



# Using AI to Derive Valuable Insights from Drug Discovery Data

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# Overview

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- The challenges of drug discovery data
- Introduction to deep learning imputation
- Example applications
- Conclusions

# Challenges of Using Data in Drug Discovery

- It's impossible to measure all of my compounds in all of my assays, how do I make the most of the data I have?
- I know there is variability in my experiments, how do I avoid being led astray by artefacts and errors?
- What are the most valuable experiments to run? What data will give me the most information with which to make decisions?
- How can I use the limited data I have to make better predictions for new compound designs, and choose the best ones for synthesis?

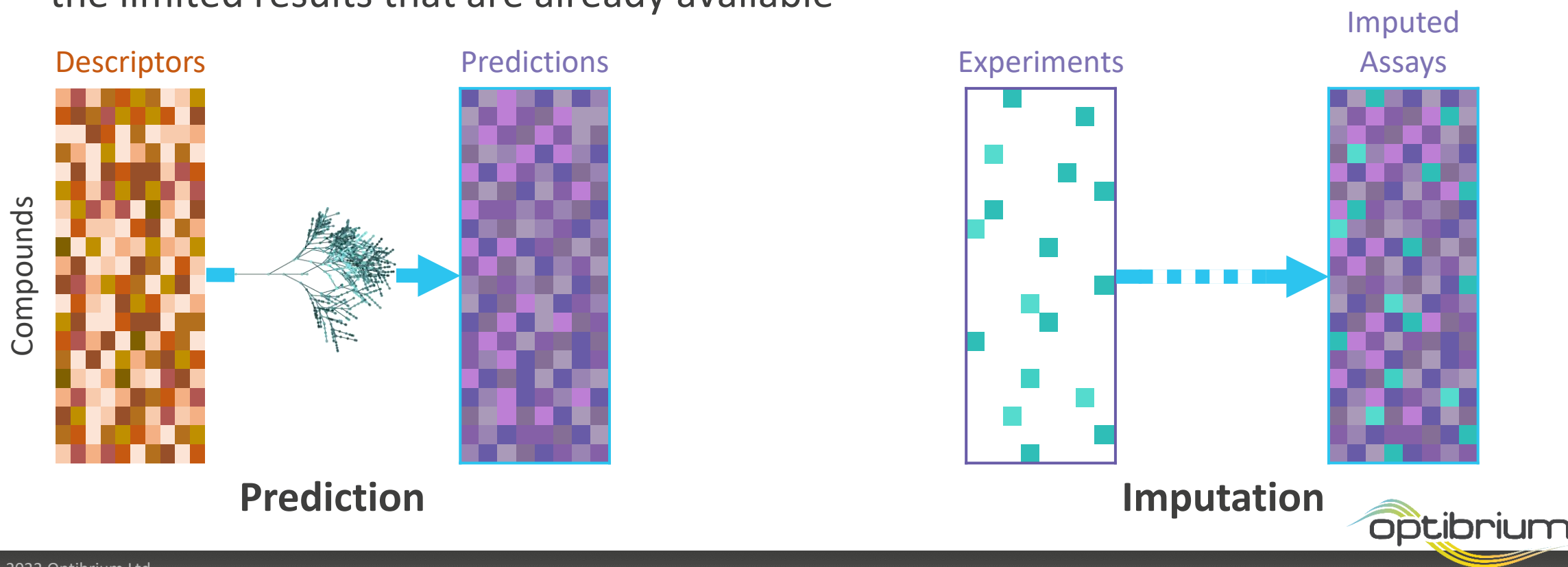




## Introduction to Deep Learning Imputation

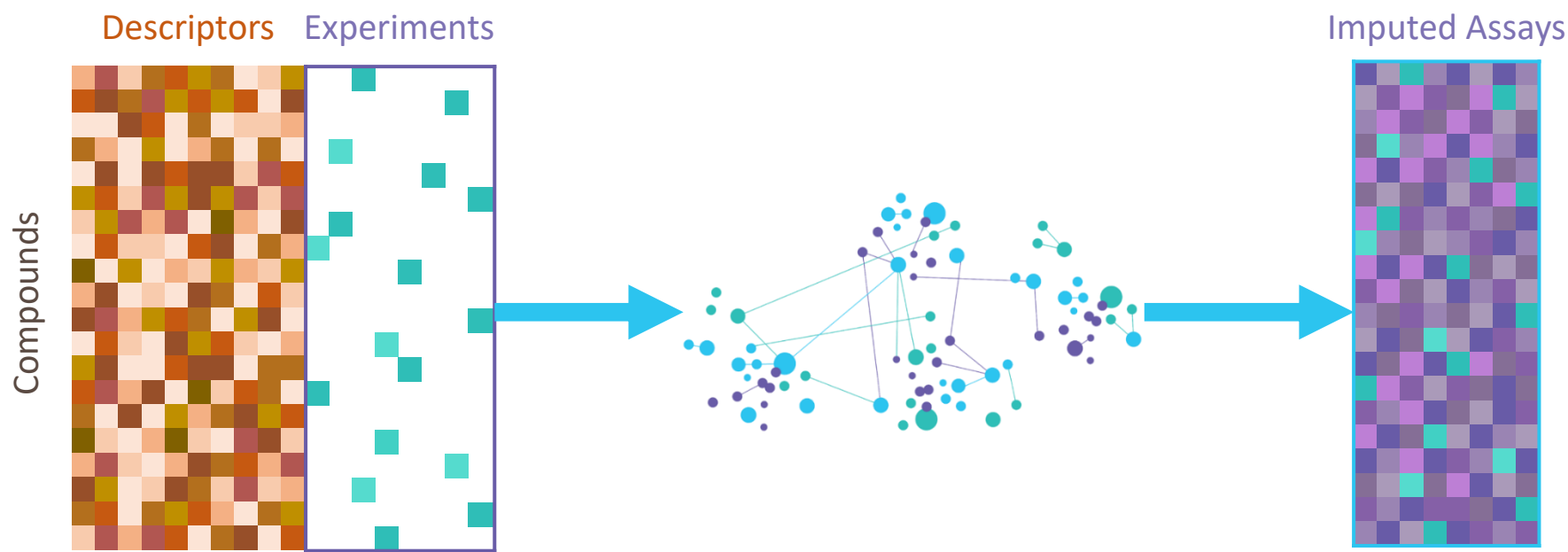
# Prediction vs. Imputation

- Prediction uses input 'features' to predict one or more property values for a compound, e.g. QSAR models
- Imputation is the process of filling in the gaps in sparse experimental data using the limited results that are already available





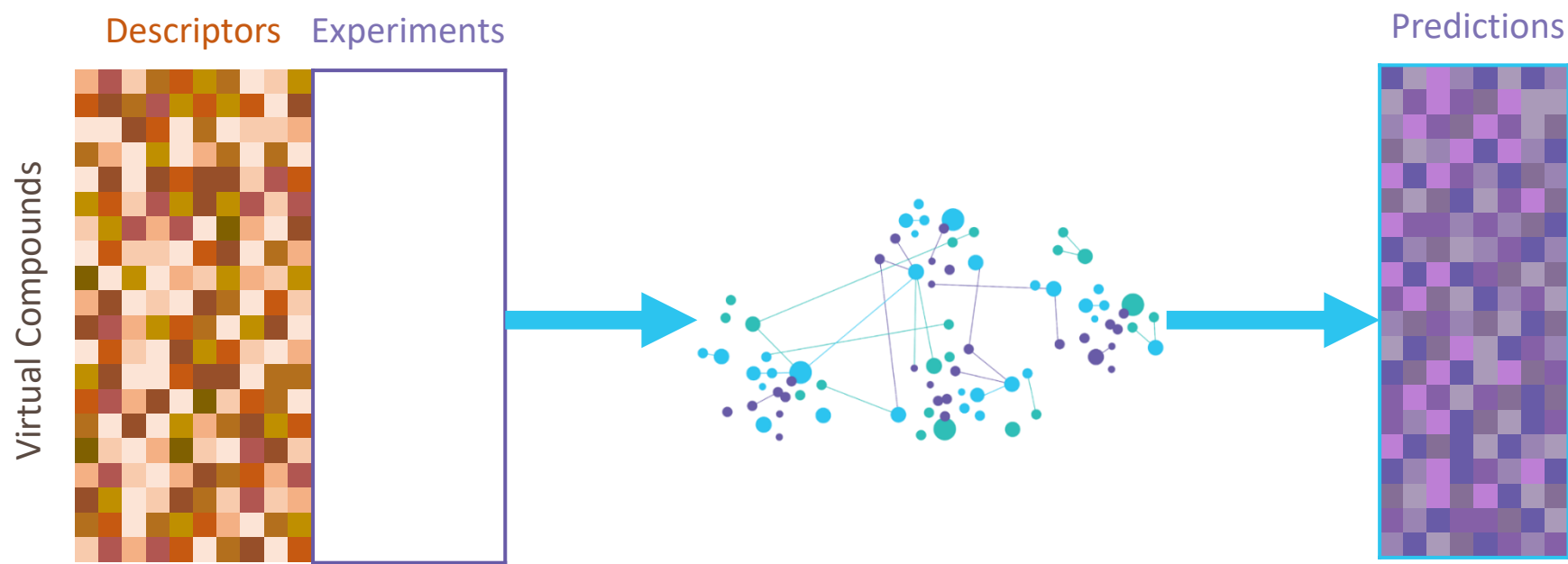
- Learns directly from relationships between experimental endpoints as well as SAR
  - Makes better use of sparse and noisy experimental data than conventional QSAR models
- ‘Fills in’ the gaps in your data and makes predictions for ‘virtual’ compounds
  - Generates more accurate predictions to target high-quality compounds



