



intellegens

Machine learning for
materials design

Gareth Conduit



Alchemite™ optimized design process

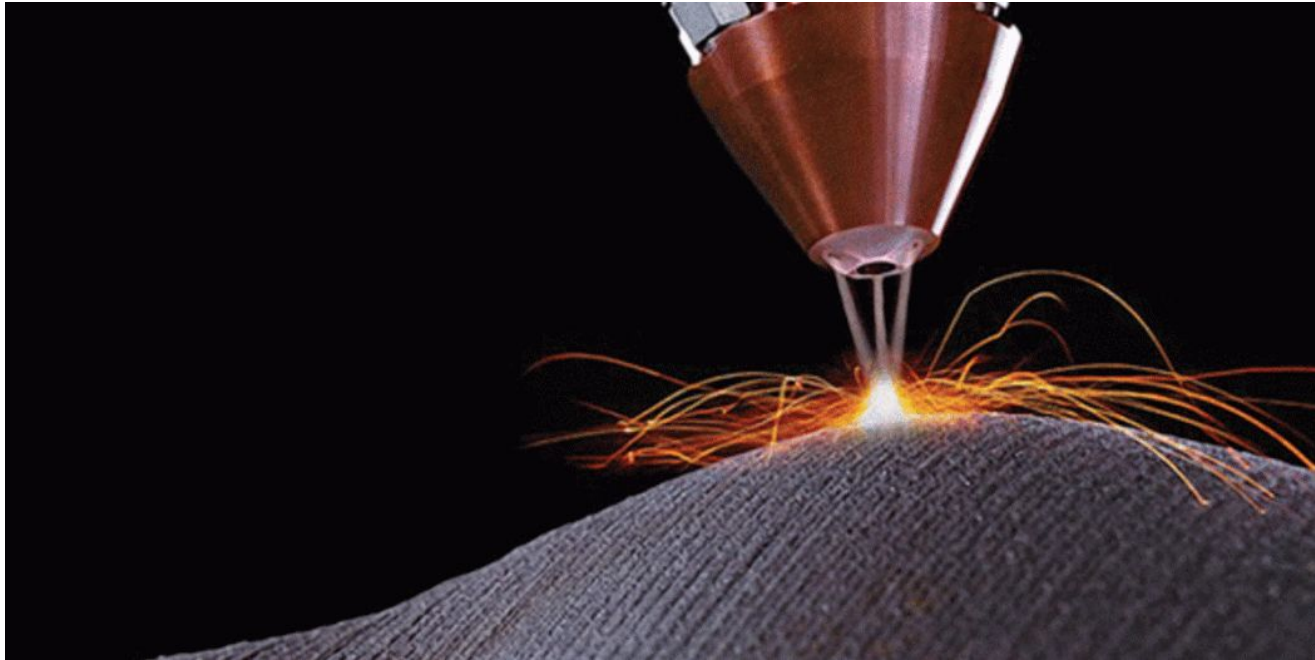
Machine learning software to aid experimental design developed at University of Cambridge, commercialized by Intellegens

Alchemite™ predicts from all **available** inputs

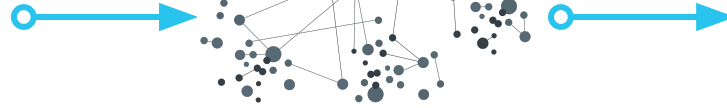
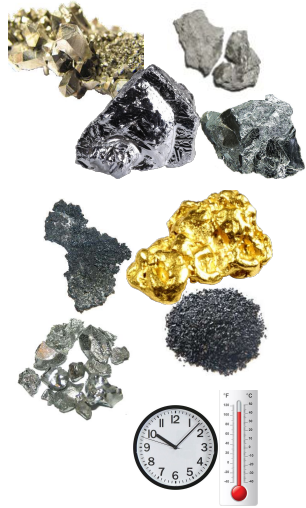
Reduce costs - 90% reduction in experiments and fewer measurements for expensive quantities

Accelerate discovery and validation to 2 years

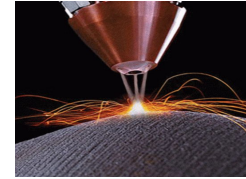
Additive manufacturing requires new alloys



