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Multi-parameter Optimisation in Drug Discovery: Quickly targeting compounds with a good balance of properties

Dr Matthew Segall

ELRIG Drug Discovery 2011, 7th September 2011

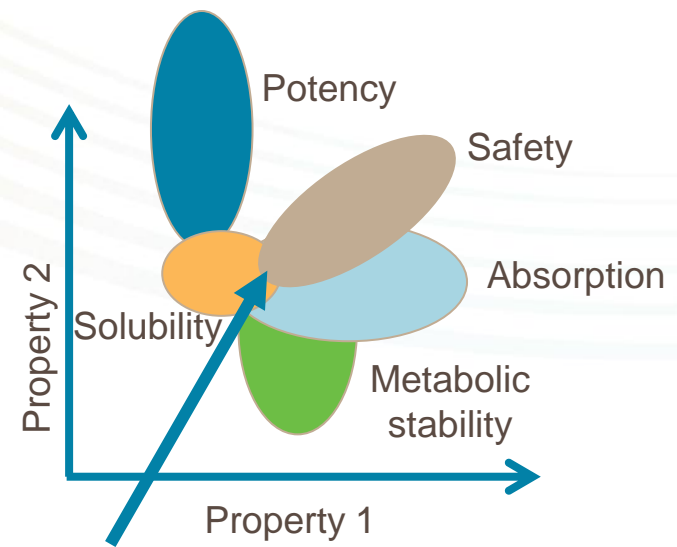
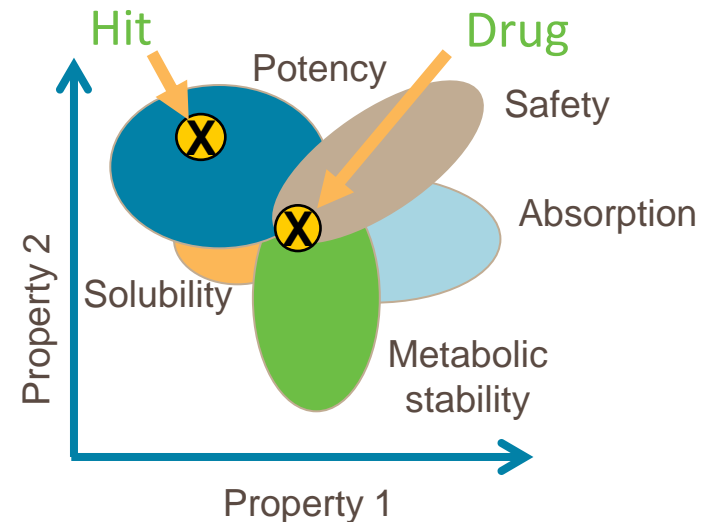
Overview

- Introduction: Balancing Properties in Drug Discovery
 - The challenges of multi-parameter optimisation (MPO)
 - Requirements for MPO in drug discovery
- Approaches for Multi-Parameter Optimisation
 - Rules-of-thumb
 - Filtering
 - Calculated metrics
 - Pareto optimisation
 - Desirability functions
 - Probabilistic scoring
- Balancing quality and diversity
- Case study
- Conclusion

The Objectives of Drug Discovery

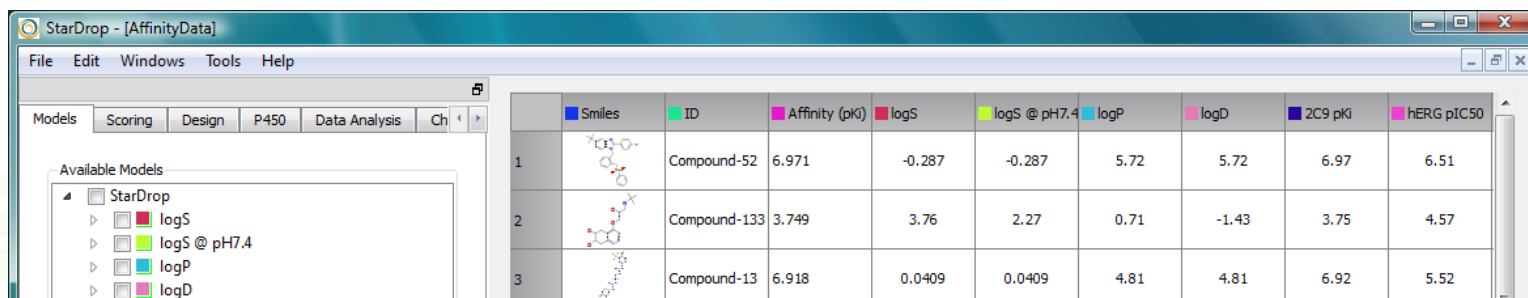
Multi-parameter optimisation

- 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**






No good drug

Challenge 1: Complexity of Data

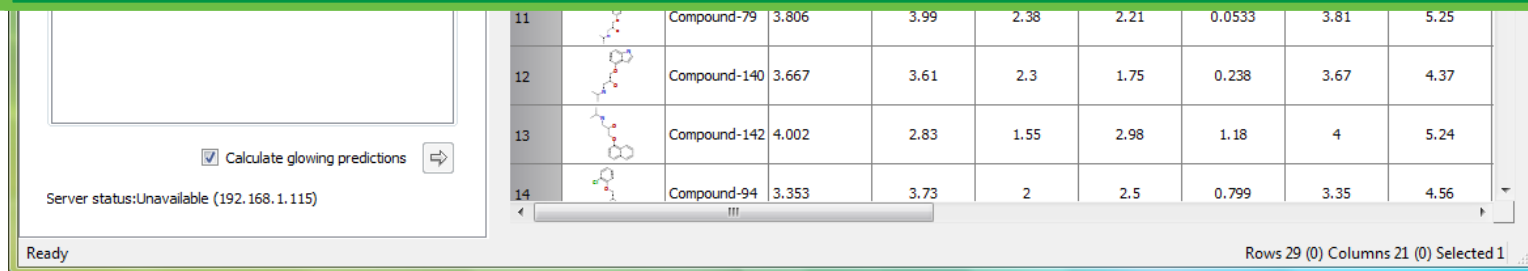


The screenshot shows the StarDrop software interface with a table of compound data. The table has columns for Smiles, ID, Affinity (pKi), logS, logS @ pH7.4, logP, logD, 2C9 pKi, and hERG pIC50. The first three rows of data are visible.





| | Smiles | ID | Affinity (pKi) | logS | logS @ pH7.4 | logP | logD | 2C9 pKi | hERG pIC50 |
|---|---|--------------|----------------|--------|--------------|------|-------|---------|------------|
| 1 |  | Compound-52 | 6.971 | -0.287 | -0.287 | 5.72 | 5.72 | 6.97 | 6.51 |
| 2 |  | Compound-133 | 3.749 | 3.76 | 2.27 | 0.71 | -1.43 | 3.75 | 4.57 |
| 3 |  | Compound-13 | 6.918 | 0.0409 | 0.0409 | 4.81 | 4.81 | 6.92 | 5.52 |

200 compounds through 8 experimental assays is 1600 data points












Q. How do you use this data to make decisions?

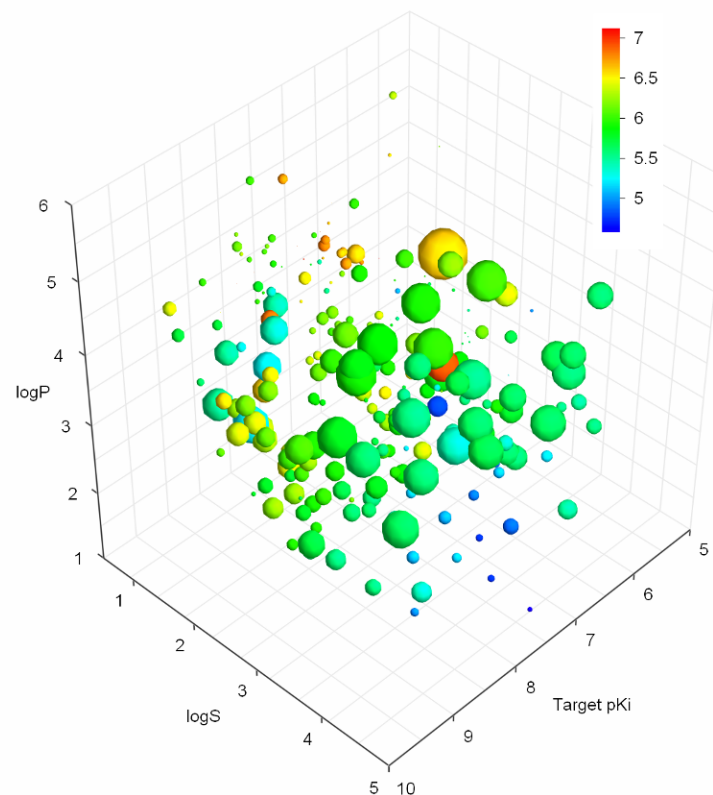


The screenshot shows the StarDrop software interface with a table of compound data. The table has columns for Smiles, ID, Affinity (pKi), logS, logS @ pH7.4, logP, logD, 2C9 pKi, and hERG pIC50. The last four rows of data are visible.

