



Visual analyses for guiding compound selection and design

Ed Champness – March 25th 2010

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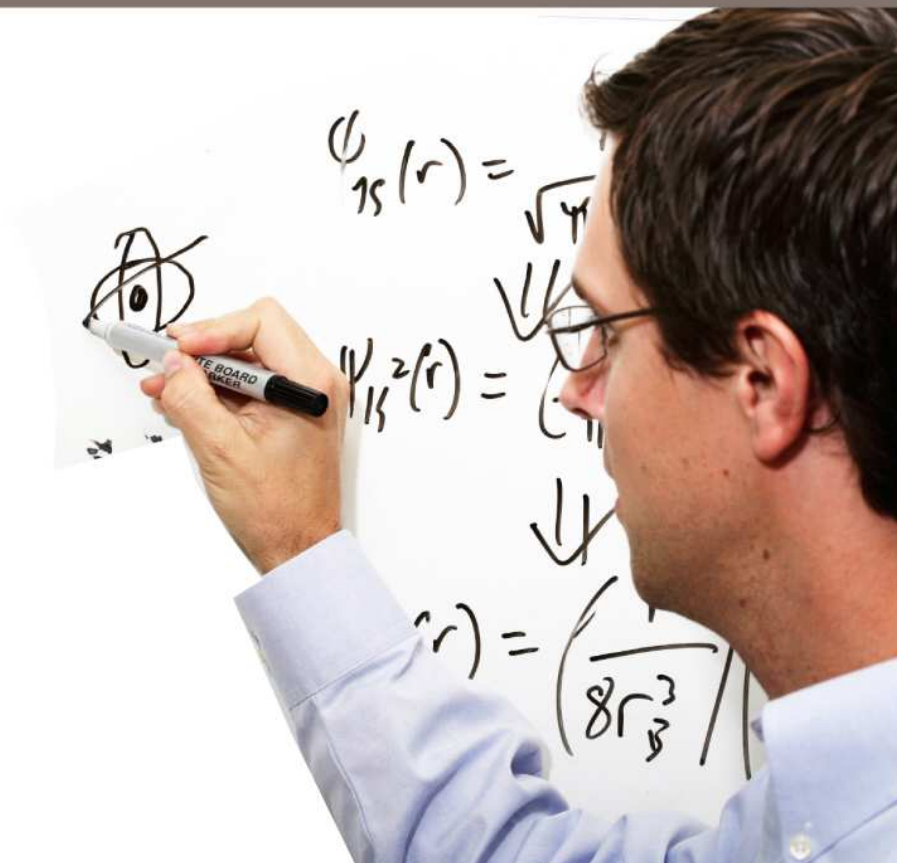
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Overview

- Challenges of decision making in Drug Discovery
- What questions do we ask?
- A workflow
 - Prioritisation
 - Selection
 - Design/redesign
- Conclusions

Challenges



Challenges

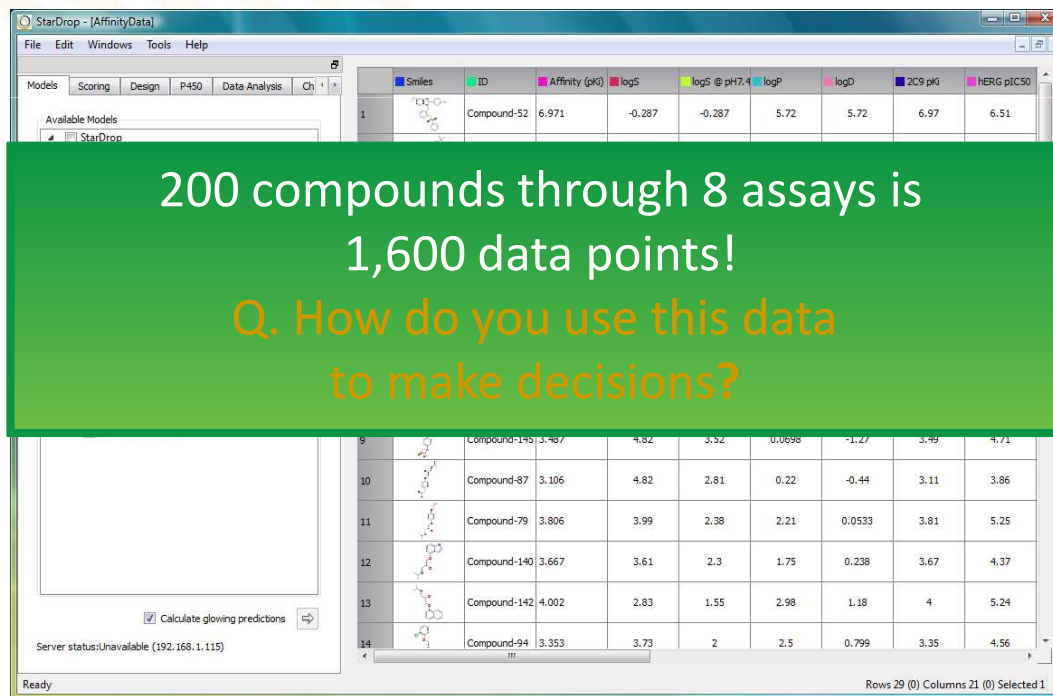
Decision-making in Drug Discovery involves:

- Potentially large volumes of information, multiple parameters, many sources
- Uncertain, sparse data
- Cross-discipline coordination/agreement

Challenges

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200 compounds through 8 assays is
1,600 data points!
Q. How do you use this data
to make decisions?

	Smiles	ID	Affinity (pK)	logS	logS @ pH7.4	logP	logD	2C9 pKi	HERG pIC50
1	<chem>CC1=CC=C(C=C1)C2=CC=CC=C2</chem>	Compound-52	6.971	-0.287	-0.287	5.72	5.72	6.97	6.51
9	<chem>CC1=CC=C(C=C1)C2=CC=CC=C2</chem>	Compound-145	3.487	4.82	3.32	0.0698	-1.27	3.49	4.71
10	<chem>CC1=CC=C(C=C1)C2=CC=CC=C2</chem>	Compound-87	3.106	4.82	2.81	0.22	-0.44	3.11	3.86
11	<chem>CC1=CC=C(C=C1)C2=CC=CC=C2</chem>	Compound-79	3.806	3.99	2.38	2.21	0.0533	3.81	5.25
12	<chem>CC1=CC=C(C=C1)C2=CC=CC=C2</chem>	Compound-140	3.667	3.61	2.3	1.75	0.238	3.67	4.37
13	<chem>CC1=CC=C(C=C1)C2=CC=CC=C2</chem>	Compound-142	4.002	2.83	1.55	2.98	1.18	4	5.24
14	<chem>CC1=CC=C(C=C1)C2=CC=CC=C2</chem>	Compound-94	3.353	3.73	2	2.5	0.799	3.35	4.56

