

# **Chemoinformatics-Supported Med Chem: Expectations, Pitfalls, and Success Stories**

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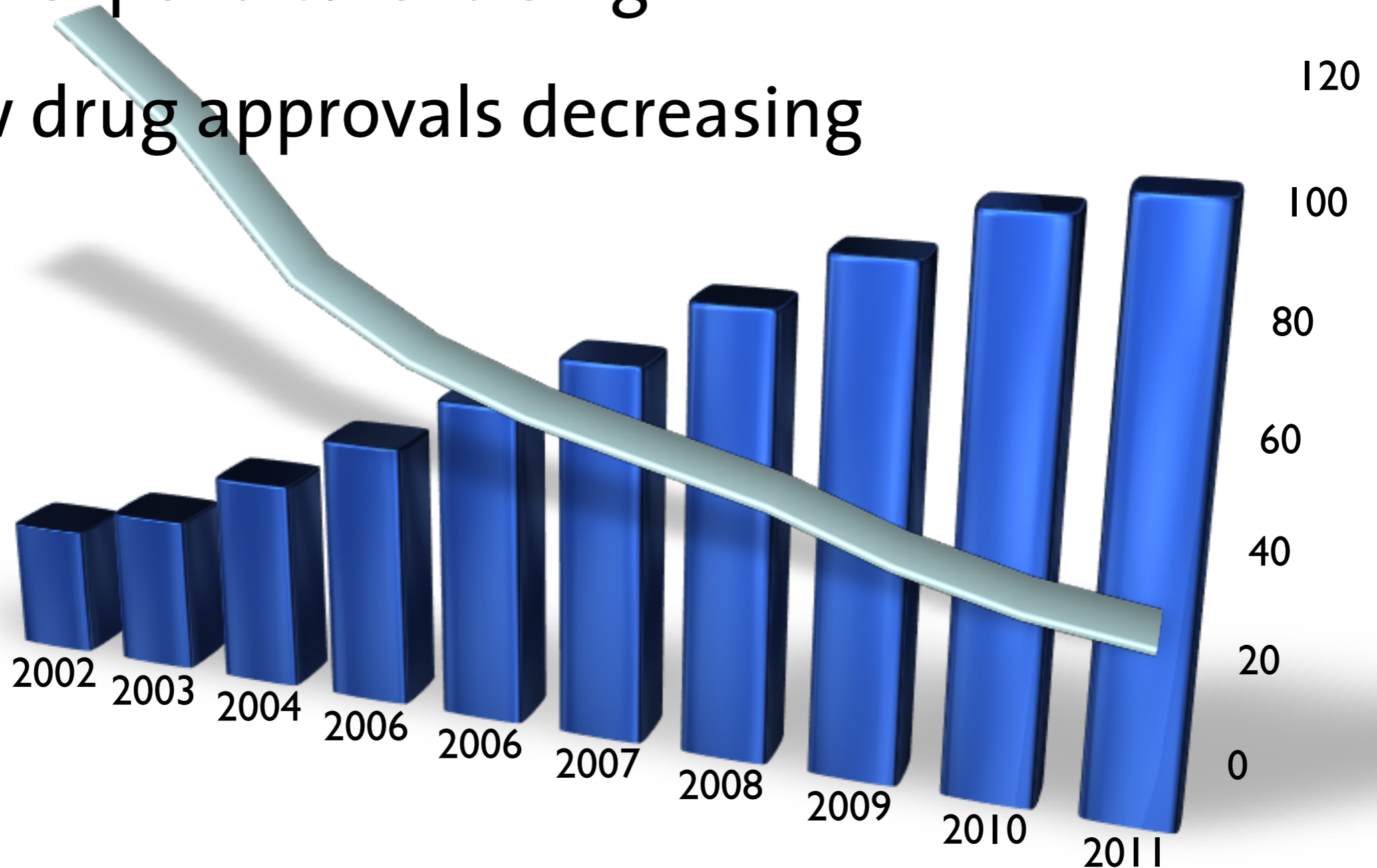
# Prestwick Chemical's Team



T. Langer, Strasbourg, 2012-06-28

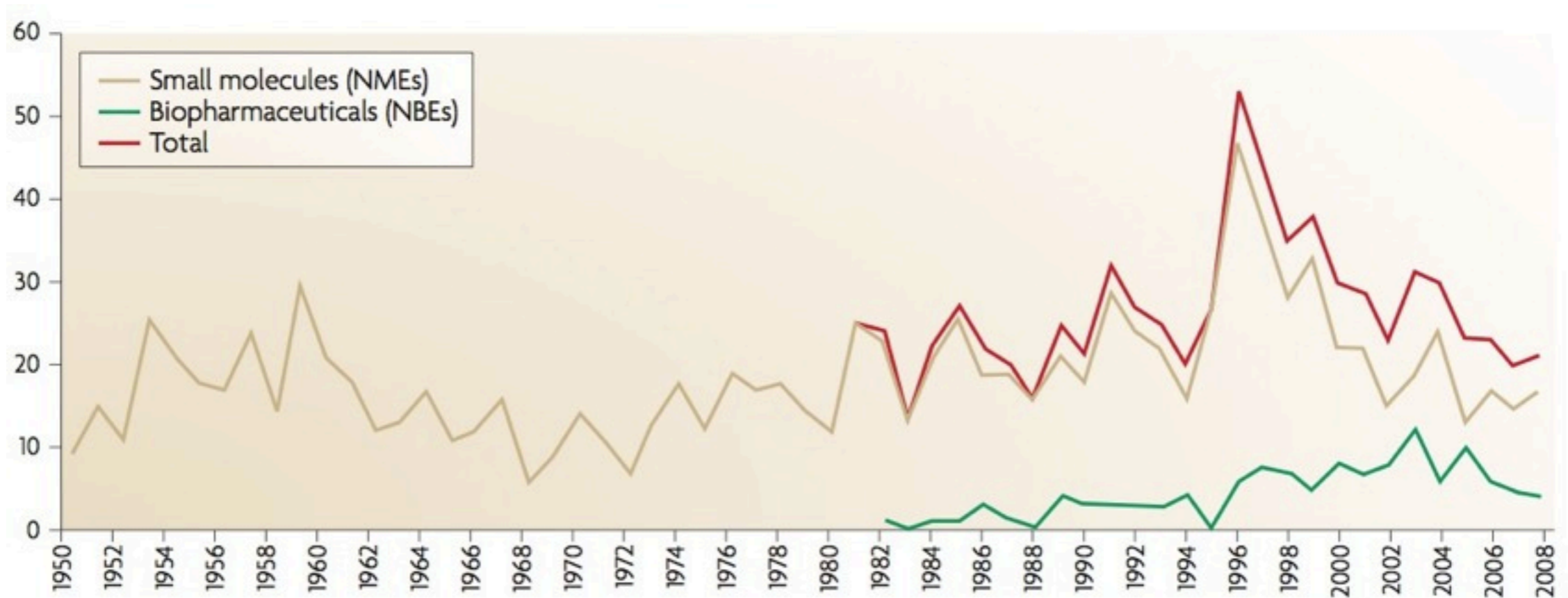
# Dramatic Situation in Big Pharma ?

- R&D expenditure raising
- New drug approvals decreasing

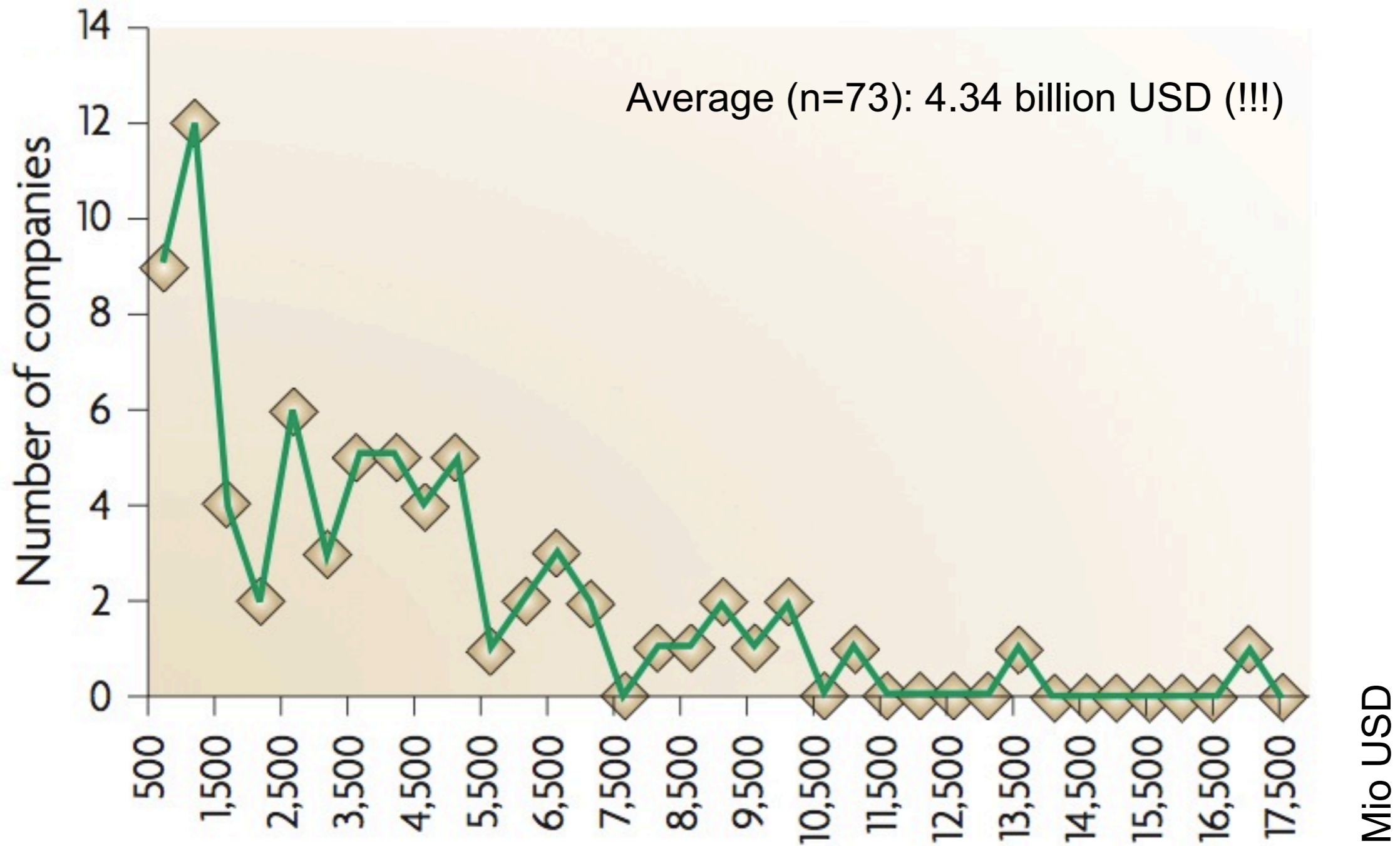


# A True Productivity Problem ?

- New drugs approved since 1950 ...
  - 1103 Small molecules
  - 119 Biologicals



# Costs Per New Drug



# ANALYSIS

## Lessons from 60 years of pharmaceutical innovation

*Bernard Munos*

**Abstract** | Despite unprecedented investment in pharmaceutical research and development (R&D), the number of new drugs approved by the US Food and Drug Administration (FDA) remains low. To help understand this conundrum, this article investigates the record of pharmaceutical innovation by analysing data on the companies that introduced the ~1,200 new drugs that have been approved by the FDA since 1950. This analysis shows that the new-drug output from pharmaceutical companies in this period has essentially been constant, and remains so despite the attempts to increase it. This suggests that, contrary to common perception, the new-drug output is not depressed, but may simply reflect the limitations of the current R&D model. The implications of these findings and options to achieve sustainability for the pharmaceutical industry are discussed.

