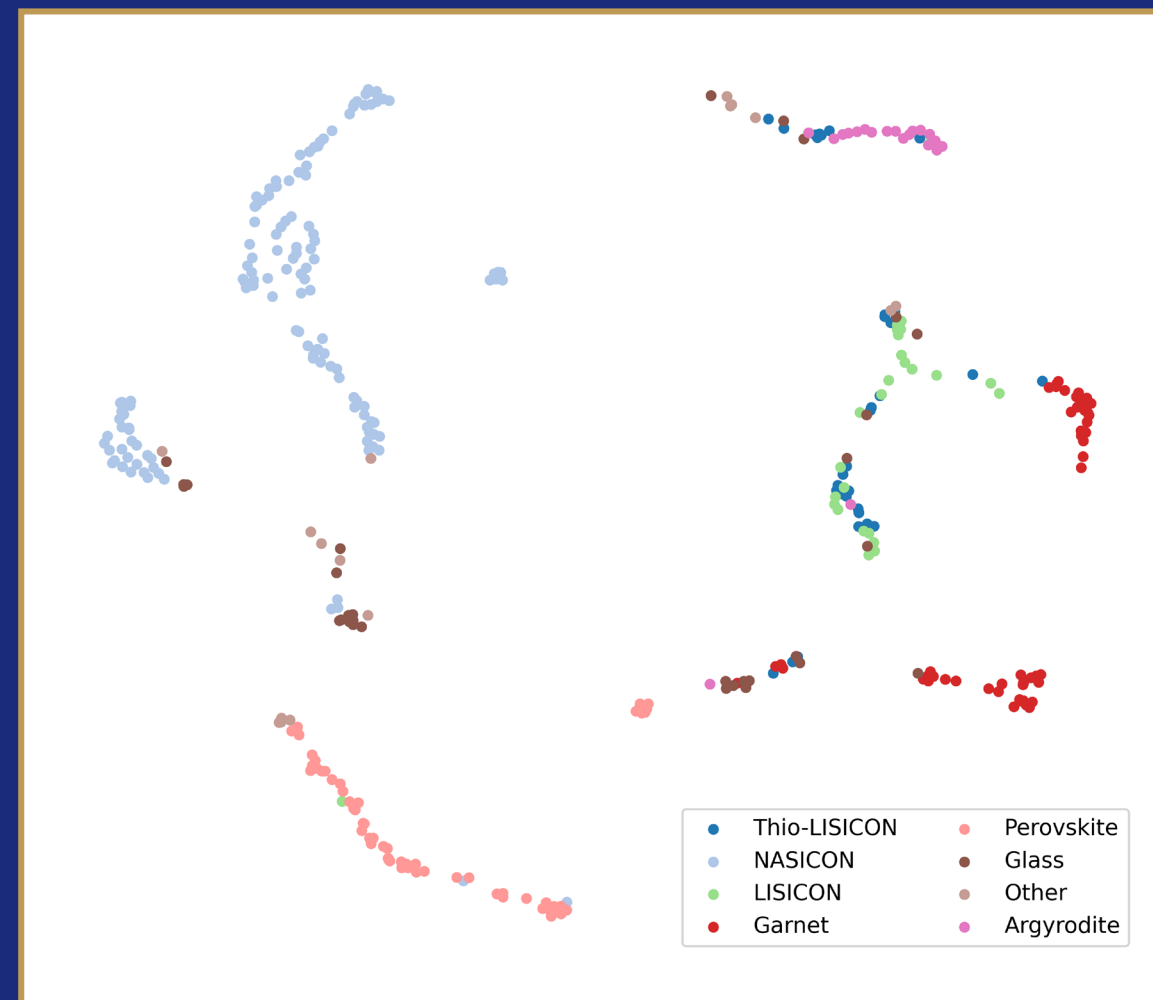
