



# Introduction to Multi-Parameter Optimization Prioritizing Compounds with a Balance of Properties

Innovative Lead Optimization and Candidate Selection by *in Silico*  
Synthesis and ADMET Prediction. December 2<sup>nd</sup> 2015

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# Overview

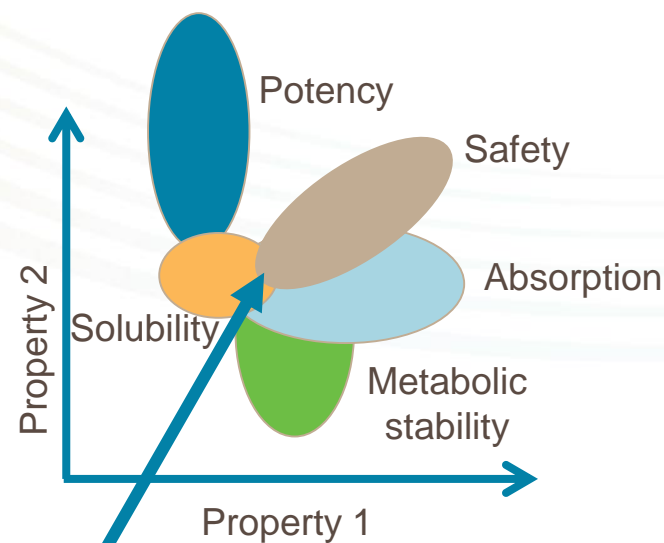
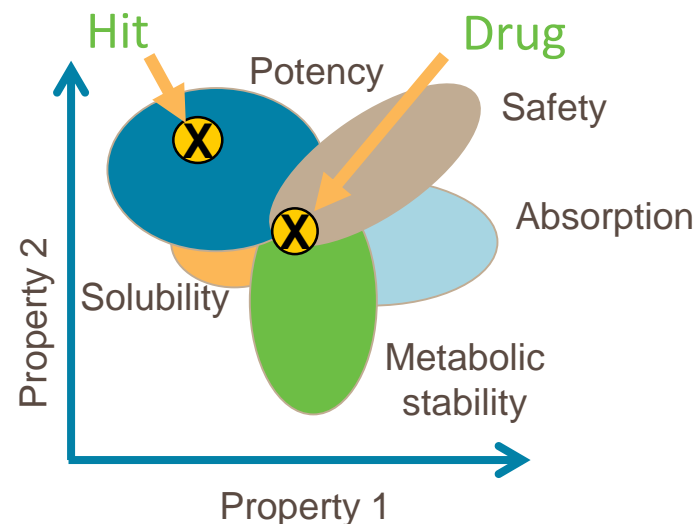
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- Introduction: Balancing Properties in Drug Discovery
  - The challenges of multi-parameter optimisation (MPO)
  - Requirements for MPO in drug discovery
- Approaches for Multi-Parameter Optimisation
- Balancing quality and diversity
- Case study
  - Rapid focus in lead optimisation
- Conclusions

# 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: Data overload

StarDrop - [5HT1A library with scores]

File Edit View Data Set Tools UCB Help

| Structure                                | 5HT1a affinity (p | logS  | logP  | 2C9 pKi | hERG pIC50 | BBB log([brain]:[ | BBB category | HIA category | P-gp category | 2D6 affinity cate | PPB90 category |
|--|-------------------|-------|-------|---------|------------|-------------------|--------------|--------------|---------------|-------------------|----------------|
| 133 <chem>N#Cc1ccc2cc3ccccc3cc2c1</chem> | 8.74              | 1.868 | 4.777 | 5.208   | 5.992      | 0.346             | +            | +            | yes           | medium            | high           |
| 140 <chem>N#Cc1ccc2cc3ccccc3cc2c1</chem> | 8.24              | 1.48  | 3.397 | 5.446   | 5.561      | -0.1064           | -            | +            | yes           | medium            | high           |
| 141 <chem>N#Cc1ccc2cc3ccccc3cc2c1</chem> | 7.32              | 1.462 | 3.88  | 5.376   | 5.585      | -0.08039          | +            | +            | yes           | medium            | high           |

Ready












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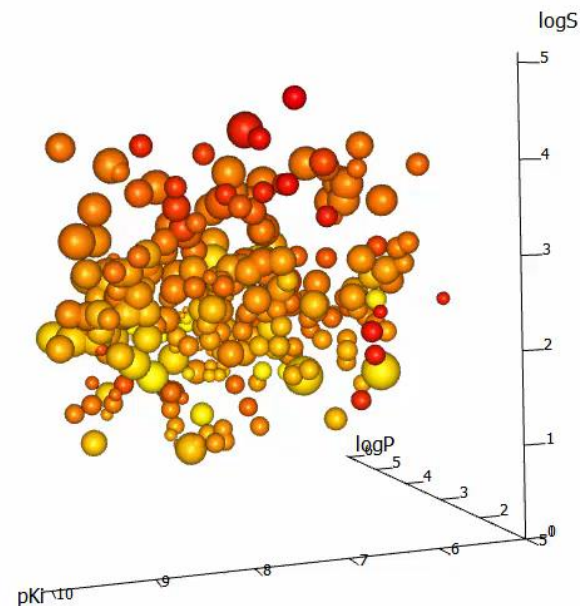
10,000 compounds through 10 *in silico* models is 100,000 data points!

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

# Challenge 1: Data overload

## Visualisation is important but not enough...

| MolName | Structure   | pKi 5HT1a affinity | logS  | logP  | 2C9 pKi | hERG pIC50 | log(BB) | BBB category | HIA category | P-gp category | 2D6 affinity category | PPB category |
|---------|---|--------------------|-------|-------|---------|------------|---------|--------------|--------------|---------------|-----------------------|--------------|
| SI-10   |  | 6                  | 3.894 | 3.322 | 3.464   | 5.836      | 0.8671  | +            | +            | no            | medium                | high         |
| SI-11   |  | 6                  | 3.697 | 3.44  | 3.485   | 5.72       | 0.7745  | +            | +            | no            | very high             | high         |
| SI-12   |  | 6.8                | 4.124 | 3.106 | 3.677   | 5.684      | 0.9036  | +            | +            | no            | medium                | high         |
| SI-13   |  | 9                  | 3.659 | 3.844 | 3.558   | 5.85       | 0.8504  | +            | +            | no            | very high             | high         |
| SI-14   |  | 6                  | 4.051 | 2.932 | 3.369   | 5.56       | 0.4056  | +            | +            | no            | high                  | high         |
| SI-15   |  | 6.5                | 2.504 | 4.33  | 4.502   | 6.175      | 0.8534  | +            | +            | yes           | medium                | high         |
| SI-16   |  | 5.3                | 3.636 | 3.832 | 3.464   | 5.646      | 0.6799  | +            | +            | no            | medium                | high         |
| SI-18   |  | 7.96               | 3.444 | 4.34  | 3.558   | 5.647      | 0.8568  | +            | +            | no            | very high             | high         |
| SI-19   |  | 6.99               | 3.327 | 3.594 | 3.677   | 5.677      | 0.6858  | +            | +            | no            | medium                | high         |
| SI-20   |  | 7.36               | 3.721 | 3.487 | 3.391   | 5.639      | 0.2327  | +            | +            | no            | very high             | high         |
| SI-21   |  | 7.84               | 3.632 | 3.964 | 3.485   | 5.725      | 0.6096  | +            | +            | no            | very high             | high         |

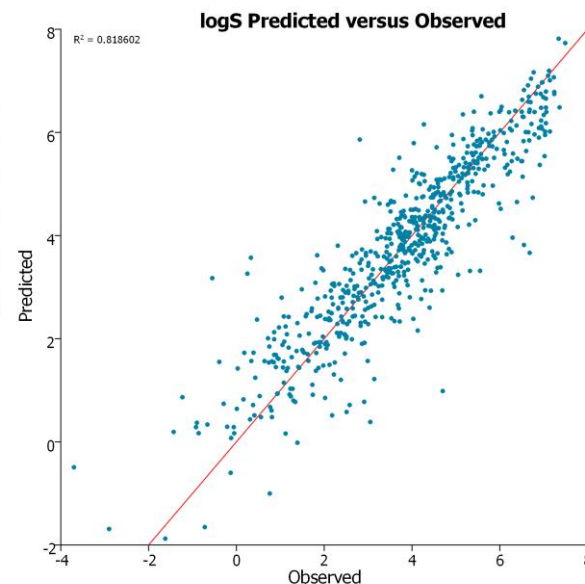


How can you make a confident decision by looking at these?