**New molecular entity (NME).** A medication containing an active ingredient that has not been previously approved for marketing in any form in the United States. NME is conventionally used to refer only to small-molecule drugs, but in this article the term includes biologics as a shorthand for both types of

From 1950 to 2008, the US Food and Drug Administration (FDA) approved 1,222 new drugs (new molecular entities (NMEs) or new biologics). However, although the level of investment in pharmaceutical research and development (R&D) has increased dramatically during this period — to US\$50 billion per year at present<sup>1</sup> — the number of new drugs that are approved annually is no greater now than it was 50 years ago. Indeed, in 2008, only 21 new drugs were approved for marketing in the United States,

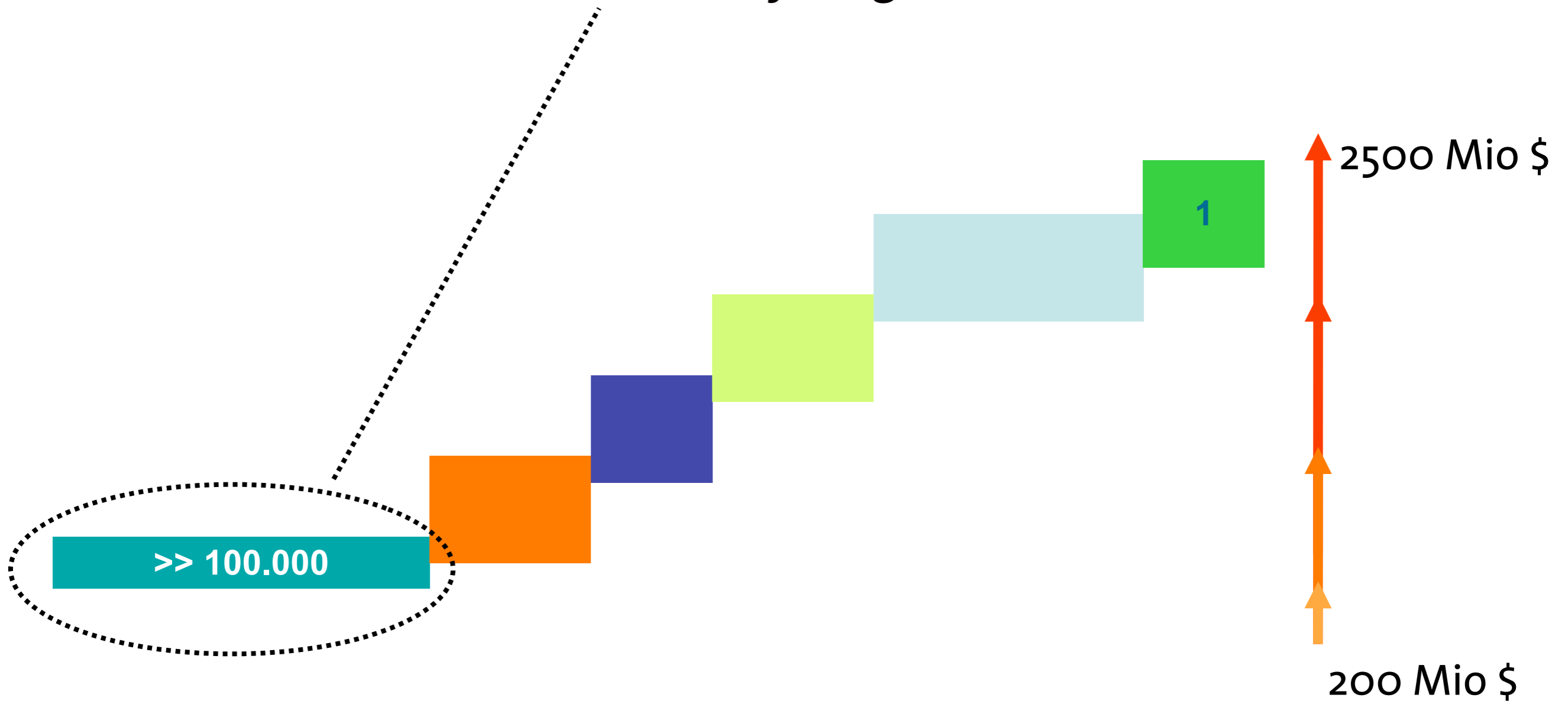
research organizations if they are to escape the increasing pressures created by linear new-drug output and rapidly rising R&D costs.

### **Rate of new drug introduction**

Of the 1,222 NMEs that have been approved since 1950, 1,103 are small molecules and 119 are biologics. FIGURE 1a shows the timeline of these approvals. Although at first glance there are no obvious patterns, on closer obser-

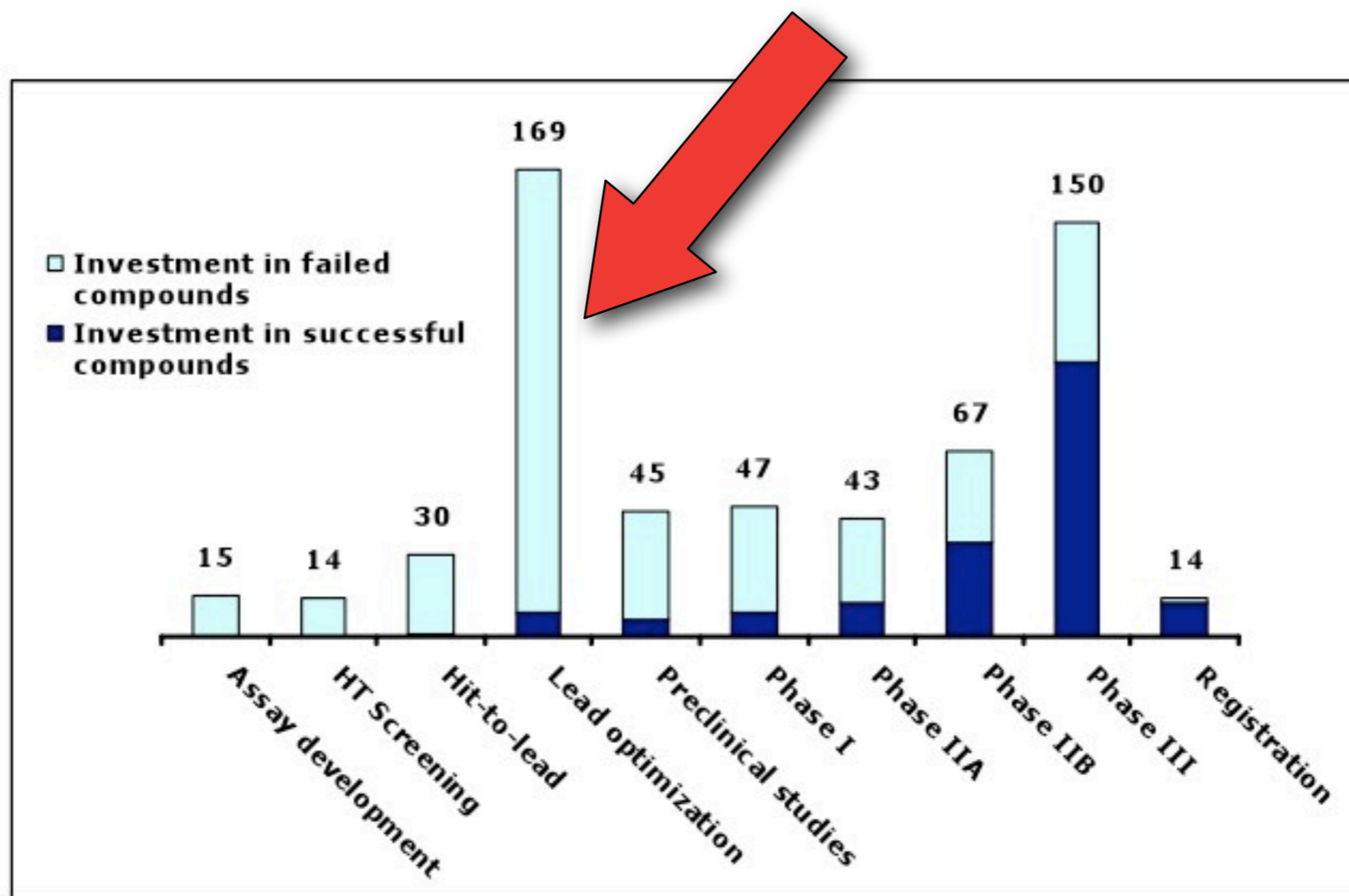
# Efficiency Deficit ...

Prediction of failure in early stage





# Costs Attributed To Drug Discovery



Investment per phase of drug discovery and development for one successful drug (USD millions)

# What are we talking about today?

- Examples of chemoinformatics methods
- Application in medicinal chemistry for early drug discovery research
- Focus on
  - Hit identification by virtual screening
  - Decision support for med chem optimization
  - Liability prediction for later development

# What Do We Need ?

- Reliable decision support tools
- Easy to use, easy to understand
- Need for speed
- Solid science behind

A word cloud of terms related to computational chemistry and machine learning. The words are arranged in a roughly circular pattern, with 'Pharmacophores' being the largest and most central word. Other prominent words include 'Docking', 'Support Vector Machine', 'Similarity Index', 'COMFA', 'Tanimoto Coefficient', 'Free Energy Calculations', '3D QSAR', 'QM/MM 2D Fingerprints', 'MEPs', 'Shape Similarity', 'Self Organizing Neural Networks', and 'QSAR'.

Tanimoto Coefficient  
Free Energy Calculations 3D QSAR  
QM/MM 2D Fingerprints  
Docking MEPs Shape Similarity  
Pharmacophores  
Self Organizing Neural Networks  
Support Vector Machine QSAR  
Similarity Index COMFA

# Expectations: The Medicinal Chemist

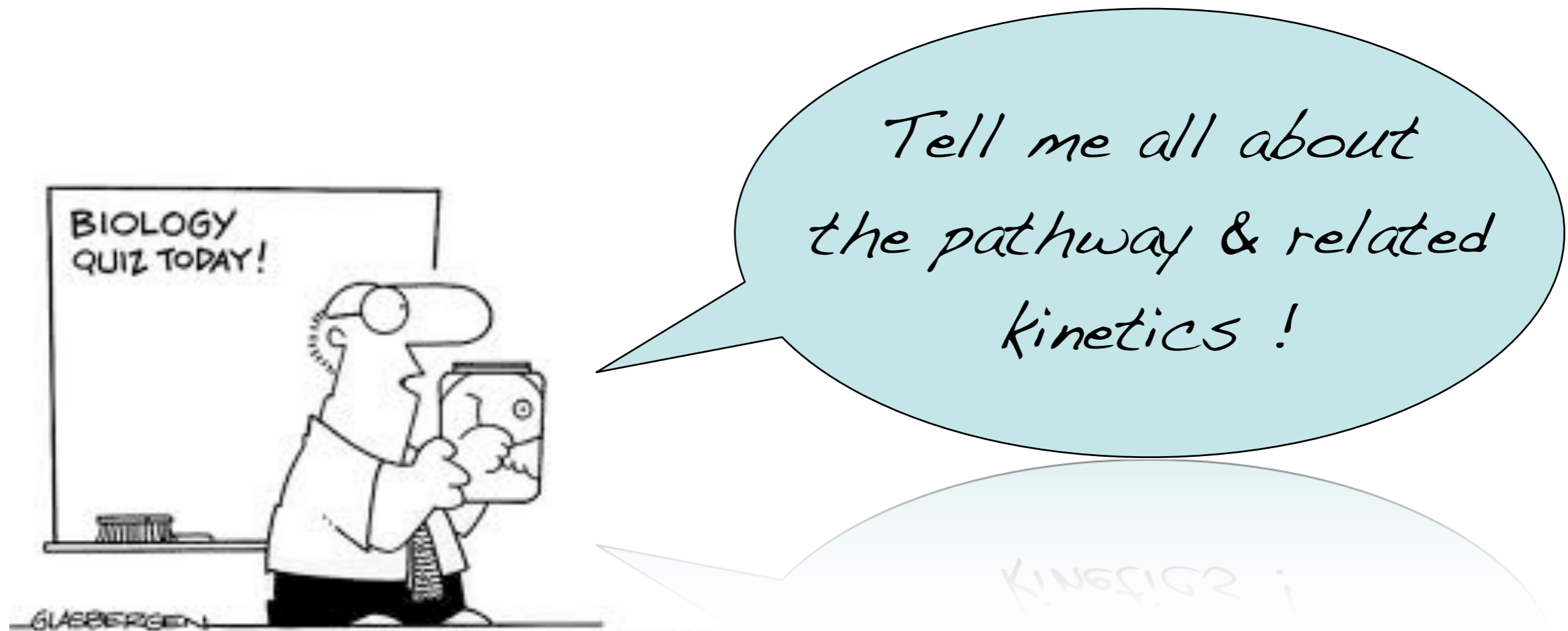
- Answer the most important question !

*Tell me: Which  
molecule shall I prepare  
next ?*



# Expectations: The Biologist

- Answer the most important question !



# The Chemoinformatician ...

- Wants to find the right answers to all the questions ...
- Wants to help the medicinal chemist by designing great molecules ...
- Wants to explain biological data based on oversimplified models ...

# Ultimate Goal - Predict Everything

- Molecular properties
  - physicochemical data
  - affinity to target(s)
- Effects of molecules
  - on cells
  - on organs
  - on the entire organism
  - ...

# The Chemoinformatician ...



**DOOMED TO FAIL ?**



# Just Try To Avoid The Pitfalls ...

- There is no “one-model-fits-all” paradigm
- Local models can only explain local phenomena
- Let’s have a closer look ...
  - Virtual screening pitfalls\*

# Some Pitfalls - In Detail

- Concerning erroneous assumptions
- Concerning data design & content
- Relating to the choice of software
- Concerning conformational sampling and molecular flexibility (target & ligand)

# VS Pitfalls (1) - Wrong Assumptions

- Expectation: Identify high affinity compounds
- Stringency of queries
- Binding pose prediction
- The role of water in mediating interactions
- Subjectivity of compound selection
- ...

