

Vilnius
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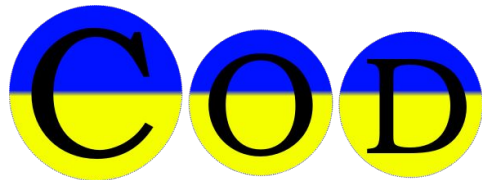


FIZINIŲ IR
TECHNOLOGIJOS MOKSLŲ
CENTRAS

ML-UFF powered validation of the COD

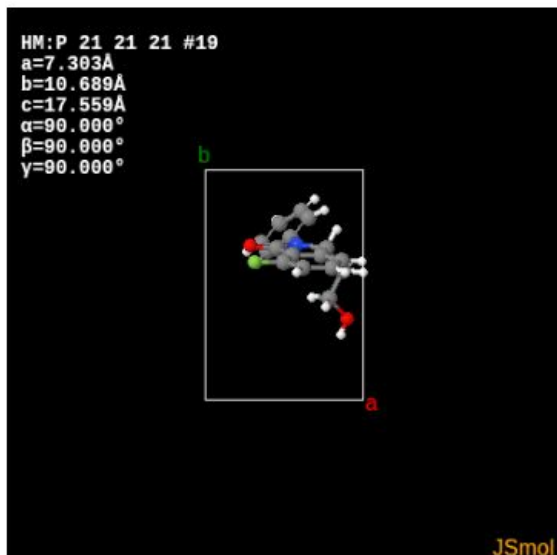
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COD



[7250815](#) << [7250816](#) >> [7700000](#)

Preview



Coordinates [7250816.cif](#)
Original paper (by DOI) [HTML](#)

▼ Structure parameters

| | |
|------------------------|--|
| Formula | C ₁₆ H ₁₄ F N O ₂ |
| Calculated formula | C ₁₆ H ₁₄ F N O ₂ |
| Title of publication | Tetrabutylammonium decatungstate-catalyzed hydroalkylation/alkoxylation of 3-methyleneisindolin-1-ones with alcohols/ethers through hydrogen atom transfer process |
| Authors of publication | Fu, Han; Wang, Feixia; Wu, Ziyang; Xie, Xiaoyu; Zhang, Yicheng; Liu, Jie; Wang, Lei |
| Journal of publication | RSC Advances |
| Year of publication | 2025 |
| Journal volume | 15 |
| Journal issue | 37 |
| Pages of publication | 30285 - 30289 |

Crystallography Open Database (COD) is an open-access collection of crystal structures of organic, inorganic, metal-organic compounds and minerals, excluding biopolymers.

It contains more than half a million structures

It would be impossible to validate all the structures using DFT

ML-UFFs

Together with the AI boom of the pandemic, Machine Learning Universal Force Fields (ML-UFFs) were introduced

ML-UFFs aim to be a 'learned' Universal ForceField trained on DFT data

The number and accuracy of MLP-UFFs introduced is increasing

Matbench is a popular ML-UFF ranking website, where ML-UFFs are tested in a systematic way

