

**HelmholtzZentrum münchen**

German Research Center for Environmental Health

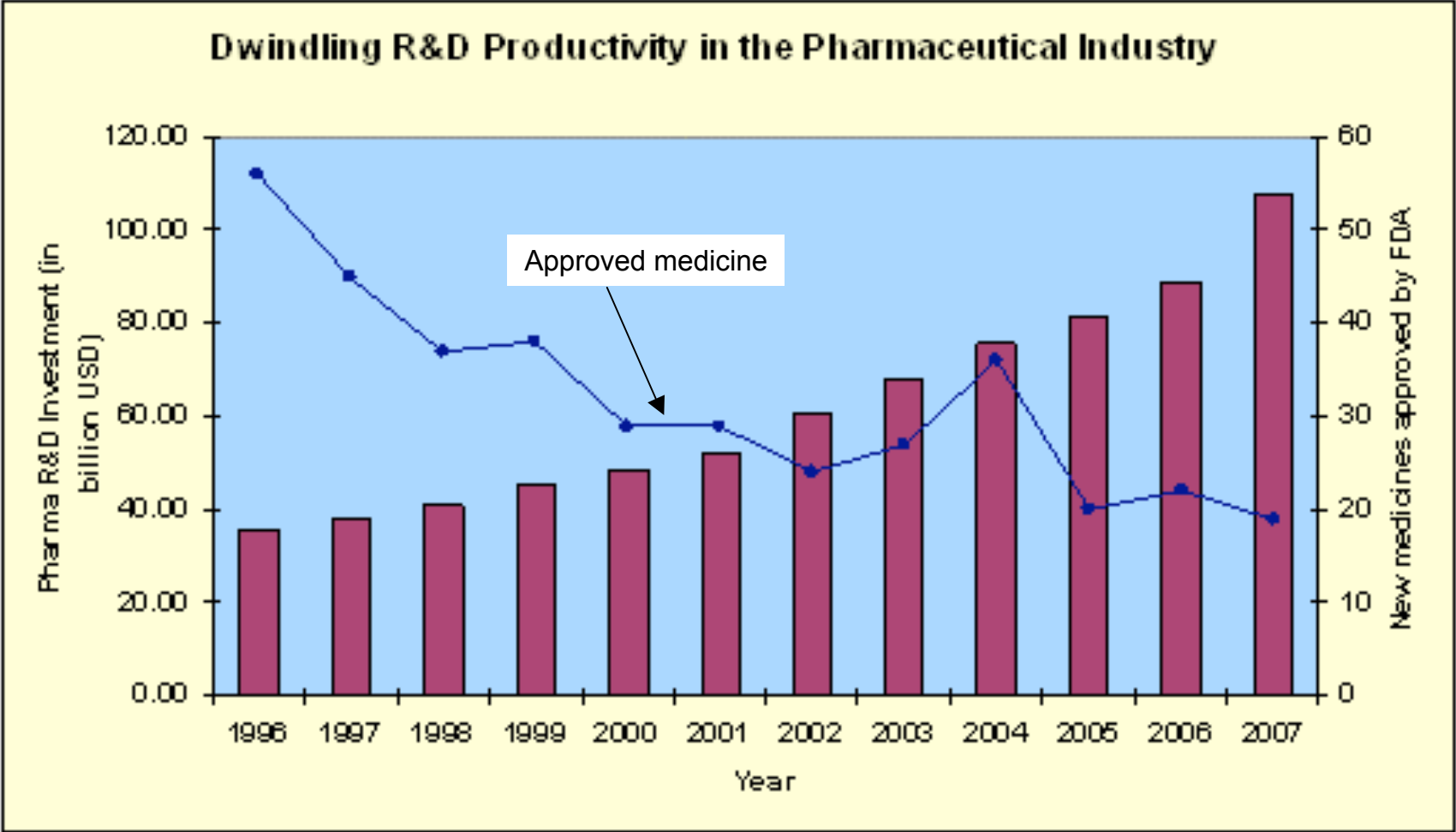
# **Speeding-up Drug Development with Confident Predictions of ADME/T properties**