| | | | | | | | | | |
|----|---|--------------|-------|------|------|------|--------|------|------|
| 11 |  | Compound-79 | 3.806 | 3.99 | 2.38 | 2.21 | 0.0533 | 3.81 | 5.25 |
| 12 |  | Compound-140 | 3.667 | 3.61 | 2.3 | 1.75 | 0.238 | 3.67 | 4.37 |
| 13 |  | Compound-142 | 4.002 | 2.83 | 1.55 | 2.98 | 1.18 | 4 | 5.24 |
| 14 |  | Compound-94 | 3.353 | 3.73 | 2 | 2.5 | 0.799 | 3.35 | 4.56 |

Visualisation is Important But Not Enough...*

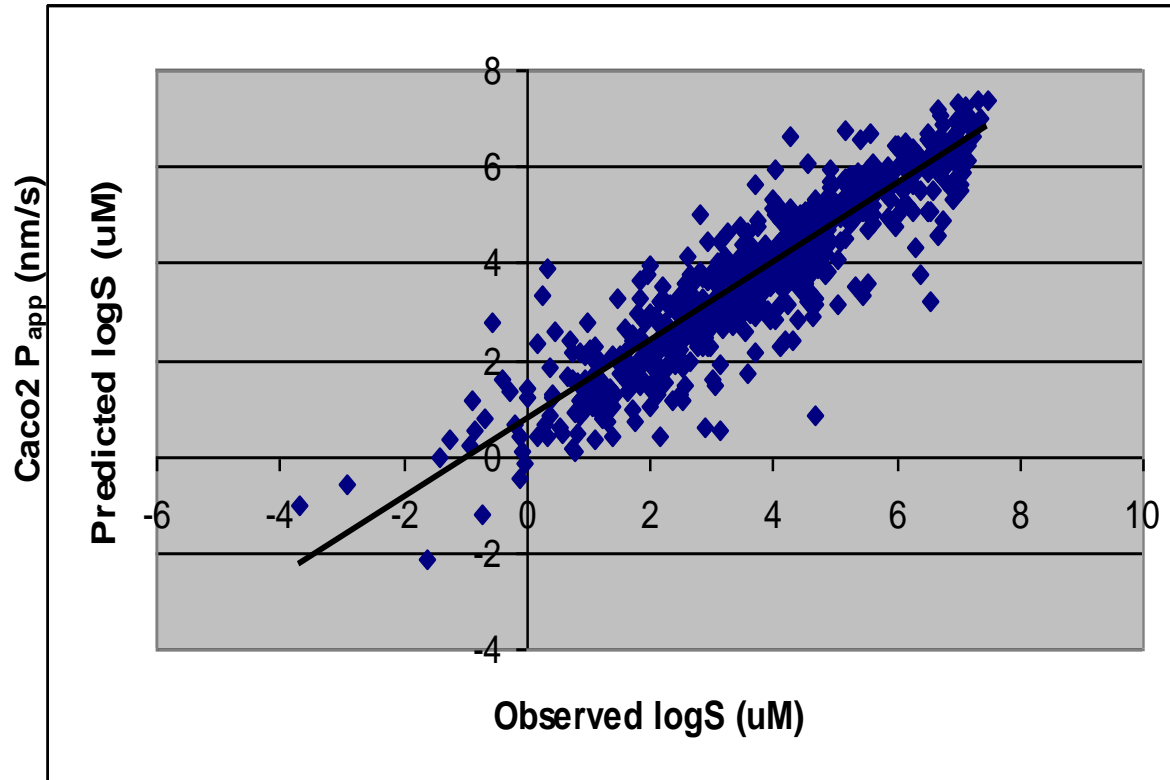
| MolName | Structure | pKi SHT1a affinity | logS | logP | 2C9 pKi | NERG pIC50 | log(BB) | BBB category | H1A category | P-gp category | ZD6 affinity category | PPB category |
|---------|---|--------------------|-------|-------|---------|------------|---------|--------------|--------------|---------------|-----------------------|--------------|
| SI-10 |  | 6 | 3.894 | 3.322 | 3.464 | 5.636 | 0.8671 | + | + | no | medium | high |
| SI-11 |  | 6 | 3.697 | 3.44 | 3.485 | 5.72 | 0.7745 | + | + | no | very high | high |
| SI-12 |  | 6.6 | 4.104 | 3.106 | 3.677 | 5.694 | 0.9036 | + | + | no | medium | high |
| SI-13 |  | 9 | 3.693 | 3.844 | 3.558 | 5.85 | 0.8504 | + | + | no | very high | high |
| SI-14 |  | 6 | 4.061 | 2.992 | 3.363 | 5.56 | 0.4096 | + | + | no | high | high |
| SI-15 |  | 6.5 | 2.554 | 4.39 | 4.502 | 6.175 | 0.8534 | + | + | yes | medium | high |
| SI-16 |  | 5.3 | 3.698 | 3.892 | 3.464 | 5.646 | 0.6799 | + | + | no | medium | high |
| SI-18 |  | 7.96 | 3.444 | 4.34 | 3.558 | 5.647 | 0.8569 | + | + | no | very high | high |
| SI-19 |  | 6.98 | 3.927 | 3.594 | 3.677 | 5.677 | 0.6898 | + | + | no | medium | high |
| SI-20 |  | 7.16 | 3.721 | 3.487 | 3.391 | 5.639 | 0.2327 | + | + | no | very high | high |
| SI-21 |  | 7.94 | 3.632 | 3.964 | 3.485 | 5.725 | 0.6096 | + | + | no | very high | high |



How can you make a confident decision by looking at these?

Challenge 2: Uncertainty in Data

Caco2 vs. Predicted Solubility*



$R^2=0.81$, RMSE=0.8 log units

Requirements for MPO in Drug Discovery

- Interprettable
 - Easy to understand compound priority and how to improve compounds' chances of success
- Flexibility
 - Define criteria depending on therapeutic objectives of project
- Weighting
 - Take into account relative importance of different endpoints to success of project
- Uncertainty
 - Take uncertainty into account, avoid missed opportunities

Approaches for MPO in Drug Discovery



$$\psi_{1s}(r) = \sqrt{\frac{4}{\pi a_0^3}} e^{-2r/a_0}$$

$$\psi_{1s}^2(r) = \frac{4}{\pi a_0^3} e^{-4r/a_0}$$

$$r) = \left(\frac{8r^3}{3} \right)$$

Multi-Parameter Optimization: Identifying high quality compounds with a balance of properties

Curr. Pharm. Des. 2011 (submitted)

Download preprint from: www.optibrium.com/community

Approaches for MPO

Rules-of-Thumb

- The most famous – Lipinski's Rule-of-Five for oral absorption

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

- Many other have been proposed, e.g. Hughes *et al.** explored risk of adverse outcomes in *in vivo* toleration studies

| | |
|--------|------------------------|
| logP<3 | TPSA>75 Å ² |
|--------|------------------------|

- Strengths:
 - Simplicity, ease of application and interpretation
- Caveats:
 - Rules tailored to specific objectives – lack of flexibility
 - Risk of too rigid application

Rules of Thumb

- How predictive are rules-of-thumb?
 - E.g. Lipinski's RoF applied to 1191 marketed drugs

| | RoF result | |
|----------|---------------------------------|------------------------------|
| | Pass (≤ 1 RoF Failure) | Fail (> 1 RoF Failure) |
| Oral | 709 | 59 |
| Non-oral | 333 | 90 |

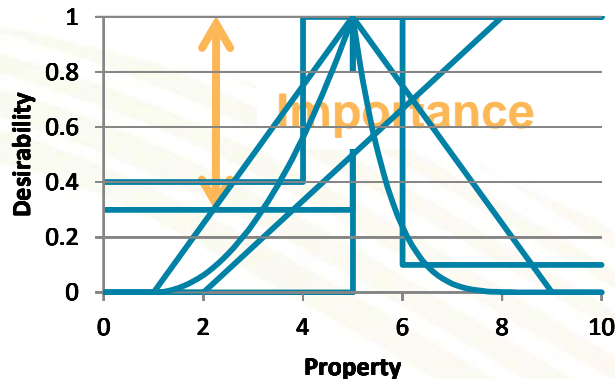
Approaches for MPO Filtering



Approaches for MPO

Desirability Functions*

- Relate property values to how 'desirable' the outcome



**Example: Property value: 5
(Derringer Function)**

- Combine multiple properties into 'desirability index'

