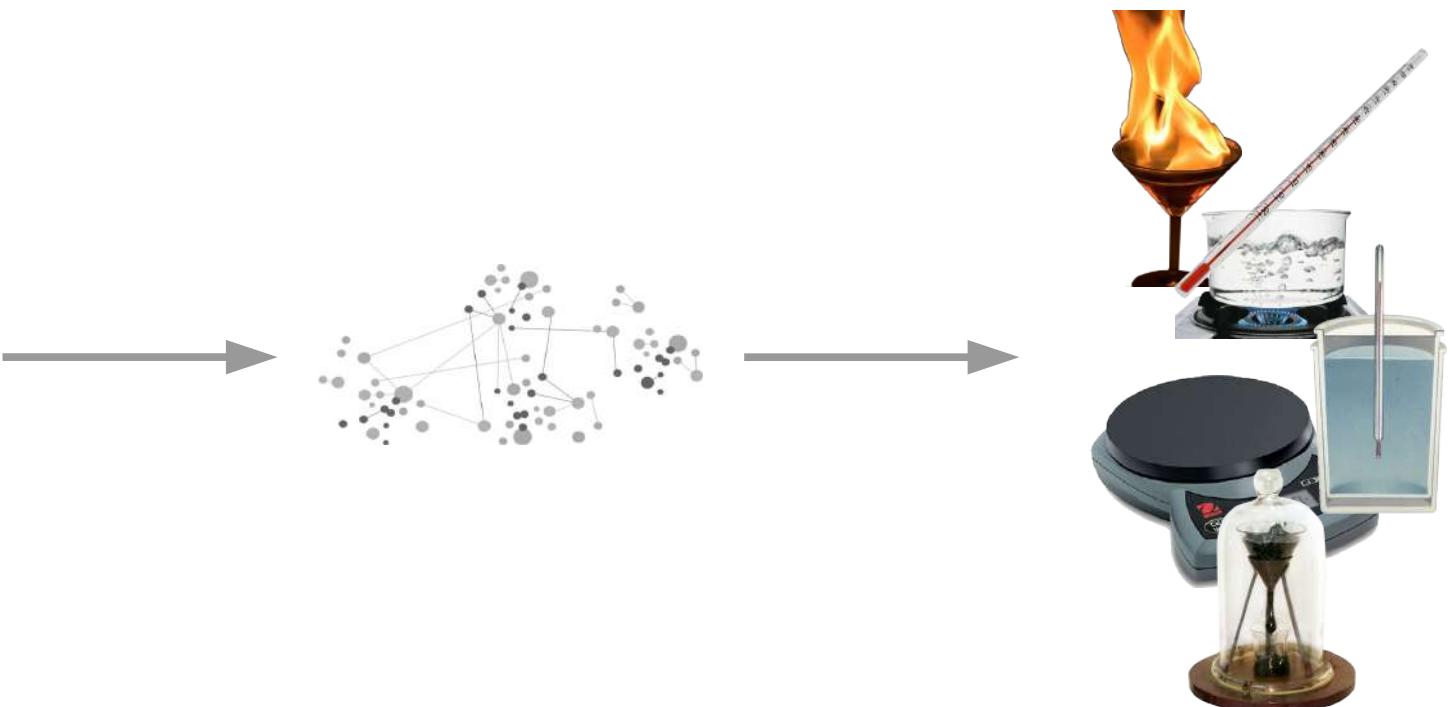
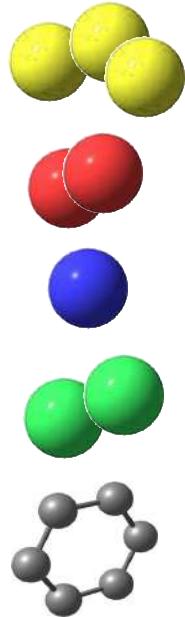


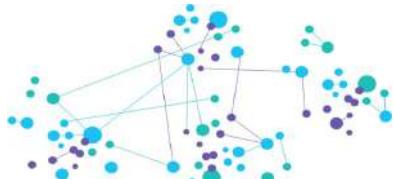
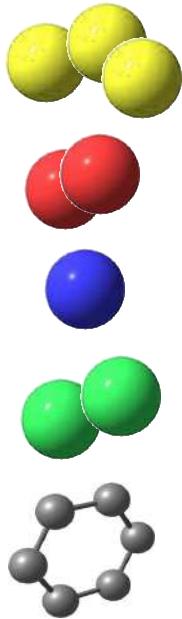
# Imputation of assay activity data using deep learning

Gareth Conduit

# Machine learning as a black box

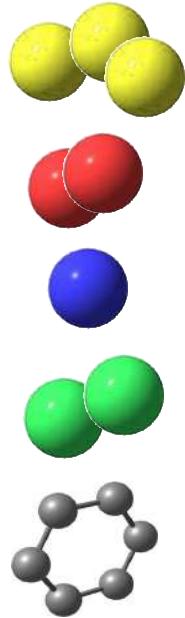


# Train from historical data



An illustration of laboratory glassware, including a round-bottom flask with a flame, a graduated cylinder with liquid, and a beaker with a stirrer. To the right of the glassware is a vertical column of green numbers. The first few numbers are 293928764790904, followed by a sequence of digits ending in 09.

# Predict new chemicals



# Alchemite™ machine learning tool to



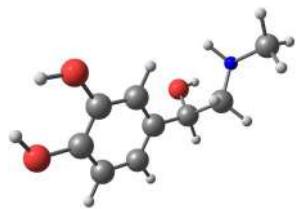
Reduce the need for experiments and accelerate discovery

Utilise all available information: computer simulations and real-life measurements

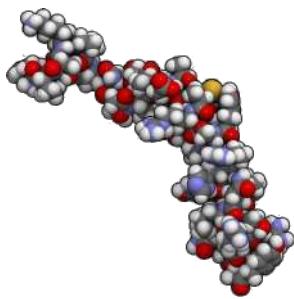
Impute values from sparse data

Broadly applicable with proven applications in drug design, industrial chemicals, and materials

# Action of a drug



Drug



Protein

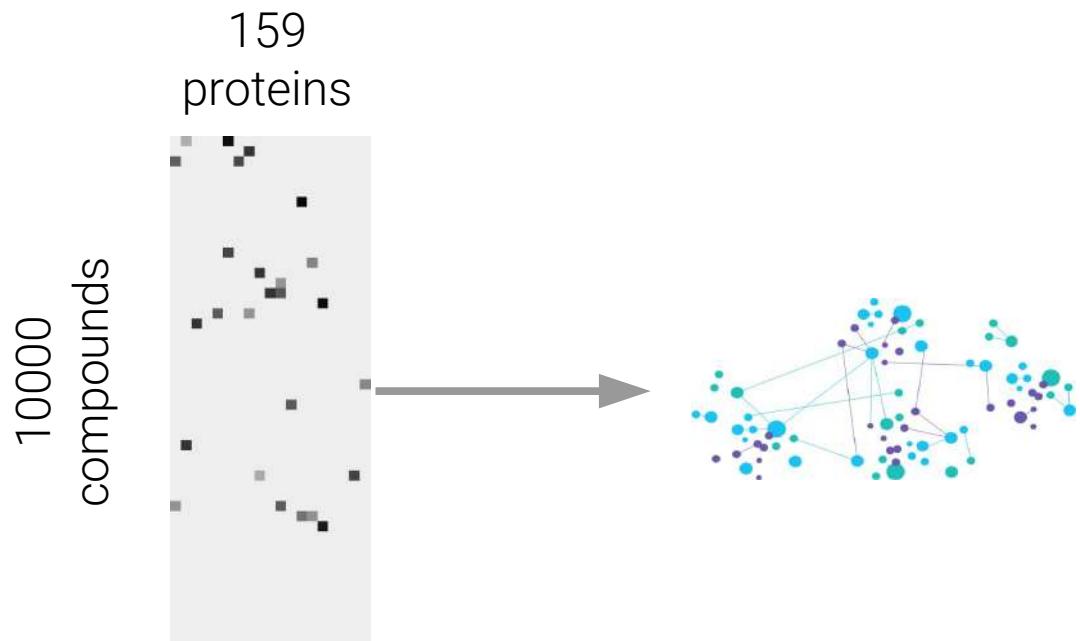


Effect

# Novartis dataset to benchmark machine learning



159 kinase proteins, 10000 compounds, data 5% complete

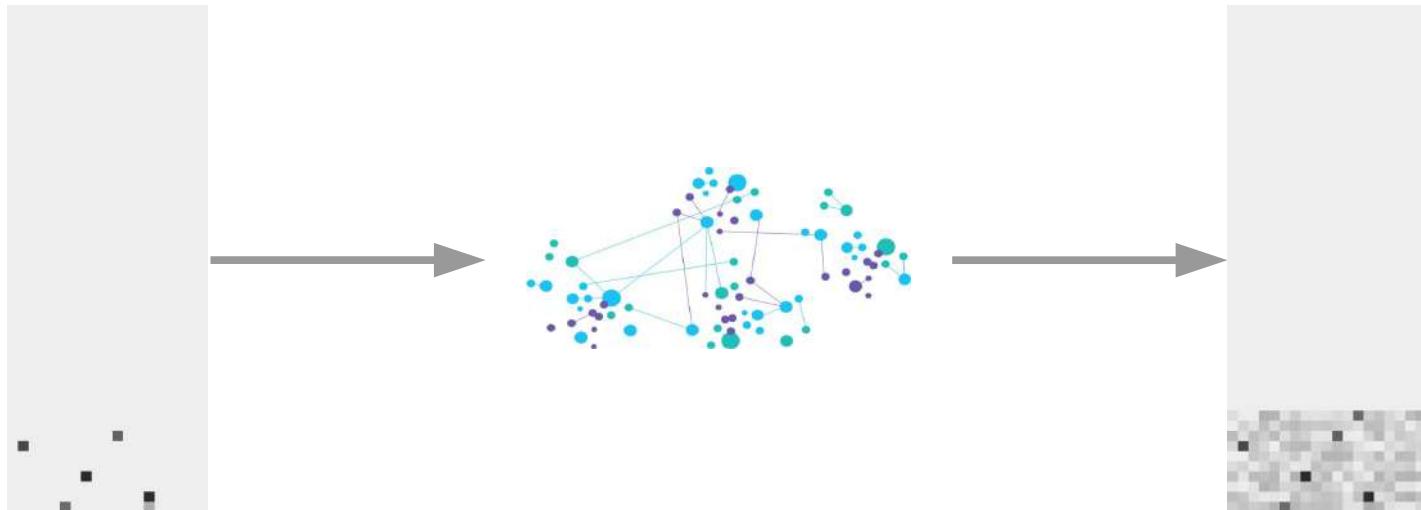


Data from ChEMBL  
Martin, Polyakov, Tian, and Perez,  
J. Chem. Inf. Model. 57, 2077 (2017)