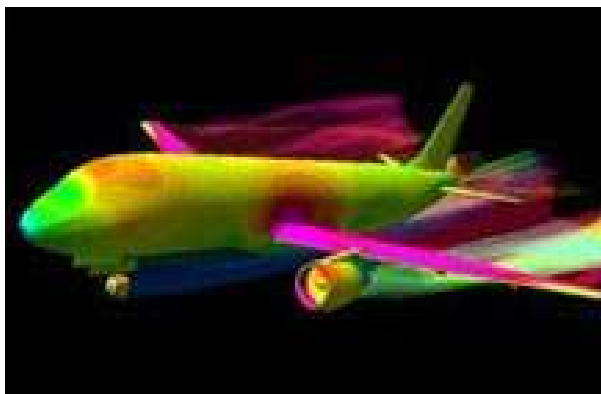
Challenges

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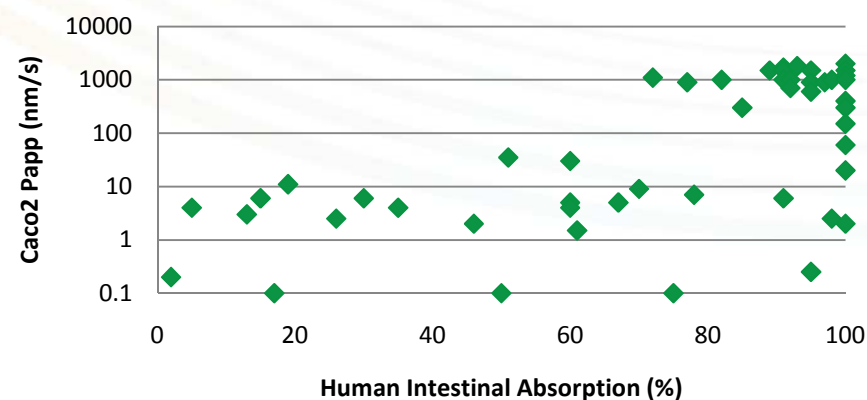
In silico, in vitro, in vivo – they're all models, but...

We don't have this:



Instead, something more like this?

Caco2 vs. Human Intestinal Absorption*

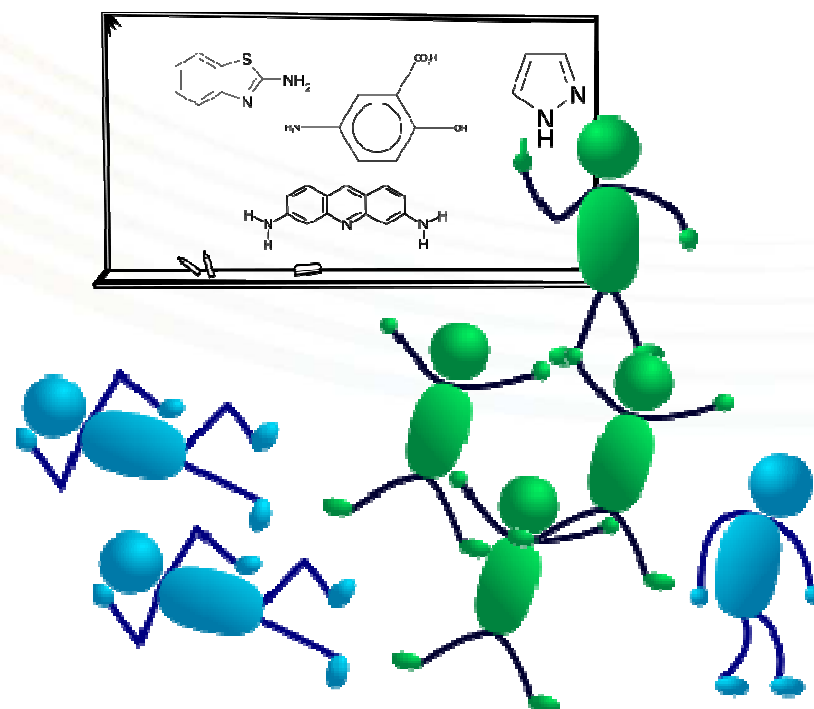
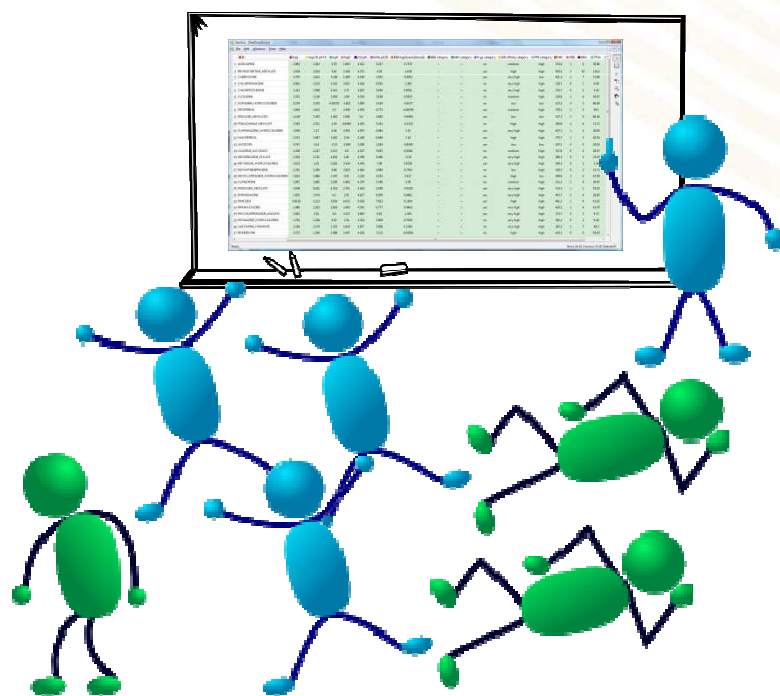


* Irvine, *et al.*, J. Pharm. Sci. 1999, 88, 28

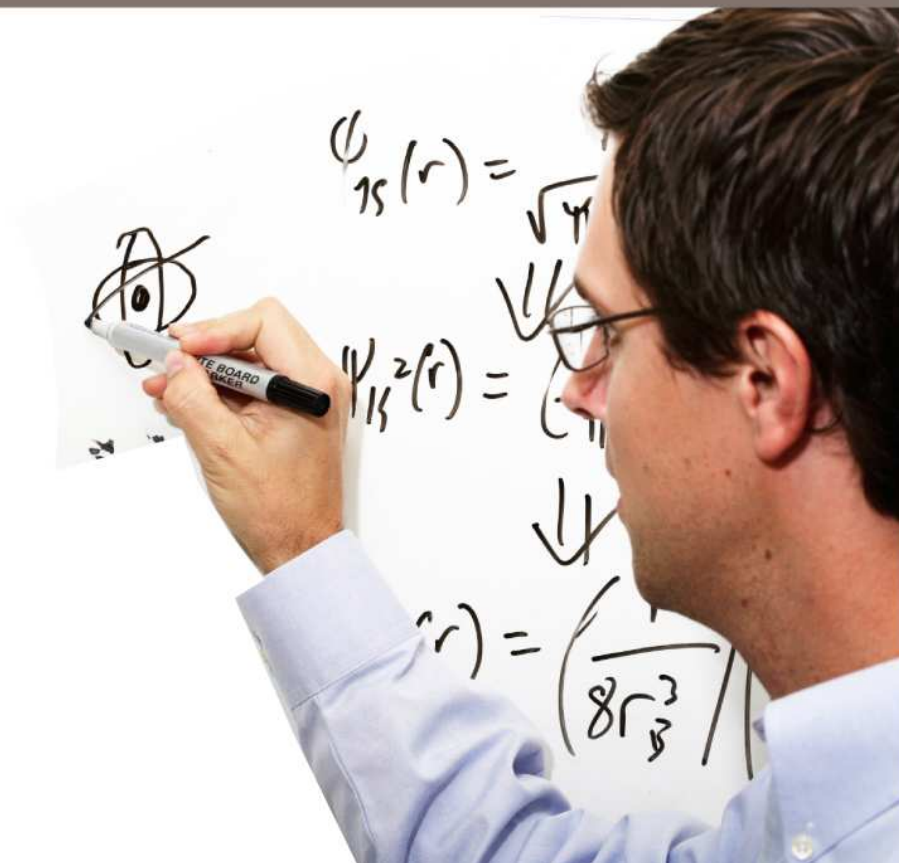
Challenges

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What questions do we ask?

