

# Binding Affinity Prediction of Protein-Ligand complexes using Machine Learning

## MSc Project

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What are proteins and ligands?

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

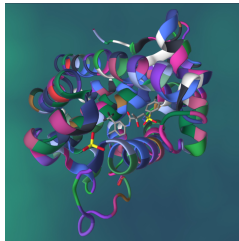


Figure: Haemoglobin transporter protein.



## Protein-Ligand complexes

- Ligands bind to proteins at "cavity" like locations called pockets.
- The pockets and the ligands are complementary in shape.

## Drugs

- Drugs are ligand molecules that bind to proteins.
- They cause a therapeutic effect after binding to the proteins.

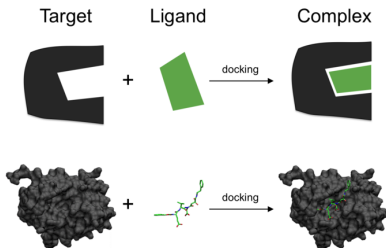


Figure: Lock and Key hypothesis in molecular docking.

## Protein-Binding Affinity

- Assume a dynamic system in which protein  $P$  and ligand  $L$  are binding and unbinding continuously.
- Let  $[P]$  be the concentration of the protein and  $[L]$  be the concentration of the ligand. Let  $[PL]$  be the concentration of the protein ligand complex.
- Binding affinity can be quantified by using  $[P]$ ,  $[L]$  and  $[PL]$  (**at equilibrium**).

$$\text{BindingAffinity} = \frac{[P][L]}{[PL]}$$



# Problem Definition

- Determining if a potential drug (ligand) can bind to a target protein is very expensive [3].
- The project tries to reduce the drug discovery costs by eliminating bad leads.
- **Problem definition:** Predict protein-ligand binding affinity using "In-Silico" methods.

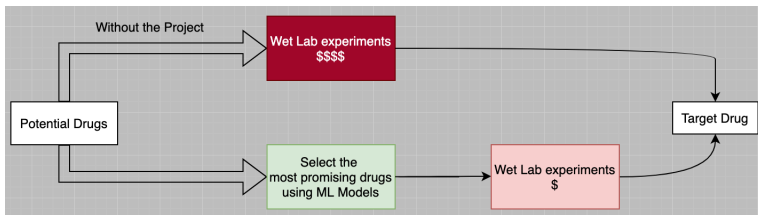


Figure: Project Overview

# Problem Definition

There are various problems in the protein-ligand domain. The following figure shows the classification tree.

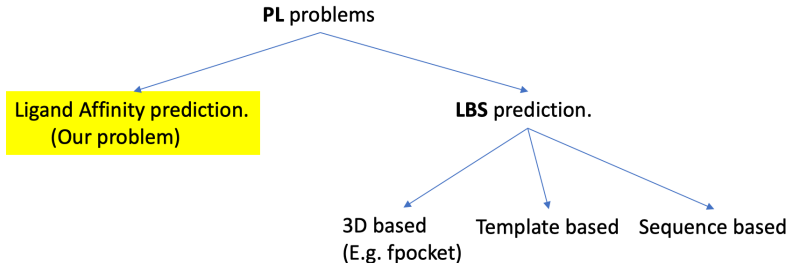


Figure: Protein-Ligand problem classification.



# Problem Definition

- The input data to the ML model is extracted from a database called PDB Data bank.
- *fpocket* and *RDKit* were used to extract the features of proteins and ligands.
- The input features contain information about the 3D structures of the proteins and the ligands.

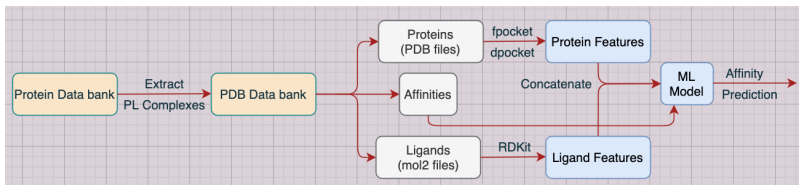


Figure: Data Input Overview.