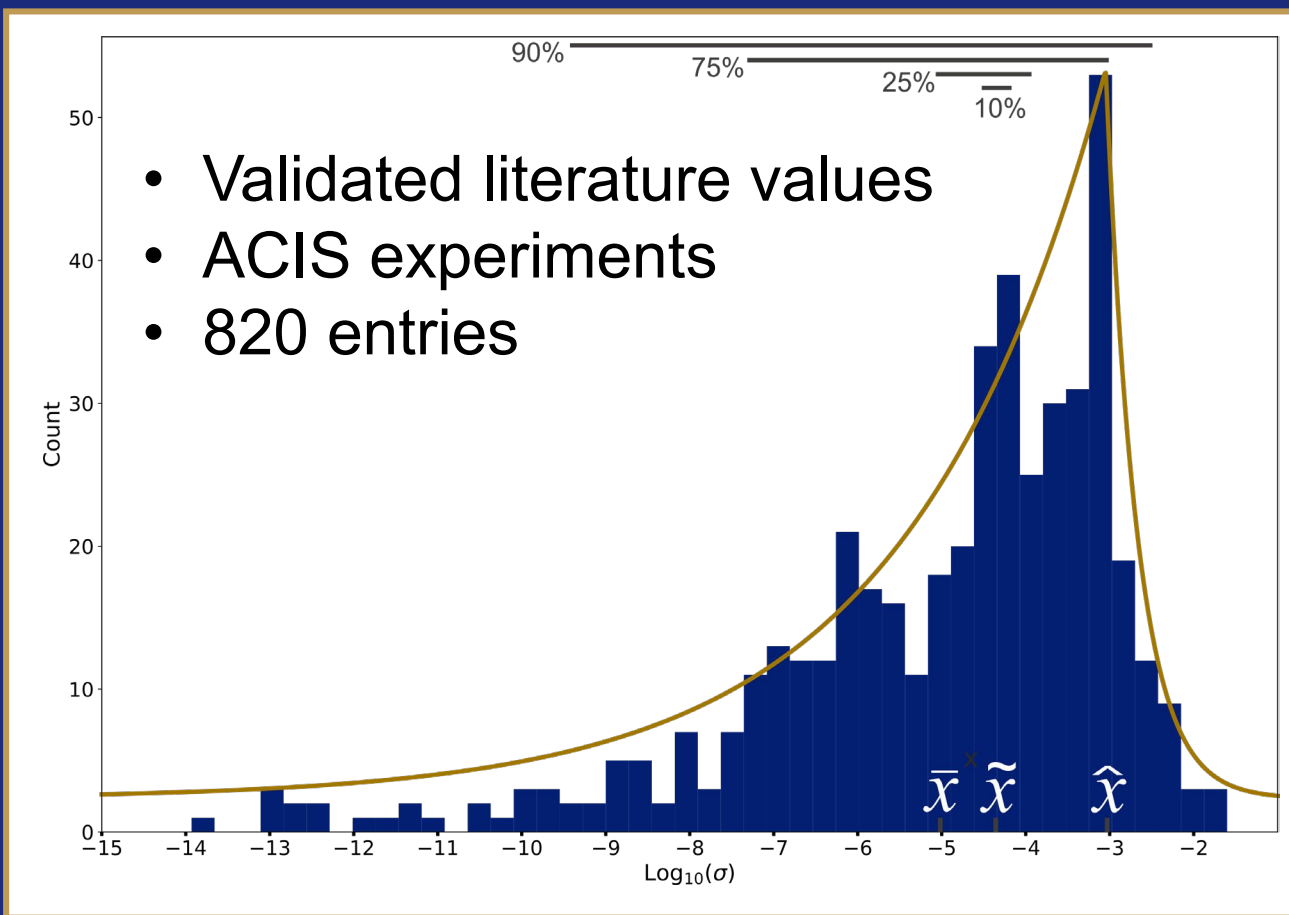






