

# **Improvements in Molecular Mechanics Sampling and Energy Models**

**Joseph Bylund**

Submitted in partial fulfillment of the  
requirements for the degree  
of Doctor of Philosophy  
in the Graduate School of Arts and Sciences

**COLUMBIA UNIVERSITY**

2013

 2013

 2013

Joseph Bylund

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# ABSTRACT

## Improvements in Molecular Mechanics Sampling and Energy Models

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The process of bringing drugs to market continues to be a slow and expensive affair. And despite recent advances in technology, the cost both in monetary terms and in terms of time between target identification and arrival of a new drug on the market continues to increase.

High throughput screening is a first step in the direction of being able to test a large number of possible bioactive compounds very quickly. However the space of possible small molecules is limitless, and high throughput screening is limited both by the size of available libraries and the cost of running such a large number of experiments.

Computational drug design, or computer assisted drug design offers a possible way of addressing some of the shortfalls of conventional high throughput screening. Using computational methods it is possible to estimate parameters such as binding affinity, of any small molecule, even those not currently present in any small molecule library, without having to first invest in the possibly slow and expensive process of finding a synthesis. Computational methods can be used to screen similar molecules, or mutations in small molecule space, seeking to increase binding affinity to the protein target, and thereby efficacy, while simultaneously minimizing binding affinity to other proteins, decreasing cross reactivity, and reducing toxicity and harmful side effects.

Computational biology methods of drug research can be broadly classified in a number of different ways. However; one of the most common classifications is along the lines of the methods used to identify possible drug compounds and later optimize those leads. The first broad category is the informatics or artificial intelligence based approaches. In these approaches artificial intelligence methods such as neural networks, support vector machines and qualitative structure-activity relationships (QSAR) are used to identify chemical or

structural properties that contribute heavily to binding affinity. Ligand based approaches are very useful when a large number of known binders are known for a specific family of proteins. In this case the ligands cluster together in some sort of chemical space and new compounds which occupy a similar chemical space are likely to also bind strongly with the protein of interest. The class explored in this thesis is the diverse class known as structural methods. These methods in the most general sense make use of a sampling method to sample a number of protein, or protein-small-molecule interaction conformations and an energy model or scoring function to measure dimensions which would be very difficult and or expensive to measure experimentally.

In this thesis a number of different sampling methods which are applicable to different questions in computational biology are presented. Additionally an improved algorithm for evaluating implicit solvent effects is presented, and a number of improvements in performance, reliability and utility of the molecular mechanics program used are discussed.

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## Chapter 1

# Introduction

### 1.1 Drug Development

#### 1.1.1 Costs of Drug Development

The process of bringing new drugs to market is a long and expensive affair. Information about both the costs and time necessary to bring a drug to clinical trials are less available than statistics for drug molecules reaching clinical trials. There is much debate over the average cost and time investment needed to develop a new drug. At the least it is necessary to identify a possible target molecule, find a small molecule with promising binding characteristics to that target which is additionally not toxic nor a strong binder to the wide variety of other proteins necessary for regular cellular function. These small molecules are then varied to maximize binding affinity to the target molecule, while attempting to simultaneously minimize cross reactivity. Finally, after this process, these drug compounds are rigorously tested through clinical trials. The final costs necessary for this process range from 400 million per new chemical entity to as much as 2 billion. Estimates for the time required also vary significantly, but many estimates place the time required at around 10 years from target identification to an approved drug. One of the largest factors affecting the average cost of each new drug compound is the low success rate for compounds which have been under active research for a number of years. Effectively screening these compounds earlier in the pipeline has the potential to significantly decrease the average cost of each

new drug molecule. [Adams and Brantner, 2006]

The average cost of identifying a new drug molecule and gaining approval for that molecule is actually growing at a rate greater than inflation. The number of new drugs introduced during the period 2005-2010 was actually 50% fewer than the number introduced during the time frame from 2000-2005. New drug compounds have been shown to have important impacts on both longevity and quality of life. In fact, during the 14 year period from 1986 to 2000, 40% of the two year increase in life expectancy can be accounted for by the effect of new drugs introduced during that period. [Paul *et al.*, 2010]

The expected period of time that a candidate drug compound will spend in clinical trials is approximately nine to fourteen years[DiMasi *et al.*, 2003; Paul *et al.*, 2010]. During the period from 1981 to 1990 the rate of approval of potential drugs decreased, as did that of self-originated drugs, or those drugs which were originally identified by a pharmaceutical research company. Of potential drug compounds which reach clinical trials, only 10% will finally be approved as new drugs [DiMasi, 2001; Paul *et al.*, 2010]. Of potential drug compounds entering clinical trials that fail to be approved as new drugs, approximately two thirds will be abandoned or fail during phase II clinical trials, which test the efficacy of a drug. This is generally viewed as a failure to find a small molecule with sufficiently high binding affinity to the target protein. Thirty percent of potential drug compounds entering clinical trials will fail in stage I, either because they are poorly tolerated, toxic to humans or cause side effects. Each of these is a potential indicator of cross reactivity with proteins other than the target molecule.

Computationally screening these compounds earlier in the process has the potential of reducing the attrition rate at this point in the process. Additionally, increasing the affinity for the target itself can allow for lower dosages which can increase survival through phase II clinical studies. Finally, approximately 20% of potential drug compounds entering clinical trials will fail in stage III. These drugs fail for a variety of reasons, though ineffectiveness is frequently cited as a reason. All told efficacy accounts for 37.6% of all drugs that are abandoned after reaching clinical trials, making it the single largest contributing factor to the failure of these compounds to eventually receive approval as new drugs. Other factors include safety, and economics. [DiMasi, 2001]



For new chemical entities introduced in the 1990's the cost of research and development increasing at a rate 7.4% above inflation. Rates for the 2000's are not yet available or are only now becoming available due to the long lead time between introduction of a new chemical entity and that new chemical entity becoming an approved drug. During the period from 1985 to 2000 the rate of spending on research and development increased at approximately twice the rate of introduction of new chemical entities. Although the largest factors in determining this cost are the costs during clinical trials significant amounts are also spent earlier in the drug discovery pipeline, such as target identification, lead identification, and lead optimization. Improved computational techniques are generally viewed as possible means of decreasing costs or times associated with the earlier steps in the process. However, by increasing the fraction of leads which survive the screening process techniques which help identify and optimize lead molecules can have a very large effect on the cost of each new molecular entity. Clinical trials consist of six sometimes overlapping stages, denoted 0 to V, though stages I to III are where the majority of drug molecules are abandoned. Of the candidate compounds which enter clinical trials only approximately 20% will finally be approved as drugs. [DiMasi *et al.*, 2003]

Since 1950, the number of new chemical entities introduced per billion dollars has decreased by 50% every 9 years. Possible problems cited as contributing to this decrease in efficiency include:

1. the ready availability of high quality and effective generic drugs as treatment options for many diseases,
2. decreased risk tolerance among regulatory agencies,
3. increased spending and personnel without understanding underlying relationships between spending and personnel and discovery of new compounds, and the long period of time between beginning research on a drug target and finally gaining approval for a new drug compound, and
4. systematic overestimation of the efficacy of high throughput screening techniques relative more classical techniques such as clinical science, and animal screening [Scannell *et al.*, 2012].

The high failure rates during clinical trials have been identified as one of the most critical factors in determining the overall costs of drug development. [Bleicher *et al.*, 2003]

### 1.1.2 Computer Assisted Drug Design

The ultimate goal of computer assisted drug design is to improve rational drug design by exploiting the continuously increasing processing power available both in high performance super computers, but also in single workstations. Seeking to supplement the ability of a researcher either by allowing examination of a large number of possible interactions quickly or providing some insight that might be much more difficult to obtain through biochemical experiments, both in terms of time and expense. Different classes of programs have been developed to help solve each of the distinct steps in the pre-clinical stages of drug development, namely:

1. Hit Identification the process of screening a large small molecule database (up to one million or more small molecules) database to identify small molecules which bind a given target protein, or hits. These hits are usually small molecules with a target binding affinity on the order of micromolar.
2. Hit to lead optimization - the process of modifying these “hit” molecules either by substitution or addition of chemical moieties or mixing and matching substructures between given hits, to produce compounds with higher binding affinities than the initial hit compounds. Hit to lead optimization seeks to improve the micromolar binding affinity of hit compounds to nanomolar affinity or better.
3. Lead Optimization the final step of modifying lead compounds to increase “druglikeness” to ensure that the molecule is sufficiently soluble, well tolerated, and does not disrupt regular cellular function.

#### 1.1.2.1 Hit Identification

The earliest form of hit identification experiments were animal screens, where mutant animals were studied to find the specific gene or protein causing a specific phenotype. This type of experiment relies on careful genetic controls and breeding, but also some

element of luck in observing a relevant phenotype in the first place. “Brute force” animal screens have since been improved with extensive mutation libraries and exhaustive non-lethal mutation libraries for organisms such as yeast and *Escherichia coli*. Even so, these screens are slow, often taking three years or longer, and error prone, as performing a large number of repetitive experiments causes even the most fastidious of scientists to lose focus. High-throughput screening seeks to supplement the human factor with robots, which are capable of performing similar experiments with greater speed and fewer errors. With the help of this automation it is possible to test the interactions of as many as 100 million different reactions per day [Agresti *et al.*, 2010]. Though the high initial cost of high-throughput screening equipment as well as the cost of the small molecule libraries necessary for screening are often prohibitive even to large research institutions. In order to make this sort of experiment available to a larger number of institutions some research institutions have instituted means of sharing this equipment, through high-throughput screening as a service type arrangements [HTSRC, 2004; MSSR, 2006].

The direct computational equivalent to high-throughput screening is virtual screening, where a library of small molecules is computational “docked” into the active site of the target protein, and some scoring metric is used to identify possible binders. In this sort of computational screen, the problem of the cost of small molecule libraries is essentially a solved problem in virtual screening as there are readily available libraries of drug-like small molecules for use in virtual screening programs. For example, the ZINC database provides a library of over seven-hundred thousand commercially available small molecules in a number of different file formats for use in virtual screening [Irwin and Shoichet, 2005]. Another possibility for hit identification *in silico* is through fragment assembly methods.