- Additive:
$$D = \frac{d_1(Y_1) + d_2(Y_2) + \dots + d_n(Y_n)}{n}$$
- Multiplicative:
$$D = (d_1(Y_1) \times d_2(Y_2) \times \dots \times d_n(Y_n))^{1/n}$$

- Strengths

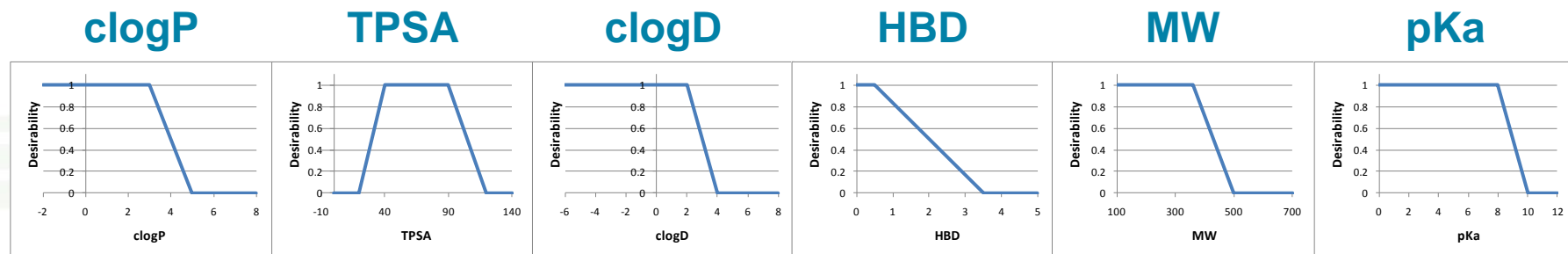
- Very flexible; Explicitly weight properties; Easy to interpret

- Caveats

- No explicit consideration of uncertainty; Need to know criteria *a priori*

Desirability Functions

CNS MPO*



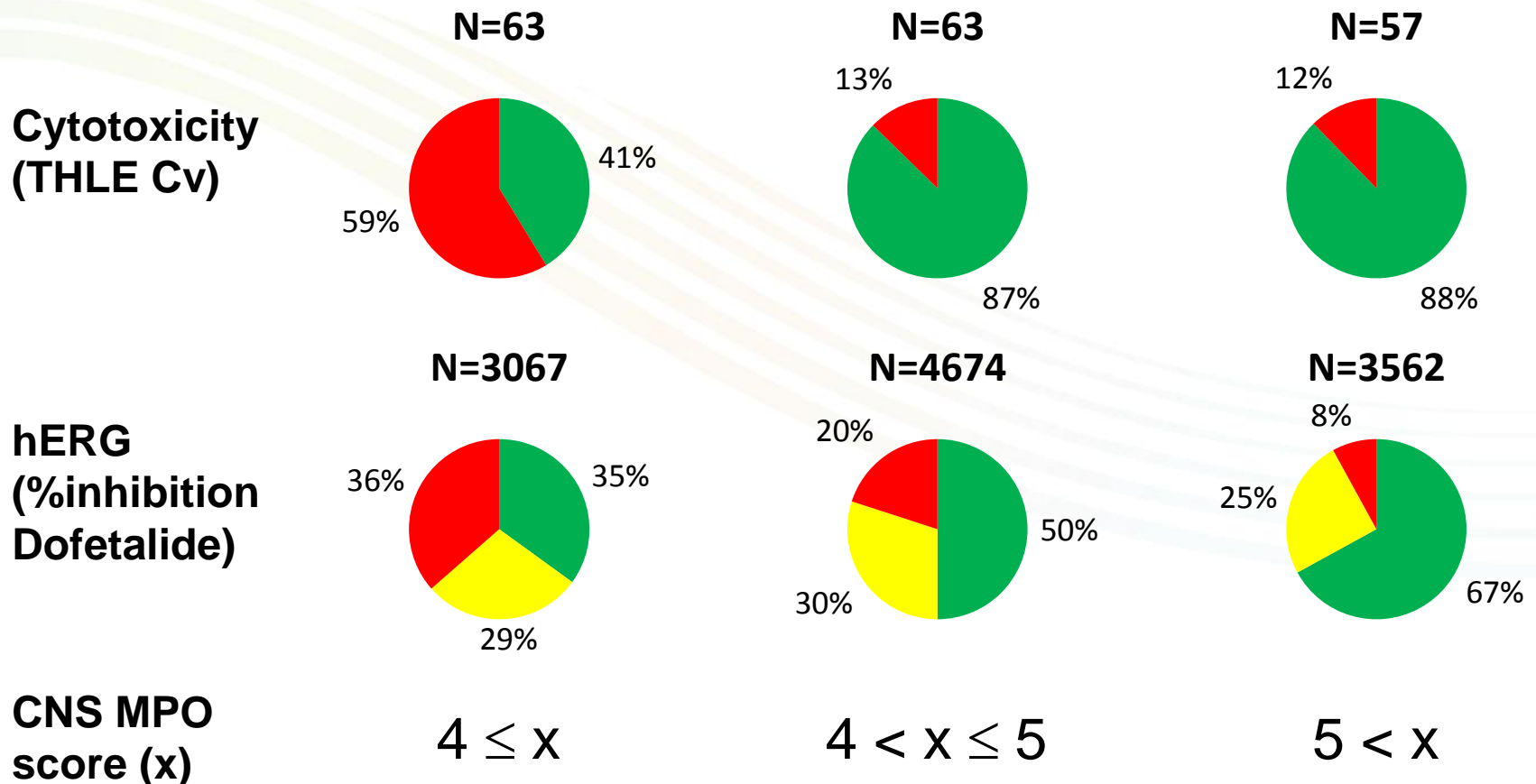
CNS MPO = sum of desirabilities for each parameter

- 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

Desirability Functions


















CNS MPO and safety*

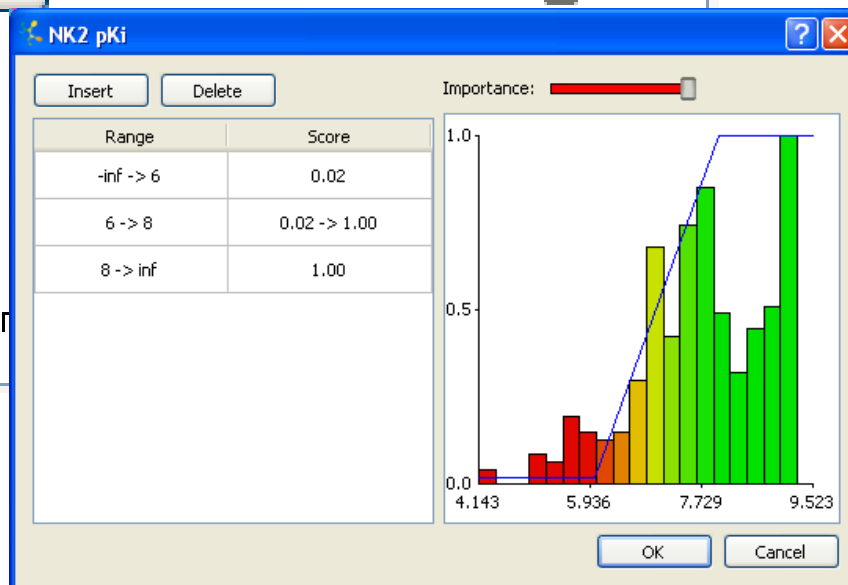
- CNS MPO score was also found to correlate with safety endpoints:



Approaches for MPO

Probabilistic Scoring* – Scoring Profile

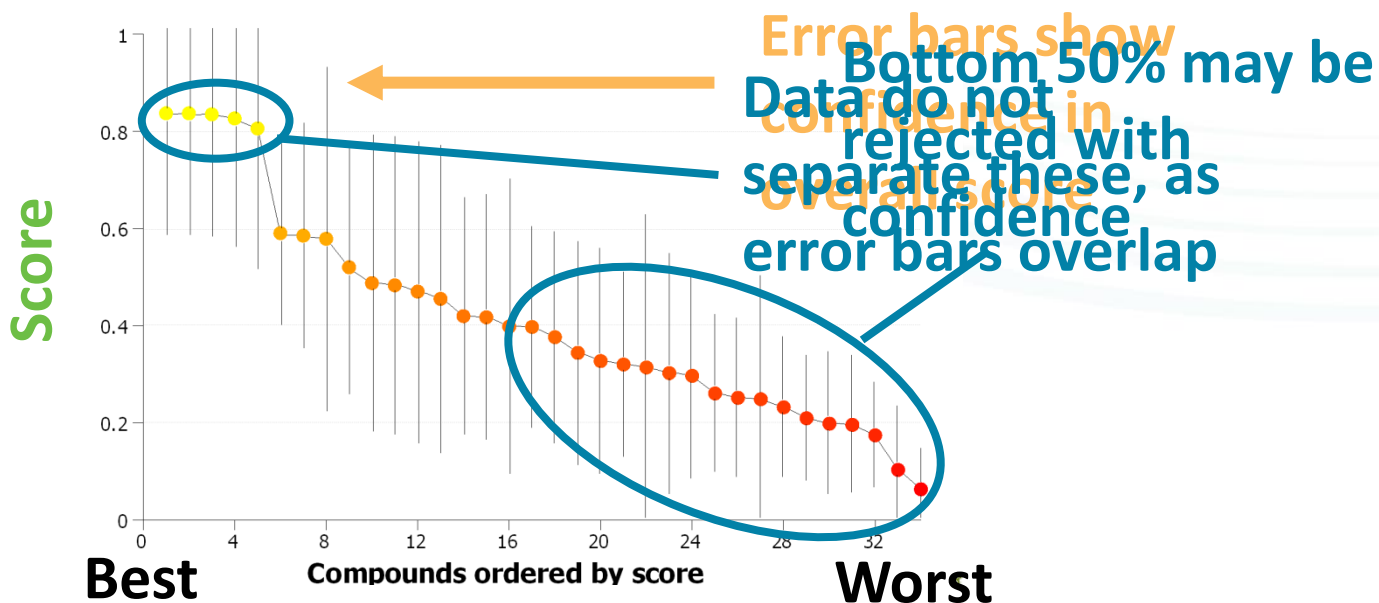
| Property | Desired Value | Importance |
|--|--|---|
|  pIC50 | > 8 |  |
|  logS | > 1 |  |
|  BBB log([brain]:[blood]) | -0.2 -> 1  |  |
|  Cytotox. (pLD50) | ≤ 5 |  |
|  logP | 0 -> 3.5  |  |
|  P-gp category | no | |
|  Ames | - | |
|  hERG pIC50 | ≤ 5 | |
|  2C9 pKi | ≤ 6 | |
|  2D6 affinity category | low medium | |



Probabilistic Scoring*

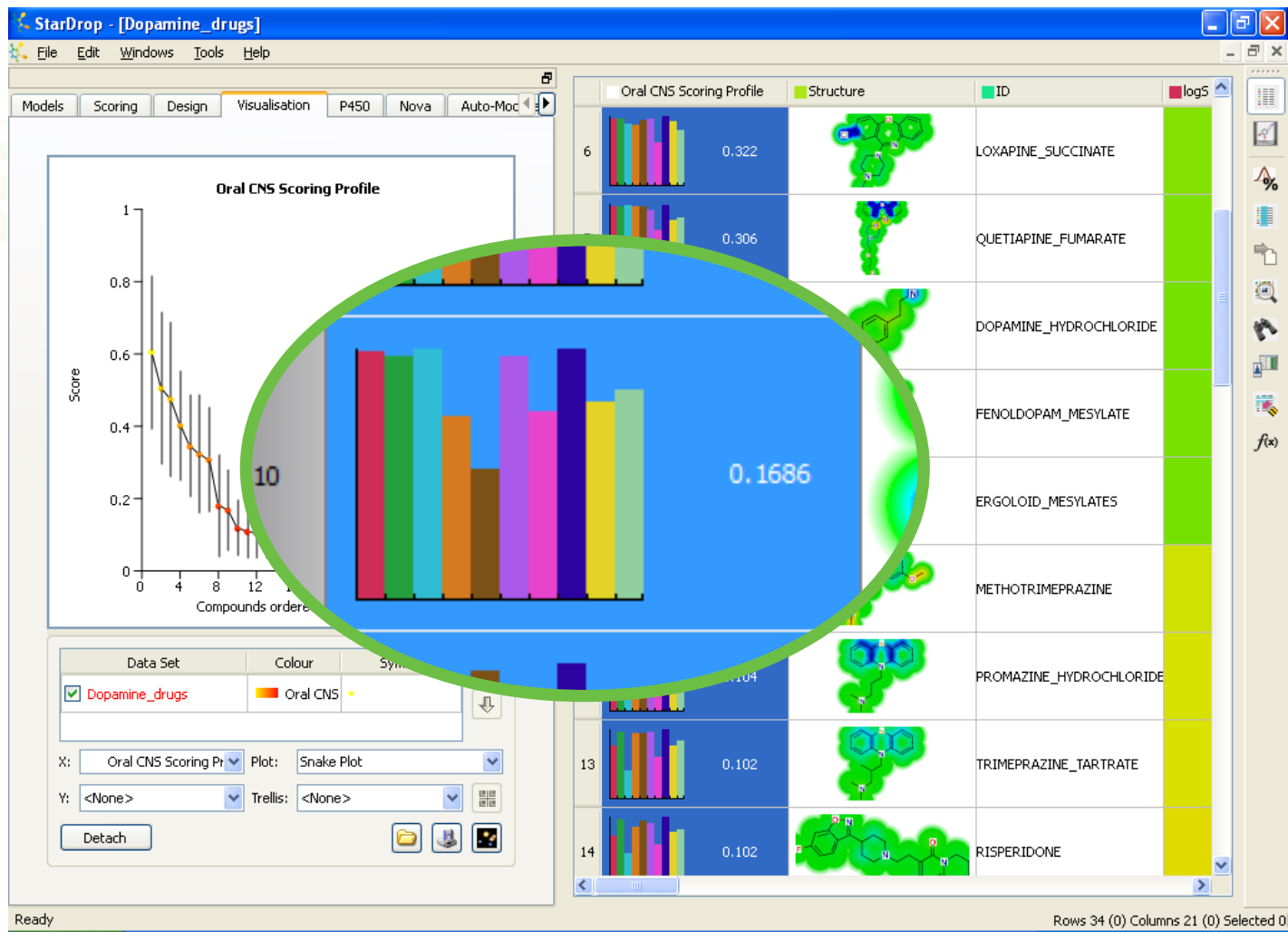
- **Property data**
 - Experimental or predicted
- **Criteria for success**
 - Relative importance
- **Uncertainties in data**
 - Experimental or statistical