# Challenge 2: Uncertainty in Data

## Statistical

- Experimental variability/error
  - Single measurements: assay variability
    - o  $pK_i/pIC_{50} \sim 0.3 - 0.7$  log units (factor of 2-5 in  $K_i/IC_{50}$ )
  - Multiple replicates: mean and standard error in mean
- Statistical uncertainty in predictions
  - Standard error of prediction (assessed from validation)
    - o  $\log P \sim 0.4 - 0.5$  log units
    - o  $\log S \sim 0.7 - 0.8$  log units
    - o  $pK_i \sim 0.9 - 1.0$  log units
  - Need to consider domain of applicability

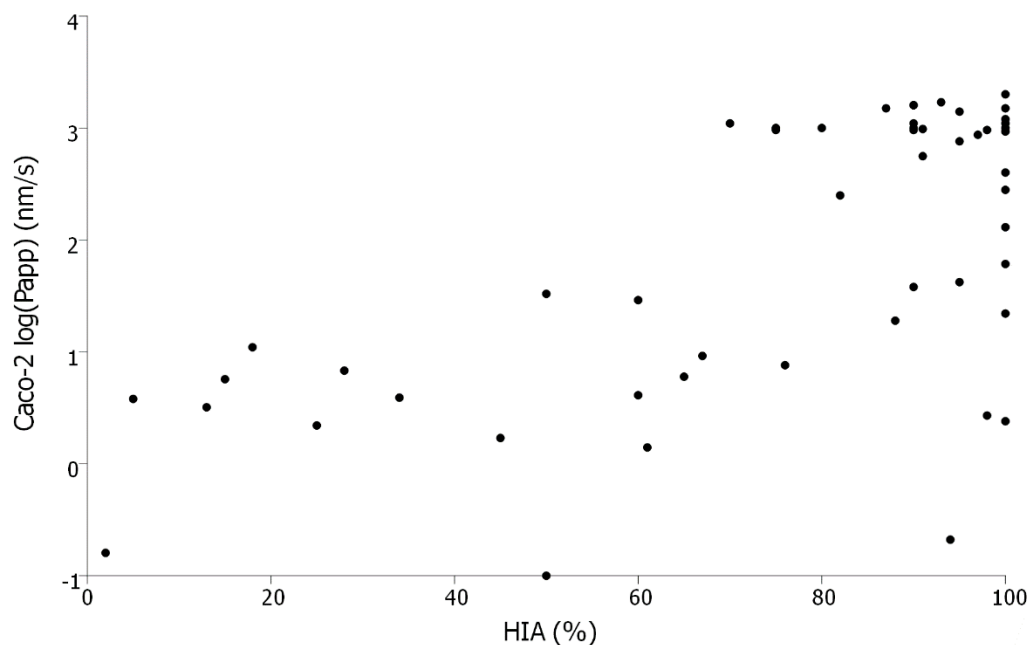


RMSE=0.8 log units

# Challenge 2: Uncertainty in Data

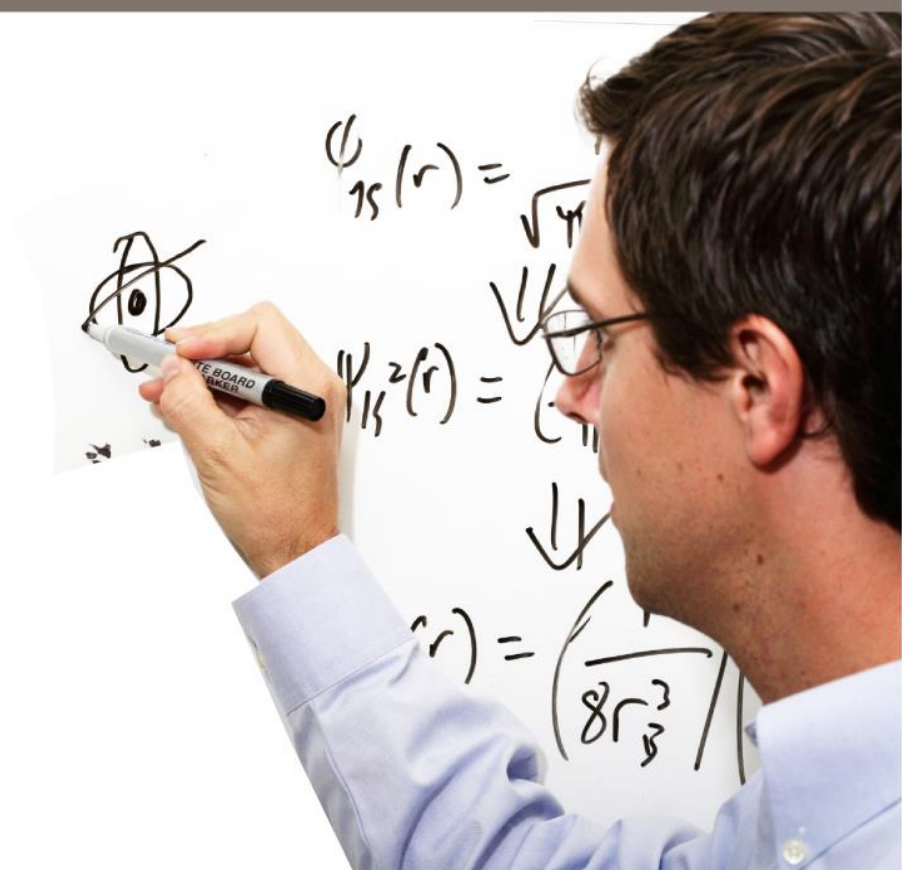
## Relevance

- All sources of data in drug discovery are **models** of the ultimate human patient
  - *In vivo*, *in vitro* or *in silico*
  - Inference/translation
- For example, Caco-2 permeation (model of absorption)\*:



\* Data from Irvine *et al.* (1999) J. Pharm. Sci. **88** pp. 28-33

# Approaches for MPO in Drug Discovery





# Requirements for MPO in Drug Discovery

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- Interpretable
  - 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

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- Many methods have been applied for MPO in drug discovery
  - **Rules-of-thumb**
  - **Filtering**
  - Calculated metrics
  - Pareto optimisation
  - **Desirability functions**
  - **Probabilistic scoring**
- For a detailed review, please see:
  - M.D. Segall Curr. Pharm. Des. **18**(9) pp. 1292-1310 (2012)

# Rules of Thumb

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

|                  |                  |
|------------------|------------------|
| <b>logP&lt;5</b> | <b>MW&lt;500</b> |
| <b>HBD&lt;5</b>  | <b>HBA&lt;10</b> |

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

|                  |                                 |
|------------------|---------------------------------|
| <b>logP&lt;3</b> | <b>TPSA&gt;75 Å<sup>2</sup></b> |
|------------------|---------------------------------|

- Simple, easy to apply and interpret
- But:
  - 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<br>( $\leq 1$ RoF Failure) | Fail<br>( $> 1$ RoF Failure) |
| Oral     | 709                             | 59                           |
| Non-oral | 333                             | 90                           |

- Neither specific nor sensitive...

