



Machine learning for battery discovery

Gareth Conduit

Alchemite™ for materials design



Train from **sparse** datasets with technology from University of Cambridge

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

Nickel-Cobalt-Manganese (NCM) battery materials



Properties of interest



Number of uses



Range



Speed



Cost

Battery properties of interest



Cycles



Charge



Potential



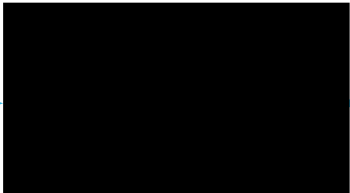
Cost



Black box machine learning for materials design



Composition

A collection of icons representing material composition, including various types of rocks and minerals, a pile of red powder, a thermometer with both Fahrenheit and Celsius scales, and a clock face.

Cycles A digital counter device with a small screen showing '000' and a button.

Charge A digital ammeter labeled 'SCHOOL AMPMETER' and 'AMPS' with a red 'A' symbol, showing '0.00' on its display.

Potential A digital voltmeter labeled 'SCHOOL VOLTMETER' and 'VOLTS' with a blue 'V' symbol, showing '0.00' on its display.

Cost A pile of US dollar bills, representing the financial cost of the materials or process.

Training machine learning



Cycles

Charge

Potential

Cost

A vertical stack of images including a digital multimeter, an analog ammeter, a digital voltmeter, and a pile of US dollar bills, representing electrical measurements and cost.

Machine learning for materials design



Cycles 

Charge 

Potential 

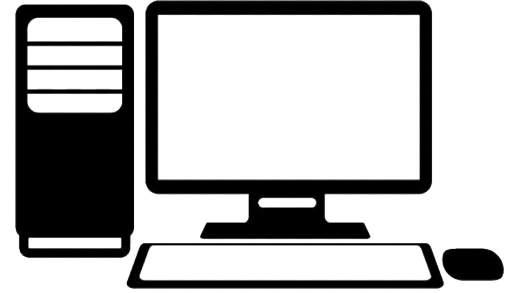
Cost 

Two sources of information



Experiment

Accurate
Quantities of interest
Lack of data
Expensive



Computational

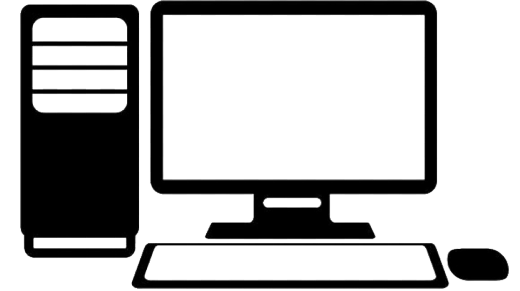
Less accurate
Atom level insights
Perform on demand
Cheap to perform

Merge information with machine learning



Experiment

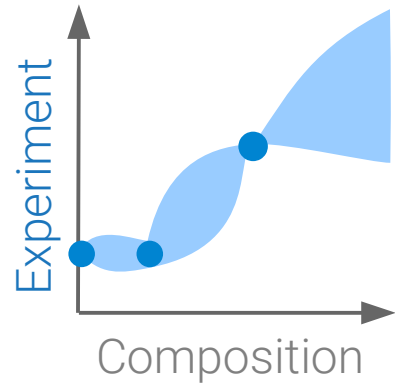
Accurate
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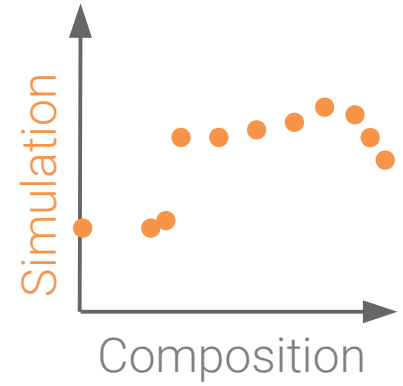
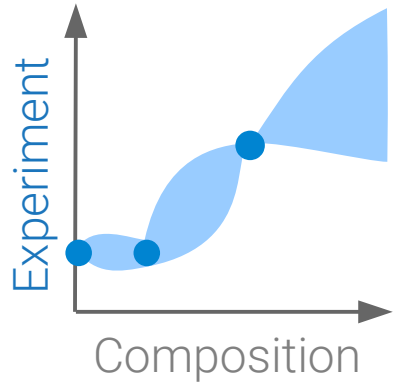
Computational

