LeMat-Traj: A Scalable and Unified Dataset of Materials Trajectories for Atomistic Modeling

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Abstract

The development of accurate machine learning interatomic potentials (MLIPs) is limited by the fragmented availability and inconsistent formatting of quantum mechanical trajectory datasets derived from Density Functional Theory (DFT). These datasets are expensive to generate yet difficult to combine due to variations in format, metadata, and accessibility. To address this, we introduce LeMat-Traj, a curated dataset comprising over 120 million atomic configurations aggregated from large-scale repositories, including the Materials Project, Alexandria, and OQMD. LeMat-Traj standardizes data representation, harmonizes results and filters for high-quality configurations across widely used DFT functionals (PBE, PBESol, SCAN, r2SCAN), significantly lowering the barrier for training transferrable and accurate MLIPs. LeMat-Traj spans both relaxed low-energy states and high-energy, high-force structures, complementing molecular dynamics and active learning datasets. By fine-tuning models pre-trained on high-force data with LeMat-Traj, we achieve a significant reduction in force prediction errors on relaxation tasks. We also present LeMaterial-Fetcher, a modular and extensible open-source library developed for this work, designed to provide a reproducible framework for the community to easily incorporate new data sources and ensure the continued evolution of large-scale materials datasets. LeMat-Traj and LeMaterial-Fetcher are publicly available at `https://huggingface.co/datasets/LeMaterial/LeMat-Traj` and `https://github.com/LeMaterial/lematerial-fetcher`.

1 Introduction

The discovery and design of novel materials are essential for technological advancement, offering solutions to pressing global challenges such as sustainable energy and climate change mitigation [31]. However, traditional lab experiments and computational approaches, particularly those involving Density Functional Theory (DFT), are resource-intensive [46]. Machine Learning Interatomic Potentials (MLIPs) have emerged as a promising alternative, offering DFT-level accuracy at a fraction of the computational cost. This acceleration is crucial for enabling large-scale molecular dynamics (MD) simulations over long timescales and rapid exploration of material properties [41, 12], potentially fast-tracking the development of materials for applications like carbon capture, improved batteries, or more efficient catalysts.

Graph Neural Networks (GNNs) have emerged as the most effective class of models for learning interatomic potentials, due to their ability to naturally represent atomic systems and to incorporate physical symmetries such as rotational and permutational equivariance [11]. As modern GNN architectures like EquiformerV2 [25] exhibit scaling laws behaviors [6], the need for even larger, more diverse, and consistently processed datasets becomes predominant. Despite several large-scale initiatives

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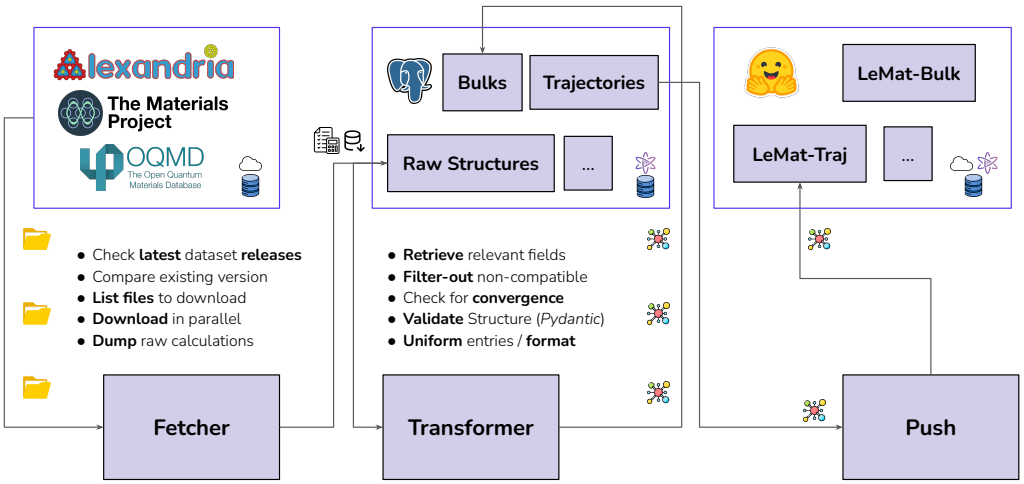