# Validate imputation of missing entries



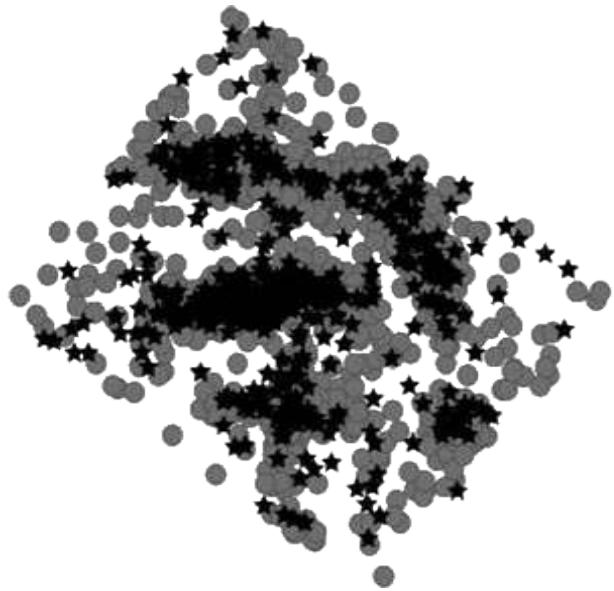
Realistically split holdout data set, extrapolate to new chemical space



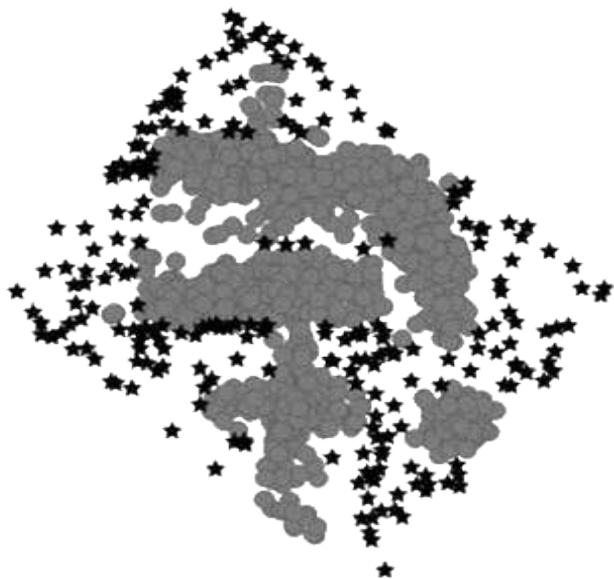
# Impute missing entries in new chemical space



Random



Realistic

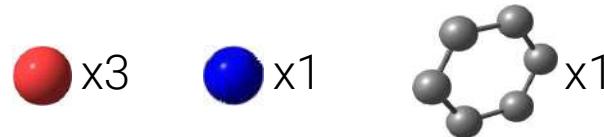
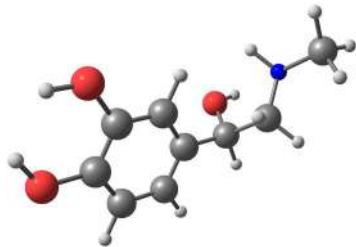


● Training

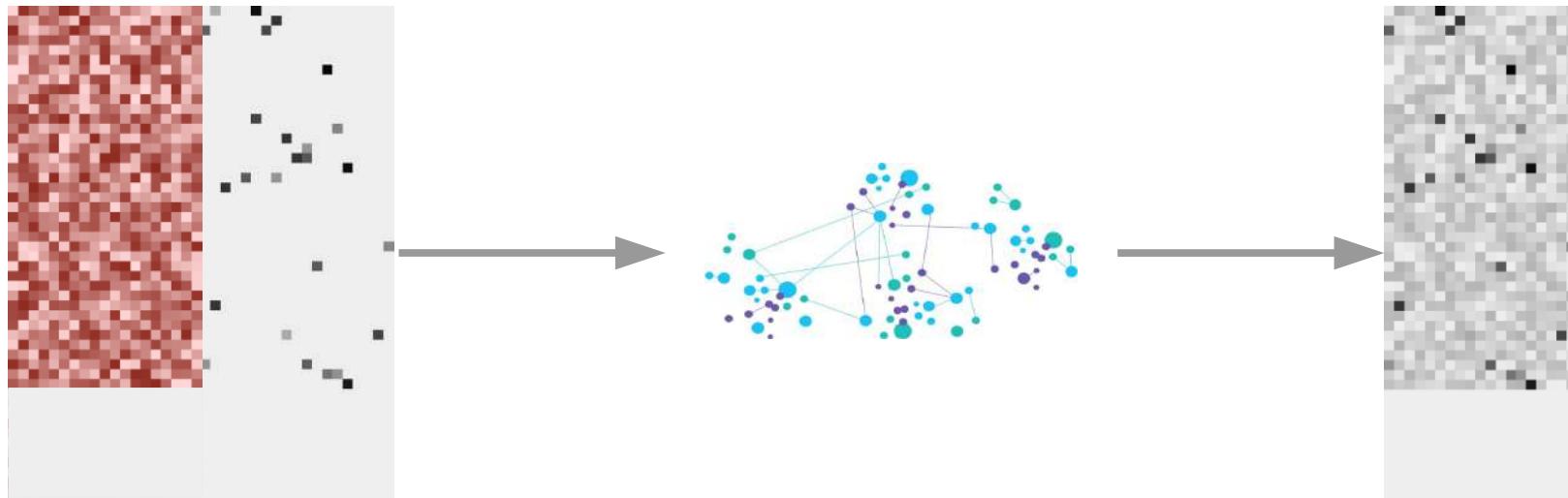
★ Validation

Data from ChEMBL  
Martin, Polyakov, Tian, and Perez,  
J. Chem. Inf. Model. 57, 2077 (2017)