The first published study using computational docking was published in 1982 by Irwin Kuntz describing a program which would later go on to become the well known DOCK program [Kuntz *et al.*, 1982]. Generally docking consists of a method of quickly screening possible protein-small-molecule interaction conformations. An emphasis is placed on the computational cost of evaluating the energy function over accuracy, as the poses generated by this step are usually fed into structural refinement programs for further sampling and

more accurate estimation of energies. For example in the original Kuntz study, the system only only had six degrees of freedom on which to sample, three translational and three rotational degrees of freedom for the ligand with the protein held fixed. Along with a hard sphere collision model this provided a sufficiently selective screen to identify the native binding geometry of the heme group to myoglobin as well as thyroid hormone analogs to prealbumin [Kuntz *et al.*, 1982].

The rate at which new structures are being deposited into the Protein Data Bank is increasing on an annual basis. But tools are necessary to draw meaningful insights from this data, hopefully leading to new drugs.

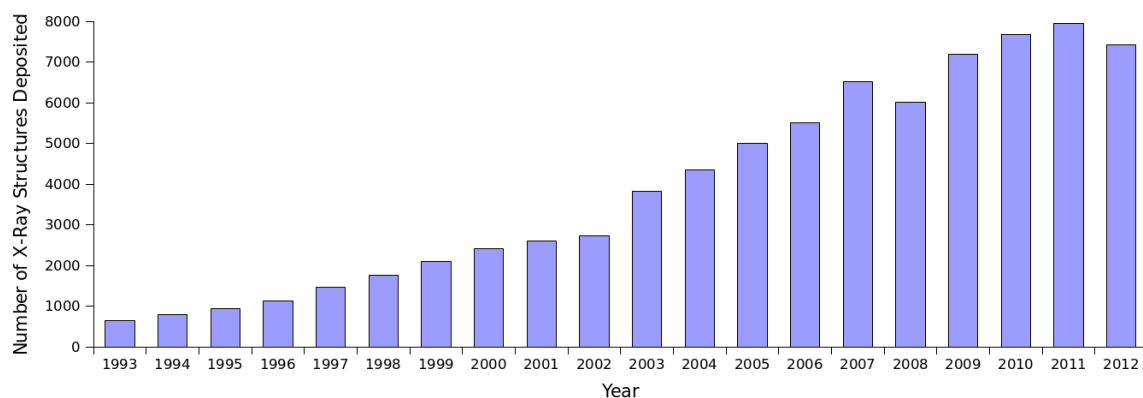


Figure 1.1: The rate at which new structures is deposited into the PDB over the last two decades. Due to a variety of improvements in the field of crystallography this rate has been steadily increasing.

For example a recent increase in the field of crystallography, is “crystal-less” crystallography in which small molecules are bound by a porous scaffold matrix. The regular structure of the matrix imparts a regular packing arrangement, necessary for interpreting diffraction patterns, onto the arrangement of small molecules. This has the potential to address one of the largest difficulties in obtaining quality structural data for proteins, which is that it is very difficult to purify and crystallize certain proteins [Inokuma *et al.*, 2013].

The number of target molecules of the set of all drugs currently available on the market consists of only about 500 proteins. The bottleneck in introduction of new chemical entities

is not virtual screening, but rather optimizing these hits into higher affinity leads and eventually balancing the requirements across all characteristics to produce a new drug [Bleicher *et al.*, 2003].

Of the total proteome only 30,000 are regulated by small molecule binding, making them reasonable targets of drug action. A large number of these possible drug targets are not implicated in any disease, due to this and a number of other factors, estimates of the total number of these proteins which are possible drug targets is much lower. Frequently cited numbers for the number of possible drug targets in humans are six-hundred to fifteen-hundred, still significantly higher than the total number of targets which are exploited by current drugs. The different families of cellular proteins are not equally likely to be targets of drugs. As of 2013 47% of current drug targets are enzymes, followed by 30% being GPCR's [Hopkins and Groom, 2002].

The consists of a number of characteristics which are generally true of drug like molecules:

1. Five or fewer hydrogen bond donors,
2. 500 Da or less total molecular mass
3. high lipophilicity
4. sum of nitrogen and oxygen atoms is not greater than 10 [Lipinski *et al.*, 1997]

Through understanding the protein-ligand conformation and specific contacts they were able to modify a known substrate There is an advantage to flexible substrates, which is that they can flex in order to create better contacts with the protein structure increasing binding affinity. This is especially important as the location of heavy atoms in the target protein is frequently only known to an accuracy of 0.4 angstroms. Further specific knowledge of the binding geometry between the initial lead compound and the target makes it possible to computationally screen possible chemical group substituents, to maximize binding affinity, increase solubility or bioavailability. One of the earliest examples of the successful application of structure based drug design is the carbonic anhydrase inhibitor dorzolamide, in which most of these ideas were applied to find a drug with very high binding affinity [Greer *et al.*, 1994].

Despite advantages in speed and cost due to limitations in accuracy computational screening has struggled to produce the same results as empirical screening. However, more recently virtual screening has succeeded in producing hit rates greater than those from empirical screening techniques. Virtual screening has been used to identify leads which were later developed into the human immunodeficiency virus (HIV) protease inhibitor Viracept, and the anti-influenza drug Relenza. A number of challenges which limit the utility of

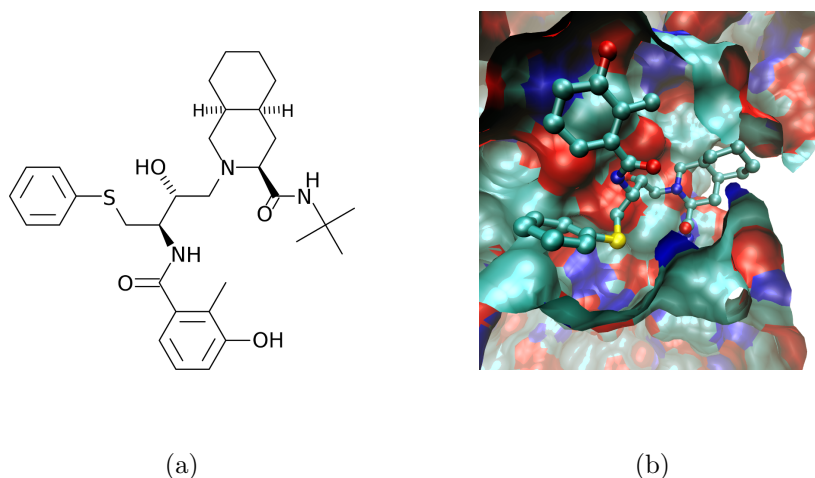


Figure 1.2: The HIV protease inhibitor, nelfinavir, marketed under the name Viracept was originally identified using a computational docking screen. It has a very high binding affinity for its target protein, 2 nM. Here it is shown crystallized with multidrug variant (ACT) (V82T/I84V) of HIV-1 protease, PDBID 3EL5. (b) generated with Visual Molecular Dynamics [Humphrey *et al.*, 1996] and [POVRAY 3.6, 2004].

docking programs have been identified

1. The number of possible small molecules is essentially unbounded, however only a very small fraction of these ligands are potentially drug compounds. Limiting sampling to this subspace is a challenging problem.
2. The number of conformations of ligand molecules rises exponentially with the number of internal degrees of freedom of the ligand. Sampling the huge conformational space of the ligand becomes a computationally difficult problem on its own.
3. The difficulty of accurately assessing or comparing the energy of different protein-

ligand complexes or conformations[Shoichet, 2004].

It has been found that introduced drugs are often very chemically similar the “hit” compounds from which they were derived [Proudfoot, 2002]. So in order to increase the diversity of drugs and find drugs which are able to treat new diseases, or diseases which have evolved resistance to current drugs it may be necessary to either increase the size of the screened database or increase the possible diversity which might be increase through the hit-to-lead step.

### 1.1.2.2 Hit-to-Lead Optimization

Hit compounds generally have a binding affinity for the target protein on the order of micromolar binding. The goals of hit-to-lead optimization are to further increase that affinity with the goal of eventually reaching binding affinities on the order of 10 nanomolar or better, find other molecules with similar chemical characteristics to increase the size and diversity of the set of lead compounds, and screening hit compounds for any obvious issues. At this stage for computational screening more accurate energy models are required than for the initial screen [Jorgensen, 2004; Gohlke and Klebe, 2002; Jorgensen, 2009].

Depending on the type of “hit” compounds identified in the initial screen, hits are either combined through molecular-growing and evolution techniques, or similar structures to the hit compounds can be sampled either by exploring the local chemical space or “mutation” of substituents. In either case, the potential lead compound is docked or grown in the known binding site.

A scoring function which is hopefully well correlated with the binding energy is then used to rank these possible compounds. Interestingly it is not necessarily the case that the scoring function is anchored in a physical force field, it is possible to use statistical or artificial intelligence approaches with success, so long as they are able to successfully solve the classification problem of distinguishing strong binders from weak binders. Docking as a means of converting hit compounds to lead compounds is very similar to docking as a means of hit generation, however in this case the small molecule library is much smaller and is generated to cover chemical space surrounding hit compounds. Additionally whereas for initial hit generation a coarse grained energy function might have been sufficient to

differentiate ligands which bind strongly from those which do not bind at all, to convert these “hits” to lead compounds it is necessary to use a more sensitive, and necessarily slower, energy model to accurately rank the binding affinity of different small molecules [Jorgensen, 2004; Gohlke and Klebe, 2002]. These energy models will be discussed briefly in 1.4.

A popular program for building, or mutating lead compounds is Biochemical and Organic Model Builder (BOMB) [Barreiro *et al.*, 2007]. BOMB can operate as either a hit identification program or as a hit to lead optimization method. Working to identify new compounds BOMB starts with a number of different small “core” scaffolds and attempts to increase binding affinity by adding or replacing substituents with favorable interactions while avoiding steric clashes. BOMB has been successfully used to evolve a hit compound which showed no inhibition of HIV reverse transcriptase into a potent non-nucleoside RT inhibitor with nanomolar level binding [Barreiro *et al.*, 2007].