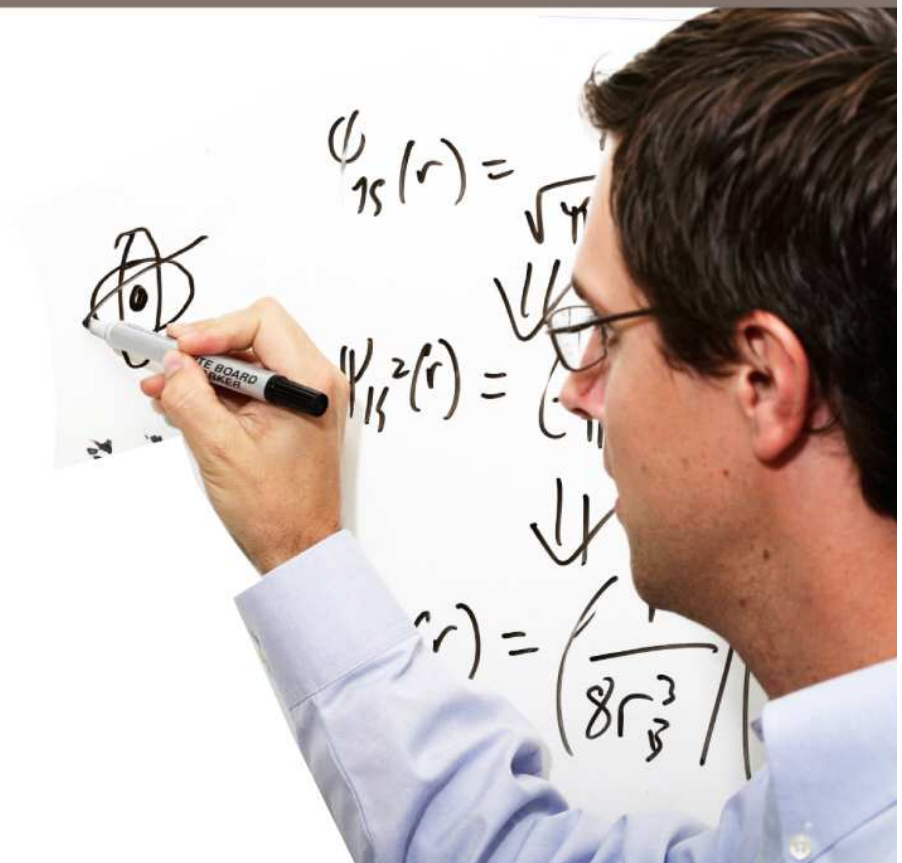


What questions do we ask?

Decision-making in Drug Discovery involves:

- Potentially large volumes of information, multiple parameters, many sources
 - “How can I get a good high level view of my data?”
 - “How do I get to the detail?”
- Uncertain, sparse data
 - “Which compound has the best overall balance of properties?”
 - “How much confidence can I have in my decisions?”
- Cross-discipline coordination/agreement
 - “Why does this structure have that property value?”
 - “What should I do to my molecule to change a property?”

Workflow

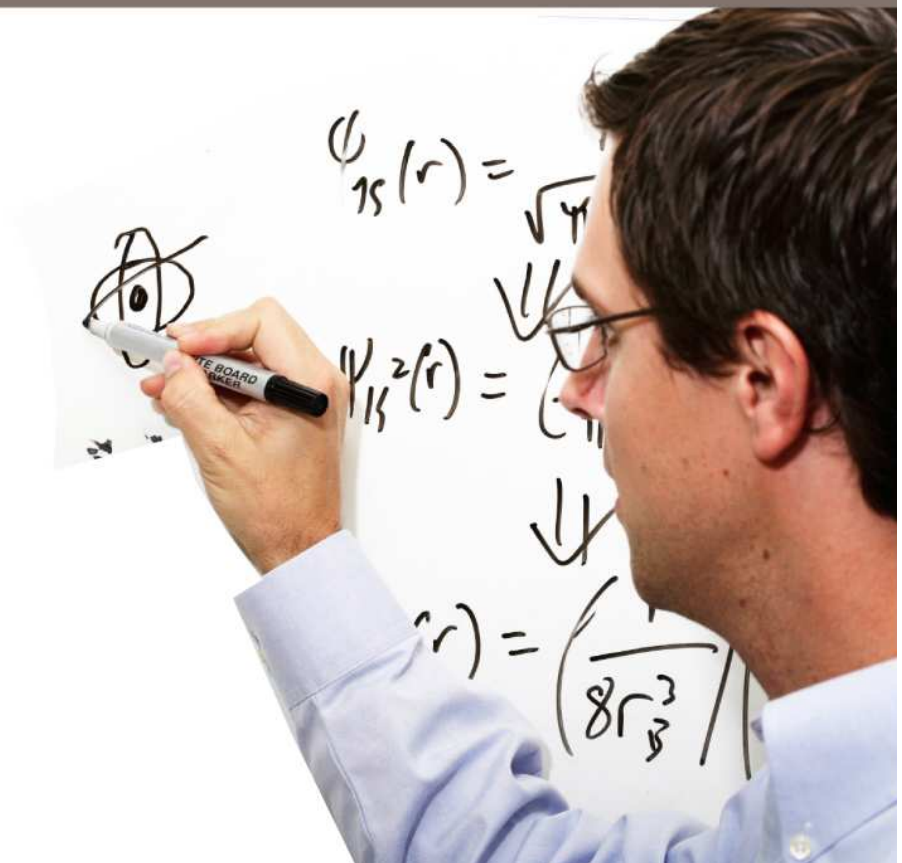


Workflow

Applying data to guide decisions

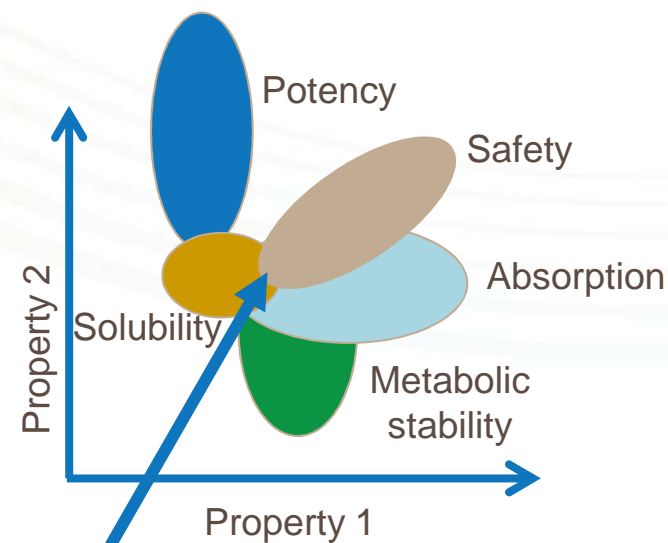
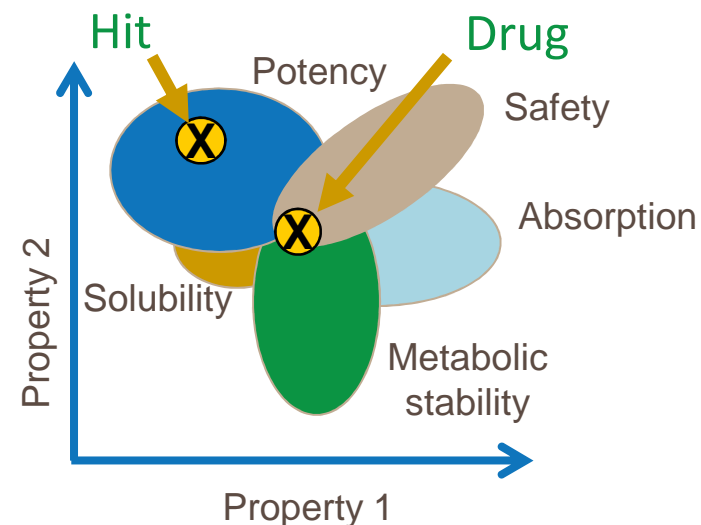