# QSAR: quantitative structure-activity relationships



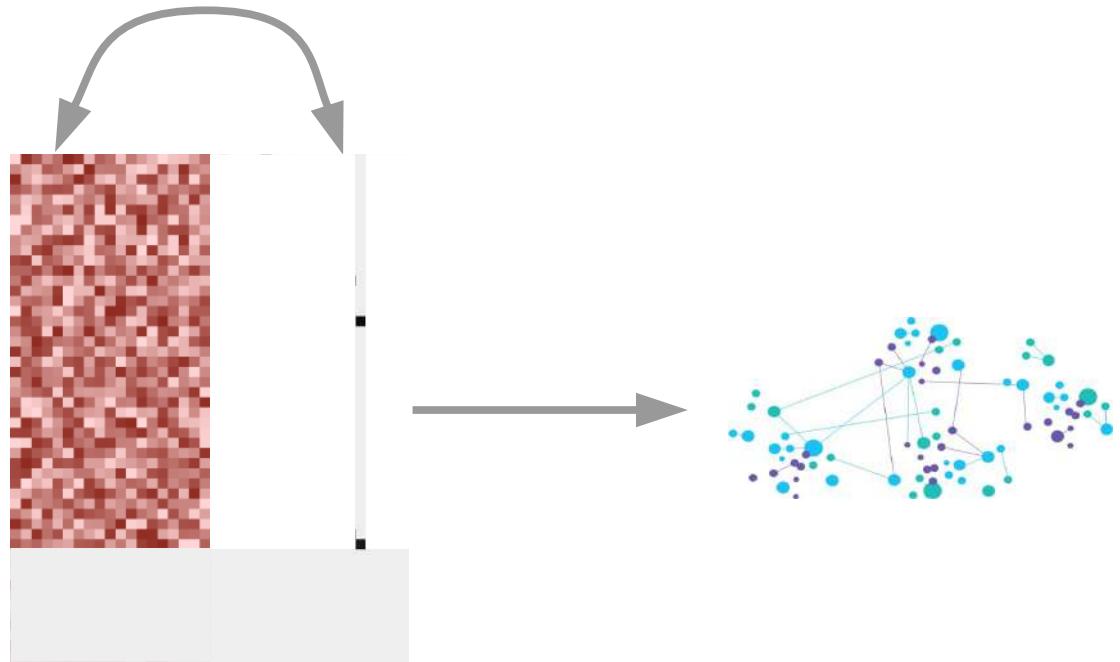
Molecular weight=183 Da



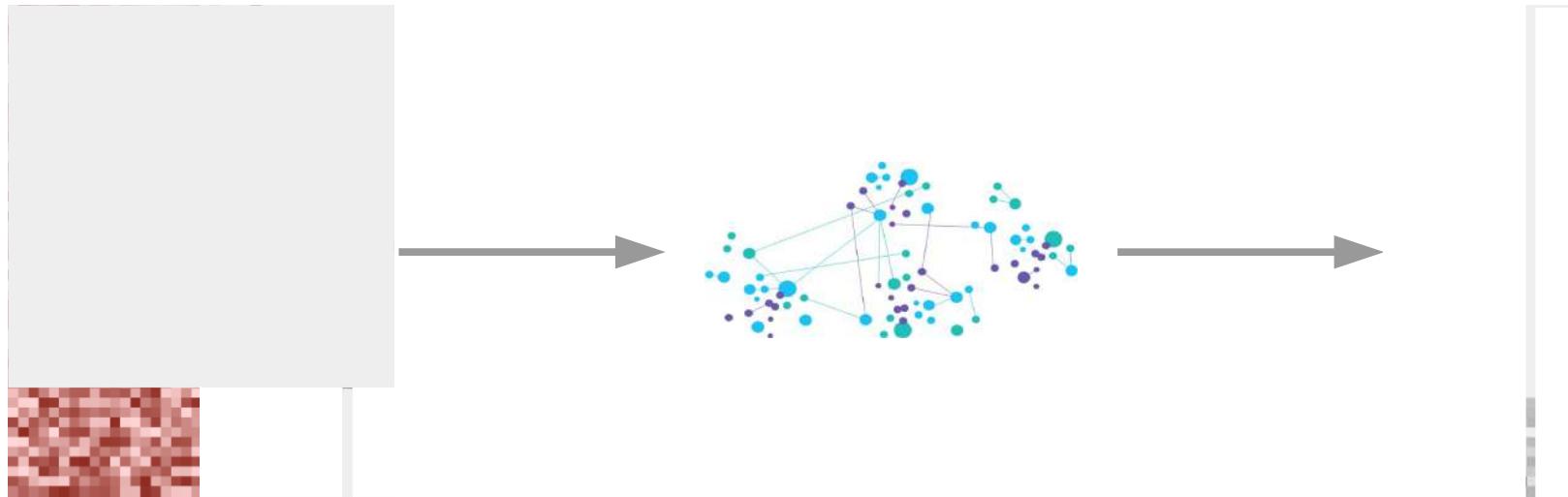
# Train off one column at a time



Standard methods learn descriptor-protein correlations



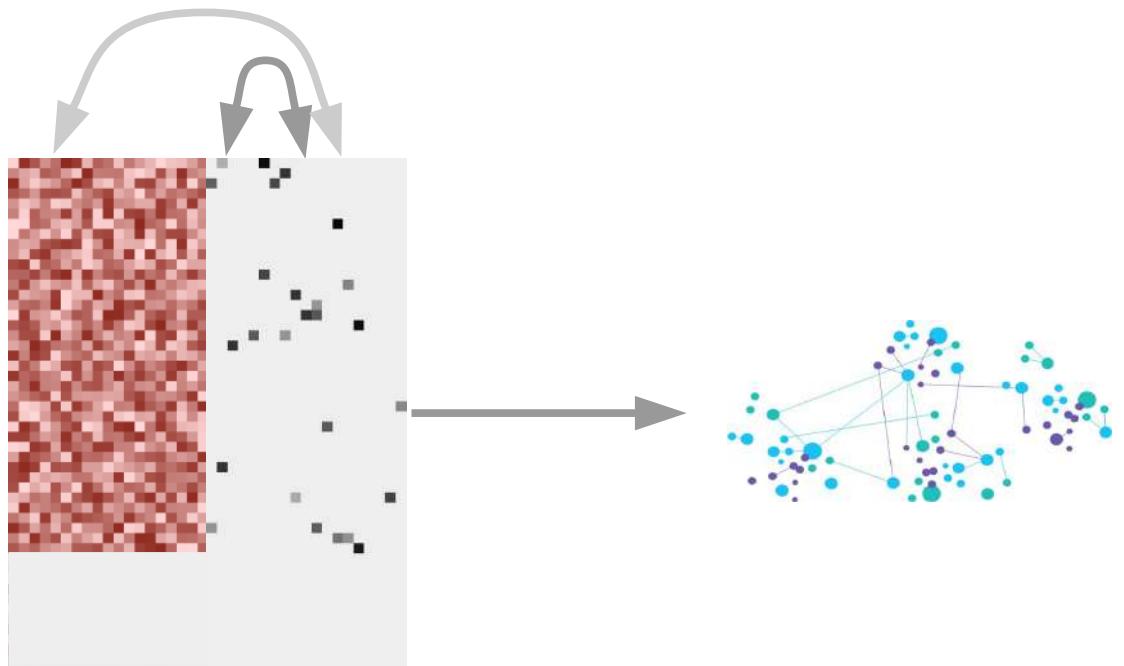
# Train and predict one column at a time



# Alchemite™ uses all available data



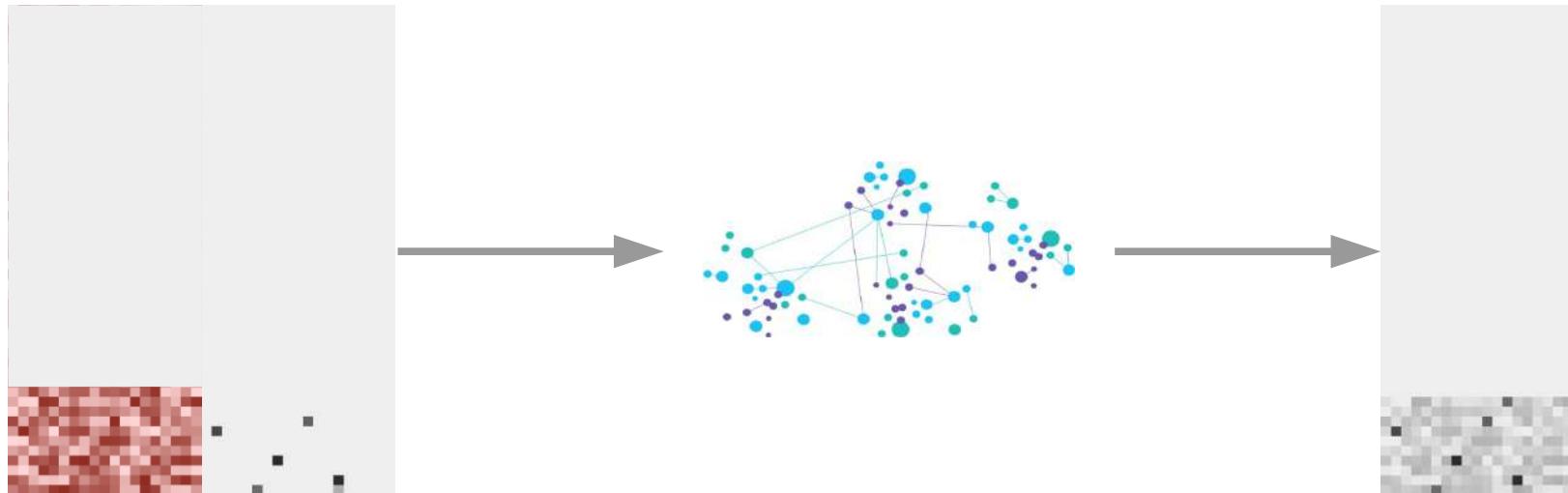
Include protein-protein correlations



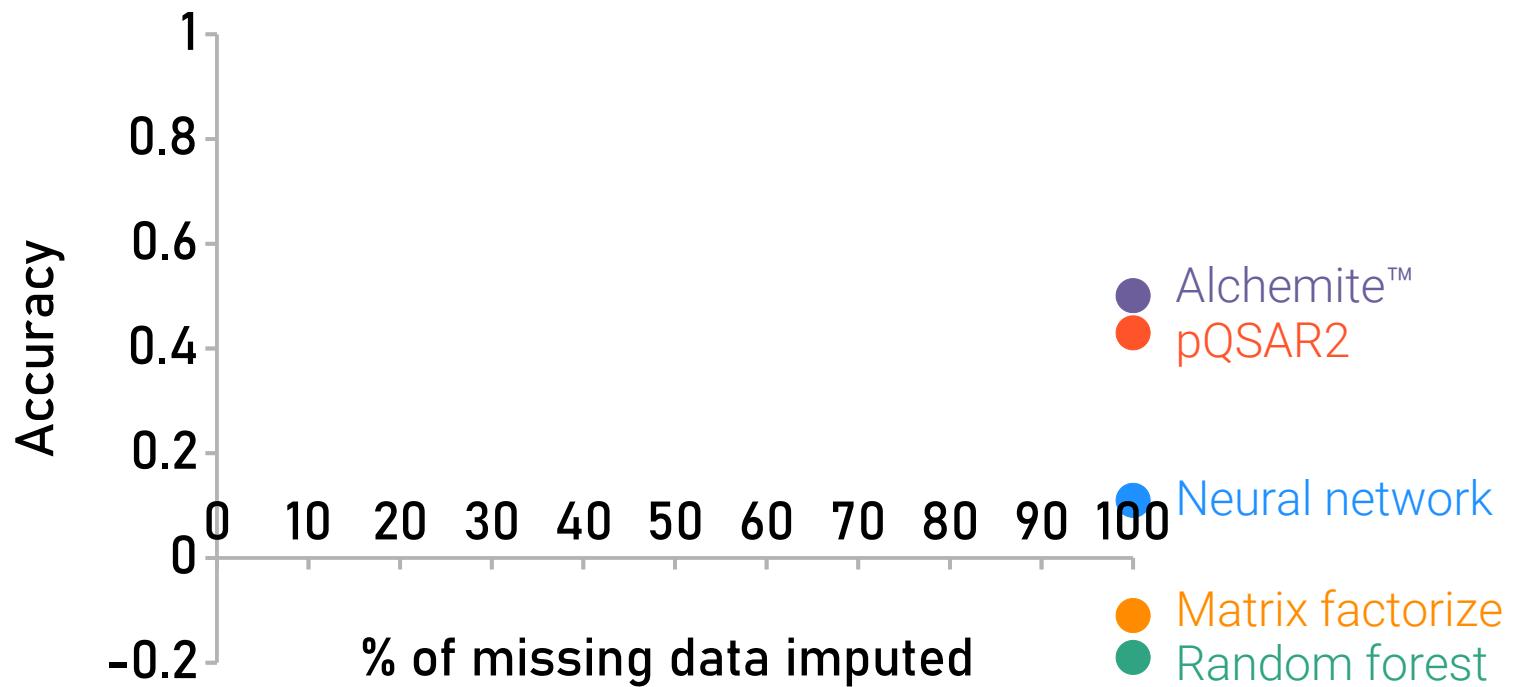
# Validate imputation of missing entries



