Predicting Five Rat Acute Toxicity Endpoints with ANNE Models using ADMET Predictor™ Pankaj R. Daga, Michael Lawless, Marvin Waldman, Robert Fraczkiewicz, Robert D. Clark, John DiBella, and Michael B. Bolger Simulations Plus, Inc., 42505 10th Street West, Lancaster, CA 93534, USA (www.simulations-plus.com)

Introduction

- Alternative methods are being explored to predict the toxicity of chemicals to reduce use of animals.
- ✓ Laboratory/Animal tests are costly in time and money
- Cheminformatics (QSTR) presents a good alternative to animal testing ✓ Once the model is ready, predictions can be made quickly

<u>Why Artificial Neural Network Ensemble (ANNE)?</u>

- Toxicity prediction is a tough problem
- ✓ Multiple underlying mechanisms of action
- ✓ Datasets studied (e.g., rat LD50) are large and chemically diverse
- Multiple and wide variety of data sources
- ✓ Simple regression methods like MLR may prove insufficient
- Ensemble methods, such as ANNE and Random Forest, have proven to be robust enough to tackle this intensive task
- Five endpoints were provided to model
 - ✓ Rat LD₅₀ and "Very Toxic", "Non Toxic", "EPA Cat" & "GHS Cat"
 - \checkmark The labels in the four end-points are dependent upon rat LD₅₀

Why is Dataset Curation Necessary?

• The "**QSAR-ready structures**" provided as training set needed careful curation

Uncertainty in structures is not useful Provided SMILES CASRN Actual Structure 36088-22-9 34465-46-8 x—ci



Correct tautomer assignment is necessary in model building exercise as well as for correct prediction

- Matched Molecular Pair Analysis shows a few large activity cliffs
- The data is questionable and hence excluded





Molecular Descriptors

ADMET Predictor[™] generated 341 molecular descriptors

- Constitutional Descriptors
- ✓ Topological Indices
- Electrotopological State Indices
- **Charge-based Descriptors**
- Hydrogen Bonding Descriptors
- **Moriguchi Descriptors**
- Functional Groups



Model	Endpoint	Validation	Training Set	Test Set	Outside	Performance	Performance On Ext Test ¹	Model Performance & Analysis
EPACat_1	EPA class (1-4)	2812	6531	1633	50 (1.8%)	0.689	0.696	 All the models show comparable
EPACat_2	EPA class (1-4)	2812	6531	1633	51 (1.8%)	0.693	0.691	performance on both training & test set
GHSCat_1	GHS class (1-5)	2882	6951	1648	51 (1.8%)	0.708	0.666	 Overall statistics suggests that models are
GHSCat_2	GHS class (1-5)	2882	6951	1648	51 (1.8%)	0.689	0.671	 Almost all compounds were predicted
LD50_1	LD ₅₀	2172	Existing Model ² $41(1.8\%)$ 0.595 0.638 within applicability (within applicability domain of models.			
LD50_2	LD ₅₀	2172	5037	1209	41 (1.8%)	0.614	0.605	 Only ~50 compounds (1.5%) were predicted out of the AD 48 contained a Si
NonTox_1	LD50 > 2,000 mg/kg	2887	7059	1246	54 (1.9%)	0.765	0.750	Se, or heavy metal atom and 2 compounds
NonTox_2	LD50 > 2,000 mg/kg	2887	7059	1246	55 (1.9%)	0.771	0.748	exceeded the 256 heavy atom limit of
VeryTox_1	LD50 ≤ 50 mg/kg	2891	6699	1675	52 (1.8%)	0.675	0.620	ADMET Predictor.
VeryTox_2	$LD50 \le 50 \text{ mg/kg}$	2891	6699	1675	53 (1.8%)	0.809	0.825	GR Simulations Plus
								SCIENCE + SOFTWARE = SUCCESS

¹ BA for EPA, GHS, NT, and VT. TST_RMSE for LD₅₀; ² Existing model from ADMET Predictor was used to predict LD₅₀





Models predicted fewer false negatives compared to false positives. Thus, they erred on the side of caution, e.g., fewer toxic compounds were incorrectly predicted. This can be seen in the EPA and GHS category predictions which show fewer incorrect compounds in the lower right-hand corner than the upper left-hand corner.

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