

# 1 SNP2SIM: A modular workflow for standardizing molecular 2 simulation and functional analysis of protein variants

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## 9 **Abstract**

10 Molecular simulations are used to provide insight into protein structure and function, and have the  
11 potential to provide important context when predicting the impact of sequence variation on protein  
12 function. In addition to understanding molecular mechanisms and interactions on the atomic scale,  
13 translational applications of those approaches include drug screening, development of novel molecular  
14 therapies, and treatment planning when selecting targeted therapies. Supporting the continued  
15 development of these applications, we have developed the SNP2SIM workflow generates reproducible  
16 molecular dynamics and molecular docking simulations for downstream functional variant analysis. Three  
17 modules execute molecular dynamics simulations of solvated protein variant structures, analyze the  
18 resulting trajectories for unique structural conformations, and bind small molecule ligands to  
19 representative variant scaffolds. In addition to availability as a command line workflow, SNP2SIM  
20 modules are also available as individual apps on the Seven Bridges Cancer Genomics Cloud.

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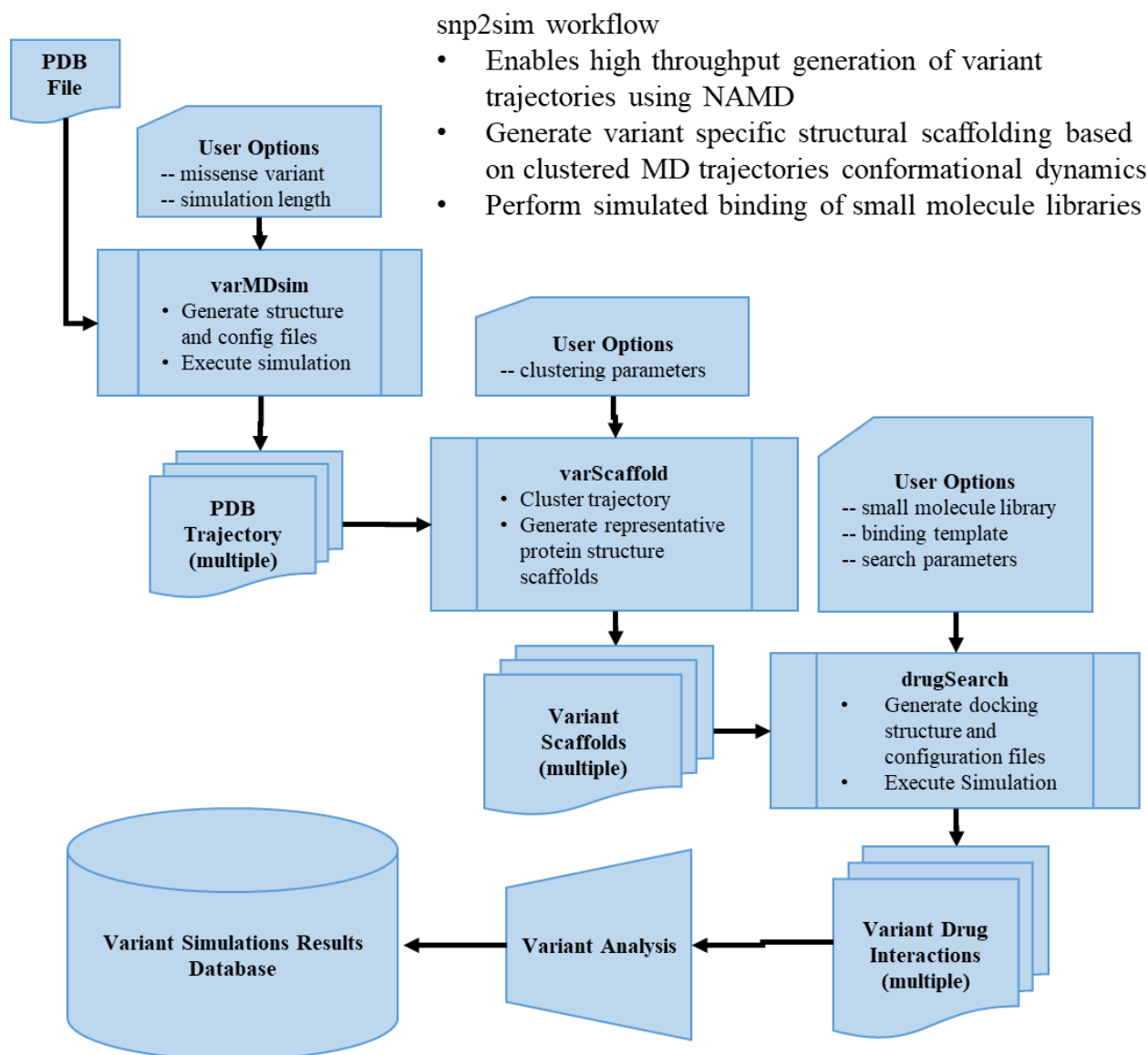
## 22 **Background**

