

Marcus Gastreich Spotting Binders in 10¹² Compounds

Estimated no. of stars in universe: 10²³ Compounds searched traditionally: 10⁷

"Interesting" compounds:

1060

Given the "Similarity Principle"...

1. Which of the 10⁶⁰ are <u>accessible</u>?

2. How to search that many compounds?

3. Four eyes may see more than two... - Right?



1. Which Ones are the Appealing Ones?

- "Lead-like", good ADME/tox properties
- Synthetically accessible
- Unpatented (but given the high number of molecules, this should be a smaller problem...)



The Synthesis Dilemma

- Many of the compounds will not be accessible
- It is un-doable to test every molecule:

Assumption:

1 millisecond compute time per compound

Example:

$$10^{12} \times 0.001 \text{s} = 10^9 \text{s}$$

- ~ 16,666,666 mins
 - ~ 277,777 hrs
 - ~ 11,500 days



Solution: Do not Enumerate!

 Instead of checking compounds afterwards, we can encode "reactions" and assemble molecules on-the-fly.



Our Approach: Fragments to Leads





Encoding Reactions in a Nutshell





What makes a Fragment Space ?

A fragment to us is a virtual molecule with link atoms



Fragments can be connected

- fragments
 - + link compatibility rules
 - = Fragment Space





The Classification of Spaces

Shred Molecules:









The Classification of Spaces

Exploit combinatorial chemistry:





The Classification of Spaces





Complete Compounds vs. Combinatorics

- Searching *n* complete ('enumerated') compounds leads to <u>*n*</u> possible compounds searched.
 - IP Gain = 0
 - Synthetic access: usually no problem.
 - Computation times are! (must touch every cpd!)

- Exploiting combinatorial chemistry surely can lead to <u>many more</u> compounds to search.
 - IP Gain much higher.
 - Synthetic access: must be taken care of!
 - Incomputable unless clever approach used.



How is This Done In Real Life?





It Works: Pfizer's PGVL Space: 10¹² Cpds

Search for 5HT3 antagonists



Böhm et al., J. Med. Chem. 51, 2468–2480, 2008



2. Search Technology



The Similarity Principle - umm... Assumption:

"What looks similar, behaves similarly."



Of course, this is not always true, but sometimes we cannot do better.



Similarity Descriptors: Bitstrings





Similarity Descriptors: FTrees

2¹/₂D FTrees descriptor:



- Molecule represented as a tree
 - no bit string
 - no 3D conformers
- Nodes: chemistry/physics
- Topology preserved

Original Idea, first implementation: M.Rarey and S.Dixon, *JCAMD*, **12** (**1998**)



Advantages of FTrees



- more than just a similarity score
- fast like 2D, but retains topology
- fuzzy



Principle of FTrees





- FTrees Similarity: 0.85
 - global for whole molecule
 - local for each match
- Mapping of substructures



FTrees "Intuition"



PAF Application by Boehringer-Ingelheim



QUERY PAF antagonist

Bio Soly

hit PAF antagonist

2D: rank 729 / 957 FTrees: rank 5 / 957

H.Briem, U.Lessel, PD3, 20, 231 (2000)

"In vitro and in silico affinity fingerprints: Finding similarities beyond structural classes"

GPCR Application by Sanofi-Aventis

				22					
		alph	pha1A 5		Г2A	D2		M1	
		-	hit		hit	-	hit		hit
% database screened		\mathbf{EF}	rate [%]	\mathbf{EF}	rate [%]	\mathbf{EF}	rate [%]	\mathbf{EF}	rate [%]
		Feat	ture T	ree m	odels				
1	$class1^b$	12.0	60	18.0	90	20.0	100	18.0	90
	$class2^{c}$	16.0	80	16.0	80	16.0	80	10.0	50
	winner ^{d}	12.0	60	20.0	100	20.0	100	20.0	100
5	class1	6.8	34	9.6	48	8.8	44	8.8	44
	class2	9.2	46	6.0	30	5.2	26	4.4	22
	winner	7.6	38	11.2	56	9.6	48	10.4	52
10	class1	4.8	24	6.8	34	5.0	25	5.0	25
	class2	5.4	27	4.2	21	4.2	21	3.2	16
	winner	5.8	29	8.0	40	6.2	31	5.8	29
		С	atalys	t mod	els				
1	class1	14.0	70	10.0	50	6.0	30	18.0	90
	class2	12.0	60	8.0	40	2.0	10	16.0	80
	winner	14.0	70	10.0	50	0.0	0	16.0	80
5	class1	6.4	32	8.4	42	4.8	24	9.2	46
	class2	10.0	50	8.4	42	4.0	20	7.6	38
	winner	10.4	52	8.8	44	4.0	20	9.2	46
10	class1	3.6	18	4.4	22	2.8	14	5.6	28
	class2	5.4	27	6.4	32	4.4	22	5.0	25
	winner	5.8	29	7.4	37	4.6	23	5.6	28

