

# INTRODUCTION TO ATOMIC CLUSTER EXPANSION

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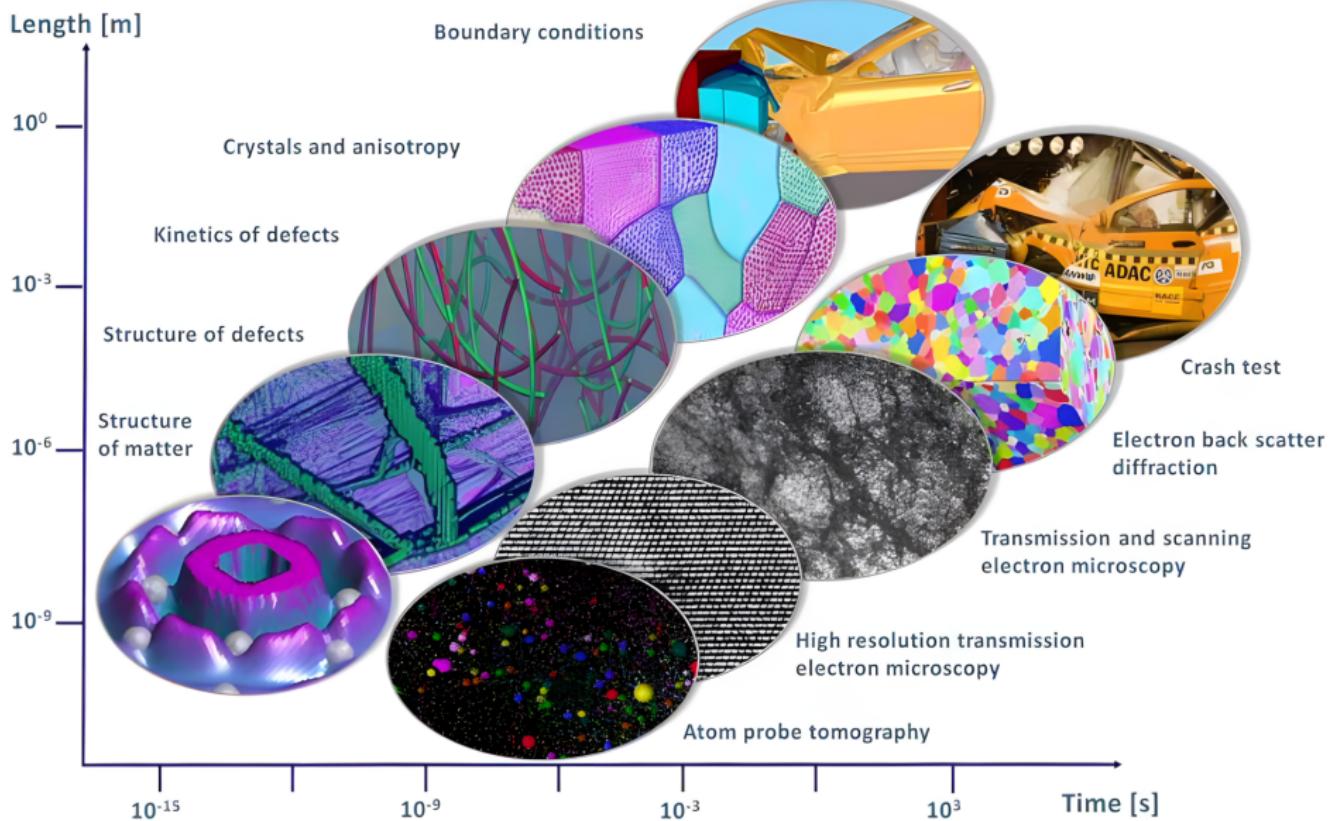
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Research  
England

Lancaster AI Reading Group

# LENGTH- AND TIME-SCALES IN MULTISCALE MODELLING



## MOTIVATION: ATOMISTIC SCALE MODELLING WITH INTERATOMIC POTENTIALS

(Live demonstration in Ovito)

# FOUNDATIONAL MODELS

The image displays six screenshots from different Nature journals, each showing a research article related to deep learning and material discovery:

