

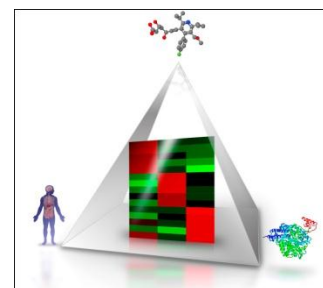
Determining Biologically Relevant Effects of Compound Exposure by Chemical, Biological and Phenotypic Data Integration

Andreas Bender, PhD

Lecturer for Molecular Informatics

Unilever Centre, University of Cambridge, UK

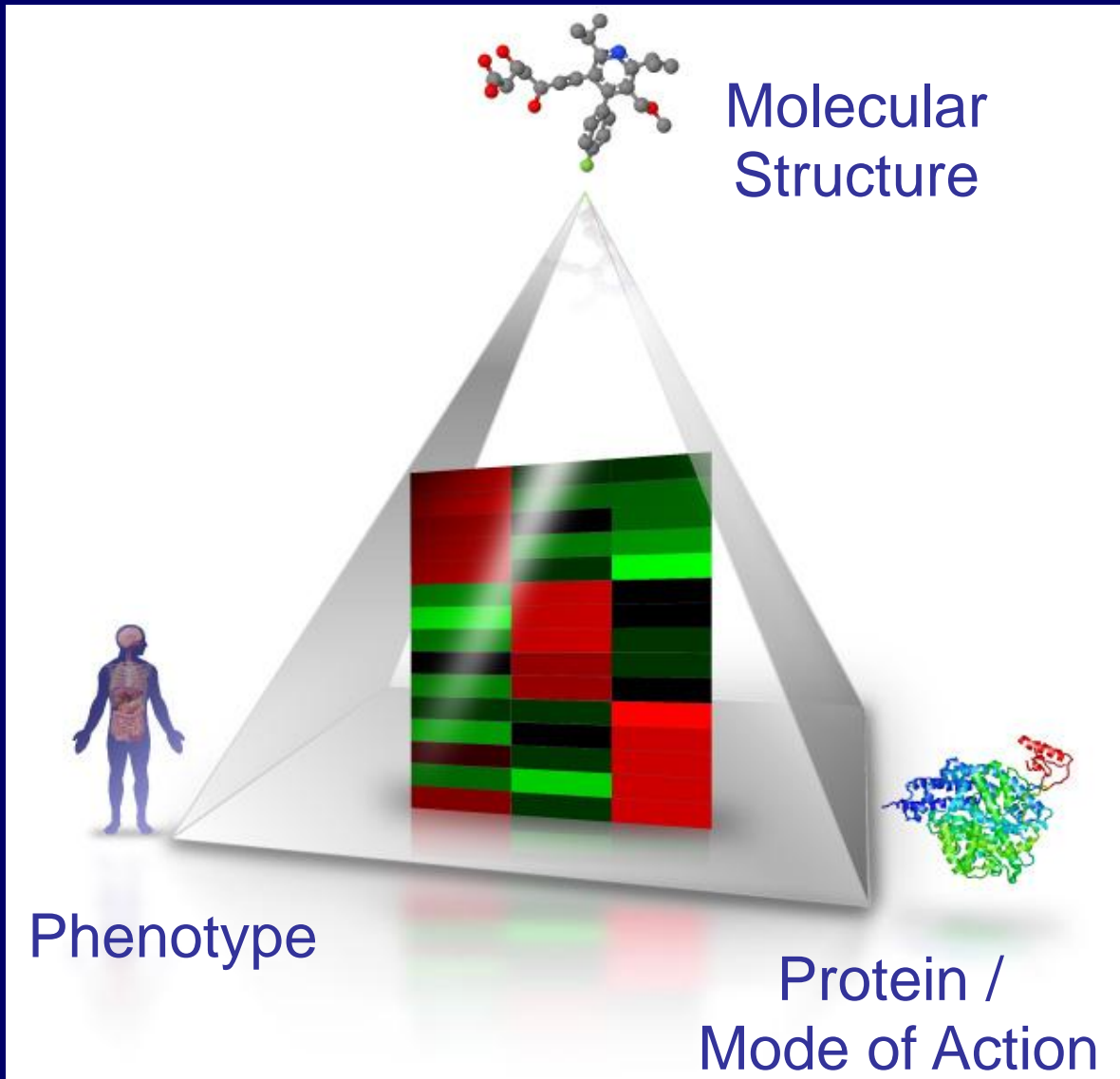
Fellow of King's College, Cambridge



More and More Data is Available...