Table 2. Enrichment Factors and Hit Rates from Screening the Virtual Screening Library Using the Alpha1A, 5HT2A, D2, and M1 Feature Tree and Catalyst Models^{*a*}

Evers et al., J.Med.Chem., 48, 5448-65 (2005)



Alignments Explain Similarities





The Actual Searching





KnowledgeSpace[™]: a Public cLib-Space (10¹⁰)



KnowledgeSpace[™] Is Publicly Available:

www.biosolveit.com/KnowledgeSpace





FTrees: Interfaces and GUIs



Payment period: Month	C Academic pricing) <u>(0) 0 USI</u>
BioSolvelT http://www.biosolveit.de/	FTrees Visual Similarities FTrees Visual Similarities is a highly efficient tool for scaffold hop screening. Its underlying topological descriptor (the Feature Tree chemical properties of functional groups. The reduced graph rep pharmacophore characteristics of the ligands in a fuzzy way enab scaffolds. Moreover, the topological Feature Tree descriptor mak fast compared to 3D approaches and is also exempt from the uno calculation.	Back to packages a point and ligand-based virtual e) captures connectivity and physico- irresentation that preserves the bles the identification of novel es similarity assessment extremely certainties of 3D coordinate
Pav-per	-Use including visua	alization



Free & simple web interface: biosolveit.de/FTreesWeb



FTrees Successes - A First Summary

- Searches synthetically accessible molecules
 - reports the reaction alongside
 - covers 10¹² possibilities in 5 minutes
- Highly efficient
 - 250.000 molecule:molecule comparisons per minute
 - high enrichment ratios
- Helps with various drug design tasks
 - scaffold hopping
 - virtual screening
 - open chain vs. ring structures are found



3. Four Eyes May See More Than Two...



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Böhm et al., J. Med. Chem. **51**, 2468–2480, 2008



Highly Effective: An Orthogonal View!





What Complements the FTrees-"View"

- FTrees do not "see" stereochemistry.
- FTrees cannot distinguish ortho-, meta-, para.
- FTrees make one "blob" per cycle.
- FTrees are conformation independent.

=> Let us use 3D then!



Prospectively: Boehringer's BI-CLAIM (10¹¹)

Search Space (BI-CLAIM): 1,600 scaffolds + 30,000 reagents -> 500,000,000,000 virtual products A typical workflow (part 1):



The typical workflow (part 2)

Bio Solut

select scaffolds → design focused lib / purchase prototypes → refinement Rapid success stories

- GPCR: 1000 virtual hits, 2 focused libs, <u>100 nM inhibitors identified</u>
- Proteinase: 1200 cmpd screened, 2 active scaffolds, refined to 10 nM

Lessel et al., ICCS'08 & J Chem Inf Model. 2009 Feb;49(2):270-9.

Boehringer Ingelheim J.Med.Chem. ASAP

This just appeared online:



21+/-15nM activity against GPR119 (a GPCR relevant for diabetes)

Wellenzohn et al., J.Med.Chem. 2012 asap:

"Identification of new Potent GPR119 Agonists by Combining Virtual Screening and Combinatorial Chemistry



The Search Cascade Used (taken from JMC)





Another, New Orthogonal Method: HYDE

If you have a protein structure...

- Visual affinity computation using HYDE
- Hydrophobic effect and H-bonds (etc.) <u>balanced</u> intrinsically



PDB: 1GKC

Methods described in a paper JUST out:

doi: 10.1007/s10822-012-9626-2 Schneider et al., JCAMD Dec2012



So... Orthogonal Views Help a Great Lot





Summary

- 1. Trillions of compounds can be searched
- 2. High likelihood of synthetic access / proven success in Pharma
- 3. Combine 2D and 3D

 CAVEAT: Searching your own chemistry <u>involves yourself</u>!

Happy FTrees Users: Pfizer, Novartis, AstraZeneca, Merck USA/NL, Merck-Serono, Hoffmann-LaRoche, Johnson&Johnson, Sanofi-Aventis, Bayer, Boehringer-Ingelheim, Dupont, and many more