- nature communications**: Article titled "E(3)-equivariant graph neural networks for data-efficient and accurate interatomic potentials" by Simon Batzner, Albert Musaelian, Lixin Sun, Mario Geiger, Jonathan P. Mailoa, Mordechai Kornbluth, Nicola Molinari, Tess E. Smidt & Boris Kozinsky. Published on 04 May 2022.
- nature machine intelligence**: Article titled "CHGNet as a pretrained universal neural network potential for charge-informed atomistic modelling" by Bowen Deng, Peichen Zhong, KyuJung Jun, Janosh Riebesell, Kevin Han, Christopher J. Bartel & Gerbrand Ceder. Published on 14 September 2023.
- nature computational science**: Article titled "A universal graph deep learning interatomic potential for the periodic table" by Chih-Chen Lin & Ghyslain Pringault. Published on 28 November 2022.
- nature**: Article titled "Scaling deep learning for materials discovery" by Alim Merchant, Simon Batzner, Samuel S. Schoenholz, Muratahan Aykol, Gowoon Cheon & Ekin Dogus Cubuk. Published on 29 November 2023.
- nature communications**: Article titled "Towards universal neural network potential for material discovery applicable to arbitrary combination of 45 elements" by So Takamoto, Chikashi Shinagawa, Daisuke Motoki, Kosuke Nakago, Wenwen Li, Iori Kurata, Taku Watanabe, Yoshihiro Yayama, Hiroki Iriuchi, Yusuke Asano, Tasuku Onodera, Takafumi Ishii, Takao Kudo, Ueda Otsu, Shigeto Suzuki, Naohiro Itohara, Masa Otsu, Taiki Yamamoto, Taekiki Kataoka, Atsushi

## Physics > Chemical Physics

[Submitted on 29 Dec 2023 (v1), last revised 1 Mar 2024 (this version, v2)]

## A foundation model for atomistic materials chemistry

Ilyes Batatia, Philipp Benner, Yuan Chiang, Alin M. Elena, Dávid P. Kovács, Janosh Reibesell, Xavier R. Advincula, Mark Asta, Matthew Avaylon, William J. Baldwin, Fabian Berger, Noam Bernstein, Arghya Bhowmik, Samuel M. Blau, Vlad Cărare, James P. Darby, Sandip De, Flaviano Della Pia, Volker L. Deringer, Rokas Elijošius, Zakariya El-Machachi, Fabio Falioni, Edvin Fako, Andrea C. Ferrari, Annalena Genreith-Schreiver, Janine George, Rhys E. A. Goodall, Clare P. Grey, Petr Grigorev, Shuang Han, Will Handley, Hendrik H. Heenen, Kersti Hermansson, Christian Holm, Jad Jaafar, Stephan Hofmann, Konstantin S. Jakob, Hyunwook Jung, Venkat Kapil, Aaron D. Kaplan, Nima Karimitari, James R. Kermode, Namu Kroupa, Jolla Kullgren, Matthew C. Kuner, Domantas Kuryla, Guoda Liepuoniute, Johannes T. Margraf, Ioan-Bogdan Magdău, Angelos Michaelides, J. Harry Moore, Akash A. Naik, Samuel P. Niblett, Sam Walton Norwood, Niamh O'Neill, Christoph Ortner, Kristin A. Persson, Karsten Reuter, Andrew S. Rosen, Lars L. Schaaf, Christoph Schran, Benjamin X. Shi, Eric Sivonxay, Tamás K. Stenczel, Viktor Svahn, Christopher Sutton, Thomas D. Swinburne, Jules Tilly, Cas van der Oord, Eszter Varga-Umbrich, Tejs Vegge, Martin Vondrák, Yangshuai Wang, William C. Witt, Fabian Zils, Gábor Csányi

Machine-learned force fields have transformed the atomistic modelling of materials by enabling simulations of ab initio quality on unprecedented time and length scales. However, they are currently limited by: (i) the significant computational and human effort that must go into development and validation of potentials for each particular system of interest; and (ii) a general lack of transferability from one chemical system to the next. Here, using the state-of-the-art MACE architecture we introduce a single general-purpose ML model, trained on a public database of 150k inorganic crystals, that is capable of running stable molecular dynamics on molecules and materials. We demonstrate the power of the MACE-MP-0 model - and its qualitative and at times quantitative accuracy - on a diverse set problems in the physical sciences, including the properties of solids, liquids, gases, chemical reactions, interfaces and even the dynamics of a small protein. The model can be applied out of the box and as a starting or "foundation model" for any atomistic system of interest and is thus a step towards democratising the revolution of ML force fields by lowering the barriers to entry.