Whitehead *et al.* J. Chem Inf. Model. (2019) **59**(3) pp. 1197-1204, Irwin *et al.* J. Chem. Inf Model. (2020) **60**(6), pp. 2848–2857



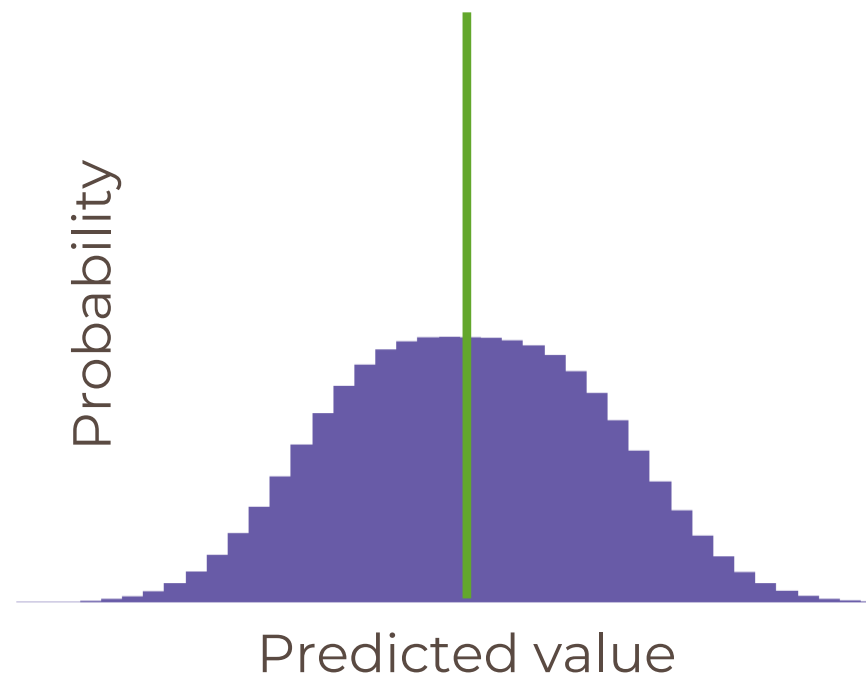
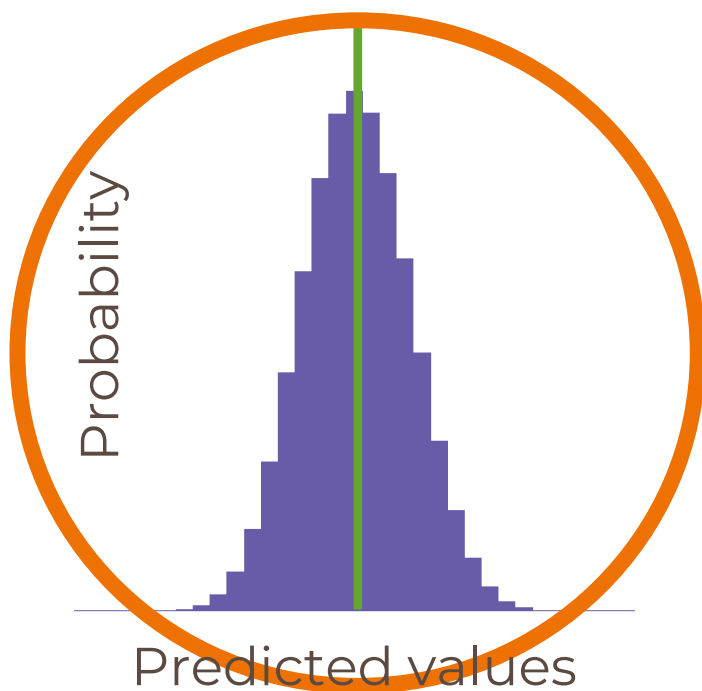
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- Estimates uncertainty in each individual prediction
  - Strong correlation between uncertainty estimates and observed accuracy on independent test sets
  - Highlights the most accurate predictions on which to base decisions
- Confidently targets high-quality compounds and prioritise experimental resources