- But how should we deal with it?
- Companies (but now also the public databases) have tens of millions of bioactivity data points, gene expression data, organ tox endpoint data, clinical trial data, ...
- *However*, integration – and utilization – of data is often not ideal
- In our group we are exploring ways to integrate data from different sources to understand bioactivities, and to design novel chemistry

The 'Magic Triangle' – Our Primary Data Sources



So what do we do?
Predict compound properties, such as adverse reactions...

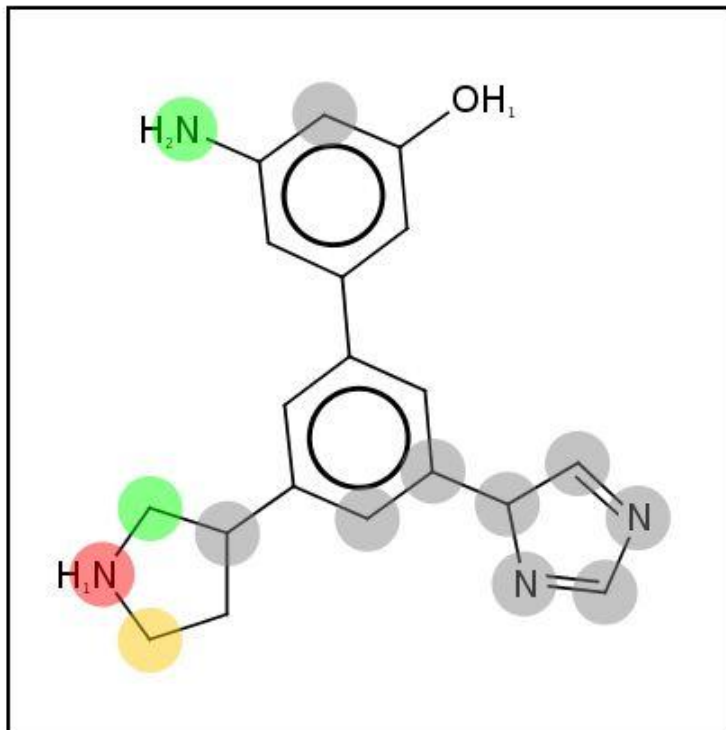


... or predicting metabolites (and their bioactivities); www-metaprint2d.ch.cam.ac.uk

MetaPrint2D metabolic site predictor

University of Cambridge > Department of Chemistry > Unilever Centre for Molecular Science Informatics

Results



Move the cursor over an atom for detailed results.

Input

SMILES: Nc4cc(O)cc(c3cc(C1C=NC=N1)cc(C2CCNC2)c3)c4

Model: METAB20081ALL

Settings: DEFAULT

Instructions

The colour highlighting an atom indicates its normalised occurrence ratio (NOR). A high NOR indicates a more frequently reported site of metabolism in the metabolite database.

Note: The normalised occurrence ratio does not indicate how likely a molecule is to be metabolised, but rather the relative likelihood of metabolism occurring at a particular site in the molecule, assuming it is metabolised.

