



Data is Like Paint... It Does No Good Until it is Applied

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Overview

Confidence

- Making decisions based on data
 - Uncertainty everywhere!
- How good do our models need to be?
- Conclusions



Knowledge is like paint... It does no good until it is applied

- Doe Zantamata

Sources of Uncertainty

Statistical

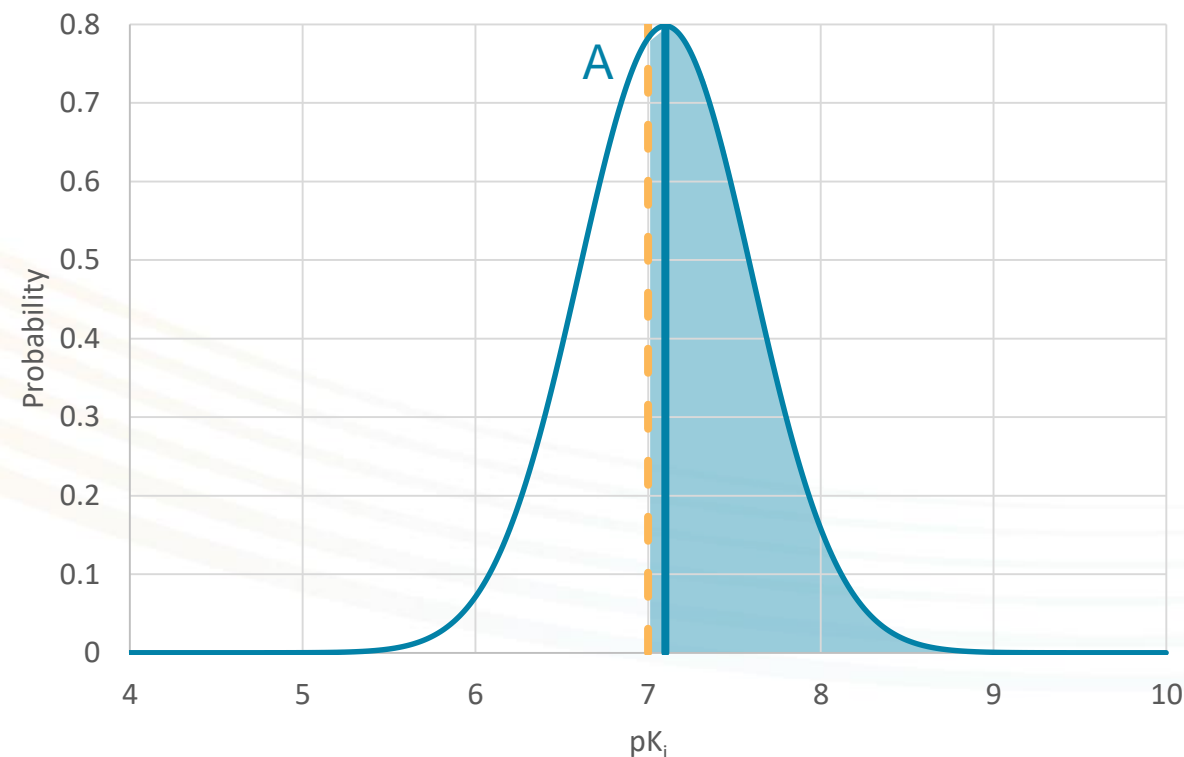
- Experimental variability/error
 - Single measurements: assay variability
 - o $pK_i/pIC_{50} \sim 0.3 - 0.7$ log units (factor of 2-5 in K_i/IC_{50})
 - Multiple replicates: mean and standard error in mean
- Statistical uncertainty in predictions
 - Standard error of prediction (assessed from validation)
 - 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

Sources of Uncertainty

Statistical

- Measured pK_i of compound A:
 $x_A = 7.1 \pm 0.5$ (1 SD)
- Does compound A meet
criterion $pK_i > 7$
(better than 100 nM)?

