

Advances in multi-parameter optimisation: Targeting the "best" profile for your project's objectives ACS Spring National Meeting, March 16th 2013 Matthew Segall, Edmund Champness

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Overview

- Multi-parameter optimisation in drug discovery
- Finding the 'best' profile for your project's objective
 - Example: Selection to reduce toxicity risk
- 'Hard' vs. 'soft' boundaries
 - Example: Selection for CNS indications
- Testing the robustness of your decisions
 - Sensitivity analysis
- Conclusions

Multi-parameter Optimisation in Drug Discovery





The Objectives Multi-parameter optimisation

Identify chemistries
 with an optimal balance
 of properties

- Quickly identify situations when such a balance is not possible
 - -Fail fast, fail cheap
 - -Only when confident



Multi-parameter Optimisation Probabilistic Scoring*



Multi-parameter Optimisation Probabilistic Scoring*

- Property data
 - Experimental or predicted
- Criteria for success
 - Relative importance
- Uncertainties in data
 - Experimental or statistical

- Score (Likelihood of Success)
- Confidence in score



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Finding the 'Best' Profile for your Project Objectives Patent pending





Finding Tailored Profiles Objectives

- Use existing data to find scoring profiles that identify compounds with improved chance of success
 - Any drug discovery objective, e.g. clinical, PK, toxicity...
 - Once developed, a profile can be applied prospectively to find new compounds
- Identify most important data with which to distinguish between successful and unsuccessful compounds
 - Any data can be used as input, calculated or experimental
- Explore multi-parametric data
 - Consider properties simultaneously, not individually
 - Avoid 'over counting' of correlated factors
- Rules must be interpretable and modifiable
 - Avoid black boxes
 - Synergy between computer and experts

*Patent pending

What is a Rule?

• A **Rule** is a set of property criteria that in **combination** identify 'good' compounds, e.g.



• For example, Lipinski RoF:

logP<5	MW<500
HBD<5	HBA<10

Finding Rules with PRIM

- A Rule is a box in multi-dimensional property space containing significantly more 'good' than 'bad' compounds
 - Use Patient Rule Induction Method (PRIM) by Friedman and Fisher* find rules in multi-dimensional data
 - Equivalent to a scoring profile



Example Application Finding rules for selection of non-toxic compounds

- In vitro assay data from CEREP Bioprint[®]
 - Percentage inhibition of 185 targets including GPCF, kinase, NR, P450s...
- Drugs labelled as 'cardiotoxic', 'hepatotoxic' or 'clean'
 - Based on FDA Adverse Event Reporting System
 - Reporting odds ratio (ROR) of 2.5 or above at System Organ Class level in MeDRA Ontology
 - Cardiotoxicity set: 408 'cardiotoxic' ,66 'non-cardiotoxic'
 - Heptotoxicity set: 302 'hepatotoxic' , 168 'non-hepatotoxic'
- Data sets divided into training, validation and test sets
 - Ratio 70:15:15

Example Application Cardiotoxicity results



- Selected only 3 targets from 185
 - Rules 'make sense': Targets identified have known CV side effects
- 5/6 compounds meeting all criteria are non-cardiotoxic (83%)
- 19/20 compounds failing all criteria are cardiotoxic (95%)

Example Application Hepatotoxicity results

Profile 5HT1D MAO_A	Desired Value > 6.93 0.99 -> 14.14	Importance	Set	Mean Improvement (%)	Support (%)
COX1_RECOMB	≤ 16.16		Train	51	12
			Val	56	14
			Test	39	11

- Rules are (just) statistically significant, but don't 'make sense'
 - Rules appear to be result of noise in small data set
- Large majority of the targets in data set are not known to relate with hepatotoxicity
 - In few examples, e.g. PPAR γ there are a statistically insignificant number of inhibitors in the data set
- Non 'black-box' method highlights limitations of data set

'Hard' vs. 'Soft' boundaries Patent pending







- Avoid hard cut-offs that draw artificially hard distinction between similar compounds
- Add 'soft' boundaries to ideal ranges



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- Add 'soft' boundaries to ideal ranges

Desirability Functions Example: CNS MPO*



CNS MPO = sum of desirabilities for each parameter

- 74% of marketed CNS drugs achieved CNS MPO > 4 vs. 60% of Pfizer candidates
- Correlations observed between high CNS MPO score and good in vitro ADME properties, e.g. MDCK P_{app}, HLM stability, P-gp transport

Determining 'Soft' Box Boundaries

- Box bounds previously only output as hard cut-offs
- Sensitivity analysis of box bounds to data sampling
 - Particularly important for sparse data
 - Incorporate uncertainty into the generated box bounds
 - Cross validation between training/validation sets



Example Application CNS Drugs

- Data set of 119 CNS Drugs and 108 Candidates published by Wager *et al.* in CNS MPO paper
- Divided into training, validation and test sets (55:25:20)
- Rule with hard cut-offs:

Profile MW	\$	Desired Value 319.4	Importance	Set	Mean	Suppor
РКА	≤	9.999			Improvement (%)	(%)
CLOGP	\$	3.434		Train	42	28
				Val	56	32
				Test	47	34

Example Application CNS Drugs – Introducing 'soft' boundaries



Example Application CNS Drugs – Comparison of ROC curves for test set



Testing the Robustness of Your Decisions Patent pending





Sensitivity Analysis

- What impact would changing a property criterion have on the *decision* we would make?
 - How large a change is necessary to have a significant impact?
- To which property criteria is compound priority most *sensitive*?
 - Which criteria/importance will, if modified, significantly change the order of compound priority?
- Highlight new avenues for exploration and avoid missed opportunities
- Considerations
 - Need to consider statistical significance of reordering (given uncertainties in scores)
 - Interested in changes to high-ranked compounds. Reordering of rejected compounds is not relevant

Sensitivity Analysis Importance of uncertainty



Modified Spearman's rank correlation coefficient accounts for uncertainty

Example Output Sensitive parameter

	Value Sensitivity	Importance Sensitivity	-
5HT1a affinity (pKi)	1.000	0.008	
logP	0.310	0.096	
BBB log([brain]:[blood])	0.249	0.015	=
hERG pIC50	0.096	0.207	
2D6 affinity category	N/A	0.107	
BBB category	N/A	0.055	
logS	0.040	0.002	
• •	-1/A	A AAP	

What parameters are most sensitive?

Value sensitivity scores for 5HT1a affinity (pKi)



Score changes for 5HT1a affinity (pKi): shift = 0.716842



What magnitude of change has a significant impact?

What compounds are most affected?

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Example Output Insensitive parameter

	Value Sensitivity	Importance Sensitivity	-
5HT1a affinity (pKi)	1.000	0.008	
logP	0.310	0.096	
BBB log([brain]:[blood])	0.249	0.015	=
hERG pIC50	0.096	0.207	
2D6 affinity category	N/A	0.107	
BBB category	N/A	0.055	
logS	0.040	0.002	
	-1/4	Score changes for BBB log([brain]:[blood]): importance =	

0.6 -

What parameters are most sensitive?

Importance sensitivity scores for BBB log([brain]:[blood])





What magnitude of change has a significant impact?

What compounds are most affected?

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Conclusion

- Rule induction can generate interpretable parameter scoring profiles tailored project objectives
- 'Soft' boundaries provide more subtle distinctions between compounds



- Sensitivity analysis of scoring criteria is important to avoid missed opportunities due to the criteria we have chosen
- Reference (Rule induction): Yusof *et al.* Drug Discov. Today (2014)
 - 10.1016/j.drudis.2014.01.005
 - www.optibrium.com/community/publications
- See a live demo at Optibrium booth #1516