

Delivering on the promise of AI-driven drug discovery with ADMET Predictor® 10

Background and application examples






Marvin Waldman
Sr. Research Fellow
30-Sep-2020

Motivation

- In-house project to develop novel anti-malarial compounds as proof of concept to use in-silico models to design compounds

Journal of Computer-Aided Molecular Design
<https://doi.org/10.1007/s10822-020-00333-x>

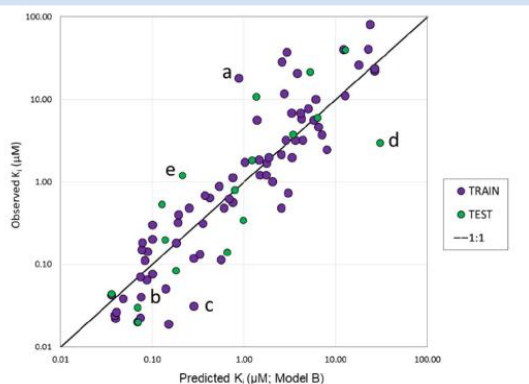
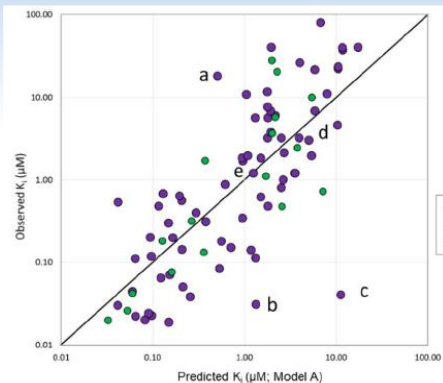
Design and tests of prospective property predictions for novel antimalarial 2-aminopropylaminoquinolones

Robert D. Clark¹  · Denise N. Morris² · Gary Chinigo^{3,6} · Michael S. Lawless¹ · Jacques Prudhomme⁴ · Karine G. Le Roch⁴  · Maria José Lafuente⁵ · Santiago Ferrer⁵  · Francisco Javier Gamo⁵ · Robert Gadwood³ · Walter S. Woltoz¹

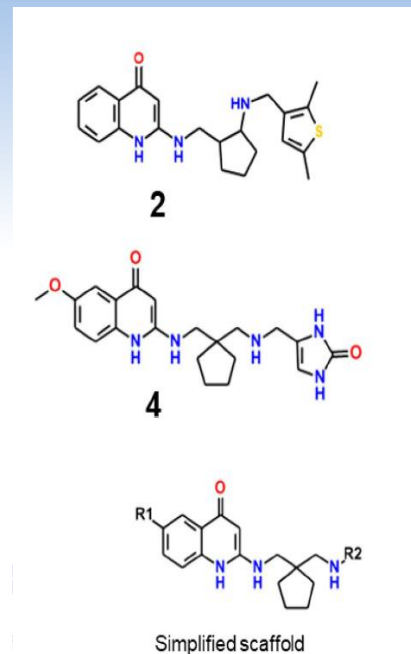
Received: 9 April 2020 / Accepted: 21 July 2020
© The Author(s) 2020

Compound Design Protocol

Activity Models



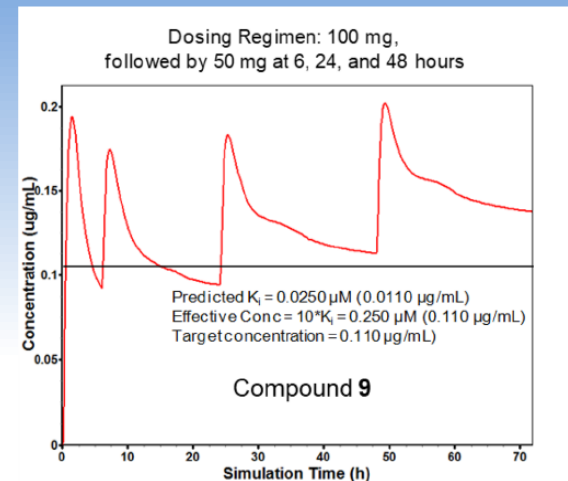
Analog Generation



Compound Design Protocol

Compound	8	9
Name	SLP0005	SLP0003
S+Sw (µg/mL)	1.8	0.32
obsd. solubility	33	0.76
S+logP	4.7	5.05
obsd. logP	4.2	4.4
S+pK _{a1}	5.24	5.24
obsd. pK _{a1}	4.95	4.80
S+pK _{a2}	8.01	7.63
obsd. pK _{a2}	8.33	7.36
S+logD _{6.8}	3.44	4.46
obsd. logD _{6.8}	2.68	3.76

Compound	Pred. <i>Pf</i> /DHODH K _i (µM)	XC ₅₀ (µM) ^{a,b}	
		3d7(-)	Dd2(+)
12a	0.049	10.0	46
12b	0.051	1.61	6.4
11a	0.023	0.55	2.3
11c	0.037	0.37	1.78
8	0.037	0.30	1.47
9	0.025	0.106	0.21
11b	0.038	0.037	0.24
CID 44534046 ^c	0.112	0.89	4.6
CID 44535189 ^c	0.077	0.85	8.6



Predict/Measure Properties

Conclusion: “It seems likely that further iterations and in vivo characterization would be productive.”

Can this be automated?

Background

- History of Computer-Based (“*De Novo*”) Drug Design
 - Early 1990’s
 - Structure (Receptor) Based
 - Ludi, MCSS/Hook, Sprout
 - Late 1990’s – Rule of 5, ADMET, Drug Design is multi-objective
 - “It ain’t just activity anymore”
 - Early to late 2000’s
 - Multi-objective ligand and structure-based design
 - Typically multi-objective “combined” into a single function
 - EA-Inventor, Muse, in-house Pharma programs
 - In the last decade
 - Pareto-based optimization
 - Deep Learning Generative algorithms

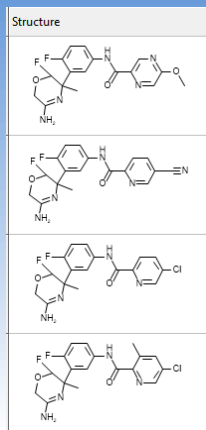
Generating Virtual Molecules

- Elementary “Transforms”
 - Modify molecules with small changes or fragment additions/deletions
 - Change/Add single atom or bond
 - Add common fragments
 - Carboxylic acid, sulfonamide, phenyl, etc.
 - Synthetic Feasibility?
 - Filter molecules based on structural alerts, e.g. hemiacetal, peroxide, etc.
 - Library of known synthetic reactions and building blocks
 - Chemical Diversity/Novelty?
 - SMIRKS-based
 - Deep Learning
 - Generative algorithms based on SMILES or graph representations

