

# The modern day blacksmith

Gareth Conduit

Theory of Condensed Matter group

# Neural network algorithm to

Train from **sparse** datasets

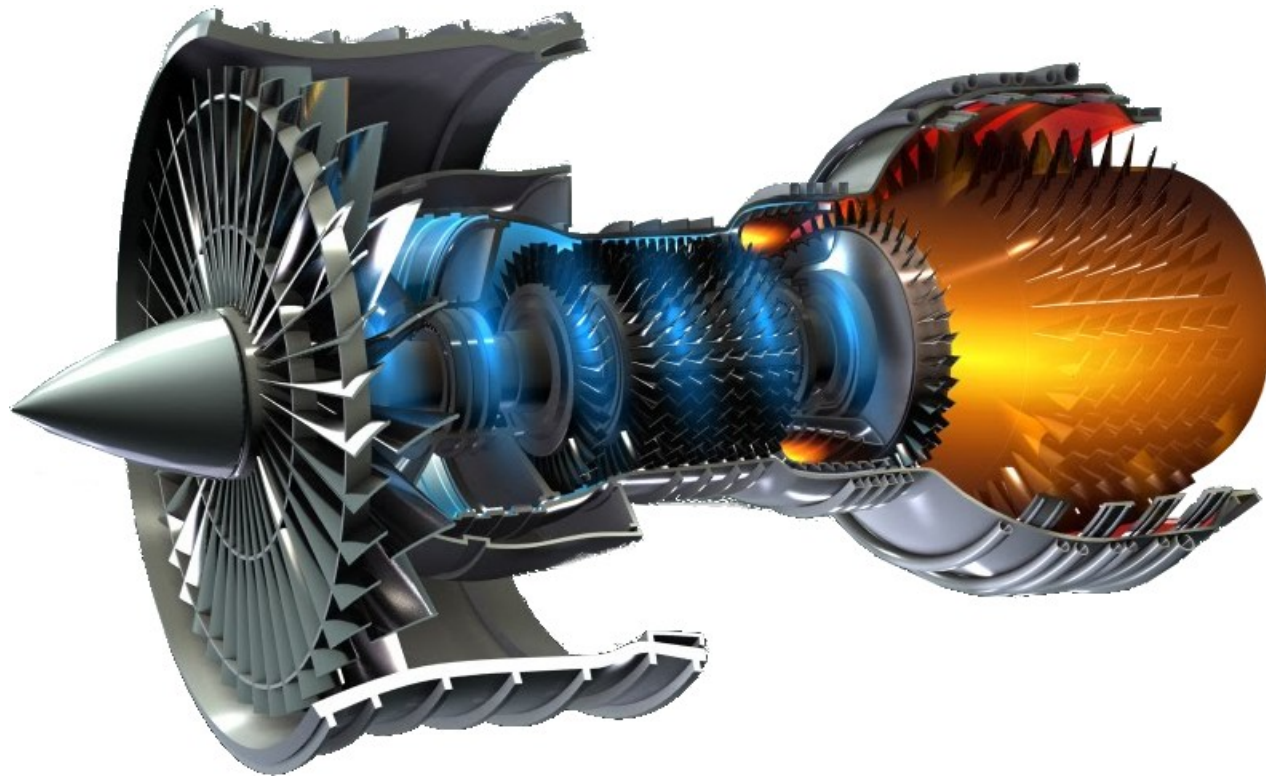
**Merge** simulations, physical laws, and experimental data

**Reduce** the need for expensive experimental development

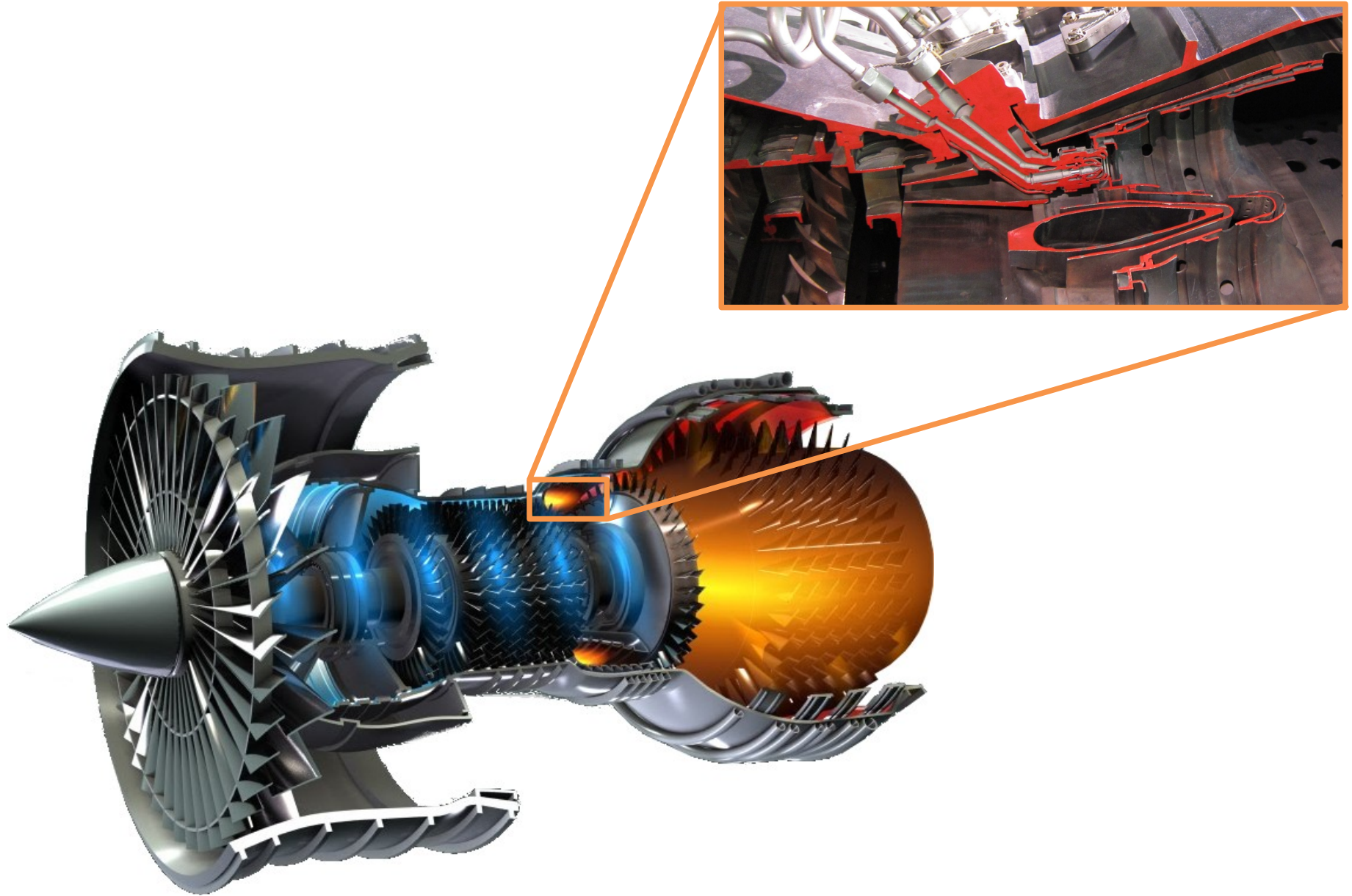
**Accelerate** materials and drugs discovery

**Generic** with **proven** applications in materials discovery and drug design

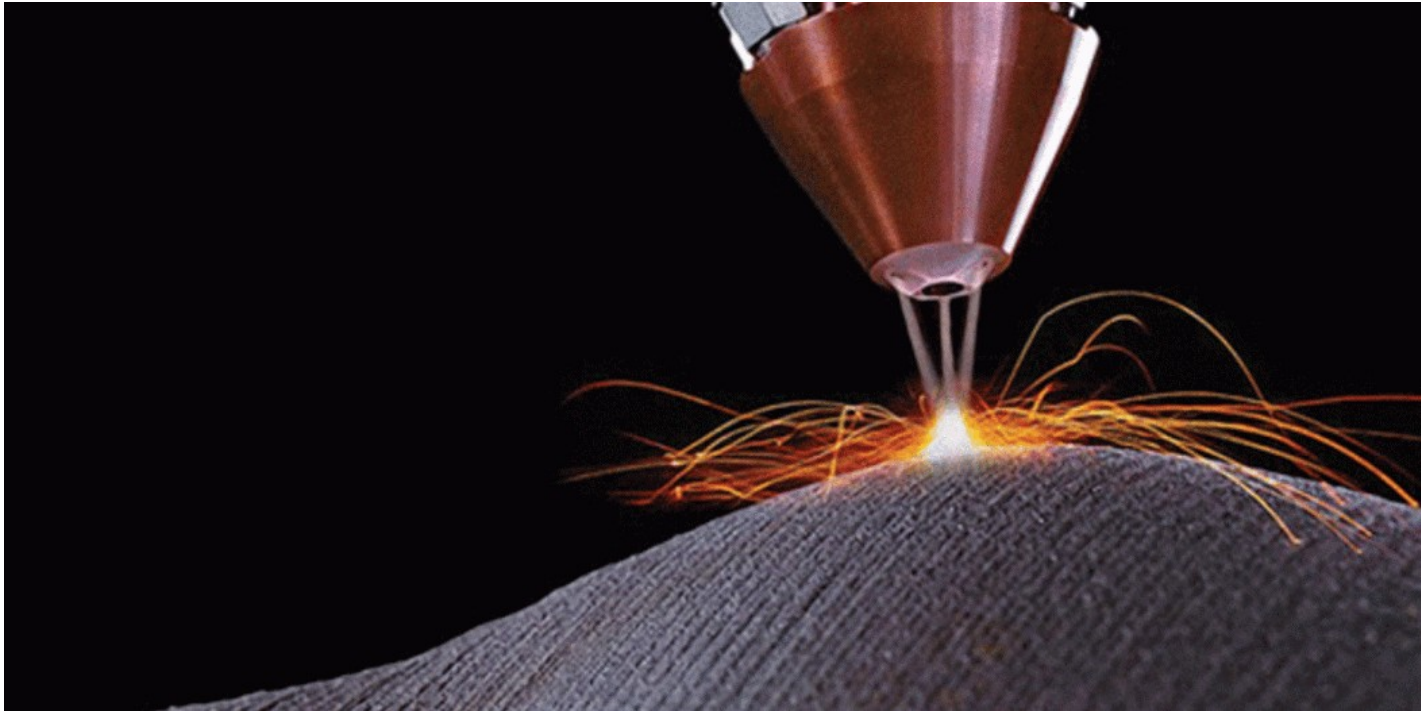
# Schematic of a jet engine



# Combustor in a jet engine

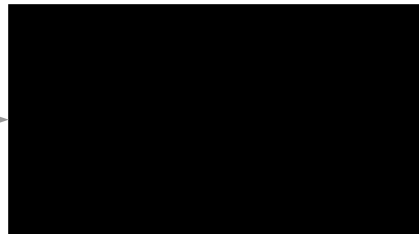


# Direct laser deposition requires new alloys



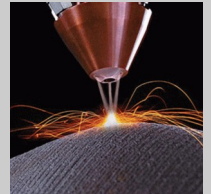
# Neural networks for materials design

## Composition



## Properties

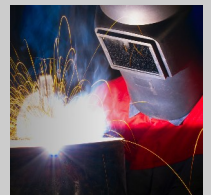
Process



Fatigue



Welding



# Neural networks for materials design

## Composition



## Properties

293928764790904  
021364010360202  
636584970508183  
703818406465007  
501066378902903  
715269094674449  
011404497494802

## Process

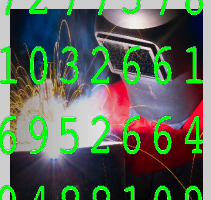
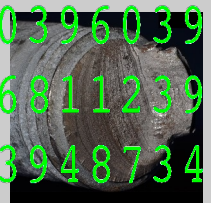
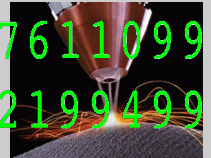
488685276110993  
203332721994995  
976579342243418