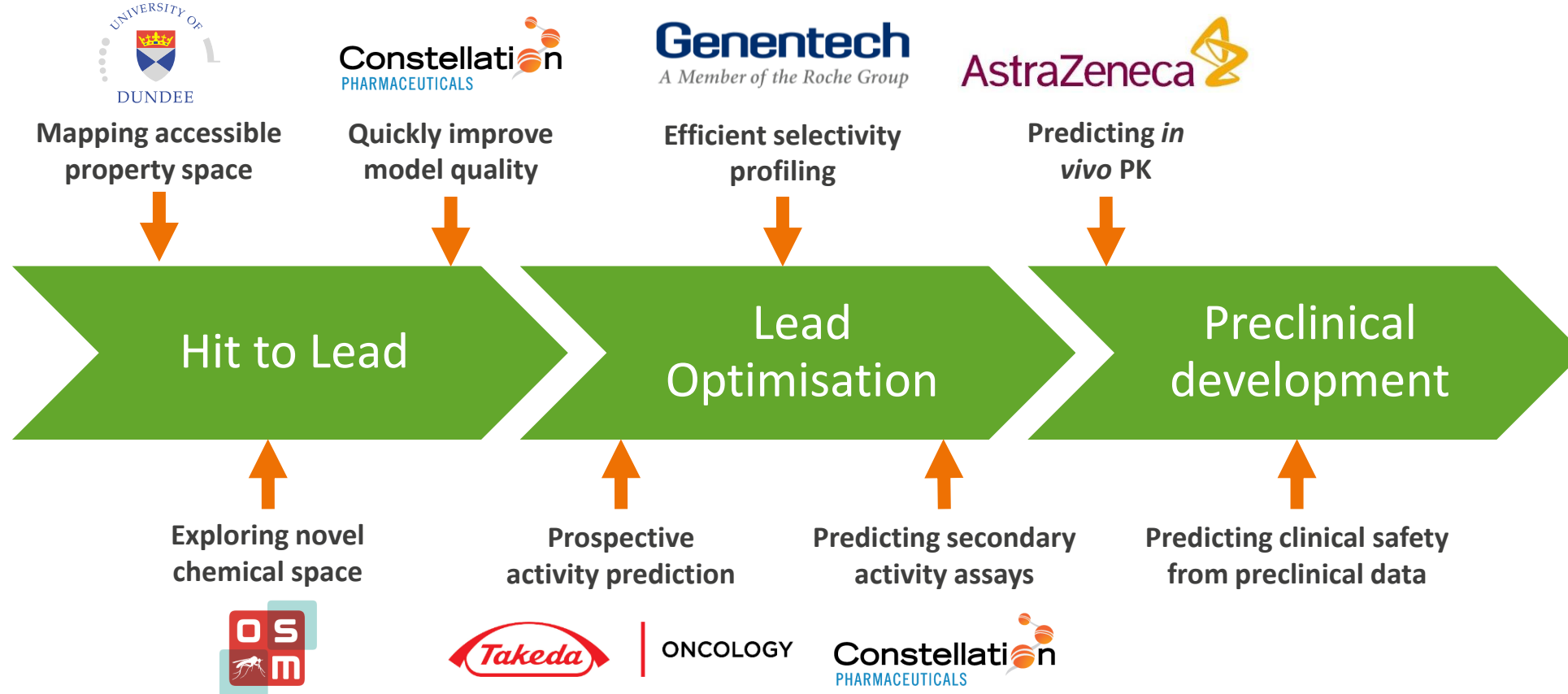






## Example Applications

# Applications of Deep Learning Imputation



## Non-pharma applications:

Imputation of *in vivo* sensory properties  
Prediction of agrochemical bioactivity profiles



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# Alchemite Application to Project Data

- Application to **heterogeneous** data across two projects
  - Target and phenotypic activities and ADME endpoints
  - 2453 compounds across 18 endpoints