Figure 1: Data curation pipeline of LeMaterial-Fetcher. The library automates the process of fetching, transforming, validating, and harmonizing data from various sources, ensuring a consistent and reproducible dataset. The pipeline currently supports the continuous integration of fully relaxed bulk structures and full relaxation trajectories.

generating vast amounts of DFT data [17, 36], these datasets often remain siloed, employ distinct data formats, and use varying DFT parameters (e.g., functionals, parameters, pseudopotentials). This fragmentation poses a challenge for researchers aiming to leverage the full spectrum of available data, as combining these sources requires considerable preprocessing and harmonization efforts. Consequently, many MLIPs are trained on scattered and non-homogeneous datasets, potentially restricting their generalizability and predictive power, while introducing chemical bias due to the way the datasets are separately being used to train these models [36]. Moreover, large architectures—some now comprising over 30 million parameters—stand to benefit from the access to even bigger and more diverse datasets, as further scaling require proportionally more data to avoid overfitting and fully realize their expressive power [25].

To overcome these limitations, we introduce LeMat-Traj, a large-scale, aggregated dataset of materials trajectories. LeMat-Traj harmonizes data from three prominent sources: Materials Project [17, 18], Alexandria [36], and OQMD [34], into a unified format, encompassing calculations performed with various DFT functionals (PBE, PBESol, SCAN, and r2SCAN). Furthermore, we introduce `LeMaterial-Fetcher`, an open-source Python library designed for the systematic and reproducible curation of materials science datasets.

Our contributions can be summarised as follows:

1. We release LeMat-Traj, to our knowledge one of the largest publicly available datasets of crystalline materials trajectories (120 million configurations). LeMat-Traj provides dense, high-quality coverage of near-equilibrium and low-force states—an underrepresented but crucial regime for accurate geometry optimization.
2. We empirically demonstrate the value of this data philosophy through extensive benchmarks. We show that by fine-tuning a MACE model with LeMat-Traj, we can reduce force prediction errors on relaxation tasks by over 36% and improve performance on the Matbench Discovery stability benchmark by 10%.
3. We introduce LeMaterial-Fetcher, a modular and extensible open-source library used to create LeMat-Traj. It provides a reproducible platform for community-driven curation, extension, and combination of large-scale materials datasets, enabling future research in multi-dataset and curriculum learning strategies.

We believe LeMat-Traj and LeMaterial-Fetcher will serve as a versatile foundation for the community, supporting not only the training of MLIPs but also a wide range of downstream tasks with crystalline materials, including benchmarking, subsampling strategies, self-supervised pretraining, and curriculum learning.

2 Related Work

The development of MLIPs has been closely correlated with the availability of suitable training datasets [7, 18, 22]. These datasets typically consist of sequences of atomic configurations, along with their corresponding energies and forces, generated from quantum mechanical simulations. Such sequences, often referred to as *trajectories*, can originate from various simulation types, including geometry optimizations (tracing paths to energy minima) or molecular dynamics (MD, exploring configurations at specific thermodynamic conditions). Large-scale computational materials science initiatives like the Materials Project [17, 18], Alexandria [35, 36], and the Open Quantum Materials Database (OQMD) [34], along with resources like AFLOW [13], NOMAD [10], and ColabFit [43], have provided invaluable data to the community.

While MLIPs are frequently trained using data derived from these sources such as MPtrj [8] which curates relaxation trajectories from the Materials Project and has been used in models like CHGNet [8], MACE [4] and subsequent architectures, practitioners frequently encounter challenges [28]. Data from these diverse sources may employ different DFT parameters (e.g., functionals, k-points, pseudopotentials), varying data formats, and inconsistent preprocessing methodologies [33]. This fragmentation means that combining data requires considerable, often repetitive, data engineering efforts [45], potentially limiting the generalizability and predictive power of the resulting MLIPs, and can introduce chemical biases depending on how individual datasets are leveraged [28].

