



intellegens

Applied machine learning

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# Sustainable formulation and battery development using machine learning

Dr Tom Whitehead

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# Introducing Intellegens



## Applied machine learning

- Key use cases: Chemicals, Materials, Life Sciences, Manufacturing Processes
- Innovative method extracts value from **sparse, noisy data** to solve complex, high-dimensional problems
- Strong focus on ease-of-deployment for **immediate ROI**

Optimise products  
and processes

Save time and cost  
in experiment

# Outline



- The sustainability challenge for formulation chemistry
- ML for formulation development
- Case study: machine learning-driven battery development

# The sustainability challenge for chemistry



Driver	Technical objectives and constraints
<b>Consumption</b>	Minimise energy required for processing Minimise raw materials
<b>Sustainability</b>	Minimise carbon footprint of ingredients and processing Maximise use of recycled feedstock
<b>Supply chains</b>	Identify alternative materials

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<b>Competitiveness</b>	Maximise 'performance' Meet market requirements Minimise time-to-market

# Keystone chemistry



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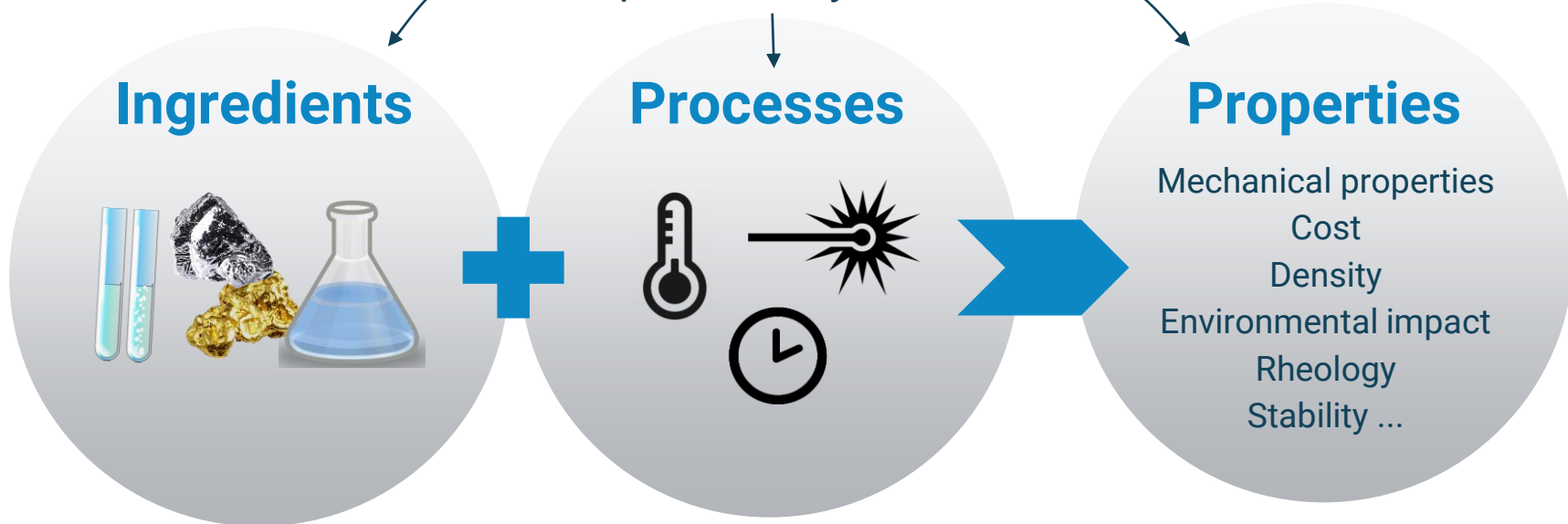
Jan Secher, CEO of Perstorp, in *Politico*



