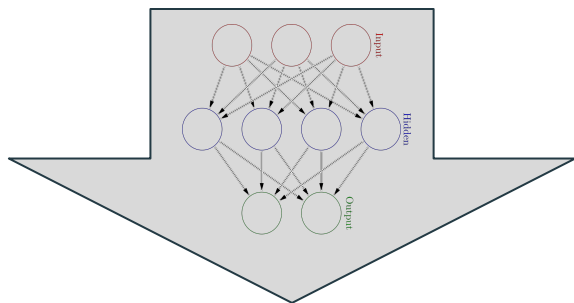
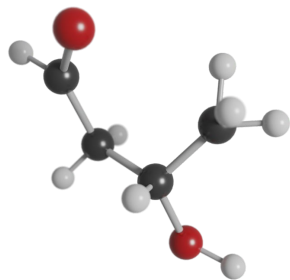


# LATTE: an atomic environment descriptor based on Cartesian tensor contractions

Franco Pellegrini, Stefano de Gironcoli, Emine Kucukbenli

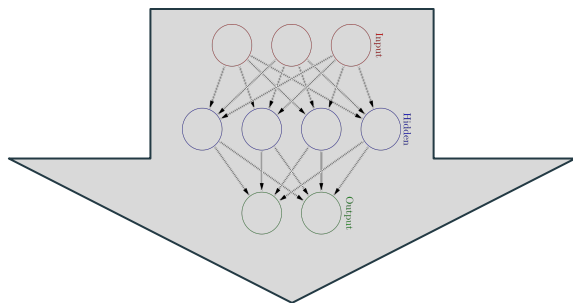
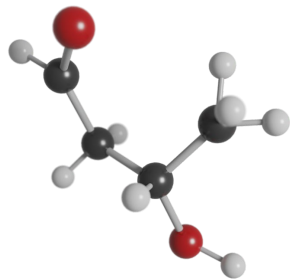


# Machine Learned Interatomic Potentials (MLIPs)



$$E(\rightarrow F)$$

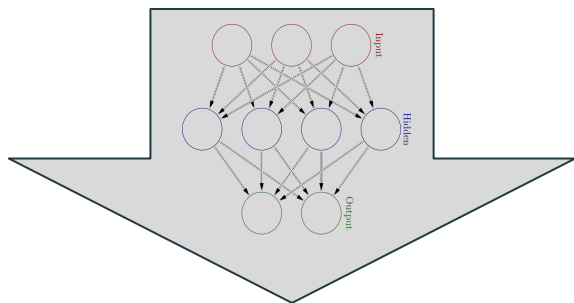
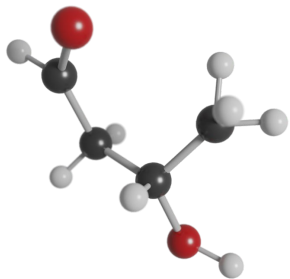
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  - It should extend to different systems
  - We want exact symmetries

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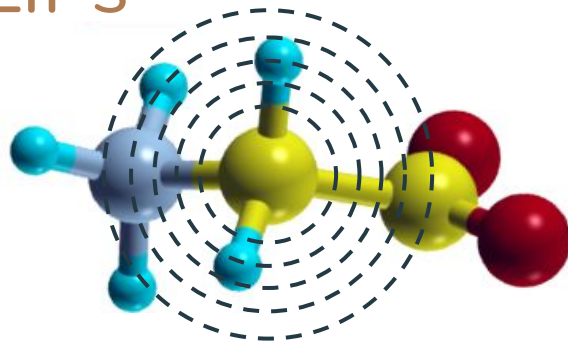


$$E(\rightarrow F)$$

- How to feed the structure to ML model?
  - It should extend to different systems
  - We want exact symmetries
- Sum of atomic energies based on local environments
  - How to describe it?
  - How to fit?