23 Molecular simulation is a powerful tool used by computational biologists to analyze the relationship  
24 between protein structure and its functional properties. Ranging from high throughput drug screening to  
25 focused characterization of protein conformational dynamics, the creative analysis has several  
26 translational applications. Large libraries of drug candidates can be evaluated to produce novel targeted  
27 therapeutics, and insight into specific molecular interactions between effective drugs and their protein  
28 targets aids the design novel molecules [1, 2]. An advantage of the computational simulations is the  
29 ability to probe how variation in the protein sequence alters those molecular interactions, and can be  
30 extended to the development of therapies targeted at specific sequence variants [3-6]. In addition to drug  
31 discovery and design, the insight can be further extended to inform treatment planning when selecting an  
32 optimal targeted therapeutic strategy [7].

33 Due to an inherent tradeoff between resolution and computational requirements, molecular simulations  
34 can be divided between approaches which only simulate a fraction of the overall molecule and those  
35 which explicitly consider all atomic interactions occurring within the molecule. Coarse grained methods  
36 which do not explicitly consider the internal interactions occurring within the protein backbone used to  
37 address the enormous search space that must be interrogated when predicting how two molecules interact  
38 [8]. For example, predicting how well a small molecule ligand will bind to a target protein depends on the  
39 sum total of all the individual atomic interactions. Depending on the chemical nature of the ligand, the  
40 conformational diversity can be quite large due to rotation around individual bonds and limited steric  
41 constraints of a single ligand molecule. Furthermore, the protein surface represents a large area of  
42 potential interactions and exponentially increases the degrees of freedom which must be explored when  
43 identifying an optimally bound structure. In order to simplify the search for optimized protein:ligand  
44 conformations and to simulate high throughput binding of large libraries of low molecular weight ligands,  
45 coarse grained docking methods will typically only model the flexibility of the ligand and a small number  
46 of interacting protein residues within a defined area of a rigid protein structure [8].

47 While the liberties taken by these types of simulations allow for a greater throughput, they fail to account  
48 for internal protein dynamics which may play a significant role in the interacting complex. All-atom  
49 molecular dynamics (MD) simulations explicitly account for atomic interactions occurring within a  
50 molecular system and provide a way to understand the overall conformational flexibility and structural  
51 dynamics [9]. However, even systems consisting of a small, solvated protein contain tens to hundreds of  
52 thousands of atoms and each simulation step requires a summation of all the forces acting on each. Even  
53 on high performance computational infrastructures, simulation runs can easily last weeks to generate  
54 usable results. The increased computing cost is offset by its unique insight and characterization of  
55 functionally relevant protein dynamics.

56 Both approaches find utility in specific applications, and their individual strengths are leveraged to  
57 understand the impact on protein sequence variation on small molecule binding. When a new amino acid  
58 is specified by a change to the genomic sequence, the change in the residue side chain has the potential to  
59 alter the functional interactions with a small molecule. If the change occurs within the defined search  
60 space of a coarse grained binding simulation, the new interactions can be simulated directly. Typically,  
61 the structures used for binding simulations are derived from x-ray crystallography, but simply swapping



**Figure 1.** The SNP2SIM workflow contains 3 functional modes; varMDsim generates molecular dynamics trajectories using NAMD, varScaffold clusters the resulting trajectories into variant specific representations of the structural variation, and drugSearch binds a library of low molecular weight ligands to each variant scaffold.