$$X_A \sim N(x_A, \sigma^2) = N(7.1, 0.25)$$
$$\Rightarrow P(X_A > 7) = 0.58$$



Sources of Uncertainty

Statistical

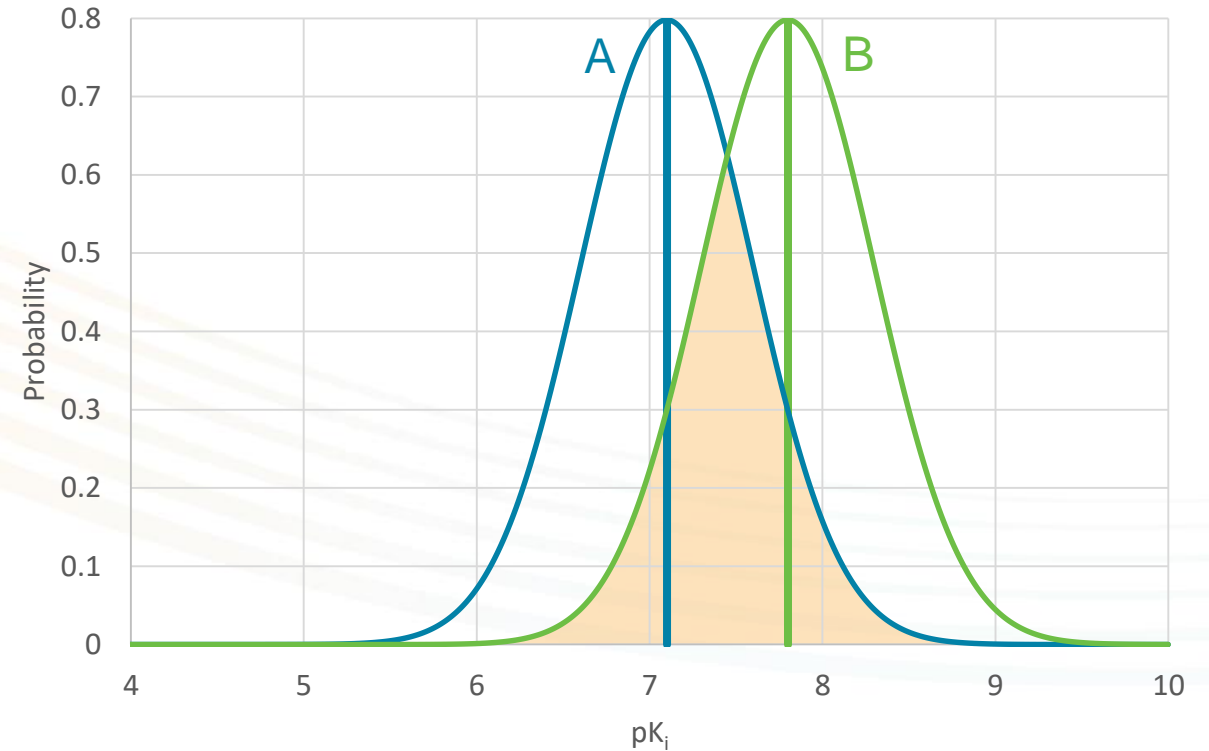
- Measured pK_i of compound B :

$$x_B = 7.8 \pm 0.5$$

- Is compound B 'better' than compound A?

$$(X_B - X_A) \sim N(x_B - x_A, \sigma_A^2 + \sigma_B^2)$$
$$= N(0.7, 0.5)$$

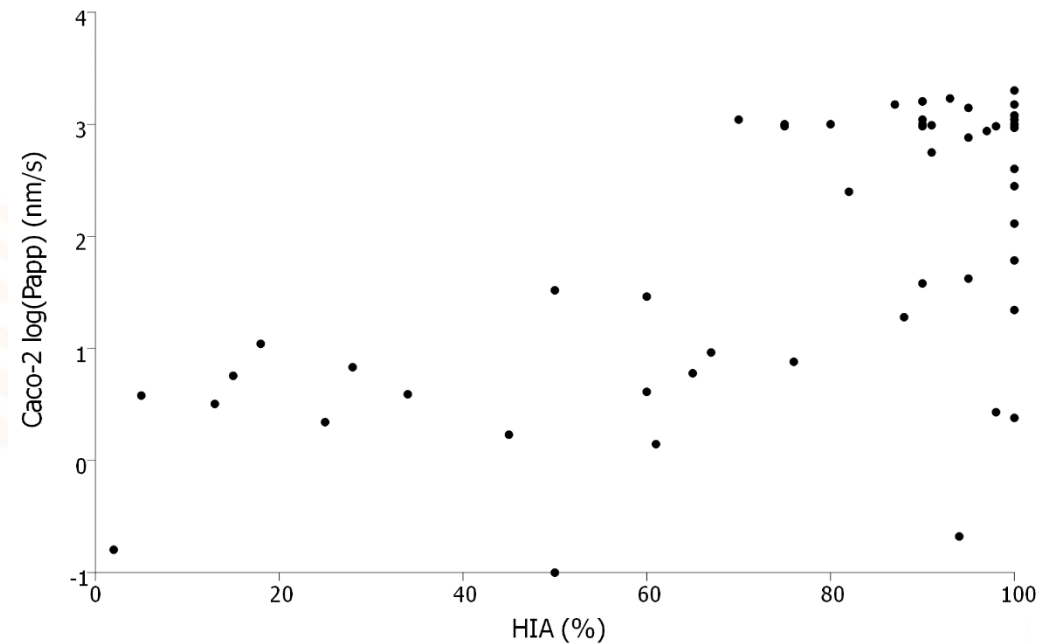
$$\Rightarrow P(X_B > X_A) = 0.84$$



Sources of Uncertainty

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):