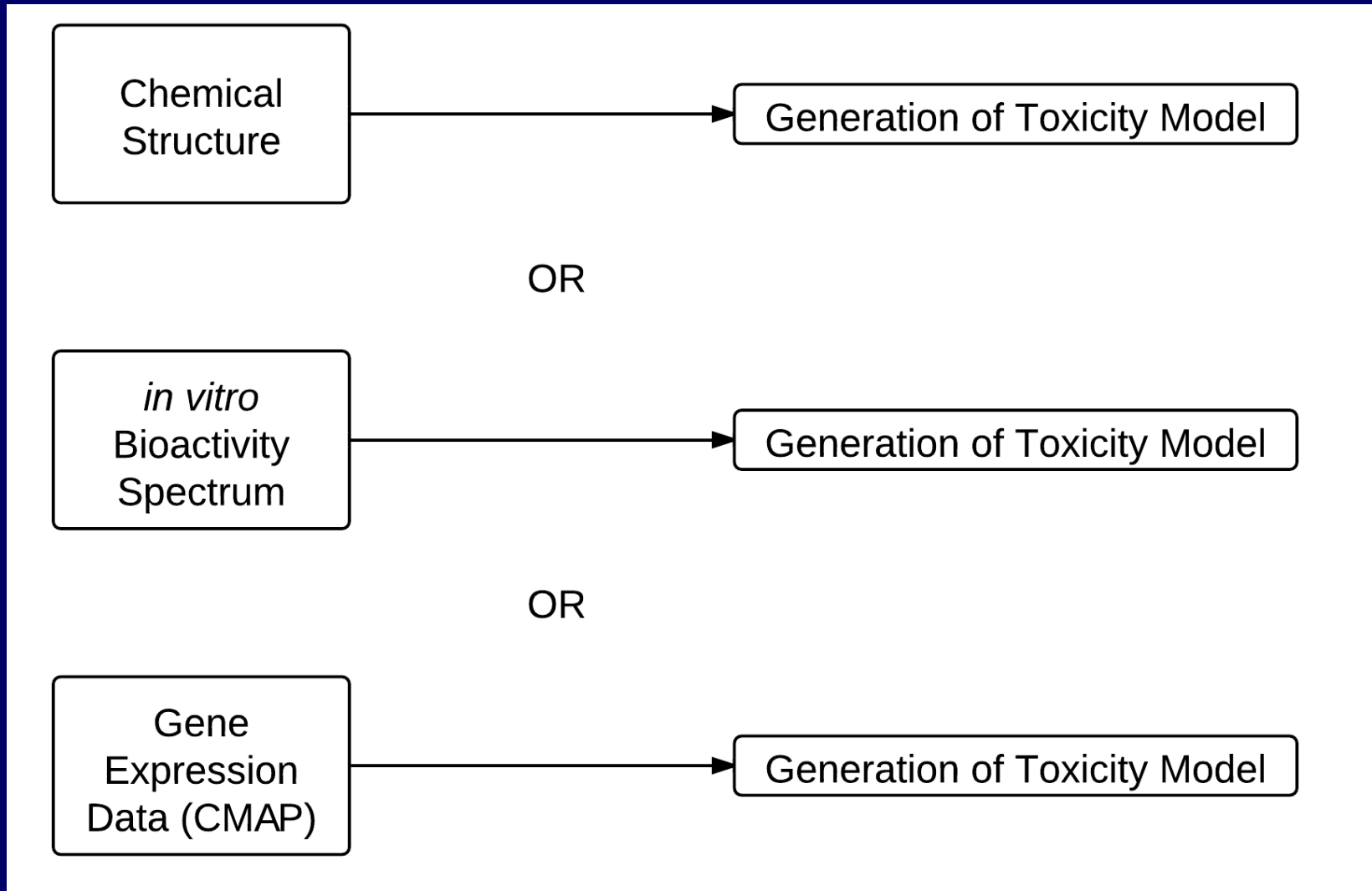
Results Colour Scheme

Red	0.66 <= NOR <= 1.00
Orange	0.33 <= NOR < 0.66
Green	0.15 <= NOR < 0.33
White	0.00 <= NOR < 0.15
Grey	Little/no data