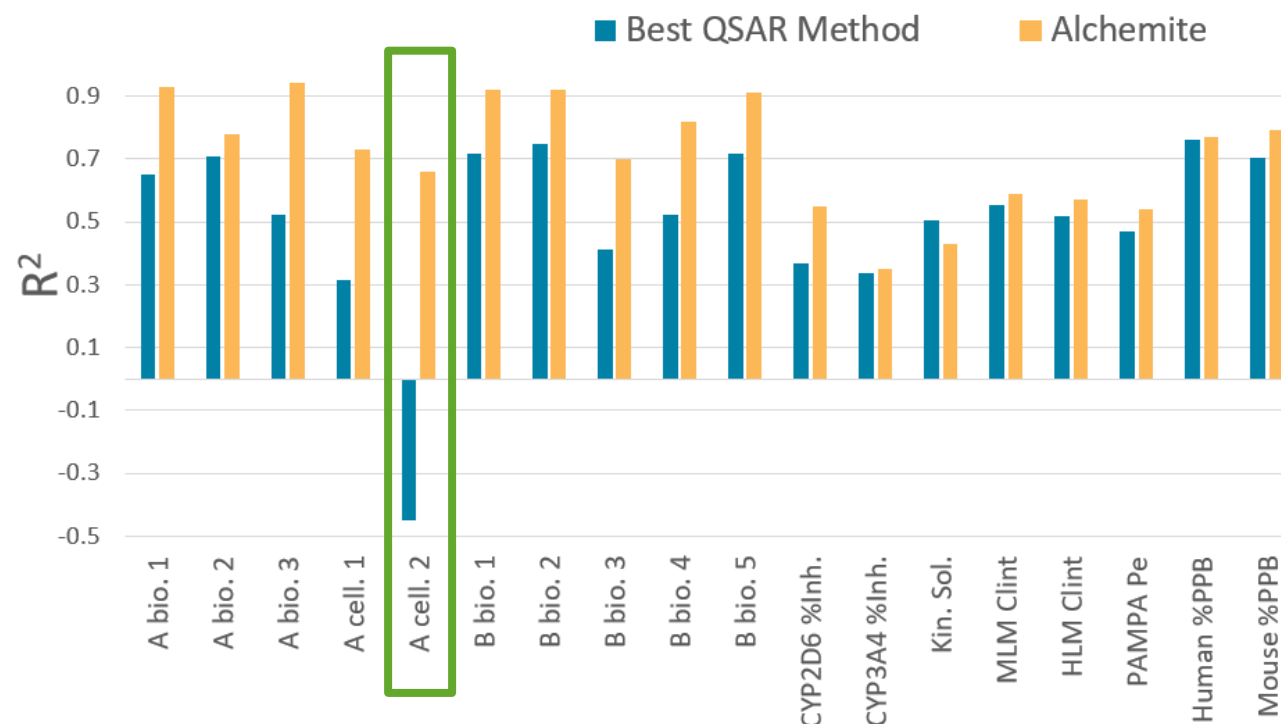
- Significant improvement in accuracy

Average  $R^2$

Best QSAR 0.50

Alchemite™ **0.72**

- Example of value delivered:
  - Few false negatives among confidently-predicted inactives – could have saved 24 FTE-months in unnecessary synthesis



Irwin *et al.* J. Chem. Inf Model. (2020) **60**(6), pp. 2848–2857

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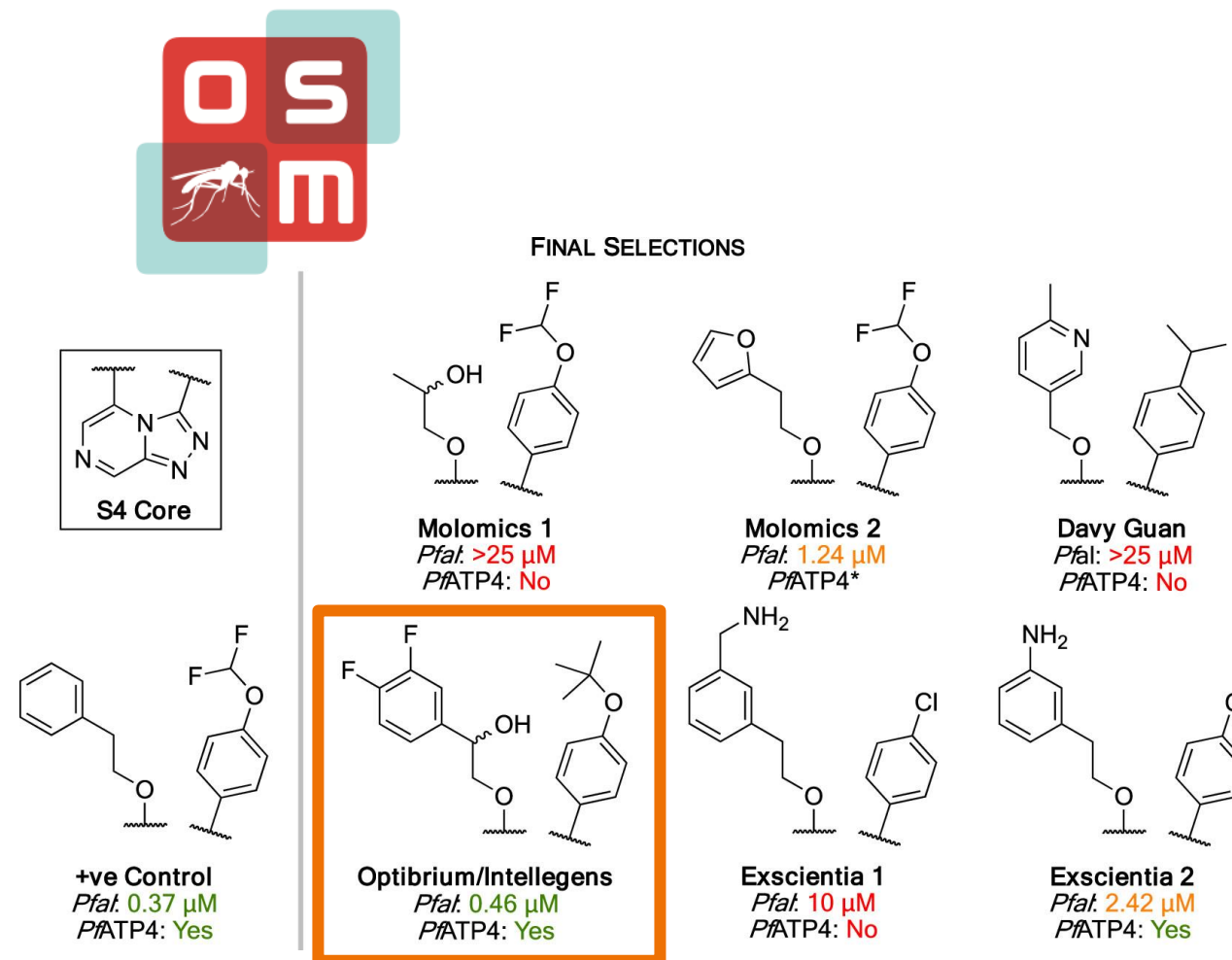
# Collaboration with Open Source Malaria (OSM)

