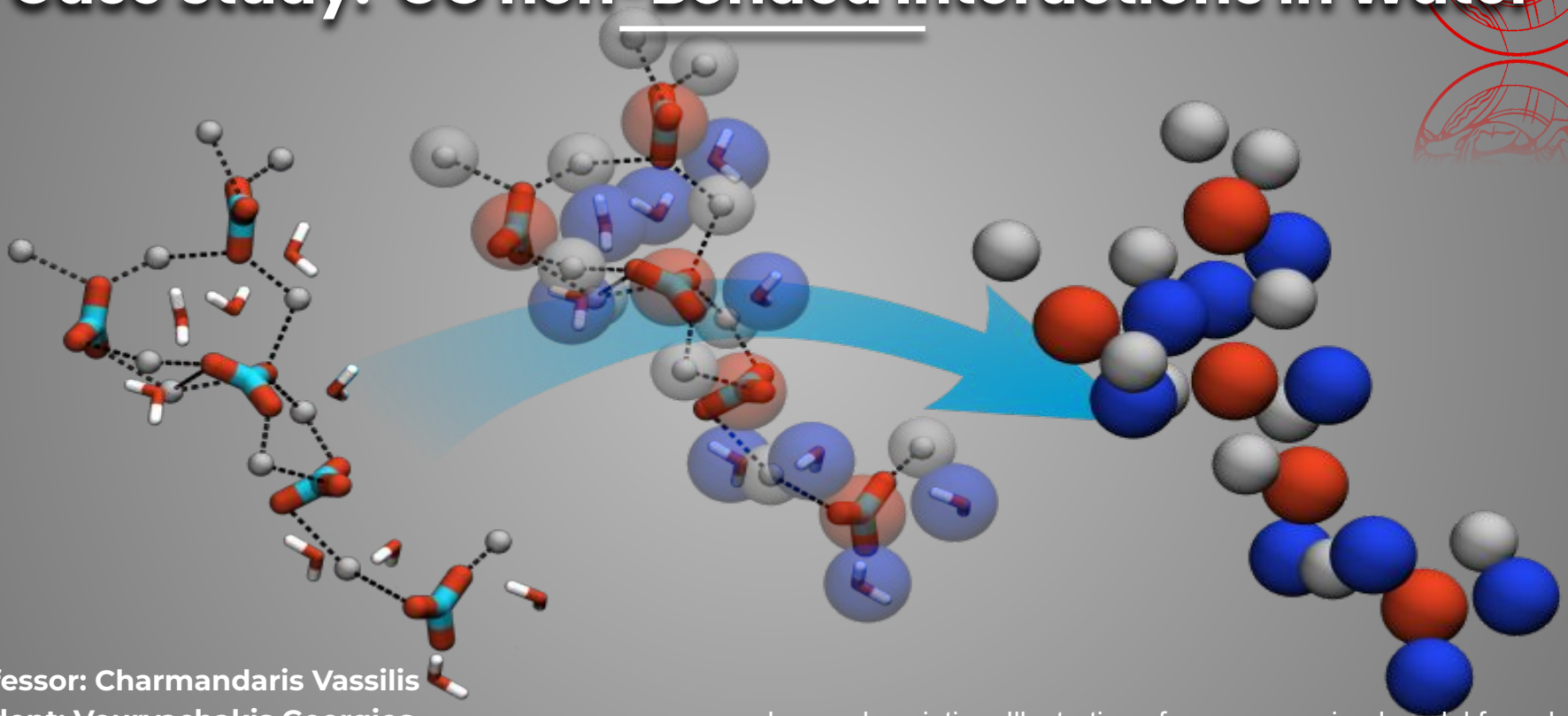


Coarse-Grained Molecular Dynamics

Case Study: CG non-Bonded Interactions in Water



Professor: Charmandaris Vassilis
Student: Vourvachakis Georgios
Date: 27/05/2025

Image description: Illustration of a coarse grained model for calcium minerals [University of Konstanz, VDM package]

High-Level
Description of
CG

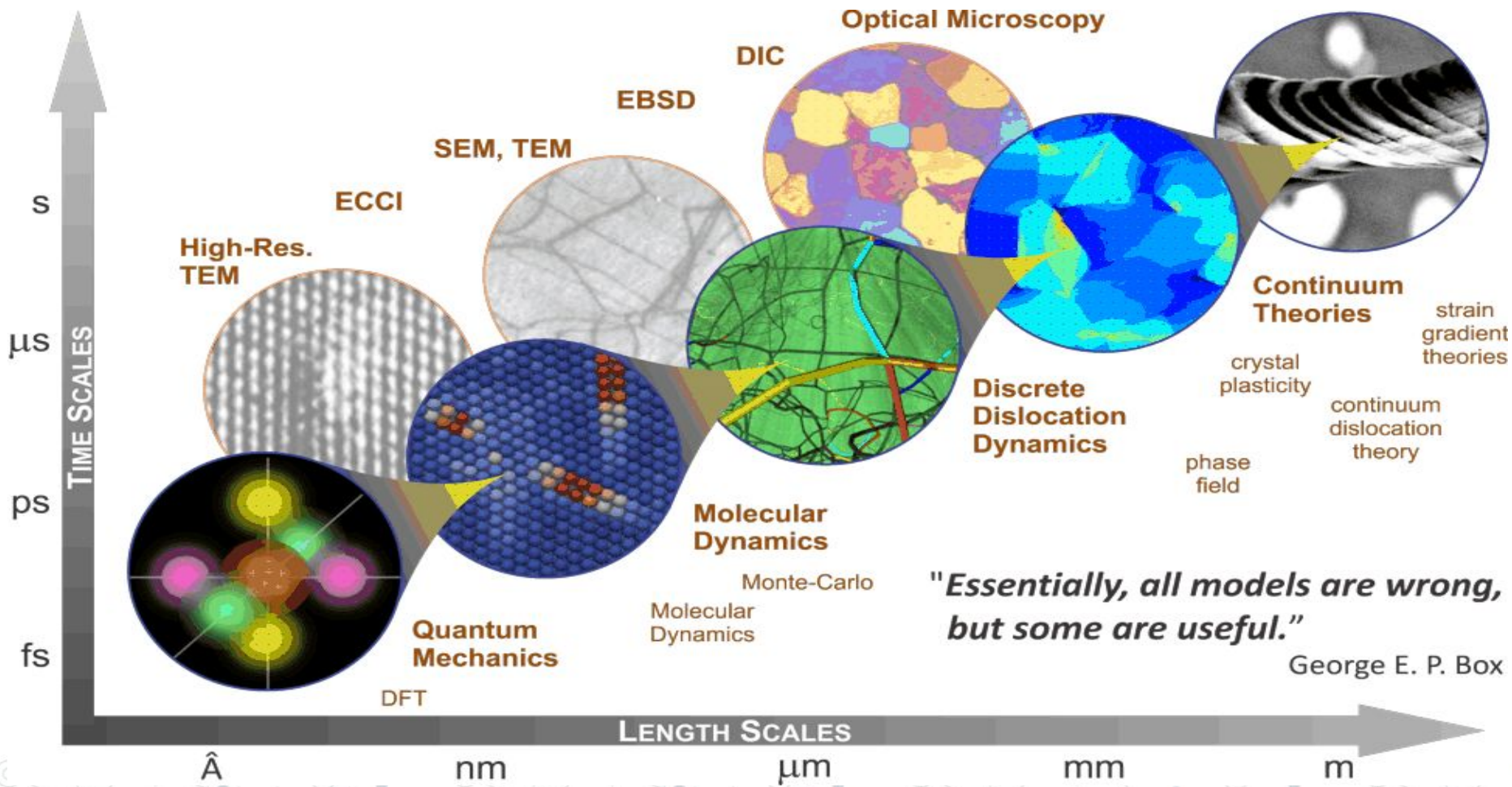
The diagram features five chevron-shaped boxes arranged in two rows. The top row contains three boxes: 'High-Level Description of CG' (orange), 'Force Matching Method' (green), and 'Bonus: Connection to MZ Formalism' (dark red). The bottom row contains two boxes: 'PMF Approximation Methods' (blue) and 'Case study on COM CG in H₂O' (dark purple). Arrows indicate a flow from the top row to the bottom row. The 'High-Level Description of CG' box has three arrows pointing to the 'PMF Approximation Methods' box. The 'Force Matching Method' box has four arrows pointing to the 'PMF Approximation Methods' box and three arrows pointing to the 'Case study on COM CG in H₂O' box. The 'Bonus' box has three arrows pointing to the 'Case study on COM CG in H₂O' box. The background is decorated with faint molecular network diagrams.

