

Large Scale Evaluation of log P Prediction Methods: Local Corrections Compensate Insufficient Accuracy and Eliminate the Need of Testing Every Other Compound

Gennadiy Poda,¹ Claude Ostermann,² Raimund Mannhold,³ Joseph McDonald,¹
Igor V. Tetko⁴

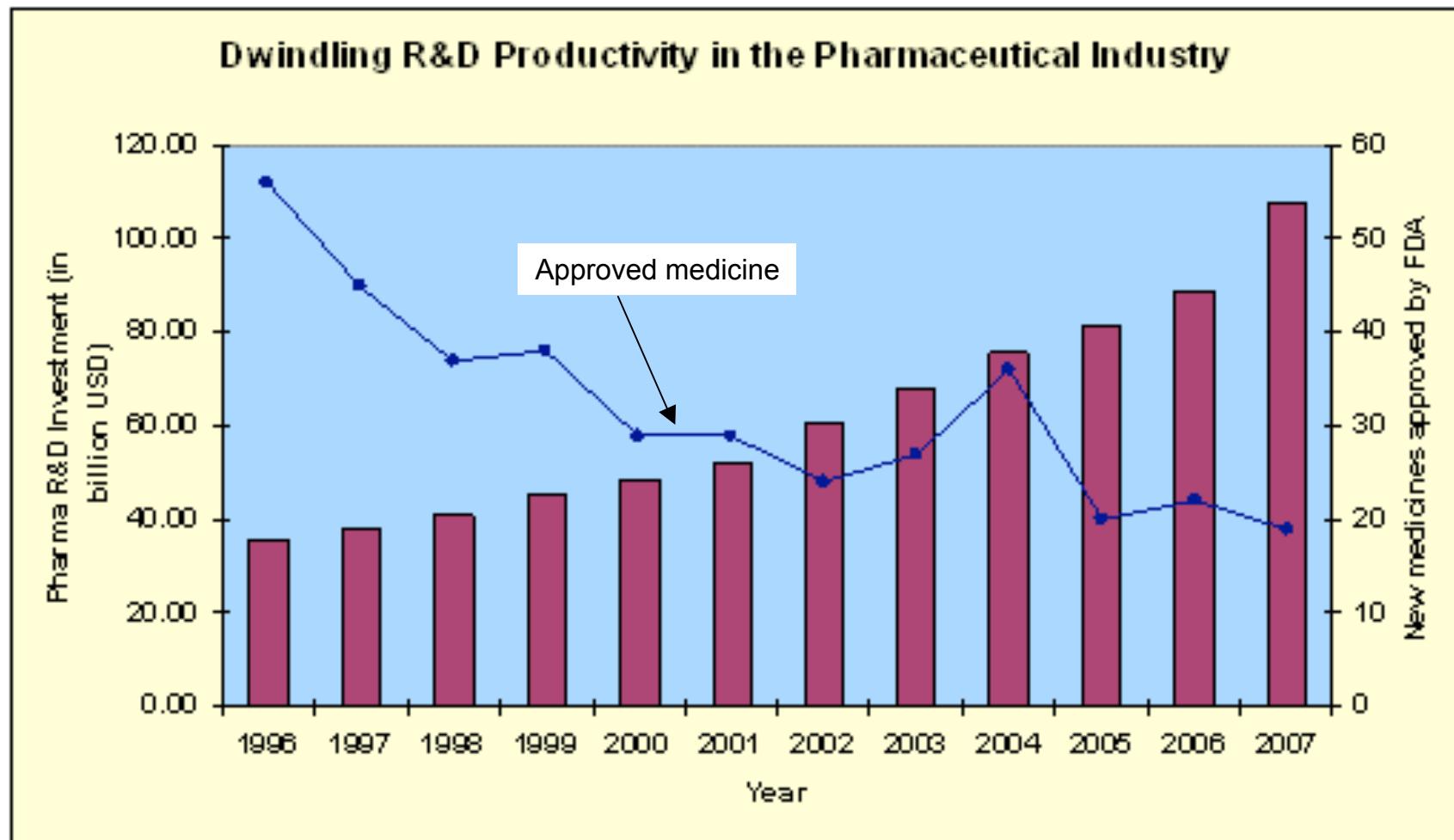
1-Structural & Computational Chemistry, Pfizer Global R & D, Chesterfield, MO 63017;

2-Nycomed GmbH, Germany;

3-Heinrich-Heine-Universität, Düsseldorf, Germany;

4-Helmholtz Zentrum München - German Research Center for Environmental Health (GmbH), Institute of Bioinformatics & Systems Biology

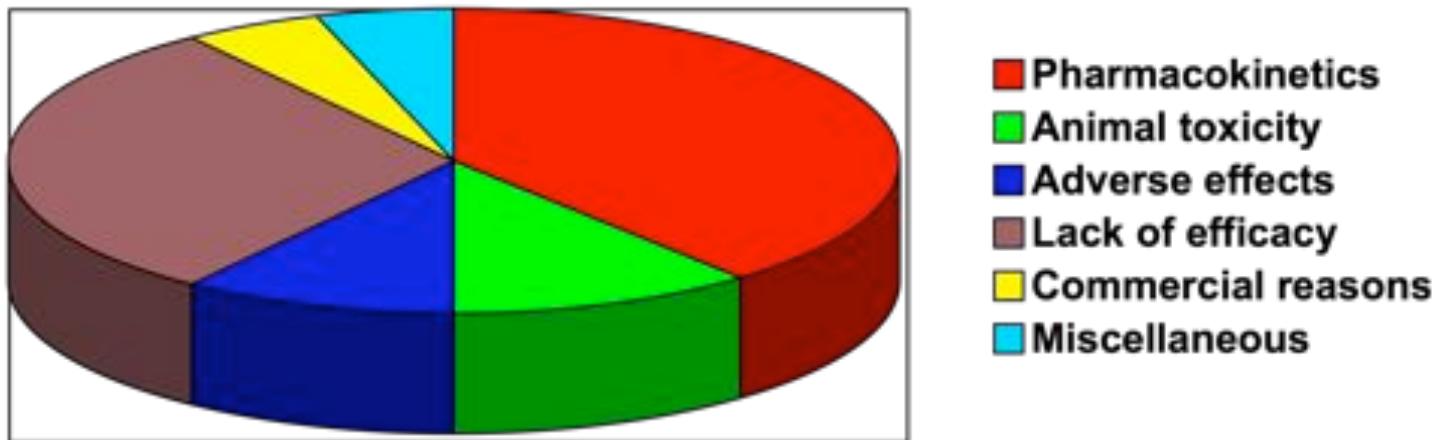
Declining R&D productivity in the pharmaceutical industry