In parallel, two main philosophies of dataset design for training such MLIPs have emerged. One emphasizes broad exploration of the potential energy surface through high-force sampling, as in OMat24 [3], MatPES [19] or MP-ALOE [20], and active-learning datasets like ANI-1x [39]. These are well suited for pretraining robust models and capturing diverse regions of the configuration space [14]. The other focuses on dense, near-equilibrium sampling from DFT geometry optimization trajectories, which provide clean, structured data in the low-force regime critical for accurate geometry optimization and stability prediction with datasets like Alexandria [36]. Since machine learning force fields often display varying accuracy across the potential energy surface, with near-equilibrium and high-force regions posing different challenges [42, 26], these two philosophies of dataset design reflect complementary but compatible strategies to address that imbalance.

Recent work has underscored the need for large, harmonized, and extensible datasets that bridge these philosophies and mitigate fragmentation [19, 36]. Our contribution follows this direction by introducing a systematically curated dataset of DFT trajectories together with an open-source pipeline to ensure reproducibility and extensibility. This places our work in line with ongoing efforts toward foundational datasets in materials science that can serve pretraining, benchmarking, and fine-tuning across a wide range of downstream MLIP applications.

Our work aims to address the data fragmentation challenge by providing not only a large, aggregated dataset but also a transparent, reproducible curation pipeline with LeMaterial-Fetcher. This aligns with the increasing need for foundational datasets in materials science [19] that are large-scale, internally coherent, and extensible, facilitating pretraining, benchmarking, and fine-tuning across a wide range of downstream MLIP applications.

3 Methodology

LeMat-Traj is constructed by aggregating and processing data primarily from three major materials databases: Materials Project, Alexandria and OQMD (Open Quantum Materials Database). The core challenge lies in developing a scalable and reproducible methodology to handle the existing heterogeneity of these sources into a single and unified dataset.

3.1 Unified Generation Pipeline

To address this, we developed LeMaterial-Fetcher, a highly parallelized Python-based open-source library described in Figure 1. It provides a unified and automated framework for:

- **Fetching**: Interfacing with open APIs and direct downloads from various data sources.
- **Transformation**: Converting diverse input formats and attributes into a consistent schema. This includes standardizing atomic structure representations, energy units, and force compo-

nents. It also handles the extraction and organization of metadata related to DFT calculations. All of this is done by allowing to interface with powerful atomistic modelling tools like `Pymatgen` [30], `Matminer` [44].

- **Validation**: Implement checks to ensure data quality and integrity, such as verifying physical plausibility or consistency across reported values.
- **Harmonization**: Aligning DFT calculation parameters where possible and creating separate splits of data based on key parameters like the DFT functional.
- **Push**: Exporting the curated dataset in a user-friendly and efficient format, for direct use with libraries like HuggingFace's `Datasets` [23]. This allows for easy integration with existing ML frameworks and tools, because they can adapt to limited computational resources, but also data versioning and metadata tracking as outlined in [10].

LeMaterial-Fetcher is designed to be modular, extensible but also scalable and fast, allowing for the easy integration of new data sources (e.g., future integration of quantum calculations sources) and adaptation to more materials science domains such catalysis, experiments, defects. This framework ensures the reproducibility of LeMat-Traj and facilitates continuous integration of new DFT calculations as they become available from the source databases. Mainly, this eliminates the need to have to manually go through every dataset one by one, download it, and then apply the updates before releasing new versions. Additional details on the pipeline design are provided in Appendix E.

3.2 Data Sources and Harmonization

LeMat-Traj specifically extracts geometry optimization trajectories from DFT calculations. A key aspect of our curation is the harmonization of data across different exchange–correlation functionals. We categorize trajectories based on the reported functional, primarily focusing on PBE, PBESol, SCAN, and r2SCAN, allowing users to train functional-specific models or to explore multi-fidelity learning across levels of theory (section 5). Table 1 gives a full summary of the dataset repartition.