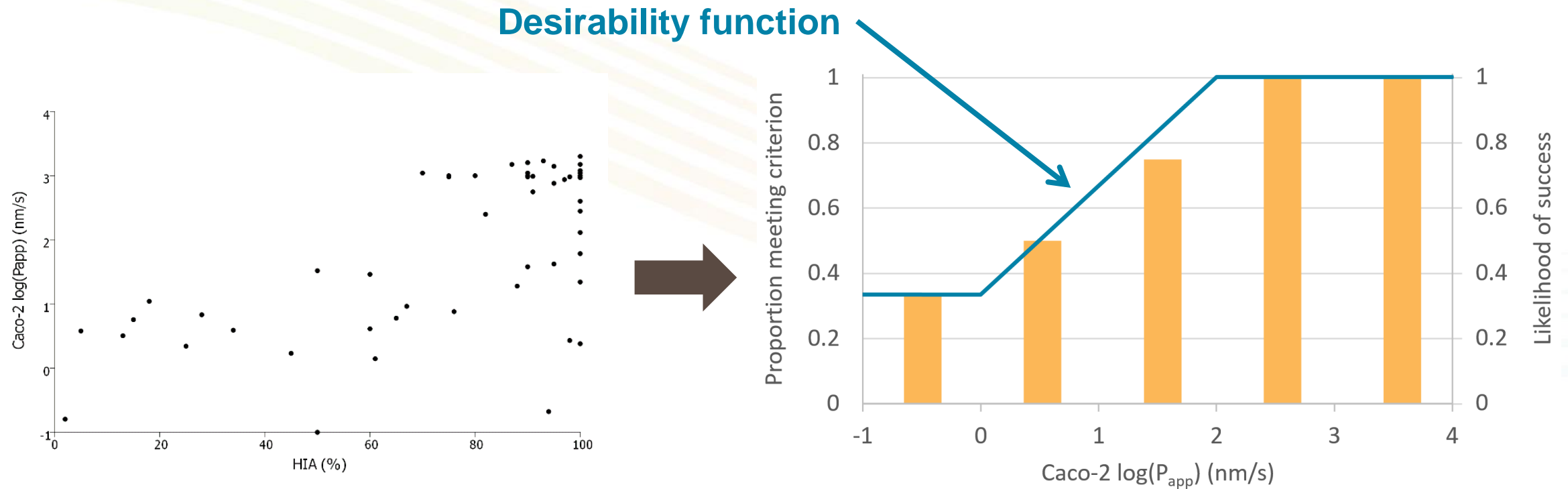


Irvine *et al.* (1999) J. Pharm. Sci. **88** pp. 28-33

Sources of Uncertainty

Relevance

- What is the impact of data on a compound's chance of success?
 - E.g. What is chance of a compound achieving human intestinal absorption (HIA) > 50%