Whereas previously, lead compounds were evaluated almost exclusively on binding affinity to the target protein, more recently more weight is being placed on identifying hit compounds which satisfy other characteristics besides binding affinity [Bleicher *et al.*, 2003]. It is important to begin to consider other characteristics of the potential drugs earlier in the pre-clinical process, because later it is difficult to make changes which affect characteristics such as solubility without significantly altering the binding affinity of an already highly modified hit compound. As “lead” compounds are rarely very chemically distinct from the hits from which they were derived, and increasing binding affinity is actually sometimes an easier problem than addressing some of the other characteristics in the “rule of five” it is reasonable to begin by first trying to optimize hit compounds to satisfy some other criteria and postpone maximizing binding affinity [Proudfoot, 2002].

### 1.1.2.3 Lead Optimization

In lead optimization the compounds which have been identified by the earlier steps in the process are optimized to drug molecules. The largest differentiating factor between hit-to-lead optimization and lead optimization is the plausibility of the compound to act as a successful drug molecule. The goals of lead optimization overlap heavily with those of the



hit-to-lead stage. Although this can include increasing binding affinity to the target even further, usually the focus is on other characteristics including selectivity, ease of synthesis, pharmacokinetic properties and intellectual property concerns [Keserü and Makara, 2006]. Computational modelling can help not only identify hit compounds, and convert those initial hits into leads, but also to help estimate absorption, distribution, metabolism, elimination, toxicology, sometimes referred to as the ADME characteristics [Kerns and Di, 2008].

Computational models for ADME characteristics ususally use regression equations or neural networks to predict these characteristics [Jorgensen, 2004].

Up to one half of all drugs which do not survive clinical trials, fail to do so because of lack of efficacy, which is influenced both by binding, but also by the absorption characteristics of the molecule. The number of drugs which fail to make it through clinical trials due to toxicity is similarly high, about 40% [Li, 2001]. Advancing a potential drug to clinical trials represents a very large financial investment, and effective computational screens of lead molecules at this point in the process can reduce the rate of failure in clinical trials, thereby having a very large impact on the final costs of new drugs brought to market.

## 1.2 Sampling Algorithms

### 1.2.1 Minimization

Minimization techniques seek to find the lowest energy conformation in a given potential well. Generally, they make no attempt to sample outside of that well, and therefore are frequently implemented as a final stage in sampling, in order to relieve any unfavorable interactions in proposed structures. There are a large number of different minimization techniques, and they will not be covered in any real depth here, please see the original papers for more details, or [Schlick, 2010] for a review. As the basic terms of the general molecular mechanics potential energy function are differentiable, and discounting for the moment the significant effects of solvent, it is possible to solve for the energy gradient, or force on every atom for a given conformation. A few minimizations methods include:

1. “Steepest descent”, conceptually the simplest minimization algorithm, in which the gradient is calculated at each step, and the size of the step is proportional to the

magnitude of the gradient [Levitt and Lifson, 1969; Bixon and Lifson, 1967].

2. “Newton” methods instead of approximating the gradient as a linear function in a small neighborhood, express the gradient, as a quadratic function. This has been shown to converge more quickly than steepest descent [Ponder and Richards, 1987]. Discrete Newton and Quasi-Newton methods use numeric estimation techniques instead of analytically solving for the gradient [Schlick, 2010].
3. “Truncated Newton” methods find an approximate solution to Newton’s equations, forcing the residual to approach zero as the series converges [Dembo and Steihaug, 1983].

### 1.2.2 Monte-Carlo Sampling

Metropolis Monte-Carlo simulation was originally developed in the 1950’s to provide rapid sampling of the solution space of many variable problems [Metropolis *et al.*, 1953; Hastings, 1970]. Monte-Carlo techniques generate a sequence of states from a distribution by proposing a new state based only on the current state. If the ensemble average is the same as the sequence average, a Monte Carlo Markov chain can be used to estimate ensemble averages, this is known as *ergodicity* [Schlick, 2010]. Another requirement is *detailed balance* that the probability of transition from a state  $X_i$  to a state  $X_{i+1}$  is the same as the probability of the reverse transition, i.e.  $X_{i+1}$  to  $X_i$ . By setting the probability of acceptance to

$$P(x \rightarrow x') = \min \left( 1, e^{-\frac{\Delta E}{k_B T}} \right) \quad (1.1)$$

these conditions are met.

In molecular mechanics, Metropolis Monte Carlo provides a very efficient means of sampling conformation space and a simple method of estimating the distribution of states. Modifications on this method, such as annealing, where the temperature is continuously decreased over the course of the simulation, or umbrella sampling, which attempts to achieve better sampling in cases where a potential energy barrier divides two or more states from each other [Torrie and Valleau, 1977]. While Monte Carlo sampling techniques are very fast to provide new states, the majority of these states reflect higher energy conformations.

Since it is of practical biological interest, Monte Carlo minimization has been developed to increase the rate at which minima are sampled [Li and Scheraga, 1987].

### 1.2.3 Analytic Loop Closure

Subsequences with regular secondary structures,  $\alpha$ -helices and  $\beta$ -sheets are generally better conserved, and therefore likely to be well covered by simple homology models [Kolodny *et al.*, 2005]. The intervening “random coil” or loop regions often play a large role in determining protein specificity for a specific ligand as in antigen-antibody binding [Bajorath and Sheriff, 1996], small protein toxins to the receptors they target [Wu and Dean, 1996], or transcription factors to specific DNA sequences [Jones *et al.*, 1999].

Loop closure or prediction is a significant part of homology modeling, and building structures consistent with X-ray refraction data. Therefore in order to accurately predict three dimensional structure through homology models, infer the protein binding partners and function, or even build a three dimensional structure consistent with both X-ray data and physical constraints, accurately predicting these loop regions is critical [Fiser *et al.*, 2000].

The question is, given two fixed endpoints and a flexible loop, or actuator, find a conformation of the loop which connects the two endpoints. Because of the similarities that this problem solves with robotics a number of algorithms have been adapted from that field [Kolodny *et al.*, 2005]. The first of these is analytical loop closure, where a conformation which satisfies the closure criteria is solved for directly by solving a system of equations. Though this problem can be solved analytically for small loops [Wedemeyer and Scheraga, 1999; Go and Scheraga, 1970; Bruccoleri and Karplus, 1985; Palmer and Scheraga, 1991], the problem becomes more difficult as loop length grows and the number of degrees of freedom of the loop section increases. Additionally these closure constraints make sampling multiple different conformations more difficult [Cortés and Siméon, 2005], though it is possible to hierarchically solve sub-loops in order to generate conformations for possible loops [Wedemeyer and Scheraga, 1999].

### 1.2.4 Random Tweak

Random tweak, like CCD is a method of producing and sampling closed loop conformations. It begins in much the same way as CCD, by randomizing  $\phi$  and  $\psi$  dihedral angles. Random tweak seeks to close the loop while retaining dihedral angles as close to the randomized starting structure as possible. By adjusting each dihedral only a small amount at a time and staying in the region where  $\sin(\Theta) \approx \Theta$  it is possible to formulate a set of linear equations to solve for a set of  $\Delta\Theta_i$  which minimizes the distance between the crystal position of the atom to be closed and the random position. Because the assumption  $\sin(\Theta) \approx \Theta$ , only holds for small  $\Theta$ , the maximum change in angle is limited, 10 degrees in the original implementation. Because almost all structures predicted using the random tweak or cyclic coordinate descent produce closed loops, a much smaller fraction of time is spent sampling loops which do not satisfy the closure criteria, and these algorithms can be very efficient [Fine *et al.*, 1986; Shenkin *et al.*, 1987].

### 1.2.5 Cyclic Coordinate Descent

Another robotics algorithm which has been successfully applied to protein loop closure is Cyclic Coordinate Descent (CCD) [Canutescu and Dunbrack, 2003]. As the length of a flexible loop grows the number of degrees of freedom increases and the possible solution space grows exponentially. Cyclic coordinate descent seeks to close the loop by adjusting the degrees of freedom, in this case the  $\phi$  and  $\psi$  dihedral angles, sequentially and possibly iterating over each degree of freedom multiple times until the loop is closed. This method is able to solve for conformations very quickly, and the likelihood of closing a loop *increases* as the number of degrees of freedom of the system increases. In cyclic coordinate descent the  $\phi$  and  $\psi$  angles of each loop backbone residue are first randomized. Then a loop dihedral is chosen at random, and varied to move the last atom of the loop as near as possible to its desired position. A new dihedral is chosen and optimized until the loop is closed. It is possible that this procedure does not converge to a closed state, however experiments have shown that this is very unlikely even for extended loops with few degrees of freedom, < 2% failure rate for 4 residue loops. Solving for the ideal dihedral angle at each step is a simple optimization problem making CCD a very fast algorithm [Wang and Chen, 1991;

Canutescu and Dunbrack, 2003]. In experiments CCD produces closed loop candidates in 1/6 the time of the random tweak method.

A variation on cyclic coordinate descent seeks to close the loop by not only requiring atom closure, but by requiring that the entire backbone of the closure residue is superimposed, within some geometric similarity tolerance, between the predicted and crystal structure. This constraint ensures that the angles and dihedrals of the closure residue are reasonable [Canutescu and Dunbrack, 2003].

### 1.2.6 Rotamer Assembly

Rotamer assembly or systematic search shares some similarity with fragment buildup techniques in that it uses a rotamer library to assemble possible loops. This rotamer library represents the common backbone dihedrals for each amino acid. This method operates by dividing the loop into two pieces, usually in half, and considering all possible half loops which can be built using rotamer library [Moult and James, 1986]. For each side of the loop a “tree” is considered in both a physical sense, that the hemi-loop branches as it grows away from its anchor, and a decision tree sense, in that every residue represents a decision where a single rotamer is selected from the rotamer library. When the hemi-trees for each side of the gap are fully constructed some closure criteria is applied.

In the case of the original systematic search geometric agreement is required of the entire mid-residue [Moult and James, 1986], however a more lax criteria is applied in the case of the PLOP where only one atom is required to be approximately superimposed [Jacobson *et al.*, 2004]. By carefully pruning trees during the building process, and biasing the search towards occupied regions of  $\phi$ - $\psi$  space, systematic search can be quite efficient, spending little time sampling implausible regions of conformation space. Additionally, by building residue pairs, using a smaller possibly restricting the rotamer library by building multiple residues at a time this sort of procedure has been used to build loops of 20+ residues [Zhao *et al.*, 2011].