# The trillion \$ formulation problem



High-dimensional,  
sparse, noisy data



*Polymers, chemicals, pharmaceuticals,  
alloys, foods, paints, cosmetics...*

High reliance on costly, time-  
consuming experiment

# How do you solve a problem like formulation design?



**Try every  
possible  
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Guaranteed to  
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- May be infinitely many possibilities
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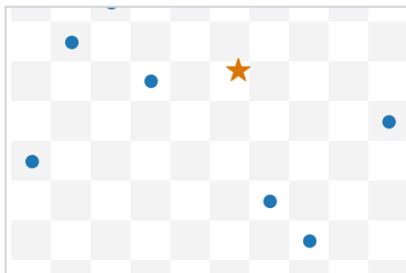
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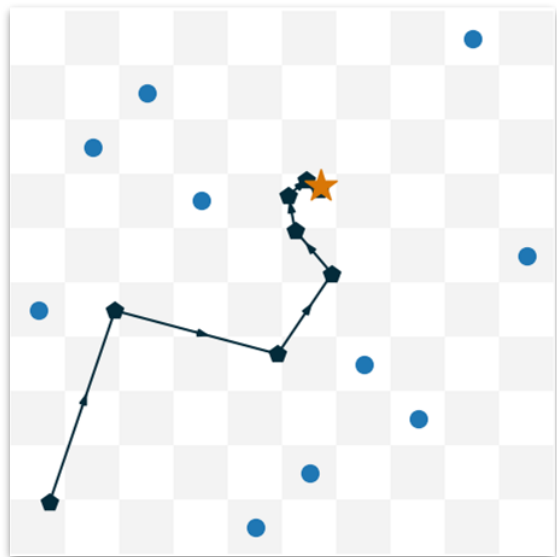


**Structured design / DoE**

Efficiently covers design space

- May require a large number of experiments
- Requires statistical knowledge

# Adaptive Experimental Design



## Machine learning-driven Adaptive Experimental Design



Target-driven: actively search for successful materials



Natively handle 100s or 1000s of variables



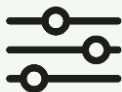
No statistical or ML knowledge needed

# Alchemite™ technology offers a unique combination



## Get value from sparse, noisy data

Unique self-consistent, iterative algorithm imputes sparse data



## Optimise against multiple targets

Solves high-dimensional problems that were intractable



Handle sparse, noisy, complex data

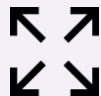
## Quantify uncertainty to enable rational decisions

Accurate method (nonparametric probability distributions)



## Make a fast start

Auto-generates models, requiring minimal assumptions



## Speed and scalability

Light CPU / memory footprint: fast and works for huge datasets



## A global view

E.g., ingredients *and* processing parameters in a combined study

A ready-to-use solution

# How can machine learning help me?

Alchemite™  
feature



**Data  
analysis**

Understand your data &  
your formulations

**Analytics**

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**Screen  
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Virtual experiments -  
'Which of my many ideas  
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Predict



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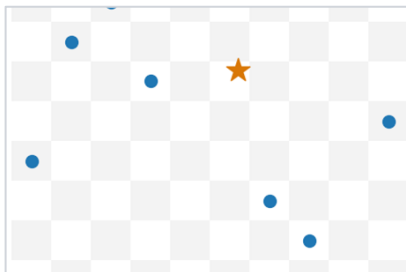
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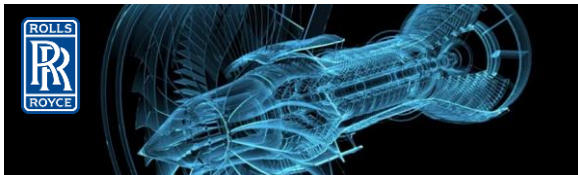


**Suggest  
experiments**

'What new formulation  
space could I explore?'  
List of potential  
experiments