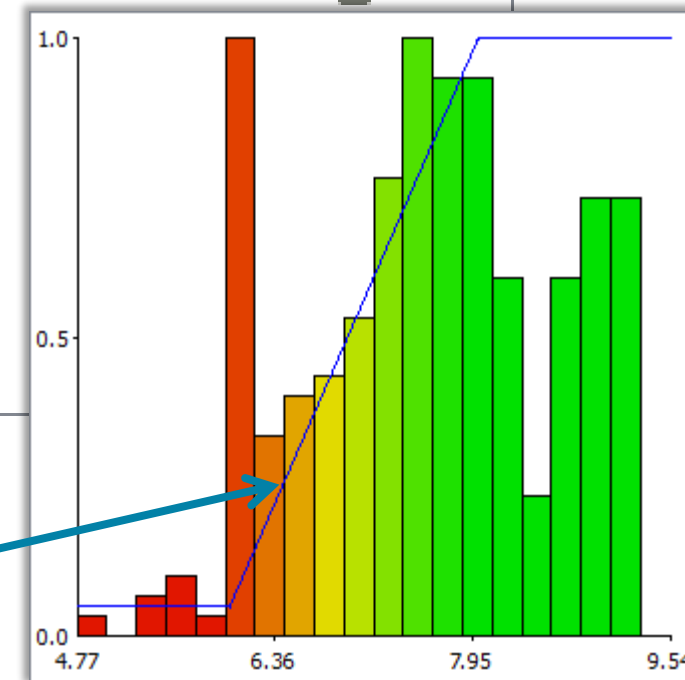
Bringing it Together



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	

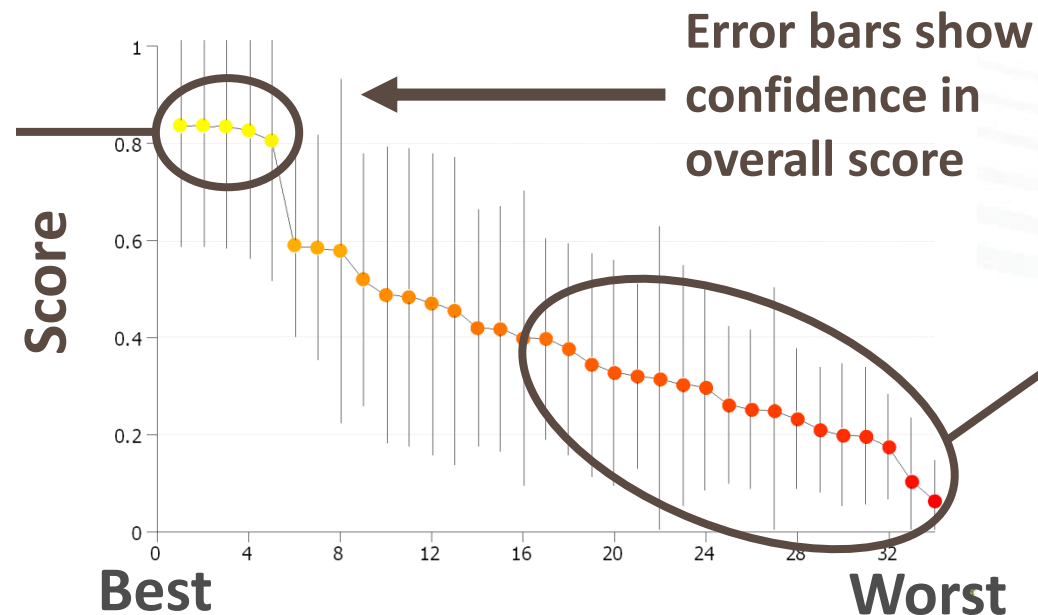


Probabilistic Scoring

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

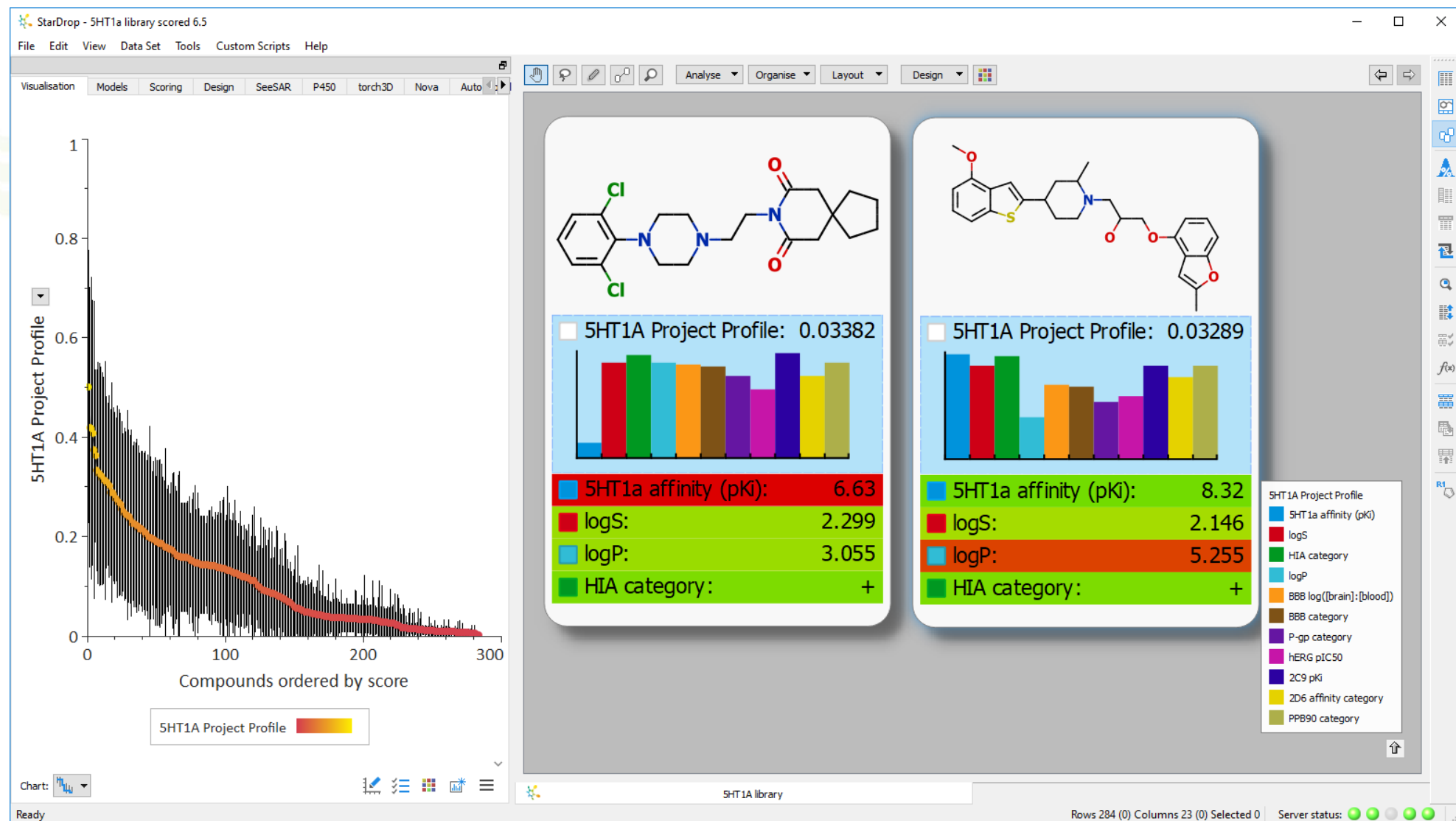
Score (Likelihood of Success)
Confidence in score