Molecule Selection/Scoring Approaches

- Multi-objective Criteria
 - Weighted Sum or “Combining” Function
 - Pareto optimal
 - Criteria
 - Activity/Docking Scoring
 - ADMET liabilities
 - Similarity to known active/lead
 - Synthetic Accessibility
 - Drug-likeness
 - Chemical Filters

AIDD Workflow



Initialize with K randomly generated analogs using chemical transforms starting from initial seed molecules

Evaluate properties:
ADMET_Risk
SynthDiff
Activity(s)
HTPK

Prune molecules using Pareto optimal layers

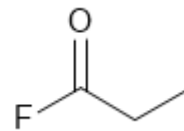
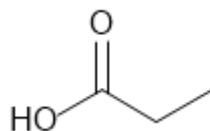
Generate M more analogs using chemical transforms and randomly selected molecules from current population

Structure	ADMET_Risk	S±logP	S±logD	S±Peff	S±Sw
	0.961	2.309	2.272	2.231	0.349
	0.930	2.705	2.667	2.687	0.023
	1.558	3.569	3.533	3.379	0.026
	1.110	3.793	3.748	3.462	0.022

Repeat N times

Generating Analogs

- Uses a library of chemically “intelligent” SMIRKS transforms
 - Example: Non-fluorine_to_fluorine
 - Simple version: [!#9:1]>>[#9:1]
 - Problem (Need to avoid)



Highly reactive acid halide

- Improved SMIRKS: [!#9;D1_S\$(*~[#6])!\$(*C=[O,N,S]):1]>>[#9:1]
- Currently ~150 transforms

Transforms

- CHANGE_FUNCTIONAL_GROUP
- CHANGE_CHAIN_LENGTH
- CREATE_RING
- BREAK_RING
- CHANGE_RING_SIZE
- CHANGE_RING_TOPOLOGY
- SHIFT_RING_SUBSTITUENTS
- CHANGE_BOND_ORDER
 - Aromatic_to_single_bond
 - Aromatize_5-membered_ring
 - Aromatize_6-membered_ring
 - De-aromatize_5-membered_ring
 - De-aromatize_6-membered_ring
 - Double_or_triple_to_single_bond
 - Double_to_triple_bond
 - Single_to_double_bond
 - Single_to_triple_bond
 - Triple_to_double_bond
- CHANGE_ATOM_TYPE
 - Non-bromine_to_bromine
 - Non-carbon_to_carbon
 - Non-chlorine_to_chlorine
 - Non-fluorine_to_fluorine
 - Non-iodine_to_iodine
 - Non-nitrogen_to_nitrogen
 - Non-oxygen_to_oxygen
 - Non-sulfur_to_sulfur
- ADD_FUNCTIONAL_GROUP
- ADD_FUSED_RING
- DELETE_FUNCTIONAL_GROUP

- CHANGE_FUNCTIONAL_GROUP
 - 2-Pyridone_to_Phenyl
 - 4-Hydroxypyridine_to_pyridone
 - 4-Pyridone_to_Phenyl
 - Acid_to_aliph_ring
 - Acid_to_arom_ring
 - Acid_to_tetrazole
 - Add_double_bond_oxygen
 - Amide_arom_insertion
 - Amide_reversal
 - Amide_to_hydroxy
 - Amide_to_hydroxy(2)
 - Amide_to_olefin
 - Arom_ring_to_ester(1)
 - Arom_ring_to_ester(2)
 - Arom_ring_to_propyl
 - CF3_to_methyl
 - Carbonyl_to_sulfonyl
 - Catechol_to_imidazole
 - Catechol_to_pyridone
 - Charged_nitrogen_to_carbon
 - Ester_to_amine
 - Ester_to_arom_ring
 - Ester_to_retroamide
 - Ester_to_sulfonamide
 - Ether_to_ethylene
 - Ethylene_to_ether
 - Het_to_sulfone
 - Hydroxy_to_amide

- ADD_FUNCTIONAL_GROUP
 - Add_1-imidazole
 - Add_1-tetrazole
 - Add_1-thiazole
 - Add_2-imidazole
 - Add_2-tetrazole
 - Add_2-thiazole
 - Add_3-piperidine
 - Add_3-tetrazole
 - Add_3-thiazole
 - Add_CF3
 - Add_amide
 - Add_amine
 - Add_bromo
 - Add_carboxylic_acid
 - Add_chloro
 - Add_cyano
 - Add_cyclohexyl
 - Add_cyclopentanone
 - Add_fluro
 - Add_hydroxyl
 - Add_iodo
 - Add_meta_furan
 - Add_meta_pyrrrole
 - Add_meta_thiophene
 - Add_methyl
 - Add_methyl_imide
 - Add_n_sulfonamide
 - Add_nitro
 - Add_ortho_furan

~50 Built-in models
%Fa, %Fb
Synthetic Difficulty+
User Models

Properties

Compound optimization

Available properties

- <Synthetic_Difficulty+>
- <Fraction absorbed (%Fa)>
- <Fraction bioavailable (%Fb)>
- Absn_Risk
- ADMET_Risk
- Bioconcn
- BSEP_IC50
- CYP3A4_Ki_midaz
- CYP3A4_Ki_testo
- CYP_HLM_CLint
- CYP_Risk
- CYP_RLM_CLint
- CYPsum_CLint
- Daphnia_LC50
- DiffCoef
- HEP_hCLint
- HEP_rCLint
- hERG_pIC50
- HIVI-ST
- HIVI-TC
- hum_fup%
- LogBB
- logHLC
- Minnow LC50

Uncheck All

Properties to optimize

Name	Direction	Capping Value
<Synthetic_Difficulty+>	Minimize	
<Fraction bioavailable (%Fb)>	Maximize	
ADMET_Risk	Minimize	
HIVI-ST	Maximize	