62 out amino acid side chains in the intersecting residues may not fully account for the structural differences  
63 of the protein variant. Since the protein backbone is treated as a rigid scaffold, the resulting predicted  
64 binding characteristics do not account for those subtle changes in the backbone geometry and could have  
65 a large influence on the results. Furthermore, these methods have nothing to offer if the variation occurs  
66 outside of the defined search space, especially those amino acids which are buried within the folded  
67 protein structure. MD simulations can address this limitation by comprehensively sampling the  
68 conformational landscape of a protein variant to generate characteristic scaffolds for downstream small  
69 molecule docking.

70 Since a protein variant can alter the functional interaction with therapeutic molecules, predicting how  
71 small molecules will bind to protein variants has a significant application in personalized medicine. Not  
72 only can simulation results be used in the development of targeted therapies, it could also be informative  
73 in the selection of second line of therapy once drug resistance has emerged. As the application of  
74 molecular profiling and sequence analysis continues to gain a foothold in clinical decision making, a well-  
75 defined, user friendly simulation workflow and methodology would be an important tool for translational  
76 computational biology. To that end, we present SNP2SIM (**Figure 1**), a scalable workflow for simulating  
77 the impact of protein sequence variation on binding to small molecule ligands.

78

## 79 **Implementation**

80 At its core, SNP2SIM is a modular set of simulation and analysis tools wrapped in a command line  
81 python script. The three functional modules correspond to the molecular dynamics simulation of a protein  
82 variant, conformational analysis of molecular dynamics trajectories, and small molecule docking to  
83 variant specific structural scaffolds. The workflow controls the generation of tool specific preprocessing  
84 and analysis scripts, configuration files, and file structure based on an initial PDB formatted protein  
85 structure file, and executes the simulation software. The command line implementation of SNP2SIM is  
86 available for download (<https://github.com/mccoymd/SNP2SIM>), and the varMDsim, varScaffold, and

87 drugSearch modules are also available as apps on the Seven Bridges Cancer Genomics Cloud [10]  
88 (<http://www.cancergenomicscloud.org/>).

### 89 *varMDsim*

90 With the minimal input of a PDB formatted protein structure file and simulation time in nanoseconds, the  
91 varMDsim module will generate a solvated, ionized water box, generate the configuration files for the all-  
92 atom simulation, and compile the results for downstream analysis. Specifying an amino acid variant will  
93 automatically mutate the input structure prior to solvation. The varMDsim module utilizes versions of  
94 Visual Molecular Dynamics (VMD) [11] and Nanoscale Molecular Dynamics (NAMD) [12] installed on  
95 the user's system, and the CHARMM36 topology and parameters [13] and simulation configurations files  
96 are hardcoded into the workflow, standardizing the resulting simulation for reuse and promoting the  
97 reproducibility of the computational simulations.

### 98 *varScaffold*

99 The simulation trajectories are analyzed using the varScaffold module to produce characteristic structures  
100 of variant proteins. The user supplied clustering parameters specify how the protein structures are first  
101 aligned, and then clustered based on root-mean-square deviation (RMSD), using VMD's Atom Selection  
102 Language and clustering plugin. This separate alignment and clustering parameters allow for the  
103 investigation into protein specific features of interest. For example aligning an entire protein structure by  
104 its backbone residues and clustering by the geometry of the binding pocket captures specific structural  
105 variation impacting the functional interaction with a ligand. Similarly, this can be used to measure  
106 internal dynamic behavior, such as the motion of a disordered region or positions of internal structural  
107 features. Representative PDB structures are generated for each unique cluster that is populated by at least  
108 10% of the simulated trajectory at a given RMSD cluster threshold. The varScaffold module will accept  
109 multiple PDB or DCD formatted trajectory files generated through parallel execution of the varMDsim  
110 module.