Data do not separate these as error bars overlap



Probabilistic Scoring

Guide redesign to improve chance of success



Example



Compound Prioritisation

Hard Cut-offs

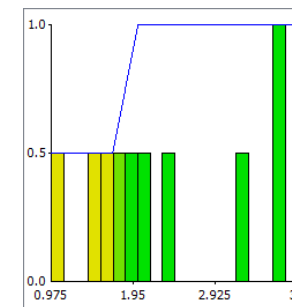
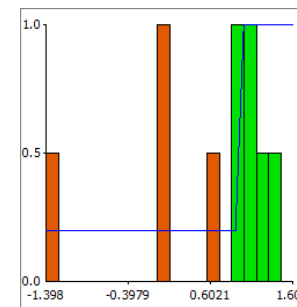
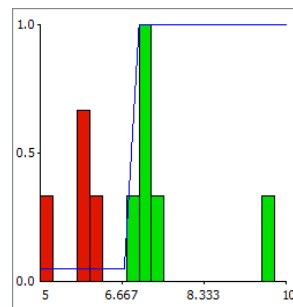
Property	Desired Value	Importance
Potency (pKi)	> 7	
log Selectivity	> 1	
log Solubility (uM)	> 2	

Compound	Potency (pKi)	log Selectivity	log Solubility (uM)
A	10	0.6	1.8
B	7.3	0.9	3.7
C	7.2	0	1.5
D	7	1	2
E	6.9	1.1	1
F	6	1.3	1.7
G	5.9	1	2.4
H	5.8	1.6	1.9
I	5	-1.4	3.9
J	7.1	?	3.2

Compound Prioritisation

Desirability Functions

Property	Desired Value	Importance
Potency (pKi)	7 -> inf	
log Selectivity	1 -> inf	
log Solubility (uM)	2 -> inf	



Filter

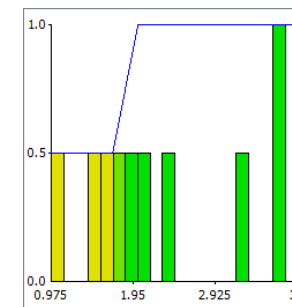
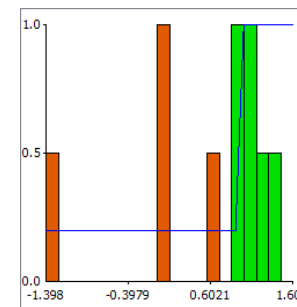
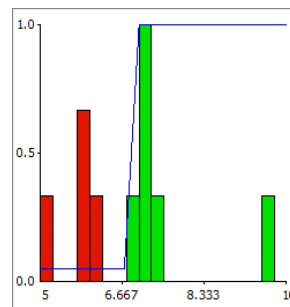
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G	5.9	1	2.4
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I	5	-1.4	3.9
J	7.1	?	3.2

Compound	Potency (pKi)	log Selectivity	log Solubility (uM)	Score
D	7	1	2	1
E	6.9	1.1	1	0.4
B	7.3	0.9	3.7	0.22
A	10	0.6	1.8	0.14
C	7.2	0	1.5	0.11
G	5.9	1	2.4	0.05
H	5.8	1.6	1.9	0.042
F	6	1.3	1.7	0.027
I	5	-1.4	3.9	0.01
J	7.1	?	3.2	?

Compound Prioritisation

Probabilistic Scoring

Property	Desired Value	Importance
Potency (pKi)	7 -> inf	
log Selectivity	1 -> inf	
log Solubility (uM)	2 -> inf	



$$\sigma_{pKi} = 0.3, \sigma_{Sel} = 0.4, \sigma_{logS} = 0.6$$

Filter

Compound	Potency (pKi)	log Selectivity	log Solubility (uM)
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B	7.3	0.9	3.7
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Desirability Function

Compound	Potency (pKi)	log Selectivity	log Solubility (uM)	Score
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E	6.9	1.1	1	0.4
B	7.3	0.9	3.7	0.22
A	10	0.6	1.8	0.14
C	7.2	0	1.5	0.11
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F	6	1.3	1.7	0.027
I	5	-1.4	3.9	0.01
J	7.1	?	3.2	?