Less accurate
Atom level insights
Perform on demand
Cheap to perform

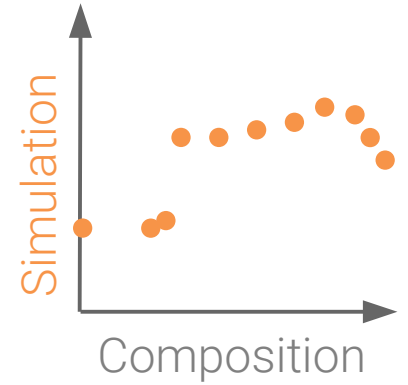
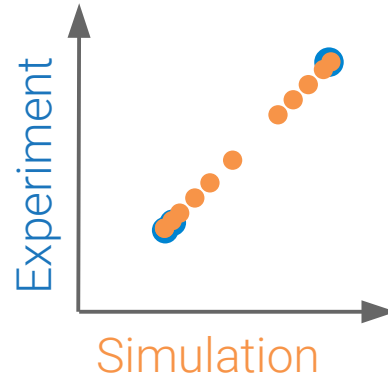
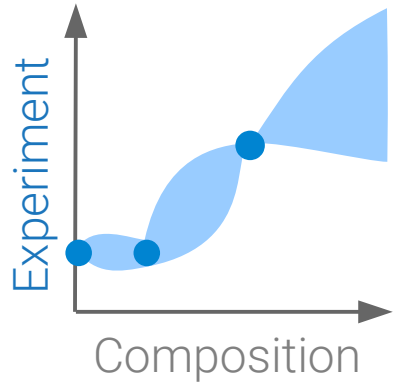
Little data to train machine learning model