# VS Pitfalls (2) - Data Design & Content

- (Non)comparability of benchmark data
- (Non)comparability of performance metrics
- Hit rate in benchmark data sets
- ‘Bad’ molecules (reactive / aggregants)
- Inactives (‘decoy’) selection

# VS Pitfalls (3) - Choice Of Software

- I/O errors & format incompatibilities
- Molecular structure preparation
- Pharmacophore feature definition
- Fingerprint selection & algorithms used
- Partial charges
- Single predictors / ensemble prediction

# VS Pitfalls (4) - Flexibility (!!!)

- Conformational coverage
- Bio-active conformation
- Conformer comparison
- Conformer energy
- Target flexibility
- ...

# Let's be more positive ...

... and have a look at real life situations and related success stories ...

# Pharmacophores @ Prestwick

- Medicinal chemists want to understand what is driving the affinity - do not like a black box !!!
- Quickly elucidate ligand-target interactions
- Pharmacophores are versatile tools for
  - Identification of starting points by virtual screening
  - Understanding structure-activity relationships
  - Supporting the molecular design process
    - Achieving better target selectivity
    - Avoiding unwanted off-target effects



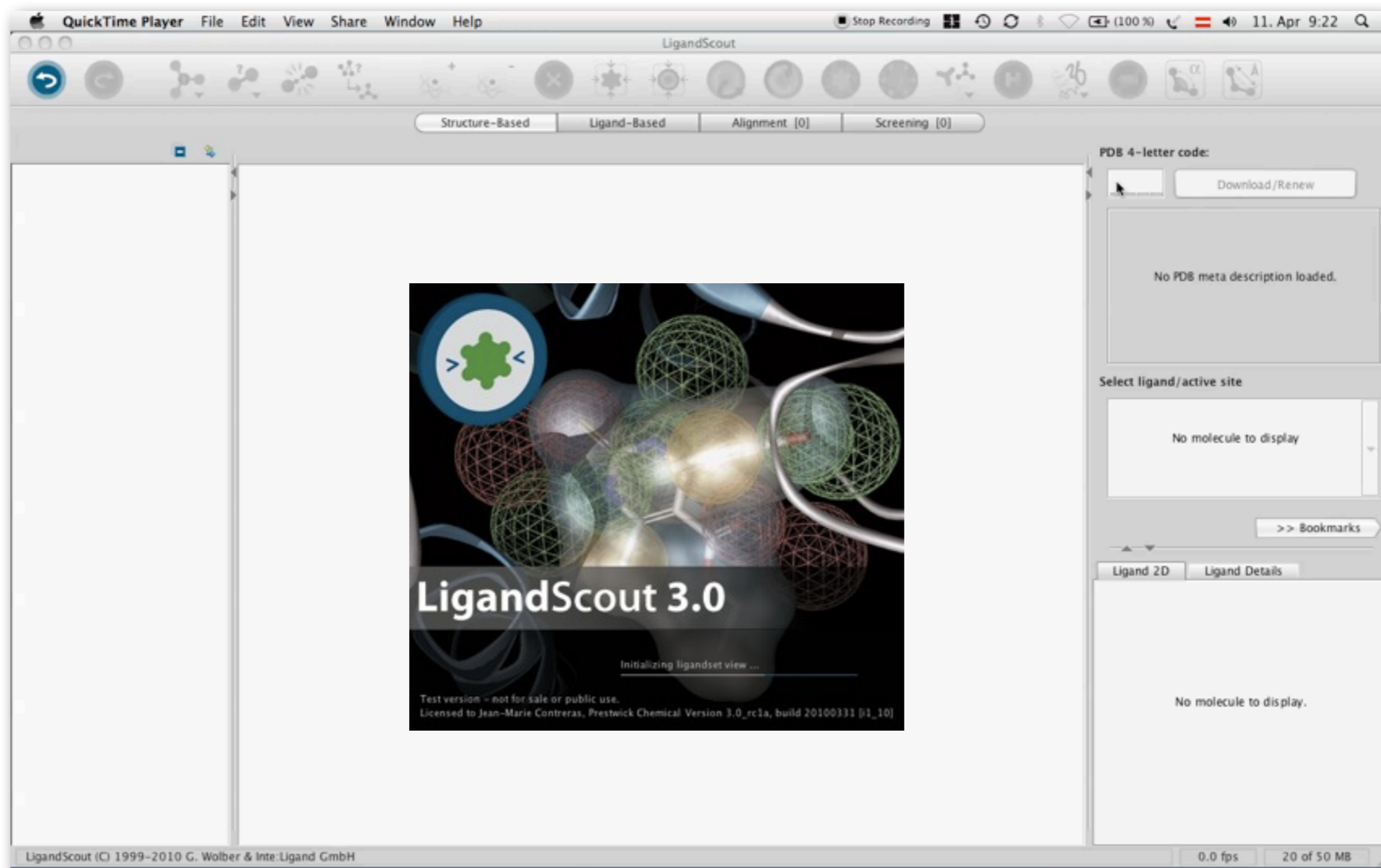
# Our Initial Aim, 15 Years Ago ...

- Create a database of pharmacophore models for activity profiling of small organic molecules
- Need for a method for rapid and reliable model generation & validation
- Developed software prototypes @ IBK university
- Creation of spin-off company Inte:Ligand

# EuroQSAR 2004: LigandScout 1.0

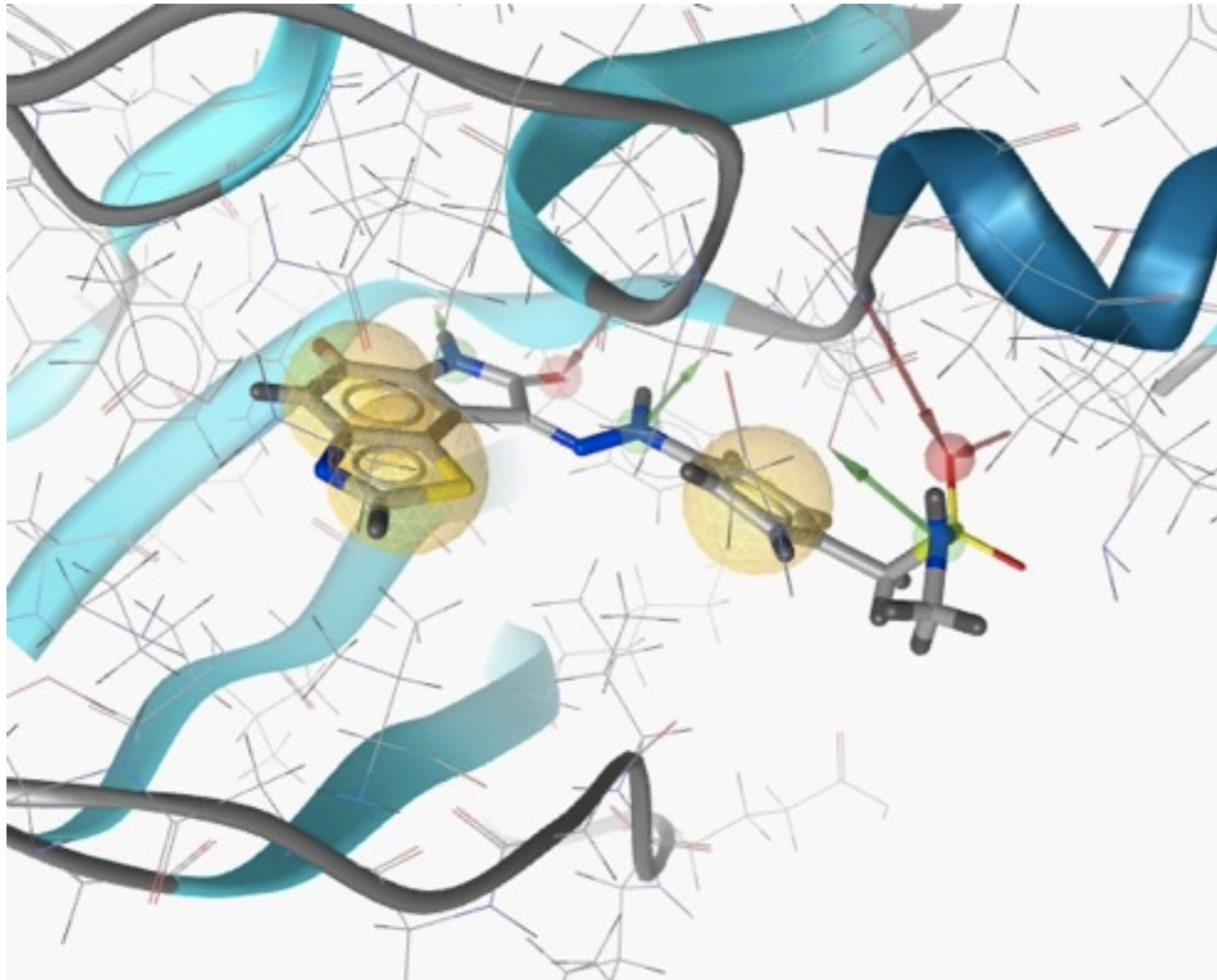
- Detect ligand and clean-up the binding site in the protein (all amino acids within 7Å default distance from the ligand)
- Interpret hybridization status and bond types in the ligand
- Perform chemical feature recognition for the ligand (H-bond donor, H-bond acceptor, positive ionizable, negative ionizable, hydrophobic, aromatic ring, metal ion coordination)
- Search for corresponding chemical features of the protein
- Add interaction features to the model only if a corresponding feature pair is found in the complex
- Add excluded volume spheres for opposite hydrophobic features

# EuroQSAR 2010: LigandScout 3.0

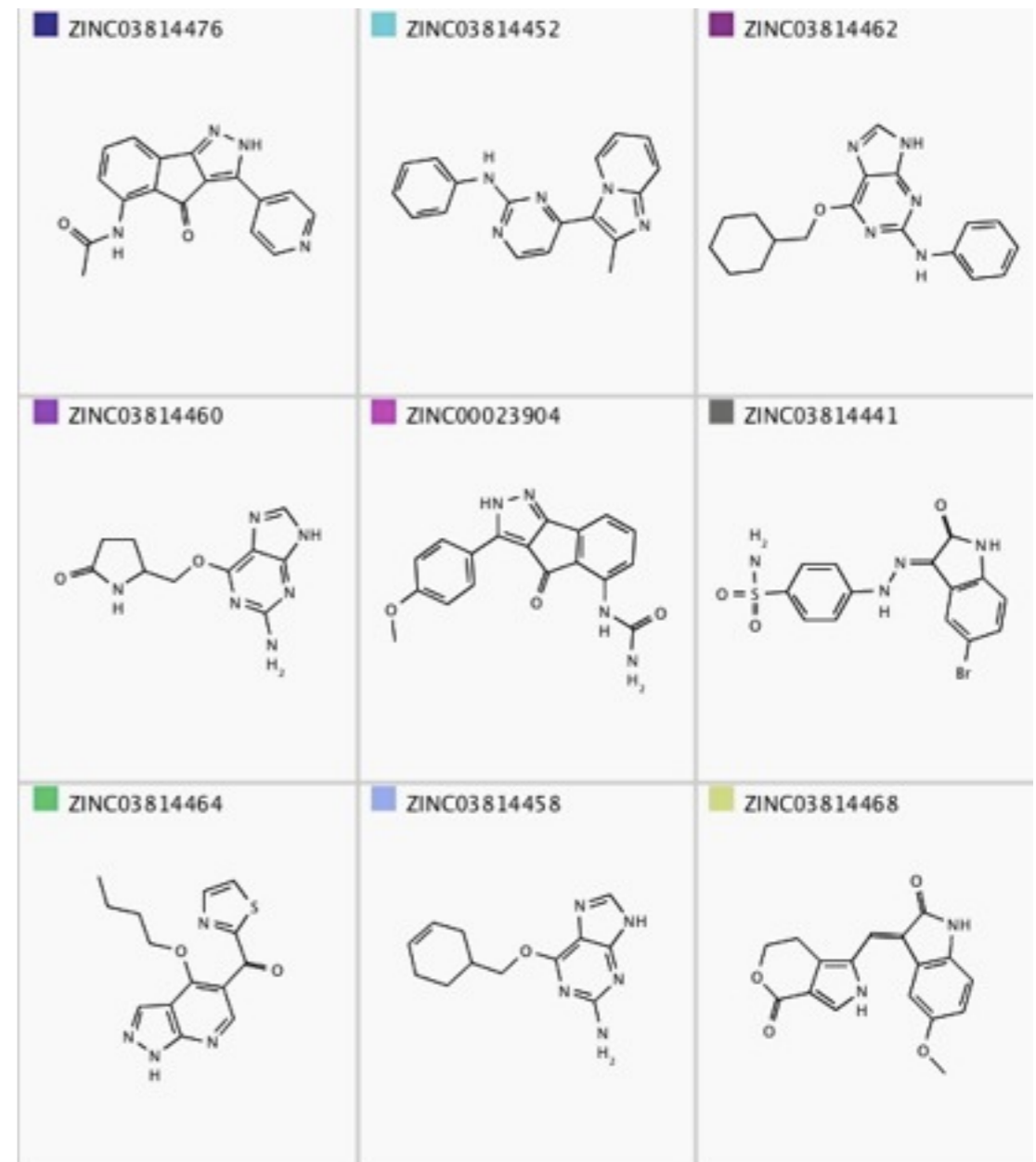


# Bridging Gaps

Structure-based



Ligand-based



# Example: CDK2 DUD Set

LigandScout

Structure-Based | Ligand-Based | Alignment [1] | Screening [11]