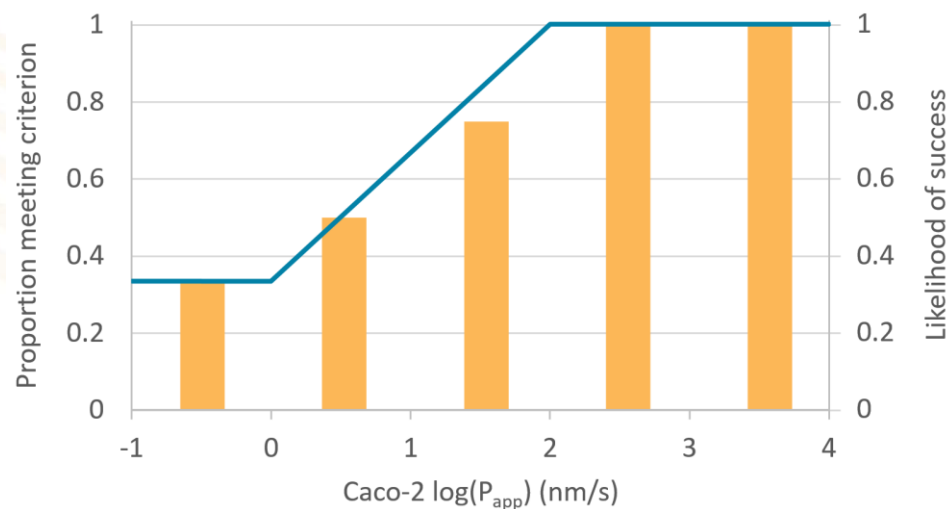
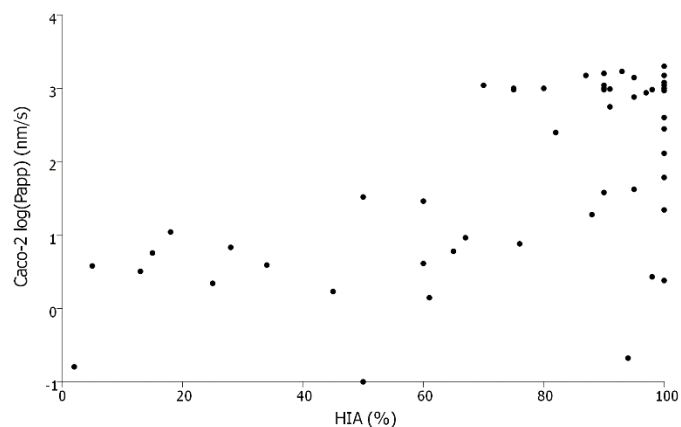
# Filtering



# Considering Relevance

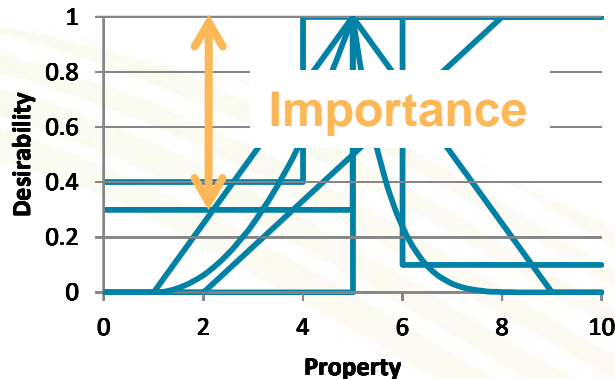
What impact does a value have on the ultimate outcome?

- Consider Caco-2 permeation again\*
  - Experimental model of human intestinal absorption (HIA)
  - What is chance of a compound achieving HIA > 50%



# Desirability Functions

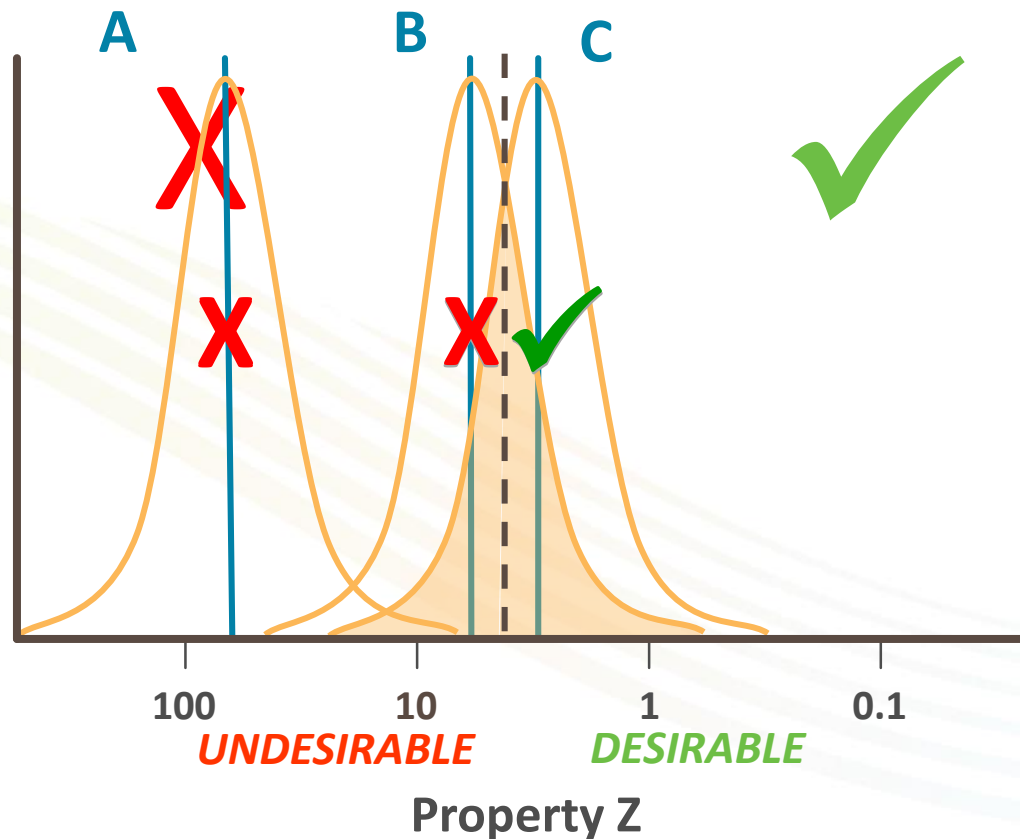
- Relate property values to how 'desirable' the outcome



Example:  $d_1(5) = 0.5$  value: 5  
(Derringer Function)

- Combine multiple properties into 'desirability index'
  - Additive:  $\frac{d_1(X_1) + d_2(X_2) + \dots + d_n(X_n)}{n}$
  - Multiplicative:  $D = \sqrt[n]{d_1(X_1) \times d_2(X_2) \times \dots \times d_n(X_n)}$
- Flexible and easy to interpret
  - Clear indication of which properties are poor