## Fatigue

394046703960393  
597692868112392  
376413439487341

## Welding

366524472773787  
144219810326510  
805556069526643  
983443994881092



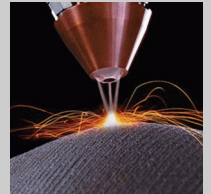
# Neural networks for materials design

## Composition



## Properties

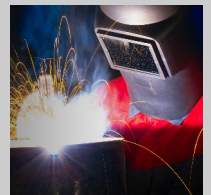
Process



Fatigue

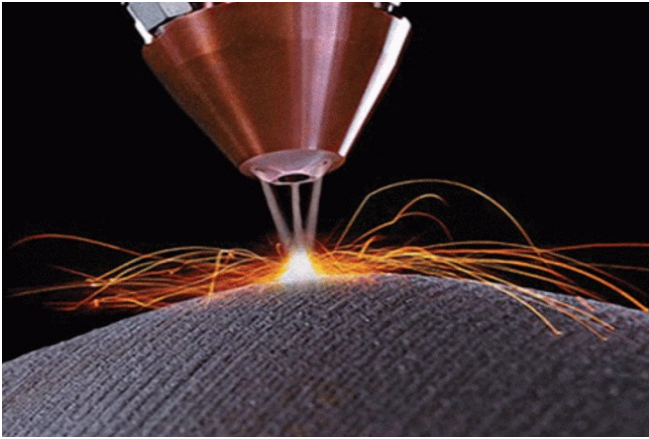


Welding





# Neural networks for materials design

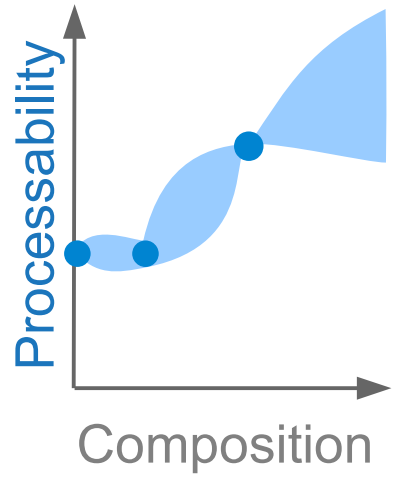


Laser

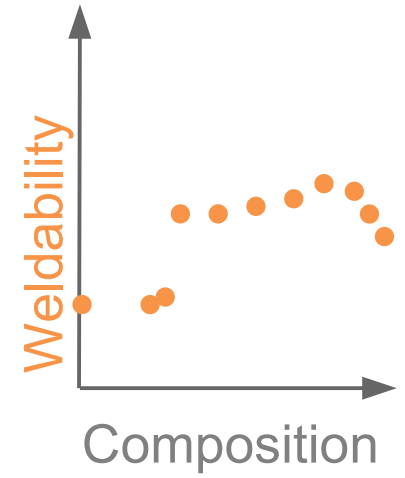
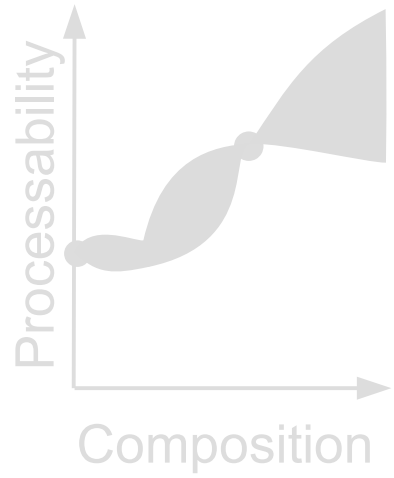


Electricity

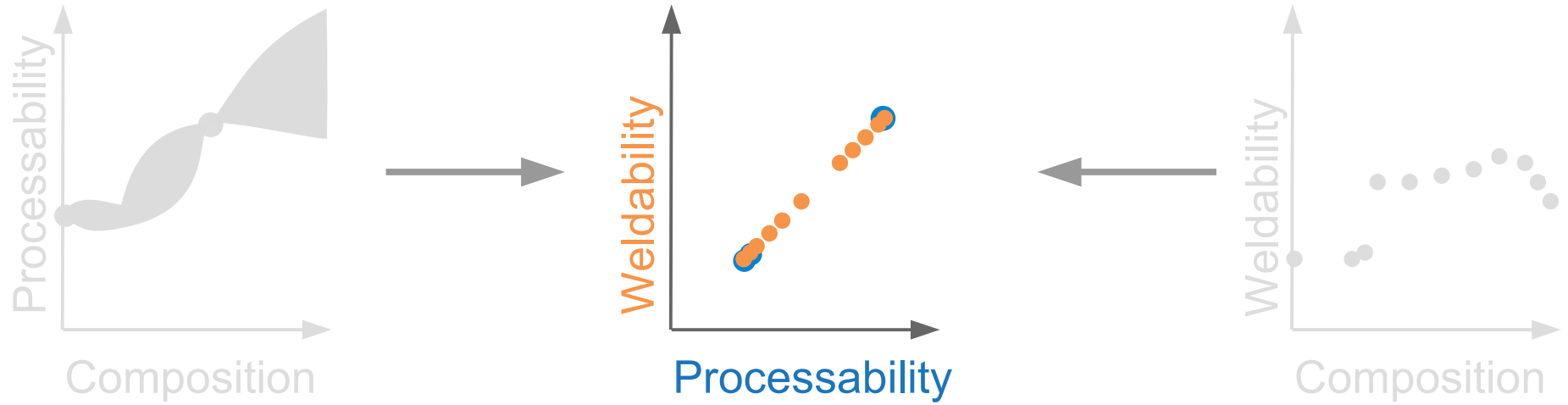
# Insufficient data for processability



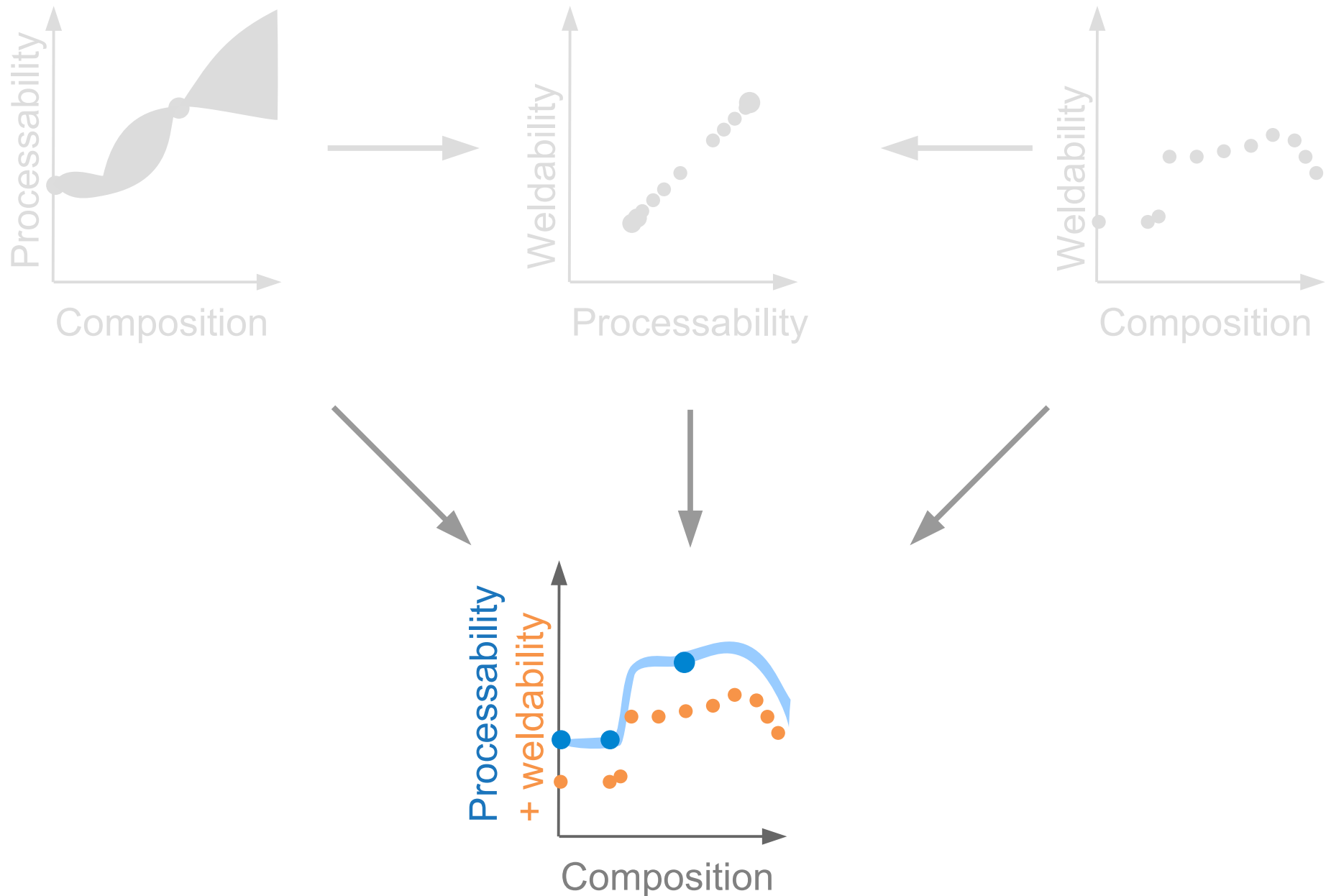
# Welding is analogous to direct laser deposition



