

Computer-Aided Approaches to Virtual Screening and Rational Design of Multitargeted Drugs

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Outline

- **Biological activity: many faces of the entity**
- **Identification of the most promising targets**
 - **Net2Drug**
- **Identification of the most promising lead compounds**
 - **PASS**
 - **PharmaExpert**
 - **GUSAR**
- **Examples of applications**
- **Summary**

Due to biological activity, chemical compound may be used as a medicine for treatment of certain disease.

Due to biological activity, chemical compound may cause adverse or toxic effects in human.

Depending on the Dose and Route of Administration, the Substance May Be either Drug or Poison

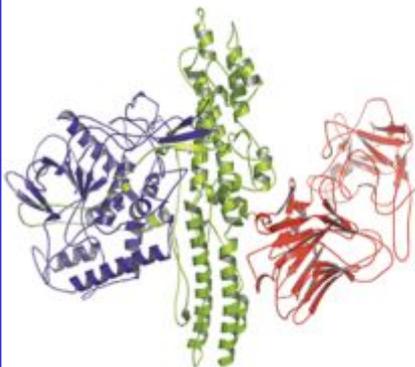
Botox

If Botox was not exactly a household word before the last presidential campaign, it became one during it. For a brief period of time, the campaign's leitmotiv was whether one of the candidates was being injected with Botox to erase the frown lines from his well-lived-in face. He denied using it, but the publicity put this nonsurgical wrinkle eraser on the map.

Botox is the trade-marked name of Allergan's purified protein--botulinum toxin Type A--derived from the anaerobic bacterium *Clostridium botulinum*. According to the company, Botox has been approved in more than 75 countries to treat 20 different neurological disorders. In addition to its cosmetic application, the toxin has been used in the U.S. for about 15 years for a range of therapeutic applications, including the treatment of crossed eyes and excessive sweating.

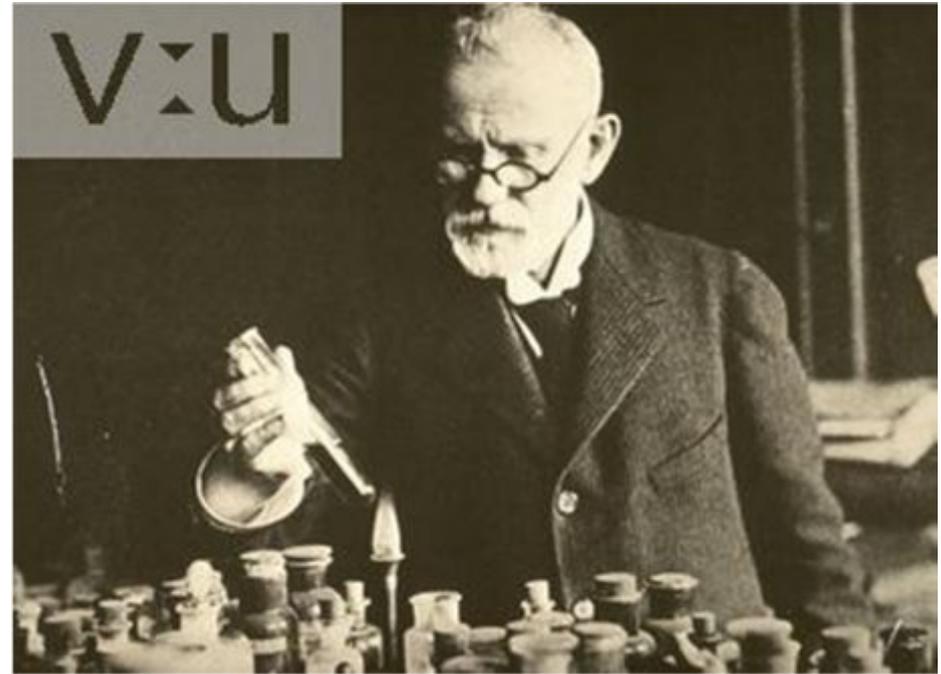
Allergan spokeswoman Caroline Van Hove notes that Botox "ranks as the number one minimally invasive cosmetic procedure in the U.S., according to recent statistics from the American Society of Plastic Surgeons." But its therapeutic uses outweigh the cosmetic, accounting for a 60% of Allergan's worldwide sales of \$705 million in 2004.

Type A is one of seven distinct botulinum toxins (identified by A-G) produced by different strains of the bacterium. Each toxin type produces different immunologic response and is made by a different manufacturing process. In the U.K. and Europe, Ipsen markets a Type A toxin as Dysport that differs slightly from Botox. The only Type B toxin available is made by Solstice Neurosciences and is sold as Myobloc/Neuroblo. No other antigenic toxins are available for therapeutic use.



Beginning of XX Century: "Magic bullet" concept

During the XX century the dominant paradigm in creation of new drugs was based on suggestion about **selectivity of action on a certain molecular target** that should lead to the **normalization of pathological process**.



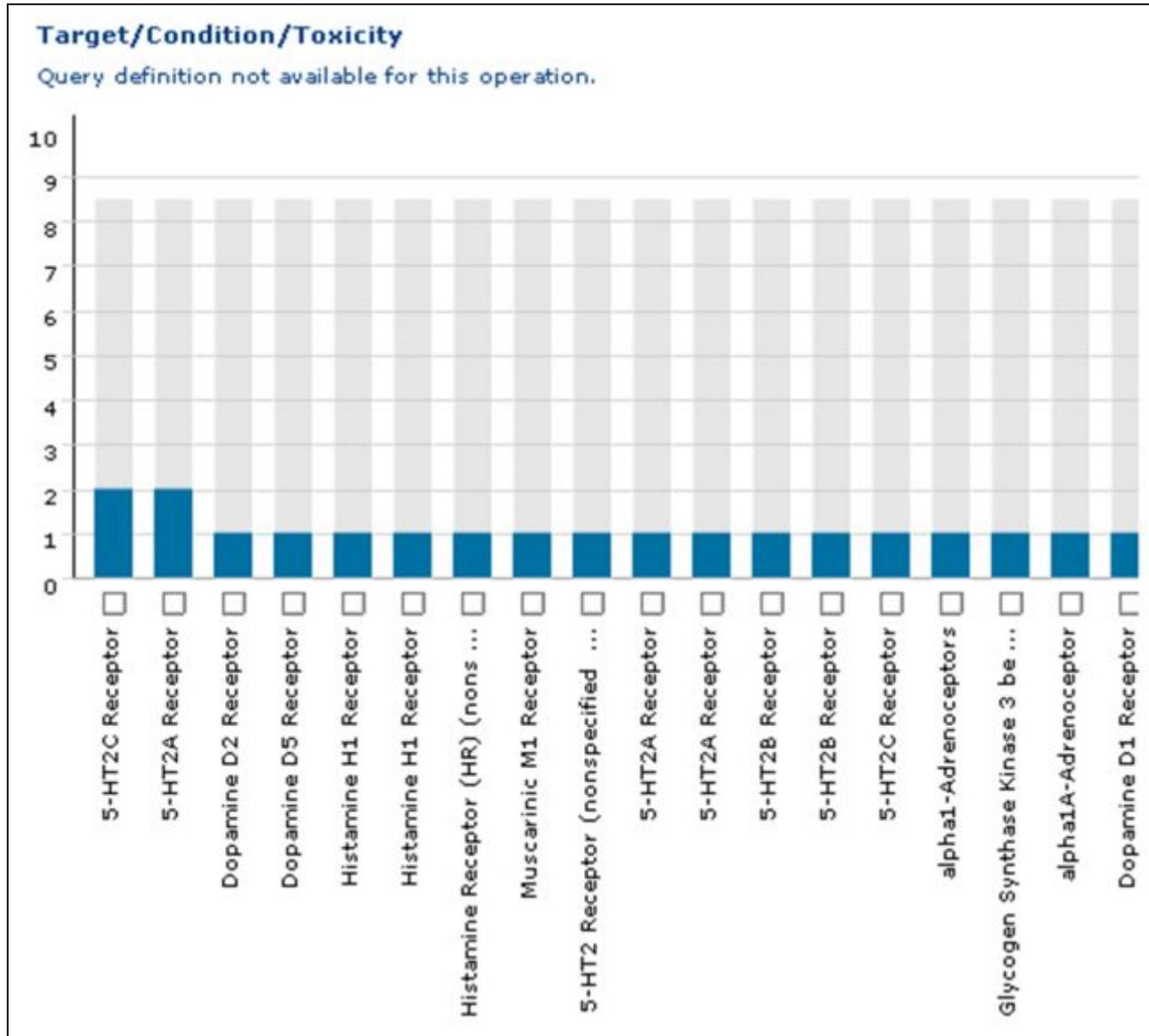
Paul Ehrlich (14 March 1854 – 20 August 1915) was a German scientist in the fields of hematology, immunology, and chemotherapy, and Nobel laureate. He is noted for curing syphilis and for his research in autoimmunity, calling it "*horror autotoxicus*". He coined the term chemotherapy and popularized the **concept of a magic bullet**.

Beginning of XXI Century: Multitargeting Reality

For example, "... popular **statins**, prescribed to decrease pathologically elevated cholesterol levels, interfere with cholesterol biosynthesis at the C₅ level (hydroxymethyl glutarate), and therefore interfere with the biosynthesis of farnesyl residues, cholic acids, sexual hormones and corticosteroids; it is really surprising that these drugs do not produce more severe side effects. **Olanzapine**, a successful neuroleptic and one of the top-selling drugs, acts as a highly unspecific, nanomolar antagonist of at least ten different neurotransmitter receptors.

Kubinyi H. *Nat. Rev. Drug Discov.*, 2003, 2: 665.

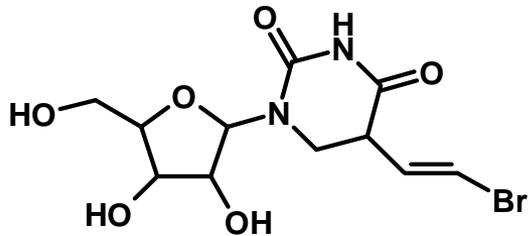
Pharmacological targets of Olanzapine ($IC_{50} < 10^{-7}$)



Source: Thomson Reuters Integrity

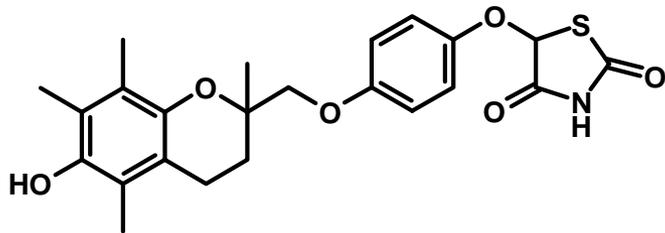
Examples of Adverse and Toxic Effects Due to the Multitargeted Drug Action

Structure → Biological Activity → Drug/Chemical



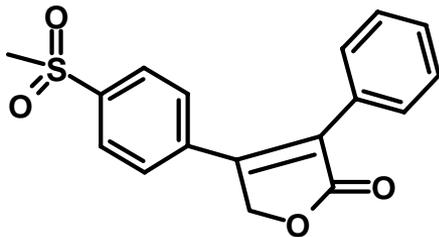
Antiviral,
Antitumor,
Neurotoxicity

Sorivudine



Antidiabetic,
Hepatotoxicity

Troglitazone



Antiarthritic,
Antiinflammatory,
COX-2 inhibitor,
Heart attack

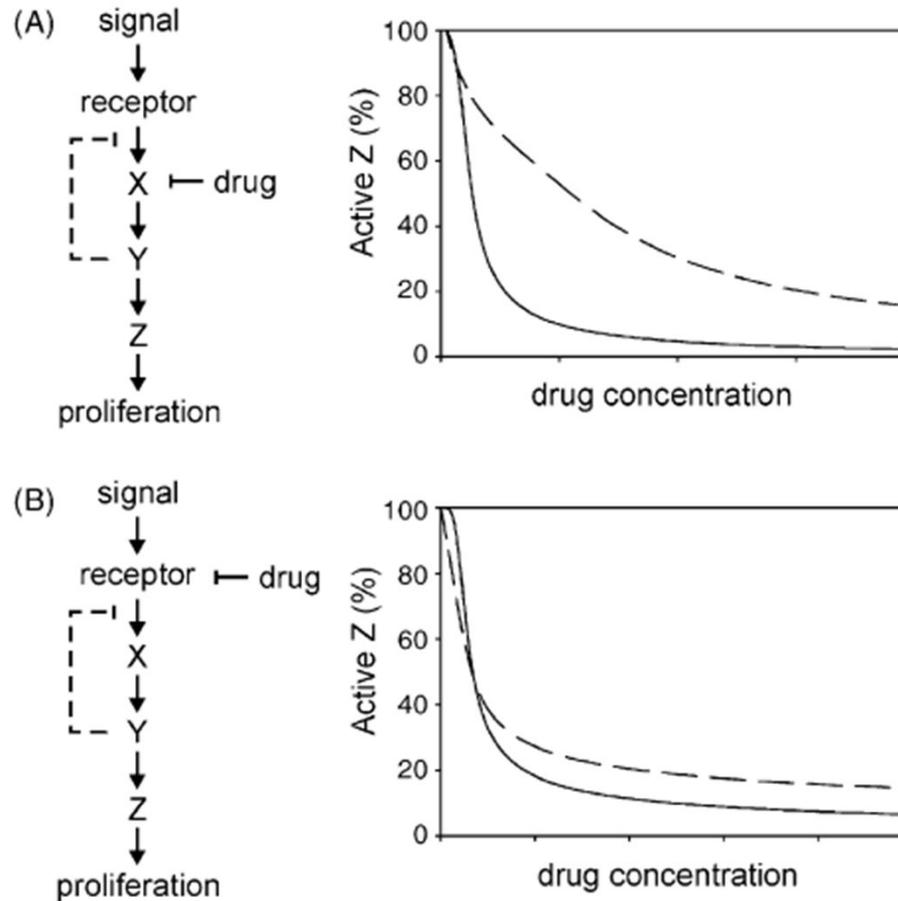
Vioxx

If some positive outcomes could
be found in the multitargeted
drugs action?

