UNIVERSITY OF CAMBRIDGE

Artificial intelligence – a tool for the modern-day blacksmith

Gareth Conduit

Model sparse datasets

Exploit property-property relationships

Merge data, computer simulations, and physical laws

Exploit uncertainties to deliver most robust predictions

Extract information from noise itself

Black box machine learning for materials design

Composition

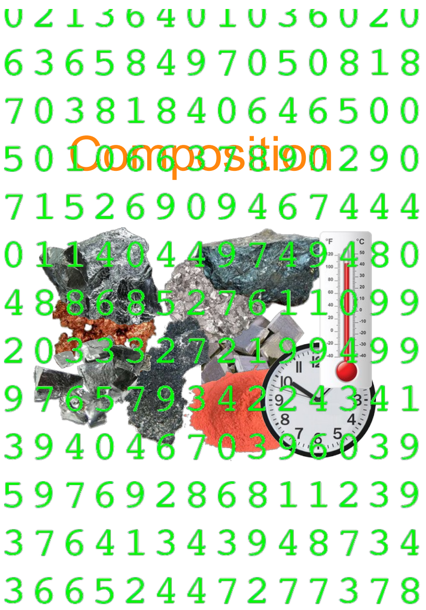
Properties

Defects

Fatigue

Strength

Train the machine learning



Machine learning predicts material properties

Composition

Properties

Defects

Fatigue

Strength

Property-property correlations to design nickel superalloy with Rolls Royce University Technology Centre

Dr Vadegadde Duggappa

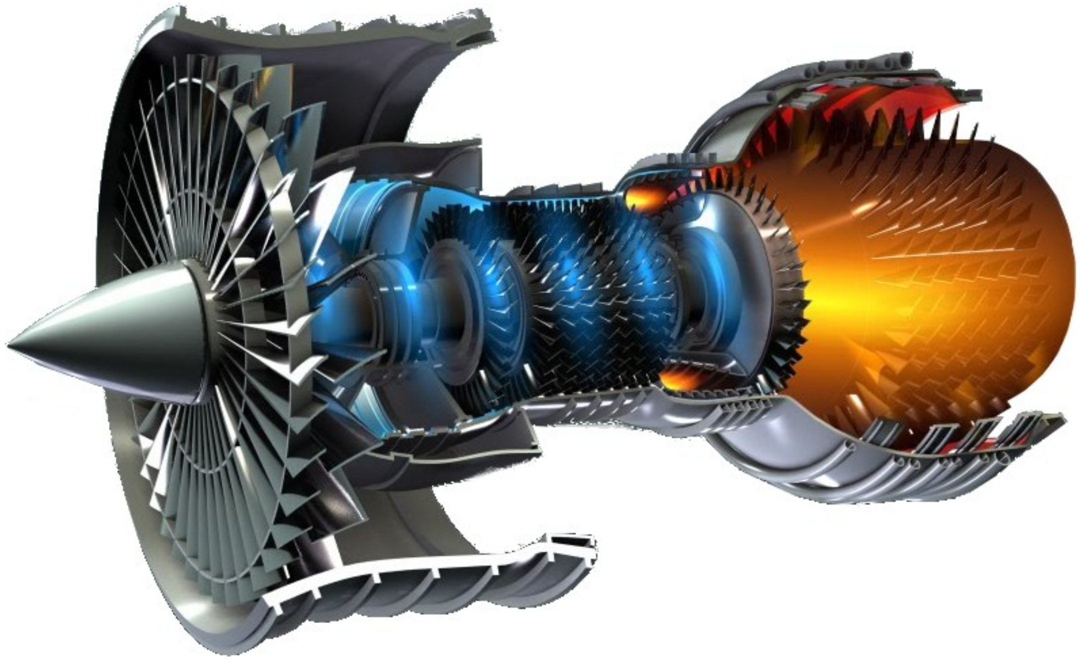
Dr Bryce Conduit

Professor Howard Stone

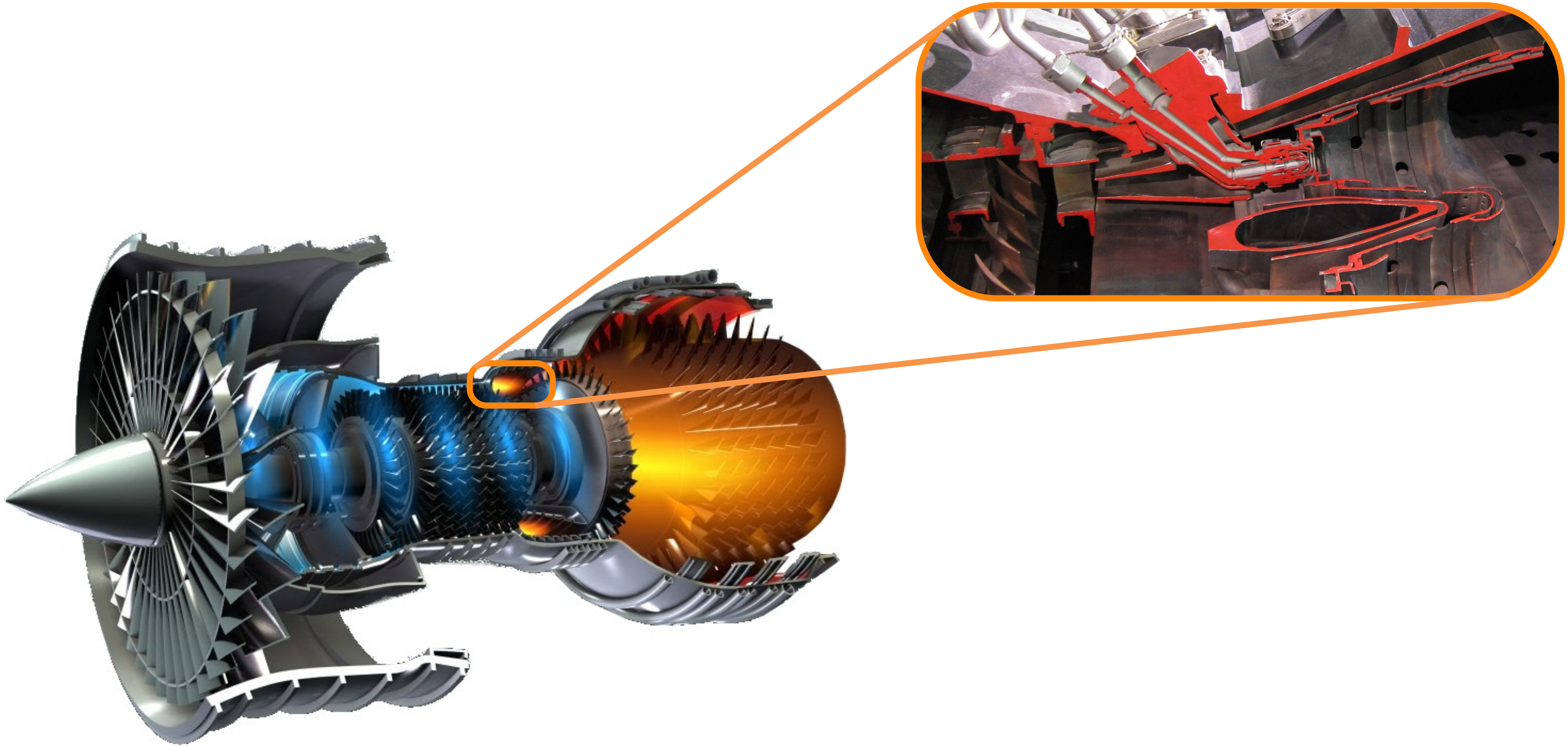
Dr Gareth Conduit

Probabilistic neural network identification of an alloy for direct laser deposition
Materials & Design 168, 107644 (2019)