Prioritisation



The Objectives

- 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**



StarDrop Prioritisation: Probabilistic Scoring

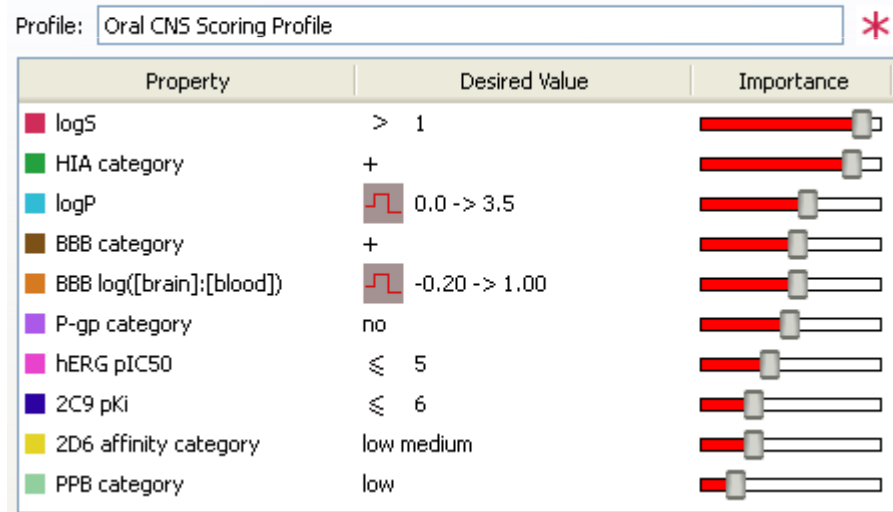
“Which compound has the best overall balance of properties?”

“How much confidence can I have in my decisions?”

Integrated assessment of data against project criteria

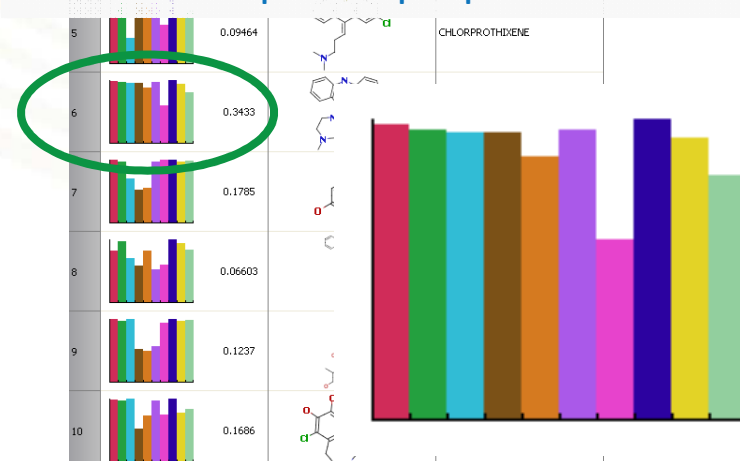
Uniquely accounts for the uncertainties in all compound-related data (experimental or calculated)

User-defined scoring profile



Compounds ranked

Histograms for quick visual guide to
compound properties



StarDrop Prioritisation: Probabilistic Scoring

“Which compound has the best overall balance of properties?”

“How much confidence can I have in my decisions?”