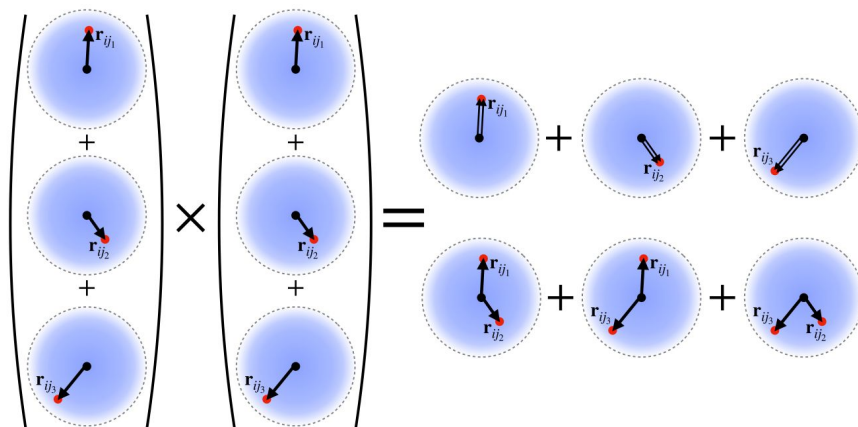
# (biased) evolution of MLIPs

- Fixed descriptor + NN (Behler-Parrinello)
  - Sampling 2, 3 bodies (bad scaling)
  - Decent accuracy with enough data



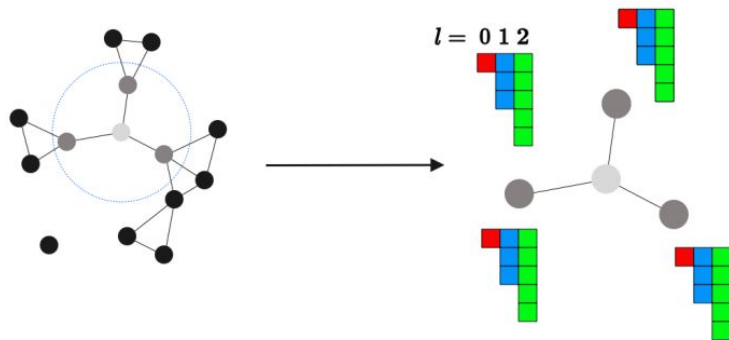
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Do we really need message passing increasing receptive field? (see Allegro)

Can we do better with invariants + MLP?



# Better descriptors (but linear models):

## Atomic Cluster Expansion

## Moment Tensor Potential

Sample local environment with radial functions and

Spherical Harmonics

$$A_{z_i, znlm} = \langle \rho_i^z | \phi_{nlm}^{z,z} \rangle = \sum_j \phi_{nlm}^{z,z}(\mathbf{r}_{ji})$$

where  $z_j = z$

Cartesian Tensors

$$M_{\mu,\nu}(\mathbf{n}_i) = \sum_j f_{\mu}(|r_{ij}|, z_i, z_j) \underbrace{\mathbf{r}_{ij} \otimes \dots \otimes \mathbf{r}_{ij}}_{\nu \text{ times}}$$

Product of  $N$  functions to obtain  $N+1$  bodies terms:

$$A_{z_i, \mathbf{v}} = \prod_{t=1}^{\nu} A_{z_i, \nu_t}, \quad \mathbf{v} = (\nu_1, \dots, \nu_{\nu})$$

$$L_{\mu, \nu} = \prod_{t=1}^N M_{\mu_t, \nu_t}$$

Symmetrize to have invariant contribution

$$B_{z_i, \mathbf{v}} := \int_{\hat{R} \in O(3)} \prod_{t=1}^{\nu} A_{z_i, \nu_t}(\{\hat{R}\mathbf{r}_{ij}\}) d\hat{R} = \sum_{\mathbf{v}'} C_{\mathbf{w}\mathbf{v}'} A_{z_i, \mathbf{v}'}$$

Contract indices to have invariant terms

$$L_{\mu} = \sum_{\nu} L_{\mu, \nu}$$

# Cartesian contractions: LATTE

(Local Atomic Tensors Trainable Expansion)

Mixed species, radially localized tensor sum:

$$A_{i,u}^{\alpha\beta} = \sum_{j \in \mathcal{N}(i)} \sigma_u(\mathbf{s}_i, \mathbf{s}_j) f_u(r_{ij}) \mathbf{r}_{ij}^\alpha \otimes \mathbf{r}_{ij}^\beta$$