Predict the ionic conductivity of potential formulations for solid state electrolytes from the composition

Li Ion Conductivity Background



<http://pcwww.liv.ac.uk/~msd30/lmds/LilonDatabase.html>

Li-Ionic Conductivity

Q Li7SiO5Cl, Li6PO5Cl, Li6PS5Cl, Li6PS5Br, Li6PS5|



Calculate

Enter the chemical composition (or a list of up to 2,000 compositions separated by commas) of a candidate Li conducting solid state electrolyte to return a binary classification prediction of whether a material will have a conductivity $> 10^{-4} \text{ S cm}^{-1}$, and a regression prediction of the materials conductivity in $\log_{10}(\text{S cm}^{-1})$. These classification predictions were found to have an accuracy of 0.71, with regression predictions having a mean absolute error of 0.99. This is based on a [CrabNet](#) architecture, trained on [The Liverpool Ionics Dataset](#), and is a hosted version of the deep learning model introduced in [A database of experimentally measured lithium solid electrolyte conductivities evaluated with machine learning](#) and reported in [The Liverpool Materials Discover server: A Suite of Computational Tools for the Collaborative discovery of Materials](#). Please consider citing these papers if you use this tool in your work.

[If you would like to access this tool via API click here for more information](#)



Li-Ionic Conductivity

Q Li7SiO5Cl, Li6PO5Cl, Li6PS5Cl, Li6PS5Br, Li6PS5I

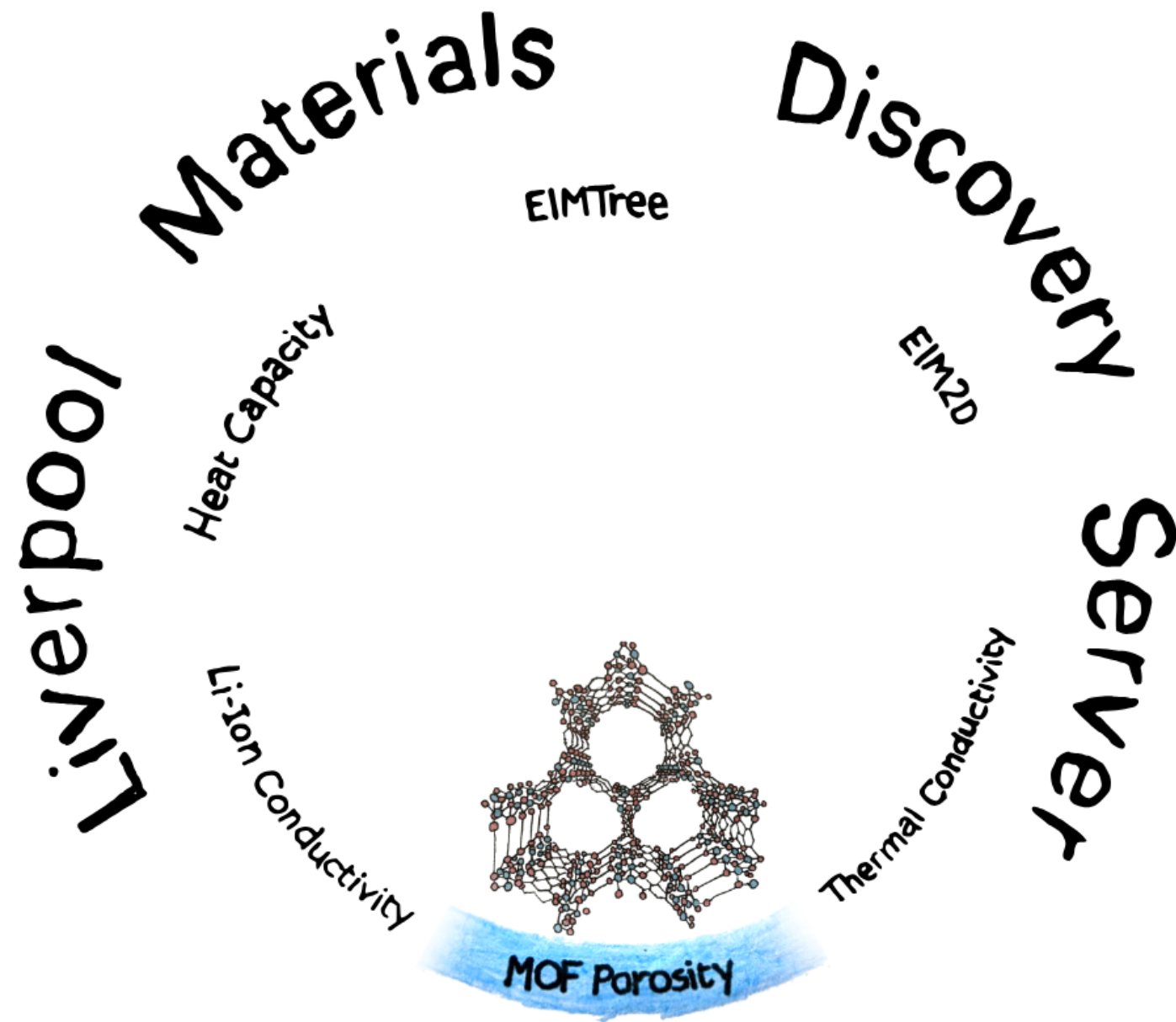
Calculate

Composition	Classification Model ($> 10^{-4}$)	Regression Model ($\log_{10}(\text{Scm}^{-1})$)
Li7SiO5Cl	0	-8.43
Li6PO5Cl	0	-9.36
Li6PS5Cl	1	-3.25
Li6PS5Br	1	-3.11
Li6PS5I	1	-3.15