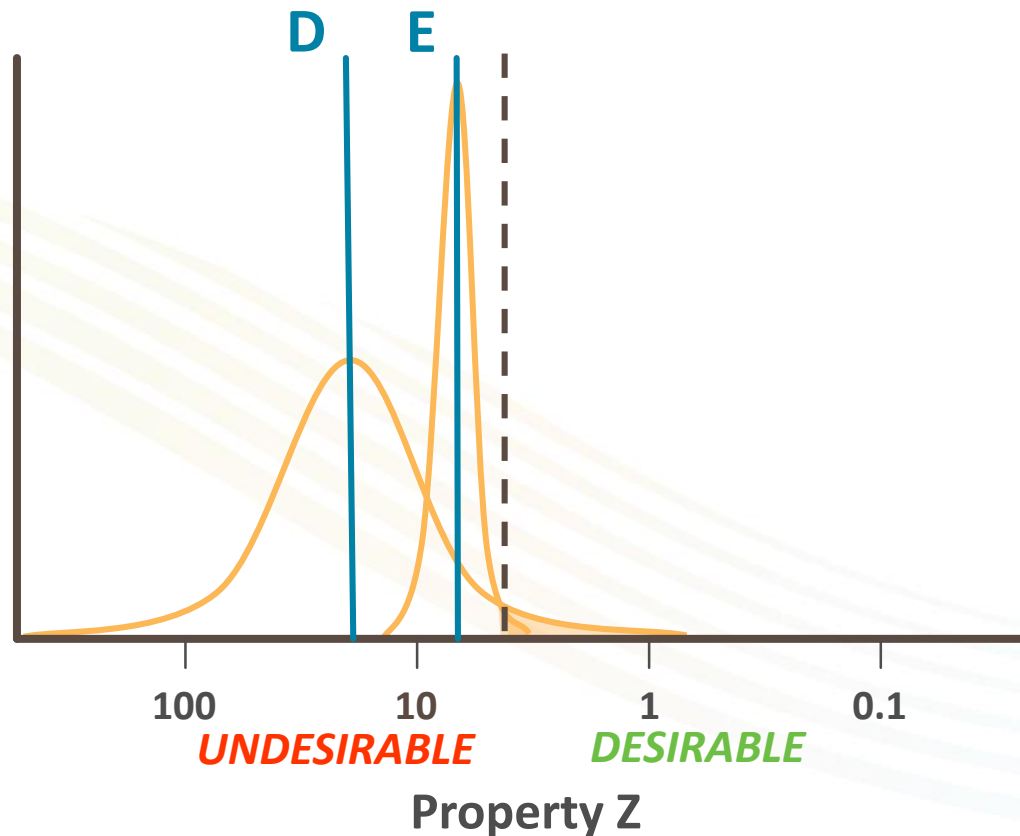
# Importance of Uncertainty



- Conclusions:
  - Reject compound A
  - Cannot confidently choose between B and C












# Importance of Uncertainty

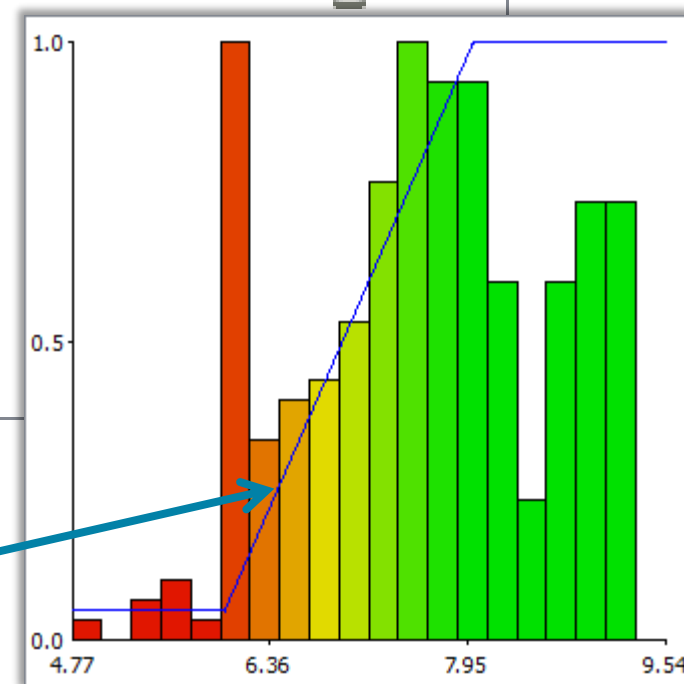


- Conclusion:
  - Compound D has higher probability of success

# Probabilistic Scoring

## Scoring Profile

| Property                 | Desired Value   | Importance  |
|--------------------------|---|---|
| 5HT1a affinity (pKi)     | 8 -> inf     |  |
| logS                     | > 1   |  |
| HIA category             | +   |  |
| logP                     | 0 -> 3.5     |  |
| BBB log([brain]:[blood]) | -0.2 -> 1    |  |
| BBB category             | +   |   |
| P-gp category            | no  |   |
| hERG pIC50               | ≤ 5   |   |
| 2C9 pKi                  | ≤ 6   |   |
| 2D6 affinity category    | low medium  |   |
| PPB90 category           | low   |   |