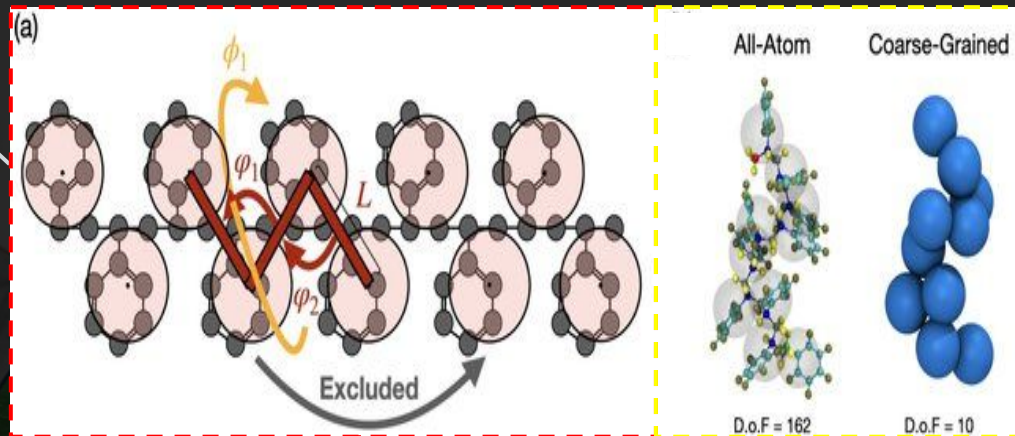
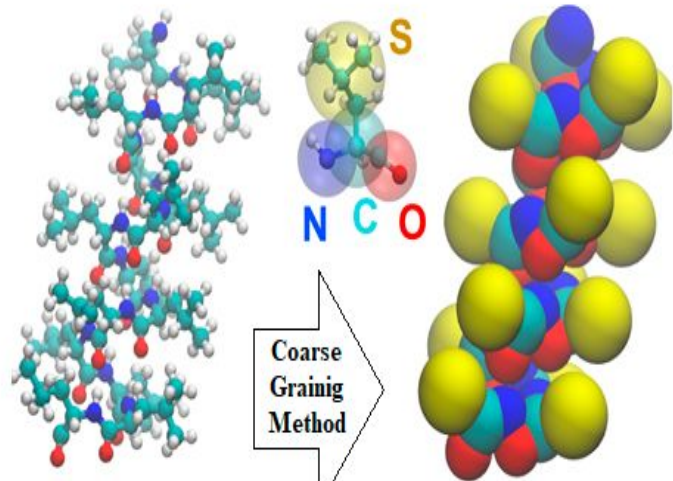
Force Matching
Method

Bonus:
Connection to
MZ Formalism

PMF
Approximation
Methods

Case study on
COM CG in H₂O





Bonded interactions separation

CG mapping between AA and CG model of a 10-monomer PS chain

Extend the **time** and **length scale** of AA and MD simulations to cover **biological scales**