- **Property data**

- Experimental or predicted

- **Criteria for success**

- Relative importance

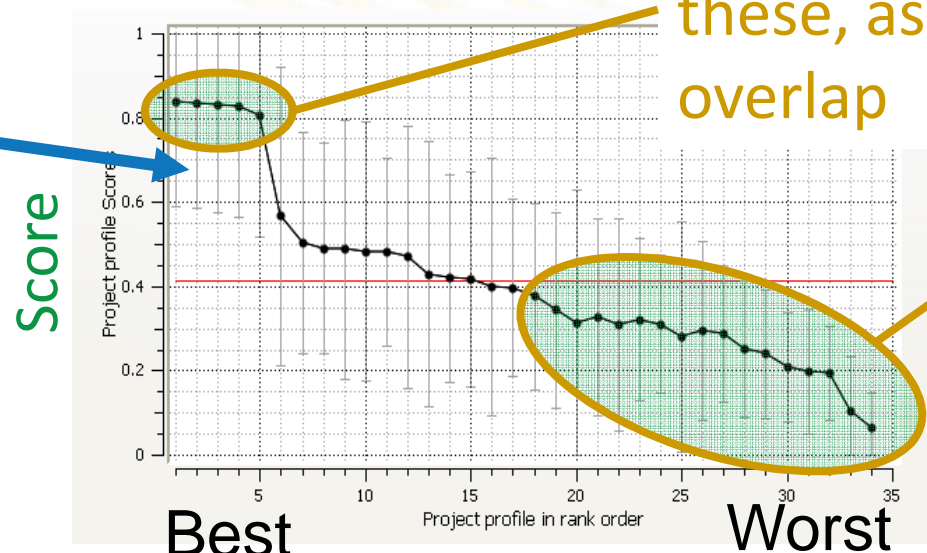
- **Uncertainties in data**

- Experimental or statistical

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

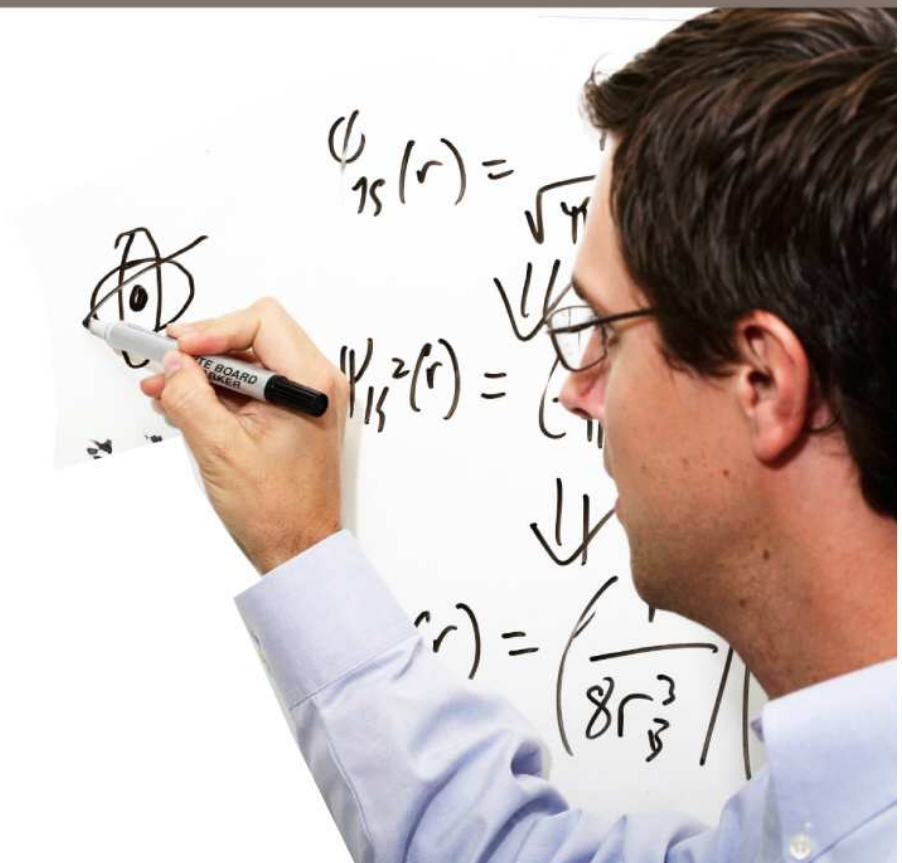
Data do not separate these, as error bars overlap

Error bars show confidence in overall score



Bottom 50% may be rejected with confidence

Selection



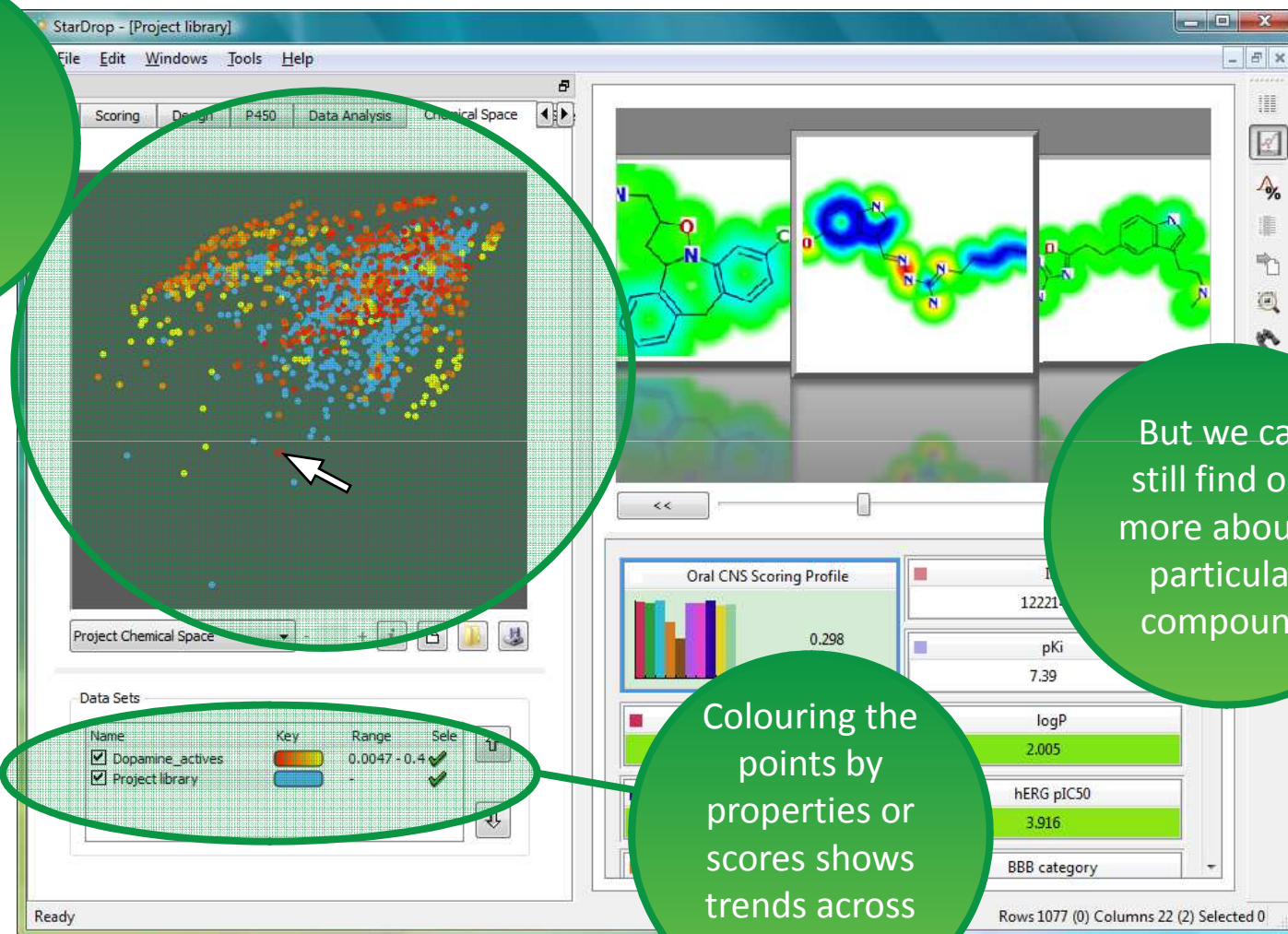
Chemical Space

Visualise chemical diversity

“How can I get a good high level view of my data?”

“How do I get to the detail?”

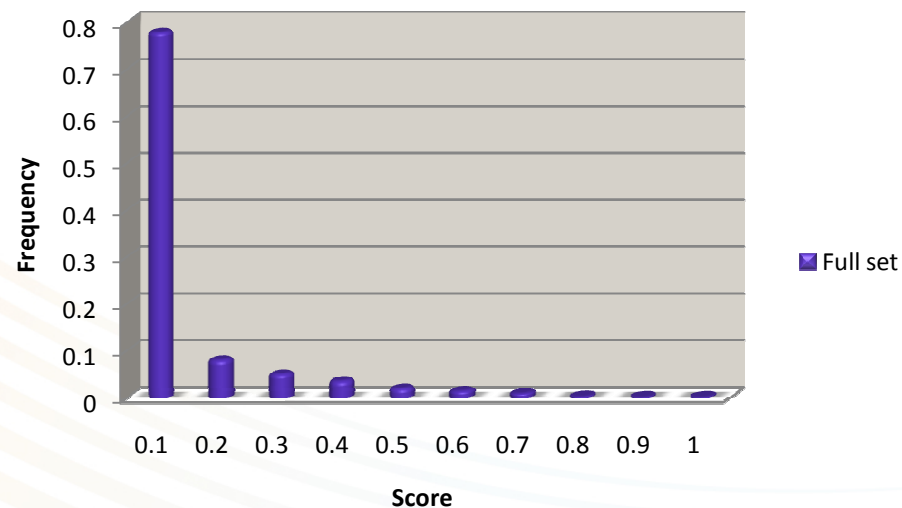
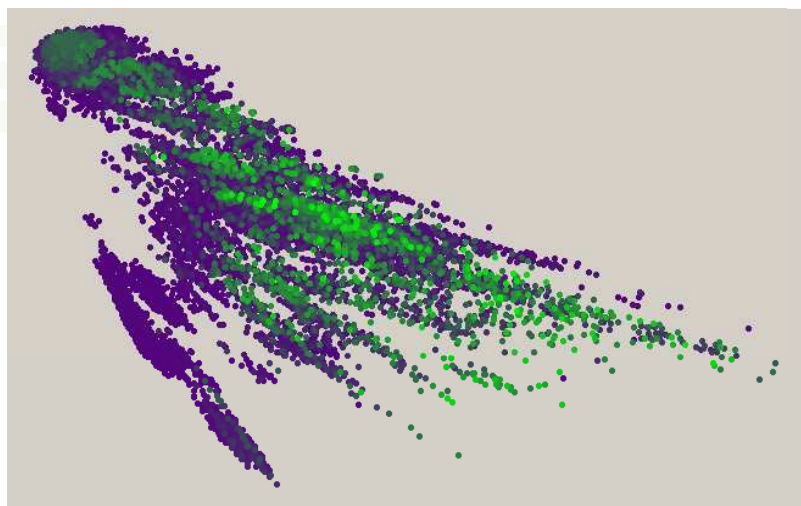
Two compounds will be close together if they are structurally similar



