Accelerating the Interplay Between Theory and Experiment in Protein Design

Thesis by

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Abstract

Protein engineering techniques such as directed evolution and structure-based design aim to improve the properties of natural proteins. The next step, the *de novo* insertion of function into previously inert protein scaffolds, is the lofty promise of computational protein design. In order to achieve this goal reliably and efficiently, computational methods can be iteratively improved by cycling between theory and experiment.

Efforts to both accelerate the rate and broaden the information exchanged within protein design cycles form the core of this thesis. Improvements in the throughput of experimental stability determination allowed the thorough assessment of new multi-state and library design tools. Intending to alleviate the fixed backbone, single native state design approximation, the study found constrained molecular dynamics ensembles useful for core repacking applications. The subsequent development of automated liquid handling protocols for common molecular biology techniques brings design experiments to new levels of sample throughput. This technology facilitated the creation of a stability database encompassing every single mutant in a small protein domain. Although constructed to facilitate future computational training efforts, we answer a multitude of questions pertaining to mutational outcomes, distributions, positional sensitivity, tolerance, and additivity in the context of a protein domain.

By expanding the constraints of experimental molecular biology, this work opens up new possibilities in the efforts to train and assay new computational methodologies for protein engineering applications.

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