| Model | RMSD | Training Set | Params | Targets | Date Added |
|---------------------|-------|--------------------------------|--------|--------------------|------------|
| eSEN-30M-OAM | 0.061 | 6.6M (113M) OMat24+MPtrj+sAlex | 30.2M | EFS _G | 2025-03-17 |
| ORB v3 | 0.075 | 6.47M (133M) MPtrj+Alex+OMat24 | 25.5M | EFS _G | 2025-04-05 |
| SevenNet-MF-ompa | 0.064 | 6.6M (113M) OMat24+sAlex+MPtrj | 25.7M | EFS _G | 2025-03-13 |
| GRACE-2L-OAM | 0.067 | 6.6M (113M) OMat24+sAlex+MPtrj | 12.6M | EFS _G | 2025-02-06 |
| DPA-3.1-3M-FT | 0.069 | 163M OpenLAM | 3.27M | EFS _G | 2025-06-05 |
| eSEN-30M-MP | 0.075 | 146k (1.58M) MPtrj | 30.1M | EFS _G | 2025-03-17 |
| MACE-MPA-0 | 0.073 | 3.37M (12M) MPtrj+sAlex | 9.06M | EFS _G | 2024-12-09 |
| AlphaNet-v1-OMA | 0.079 | 6.6M (113M) OMat24+sAlex+MPtrj | 4.65M | EFS _G | 2025-05-12 |
| MatterSim v1 5M | 0.073 | 17M MatterSim | 4.55M | EFS _G | 2024-12-16 |
| GRACE-1L-OAM | 0.072 | 6.6M (113M) OMat24+sAlex+MPtrj | 3.45M | EFS _G | 2025-02-06 |
| Eqnorm MPtrj | 0.084 | 146k (1.58M) MPtrj | 1.31M | EFS _G | 2025-05-26 |
| Nequix MP | 0.085 | 146k (1.58M) MPtrj | 708k | EFS _G | 2025-08-17 |
| DPA-3.1-MPtrj | 0.080 | 146k (1.58M) MPtrj | 4.81M | EFS _G | 2025-06-05 |
| SevenNet-I3i5 | 0.085 | 146k (1.58M) MPtrj | 1.17M | EFS _G | 2024-12-10 |
| HIENet | 0.080 | 146k (1.58M) MPtrj | 7.51M | EFS _G | 2025-07-01 |
| MatRIS v0.5.0 MPtrj | 0.077 | 146k (1.58M) MPtrj | 5.83M | EFS _G M | 2025-03-13 |
| GRACE-2L-MPtrj | 0.090 | 146k (1.58M) MPtrj | 15.3M | EFS _G | 2024-11-21 |
| MACE-MP-0 | 0.091 | 146k (1.58M) MPtrj | 4.69M | EFS _G | 2023-07-14 |
| eqV2 M | 0.069 | 3.37M (102M) OMat24+MPtrj | 86.6M | EFS _D | 2024-10-18 |
| ORB v2 | 0.097 | 3.25M (32.1M) MPtrj+Alex | 25.2M | EFS _D | 2024-10-11 |
| eqV2 S DeNS | 0.076 | 146k (1.58M) MPtrj | 31.2M | EFS _D | 2024-10-18 |
| ORB v2 MPtrj | 0.101 | 146k (1.58M) MPtrj | 25.2M | EFS _D | 2024-10-14 |
| M3GNet | 0.112 | 62.8k (188k) MPF | 228k | EFS _G | 2022-09-20 |
| CHGNet | 0.095 | 146k (1.58M) MPtrj | 413k | EFS _G M | 2023-03-03 |