Needs for Multi-Targeted (Anticancer) Agents

- In order to optimize the efficacy of single target therapy, we should be able **to identify in each patient the oncogene to which the tumor is addicted, if any, but this is at present unrealistic.**
- In many tumors, **cross-talks between different signalling networks** have been identified and **inhibition of a single pathway might not be sufficient to hamper tumor progression.**
- Almost invariably **patients treated with single target agents acquire pharmacological resistance and undergo relapse, often due to the activation of alternative signalling pathways.**

Simple Case of Negative Feedback

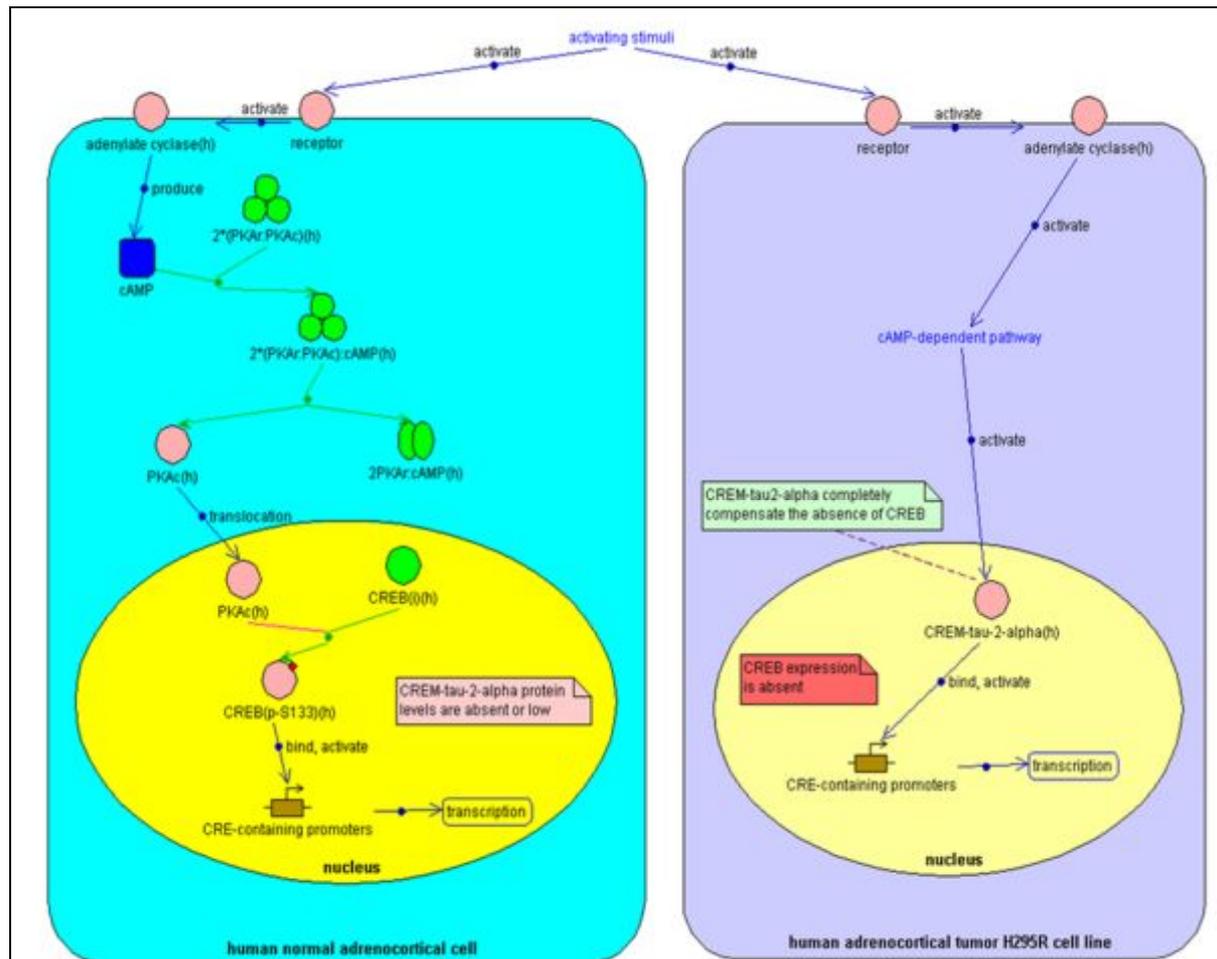


Hornberg J.J. et al. *BioSystems* 83 (2006) 81–90.

Loss of Expression of the Ubiquitous Transcription Factor cAMP Response Element-Binding Protein (CREB) and Compensatory Overexpression of the Activator CREM τ in the Human Adrenocortical Cancer Cell Line H295R*

LIONEL GROUSSIN, JEAN FRANCIS MASSIAS, XAVIER BERTAGNA, AND JÉRÔME BERTHERAT

Groupe d'Etude en Physiopathologie Endocrinienne, Centre National de la Recherche Scientifique, UPR1524, Institut Cochin de Génétique Moléculaire, Université René Descartes-Paris V, 75014 Paris, France



Multitargeted Drugs: The End of The “One-Target-One Disease Philosophy?”



update | discussion forum

DDT Vol. 9, No. 19 October 2004

The Discussion Forum provides a medium for airing your views on any issues related to the pharmaceutical industry and obtaining feedback and discussion on these views from others in the field. You can discuss issues that get you hot under the collar, practical problems at the bench, recently published literature, or just something bizarre or humorous that you wish to share. Publication of letters in this section is subject to editorial discretion and company-promotional letters will be rejected immediately. Furthermore, the views provided are those of the authors and are not intended to represent the views of the companies they work for. Moreover, these views do not reflect those of Elsevier, *Drug Discovery Today* or its editorial team. Please submit all letters to Steve Carney, Editor, *Drug Discovery Today*, e-mail: S.Carney@elsevier.com

Multitargeted drugs: the end of the ‘one-target-one-disease’ philosophy?

In a recent issue of *Drug Discovery Today*, Morphy *et al.* [1] discuss the opportunities and advantages associated with the design of ligands that act on two (or more) specific targets in an article entitled ‘From magic bullets to designed multiple ligands’.

Several highly specific drugs that have only one target have clearly proven the usefulness of monotarget medicine.

inhibitors and one protease inhibitor is administered, in the treatment of infection, where the β -lactamase inhibitor clavulanic acid is used in conjunction with amoxicillin, and in the treatment of Parkinson’s disease, where L-4-dihydroxyphenylalanine (DOPA) is concomitantly administered with DOPA-decarboxylase and catechol-O-methyltransferase inhibitors. The risk with combination therapies is that the use of multiple drugs introduces problems with pharmacokinetics, toxicity and patient compliance. To circumvent these difficulties, and after

authors use the term pharmacophores to define functional or structural elements that possess biological activity. However, this does not correspond to the official definition [6]: ‘A pharmacophore is the ensemble of steric and electronic features that is necessary to ensure the optimal supramolecular interactions with a specific biological target structure and to trigger (or to block) its biological response.’ A pharmacophore does not represent a real molecule or an actual association of functional groups, but is a purely abstract concept that encompasses the common molecular interactions of a group of compounds with their target structure. Pharmacophores are not ‘pieces of molecules’, and for this reason a truly rational computer-generation of DM ligands should not be based on the interactions of structural elements, but rather the comparison and association of true pharmacophores.

The second approach (screening approach) to DM ligands is based on the screening of large libraries for the two relevant bioassays. The substantial screening of a large number of compounds, which therefore have a

“In conclusion, the preparation of dual- or multiple-ligands on an almost rational basis is now conceivable and it can be expected that many of these molecules will yield drugs of superior clinical value compared with monotarget formulations”.

Wermuth C. *Drug Disc. Today*, 2004, 9.

Designed Multiple Ligands. An Emerging Drug Discovery Paradigm

Richard Morphy* and Zoran Rankovic

The Physicochemical Challenges of Designing Multiple Ligands

Richard Morphy* and Zoran Rankovic

Medicinal Chemistry Department, Organon Laboratories, Newhouse, Lanarkshire, ML1 5SH, U.K.

Received March 16, 2006

Compounds designed to bind more than one target can provide a therapeutic benefit relative to highly selective ligands. The physicochemical properties of designed multiple ligands were found to be less than those for preclinical compounds in general. These properties are controlled by the superfamily of targets and the lead discovery strategy that was followed. The properties for peptide coupled receptor (GPCR) ligands were the least favorable for oral delivery, whereas transporter, GPCR, and oxidase ligands were the most druglike. The lead discovery strategy, framework com-

The topology of drug–target interaction networks: implicit dependence on drug properties and target families^{†‡}

Jordi Mestres,^{*,a} Elisabet Gregori-Puigjané,^a Sergi Valverde^{bc} and Ricard V. Solé^{bd}

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DOI: 10.1039/b905821b

Opinion

The availability of interaction data has increased substantially in a total of 4767 unique interactions. On average every drug is currently connected to the network theory to the drug–target interactions. This implicitly on data comple-

Novel paradigms for drug discovery: computational multitarget screening

Ekachai Jenwitheesuk^{1,2}, Jeremy A. Horst^{1,3}, Kasey L. Rivas⁴, Wesley C. Van Voorhies^{1,3} and Ram Samudrala^{1,3}

Analysis of multiple compound–protein interactions reveals novel bioactive molecules

Hiroaki Yabuuchi^{1,5}, Satoshi Nijima^{1,5}, Hiroemu Takematsu², Tomomi Ida¹, Takatsugu Hirokawa², Takafumi Hara⁴, Teppel Ogawa¹, Yohsuke Minowa¹, Gozoh Tsujimoto⁶ and Yasushi Okuno^{1,*,7}

Cell

Items Bioscience for Drug Discovery, Graduate School of Pharmaceutical Sciences, Kyoto University, Kyoto, Japan, ² Laboratory of Membrane Biology, Graduate School of Bioscience, Kyoto University, Kyoto, Japan, ³ Computational Protein Research Center, National Institute of Advanced Industrial Science and Technology, Tsukuba, Japan, ⁴ Department of Pharmacology, Faculty of Medicine, Kyoto University, Kyoto, Japan, ⁵ Department of Pharmacology, Faculty of Medicine, Kyoto University, Kyoto, Japan, ⁶ Department of Pharmacology, Faculty of Medicine, Kyoto University, Kyoto, Japan, ⁷ Department of Pharmacology, Faculty of Medicine, Kyoto University, Kyoto, Japan

Botanical Drugs, Synergy, and Network Pharmacology: Forth and Back to Intelligent Mixtures

Author: Jing Gertsch

Affiliation: Institute of Biochemistry and Molecular Medicine, University of Bern, Bern, Switzerland

Key words: polypharmacology, network pharmacology

Abstract: For centuries the science of pharmacognosy has

over monosubstances, mixtures of bioactive compounds in botanical drugs allegedly exert synergistic therapeutic effects. Despite evolutionary

J. Med. Chem. 2010, 53, 36

DOI: 10.1021/jm

nature biotechnology

Synergistic drug combinations tend to improve therapeutically relevant selectivity

Joseph Lehar^{1–3}, Andrew S. Krueger², William Avery¹, Adrian M. Heilbut¹, Lisa M. Johansen¹, E. Roydon Price¹, Richard I. Rickles¹, Glenn F. Short III¹, Jane F. Staunton¹, Xiaowei Jin¹, Margaret S.

Drug combinations limit the utility of synergy of a and 94,110 generally mor

Multi-Target QPDR Classification Model for Human Breast and Colon Cancer-Related Proteins using Star Graph Topological Indices

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¹REQUIMTE/Faculty of Science, Chemistry Department, University of Porto 4169-007, Portugal,

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Journal Medicinal Chemistry Article

Bivalent β -Carbolines as Potential Multitarget Anti-Alzheimer Agents

¹ Kai-Uwe Schmidtke,² Friedemann Gaube,³ Dirk Schepmann,⁵ Bernhard Wünsch,⁵ Jörg Heilmann,¹ and Thomas Winckler^{*,2}

¹ Pharmazie, Lehrstuhl für Pharmazeutische/Medicinische Chemie, Friedrich-Schiller-Universität Jena, Germany, ² Pharmazie, Lehrstuhl für Pharmazeutische Biologie, Friedrich-Schiller-Universität Jena, Semmelweisstrasse 10, D-07747 Jena, Germany, ³ Institut für Pharmazeutische und Medizinische Chemie der Westfälischen Wilhelms-Universität Münster, Germany, ⁴ Pharmazeutische Biologie, Universität Regensburg, Germany

July 4, 2010

Alzheimer's disease (AD) is a prevalent neurodegenerative disorder with multifactorial causes. It requires multitargeted treatment. Inhibitors of acetylcholinesterase (AChE) and butyrylcholinesterase (BChE) improve cholinergic signaling in the central nervous system and thus AChE inhibitors are highly effective in the therapy of AD. In addition, memory dysfunction and other cognitive symptoms

Outline

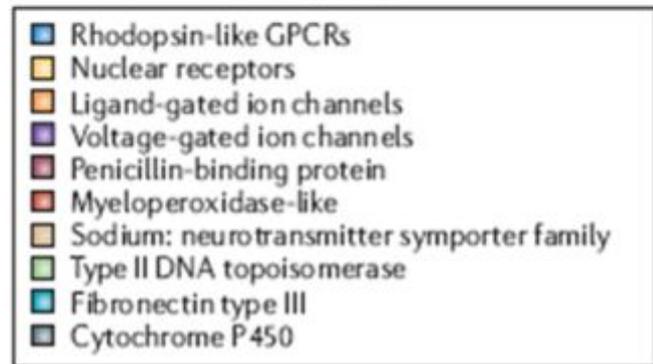
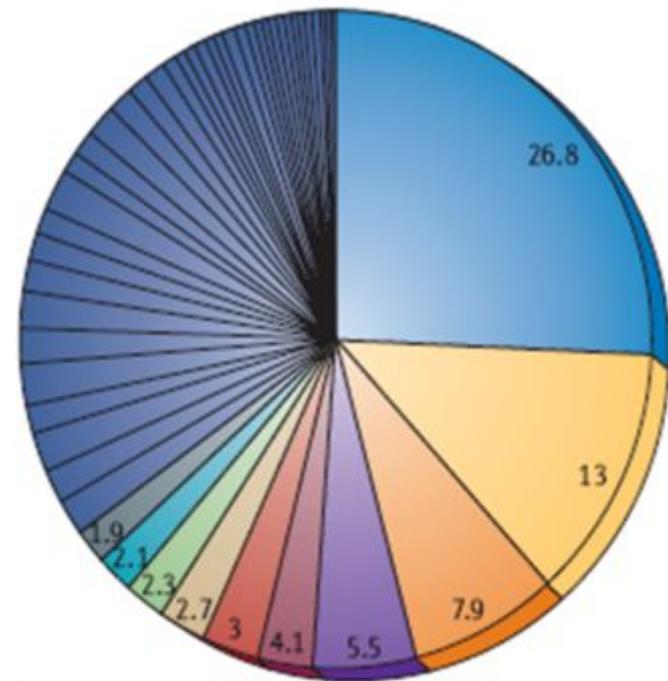
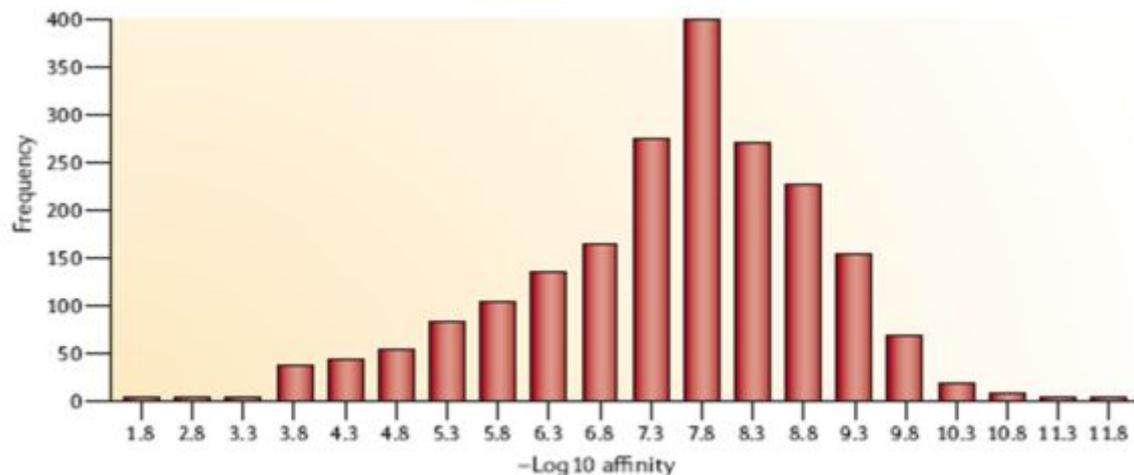
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How Many Drug Targets are There?