The dataset follows the OPTIMADE specification [2], enabling interoperability with other datasets that follow the same standard. We introduce a slight adaptation to accommodate trajectory data: each entry in the database corresponds to an individual atomistic configuration, which is part of a trajectory and is associated with energy and force information. Full optimization trajectories can be reconstructed by grouping entries by a shared trajectory identifier. This design choice facilitates seamless integration into machine learning interatomic potential (MLIP) training pipelines, where per-frame forces and energies are required.

To support trajectory-specific use cases, two new fields are introduced into the schema:

1. **Relaxation Step**: An integer indicating the step number of the structure within a given geometry optimization sequence.
2. **Relaxation Number**: An identifier that distinguishes different optimization runs for the same initial structure. This is particularly useful in high-throughput settings, where structures may undergo coarse relaxations before being re-relaxed with tighter thresholds or more accurate methods.

Table 1: Number of trajectories and atomic configurations per source database and functional.

Functional	Database	Number of Trajectories	Number of configurations
PBE	Materials Project	195,721	3,649,785
	Alexandria	3,414,074	110,804,226
	OQMD	135,966	264,782
PBESol	Materials Project	39,981	309,873
	Alexandria	252,791	6,099,623
SCAN	Materials Project	7,756	180,528
r2SCAN	Materials Project	37,888	516,576

3.3 Data Filtering

Our data filtering strategy prioritizes retaining a large volume of diverse configurations while establishing essential quality control. To this end, several criteria were applied: First, any atomic configuration lacking either energy or atomic force data was discarded. Second, entire trajectories were removed if the energy difference between the penultimate and final optimization step exceeded a threshold of 2×10^{-2} eV, a criterion adapted from MPtrj [8] to ensure reasonable convergence. Third, trajectories were also excluded if the maximum atomic force norm in the final configuration surpassed 0.2 eV/Å, i.e. the structure is not fully relaxed. While this force threshold is relatively high, it allows the inclusion of structures that, despite not being fully relaxed, still provide valuable information about the potential energy surface far from equilibrium, enriching the dataset for training robust force fields. Finally, all configurations were validated against the OPTIMADE format specifications, and any entry failing these schema checks or other implemented validation tests was removed.

4 Coverage of Chemical and Configurational Space

LeMat-Traj comprises approximately 120 million atomic structures derived from geometry optimization trajectories. The dataset is partitioned based on the DFT functional used for the calculations: PBE, PBESol, SCAN, and r2SCAN. This partitioning facilitates targeted model training and research into multi-fidelity approaches.

4.1 Chemical and Structural Diversity

We compare the elemental and structural diversity of LeMat-Traj with other popular datasets such as MPtrj [8] and MatPES [19]. LeMat-Traj aims to offer a broader coverage by combining multiple sources as illustrated in Figure 2. While MPtrj primarily focuses on Materials Project data, LeMat-Traj's explicit harmonization and inclusion of OQMD and Alexandria data offer a unique combination of scale and more balanced distribution.