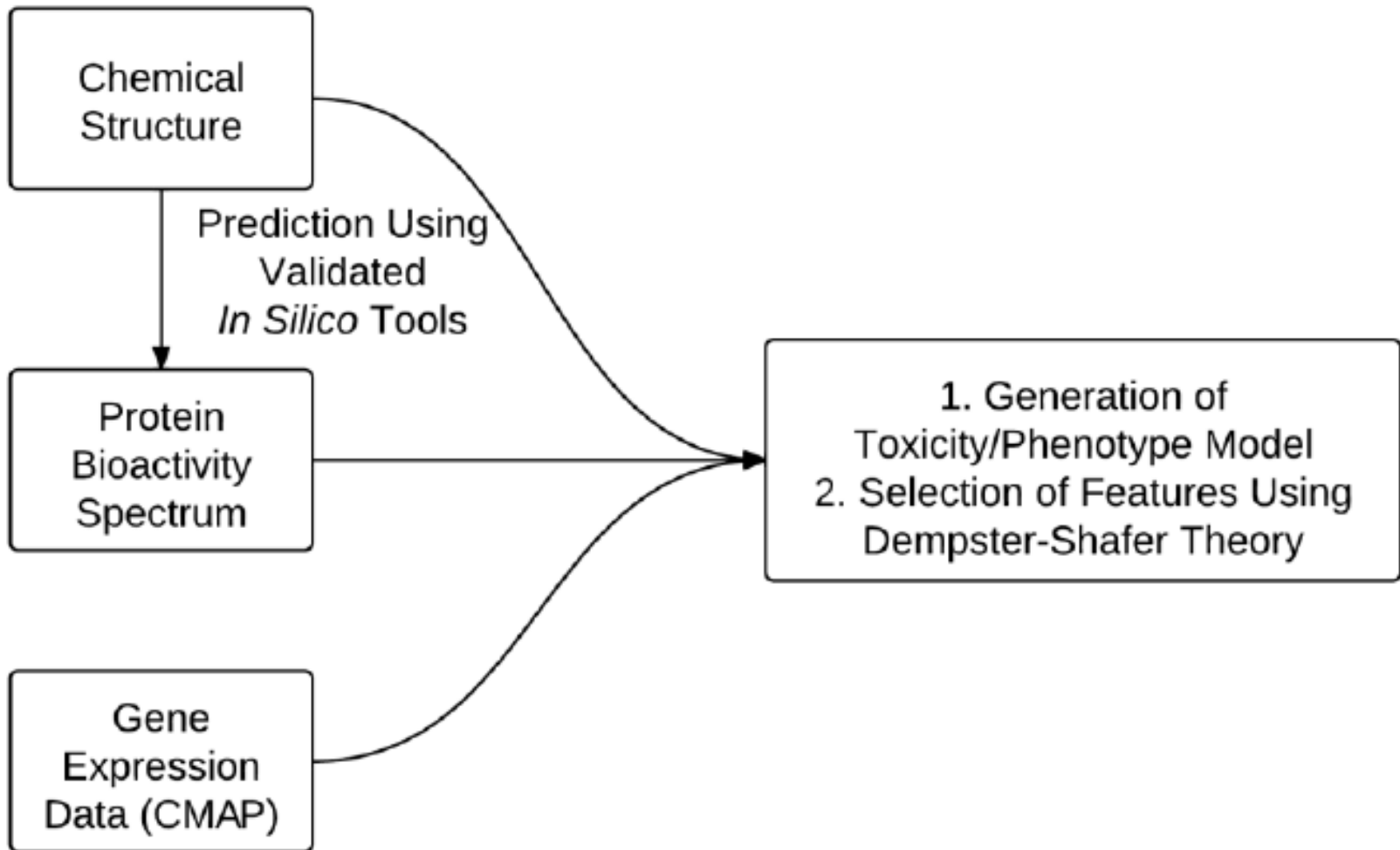
Links

- [New Query](#)
- [Predict metabolites \(experimental\)](#)
- [About MetaPrint2D](#)
- [sourceforge project](#)
- [bioclipse plugin](#)

What has been done *previously*? Toxicity models are based on *single-domain* data