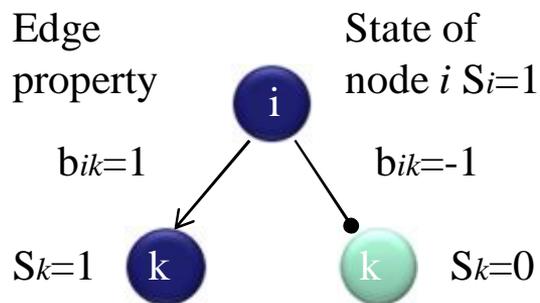
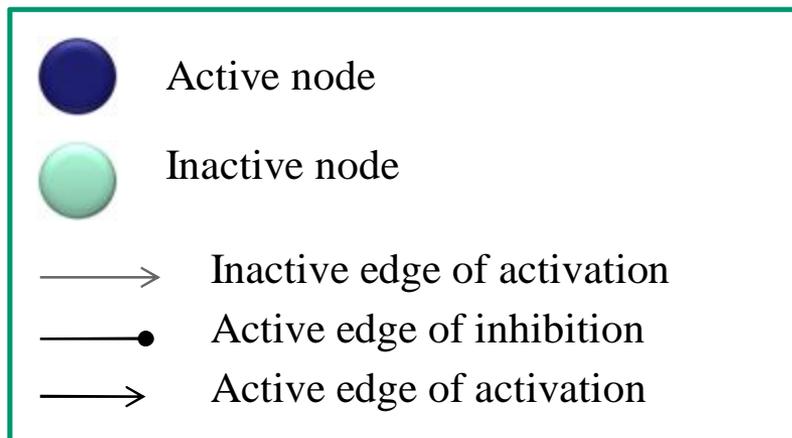
(Overington J.P et al. *Nat. Rev. Drug Discov.*, 2006, 5: 993-996)

Table 1 | Molecular targets of FDA-approved drugs

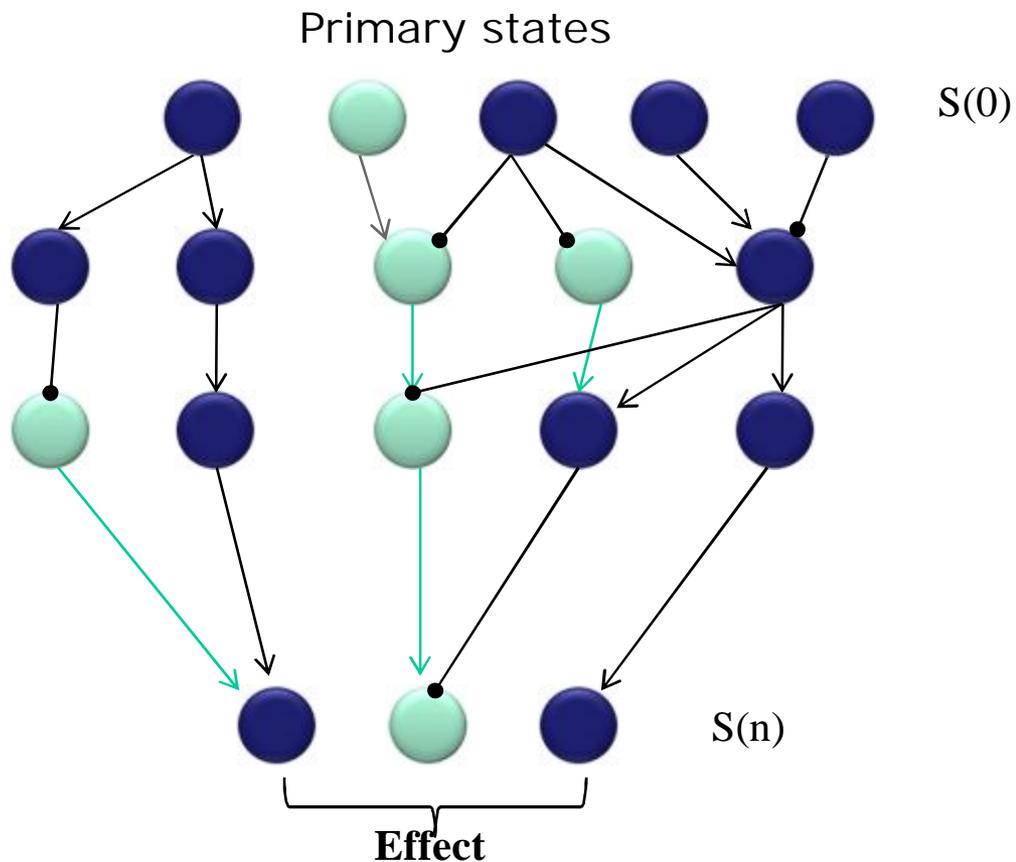
Class of drug target	Species	Number of molecular targets
Targets of approved drugs	Pathogen and human	324
Human genome targets of approved drugs	Human	266
Targets of approved small-molecule drugs	Pathogen and human	248
Targets of approved small-molecule drugs	Human	207
Targets of approved oral small-molecule drugs	Pathogen and human	227
Targets of approved oral small-molecule drugs	Human	186
Targets of approved therapeutic antibodies	Human	15
Targets of approved biologicals	Pathogen and human	76



Dichotomic Modeling of Regulatory Networks in NetFlowEx program



$$F_i(S_1, S_2, \dots, S_n) = \Theta(a_i + \sum_k S_k b_{ki})$$



Input Data for Breast Cancer Modeling

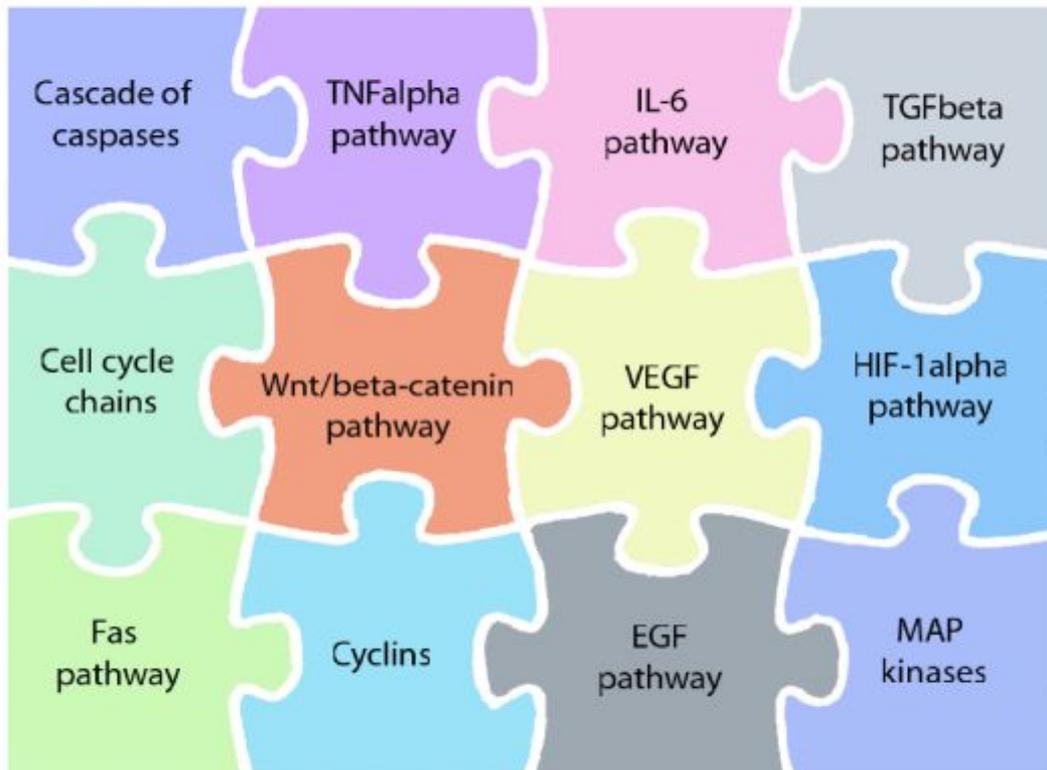
Regulatory network
TRANSPATH® database

Fragment: 2336 edges and 1405 nodes

**Microarray data for
breast cancer**

Cyclonet database

<http://cyclonet.biouml.org>



- ✓ HER2/neu-positive breast carcinomas.
- ✓ Ductal carcinoma.
- ✓ Invasive ductal carcinoma and/or a nodal metastasis.
- ✓ Generalized breast cancer.

Identified drug targets

Effect	Mechanism	HER2/neu positive breast carcinomas,	Ductal carcinoma	Invasive ductal carcinoma and/or a nodal metastasis	Generalized breast cancer
Cell cycle arrest	Cyclin D1:CDK4, Cyclin D1:CDK6 (G1 phase)	CYCD1, CYCLIN D1			
	Cyclin E:CDK2 (G1/S phase), Cyclin A:CDK2 (S phase)	CYCE, CYCLIN E, CDK2, PLK1, AKT-1			
		SYK	N/A	SRC	N/A
	Cyclin B:CDK1 (G2/M phase)	SYK	N/A	N/A	N/A
Induction of apoptosis	Cytochrome C	BCL-2			
		N/A	N/A	RAF-1, GRB-2, PKC, RACK1	Alpha5 Beta1 Fibronectin receptor, Fibronectin
	Caspase-3	MKK4, PI3K, MKK6, P38ALPHA, CRKL, HPK1			
N/A		N/A	VEGF-A, VEGFR-2, HIF-1ALPHA	N/A	

Some Double and Triple Targets' Combinations Identified For Breast Cancer

No	Number of compounds	Activity type	Activity type	Activity type
1	4	Bcl2 antagonist	Cyclin-dependent kinase 2 inhibitor	
2	10	Bcl2 antagonist	Myc inhibitor	
3	10	Bcl2 antagonist	Phosphatidylinositol 3-kinase beta inhibitor	
4	3	Cyclin-dependent kinase 2 inhibitor	Myc inhibitor	
5	7	Hypoxia inducible factor 1 alpha inhibitor	Myc inhibitor	
6	10	Hypoxia inducible factor 1 alpha inhibitor	Phosphatidylinositol 3-kinase beta inhibitor	
7	10	Myc inhibitor	Phosphatidylinositol 3-kinase inhibitor	
8	10	Bcl2 antagonist	Myc inhibitor	Phosphatidylinositol 3-kinase beta inhibitor

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- **Biological activity: many faces of the entity**
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PASS: Prediction of Activity Spectra for Substances

The screenshot displays the PASS software interface. At the top, the window title is "PASS - D:\AUREUS\Data Sets\Top 200 Drugs 2009.sdf". The menu bar includes "File", "Base", "Predict", "View", "Options", and "Help". The toolbar shows icons for file operations and a dropdown menu set to "Pa > Pi". The main window shows a list of chemical structures with their corresponding activity predictions. Structure 29 is highlighted, showing a chemical structure and an "Activity Description" window that reads: "Purinergic P2Y12 antagonist. Substance that binds to purinergic P2Y12 receptor and prevents its stimulation." To the right, a "Purinergic P2Y12 antagonist" chart is visible, showing a heatmap of activity predictions across various categories. Below the main window, an "About PASS" dialog box is open, providing details about the software version and copyright information.