## Protein Features:

- *fpocket* is an LBS prediction algorithm used to predict ligand binding pockets.
- There can be multiple binding pockets for a PL complex.
- Using *dpocket*, 55 descriptors were obtained for every (potentially) binding pocket as real values.

## Ligand Features:

- Using *RDKit.Chem.Descriptors* module, 402 features were extracted as real values.

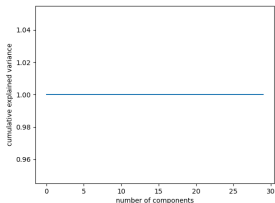
## Concatenation:

- The (concatinated) input feature space to the model was  $\mathbf{R}^{457}$ .
- It was less than  $\mathbf{R}^{457}$  if feature selection is done before model training.

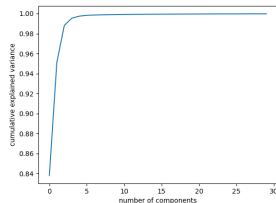


# Data Preprocessing

- Data points containing NaN (Not a number) values were removed from the data.
- PCA (Principle Component Analysis) was used to find the variance contribution of the features.
- Feature *IPC* was log scaled for numerical safety during training.



(a) With original Ligand feature IPC.



(b) With log scaled Ligand feature IPC.

Figure: Cumulative PCA of ligand features.



Feature selection strategies:

- **Manual:** 121 ligand descriptors + all protein descriptors.
- **Output Correlation:** Features with the best *Pearson* or *Spearman* correlation w.r.t the affinity score (output) were selected.
- **Genetic Algorithms:** Genetic algorithms with a population score function " $R^2$  score \* Features Eliminated" was used to select the best features [4]:

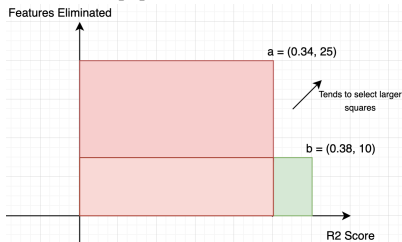


Figure: Genetic Algorithm score function representation.



# Dealing with measurement resolution

- In PDB bind databank, each complex has a corresponding measurement resolution ( $\text{\AA}$  units).
- 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 (or) linear formulae:

$$W_{\text{Hyperbolic}} = \frac{\max R_{1\dots n}}{R_i} \quad W_{\text{Linear}} = (\max R_{1\dots n} + 1) - R_i$$

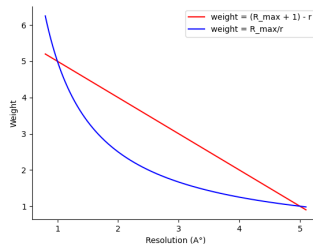


Figure: Weight calculation formulae.



# Feature Family Correlations

- Features can be divided into families.
- Important ones are - AUTOCORR2d\_, Chi, EState\_VSA, PEOE\_VSA, SMR\_VSA, SlogP\_VSA, VSA\_EState, and fr\_.
- Within Chi and AUTOCORR2d\_, the features are correlated.
- ML models need to take into account this issue.

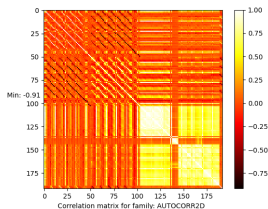
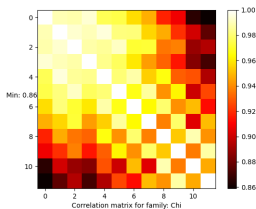


Figure: Correlation Heat Map.



For every execution, we report the **random seed** used in it. This random seed can be used as a script argument (Execution ID) to reproduce the exact results. To determine the result quality we use:

- **$R^2$  score** (*Coefficient of determination*):  $R^2 \in (-\infty, 1.0]$  where 1.0 is the best score.
- **Visualization**: The model's prediction is visualized as a 2D scatter plot. The best plot is  $y = x$  line which corresponds to the best  $R^2$  score of 1.0.