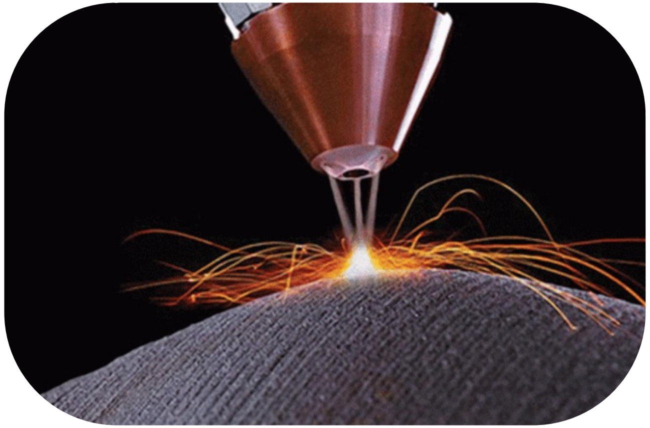
Jet engine schematic



Combustor in a jet engine



Direct laser deposition



Data available to model defect density

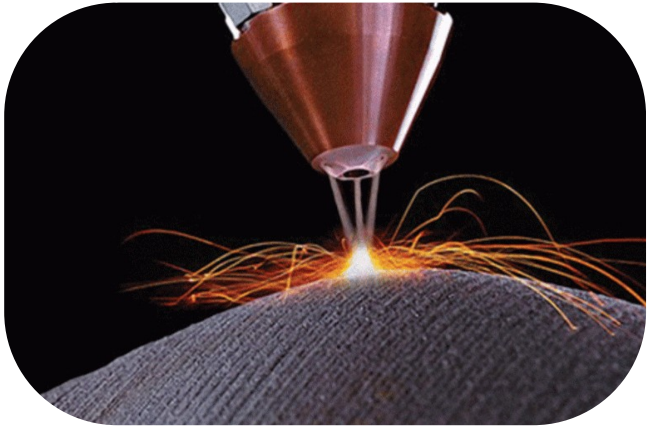
10 entries

Composition and heat treatment space 30 dimensions

Requires 31 points to fit a hyperplane

Just 10 data entries available to model defect density

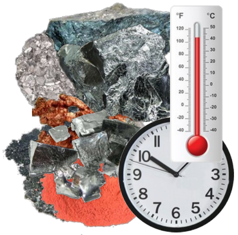
Ability for printing and welding are strongly correlated



Laser

Electricity

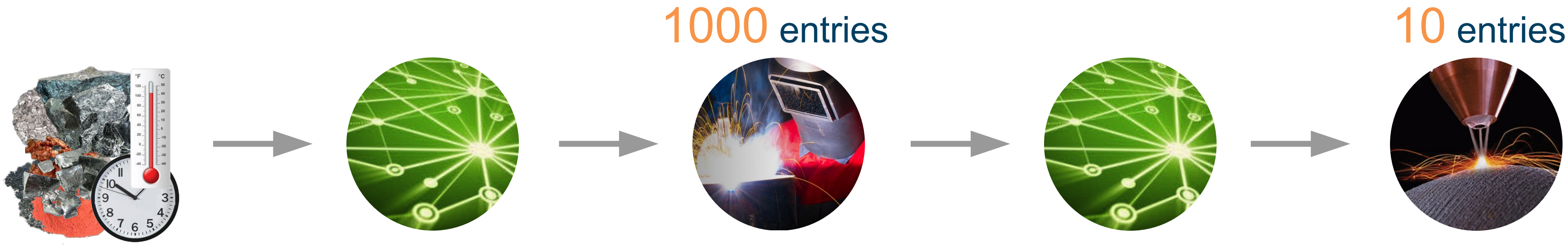
First predict weldability



1000 entries

Use 1000 weldability entries to understand complex composition → weldability model

Use weldability to predict defects formed



Use 1000 weldability entries to understand complex composition → weldability model