- **Score (Likelihood of Success)**
- **Confidence in score**

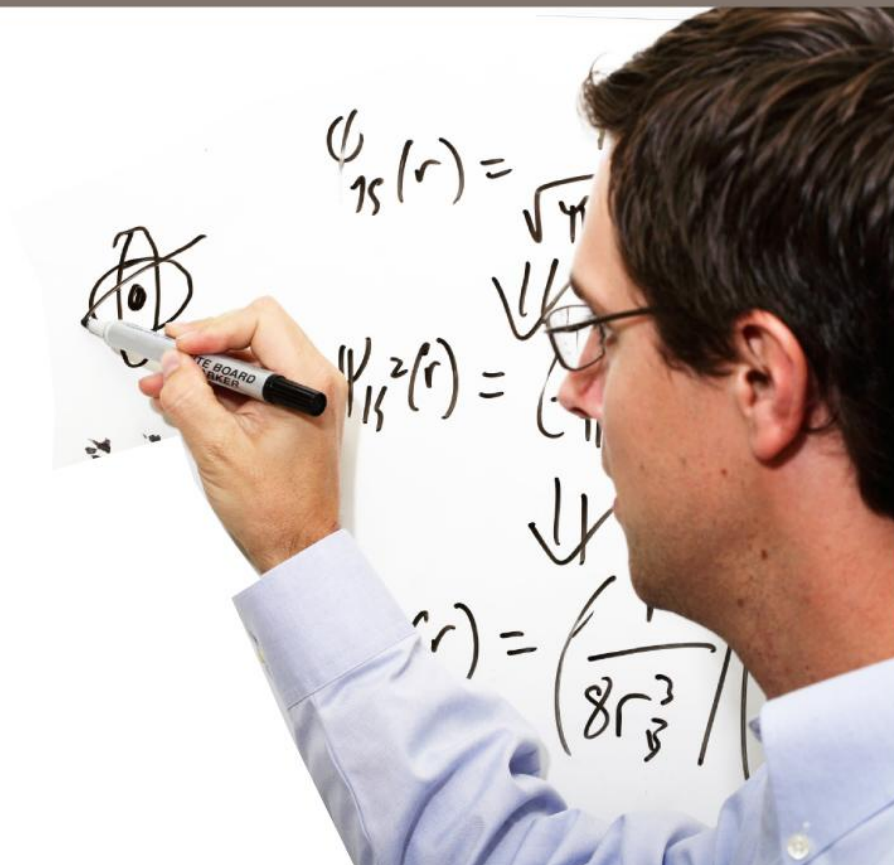


Provide Feedback on Influence of Properties

Guide redesign to improve chance of success

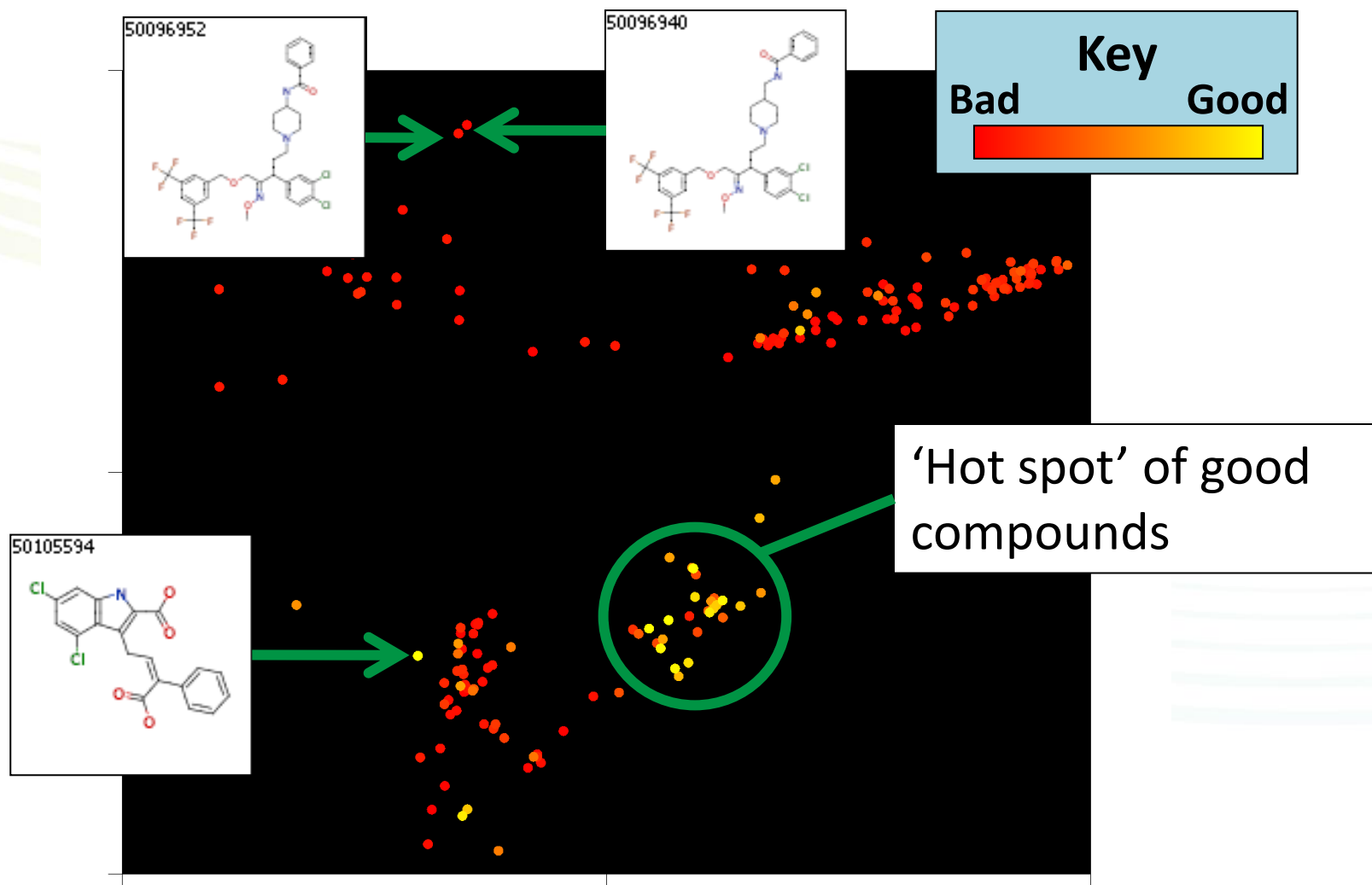


Balancing Quality and Diversity



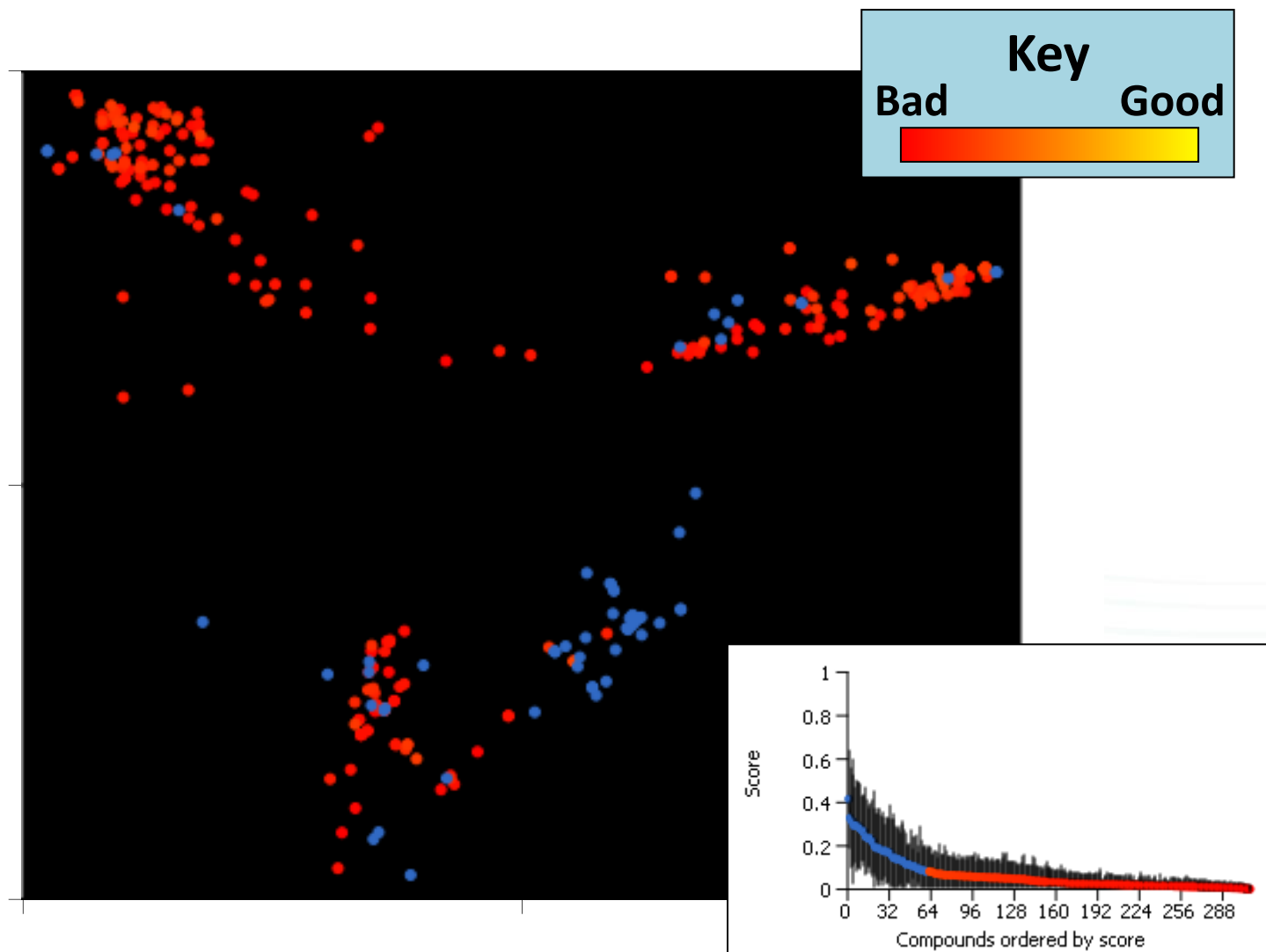
Visualising 'Chemical Space'