Modify Selected Remove Selected Remove All

Parameters for selected properties

1 Out-of-scope factor for risk models

10 Out-of-scope penalty for standard models

7.4 pH for pH dependent properties

Species for pharmacokinetic properties

Rat Human

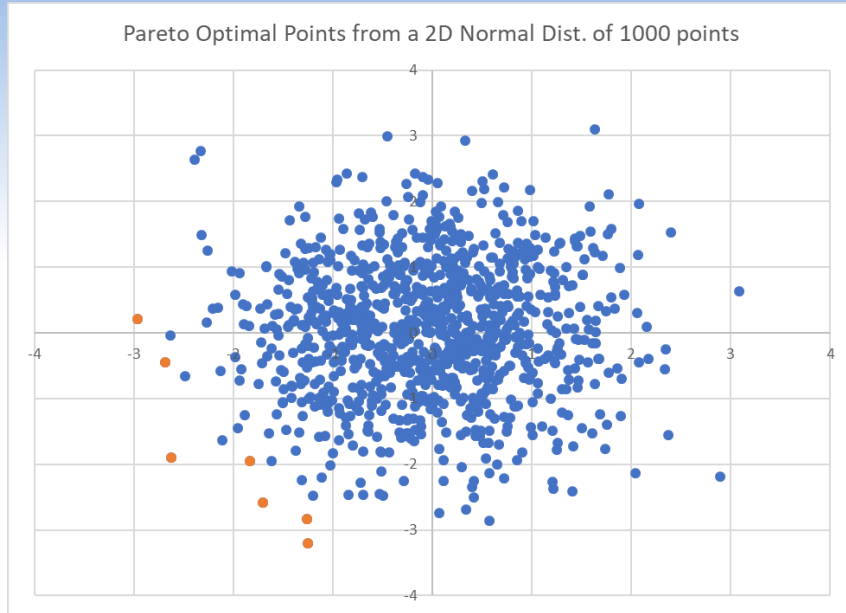
10.0 Dose for pharmacokinetic properties [mg]

Cancel Next >

Compromise Solution

- Multi-objective, but combine related objectives (e.g. ADMET) into one : ADMET_Risk™
- Typical/Recommended use: 4-5 objectives
 - ADMET_Risk
 - Synthetic Difficulty
 - 1-2 activity models (e.g., activity and selectivity)
 - Good PK (e.g, bioavailability)

Pareto Selection



- Pareto Results
 - 1000 normally distributed points
 - 2-dim. : 7 Pareto optimal points
 - 5-dim. : ~100 Pareto optimal points

Too Many objectives leads to too many molecules!

Most of them are good in just one or a few properties.

ADMET Risk™

Identifier	Weight	Rule logic
Size	1.0	MWt > 450{500} OR N_Atoms > 30{35} OR MolVol > 470{520} OR N_Bonds > 35{40}
RotB	1.0	N_FrRotB > 8{10}
HBD	1.0	HBDH > 3{5} AND HBDch > 1.5{2.0}
HBA	1.0	HBA > 7{10} AND HBACH < -6.0{-5.0}
ch	1.0	NPA_ABSQ > 19{21} OR T_PSA > 120{140}
Kow	1.0	S+logP > 4.5{5.0} OR S+logD > 3.5{4.0} OR MlogP > 3.5{4.0}
Peff	1.0	S+Peff < 0.40{0.60} OR S+MDCK < 10{25}
Sw	1.0	S+Sw < 0.005{0.010}
fu	1.0	hum_fup% < 4{6}
Vd	1.0	Vd > 4{5}
hERG	1.0	hERG_Filter = Yes AND hERG_pIC50 > 5.5{6.0}
rat	1.0	Rat_Acute < 200{300}
Xr	1.0	Rat_TD50 < 2.5{5.0}
Xm	1.0	Mouse_TD50 < 25{40}
HEPX	1.0	Ser_AST = Elevated AND Ser_ALT = Elevated AND Ser_LDH = Elevated
MUT	1.0	MUT_Risk > 1
1A2	1.0	(CYP1A2_CLint > 20{40} AND CYP1A2_Substr = Yes)
2C9	1.0	(CYP2C9_CLint > 10{20} AND CYP2C9_Substr = Yes)
2C19	1.0	(CYP2C19_CLint > 10{20} AND CYP2C19_Substr = Yes)
2D6	1.0	(CYP2D6_CLint > 10{20} AND CYP2D6_Substr = Yes)
3A4	1.0	(CYP3A4_CLint > 20{50} AND CYP3A4_HLM_CLint > 30{75} AND CYP3A4_Substr = Yes)
CL	1.0	CYP_HLM_CLint > 90{150} OR HEP_hCLint > 60{90}