10 defects entries capture the simple weldability → defect relationship

Two interpolations aid composition → defects extrapolation

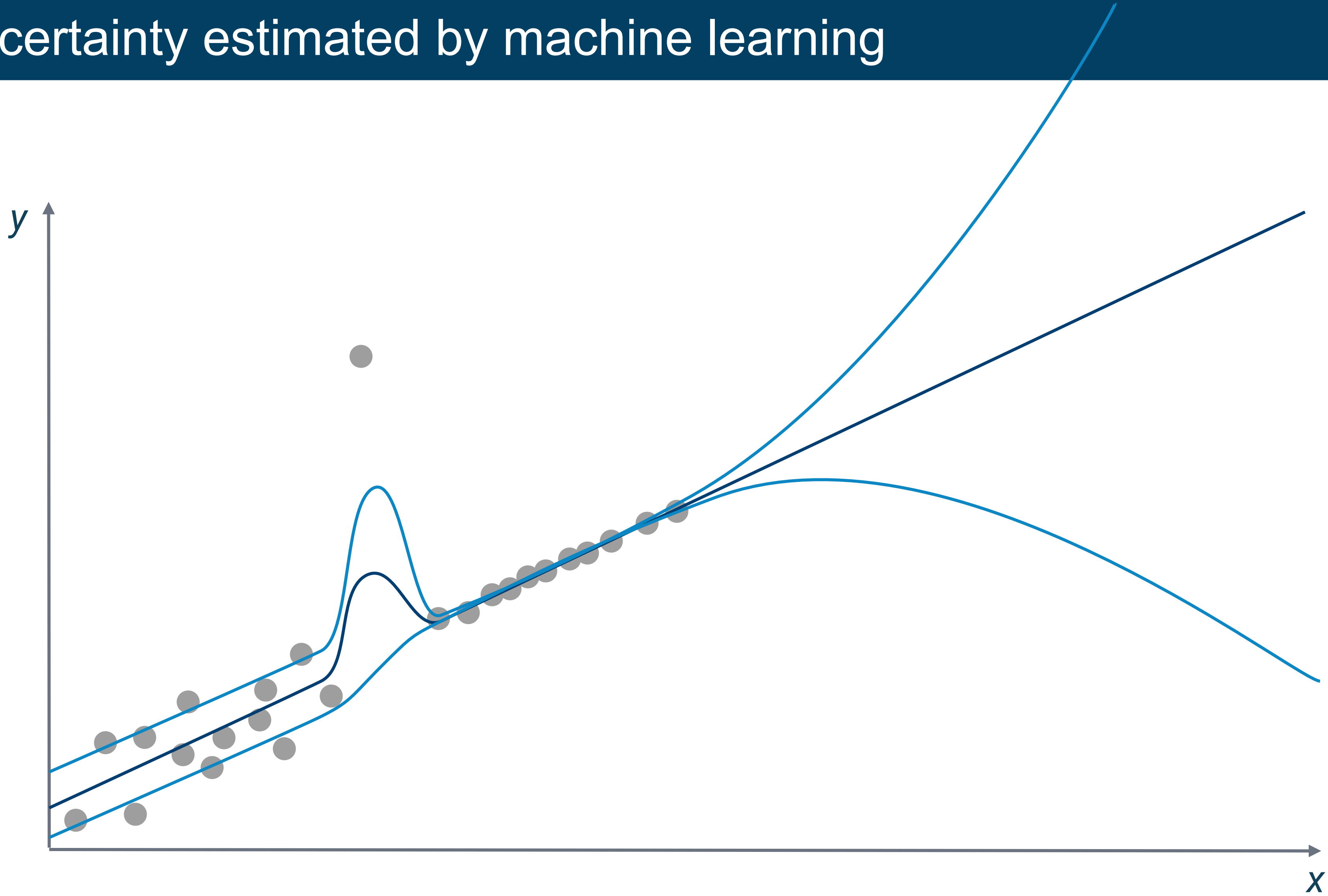
Use CALPHAD to predict strength

100,000 CALPHAD results to model complex composition → phase behavior

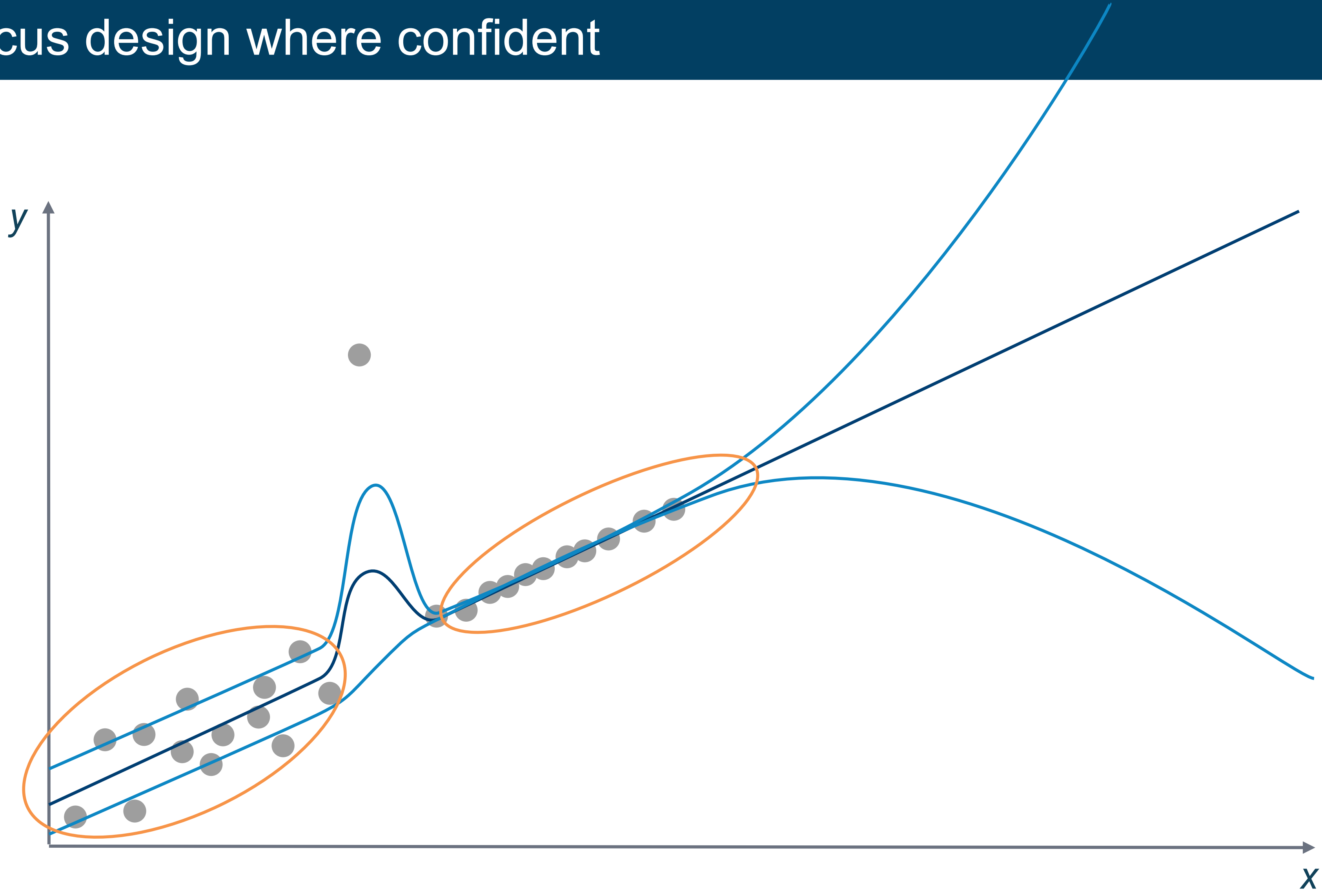
500 strength entries capture the phase behavior → strength relationship

Two interpolations aid the composition → strength extrapolation

Uncertainty estimated by machine learning



Focus design where confident



Target properties

Elemental cost	< 25 $\$kg^{-1}$
Density	< 8500 kgm^{-3}
γ’ content	< 25 wt%
Oxidation resistance	< 0.3 $mgcm^{-2}$
Defects	< 0.15% defects
Phase stability	> 99.0 wt%
γ’ solvus	> 1000˚C
Thermal resistance	> 0.04 $K\Omega^{-1}m^{-3}$
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	> 10^5 cycles

Composition and processing variables

Cr 19%

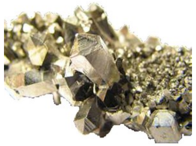
Co 4%

Mo 4.9%

W 1.2%

Zr 0.05%

Nb 3%



Al 2.9%

C 0.04%

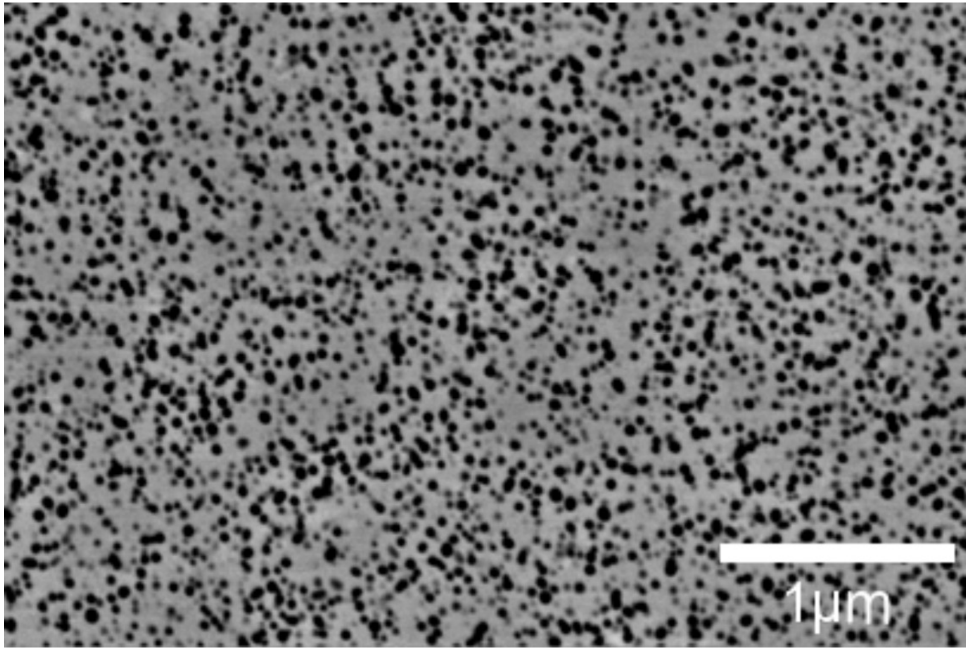
B 0.01%

Ni

Expose 0.8

T_{HT} 1300ºC

Microstructure



Probabilistic neural network identification of an alloy for direct laser deposition
B. Conduit, T. Illston, S. Baker, D. Vadegadde Duggappa, S. Harding, H. Stone & GJC
Materials & Design **168**, 107644 (2019)

Defects target

Elemental cost	< 25 $\$kg^{-1}$
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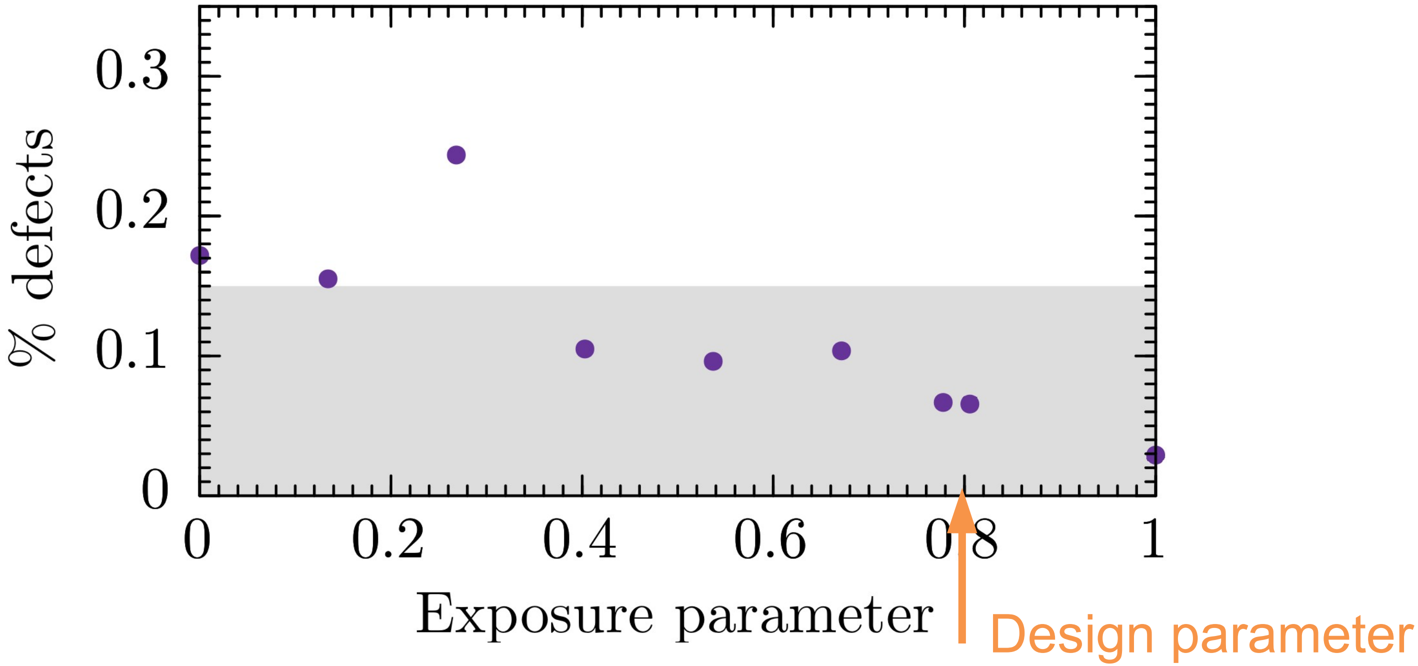
Testing the defect density