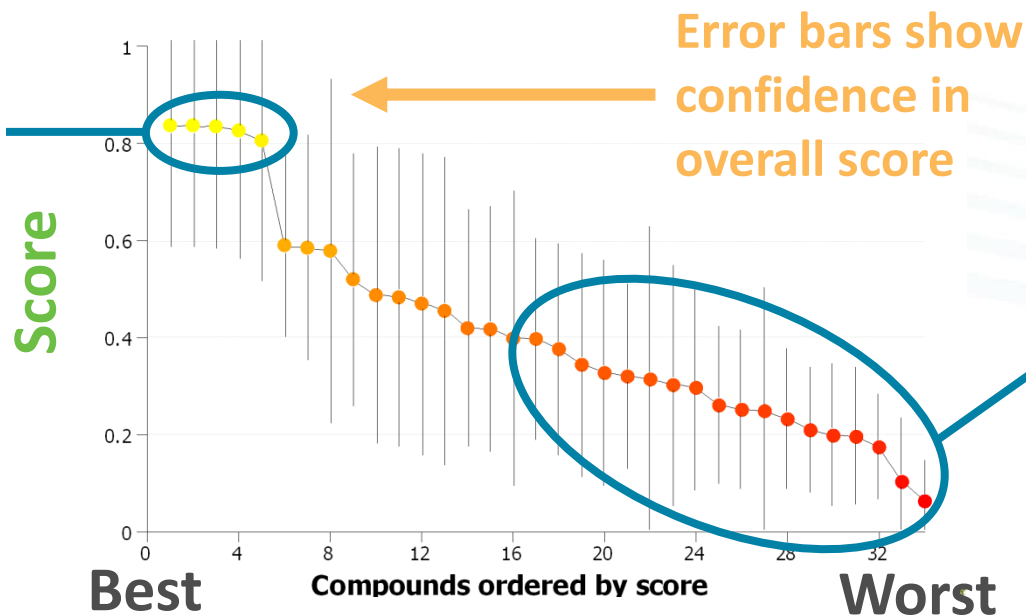
Desirability function

# Probabilistic Scoring

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

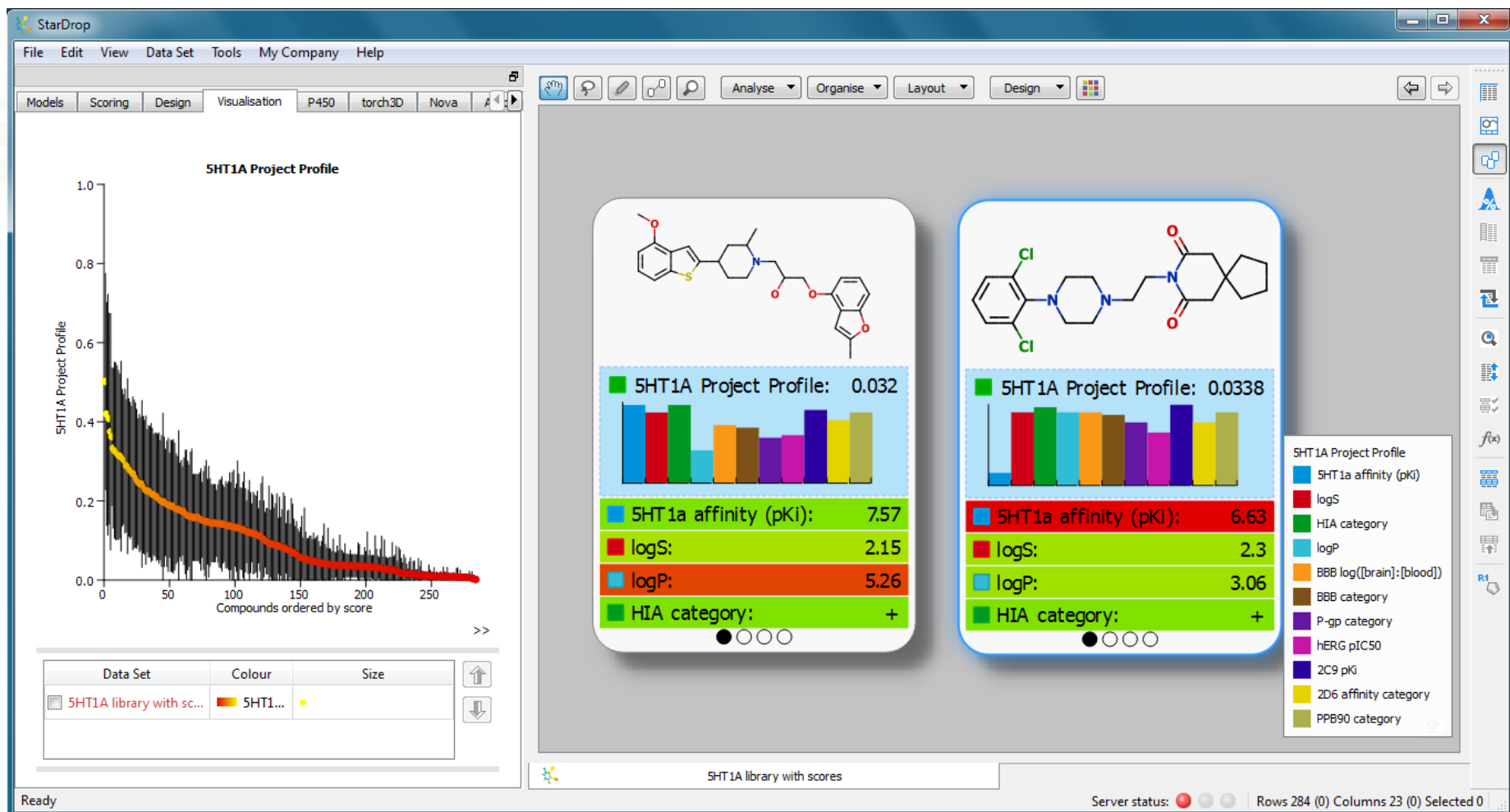
- **Score (Likelihood of Success)**
- **Confidence in score**