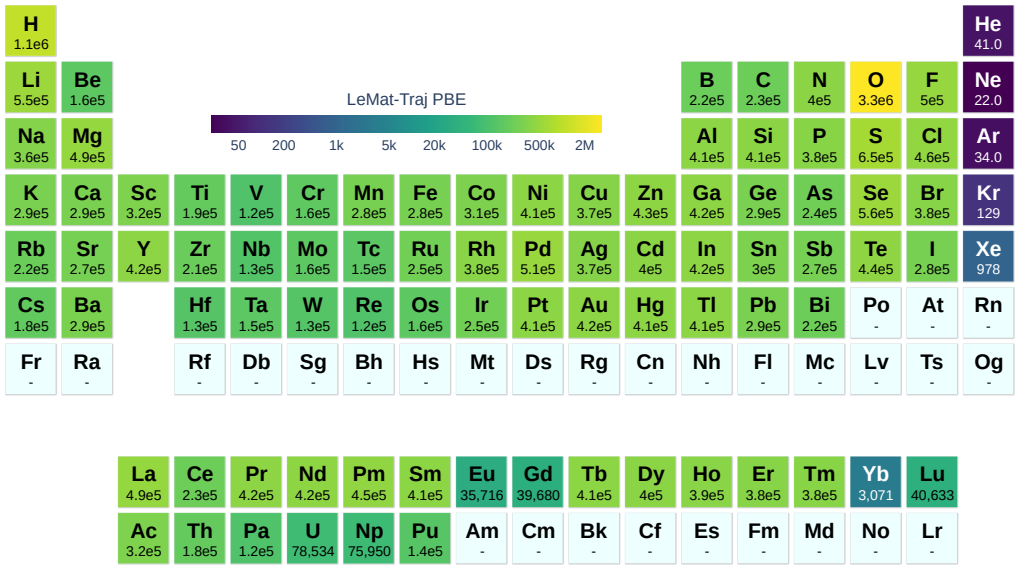


Figure 2: Chemical distribution in number of trajectories for the PBE split of LeMat-Traj using `Pymatviz` [32].

While the Alexandria dataset constitutes the majority of the PBE split by volume (approx. 92%), the inclusion of data from Materials Project and OQMD is critical for diversity. First, it enriches the chemical space; Materials Project contains a higher concentration of oxides and battery materials, balancing the bi-metallic bias present in Alexandria. Second, it diversifies the force distribution; the average maximum force norm in Materials Project trajectories is significantly higher (593 meV/Å)

than in the rest of the dataset (110 meV/Å), providing crucial high-force examples that help prevent models from under-estimating forces during relaxation.

Inclusion of Equilibrium Structures. A notable feature of LeMat-Traj is the inclusion of equilibrium structures from OQMD, which is rarely leveraged by ML practitioners when training machine-learned interatomic potentials (MLIPs). These configurations, characterized by near-zero atomic forces, serve as valuable reference points for MLIPs, particularly in capturing energy minima accurately. While relaxation trajectories naturally include low-force structures near convergence, the explicit addition of a large and diverse set of OQMD equilibrium configurations enhances the dataset's richness. Although these single-point structures may be underrepresented compared to the total number of frames in full trajectories, they can be strategically leveraged by models focused on accurately learning stable configurations.

4.2 Trajectory Analysis

Trajectory Length. Figure 3 shows the distribution of trajectory lengths in LeMat-Traj. LeMat-Traj exhibits a broad distribution, with many trajectories across all length scales. It uniquely features a long tail with a significant number of trajectories extending beyond 100 frames, and even exceeding 1000 frames. In contrast, MPtrj is predominantly characterized by shorter trajectories, with the majority having fewer than 50 frames and a pronounced spikiness in its distribution at very short lengths. MatPES shows a broader distribution than MPtrj, with more medium-length trajectories (up to 100-200 frames), but still lacks the extensive representation of very long trajectories seen in LeMat-Traj. These longer trajectories are not indicative of optimization issues but are rather a feature of the highly stringent convergence criteria used in the source calculations, representing valid, but slow, convergence paths to energy minima.