Compound	Potency (pKi)	log Selectivity	log Solubility (uM)	Score
B	7.3	0.9	3.7	0.52
J	7.1	?	3.2	0.49
D	7	1	2	0.36
A	10	0.6	1.8	0.27
E	6.9	1.1	1	0.24
C	7.2	0	1.5	0.12
H	5.8	1.6	1.9	0.038
F	6	1.3	1.7	0.033
G	5.9	1	2.4	0.031
I	5	-1.4	3.9	0.01

Score Distribution



Conclusion: Only compounds H, F, G and I can be confidently rejected...

How Good to Our Models Have to Be?



How Well Does This Model Conserve Your Options?

- You are considering purchasing a library of compounds:
 - You expect 1% of your compounds have a particular kind of toxicity
 - You apply a model to all the compounds that is 90% reliable (both 90% sensitive and 90% specific)
 - What percentage of the compounds that are predicted to fail, genuinely have the toxicity?
 - a) About 1%
 - b) About 2%
 - c) About 10%
 - d) About 50%
 - e) About 90%
- Answer?
 - c) Of 1000 compounds, $990 \times 0.1 + 10 \times 0.9 = 108$ would be reported as toxic by the model, of which only 9 really are toxic.
- Easy to overreact to negative results
 - Availability bias (neglect of the prior)*

Prior

Example Application

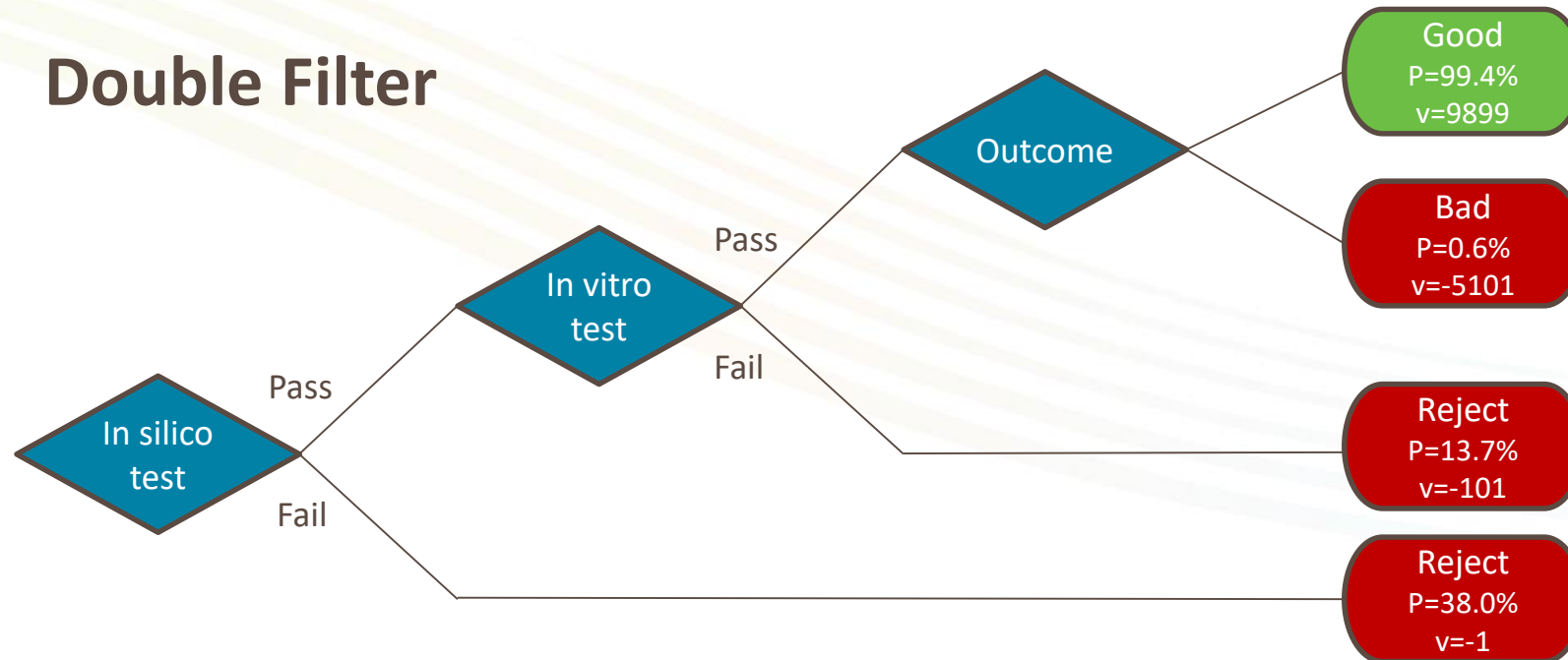
Screening Strategy

- Two screens for property: *in silico* and *in vitro*
 - *In silico*: cost 1, accuracy 80%
 - *In vitro*: cost 100, accuracy 95%
 - Cost to prove *in vivo* 5,000
 - Net value of good compound 10,000
- 5 Possible screening strategies