Data do not separate these as error bars overlap

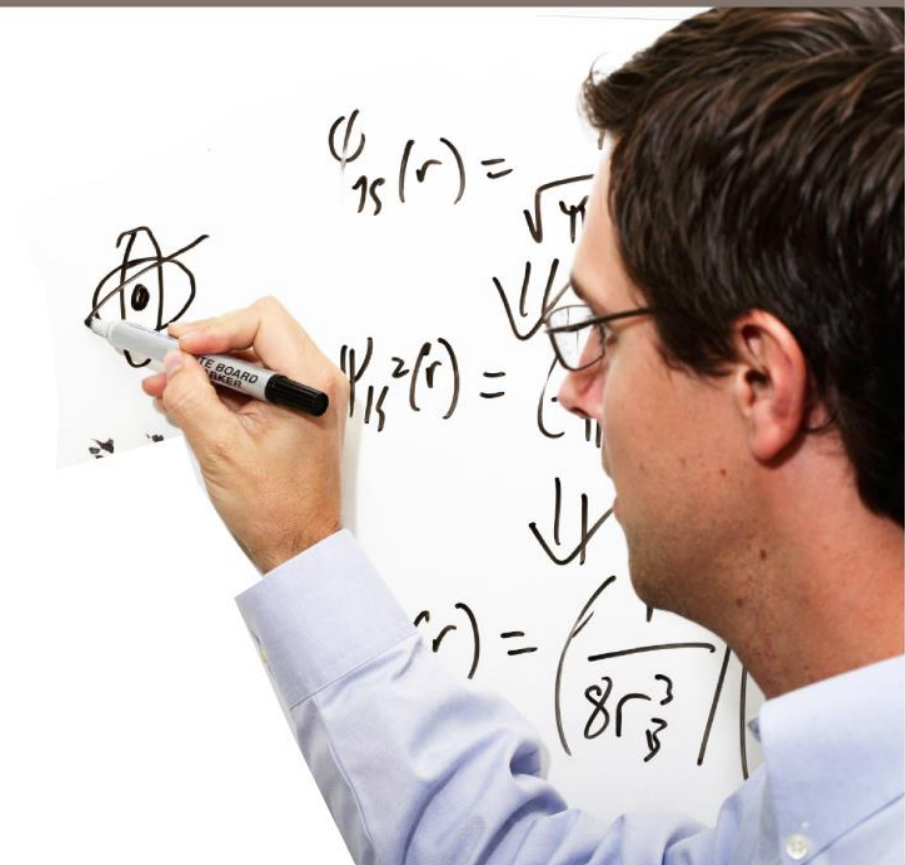


# Probabilistic Scoring

## Guide redesign to improve chance of success

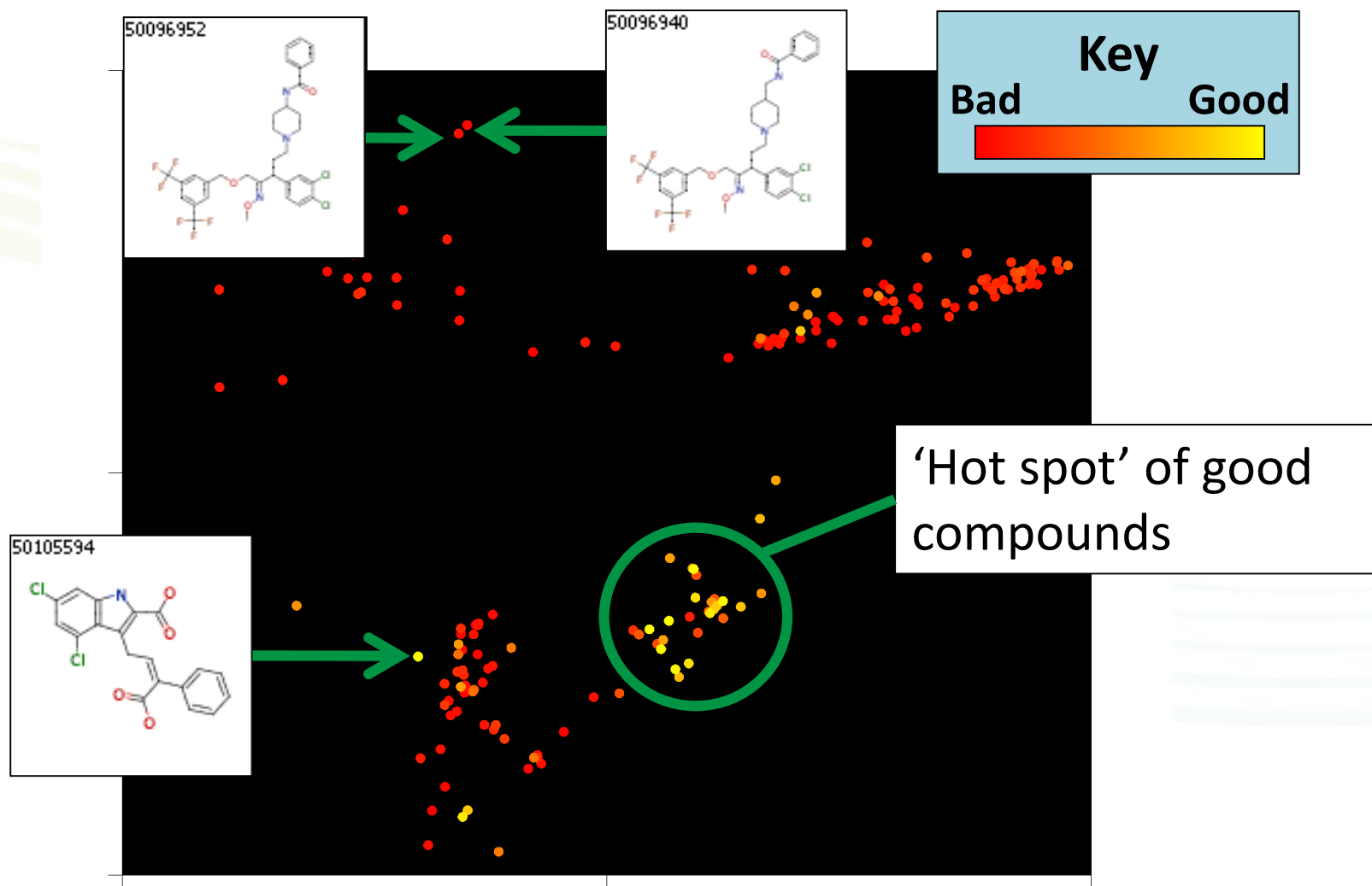


# Balancing Quality and Diversity



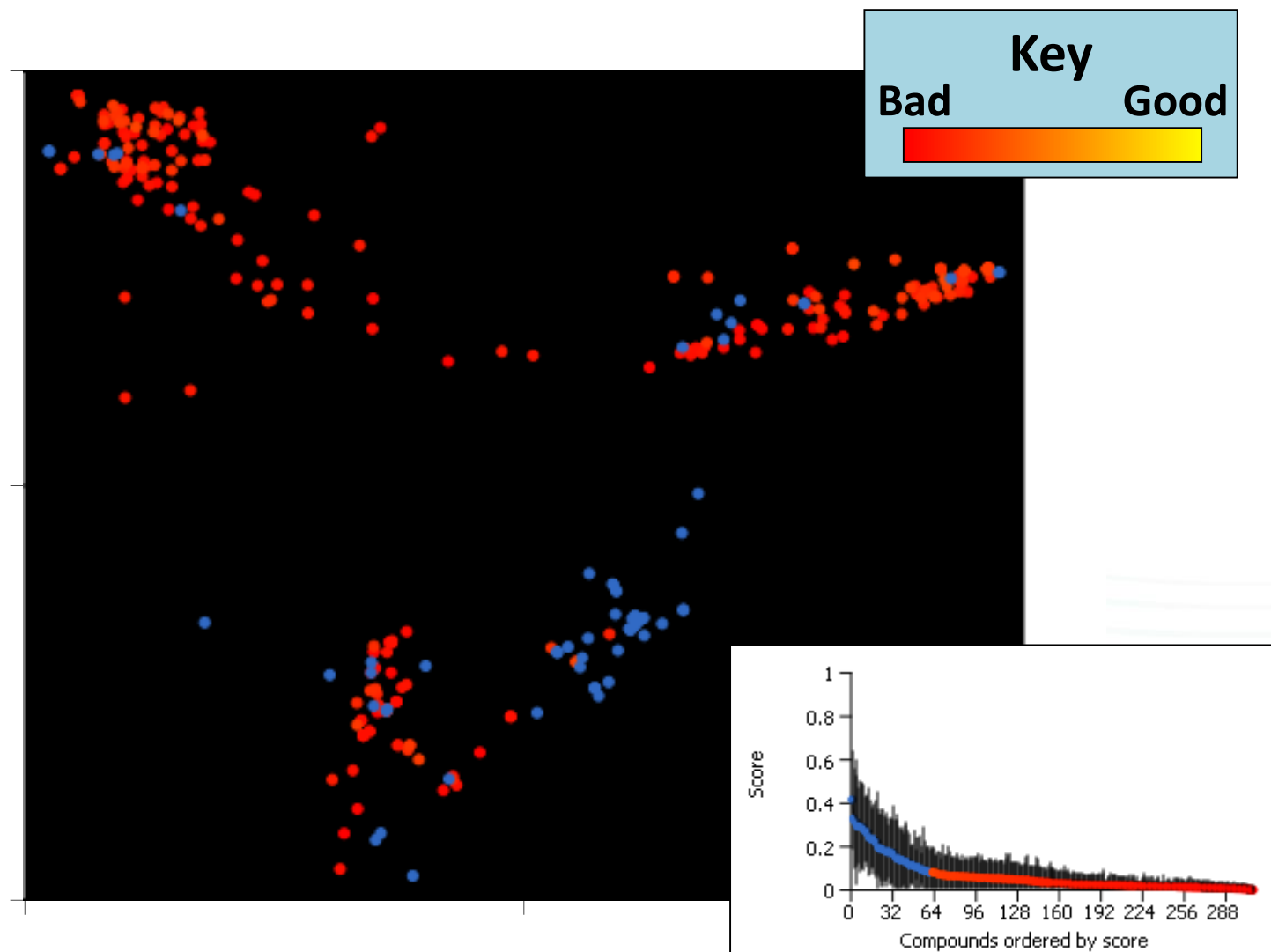
# Visualising 'Chemical Space'