Absorption

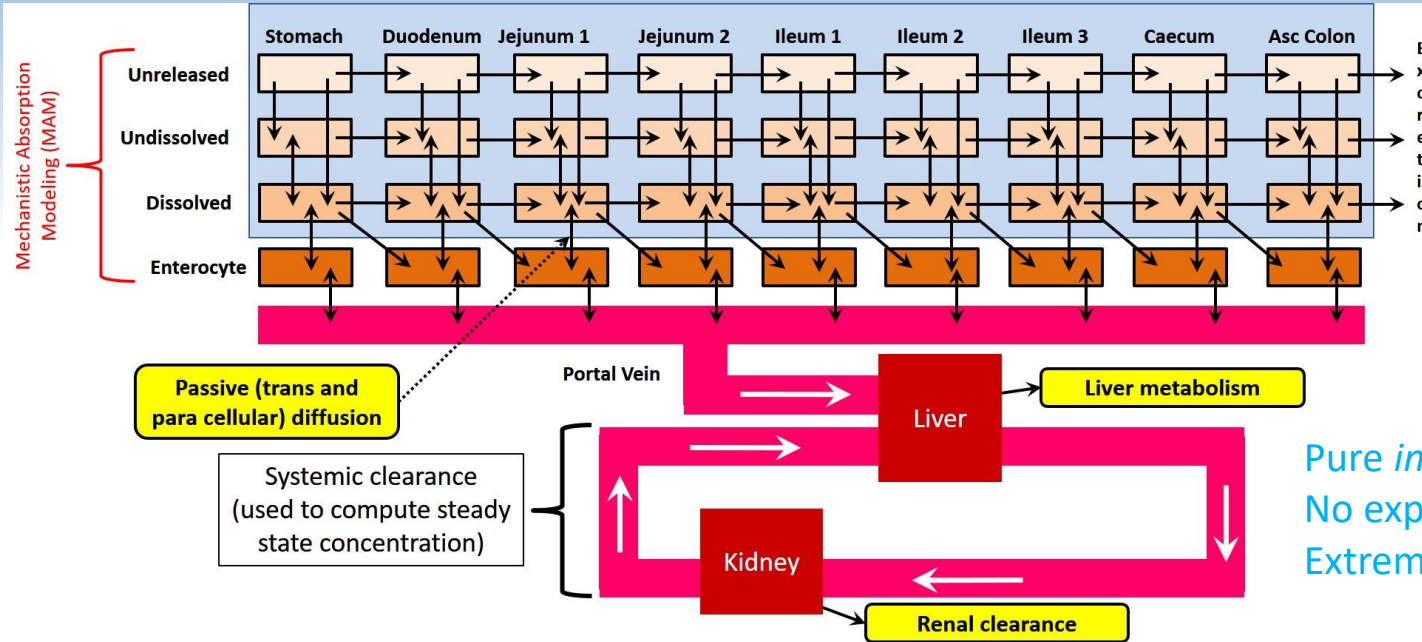
Distribution

Toxicity

Metabolism

PBPK Simulation: Methodology

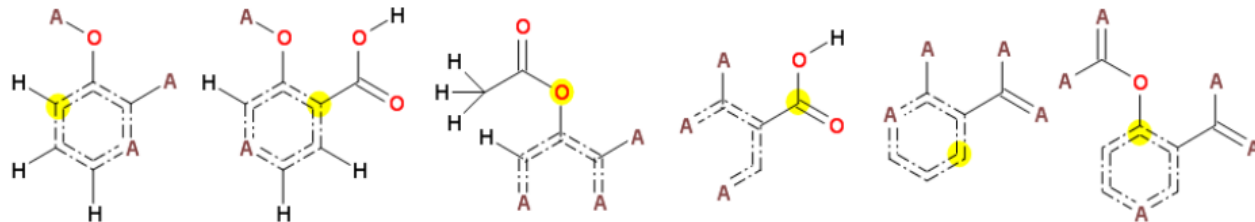
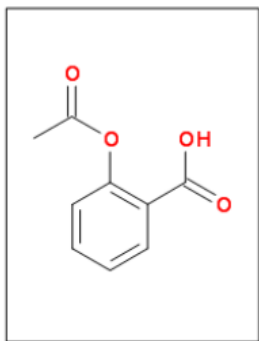
ACAT™ Model* + Compartmental Model



Pure *in silico* simulation
No exptl properties required
Extremely rapid, multi-threaded

* Advanced Compartmental Absorption
and Transit Model

Synthetic Accessibility/Difficulty



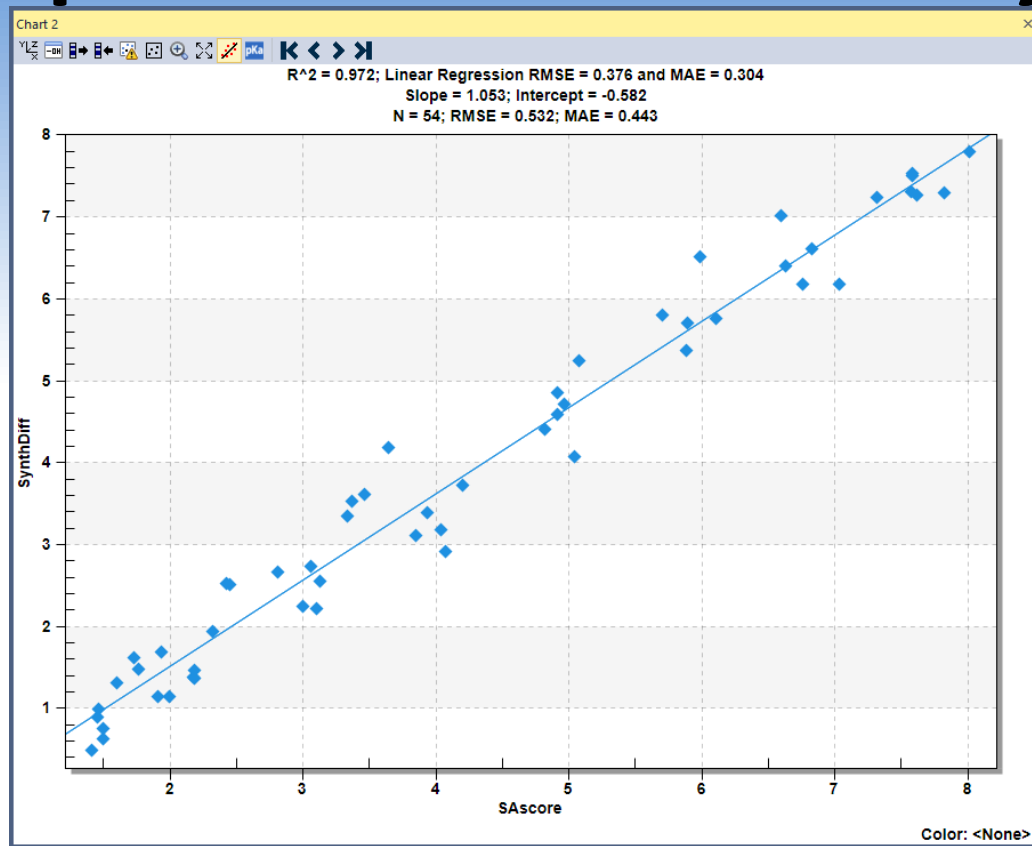
Score = fragmentScore – complexityPenalty

Fragment
frequencies

Heavy Atoms
Macrocycles
Stereocenters
Spiro centers
Bridges

	SA Ertl	Synth Diff
Training	~1 million	~47 million
Outer Layer	Any	aromatic vs. aliphatic
Complexity	Same	Same
Range	1-10	0-10