Screening Environment: 6 pharmacophore

Pharmacophore Cluster-11- | Pharmacophore Cluster-12- | Pharmacophore Cluster-13- | Pharmacophore Cluster-14- | Pharmacophore Cluster-15- | Pharmacophore Cluster-7-1

Copy to other perspectives

Show advanced options

Screening Databases:

- PCL2.ldb - PCL2.ldb
- DrugBank.ldb - DrugBank.ldb
- cdk2\_ligands.ldb - cdk2\_ligands.ldb
- cdk2\_decoys.ldb - cdk2\_decoys.ldb

Pharmacophores:

- (1KE5) LS11
- (1KE6) LS2201
- (1KE7) LS3201
- (1KE8) LS42
- (1KE9) LS51
- Cluster-11-1 (1)
- Cluster-12-1 (2)
- Cluster-13-1 (3)
- Cluster-14-1 -not-so-good (4)
- Cluster-15-1 (5)
- Cluster-7-1 (6)

1 or 2 or 3 or 5 or 6

Hits for Query Set >=1 or <2 or <3 or <5 or <6|<= Hitrate: 9.64% (188 of 1950) (Add Filter)

Mark	Name	Matching Features	#	mol index	Source Database	Pharmacophore fit Score	Active/Decoy	# Confs.	Score T	Best Match
9	ZINC00582	■■■■■	13	20	cdk2_ligands.ldb	87.29	active	25	87.2877	Cluster-12-1
10	ZINC03814	■■■■■	21	32	cdk2_ligands.ldb	87.15	active	22	87.14698	Cluster-12-1
11	ZINC00026	■■■■■	41	22	cdk2_decoys.ldb	87.13	decoy	20	87.13231	Cluster-12-1
12	ZINC00013	■■■■■	38	7	cdk2_decoys.ldb	87.11	decoy	10	87.105865	Cluster-12-1
13	ZINC01647	■■■■■	111	865	cdk2_decoys.ldb	86.62	decoy	20	86.61884	Cluster-12-1
14	ZINC01487	■■■■■	16	17	cdk2_ligands.ldb	86.59	active	17	86.58864	Cluster-12-1
15	ZINC03814	■■■■■	8	22	cdk2_ligands.ldb	86.46	active	25	86.457344	Cluster-12-1
16	ZINC03814	■■■■■	15	18	cdk2_ligands.ldb	86.09	active	16	86.08583	Cluster-13-1
17	ZINC04617	■■■■■	20	33	cdk2_ligands.ldb	85.99	active	10	85.99431	Cluster-13-1
18	ZINC00108	■■■■■	46	90	cdk2_decoys.ldb	85.64	decoy	25	85.6413	Cluster-13-1
19	ZINC03814	■■■■■	24	37	cdk2_ligands.ldb	78.95	active	1	78.945435	Cluster-7-1
20	ZINC00023	■■■■■	6	2	cdk2_ligands.ldb	78.94	active	2	78.935455	Cluster-7-1
21	ZINC03814	■■■■■	25	40	cdk2_ligands.ldb	78.94	active	2	78.935104	Cluster-7-1

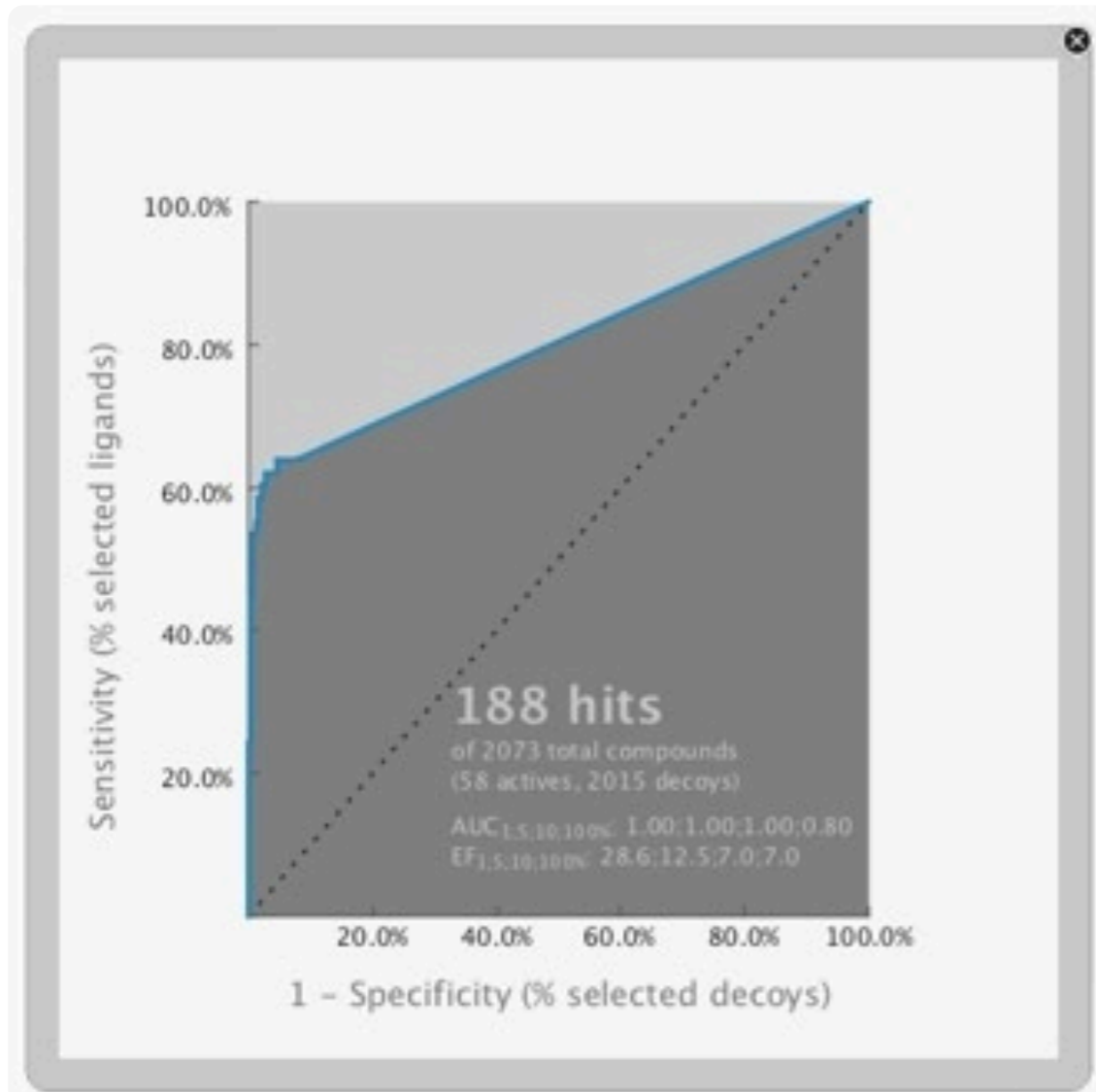
LigandScout (C) 1999-2010 G. Wolber & InTeLigand GmbH

31.1 fps 77 of 495 MB

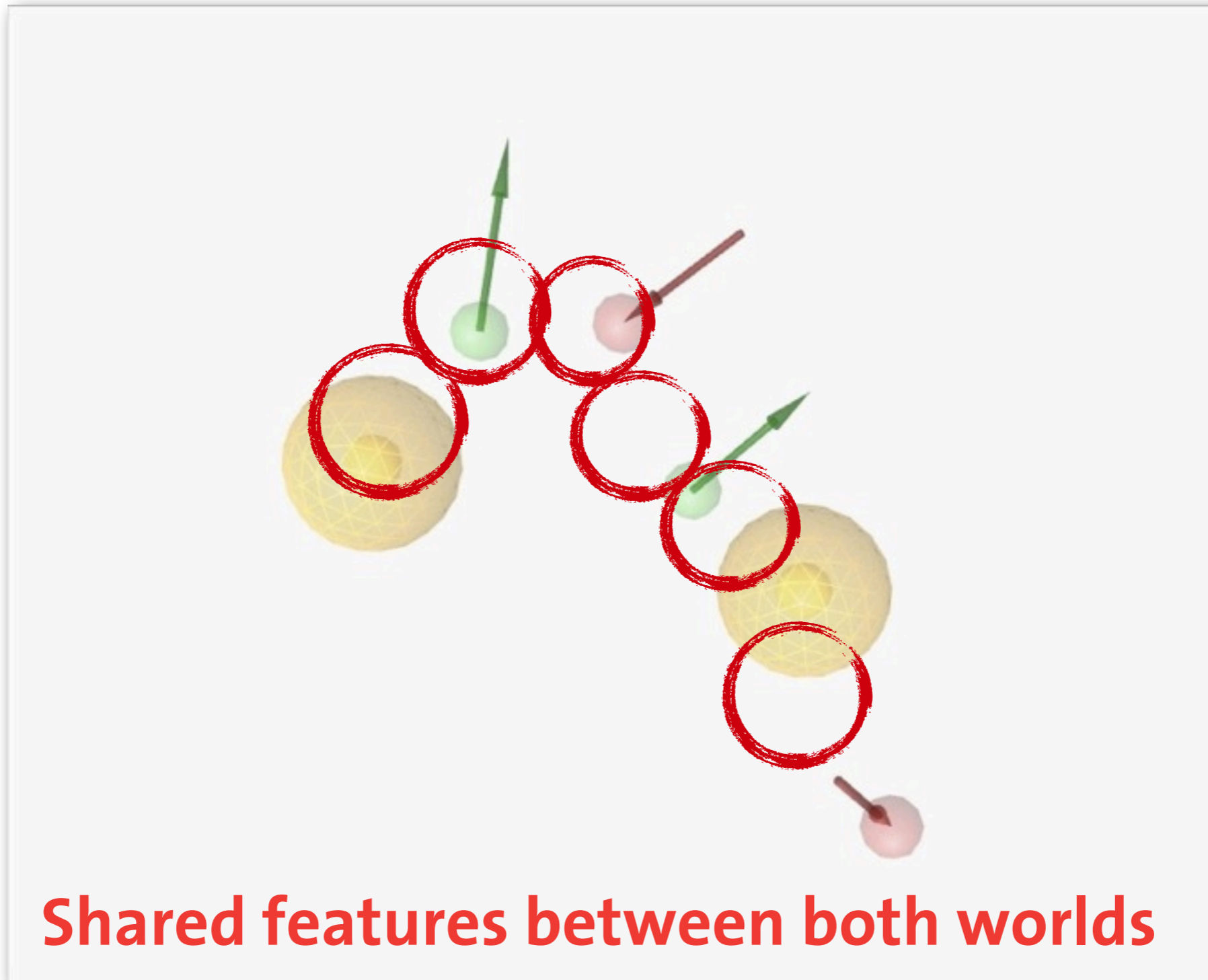
No molecule to display.