## Combination with generative methods

- Application to **sparse antimalarial activity data**
  - Targeting novel MoA – *Pf*ATP4
  - Alchemite generated one of the top-ranked models
- New compound ideas were generated using the Nova™ module in StarDrop™
  - Prioritised with Alchemite model
  - Good activity profile and properties
- A **confidently** predicted compound was synthesised and tested by OSM
  - **Only confirmed active** of those proposed by four organisations
- “[this] suggestion... was thought by the human team to be a certain inactive... yet this compound displayed good potency and is a particularly useful outcome (i.e., **the “Machine Overlords” class**)”\*

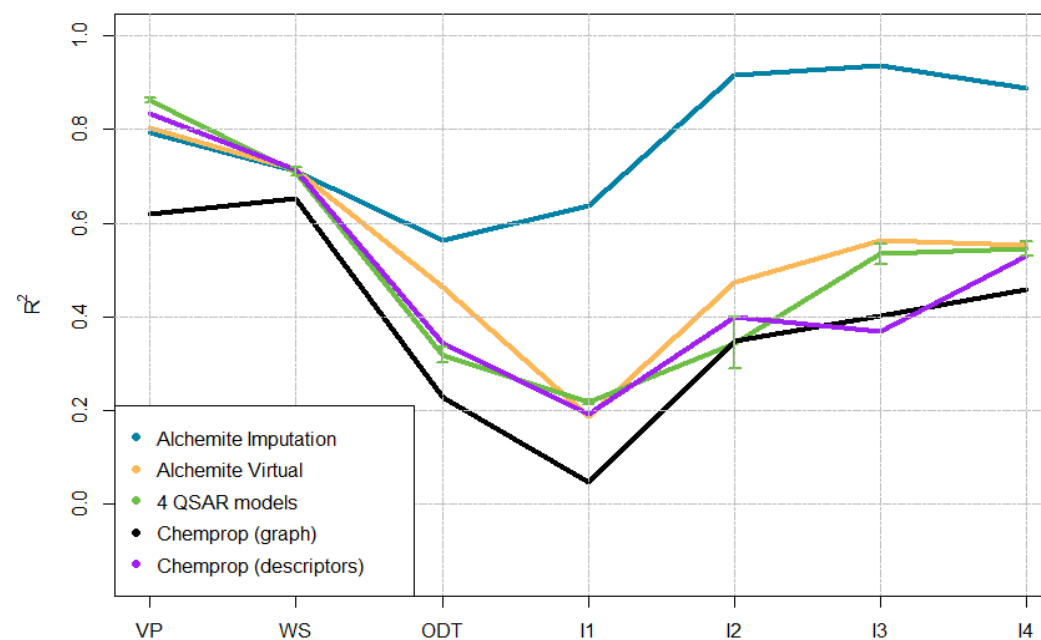
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\*Tse et al. J. Med. Chem. (2021) **64**(22) pp 1645-16463



# Imputation of Sensory Properties

- Sensory properties are measured in panels of human subjects
  - Expensive and subjective
  - Noisy data
- Deep learning imputation is more accurate than QSAR methods
  - Including multi-target deep neural networks
- Accurate prediction of activity cliffs that are missed by QSAR methods
  - Small changes in structure that drive a large change in property