# Simple processability-welding relationship



# Merging properties with the neural network



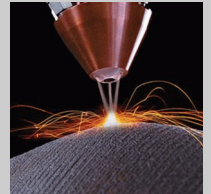
# Neural networks for materials design

## Composition



## Properties

Process



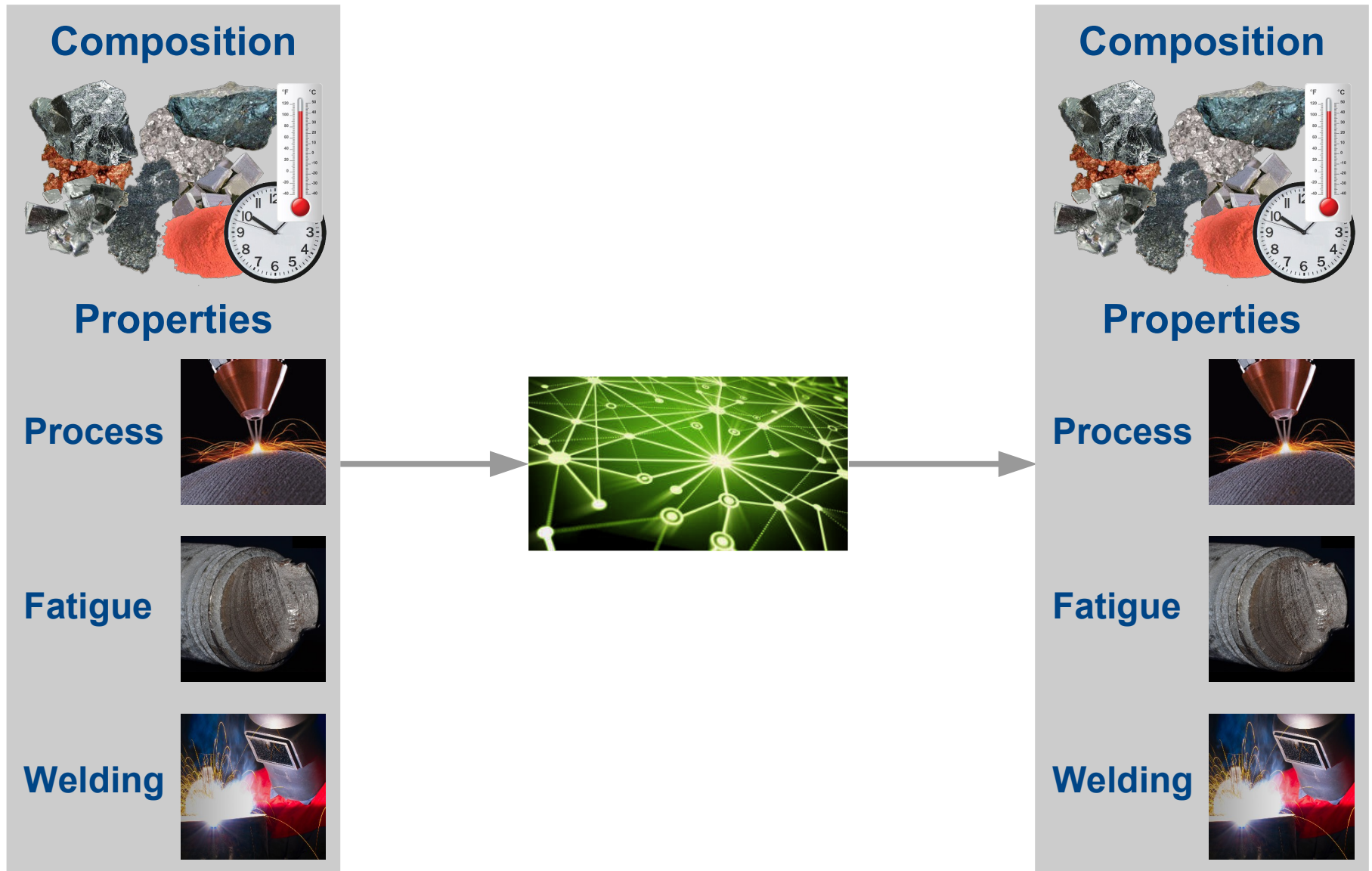
Fatigue



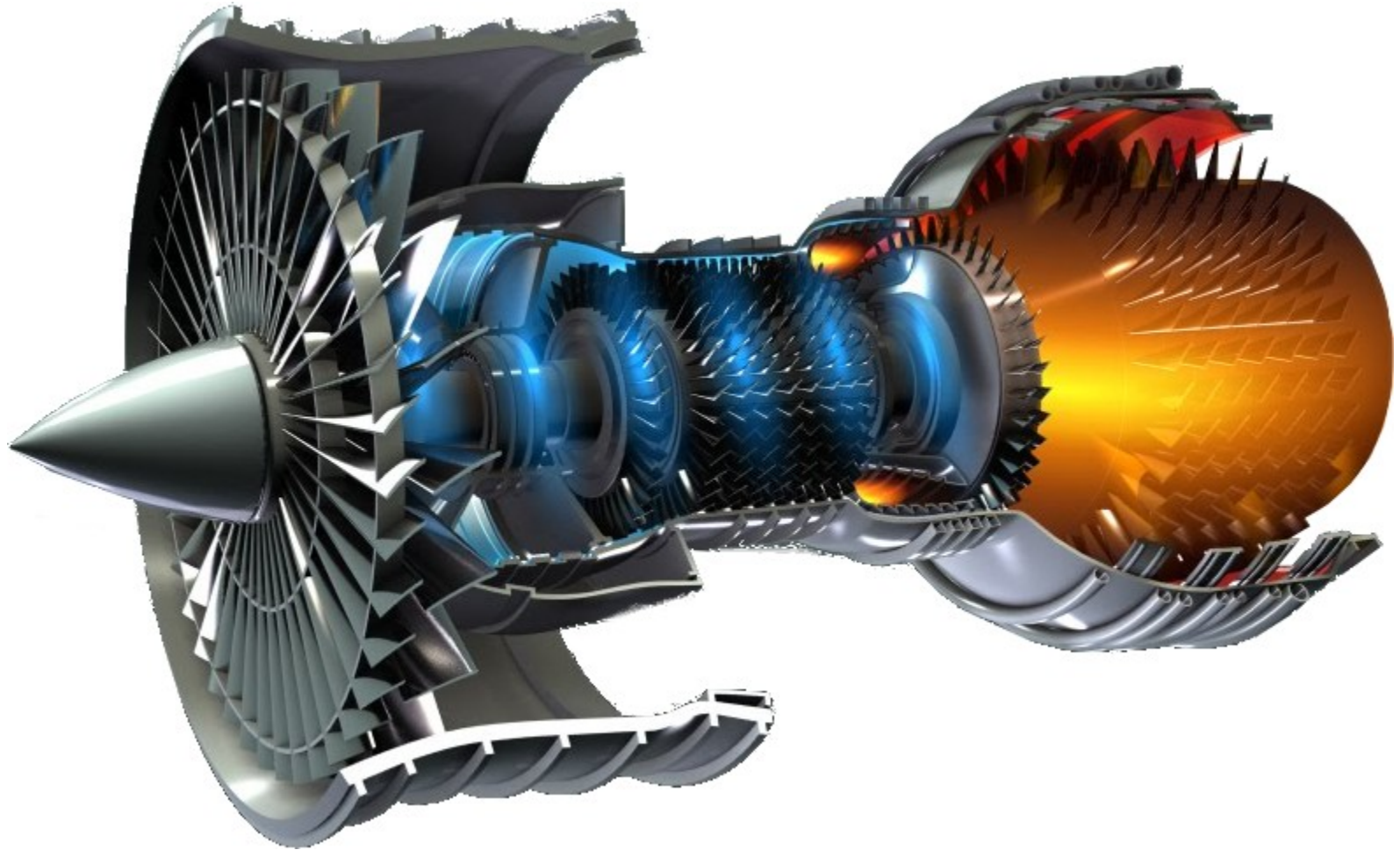
Welding



# Neural networks for materials design



# Schematic of a jet engine





# Target properties

- Elemental cost < 25 \$kg<sup>-1</sup>
- Density < 8500 kgm<sup>-3</sup>
- γ' content < 25 wt%
- Oxidation resistance < 0.3 mgcm<sup>-2</sup>
- Processability < 0.15% defects
- Phase stability > 99.0 wt%
- γ' solvus > 1000°C
- Thermal resistance > 0.04 KΩ<sup>-1</sup>m<sup>-3</sup>
- Yield stress at 900°C > 200 MPa
- Tensile strength at 900°C > 300 MPa
- Tensile elongation at 700°C > 8%
- 1000hr stress rupture at 800°C > 100 MPa
- Fatigue life at 500 MPa, 700°C > 10<sup>5</sup> cycles