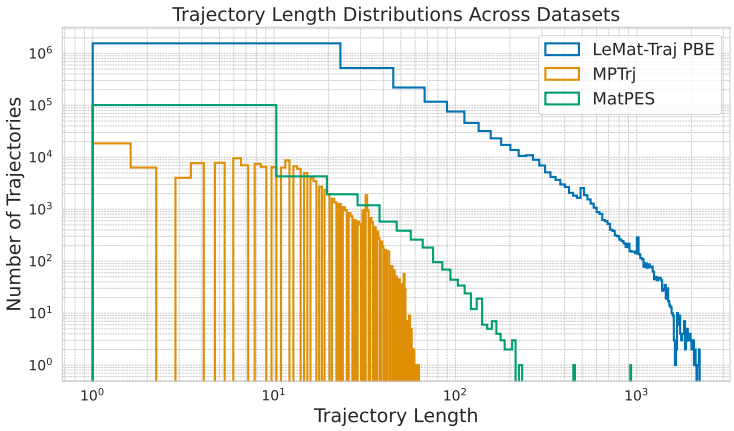
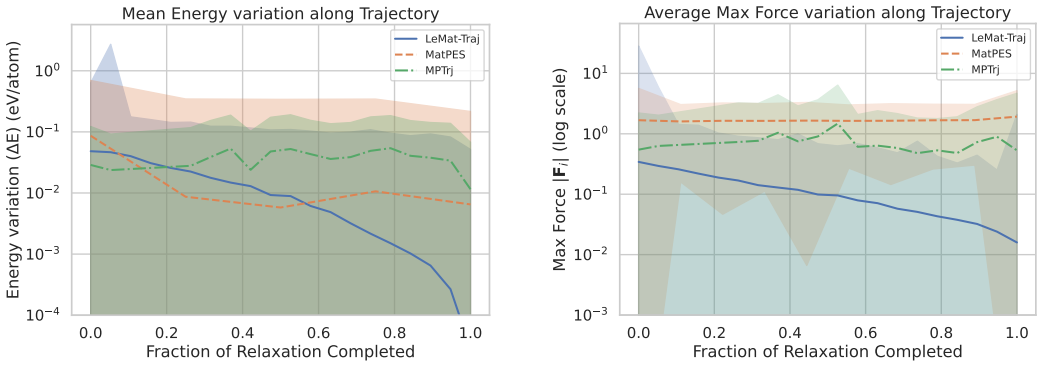


Figure 3: Comparison of trajectory length distributions for LeMat-Traj (PBE split), MPtrj, and MatPES, on a log-log scale. For every trajectory, the number of configurations associated is computed. LeMat-Traj exhibits a broader range of trajectory lengths.

Targets spread along trajectories. Figure 4 illustrates the evolution of mean energy variation (ΔE relative to the final relaxed state) and average maximum atomic forces norm throughout the relaxation trajectories of LeMat-Traj, MatPES, and MPtrj. LeMat-Traj uniquely demonstrates comprehensive sampling across the entire relaxation pathway. At the initial stages (low fraction of relaxation completed), it encompasses a wide distribution of high-energy and high-force configurations, with mean ΔE around 0.05 eV/atom (and variance extending >1 eV/atom from structures that are very far from their relaxed states iniially) and mean maximum forces around 0.3-0.4 eV/Å (variance extending >1 eV/Å). Crucially, as relaxations progress towards completion, LeMat-Traj systematically converges to very low ΔE (approaching $10^{-3} - 10^{-4}$ eV/atom) and near-zero maximum forces (mean 0.01-0.02 eV/Å, with significant density below 10^{-3} eV/Å). This shows a robust sampling both far-from-equilibrium states and accurately representing near-equilibrium energy minima and low-force structures, making LeMat-Traj well-suited for training versatile MLIPs capable of both high accuracy for stable configurations and robustness across diverse energy landscapes.



(a) $\Delta E = E^t - E^T$ (b) Maximum Force Norm

Figure 4: Evolution of mean energy variation ($\Delta E = E^t - E^T$, where E^t is current step energy and E_T is final relaxed energy) per atom (a) and average maximum atomic force (b) as a function of the fraction of relaxation completed. Trajectories from LeMat-Traj, MatPES, and MPtrj are binned by their normalized progress. Solid lines represent the mean values, and shaded areas depict one standard deviation, both on a logarithmic y-axis. LeMat-Traj demonstrates comprehensive sampling from high-energy/high-force initial states to well-converged, low-energy/low-force final states.

5 Results

To empirically validate the utility of LeMat-Traj, we conduct a series of benchmark experiments using the MACE architecture [4], a well-established and performant equivariant model. These experiments are designed to demonstrate the dataset's value for improving model accuracy on relaxation-focused tasks, both through fine-tuning and in downstream applications. A key hypothesis of our work is that LeMat-Traj's dense sampling of near-equilibrium states is complementary to datasets focused on high-force configurations. While high-force data, such as in OMat24, provides strong gradients that facilitate stable initial training and learning of the general energy landscape, LeMat-Traj is designed to refine model accuracy in the low-force regime critical for geometry optimization.