## Exploring trends across chemical diversity



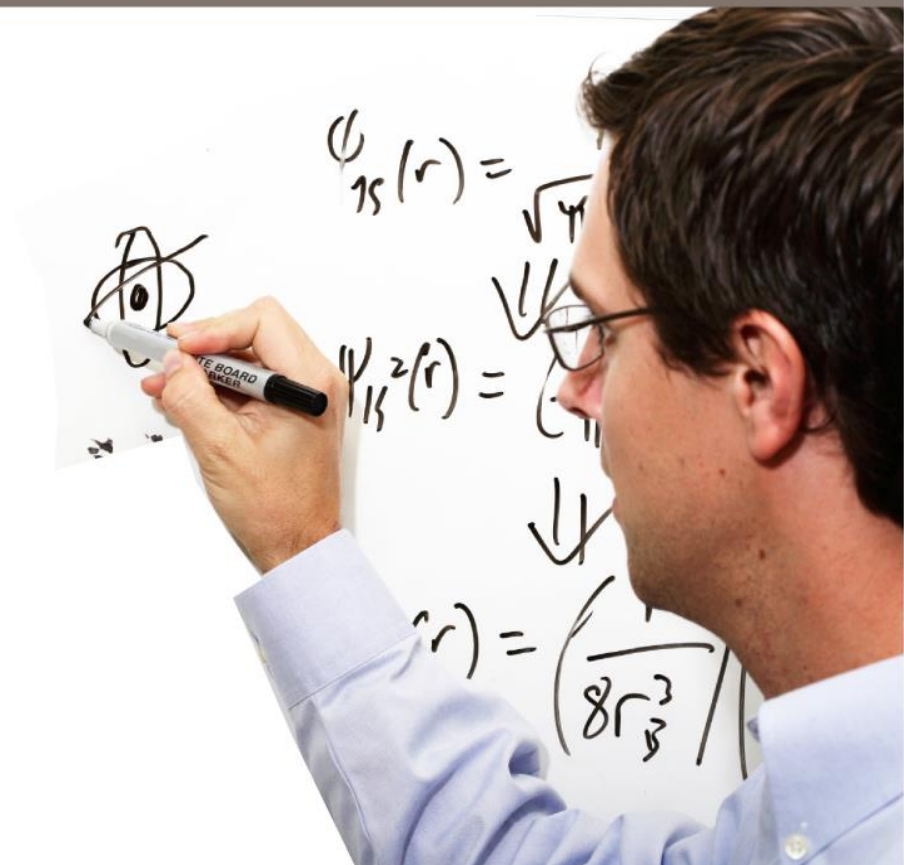
# Balance Quality Against Diversity

## Mitigating risk



# Case Study

## Rapid Focus in Lead Optimisation



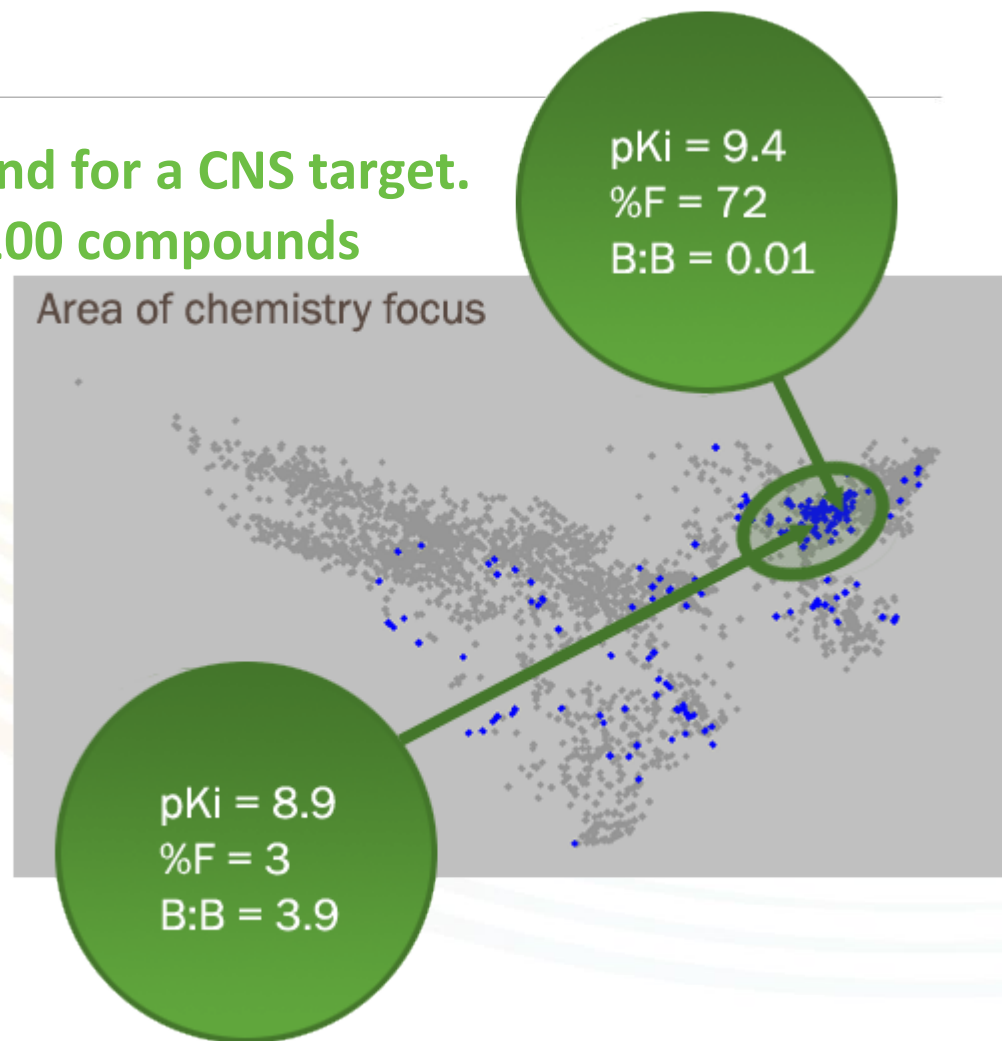


# Challenge

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



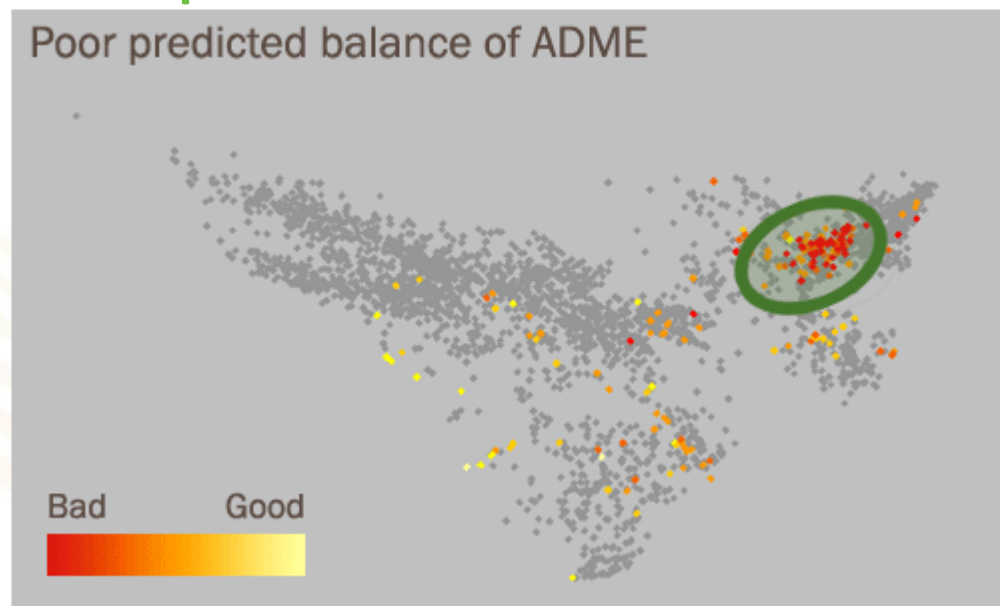
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Identify orally active compound for a CNS target.  
Project 'chemical space' of 3100 compounds