Realistically split holdout data set, extrapolate to new chemical space, and calculate the accuracy



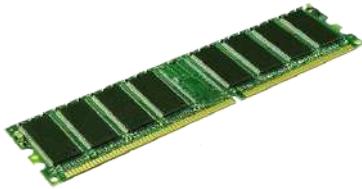
# Alchemite™ outperforms other methods



# Computational cost



Seek  $R^2 = 0.465$



0.53 GB



13 s



7 GBs

Alchemite™

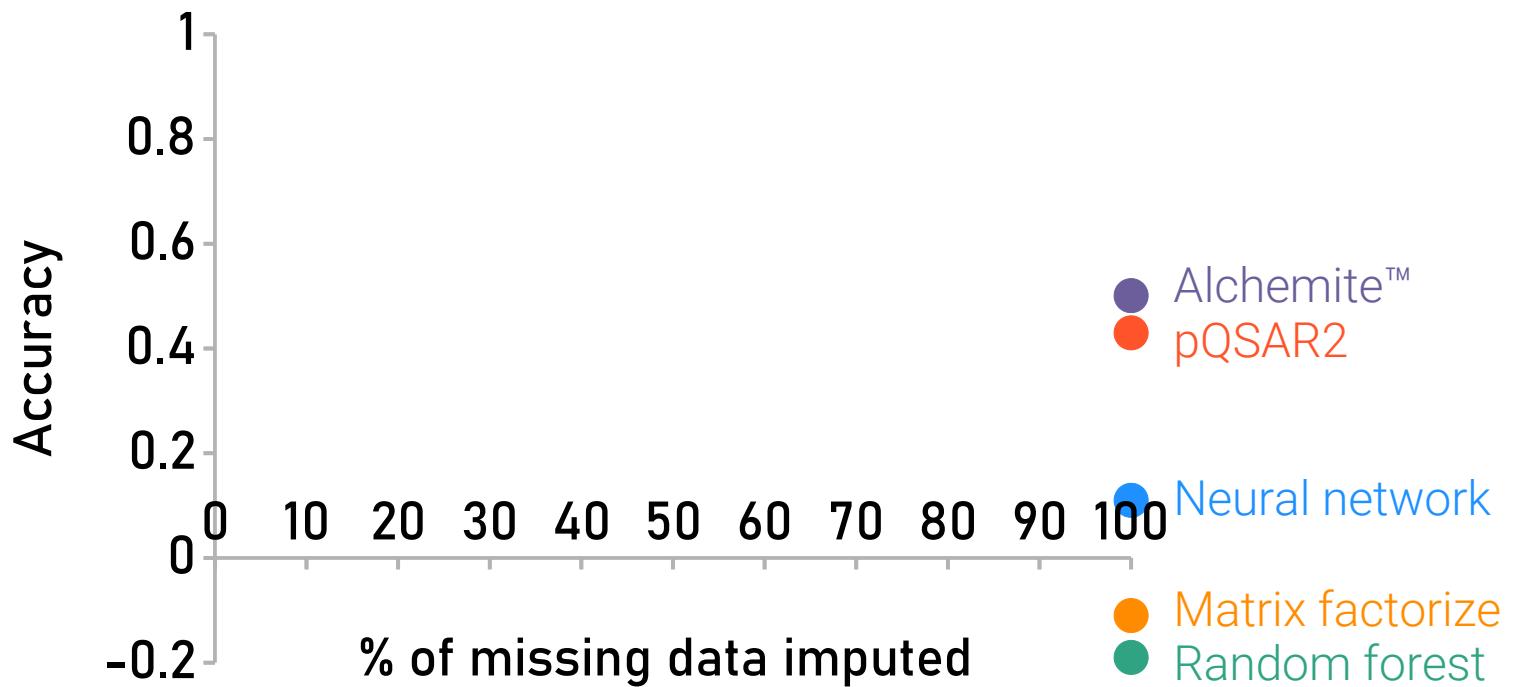
6.53 GB

