



Application of the Alchemite deep-learning methodology to categorical modelling of PK endpoints

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Overview

- Introduction
- Alchemite™ - the unique deep learning method
- Alchemite™ Proven Success
 - Regression model applications and case studies
- Categorically modelling using Alchemite™
- Conclusions

Challenges of Using Data in Drug Discovery

- It is impossible to measure all of the compounds in all assays - how to make the most of the data available?
- The sparse and noisy nature of the data causes common methods for predictions to struggle
- How can the limited data be used to make better predictions for new compound designs?



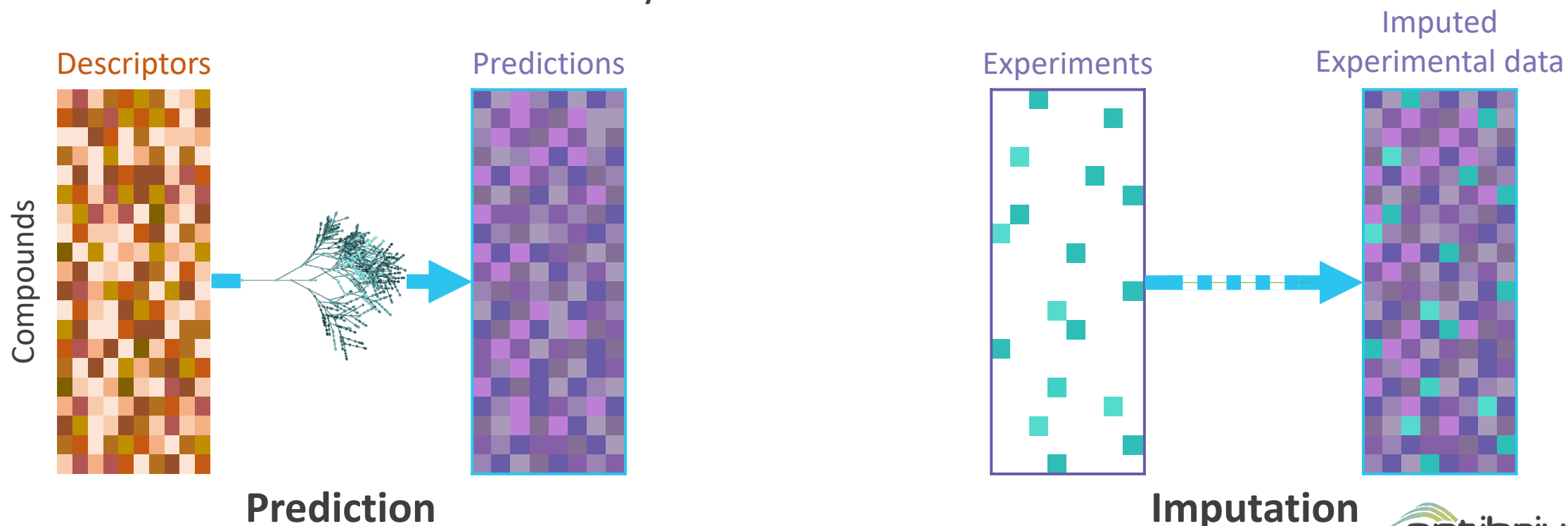


Augmented Chemistry

A decorative graphic at the bottom of the slide consists of four wavy, horizontal lines that curve upwards from left to right. The lines are colored in a gradient from light blue to bright yellow, matching the Optibrium logo.