Machine learning



Processability



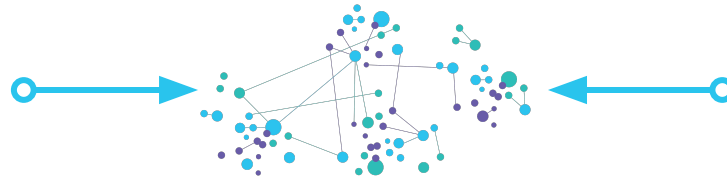
Fatigue life



Cost



Machine learning



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Processability



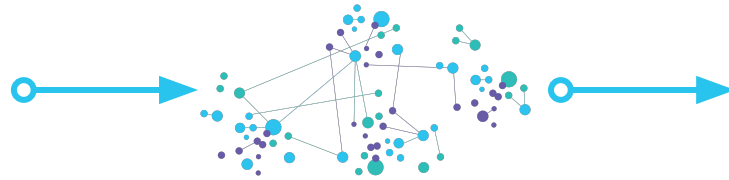
Fatigue life



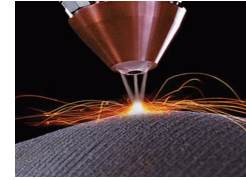
Cost



Machine learning



Processability



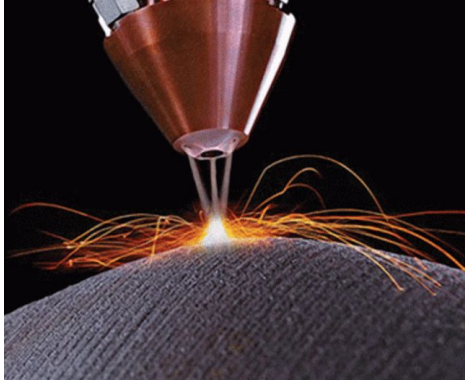
Fatigue life



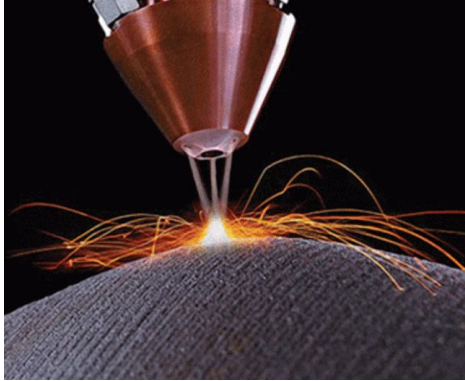
Cost



Case study: alloy for direct laser deposition



Direct laser deposition is similar to welding



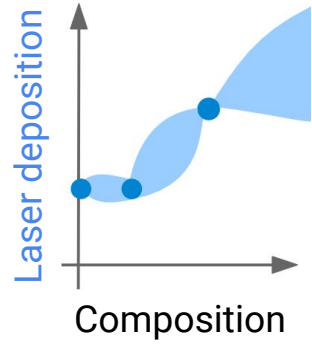
Direct laser
deposition



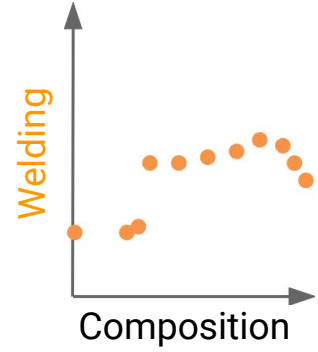
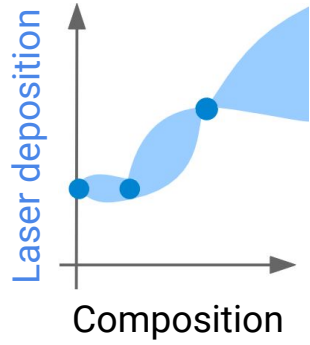
Welding



Lack of data for laser deposition

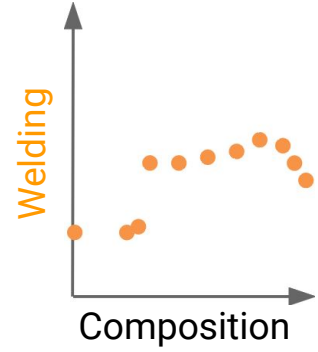
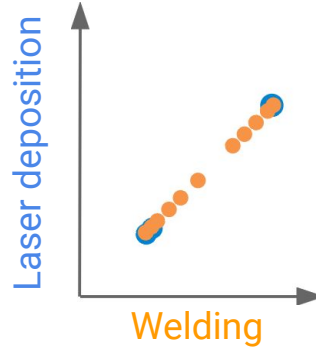
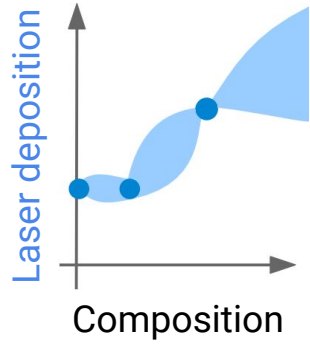


Large amount of welding data



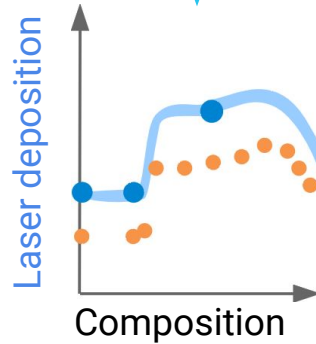
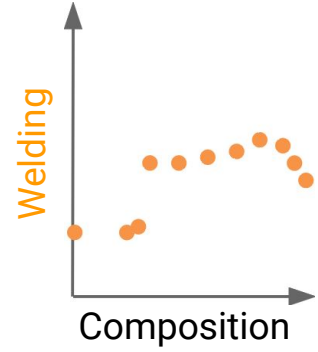
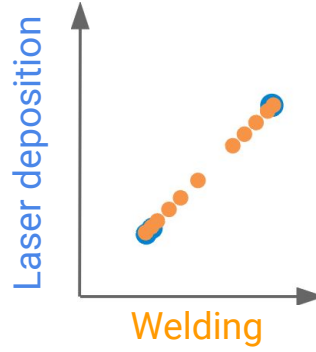
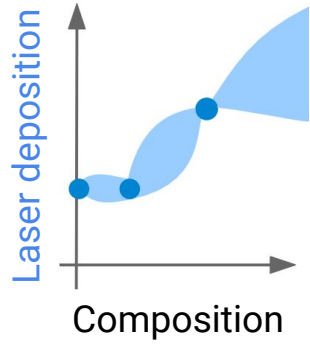


