Machine Learning in Protein Solubility Engineering

Jan Velecký | <u>velda@mail.muni.cz</u> | S live:vvelda



Machine learning

Not only does ML prove a hypothesis but it also finds this hypothesis





2) Data collection



Use cases:

- traditional methods are insufficient
- possession of **big data** about the problem
- high-dimensionality of the problem

Solubility engineering

Where solubility matters:

- Proteins manufacturing the higher solubility, the higher yield Insoluble protein is usually aggregated or having other abnormality and is short of the intended **function** (bioenzyme), alternatively may even turn harmful (drug) Insoluble fraction = waste
- Crystallization experiments For proteins without known structures, too low/high solubility impedes crystallization

Simplistic definition: "Degree to which a substance dissolves in a solvent to make a solution"

Multiple usages:

- soluble fraction [%]
- soluble expression [g/l] = yield
- expression/expressibility [g/l]
- aggregation propensity
- binary solubility above/below a specific level



experiments

Disease prediction Revealing genetic mutations causing **low-**

solubility-related diseases



ambiguous data

The state of tools

Several overall-solubility predictors – usually cannot predict effects of mutations.

A few solubility-change predictors:

- SOLPro (2009)
- OptSolMut (2010)
- CamSol (2014)
- PON-Sol (2016)
- SODA (2017)

Accuracy of 60–80 %

None utilize big data from deep mutational scanning

The state of data

Old & overlapping datasets for predictions: CamSol, OptSolMut, PON-Sol, A3D:

- tens of proteins
- hundreds of mutations
- often low-soluble proteins

Deep mutational scanning (high-throughput) data:

- units of proteins
- thousands of mutations

Common characteristics:

- solubility change upon mutation
- mostly desolubilizing

The 1st database of protein solubility upon mutation

UNDER DEVELOPMENT: the preview version expected in June 2021 Jan Velecký, Stanislav Mazurenko, Marie Jankůjová, Jan Štourač, David Bednář

Highlights: • Solubility-prediction tools could perform better



- Low solubility affects yields in industry
- No big data regarding solubility present at single place
- Loosely defined data make machine learning challenging

experiments.

021

Mutational solubility data

Effect of a mutation(s) on the protein's solubility:

- mutation site & AA^{*} substitution
- effect classification
 - $N + ++ (\leq 5 \text{ bins})$ for ML classification models
- conditions of the experiment \bullet
- pre-computed (HotSpot Wizard) per-AA features, like: residue conservation, accessible surface area, ...

Systemization of reported values in the literature:



Objectives

- Single and complete source for solubility mutagenesis
- Ready-made for ML^{*} training with labels and features
- Error-free data
- Enhance accuracy of solubility prediction
- Invite out-of-the-field ML ulletexperts to try their models on these data

MUNI RECETOX

Functionality

- On-the-web browsable DB advanced search filters
- Export tool for data scientists values conversion to a target scheme, data



- usually, discreet, loose values are reported
- nonetheless, reports follows one of the schemes (columns) below
- the table also defines **comparability** between different schemes

	reported change					roal change
	unipolar	2-value	3-value	4-value	5-value	real change
++	enhancing			significantly enhancing		++
+				slightly enhancing		+
Ν	non-		neutral		neutral	neutral
-	enhancing	deteriorating		slightly deteriorating		-
	(NE)			significantly deteriorating		

augmentation using symmetrisation

Outlook

- Target the special database issue in Nucleic Acid Research
- Conduct high-throughput experiments in Loschmidt Laboratories
- Train our own predictive models on these data
- Combine solubility and other pressing tasks in protein engineering

* AA: amino acid | DB: database | ML: machine learning

RECETOX PhD Conference | May 2021