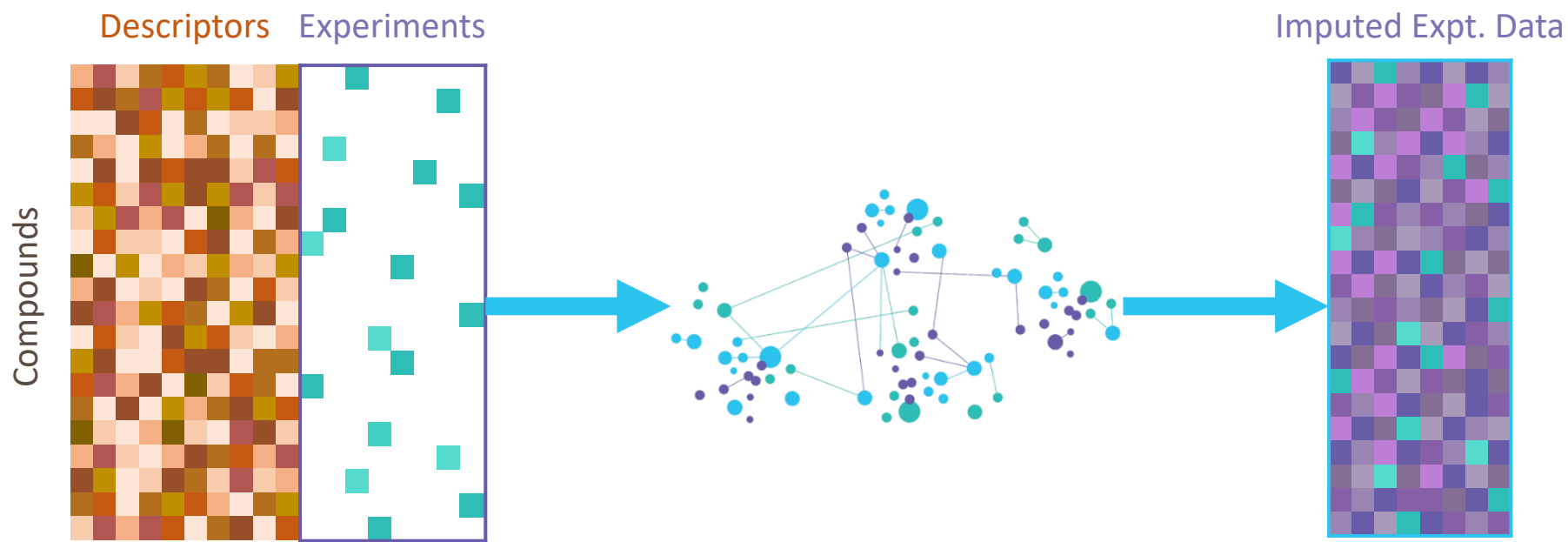
Prediction vs. Imputation

- 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





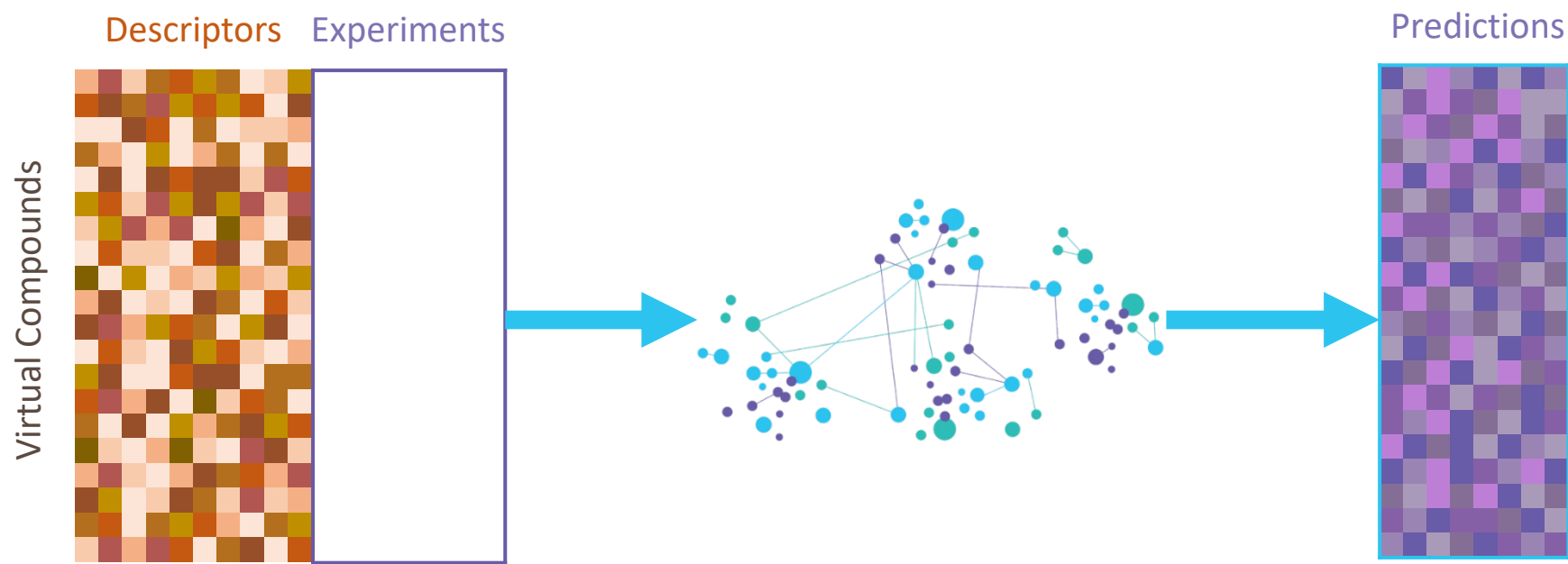
- Learns directly from relationships between experimental endpoints as well as SAR
 - Makes better use of sparse and noisy experimental data than conventional QSAR models
- 'Fills in' the gaps in your data and makes predictions for 'virtual' compounds
 - Generates more accurate predictions to target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