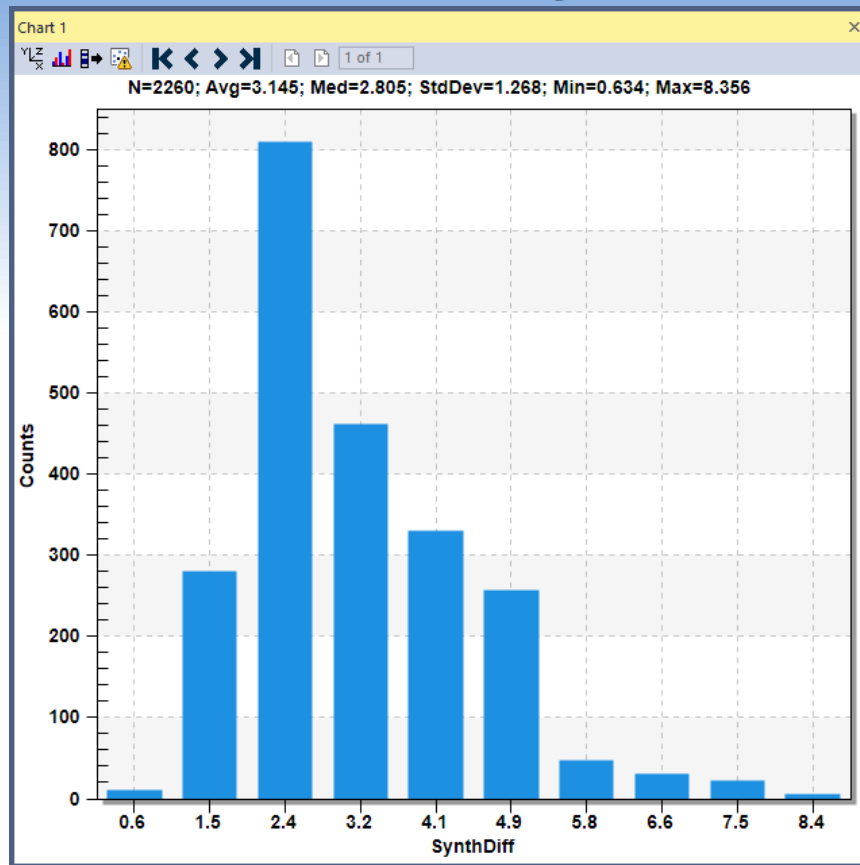
Comparison: SAScore vs. SynthDiff



Ertl and Shuffenhauer, J Cheminf, 2009, doi:10.1186/1758-2946-1-8

Li et al., J Cheminf, 2018, doi:10.1186/s13321-018-0287-6

Distribution of SynthDiff Scores

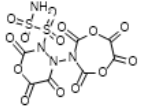
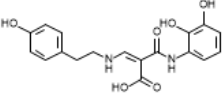
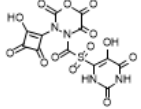
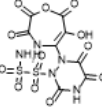
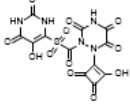
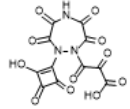


WDI Focused Set of
2260 compounds

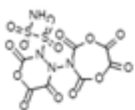
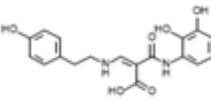
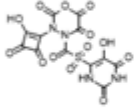
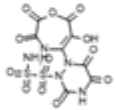
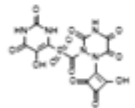
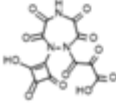
SynthDiff+

- SynthDiff was designed to “score” real molecules
- Performance on virtual molecules sometimes too “optimistic”
 - Add additional penalties based on drug-likeness filters
 - Brenk et al., ChemMedChem, 3, 435 (2008)
 - Rishton, Drug Disc. Today, 2, 382 (1997)
 - Maximum penalty of 4
 - Augmented version preferred over adding another Pareto objective

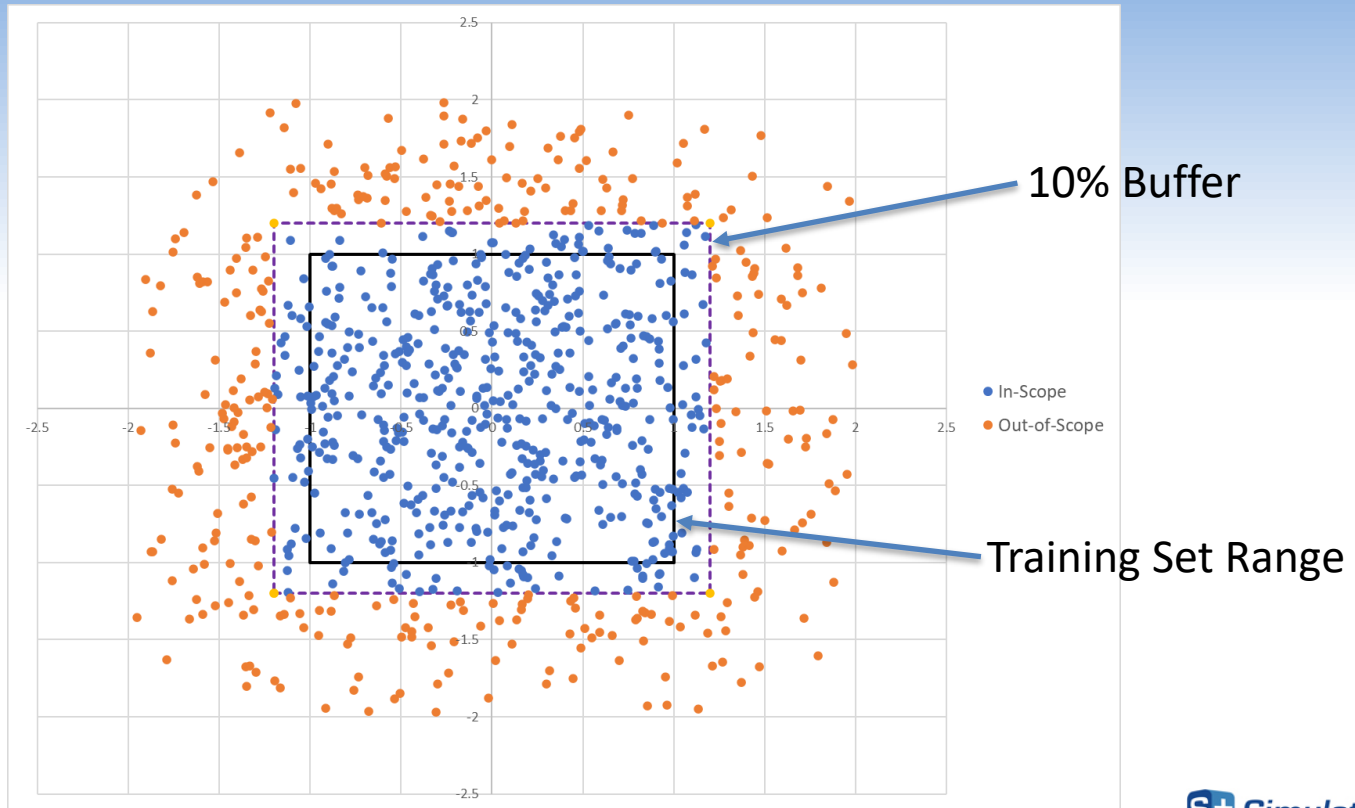
Early Results

	Structure	OBJ_HIVI-ST	ADMET_Risk	SynthDiff
1		12.799	3.000	4.256
2		6.525	3.956	2.313
3		12.248	3.500	4.181
4		12.163	6.000	4.132
5		11.952	4.000	4.082
6		11.051	1.694	3.674

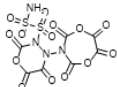
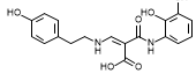
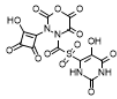
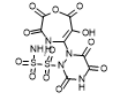
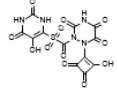
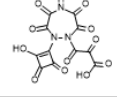
Out-of-Scope Predictions