A material graph neural network

M3G-Net

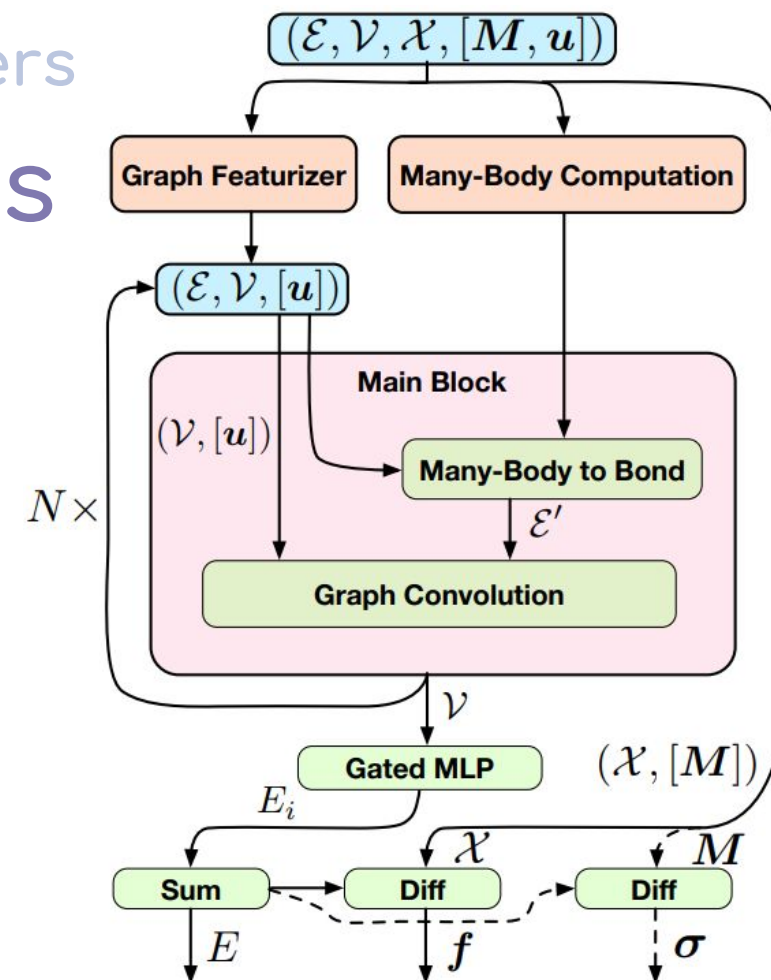
188k Training Structures

211k Parameters

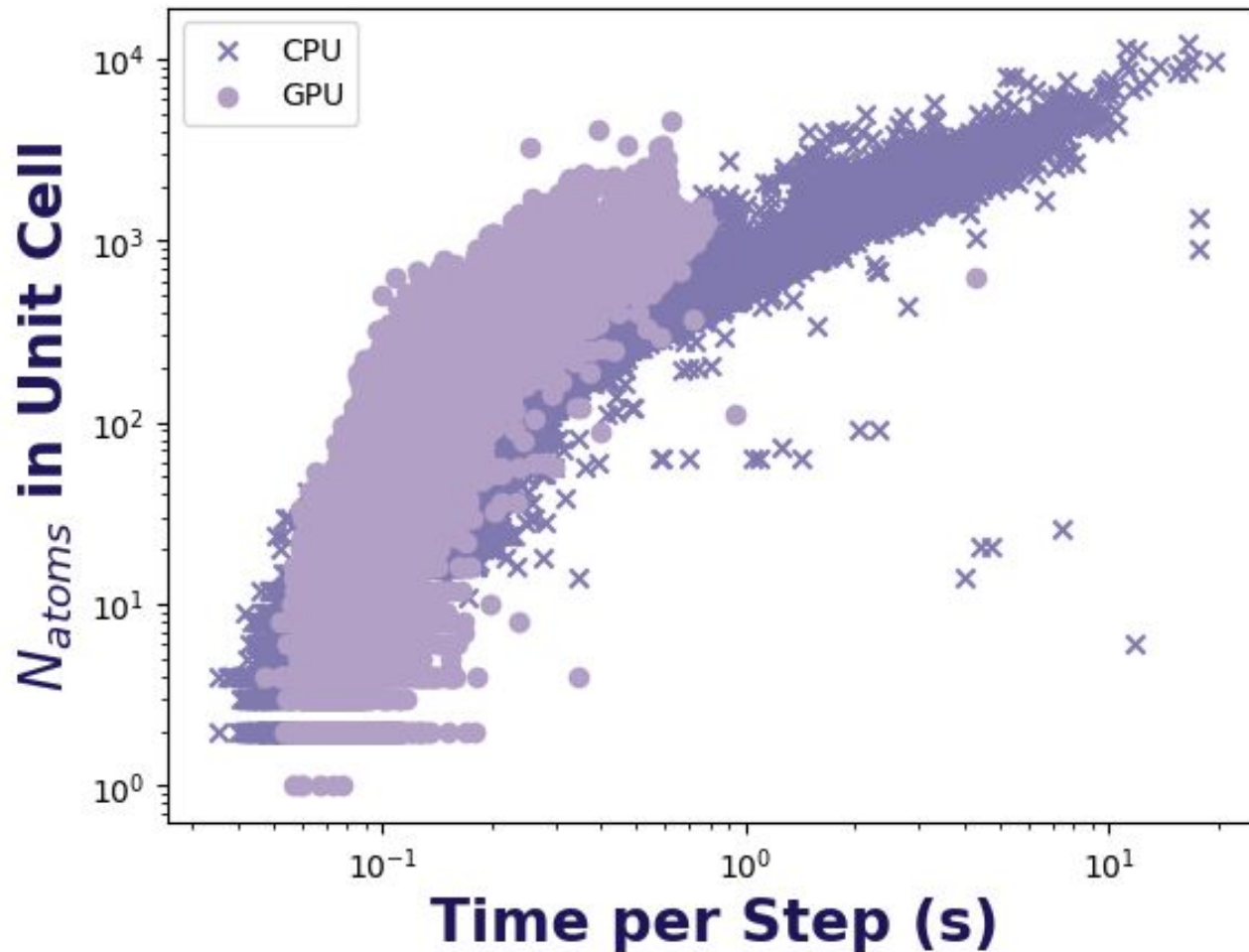
Incorporates 3 body interactions

Works for all elements up to Ac