<http://www.frost.com/prod/servlet/market-insight-top.pag?docid=128394740>

Source : PhRMA 2007, FDA

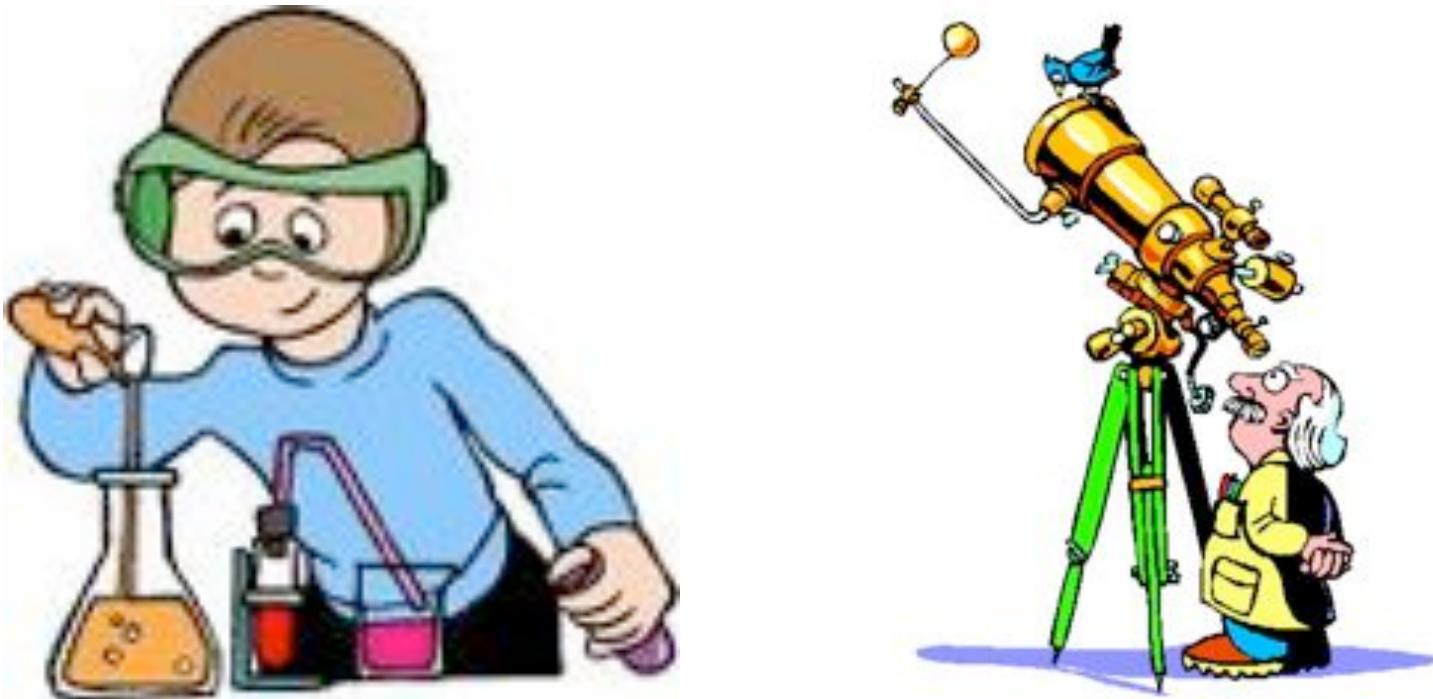
Pharma R&D Cost and productivity: Reasons for compound failure



TOP four reasons are connected to compound **Absorption, Distribution, Metabolism and Excretion**, all of which may contribute to lack of efficacy and Toxicity: **ADME/T** issues

Solutions: *in vitro* tests? *In vivo* animal tests? Costs... Time...

What is about *in silico*? Not accurate enough? Or incorrectly interpreted...



"One can not embrace the unembraceable."



Possible: $10^{60} - 10^{100}$ molecules theoretically exist
($> 10^{80}$ atoms in the Universe)

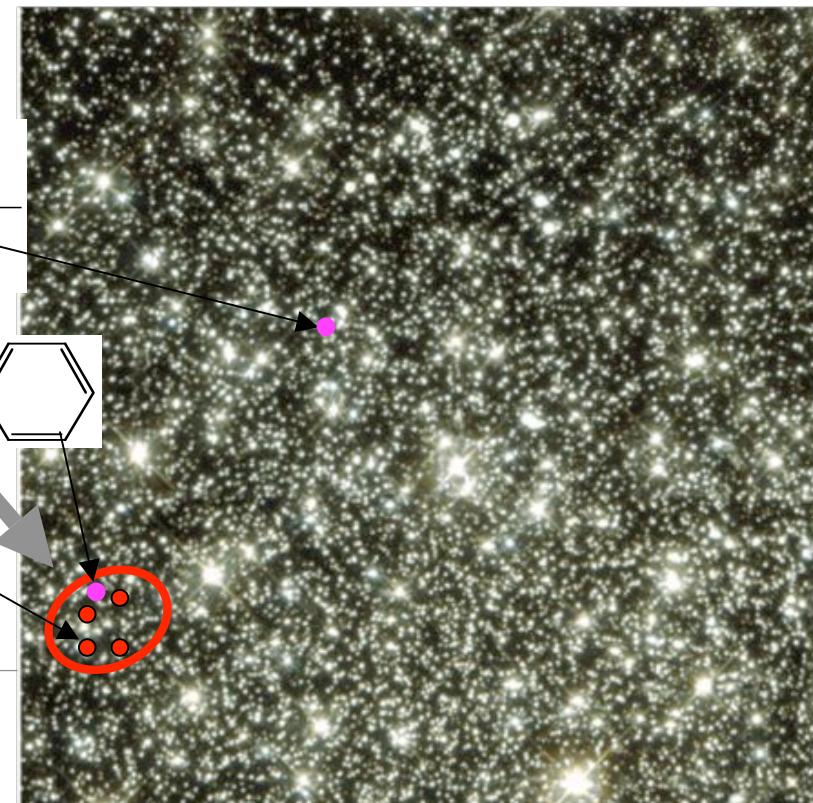
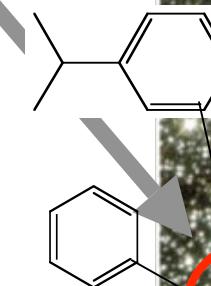
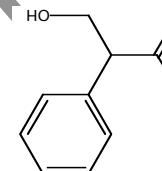
Achievable: $10^{20} - 10^{24}$ can be synthesized now
by companies (weight of the Moon is ca 10^{23} kg)

Available: 2×10^7 molecules are on the market

Measured: $10^2 - 10^4$ molecules with ADME/T data

Problem: To predict ADME/T properties of just molecules on the market we must extrapolate data from one to 1,000 - 100,000 molecules!

**There is a need for methods
which can estimate
the accuracy of predictions!**



Kozma Prutkov

Existing Dogma

- Prediction of physico-chemical properties, in particular **log P**, is simple
- There is no need to measure them
- We have enough number of good computational methods
- **Is this true?**

Performance of algorithms for the public dataset

Method	Star set (<i>N</i> = 223)						Non-Star set (<i>N</i> = 43)						
	RMSE	rank	% within error range			RMSE	rank	% within error range			<0.5	0.5-1	>1
			<0.5	0.5-1	>1			<0.5	0.5-1	>1			
AB/LogP	0.41	I	84	12	4	1.00	I	42	23	35			
S+logP	0.45	I	76	22	3	0.87	I	40	35	26			
ACD/logP	0.50	I	75	17	7	1.00	I	44	33	23			
Consensus log P	0.50	I	74	18	8	0.80	I	47	28	26			
CLOGP	0.52	II	74	20	6	0.91	I	47	28	26			
VLOGP OPS	0.52	II	64	21	7	1.07	I	33	28	26			
ALOGPS	0.53	II	71	23	6	0.82	I	42	30	28			
MiLogP	0.57	II	69	22	9	0.86	I	49	30	21			
XLOGP	0.62	II	60	30	10	0.89	I	47	23	30			
KowWIN	0.64	II	68	21	11	1.05	I	40	30	30			
CSlogP	0.65	II	66	22	12	0.93	I	58	19	23			
ALOGP (Dragon)	0.69	II	60	25	16	0.92	I	28	40	33			
MolLogP	0.69	II	61	25	14	0.93	I	40	35	26			
ALOGP98	0.70	II	61	26	13	1.00	I	30	37	33			
OsirisP	0.71	II	59	26	16	0.94	I	42	26	33			
VLOGP	0.72	II	65	22	14	1.13	I	40	28	33			
TLOGP	0.74	II	67	16	13	1.12	I	30	37	30			
ABSOLV	0.75	II	53	30	17	1.02	I	49	28	23			
QikProp	0.77	II	53	30	17	1.24	II	40	26	35			
QuantlogP	0.80	II	47	30	22	1.17	II	35	26	40			
SLIPPER-2002	0.80	II	62	22	15	1.16	II	35	23	42			
COSMOFrag	0.84	II	48	26	19	1.23	II	26	40	33			
XLOGP2	0.87	II	57	22	20	1.16	II	35	23	42			
QLOGP	0.96	II	48	26	25	1.42	II	21	26	53			
VEGA	1.04	II	47	27	26	1.24	II	28	30	42			
CLIP	1.05	II	41	25	30	1.54	III	33	9	49			
LSER	1.07	II	44	26	30	1.26	II	35	16	49			
MLOGP (Sim+)	1.26	II	38	30	33	1.56	III	26	28	47			
NC+NHET	1.35	III	29	26	45	1.71	III	19	16	65			
SPARC	1.36	III	45	22	32	1.70	III	28	21	49			
MLOGP(Dragon)	1.52	III	39	26	35	2.45	III	23	30	47			
LSE UFZ	1.60	III	36	23	41	2.79	III	19	12	67			
AAM	1.62	III	22	24	53	2.10	III	19	28	53			
VLOGP-NOPS	1.76	III	1	1	7	1.39	III	7	0	7			
HINT	1.80	III	34	22	44	2.72	III	30	5	65			
GBLOGP	1.98	III	32	26	42	1.75	III	19	16	65			