154 s

1006 GBs

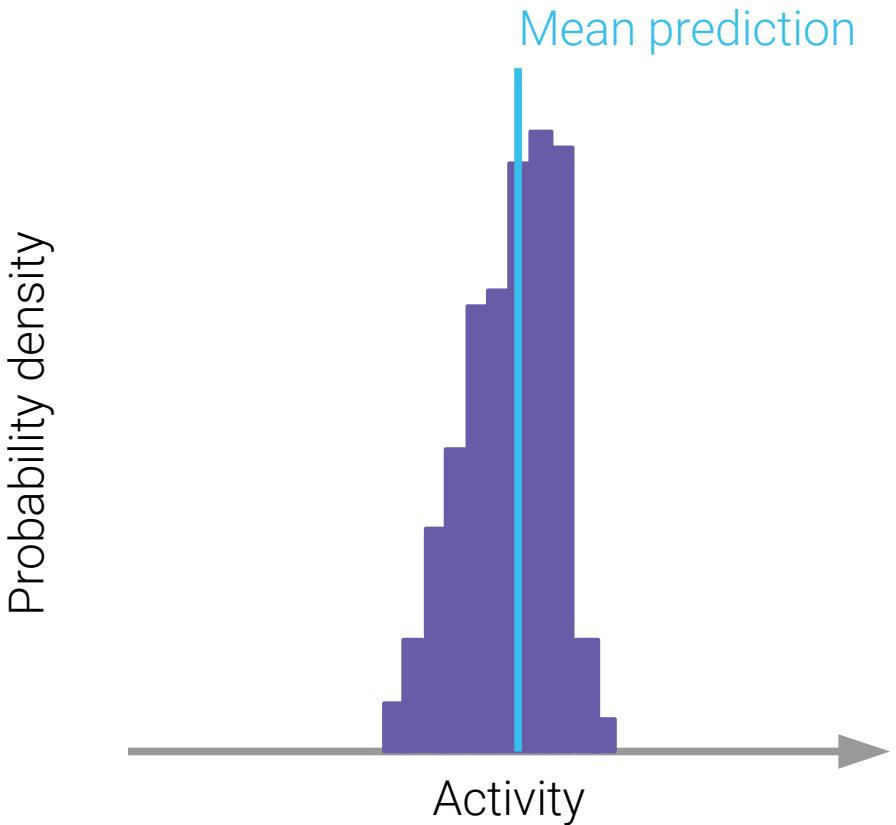
pQSAR2

# Alchemite™ outperforms other methods



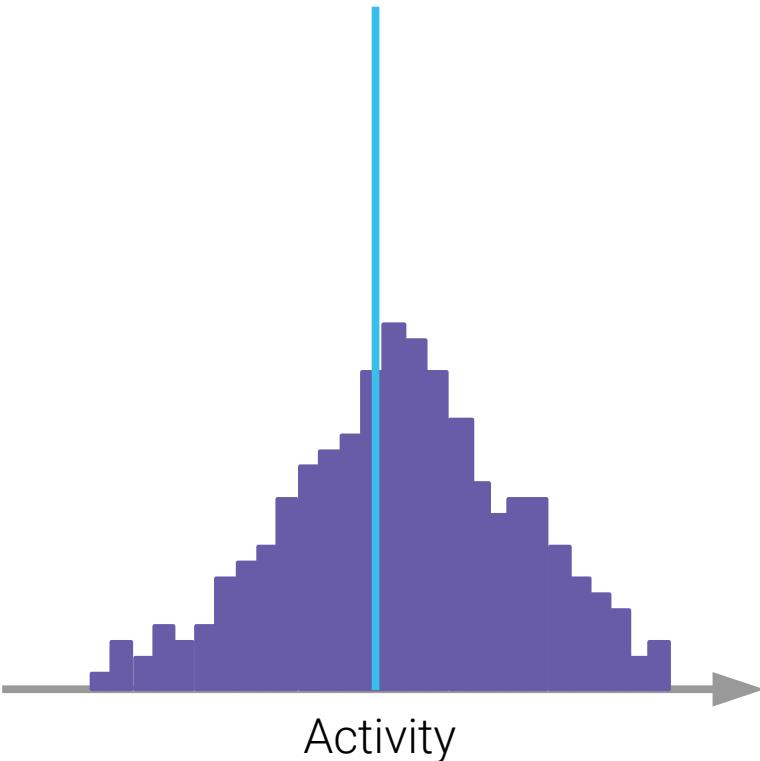
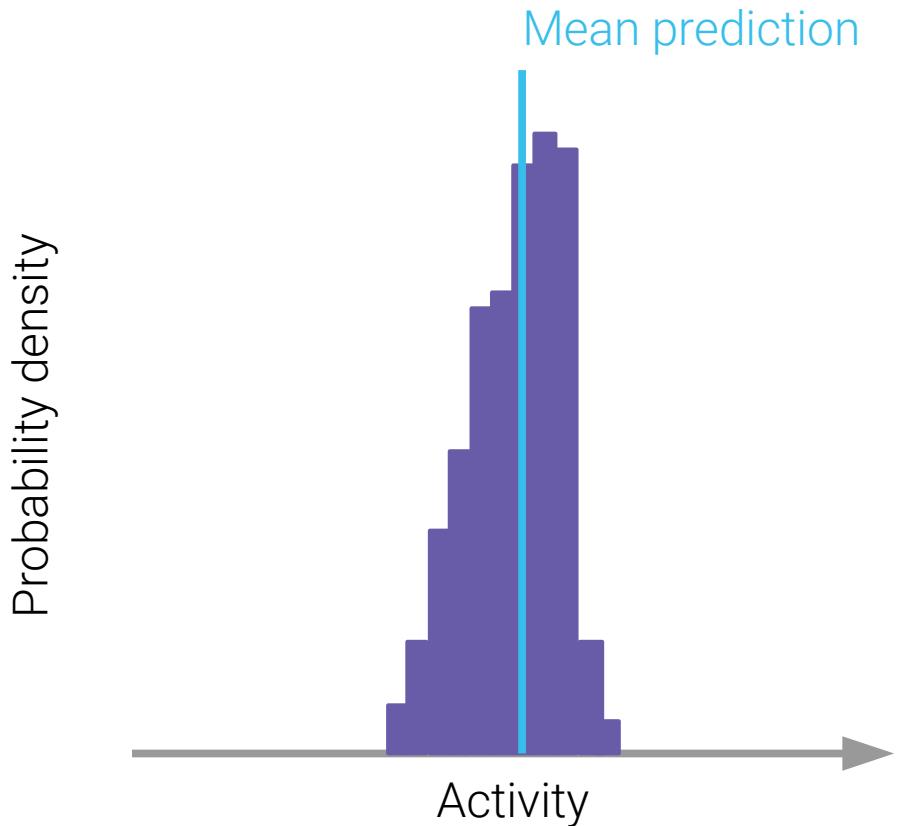


# Calculate probability distribution

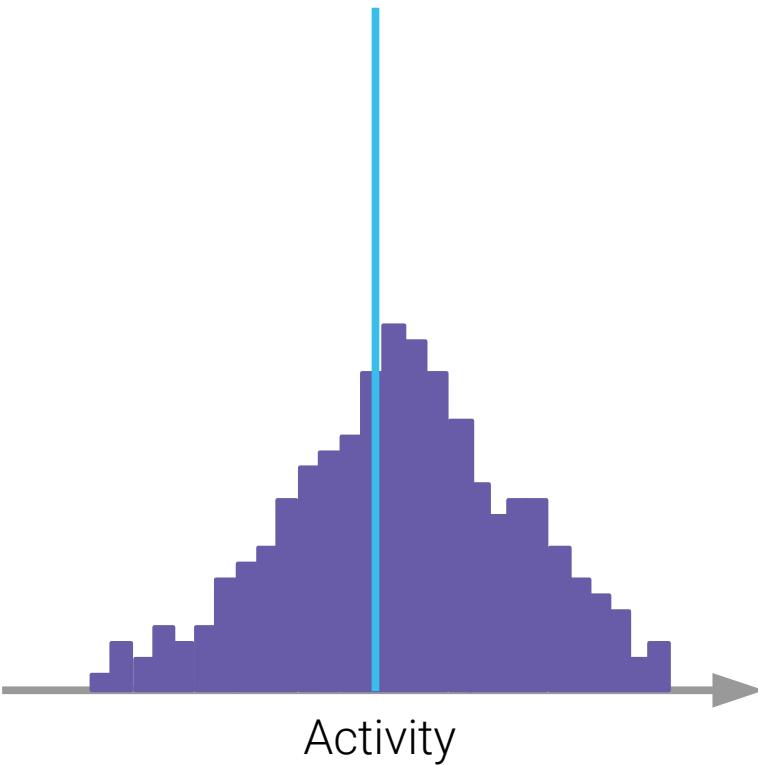
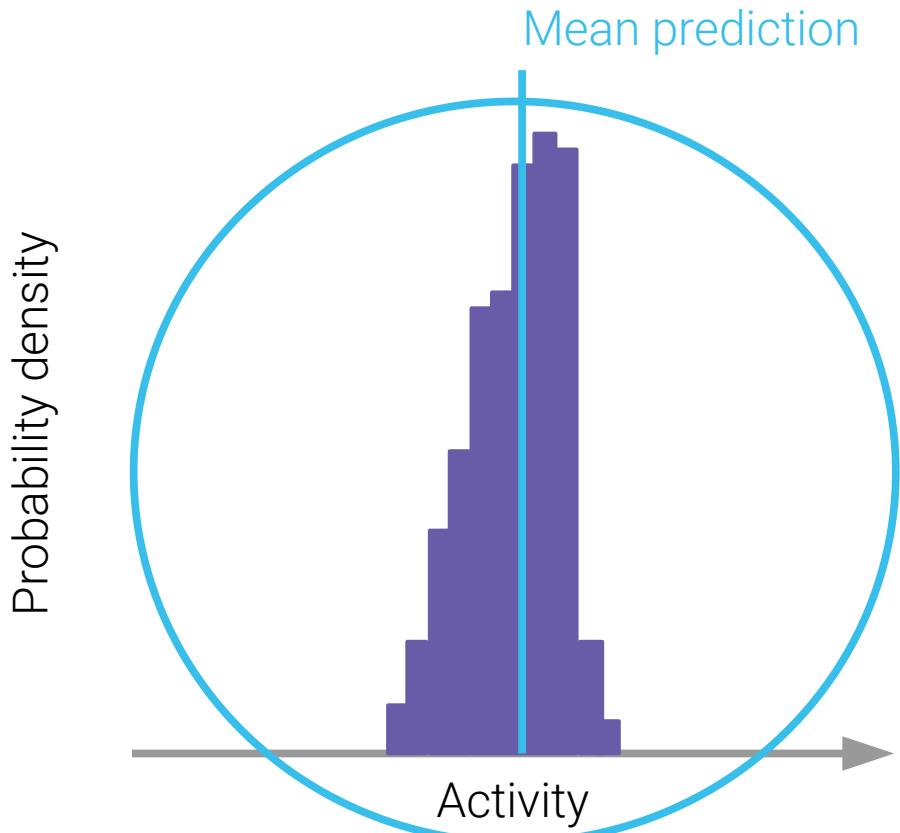