5.1 Complementary Value for Fine-Tuning

To test our hypothesis, we evaluate the performance of a MACE model pre-trained on the general-purpose OMat24 dataset and then fine-tune it on LeMat-Traj. As shown in Table 2, while the OMat24-trained model serves as a strong baseline, fine-tuning on LeMat-Traj reduces the Forces MAE on our held-out test set of relaxation trajectories by over 36%. This result provides direct evidence that LeMat-Traj contains critical information for achieving high fidelity in force predictions near energy minima, a crucial capability for accurate geometry optimization.

Table 2: Performance of MACE on the LeMat-Traj PBE 10K held-out test set. Fine-tuning a model pre-trained on OMat24 with LeMat-Traj significantly reduces prediction errors, demonstrating the complementary nature of the datasets.

MACE Training Dataset	Energy MAE (meV) ↓	Forces MAE (meV/Å) ↓	Forces Cos ↑
OMat24	59.5	42.7	0.29
MPtrj	49.8	81.7	0.23
MatPES PBE	316.4	88.7	0.16
LeMat-Traj only	25.3	50.8	0.23
OMat24 + ft LeMat-Traj	**18.8**	**27.2**	**0.30**

5.2 Downstream Performance on Matbench Discovery

To assess practical utility, we evaluate our models on a subset of the Matbench Discovery benchmark, which measures a model's ability to predict the stability of novel crystalline materials. This task relies heavily on accurate structural relaxation. Table 3 shows that the MACE model trained on a split of LeMat-Traj with left-out matching protocol from Matbench Discovery following the method in Barroso-Luque et al. [3] significantly outperforms the same model architecture trained on OMat24 or MPtrj alone, achieving a 10% higher F1 score. The best performance is achieved by the model pre-trained on OMat24 and fine-tuned on LeMat-Traj, reinforcing the value of combining high-force and near-equilibrium data,

Table 3: Matbench Discovery benchmark results on a 50k uniform subset. Models incorporating LeMat-Traj data achieve superior performance in predicting material stability.

Model (Training Set)	**F1 Score ↑**	**MAE (meV) ↓**	**RMSE (meV) ↓**
MACE (OMat24)	0.575	87.8	172.8
MACE (MPtrj)	0.694	47.2	83.9
MACE (LeMat-Traj Full)	0.768	37.2	69.0
MACE (OMat24 + ft-LeMat-Traj)	**0.772**	**33.4**	**67.8**

5.3 Multi-Fidelity Learning.

A notable challenge in materials modeling is the transferability of MLIPs trained on data from one level of theory (e.g., a specific DFT functional) to another. LeMat-Traj, with standardized formats of its different splits for PBE, PBESol, SCAN, and r2SCAN, provides a natural testbed for multi-fidelity learning strategies. We conduct experiments to assess how well models trained on one functional (e.g., PBE) can be fine-tuned or adapted for tasks involving another functional (e.g., PBESol and r2SCAN). For each of the PBESol and r2SCAN datasets, we use the subset described in Appendix D.1 during the experiments.

1. We train a MACE model from scratch (using the same number of parameters as `MACE-MPA-0` [5]). The training procedure is done in two stages (similar to how the foundation model is trained from scratch). During the first stage, the forces' weight in the loss computation is way higher than the other predicted targets, then during the second stage, we match the energy weight to that of the forces weight.
2. We fine-tune that same model separately on the split.

Evaluation results on the test set are reported in Table 4. LeMat-Traj helps facilitate effective transfer learning across functionals, especially when data or computational resources are limited, and can help in the development and research of general cross-atomic data source learning methods like Shoghi et al. [37], Huang et al. [16]. Results show that using a model pre-trained on one functional helps transferring to another functional more easily and in fewer steps.