### 1.3 Molecular Modeling

Molecular modeling seeks to gain new insights into the real world behavior of molecules by mimicking these molecules, usually using computer simulations. According to the theory of “minimal frustration” the protein native state is not only a low energy state, but is also stable [Bryngelson and Wolynes, 1987]. So the prediction of native or native-like conformations focuses on finding those conformations which have a low potential energy. As measuring the true potential energy of a system is very difficult or impossible computational models seek to reproduce the qualitative behavior of the energy surface. Quantum mechanics calculations are often viewed as the gold standard with respect to intramolecular energy calculations. However, despite the accuracy of quantum mechanics, its application to large systems such as proteins is currently limited due to the amount of time necessary to perform quantum mechanics calculations on a large number of atoms. Instead quantum mechanics calculations have been used to parameterize a majority of the most popular molecular mechanics force fields currently in use, including:

1. AMBER [Weiner *et al.*, 1984],
2. OPLS-AA [Kaminski *et al.*, 1994],
3. and CHARMM [MacKerell *et al.*, ].

The earliest molecular mechanics force fields either modeled groups of atoms as a unit, hydrogens being grouped with their bound heavy atom [Jorgensen and Tirado-Rives, 1988], or even each residue as a unit [Lee *et al.*, 1999], both to reduce the number of parameters in the model and to increase the speed of computations. Although *ab initio* folding experiments are theoretically interesting, they are generally not practical both because of the difficulty in simulating such a large system for the time-frame necessary to observe behaviors like folding, and also because structural models for many proteins are available either directly as X-ray structures, or indirectly through homology.

Because of the evolutionary cost of mis-folded proteins, proteins have been selected to minimize mis-folding, making the general shape of the potential energy surface roughly funnel shaped with the native structure at the minimum [Leopold *et al.*, 1992]. Despite this

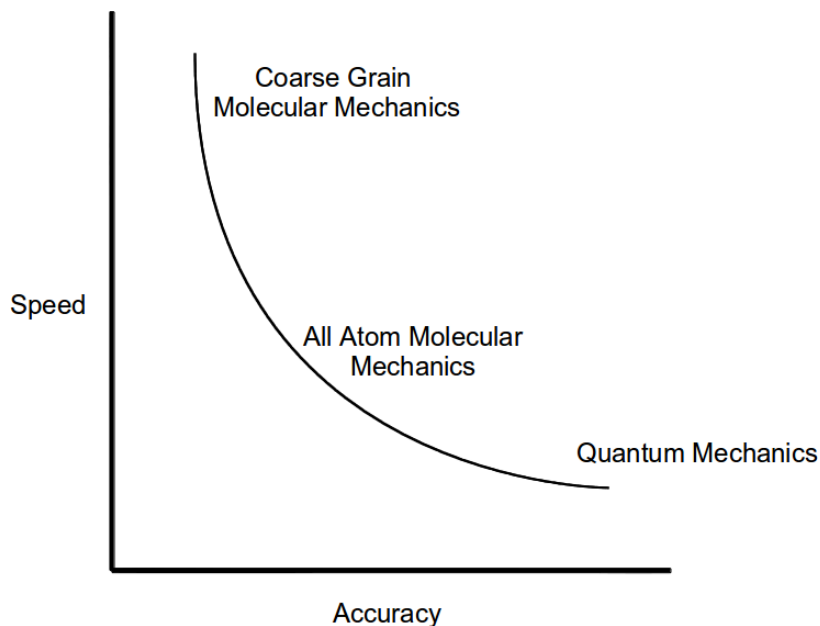


Figure 1.3: To an extent it is always possible to either increase accuracy or decrease running time, or the cost of an experiment. New scientific methods should allow one to increase accuracy while not spending additional time.

shape, the energy landscape of proteins is a very “jagged” surface with a large number of local minima [Tsai *et al.*, 1999].

Even the smallest enzyme contains 62 amino acids, and has thousands of degrees of freedom [Chen *et al.*, 1992], and larger enzymes are regularly more than 1000 amino acids. The number of degrees of freedom of these systems make any attempt to analytically solve for a global minimum energy conformation impossible, and require other methods of generating plausible conformations. In order to compensate for this a number of different sampling methods have been developed.

## 1.4 Energy Functions

Some energy models do not seek to accurately rank potential conformations, fast “screening” functions attempt to quickly differentiate physically impossible conformations from plausible conformations without performing an expensive minimization or energy calculation step.

Application of these screening functions has the potential to greatly reduce the number of potential conformations that must be scored using the full detail energy function, greatly decreasing the overall cost of conformation prediction. These screening criteria can be applied either during the sampling procedure, potentially eliminating sampling of a large area of excluded conformation space, or after sampling before a more expensive energy function is applied to rank conformations. Effective screening criteria have a large impact on the total performance of a structure prediction method.

One of the earliest screening criteria was the hard sphere overlap collision detection [Levinthal, 1966], and this method is consistently included in screening criteria. Other screens include:

1. bounds on bond lengths and angles, as a single bond which deviates significantly from equilibrium can dominate the energy of a conformation,
2. limitations on  $\phi$ - $\psi$  space occupied by backbone dihedrals corresponding to the Ramachandran plot of the residue,
3. limiting side chain dihedrals to staggered conformations, which correspond to the low energy well of side chain dihedral space [Moult and James, 1986],
4. excluding structures which present excessive solvent accessible surface area, as this conflicts with the hydrophobic effect, which has a large effect on the conformation of the native state [Chothia and Janin, 1975]
5. limitations on the number of “dry” cavities, and the number of internal charged residues [Moult and James, 1986]

### 1.4.1 The General Form of the Energy Model

The general form of most molecular mechanics energy potentials is reasonably consistent, with bonds and angles being modeled as a spring, dihedrals as a Fourier series.

$$E(r^N) = E_{\text{bonds}} + E_{\text{angles}} + E_{\text{dihedrals}} + E_{\text{nonbonded}} \quad (1.2)$$

$$E_{\text{bonds}} = \sum_{\text{bonds}} K_r (r - r_0)^2 \quad (1.3)$$



$$E_{\text{angles}} = \sum_{\text{angles}} k_{\theta}(\theta - \theta_0)^2 \quad (1.4)$$

$$E_{\text{dihedrals}} = \sum_{i=1\dots4} \frac{V_i}{2} [1 + \cos(i * (\phi - \phi_0))] \quad (1.5)$$

The non-bonded terms are modeled as a Columbic potential between any point charges and a Lennard-Jones or 6-12 potential between any non-bonded atoms. These non-bonded atoms are phased in by a “fudge factor” for atoms in a 1-4 configuration.

$$E_{\text{nonbonded}} = \sum_{i>j} f_{ij} \left( \frac{q_i q_j e^2}{r_{ij}} + 4\epsilon_{ij} \left[ \left( \frac{\sigma_{ij}}{r_{ij}} \right)^{12} - \left( \frac{\sigma_{ij}}{r_{ij}} \right)^6 \right] \right)$$

$$f_{ij} = \begin{cases} 0 & \text{if } i \text{ and } j \text{ are separated by 2 or fewer bonds} \\ 0.5 & \text{if } i \text{ and } j \text{ are separated by 3 bonds} \\ 1.0 & \text{otherwise} \end{cases} \quad (1.6)$$

Where  $\sigma_{ij} = \sqrt{\sigma_{ii}\sigma_{jj}}$  and  $\epsilon_{ij} = \sqrt{\epsilon_{ii}\epsilon_{jj}}$  [Jorgensen *et al.*, 1996].

### 1.4.2 Molecular Surfaces

Central to the discussion of solvent is a discussion of how to formulate the surface of a protein. The most frequently used formulations of surface area include:

1. The Van der Waals (VDW) surface is the surface formed by the VDW radius of each molecule, though sometimes differing parameters are used for the VDW radii, and the ideal radii may even vary by application.
2. The solvent accessible surface, which is defined as the surface traced by the center of a spherical probe “rolled” over the VDW surface [Richards, 1977]. This idea is very closely related to the idea of the solvent excluded volume, or the shape of the solvent cavity enforced by the VDW surface of the molecule [Richmond, 1984].
3. The molecular surface, or Connolly surface, is composed of the VDW surface in areas where the spherical probe touches the VDW surface, in union with all points on the probe “between” two points on the VDW surface when the probe is contacting multiple atoms [Connolly, 1983], put another way the surface of the volume which intersects no possible probe location.

Frequently these surfaces are approximated numerically, using the Shrake-Rupley algorithm [Shrake and Rupley, 1973], by considering a spherical mesh about every atom and including only points which satisfy the definition of the surface, or using these points to interpolate a surface.

The significance of surface area is determined by physical constraints but can be well illustrated by a number of observations about proteins. First the ratio of total area of a theoretical unfolded, i.e. linearly arranged, protein to its length is almost among proteins, only varying by  $\sim 3\%$  between different proteins.

### 1.4.3 Solvent Models

Beyond covalent terms and electrostatic effects, solvation effects have a very large effect on protein structure, and the interactions between proteins and small molecules. Therefore it is critical to accurately model the effect of the solvent on the molecule. While explicitly modeling each water molecule and sampling over possible conformations is the most realistic possible model, doing so requires calculating both a large number of solute-solute interactions as well as sampling extensively different solvent configurations. In this case it is likely that more time will be spent determining the behavior of the solvent than that of the solute. Because of these complexities even with efficient methods of sampling explicit solvent models, these simulations are too expensive to use on systems the size of proteins [Figueirido *et al.*, 1997; Zhang *et al.*, 2001].

Therefore there is significant interest in continuum models which accurately describe the mean force of water, without requiring additional sampling or interactions as in explicit models [Zhang *et al.*, 2001; Still *et al.*, 1990; Qiu *et al.*, 1997]. These methods have the potential to be three orders of magnitude, or even more, faster than explicit solvent experiments, and a number of different methods have been shown to accurately describe solvent effects [Zhang *et al.*, 2001].

The total free energy of solvation can be separated into polar and non-polar components, which correspond to the work done inserting the uncharged solute molecule, or protein, into the solvent and then building the charges to their native values [Roux and Simonson, 1999].

$$E_{\text{solvent}} = \Delta W_{\text{non-polar}} + \Delta W_{\text{electrostatic}} \quad (1.7)$$

According to scaled particle theory the non-polar work done by inserting a sphere into a solvent can be approximated if the radius of the sphere is neither too large nor too small as

$$\Delta W_{np}(s) = \gamma SA(X) \quad (1.8)$$

where  $\gamma$  is the surface tension of the solvent and the surface area corresponds most closely to the Connolly surface.