Download as csv

Accuracy ~ 81 %

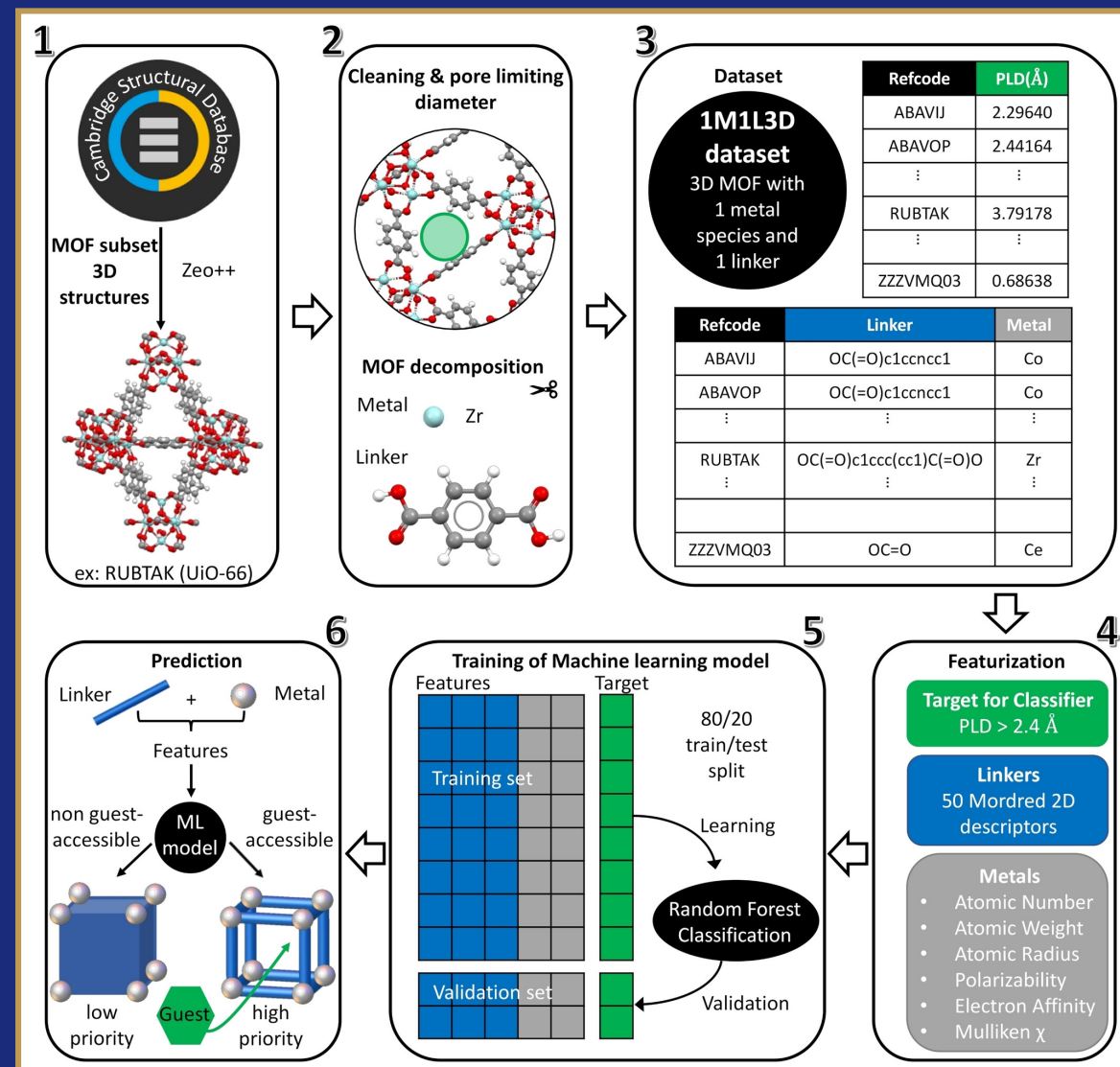
MAE on $\log_{10}(\text{conductivity}) = 0.85$