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LEARNABLE

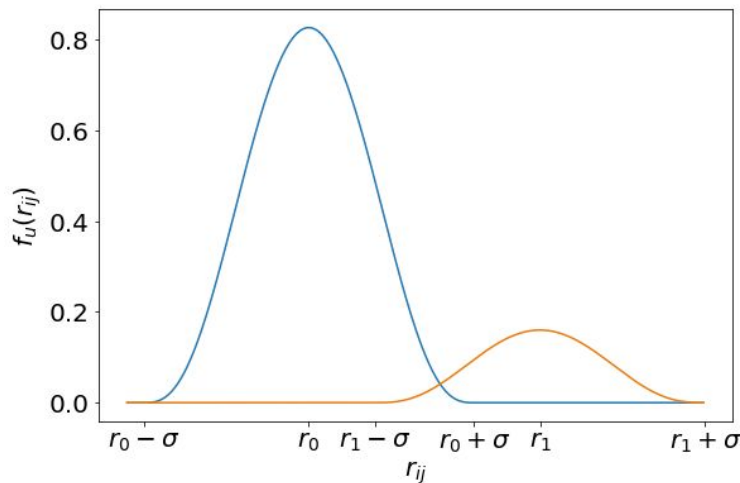
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$$f_u(r) = \frac{1}{r_u^2} \left[ \text{ReLU} \left( 1 - \left( \frac{r - r_u}{w_u} \right)^2 \right) \right]^3$$



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(Local Atomic Tensors Trainable Expansion)

Mixed species, radially localized tensor sum:

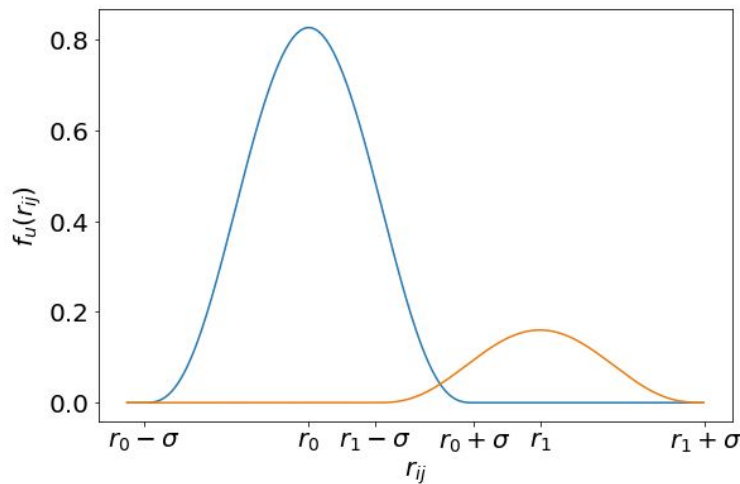
$$A_{i,u}^{\alpha\beta} = \sum_{j \in \mathcal{N}(i)} \sigma_u(s_i, s_j) f_u(r_{ij}) r_{ij}^\alpha \otimes r_{ij}^\beta$$

Tensor contraction to invariant descriptor element:

$$B_{i,u}^{(\alpha,\beta,\alpha\beta)} = \sum_{\alpha\beta} A_{i,u_1}^\alpha A_{i,u_2}^\beta A_{i,u_3}^{\alpha\beta}$$