The electrostatic contribution to the solvent energy is the work necessary to add a charge to a hard sphere atom already in the solvent. The charge density in the solvent can be given by the Poisson-Boltzmann equation

$$\nabla \cdot [\epsilon(r) \nabla \psi(r)] = -4\pi \rho_u(r) \quad (1.9)$$

Though it is possible to solve this at every step of a simulation, it becomes rather expensive, therefore faster approximations are sought [Nicholls and Honig, 1991]. The total work can be approximated by the Born model

$$\Delta W_{electrostatic} = \frac{Q^2}{2R} \left( \frac{1}{\epsilon_v} - 1 \right) \quad (1.10)$$

However, this assumes that the induced charge in the solvent is entirely concentrated on the surface of the ion, which is impossible, therefore  $R$ , or the Born  $\alpha$  radius becomes a fit parameter, representing the effective radius of a charged sphere in the solvent.

The electrostatic solvation contribution can also be expressed as

$$\Delta W_{electrostatic} = \frac{1}{2} \sum_{i,j} q_i q_j f(x_i, x_j) = \frac{1}{2} \sum_i q_i^2 f(x_i, x_i) + \frac{1}{2} \sum_{i \neq j} q_i q_j f(x_i, x_j) \quad (1.11)$$

where  $f$  is a weighting function for the interaction between charges  $q_i$  and  $q_j$ . Historically there are a variety of methods of approximating this weighting function, however one of the most popular is the generalized Born (GB) [Still *et al.*, 1990]. In the generalized Born approach

$$f(x_i, x_j) = \sqrt{d(x_i, x_j) + R_i R_j e^{\frac{-d(x_i, x_j)^2}{4R_i R_j}}} \quad (1.12)$$

and one of the limiting factors to accuracy becomes obtaining proper estimates of the effective radii, since charges are not uniformly exposed to the solvent [Schaefer and Karplus, 1996].

Another approach is to estimate both the nonpolar and electrostatic contributions to solvation as proportional to the surface area, with different proportionality constants for different atoms.

$$\Delta W = \sum_{atoms} \gamma_{atom} SA(atom) \quad (1.13)$$

Although this method is very inexpensive to compute, it can be somewhat difficult to solve for the force on an atom, due to the way the surface changes as atoms move [Roux and Simonson, 1999].

## Chapter 2

# A Cell Based Method for Evaluating Implicit Solvation Effects

One can see in the Generalized Born model (1.12), computing the electrostatic contribution to solvation requires computing the distance between every two atoms.

### 2.1 Introduction

Computational protein structure prediction and related areas of research such as target screening and lead optimization continue to be areas of active research in both pure chemistry and pharmaceutical applications[Jorgensen, 2009]. These methods range from identifying leads using chemical similarity metrics, to artificial intelligence methods such as neural networks and support vector machines, to structural based methods[Geppert *et al.*, 2010]. In the recent past, structural methods have contributed to the identification of bioactive drug compounds[Corsino *et al.*, 2009], making computational protein structure prediction highly important to the medical field, and because of its pharmaceutical applications, economically relevant as well.

There are over 81,000 X-ray structures presently in the PDB, more than 8,500 of which have been added in the last 12 months, and the rate at which new structures are deter-

mined by X-ray crystallography continues to accelerate[Berman *et al.*, 2007]. The chemical space of small molecules, i.e. potential drug compounds, is essentially unlimited, and at the least too large to effectively screen using conventional experimental methods[Jorgensen, 2009]. Furthermore, computational loop prediction experiments are predicting longer loops, increasingly relying on the output of initial predictions as the input to a later “fixed stage” refinement step that re-predicts some central region of the same loop. This has been shown to increase accuracy [Jacobson *et al.*, 2004] at the cost of an increased number of experiments and corresponding increase in computational cost. Taken together, these factors necessitate the development of more accurate and efficient methods of generating and evaluating protein-protein and protein-small molecule conformations and interactions.

The Protein Local Optimization Program (PLOP), originally developed by Friesner and co-workers, is a popular program used to predict, sample, and evaluate protein conformations[Jacobson *et al.*, 2002a; Jacobson *et al.*, 2002b; Jacobson *et al.*, 2004]. PLOP makes use of the OPLS-AA energy model, an atomic detail force field optimized for organic, including protein, interactions [Jorgensen *et al.*, 1996]. In addition to the terms defined by the OPLS-AA model, it has been shown that solvent effects can have a large contribution to prediction accuracy. The solvent contribution to an energy model can be evaluated either by explicitly modeling and sampling solvent molecules (usually water) or by treating the solvent as a continuous medium, i.e. implicit solvation. PLOP, like many other molecular mechanics programs, makes use of an implicit solvent model. This is largely because explicitly modeling solvent molecules, while possibly very accurate, requires extensive, and therefore very time consuming, sampling of a large number of small molecules[Zhang *et al.*, 2001]. Further, energy errors using explicit solvent models can be due to either an unrealistic force field parameters or insufficient sampling of solvent molecule conformations[Zhou, 2003]. Continuum solvation methods, or implicit solvent methods, attempt to address these issues by removing the dependence on sampling of solvent molecules and introducing approximations that reduce the cost of calculating the solvent contribution to energy[Roux and Simonson, 1999].

Among implicit solvent methods, the surface area based generalized Born (S-GB) model is one of the most popular and has been shown to produce results in good agreement with

experimental data[Zhang *et al.*, 2001; Gallicchio *et al.*, 2002]. The surface area based generalized Born implicit solvent model provides an approximate solution to the Poisson–Boltzmann equation based on a surface integral[Ghosh *et al.*, 1998]. However, in a naive implementation of this model, the electrostatic contribution is a sum over every charge–charge pair in the system, in this case the protein and its crystal copies.

$$U = \sum_{\text{charges}} U_{\text{self}}(q_k, r_k) + \sum_{\text{charges, } i \neq j} U_{\text{pair}}(q_i, q_j, r_i, r_j) \quad (2.1)$$

Electrostatic contribution to solvation free energy, decomposed into self, and pair terms. The time complexity of evaluating the pair term is quadratic in the number of charges in the system [Ghosh *et al.*, 1998]. This means that calculating the electrostatic solvation contribution for a single atom requires a linear search over all other charges in the system, which for large systems becomes the bottleneck of the computation. A common optimization is to assume that the electrostatic contribution to the solvation term for point charges separated by a distance greater than a defined cutoff distance is negligible[Gallicchio and Levy, 2004]. However, making this assumption does not improve the underlying quadratic time complexity of evaluating the solvation term, as it is necessary to compute the inter-charge distance for every charge pair in the system, before possibly excluding the interaction. In the implementation of S-GB in the Protein Local Optimization Program, computing the solvation term of a large structure is the rate limiting step of energy calculations, accounting for over 80% of the total time spent computing the energy (see figure 2.2). Therefore, less expensive methods of evaluating the implicit solvent contribution to the energy of a system can allow for increased sampling with the same available resources, thus improving efficiency of computational modeling.

We present an application of a geometric hashing method, grid based spatial indexing, to implicit solvent calculations in PLOP. The hashing method proceeds by dividing space into cubical regions, or cells, and distributing atoms into those cells, while maintaining a list of the contents of each. Retrieval of atoms within a cell can then be performed in constant time, and retrieval of a superset of atoms contained within a region can be performed in time proportional to the number of cells intersecting the region. This efficient geometric lookup allows one to replace a loop over all atoms inside the structure with a loop over

only the atoms contained in cells intersecting the sphere with radius corresponding to the distance cutoff of the force in question. While maintaining a list of atoms for each of these grid boxes introduces some overhead when updating atomic coordinates during a simulation, updating atomic coordinate is still a constant time operation. Thus, the benefits outweigh the costs, especially for large systems. As long as the cell size is bounded below, the number of cells necessary to consider when evaluating a fixed distance interaction is constant. Physical limitations provide an upper limit to atom density. Constant time retrieval of the contents of each hash cell, along with upper bounds on the number of atoms per cell and the necessary number of cells to consider for each charge, guarantee constant time lookup of all atoms within a given sphere. This reduces the time complexity of evaluating the electrostatic contribution from  $O(n^2)$  to  $O(n)$ . We show that an implementation of this hashing method can reproduce results obtained with a non-hash based implementation while providing significant performance improvements.

## 2.2 Methods

### Data Sets

The data set used for energy calculation experiments consisted of large protein structures, containing neither DNA, RNA, or modified residues with molecular masses between 100 and 150 kDa. All samples had resolutions better than 2 angstroms. The data set was filtered at 30% sequence identity, and from this, 20 structures were selected at random, though two were later excluded due to technical reasons.

The structures used in side chain prediction experiments consisted of high resolution enzyme structures. Structures without an enzyme classification were excluded, as were structures with X-ray resolution less than 1.5 angstroms, or those with modified protein residues. This resolution requirement was imposed to make high resolution side chain prediction comparisons more meaningful. All structures had a molecular mass between 11 kDa and 110 kDa. Structures containing DNA, RNA or modified side chain residues were excluded, as were those that had unreasonable steric clashes either within the canonical structure or with crystal neighbors. Structures containing certain small molecules without



energy parameterizations currently defined within PLOP were also excluded.

## Structure Preparation

In preparing the crystal structures for energy calculation and side chain prediction experiments, the first step was to add the crystal copies of the protein of interest. PLOP completes this step for all space groups according to the crystal symmetry identified in the PDB file. Before modeling a structure using an all atom force field, it is also necessary to add hydrogens and any missing heavy atoms. When possible, PLOP uses the positions of bonded heavy atoms to build missing atoms into the structure. However, adding hydrogens, especially for titratable residues, is a more complicated problem. To address this, PLOP uses the independent cluster decomposition algorithm (ICDA) to determine the protonation states of any titratable residues, as well as the positions of polar hydrogens[Li *et al.*, 2007]. Generally speaking, this proceeds by dividing titratable and polar residues into independent groups using a distance cutoff, and optimizing each group independently. Structures with unreasonable steric clashes with crystal neighbors were removed from the data set on the basis that such structures are physically unlikely.