Igor V. Tetko

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

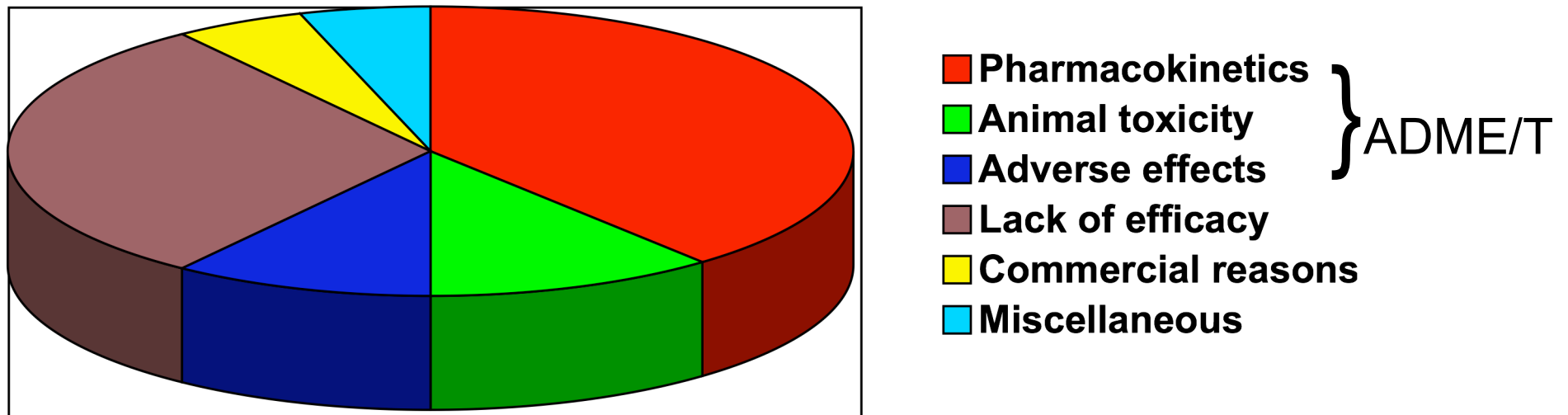
Heidelberg, 11 October 2008

# Declining R&D productivity in the pharmaceutical industry



Source : PhRMA 2007, FDA

# Reasons for failure in drug development



> 60% of drug failures are due to absorption, distribution, metabolism, excretion and toxicology (ADME/T) problems

# Chemists can not embrace the future of AI methods

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

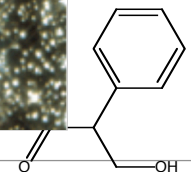
**Achievable:**  $10^{20}$  -  $10^{24}$  can be synthesized  
(weight of the Moon is ca  $10^{23}$  kg)

**Available:**  $2 \cdot 10^7$  molecules are on the market

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

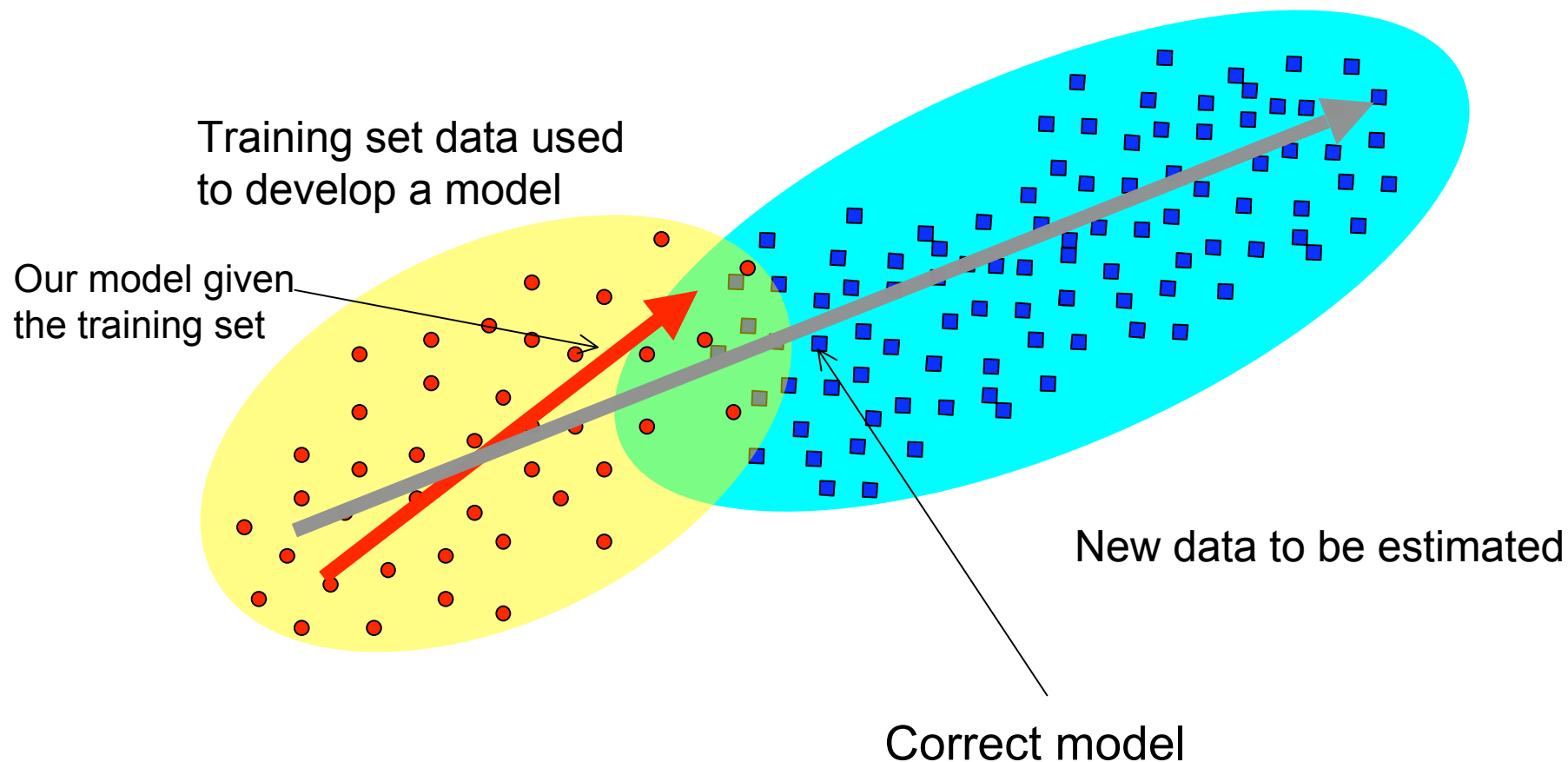
**Problem:** To predict ADME/T properties in the market we must extrapolate data from a few molecules!