Embeddings trivialize the calculation of outputs



Results M3G-Net (Speed)

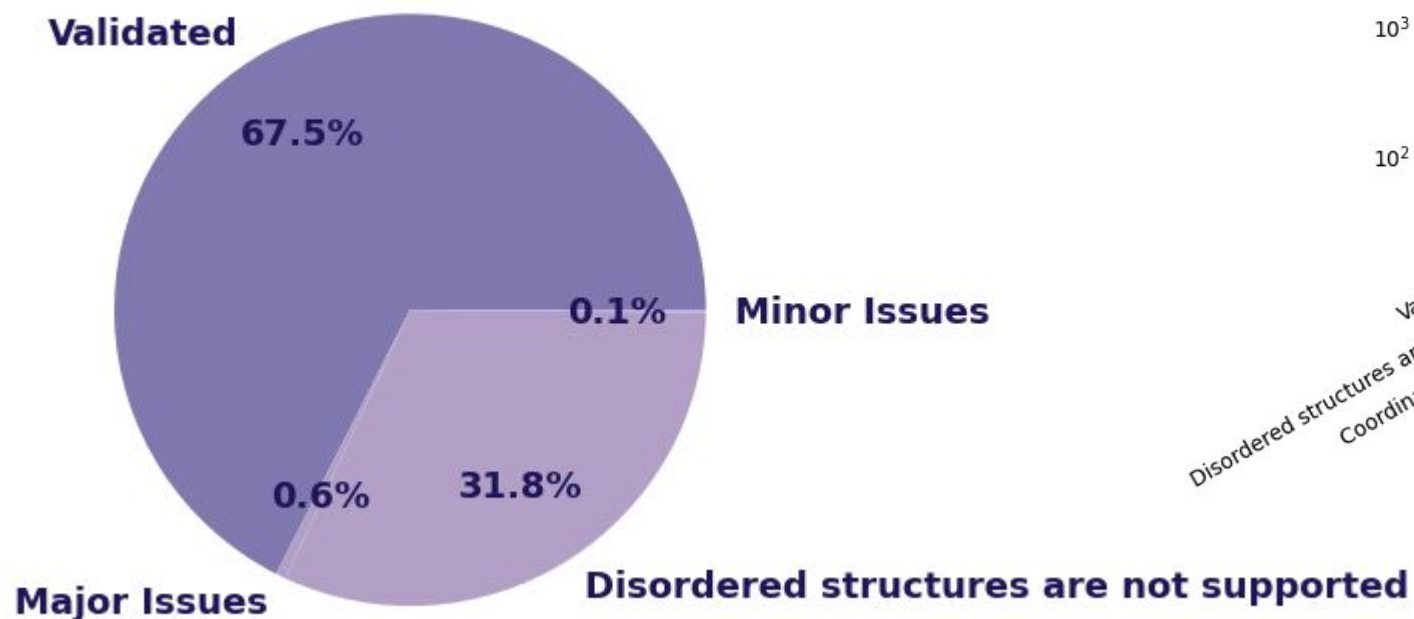


Many of the structures could be relaxed on the CPU with not a large time increase