## Grid-Based Spatial Indexing

Grid-based spatial indexing is a well known algorithm in computer science, especially computer graphics, that allows for efficient lookup based on geometric criteria and also provides fast collision detection[Bentley and Friedman, 1979]. Critical to the present application, it allows constant time retrieval of a superset of atoms guaranteed to contain all atoms within a given euclidean distance. In our implementation, the bounding box of the protein and its symmetric copies is subdivided along each of the orthogonal axes to form grid boxes or cells. A simple convention for handling atoms that are positioned along cell boundaries guarantees that each atom is hashed to a unique cell. For a single dimension,  $d$ , the cell index, or hash, of a point  $p$  is

$$i_d(p) = \text{int} \left( N * \frac{p_d - \min_d(P)}{\max_d(P) - \min_d(P)} \right) \quad (2.2)$$

where  $\min_d(P)$  and  $\max_d(P)$  are the minimum and maximum coordinates in dimension  $d$  over the set of points  $P$ ,  $N$  is the number of cells in dimension  $d$  and  $p_d$  is the coordinate of  $p$  in  $d$ . Following the same procedure in each dimension gives a unique cell location for every atom. In this way, at the beginning of the simulation, each atom is assigned to a specific cell, or grid box. A list of the atoms in each grid box is then maintained over the course of the simulation. When computing the electrostatic contribution to solvent free energy of an atom,  $a$ , it is only necessary to loop over the atoms contained in boxes that intersect the sphere corresponding to the distance cutoff around atom  $a$ . Beyond that cutoff, charge effects are considered to be negligible [Gallicchio and Levy, 2004].

In the present implementation, cell size is at first set to 2.745 angstroms, and the number of cells in a given dimension depends on the "length" of the system in that dimension. If the number of cells that this would require is unmanageably large, cells are then grown simultaneously in all dimensions such that the cell size is 1/250th of the longest dimension of the structure.

## Experiments

For side chain prediction, the specific side chains used were those which had at least 30% solvent accessible surface area when evaluated in the absence of other chains or crystal neighbors. Glycine and proline residues were also excluded, as they do not have free side chains. Residues missing heavy atoms in the crystal structure were predicted; however, RMSD was not measured for these residues because there is no experimental data. Side chain prediction experiments were performed as described in [Jacobson *et al.*, 2002a].

The experiment in this case consisted of multiple energy calculations, using the modified version of the OPLS-AA force field described in Li *et al.* 2011 [Li *et al.*, 2011]. In the control experiments, the same method for evaluating the implicit solvent term was used as in previous works.

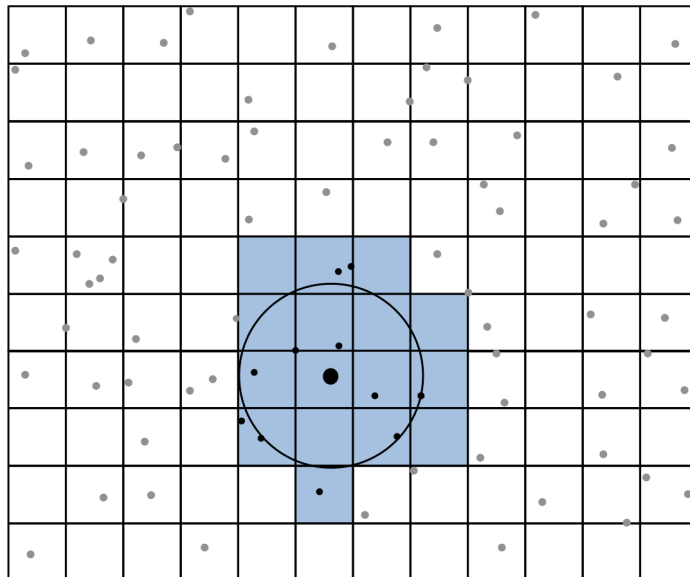


Figure 2.1: This illustrates, in two dimensions, the grid based spatial indexing method. The naive S-GB method would require a distance computation to every other atom in the system. By only considering atoms in cells intersecting the radius of influence, represented here in blue, it is possible to consider far fewer interactions. Although only atoms inside the circle in this illustration contribute to surface charge, it is necessary to compute the distance over all black points.

## 2.3 Results

### Qualitative Measures of Prediction Quality

For side chain prediction experiments, 85.2% of side chain prediction conformations (9406 of 11030 total) predicted with the new cell based solvation model are within 0.2 angstrom heavy atom RMSD of the prediction using the naive implementation. In other metrics, the quality of prediction is comparable between the two solvent models. Median side chain heavy atom RMSD is 0.567 and 0.558 angstroms for the cell based method and the non-cell based method, respectively. Average RMSD to the crystal structure is similarly close, 1.11 angstroms for both methods, with 79.9% of side chain predictions within 2 angstroms RMSD of the native using the cell based model and 79.4% within two angstroms using the

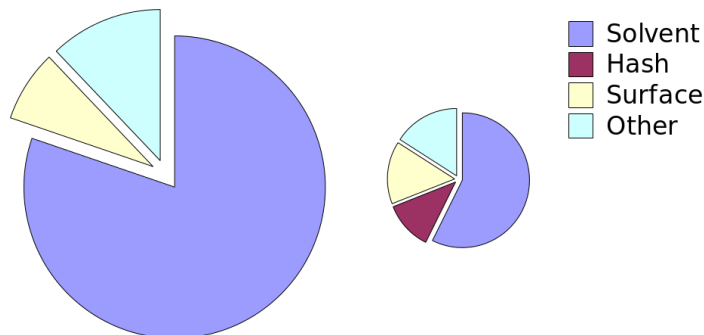


Figure 2.2: Time spent during energy calculations on different parts of the energy model. The left pie represents the non-cell based approach and the right pie the cell based approach, the charts are scaled relative the total cost of computing the energy. One can see that although some overhead is introduced in maintaining the hash structure this significantly reduces the total cost of the solvent term, and as the solvent is such a large contributor to the total, also the total cost of computing the energy.

naive approach. Of side chains which are predicted differently by the two implementations there is no correlation between solvation model and prediction quality. The distribution of side chain predictions with respect to RMSD to native is also indistinguishable between the two methods of computing the solvation term.

Data for energy calculations is not presented here because it is identical in every case. This is expected, given that the two models represent two methods of computing the same quantity. Thus, on the whole, prediction accuracy of the hash based model is comparable with the old implementation.

### Performance Improvement

The principal goal of the hash based approach is to improve the performance of the implicit solvent models. Thus, the key metric of performance improvement is the speedup over the previous implementation. Energy computations were found to be from 1.6 to 2.5 times as fast, and the trend indicates that even larger improvements would be obtained in larger system. This sort of experiment represents a “best case” for the expected performance increase of a hash based solvent, as they represent a minimum amount of time spent on

other parts of the experiment. Implicit solvent calculations, and energy calculations in general, compose a smaller fraction of time in simultaneous side chain prediction therefore the observed performance improvement is less than that of energy calculations. The observed performance increase in this sort of experiment is still on approximately 20%.

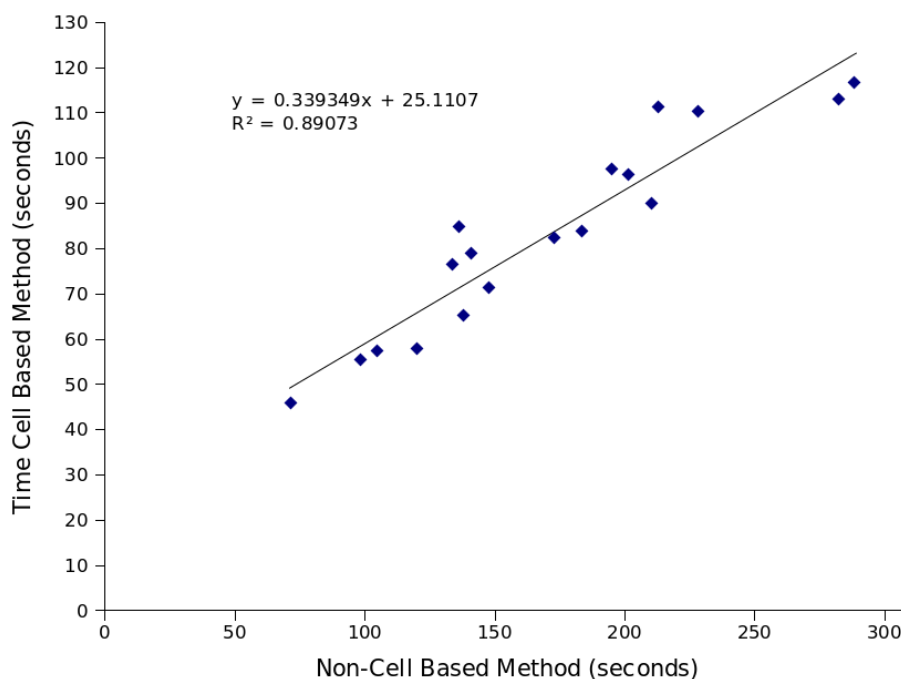


Figure 2.3: Energy computations using a grid based method yields approximately a three times performance improvement, though in the case of some very small structures it is possible that the overhead introduced by maintaining the grid structure outweighs the improvement.

| PDB id | Naive Method | Cell Based Method |
|--------|--------------|-------------------|
| 1F5Z   | 201.75       | 96.37             |
| 1H2V   | 98.31        | 55.32             |
| 1HRD   | 228.38       | 110.12            |
| 1M1Z   | 147.83       | 71.28             |
| 1M9X   | 282.35       | 113.04            |
| 1O60   | 172.82       | 82.34             |
| 1R0V   | 210.35       | 90.0              |
| 1XMP   | 213.25       | 111.25            |
| 2E3Z   | 141.11       | 78.79             |
| 2H6U   | 138.25       | 65.07             |
| 2OU1   | 104.93       | 57.24             |
| 2XI9   | 71.68        | 45.73             |
| 3AMD   | 288.58       | 116.52            |
| 3DEL   | 133.62       | 76.48             |
| 3E1E   | 183.8        | 83.8              |
| 3FGN   | 120.38       | 57.75             |
| 3HHP   | 195.25       | 97.58             |
| 4GVR   | 136.35       | 84.78             |

Table 2.1: The specific timings for a series of energy computations presented in Figure 2.3. These represent a “best case” scenario, as the majority of time in these experiments is spent computing the solvent contribution.