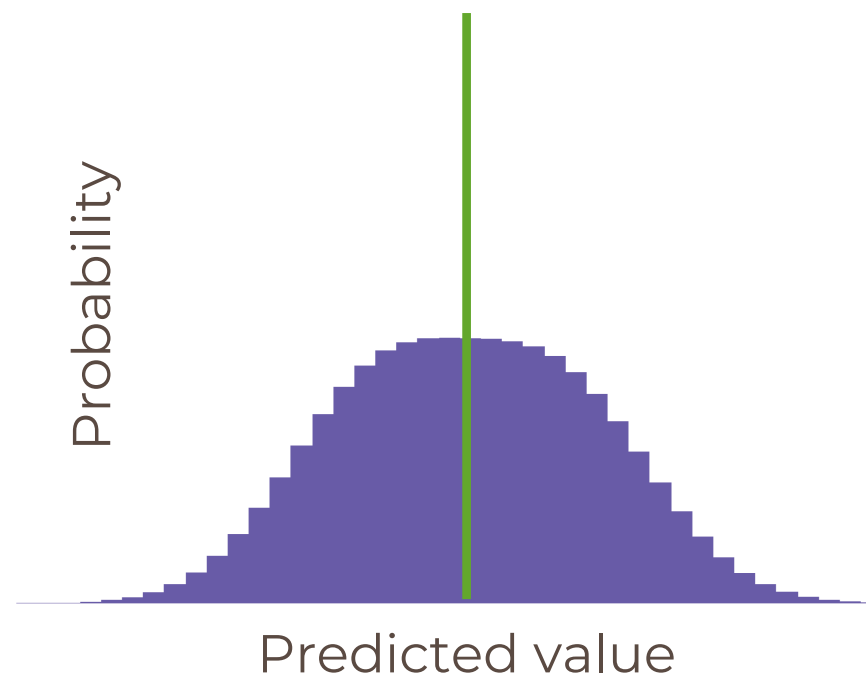
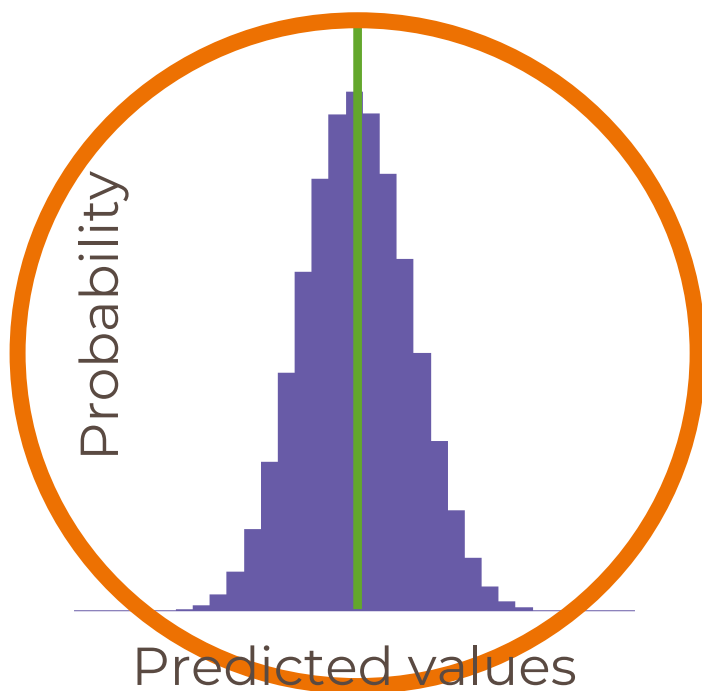
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- Estimates uncertainty in each individual prediction
 - Strong correlation between uncertainty estimates and observed accuracy on independent test sets
 - Highlights the most accurate predictions on which to base decisions
- Confidently targets high-quality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