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Oxidation target

Elemental cost	< 25 $\$kg^{-1}$
Density	< 8500 kgm^{-3}
γ' content	< 25 wt%
Oxidation resistance	< 0.3 $mgcm^{-2}$
Defects	< 0.15% defects
Phase stability	> 99.0 wt%
γ' solvus	> 1000˚C
Thermal resistance	> 0.04 $K\Omega^{-1}m^{-3}$
Yield stress at 900˚C	> 200 MPa
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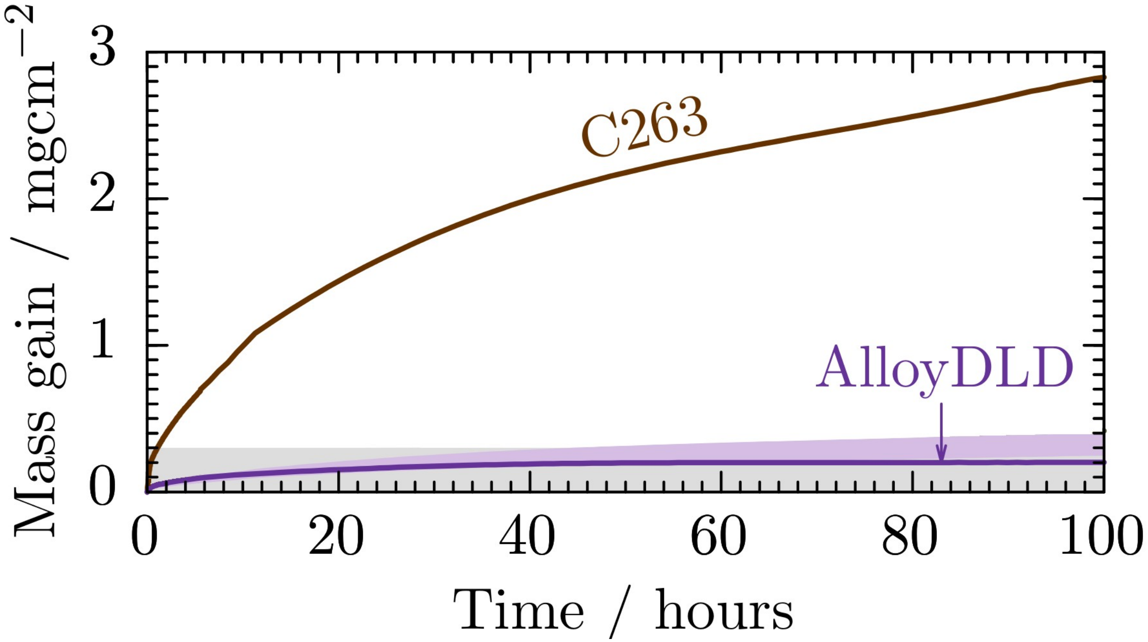
Testing the defect density



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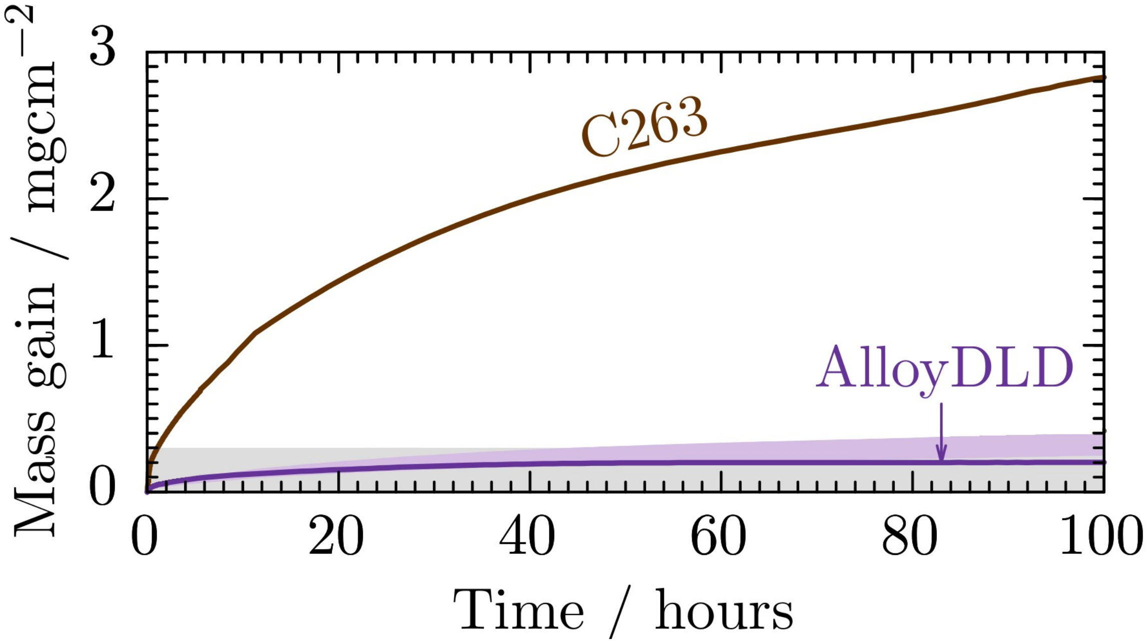

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Materials & Design **168**, 107644 (2019)

Exploit uncertainty to design concrete with Department of Civil Engineering

Bogdan Zviazhynski

Jess Forsdyke

Professor Janet Lees

Dr Gareth Conduit

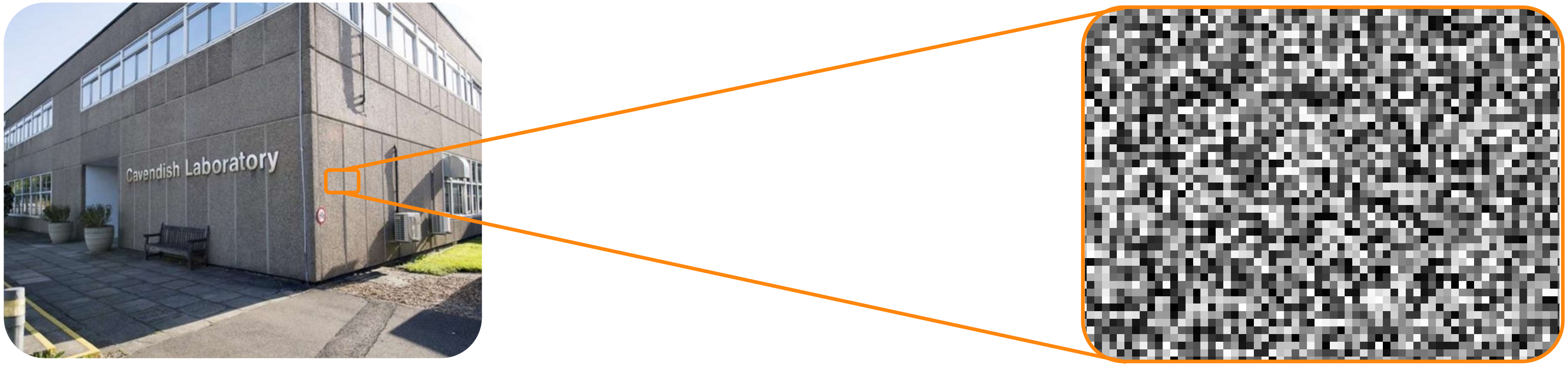
Unveil the unseen: exploit information hidden in noise, Applied Intelligence (2022)