Molecular Dynamics

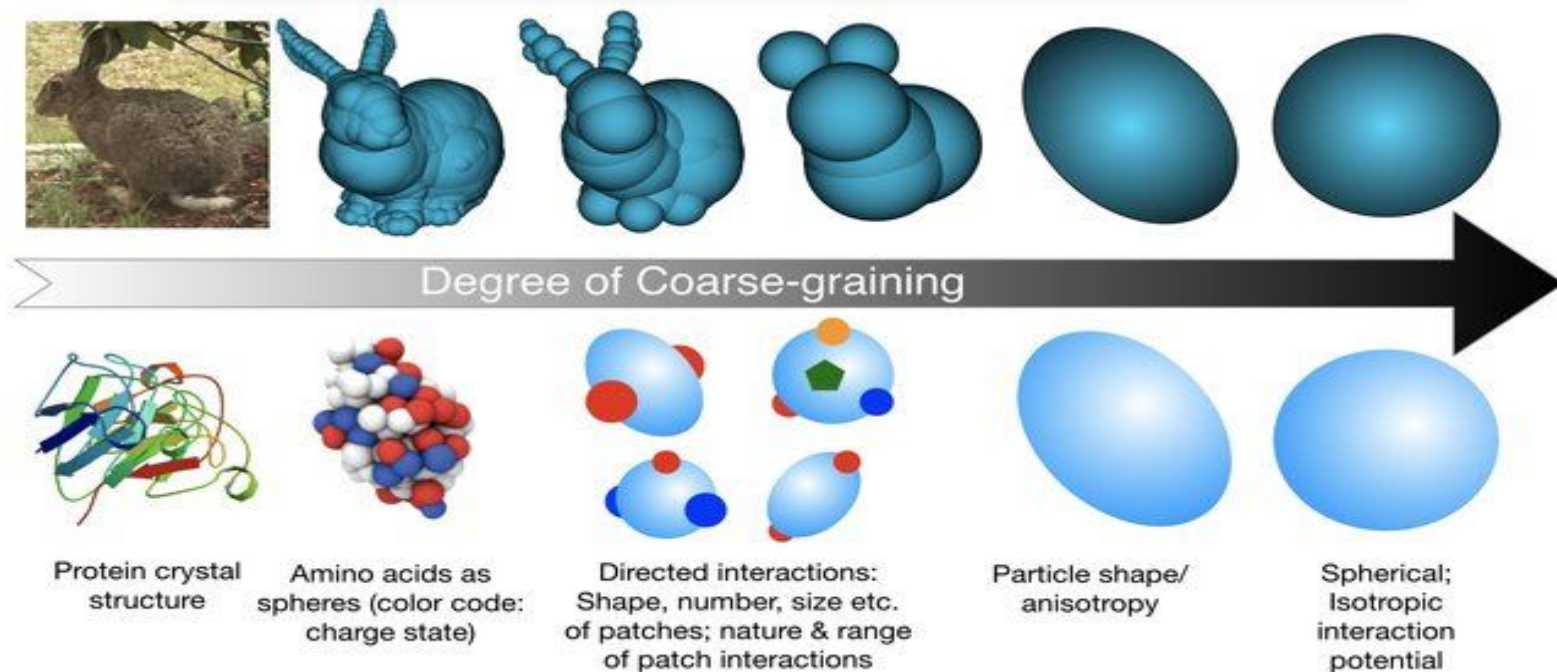
Monte-Carlo

Molecular Dynamics

LENGTH SCALES

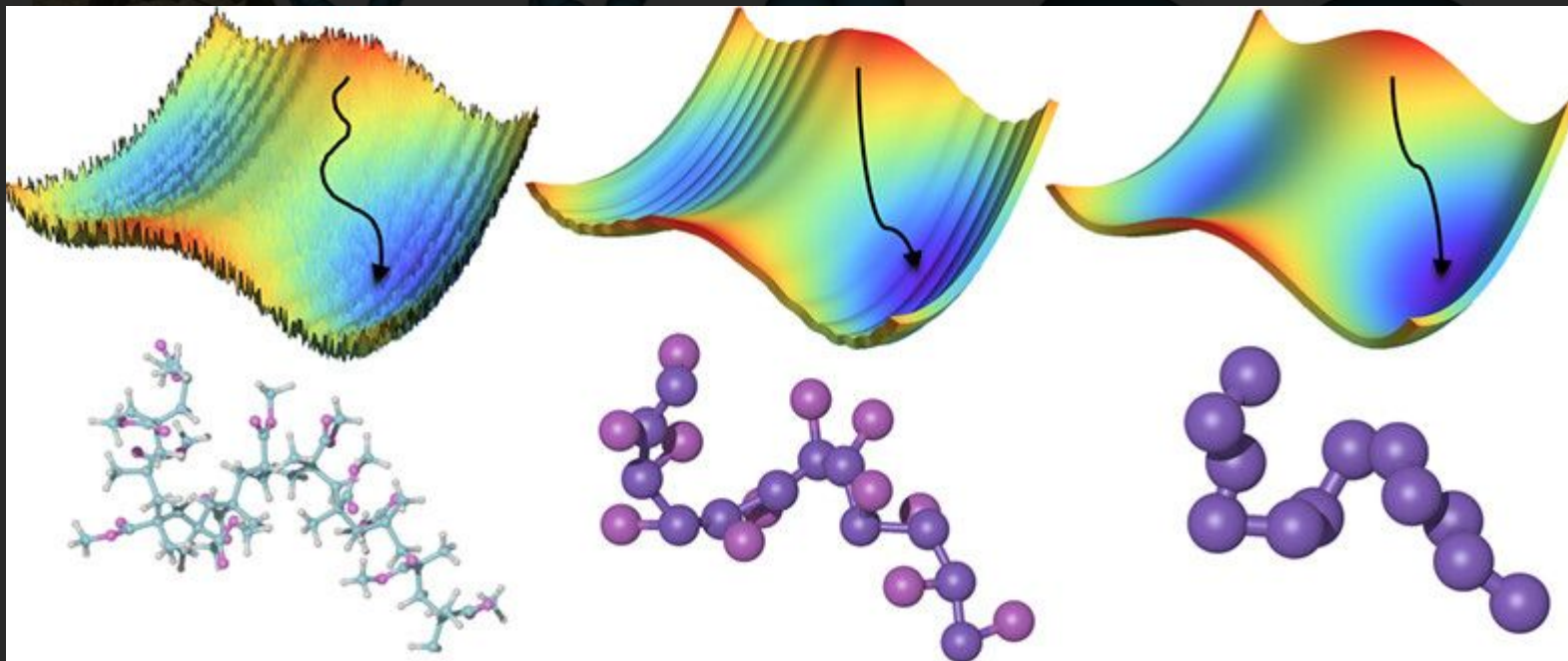
"Essentially, all models are wrong, but some are useful"

Optimal Coarse-Graining Strategy



CG approaches must be developed to simultaneously **reduce computational complexity** and **retain necessary chemical details** for large-scale systems, encompassing more than $\sim 10^7$ atoms and larger than ~ 100 nm in space

Optimal Coarse-Graining Strategy

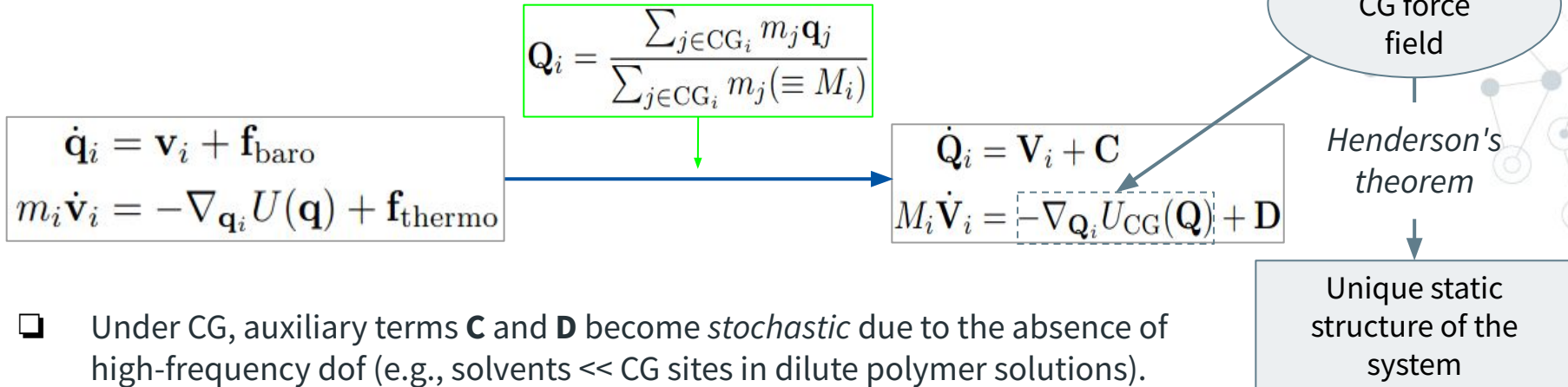


CG approaches must be developed to simultaneously **reduce computational**

The dynamics of the system is ***artificially accelerated*** since the PES is smoothed

Paradigm of Coarse-Graining

- ❑ The governing equations of AA MD \rightarrow CG:



- ❑ Under CG, auxiliary terms \mathbf{C} and \mathbf{D} become *stochastic* due to the absence of high-frequency dof (e.g., solvents \ll CG sites in dilute polymer solutions).

The purpose of coarse-graining is to find an **appropriate set of parameters** that describe $U (\approx U_{PMF})$, \mathbf{C} , and \mathbf{D} from atomistic (AA) models, reproducing the same structures and dynamics generated from the fine-grained (DEM in our case study) EoM.

PMF Estimator(s) (discussed here):
Force Matching (or MSCG)

resolved (CG)
unresolved
(orthogonal)

EoM (\mathbf{C} and \mathbf{D}):
Mori-Zwanzig projection operator formalism

PMF Description and Approximation

General objective of PMF approximators (FM, RE, structural-based): Propose a family of interaction potential functions $\bar{U}_{\text{eff}}(\mathbf{Q}; \theta \in \Theta)$, and seek for the optimal $\bar{U}_{\text{eff}}(\mathbf{Q}; \theta^*)$ that “best approximates” the PMF (canonical ensemble),

$$\bar{U}^{\text{PMF}}(\mathbf{Q}) = -\frac{1}{\beta} \log \int_{\Omega(\mathbf{Q})} e^{-\beta U(\mathbf{q})} d\mathbf{q}.$$

Equilibrium marginal
of the full atomistic
distribution

$\mathbf{Q} \in \mathbb{R}^{3M}$ denotes the configuration of generalized coordinates in CG space with $M(<N)$ particles and $\Omega(\mathbf{Q}) := \{\mathbf{q} \in \mathbb{R}^{3N} : \Pi(\mathbf{q}) = \mathbf{Q}\}$ entities on the CG space are annotated with the “-” symbol).

$\bar{Z} = \int e^{-\beta \bar{U}_{\text{eff}}(\mathbf{Q})} d\mathbf{Q}$ is the corresponding *partition function*.

- The many body PMF can be described as being composed by two-body, three-body, e.t.c., interactions (pairwise distance $R_{ij} = \|\mathbf{Q}_i - \mathbf{Q}_j\|$, $i, j = 1, \dots, M$):
(a two-body effective pair potential usually suffices, $\bar{U}_{\text{eff}}(\mathbf{Q}) = \sum_{i,j} u(R_{ij}) \approx \bar{U}^{\text{PMF}}(\mathbf{Q}).$)

$$\bar{U}^{\text{PMF}}(\mathbf{Q}) = \sum_{i,j} u_2(R_{ij}) + \sum_{i,j,k} u_3(R_{ij}, R_{ik}, R_{jk}) + \dots$$

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- We denote the *mean force* $\bar{F}^{\text{PMF}} : \mathbb{R}^{3M} \rightarrow \mathbb{R}^{3M}$ corresponding to the PMF assuming it exists, by $\bar{F}_i^{\text{PMF}}(\mathbf{Q}) = -\nabla_{Q_i} \bar{U}^{\text{PMF}}(\mathbf{Q}), i = 1, \dots, M.$

- We denote by $\bar{\mu}(d\mathbf{Q}) = \bar{Z}^{-1} \exp\{-\beta \bar{U}_{\text{eff}}(\mathbf{Q})\} d\mathbf{Q}$ the *equilibrium probability measure* at the CG configurational space for the given CG potential function $\bar{U}_{\text{eff}}(\mathbf{Q}; \theta)$, where $\bar{Z} = \int e^{-\beta \bar{U}_{\text{eff}}(\mathbf{Q})} d\mathbf{Q}$ is the corresponding *partition function*.