**We need methods which can estimate the accuracy of predictions!**





# Models can fail due to chemical diversity of training & test sets



# Benchmarking of logP methods for in-house data of Pfizer & Nycomed

LogP - octanol/water partition coefficient

One of the most important descriptors in the drug discovery

Correlates with many biological and ADME/T properties of molecules

Supported with one of the largest experimental database

3rd dedicated conference will be in Zurich next year (logP2009)

## Performance of algorithms for *in-house* datasets

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

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

## 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., 2004, 2002, 42, 1136-1145.*

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

Upload a file with molecule(s) in 48 formats

2-Aminobenzoic Acid

<a href="#">CAS RN</a>	118-92-3	<a href="#">formula</a>	C7H7NO2
<a href="#">SMILES</a>	OC(C1=CC=CC=C1N)=O		
<a href="#">logP (exp)</a>	1.21	<a href="#">logS (exp)</a>	-1.52 (4.14 g/l)
<a href="#">ALOGPs</a>	0.84 <-0.37>	<a href="#">ALOGpS</a>	-1.31 (6.78 g/l) <+0.21>
<a href="#">IA_logP</a>	0.67 <-0.54>	<a href="#">IA_logS</a>	-1.40 (5.46 g/l) <+0.12>
<a href="#">AB/LogP</a>	1.36 <+0.15>	<a href="#">AB/logS</a>	-1.63 (3.21 g/l) <-0.11>
<a href="#">COSMOFrag</a>	1.13 <-0.08>		
<a href="#">QlogP</a>	0.72 <-0.49>	<a href="#">AB/pKa (Base)</a>	2.40
<a href="#">miLogP</a>	1.46 <+0.25>	<a href="#">AB/pKa (Acid)</a>	5.00
<a href="#">KOWWIN</a>	1.36 <+0.15>		
<a href="#">XLOGP</a>	1.46 <+0.25>	<a href="#">PhysProp reference</a>	
<a href="#">Average logP</a>	1.13(+/-0.34) <-0.08>	<a href="#">Sangster's reference</a>	

User's [LogP\\_LIBRARY](#)  User's [LogS\\_LIBRARY](#)

Click on calculated result to see method description or details of calculations.  
Press LogP or LogS LIBRARY to read how to improve your predictions.  
We wish you to have only good results!

The calculated results are available.

# Methodology: Associative Neural Network (ASNN)



Some software tools rely just on one “best” model.

Other software tools rely on the ensemble average (“panel of experts”).

ASNN explores disagreement of individual models in the ensemble to improve its accuracy and to derive a confidence score.