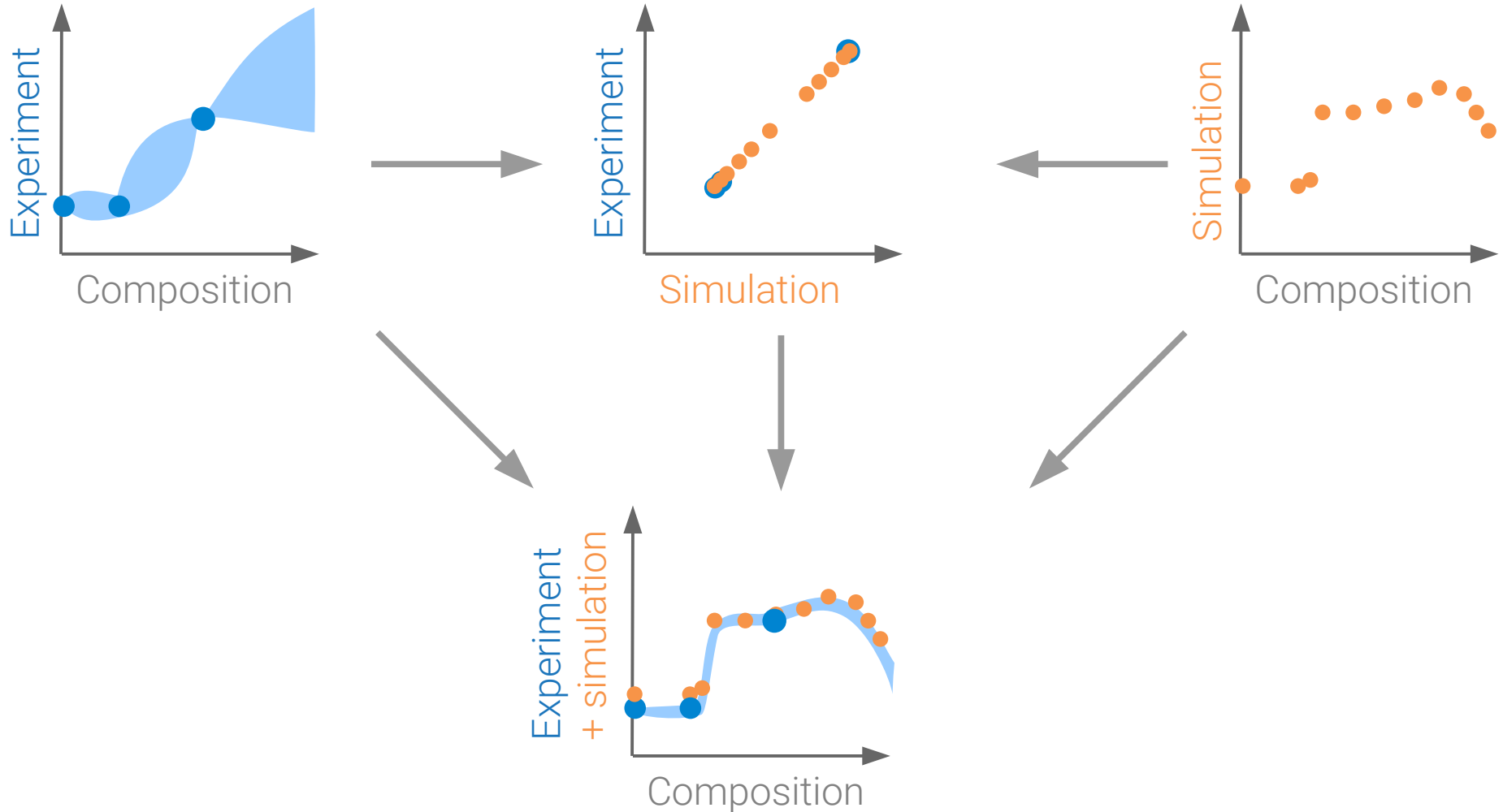
Complementary computer simulations



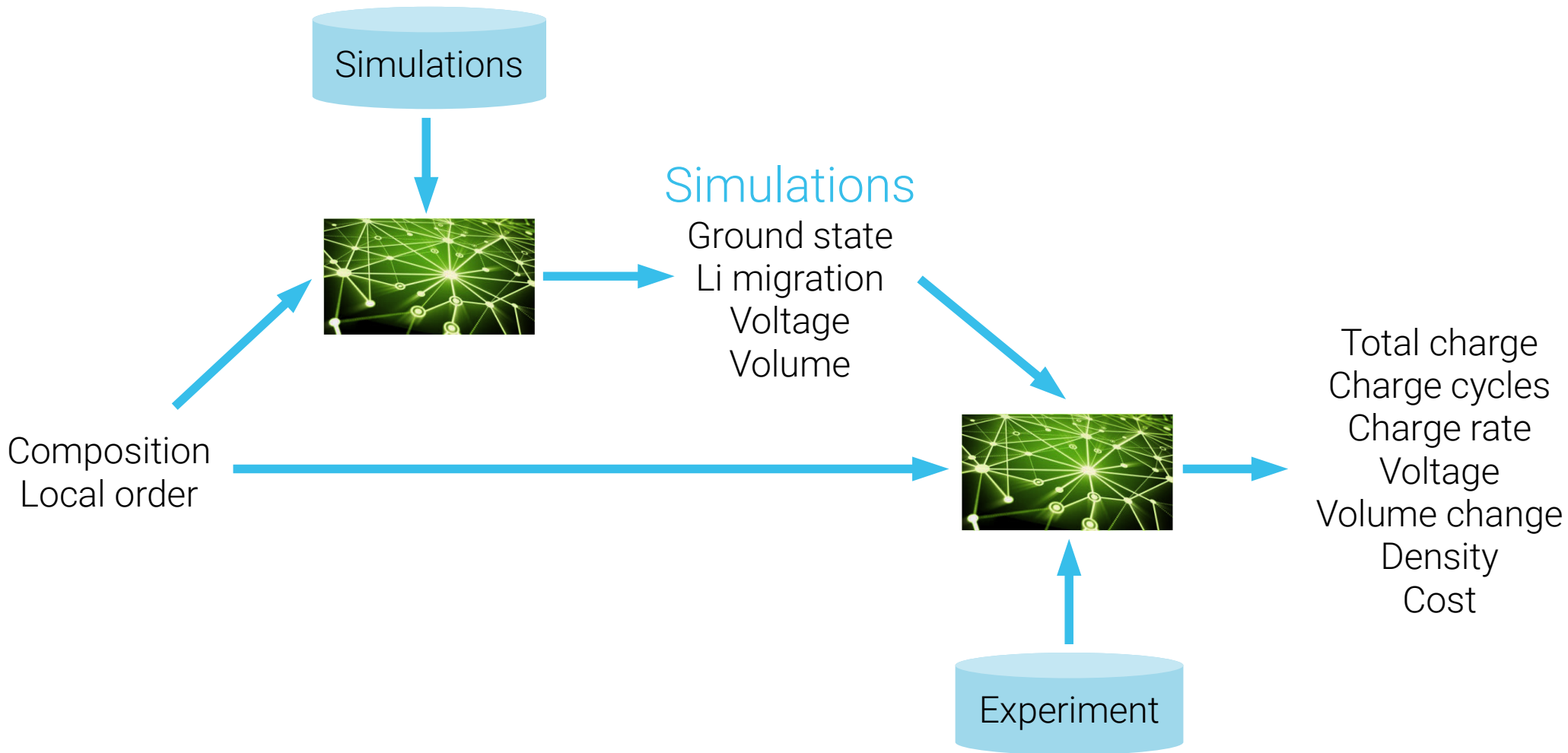
Simulations make accurate but not perfect predictions