Improve  
Model

# Successful applications



Design of an aero alloy

Multi-million \$ savings in discovery of new alloy



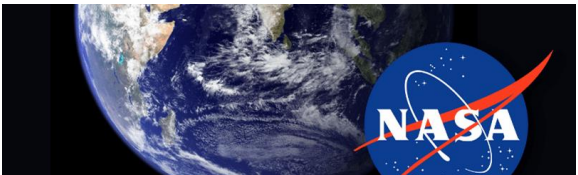
Ink reformulation

Cut experimental timescales from months to minutes



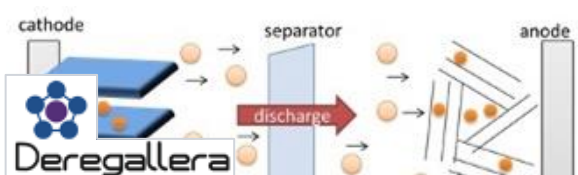
Drug discovery

Predict pharmacokinetics to improve compound selection



Component design

Validating Alchemite™ for advanced engineering at NASA



Sodium-ion batteries

Focus experiment to explore a daunting parameter space



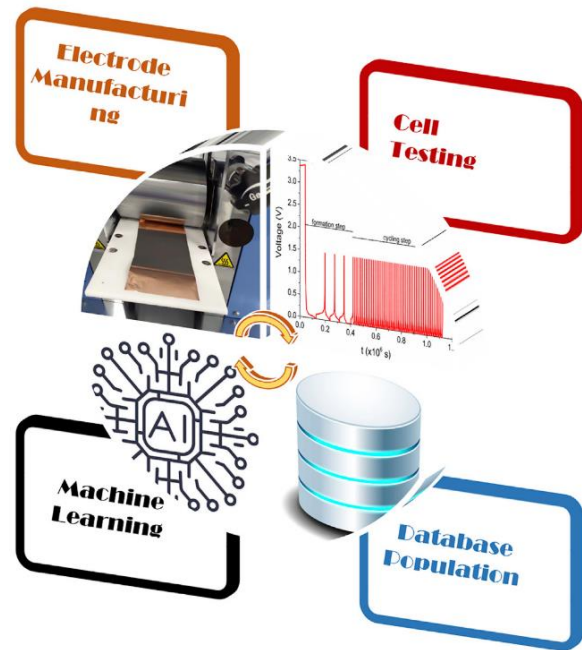
Flavours and fragrances

Predict the sensory properties of compounds

# Battery formulation and manufacturing optimization

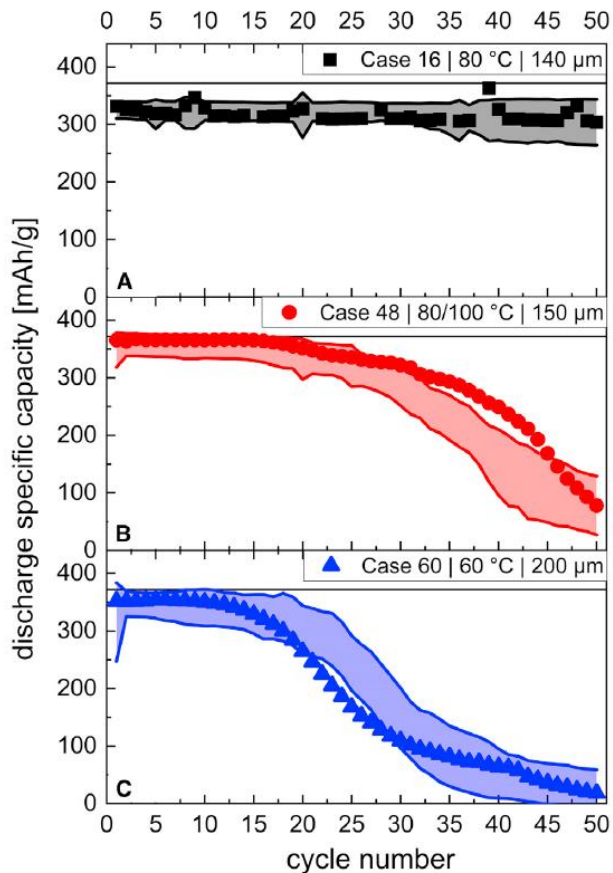


- Optimization of lithium-ion graphite-based electrodes
- Formulation and manufacturing protocols both have large impact on eventual performance
  - Difficult to uncouple



*Cell Reports Physical Science* **2**, 100683 (2021)

# Predicting discharge performance

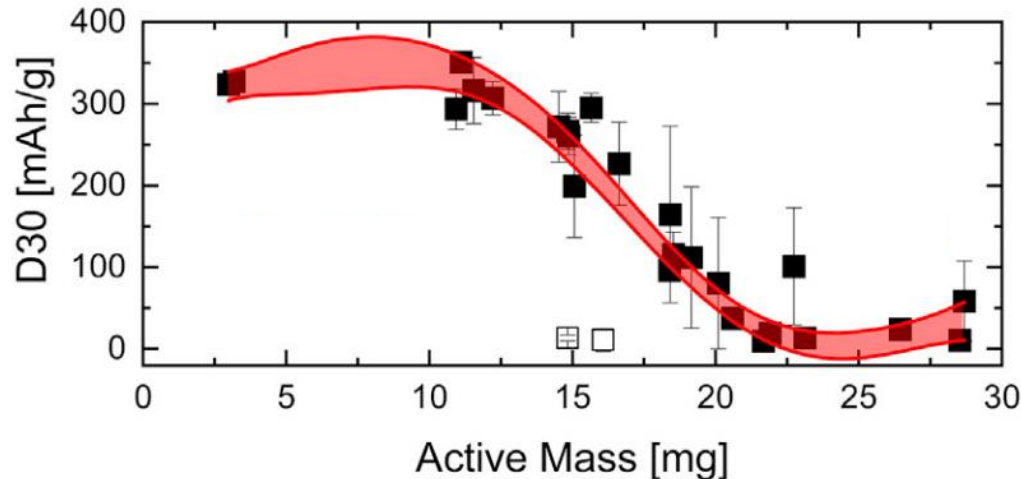


- Alchemite™ model trained on 85 cells
- Tested against cells generated after training data collected, with different manufacturing processes
- Good qualitative and quantitative agreement between model and predictions