# Example: CDK2 DUD Set

- ROC Curve Analysis
  - 58 actives / 2015 decoys
  - 188 hits
  - Enrichment Factor: 28.6 (first 1% of screening)



# Comparison - Structure & Ligand Based

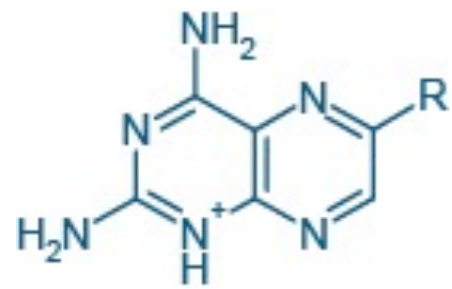


# Pharmacophore Models for Rapid VS

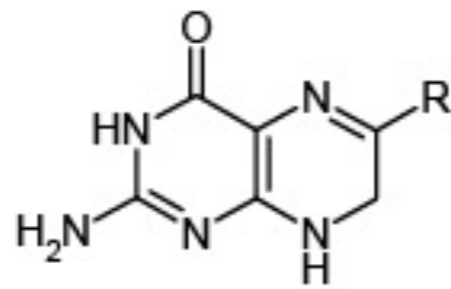
- The alignment problem
  - Which type of matching ?
  - How to define matching pairs of features ?
  - How to define a fast and accurate scoring function ?
- The solution
  - Pharmacophore elements-based matching
  - Adaptation of the hungarian matcher algorithm



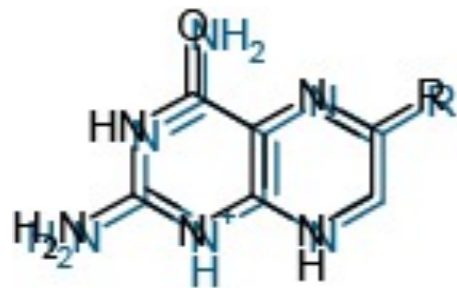
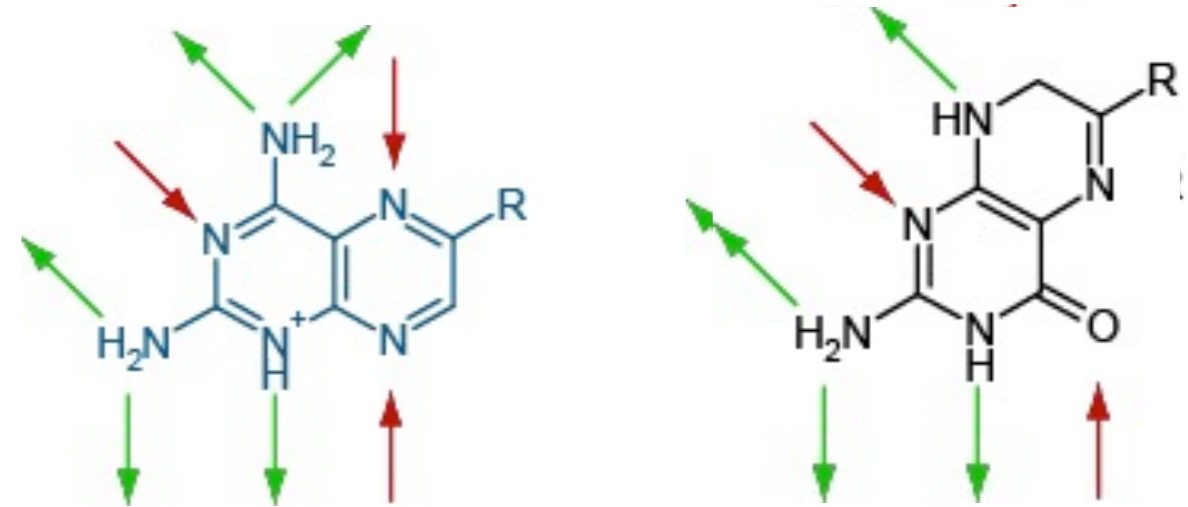
# Alignment By Pharmacophore Points



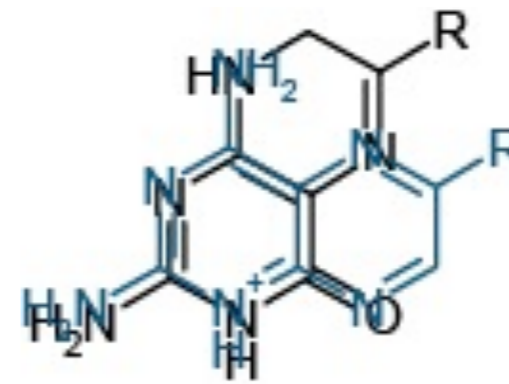
Methotrexate



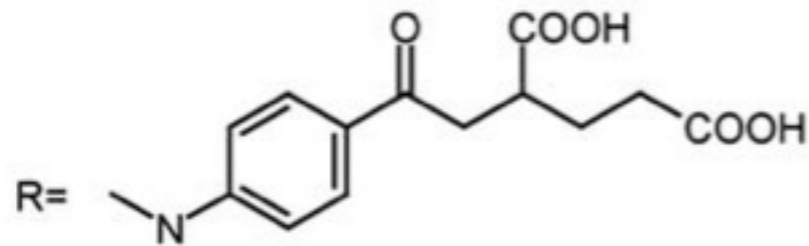
Dihydrofolate



Wrong



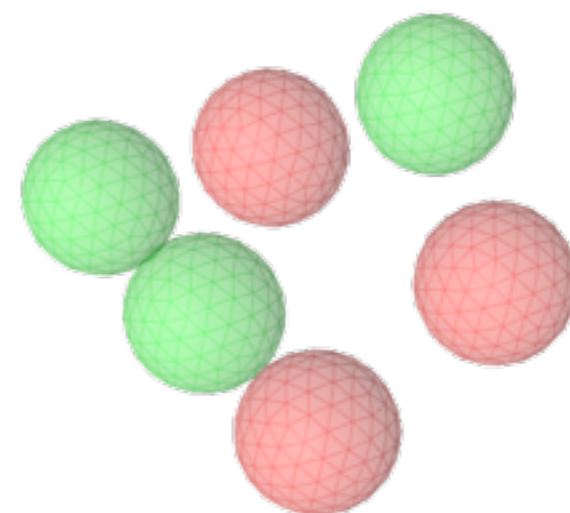
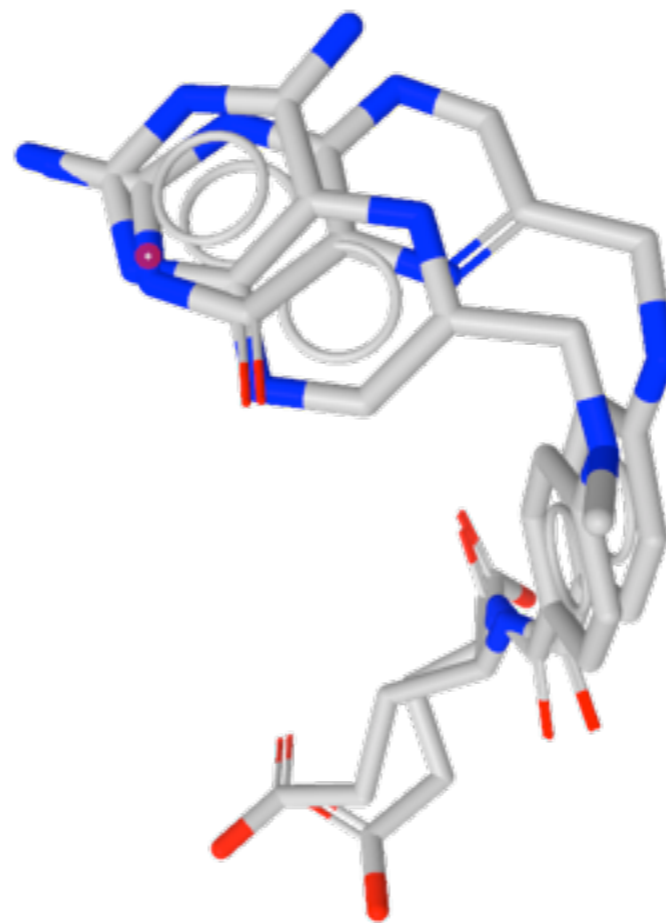
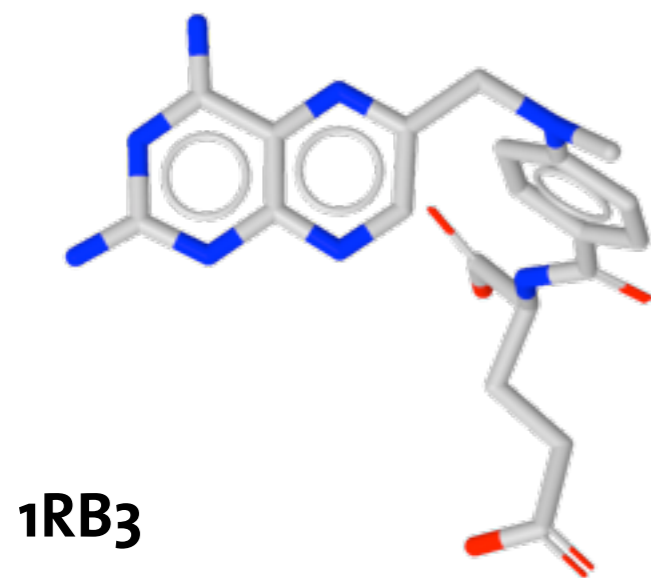
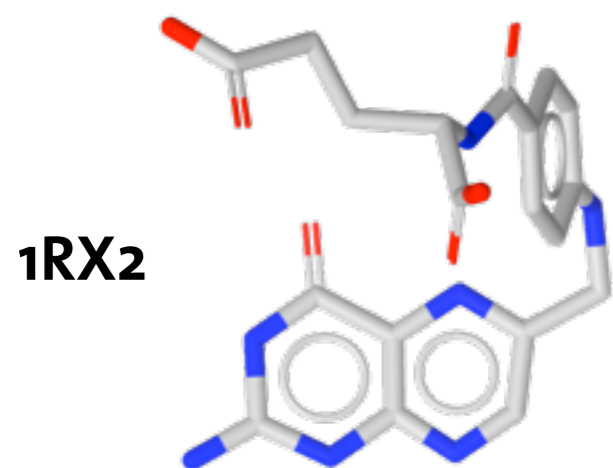
Correct



Bystroff, Oatley, Kraut: Biochemistry. (1990) 29, 3263-77

Böhm, Klebe, Kubinyi: Wirkstoffdesign (1999) p. 32of

# Alignment By Pharmacophore Points



# First Achievements

- Universal method for **accurate** feature-based pharmacophore model generation
- New pattern recognition-based alignment
- Highly **selective** models will retrieve low number of false positives / false negatives
- **High enrichment** factor can be obtained
- **Speed** allows for implementation of massive parallel screening

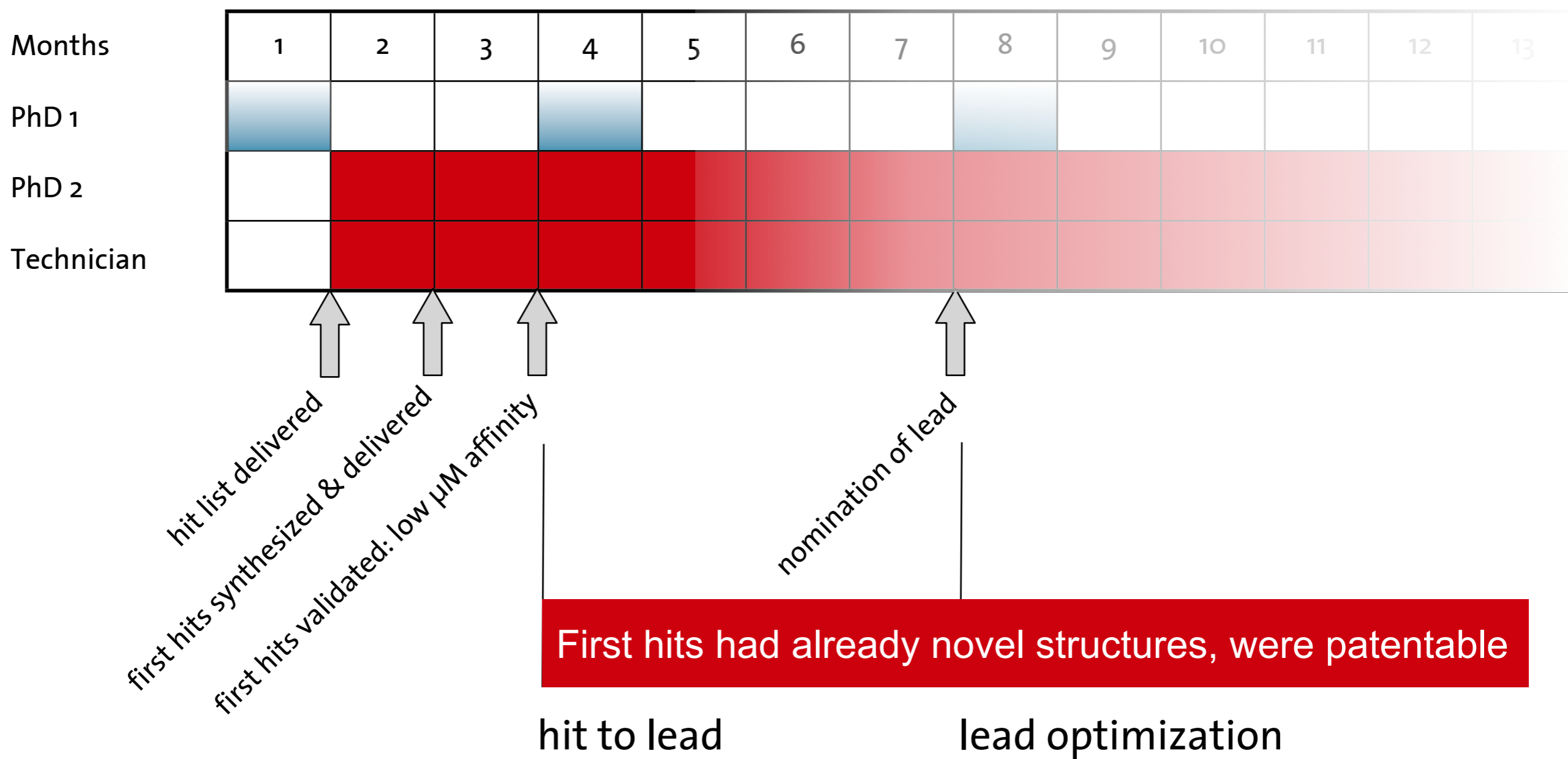
# Use Cases / Success Stories

- Finding starting points for medicinal chemistry program: Hit identification by virtual screening
- Medicinal chemistry decision support in hit to lead and lead optimization
- Activity profile estimation by parallel screening
- Target fishing for natural products