VECTOR                      VECTOR                      TENSOR

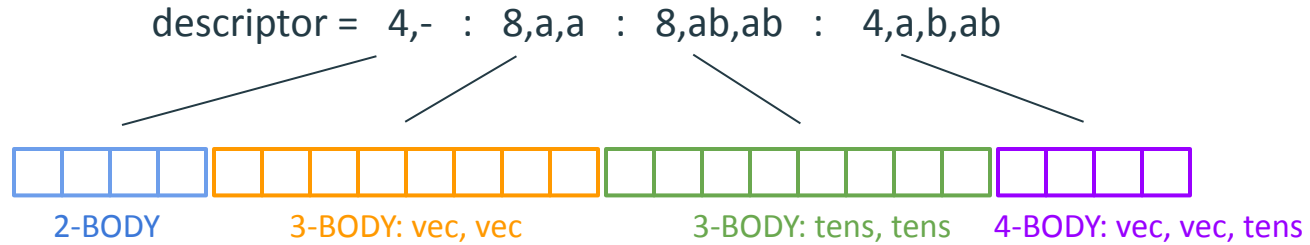
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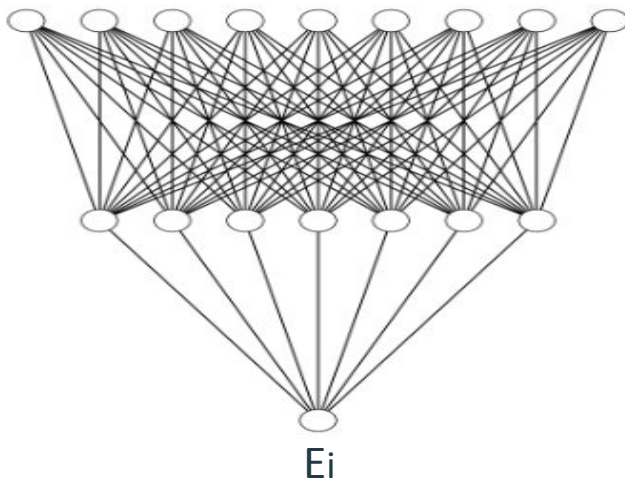
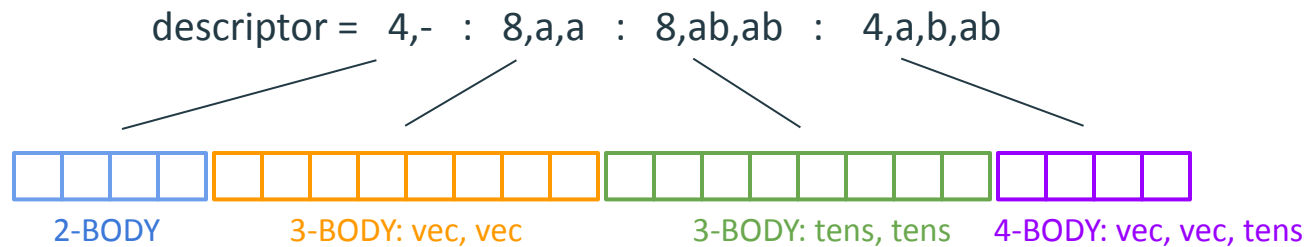
# Freely specify descriptor terms

descriptor = 4,- : 8,a,a : 8,ab,ab : 4,a,b,ab

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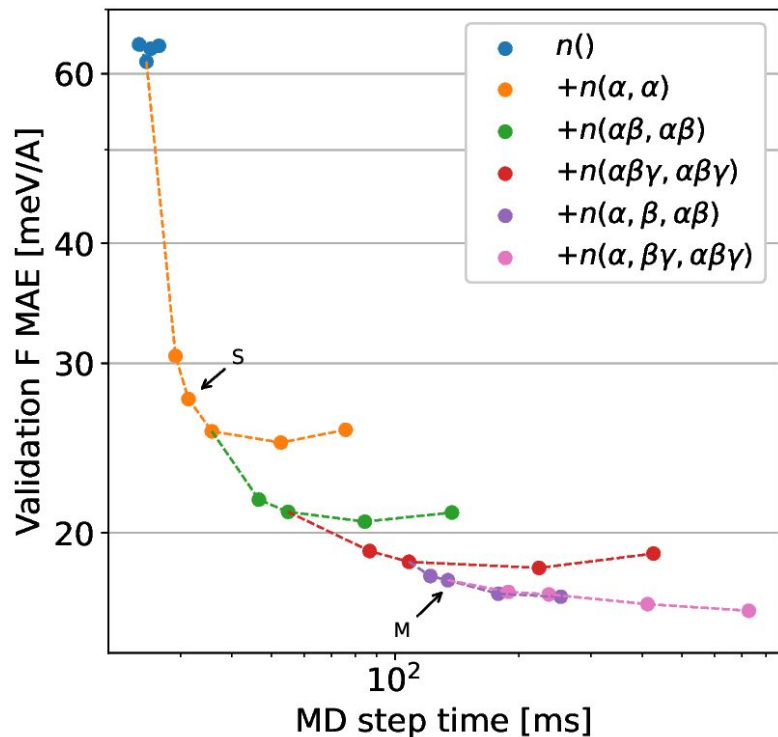