**Mannhold, Poda,
Ostermann, Tetko, J.
Pharm. Sci., 2009,
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Background models

Arithmetic Average Model (AAM):

mean $\log P$, used as model predicting the same value for all dataset molecules

Rank III: models with root mean squared errors (*RMSE*) close to or larger than that of AAM, **i.e. models are non-predictive**

Rank I: methods with *RMSE* identical or close to AB/LogP and ALOGPS

Rank II: remaining models

NC+NHET: $\log P = 1.46 + 0.11 (\text{NC} - \text{NHET})$
 $N=95\,809$, $\text{RMSE}=1.04$, $R^2=0.2$

Consensus logP: average of predicted $\log P$ from all rank I and II methods

Performance of algorithms for the public dataset

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AB/LogP	0.41	I	84	12	4	1.00	I	42	23	35			
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CLOGP	0.52	II	74	20	6	0.91	I	47	28	26			
VLOGP OPS	0.52	II	64	21	7	1.07	I	33	28	26			
ALOGPS	0.53	II	71	23	6	0.82	I	42	30	28			
MiLogP	0.57	II	69	22	9	0.86	I	49	30	21			
XLOGP	0.62	II	60	30	10	0.89	I	47	23	30			
KowWIN	0.64	II	68	21	11	1.05	I	40	30	30			
CSlogP	0.65	II	66	22	12	0.93	I	58	19	23			
ALOGP (Dragon)	0.69	II	60	25	16	0.92	I	28	40	33			
MolLogP	0.69	II	61	25	14	0.93	I	40	35	26			
ALOGP98	0.70	II	61	26	13	1.00	I	30	37	33			
OsirisP	0.71	II	59	26	16	0.94	I	42	26	33			
VLOGP	0.72	II	65	22	14	1.13	I	40	28	33			
TLOGP	0.74	II	67	16	13	1.12	I	30	37	30			
ABSOLV	0.75	II	53	30	17	1.02	I	49	28	23			
QikProp	0.77	II	53	30	17	1.24	II	40	26	35			
QuantlogP	0.80	II	47	30	22	1.17	II	35	26	40			
SLIPPER-2002	0.80	II	62	22	15	1.16	II	35	23	42			
COSMOFrag	0.84	II	48	26	19	1.23	II	26	40	33			
XLOGP2	0.87	II	57	22	20	1.16	II	35	23	42			
QLOGP	0.96	II	48	26	25	1.42	II	21	26	53			
VEGA	1.04	II	47	27	26	1.24	II	28	30	42			
CLIP	1.05	II	41	25	30	1.54	III	33	9	49			
LSER	1.07	II	44	26	30	1.26	II	35	16	49			
MLOGP (Sim+)	1.26	II	38	30	33	1.56	III	26	28	47			
NC+NHET	1.35	III	29	26	45	1.71	III	19	16	65			
SPARC	1.36	III	45	22	32	1.70	III	28	21	49			
MLOGP(Dragon)	1.52	III	39	26	35	2.45	III	23	30	47			
LSE UFZ	1.60	III	36	23	41	2.79	III	19	12	67			
AAM	1.62	III	22	24	53	2.10	III	19	28	53			
VLOGP-NOPS	1.76	III	1	1	7	1.39	III	7	0	7			
HINT	1.80	III	34	22	44	2.72	III	30	5	65			
GBLOGP	1.98	III	32	26	42	1.75	III	19	16	65			

**Mannhold, Poda,
Ostermann, Tetko, J.
Pharm. Sci., 2009,
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Performance of algorithms for *in-house* datasets

Method	Pfizer set (N = 95 809)						Nycomed set (N = 882)					
	RMSE	Failed ¹	rank	% in error range			RMSE, zwitterions excluded ²	RMSE	rank	% in error range		
				<0.5	0.5-	>1				<0.5	0.5-	>1
Consensus log P	0.95		I	48	29	24	0.94	0.58	I	61	32	7
ALOGPS	1.02		I	41	30	29	1.01	0.68	I	51	34	15
S+logP	1.02		I	44	29	27	1.00	0.69	I	58	27	15
NC+NHET	1.04		II	38	30	32	1.04	0.88	III	42	32	26
MLOGP(S+)	1.05		II	40	29	31	1.05	1.17	III	32	26	41
XLOGP3	1.07		II	43	28	29	1.06	0.65	I	55	34	12
MiLogP	1.10	27	II	41	28	30	1.09	0.67	I	60	26	14
AB/LogP	1.12	24	II	39	29	33	1.11	0.88	III	45	28	27
ALOGP	1.12		II	39	29	32	1.12	0.72	II	52	33	15
ALOGP98	1.12		II	40	28	32	1.10	0.73	II	52	31	17
OsirisP	1.13	6	II	39	28	33	1.12	0.85	II	43	33	24
AAM	1.16		III	33	29	38	1.16	0.94	III	42	31	27
CLOGP	1.23		III	37	28	35	1.21	1.01	III	46	28	22
ACD/logP	1.28		III	35	27	38	1.28	0.87	III	46	34	21
CSlogP	1.29	20	III	37	27	36	1.28	1.06	III	38	29	33
COSMOFrag	1.30	1088 ³	III	32	27	40	1.30	1.06	III	29	31	40
QikProp	1.32	103	III	31	26	43	1.32	1.17	III	27	24	49
KowWIN	1.32	16	III	33	26	41	1.31	1.20	III	29	27	44
QLogP	1.33	24	III	34	27	39	1.32	0.80	II	50	33	17
XLOGP2	1.80		III	15	17	68	1.80	0.94	III	39	31	29
MLOGP(Dragon)	2.03		III	34	24	42	2.03	0.90	III	45	30	25

Different MlogP implementations demonstrate different performances for both sets

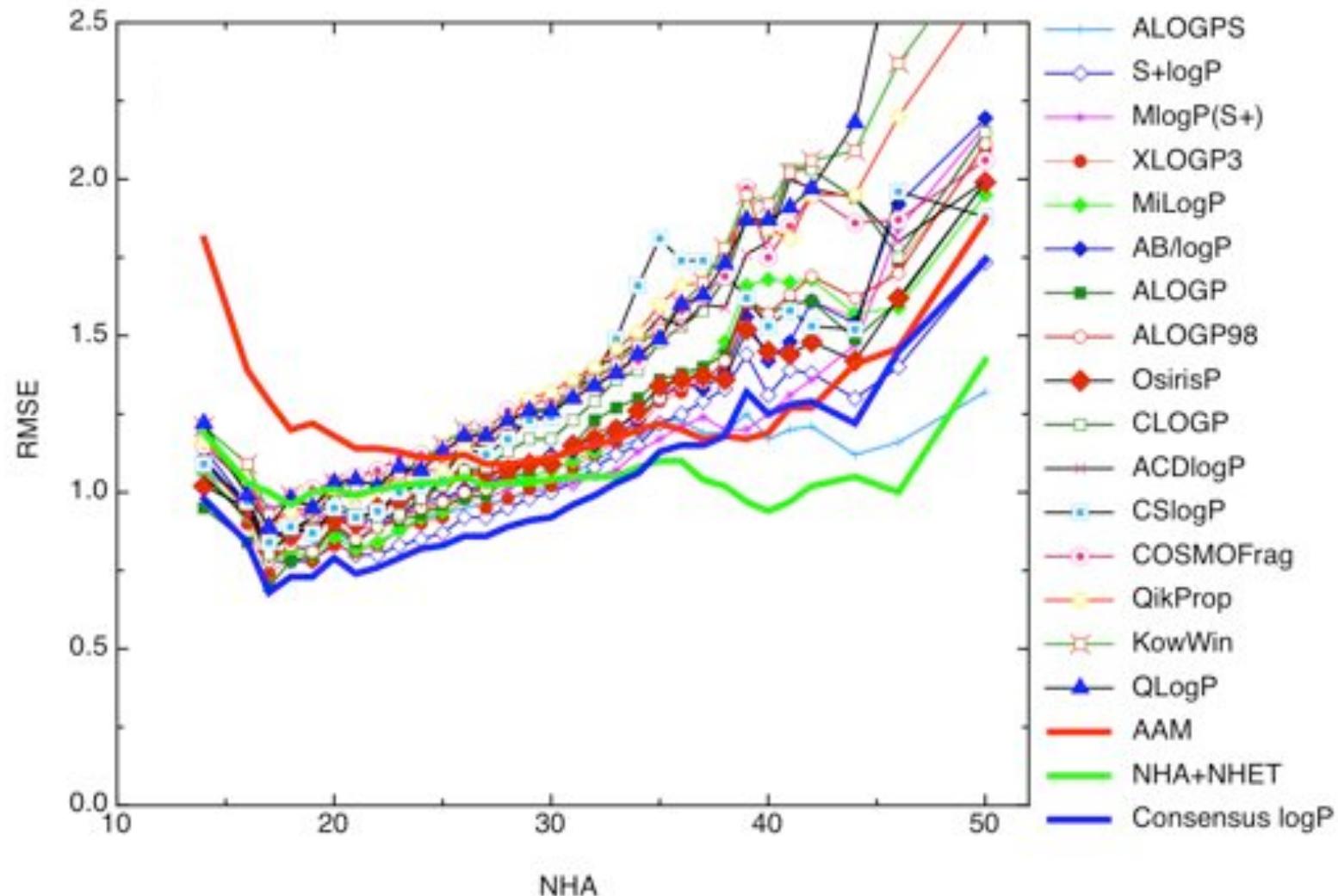
Mannhold, Poda, Ostermann, Tetko, J. Pharm. Sci., 2009, 98(3), 861-893