Predict whether a MOF is likely to be porous using the SMILES representation of the linker and a chosen metal

MOF Porosity Background

- Metal organic frameworks are porous materials with inorganic and organic fragments
- Experimentally determined structures are reported in the CSD
- We took these and split them into separate metal / organic fragments to enable machine learning prediction of porosity



MOF Porosity



Enter the formulation of a potential MOF using the SMILES representation of the linker and the metal(s) to be combined, to predict the likelihood of pores of different sizes forming in the resultant structure. Due to limitations in the training dataset only some elements are supported as metal, [find the list of elements supported here](#). Predictions were found to have an accuracy of 80.5% on a test set. This application was reported in [The Liverpool Materials Discovery Server: A suite of tools for the collaborative discovery of materials](#), and is based on the model first reported in [Machine-Learning Prediction of Metal–Organic Framework Guest Accessibility from Linker and Metal Chemistry](#). Please consider citing these papers if you use this in your work.

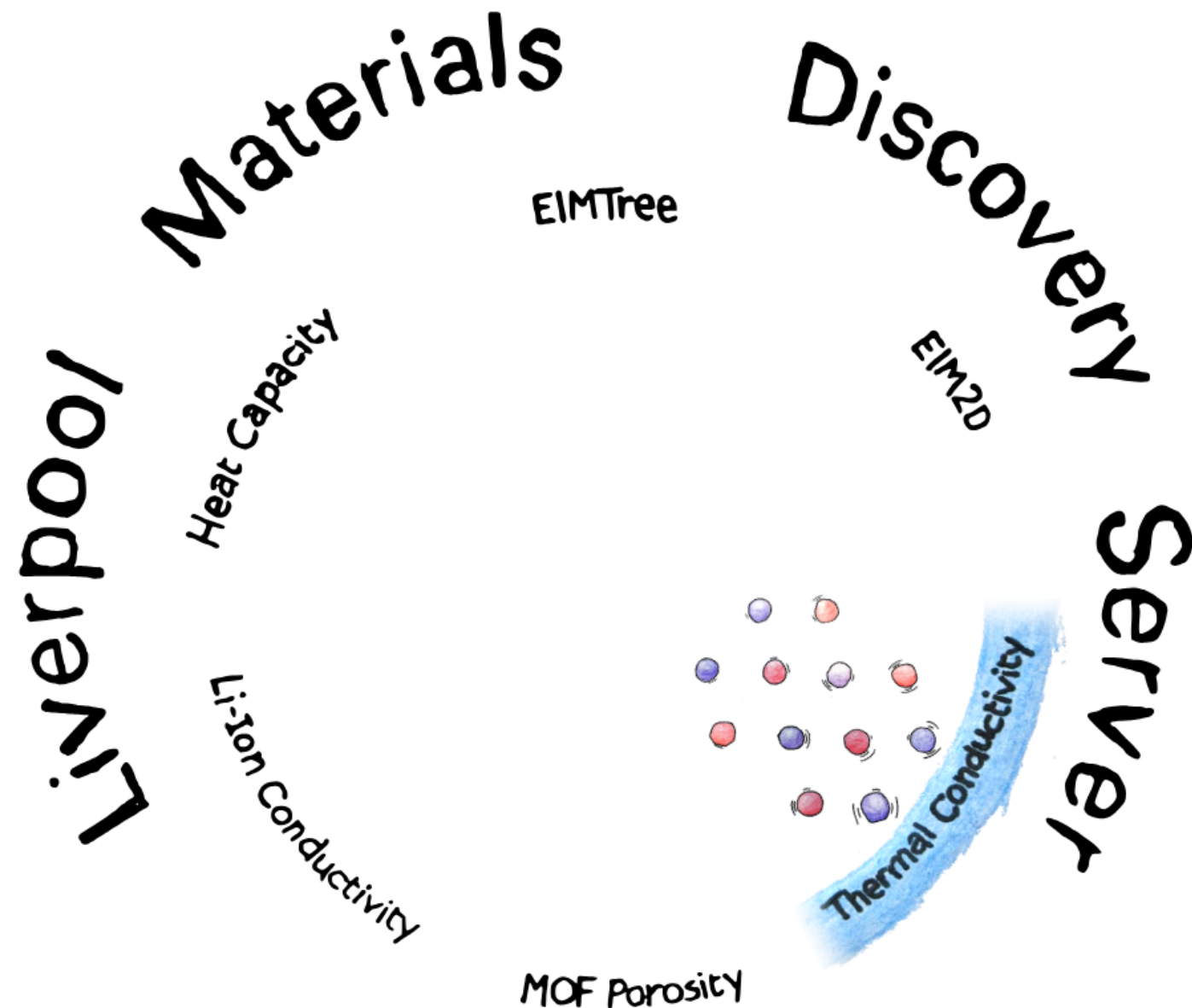
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MOF Porosity