Selection:

Balancing Quality and Diversity

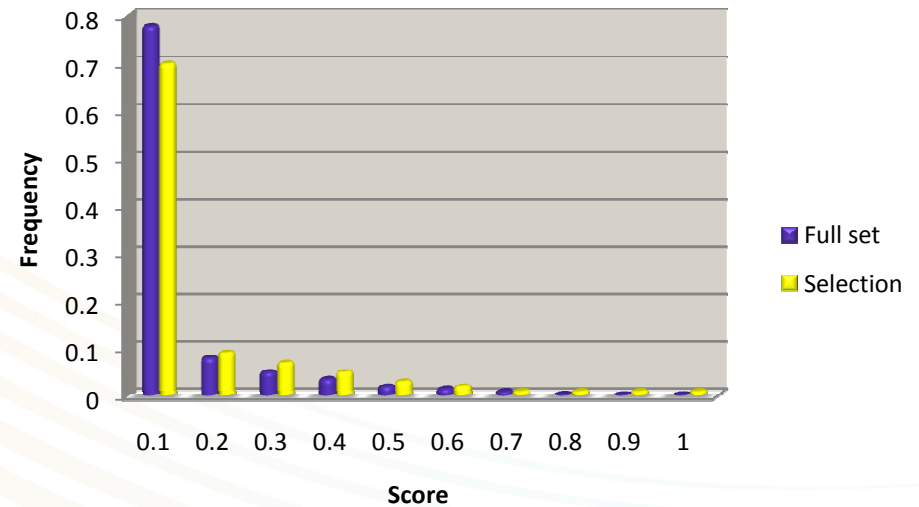
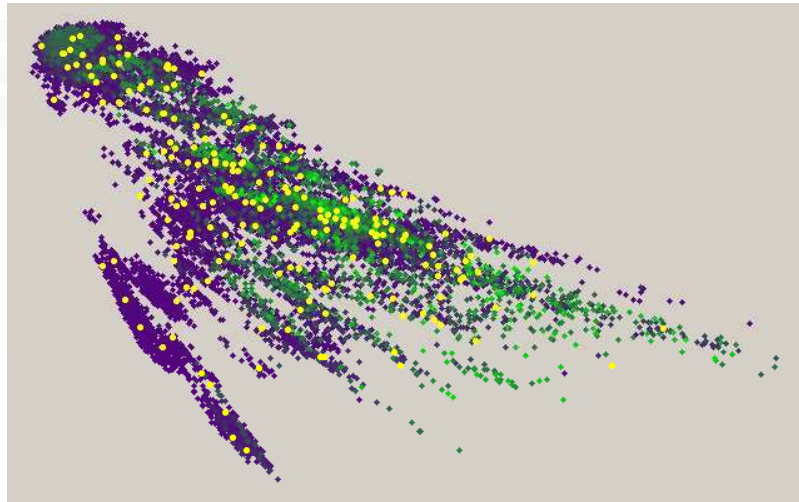
“How can I get a good high level view of my data?”



Objective: Select 200 compounds from scored library of 13,000 compounds

Selection: Balancing Quality and Diversity

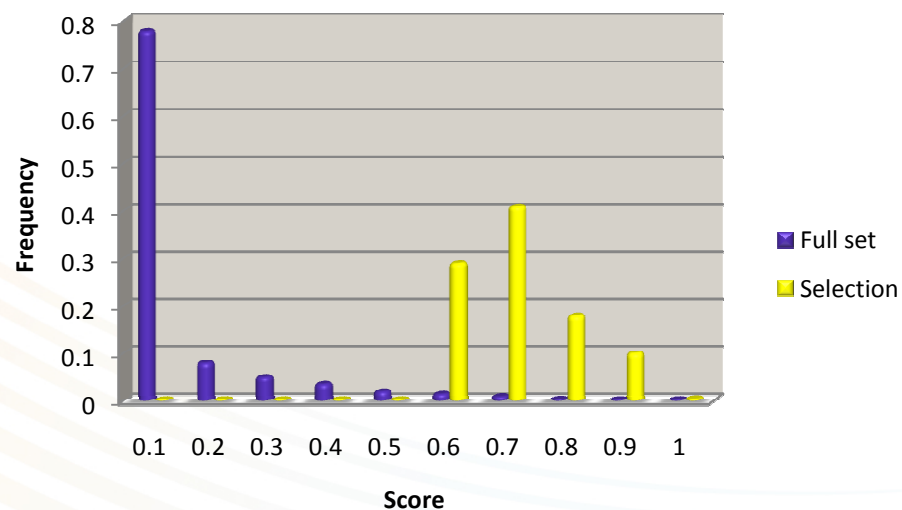
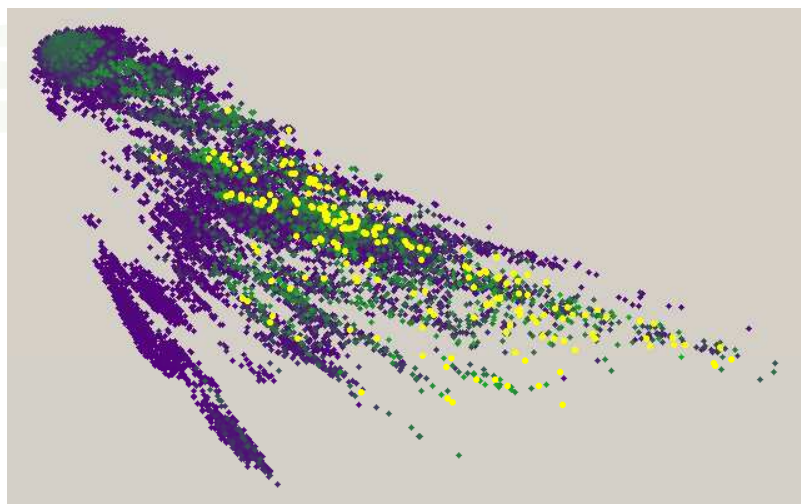
“How can I get a good high level view of my data?”