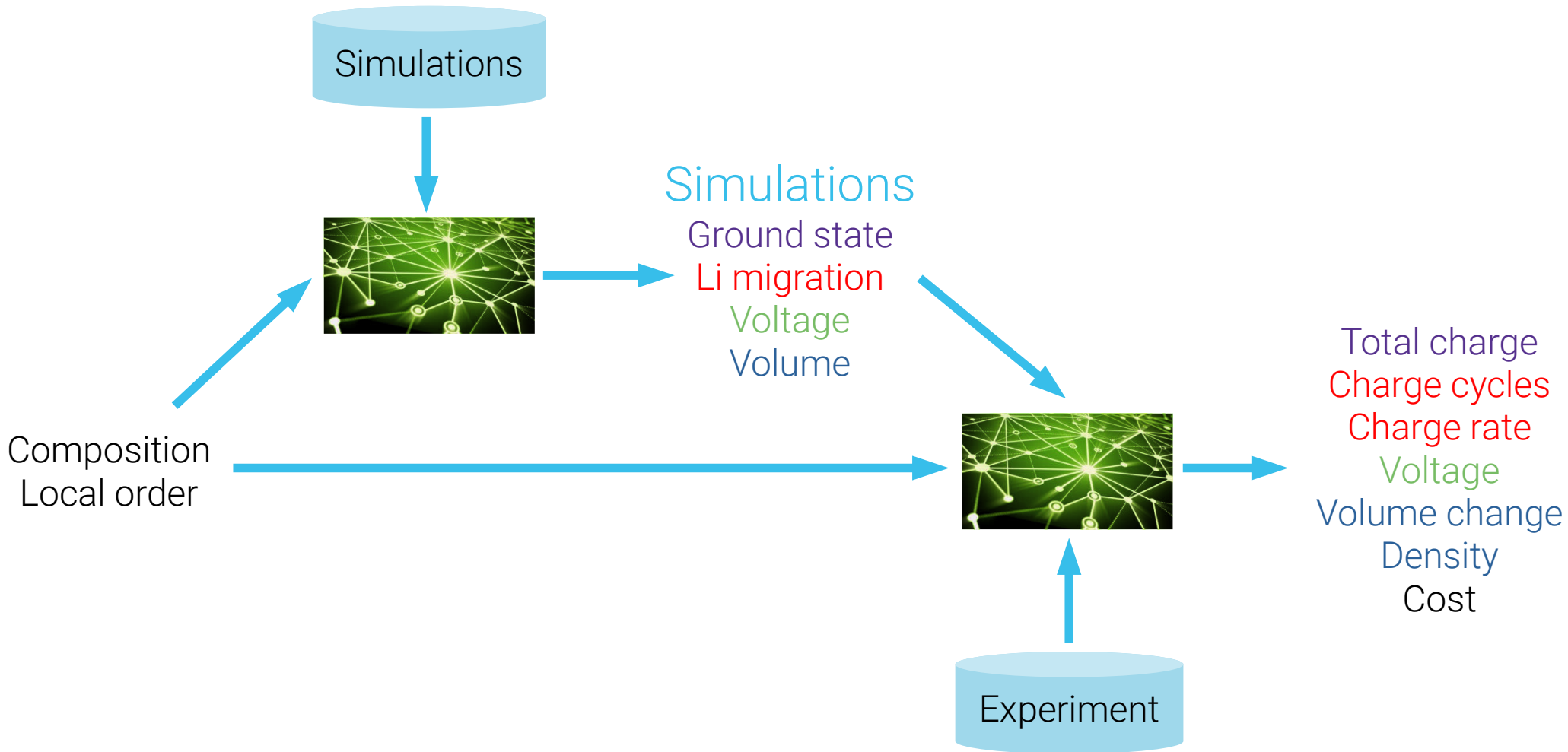
Simulations guide extrapolation of experimental data



Merge computational and experimental data



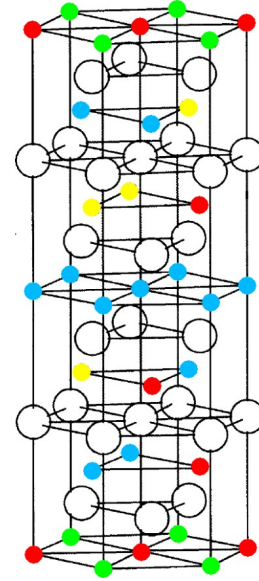
Merge computational and experimental data