Comments: 119 pages, 63 figures, 37MB PDF

Subjects: Chemical Physics (physics.chem-ph); Materials Science (cond-mat.mtrl-sci)

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(or arXiv:2401.00096v2 [physics.chem-ph] for this version)

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## SETUP

- Configuration space  $\Omega$  for particles  $\mathbf{x}_j \in \Omega$ . Examples:
    - Atoms with positions and chemical species:  
 $\mathbf{x}_j = (\mathbf{r}_j, Z_j) \in \Omega = \mathbb{R}^3 \times \mathbb{Z}$
    - Electrons with positions and spins:  
 $\mathbf{x}_j = (\mathbf{r}_j, \sigma_j) \in \Omega = \mathbb{R}^3 \times \{+1, -1\}$
    - Agents with beliefs/descriptors:  
 $\mathbf{x}_j = (\mathbf{r}_j, \mathbf{b}_j) \in \Omega = \mathbb{R}^3 \times B \quad (?)$
  - Generic configuration  $\mathbf{X} = \{\mathbf{x}_j\}_{j=1}^M \subset \mathbb{R}^3 \times \mathbb{R}^d$  (today  $d = 0$ ).
  - We want to derive an energy  $\mathbf{X} \mapsto E(\mathbf{X})$  that will match "the truth" very well [more on that later]
  - Often natural to expand  $E$  as a sum of site energies
- $$E(\mathbf{X}) = \sum_{i=1}^M E_i(\mathbf{X}_i), \quad \mathbf{X}_i = \{\mathbf{x}_{ij}\}_{j=1}^M, \quad \mathbf{x}_{ij} := \mathbf{x}_i - \mathbf{x}_j$$
- (translation invariance)
- Let  $G$  be a Lie group acting on  $\Omega$ . Function  $E_i$  is invariant under  $G$ :

$$E_i(g\mathbf{X}_i) = E_i(\mathbf{X}_i), \quad \forall g \in G$$

## MANY-BODY (CLUSTER) EXPANSION

$$E(\textcolor{brown}{X}) = \sum_{i=1}^M E_i(\textcolor{violet}{X}_i)$$

- Naive / historical expansion:

$$\begin{aligned} E_i(\textcolor{violet}{X}_i) &= V_0(\textcolor{violet}{x}_i) + \sum_{j_1=1}^M V_1(\textcolor{violet}{x}_{ij_1}) + \sum_{j_2=1}^M \sum_{j_1=1}^{j_2-1} V_2(\textcolor{violet}{x}_{ij_1}, \textcolor{violet}{x}_{ij_2}) \\ &\quad + \dots + \sum_{j_1 < \dots < j_N}^M V_N(\textcolor{violet}{x}_{ij_1}, \dots, \textcolor{violet}{x}_{ij_N}) \end{aligned}$$

- ACE expansion:

$$\begin{aligned} E_i(\textcolor{violet}{X}_i) &= U_0(\textcolor{violet}{x}_i) + \sum_{j_1=1}^M U_1(\textcolor{violet}{x}_{ij_1}) + \sum_{j_2=1}^M \sum_{j_1=1}^M U_2(\textcolor{violet}{x}_{ij_1}, \textcolor{violet}{x}_{ij_2}) \\ &\quad + \dots + \sum_{j_1, \dots, j_N}^M U_N(\textcolor{violet}{x}_{ij_1}, \dots, \textcolor{violet}{x}_{ij_N}) \end{aligned}$$

(spurious self-interactions added, worse scaling, so why bother?)

