

# Ensembler: Enabling high-throughput molecular simulations at the superfamily scale

Daniel L. Parton,<sup>1</sup> Patrick B. Grinaway,<sup>1</sup> and John D. Chodera<sup>1,\*</sup>

<sup>1</sup>Computational Biology Center, Memorial Sloan Kettering Cancer Center, New York, NY 10065

(Dated: February 24, 2015)

The rapidly expanding body of available genomic and protein structural data provides a rich resource for understanding protein dynamics with biomolecular simulation. However, simulations on an *omics* scale are not yet widely performed, partly because software infrastructure to enable this has not kept pace. For example, it should now be possible to study protein dynamics across entire (super)families, exploiting the entire variety of available structural biology data and conformational similarities across homologous proteins. Here, we present a new tool for enabling high-throughput simulation in the genomics era. Ensembler takes any set of sequences—from a single sequence to an entire superfamily of interest—and shepherds them through various stages of modeling and refinement to produce simulation-ready structures. This includes comparative modeling to all relevant PDB structures (which may span multiple conformational states of interest), reconstruction of missing loops, addition of missing atoms, culling of nearly identical structures, assignment of appropriate protonation states, solvation in explicit solvent, and refinement with molecular simulation to ensure stable simulation. The output of this pipeline is an ensemble of structures ready for subsequent parallel or distributed molecular simulations using clusters, supercomputers, or distributed computing projects like Folding@home. Ensembler automates much of the time-consuming process of preparing protein models suitable for simulation, while allowing scalability up to entire superfamilies. A particular advantage of this approach can be found in the construction of kinetic models of conformational dynamics—such as Markov state models—which benefit from a diverse array of initial configurations that span the accessible conformational states to aid sampling. We demonstrate the power of this approach by constructing models for all catalytic domains in the human tyrosine kinase family, using all available kinase catalytic domain structures from any organism as structural templates.

Ensembler is free of charge, and is made available under the terms of the GNU General Public License (GPL) v2. It should run on all major operating systems, and has been tested on Linux and OS X. The latest release can be installed via the *conda* package manager, and the latest source can be downloaded from <https://github.com/choderalab/enssembler>.

*Keywords: molecular dynamics simulation; comparative modeling*

## I. INTRODUCTION

Proteins play a diverse variety of roles in biology, and the understanding of their function—and how mutations can cause dysfunction and disease—is the preoccupation of much of modern biology. The diminishing cost of nucleic acid sequencing technologies has produced an enormous wealth of sequence data, yielding a large collection of protein-coding open reading frames that provide basic information about these proteins (at the level of primary amino acid sequences) for numerous organisms [CITE]. Complementing this, large-scale structural biology efforts such as the Protein Structure Initiative (PSI) and Structural Genomics Consortium (SGC) have yielded a great number of protein structures, allowing comparative modeling to provide insight into the static structures many of these proteins adopt [CITE review of structural biology efforts or current comparative modeling?].

Static structures, however, provide only a snapshot of the rich dynamical behavior of proteins. Many functional properties—such as the ability to bind small molecules or interact with signaling partners—require conformational changes.

Molecular dynamics simulations have proven to be a useful tool for revealing the dynamics of individual proteins,

with a number of software packages and forcefields available for biomolecular simulation. Advances in computing architectures—especially the availability of GPUs, which provide a hundredfold increase in computational power per unit cost for a variety of applications—and the proliferation of scalable computing technologies (such as those that drive the Folding@home distributed computing resource [CITE]) now provide new hardware platforms on which to study the dynamics of these proteins. In parallel, techniques for aggregating molecular dynamics simulation data to survey the kinetic landscape of biomolecules, such as Markov state modeling approaches [CITE MSM reviews], are now reaching maturity.

Despite this, a critical gap remains in the ability to bridge genome-scale sequence information and molecular simulations to enable the study of entire families or superfamilies of proteins in a single organism or across organisms. Molecular simulations must largely be set up by hand, with little in the way of automation available to provide practitioners a way of studying many members of a family where only a subset may have structural data.

Complicating matters further, in protein families known to be able to adopt multiple conformations—such as kinases—structural data may only exist for one or two conformations for any individual member of the family for which there is structural data. This poses a challenge for biomolecular simulation methods such as Markov state models, which can provide detailed insight, but require

\* Corresponding author; [john.chodera@choderalab.org](mailto:john.chodera@choderalab.org)

57 global coverage of the conformational landscape to realize  
58 their full potential.

59 Here, we present the first steps toward a resolution of  
60 this problem: a fully automated open source framework for  
61 building simulation-ready protein models scalable to the  
62 superfamily scale. We demonstrate the utility of this tool by  
63 constructing models for the entire set of human tyrosine ki-  
64 nase catalytic domains, and demonstrate that the resulting  
65 models provide good coverage of the known functional re-  
66 gions of structure space. This tool forms the foundation for a  
67 new era of superfamily-scale molecular simulations for the  
68 Folding@home project.