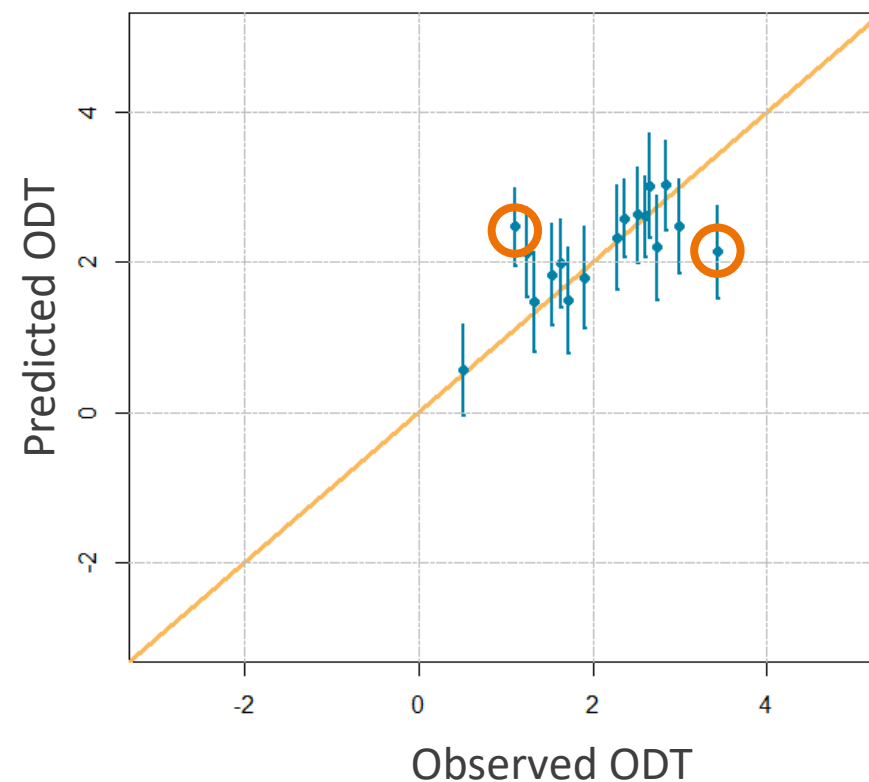
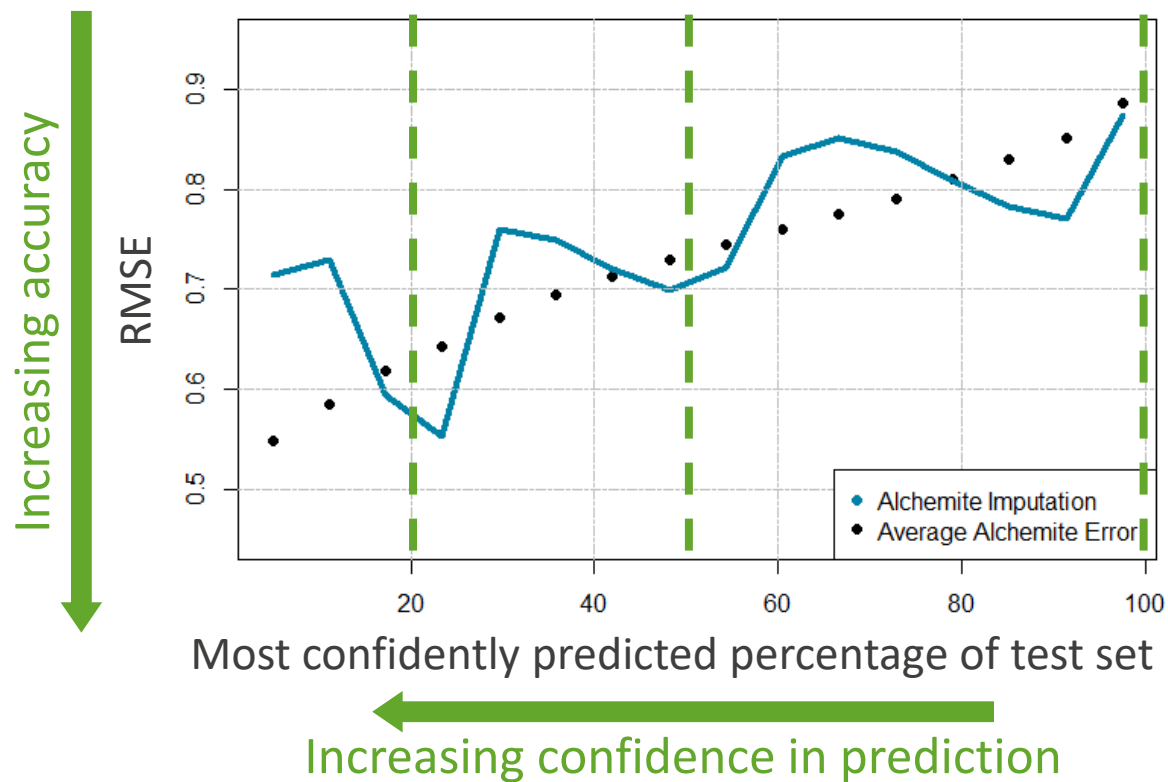


Mahmoud *et al.* J. Comput. Aided Mol. Des. (2021) **35**(11) pp. 1125-1140

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# Focusing on the Most Confident Results

## ODT Endpoint

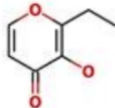
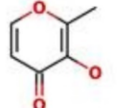
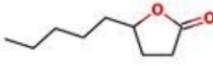
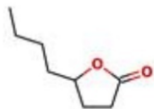
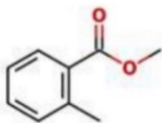
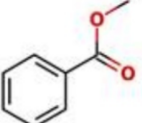


- Excellent correlation between model confidence (error bars) and observed accuracy
- The model can reliably identify the most accurate predictions
- Identify experimental outliers for retest