¹Nr of molecules with calculations failures due to errors or crash of programs. All methods predicted all molecules for the Nycomed dataset. ²RMSE calculated after excluding of 769 zwitterionic compounds from the Pfizer dataset. ³Most molecules failed by COSMOFrag are zwitterions.

Highlighted Recipes

- Identification and distinction of accurate and inaccurate predictions for global model
- Development of focused (local) models
- Estimation of the accuracy of predictions
- Conclusions

Methods performances for the Pfizer dataset



Development of focused (local) models

**The model does not work for my
data...**

**Is it possible to improve the
model by incorporating new
measurements?**

ALOGPS 2.1

- LogP: 75 variables,
12908 molecules,
RMSE=0.35,
MAE=0.26

- LogS: 33 variables,
1291 molecules,
RMSE=0.49,
MAE=0.35

Tetko et al, *J. Comput. Aided Mol. Des.* 2005, 19, 453-463.

Tetko & Tanchuk, *J. Chem. Info. Comput. Sci.*, 2002, 42, 1136-1145.

Welcome to the ALOGPS 2.1

Provide CAS RN or SMILES of a molecule and press the "submit" button

C1(C(=O)O)=C(N)C=CC=C1

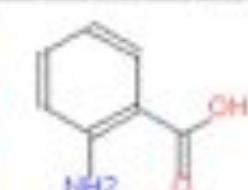
Upload a file with molecule(s) in 48 formats

C1(C(=O)O)=C(N)C=CC=C1

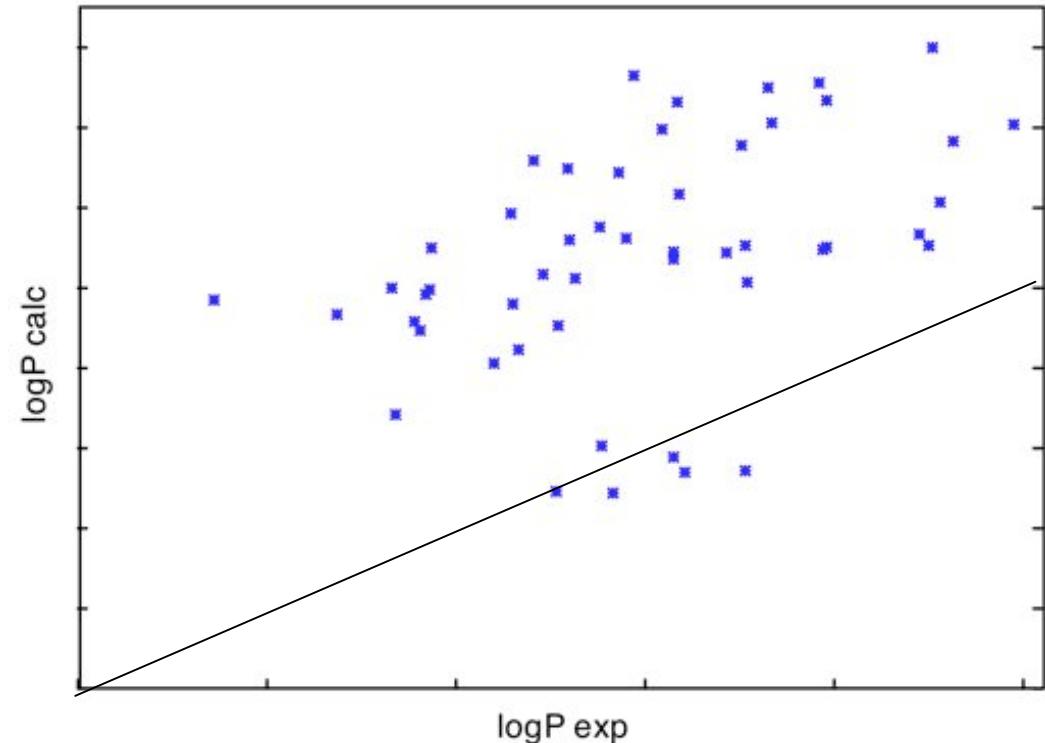
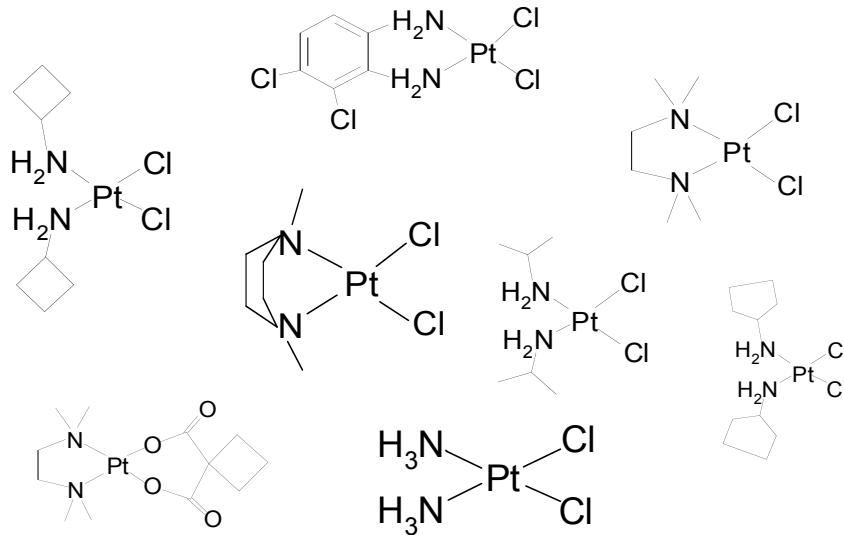
CAS RN	118-92-3	formula	C7H7NO2
SMILES	<chem>C1(C(=O)O)=C(N)C=CC=C1</chem>		
logP (exp)	1.21	logS (exp)	-1.30 (-6.81 g/l)
ALOGPs	0.78 <-0.43>	ALOGps	-1.71 (2.71 g/l)
AC_logP	0.78 <-0.43>	AC_logS	-1.63 (3.22 g/l)
AB/LogP	1.36 <+0.15>	AB/LogS	-1.55 (<-0.21)
COSMO(logS)	0.94 <-0.27>	Average logS	
mllogP	1.46 <+0.25>		
ALOGP	0.69 <-0.52>		
MLOGP	1.64 <+0.43>		
KOWWIN	1.36 <+0.15>	AB/pKa (Base)	2.40
XLOGP2	1.46 <+0.25>	AB/pKa (Acid)	5.00
XLOGP3	1.21 <0.00>	PkaProp.ref	Sangster's.ref
Average logP	1.17(<-0.34> <-0.04>)		

User's LogP LIBRARY upload library User's LogS LIBRARY upload library

The calculated results are available.