# Highlighted Examples

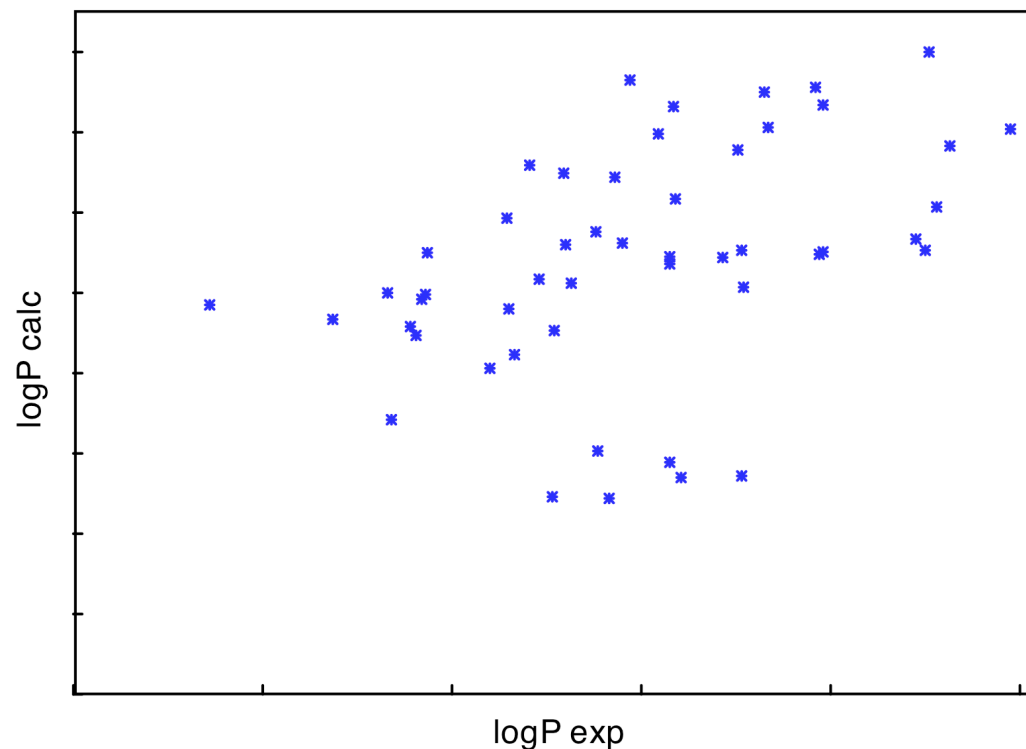
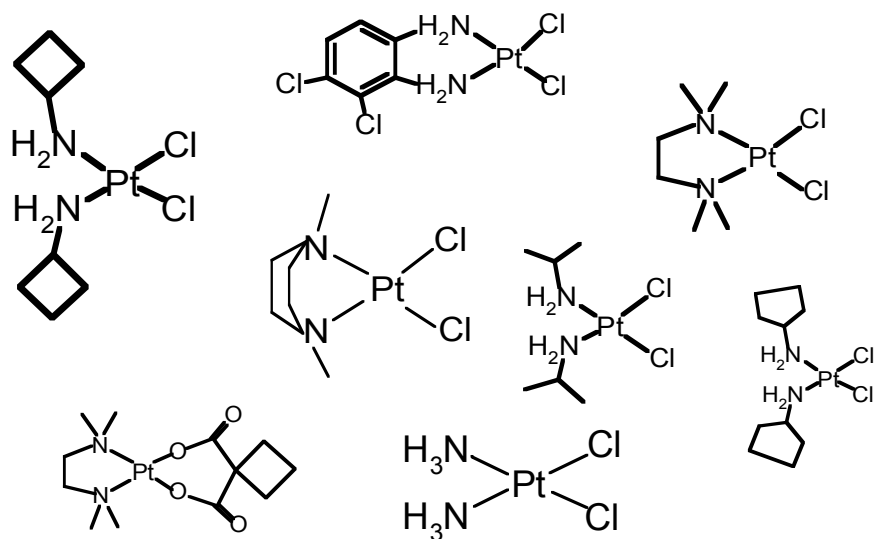
- Development of focused (local) models
- Estimation of accuracy of predictions
- Multi-task learning



**This model does not work for these data...**

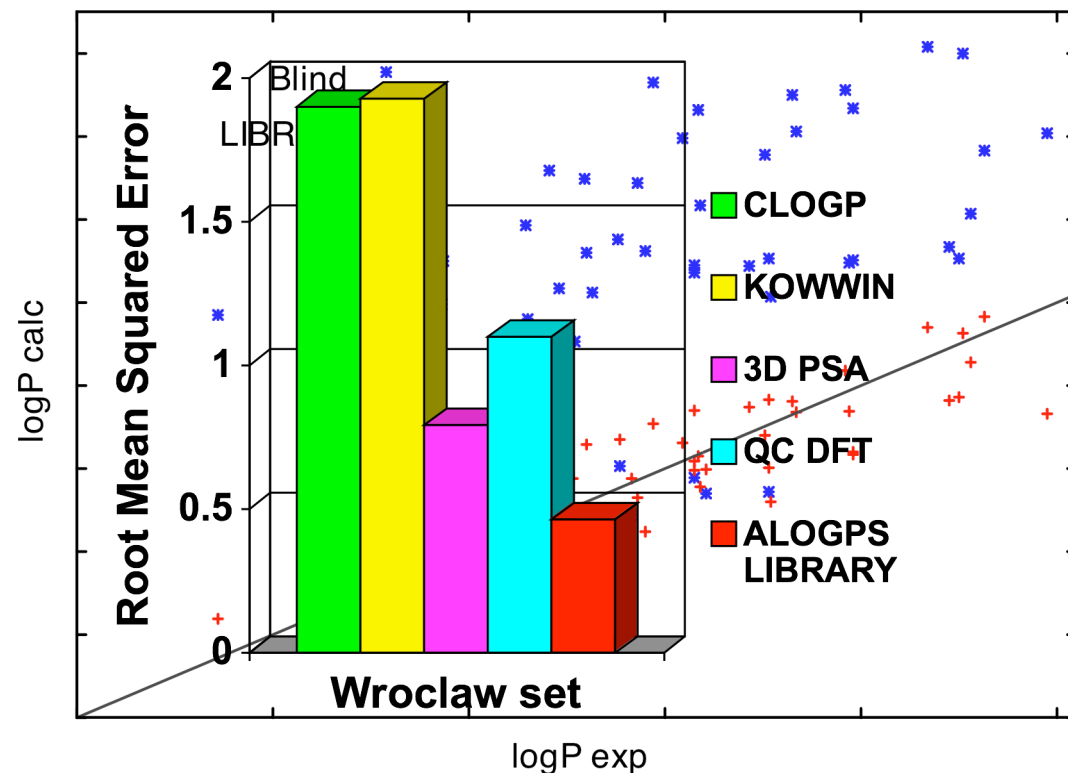
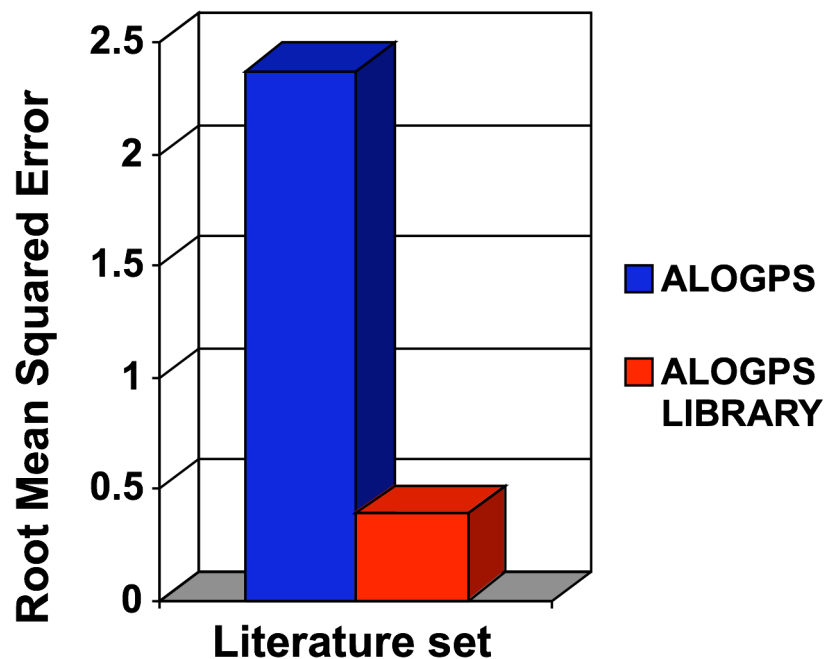
**Is it possible to improve it by using new  
measurements?**