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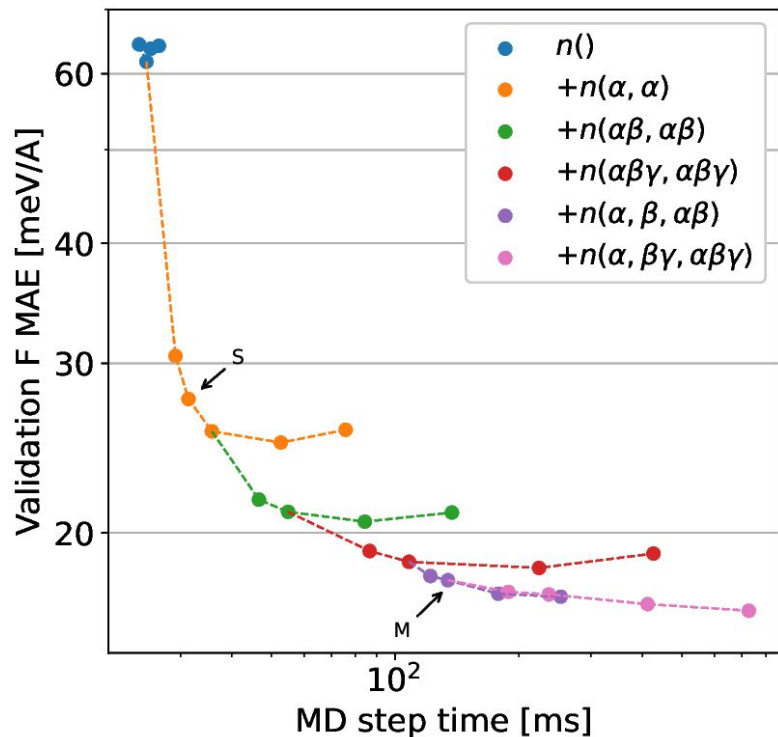




# Scaling with descriptor size/shape: rMD17



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		ACSF <sup>6</sup>	ACE <sup>20</sup>	LATTE small	LATTE medium	SOTA
Aspirin	E	10.6	6.1	9.5	5.7	2.2 <sup>25</sup>
	F	32.9	17.9	27.5	17.8	6.6
Azobenzene	E	5.8	3.6	7.0	3.3	1.2 <sup>26</sup>
	F	18.4	10.9	19.5	10.4	2.6
Benzene	E	1.0	0.04	0.73	0.42	0.3 <sup>26</sup>
	F	5.4	0.5	4.6	1.1	0.2
Ethanol	E	2.9	1.2	2.5	1.2	0.4 <sup>25,26</sup>
	F	16.5	7.3	14.2	6.3	2.1
Malonaldehyde	E	4.0	1.7	3.9	1.7	0.6 <sup>26</sup>
	F	24.3	11.1	20.4	10.6	3.6
Naphthalene	E	3.0	0.9	3.6	1.6	0.2 <sup>26</sup>
	F	13.2	5.1	15.1	6.3	0.9
Paracetamol	E	6.3	4.0	5.8	3.5	1.3 <sup>25</sup>
	F	22.0	12.7	20.9	12.6	4.8
Salicylic acid	E	4.1	1.8	4.1	2.4	0.9 <sup>26</sup>
	F	19.4	9.3	18.3	9.6	2.9
Toluene	E	3.9	1.1	3.6	1.5	0.5 <sup>25</sup>
	F	15.9	6.5	15.3	6.6	1.5
Uracil	E	2.4	1.1	3.2	1.1	0.6 <sup>26</sup>
	F	13.7	6.6	12.2	5.7	1.8

# Multi species: SPICE

- Drug-like molecules and peptides
- **15 species** (H, Li, C, N, O, F, Na, Mg, P, S, Cl, K, Ca, Br, I)
- 19k systems, **1.1M** configurations
  
- **SOTA: Allegro: 25 meV/Å** validation force MAE, speed  $\sim 10 \mu\text{s}/\text{step}/\text{atom}$
- **DeepMD** (transformer emb.): **233 meV/Å** validation force RMSE, speed  $\sim 20 \mu\text{s}/\text{step}/\text{atom}$
- **LATTE+NN**: down to **45 meV/Å** validation force MAE
  - JAX-MD: DHFR (23k atoms) on 1 A100 @1.7  $\mu\text{s}/\text{step}/\text{atom}$

# Conclusions

- Simple and fast descriptor + NN can reach good accuracy
- Can handle multiple bodies and species with good performance
- Implemented in PANNA package (JAX)

# The future

- Improve performance
- Better species embedding (generalization, ask Mina)



Thank you  
arXiv:2405.08137