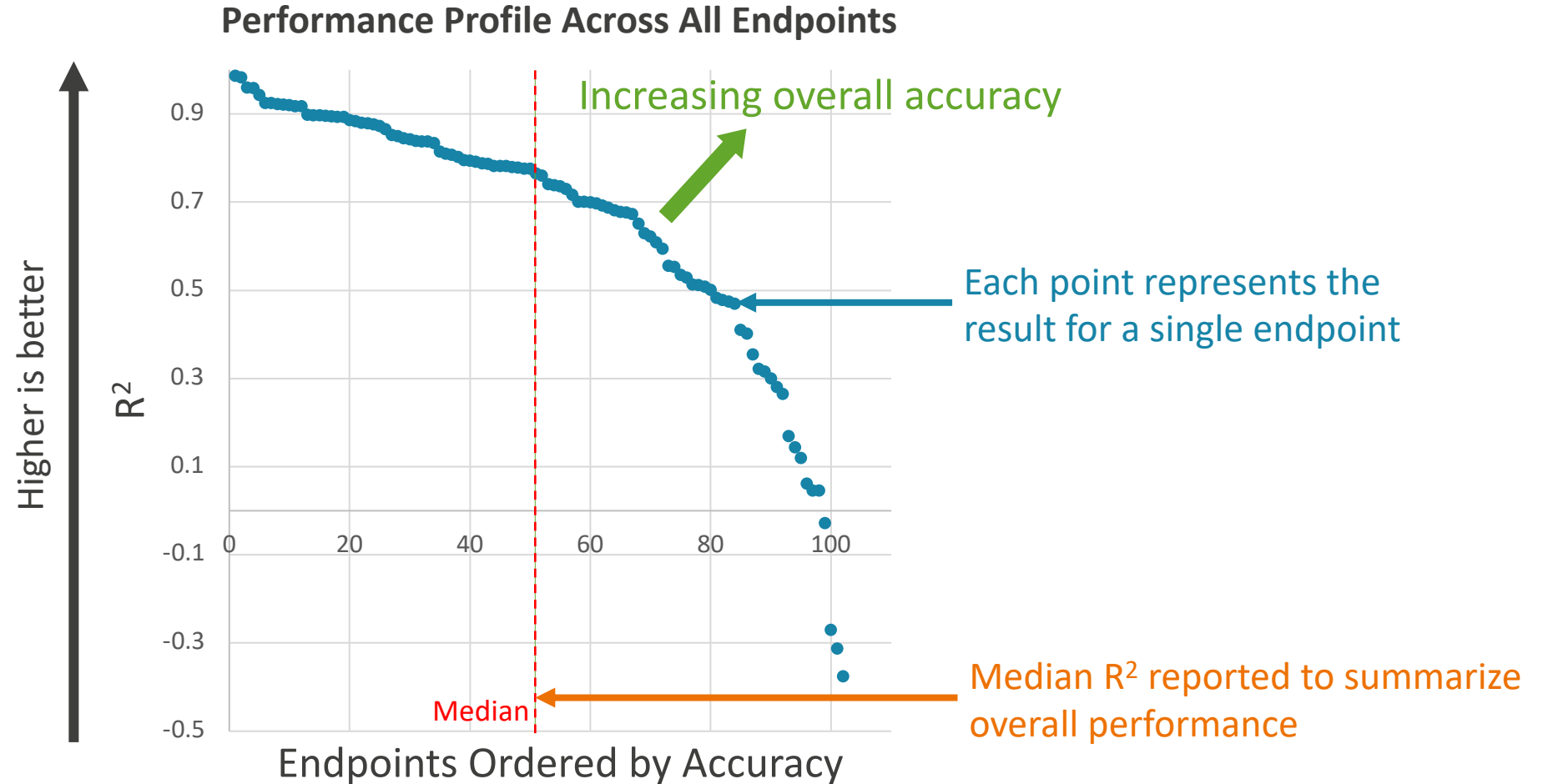


Definitions

- **Endpoint:** An experimental measurement that may be made on a compound
 - E.g. IC_{50} against a target, solubility, Cl_{int} in human liver microsomes, C_{max} in rat PK
- **Imputation Model:** These models generate predictions for compounds using sparse assay data as input, in addition to molecular descriptors
 - These models ‘fill in the gaps’ in the experimental data for compounds that have been synthesised and tested in some assays
- **Virtual Model:** These models generate predictions for compounds using only molecular descriptors as input
 - These models make predictions based only on compound structure, i.e., for a compound that has not yet been synthesised or tested

Assessment of Results

Performance Profile



R^2 – Coefficient of Determination (1 = perfect prediction, 0 = random, <0 = worse than random)