# Composition

Cr: 19%



Co: 4%



Mo: 4.9%



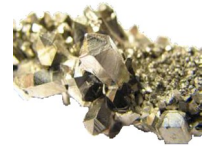
W: 1.2%



Zr: 0.05%



Nb: 3%



Al: 2.9%



C: 0.04%



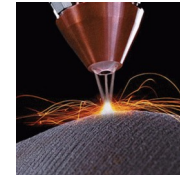
B: 0.01%



Ni



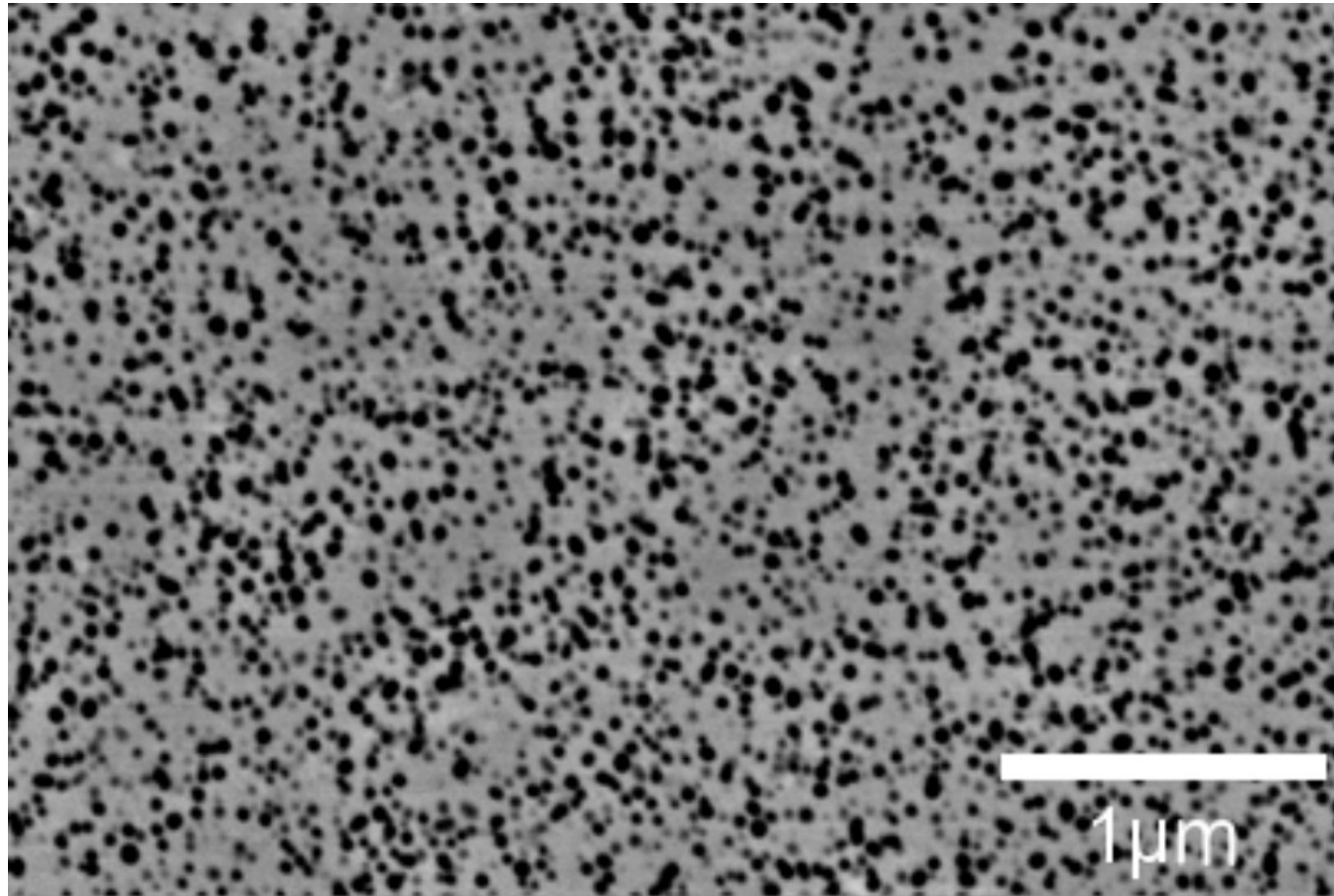
Expose 0.8



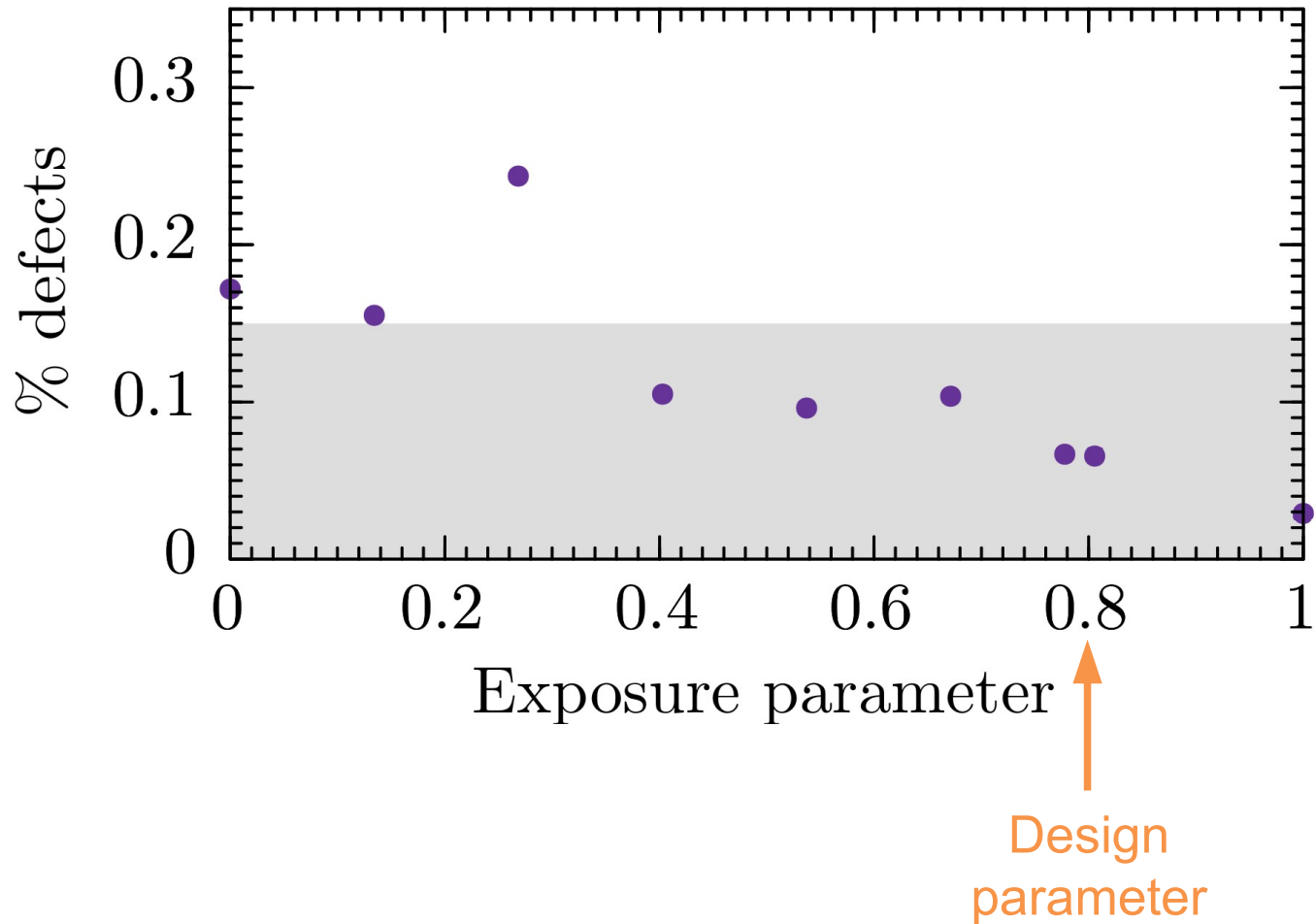
$T_{HT}$  1300°C



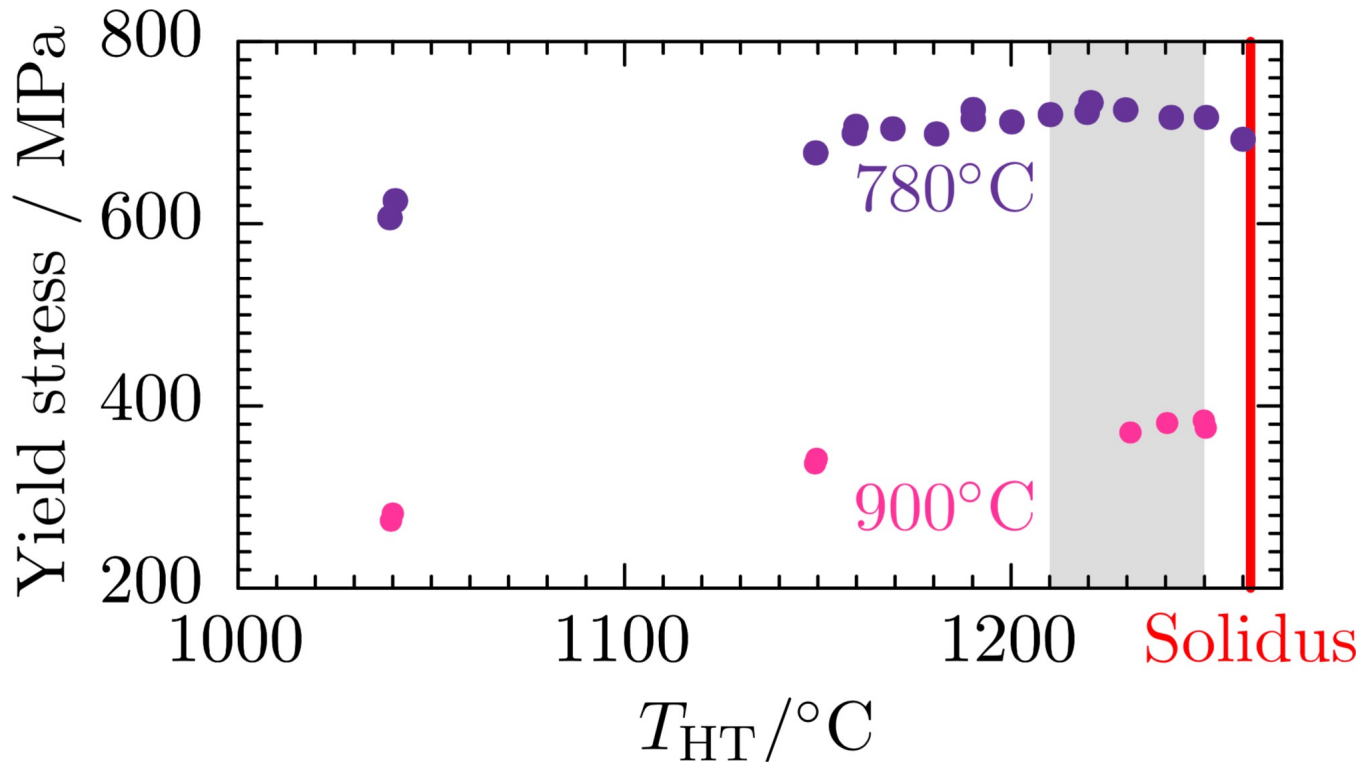
# Microstructure



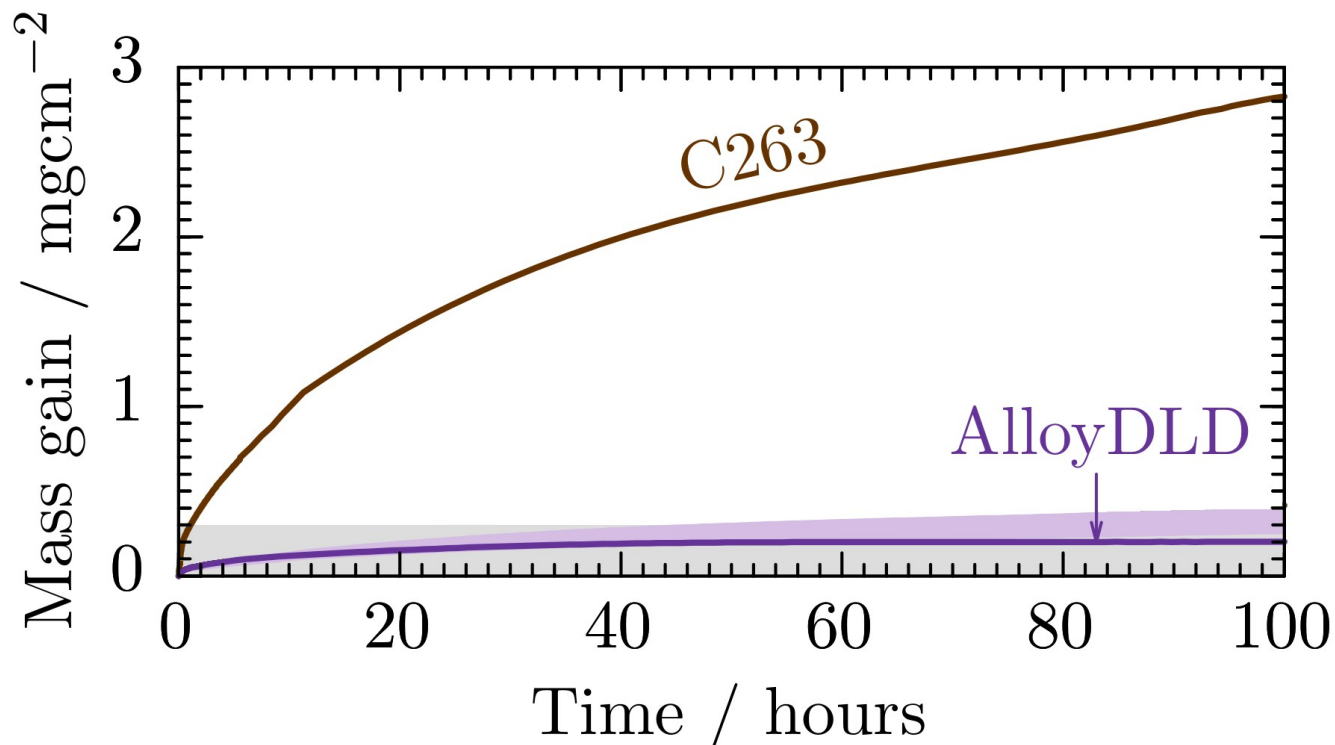
# Testing the processability: horizontal printing



# Testing the processability: horizontal printing



# Testing the oxidation resistance

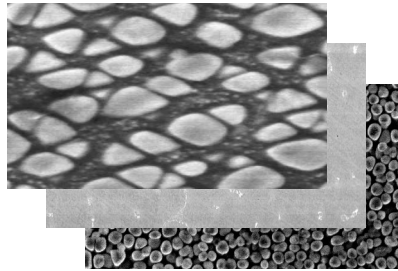


# Printing components for an engine



# More materials designed

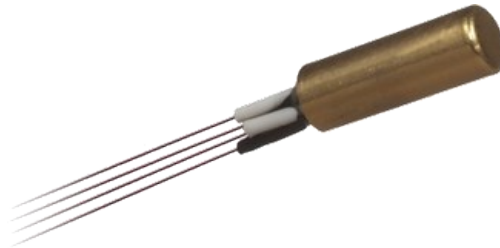
Nickel and molybdenum



Steel for welding



Steel for turbos



UNIVERSITY OF  
CAMBRIDGE

Experiment and DFT for batteries



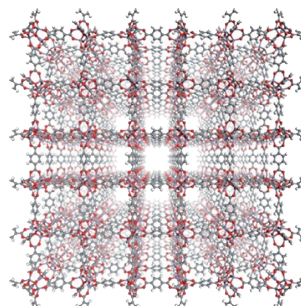


# Application to chemicals and drugs

Design concrete mixtures on site



Metal organic framework



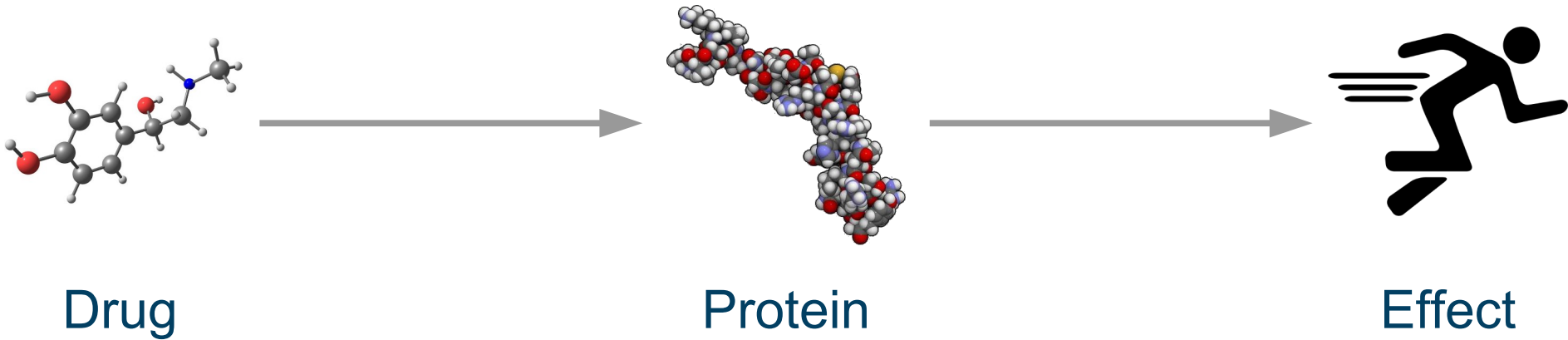
Lubricants with molecular dynamics and experiments