Probabilistic selection and design of concrete using machine learning
Data-Centric Engineering **4**, e9 (2023)

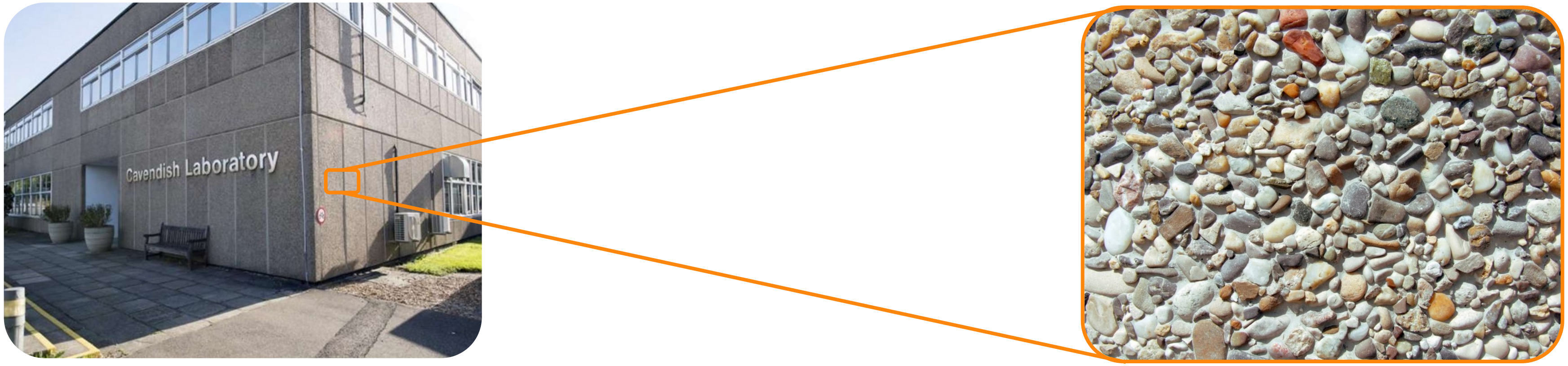
Concrete in construction

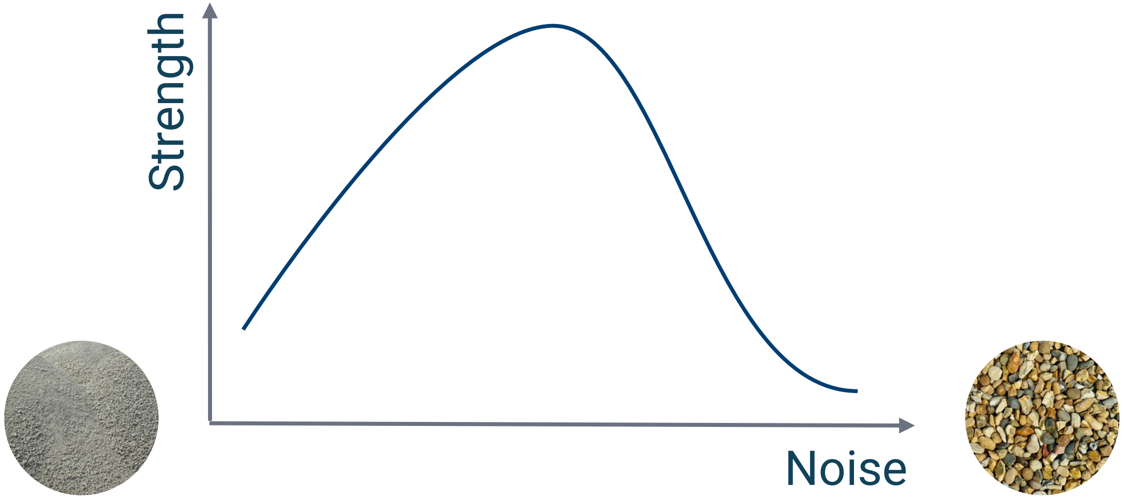
Cement & aggregate look like noise

Cement & aggregate look like noise

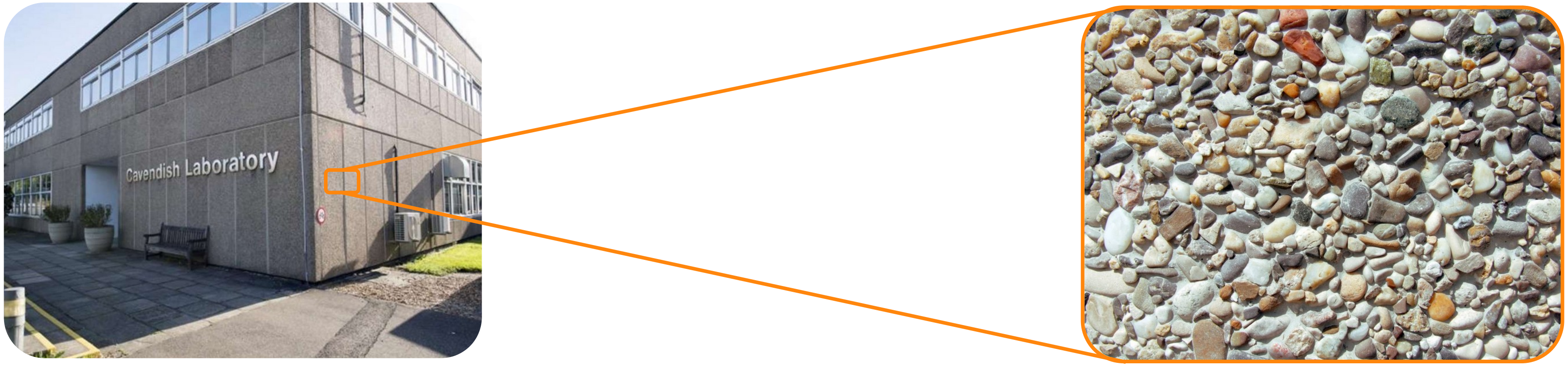


Strength is related to noise



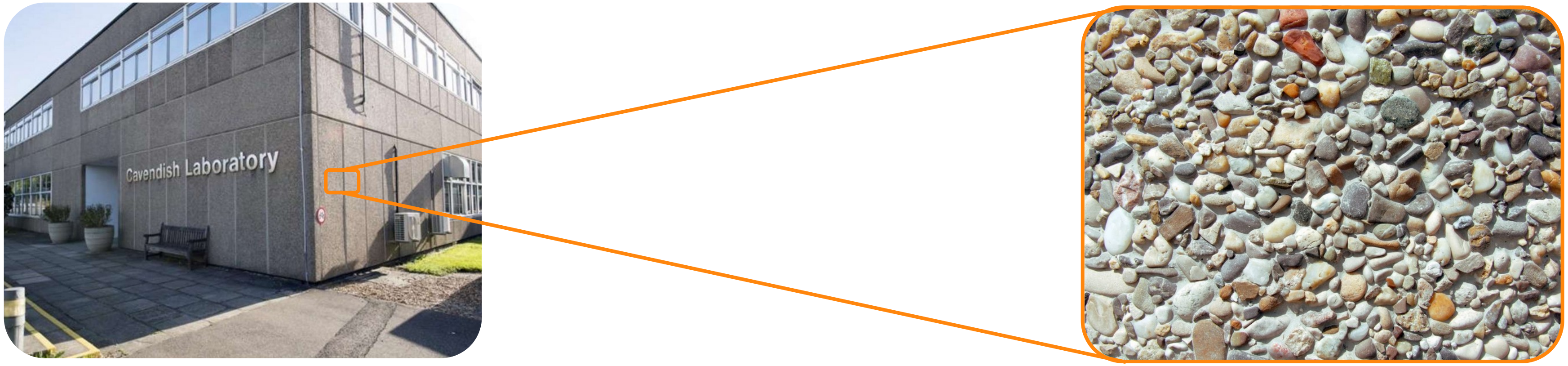


Mission



Design environmentally friendly concrete

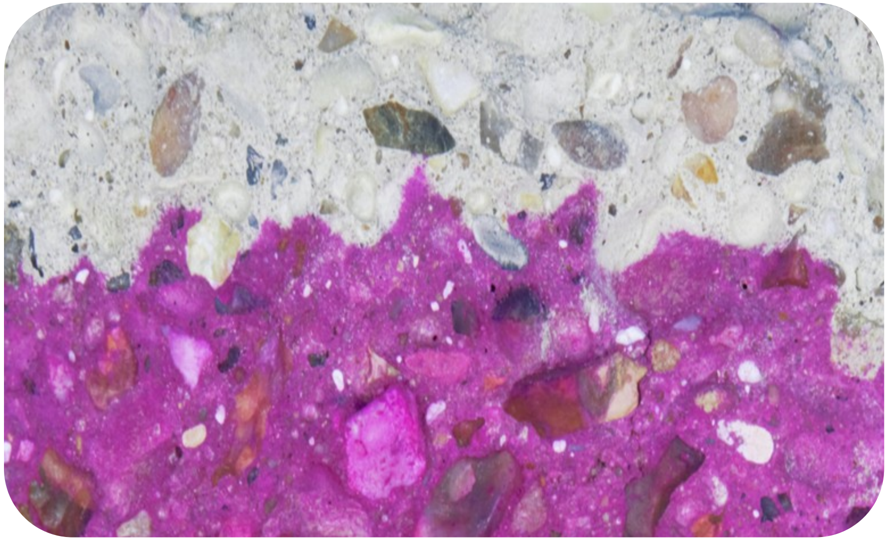
Mission