# Local models: Instance learning of logP for PtII molecules



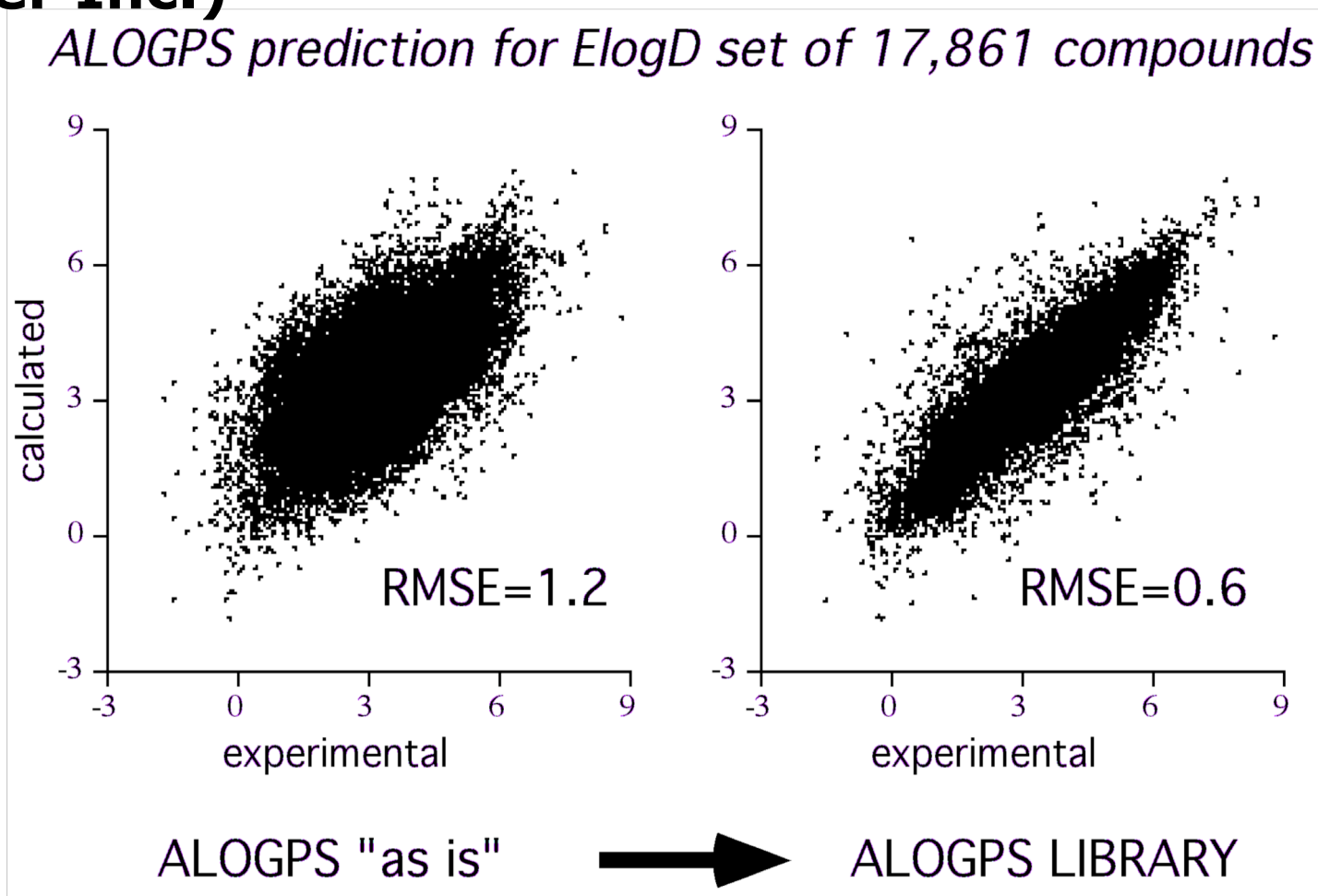
The Figure shows that prediction of new classes of compounds can be extremely difficult as exemplified by an absence of correlations between predicted and experimental values.