SAR Base Information

Substances	266697
Descriptors	69734
Activity Types	5825
Selected Activity Types	4130
Average IEP	4.477, %
Prediction	<input checked="" type="checkbox"/> Enabled

About PASS

PASS Prediction of Activity Spectra for Substances

Version 10.1 *Professional*

Copyright © 1992-2010

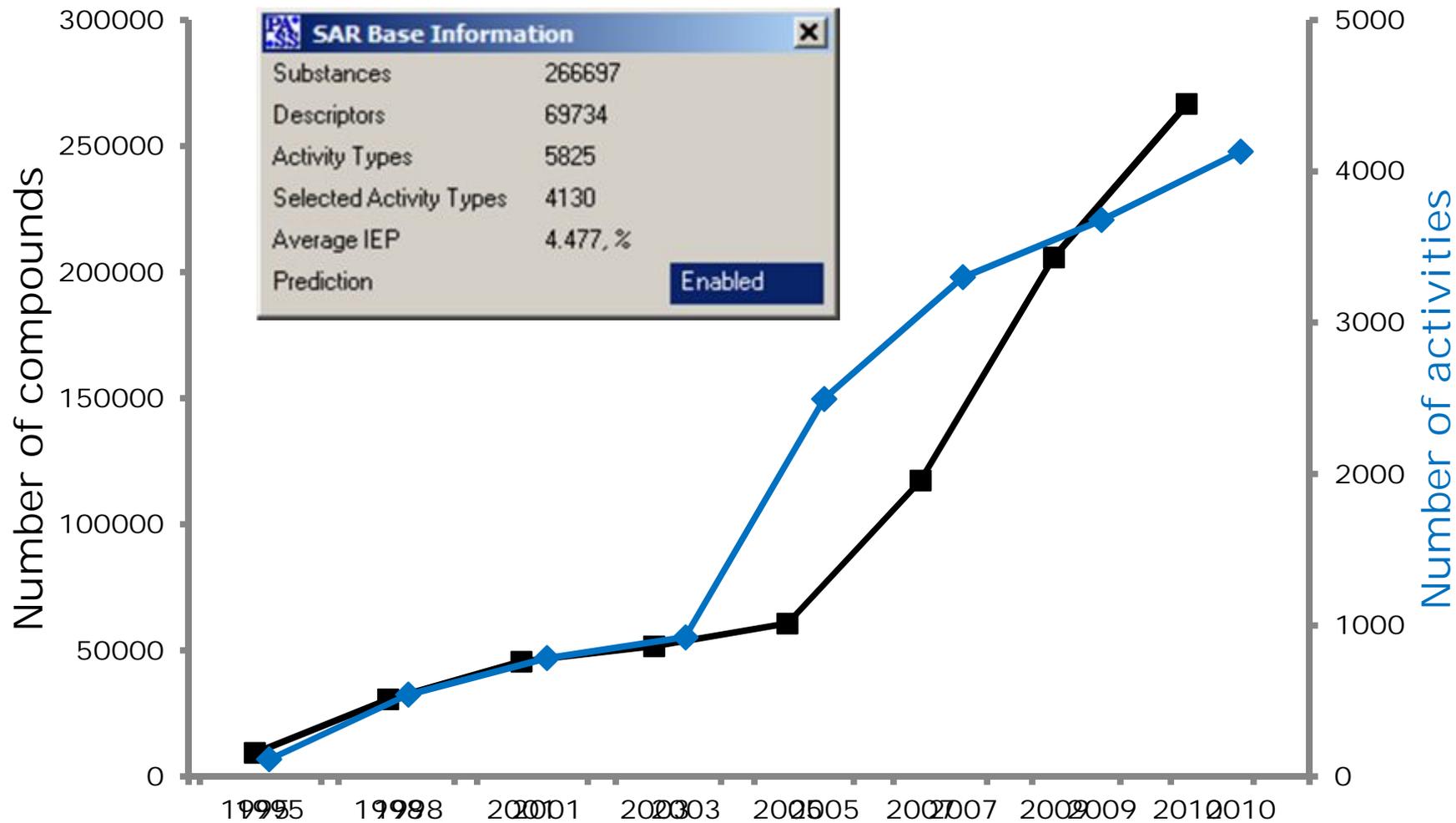
V. Poroikov, D. Filimonov & Associates

<http://www.ibmc.msk.ru/PASS>

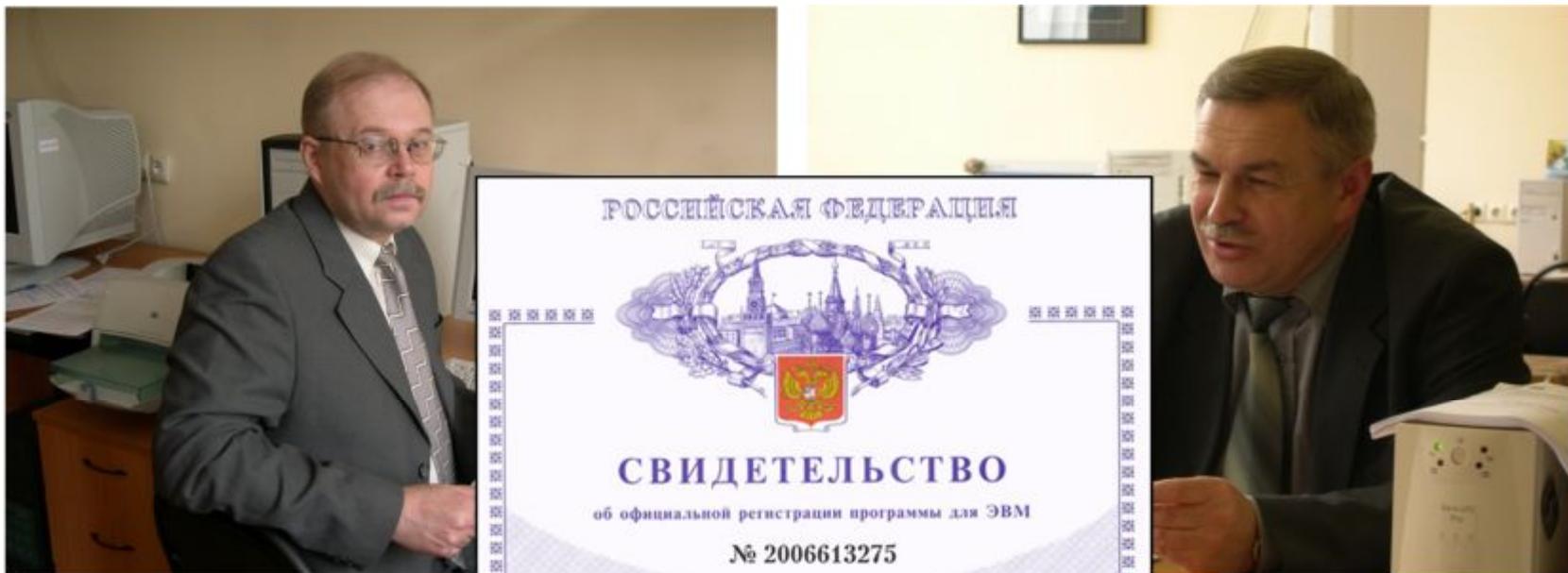
53 of 501 Possible Pharmacological Effects
69 of 3295 Possible Molecular Mechanisms
4 of 57 Possible Side Effects and Toxicity
16 of 199 Possible Metabolism-Related Actions
3 of 29 Possible Gene Expression Regulation
1 of 49 Possible Transporters-Related Actions

29/154 0.868 0.001 Purinergic P2Y12 antagonist

PASS Training Set



The key persons in PASS development



PASS Approach is Described in Detail:

Filimonov D.A., Poroikov V.V. (2008). Probabilistic Approach in Virtual Screening. In: *Chemoinformatics Approaches to Virtual Screening*. Alexander Varnek and Alexander Tropsha, Eds. RSC Publishing, 182-216.

Filimonov D.A., Poroikov V.V. (2006). Prediction of biological activity spectra for organic compounds. *Russian Chemical Journal*, 50 (2), 66-75.

Poroikov V., Filimonov D. (2005). PASS: Prediction of Biological Activity Spectra for Substances. In: *Predictive Toxicology*. Ed. by Christoph Helma. N.Y.: Taylor & Fransis, 459-478.

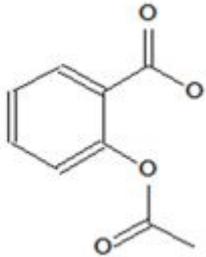
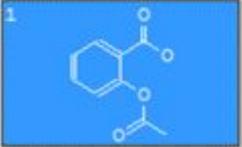
<http://pharmaexpert.ru/passonline>

Structural Formula of Acetylsalicylate

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GRAPH | TEXT | MNA

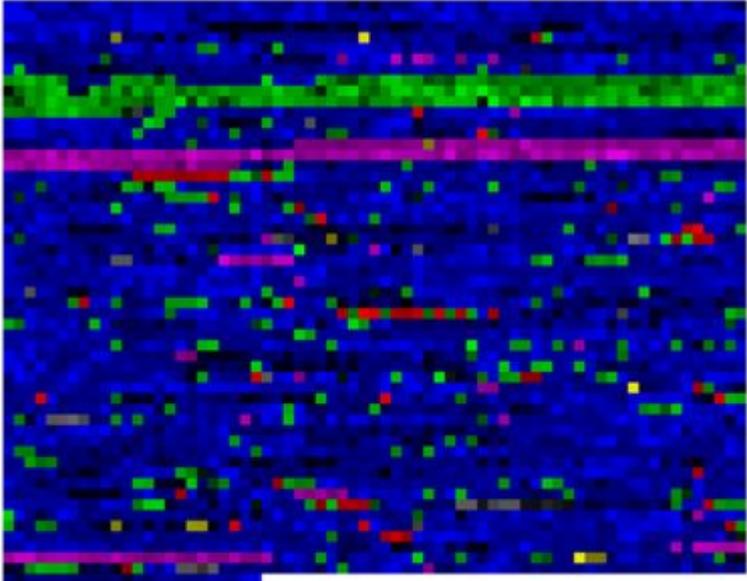
1



CC(=O)Oc1ccc(cc1)C(=O)O

No Selected Activity

Chart | General | Effects | Mechanisms | Toxicity | Metabolism | Genes | Transporters



25 Substructure Descriptors; 0 new.
There are 62 known activities.
Drug-Likeness: 0.554

1217 of 3750 Possible Activities
160 of 417 Possible Pharmacological Effects
937 of 3036 Possible Molecular Mechanisms
40 of 55 Possible Side Effects and Toxicity
75 of 196 Possible Metabolism-Related Actions
3 of 11 Possible Gene Expression Regulation
2 of 35 Possible Transporters-Related Actions