Drug design

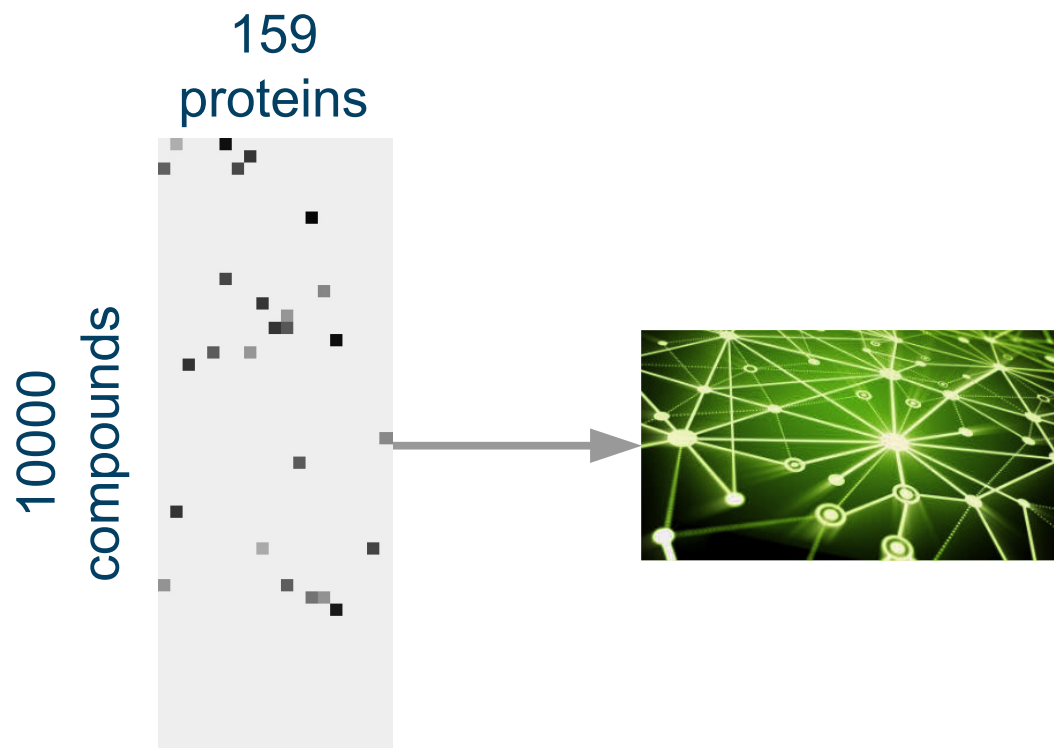


# Action of a drug



# Novartis dataset to benchmark machine learning

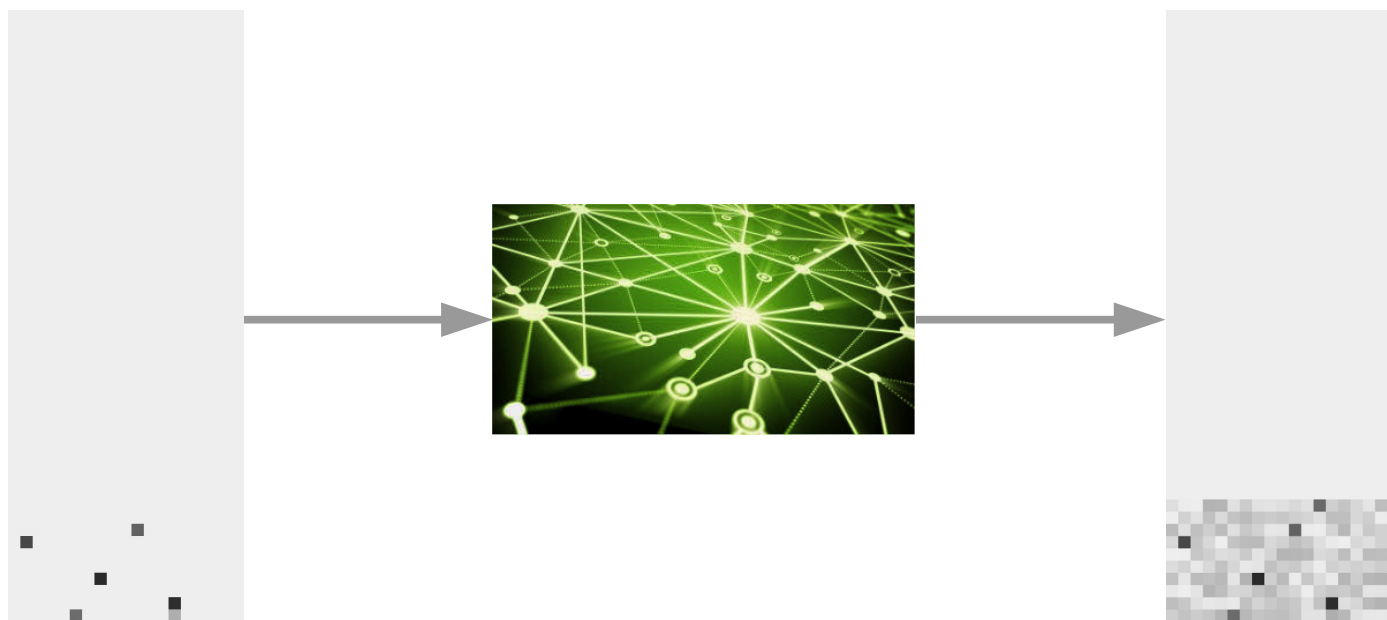
159 kinase proteins, 10000 compounds, data 5% complete



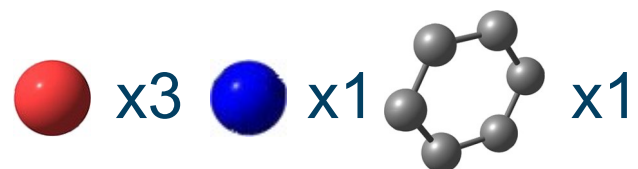
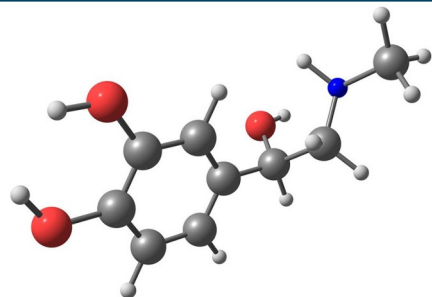
Data from ChEMBL  
Martin, Polyakov, Tian, and Perez,  
J. Chem. Inf. Model. 57, 2077 (2017)

# Impute missing entries to validate

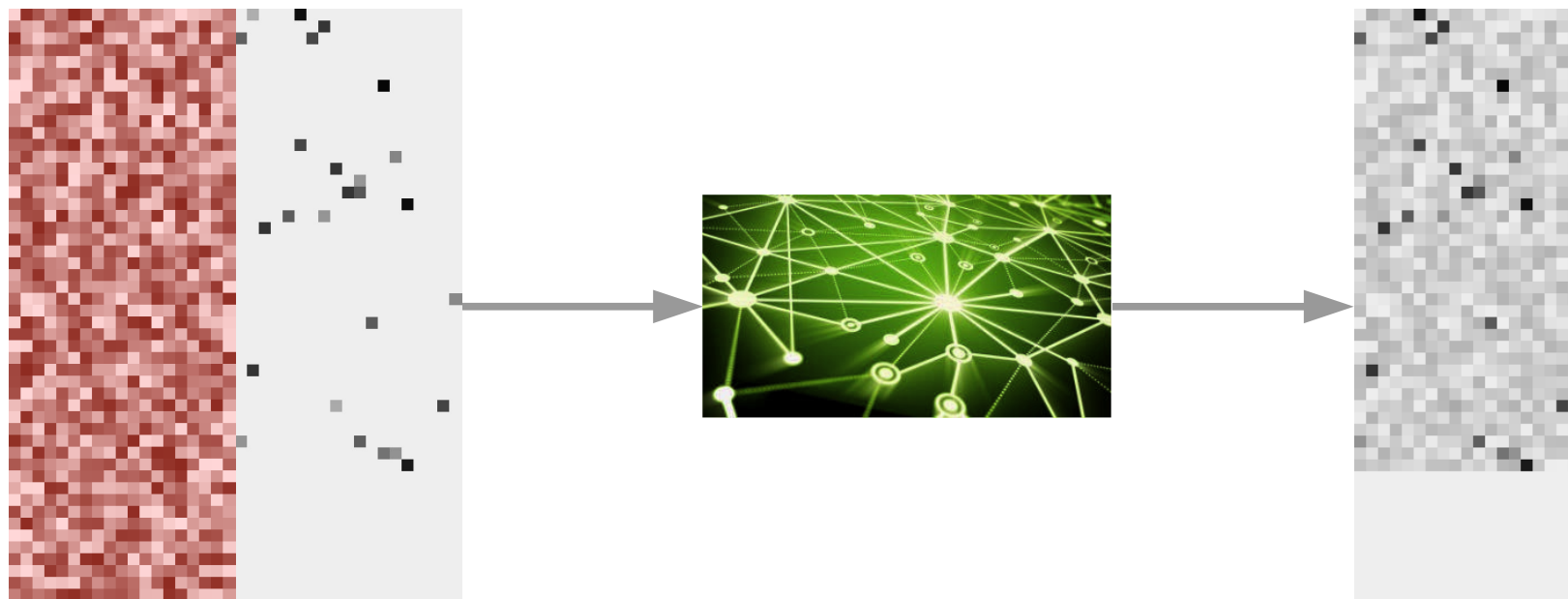
Validate using a realistically split holdout data set, extrapolate to new chemical space



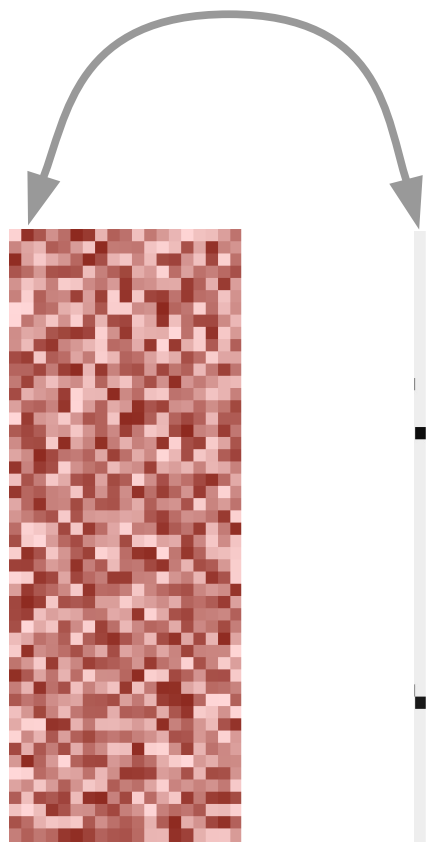
# Quantitative structure-activity relationships