## HISTORICAL PERSPECTIVE: EMPIRICAL POTENTIALS

- Pair potential (Morse):

$$E_i(X_i) = \sum_{j=1}^M V_1(\mathbf{x}_{ij}), \quad V_1(\mathbf{x}) = \phi(|\mathbf{x}|),$$

$$\phi(r) = a_1 \left( \exp \left( -2a_2(r - a_3) \right) - 2 \exp \left( -a_2(r - a_3) \right) \right),$$

$$\mathbf{a} = (a_1, a_2, a_3) \in \mathbb{R}^3$$



## HISTORICAL PERSPECTIVE: EMPIRICAL POTENTIALS

- Many body potential (Stillinger-Weber):

$$E_i(X_i) = \sum_{j=1}^M V_1(\mathbf{x}_{ij}) + \sum_{j=1}^M \sum_{k=1}^{j-1} V_2(\mathbf{x}_{ij}, \mathbf{x}_{ik}),$$

$$V_1(\mathbf{x}_{ij}) = \psi(|\mathbf{x}_{ij}|), \quad \psi(r) = (a_1 r^{-a_2} - a_3 r^{-a_4}) \exp\left(\frac{1}{r - a_5}\right)$$

$$V_2(\mathbf{x}_{ij}, \mathbf{x}_{ik}) = \eta(|\mathbf{x}_{ij}|, |\mathbf{x}_{ik}|, \theta_{ijk})$$

$$\eta(r, t, \theta) = a_6 \exp\left(\frac{a_7}{r - a_8} + \frac{a_9}{t - a_{10}}\right) (\cos \theta_{ijk} + a_{11})^2$$

$$\mathbf{a} = (a_1, \dots, a_{11}) \in \mathbb{R}^{11}$$

## MANY-BODY (CLUSTER) EXPANSION

$$E(\textcolor{brown}{X}) = \sum_{i=1}^M E_i(\textcolor{violet}{X}_i)$$

- Naive expansion:

$$\begin{aligned} E_i(\textcolor{violet}{X}_i) &= V_0(\textcolor{violet}{x}_i) + \sum_{j_1=1}^M V_1(\textcolor{violet}{x}_{ij_1}) + \sum_{j_2=1}^M \sum_{j_1=1}^{j_2-1} V_2(\textcolor{violet}{x}_{ij_1}, \textcolor{violet}{x}_{ij_2}) \\ &\quad + \dots + \sum_{j_1 < \dots < j_N}^M V_N(\textcolor{violet}{x}_{ij_1}, \dots, \textcolor{violet}{x}_{ij_N}) \end{aligned}$$

- ACE expansion:

$$\begin{aligned} E_i(\textcolor{violet}{X}_i) &= U_0(\textcolor{violet}{x}_i) + \sum_{j_1=1}^M U_1(\textcolor{violet}{x}_{ij_1}) + \sum_{j_2=1}^M \sum_{j_1=1}^M U_2(\textcolor{violet}{x}_{ij_1}, \textcolor{violet}{x}_{ij_2}) \\ &\quad + \dots + \sum_{j_1, \dots, j_N}^M U_N(\textcolor{violet}{x}_{ij_1}, \dots, \textcolor{violet}{x}_{ij_N}) \end{aligned}$$

(spurious self-interactions added, worse scaling, so why bother?)

## EXPLOITING TENSOR PRODUCT STRUCTURE

- Each  $U_N : \mathbb{R}^{3N} \rightarrow \mathbb{R}$  is to be represented as a linear combination in a tensor product basis:

$$U_N(\mathbf{x}_{ij_1}, \dots, \mathbf{x}_{ij_N}) = \sum_{\mathbf{k}} a_{\mathbf{k}} \prod_{t=1}^N \phi_{\mathbf{k}_t}(\mathbf{x}_{ij_t})$$

where  $\mathbf{k} = (\mathbf{n}, \mathbf{l}, \mathbf{m}) \in \mathbb{R}^{3N}$  and

$$\phi_{(\mathbf{n}_t, \mathbf{l}_t, \mathbf{m}_t)}(\mathbf{x}_{ij_t}) = \underbrace{P_{\mathbf{n}_t}(|\mathbf{x}_{ij_t}|)}_{\text{radial part}} \underbrace{Y_{\mathbf{l}_t}^{m_t} \left( \frac{\mathbf{x}_{ij_t}}{|\mathbf{x}_{ij_t}|} \right)}_{\text{angular part}}$$