# Identification of Starting Points

- Real life example
- Target with known 3D structure (x-ray)
- Pharmacophore derived in direct approach
- Virtual library built ab-initio using a fragment-based approach (90k compounds)
- Screening delivers reasonable small number of hits (0.05% range)
- Synthesis and biological testing

# Time Line & Results



# Ligand Profiling: Proof of Principle

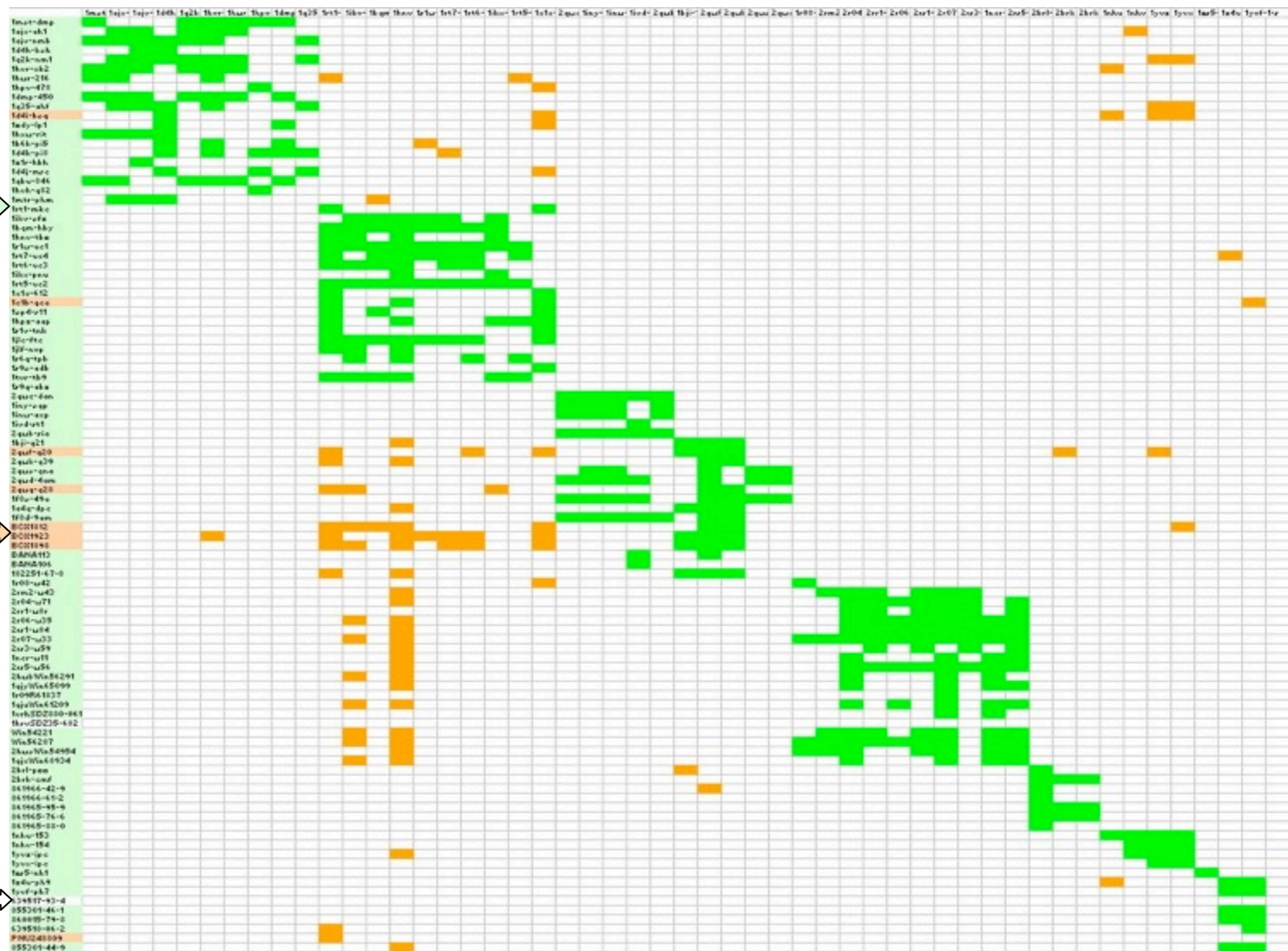
- First pharmacophore-based ligand profiling
- Case study: Five targets relevant in viral diseases
  - 10 pharmacophore models per target
- Investigation on 100 antiviral compounds
  - 20 compounds per target
- Target profile estimation by parallel screening

# Ligand-directed Analysis

Ratio  $\geq 1$   
90% of the compounds  
correctly predicted

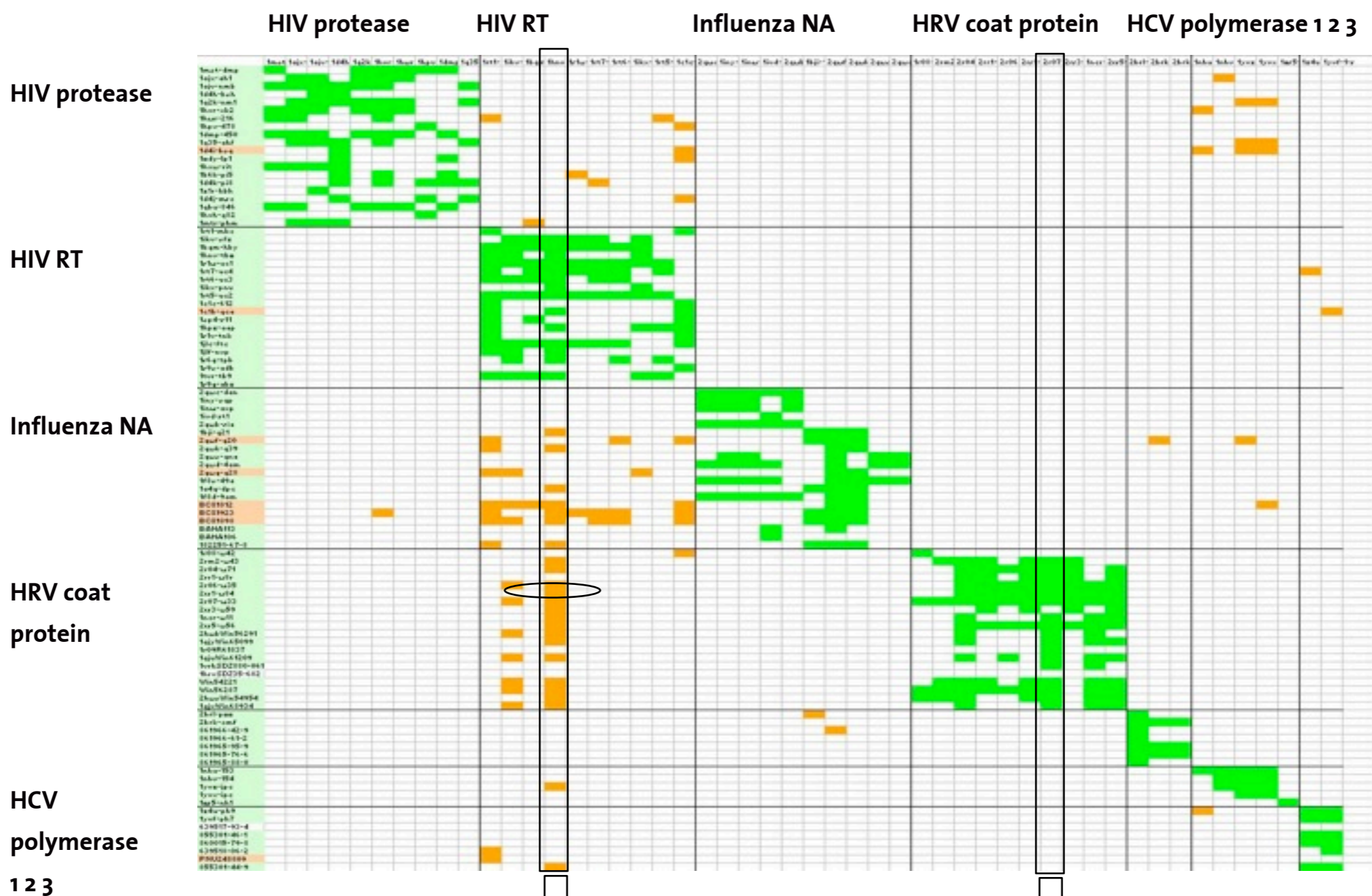
Ratio  $< 1$   
8% more often  
predicted for one  
specific false target  
than for correct one

for 2% of the  
compounds no activity  
prediction possible





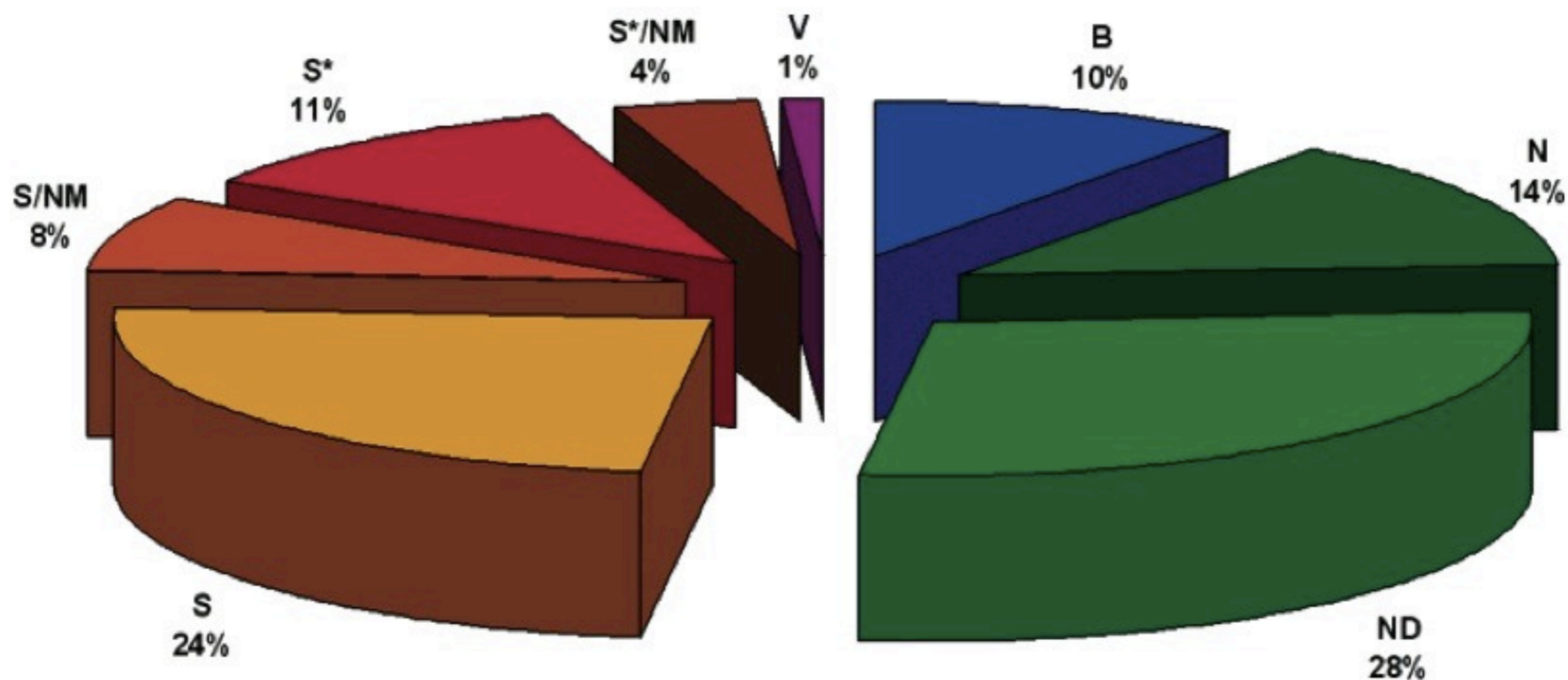
# Pharmacophore-directed Analysis



Model with low selectivity:  
70% of actives (HIV RT), but 75% from one specific false target (HRV coat protein)  
40% active and 60% inactive compounds in hit list

Model with high selectivity:  
95% of actives (HRV coat protein),  
0% inactive compounds in hit list

# Target Fishing With Natural Products



Small molecule new chemical entities organized by source/year (N =974).