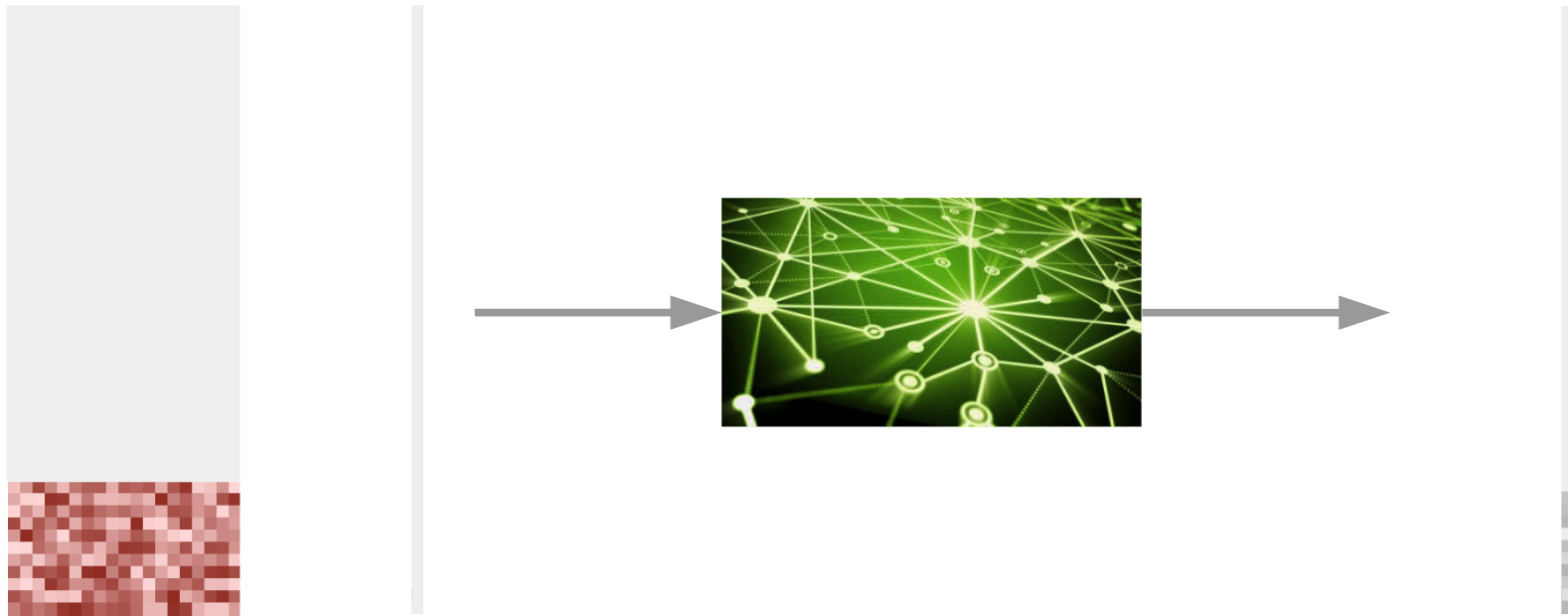
Molecular weight=183 Da



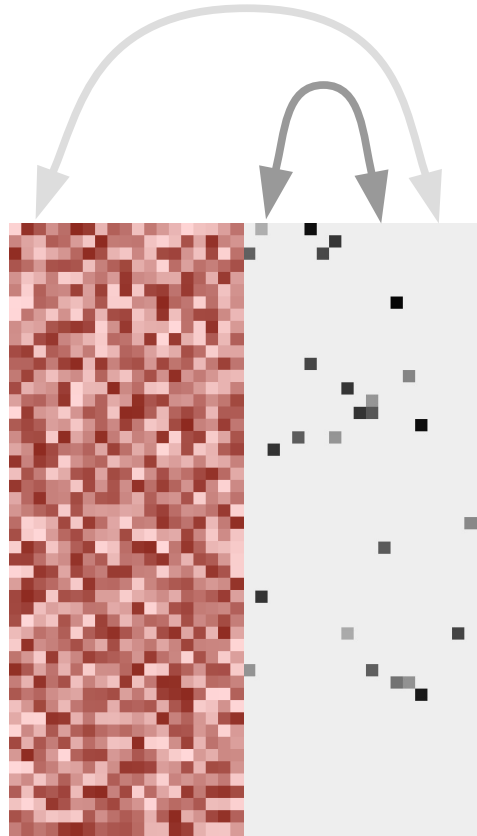
# Quantitative structure-activity relationships