# Local models: Instance learning by knowledge transfer



The right panel shows that our methodology (red column) allowed to calculate superior prediction (lower errors) compared to traditional methods.

# Local models: Instant learning of in-house data (Pfizer Inc.)



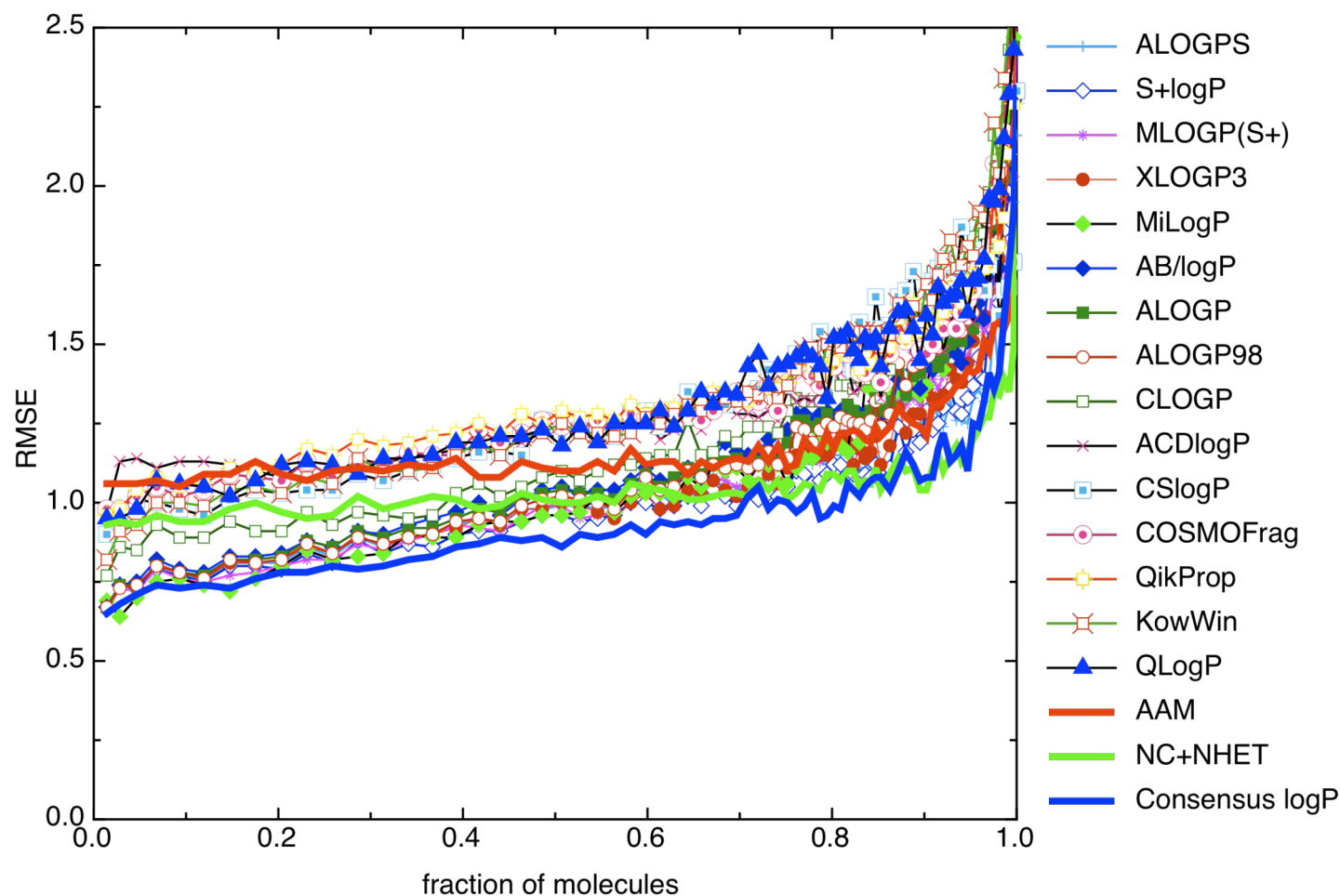
The LIBRARY mode produced local models and dramatically decreased the error for a very large set of compounds in just less than 10 minutes of calculations.