David J. Newman, and Gordon M. Cragg, *J. Nat. Prod.*, 2007, **70**, 461-477

# Target Fishing With Natural Products



## Leoligin, the major lignan from Edelweiss, activates cholesteryl ester transfer protein

Kristina Duwensee<sup>a</sup>, Stefan Schwaiger<sup>b</sup>, Ivan Tancevski<sup>a</sup>, Kathrin Eller<sup>c</sup>, Miranda van Eck<sup>d</sup>, Patrick Markt<sup>e</sup>, Tobias Linder<sup>c</sup>, Ursula Stanzl<sup>a</sup>, Andreas Ritsch<sup>a</sup>, Josef R. Patsch<sup>a</sup>, Daniela Schuster<sup>e</sup>, Hermann Stuppner<sup>b</sup>, David Bernhard<sup>f</sup>, Philipp Eller<sup>g,\*</sup>

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### ABSTRACT

**Objective:** Cholesteryl ester transfer protein (CETP) plays a central role in the metabolism of high-density lipoprotein particles. Therefore, we searched for new drugs that bind to CETP and modulate its activity.

**Methods:** A preliminary pharmacophore-based parallel screening approach indicated that leoligin, a major lignan of Edelweiss (*Leontopodium alpinum* Cass.), might bind to CETP. Therefore we incubated leoligin *ex vivo* at different concentrations with human ( $n=20$ ) and rabbit plasma ( $n=3$ ), and quantified the CETP activity by fluorimeter. Probucol served as positive control. Furthermore, we dosed CETP transgenic mice with leoligin and vehicle control by oral gavage for 7 days and measured subsequently the *in vivo* modulation of CETP activity ( $n=5$  for each treatment group).

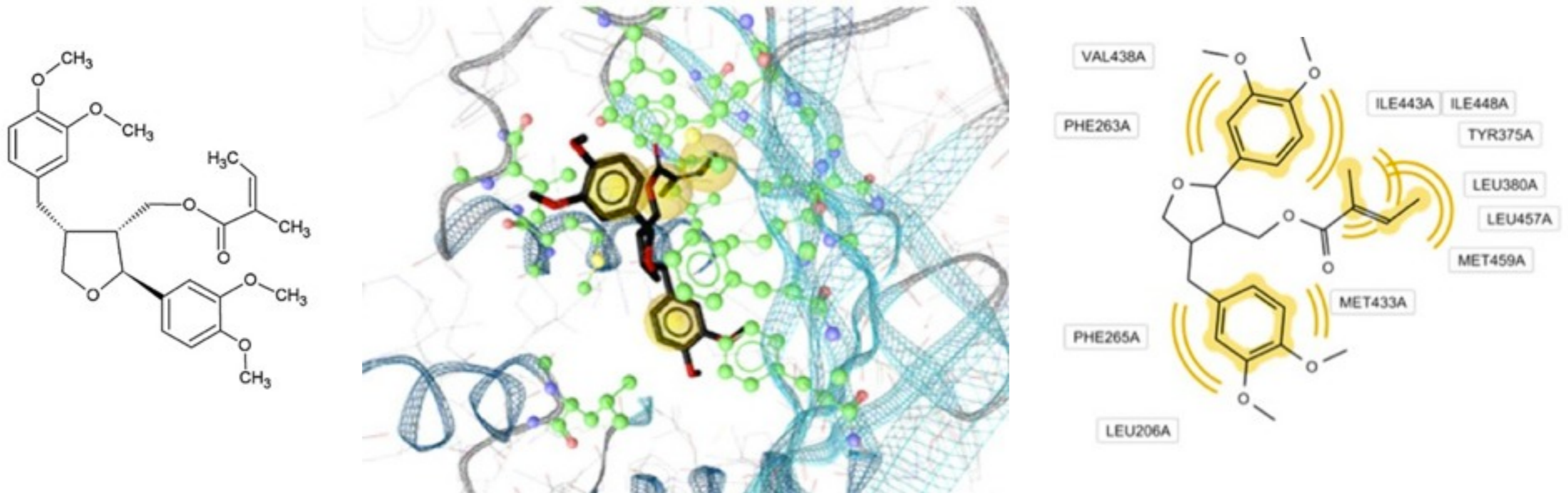
**Results:** *In vitro*, leoligin significantly activated CETP in human plasma at 100 pM ( $p=0.023$ ) and 1 nM ( $p=0.042$ ), respectively, whereas leoligin concentrations of 1 mM inhibited CETP activity ( $p=0.012$ ). The observed CETP activation was not species specific, as it was similar in magnitude for rabbit CETP. *In vivo*, there was also a higher CETP activity after oral dosage of CETP transgenic mice with leoligin ( $p=0.015$ ). There was no short-term toxicity apparent in mice treated with leoligin.

**Conclusion:** CETP agonism by leoligin appears to be safe and effective, and may prove to be a useful modality to alter high-density lipoprotein metabolism.

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K. Duwensee, et al.,  
Atherosclerosis (2011) 219, 109-115

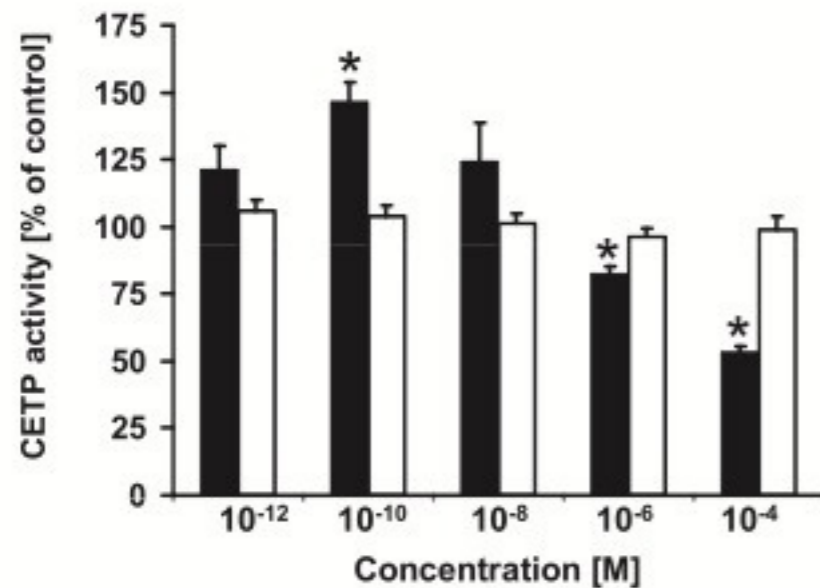
# Pharmacophore Profiling of Leoligin



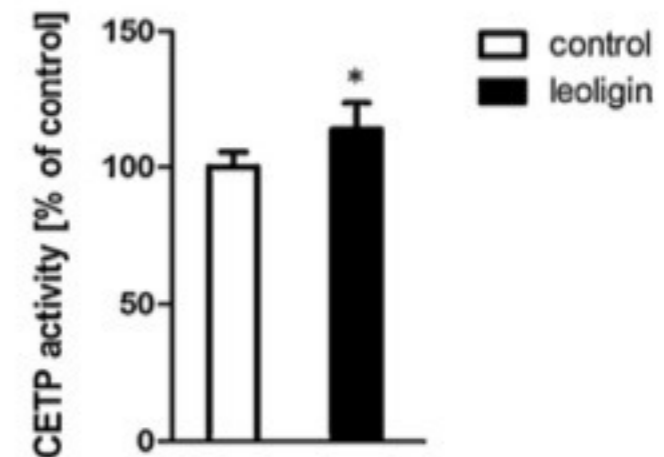
Leoligin matches the pharmacophore model encoding for the interaction site of cholesteryl ester transfer protein (CETP)

K. Duwensee, et al.,  
Atherosclerosis (2011) 219, 109-115

# Biological Testing



Leoligin enhances the activity of human and rabbit CETP in vitro when applied in **subnanomolar concentration** (control Probucol)



Leoligin activates CETP in vivo (7 days test with CETP transgenic mice, leoligin dosed orally, 1 mg/kg)

K. Duwensee, et al.,  
Atherosclerosis (2011) 219, 109-115

# Summary ...

## First published examples of applications of extensive parallel screening approach based on pharmacophores

- Multitude of pharmacophore models (up to several thousand ...)
- Large set of molecules (up to several million ...)

## Results indicate

- Correct assignment of selectivity in most cases
- Independent of search algorithms used

**Fast, scalable *in silico* activity profiling is now possible !**

# Recent Success Stories

# Protein Protein Interfaces



Available online at [www.sciencedirect.com](http://www.sciencedirect.com)

ScienceDirect

Current Opinion in  
Chemical Biology

## Small molecular weight protein–protein interaction antagonists – an insurmountable challenge?

Alexander Dömling

Several years ago small molecular weight protein–protein interaction (PPI) antagonists were considered as the Mount Everest in drug discovery and generally regarded as too difficult to be targeted. However, recent industrial and academic research has produced a great number of new antagonists of diverse PPIs. This review structurally analyses small molecular weight PPI antagonists and their particular targets as well as tools to discover such compounds. Besides general discussions there will be a focus on the PPI p53/mdm2.

### Address

Departments of Pharmaceutical Sciences and Chemistry, University of Pittsburgh, United States

Corresponding author: Dömling, Alexander ([asd30@pitt.edu](mailto:asd30@pitt.edu))