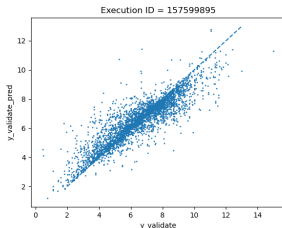


Figure: (Sample) Visualizing accuracy.  $R^2 \approx 0.805$ .



# Machine Learning models

The ML model should approximate the following function:

Binding affinity prediction :  $\mathbf{R}^n \mapsto \mathbf{R}$  where  $n \in \mathbf{I}^+$

The following ML models were studied

- Simple Linear Regression
- Random Forest Regression
- Support Vector Regression
- Rotation Forest Regression

Also Note:

- DNNs could not be used due to lack of data.
- The project only had  $\approx 16000$  data points to train.
- A simple DNN a model of size  $[457, 20, 10, 1]$  has 9350 parameters.
- The DNN would overfit drastically.



# Simple Linear Regression

- This model approximates the binding affinity using a linear hyperplane. (By minimizing the square of errors).
- It is the cheapest computational model.
- Assumes strong linear relationship between input features and binding affinity.
- Genetic algorithms successfully used for feature selection.

| No. features | Feature selection    | Weighting              | Training      | Validation    | Testing       |
|--------------|----------------------|------------------------|---------------|---------------|---------------|
| 457          | -                    | -                      | 0.461         | 0.415         | 0.320         |
| 457          | -                    | Hyperbolic             | 0.454         | 0.427         | 0.337         |
| 457          | -                    | Hyperbolic duplication | 0.465         | 0.416         | 0.326         |
| 457          | -                    | Linear                 | 0.458         | 0.419         | 0.328         |
| 457          | -                    | Linear Duplication     | 0.460         | 0.428         | 0.327         |
| <b>49</b>    | <b>Genetic</b>       | <b>Hyperbolic</b>      | <b>≈0.377</b> | <b>≈0.374</b> | <b>≈0.364</b> |
| 40           | Pearson Correlation  | Hyperbolic             | 0.287         | 0.278         | 0.285         |
| 40           | Spearman Correlation | Hyperbolic             | 0.289         | 0.294         | 0.290         |
| 176          | Manual               | Hyperbolic             | 0.362         | 0.346         | 0.331         |

Table:  $R^2$  scores of the Linear Regression Model.





# Random Forest Regression



# Support Vector Regression



# Rotation Forest Regression



## Notable points:

- Best models: Linear Regression and Random Forest Regression.
- RF uses correlated features to make itself more robust.
- RF can deal with both discrete and real valued features.

## Limitations:

- Linear regression assumes data linearity.
- RF has heavy reliance on ligand features.
- Both models were black box models.
- Testing results were sometimes better than validation results. This is because test data  $<$  validation data. But the difference is minimal.



Further work:

- A new weighting strategy: Weighting a pocket descriptor based on the overlap between the pocket and the ligand. For example,






$$W_{\text{Total}} = W_{\text{Hyperbolic}} * W_{\text{Overlap}}$$

- Improvement of feature selection: Build 1 model per family of features. Use the best feature as a family surrogate.
- A more explainable model can be built.



## Q & A



-  Du, Li, Xia, Ai, Liang, Sang, Ji and Liu; Insights into Protein–Ligand Interactions: Mechanisms, Models, and Methods (2016)
-  Le Guilloux, Schmidtke, and Tuffery; Fpocket: An open source platform for ligand pocket detection(2009)
-  DiMasi, Grabowski and Hansen; nnovation in the pharmaceutical industry: New estimates of R & D costs (2016)
-  John H. Holland. Genetic Algorithms. (1960)
-  Is rotation forest the best classifier for problems with continuous features? A. Bagnall, M. Flynn, J. Large, J. Line, A. Bostrom, and G. Cawley (2020)



- 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%.

