

Learning to commercialize deep learning

Gareth Conduit

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



Design new materials that fulfil **multiple target** criteria in yield, hardness, melting, oxidation, cost, density, fatigue, toughness, creep, and processibility



Design new materials that fulfil **multiple target** criteria in yield, hardness, melting, oxidation, cost, density, fatigue, toughness, creep, and processibility

Use a standard neural network to predict each property, **Combine results** by multiplying likelihoods

Ltot=Lyield Lhardness Lmelting Loxidation Lcost Ldensity Lfatigue Ltoughness Lcreep Lprocessibility







Ti: 3.0



Co: 20.0

Fe: 3.9



Mn: 0.2

Mo: 0.5



W: 0.5

Si: 0.2



Ta: 4.9

C: 0.02



B: 0.06

Nb: 1.1



AI: 2.4

Zr: 0.18















Ni: 47.2



900°C





2012: Microstructure







2012: Predict the yield stress





2012: Test the yield stress





2012: Test the yield stress









2012: Alloys designed



Cr-Cr₂Ta alloys Intermetallics, 48, 62



Combustor alloy GB1408536



Discovery algorithm EP14153898 US 2014/177578



Mo-Hf forging alloy EP14161255 US 2014/223465



Mo-Nb forging alloy EP14161529 US 2014/224885

RR1000 grain growth

Acta Materialia, 61, 3378



Ni disc alloy EP14157622 US 2013/0052077 A2



2013: Property-property correlations







::: Materials

Solutions

2013: Alloy for 3D printing: property-property correlations

Extrapolate ten results for processibility with weldability

CompositionCompositionImage: Sector Sector



:: Materials

 \equiv Solutions

2013: Alloy for 3D printing: property-property correlations



Extrapolate ten results for processibility with weldability







2014: Further materials design

Battery design with DFT and experimental data





2014: Further materials design

Battery design with DFT and experimental data





Designing lubricants with DFT and experimental data







2014: Further materials design

Battery design with DFT and experimental data

SAMSUNG



Designing lubricants with DFT and experimental data

Identified and corrected errors in materials database











2015: Further capabilities

Extract information out of noise



2015: Further capabilities

Extract information out of noise

Merge two datasets together







2015: Further capabilities

Extract information out of noise

Merge two datasets together





Train on encrypted data





2016: Understanding of business models





2016: Understanding of business models





2016: Drug discovery



Protein activity dataset from 0.1% complete







Enhance protein activity dataset from 0.1% to 20% complete





2017: Startup Intellegens



Dr Gareth Conduit



Ben Pellegrini

2017: Startup Intellegens



Dr Gareth Conduit



Ben Pellegrini



Graham Snudden



Dr Elaine Loukes

2017: Startup Intellegens



Dr Gareth Conduit



Ben Pellegrini



Graham Snudden



Dr Elaine Loukes



Dr Thomas Whitehead





2017: Startup: initial contracts



Drug discovery





2017: Startup: initial contracts



Drug discovery







BenevolentAl

2017: Startup: initial contracts

Drug discovery

Materials design

e-therapeutics

BenevolentAl

Drug discovery





2018: Startup: plan to productize

ut composition				\bigcirc	Output properties - predicted
Iron	52.93	 •	remain %	BREDICT	
Carbon	0.2		0 to 0.43 %	PACEDIOT	Ultimate t
Manganese	1		0 to 3.0 %		2021
Silicon	2		0 to 4.75 %		
Chromium	9		0 to 17.5 %		
Nickel	10		0 to 21.0 %		
Molybdenum	4.5	•	0 to 9.67 %		
Vanadium	2.1		0 to 4.32 %		
Nitrogen	0.07		0 to 0.15 %		
Niobium	1.2		0 to 2.5 %		toon monit
Cobalt	10		0 to 20.1 %		C (Ca) Cr (C) Mm
Tungsten	4	•	0 to 9.18 %	Cr (ch	(carbon)
Aluminium	1	۲	0 to 1.8 %	Mn (mai	nganese)
Titanium	2	•	0 to 2.5 %	Mo (moly	bdenum)
Heat treatment	1000	 	800-1150 C	N	i (nickel)
				Si	(silicon)
				Young's	modulus

Yield stress	1320	± 322 MPa
Ultimate tensile strength	1951	± 209 MPa
Elongation	9	+ 3 %



2018: Exploring other verticals

Autonomous vehicles





2018: Exploring other verticals

Autonomous vehicles

Healthcare









2018: Exploring other verticals

Autonomous vehicles

Healthcare

Infrastructure











SKANSKA



Develop technology motivated by problems





Develop technology motivated by problems



Flexibility to adapt to market need



Develop technology motivated by problems



Flexibility to adapt to market need

Willingness to take risks to enable greater returns