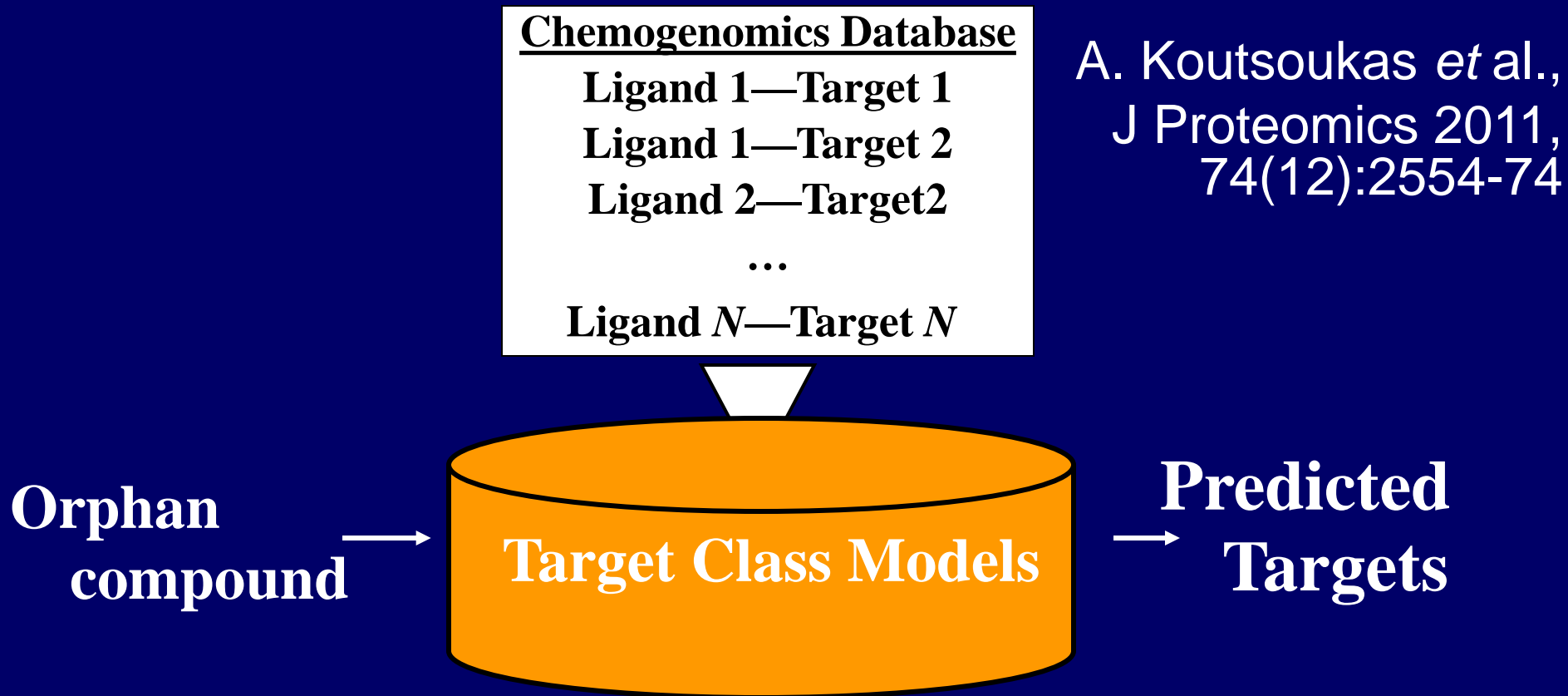


Not 'OR' – Different Information Contents, Hence *AND*!