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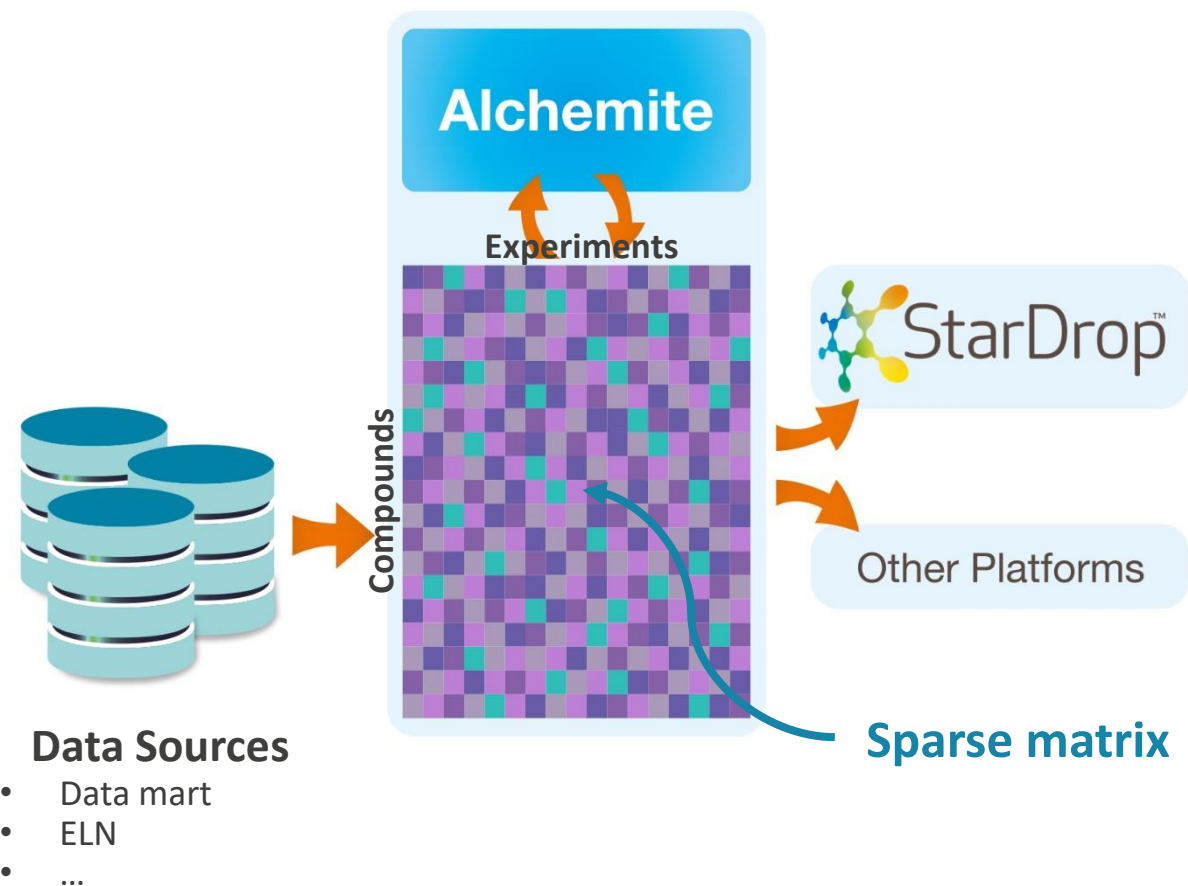


Structure of Nearest Neighbour in Training Set	Observed ODT of Nearest Neighbour in Training Set	Test Compound	Observed ODT of Test Compound	Predicted ODT by the Alchemite Imputation model	Predicted ODT by the best QSAR model
	0.93		-0.6	-0.7	1.43
	1.93		-0.12	-0.05	0.98
	0.52		1.99	1.89	0.89

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- **Automatically** updates and prepares experimental data for model building
  - Connects seamlessly to data repositories
  - Applies cleaning, business rules and transformations to data for best model performance
- **Automatically** updates Alchemite models as new data become available
  - Always work with results based on the latest information
  - Remove the burden of manually building and updating models
- Manage ‘massive matrix’ of imputed results for easy access
  - May contain  $O(10^{10})$  data points!
- Provide seamless access to results
  - Using StarDrop<sup>TM</sup> or any platform via a RESTful API



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# Conclusions

## Reducing the time and cost of discovery cycles

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Deep learning imputation gains more value than prediction from experimental data than conventional compounds


- Proactively **highlight high-quality compounds** by more accurately ‘filling in’ sparse data (imputation)
- **Increase confidence** in decision making, identify **hidden opportunities**, flag outliers and false negatives
- Translate AI insights into planning of experiments and **focus on the most valuable measurements**
- Gain more value from your compound data, **accurately predicting complex endpoints**, intractable with conventional QSAR modelling


For more information: [www.optibrium.com](http://www.optibrium.com), [matt@optibrium.com](mailto:matt@optibrium.com) or booth #35



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  - Tom Whitehead



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- Takeda  | ONCOLOGY
  - Scott Rowland



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