**Is it possible to distinguish reliable vs. non-reliable predictions?**

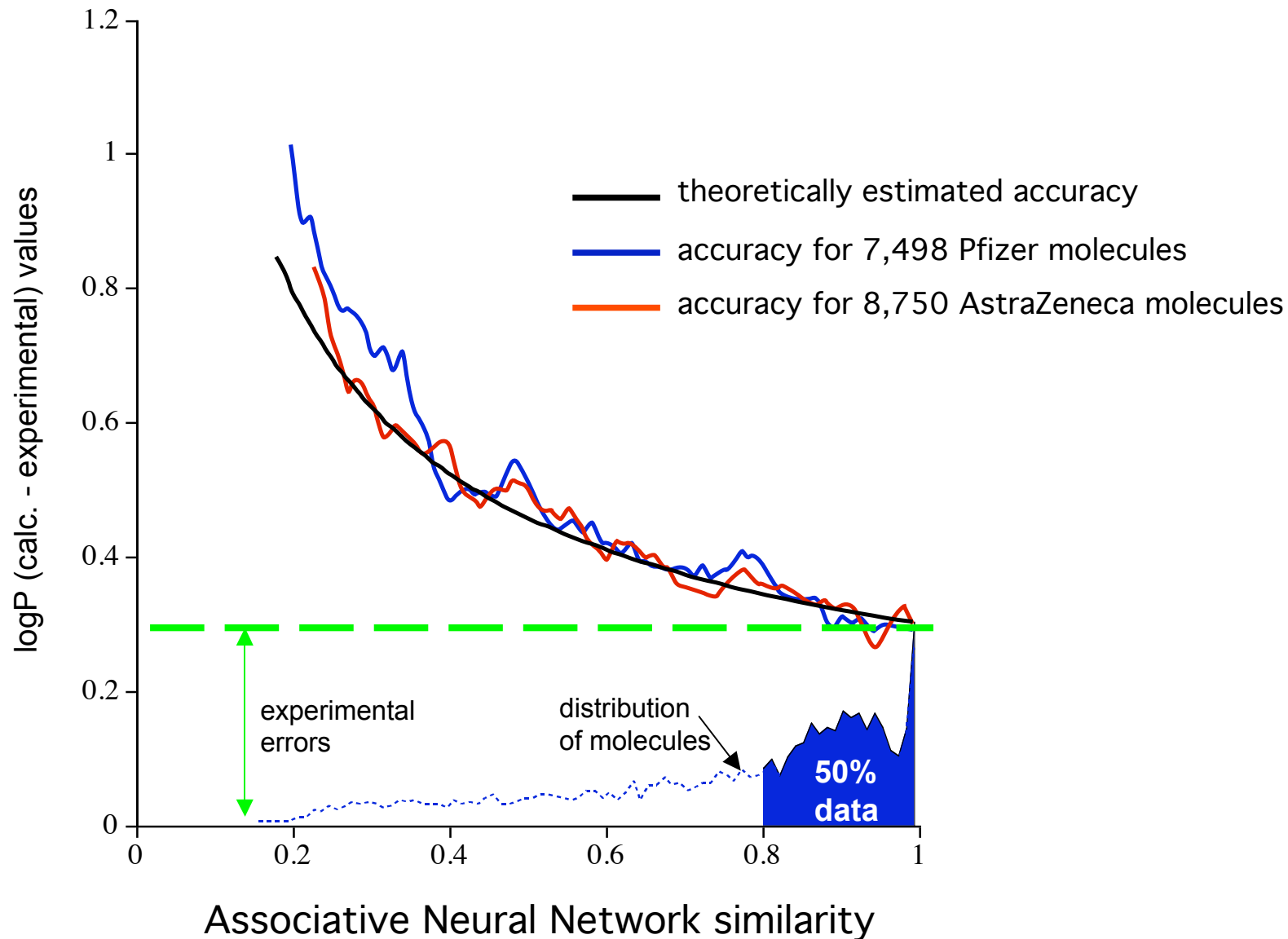
**Is it possible to save costs by skipping measurements of some molecules?**