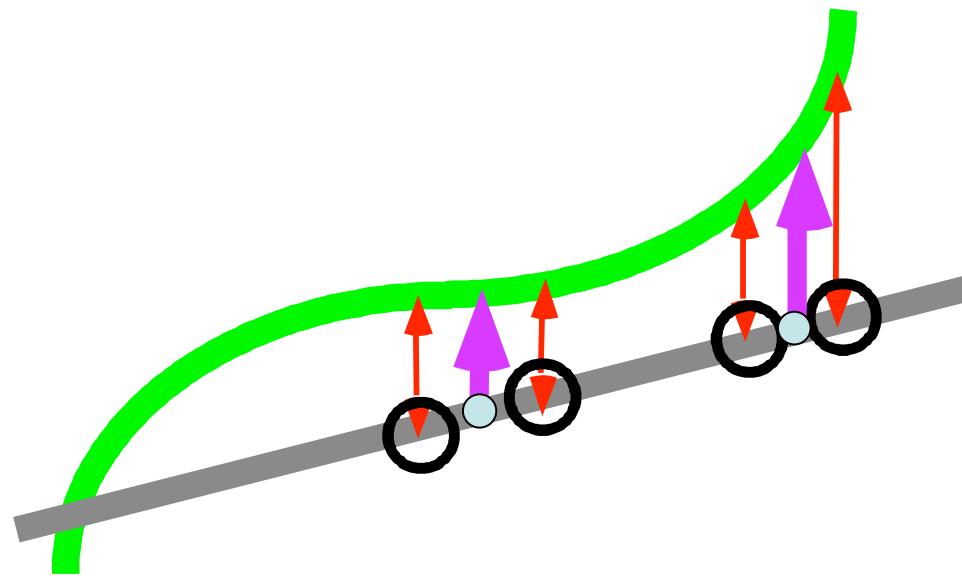


Local models: Instant learning of logP for Pt(II) molecules

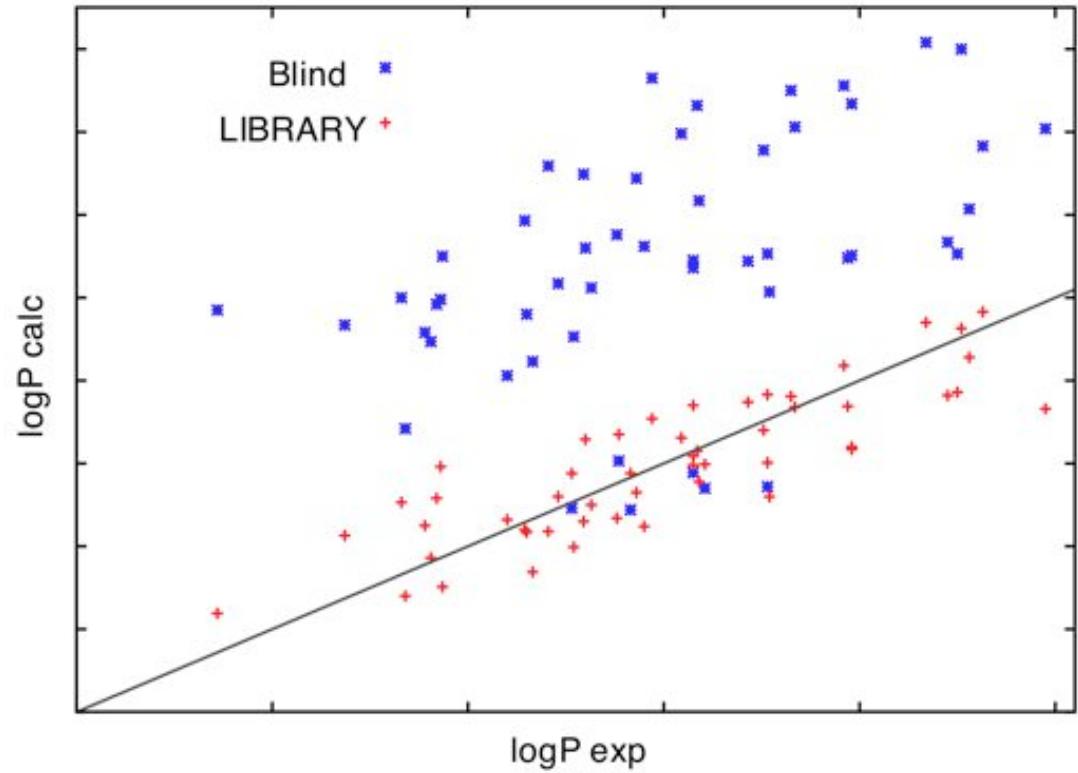
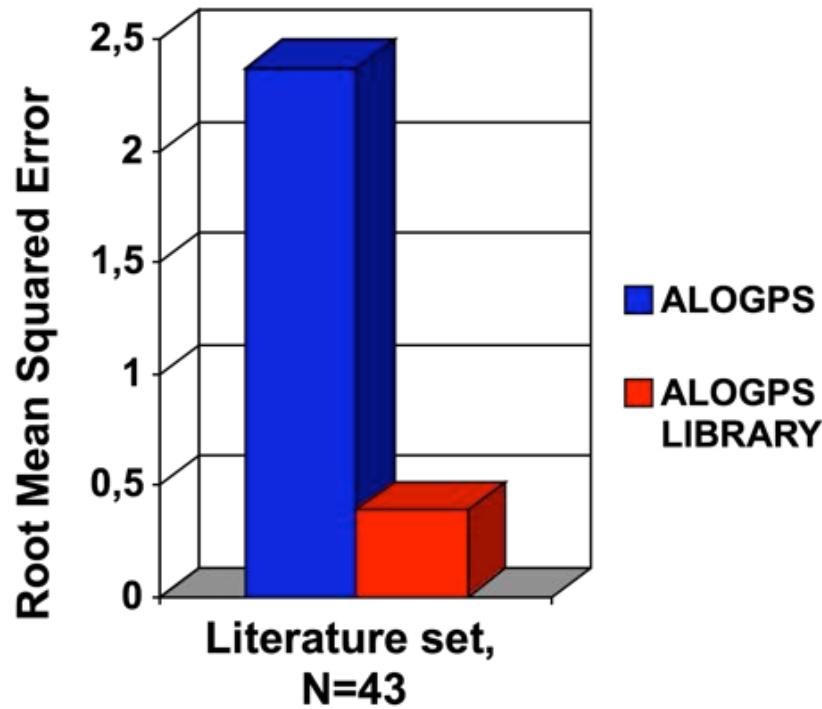


Prediction of new classes of compounds can be extremely difficult as exemplified by an absence of correlations between predicted and experimental values using the ALOGPS program.

Local correction of a model based on nearest neighbors



Local models: Instant learning by knowledge transfer



The use of LIBRARY mode (local correction of the global model) dramatically (5 times!) decreased logP errors,