Diverse Sample

Selection: Balancing Quality and Diversity

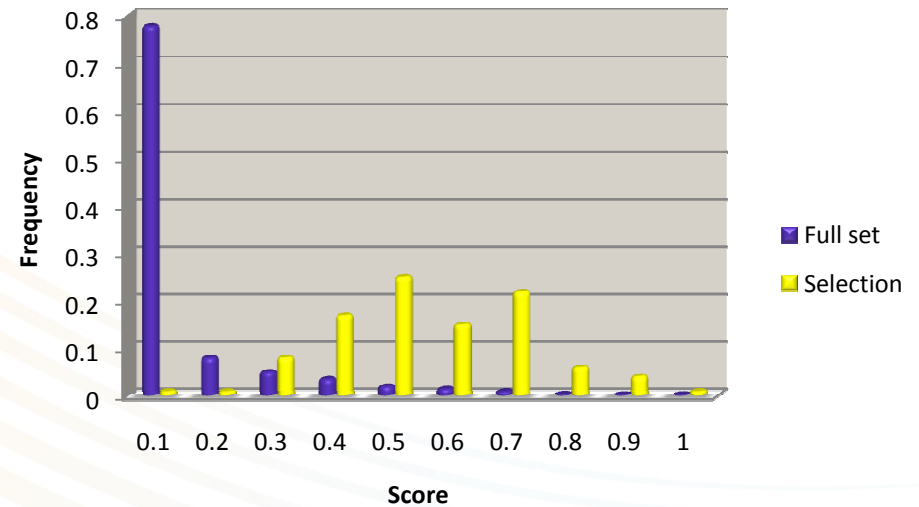
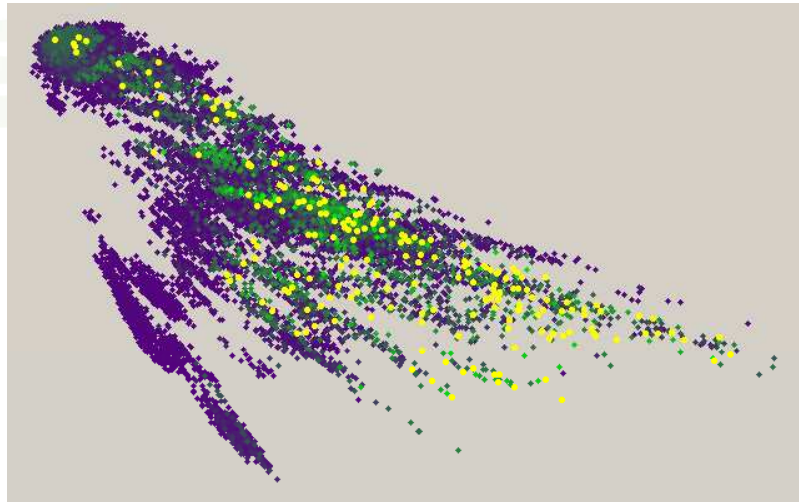
“How can I get a good high level view of my data?”



Top 200 ranked compounds

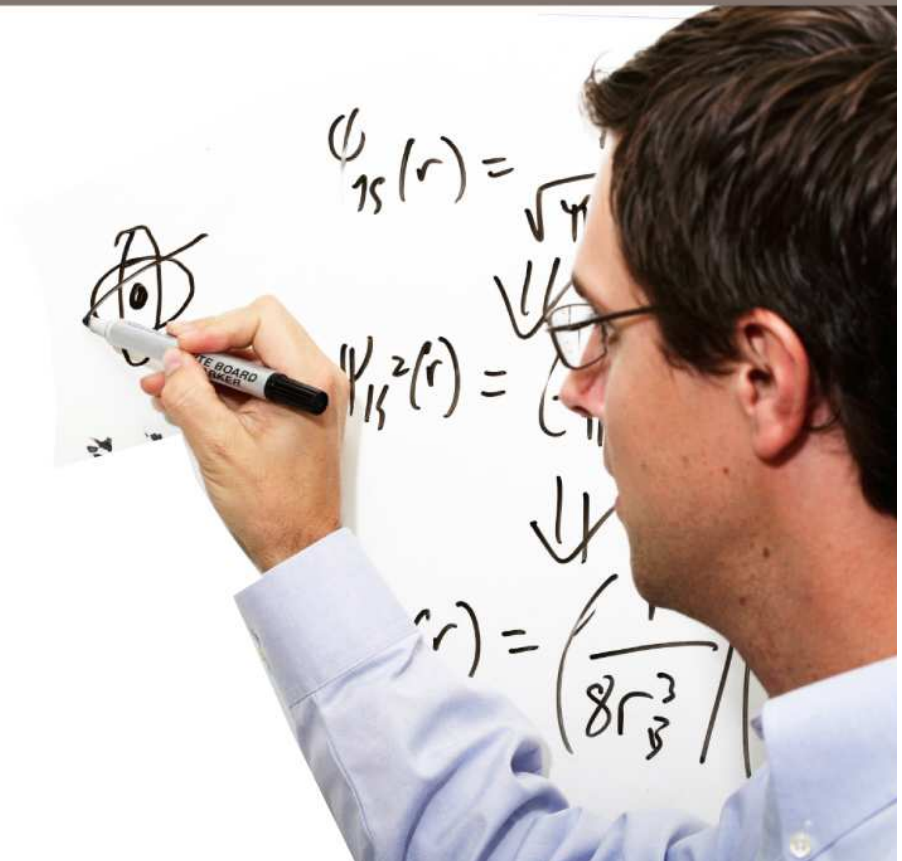
Selection: Balancing Quality and Diversity

“How can I get a good high level view of my data?”