## 69 II. DESIGN AND IMPLEMENTATION

70 Ensembler is written in Python, and can be used via a  
71 command-line tool (`ensembl`), or via the flexible Python  
72 API.

73 The Ensembler modeling pipeline entails a series of  
74 stages which are performed in a defined order. A visual  
75 overview of the pipeline is shown in Fig. 1, and a detailed  
76 description follows.

### 77 1. Target selection

78 The output from this stage is simply a FASTA-formatted  
79 sequence file containing the selected target sequences and  
80 identifiers. The `ensembl` command-line tool provides  
81 methods for selecting targets from either UniProt (a freely  
82 accessible resource for protein sequence and functional  
83 data—`uniprot.org`) or TargetExplorer (a database frame-  
84 work for aggregating various types of biological data; work  
85 to be published). This allows the user to easily select a sin-  
86 gle protein, many proteins, or an entire superfamily. Alter-  
87 natively, the targets file can be generated using any other  
88 software, and stored at the appropriate filepath.

89 The method for selecting targets from UniProt is de-  
90 scribed here. A query string is required as input, using  
91 the same syntax as the search function on the UniProt  
92 website. For example, `'domain:"Protein kinase" AND`  
93 `taxonomy:9606 AND reviewed:yes'` would select all hu-  
94 man protein kinases which have been reviewed by a hu-  
95 man curator. Ensembler is designed to work with pro-  
96 tein *domains*, rather than full-length proteins, and the de-  
97 sired protein domain(s) can be selected using a regular ex-  
98 pression. For example, the string `'^Protein kinase(?!;`  
99 `truncated)(?!; inactive)'` would match domains an-  
100 notated as "Protein kinase", "Protein kinase; 1" or "Protein  
101 kinase; 2", but would exclude the domains "Protein kinase;  
102 truncated" and "Protein kinase; inactive". The program  
103 then extracts sequences and identifiers from the UniProt  
104 data, and saves these to a FASTA-format text file.

### 105 2. Template selection

106 As for target selection, the `ensembl` tool provides  
107 methods for selecting templates from various resources—  
108 UniProt, the Protein Data Bank (PDB; `pdb.org`) or a TargetEx-  
109 plorer database. From the user perspective, selection from  
110 UniProt proceeds in a similar fashion as described above.  
111 The returned data for each UniProt entry includes an up-  
112 to-date list of PDB structures and their residue spans. PDB  
113 files are downloaded from the PDB for structures which  
114 include the desired domain. Data from the SIFTS ser-  
115 vice ([www.ebi.ac.uk/pdbe/docs/sifts](http://www.ebi.ac.uk/pdbe/docs/sifts)) (CITE: Velankar Nu-  
116 cleic Acids Res 2013), which provides residue-level map-  
117 pings between PDB and UniProt entries, is then used to fil-  
118 ter out PDB chains with  $< 70\%$  resolved residues within the  
119 domain span. Template sequences and structures are then  
120 extracted and written as FASTA-format sequence and PDB-  
121 format coordinate files respectively.

122 Selection from the PDB simply requires specifying a list of  
123 PDB IDs. These are matched to UniProt entries via the SIFTS  
124 service, and the same procedure is then followed to extract  
125 template sequences and structures.

126 Unresolved template loops can optionally be remodeled  
127 with a kinematic closure algorithm, which is provided via  
128 the `loopmodel` tool of the Rosetta software suite (CITE:  
129 Rosetta and/or `loopmodel`). This tends to provide higher-  
130 quality models following the subsequent modeling process.

### 131 3. Modeling

132 In this stage, models are generated for each target-  
133 template pair, using the `Modeller` automodel function (CITE:  
134 `Modeller`), which implements comparative structure model-  
135 ing by satisfaction of spatial restraints (CITE: Sali Blundell J  
136 Mol Biol 1993; Fiser Sali Prot Sci 9 2000). `Modeller` requires  
137 the user to first provide a target-template sequence align-  
138 ment. This is implemented in Ensembler using the `BioPy-`  
139 `thon pairwise2` module (CITE: `BioPython`)—which uses a  
140 dynamic programming algorithm—with the PAM 250 scor-  
141 ing matrix of Gonnet *et al* (CITE: Gaston Gonnet Science  
142 1992).

143 Non-unique models are then filtered out using struc-  
144 tural similarity-based clustering. The `mdtraj` (CITE: `mdtraj`)  
145 Python library is used to calculate RMSD with a fast quater-  
146 nion characteristic polynomial (QCP) implementation, and  
147 the leader algorithm is then used to populate clusters. A  
148 minimum distance cutoff (default:  $0.6 \text{ \AA}$ ) is used to retain  
149 only a single model per cluster.