	Structure	OBJ_HIVI-ST	ADMET_Risk	SynthDiff	HIVI-ST
1		12.799	3.000	4.256	<u>12.799</u>
2		6.525	3.956	2.313	<u>6.525</u>
3		12.248	3.500	4.181	<u>12.248</u>
4		12.163	6.000	4.132	<u>12.163</u>
5		11.952	4.000	4.082	<u>11.952</u>
6		11.051	1.694	3.674	<u>11.051</u>

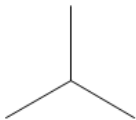
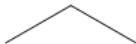



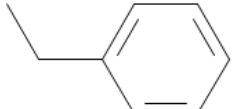
Applicability Domain



After Applying "Penalties"

	Structure	OBJ_HIVI-ST	ADMET_Risk	SynthDiff	HIVI-ST	HIVI-ST+	ADMET_Risk+	SynthDiff+
1		12.799	3.000	4.256	<u>12.799</u>	2.799	14.000	8.253
2		6.525	3.956	2.313	<u>6.525</u>	-3.475	11.956	6.312
3		12.248	3.500	4.181	<u>12.248</u>	2.248	13.500	7.897
4		12.163	6.000	4.132	<u>12.163</u>	2.163	15.000	7.848
5		11.952	4.000	4.082	<u>11.952</u>	1.952	15.000	6.848
6		11.051	1.694	3.674	<u>11.051</u>	1.051	13.404	7.674

Flip Side of the Coin: Capping Values

	Structure	OBJ_HIVI-ST	ADMET_Risk	SynthDiff
1		3.645	1.000	0.000
2		3.676	1.000	0.000
3		3.846	1.000	0.000
4		3.506	0.431	0.131
5		3.173	1.000	0.243
6		3.250	1.000	0.384

Properties to optimize

Name	Direction	Capping Value
<Synthetic_Difficulty+>	Minimize	2.5
ADMET_Risk	Minimize	
<Fraction bioavailable (%Fb)>	Maximize	90

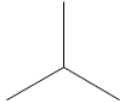
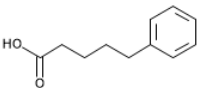

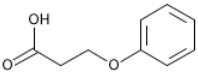

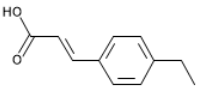


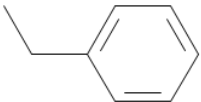
Modify Selected Remove Selected Remove All

Trivially Simple Molecules:
Very easy to make
Very good in one objective

Assigning a capping value tends to filter out such molecules.

The capping value is assigned as the result when the actual result is “better”, because this value is “good enough”.

Applying Capping Values: Example

	Structure	OBJ_HIVI-ST	ADMET_Risk	SynthDiffCap		Structure	OBJ_HIVI-ST	ADMET_Risk	SynthDiff+	SynthDiffCap
1		3.645	1.000	2.500	1		4.524	0.000	1.880	2.500
2		3.676	1.000	2.500	2		4.228	0.000	1.907	2.500
3		3.846	1.000	2.500	3		4.701	0.000	2.356	2.500
4		3.506	0.431	2.500						
5		3.173	1.000	2.500						
6		3.250	1.000	2.500						

Molecules on right “dominate” molecules on left after applying capping to SynthDiff

Restricting Chemical Space

Filter rules

Skeleton query (optional)

Clear Query

MedChem Designer

Paste From Clipboard

Load From File

Display query using:

Structure

Text

Input file containing product filter criteria (optional)

C:\Users\<User>\AppData\Local\Simulations Plus, Inc\AD\ Browse

Clear File Open File Query Wizard

Successful compounds must Pass Fail every query filter

Cancel < Back Next >

User Definable Scaffold

- Drawn using MedChem Designer
- Specified via SMARTS

Filtering Criteria

- Default file supplied
- Can be modified/replaced or omitted
- SMARTS patterns or more general queries

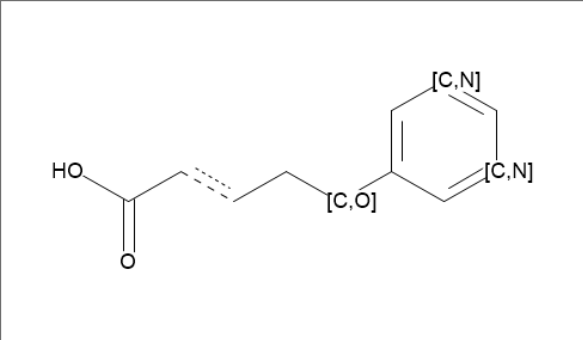
SLQ [#6]C(=O)N U >= 4 SCORE 1

NPQ AtomCount >= 66 SCORE 1

Scaffold Query Examples

Filter rules

Scaffold query (optional)



Clear Query

MedChem Designer

Paste From Clipboard

Load From File

Display query using:

Structure

Text

Input file containing product filter criteria (optional)

C:\Users\<User>\AppData\Local\Simulations Plus, Inc\AD\ Browse

Clear File Open File Query Wizard

Successful compounds must Pass Fail every query filter

Cancel < Back Next >

Structure-Based scaffold

Filter rules

Scaffold query (optional)

```
[E]Q [NH2][C;x5,x6](@[R1]@[R1])@=N[_S](~*)(@*)c1[cH]c([NH]C(=
```

Clear Query

MedChem Designer

Paste From Clipboard

Load From File

Display query using:

Structure

Text

Input file containing product filter criteria (optional)

C:\Users\<User>\AppData\Local\Simulations Plus, Inc\AD\ Browse

Clear File Open File Query Wizard

Successful compounds must Pass Fail every query filter

Cancel < Back Next >

SMARTS-Based scaffold

Run Parameters

Run parameters

Input file containing transform rules
C:\Users\Marv\AppData\Local\Simulations Plus, Inc\ADM Browse