Performance of algorithms for *in-house* datasets

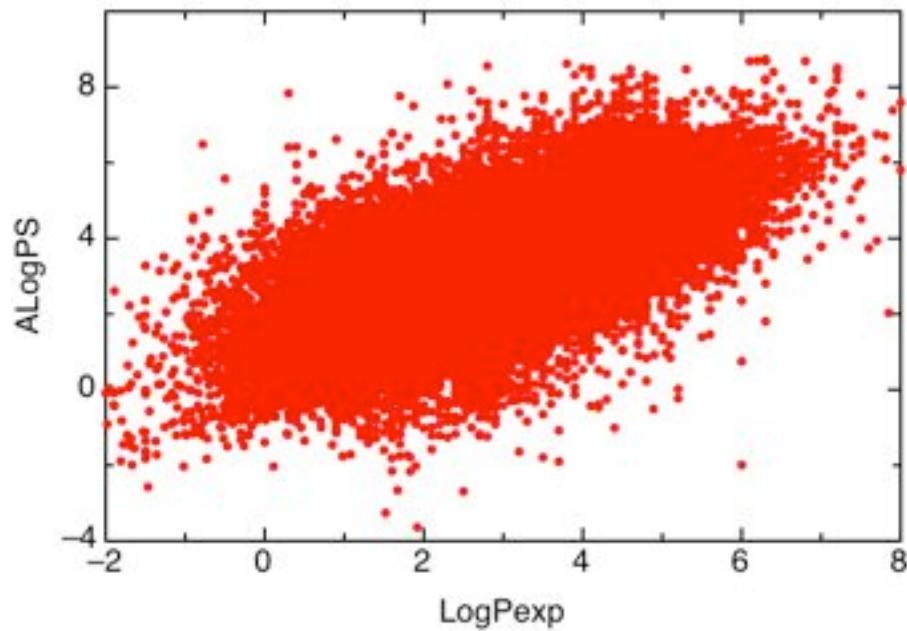
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	RMSE	Failed ¹	rank	% in error range			RMSE, zwitterions excluded ²	RMSE	rank	% in error range			
				<0.5	0.5-	>1				1	<0.5	0.5-	
Consensus log P	0.95	I	48	29	24	0.94	0.58	I	61	32	7		
ALOGPS	1.02	I	41	30	29	1.01	0.68	I	51	34	15		
S+logP	1.02	I	44	29	27	1.00	0.69	I	58	27	15		
NC+NHET	1.04	II	38	30	32	1.04	0.88	III	42	32	26		
MLOGP(S+)	1.05	II	40	29	31	1.05	1.17	III	32	26	41		
XLOGP3	1.07	II	43	28	29	1.06	0.65	I	55	34	12		
MiLogP	1.10	27	II	41	28	30	1.09	0.67	I	60	26	14	
AB/LogP	1.12	24	II	39	29	33	1.11	0.88	III	45	28	27	
ALOGP	1.12		II	39	29	32	1.12	0.72	II	52	33	15	
ALOGP98	1.12		II	40	28	32	1.10	0.73	II	52	31	17	
OsirisP	1.13	6	II	39	28	33	1.12	0.85	II	43	33	24	
AAM	1.16	III	33	29	38	1.16	0.94	III	42	31	27		
CLOGP	1.23	III	37	28	35	1.21	1.01	III	46	28	22		
ACD/logP	1.28	III	35	27	38	1.28	0.87	III	46	34	21		
CSlogP	1.29	20	III	37	27	36	1.28	1.06	III	38	29	33	
COSMOFrag	1.30	1088 ³	III	32	27	40	1.30	1.06	III	29	31	40	
QikProp	1.32	103	III	31	26	43	1.32	1.17	III	27	24	49	
KowWIN	1.32	16	III	33	26	41	1.31	1.20	III	29	27	44	
QLogP	1.33	24	III	34	27	39	1.32	0.80	II	50	33	17	
XLOGP2	1.80		III	15	17	68	1.80	0.94	III	39	31	29	
MLOGP(Dragon)	2.03		III	34	24	42	2.03	0.90	III	45	30	25	

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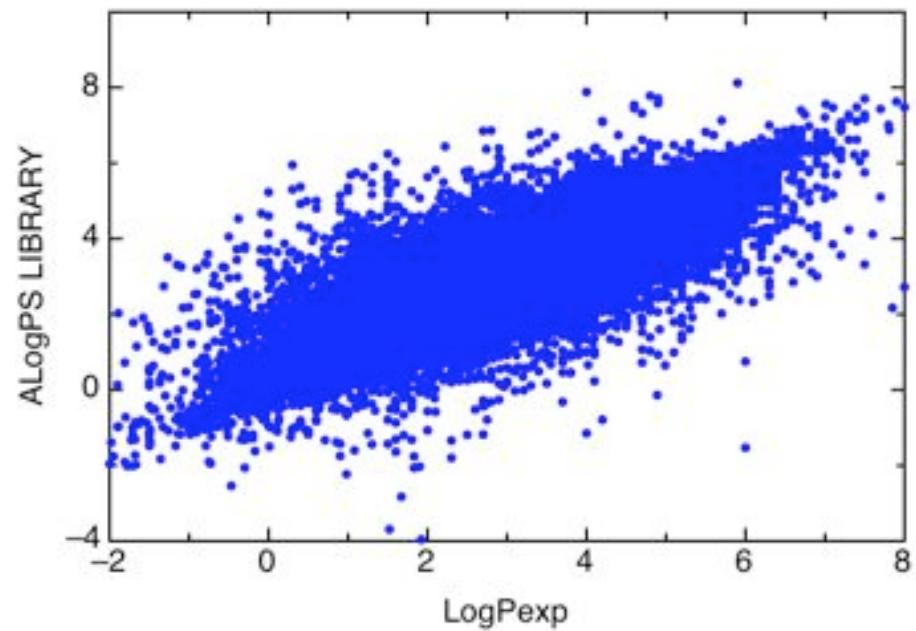
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Local models: Instant learning of in-house data (Pfizer Inc.), N=95809