Exploring trends across chemical diversity



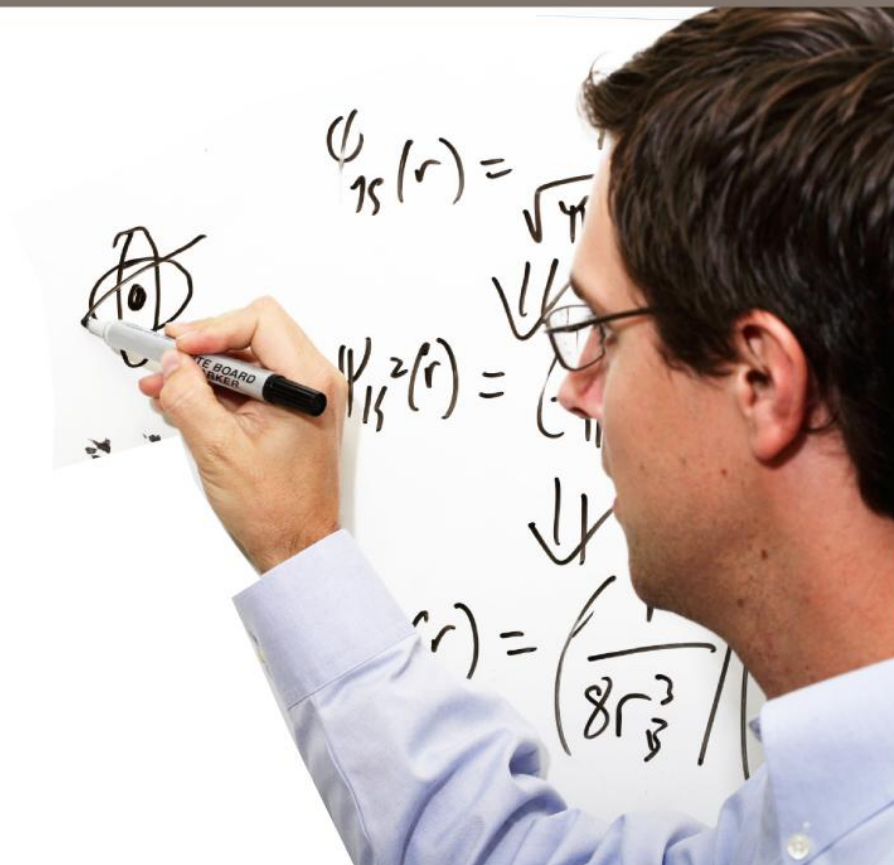
Balance Quality Against Diversity

Mitigating risk



Case Study

Rapid Focus in Lead Optimisation



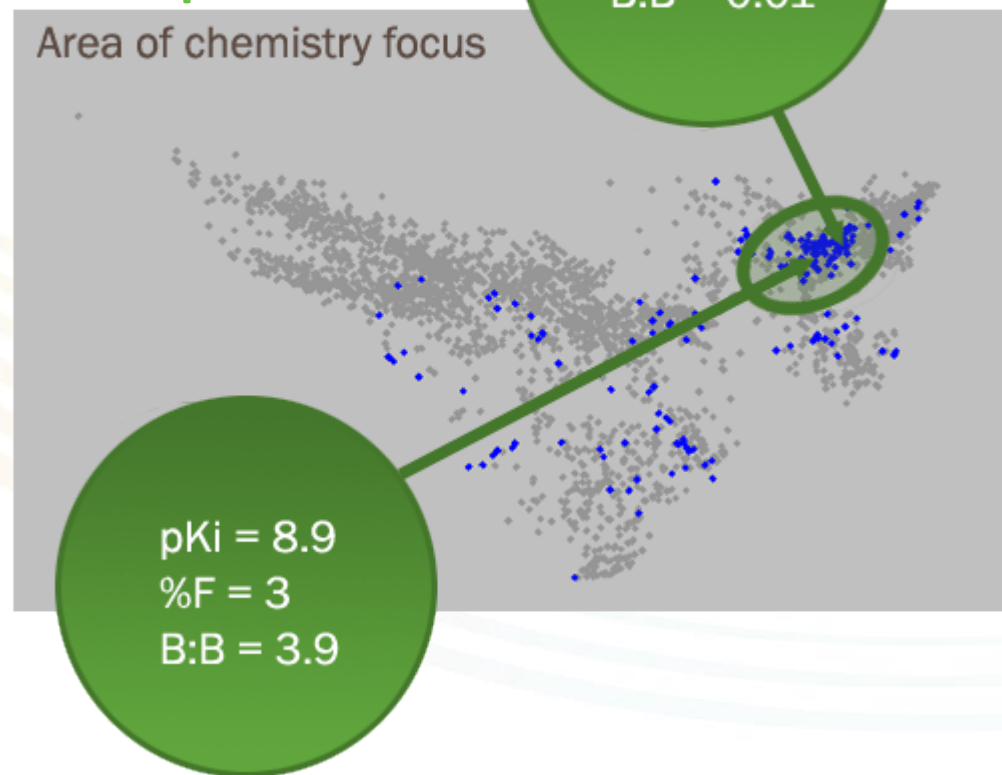
Challenge

Identify orally active compound for a CNS target.
Project 'chemical space' of 3100 compounds

Summary of original project progress

- Focus biased towards one area of chemistry space

Area of chemistry focus



pKi = 9.4
%F = 72
B:B = 0.01

pKi = 8.9
%F = 3
B:B = 3.9

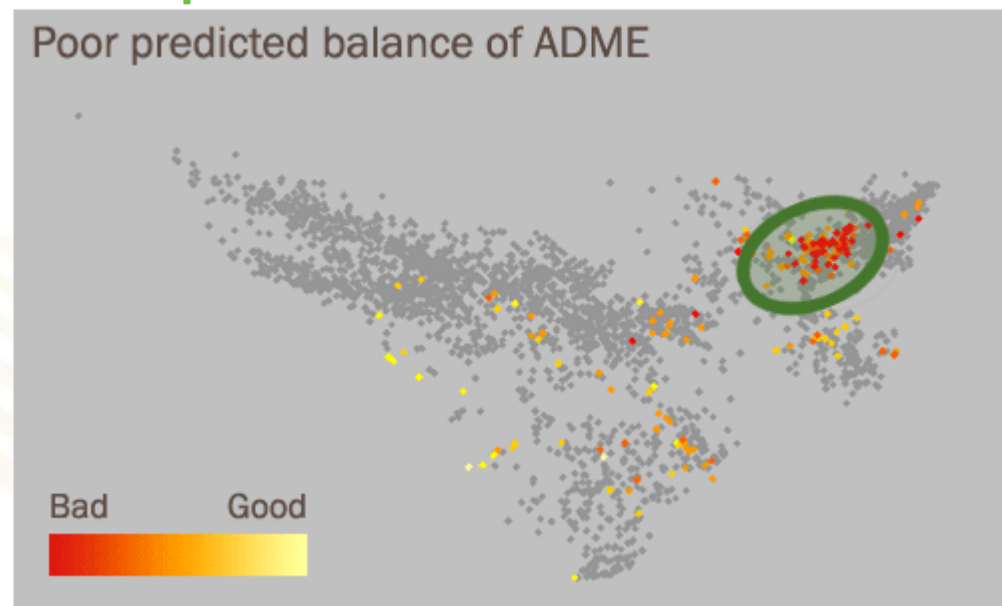
Challenge

Identify orally active compound for a CNS target.
Project 'chemical space' of 3100 compounds

Summary of original project progress

- Focus biased towards one area of chemistry space
- Poor ADME properties

| Property | Desired Value | Importance |
|--------------------------|---------------|------------|
| logS | > 1 | |
| HIA category | + | |
| BBB log([brain]:[blood]) | > -0.5 | |
| logP | ≤ 3.5 | |
| 2D6 affinity category | low medium | |
| 2C9 pKi | ≤ 6 | |
| P-gp category | no | |



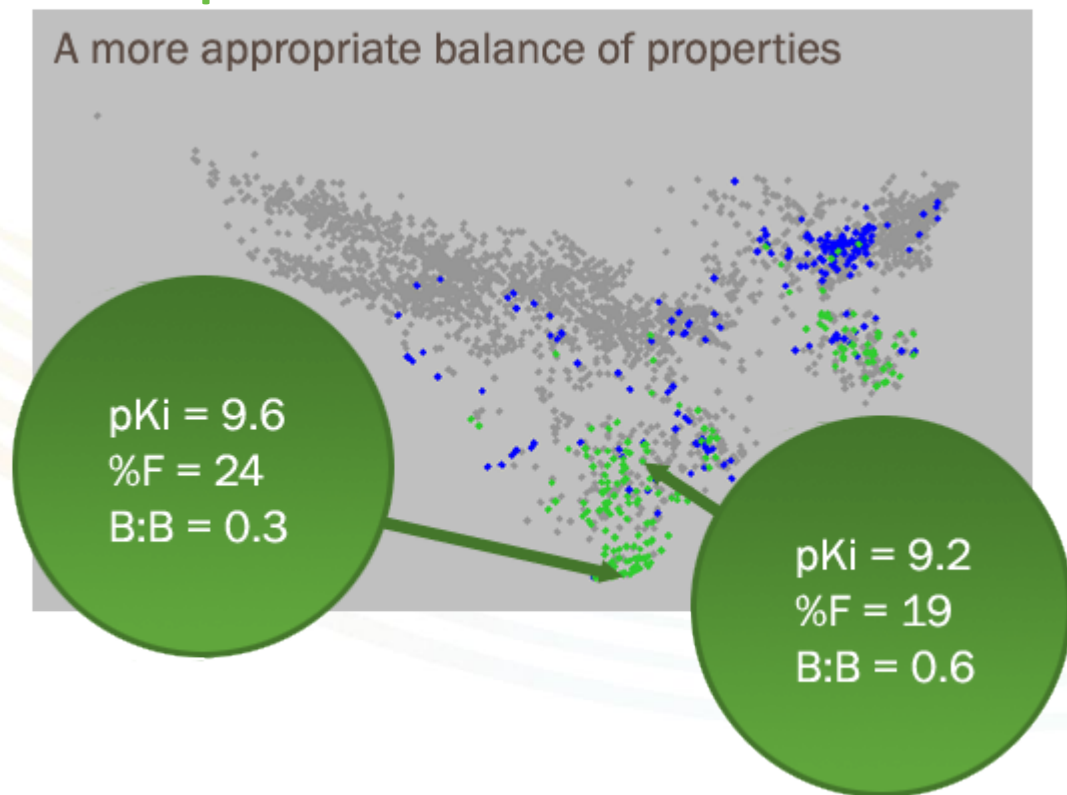
Challenge

Identify orally active compound for a CNS target.
Project 'chemical space' of 3100 compounds

Summary of original project progress

- Focus biased towards one area of chemistry space
- Poor ADME properties
- Follow-up chemistry exploration
- Nowhere obvious to go next!