View Transforms Enable or disable individual transform rules

100 Number of optimization generations
777 Random seed

500 Number of candidate molecules per generation
10 Intermediate file frequency (%)

1000 Size of initial population
 Use multithreading for product generation

500 Minimum size of population after each pruning cycle

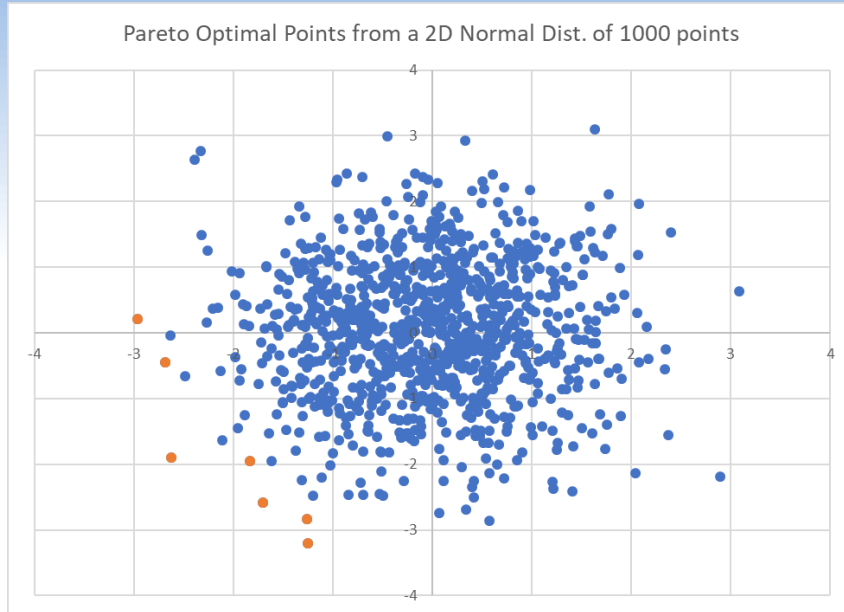
Folder for result files
C:\Users\Marv\AppData\Local\Simulations Plus, Inc\ADM Browse

Write input compound(s) to the output
 Display results in new window

Cancel < Back Run

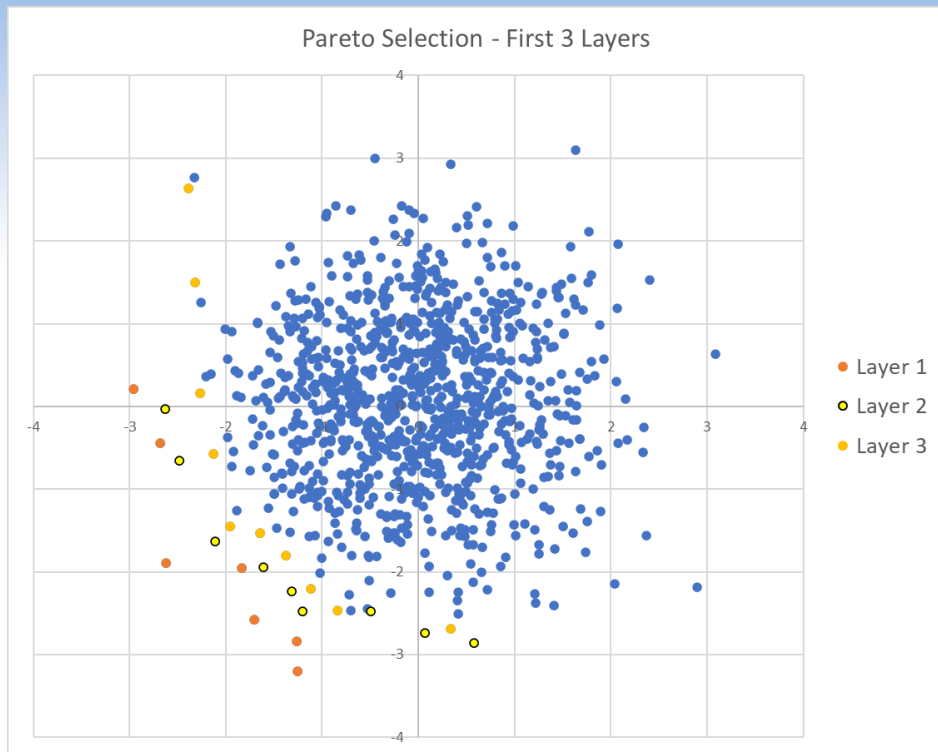
Minimum Size?

Pareto Selection



- Pareto Results
 - 1000 normally distributed points
 - 2-dim. : 7 Pareto optimal points

Pareto Selection – Multiple Layers



If initial Pareto-based selection results in too few molecules, repeat the selection using the remaining candidate molecules => Pareto Layers.

Enforced after running 50% of generations. Avoids “bad” molecules entering the population too early.

Summary/Key Points

- Highly automated customizable protocol commercially available
- ~150 chemically intelligent transforms
 - Customizable, user-controllable
- Property objectives
 - ~50 built-in property models available including ADMET Risk to combine them
 - HTPK simulations
 - User models from ADMET Modeler™
- Many options for controlling/limiting chemical space to avoid “chemical nonsense”
 - User-specified scaffold definition
 - Chemical filters – built-in or user-specified
 - Out-of-scope penalties
 - Augmented synthetic difficulty
- Performance!
 - Up to ~10 million molecules evaluated per 24 hours on i7-8 core laptop running 7-8 threads

Evaluation



Sept. 22, 2020 12:30 UTC

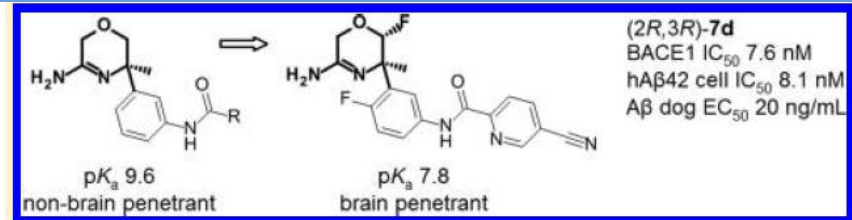
Simulations Plus Partners with Large Pharmaceutical Company to Validate AI-Driven Drug Design Capabilities in ADMET Predictor®

New AIDD Module applied to active therapeutic program to provide lead optimization support

LANCASTER, Calif.--(BUSINESS WIRE)-- [Simulations Plus, Inc.](#) (Nasdaq: SLP), the leading provider of modeling and simulation solutions for the pharmaceutical, biotechnology, chemicals, and consumer goods industries, today announced that it entered into a collaborative research agreement with a large pharmaceutical company to evaluate the new [AIDD Module](#) in the recently launched version of [ADMET Predictor®](#).