# Global model: Accuracy of logP predictions for 96,000 molecules



# Local model: Accuracy of logP predictions for a subset of data



**The measurements are very expensive...**

**Is it possible to use some related  
measurements to develop a better model?**

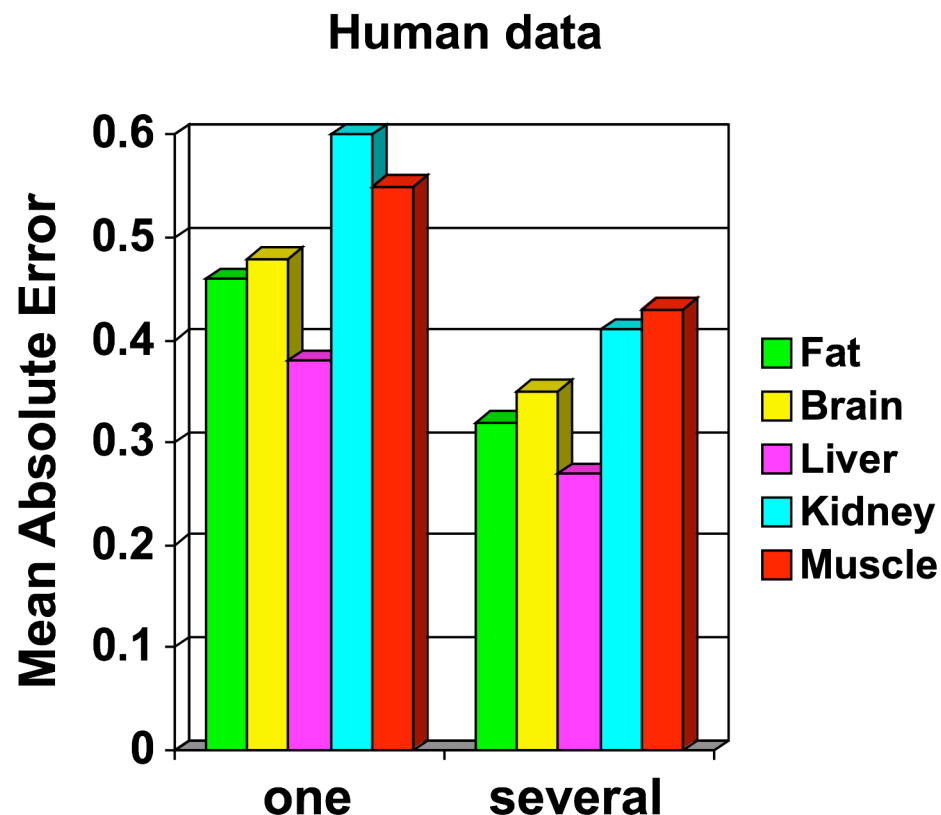
# Multi-task learning

## Problem:

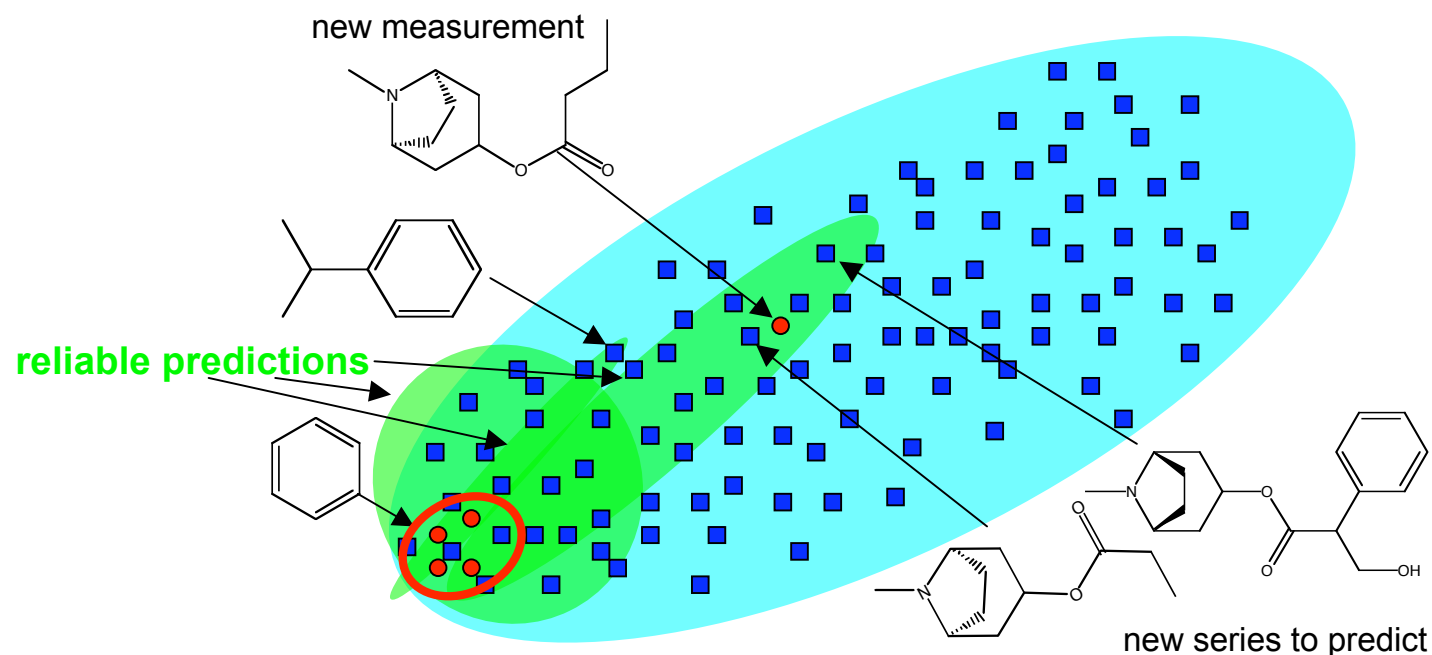
- prediction of tissue-air partition coefficients
- small datasets 30-100 molecules (human & rat data)

## Results:

simultaneous prediction of several properties increased the accuracy of models



# Challenges and solutions



New methodology allows navigation in space of molecules with a confidence.

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



## Acknowledgement

Dr. G. Poda (Pfizer)

Dr. P. Bruneau (AstraZeneca)

Dr. C. Ostermann (Nycomed)

Prof. R. Mannhold (Dusseldorf University)

+ many other colleagues & co-authors

Prof. G. Wess

Prof. H.W. Mewes

Go-Bio BMBF

FP6 INTAS (VCCLAB, <http://www.vcclab.org>)