## Less confident prediction



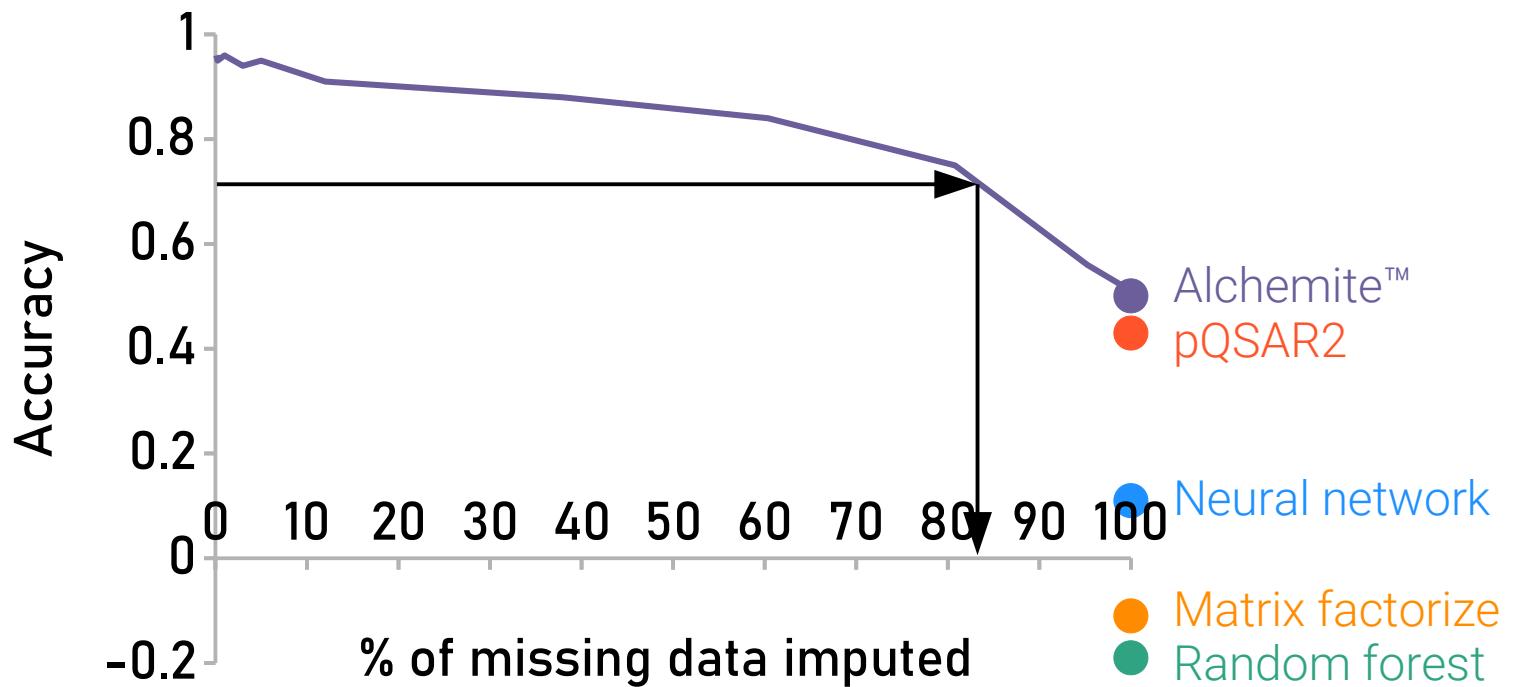
# Focus on most confident predictions



# Reporting on only most confident predictions



# Select performance level

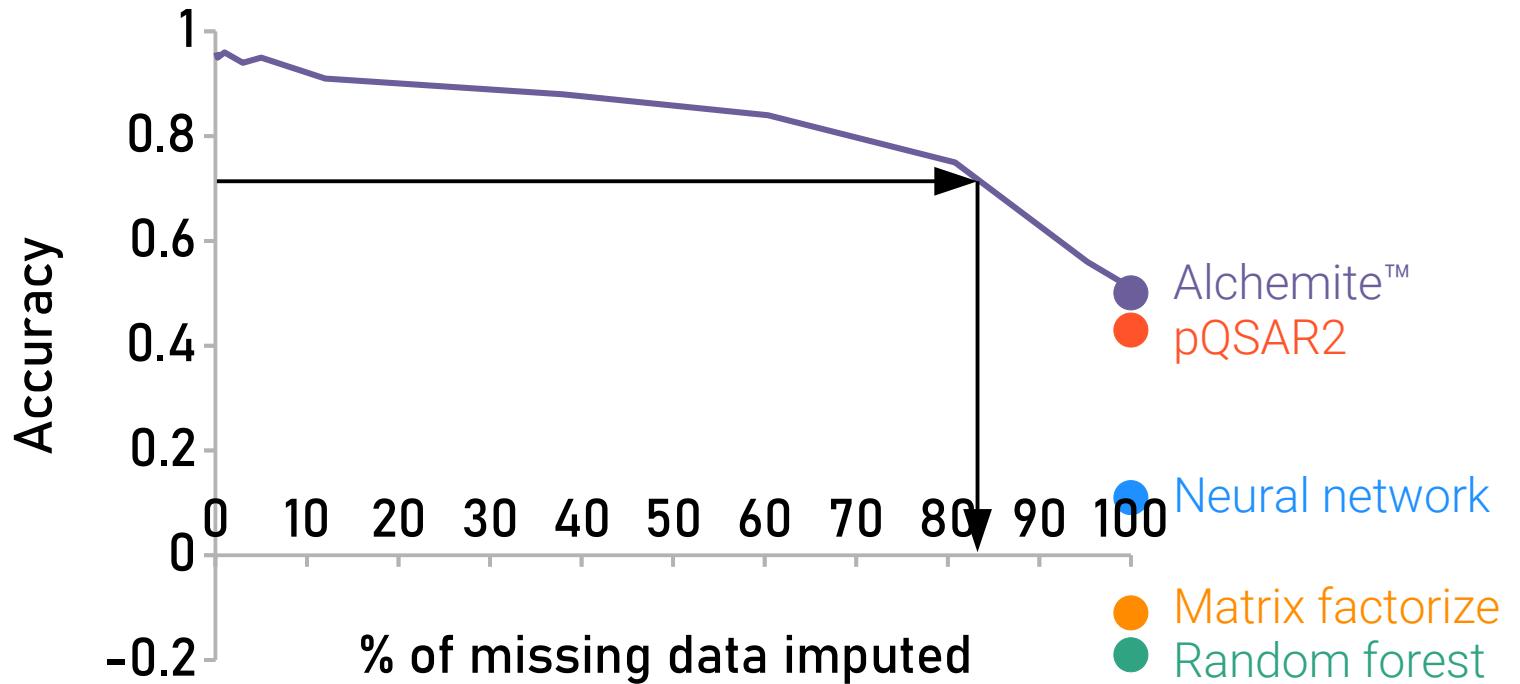


# Different drugs can treat the same ailment





## Focus on most promising hits



# Open Source Malaria competition



**OPEN SOURCE MALARIA**  
Looking for New Medicines

# Open Source Malaria entrants



Entrant	Precision
Molomics	82%
Davy Guan	82%
Optibrium & Intellegens	81%
Exscientia	81%
Slade Matthews	64%
Auromind	58%
Raymond Lui	58%
KCL	36%
Interlinked TX	36%

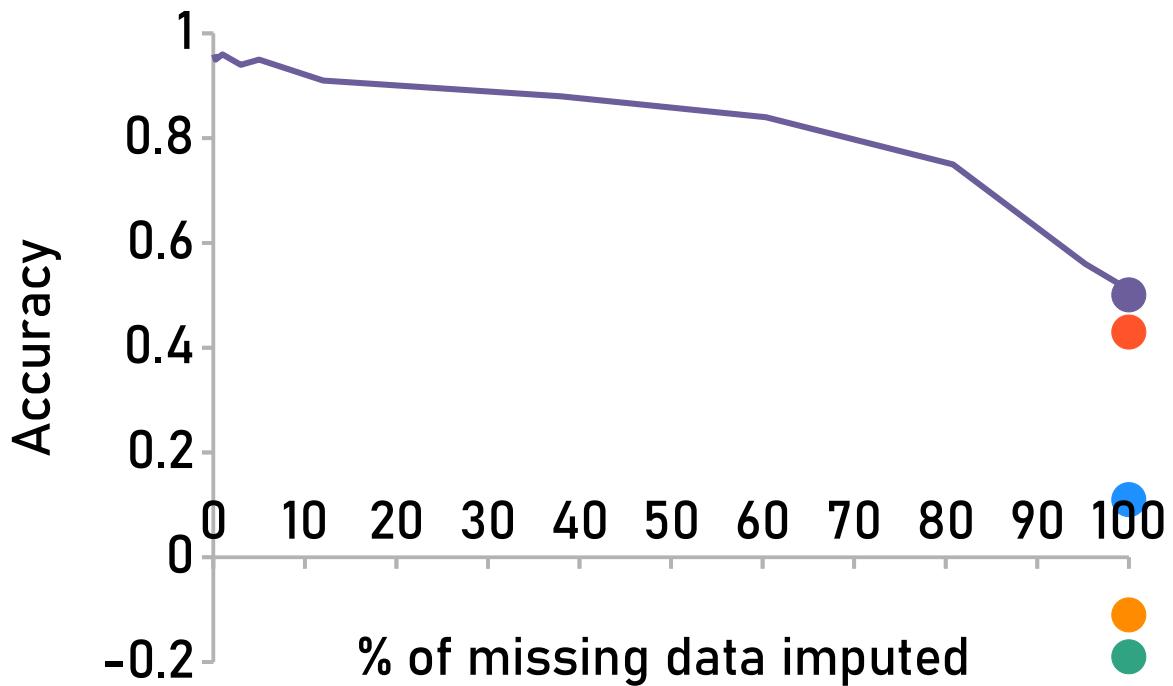
# Open Source Malaria entrants



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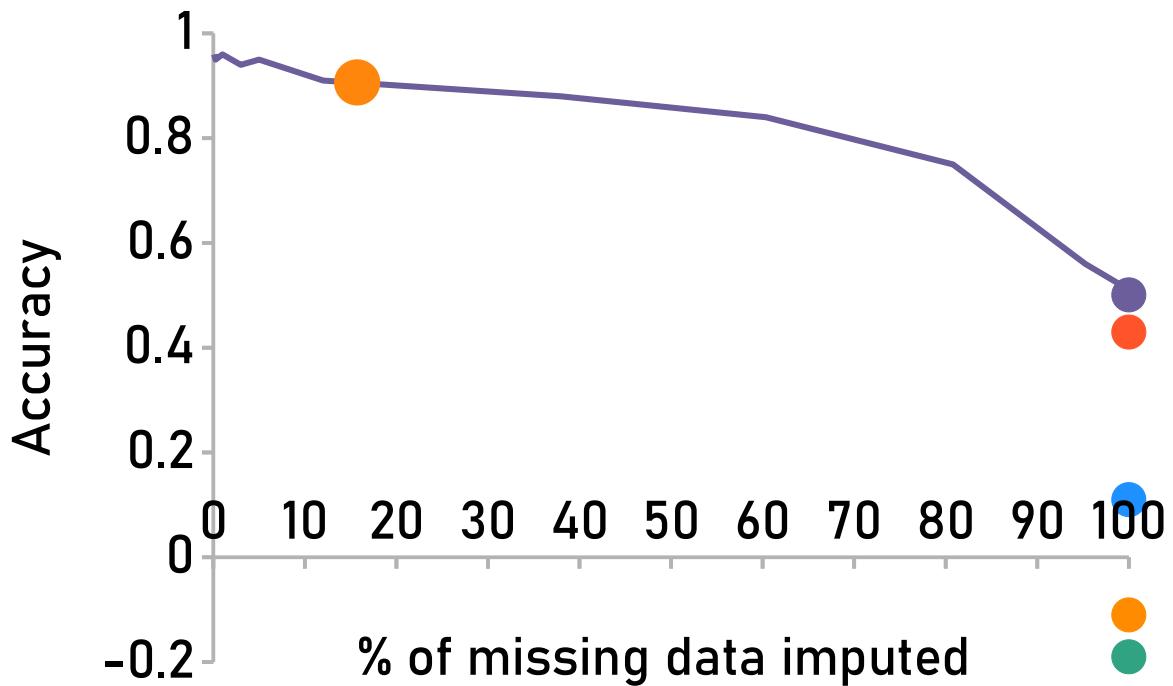