Regression Models



Alchemite Application to Project Data

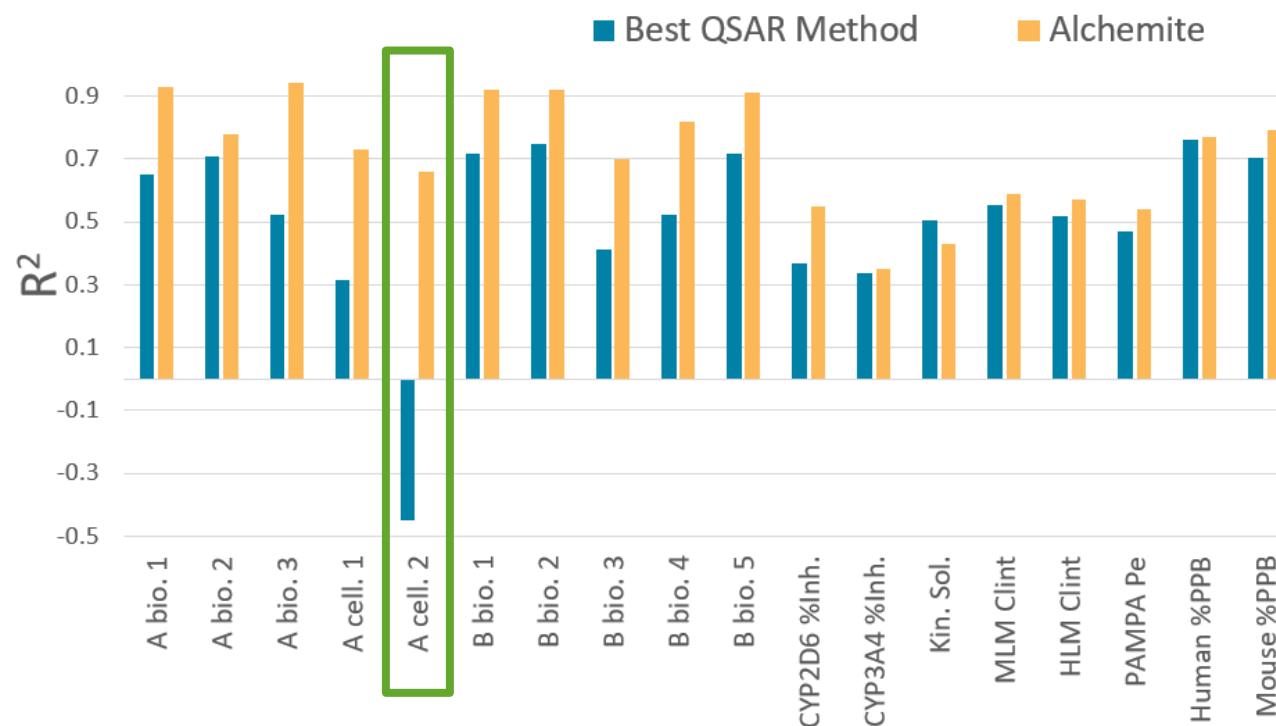


- Application to **heterogeneous** data across two projects
 - Target and phenotypic activities and ADME endpoints
 - 2453 compounds across 18 endpoints

- 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 >\$600,000 in unnecessary synthesis



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

Watch our webinar: http://bit.ly/practical_deeplearning



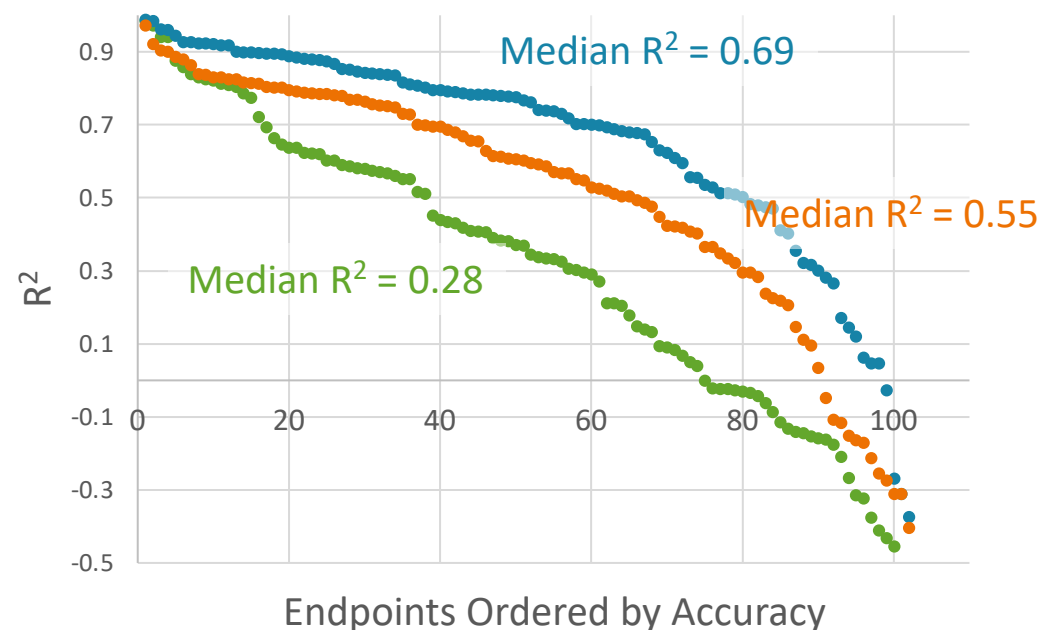


- Application to large data set
 - 678,994 compounds
 - 1,116 experimental endpoints
 - 2% complete
- Covering a **full range** of drug discovery assays, including compound activities and ADME properties
- Example of value delivered:
 - “...an extension of what medicinal chemists... do in a discovery project, but at much larger scale than would be possible for a person.”