## 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            |            |

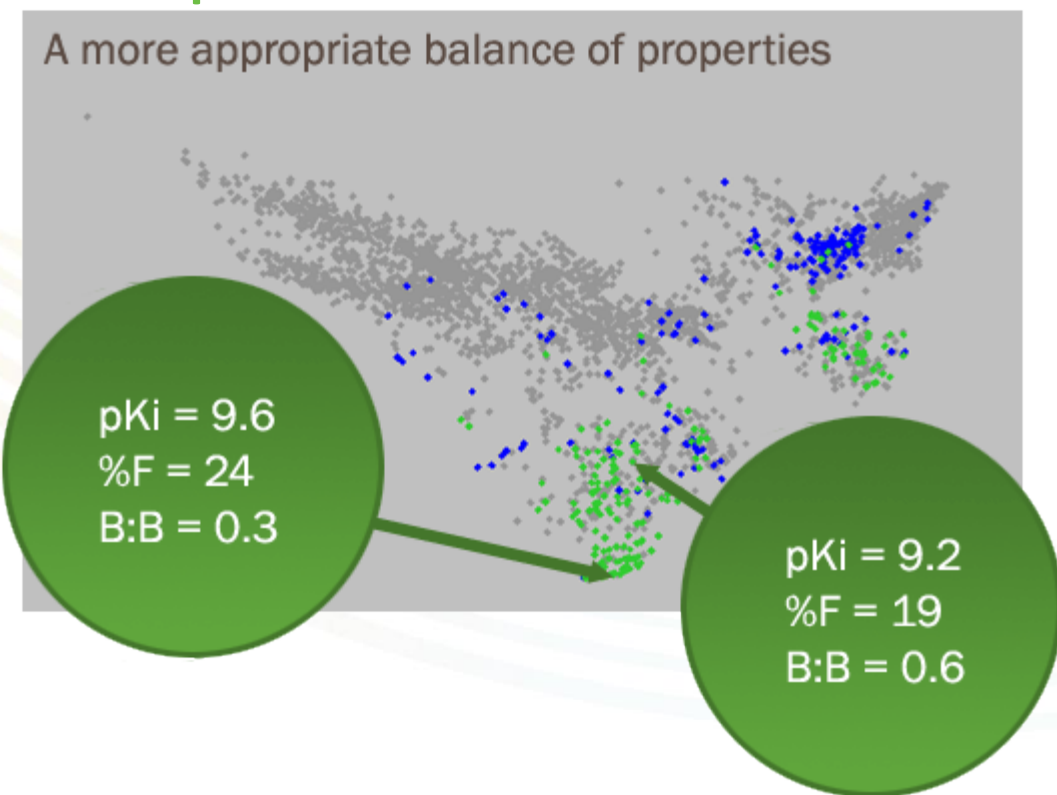


# Challenge

Identify orally active compound for a CNS target.  
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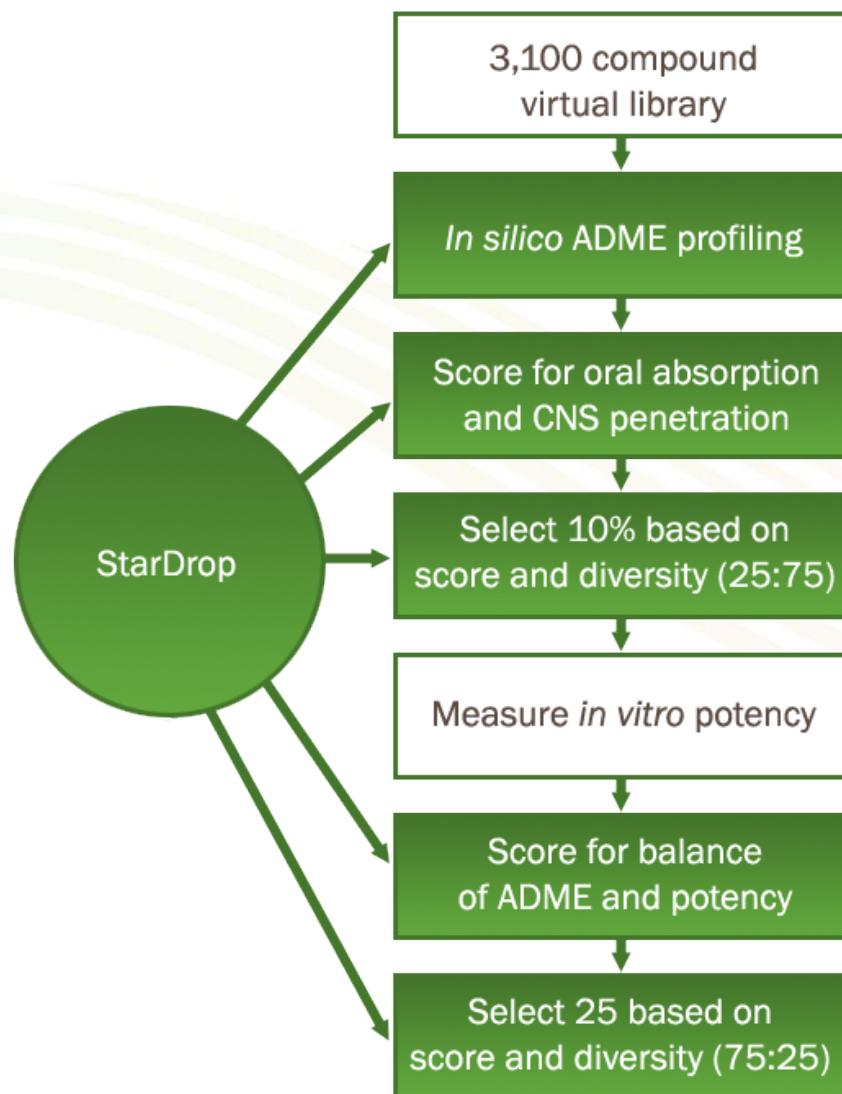
- Focus biased towards one area of chemistry space
- Poor ADME properties
- Follow-up chemistry exploration
- Nowhere obvious to go next!



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



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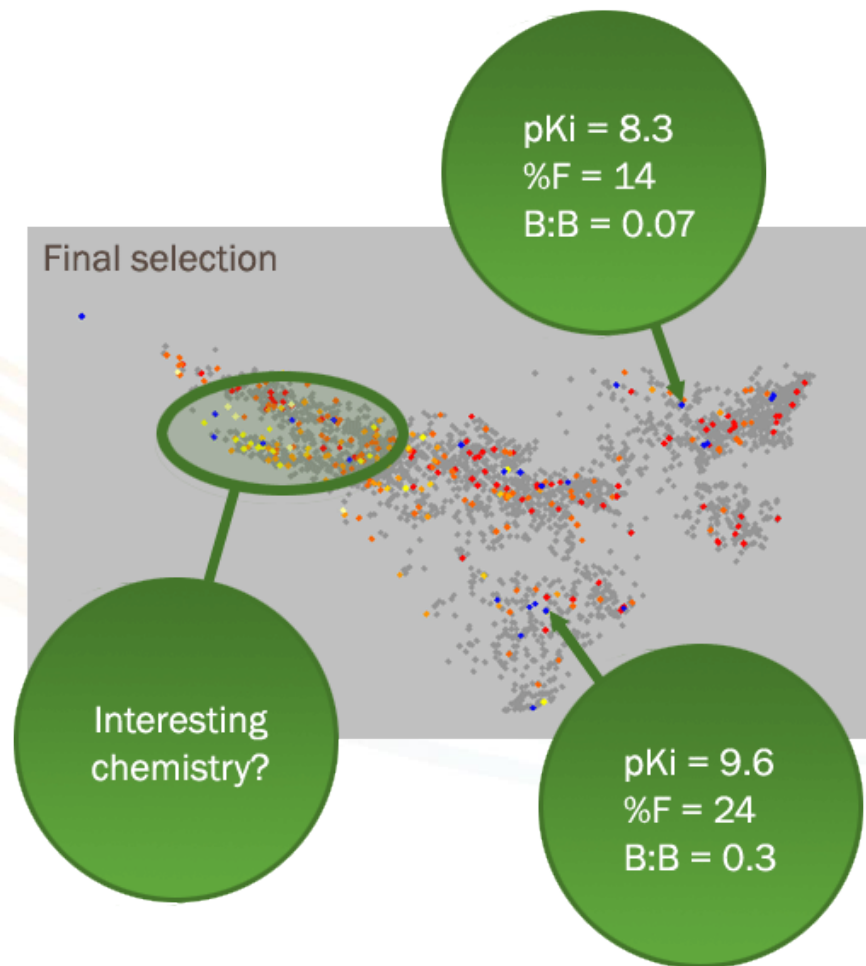
| Property                 | Desired Value | Importance |
|--------------------------|---------------|------------|
| Potency (pKi)            | > 8           |            |
| logS                     | > 1           |            |
| HIA category             | +             |            |
| BBB log([brain]:[blood])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

# 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!**



# Conclusion

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- MPO is a powerful approach to select and design high quality compounds
  - Quickly target compounds with high chance of success
  - Avoid missed opportunities
- Be aware of the limitations of drug discovery data
  - Relevance
  - Uncertainty
- A 'balanced' strategy can dramatically reduce the time and resources required for compound optimisation
- For more details, please see:
  - M.D. Segall Curr. Pharm. Des. **18**(9) pp. 1292-1310 (2012)