111 *drugSearch*

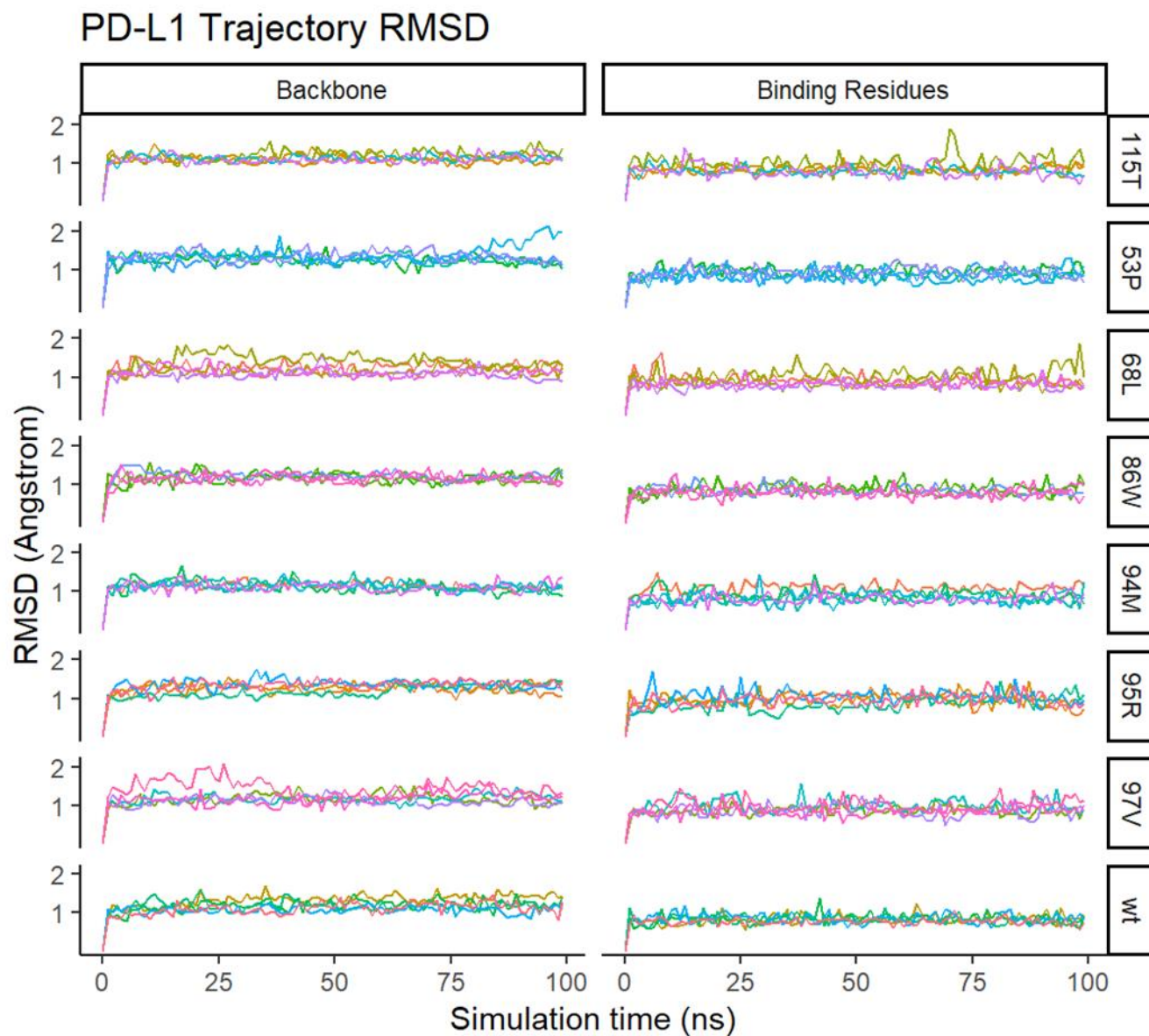
112 The drugSearch module uses AutoDock Vina [14] to bind a predefined library of low molecular weight  
113 molecules into the variant scaffolds. This requires the user to supply a PDB formatted protein structure,  
114 and an associated parameter file that defines the search space for ligand binding. Additionally, the user  
115 can specify a set of residues within that search space model with flexible sidechains. Variant scaffolds are  
116 aligned to the reference coordinates, and the associated configuration files are generated for each ligand in  
117 the drug library. General analysis tools included along with the SNP2SIM package include bash scripts to  
118 compile the quantified AutoDock Vina results from multiple files, generate PDB formatted files of the  
119 ligand and flexible side chain orientations, and to visualize the relative binding affinity between wildtype  
120 and variant structures.