## Focus on compounds with low uncertainty

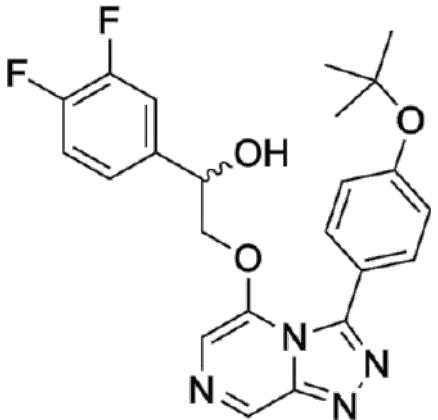




## Focus on compounds with low uncertainty



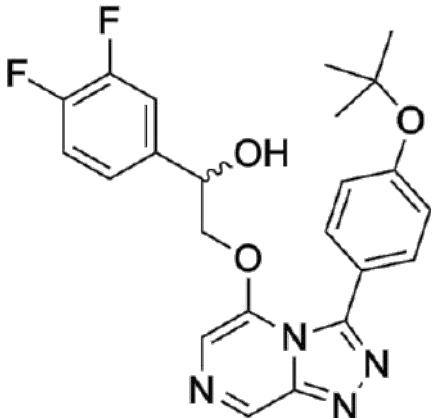
# Open Source Malaria experimental validation



Optibrium & Intellegens

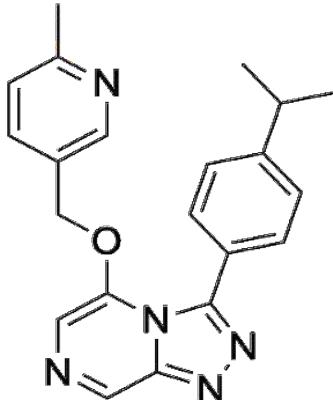
0.647 μM

# Open Source Malaria other compounds



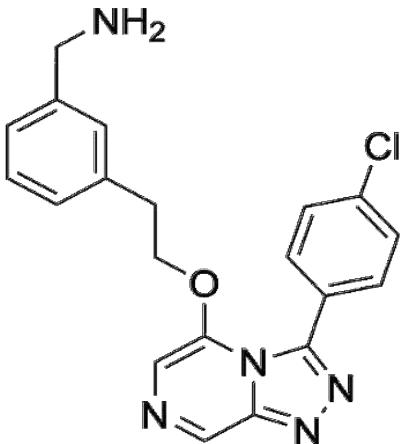
Optibrium & Intellegens

0.647  $\mu\text{M}$



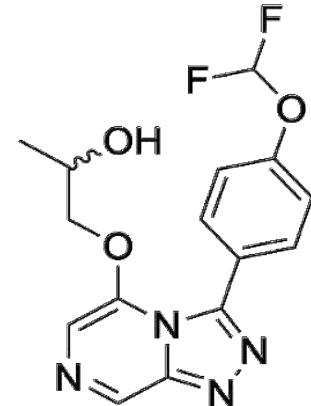
Davy Guan

>25  $\mu\text{M}$



Exscientia

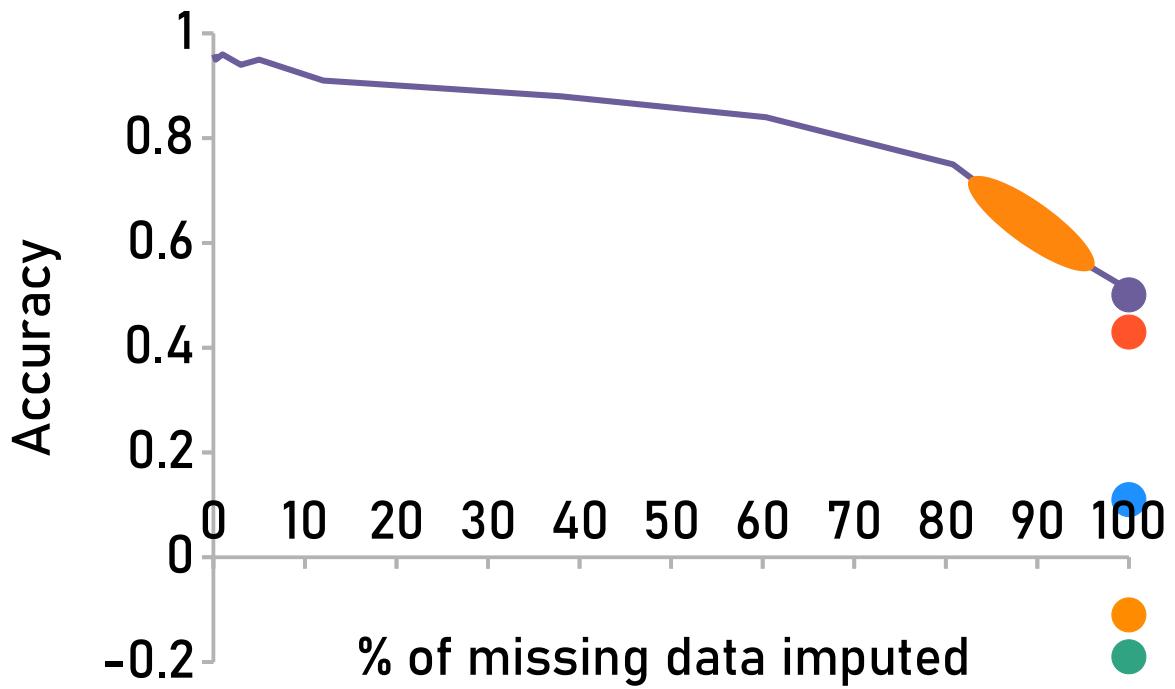
10.9  $\mu\text{M}$



Molomics

>25  $\mu\text{M}$

# Open Source Malaria other compounds

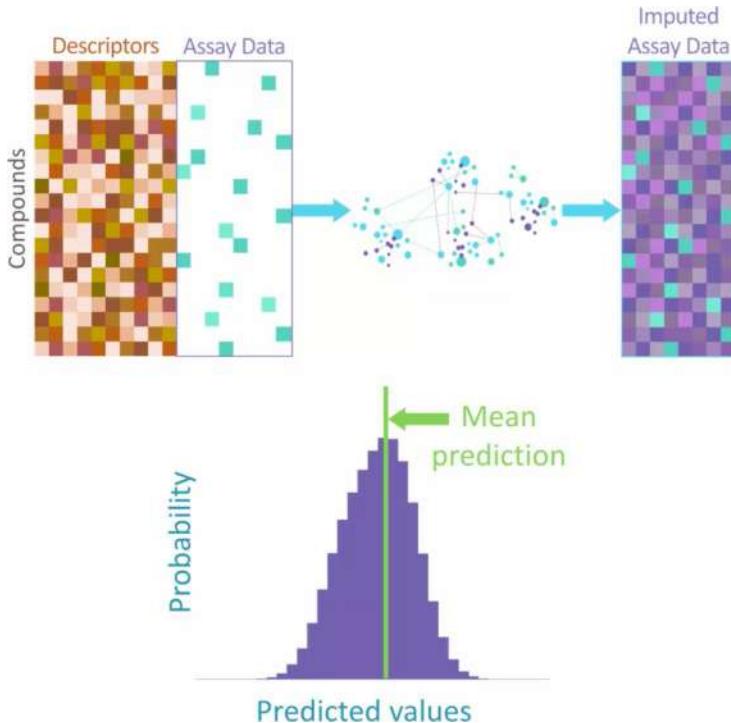


# Imputation Versus Prediction and Applications in Drug Discovery

Matthew Segall, Benedict Irwin, Thomas Whitehead, Gareth Conduit



P36



Practical applications:

- Project optimisation
  - 2,453 compounds and 18 heterogeneous endpoints
- Global pharma data
  - 678,994 compounds and 1,166 endpoints
- Combined with generative methods
  - Design of active anti-malarial compounds

[matt@optibrium.com](mailto:matt@optibrium.com) Skype: matthew.d.segall

Whitehead *et. al.* J. Chem. Inf. Model (2019) 59(3) p. 1197

Irwin *et al.* Future Drug Discovery (2020) 2(2) DOI: 10.4155/fdd-2020-0008

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

# Demonstrated Benefits of Alchemite in Drug Discovery

Exclusive Partnership with Optibrium



P36

- ‘Fill in’ missing data to proactively highlight high-quality compounds
  - Identify new opportunities with confidence
- Identify experimental outliers
  - Highlight unlikely results – experimental errors or unexpected SAR
  - Highlight potential false negatives
- Suggest the most valuable measurements to improve predictions for target assays and chemistry
  - Prioritise experimental resources
  - Confidently progress the best compounds to expensive, downstream experiments
- Virtual screening across endpoints for multi-parameter optimisation

# Lubricants

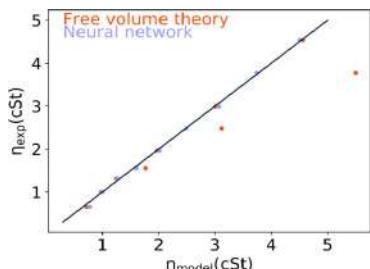
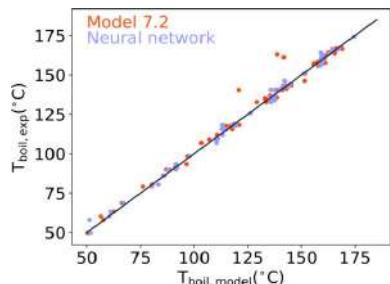
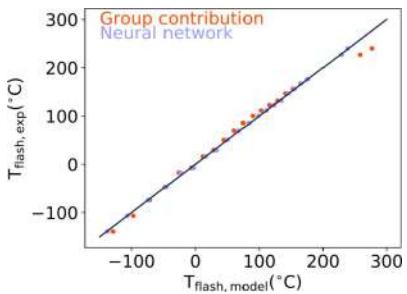