## 2.4 Discussion

We have developed an application of a classic computer science grid based hashing algorithm to the implicit solvent model of PLOP. We demonstrate that this application does not affect accuracy of results compared with the previous implicit solvent model implementation in PLOP. Though in a small number of cases side chain conformations are predicted in widely

different conformations by the hash based method and the old implementation, the two methods are equally likely to predict the more native-like structure, so this variance can be attributed to noise. We have also found in other experiments that the final predicted structure of a minimization is very sensitive to both small changes in pre-minimization coordinates, of a magnitude far less than bond distances, and minimization parameters. It is possible that these effects magnify small differences present early in the experiment, resulting in much larger differences between the final predicted structures. Finally, we present data showing that the reduced computational cost of evaluating the solvent contribution using this hash based approach dramatically reduces the total time spent evaluating the energy model by a factor of 1.6 to 2.5.

Note that any such geometric hashing will introduce some overhead for maintaining the data structure. As discussed by Bentley and Friedman [Bentley and Friedman, 1979], the total storage necessary for the hash structure and the time necessary to sort atoms into cells are both linear in the number of atoms, and placing or updating a single atom in the structure is a constant time operation. The improvement in retrieval using this structure dominates the cost of maintaining the structure, and the difference becomes more pronounced as system size grows. Bentley and Friedman also present a thorough review of the performance characteristics of a number of other geometric hashing techniques, though they compare the algorithms in a data agnostic means. Taking advantage of the characteristics of physical data, in this case atomic coordinates, has some effect of the relative advantages and disadvantages of specific hashing techniques. Specifically, the maximum number of atoms per cell is limited by physical constraints of atomic interactions. An octree is a similar, though hierarchical, hash structure used in computer graphics for fast location based retrieval. However, because the criteria for “collision” in this case is a fixed distance cutoff, and the data is roughly uniformly distributed it is efficient to use a fixed cell size [Turk, 1989].

Though the implicit solvent term was initially targeted, because it dominates the time spent in energy calculations, it is possible to apply this method to any pair-pair interaction. Though especially for shorter range interactions it might be beneficial to either maintain a higher resolution hash, or implement a hierarchical spatial hash, such as an octree. We

are also applying this geometric hashing technique to collision detection between simultaneous loop predictions. This will allow efficient screening of neighboring loop prediction candidates, which will be particularly useful in predicting structures with multiple nearby solvent exposed loops, such as G-protein coupled receptors.

Implicit solvation models offer a very tangible benefit over explicit solvent models, both in performance and experimental complexity. Though explicit solvation is sometimes viewed as a “gold standard”, it has been shown that current implicit solvent models can, at least sometimes, reproduce predictions of explicit solvent models. However, development of implicit solvent models is important since improved performance compared with explicit solvent methods allows modeling of larger systems, longer timescales, or improved sampling. The complexity of the experiment is also reduced, using implicit solvent models, because results are not dependent on sampling of water conformations in addition to protein conformations. However, implicit solvent models can still be very computationally expensive. For instance, in the PLOP implementation of the OPLS-AA energy model with SG-B solvation term, evaluating the solvation term consumes up to 80% of the total time spent in energy calculations, dependent on size of the symmetric system. This is in large part due to the time complexity of evaluating the SG-B solvation term. Thus an algorithm that offers further reduction in experimental cost without a tradeoff in accuracy represents valuable progress in the development of implicit solvent models.

Because the size of protein systems are limited, at some level, by physical limits, the maximum system size expected to be encountered is limited. Therefore, although the new method reduces the time complexity of implicit solvent calculations, the maximum expected speedup is limited to about a factor of three in large systems. The actual speedup depends on both the system size, and the amount of time that a given experiment spends evaluating the solvent contribution. The speedup observed in side chain prediction experiments was much less, around 20%, though it is possible that applying a similar method to terms of the gradient during minimization would increase that amount. Nonetheless, even a 20% speedup represents a significant improvement, especially as structure prediction methods continue to depend on parallel prediction and reprediction of the same region as a method of structure refinement[Goldfeld *et al.*, 2013]. Although this algorithm improves on the



theoretical time complexity of the S-GB implicit solvent model, parameterization such as the number, and size of cells in the grid structure could have a significant effect on run time. Some effort was made towards choosing reasonable parameters, but they are likely not optimal. Hardware that is optimized for this sort of spatial indexing and collision detection, or proximity detection, exists in modern video cards, and along with general purpose programming for this sort of hardware it should be possible to further parallelize computation of implicit solvation effects for even greater performance improvements[Harris, 2008].

## Chapter 3

# Progress in Computational Mutation Scanning

### 3.1 Introduction

In order to determine which amino acids in a protein play the largest role in determining binding affinity it is convenient to compare the binding affinity of the native protein with that of a single residue mutant. If the change in residue does not affect the folding of the protein, which with the exceptions of mutations to glycine, proline, or depending on the local structure possibly large amino acids, is unlikely. Alanine is the most frequently occurring amino acid, appearing in both solvent exposed and buried positions [Chothia, 1976; Rose *et al.*, 1985], and is unlikely to disrupt the protein fold in the same way glycine or proline might [Klapper, 1977]. Additionally because it lacks a charge it does not interact electrostatically with the ligand. These reasons makes it an attractive choice as a “control” amino acid for mutation scanning experiments. Mutation scanning experiments, seek to identify residues which are have the largest contributions to binding affinity or “hot spot” residues. By identifying single residue mutants which have a significantly decreased binding affinity when mutated to alanine [Cunningham and Wells, 1989].

The immune system maturation response, selects antibodies which have a reasonable affinity for an antigen, and creates a large number of variants of these antibodies. The effect of this is that the body produces antibodies with increasing affinity for an antigen some

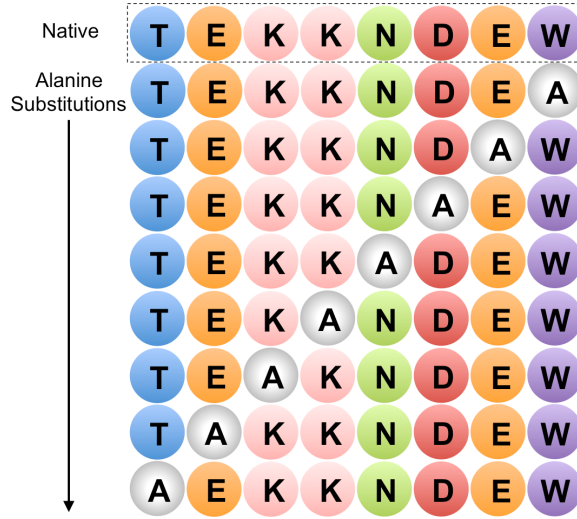


Figure 3.1: The sequences which would be evaluated during an alanine scan for Fc domain of a human IgG for streptococcal protein G. The residues identified here were taken from the AESDB. The native protein is represented in the top row [Sauer-Eriksson *et al.*, 1995; Thorn and Bogan, 2001].

time after the initial exposure [Griffiths *et al.*, 1984]. In vitro affinity maturation attempts to select molecules, frequently antibodies, with high affinity for some target molecule by creating a library of bacteria displaying variants of these antibodies on their cellular surface. The means of doing this is bacteriophage display, which provides a method of pairing the protein represented on a bacteria's surface with the genetic material contained by that bacteria [Smith, 1985]. A bacteria is infected by a library of bacteriophages, containing a large number of variants of antibody of interest. The phage will cause the bacteria to display their specific variant of the antibody on the bacteria surface, allowing sorting of the bacteria according to their affinity of the antigen, though affinity column purification or similar technique. This step greatly enriches the fraction of antibody variants which bind the protein. It is then possible to allow the bacteria to reproduce, sometimes causing more mutations to increase diversity of the antibody library and perform this affinity purification step again. Sequential application of this affinity maturation makes it possible to identify a handful of antibody variants with high affinity from as many as  $10^6$  different variants [Gram *et al.*, 1992; Hawkins *et al.*, 1992]. However, the number of possible variants of

the complementarity determining region (CDR) of an antibody many orders of magnitude larger than this.

Computational mutation scanning attempts to replicate the same sort of experiment *in silico*. Making the same assumptions as above, namely that the backbone conformation is not altered by mutating a single residue to alanine, computational experiments attempt to identify hot spot residues by measuring the  $\Delta\Delta G$  between the bound states of the native and mutated protein.

Mutated structures were generated by truncating sidechain at C $_{\gamma}$  [Massova and Kollman, 1999]

Varying cutoffs for *hot spot* residues are used, usually from 1.0 kcal/mol [Kortemme and Baker, 2002] to 4.0 kcal/mol [Pons *et al.*, 1999].

Mutations at these *hot spot* residues tend to be strongly deleterious leading to above average conservation [Hu *et al.*, 2000; Lichtarge *et al.*, 1996].

### 3.1.1 Entropy-Enthalpy Compensation

Some computational alanine scanning experiments explicitly compute or approximate the entropic contribution to the change in the free energy of binding [Hao *et al.*, 2010; Guerois *et al.*, 2002]. However, other models have achieved good agreement with experimental data while assuming these effects are either accounted for by the correlation between entropy and enthalpy for small changes in protein structure [Sharp, 2001] or to be small relative the entropic changes [Kortemme *et al.*, 2004]. PLOP has not made use of entropic contributions to free energy and has in many cases achieved good agreement with experiment, so in these experiments it is assumed that contributions due to entropy are small relative entropic contributions.

## 3.2 Methods

Three protein complexes, 1FCC, 1BRS, and 1DVF, with both experimental data for binding affinity and crystal structures were identified using the ASEdb [Thorn and Bogan, 2001]. Protonation states and locations of polar hydrogens were assigned for all residues as in [Li *et*

*al.*, 2007]. A crystal context was built for each structure using symmetry data determined by experiment. For each residue for which alanine mutation data was available the conformation of the side chain was predicted. These side chain predictions were performed by choosing at random from a high resolution rotamer library an initial conformation. Each residue was then replaced sequentially by the lowest energy conformation present in the rotamer library. This procedure was continued until all residues were static. Five iterations of this procedure, from randomization to a static conformation, were performed for each structure [Jacobson *et al.*, 2002b; Jacobson *et al.*, 2002a].