Linker	Metal	Predicted porosity category
OC(=O)C(=O)O	Zr	porosity < 2.4 Å
OC(=O)C(=O)O	Zn	2.4Å < porosity < 4.4Å
OC(=O)C(=O)O	Cu	4.4Å < porosity < 5.9Å
OC(=O)C(=O)O	Fe	2.4Å < porosity < 4.4Å

Accuracy ~ 80 %



Predict the thermal conductivity of a candidate thermoelectric material from its composition

Thermal Conductivity



Calculate

Enter a composition, or a list of up to 2000 compositions separated by commas, to return a prediction of the thermal conductivity of each formulation. The prediction was found to have a R^2 of 0.71, and root mean squared error of $0.55 \log_{10}(\text{W m}^{-1} \text{K}^{-1})$ on a test set of thermoelectric materials comparing the true logarithm of thermal conductivity to the predicted logarithm of thermal conductivity. This application was reported in [The Liverpool Materials Discovery Server: A suite of tools for the collaborative discovery of materials.](#), and is an improved version of the model first used in [Discovery of a Low Thermal Conductivity Oxide Guided by Probe Structure Prediction and Machine Learning](#). Please consider

citing these papers if you use this in your work.

[Click here for information as to how to use this model with an API](#)



Thermal Conductivity

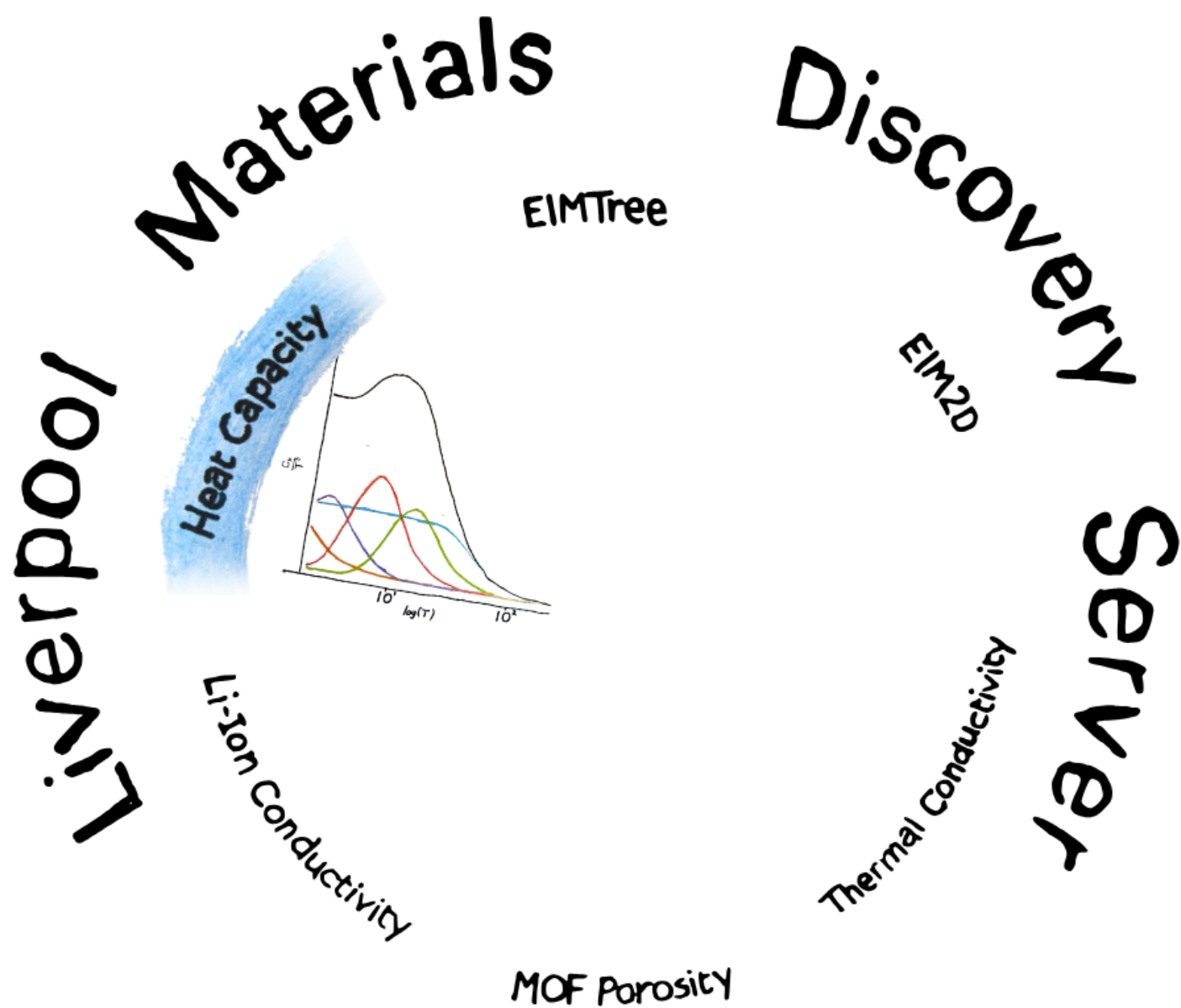
Q Cu9Al4, Sr2Ti6O13, Ti2FeNiSb2, Cu2SnZnS4