Example Application

Screening Strategy

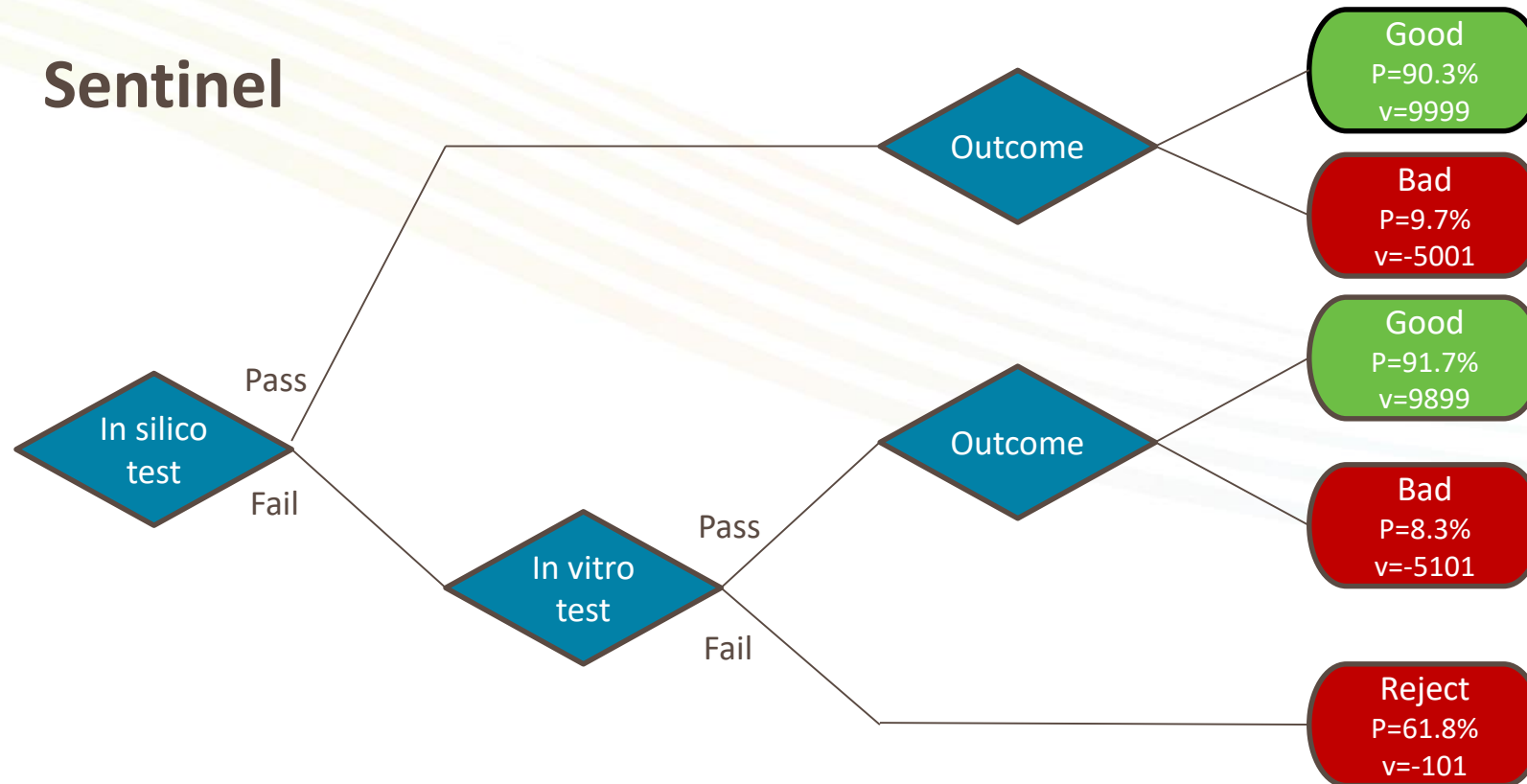
- Two screens for property: *in silico* and *in vitro*
- 5 Possible screening strategies:



Example Application

Screening Strategy

- Two screens for property: *in silico* and *in vitro*
- 5 Possible screening strategies:



Example Application

Screening Strategy

- Two screens for property: *in silico* and *in vitro*
- 5 Possible screening strategies:

In Silico Only

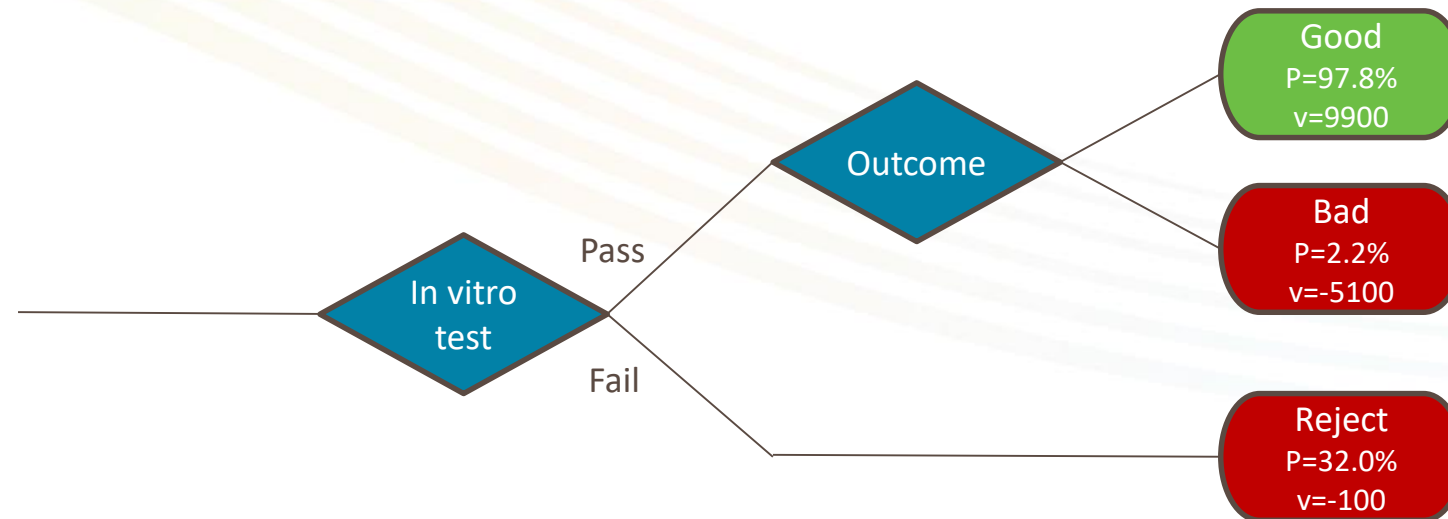


Example Application

Screening Strategy

- Two screens for property: *in silico* and *in vitro*
- 5 Possible screening strategies:

In Vitro Only



Example Application

Screening Strategy

- Two screens for property: *in silico* and *in vitro*
- 5 Possible screening strategies:

No Screen



Example Application

Screening Strategy

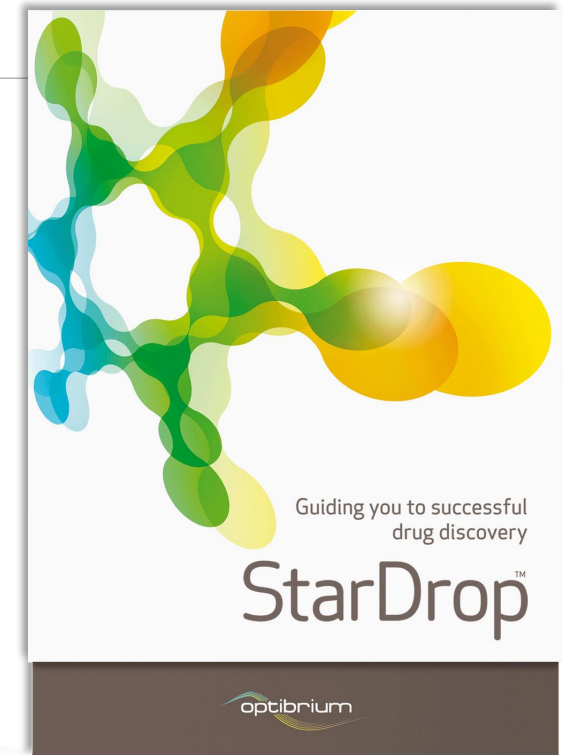
- Parameters:
 - In silico*: cost 1, accuracy 80%
 - In vitro*: cost 100, accuracy 95%
 - Cost to confirm 5,000; Net value of good compound 10,000

Strategy	Value	Value
	(Prior for risk 30%)	(Prior for risk 40%)
Double filter	5242	4483
Sentinel	6531	5415
<i>In silico</i> only	5299	4399
<i>In vitro</i> only	6475	5500
No screen	5500	4000

Interactive example <http://www.tessella.com/screening-strategy-explorer>

Conclusions

- Data only add value when used to make good decisions in the context of a discovery project
- The value of data can only be assessed when we understand its confidence
 - Avoid wasted effort and missed opportunities
- We can only know if our assays/models add value when we know the priors for the risks we are addressing
 - **BIG opportunity for pre-competitive collaboration**
- For more information and references, please visit:
 - www.optibrium.com/stardrop/
 - www.optibrium.com/community/



Acknowledgements

- The Optibrium team, in particular Ed Champness
- Andrew Chadwick (formerly of Tessella)