# Predict one column at a time

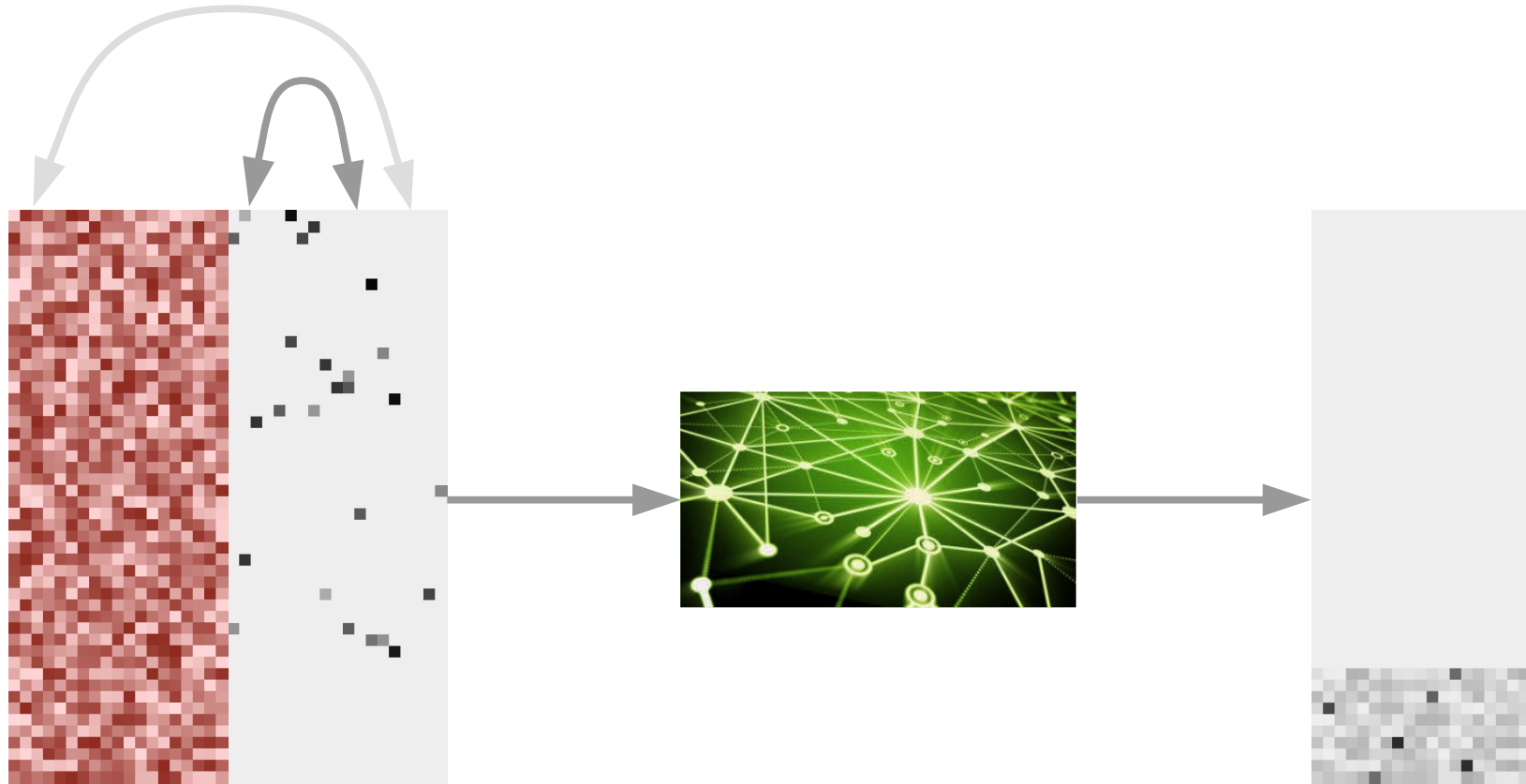


# Learn protein-protein correlations

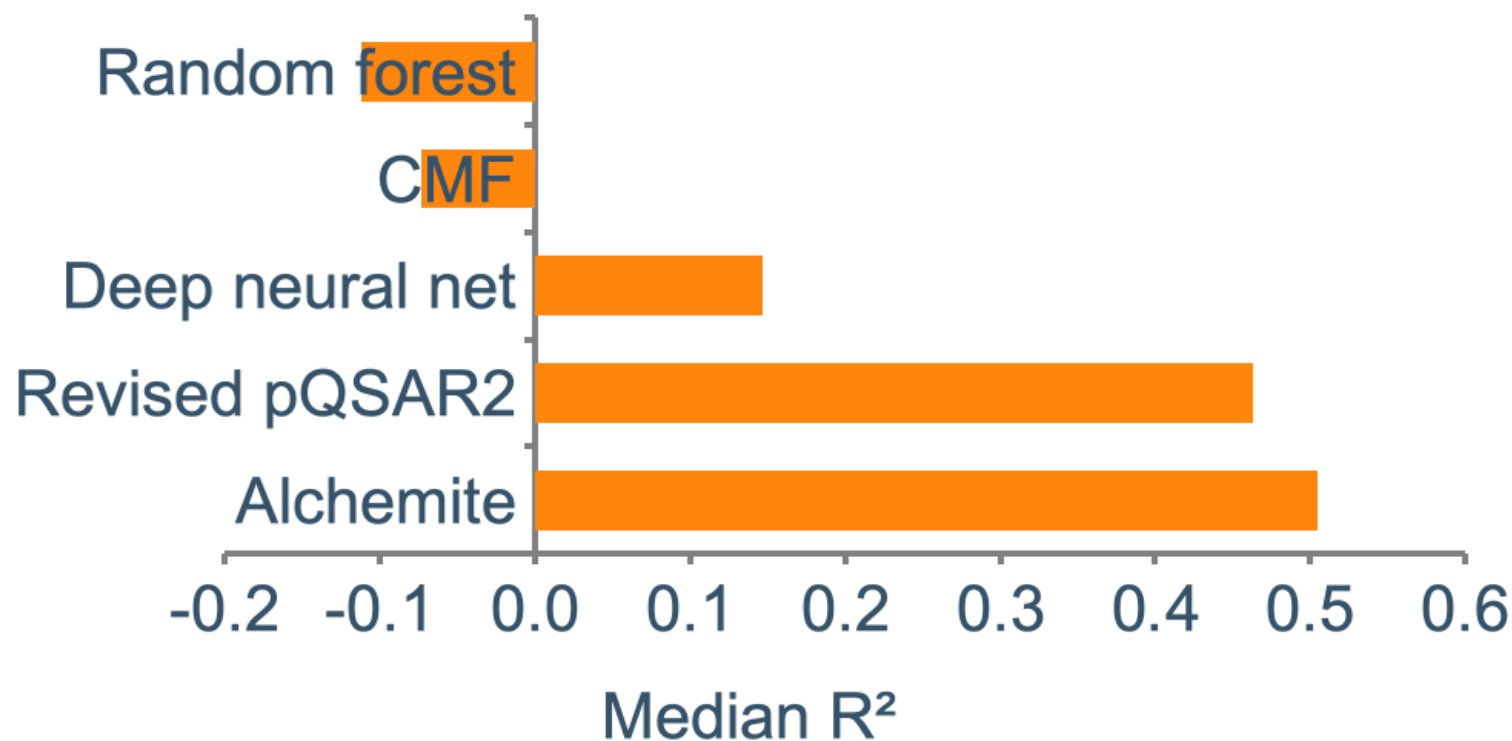




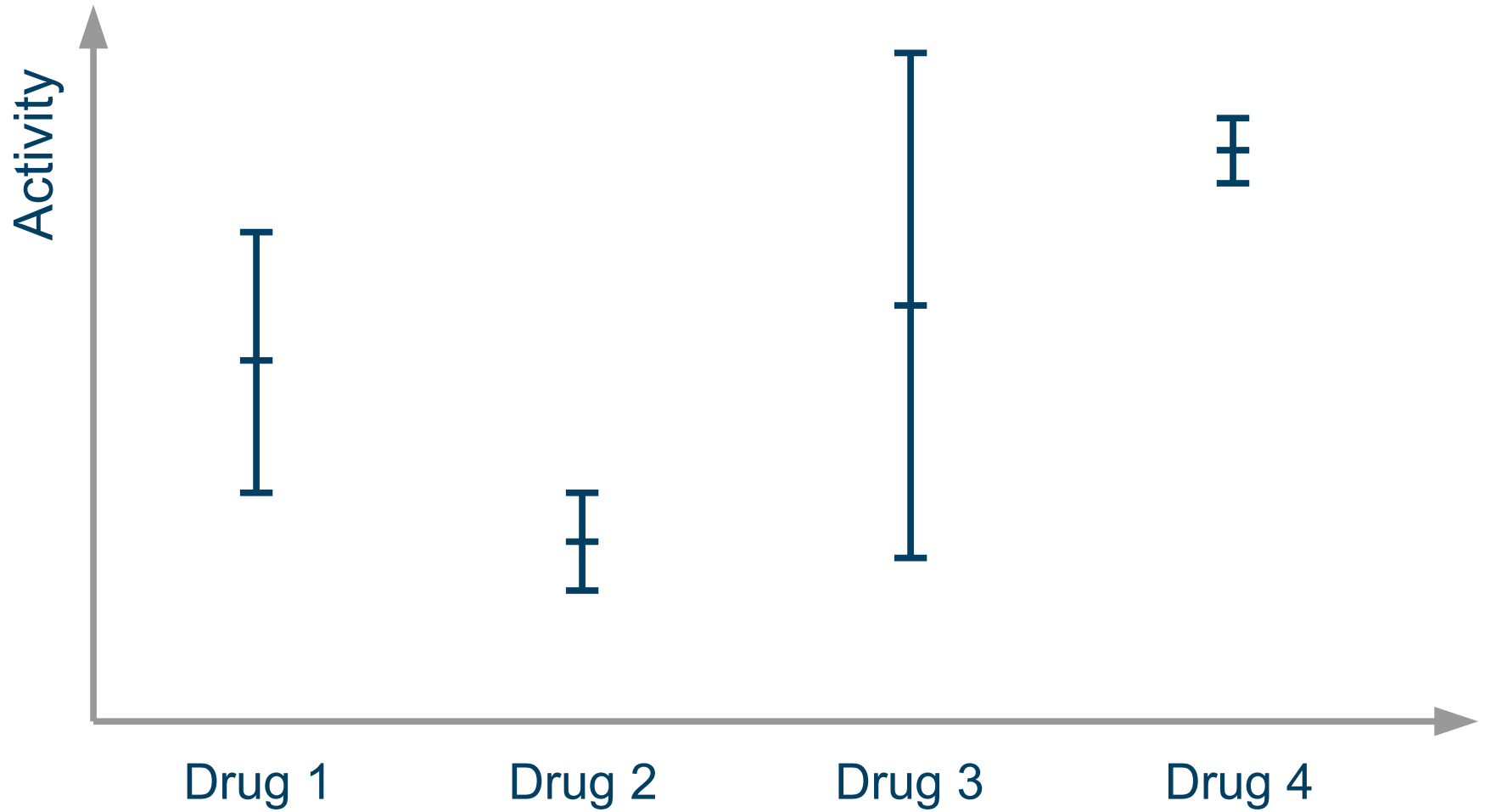
# Learn protein-protein correlations



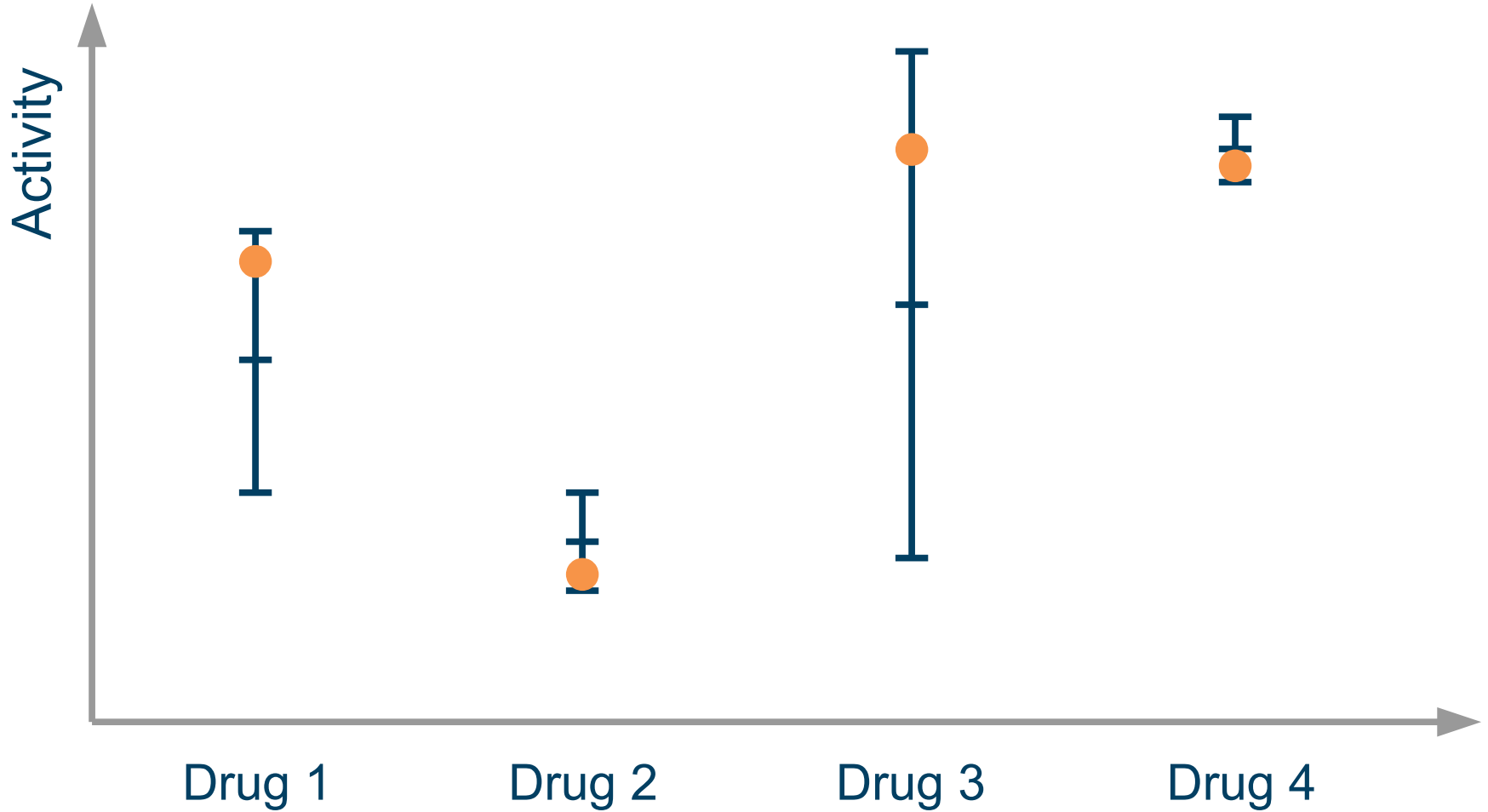
# Comparison of techniques



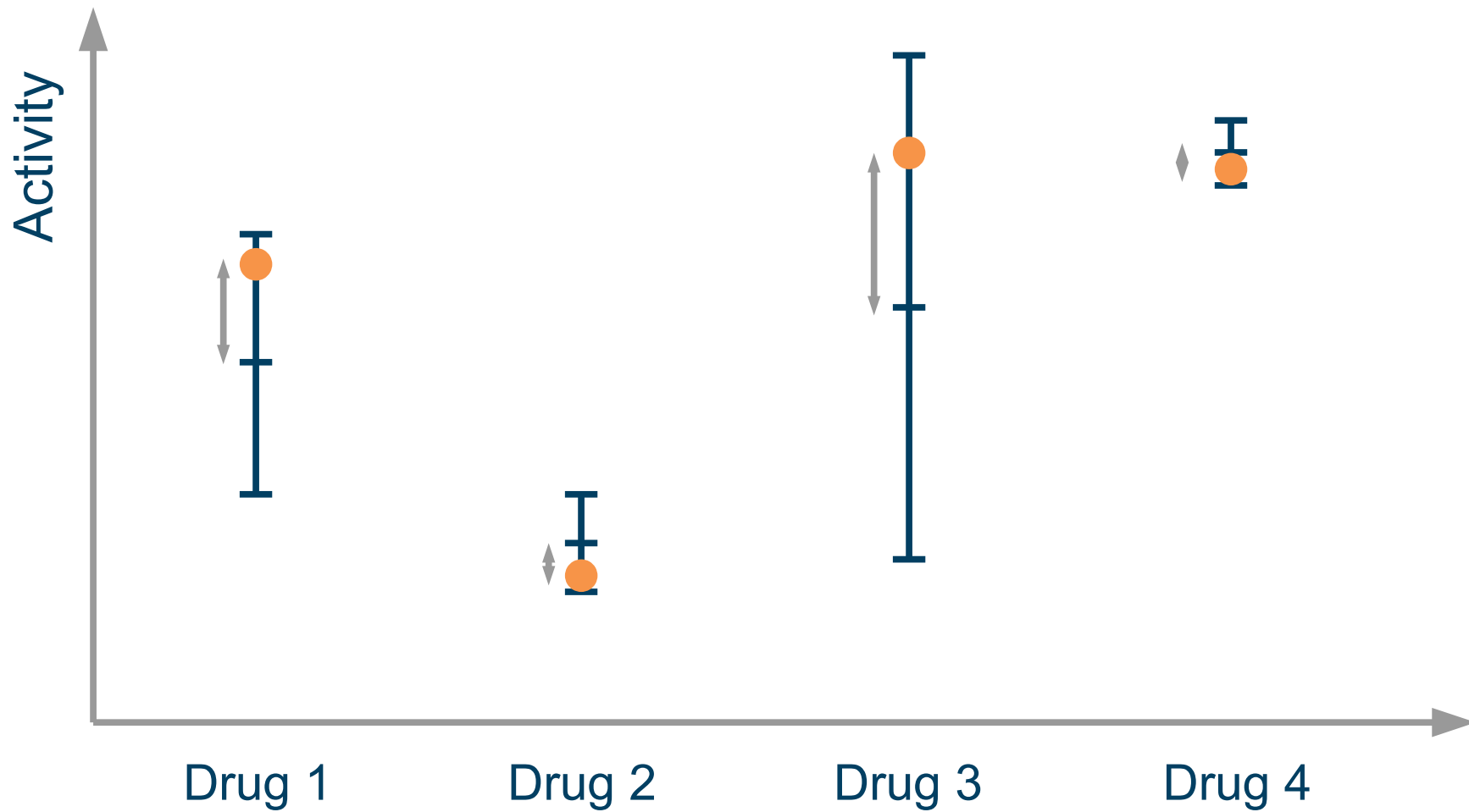
# Predictions have an uncertainty



# Validation data typically within one standard deviation



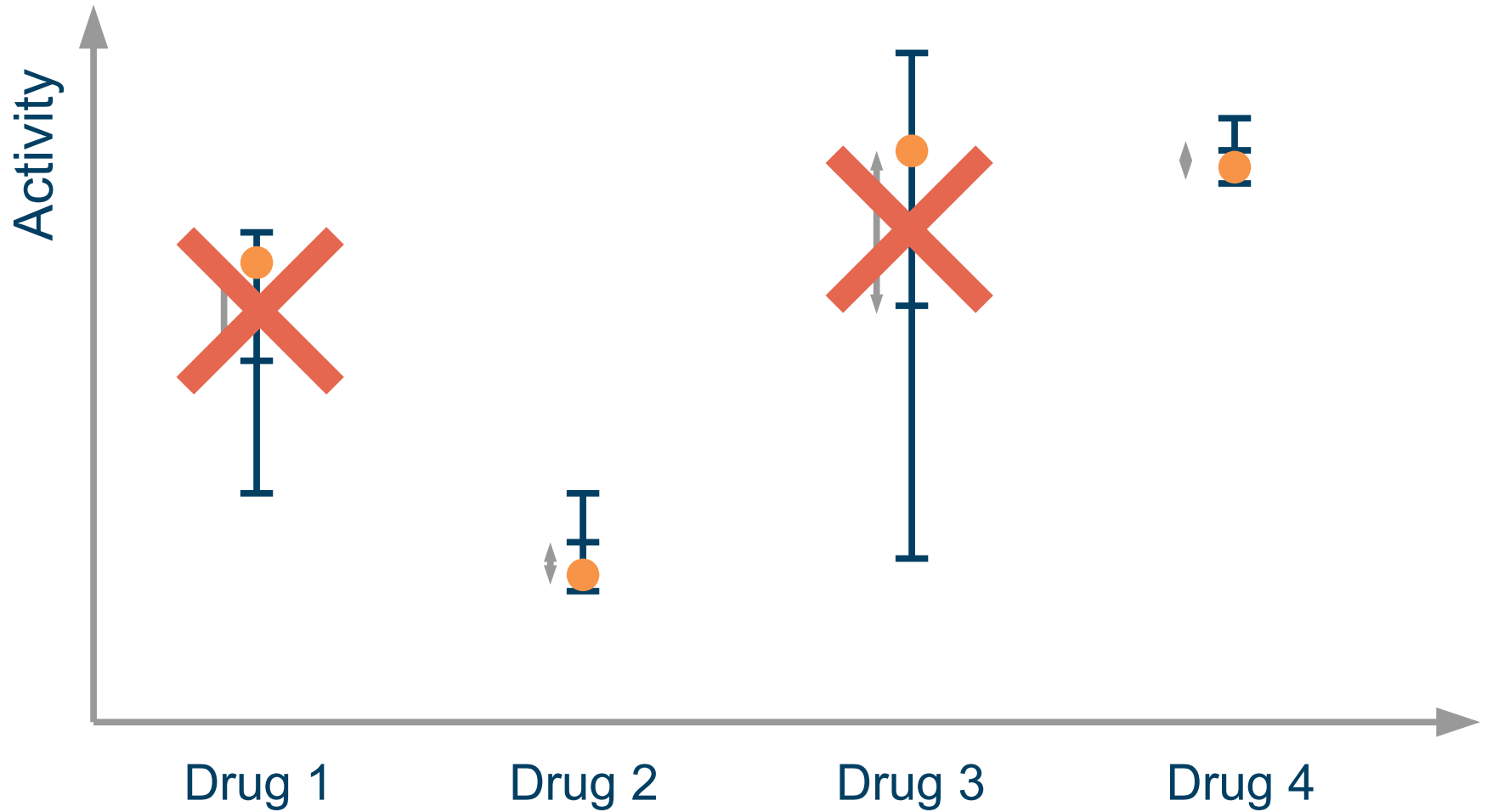
# $R^2$ metric calculated with difference from mean