Design environmentally friendly concrete

Experimentally validate the concrete

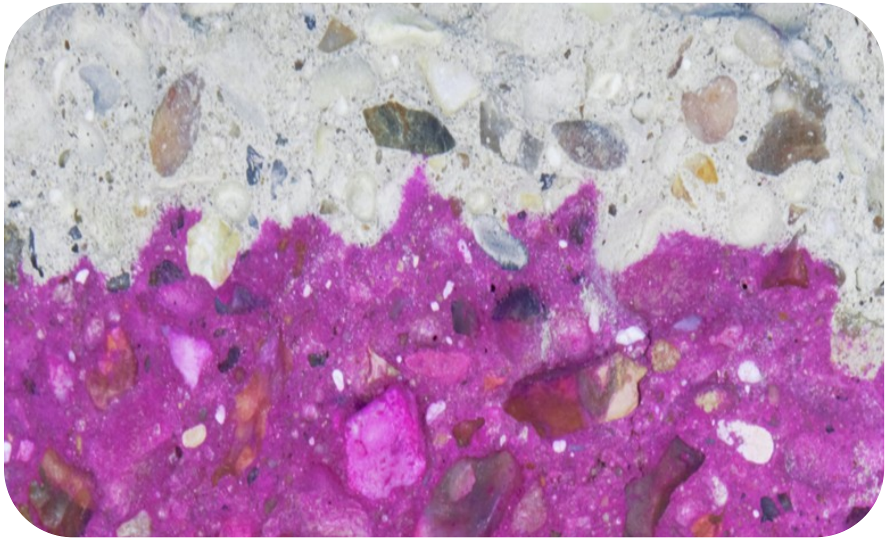
Carbonation is the probe of noise



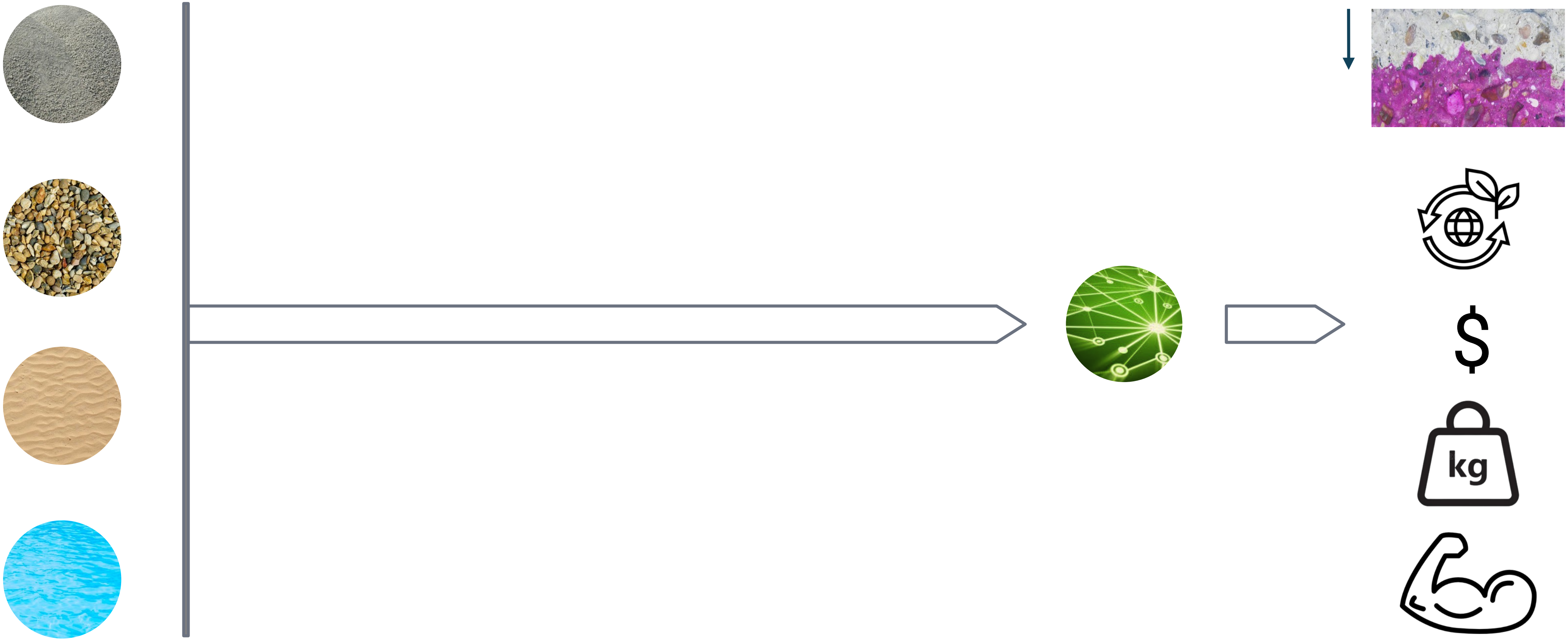
Depth and uncertainty in carbonation

Depth

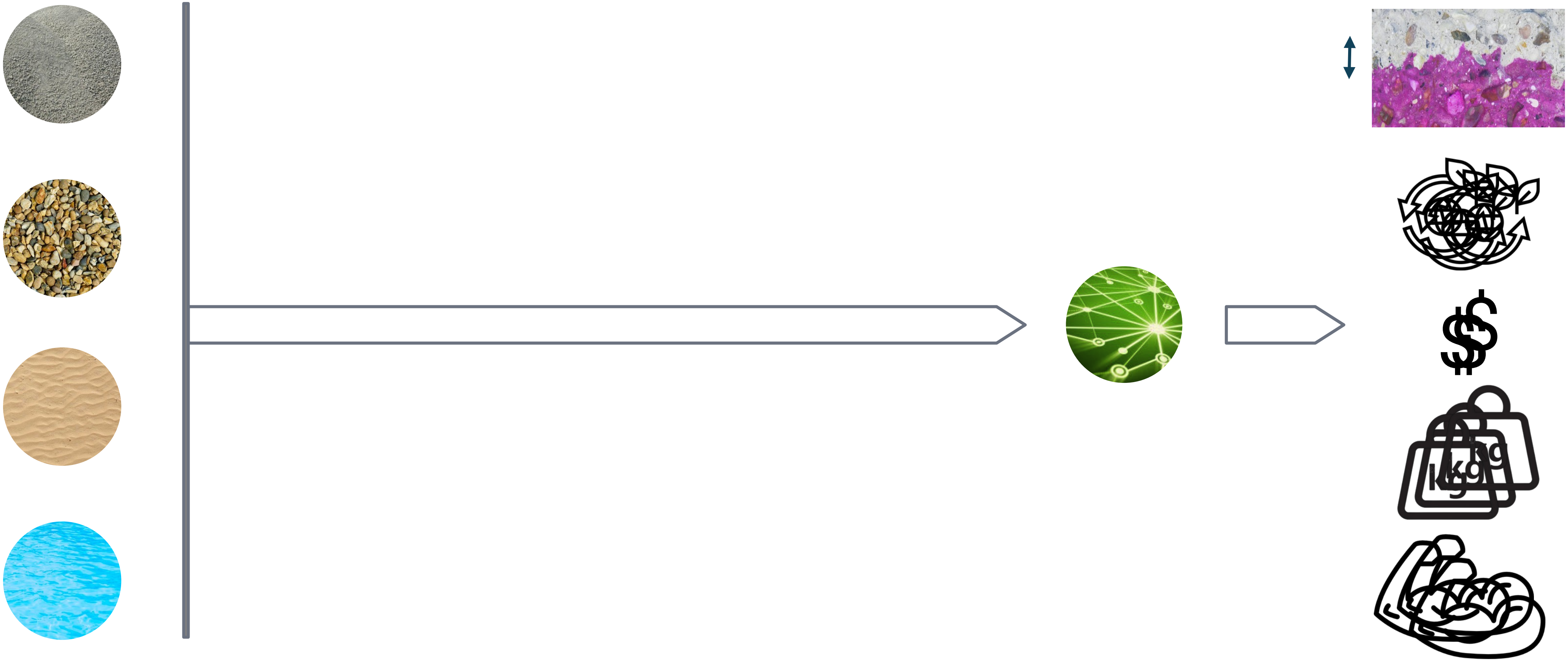
Uncertainty



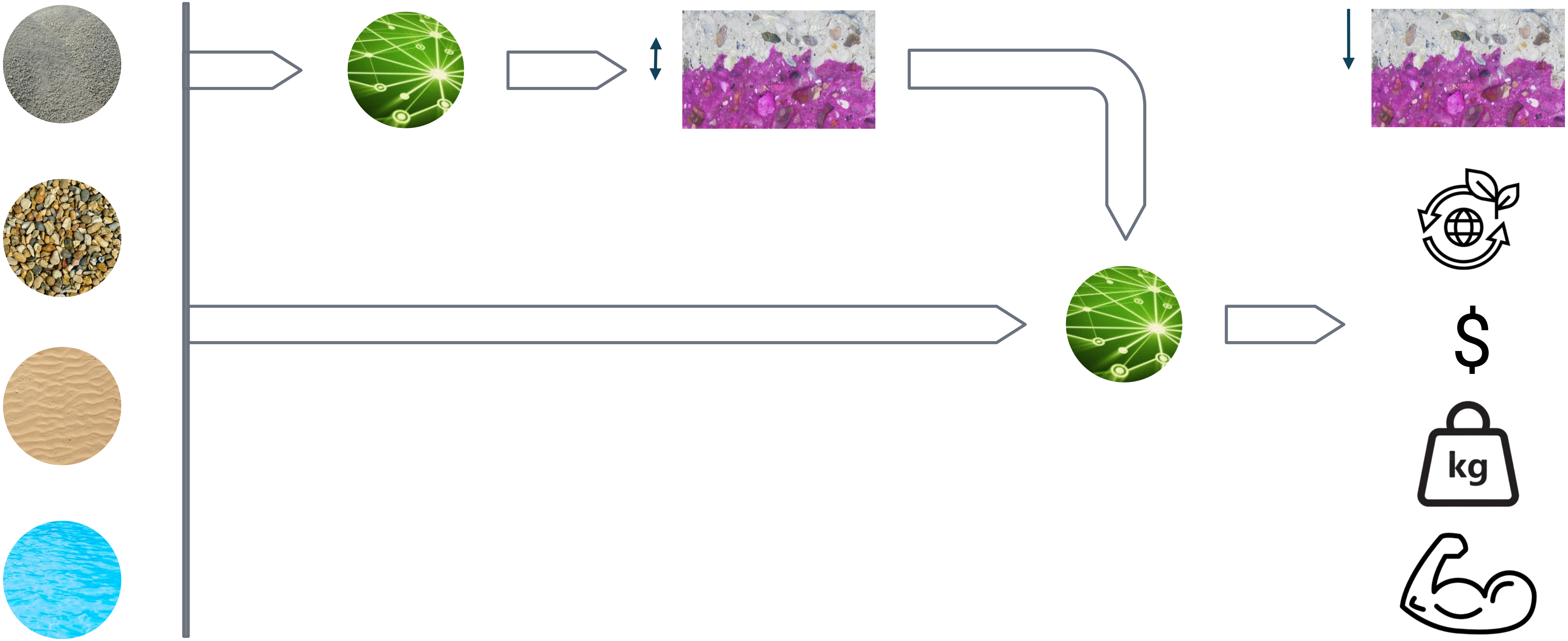
Standard machine learning predicts expectation values



Exploit machine learning uncertainty estimates for robust designs



Machine learning exploits uncertainty



