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Sage, the Open Force Field 2.0.0 and the road map forward

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https://openforcefield.org/about/team/

There are still lots of opportunities to improve small molecule force fields even at low levels of physics

- Simple and effective functional forms have been in use for 30+ years
- We can still improve these force fields with **better chemical perception**, **better optimization** techniques, and **better training datasets**
- This is a large undertaking!

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Various groups have been working on improving these force fields for decades

Figure adapted from Riniker S *J. Chem. Inf. Model.* 2018, 58, 3, 565–578

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OPEN SOFTWARE - OPEN DATA - OPEN SCIENCE: Rapidly facilitating force field science!

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OPEN SOFTWARE

Automated infrastructure enables rapid experimentation with minimum human intervention

JUID 100101

OPEN DATA

Access to large, high quality experimental and quantum chemical data facilities easy curation of balanced train / test sets

OPEN SCIENCE

Exploring new force field science: hypothesis - build software - train - test - iterate is now almost routine

We're generating a series of force fields

OpenFF force field progression since the Initiative's inception

What makes the Open Force Field Initiative different?

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Develop infrastructure to **rapidly evaluate the effect of parameters** on physical properties of interest

Creating workflows for fragmenting and generating **QM data for torsions** and other **valence terms**

Using **chemical perception** (SMARTS/ SMIRKS) to assign force field parameters

Distinguishing scientific elements of the Open Force Field Initiative

Enabling the use of **Bayesian inference** as a framework for making force field science decisions

Curate and generate **experimental and QM datasets** for force field parameterization and assessment

The SMIRKS Native Open Force Field (SMIRNOFF)

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SMIRNOFF avoids atom typing and simplifies parameter assignment!

Use of industry-standard SMARTS/SMIRKS chemical perception greatly simplifies tooling for parameter assignment while solving issues with extensibility and flexibility.

Ditching "atom types" for SMIRKS ("parameter types") allows parameter simplification

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For example, GAFF2 has 16 vdW types for carbon

But this should be three SMIRKS strings

Very relevant when attempting to automatically fit parameters — are there 32 parameters here, or 6?

Why all these atom types? The larger issue is more fundamental

Atom typing discards bond order, but we *need* bond order for parameter assignments

- With knowledge of which bonds are single, double, aromatic, have formal charges, etc., parameter assignment is straightforward
- Without it, atom types must "carry" bond order information, which is almost impossible to do in general
- SMIRKS force fields handle this seamlessly

SMIRNOFF allowed significant compression of smirnoff99Frosst, our AMBER-lineage starting point

- Less than 1/10 the size of the original force field
- Removes redundancy
- Almost completely covers pharmaceutical chemical space

Chris Bayly Caitlin Bannan

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BENCHMARK ASSESSMENT OF MOLECULAR ENERGIES AND GEOMETRIES WITH RESPECT TO QM DATA1

1. Geometry optimization: Molecular geometries are optimized with various FFs starting from the same QM geometry.

3. Geometry comparison: Geometry is evaluated through rootmean-square deviation (RMSD) and torsion fingerprint deviation (TFD)2.

TFD uses Gaussian-weighted differences of torsion angles between two conformations and may be more independent of molecular size for structure comparison purposes.

2. Energy comparison: The *ddE* for some conformer *i* is calculated relative to the conformer with the lowest QM energy (0) for different force fields:

$$
ddE = dE_{FF,i} \,- dE_{QM,i} = (E_{FF,i} - E_{FF,0}) - (E_{QM,i} - E_{QM,0})
$$

4. ddE vs TFD plots: Compare high density regions of energy vs. geometry data. A perfect match between FF and QM would result with all points at (0, 0).

There is not a direct relationship between the accuracy in geometry and the accuracy in relative energies.

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We've been doing automated benchmarking in collaboration with our industry partners

OpenFF 2.0.0 showed excellent performance when benchmarked against the **Public**

OpenFF Industry Benchmark Season 1 versus 1.x

Our work showed that we should train OpenFF 2.0.0 "Sage" LJ parameters against liquid mixtures

- Improved data availability
- Better for capturing diverse interactions
- Limited changes in molecular polarization
- Performed a pilot study over a subset of molecules Binary Enthalpy Of Mixing (kJ/mol)

Owen Madin Simon Boothroyd

Validated improved Lennard-Jones parameters versus solvation free energies.

OpenFF 2.0.0 (Sage) slightly improved results over OpenFF 1.0.0 (Parsley) for protein ligand binding free energies

- RMSE based on $\triangle\triangle G$ in kcal/mol
- Error bars are 95% CI
- OpenFF 2.0.0 (Sage) is generally slightly, but non-significantly better

Vytas Gapsys

Next generation of OpenFF force fields

Rosemary (OpenFF 3.x) series:

- In early 2023
- **First support of biopolymers (proteins)**
- A number of other science goals:
	- Refit electrostatics
	- Off-atom charge sites

- If we have great **small molecule** force fields, it should be possible to construct great **biomolecule** force fields.
- May require additional evaluation of torsional potentials that are perhaps overly general
- MORE importantly: How do we know if we have a good protein force field?
- Establishing community benchmarks and experimental datasets:
	- NMR spin relaxation, chemical shifts, NOEs
	- X-ray data from protein crystal simulations

COMING UP: Refit charge models - AM1BCC charge model currently being re-trained against QC and experimental data

COMING UP: Virtual sites - OpenFF infrastructure implementation enables new science

Describing chemical environments using convolutional graph neural networks

- Chemical environment is more complex than can be described by strings
- Use **convolutional graph neural nets** to describe the environment as vectors
- Then train to energies (or other observables)
- STILL the same functional form, but **continuous** parameters.
- Testing now to fit to AM1-BCC charges
- ESPALOMA proof-of-concept
- *Chem. Sci.*, 2022, **13**, 12016-12033

for directly computing molecular mechanics force eld parameters \mathcal{L} or biopolymer via a process that is fully dierentiable in the model parameters NN. In **Stage 1**, a graph neural network is u_{α} used atom embeddings describing local chemical environments from the chemical graph.

Now Rapidly Approaching:

- Organic polymers that are fully small molecule compatible
- Surrogate modeling for fitting condensed phase properties
- Co-fitted water model
- Making the functional more complex in a data-driven manner
- Bayesian decision-making on complexity of models

SUMMARY

OpenFF tools are freely available for you to use

• All code, datasets, force fields available online at:

https://github.com/openforcefield

Keep up to date with our progress and find tutorials:

https://openforcefield.org/

• You can start fitting your own force fields with our tools **today**!

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