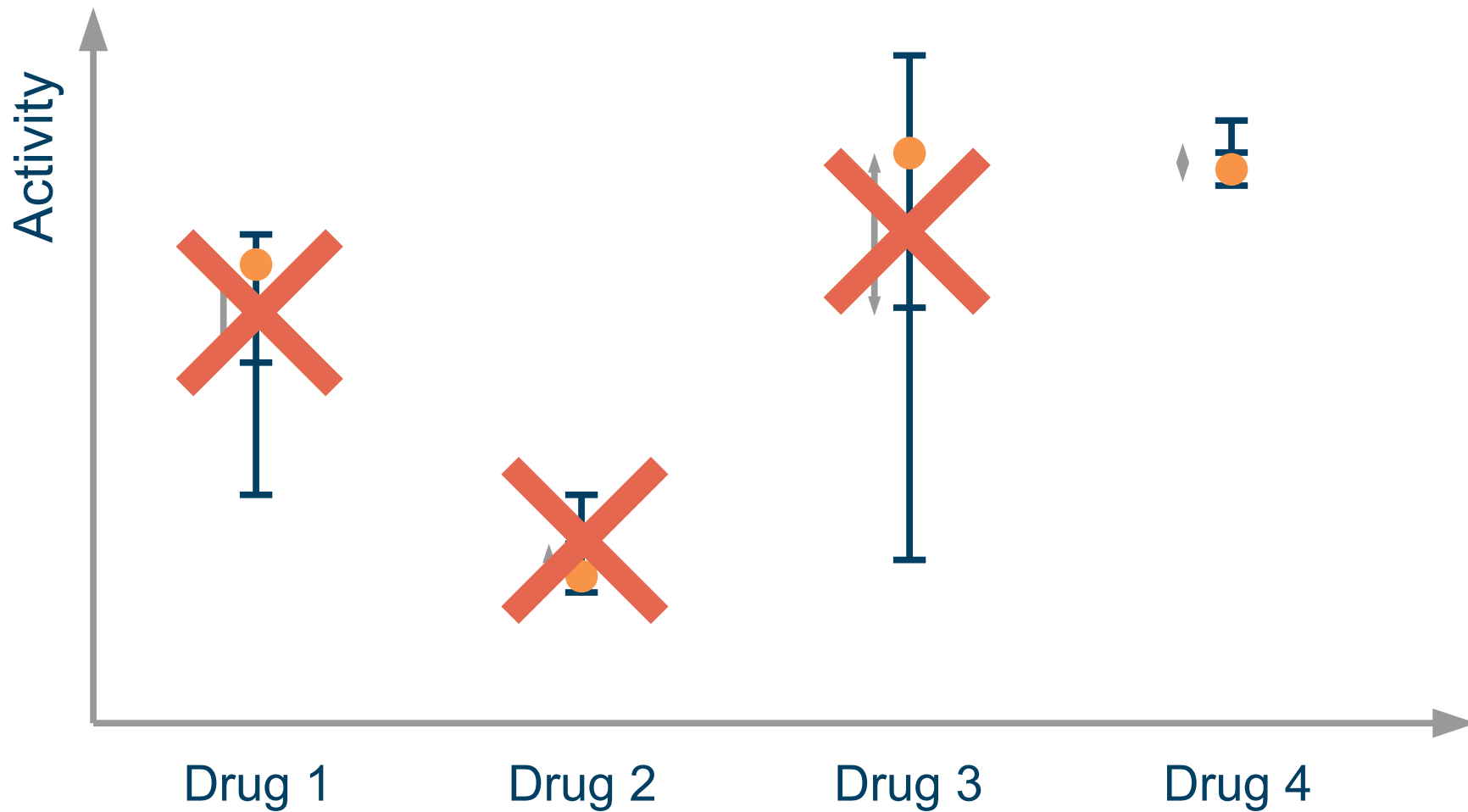
# Impute 75% of data with smallest uncertainty



# Impute 50% of data with smallest uncertainty

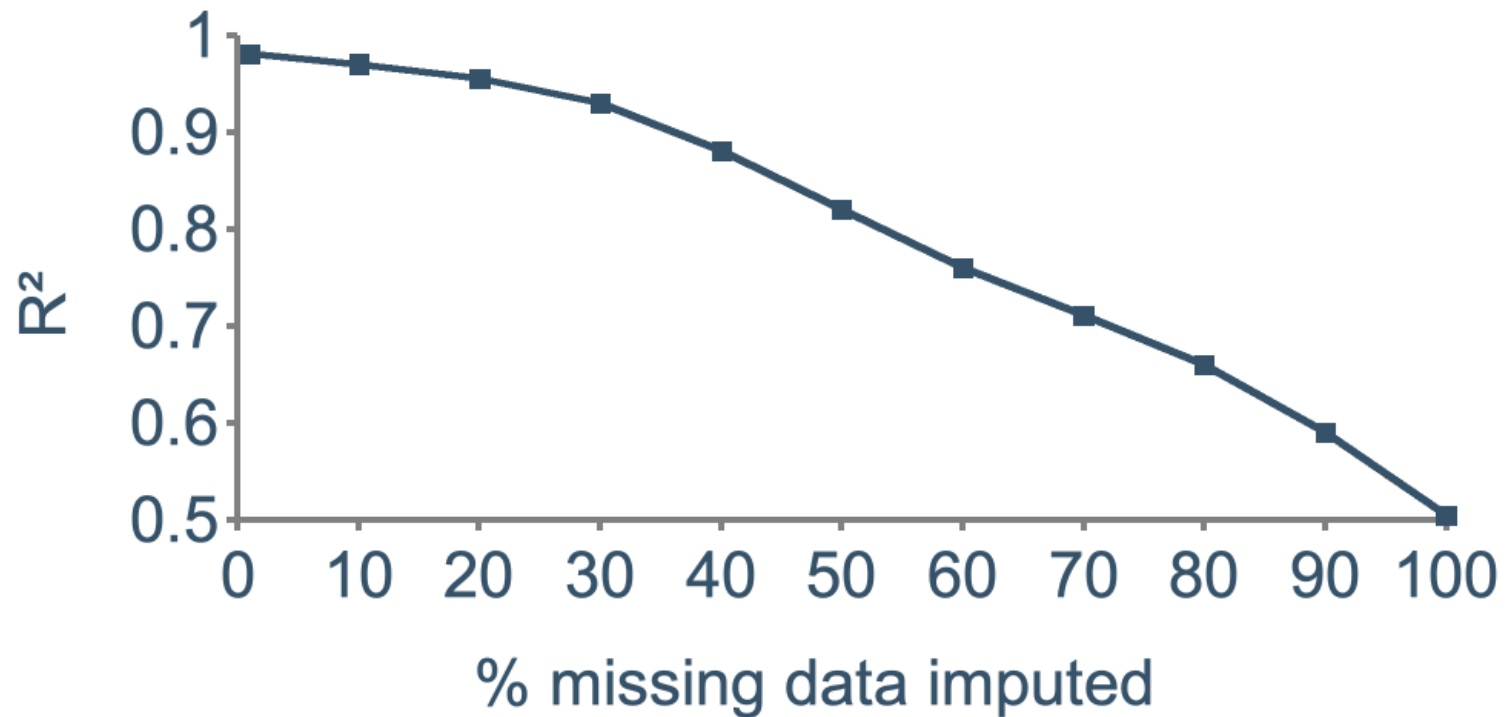


# Impute 25% of data with smallest uncertainty

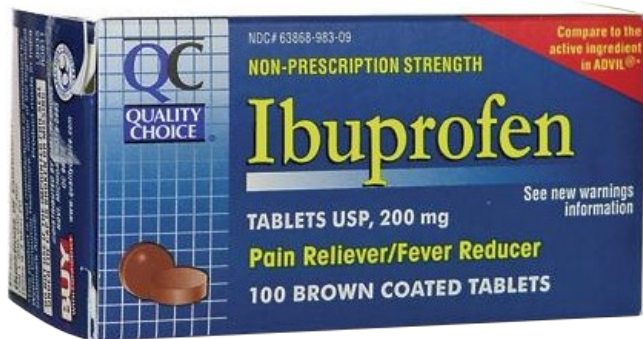




# Improved performance by exploiting uncertainty



# Different drugs can treat the same ailment



# Open Source Malaria contest



**OPEN SOURCE MALARIA**

Looking for New Medicines

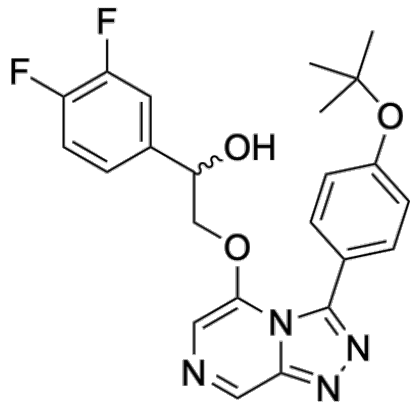
# Open Source Malaria entrants

<b>Entrant</b>	<b>Precision</b>	<b>Result</b>
Molomics	82%	<b>Winner (company)</b>
Davy Guan	82%	<b>Winner (non-company)</b>
Optibrium/Intellegens	81%	<b>Second place</b>
Exscientia	81%	<b>Second place</b>
Slade Matthews	64%	Runner-up
Auromind	58%	Runner-up
Raymond Lui	58%	Runner-up
KCL	36%	Runner-up
Interlinked TX	36%	Runner-up

# Focus on compounds with low uncertainty



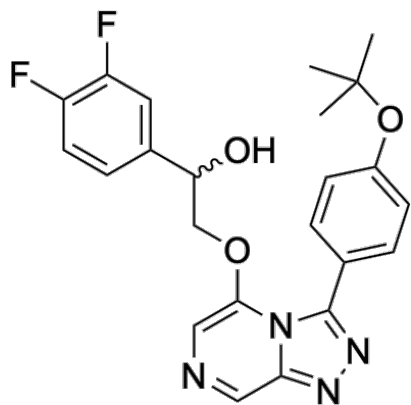
# Open Source Malaria experimental validation



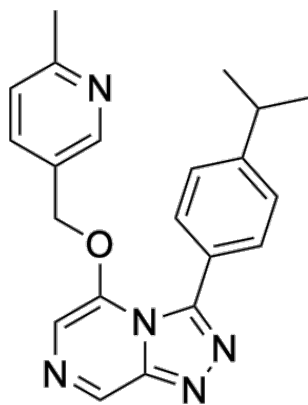
**Optibrium/Intellegens**

0.647  $\mu\text{M}$

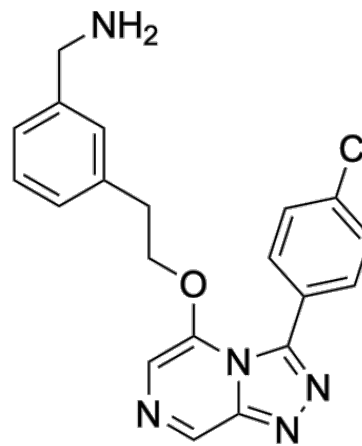
# Open Source Malaria other compounds



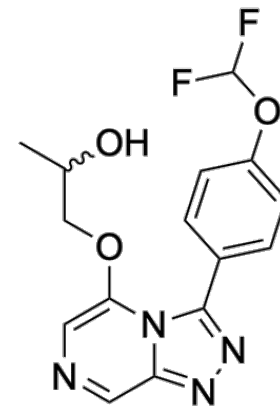
**Optibrium/Intellegens**  
0.647  $\mu\text{M}$



**Davy Guan**  
>25  $\mu\text{M}$



**Exscientia**  
10.9  $\mu\text{M}$



**Molomics**  
>25  $\mu\text{M}$

# Other compounds have large uncertainty





# Commercialization

Products and consultancy projects for materials and chemicals with **Intellegens**

Reseller agreement with drug discovery software company **Optibrium**

Machine learning tool embedded into next generation of Optibrium software for release in **October 2020**



# Summary

Merge different experimental quantities and computer simulations into a **holistic** design tool

Designed and experimentally verified alloy for **direct laser deposition**

Designed experimentally verified **drug** in Open Source Malaria competition

Taken to market through startup **Intellegens**