Calculate

Download as csv

Composition	Predicted thermal conductivity ($\text{W m}^{-1} \text{K}^{-1}$)
Cu9Al4	15.78
Sr2Ti6O13	9.91
Ti2FeNiSb2	6.19
Cu2SnZnS4	7.5

RMSE on $\log_{10}(\text{conductivity}) = 0.55$



Model the heat capacity of a material from a csv of temperature readings and the corresponding Einstein and Debye components



Heat Capacity

Jon Newnham

ExampleData.csv

Einstein components

Add Einstein component

Remove Einstein component

Debye Components

Debye Temperature 1 (K)

Q 300

Pre-factor component for 1

Q 1

Add Debye component

Remove Debye component

Linear (γ) component

Q 0

Plot data as C_p/T^n ($n = 0$ for high T fitting, 3 for low T fitting)

Q 0

Model Starting Temperature (K)

Q 2

Model Ending Temperature (K)

Q 250



X axis log scale? ☐

Y axis log scale? ☐

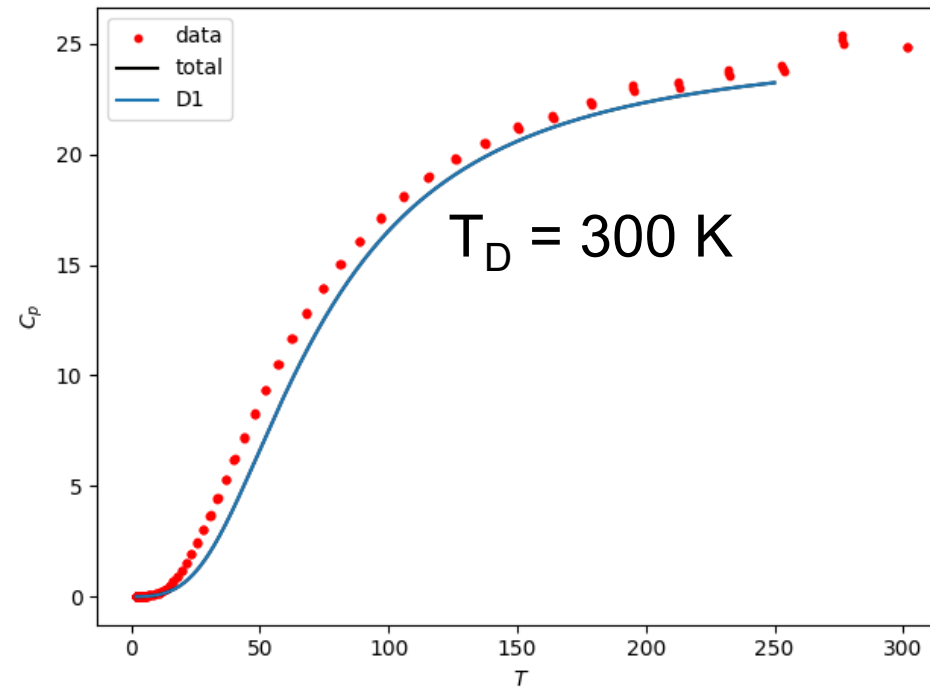
Calculate



Heat Capacity

[Choose File](#) No file chosen

Your file is already uploaded and will be stored for 15 minutes, there is no need to reupload file unless wish to change the data you are operating on



