## Systematic Coarse-Graining using VOTCA

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## **VOTCA Contributors**

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#### Implementations

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Interface to ESPResSo Interface to AdResS Simplex algorithm Parallel analysis engine Force-matching Relative entropy method Coarse-graining is an essential part of multiscale simulations:

#### **Benefits**:

- Less interactions to evaluate
- Less degrees of freedom to integrate
- Intrinsic speedup of dynamics



#### Enhances accessible range of time- and lengthscales

#### **Motivation**



## **Polymer models**

#### Example: Gaussian chain

• Represent polymer by beads which are connected by strings



- Works well to obtain scaling laws if  $r \gg l_p$  (end-end distance, ...)
- Various modifications / extensions (e.g. add stiffness)
- Often analytical solution available

**Problem**: No connection to underlying chemistry

#### Systematic coarse-graining

Is there a coarse-grained model which reproduces selected properties of a given (atomistic) reference system?



- Mapping from atomistic to coarse-grained system
- Structure based mapping allows to reintroduce atomistic details (back-mapping)

#### Mapping operator

$$\mathbf{r}^{n} = \{\mathbf{r}_{1}, \dots, \mathbf{r}_{n}\} \longrightarrow \mathbf{R}^{N} = \{\mathbf{R}_{1}, \dots, \mathbf{R}_{N}\}$$
$$R_{I} = M_{I}R_{I} = \sum_{i} c_{Ii}r_{i}$$

Equilibrium probability density  $p_R(\mathbf{R}^N) = \int d\mathbf{r}^n p_r(\mathbf{r}^n) \delta(M_R(\mathbf{r}^n) - \mathbf{R}^N)$ for mapped CG variables

Consistency of the coarse-grained and the atomistic models

$$p_R(R^N) = P_R(R^N)$$

Problem: Full multibody distribution function

#### Bonded interactions: Boltzmann inversion

 Assume that probability distributions for bond, angle, torsion factorize

 $P(r,\varphi,\theta) = P(r)P(\varphi)P(\theta)$ 

Invert Boltzmann distribution to obtain potential

$$P(r) = \exp\left(-\frac{U(r)}{k_BT}\right), \qquad U(r) = -k_BT\ln P(r)$$

Important: use scaled distributions!

$$P(r) = \frac{P'(r)}{r^2}, \qquad P(\varphi) = \frac{P'(\varphi)}{\sin(\varphi)}$$



VOTCA: csg\_boltzmann

E. Tschöp et al, Acta Polymer. 49, 61 – 74 (1998)

## Henderson theorem

 Formulate coarse-graining based on correlation functions

 $\begin{array}{ll} \rho_1(r_1) & \text{density} \\ \rho_2(r_1,r_2) & \text{radial distribution function (RDF)} \\ \rho_3(r_1,r_2,r_3) & 3-\text{body correlations} \\ \end{array}$ 

- Fruncate after  $\rho_1$ ,  $\rho_2$  (easy to compute)
- Henderson theorem:

For every  $\rho_2(r)$  exists a unique (coarse-grained) pairwise potential U(r)

All structure based iterative method ( $\rho_1$ ,  $\rho_2$ -based) must converge to the same coarse-grained potential

R. Henderson, Phys. Lett. A, A49, 197-198 (1974)

#### **Iterative Boltzmann Inversion (IBI)**



 Iteratively fit radial distribution function using tabulated potentials

$$U_0(r) = -k_B T \ln g^{Ref}(r)$$

$$\Delta U_n(r) = k_B T \ln \frac{g_n(r)}{g^{Ref}(r)}$$

Features:

- Easy to implement
- no correlations (local update)
- robust

VOTCA: csg\_inverse

D. Reith et al., J. Comp. Chem. 24 (13), 1624 (2003) A. Lyubartsev et al., Phys. Rev. E 52 (4), 3730 (1995)

#### **Inverse Monte Carlo update**



**Idea:** Tabulate the interaction potential and rewrite all interactions using the number of particles in a shell  $\alpha$ 

$$H = \sum_{i,j} U(r_{ij}) = \sum_{\alpha} S_{\alpha} U_{\alpha}$$

Expand the expectation value of the number of particles in a shell to the change of the potential

$$< S_{\alpha} > -S_{\alpha}^{ref} = \sum_{\gamma} \frac{\partial < S_{\alpha} >}{\partial U_{\gamma}} \Delta U_{\gamma} + \mathcal{O}(\Delta U^{2})$$
$$\frac{\partial < S_{\alpha} >}{\partial U_{\gamma}} = \frac{\partial}{\partial U_{\gamma}} \frac{\int dq \, S_{\alpha}(q) \exp[-\beta H(q)]}{\int dq \, \exp[-\beta H(q)]}$$

$$\Delta \langle S_{\alpha} \rangle = \sum_{\gamma} \frac{\langle S_{\alpha} \rangle \langle S_{\gamma} \rangle - \langle S_{\alpha} S_{\gamma} \rangle}{k_B T} \Delta U_{\gamma}$$

non-local, correlations included

A. Lyubartsev et al., Phys. Rev. E 52 (4), 3730 (1995)

## Efficiency of the iterative methods



- IMC converges faster but needs longer iterations
- In this example: less computational costs for IBI
- What if correlations are present?