121 *Case Study: PD-L1 small molecule inhibitors*

122 The immunomodulatory protein PD-L1 was used to demonstrate the application of the SNP2SIM  
123 workflow to drug development in personalized medicine. Development of small molecule inhibitors has  
124 clinical applications, and a number of molecules are currently being investigated for therapeutic use in  
125 cancer. To understand how these molecules may differentially bind to variants of PD-L1, known  
126 mutations in the binding domain were processed through the SNP2SIM workflow. The initial starting  
127 structure used the Ig-like V-type domain from PDB: 4Z18, and 500 ns of simulation were generated for  
128 each protein variant. Variants were selected based on their occurrence in PD-L1 expressing cell lines as  
129 well as those most commonly occurring across all cancer types (L53P, V68L, R86W, L94M, G95R,  
130 A97V, M115T). Variant trajectories were aligned using the entire domain backbone and clusters were  
131 defined using a 0.7 RMSD cluster threshold for the backbone atoms in residues interacting with low  
132 molecular weight inhibitors in PDB crystal structures(cite) (Residues 19, 20 54, 56, 66, 68, 115, 116, 117,  
133 121, 122, 123, 124, 125). These same interacting residues were also modeled with flexible side changes  
134 when bound to a library of 17 small molecule ligands. The SNP2SIM workflow was run using the Seven  
135 Bridges Cancer Genomics Cloud infrastructure (cite).



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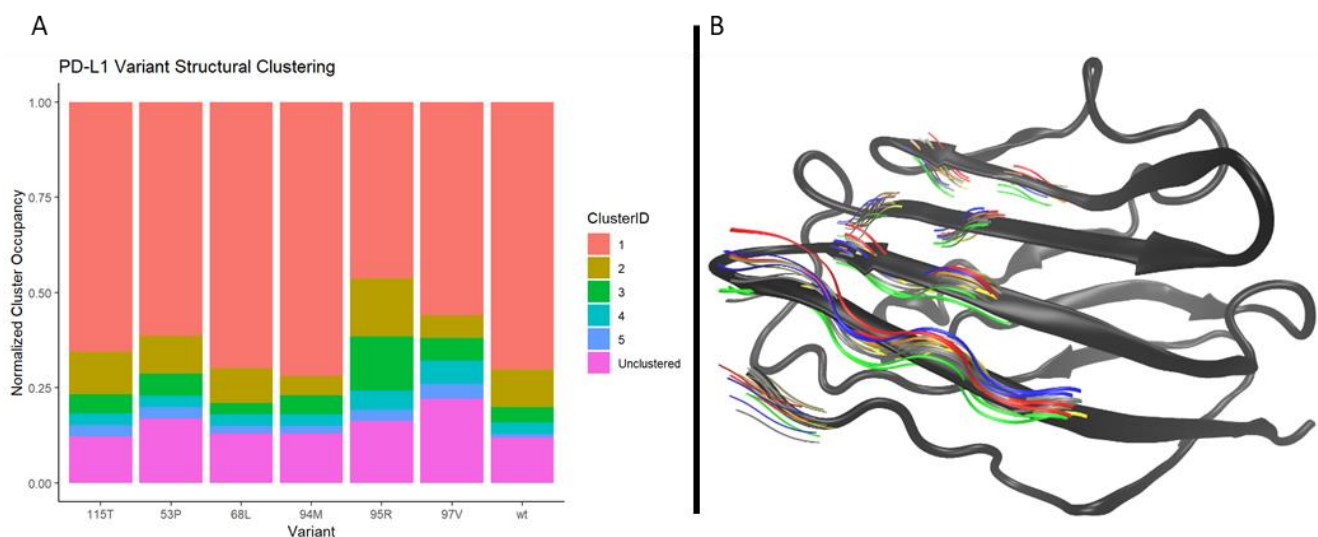
**Figure 2.** The SNP2SIM results from the varMDsim module. Each color represents an independent 100 ns NAMD simulation of the solvated PD-L1 variant structure (5 per structure variant). Root-mean-squared deviation (RMSD) of the domain backbone (alignment residues) and binding show (clustering residues) reveal differences in wildtype and variant conformational dynamics.