# Electrode optimization



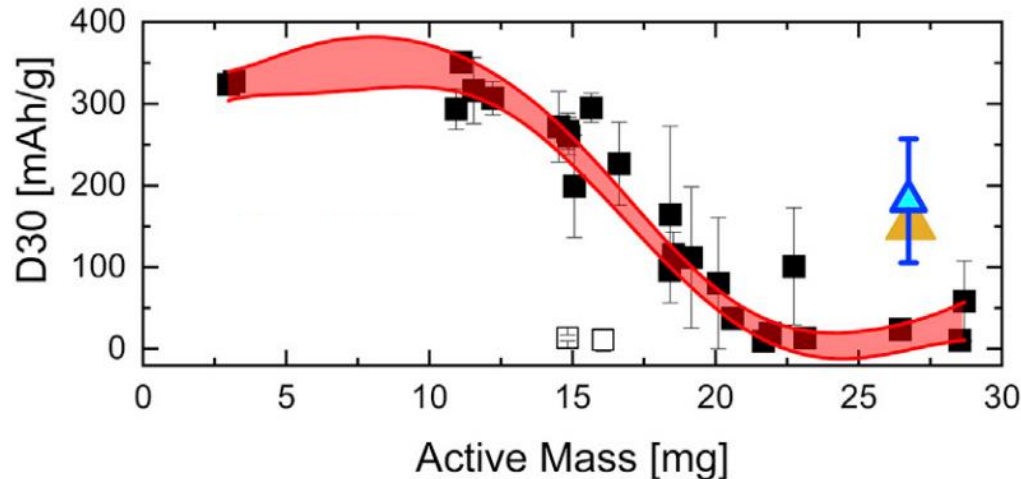
- High specific capacity ( $D_{30} > 150$  mA.h/g) only achieved for cells with low active mass ( $< 20$  mg) and thickness ( $< 100$   $\mu\text{m}$ ) in existing cells
  - Faster lithiation and delithiation
- For high-energy-density applications we need improved areal capacity



# Electrode optimization



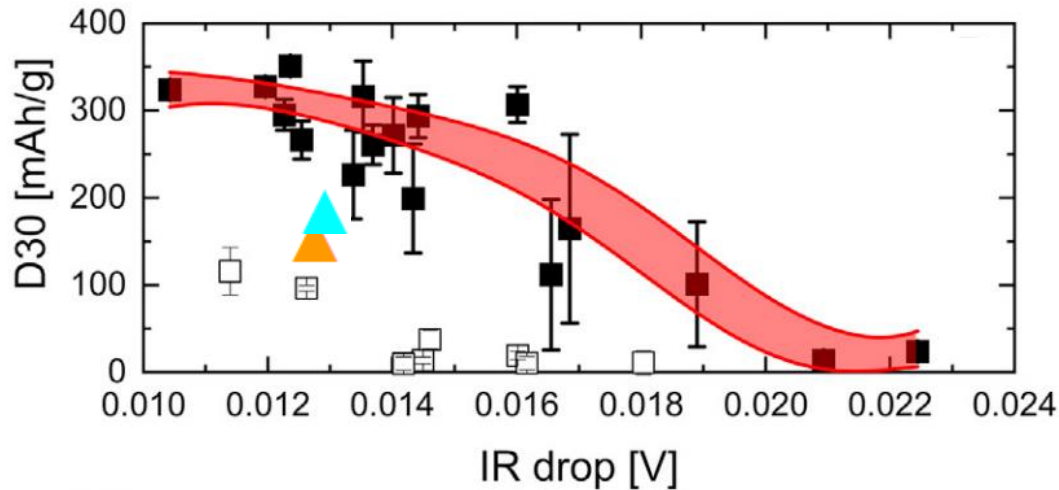
- Alchemite™ proposed cell with lower carbon black, reducing binder requirement and increasing graphite content
- Alchemite™ predictions (▲) confirmed by experiment (▲)
- **2.5x** higher D30 (152 mA.h/g) than cells with similar active mass



# Other properties



- Internal resistance of cell gives clues to mechanism
- Alchemite™ able to predict all experimental properties simultaneously: analyse mechanism without running all experiments



# Acknowledgements



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  - Emma Kendrick

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# Any questions?

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