## Potential of Mean Force (PMF)

Starting from consistency relation of the coarse-grained and the atomistic models  $p_R(R^N) = P_R(R^N)$ 

$$exp[-\beta U(R^{N})] \sim \int dr^{n} \exp[-\beta u(r^{n})] \delta(M_{RI}(r^{n}) - R^{N})$$
  
or  
$$F_{I}(R^{N}) = \langle \mathcal{F}_{I}(r^{n}) \rangle_{R^{N}}$$

- The many-body potential of mean force (PMF) is a conditioned free energy surface in the coordinate space of the CG variables
- The CG force-field is  $F_I$  a conditioned expectation value of  $\mathcal{F}_I$  for an atomistic system

PMF provides exact mapping of the atomistic onto CG system

**Problem:** PMF requires many-body potential functions, while MD force-fields provide a limited set basis set (pair-wise potentials, bonds, angles, dihedrals)

#### Force matching (Multiscale coarse-graining)

 Solution: Use variational principle to project the many-body potentials on the functions provided by the force-field

$$x^{2} = \left| \sum_{I} \left| F_{i}^{CG} - \sum_{i \in \mathbb{1}} c_{i} f_{i}^{Ref} \right|^{2} \right|$$

- Splines or step functions  $\rightarrow$  linear least squares fit
- Not iterative → need to add additional terms to the coarse-grained force-field to improve results
- Requires reference forces

VOTCA: csg\_fmatch

S. Izvekov and G. Voth, J. Chem. Phys. 123, 134105 (2005). W. Noid et al., J. Chem. Phys. 120, 244114 (2008)

## VOTCA

- Consistent implementation of methods
  → allow for direct comparison
- Framework for the implementation of new methods



# Examples







#### Water

<cg\_molecule> <name>SOL</name> <ident>SOL</ident> <topology> <cg\_beads> <cg\_bead> <name>CG</name> <type>CG</type> <mapping>A</mapping> <beads> 1:SOL:OW 1:SOL:HW1 1:SOL:HW2 </beads> </cg\_bead> </cg\_beads> </topology> <maps> <map> <name>A</name> <weights>16 1 1</weights> </map></maps></cg\_molecule>

1 cg bead centre of mass mapping spherical potential



## SPC/E water



- IBI and IMC reproduce RDF and give similar potentials
- Force matching does not reproduce RDF
  - $\rightarrow$  lack of 3-body term (tetrahedral packing)

#### SPC/E water: extension of the basis set



Adding a three-body potential fixes the small basis set problem

Luca Larini, Lanyuan Lu, and Gregory A. Voth, J. Chem. Phys. 132, 164107 (2010)

#### Force-matching & bonded interactions



Hexane: angle distribution not reproduced



## Correlations

- Bond-angle correlations not reproduced
  - affects chain stiffness, end-end distance
  - Problems when backmapping to atomistic details
  - Add further terms to CG force field or adjust mapping



## Hybrid approaches

#### Mix force-matching + Boltzmann inversion

- apply force matching to derive only those potentials which can be well projected on the basis functions of the CG force-field (typically non-bonded potentials)
- exclude all forces except those of interest

#### Advantages

 can be used for heterogeneous systems where RDF is not well defined



Example: liquid hexane



V. Rühle et. al, Macromol. Theory Simul. 20, 472-477 (2011)

## **Avoiding correlations**

- Adjusting the mapping can avoid correlations.
  - Polythiophene with centre of mass mapping shows correlations due to backbone torsion
  - Use centre of ring mapping avoids correlations since coarse-grained bond corresponds to C-C bond



## Successful models (incomplete list)

- Kremer group
  - Polycarbonate
  - Polystyrene
    - Different tacticity, diffusion scaling
    - Fritz et al, Macromolecules 42 (19), 7579-7588 (2009)



- Voth group, bio systems:
  - Multiscale Coarse-Graining of the Protein Energy Landscape Hills et al, PLoS Comput Biol. 6(6), e1000827 (2010)

## Summary

- Coarse-graining provides a systematic way to parameterize a force-field based on selected properties of a reference system. Can be based on
  - Pair distribution functions
    - Boltzmann inversion
    - Iterative Boltzmann Inversion
    - Inverse Monte Carlo
  - Many-body potential of mean force
    - force matching
  - Desired thermodynamic property
    - Simplex algorithm

#### Be careful

- CG models never reproduce all properties
- CG force-fields parameterized at a specific state point
- RDF reproduced, but no predictions for other (thermodynamic) properties and higher order correlations (e.g. pressure, tetrahedral packing)

## Thank you for your attention!



#### www.votca.org