Simple welding-deposition relationship





Welding data guides extrapolation



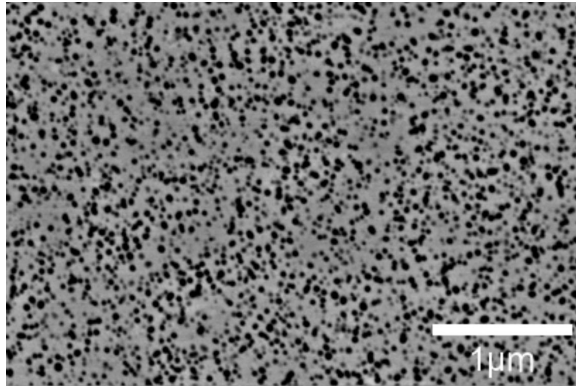


Targets for direct laser deposition alloy

Elemental cost	< 25 \$kg ⁻¹
Density	< 8500 kgm ⁻³
γ' content	< 25 wt%
Oxidation resistance	< 0.3 mgcm ⁻²
Processability	< 0.15% defects
Phase stability	> 99.0 wt%
γ' solvus	> 1000°C
Thermal resistance	> 0.04 KΩ ⁻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

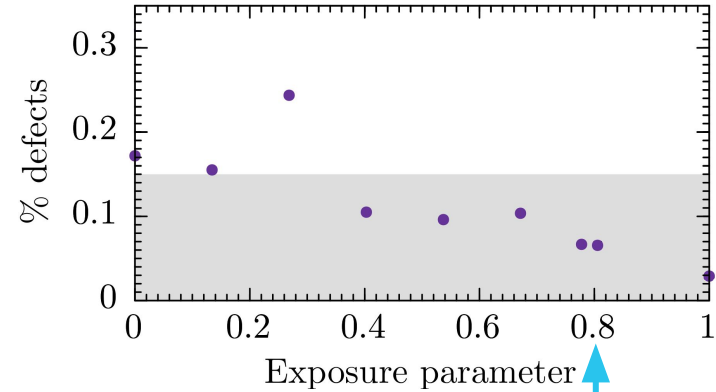
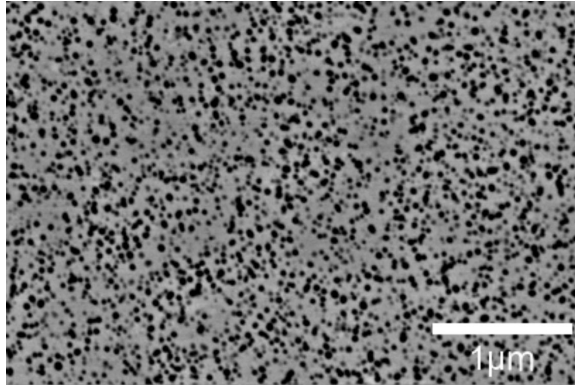


Experimental validation: microstructure





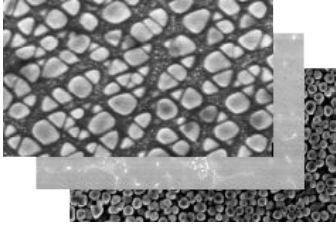
Experimental validation: defects



Design
parameter



Further materials and drug design



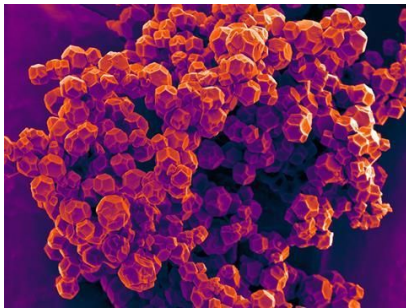
Nickel & moly alloys



Batteries



Steels for welding



Metal-organic framework



Concrete



Drug design



OPTiMaDe, an API for materials data

OPTiMaDe consortium developed **common API** to access electronic structure databases: [AFLOW](#), [COD](#), [TCOD](#), [Materials Cloud](#), [Materials Mine](#), [MPDS](#), [Materials Project](#), [NoMaD](#), [Open Materials Database](#), [OQMD](#)

Funding from CECAM to extend to **molecular dynamics** data

Next workshop at CECAM: 8-12 June 2020

<https://www.optimade.org/>



Interest in technical committee

Curation, dissemination, and exploitation of materials data

Knowledge of application of machine learning to materials data

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Website

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Demo

https://app.intellegens.ai/steel_optimise

Papers

<https://intellegens.ai/article-type/papers/>