ONCOLOGY

Prospective Prediction of Project Target Activities



• Random Forest • Alchemite Imputation • Alchemite Virtual

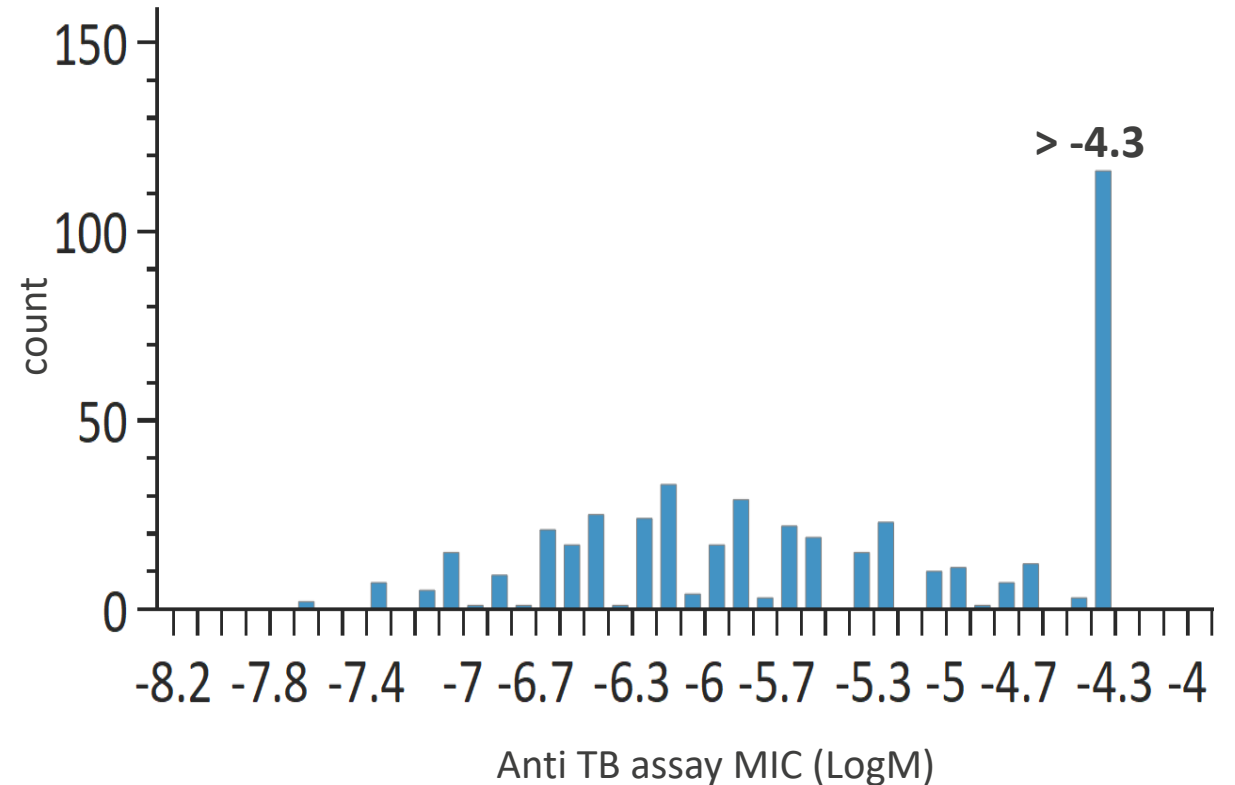
Irwin *et al.* App. AI Lett. (2021) DOI: 10.1002/ail2.31

Watch our webinar: http://bit.ly/largescale_imputation



Limitations of Regression Models

- Qualified values (continuous values with $<$, $>$ signs) are removed prior to building the model to prevent a skewed distribution
- Noisy data as input can lead to low-quality predictions
- Labelled data or inherently categorical endpoints cannot be modelled