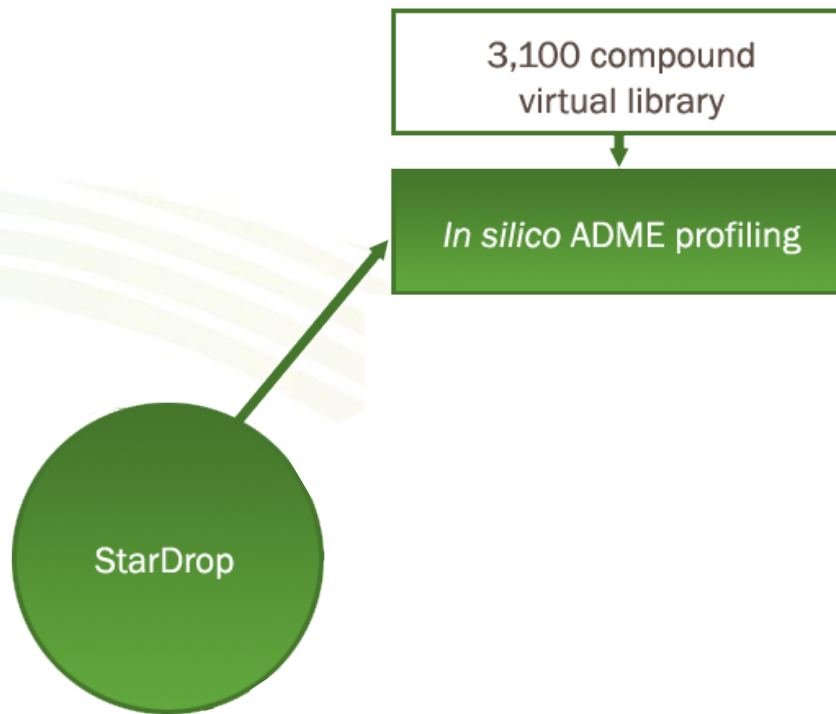
A more appropriate balance of properties



Cost so far: >**3000** compounds synthesised, **400** compounds tested *in vitro* and **70** compounds tested *in vivo*

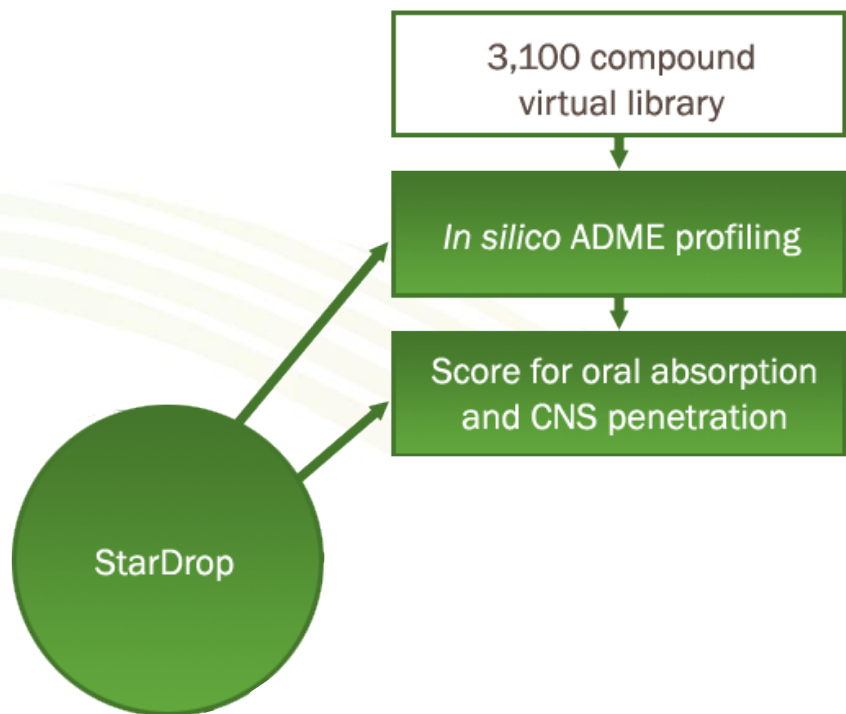
StarDrop Process

Select 25 compounds for *in vivo* testing



StarDrop Process

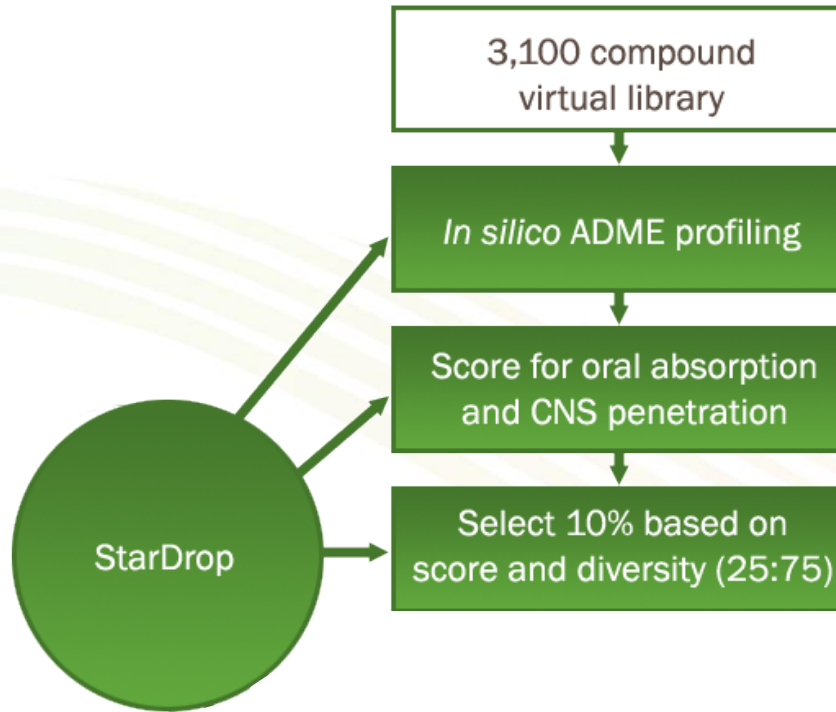
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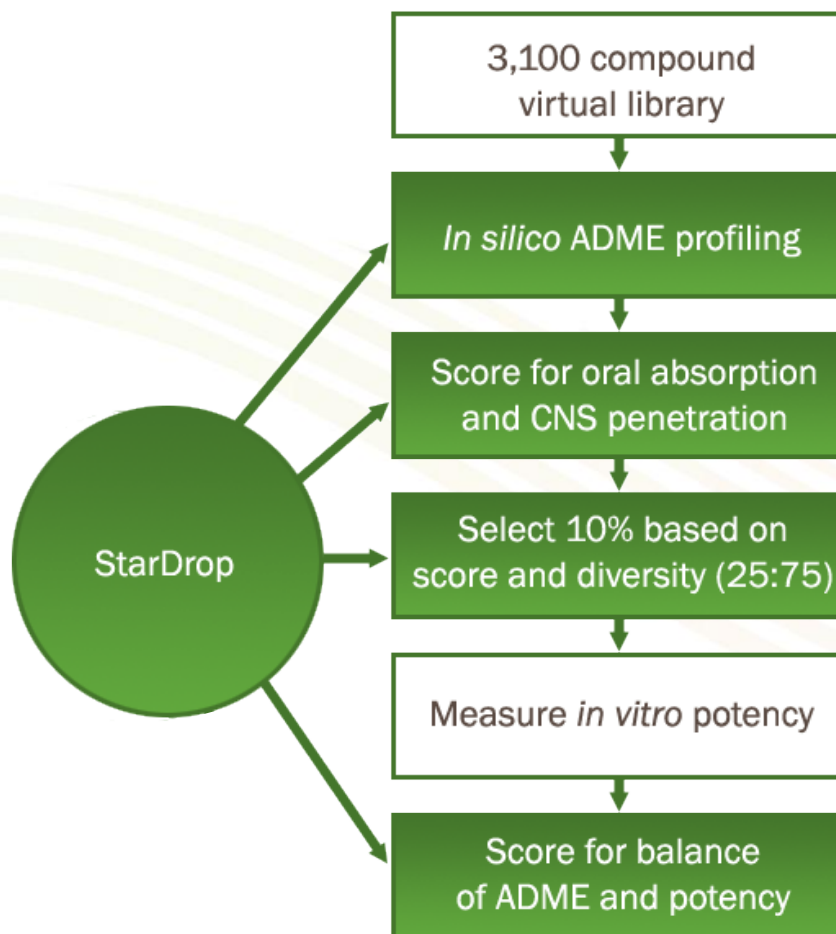
StarDrop Process