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[E. Kalligiannaki et al., EPJST. **225**, 1347–1372 (2016)]

Force Matching: A Least Squares Problem

- Since the PMF bridges the gap between chemical-specific CG and AA models, evaluating the mean force directly provides a natural CG parametrization approach (Ercolessi and Adams (1994)). We construct the following mean *least-square minimization*:

$$\min_{\theta \in \Theta} \mathbb{E}_{\mu} [\|h(\mathbf{q}) - \bar{F}(\mathbf{\Pi}(\mathbf{q}); \theta)\|^2]$$

where $\|\cdot\|$ denotes the Euclidean norm in \mathbb{R}^{3M} and $\mathbb{E}_{\mu}[\cdot]$ averages with respect to the *Gibbs canonical (probability) measure (ensemble average)* $\mu(d\mathbf{q}) = Z^{-1} \exp\{-\beta U(\mathbf{q})\} d\mathbf{q}$, given a CG (contraction) mapping $\mathbf{\Pi} : \mathbb{R}^{3N} \mapsto \mathbb{R}^{3M}$ s.t. $\mathbf{q} \mapsto \mathbf{\Pi}(\mathbf{q}) \in \mathbb{R}^{3M}$ on the microscopic state space.

- The reference field $h(\mathbf{q}) \in \mathbb{R}^{3M}$ is the local mean force where each component, $h_i(\mathbf{q})$, is the force exerted at the i^{th} CG site that is a function of the microscopic forces.
- One can interpret FM as a geometrical projection of the atomic forces (Voth et al. (2008)). Namely, the $\bar{F}^{\text{PMF}}(\mathbf{Q})$ is a projection of a local mean force $h(\mathbf{q})$ onto the space of square integrable functions w.r.t $\mu(d\mathbf{q})$:
$$L^2(\mu; \mathbf{\Pi}) = \{F \in L^2(\mu) \mid \exists \bar{F} : \mathbb{R}^{3M} \mapsto \mathbb{R}^{3M} \text{ s.t. } F(\mathbf{q}) = \bar{F}(\mathbf{\Pi}(\mathbf{q}))\}$$

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[V. Harmandaris et al., *J. Chem. Phys.* **143**(8), 084105 (2015)]

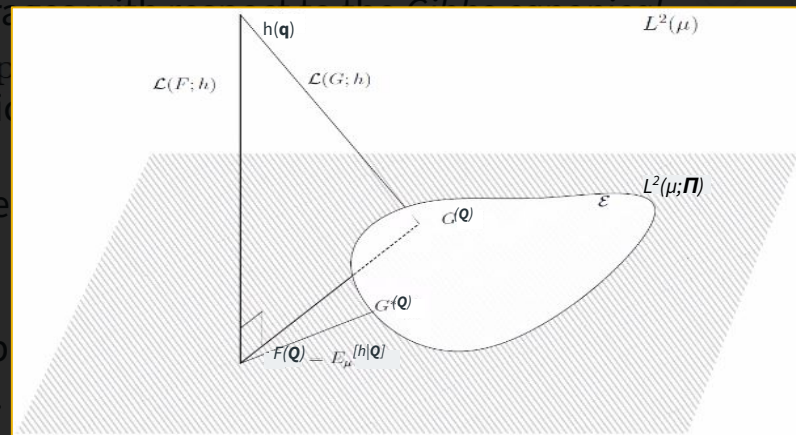
For a given $h \in L^2(\mu)$ the minimization problem

$$\inf_G \mathcal{L}(G; h) = \inf_G \mathbb{E}_{\mu} [\|h - G \circ \mathbf{\Pi}\|^2],$$

where inf is taken over all $G \in L^2(\mu; \mathbf{\Pi})$ has the unique solution

$$F^*(\mathbf{Q}) = \mathbb{E}_{\mu}[\mathbf{h}|\mathbf{Q}], \quad \mathbf{Q} \in \mathbb{R}^{3M}.$$

$$F^{PMF}(\mathbf{Q}) = \mathbb{E}_{\mu}[\mathbf{h}|\mathbf{Q}], \text{ for the chosen } h$$



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Case Study on Water Molecules: CG procedure

- After identifying each molecule's atom indices $\{j \in I\}$ ($CG_I = I$), the CG position \mathbf{Q}_I is computed as the mass-weighted CoM:

$$\mathbf{Q}_I = \frac{\sum_{j \in I} m_j \mathbf{q}_j}{M_I} \text{ where } m_O = 15.9994, m_H = 1.008 \text{ u}$$

This mapping eliminates *internal vibrational dof*.

- To ensure consistent dynamics, atomic forces \mathbf{f}_j are projected to CG sites by the same mass weights:

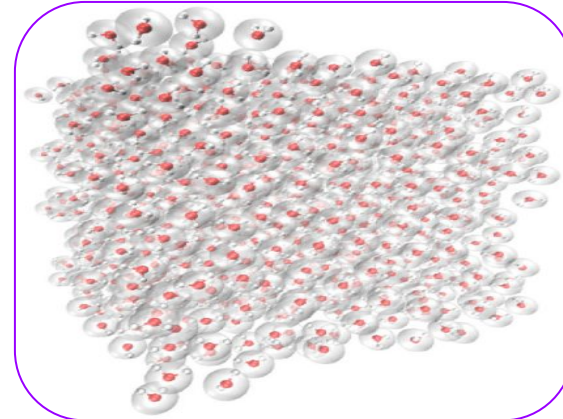
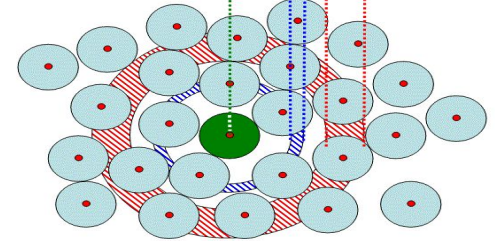
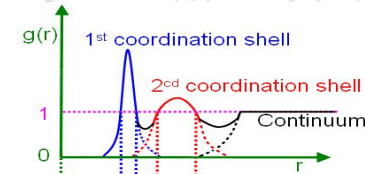
$$\mathbf{F}_I = \frac{\sum_{j \in I} m_j \mathbf{f}_j}{M_I}$$

- Pair correlation or Radial Distribution Function (RDF) ($CG_I = I$):

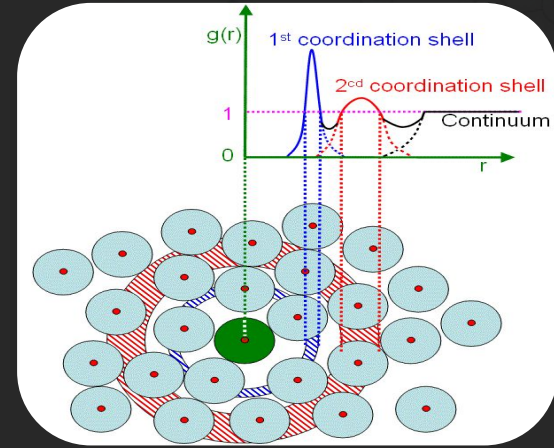
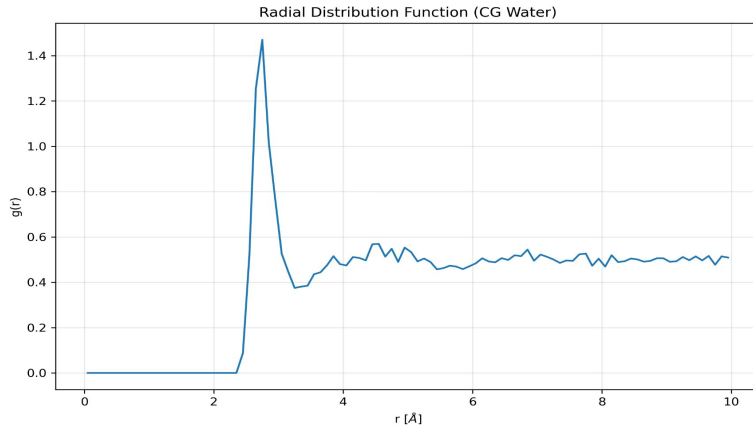
$$g(r) = (4\pi r^2 \Delta r \rho M)^{-1} \sum_{I < J} \delta^{(3)}(r - r_{IJ})$$

- Complexity and KD-Tree Acceleration:

- **Brute-Force Cost:** Naive pairwise check costs $O(N_H N_O)$.
- **KD-Tree:** Tiling positions to handle PBC and indexing with a cKDTree reduces the neighbor-search cost to $O(N_O \log N_H)$ ([Friedman et al. \(1977\)](#)).