Unveil the unseen: exploit information hidden in noise, Applied Intelligence (2022)

Concrete specification

✔	carbonation	< 2.34 mm $day^{-1/2}$
⬇	environmental impact	< 0.107 kg CO_2 e kg^{-1}
✔	cost	< 0.028 £ kg^{-1}
✔	density	< 2350 kg m^{-3}
✔	strength	> 20 MPa

Concrete design

10.5% cement

48.4% gravel

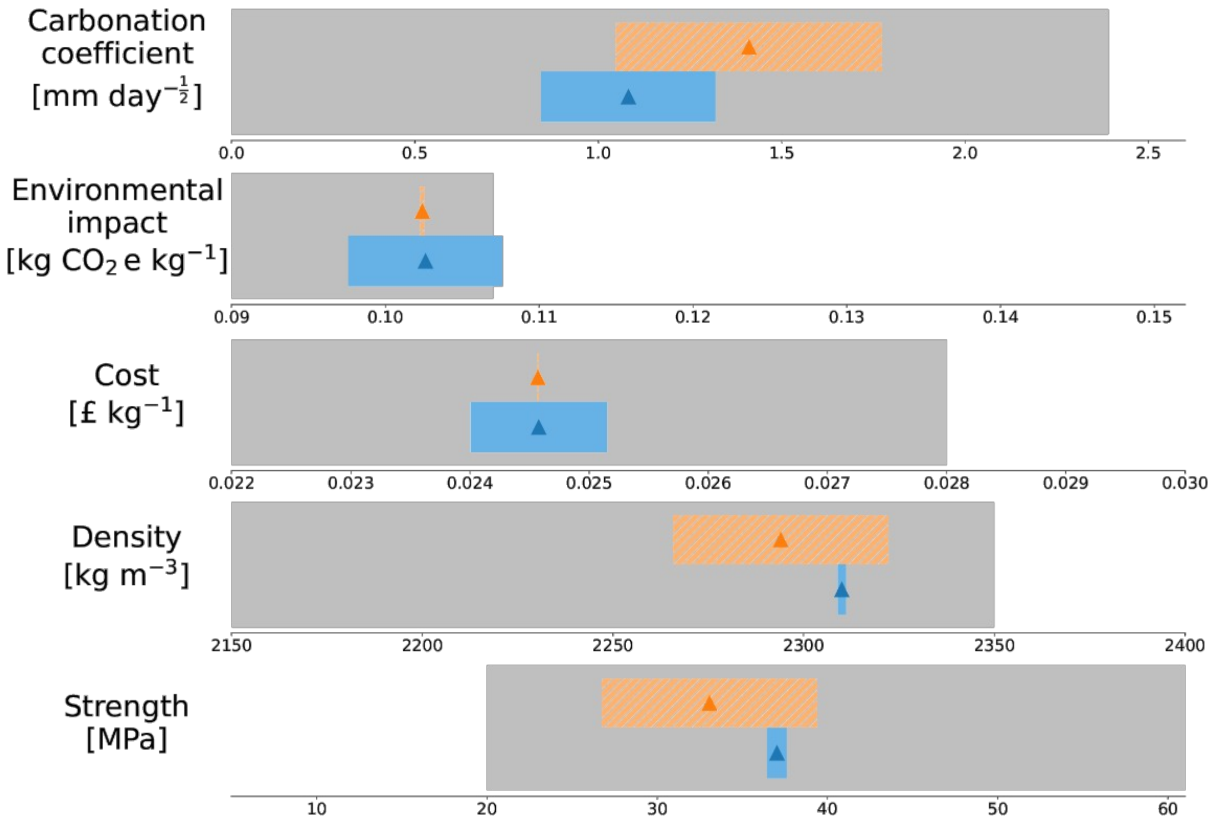
32.6% sand

8.5% water

Concrete manufacture

Probabilistic selection and design of concrete using machine learning
JCF, BZ, JML & GJC, Data-Centric Engineering **4**, e9 (2023)