- Angular part is given by complex spherical harmonics

$$Y_l^m(\hat{x}) = P_l^m(\cos \theta) \exp(im\phi), \quad \hat{x} = (\cos \phi \sin \theta, \sin \phi \sin \theta, \cos \theta) \in \mathbb{R}^3$$

- $n_t, l_t \in \{0, 1, 2, \dots\}$  and  $m_t \in \{-l_t, \dots, 0, \dots, l_t\}$
- Truncation: sum over all  $\mathbf{k}$  such that  $|\mathbf{k}|_1 \leq T$  (defines set  $\mathcal{A}^N$ )

# DENSITY TRICK FOR COMPUTATIONAL TRACTABILITY

- Fubini's Theorem aka "density trick":

$$\sum_{j_1, \dots, j_N=1}^J \sum_{\mathbf{k} \in \mathcal{A}^N} a_{\mathbf{k}} \prod_{t=1}^N \phi_{\mathbf{k}_t}(\mathbf{x}_{ij_t}) = \sum_{\mathbf{k} \in \mathcal{A}^N} a_{\mathbf{k}} \prod_{t=1}^N \sum_{j=1}^J \phi_{\mathbf{k}_t}(\mathbf{x}_{ij})$$

- meaning that overall

$$\begin{aligned} E_i(\mathbf{X}_i) &= \sum_{N=1}^{\mathcal{N}} \sum_{j_1, \dots, j_N=1}^M U_N(\mathbf{x}_{ij_1}, \dots, \mathbf{x}_{ij_N}) \\ &= \sum_{N=1}^{\mathcal{N}} \sum_{\mathbf{k} \in \mathcal{A}^N} a_{\mathbf{k}} \underbrace{\prod_{t=1}^N \sum_{j=1}^J \phi_{\mathbf{k}_t}(\mathbf{x}_{ij})}_{=: A_{\mathbf{k}}^{(i)}} \\ &= \mathbf{a} \cdot A^{(i)} \end{aligned}$$

→ a linear model (!) with parameters  $\mathbf{a}$

$$(\mathbf{a} \in \mathbb{R}^\alpha, \alpha \sim 1000 - 100000)$$

## LAST STEP: ENFORCEMENT OF SYMMETRIES

- Recall that  $A_{\mathbf{k}}^{(i)} = \prod_{t=1}^N \sum_{j=1}^J \phi_{k_t}(x_{ij})$
- Basic idea is to "average over  $G$ :

$$B_{\mathbf{k}}^{(i)} := \int_G A_{\mathbf{k}}^{(i)} \circ \mathbf{g} H(d\mathbf{g}).$$

- Possible analytically (or with simple numerical scheme) if the basis is compatible with group  $G$ :

$$\phi_{k_t}(\mathbf{g}(\mathbf{x}_{ij_t})) = \sum_{k'} \underbrace{\alpha_{k_t k'_t}(\mathbf{g})}_{\in \mathbb{R}} \phi_{k'_t}(\mathbf{x}_{ij_t})$$

(applying group element to "relative particle" the same as a linear combination of the original basis).

- Bottom line:

$$B^{(i)} = \mathcal{C} A^{(i)}$$

where  $\mathcal{C}$  are (generalised) Clebsch-Gordan coefficients ( $\rightarrow$  can be precomputed, typically very sparse)

## GROUND TRUTH: A "PRIMER" ON QUANTUM MECHANICS

- In the Born-Oppenheimer approximation and further Hartree-Fock approximation, the ground energy of a system of  $M$  atomic nuclei at positions  $\mathbf{R} = \{\mathbf{R}_I\}_{I=1}^M$  with  $N$  electrons is given by

$$\mathcal{E}^{\text{QM}}(\mathbf{R}) \approx \min_{\{\Psi_1, \dots, \Psi_N\}} \left\{ \langle \hat{H} \psi^{\text{HF}}, \psi^{\text{HF}} \rangle \mid \langle \psi_i, \psi_j \rangle = \delta_{ij} \right\}.$$