Case Study on Water Molecules: CG procedure



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Case Study on Water Molecules: Cubic Spline Representation

- Each CG pair interaction $U_{IJ}(R)$ is modeled as a cubic spline through K knot points $\{(R_k, \theta_k)\}$, such that

$$U_{IJ}(R) := \sum_{k=1}^K \theta_k B_k(R)$$

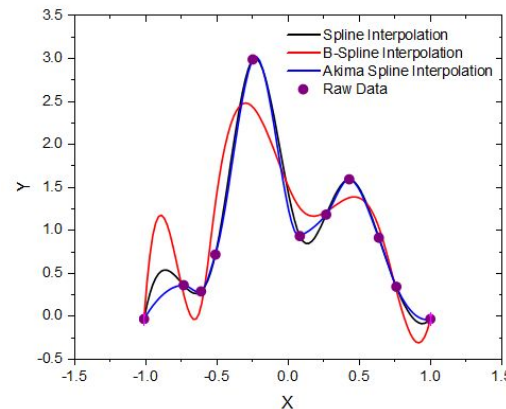
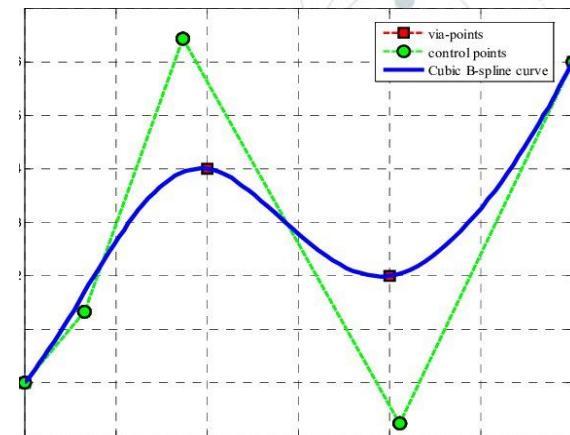
where $B_k(R)$ are the **cubic B-spline basis functions** with *local support* between adjacent knots.

- The force between sites I and J follows from the negative derivative:

$$\bar{F}_{IJ}(R) = -U'_{IJ}(R) = -\sum_{k=1}^K \theta_k B'_k(R)$$

and the vector force on site I is

$$\bar{\mathbf{F}}_I \approx -\nabla_I U_{eff}(\mathbf{Q}; \theta) = \sum_{J \neq I} \bar{F}_{IJ}(R_{IJ}) \hat{\mathbf{R}}_{IJ}, \quad \hat{\mathbf{R}}_{IJ} = \frac{\mathbf{Q}_I - \mathbf{Q}_J}{\|\mathbf{Q}_I - \mathbf{Q}_J\| (\equiv R_{IJ})}$$



Case Study on Water Molecules: FM Optimization

- Minimizing the discrepancy between CG forces $\bar{\mathbf{F}}_I$ derived from a parametric potential and reference atomistic forces \mathbf{h}_I mapped onto the same CG sites. The *mean-squared error* objective

$$\mathcal{L}(\boldsymbol{\theta}; \mathbf{h}) = \frac{1}{n_{\text{conf}}} \sum_{k=1}^{n_{\text{conf}}} \sum_{I=1}^M \|h(\mathbf{q}_k \in I) - \bar{\mathbf{F}}_I(\mathbf{Q}_k; \boldsymbol{\theta})\|^2$$

- Optimization employs deterministic (L-BFGS-B) or stochastic (Adam) minimizers, using either full batches or random subsets of configurations to compute gradients via finite differences.
- For large datasets ($n_{\text{conf}} \gg 1000$), the algorithm performs **mini-batch** updates:
 - Randomly sample subset of configurations,
 - Compute batch MSE and approximate gradient $\nabla_{\boldsymbol{\theta}} \mathcal{L}$ via central differences ($\delta=1\text{e-}6$),
 - Update parameters $\boldsymbol{\theta}$ by Adam's updating rule:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) \nabla_{\boldsymbol{\theta}} \mathcal{L}, \quad v_t = \beta_2 v_{t-1} + (1 - \beta_2) (\nabla_{\boldsymbol{\theta}} \mathcal{L})^2,$$

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}, \quad \hat{v}_t = \frac{v_t}{1 - \beta_2^t}, \quad \boldsymbol{\theta}_{t+1} = \boldsymbol{\theta}_t - \alpha \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$

Tested Hyperparameters: $\alpha=1\text{e-}2, 1\text{e-}3$, decay=0.98, $\beta_1=0.9$, $\beta_2=0.999$, $\epsilon=1\text{e-}8$, K=20, frames-per-step = 100

Case Study on Water Molecules: Initial Guess Scheme

1. **Lennard-Jones-Like Potential:** Naive LJ-like formula with a *constant repulsive core* for $R < \sigma$:

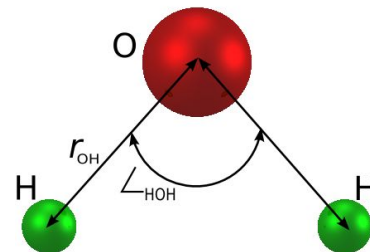
$$U(R_i) = \begin{cases} \epsilon & R_i < \sigma \\ \epsilon \left[\left(\frac{\sigma}{R_i} \right)^{12} - 2 \left(\frac{\sigma}{R_i} \right)^6 \right] & R_i \geq \sigma \end{cases}$$

where $\epsilon=0.1$ kcal/mol is the energy scale, $\sigma=3.0$ Å is the location of the potential minimum, $R_i \in \{R_1, R_2, \dots, R_K\}$ are the spline knot positions. This gives the initial value $\theta_i^{(0)} = U(R_i)$, $\forall i \in [K]$

2. **SPC/E-Inspired Initialization:** The potential is defined piecewise as

$$U(R_i) = \begin{cases} 100 \left(\frac{\sigma}{R_i} \right)^{12} & R_i < R_{\text{cut,hard}} \\ 4\epsilon \left[\left(\frac{\sigma}{R_i} \right)^{12} - \left(\frac{\sigma}{R_i} \right)^6 \right] & R_{\text{cut,hard}} \leq R_i \leq R_{\text{cut}} \end{cases}$$

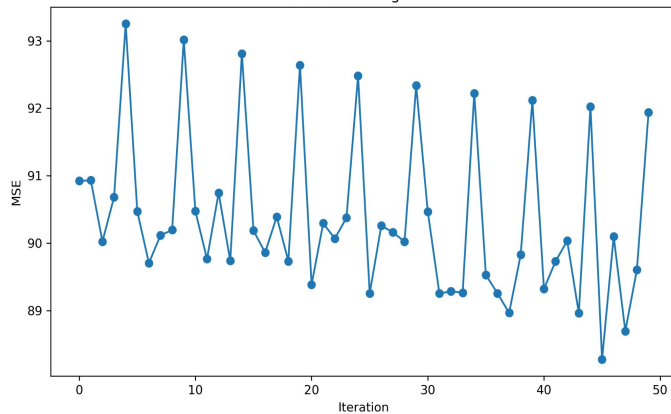
where (parameters from the SPC/E water model) $\epsilon = 0.65$ kcal/mol, $\sigma = 3.166$ Å, $R_{\text{cut,hard}} = 2.5$ Å (transition from hard core to LJ form), $R_{\text{cut}} = 10$ Å. Then *Savitzky-Golay smoothed* to remove oscillations and shifted s.t. $\theta_K^{(0)} = 0$.