Application of Categorical Modelling

Categorical Modelling Methods

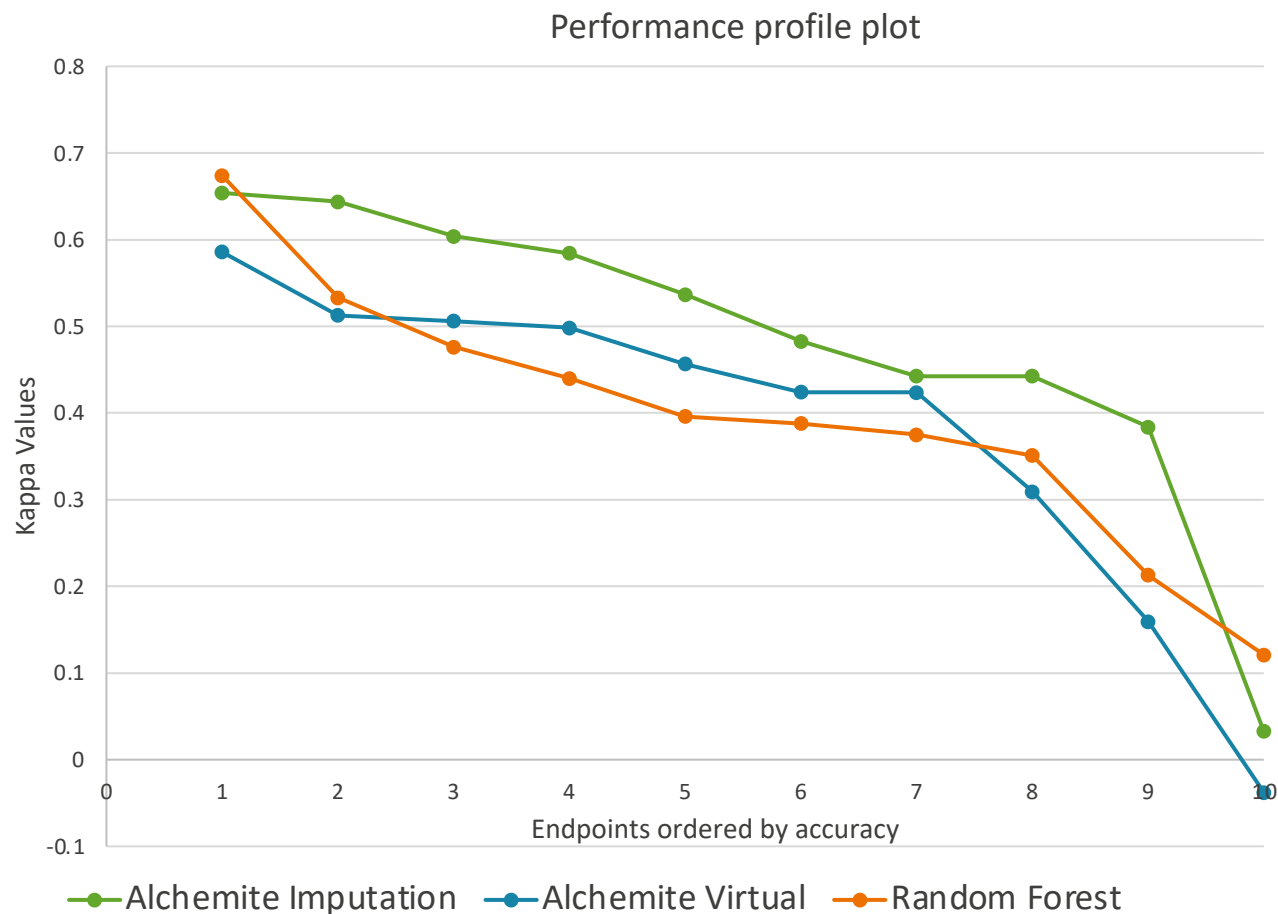
- Handling qualified data
 - Continuous data may contain qualified data, e.g. <, >
 - Define cut-offs to “bin” the data into classes and include these values in the model
- Model building
 - The library of descriptors were provided by StarDrop and consists of 10 whole molecule Descriptors and 320 Auto-Modeller descriptors based on 2D SMARTS, logP, TPSA, MW, charge etc
 - Training and test sets consist of discrete values (0s and 1s) for binary categorical models
 - The predictions are discrete values
 - Cohen’s Kappa values are used to indicate performance
- Alchemite (imputation and virtual) categorical models were built and compared with the categorical QSAR model
 - Consistent training and test sets
 - Consistent cut-offs for the same assay in the different model

Deep learning methods Vs QSAR

- Application to the publicly available **AZ data** set: *document_chembl_id:CHEMBL3301361*
 - 5788 compounds
 - 10 PK assays from different species
 - 13% complete
- Model building
 - The continuous data were “binned”
 - Alchemite imputation and virtual categorical models Vs Random Forest categorical model
- Improvements in accuracy