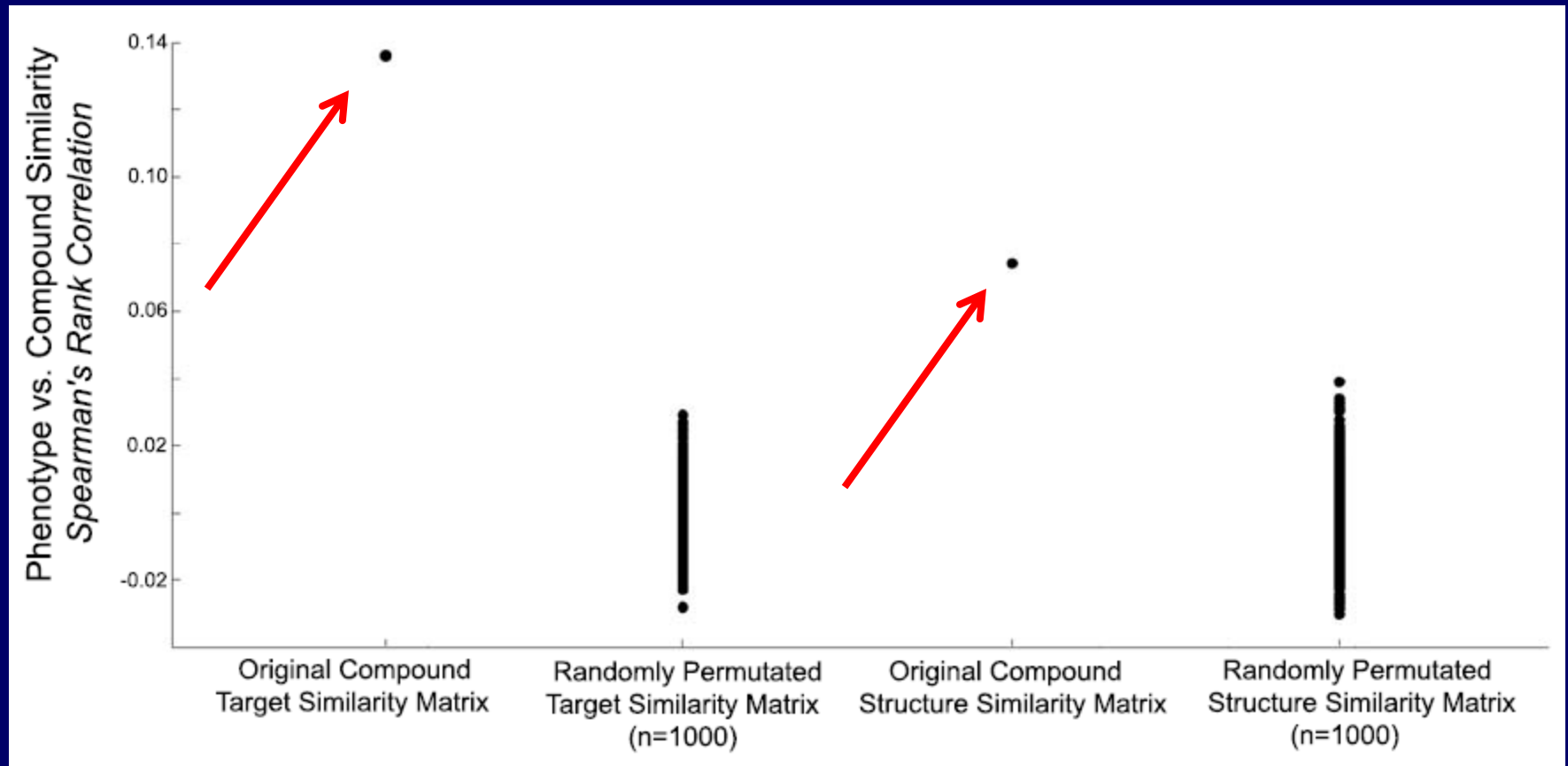


Exploiting known bioactivity data for new decisions: Target predictions

- The models enable automated prediction of the targets or target families of orphan ligands given only their chemical structures.