[Click here to download your model](#)

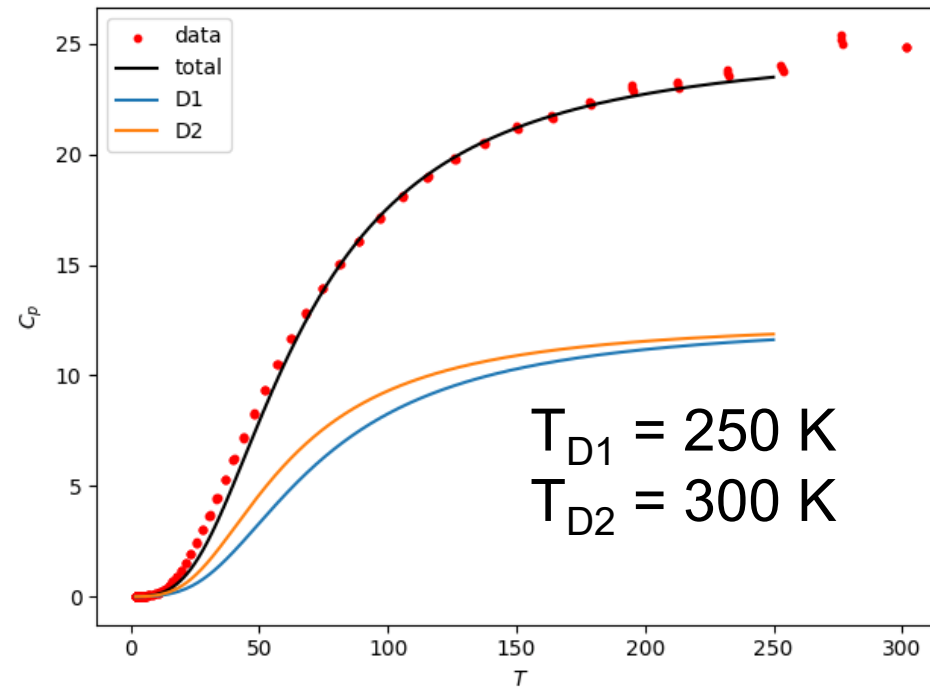
Einstein components



Heat Capacity

[Choose File](#) No file chosen

Your file is already uploaded and will be stored for 15 minutes, there is no need to reupload file unless wish to change the data you are operating on



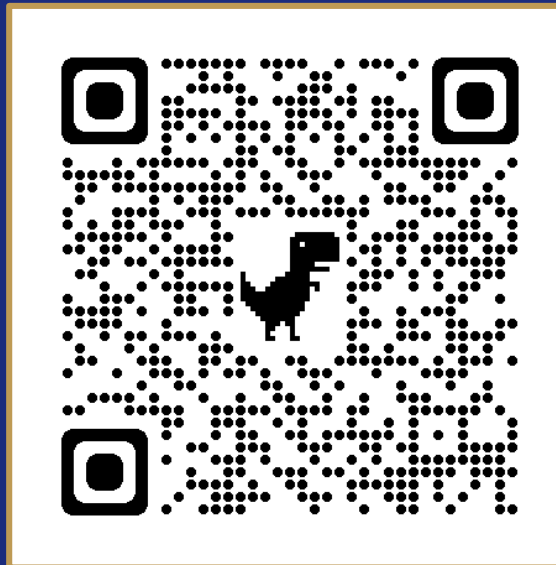
[Click here to download your model](#)

Einstein components



Conclusions

- The LMDS is up and running, and freely available to all
- Cloud based web-servers like the LMDS are a good way to make computational models available for wide use
- The LMDS server will be expanded in the future, so watch this space!



<https://lmds.liverpool.ac.uk>

Acknowledgements

- Sam Durdy
- Cameron Hargreaves
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