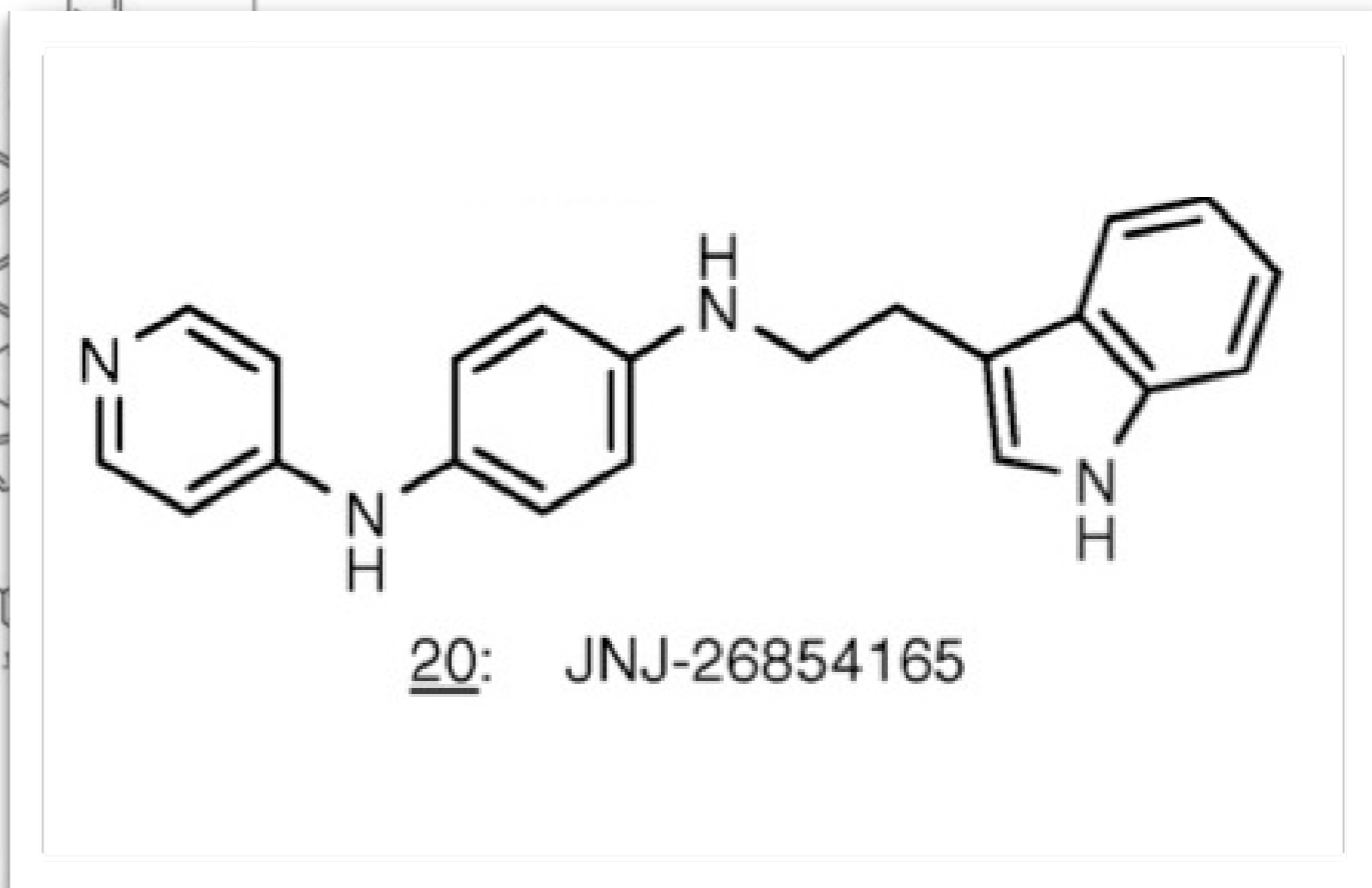
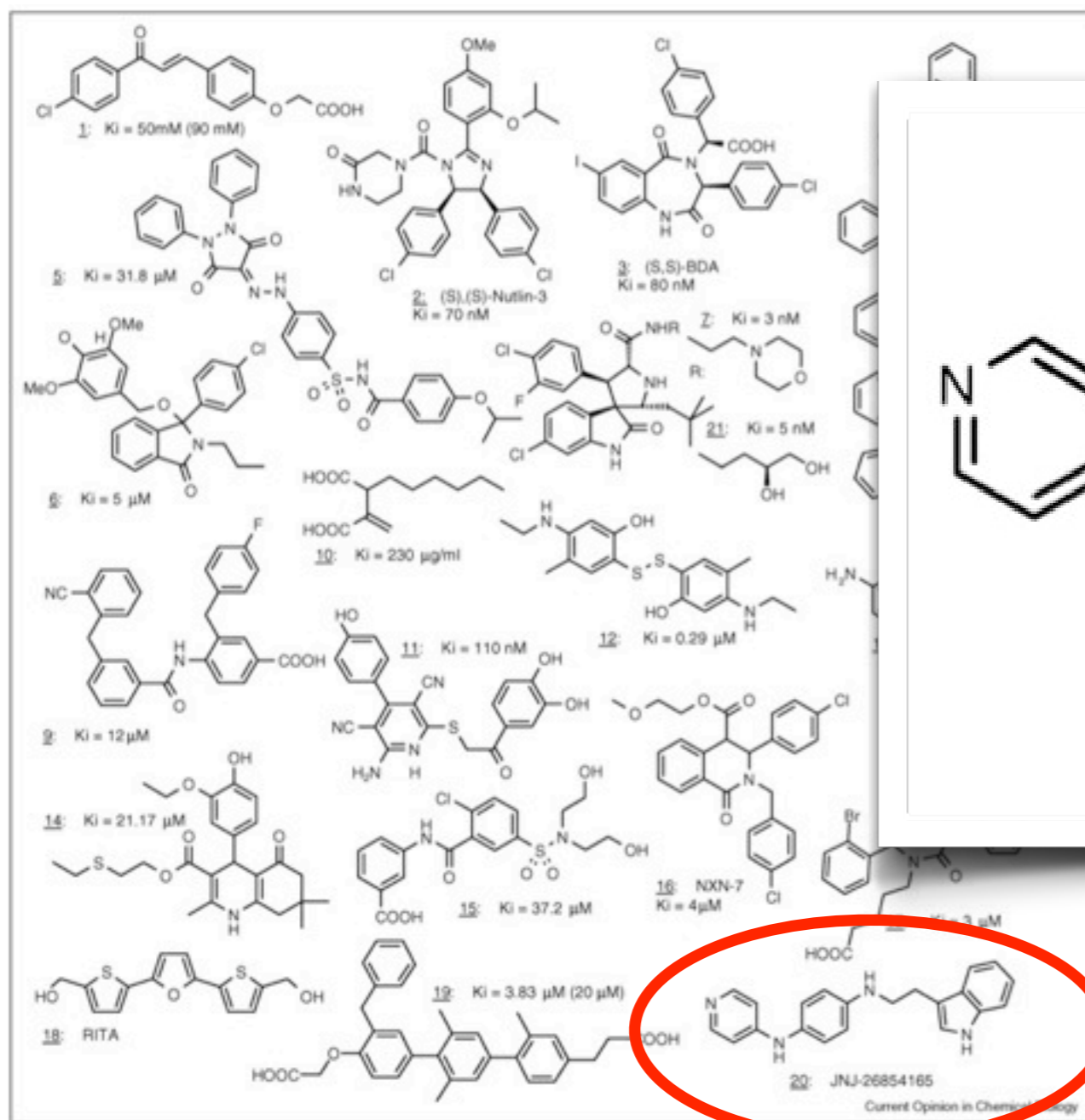
However, more and more scientists recognize the eigenvalue of protein interaction antagonization. The growing importance of PPIs as oncology targets was underlined by many talks and posters at the recent AACR-EORTC meeting in San Francisco. Covered examples included p53/mdm2/mdm4, Bcl family interactions, IAPs, c-Myc, SPRY2-Cb, ERCC1/XPF, FAK–protein interactions, orphan nuclear receptor COUP-TFI, Smad4-SKI, c-Src-SH3, Smad2/3/4, Rb/Raf-1, SDF-1/CXCR4, tissue factor/FVIIa, HOX/PBX and tubulin. In the following the small molecule antagonists of the p53/mdm2 interaction are discussed, as an example of a successfully targeted PPI.

### The p53/mdm2 case

Structure



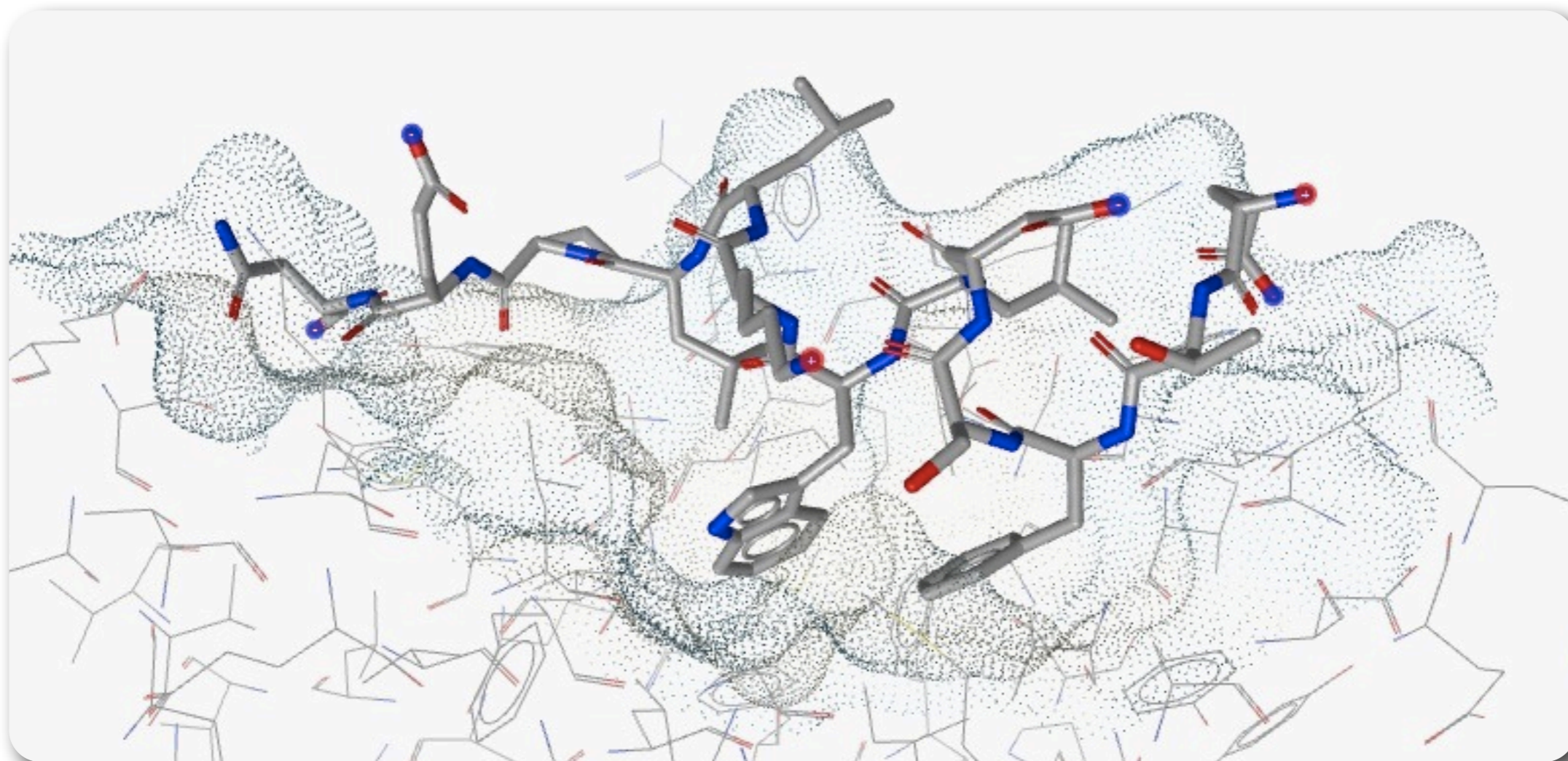
# Described p53/mdm2 Inhibitors



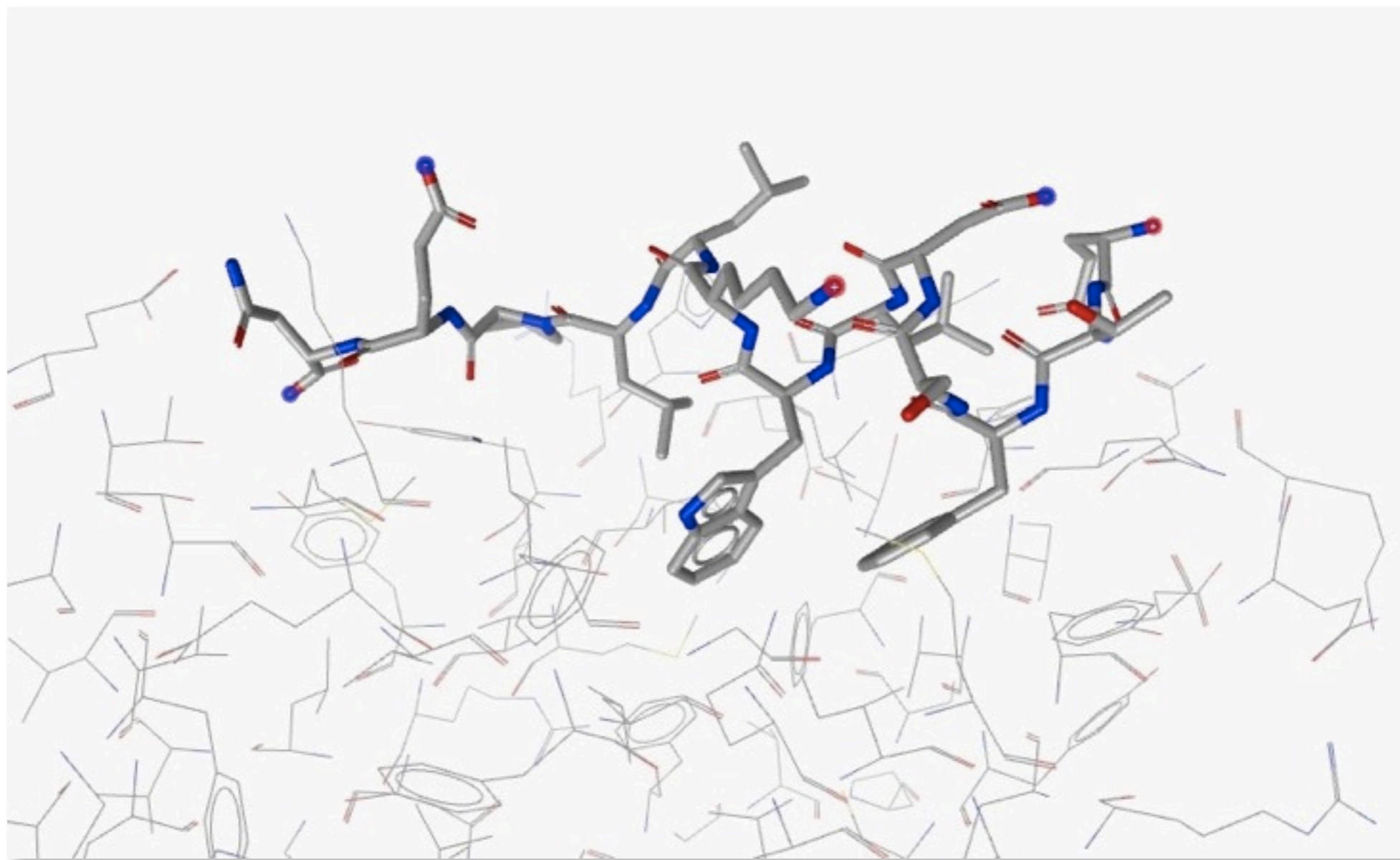
Dömling, A. *Curr. Opin. Chem. Biol.* 2008, 12, 281-291.

# Structure-based Pharmacophore

- p53/mdm2 complex structure (PDB: 1YCR)



# Comparison with JNJ-26854165



# Conclusions

- Smart medicinal chemistry, supported by cutting-edge chemoinformatics methods is a straightforward and rapid method for the generation of promising new lead compounds
- Assessment of risks in later development stages becomes possible on a rational & transparent basis
- Translation into an academic research environment is feasible

**Thank you for your attention**

**NEVER GIVE UP!!!**