Binding Affinity Prediction of Protein-Ligand complexes using Machine Learning

MSc Project

Abdus Salam Khazi

Supervisors: Simon Bray & Alireza Khanteymoori

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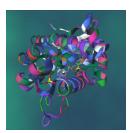
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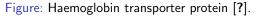


Biological Background

What are a proteins and ligands?

- **Proteins:** Complex molecules that are work-horses (machines) of a living organism.
- Ligands: Molecules that bind to particular proteins, called receptor proteins.
- Proteins and ligands bind together to form protein-ligand complexes.







Biological Background

Protein-Ligand complexes

- Any potential binding location in the 3D structure of a protein is called a pocket.
- The pockets of proteins only bind to ligands of complementary shape.
- Drugs are just ligand molecules that bind to protein to cause a therapeutic effect.

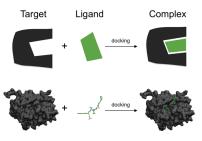


Figure: Lock and Key hypothesis in molecular docking [?].

Biological Background

Understanding Protein-Binding Affinity.

- Binding affinity between a protein and a ligand is quantified by the K_d , K_i and IC_{50} . Here K_d refers to the dissociation constant, K_i to inhibition constant, and IC_{50} to inhibitory concentration 50%.
- K_d can be quantified by using protein concentration [P] and ligand concentration [L] at equillibrium [1].

$$K_d = \frac{[P][L]}{[PL]}$$

• K_i and IC_{50} are similarly defined.



Problem Definition

- Determining if a potential drug (ligand) can bind to a target protein is very costly processes [3].
- The project aims to predict the ligand affinity based on previously recorded data ("In-Silico" method). This reduces the drug discovery costs.
- We use PDB databank, which holds PL affinity data collected over many decades.

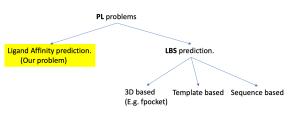
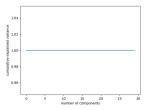


Figure: Protein-Ligand problem classifcation.

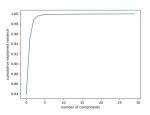


Data Preprocessing

- Anomalies such as NaN (Not a number) values were removed from the data before sending them as input to the model.
- We used PCA (principle component analysis) to find that the ligand feature *IPC* was having log scale values.



(a) With original Ligand feature IPC.



(b) With log scaled Ligand feature IPC.



Feature Extraction

PDB databank (v2019) was used to extract input features.

- We use *fpocket/dpocket* ligand binding site prediction library to get the features of pockets pockets in proteins.
- RDKit library is used to extract features for each ligand.
- Ligand Features: Using RDKit.Chem.Descriptors, 402 features were extracted for each ligand. Hence the ligand features space was R⁴⁰².
- Protein Features: For every pocket, 55 descriptors are obtained in total. Hence, the input space for protein features is R⁵⁵

The concatinated input feature space before input feature elimination \mathbf{R}^{457} .



Feature Selection

We only had 16000 data points to train a feature space of \mathbf{R}^{457} . We reduced our features using the following feature selection strategies:

- Output Correlation: The input features that have the best *Pearson* and *Spearman* correlation were selected. [?].
- **Genetic Algorithms**: Genetic algorithms with the following score function was used to select the best features [4]:

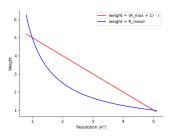
$$score = \mathbf{R}^2 score * Features Eliminated$$

 Manual Feature Selection: A selected list of 121 ligand descriptors was used with all protein descriptors as input to the model.

Dealing with measurement resolution

- In the PDB databank, each complex also has a corresponding measurement resolution.
- The structural detail of the 3D image is inversely proportional to the measurement resolution.
- The weighting of each data point was done according to hyperbolic formulae and linear formulae.

$$W_i = \frac{\max \mathrm{R}_{1...\mathrm{n}}}{R_i}$$
; $W_i = (\max \mathrm{R}_{1...\mathrm{n}} + 1) - R_i$







Machine Learning models

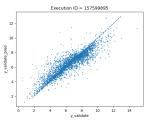




Testing strategy

We use the following methods to determine the quality of results and reproducing them:

- Reproducibility: To reproduce the results, we use report random seed (Execution ID) for every execution.
- R^2 score (Coefficient of determination) [?]: $R^2 \in (-\infty, 1.0]$ where 1.0 is the best score.
- **Visualization:** Our model's approximated function $f: \mathbf{R}^n \mapsto \mathbf{R} \text{ where } n \in \mathbf{I}^+ \text{ is visualized as a 2D scatter plot.}$







Results

The following are the results:

- 2,3,4
- 0



Discussion

The following points can be noted:

• Testing results were sometimes better than validation results.

•



Q & A



References

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