Experimental validation of the proposed mix



Model
Experiment
Target

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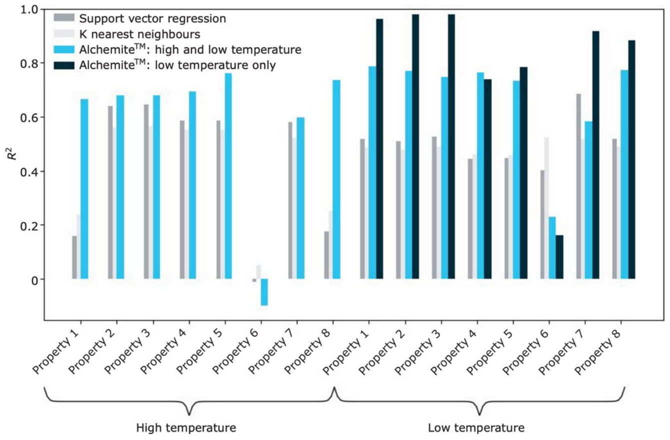
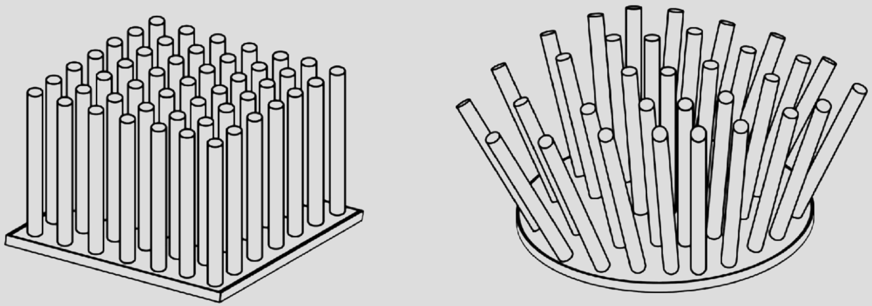
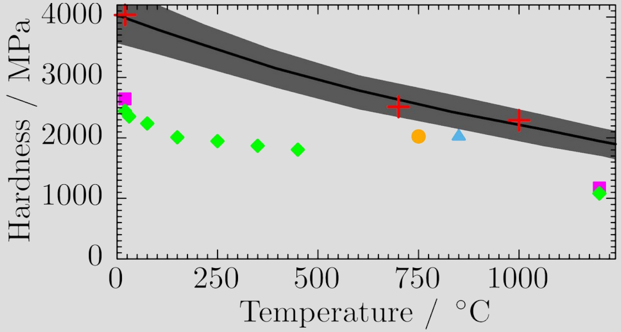


Johnson Matthey Technology Review
66, 130 (2022)



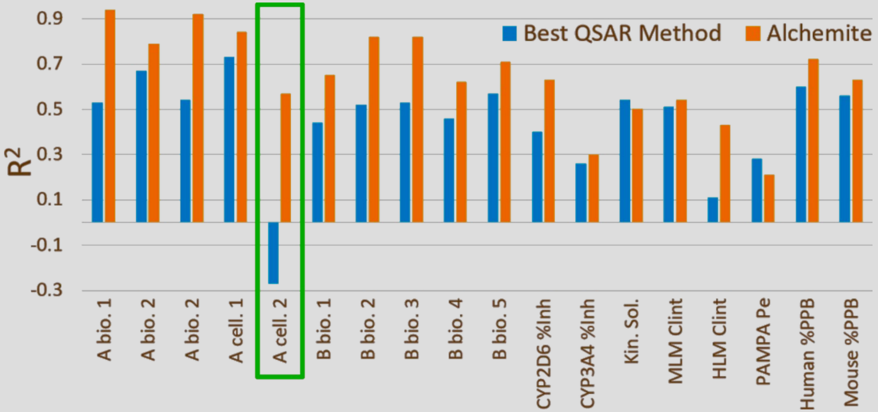
NASA Technical Memorandum
20220008637



Materials & Design **131**, 358 (2017)
Scripta Materialia **146**, 82 (2018)
Data Centric Engineering **3**, e30 (2022)

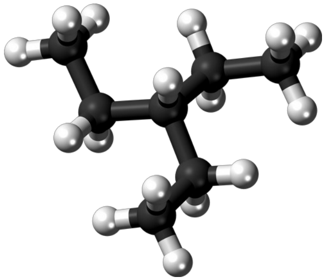
Alloy	**Source**	**ANN**	Δ_σ	**Actual**
Steel AISI 301L	193	269	5	238[23]
Steel AISI 301	193	267	5	221[23]
Al 1080 H18	51	124	5	120[23]
Al 5083 wrought	117	191	14	300,190[4, 23]
Al 5086 wrought	110	172	11	269,131[4, 23]
Al 5454 wrought	102	149	14	124[23]
Al 5456 wrought	130	201	11	165[23]
INCONEL600	223	278	10	≥550[23]

Computational Materials
Science **147**, 176 (2018)

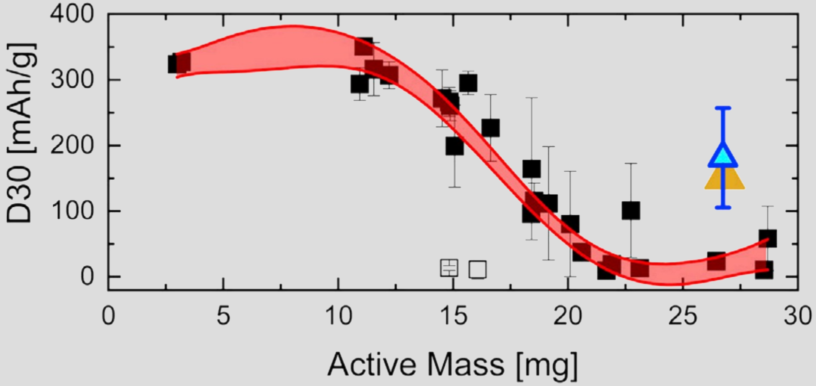


J. of Chem. Info. & Model. **60**, 2848 (2020)
Applied AI Letters **2**, e31 (2021)
Molecular Pharmaceutics **19**, 1488 (2022)

Journal of Computer-Aided Molecular Design **35**, 112501140 (2021)



Fluid Phase Equilibria **501**, 112259 (2019)
Journal of Chemical Physics **153**, 014102 (2020)



Nature Machine Intelligence **2**, 161 (2020)
Cell Reports Physical Science **2**, 100683 (2021)

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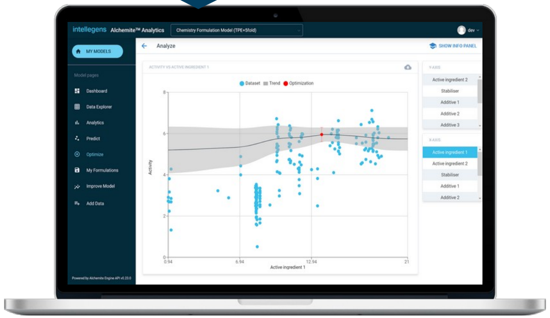

Option to deploy models

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Alchemite™ Engine

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Alchemite™ Academic Programme

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Merge computer simulations with experimental data and exploit property-property relationships to circumvent missing data

Designed and experimentally verified alloy for direct laser deposition

Exploited information in noise to design experimentally verified concrete

Software product taken to market through startup Intellegens