- Hamiltonian operator  $\hat{H}$  is given by

$$\hat{H} = \left( \sum_{i=1}^N -\frac{1}{2} \nabla_i^2 + \sum_{\substack{i,j=1 \\ j \neq i}}^N \frac{1}{|\mathbf{r}_i - \mathbf{r}_j|} - \sum_{i=1}^N \sum_{I=1}^M \frac{Z_I}{|\mathbf{r}_i - \mathbf{R}_I|} + \frac{1}{2} \sum_{\substack{I,J=1 \\ J \neq I}}^M \frac{Z_I Z_J}{|\mathbf{R}_I - \mathbf{R}_J|} \right)$$

- The Euler-Lagrange equation is a nonlinear eigenvalue problem.  
By-product: Forces  $\mathcal{F}^{\text{QM}}(\mathbf{R}) = \nabla \mathcal{E}^{\text{QM}}(\mathbf{R})$ .

[VERY EXPENSIVE COMPUTATION]

- Training data:  $\{\mathbf{R}^{(i)}, \mathcal{E}^{\text{QM}}(\mathbf{R}^{(i)}), \mathcal{F}^{\text{QM}}(\mathbf{R}^{(i)}), \dots\}_i$

## TRAINING

- Let  $\mathcal{R} = \{\mathbf{R}^{(i)}\}_{i=1}^J$  be the training set of atomic configurations and  $\mathcal{E}_{\mathcal{R}} = \{\mathcal{E}_i^{\text{QM}}\}_{i=1}^J$  the corresponding “true” energy and  $\mathcal{F}_{\mathcal{R}} = \{\mathcal{F}_i^{\text{QM}}\}_{i=1}^N$  the “true” forces.
- Least squares  $\min_{\mathbf{a}} I(\mathbf{a})$  where

$$I(\mathbf{a}) = \sum_{i=1}^J \left( W_E^2 |E_{\mathbf{a}}(\mathbf{R}^{(i)}) - \mathcal{E}_i|^2 + W_F^2 |F_{\mathbf{a}}(\mathbf{R}^{(i)}) - \mathcal{F}_i|^2 \right)$$

- Rewrite as  $I(\mathbf{a}) = \|\mathbf{B}\mathbf{a} - \mathbf{Y}\|_{Q^{-1}}^2$ , where  $\mathbf{B} : \mathbb{R}^\alpha \rightarrow \mathbb{R}^{(3M+1)J}$  and  $\{\mathbf{B}\mathbf{a}\}_{i=1}^M = \{E_{\mathbf{a}}(\mathbf{R}^{(i)})\}_{i=1}^M$  and the remaining entries are forces and

$$Q^{-1} = \text{diag}(\underbrace{W_E^2, \dots, W_E^2}_{J-\text{times}}, \underbrace{W_F^2, \dots, W_F^2}_{3MJ-\text{times}})$$

- Tikhonov regularisation  $\min_{\mathbf{a}} \tilde{I}(\mathbf{a})$  where

$$\tilde{I}(\mathbf{a}) = \|\mathbf{B}\mathbf{a} - \mathbf{Y}\|_{Q^{-1}}^2 + \|\mathbf{a} - \bar{\mathbf{a}}\|_{P^{-1}}^2.$$

- (connection to Bayesian inference)

## SUMMARY

- Atomic Cluster Expansion is an instance of a Geometric Shallow Learning framework on graphs.
- It uses a decades-old idea of a body order expansion and makes it computationally tractable in the age of enormous computational resources.
- It prescribes geometric prior information which allows an explicit enforcement of symmetries and physical constraints and assumptions.
- It works amazingly well for atom-based systems!
- Perhaps there is scope to employ it in agent-based models?
- Robust UQ is surprisingly difficult (my on-going work on this)  
[MARS Summer Internship]

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