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### Introduction

### Molecular dynamics (MD)

- •Use classical physics to obtain a time series of coordinates for every atom
- Model structural ensembles that mediate biological functions of macromolecules
- Generate hypotheses about structure that can then be tested experimentally
- Relies on the accuracy of the energy model, a parameterized function called a force field
- RNA force fields
- Accurate for A-form helices composed of canonical Watson-Crick base pairs
- Poor description of non-canonical base pairs<sup>1</sup> and relative orientation of helices interrupted by single-stranded loops<sup>2</sup>
- Development of an accurate field that fixed-charge force transferable to structurally diverse RNAs remains an open challenge

 $U_{\text{nonbonded}}\left(R_{jk}\right) = \sum_{i < k} \left( \frac{\varepsilon_{jk}}{R_{jk}} \right)^{-1} - 2 \left( \frac{\varepsilon_{jk}}{R_{jk}} \right)^{$ 

We are developing an accurate fixed-charge force field for RNA using the Amber functional form by fitting to quantum mechanics (QM) energies that are implicitly polarized to account for the influence of solvent.

## Implicitly polarized charges<sup>3</sup> strategy



## Clustering improves efficiency of the fitting dataset

• Initial dataset is non-redundant representative set<sup>4</sup> of experimental RNA structures

• Extract all pairs of RNA residues with interacting nucleobases (~260 000 pairs) • Compute nonbonded interaction energies with Amber ff99+bsc0+ $\chi_{OL3}$  force field<sup>5,6</sup>

• Train nonbonded parameters to reproduce Amber energies for subset of conformations



- •Random training conformations were selected randomly ten times; boxes show interquartile range with median, and bars show minimum and maximum
- Clustered training conformations were clustered by heavy atom pairwise distance • Vertical line indicates where there are more conformations than parameters to fit
- Clustering retains diversity of training dataset and outperforms random selection

# Developing an accurate all-atom fixed-charge force field for RNA with implicitly polarized charges

## Strategy for obtaining time-averaged electrostatic interaction with solvent

Extract RNA context around QM dimer from experimental structure





Example of a nucleoside-nucleoside dimer (magenta) and the context from an experimental structure (gray) solvated in water and salt (cyan).

## Is solvent density converged from simulation length and amount of solvent?

### Replicas give similar estimates of solvent density

- •Assess convergence of solvent density for a single conformation with respect to sampling interval, simulation length, and solvent cutoff distance
- Electrostatic energy (ESE) between RNA and solvent
- Standard deviation,  $\sigma$ , in ESE (left) across 10 replicas
- Relative error in ESE (right) compared to 2 ps, 40 ns, and 40 Å; mean  $\pm$  SEM across RNA atoms
- Colors represent sampling interval
- Intrinsic  $\sigma$  across replicas is 0.25 kcal mol<sup>-1</sup> per atom Sampling at 200 ps does not change variance or relative error in ESE compared to sampling at 2 ps

### Large system size is required to converge solvent density

- Relative error in ESE for 200 ps sampling vs. simulation length (left) or solvent cutoff distance (right), mean  $\pm$  SEM across RNA atoms
- Relative error in ESE stops changing after 20 ns
- Relative error in ESE is still changing up to 30 Å

### Large size requirement due to salt • Radial distribution function (RDF) gives the probability density for pairwise distances compared to an ideal gas (RDF = 1)

- RDFs of solvent atoms to RNA phosphorus atoms for sampling rate of 2 ps (left) and 200 ps (right), mean  $\pm$ SEM across 10 replicas
- Water oxygens are unstructured after 10 Å
- Salt ions are structured up to 25 Å
- Variance across replicas is higher for salt than for water at 200 ps sampling interval







• OPC water<sup>7</sup> and 150 mM KCl with 40 Å padding • 10 kcal mol<sup>-1</sup> Å<sup>-2</sup> position restraints on RNA

• Monte Carlo pressure equilibration at 1 atm

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Mesh of equidistant points (yellow) at radius 3 Å from Mesh of point charges at radius R > 3 Å reproduce the QM dimer (magenta). Point size represents magnitude solvent ESP at 3 Å (yellow). Point size represents of ESP at that point due to solvent farther than R > 3 Å. magnitude of the charge, red positive or green negative.

	Radius (Å)	Number of point charges	QM energy (kcal mol <sup>-1</sup> )	Time (h)	Solvent ESP relative error
RNA		134	-14.804380	0.22	
Solvent	10	134415	-15.050562	22.51	Reference
Mesh	9	105813	-15.050563	17.66	0.003068
Mesh	8	80388	-15.050567	13.46	0.003064
Mesh	7	59322	-15.050566	10.03	0.002997
Mesh	6	39819	-15.050557	6.08	0.003914

Mesh radii (Å)	Density (Å <sup>-2</sup> )	Number of point charges	QM energy relative error	Time (h)	Solvent ESP relative error
10	1.000	122009	0.0000	21.02	0.0007
4	1.000	1030	0.0005	2.67	0.0032
10 4	1.000	3968	0.0005	3.12	0.0033
10 8 6 4	1.000	7754	0.0017	3.70	0.0032
4	0.333	341	0.0012	2.56	0.0032
10 4	0.333	1324	0.0033	2.73	0.0032
10 8 6 4	0.333	2590	0.0030	2.90	0.0033
4	0.083	91	0.0481	2.51	0.0036
10 4	0.083	324	0.0440	2.55	0.0044
10 8 6 4	0.083	650	0.0126	2.62	0.0037

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- across the dataset

- Point charge meshes reproduce influence of solvent density on QM energy

• Data analysis performed in LOOS<sup>9</sup>

## Do meshes capture influence of solvent density on QM energy?

Meshes reproduce QM energy of explicit solvent density •QM interaction energy of a nucleoside-nucleoside dimer computed using symmetry-adapted perturbation theory<sup>10</sup>, sSAPT0/jun-cc-pVDZ, in PsI4<sup>11</sup> • Approximate solvent density with point charge mesh to reduce computational burden • "RNA" contains only point charges from RNA context of experimental structure • "Solvent" contains explicit solvent density for solvent within 10 Å of the QM atoms • "Mesh" contains explicit solvent density up to a radius R and fits point charges on a mesh to reproduce solvent ESP for solvent between R and 10 Å

Meshes reduce QM job time by 10-fold • Include solvent within 40 Å; vary number of meshes, mesh radii, and point density • QM energy relative error with respect to 10 Å mesh with 1 Å<sup>2</sup> per point • Best mesh reproduces QM energy within 0.1 % and reduces job time by 10-fold

Extent of solvent influence is diverse across clustered dataset

• Compute QM interaction energy for 300 clustered nucleoside dimers • Histogram of difference in QM energy with  $(E_{sol})$  and without  $(E_{vac})$  mesh Solvent mesh typically makes interaction energy more unfavorable Magnitude of energy difference varies

## Conclusions

• Clustering RNA dataset on heavy atom pairwise distance improves efficiency is converged in time and space



### Future directions

- Compute QM interaction energies for nucleoside-phosphate dimers
- Estimation of solvent density from MD Fit nonbonded parameters to QM energies •Refit torsions in the context of new nonbonded parameters
  - RNA simulations to benchmark force field

### References

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