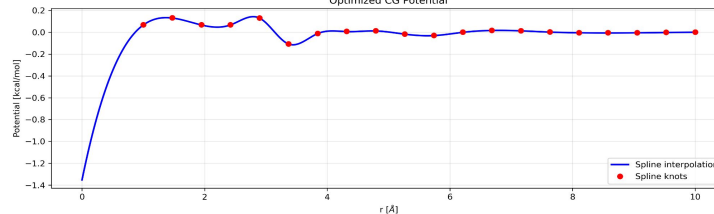
Initializing spline parameters: a good “starting potential” can accelerate convergence and avoid unphysical wells or barriers during optimization.

Results on Naive Initialization with $\alpha=1e-3$

Adam Convergence

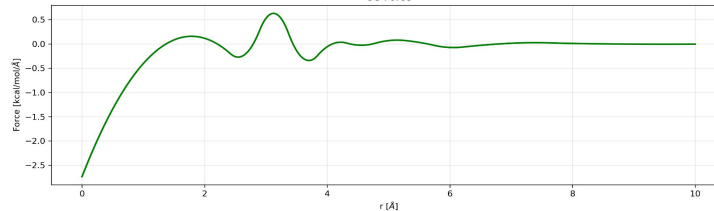


Optimized CG Potential



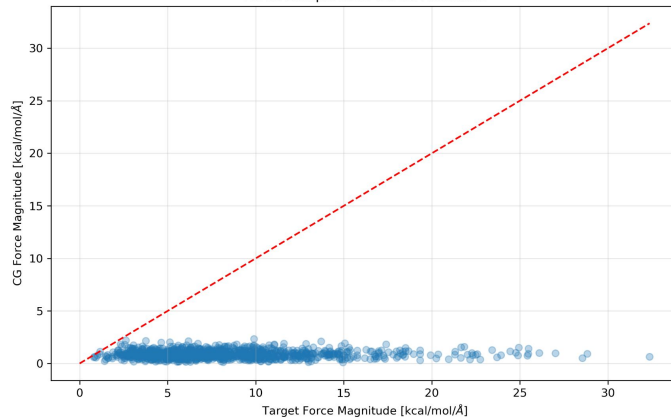
A single-site CG bead per water molecule cannot capture directional hydrogen-bond forces or intramolecular stiffness, hence the low variance in CG forces.

CG Force

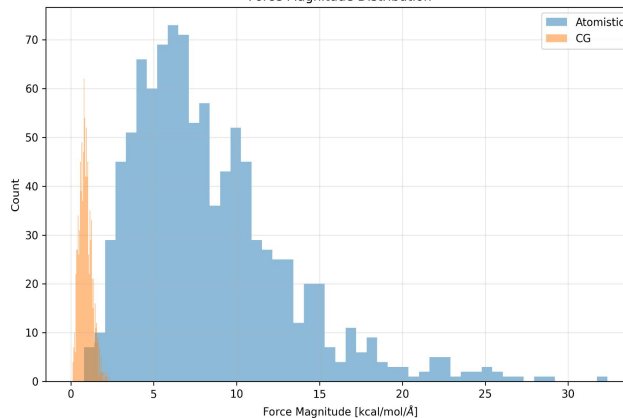


The inherent limitations of *a purely pairwise, single-site* model manifest as significant underestimation of force variability and a high MSE

Force Comparison: CG vs. Atomistic

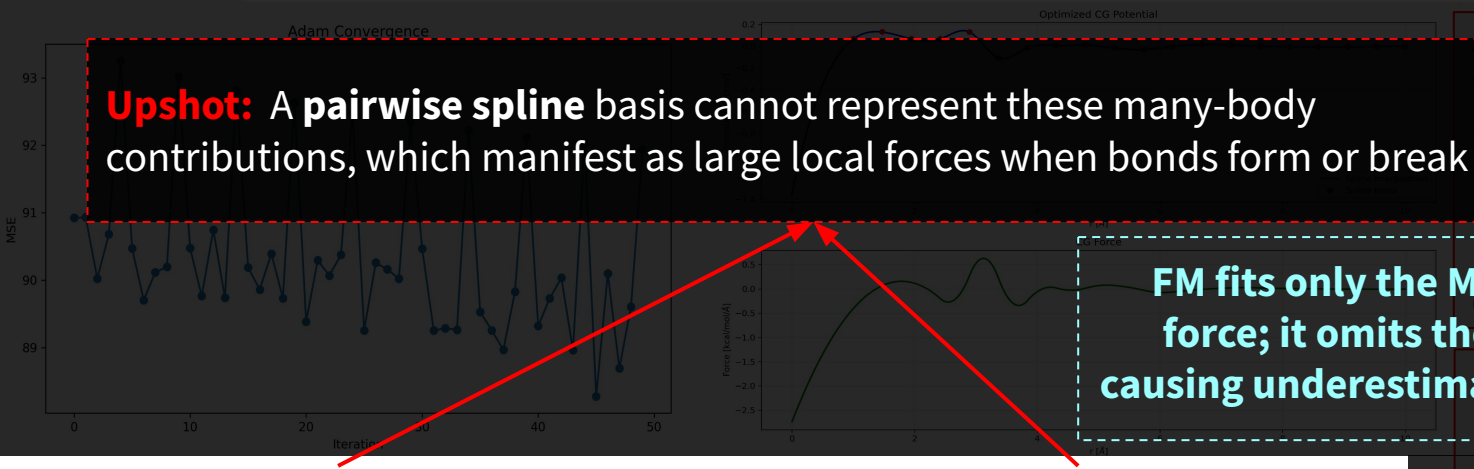


Force Magnitude Distribution



MSE: 89.13 kcal/mol/Å
Best Val Loss: 91.94

Results on Naive Initialization with $\alpha=1e-3$

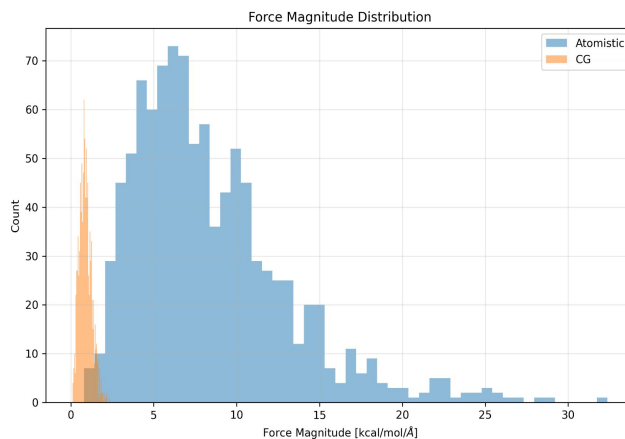
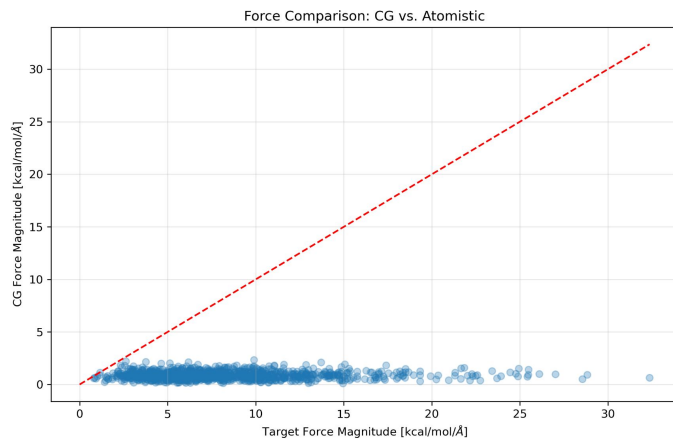


A single-site CG bead per water molecule cannot capture directional hydrogen-bond forces or local molecular stiffness, hence the low variance in CG forces.