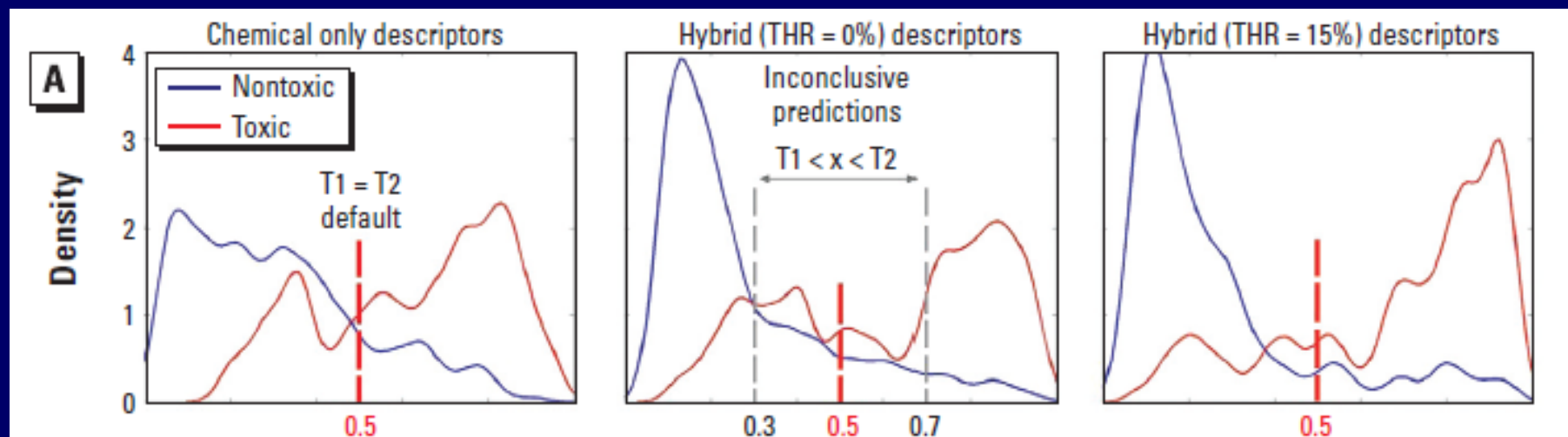


Higher Correlation of Predicted Targets Than Structures With Phenotypes



Young, Bender et al., Nature Chem. Biol. 2008, 4, 59 - 68

Sedykh *et al.* 2011: Chemical + *in vitro* descriptors for rat LD50 prediction



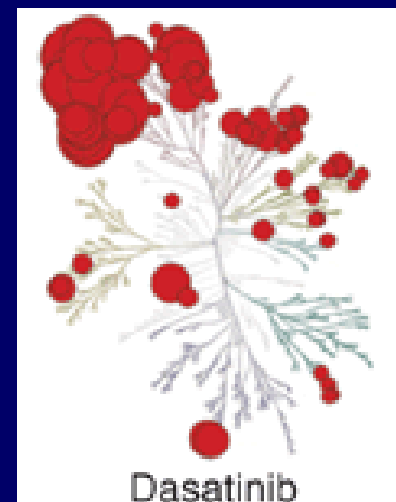
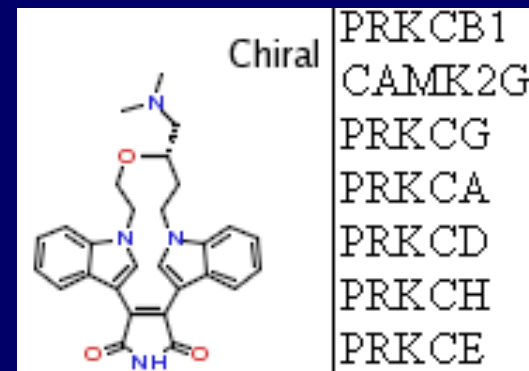
Use of *in Vitro* HTS-Derived Concentration–Response Data as Biological Descriptors Improves the Accuracy of QSAR Models of *in Vivo* Toxicity, A. Sedykh *et al.*, *Environ. Health Persp.*, 2011, 119 (3), 364 – 370

How? Use of Funding, Data Sources

- PhD Student financed by the award; started his work last month (October 2012)
- Previous literature datasets
- ToxCastDB + ToxRefDB (Assays, Animal Data)
 - ToxRefDB (30 years and \$2 billion worth of animal toxicity studies)
 - ToxCastDB (data from screening 1,000 chemicals in over 500 high-throughput assays)
- Unspecific effects; dose/time (PK/PD) are (current) limitations of the project

Relating chemistry, targets and phenotypes

- We have information from chemistry, biology, and phenotypes
- *Joint modeling* very likely improves predictivity (see preliminary results)
- This is the goal of this project



Acknowledgments



Fazlin Mohd Fauzi
Sonia Liggi
Sudeshna Guha Neogi
Alexios Koutsoukas
Daniel Murrell
Oscar Mendez Lucio
Georgios Drakakis
Aakash Ravindranath
Rucha Chiddarwar
Yasaman Motamedi
Vignir Isberg
Shardul Paricharak
Ain Qurrat
Avid Afzal
Chad Allen
Emmy Han
Richard Lewis
Bobby Glen



Gerard J. P. van Westen
Ad P. IJzerman



Sebastian Rohrer
Klaus-Juergen Schleifer



Martin Augustin
Tom Klenka



Ian Stott



Hinrich Goehlmann
Herman van Vlijmen
Joerg K. Wegener



Mike Bodkin
David Evans
Suzanne Brewerton