For each mutation represented in the alanine scan database single residue was mutated to alanine and this side chain prediction was repeated. The resulting structures were examined side chain conformation agreement with crystal structures and the change in binding free energy to native was recorded.

### 3.3 Results

A strong correlation between observed and expected  $\Delta\Delta G$  was not found for any of the structures nor for the set of mutations taken as a whole. Despite this single side chain conformations were in very good agreement between predicted sidechain locations and crystal structures, suggesting that sufficient sampling was done in the side chain prediction step.

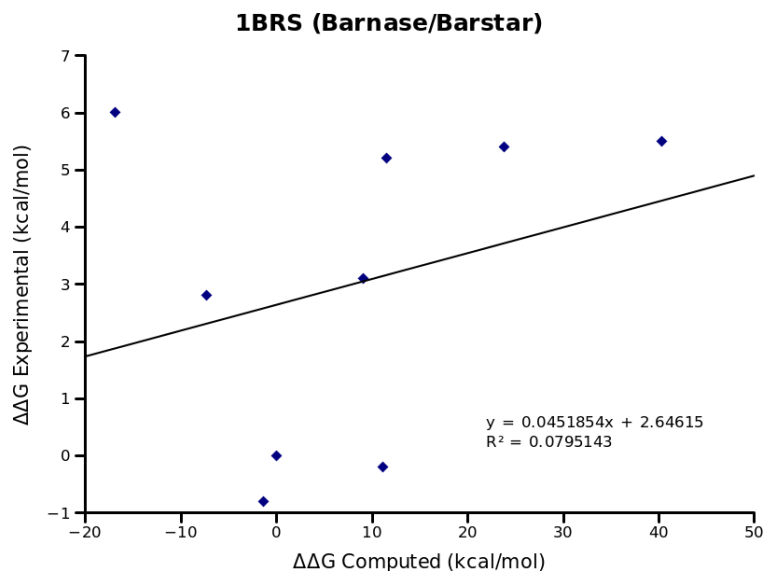


Figure 3.2: Computed versus experimental  $\Delta\Delta G$  binding for 8 alanine mutations in the Barstar-Barnase binding pair. Crystal structure used for computations was 1BRS. Specific amino acids mutated were residues 27, 54, 58, 59, 60, 73, 87, and 102, all of chain A. Experimental binding affinity taken from [Thorn and Bogan, 2001].

| Residue | $\Delta\Delta G$ calculated | $\Delta\Delta G$ experimental |
|---------|-----------------------------|-------------------------------|
| native  | 0                           | 0                             |
| 27      | 23.82                       | 5.4                           |
| 54      | -1.37                       | -0.8                          |
| 58      | 9.09                        | 3.1                           |
| 59      | 11.58                       | 5.2                           |
| 60      | 11.15                       | -0.2                          |
| 73      | -7.28                       | 2.8                           |
| 87      | 40.32                       | 5.5                           |
| 102     | -16.83                      | 6                             |

Table 3.1

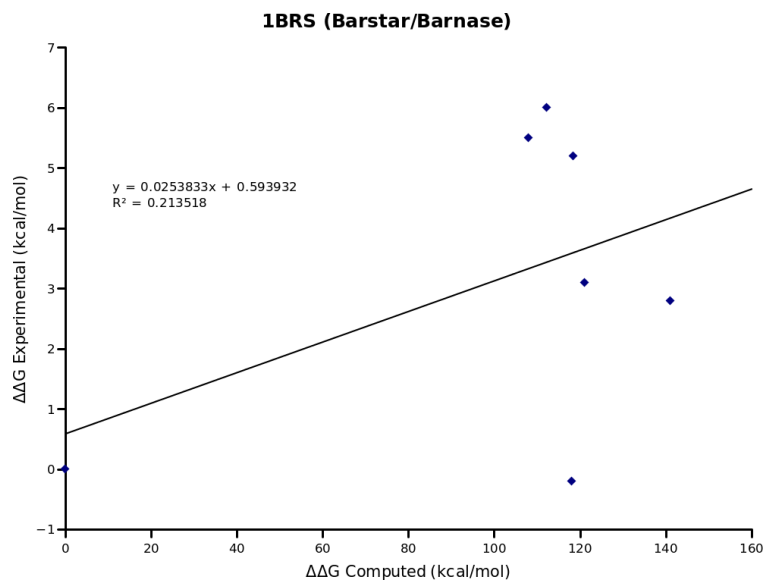


Figure 3.3: Computed versus experimental  $\Delta\Delta G$  binding for 6 alanine mutations in the Barstar-Barnase binding pair. Crystal structure used for computations was 1BRS [Buckle *et al.*, 1994]. Specific amino acids mutated were residues 29, 35, 39, 42, 74, and 78, all of chain D. Experimental binding affinity taken from [Thorn and Bogan, 2001].

| Residue | $\Delta\Delta G$ calculated | $\Delta\Delta G$ experimental |
|---------|-----------------------------|-------------------------------|
| native  | 0                           | 0                             |
| 29      | 121.07                      | 3.1                           |
| 35      | 118.37                      | 5.2                           |
| 39      | 118.09                      | -0.2                          |
| 42      | 141.09                      | 2.8                           |
| 74      | 107.92                      | 5.5                           |
| 78      | 112.14                      | 6                             |

Table 3.2

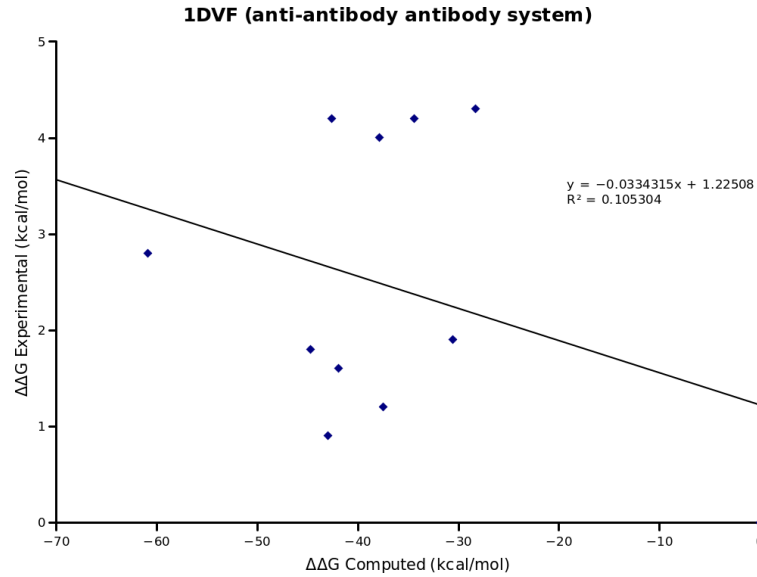


Figure 3.4: Computed versus experimental  $\Delta\Delta G$  binding for 10 alanine mutations in the anti-hen-egg-white lysozyme antibody (D1.3) anti-idiotopic antibody (E5.2) complex. Crystal structure used for computations was 1DVF [Braden *et al.*, 1996]. Specific amino acids mutated were residues 30, 32, 52, 54, 56, 58, 98, 99, 100, and 101, all of chain A. Experimental binding affinity taken from [Thorn and Bogan, 2001].

| Residue | $\Delta\Delta G$ calculated | $\Delta\Delta G$ experimental |
|---------|-----------------------------|-------------------------------|
| native  | 0                           | 0                             |
| 30      | -42.93                      | 0.9                           |
| 32      | -44.68                      | 1.8                           |
| 52      | -42.6                       | 4.2                           |
| 54      | -28.29                      | 4.3                           |
| 56      | -37.5                       | 1.2                           |
| 58      | -41.91                      | 1.6                           |
| 98      | -34.38                      | 4.2                           |
| 99      | -30.51                      | 1.9                           |
| 100     | -60.9                       | 2.8                           |
| 101     | -37.84                      | 4                             |

Table 3.3



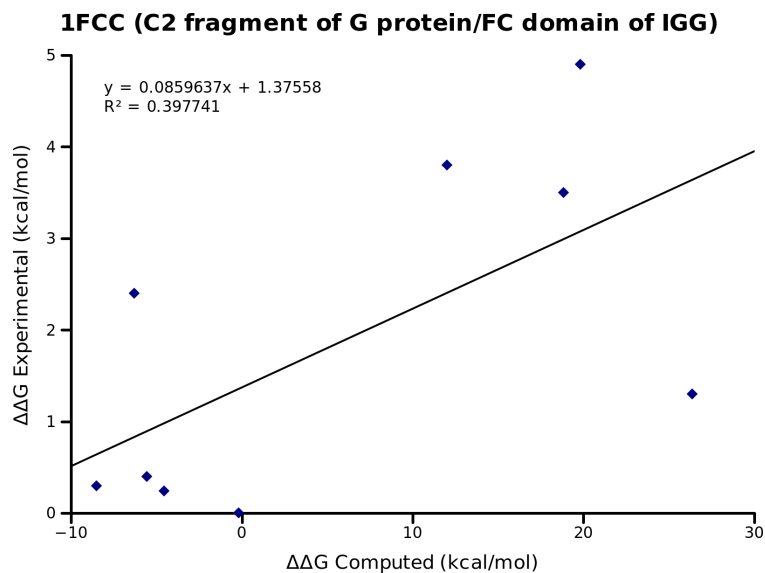


Figure 3.5: Computed versus experimental  $\Delta\Delta G$  binding for 8 alanine mutations in binding pair. Crystal structure used for computations was 1FCC. Specific amino acids mutated were residues 25, 27, 28, 31, 35, 40, 42, and 43, all of chain A. Experimental binding affinity taken from [Thorn and Bogan, 2001].

| Residue | $\Delta\Delta G$ calculated | $\Delta\Delta G$ experimental |
|---------|-----------------------------|-------------------------------|
| native  | -0.18                       | 0                             |
| 25      | -4.55                       | 0.24                          |
| 27      | 19.8                        | 4.9                           |
| 28      | 26.37                       | 1.3                           |
| 31      | 18.82                       | 3.5                           |
| 35      | -6.31                       | 2.4                           |
| 40      | -8.51                       | 0.3                           |
| 42      | -5.56                       | 0.4                           |
| 43      | 12.0                        | 3.8                           |

Table 3.4

### 3.4 Discussion

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