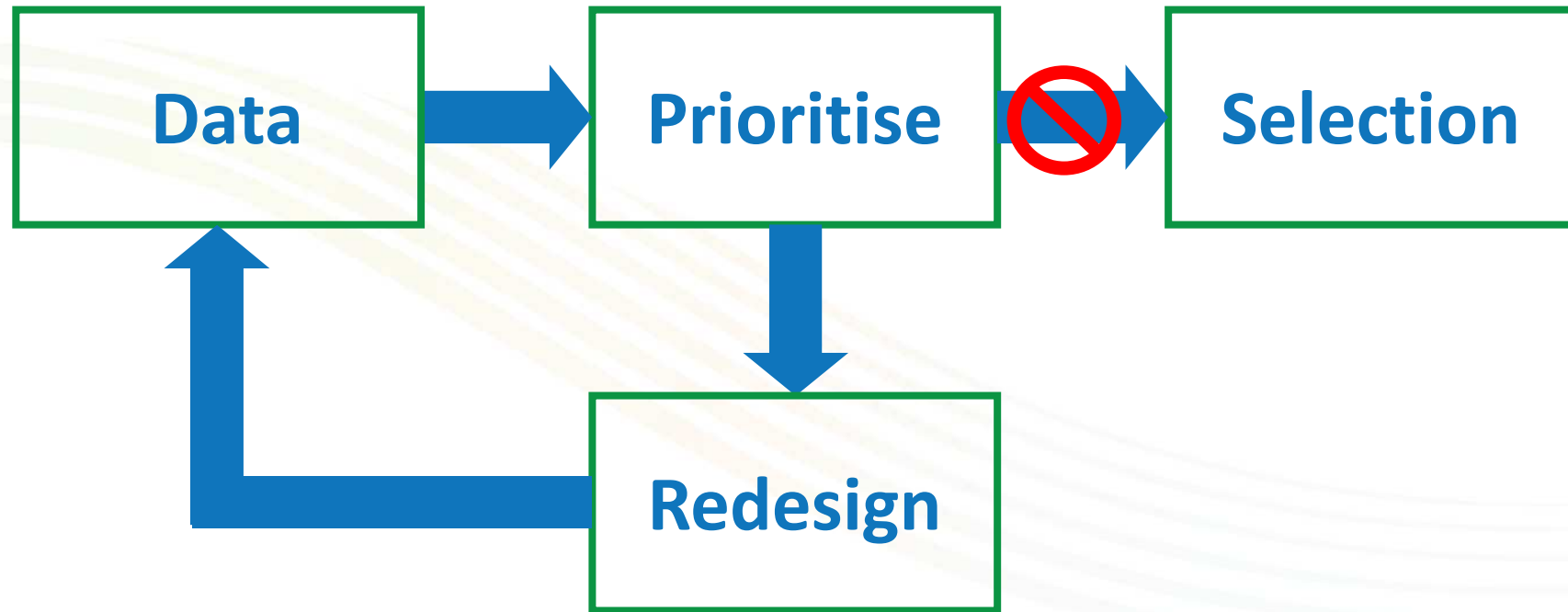
Balance Diversity:Rank = 80:20

Design/Redesign



Workflow

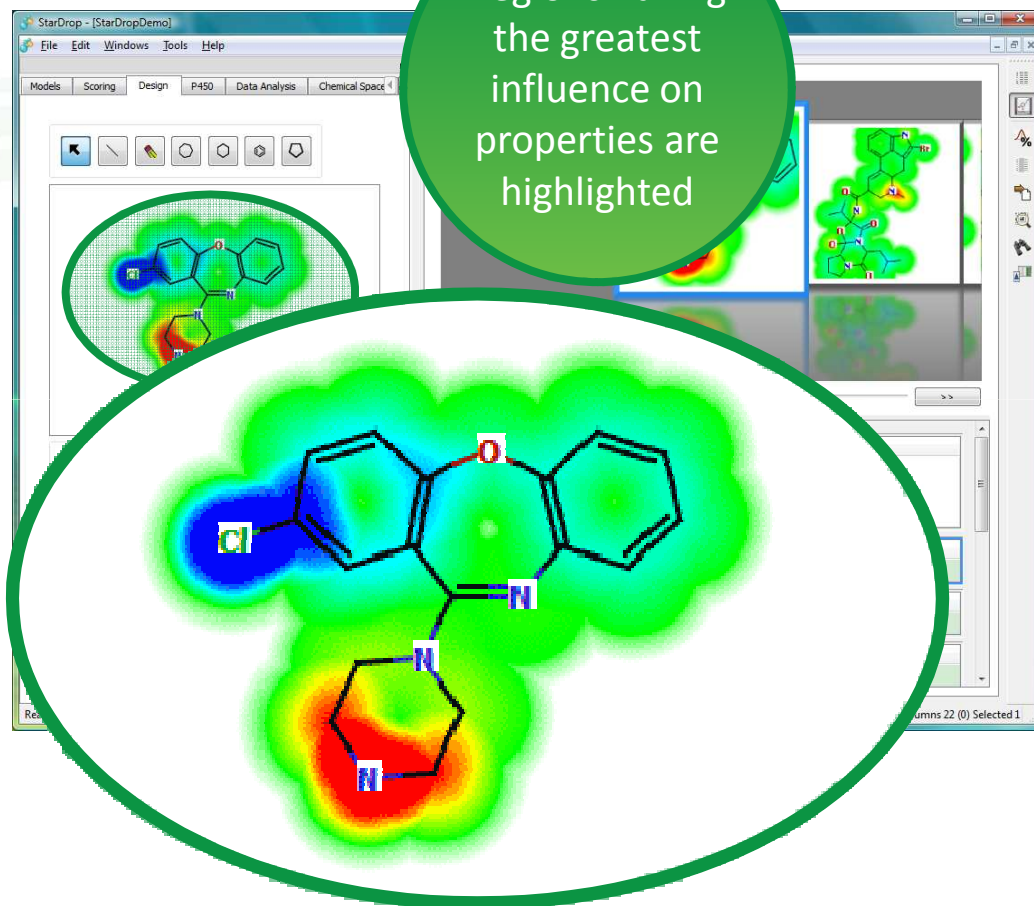
Applying data to guide decisions



Interactive Redesign: The 'Glowing Molecule'

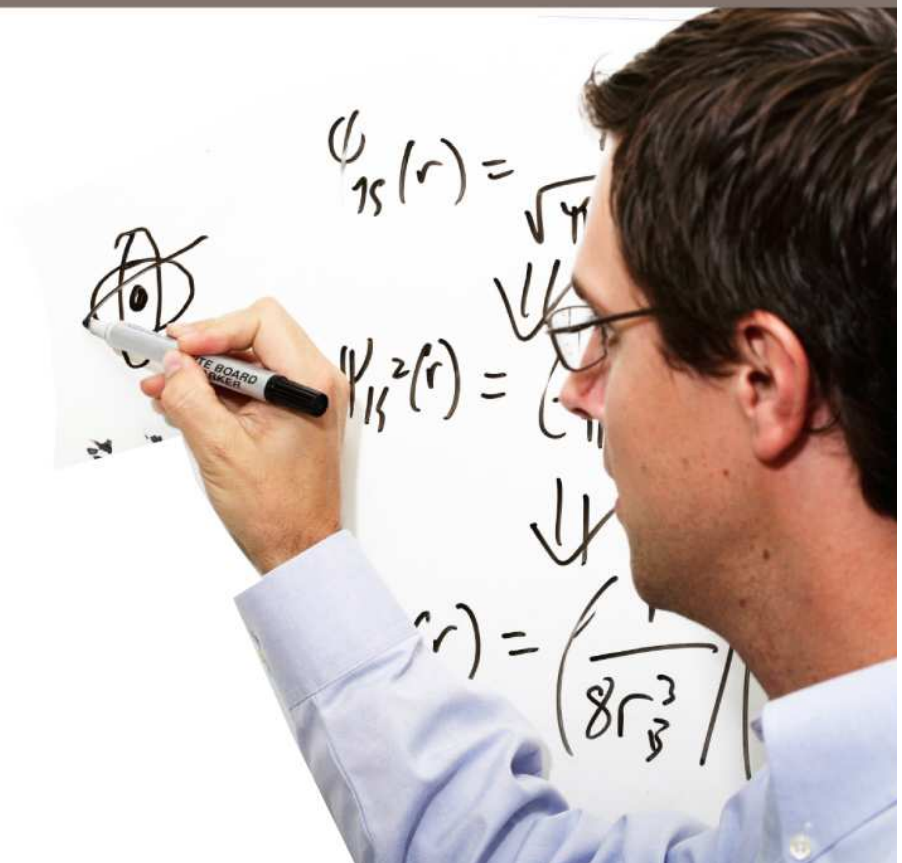
- “Why does this structure have that property value?”
- “What should I do to my molecule to change a property?”

Regions having
the greatest
influence on
properties are
highlighted



- Interactive redesign to explore new ideas
- Visual feedback on structural influences on predicted properties
 - Interpret SAR to guide redesign of molecules
 - Individual properties or scores

Conclusions



Conclusions

- The data we have available is only as valuable as the decisions we are able to make with it
- The decisions we make are dependant on the quality of our data, but we can take the uncertainty into account
- Given that we have multiple parameters with uncertainty wrapped into our decisions we need both high level and detailed views together allows us to understand the decisions our data is leading us towards

Acknowledgements

- Matt Segall
- Chris Leeding
- Andy Usher
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- Brett Saunders