## 138 Results

139 The SNP2SIM workflow enables the efficient parallelization of the computationally intensive molecular  
140 dynamics simulations. Variant structures of PD-L1 were simulated for 5 independent runs of 100 ns each



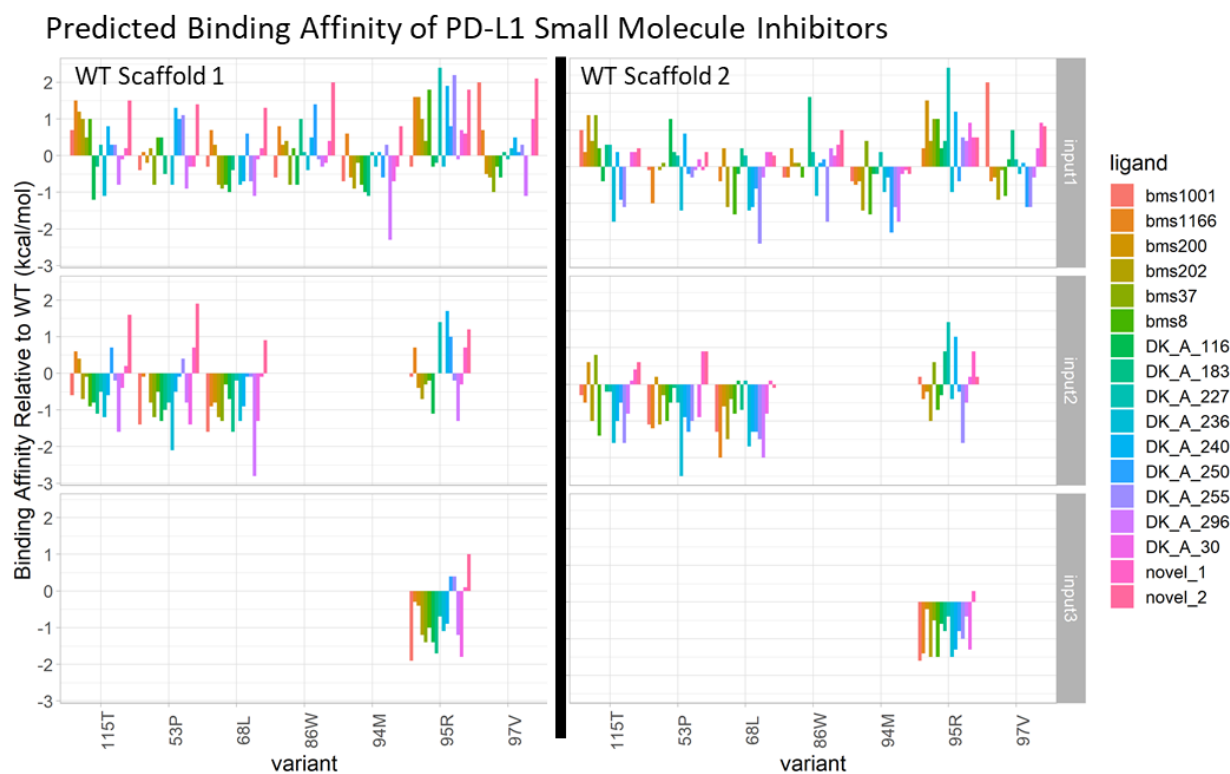
141 (total 50 ns), and the resulting trajectories were combined for downstream analysis. The RMSD of both  
142 the domain backbone and small molecule binding residues (**Figure 2**), show the variants all maintain a  
143 relatively stable conformational population. Despite the overall lack of molecular motion on a global  
144 scale, the results show the variant structures behave differently relative to wildtype. This is reflected in  
145 the deviation of the entire PD-L1 domain backbone, which is even more pronounced when only  
146 considering the residues which interact with small molecule inhibitors (**Figure 3**).



**Figure 3.** The (A) breakdown of the results from the varScaffold module of the SNP2SIM workflow show the characteristic variation induced by each missense mutation in PD-L1. Depending on the variant, molecular dynamics simulations revealed novel structural conformations (Occupancy > 10%). (B) The backbone atoms from PD-L1 binding residues from trajectory based scaffolds, where the colors correspond to the different populated clusters of a given variant relative to the crystal structure (grey).