ALOGPS Blind prediction



ALOGPS LIBRARY



RMSE=1.02

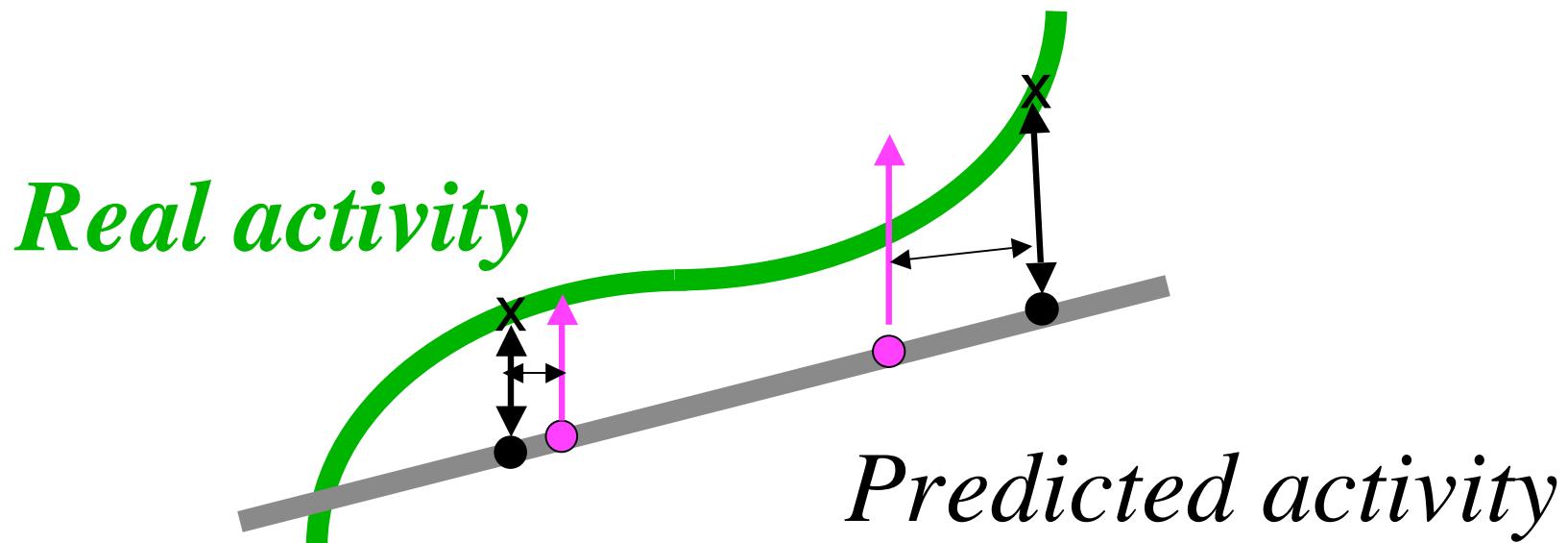


RMSE=0.59

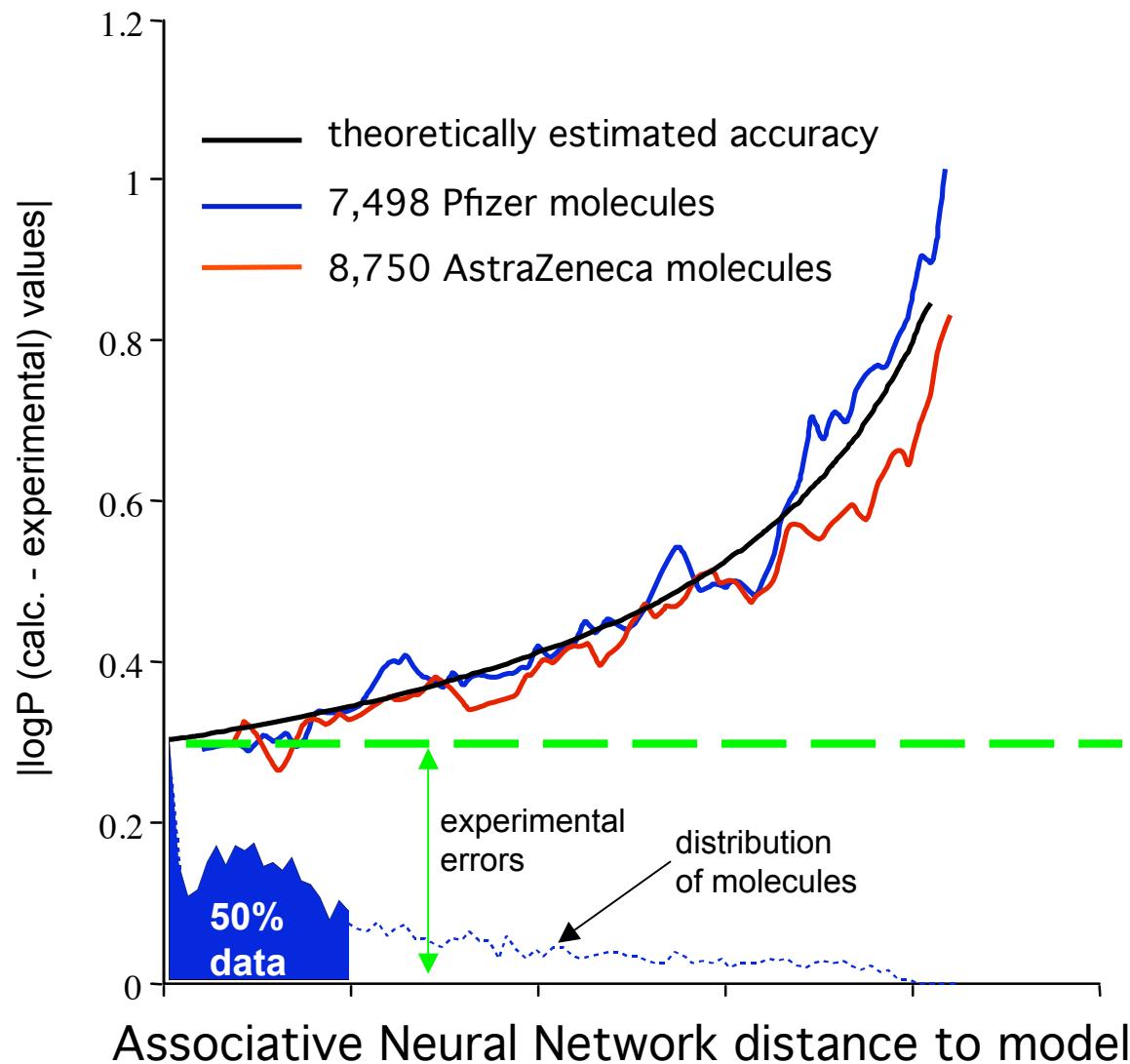
in less than 30 minutes of calculations on a notebook!

**Is it possible to save costs by skipping
measurements of some compounds
and
be satisfied with the calculated values?**

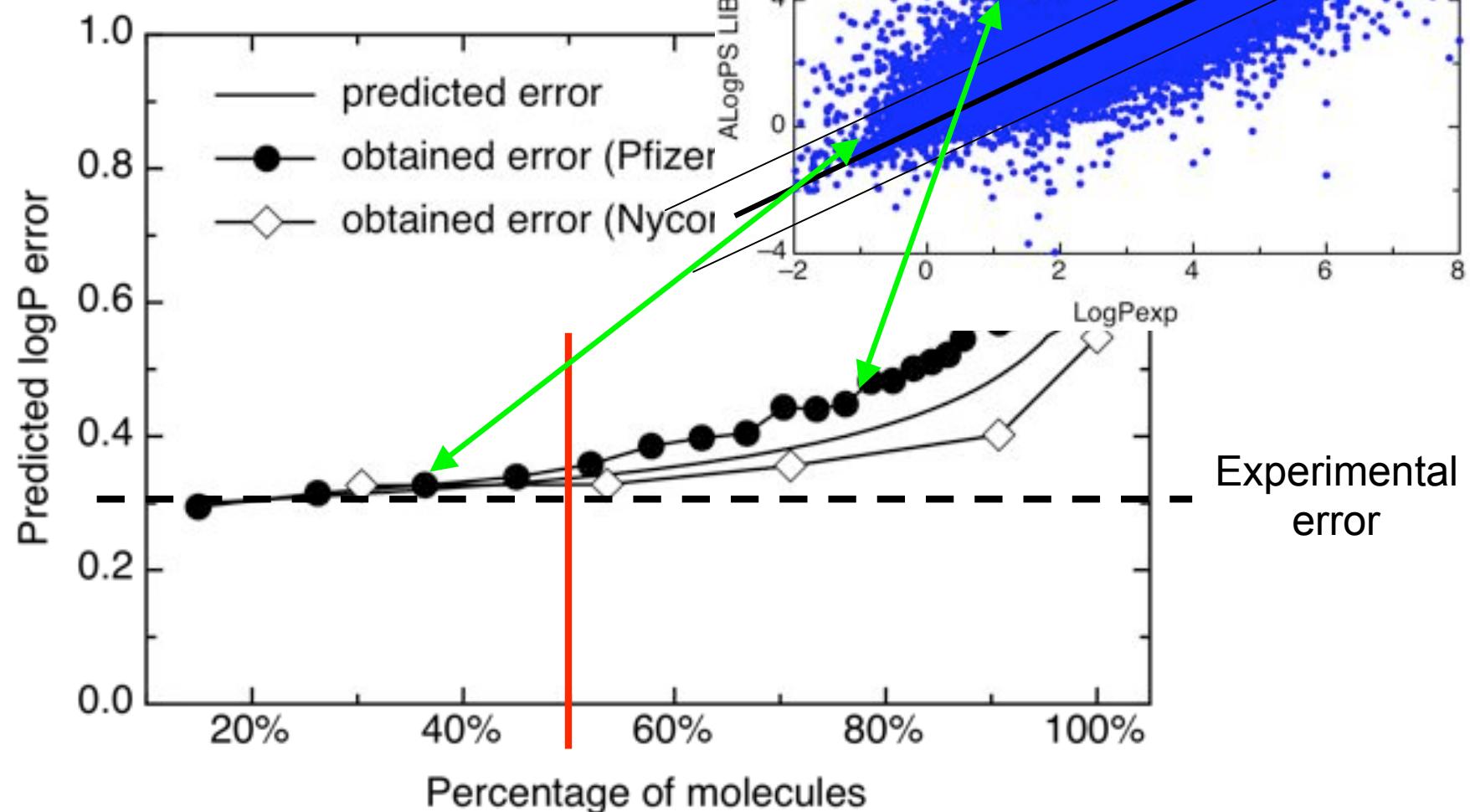
Estimation of the model accuracy by the distance to nearest neighbors