Working Example/Demo

- Design BACE1 inhibitors starting from a known active “seed”
 - BACE1 inhibition has been investigated as a potential target for treating Alzheimer’s disease
- Use activity model based on 370 known BACE1 inhibitors
- Augment ADMET Risk with an additional Risk model blood-brain barrier penetration
- Specify scaffold and filtering criteria based on literature “pharmacophore”
- Illustrate scaffold hopping to find alternative scaffolds and compounds that were previously synthesized/tested



1,4-Oxazine β -Secretase 1 (BACE1) Inhibitors: From Hit Generation to Orally Bioavailable Brain Penetrant Leads

Frederik J. R. Rombouts,^{*,†} Gary Tresadern,[#] Oscar Delgado,[‡] Carolina Martínez-Lamenca,[†] Michiel Van Gool,[‡] Aránzazu García-Molina,[‡] Sergio A. Alonso de Diego,[‡] Daniel Oehlrich,[†] Hana Prokopcova,[†] José Manuel Alonso,[#] Nigel Austin,^{||} Herman Borghys,^{||} Sven Van Brandt,[†] Michel Surkyn,[†] Michel De Cleyn,[†] Ann Vos,^{||} Richard Alexander,[⊥] Gregor Macdonald,[†] Dieder Moechars,[§] Harrie Gijsen,[†] and Andrés A. Trabanco^{*,‡}

[†]Neuroscience Medicinal Chemistry, Janssen Research & Development, Janssen Pharmaceutica NV, Turnhoutseweg 30, B-2340 Beerse, Belgium

[‡]Neuroscience Medicinal Chemistry, Janssen Research & Development, Janssen-Cilag SA, C/Jarama 75A, 45007 Toledo, Spain

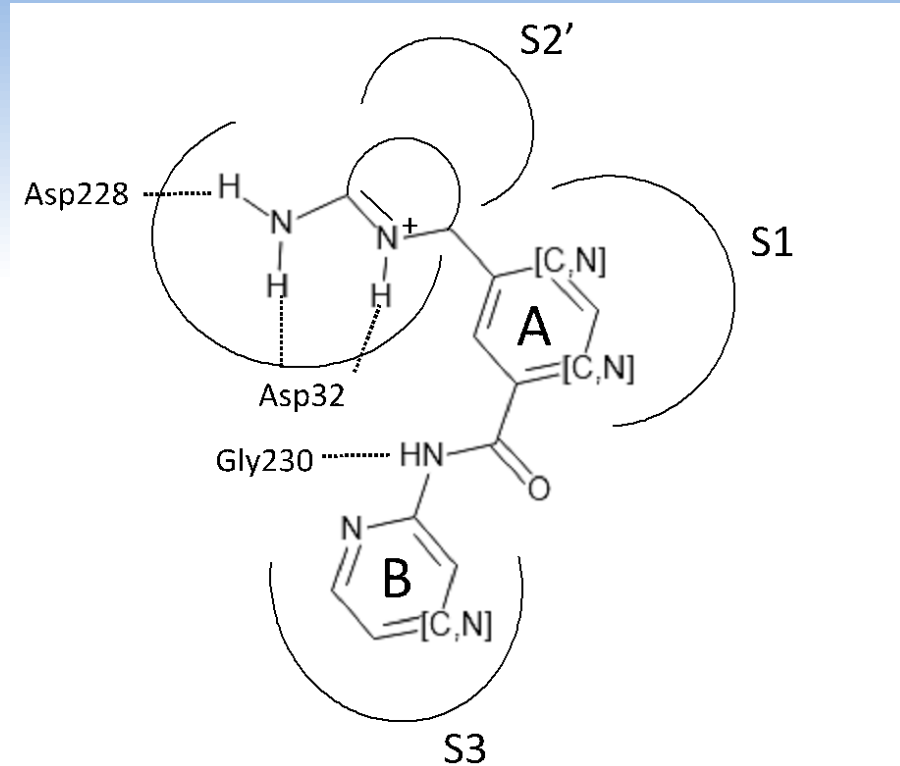
[§]Neuroscience Biology, Janssen Research & Development, Janssen Pharmaceutica NV, Turnhoutseweg 30, B-2340 Beerse, Belgium

^{||}Discovery Sciences, Janssen Research & Development, Janssen Pharmaceutica NV, Turnhoutseweg 30, B-2340 Beerse, Belgium

[⊥]Biologics Research, Janssen Research & Development, 1400 McKean Road, Spring House, Pennsylvania 19477, United States

[#]Discovery Sciences, Janssen Research & Development, Janssen-Cilag SA, C/Jarama 75A, 45007 Toledo, Spain

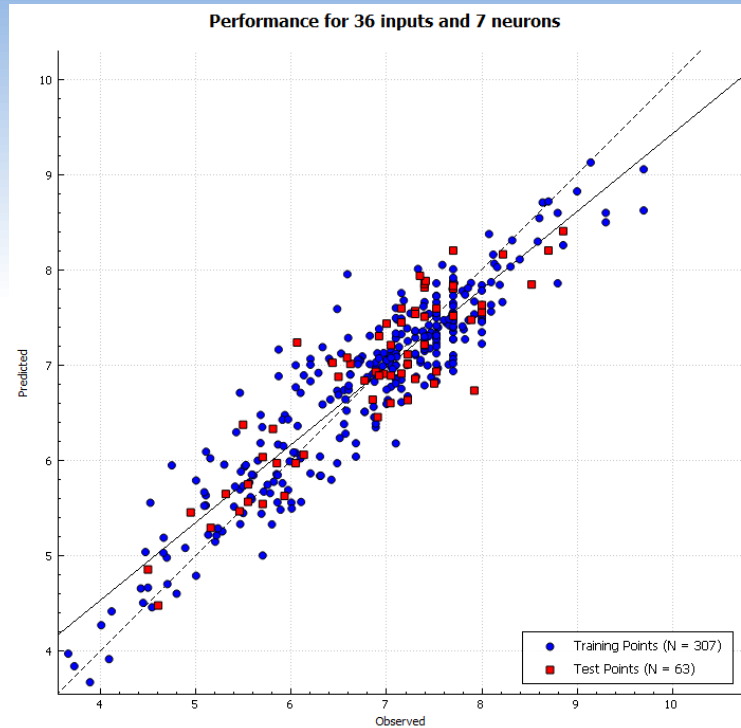
BACE1 Pharmacophore/Scaffold



Customized Risk Rule for BBB

Identifier	Weight	Rule logic
BBB	1.0	BBB_Filter = Low OR LogBB < -2{-1}
Pgp	1.0	Pgp_Substr = Yes
Fcat	1.0	FCation > 0.5{0.975}

BACE1 Activity Model



ALL: Slope=0.816 Intercept=1.259 QSqd=0.851 RMSE=0.418 MAE=0.326 RMSU=0.424

TRAIN: Slope=0.817 Intercept=1.250 QSqd=0.857 RMSE=0.418 MAE=0.324 RMSU=0.423

TEST: Slope=0.812 Intercept=1.322 QSqd=0.812 RMSE=0.420 MAE=0.338 RMSU=0.430

Acknowledgments

David Miller

Robert D. Clark

Michael Lawless

**For more information, visit our
website at:**

www.simulations-plus.com