1/1

MOL File of Acetylsalicylate

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GRAPH TEXT MNA

1

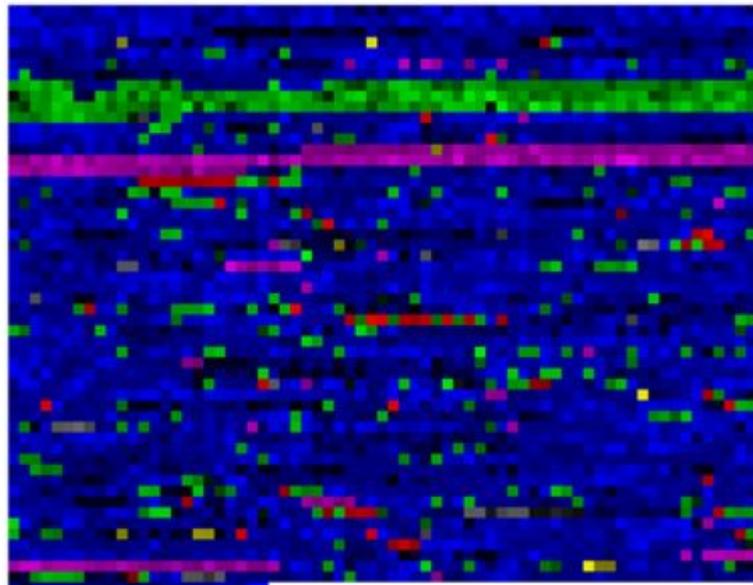


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3.5099 -4.1732 0.0000 C 0 0 0 0 0 0 0 0 0 0 0 0
4.2190 -4.5875 0.0000 C 0 0 0 0 0 0 0 0 0 0 0 0
4.9340 -4.1799 0.0000 C 0 0 0 0 0 0 0 0 0 0 0 0
4.9353 -3.3535 0.0000 C 0 0 0 0 0 0 0 0 0 0 0 0
4.2255 -2.9428 0.0000 C 0 0 0 0 0 0 0 0 0 0 0 0
5.6458 -2.9333 0.0000 C 0 0 0 0 0 0 0 0 0 0 0 0
5.6417 -2.1083 0.0000 O 0 0 0 0 0 0 0 0 0 0 0 0
6.3583 -3.3458 0.0000 O 0 0 0 0 0 0 0 0 0 0 0 0
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5.6417 -5.4167 0.0000 O 0 0 0 0 0 0 0 0 0 0 0 0
4.9250 -5.8250 0.0000 O 0 0 0 0 0 0 0 0 0 0 0 0
6.3542 -5.8292 0.0000 C 0 0 0 0 0 0 0 0 0 0 0 0
1 2 2 0 0 0 0
5 7 1 0 0 0 0
3 4 2 0 0 0 0
7 8 2 0 0 0 0
7 9 1 0 0 0 0
4 5 1 0 0 0 0
4 10 1 0 0 0 0
2 3 1 0 0 0 0
10 11 1 0 0 0 0
5 6 2 0 0 0 0
11 12 2 0 0 0 0
6 1 1 0 0 0 0
11 13 1 0 0 0 0
M END
```

No Selected Activity

Chart General Effects Mechanisms Toxicity Metabolism Genes Transporters



25 Substructure Descriptors: 0 new.
There are 62 known activities.
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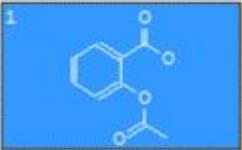
1/1

MNA Descriptors of Acetylsalicylate

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GRAPH | TEXT | MNA

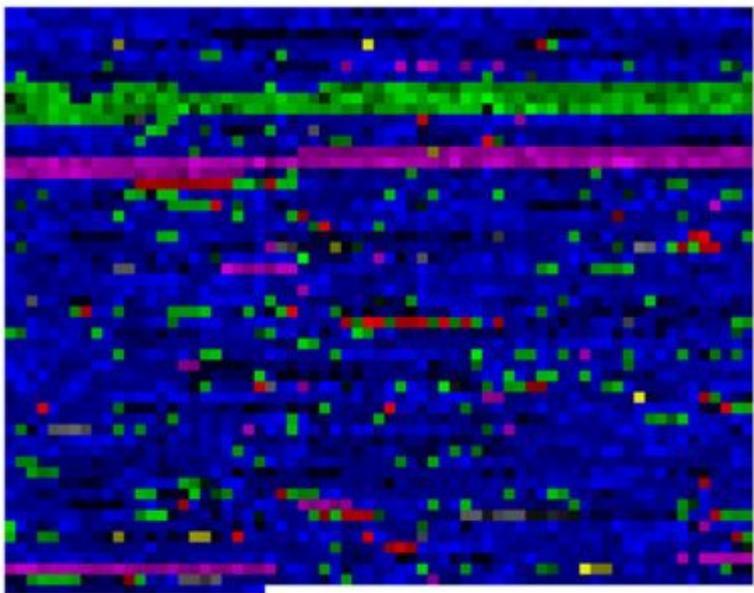
1



HC
HO
CHHHC
CHCC
CCCC
CCCO
CCOO
OHC
OC
OCC
C(C(C(H)C(C(H)H(C))
C(C(C(H)C(C(C)H(C))
C(C(C(H)C(C(C)O(C(C))
C(C(C(H)C(C(O)H(C))
C(C(C(H)C(C(O)C(C(O)O))
-H(C(C(H))
-H(C(H-H-H-C))
-H(O(H-C))
-C(C(C(C)O(H-C)O(C))
-C(H(C)H(C)H(C)C(C(O)O))
-C(C(H-H-H-C)O(C(C)O(C))
-O(C(C(O)C(C(O)O))
-O(H(O)C(C(O)O))
-O(C(C(O)O))
-O(C(C(O)O))

No Selected Activity

Chart | General | Effects | Mechanisms | Toxicity | Metabolism | Genes | Transporters



25 Substructure Descriptors; 0 new.
There are 62 known activities.
Drug-Likeness: 0.554

1217 of 3750 Possible Activities
160 of 417 Possible Pharmacological Effects
937 of 3036 Possible Molecular Mechanisms
40 of 55 Possible Side Effects and Toxicity
75 of 196 Possible Metabolism-Related Actions
3 of 11 Possible Gene Expression Regulation
2 of 35 Possible Transporters-Related Actions

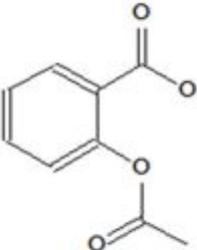
1/1

Biological Activity Predicted for Acetylsalicylate

C:\ACTUAL\DATABASES\TEST-MOLECULES\acetylsalicylate.mol

GRAPH | TEXT | MNA

1



1217 of 3750 Possible Activities at Pa > 0.300

0.956	0.003	Fibrinolytic
0.935	0.013	Transferase stimulant
0.924	0.003	Prolyl aminopeptidase inhibitor
0.921	0.004	Antiseborrheic
0.917	0.005	Alkylglycerophosphocholine hydrolase inhibitor
0.912	0.005	Chlordecone reductase inhibitor
0.909	0.003	Dehydro-L-gulonate decarboxylase inhibitor
0.907	0.003	Arginine 2-monooxygenase inhibitor
0.910	0.009	Methylenetetrahydrofolate reductase (NADPH) inhibitor
0.904	0.005	Glucose oxidase inhibitor
0.905	0.009	Retinal oxidase inhibitor
0.897	0.003	Antiinflammatory, pancreatic
0.896	0.003	Glutathione thioesterase inhibitor
0.897	0.004	Monodehydroascorbate reductase (NADH) inhibitor
0.900	0.009	Testosterone 17beta-dehydrogenase (NADP+) inhibitor
0.895	0.004	Phosphatidylethanolamine N-methyltransferase inhibitor
0.893	0.006	Sugar-phosphatase inhibitor
0.889	0.003	Phosphatidylcholine-retinol O-acyltransferase inhibitor
0.888	0.003	NADPH-cytochrome-c2 reductase inhibitor
0.888	0.004	Dextranase inhibitor
0.888	0.004	Arylsulfate sulfotransferase inhibitor
0.884	0.005	Arylacetonitrilase inhibitor
0.879	0.002	Glycerol dehydratase inhibitor
0.879	0.003	Antipyretic

25 Substructure Descriptors; 0 new.
There are 62 known activities.
Drug-Likeness: 0.554

1217 of 3750 Possible Activities
160 of 417 Possible Pharmacological Effects
937 of 3036 Possible Molecular Mechanisms
40 of 55 Possible Side Effects and Toxicity
75 of 196 Possible Metabolism-Related Actions
3 of 11 Possible Gene Expression Regulation
2 of 35 Possible Transporters-Related Actions

1/1

Online Biological Activity Prediction with PASS

The screenshot displays the PHARMAEXPERT Predictive Services website. At the top left is the logo "PHARMAEXPERT PREDICTIVE SERVICES". A navigation menu includes links for Home, Definition, Products, Services, FAQ, and Contacts. The main banner features the text "PASS online" in large blue letters, with the tagline "Better solutions for your research and development" and "It is easy to use" below it. A "GO" button is positioned to the right of the banner. Below the banner, there is a section titled "Get more information about biological potential of your compounds." and another section titled "News" with a date "29 Mar" and a snippet of text: "In silico finding of multitargeted pharmacological agents. Oral presentation of Vladimir Poroikov 'Computer-aided approaches to virtual screening and rational design of multitargeted drugs' at the 23 Conference in Computational".

<http://pharmaexpert.ru/passonline>

Input of the Structural Formula (Clopidogrel)

PASS PREDICTION

Please, enter your structure

Attach MOL file

Обзор...

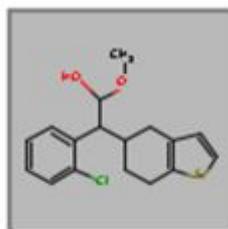
Get Prediction

To find out the information about MOL file, click [here](#)

OR

Use of Marvin Applet (<http://www.chemaxon.com>)