147  
148 From the initial analysis of the variant trajectories, it's clear that certain variants induce more  
149 conformational flexibility than others. This is highlighted in the breakdown of the trajectory clustering  
150 results (**Figure 3**), where clusters were defined by the RMSD of residues involved in binding small  
151 molecules. The wildtype PD-L1 structure had two populated clusters, one just meeting the threshold of  
152 10% of all sampled structures. Depending on the variant, the occupancy of additional clusters decreased  
153 to one (86W, 94M, and 97V), increased to three (95R), or stayed the same (53P, 68L, and 115T),  
154 illustrating the differential impact of sequence variation on the overall conformational flexibility.

155 The differences in flexibility translate to changes in the predicted binding affinity, and the difference can  
156 be used to predict if a given variant will be more or less likely to bind a particular ligand (**Figure 4**).  
157 Since there were two wildtype scaffolds, each was compared separately to each variant scaffold. For the  
158 same variant, the relative binding affinities are largely similar in direction and magnitude for both the  
159 wildtype conformations. But it's not always the case, and close inspection of instances where the pattern  
160 diverges had the potential to yield significant insight into the functional nature of the protein. The same  
161 applies to differences between input scaffolds for individual variants, where the inhibitory function of  
162 certain small molecules may be related to differential binding to conformational populations.



**Figure 4.** The SNP2SIM drugBinding results for trajectory-derived PD-L1 scaffolds bound to small molecule inhibitors are used to calculate the binding affinity relative to that predicted for the wildtype structure. Positive values correspond to a decreased affinity of the small molecule for the variant structure compared to the wildtype.

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164

165 **Discussion**

166 The growing prevalence of genomic testing is revealing an enormous amount of rare variants with  
167 unknown functional significance [15], underscoring the need for predictive computational analysis to  
168 determine their functional significance. This is especially true for variants which occur in proteins where  
169 the effectiveness of targeted therapeutic strategies may be disrupted. For example, missense mutations  
170 emerge in response to evolutionary pressures in a growing tumor which disrupt binding of targeted  
171 inhibitor molecules [16]. SNP2SIM enables the profiling of multiple approved inhibitors to inform the  
172 selection or design of an optimal therapy which maintains a positive clinical response [7].

173 By simulating the variant specific contributions to the overall protein conformational dynamics and ligand  
174 binding, the unique impact of a variant can be quantified even when the mutated residues do not occur at  
175 the interaction interface. As seen in **Figure 3**, the proportions populations of distinct protein structures is  
176 impacted in a variant specific manner. Even for the wildtype structure, two populated conformations were  
177 identified which show slightly modified geometries of the protein backbone found in the crystal structure.  
178 The results of small molecule docking show the different scaffolds bind to the small molecule ligands  
179 with different affinities (**Figure 4**). This additional information will ultimately produce more robust  
180 analysis and improve predictive models used for downstream drug development, design, and utilization.

181 The widespread use of molecular simulations to generate predictive data, and the insight it can provide to  
182 understanding the functional changes of protein sequence variants, is rate-limited by computational costs  
183 and scale of potential variation. Both of these barriers are being overcome through access to cheap cloud  
184 computing and the development of reproducible workflows. And while a lot has been done to lower the  
185 barrier for novice users to access these tools through widely available infrastructure such as the NCI cloud  
186 pilots, creating an easy-to-use simulation and analysis workflow opens the doors to many researchers who  
187 would otherwise not have access. As demonstrated through the case study of PD-L1, SNP2SIM can  
188 address all these issues. The modular nature and implementation as independent apps on Seven Bridges  
189 Cancer Genomics Cloud allow for parallelization, access to high performance computing resources, and a  
190 user-friendly interface.

191 **Conclusions**

192 Overall, the SNP2SIM workflow represents a higher resolution approach to the *in silico* functional  
193 predictions compared to methods that provide a limited characterization of variant pathenogenicity. Not  
194 only does a simulation based approach provide detail about disruption of specific functional interactions,  
195 it can evaluate the differential impact of somatic variation on targeted therapies.

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