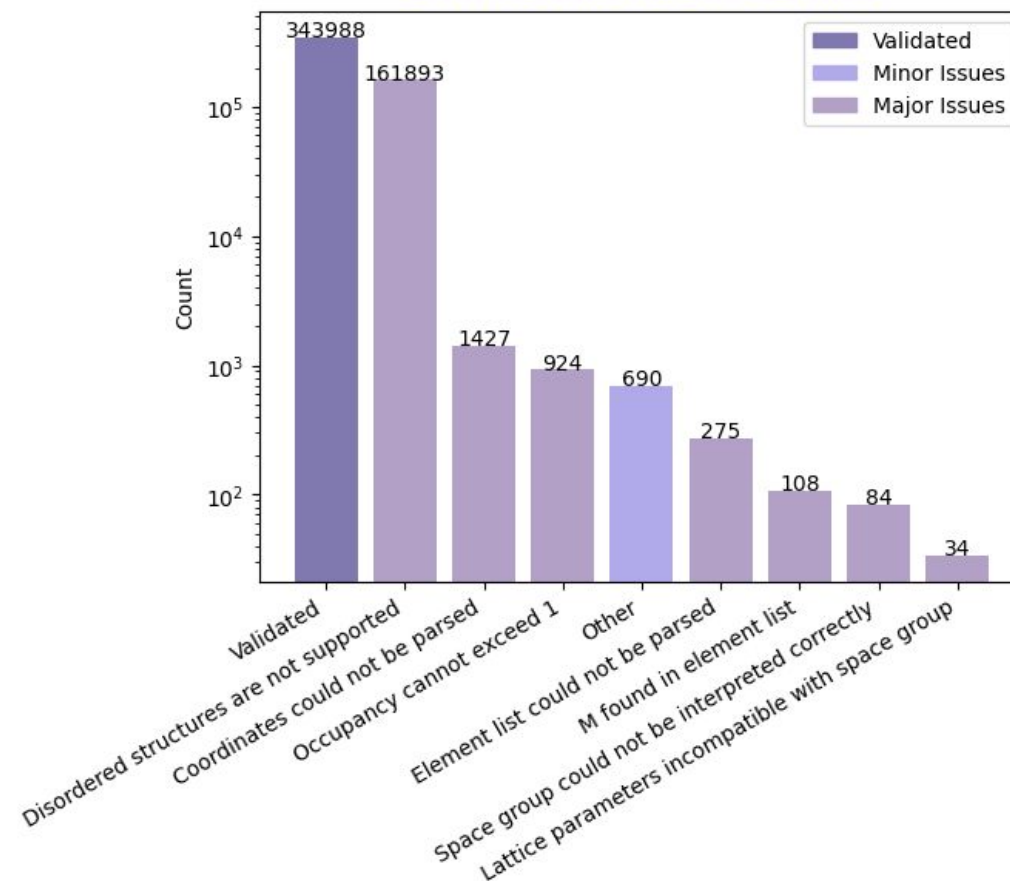
The CPU runs were done for structures that required too much CUDA Memory

Results M3G-Net (Errors)