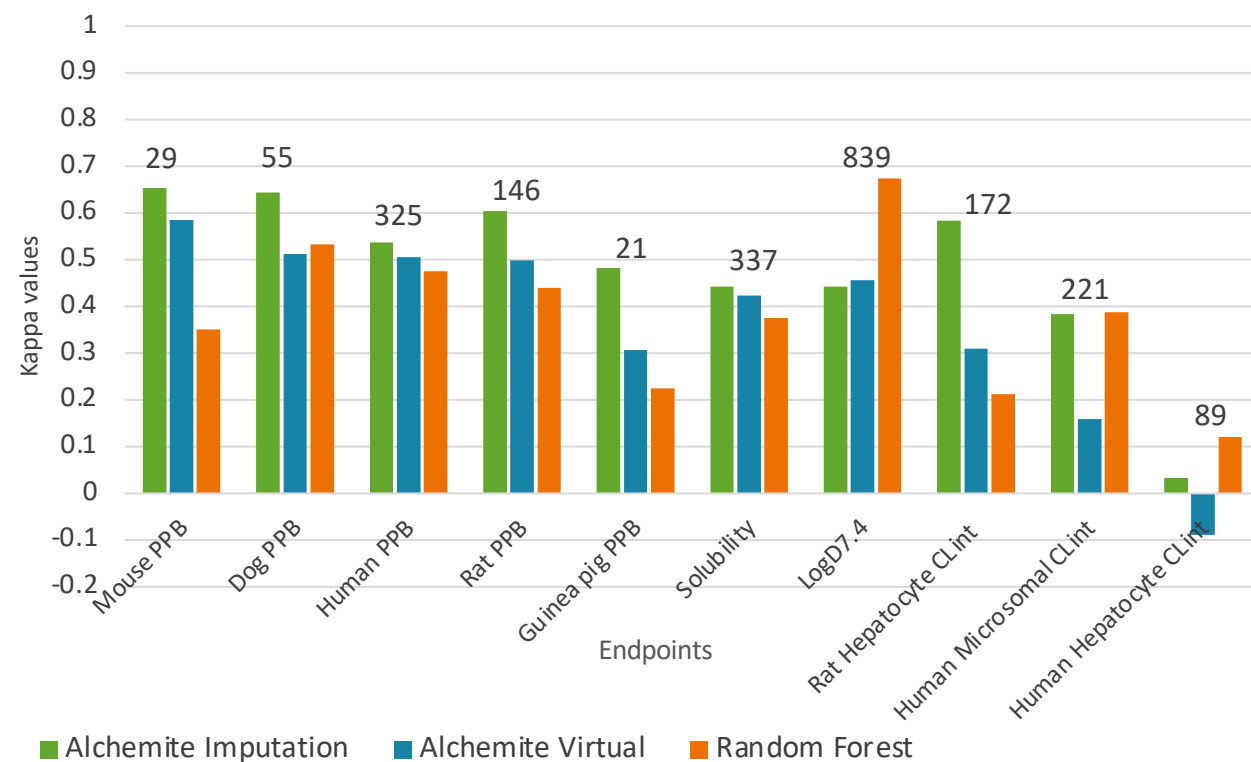
Median Kappa Value

Random Forest	0.39
Alchemite Virtual	0.44
Alchemite Imputation	0.51



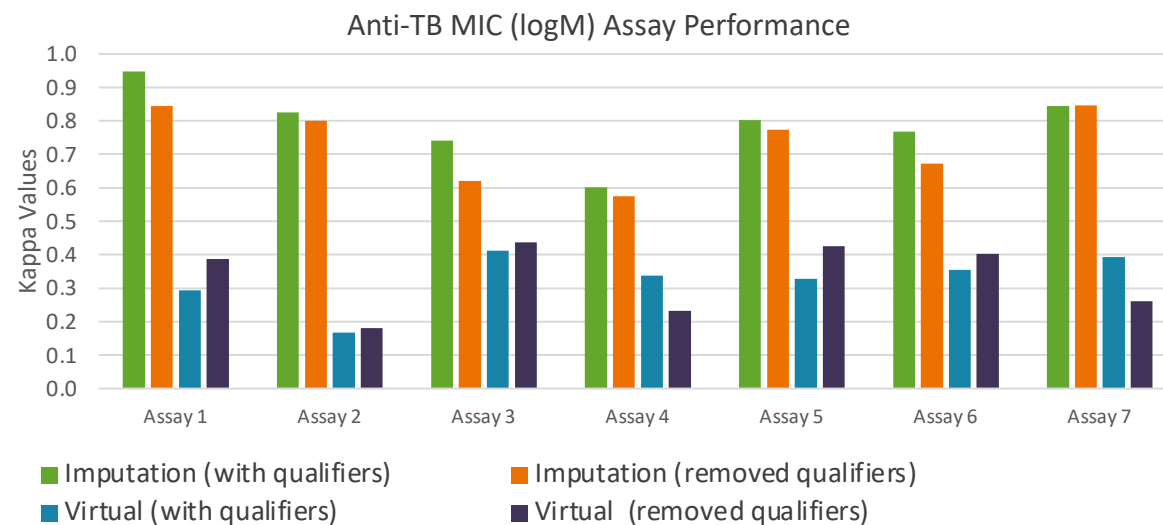
PK Endpoint Performance - Deep learning methods vs QSAR

- Analysing the performance for each ADME/PK endpoint
- PPB: Plasma protein binding
 - 5 species
 - Alchemite Imputation model is consistently outperforming the virtual and RF models
- CL int: Intrinsic clearance
 - 2 different species
 - Hepatocyte and Microsomal
- The number of data points in the test set are included



Application of Categorical Modelling to Qualified Data

- Categorical modelling on a **global health data set** with qualified data
- The data set
 - **495** compounds
 - **34** endpoints (in-vitro and in-vivo activity, PK and ADME data)
- Including qualified data changes the sparsity of the overall data set from **20%** to **30%** data points present
- More data leads to a wider chemical spaces and a more accurate model
 - Alchemite imputation and virtual categorical models were built on the datasets with and without the qualified data included
 - Anti-TB MIC (LogM) assays showed the greatest improvements for the imputation methods with the additional qualified data included



Conclusions

- Advantages of Alchemite deep learning imputation
 - Gains more value than prediction from experimental data
 - Outperforms traditional QSAR methods
- We have demonstrated the successful application of Alchemite in a range of categorical modelling scenarios
 - Heterogenous data across multiple drug discovery endpoints
 - Sparse data sets
 - Large data sets with qualified data
- The categorical feature of Alchemite has shown success where regression models struggle
 - Qualified data
 - Labelled or classified data

Acknowledgements



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For more information visit www.optibrium.com