FM fits only the Markovian projected force; it omits the fluctuating term, causing underestimation of force variance

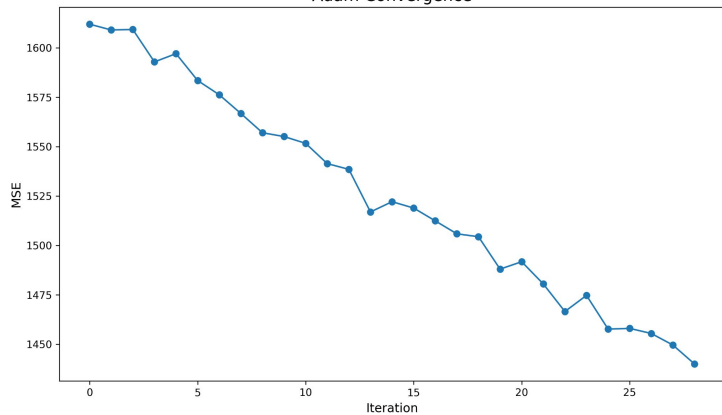
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MSE: 89.13 kcal/mol/Å
Best Val Loss: 91.94

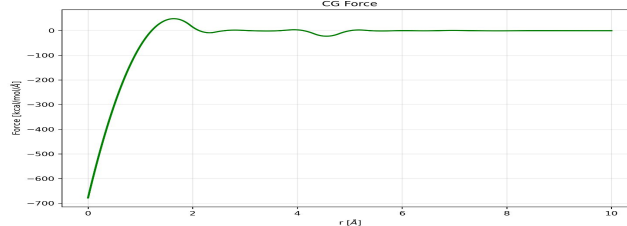
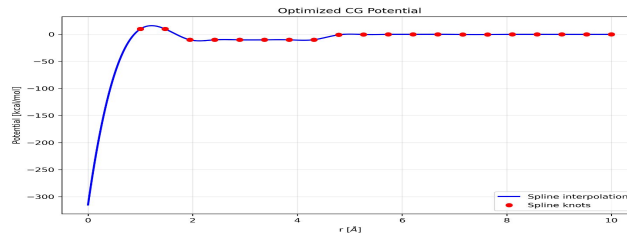
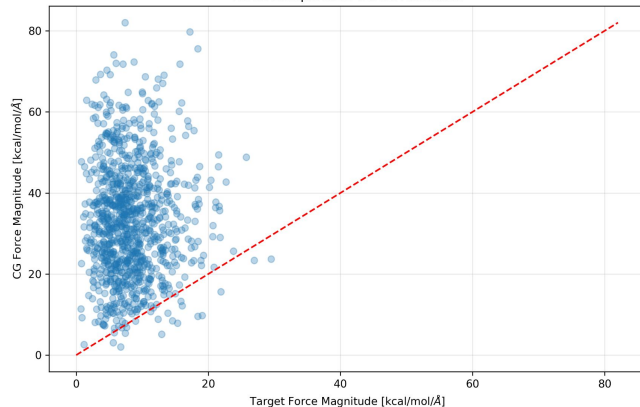


Results on SPC/E Initialization with $\alpha=1e-2$

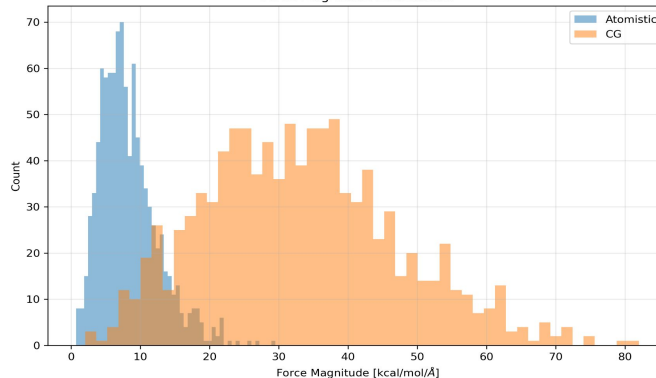
Adam Convergence



Force Comparison: CG vs. Atomistic



Force Magnitude Distribution

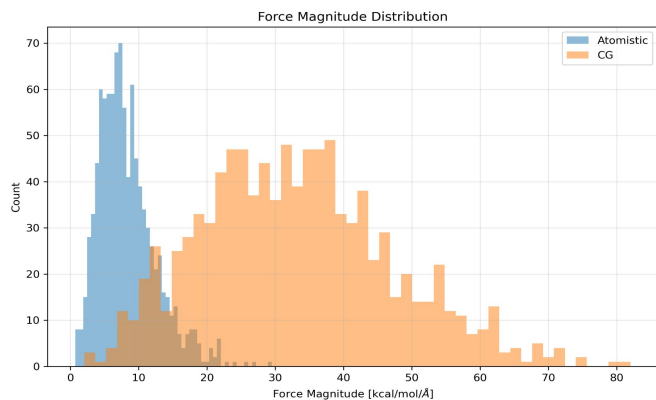
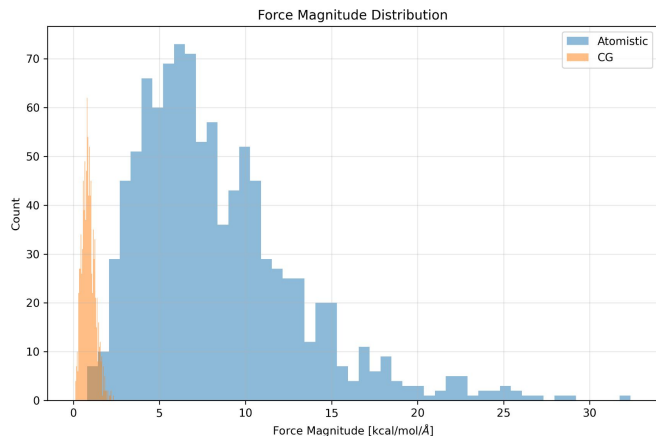


Swings to the other extreme, overestimating the spread, and in fact pays for it in a worse cross-validated MSE

SPC/E behaves like an overly “flexible” model (high variance, possibly overfitting)

MSE: 1439.47 kcal/mol/Å
Best Val Loss: 1424.55

Remarks on Initialization Strategies



Adaptive weighting during training

Regularize deviation in standard deviation from the reference force set

Central tendency \oplus spread

$$\mathcal{L} = \text{MSE}(\mathbf{F}_{\text{CG}}; \mathbf{h}) + \lambda |\text{std}(\mathbf{F}_{\text{CG}}) - \text{std}(\mathbf{h})|$$

“Tight” LJ \oplus “broad” SPC/E baseline

Convex combination of LJ and SPC/E coefficients (**hybrid initialization**)

$$\text{MSE}_{(\text{batch})}(\mathbf{F}_{\text{CG}}; \mathbf{h}) = \frac{1}{N_{\text{batch}}} \sum_{k=1}^{N_{\text{batch}}} \sum_{I=1}^M \|\mathbf{h}_I(\mathbf{q}_k) - \mathbf{F}_{\text{CG},I}(\mathbf{Q}_k; \boldsymbol{\theta})\|^2$$



Thank you for your attention!

I am here because

I enjoy creating and presenting ideas.