Select 25 compounds for *in vivo* testing



StarDrop Process

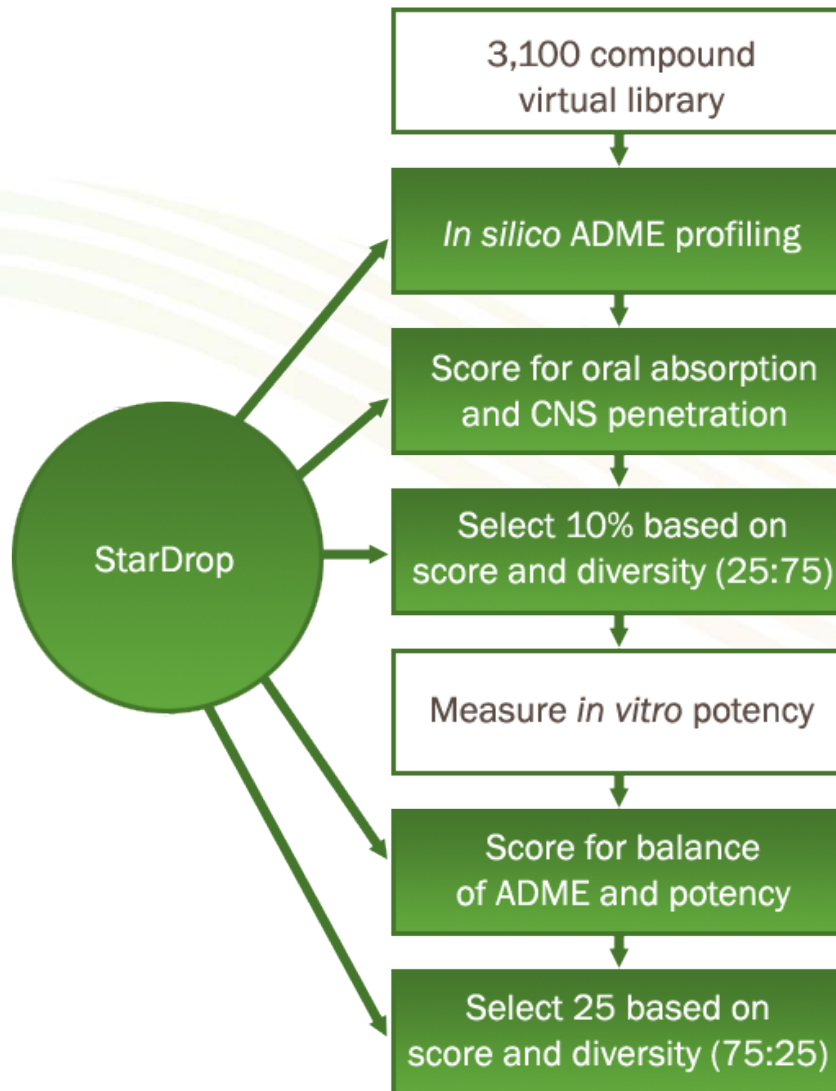
Select 25 compounds for *in vivo* testing



| Property | Desired Value | Importance |
|--------------------------|---------------|------------|
| Potency (pKi) | > 8 | |
| logS | > 1 | |
| HIA category | + | |
| BBB log([brain]:[blood]) | > -0.5 | |
| logP | ≤ 3.5 | |
| 2D6 affinity category | low medium | |
| 2C9 pKi | ≤ 6 | |
| P-gp category | no | |

StarDrop Process

Select 25 compounds for *in vivo* testing

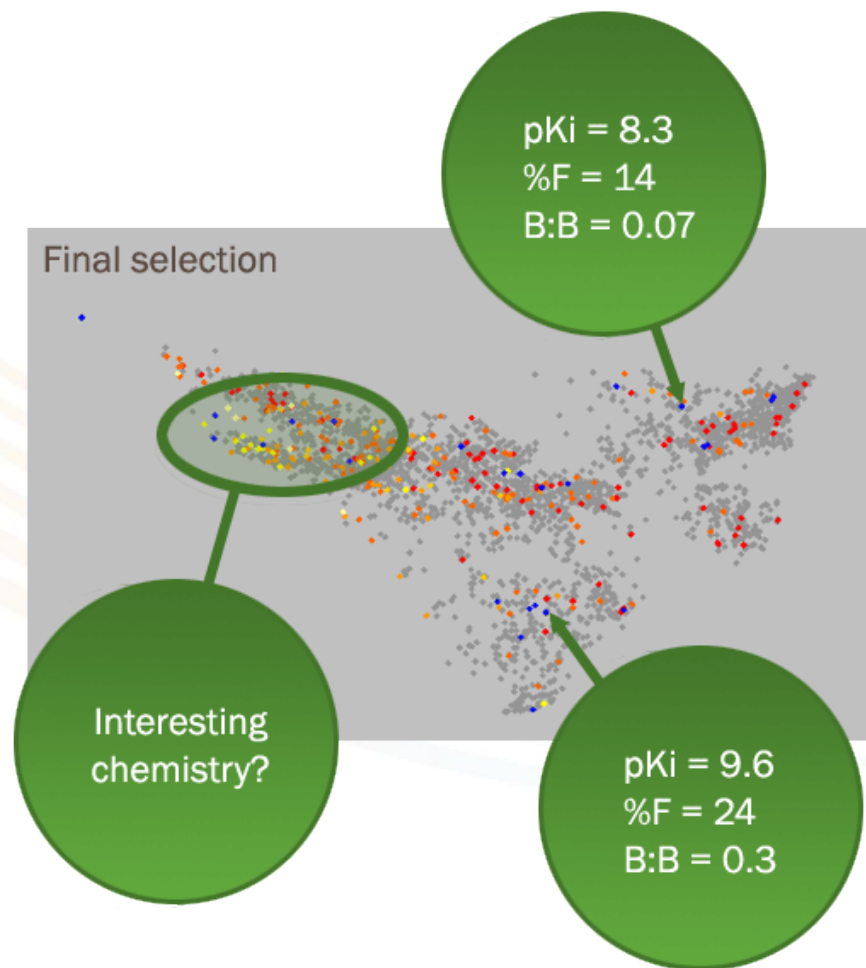


Results

Successfully selected same key compounds identified by the project but with:

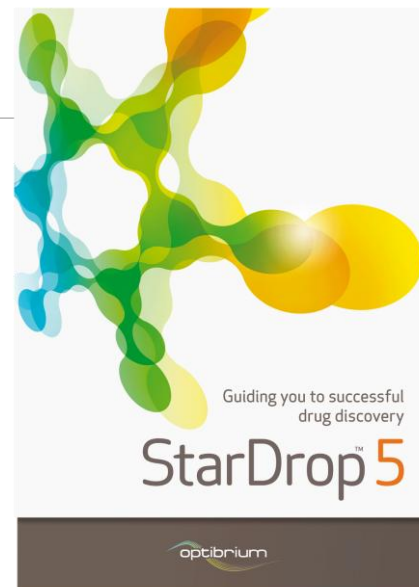
- **90%** fewer compounds synthesised
- **90%** less potency screening
- **70%** less *in vivo* testing

In addition, identified a new area of chemistry with good potential!



Conclusions

- In drug discovery, we must make confident decisions on complex multi-dimensional data
 - Uncertainty in all data
- Requirements for MPO in Drug Discovery
 - Interpretable
 - Flexible
 - Weighting
 - Uncertainty
- Detailed review (submitted to Curr. Pharm. Des.)
 - **Multi-Parameter Optimization: Identifying high quality compounds with a balance of properties**
 - www.optibrium.com/community
 - matt.segall@optibrium.com



Acknowledgements

- StarDrop group past and present, including:
 - Ed Champness
 - Chris Leeding
 - Iskander Yusof
 - James Chisholm
 - Olga Obrezanova
 - Alan Beresford
 - Dawn Yates
 - Dan Hawksley
 - Joelle Gola
 - Brett Saunders
 - Simon Lister
 - Mike Tarbit