Table 4: Performance of pre-trained MACE and ORB Models on Different DFT Functionals split when fine-tuning on a functional split (referred to with `<split>`) and after fine-tuning (`-<split>-ft`). Energy MAE is reported in meV/atom, Force MAE in meV/Å, Stress MAE in meV/Å^3, and Cosine Similarity is averaged over the forces vectors. All measures are across the test split described in Appendix D.

Model	PBESol				r2SCAN		
	Energy MAE	Force MAE	Stress MAE	Cosine Sim.	Energy MAE	Force MAE	Cosine Sim.
`MACE-MPA-0`	370.9	101	14.7	0.13	9204.9	111	0.15
`MACE-PBESol`	51.2	33	2.1	0.04	/	/	/
`MACE-MPA-0-PBESol-ft`	18.0	27	1.6	0.19	/	/	/
`MACE-r2SCAN`	/	/	/	/	141.7	36	0.09
`MACE-MPA-0-r2SCAN-ft`	/	/	/	/	96.3	28	0.22

5.4 Limitations and Future Work

While LeMat-Traj and LeMaterial-Fetcher mark substantial advancements, several areas offer opportunities for improvement. The current dataset primarily consists of DFT geometry optimization trajectories, and does not include molecular dynamics (MD) trajectories, which could enhance modeling of dynamic properties. Additionally, although the dataset is chemically diverse, the PBE split is largely drawn from the Alexandria database, potentially introducing some data source bias. Future work should aim to incorporate MD trajectories and correctly identify them to diversify data origins, while ensuring compatibility and avoid incorporating noisy data points. This initial release primarily focuses on dataset construction and characterization; comprehensive benchmarking of MLIPs trained on LeMat-Traj is planned to fully demonstrate its utility (preliminary results in Appendix D). Finally, the pipeline in LeMaterial-Fetcher is designed to gather detailed DFT calculation parameters if available from the source (e.g., k-point meshes, pseudopotentials). While not fully exploited in the current version of LeMat-Traj for all entries, this capability can help introduce future MLIP architectures that explicitly embed these parameters as inputs, leading to more versatile multi-fidelity models, enabling LeMat-Traj to continually evolve as a richer resource for the community. Aggregating data from sources using different underlying DFT parameters (e.g., k-point grids, pseudopotentials) without explicit harmonization risks introducing noise. While we ensure pseudopotential compatibility for included elements following the method in Siron et al. [38], a deeper quantitative analysis of these potential cross-database biases is an important area for future investigation. We note that LeMaterial-Fetcher's provenance tracking is a first step, enabling researchers to isolate and study these effects.

6 Conclusion

In this work, we introduced LeMat-Traj, a scalable, high-quality and unified dataset comprising over 120 million atomic configurations from DFT relaxation trajectories, and LeMaterial-Fetcher, the open-source library enabling its creation and continued evolution. By aggregating, standardizing, and harmonizing data from prominent repositories across multiple DFT functionals, LeMat-Traj lowers the barrier for training robust, transferable, and accurate MLIPs, which are essential technical bricks of accelerated materials discovery. Our analysis demonstrates its comprehensive sampling of the potential energy surface along relaxation pathways, capturing both high-energy structures and near-equilibrium states, making it a valuable resource for researchers to develop next-generation interatomic potentials, explore multi-fidelity learning, and advance self-supervised learning techniques in materials science.

While LeMat-Traj currently focuses on geometric optimization trajectories, the modularity of LeMaterial-Fetcher enables future expansions. With the incorporation of compatible molecular dynamics simulations, diversifying data sources further, and implementing dataset-level sampling strategies for more coherent fine-tuning datasets. Integrating LeMaterial-Fetcher with automated active learning and DFT calculation workflows can enable the continuous enrichment of LeMat-Traj with high-fidelity data. We believe LeMat-Traj and LeMaterial-Fetcher represent a step towards democratizing access to high-quality, curated training data, fostering community collaboration, and ultimately accelerating the pace of data-driven materials discovery

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