To run the applet, you need the [Java](#) x86 installed on your PC



Get Prediction

Results of Prediction for Clopidogrel

Results

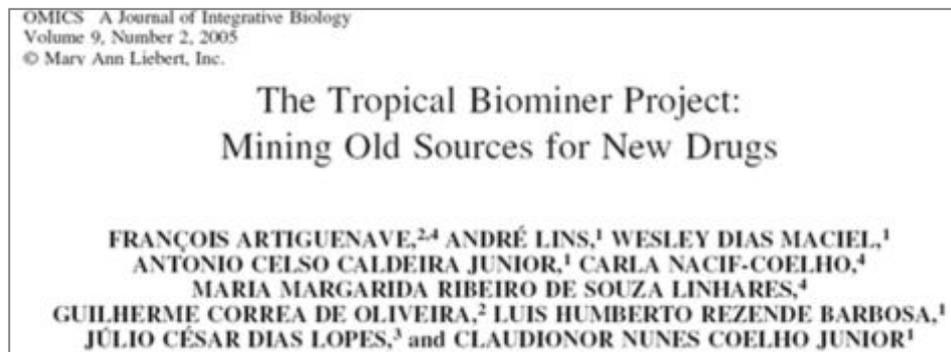
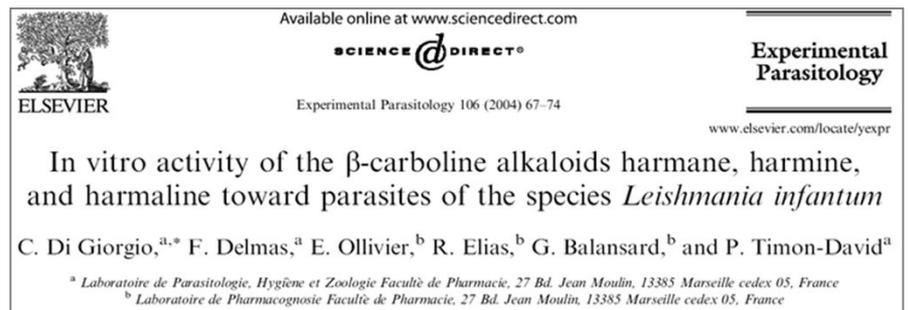
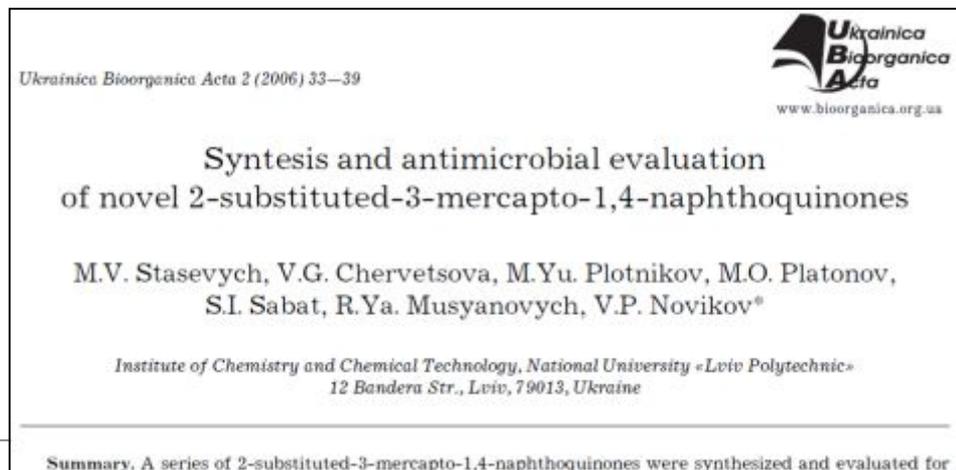
All
 Pa>Pi
 Pa>30%
 Pa>70%

ok

Pa	Pi	Activity	
0,947	0,005	Neuroprotector	+
0,801	0,007	Antithrombotic	+
0,740	0,037	Amyotrophic lateral sclerosis treatment	
0,697	0,005	Platelet aggregation inhibitor	+
0,687	0,012	Acute neurologic disorders treatment	+
0,679	0,013	Atherosclerosis treatment	
0,625	0,009	Sleep disorders treatment	
0,597	0,010	Angiogenesis inhibitor	+
0,596	0,025	Analgesic	
0,667	0,099	Cardioprotectant	
0,634	0,082	Hepatotoxic	
0,605	0,075	Dopamine D4 agonist	
0,549	0,022	Antianginal	
0,536	0,032	Antipsoriatic	+
0,520	0,051	Antiarthritic	+
0,435	0,004	Platelet antagonist	+
0,423	0,009	Glutamate (mGluR1) antagonist	+
0,412	0,011	Glutamate (mGluR group I) antagonist	+
0,426	0,035	Monoamine uptake inhibitor	
0,410	0,030	Anticoagulant	+

...

Over Forty Publications with Independent Confirmation of PASS INet Predictions



For review see: Geronikaki A. et al. *SAR & QSAR Environ. Res.*, 2008, 19, 27.

PharmaExpert: Selection of Multitargeted Ligands

PharmaExpert

File Tools View Help

Pa > 0.100

Prediction & Interpretation - G:\work\Net2Drug>Last_report\twenty_structures-analogi-mol-2_PASS.SDF, 4/20

1 2 3 4 5 6 7

Save TXT Save SD Clipboard Exclude

Pa Pi Types of Activities Pa/Pi descending

Pa Pi AutoID

Pa	Pi	Types of Activities
0.681	0.003	Myc inhibitor
0.323	0.005	Mcl-1 antagonist
0.331	0.140	Kinase inhibitor
0.162	0.022	Bcl2 antagonist
0.291	0.237	Interleukin alpha agonist
0.145	0.094	Bcl-xL inhibitor
0.255	0.215	Transforming growth factor agonist
0.110	0.067	Interleukin 2 antagonist

Check non predicted activities Calculation

Effect Mechanisms Toxicity Metabolism Transport Gene Expression

Pa Pi (-)-limonene 6-monooxygenase inhibitor Drug-likeness > 0 New Descriptors >= 0

Number of selected compounds:

AutoID 4: < DRUG_LIKENESS > 0.339; 52 Substructure descriptors, 2 new; 8 Possible activities.

Multitargeted actions

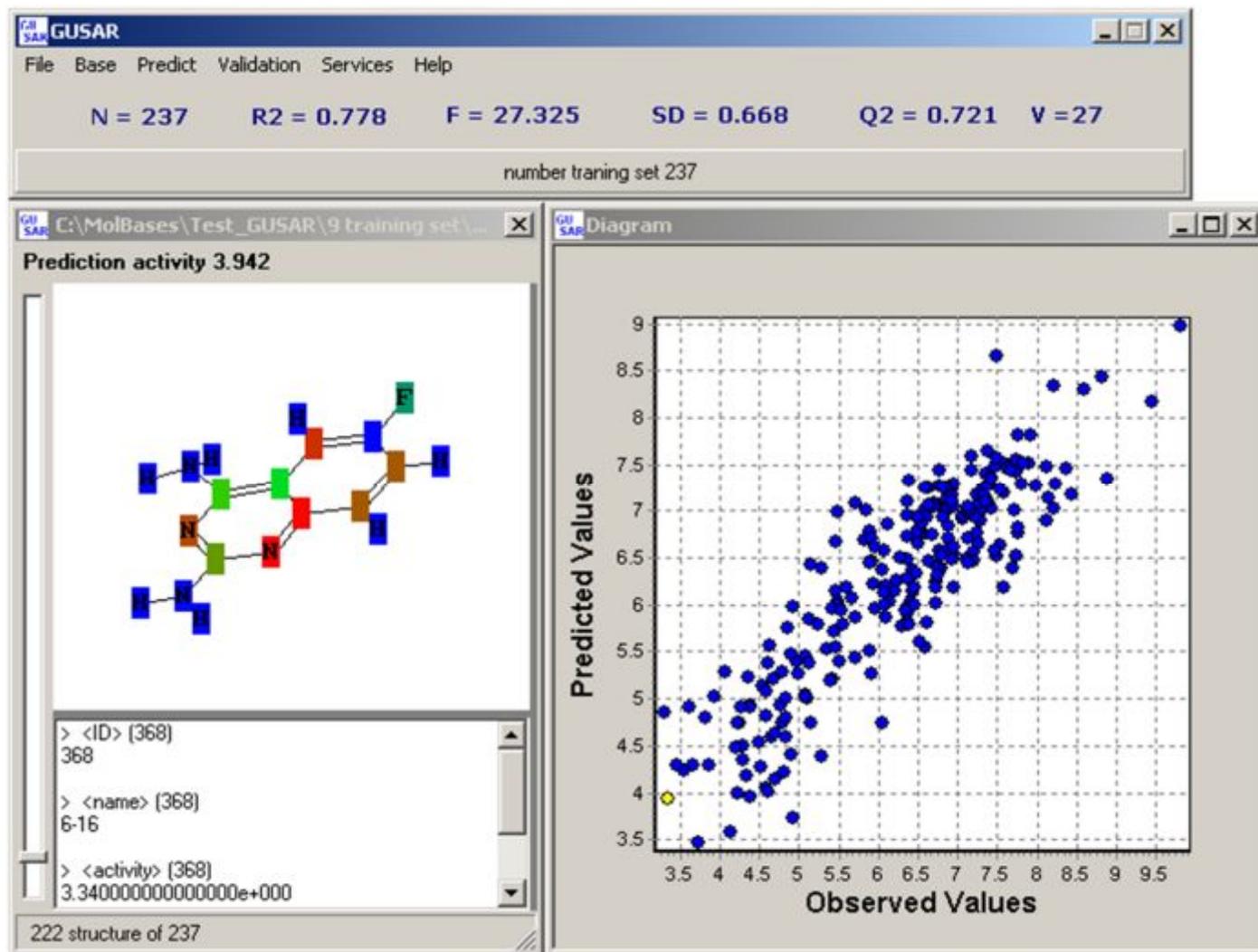
Effects

Number of targets: 3 Run Load Save

[N-acetylneuraminyl]galactosylglucosylceramide N-acetylgalactosaminyltransferase inhibitor
 3 Beta-hydroxy-delta 5-steroid dehydrogenase inhibitor
 5 Lipopase inhibitor
 5 Alpha-reductase inhibitor
 ABCA1 expression enhancer
 Abl kinase inhibitor
 Acetylcholine nicotinic antagonist
 ADAM10 endopeptidase inhibitor
 Adenosine A3 receptor agonist
 Adenylate cyclase inhibitor
 ADP ribose polymerase 1 inhibitor
 ADP ribose polymerase inhibitor
 Aggrucanase inhibitor
 AICAR transforlyase inhibitor
 Alkylphospholipid
 Aminopeptidase microsomal inhibitor
 Aminopeptidase N inhibitor
 AMPA receptor antagonist
 Androgen antagonist
 Aromatase inhibitor
 Aspartate carboxyltransferase inhibitor
 ATM kinase inhibitor
 ATPase (Vacuolar H+) inhibitor

No	Pa	Number	Activity type	Activity type
1	0.146	2	Bcl2 antagonist	Bcl-xL inhibitor
2	0.227	1	Bcl2 antagonist	Cyclin-dependent kinase 9 inhibitor
3	0.291	1	Bcl2 antagonist	Interleukin alpha agonist
4	0.121	3	Bcl2 antagonist	Interleukin 2 antagonist
5	0.364	3	Bcl2 antagonist	Kinase inhibitor
6	0.323	3	Bcl2 antagonist	Mcl-1 antagonist
7	0.706	3	Bcl2 antagonist	Myc inhibitor
8	0.255	1	Bcl2 antagonist	Transforming growth factor agonist
9	0.227	1	Bcl-xL inhibitor	Cyclin-dependent kinase 9 inhibitor
10	0.291	1	Bcl-xL inhibitor	Interleukin alpha agonist
11	0.110	2	Bcl-xL inhibitor	Interleukin 2 antagonist
12	0.331	2	Bcl-xL inhibitor	Kinase inhibitor
13	0.323	2	Bcl-xL inhibitor	Mcl-1 antagonist
14	0.681	2	Bcl-xL inhibitor	Myc inhibitor
15	0.255	1	Bcl-xL inhibitor	Transforming growth factor agonist
16	0.582	1	Cyclin-dependent kinase 2 inhibitor	Cyclin-dependent kinase 4 inhibitor
17	0.167	1	Cyclin-dependent kinase 2 inhibitor	Gelatinase inhibitor
18	0.303	1	Cyclin-dependent kinase 2 inhibitor	Guanylate cyclase stimulant
19	0.404	2	Cyclin-dependent kinase 2 inhibitor	Kinase inhibitor
20	0.676	2	Cyclin-dependent kinase 2 inhibitor	Myc inhibitor
21	0.284	1	Cyclin-dependent kinase 2 inhibitor	Neuropeptide antagonist
22	0.303	1	Cyclin-dependent kinase 4 inhibitor	Guanylate cyclase stimulant

GUSAR: General Unrestricted Structure-Activity Relationships



Multitargeted QSAR



RELIABLE QUANTITATIVE-STRUCTURE ACTIVITY
RELATIONSHIPS FOR YOUR CHEMICAL COMPOUNDS

WWW.PHARMAEXPERT.RU

GUSAR

QSAR METHOD

APPLICABILITY DOMAIN

CONSENSUS

REFERENCES

Acute Rat Toxicity

Antitargets

Environmental



SOLUTIONS
FOR YOUR RESEARCH

[DRAW STRUCTURE](#)

APPROACH TO YOUR QSAR MODELLING

GUSAR software was developed to create QSAR/QSPR models on the basis of the appropriate training sets represented as SDfile contained data about chemical structures and endpoint in quantitative terms.



<http://pharmaexpert.ru/gusar>

Outline

- Biological activity: many faces of the entity
- **Identification of the most promising targets**
 - **Net2Drug**
- Identification of the most promising lead compounds
 - **PASS**
 - **PharmaExpert**
 - **GUSAR**
- **Examples of applications**
- Summary