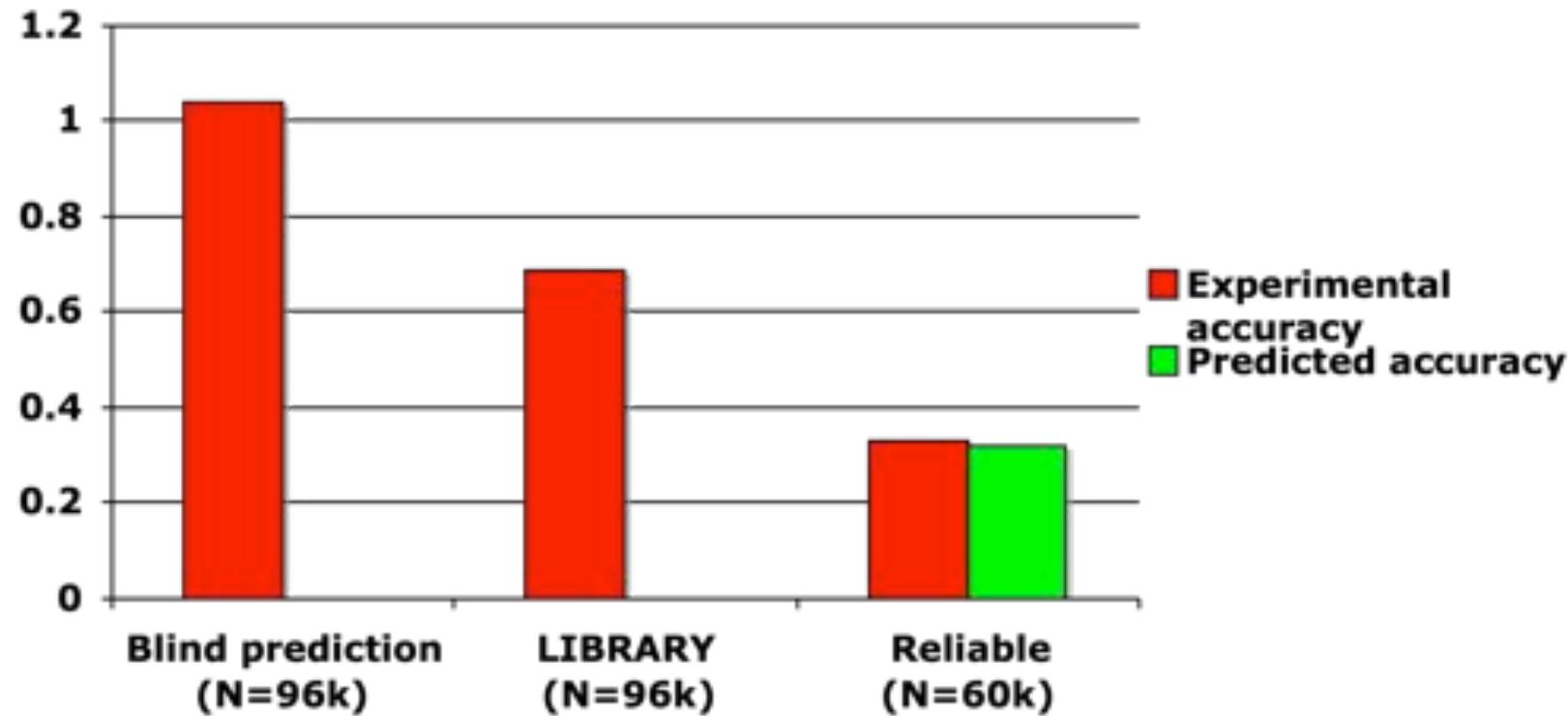
Local model: Accuracy of logP predictions



Our methodology identifies molecules (>50%!) predicted with about experimental accuracy



Improving accuracy with proposed methodology



CAse studies on the development and application of in-silico techniques for environmental hazard and risk assessment

www.CADASTER.eu

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About CADASTER

Implementation of REACH requires demonstration of the safe manufacture and use of chemicals. REACH aims to achieve a proper balance between societal, economic and environmental objectives, and attempts to efficiently use the scarce and scattered information available on the majority of substances. Thereupon REACH aims to reduce animal testing by optimized use of in silico and in vitro information on related compounds.

The REACH regulation advocates the use of non-animal testing methods, but guidance is needed on how these methods should be used. The procedures include alternative methods such as chemical and biological read-across, in vitro results, in vivo information on analogues, (Q)SARs, and exposure-based waiving. The concept of Intelligent Testing Strategies for regulatory endpoints has been outlined to facilitate the assessments. Intensive efforts are needed to translate the concept into a workable, consensually acceptable, and scientifically sound strategy.

CADASTER aims at providing the practical guidance to integrated risk assessment by carrying out a full hazard and risk assessment for chemicals belonging to four compound classes. A Decision Support System (DSS) will be developed that will be updated on a regular basis in order to accommodate and integrate the alternative methods mentioned above.

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September 14-17, Limassol, Cyprus

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Challenge



Organizers

This challenge is organized by ICANN09: International Conference on Artificial Neural Networks, European Neural Network Society (ENNS) and CADASTER project.

Goals of this study

- Develop *in silico* models to predict environmental toxicity of molecules against *T. pyriformis* using data from [1].
- Estimate the accuracy of prediction of new compounds. Further information can be found [here](#).

Important key dates

- May 26 2009 All data for the challenge are available.
- June 1 The submission of results is open.
- August 31 The submission of results is closed.
- September 14-17 2009 The winner will be announced at ICANN09 conference in September.

Latest news

- Challenge on
www.CADASTER.eu

The winner will be identified according to the criteria defined below and (s)he will receive a prize. It is expected that the winner as well as other participants will submit articles describing their methodological approaches for publication in a peer-reviewed journal (under discussion). Information on how you can participate can be found [here](#).

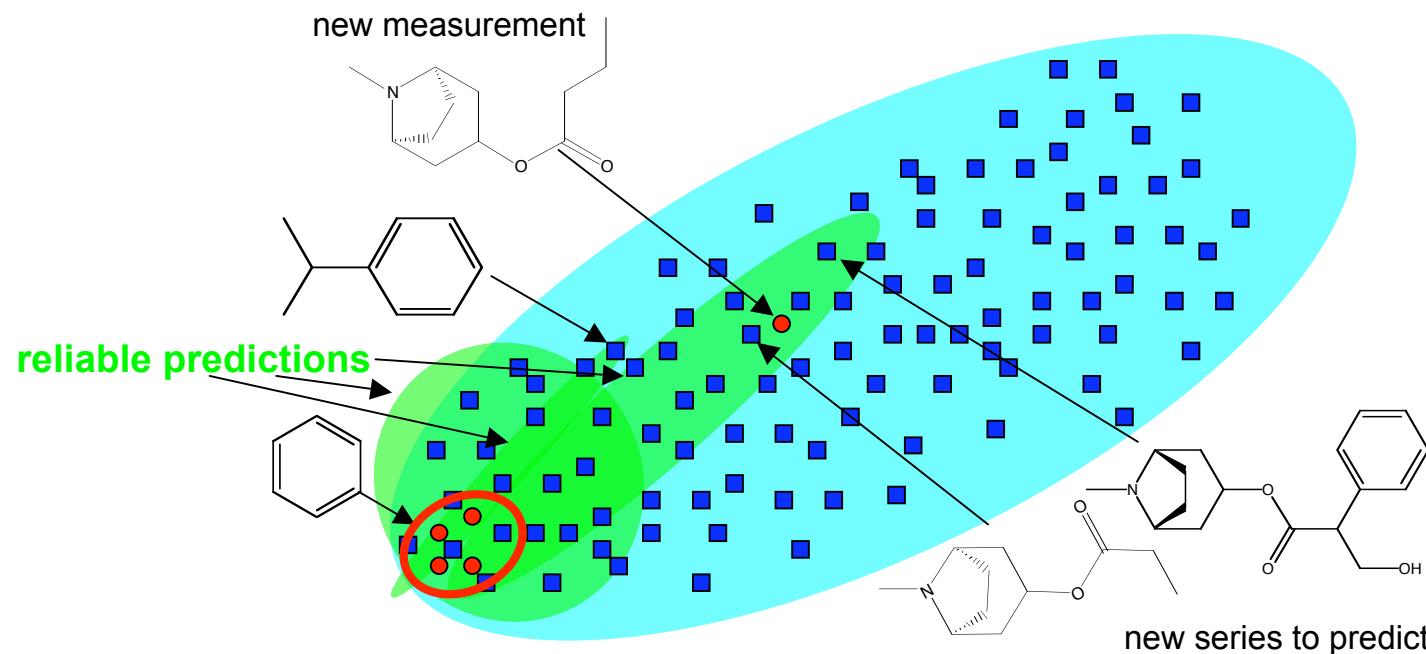
Grand prize for the competition-winners is 1.000 € !

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Challenges and solutions



Our methodology allows confident navigation in a defined molecular space.

- ✓ It can be used to develop targeted (local) models covering specific series.
- ✓ It can be used to reliably estimate which compounds can/can't be reliably predicted.
- ✓ It can be used to guide experimental design and to minimize costs of new measurements.

Acknowledgements

My group

Mr I. Sushko
Mr S. Novotarskyi
Mr A.K. Pandey
Mr R. Körner
Mr S. Brandmaier
Mrs F. Ruggiu
Dr M. Rupp



preprints?
presentation?
google “tetko”

Visiting Scientists

Dr. V. Kovalishyn
Dr. V. Prokopenko
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Funding

GO-Bio BMBF <http://qspr.eu>
Germany-Ukraine grant UKR 08/006
DFG TE 380/1-1

FP7 MC ITN ECO
FP7 CADASTER <http://www.cadaster.ue>
FP6 INTAS VCCLAB <http://www.vcclab.org>