### 150 4. Refinement

151 Models are then refined with a steepest descent en-  
152 ergy minimization and a short molecular dynamics (MD)  
153 simulation with implicit solvent. This is implemented us-  
154 ing the `OpenMM` molecular simulation toolkit (link and  
155 CITE: `OpenMM`), chosen for its flexible Python API, and

high performance GPU-accelerated simulation code. The Amber99SB-ILDN force field is used (CITE: amber99sbildn refs) with a modified generalized Born solvent model (GBSA-OBC) (CITE: GBSA-OBC). The simulation is run for a default of 100 ps. This refinement process helps to prepare models for subsequent production simulation, and also helps to filter out poor quality models.

Ensembler also provides optional routines for solvating models with explicit solvent and performing a second MD refinement. The solvation step solvates each model for a given target with the same number of waters, as this is (currently) a requirement for building MSMs from multiple independent MD trajectories. The target number of waters is selected by first solvating each model with a specified padding distance (default: 10 Å), then taking a percentile value from the distribution (default: 68th percentile). Models are resolvated with the target number of waters by first solvating with zero padding, then incrementally increasing the box size and resolvating until the target is exceeded, then finally deleting sufficient waters to match the target value. The explicit solvent MD simulation is also implemented using OpenMM, with the Amber99SB-ILDN force field and TIP3P water.

#### 5. Packaging

Finally, Ensembler provides a packaging module, which can be used to compress models in preparation for data transfer, or to prepare models with the appropriate di-

rectory and file structure for subsequent production simulations on the distributed computing platform Folding@Home (CITE: F@H).

#### 6. Other features

The command-line tool also provides a `quickmodel` function, which performs the entire Ensembler pipeline for a single target with a small number of templates. For larger numbers of models (such as entire protein families), the main pipeline functions should be used. The modeling and refinement functions use MPI to trivially parallelize computation across each model (or across each template, in the case of the loop reconstruction code).

Each pipeline function also outputs a metadata file, which helps to link data to the software version used to generate it (both Ensembler and its dependencies), and also provides timing and performance information, and other data such as hostname.

### III. RESULTS

#### IV. AVAILABILITY AND FUTURE DIRECTIONS

#### V. ACKNOWLEDGMENTS

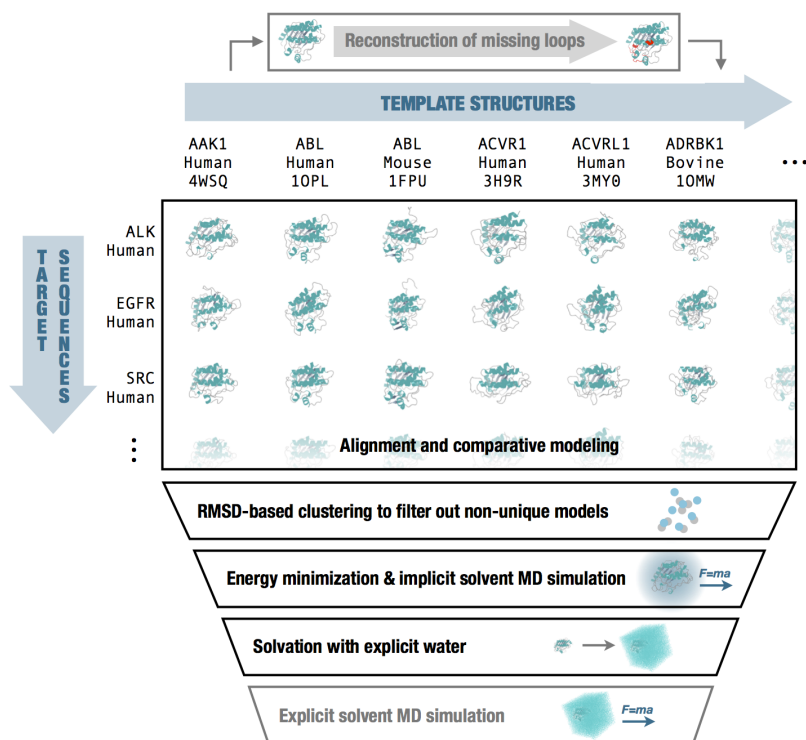


FIG. 1. Ensembler pipeline

	SRC	ABL	All 90 TKs
Templates	4433	4433	398,970
Models	4248	4250	382,568
Unique models	4093	4247	378,839
Refined models	4023	4241	373,513

TABLE I. Model counts for the kinase domains of human SRC and ABL, and for all of the 90 human TK targets, at various stages of the Ensembler pipeline.

	Timing (h:m:s)
Template reconstruction	03:00:00
Modeling	00:01:19
Refinement (100 ps implicit solvent MD)	00:01:58

TABLE II. Average timings per template/model for the compute-intensive stages of the Ensembler pipeline.