Reduce friction between surfaces, protect surfaces from wear, transfer heat, remove dirt, prevent surface corrosion

Molecules are heavy hydrocarbons with branches and functional groups, and a lubricant blends many molecules and inorganic additives

Machine learning to juxtapose experimental data and computational methods including molecular dynamics

# Predicting properties to lubricants



## Flash point

Alchemite™  $R^2=0.997$

Group contribution  $R^2=0.971$

## Boiling point

Alchemite™  $R^2=0.992$

Fitting model  $R^2=0.976$

## Kinematic viscosity

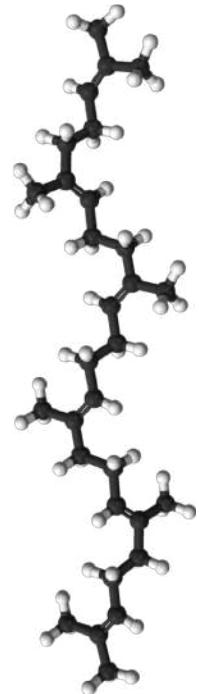
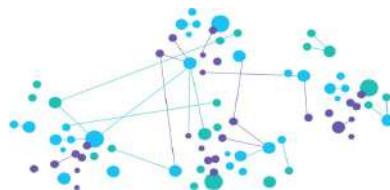
Alchemite™  $R^2=0.998$

Free volume theory  $R^2=0.899$

# Designing a lubricant



Flashpoint	> 122.55°C
Viscosity	< 3.78cSt
Boiling point	> 270°C
Density	< 769mgmL <sup>-1</sup>



# Improving inks

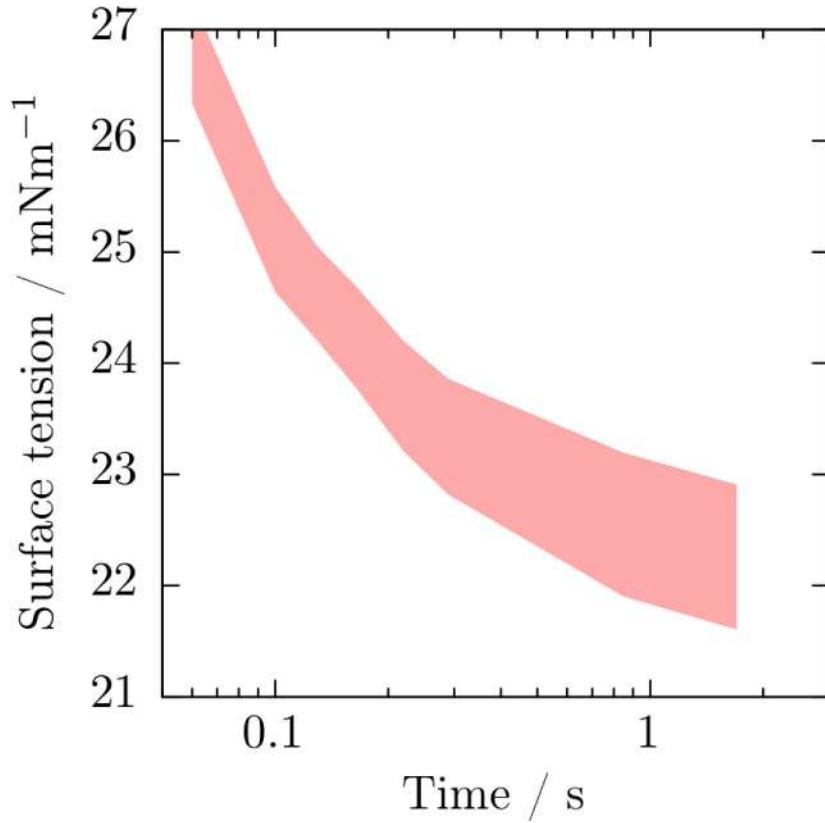


Inks can comprises over **30** individual chemicals

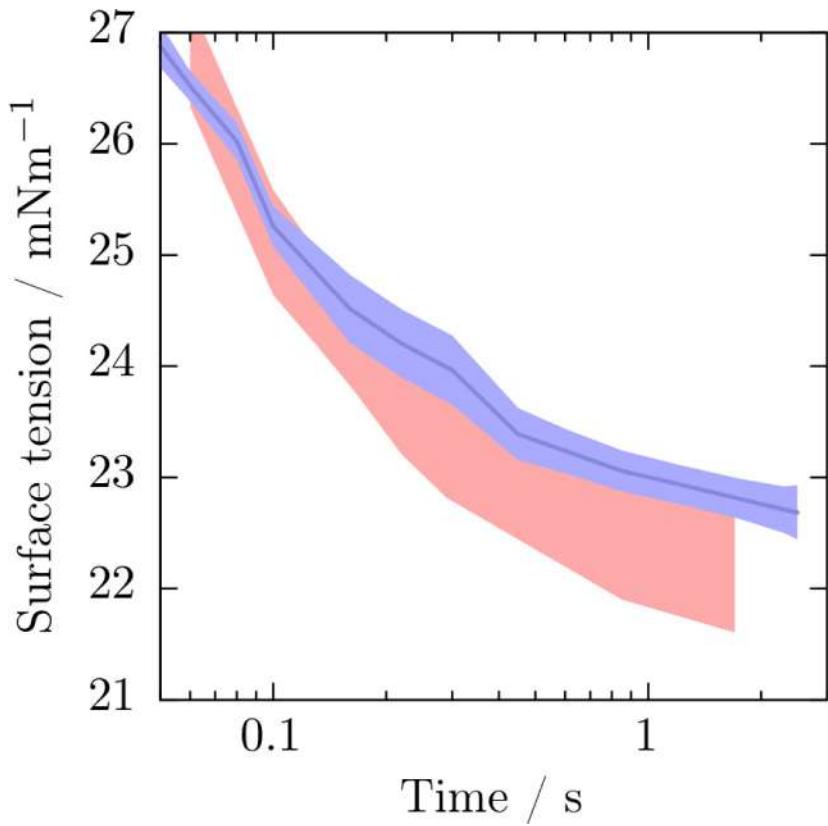
Domino Ink wish to remove two chemicals to improve **sustainability**

Limited access to laboratory during **COVID-19** so turn to machine learning

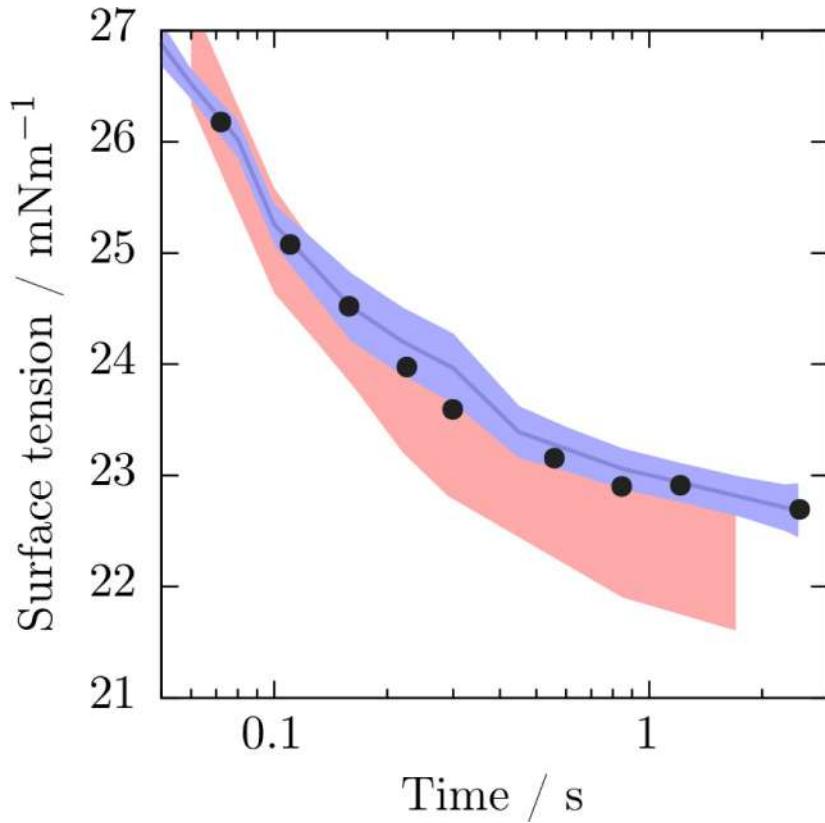
# Target for a new ink



# Alchemite™ proposes a new ink



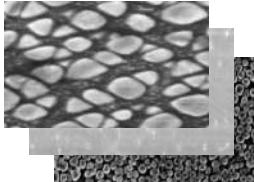
# Experimental validation of the proposed ink



# Materials



High temperature alloys



Batteries



Direct laser deposition



# Summary



Alchemite™ trains across all endpoints to capture **property-property** correlations

Understand and exploit **probability distribution** to focus on most confident results

Impute results of missing properties to high accuracy, enabling computational screening of compounds to identify **new hits**

Partnership with **Optibrium** for small molecule drug design



intellegens



gareth@intellegens.ai