Finding of New Antihypertensive Agents with Dual Mechanisms of Action

About 30 mechanism of antihypertensive action was available in PASS in 2001.

Prediction of Biological Activity Spectra were performed for ~180,000 compounds from ChemBridge и AsInEx databases.

Compounds with predicted dual mechanisms of antihypertensive action were identified.

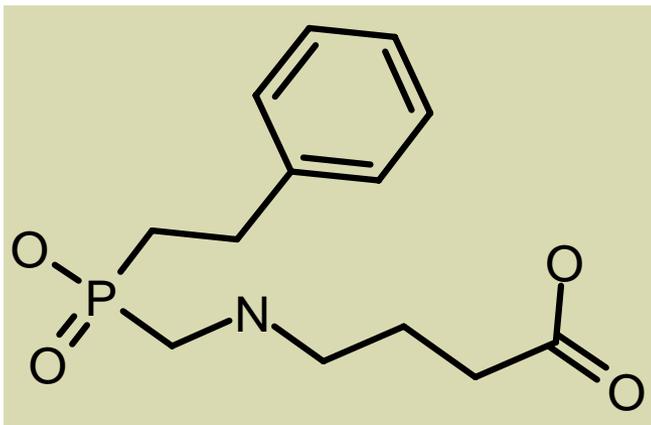
Four selected compounds were tested *in vitro* as inhibitors of ACE and NEP.

Some unknown combinations of the antihypertensive mechanisms were found.

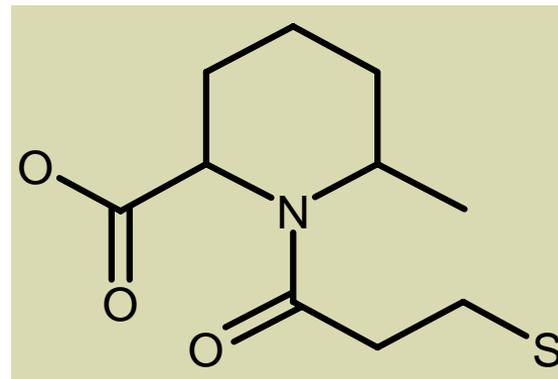
Lagunin A.A. et al. J. Med. Chem., 2003, 46, 3326.

All four studied compounds were shown to be the inhibitors of both ACE and NEP with IC_{50} in range 10^{-7} - 10^{-9} M.

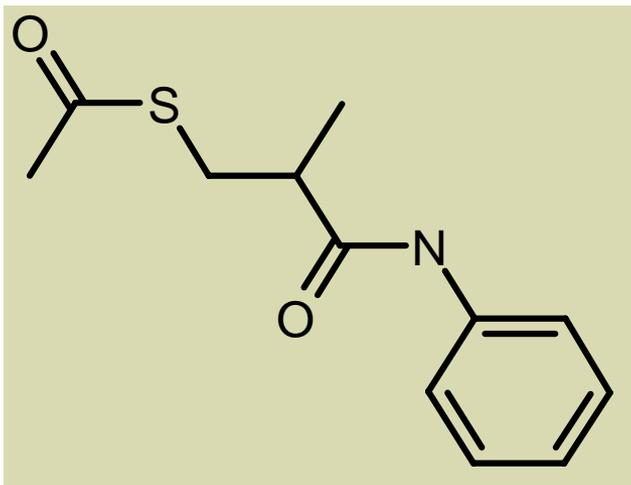
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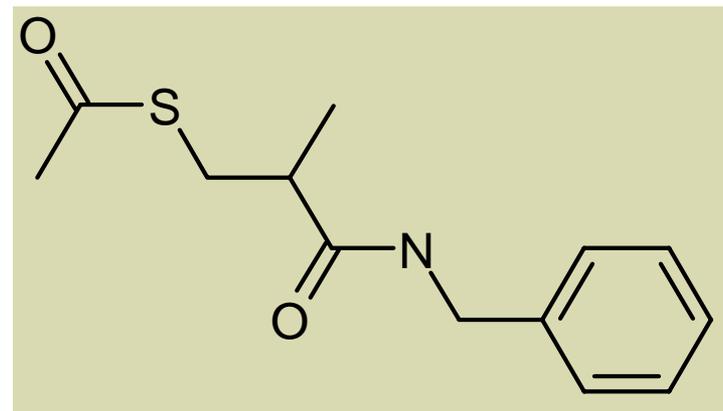
2



3



4



Lagunin A.A. et al. J. Med. Chem., 2003, 46, 3326.

ChemNavigator Library: The Biggest Source of Commercially Available Samples



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iResearch™ Library

The iResearch Library is ChemNavigator's up-to-date compilation of commercially accessible screening compounds from international chemistry suppliers. The database currently tracks over 91.5 million chemical samples. Database licenses include access to regular updates, sourcing information, and ChemNavigator's optional Chemistry Procurement Service. The database may be licensed on CD/DVD ROM or accessed through an on-line iResearch System subscription.

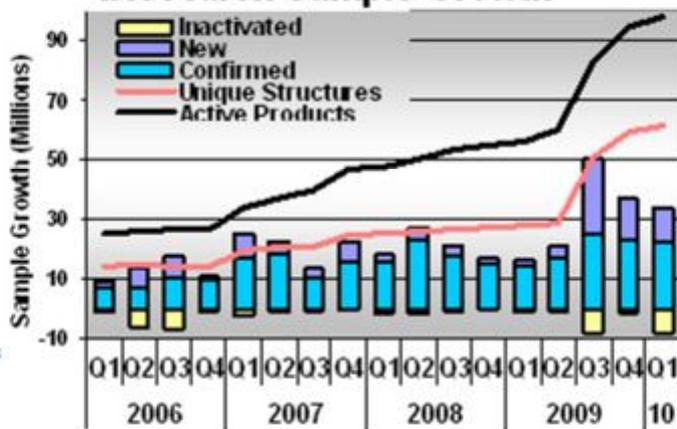
Sample Growth

Over the past 3 years the number of chemical samples registered into the iResearch Library has grown to over 91.5 Million chemical samples.

Update Frequency

The iResearch Library is updated on a weekly basis. We process over 1 million sample record updates per month to provide our clients the most comprehensive and up-to-date view of chemistry for drug discovery.

iResearch Sample Growth



Year	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1
2006	10	10	10	10	10	10	10	10	10	10	10	10	10
2007	15	15	15	15	15	15	15	15	15	15	15	15	15
2008	20	20	20	20	20	20	20	20	20	20	20	20	20
2009	25	25	25	25	25	25	25	25	25	25	25	25	25
2010	30	30	30	30	30	30	30	30	30	30	30	30	30

iResearch Library Facts

- Over **91.5** million chemical structures (over **55.3** million unique)
- More than **301** chemistry suppliers represented
- Broad diversity (more than **56000** unique ring systems)
- Database represents current view of commercial compounds

Suppliers

Chemical suppliers, Looking to grow your chemistry business? Over 30 commercial pharmaceutical research organizations use the iResearch Library to identify chemistry for their research programs.

[Read more](#) about the ChemNavigator suppliers.

Finding of Multitargeted Anticancer Agents in ChemNavigator Library

PASS prediction of selected anticancer activities were executed for 24 mln chemical compounds from ChemNavigator library (<http://chemnavigator.com>).

About 335,000 chemical compounds were identified as probable anticancer hits at cutoff $P_a > 50\%$.

Hits for 23 double and 4 triple combinations of targets with $P_a > 50\%$ were found (~6,500 compounds).

Sixteen GUSAR models were applied for identification of probable mechanisms of action.

Net2Drug program was used for the analysis of double and triple nodes' blockade influence on the network behavior.

64 chemical compounds were selected on the basis of PASS predictions; 26 samples were purchased for anticancer testing in Karolinska Institute (Sweden).

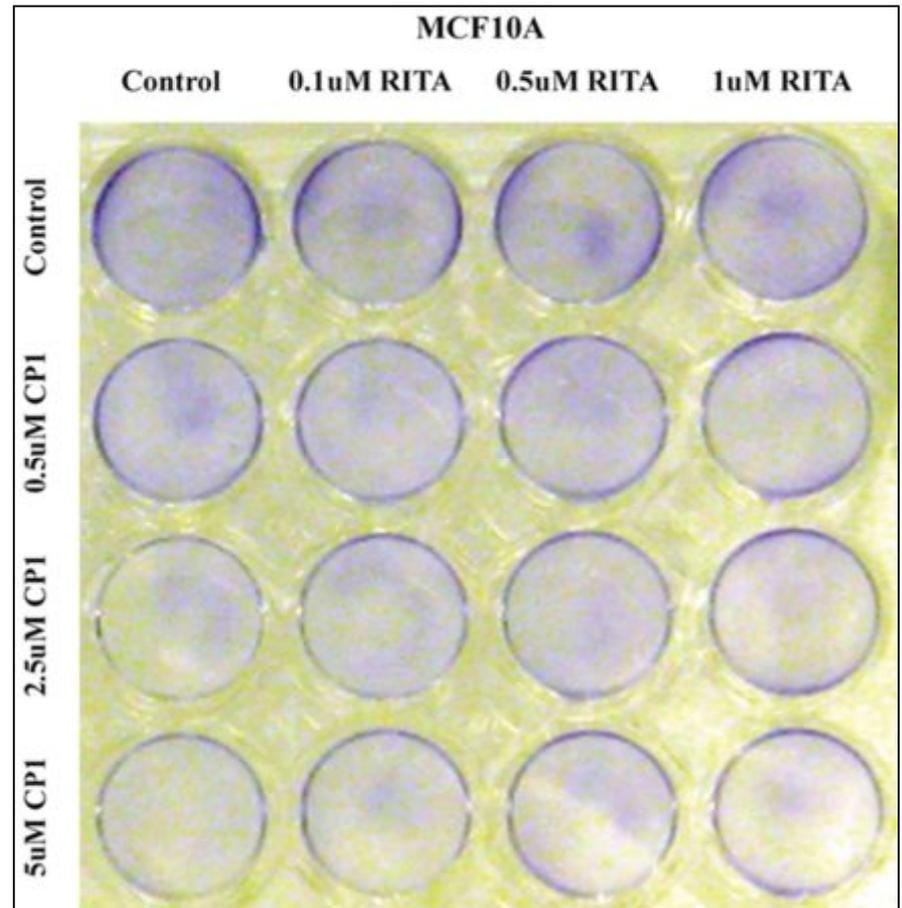
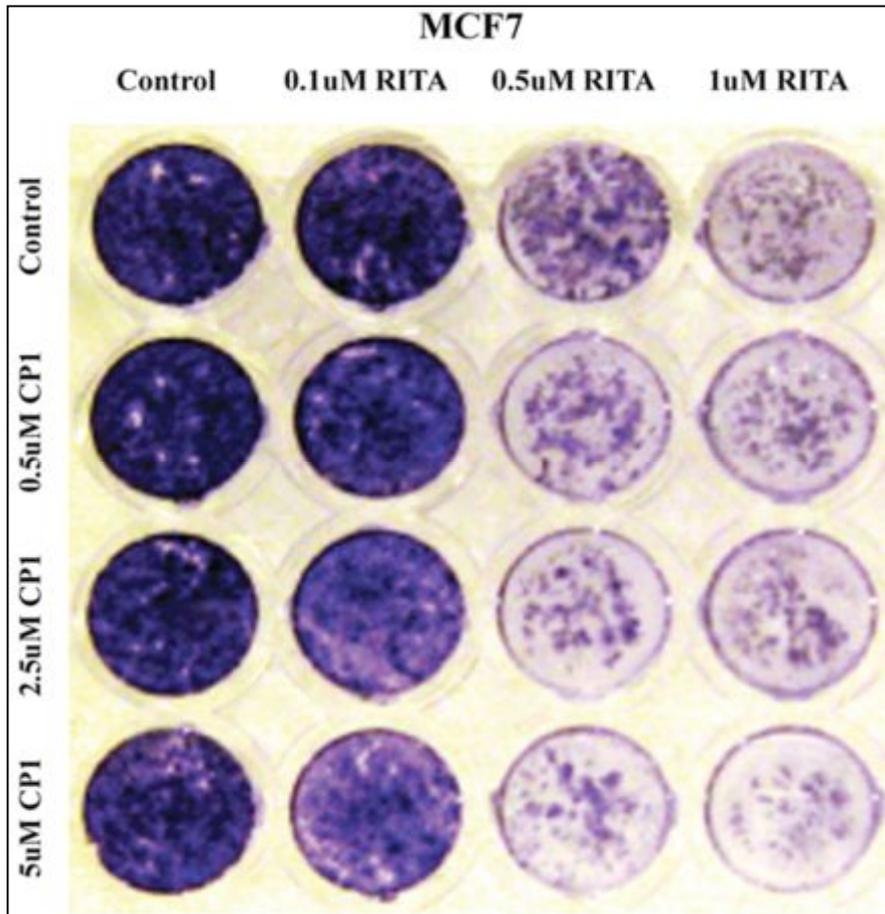
Results of Biological Testing in Cancer Cell Lines

Out of 16 soluble compounds only one (**Molecule I, CPI**) showed growth suppression in 3 different **breast cancer** cell lines - at 10 μM . Quite good killing of breast cancer cells, but still 1 μM RITA was much better (it was used in parallel as a positive control). The effect appears to be p53-independent (kills p53-null colon cancer cells) and it does not affect the growth of non-transformed mammary epithelial cells.

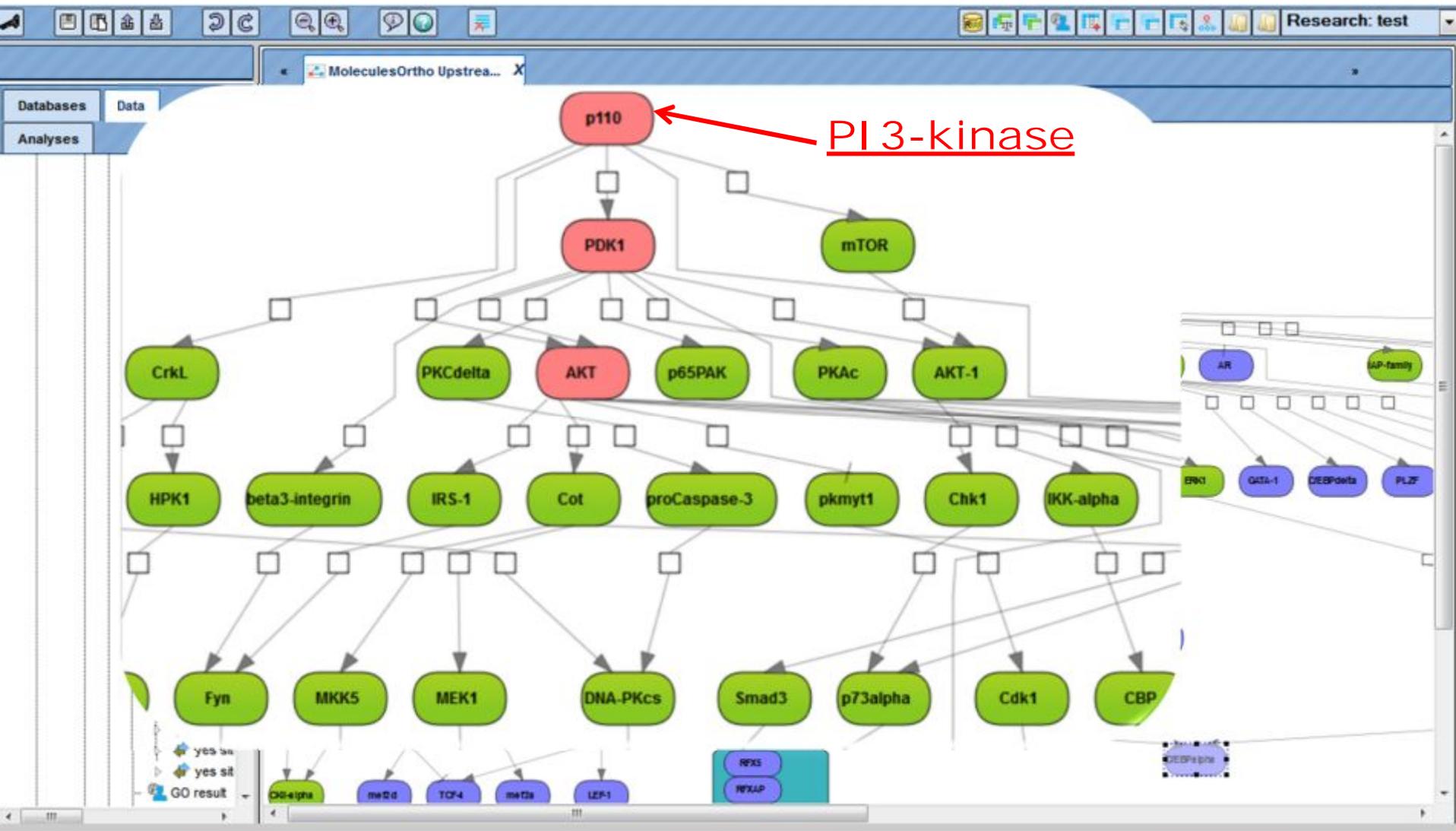
One more compound (**Molecule II**) could be interesting - but not in breast cancer. Out of panel of 7 different cancer lines it killed only **melanoma** cells. It kills only melanoma cells without any effects in other cell lines.

Galina Selivanova, Karolinska Institute, Sweden

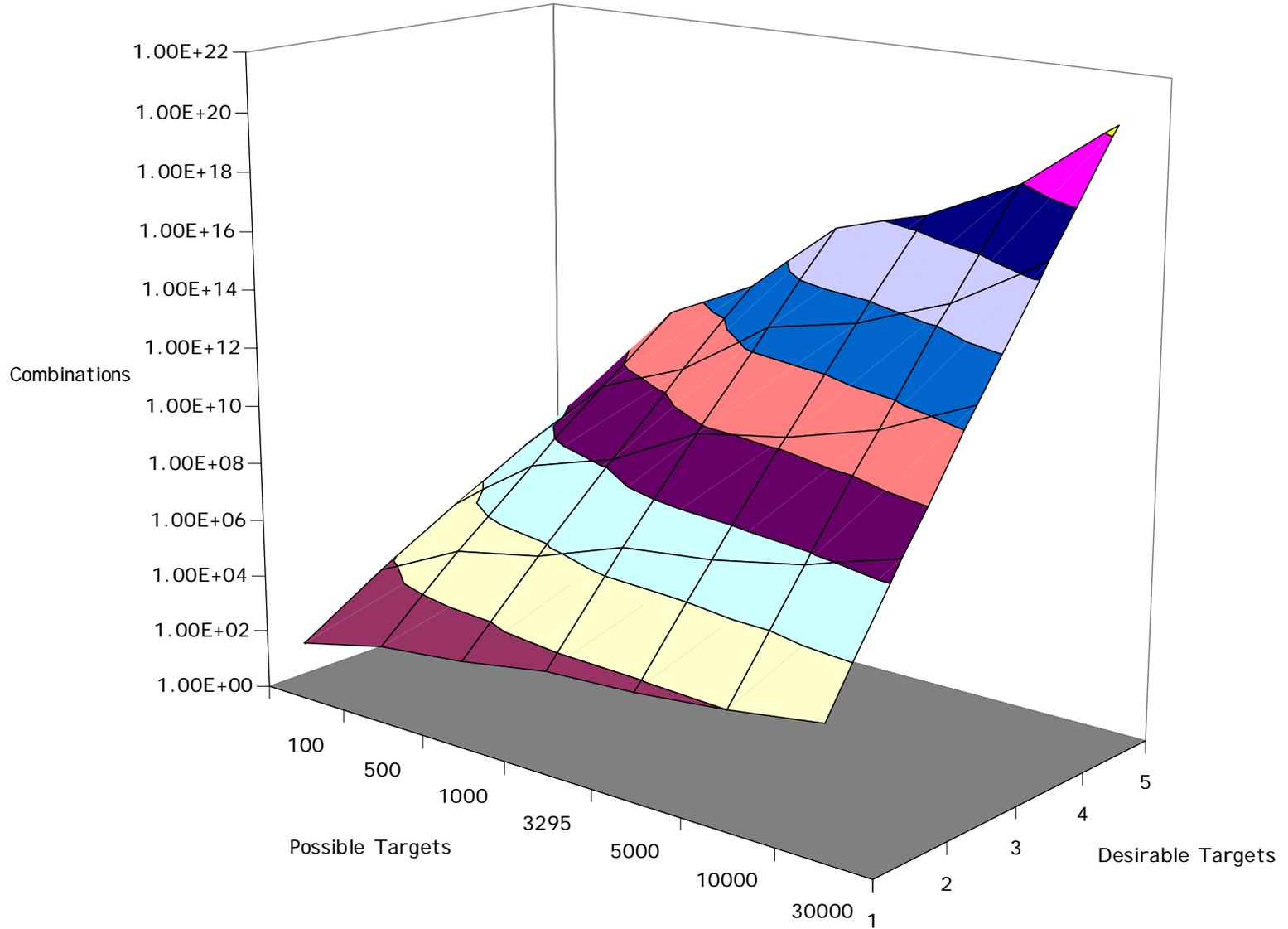
Synergistic effect was observed between CPI and Rita in several breast cancer cell lines, but not in non-transformed mammary epithelial cell line



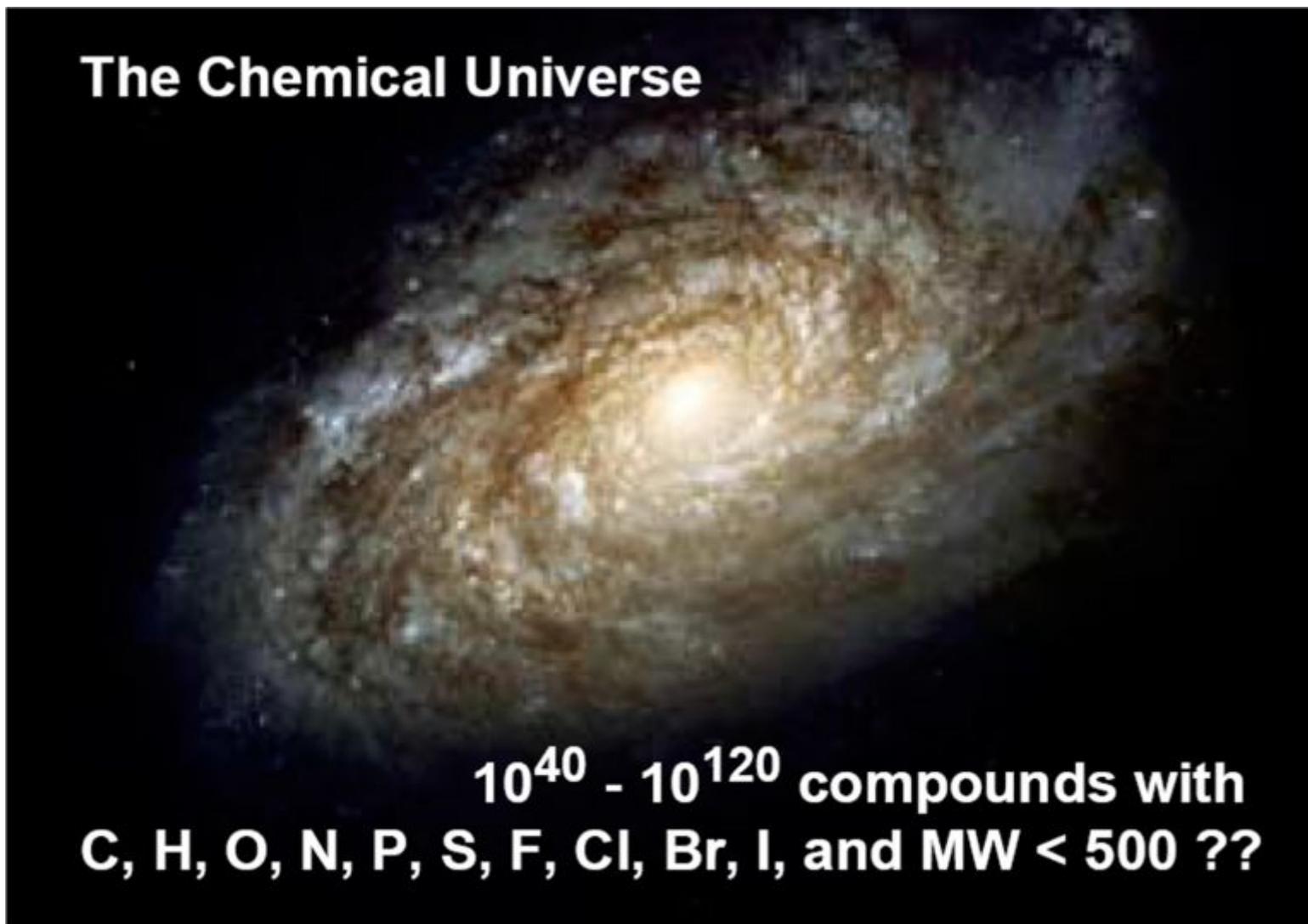
Molecular mechanisms of Rita action and potential target proteins for a complementary compound



Targets' Combinatorics: $N! / ((N-M)!M!)$



Chemogenomics: Chemical Space (Estimated)



Influence of Individual Atoms on a Particular Activity

For each atom in a molecule all MNA descriptors are generated. Using these descriptors for each particular activity P_a и P_i values are calculated. Each atom is colored in accordance with the following:

Red	$:= 0.3+0.7*P_i$	(negative impact on activity)