Validation Outcomes of the COD



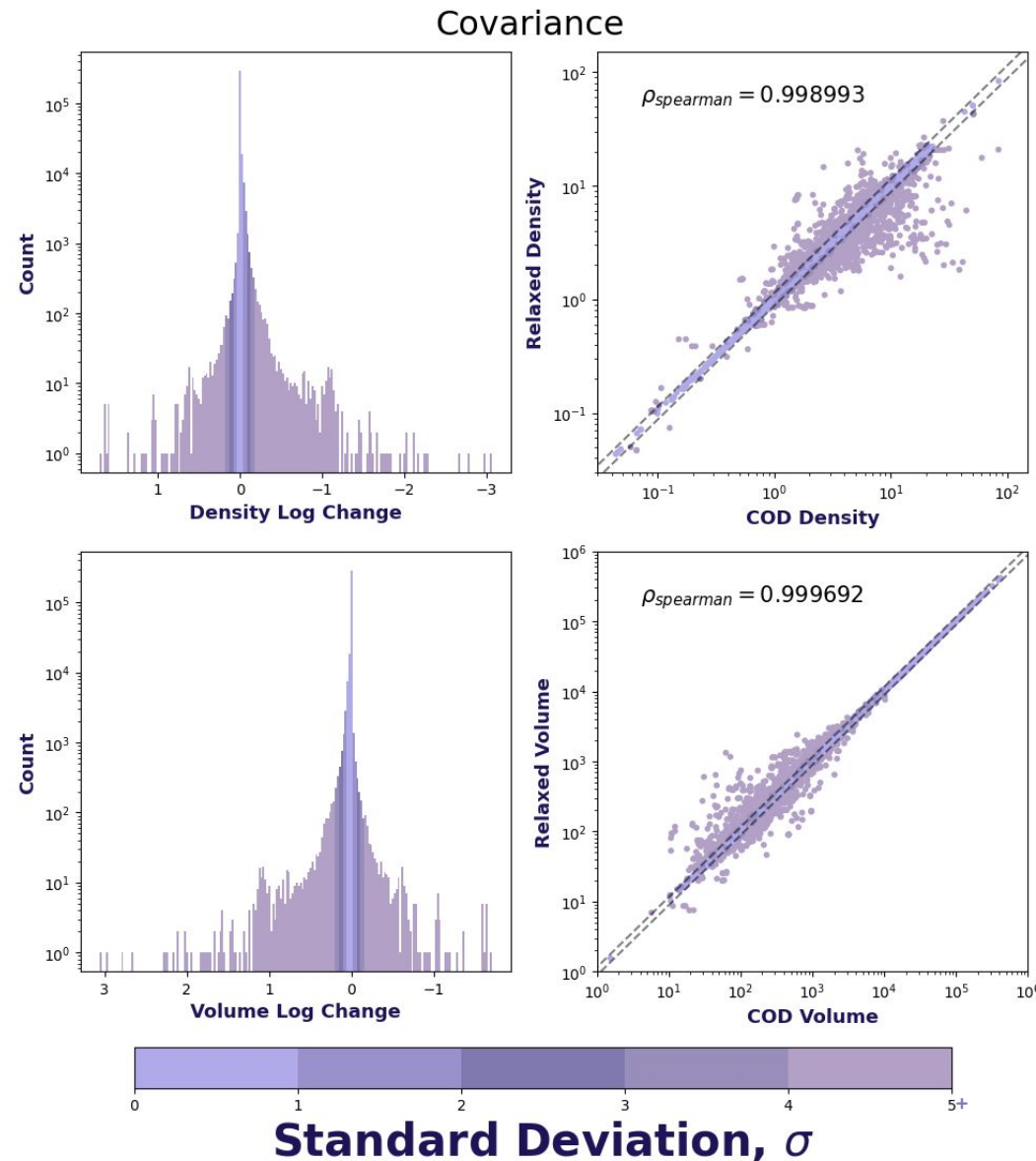
Error reasons for 509423 files



Results M3G-Net (Covariance)

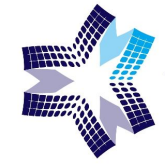
$$\text{Log Change} = \ln\left(\frac{y}{x}\right)$$

Both density and volume have a very strong peak at 0 log change



$$\rho_{\text{Pearson}} = \frac{\text{cov}(x, y)}{\sigma_x \sigma_y}$$

The correlation coefficients of both values are very high, but there are surrounding 'clouds' of data points around the $y=x$ line



Verification during submission

To add an extra layer of certainty to submitted structures, M3G-Net can be used for validation during submission to the COD

This could be achieved using a standalone compiled binary



Conclusions

- ML-UFFs can be used to verify the COD due to its low computational cost compared to quantum mechanical methods
- M3G-Net was used to validate more than 67% of the entries, with the vast majority of unvalidated entries being disordered structures
- Pearson coefficients show a very good agreement (>0.998) between the original and relaxed values of density and volume
- This method can be implemented for validation during submission

Acknowledgements

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Thank You!

Any Questions?