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Dynamics of the CG Model: The Mori-Zwanzig Formalism

- ❑ The MZ formalism originates from the **microscopic Hamiltonian** and utilizes a projection operator to decompose the dynamics into slower macroscopic dynamics.
- ❑ Heisenberg time-evolution of an observable operator $A(t)$: $\dot{A} = iLA$ with solution $A(t) = e^{iLt}A_0$ and $iL = [H, \cdot]$, the Liouville operator.
- Let $P = (A_0, A_0)^{-1}(\cdot, A_0)A_0$, the projection operator onto the initial observable, and $Q = 1 - P$ the one onto P 's orthogonal subspace. Then, applying the operator identity (*Duhamel identity* or *Dyson expansion*):
$$e^{iLt} = e^{iQLt} + \int_0^t ds e^{iL(t-s)} P iL e^{iQLs}$$
 into the equation $\dot{A}(t) = iL e^{iLt} A_0$ and defining the *fluctuation term* $F(t) = \exp(iQLt) iQL A_0$, the *frequency term* $\Omega = (iL A_0, A_0)(A_0, A_0)^{-1}$ s.t. $\Omega A_0 = iPL A_0$, and the memory kernel $K(t) = (iLF(t), A_0)(A_0, A_0)^{-1} = (F(t), F(0))(A_0, A_0)^{-1}$ (2nd FD Theorem) we obtain the **GLE form** of the MZ formalism (after invoking the *Mori identity*):

$$\dot{A} = \Omega A + \int_0^t ds K(s) A(t-s) + F(t)$$

- ❑ The time evolution is decomposed into its **slow counterpart**, represented by A (i.e., ΩA), and the term $F(t)$ corresponds to the **orthogonal residue dynamics**. These two parts are connected through the memory kernel K , which accumulates all the unresolved components from the initial stages.

Dynamics of the CG Model: The Mori-Zwanzig Formalism

Markovian approximation

→ rapid decay of $\zeta(t)$

$\zeta(t) \sim \delta(t) \rightarrow$

Langevin dynamics

$C(t)$ (memory)

$D(t)$ (noise)

$$\dot{\mathbf{P}}(t) = -\nabla_{\mathbf{Q}_i} \bar{U}^{\text{PMF}}(\mathbf{Q}) - \int_0^t \bar{\zeta}(t-\tau) \mathbf{P}(\tau) d\tau + \mathbf{F}_R(t), \quad t > 0$$

[pairwise decomposition] $\mathbf{A} \equiv [\mathbf{P}_1, \mathbf{P}_2, \dots, \mathbf{P}_M]$

$$\langle \mathbf{F}_R(t) \mathbf{F}_R(t') \rangle = 2\beta^{-1} \bar{\zeta}(t-t'), \quad t > t'$$

Fluctuation-Dissipation
Theorem

$$\dot{\mathbf{A}}(t) = \underbrace{\Omega \mathbf{A}}_{\text{Instantaneous (Markovian) Drift}} - \int_0^t \zeta(t-\tau) \mathbf{A}(\tau) d\tau + \mathbf{F}(t)$$

Instantaneous (Markovian) Drift

The time evolution is decomposed into its **slow counterpart**, represented by \mathbf{A} (i.e., $\Omega \mathbf{A}$), and the term $\mathbf{F}(t)$ corresponds to the **orthogonal residue dynamics**. These two parts are connected through the

Fun Fact: if the kernel follows $\zeta \sim t^{-s}$ with $s \in (0,1)$, the “random” force exhibits **pink noise characteristics**.

Dynamics of the CG Model: The Mori-Zwanzig Formalism

Elimination \Rightarrow Memory & Noise: By **eliminating** fast variables, one loses their explicit EOM but cannot erase their effects.

Heisenberg time-evolution of an observable operator $A(t)$: $\dot{A} = iLA$ with solution $A(t) = e^{iLt}A_0$ and $iL = [H, \cdot]$, the Liouville operator.

$C(t)$ (memory) $D(t)$ (noise)

- Let $P = (A_0, A_0)^{-1}(\cdot, A_0)$ be the projection onto the subspace spanned by A_0 . Let $Q = 1 - P$ be the one onto P 's orthogonal sub. $\dot{P}(t) = -\nabla_{\mathbf{Q}_i} \bar{U}^{\text{PMF}}(\mathbf{Q}) - \int_0^t \bar{\zeta}(t-\tau) \mathbf{P}(\tau) d\tau + \mathbf{F}_R(t)$, $t > 0$ (Dyson expansion):

$e^{iLt} = e^{iQLt} + \int_0^t ds e^{iL(t-s)} P iL e^{iQLs}$ into the equation $\dot{A}(t) = iL e^{iLt} A_0$ and defining the fluctuation term $F(t) = \exp(iQLt) iQL A_0$, the frequency term $\Omega = (iL A_0, A_0) (A_0, A_0)^{-1}$ s.t. $\Omega A_0 = iPL A_0$, and the memory kernel $K(t) = \langle \bar{\zeta}(t) \bar{\zeta}(0) \rangle$ [pairwise decomposition] $A \equiv [P, P_1^{\text{nd}}, \dots, P_M]$ (Theorem 1.1 of Mori, 1965) the MZ formalism (after invoking the Mori identity):

$$\dot{A}(t) = \underbrace{\Omega A}_{\text{Instantaneous (Markovian) Drift}} - \int_0^t \zeta(t-\tau) A(\tau) d\tau + F(t)$$

$$\langle F_R(t) F_R(t') \rangle = 2\beta^{-1} \bar{\zeta}(t-t'), \quad t > t'$$

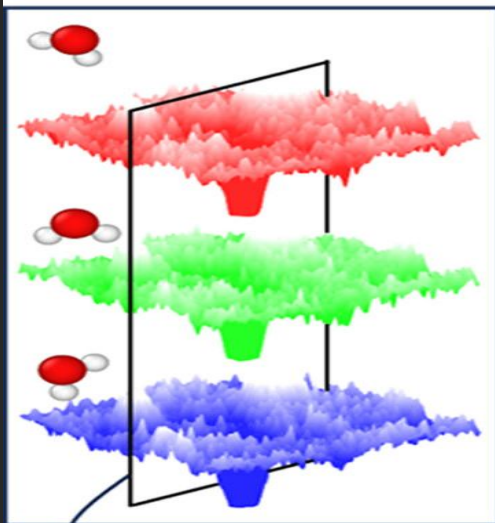
Fluctuation-Dissipation Theorem

- The time evolution is decomposed into its **slow counterpart**, represented by A (i.e., ΩA), and the term $F(t)$ corresponds to the **orthogonal residue dynamics**. These two parts are connected through the [Sergei Izvekov, J. Chem. Phys. **138**(13), 134106 (2013)]

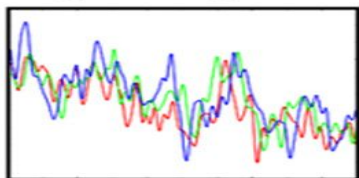
Fun Fact: if the kernel follows $\zeta \sim t^{-s}$ with $s \in (0, 1)$, the “random” force exhibits **pink noise characteristics**.

Optimal Coarse-Graining Strategy

AA PES



High roughness

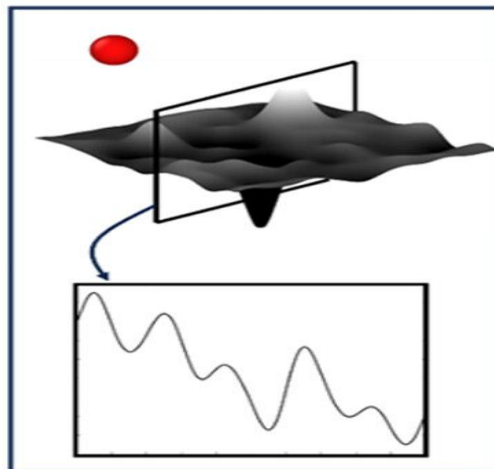


CG Mapping

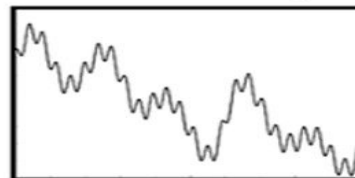


$$R = M(r)$$

CG PES



Recovered roughness



Visualization of an idealized schematic of a rugged **all-atom landscape** (top-left) and a smoothed **CG landscape** (top-right). The sliced potential energy surface at the bottom provides a qualitative representation of **high-frequency “rough” features**, which can be emulated by **introducing perturbation to the CG potential**.