Green	$:= 0.3+0.7*P_a$	(positive impact on activity)
Blue	$:= 1-0.7*(P_i+P_a)$	(neutral impact on activity)

This can be interpreted in the following way:

If $P_a = 0$ and $P_i = 1$, then Red = 1, Green = 0.3, Blue = 0.3 – **bright red color**;

If $P_a = 1$ and $P_i = 0$, then Red = 0.3, Green = 1, и Blue = 0.3 – **bright green color**;

If $P_a = 0$ and $P_i = 0$, then Red = 0.3, Green = 0.3, Blue = 1 – **bright blue color**;

If $P_a = 0.33$ and $P_i = 0.33$, then Red = 0.53, Green = 0.53, Blue = 0.53 – **grey color**.

Example: sulfathiazole has antibacterial activity, and also it is a weak antagonist of ET_A receptors

PASS PREDICTIONS

Antibacterial Activity

ET_A Receptor Antagonist

PASS - C:\DATABASES\TEST-MOLECULES\sulphathiazole.sdf

File Base Predict View Options Help

C:\Program Files\PASS-ETC-AUG-2005\MNICKLAUS-AUG-2005\RunImage\PASS.SAR

C:\DATABASES\TEST-MOLECULES\sulphathiazole.sdf

Antibacterial 0.443 0.012

Activity Spectrum

Chart General Effects Mechanisms Toxicity

Dihydropteroste synthase inhibitor
Iodide peroxidase inhibitor

139 of 2005 Possible Activities at Pa > Pi

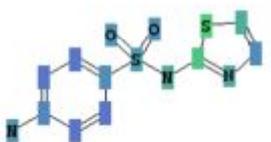
0.889	0.005	Antiobesity
0.835	0.005	Para amino benzoic acid antagonist
0.736	0.006	Dihydropteroste synthase inhibitor
0.721	0.006	Antidiabetic
0.556	0.006	Antiprotozoal (Coccidial)
0.552	0.019	Prostaglandin E1 antagonist
0.509	0.026	Prostaglandin H2 antagonist
0.485	0.045	Potassium channel antagonist
0.453	0.013	Cyclooxygenase inhibitor
0.468	0.028	Antiprotozoal
0.443	0.012	Antibacterial
0.412	0.021	Diuretic inhibitor
0.408	0.024	Gingipain R inhibitor
0.421	0.053	Antiinfective
0.371	0.006	Hypoglycemic
0.328	0.015	Antineoplastic (breast cancer)
0.362	0.054	Antimycobacterial
0.351	0.047	Antituberculosic
0.325	0.023	Saluretic
0.345	0.052	Myelodysplastic syndrome treatment

> <id> (2)
2

32 Substructure Descriptors: 0 new.
There are 3 known activities.
Drug-Likeness: 0.156

139 of 2005 Possible Activities
35 of 224 Possible Pharmacological Effects

2 structure of 2



PASS - C:\DATABASES\TEST-MOLECULES\sulphathiazole.sdf

File Base Predict View Options Help

C:\Program Files\PASS-ETC-AUG-2005\MNICKLAUS-AUG-2005\RunImage\PASS.SAR

C:\DATABASES\TEST-MOLECULES\sulphathiazole.sdf

Endothelin receptor antagonist 0.158 0.019

Activity Spectrum

Chart General Effects Mechanisms Toxicity

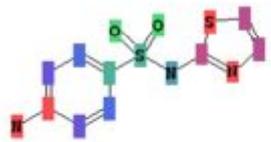
0.280	0.048	Ribonucleoside triphosphate reductase inhibitor
0.288	0.061	Channel-conductance-controlling ATPase inhibitor
0.254	0.029	Tubulin antagonist
0.269	0.061	Antiprotozoal (Trichomonas)
0.248	0.044	Thromboxane A2 antagonist
0.204	0.004	5-Hydroxytryptamine 6 antagonist
0.244	0.045	Lipoxygenase inhibitor
0.287	0.093	CYP2E2 substrate
0.246	0.060	Oligopeptidase B inhibitor
0.205	0.021	Thromboxane antagonist
0.235	0.059	Benzodiazepine inverse agonist
0.176	0.001	11-Beta-hydroxysteroid dehydrogenase 1 inhibitor
0.176	0.001	11-Beta-hydroxysteroid dehydrogenase inhibitor
0.264	0.100	Serine-phosphoethanolamine synthase inhibitor
0.241	0.083	Antithrombocytopenic
0.235	0.079	Poly(ADP-ribose) glycohydrolase inhibitor
0.216	0.066	Corticosteroid antagonist
0.154	0.008	Thyroid hormone antagonist
0.219	0.074	Granzyme A inhibitor
0.246	0.106	Carcinogenic
0.279	0.139	Antiulcerative
0.155	0.016	Beta tubulin antagonist
0.256	0.117	Carcinogenic, male mice
0.158	0.019	Endothelin receptor antagonist
0.237	0.107	(S)-3-hydroxyacid ester dehydrogenase inhibitor

> <id> (2)
2

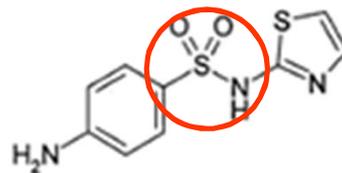
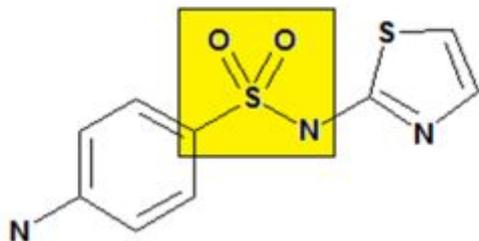
32 Substructure Descriptors: 0 new.
There are 3 known activities.
Drug-Likeness: 0.156

139 of 2005 Possible Activities
35 of 224 Possible Pharmacological Effects

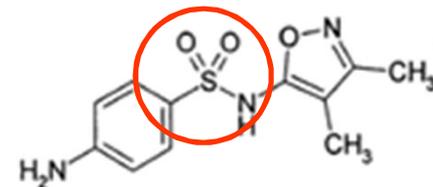
2 structure of 2



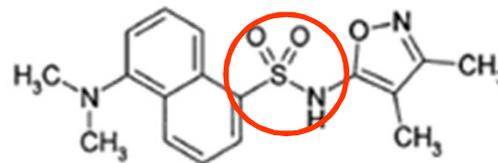
The fragment of sulfathiazole identified by PASS as having “positive” influence on ET_A antagonistic activity:



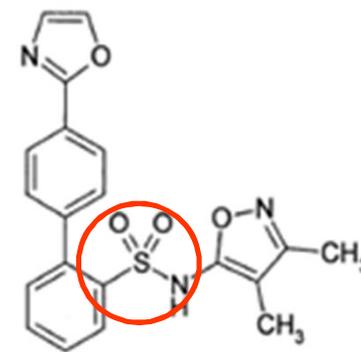
1 sulfathiazole
 ET_A IC_{50} = 69 μ M



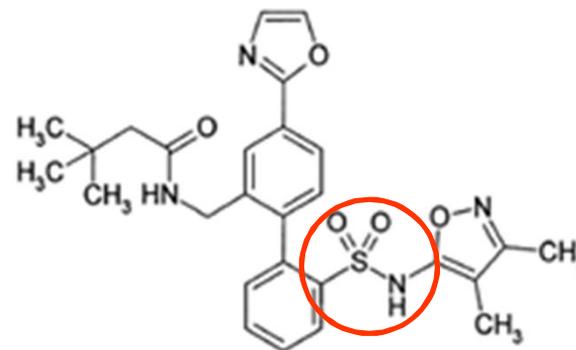
2 sulfisoxazole
 ET_A IC_{50} = 0.78 μ M



3 BMS-182874
 ET_A IC_{50} = 0.15 μ M

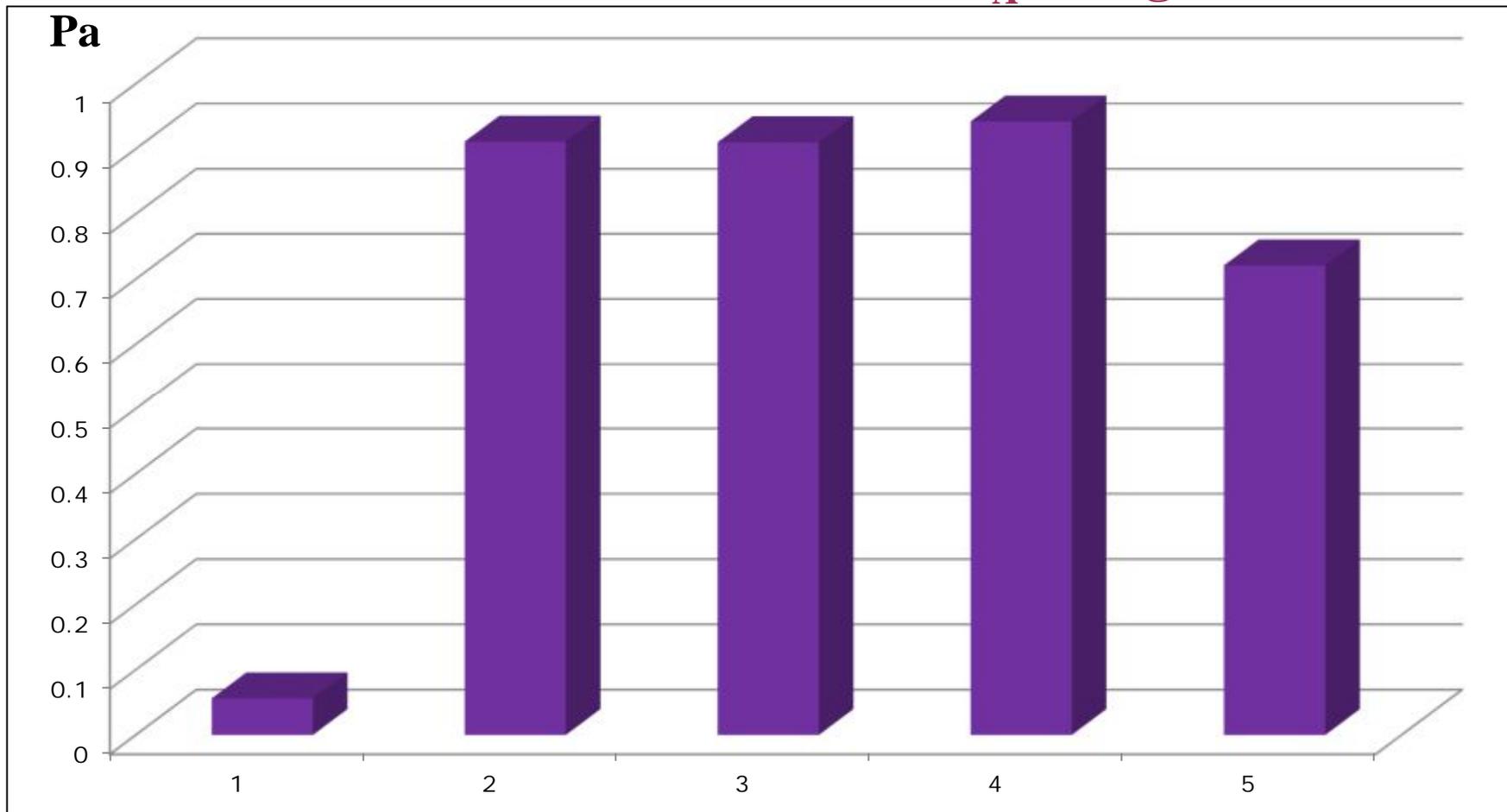


4 BMS-193884
 ET_A K_i = 1.4 nM

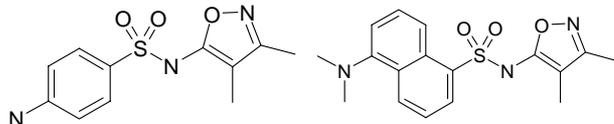


5 BMS-207940
 ET_A K_i = 0.010 nM

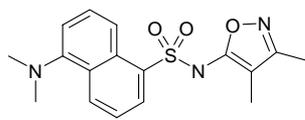
From Sulfathiazole to Potent ET_A Antagonist



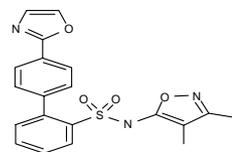
IC₅₀: 60 μM



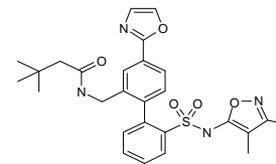
0.78 μM



0.15 μM



1.4 nM



0.01 nM

Afternoon session, 16:00-16:15

Olga Filz, IBMC

**In silico fragment-based design of novel
anti-inflammatory agents**

Summary

- 1. Multi-targeted agents may have advantages comparing to the ligands acting on a single target.**
- 2. The most prospective targets and their combinations can be identified by different simulations of processes in regulatory pathways.**
- 3. Compounds that likely have the targeted activities can be found by virtual screening in the databases of available samples.**
- 4. In silico fragment-based design may be another prospective way of finding multitargeted ligands.**

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