Battery cathode design

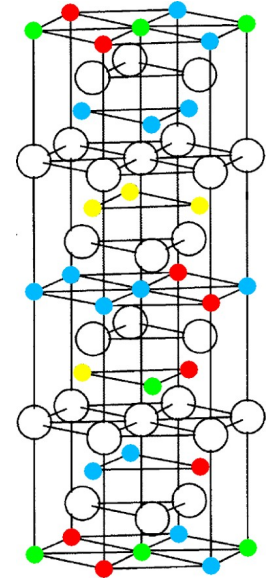


Reduce Li migration so improve battery life



Original

82% robust



Proposed

100% robust

Battery cathode design

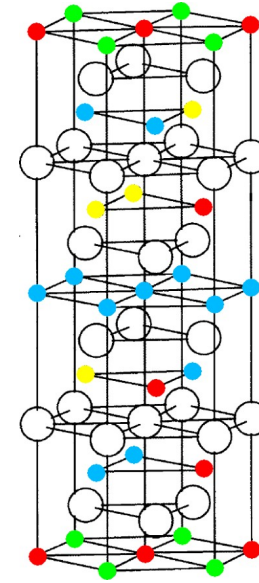


Reduce Li migration so improve battery life

Maintain voltage, charge stored, density, and cost

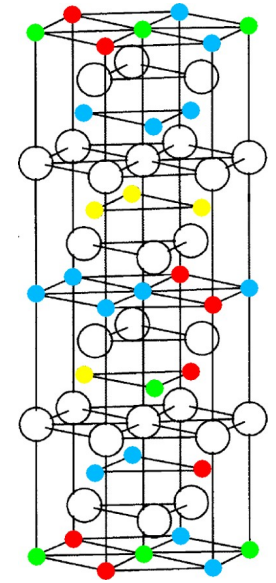
Empowers specification of the optimal components

Bespoke battery design for each customer



Original

82% robust



Proposed

100% robust

Battery management system



In-service data from a **particular battery** and **others deployed** to make bespoke predictions of remaining useful life



Predicting the state of charge and health of batteries using data-driven machine learning

Man-Fai Ng¹, Jin Zhao², Qingyu Yan², Gareth J. Conduit³ and Zhi Wei Seh⁴

Machine learning is a specific application of artificial intelligence that allows computers to learn and improve from data and experience via sets of algorithms, without the need for reprogramming. In the field of energy storage, machine learning has recently emerged as a promising modelling approach to determine the state of charge, state of health and remaining useful life of batteries. First, we review the two most studied types of battery models in the literature for battery state prediction: the equivalent circuit and physics-based models. Based on the current limitations of these models, we showcase the promise of various machine learning techniques for fast and accurate battery state prediction. Finally, we highlight the major challenges involved, especially in accurate modelling over length and time, performing in situ calculations and high-throughput data generation. Overall, this work provides insights into real-time, explainable machine learning for battery production, management and optimization in the future.

With rising concerns about global warming, electrification of transport has recently emerged as an important vision in many countries. The successful development of electric vehicles (EVs) depends highly on the cycling performance, cost and safety of the batteries. Rechargeable lithium-ion (Li-ion) batteries are currently the best choice for EVs due to their reasonable

where C_{cur} is the capacity of the battery in its current state, C_{full} is the capacity of the battery in its fully charged state, C_{nom} is the nominal capacity of the brand-new battery².

In essence, SOC denotes the capacity of the battery in its current state compared to the capacity in its fully charged state (equivalent of a fuel gauge), while SOH describes the capacity of the battery

Predicting the State of Charge and Health of Batteries using Data-Driven Machine Learning
Nature Machine Intelligence 2, 161 (2020)

Battery management system



In-service data from a **particular battery** and **others deployed** to make bespoke predictions of remaining useful life

Model that spans time-scales to permit simultaneous **state-of-health** and **state-of-charge** predictions

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Battery management system



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Model that spans time-scales to permit simultaneous **state-of-health** and **state-of-charge** predictions

Data from testing in **first few cycles** with in-house **long-term** testing to predict long-term battery performance



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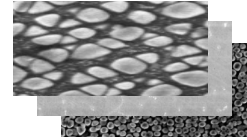
Other materials designed



Titanium additive manufacturing



High temperature alloys



Lubricants



Pharmaceuticals



Journal of Chemical Physics 153, 014102 (2020)

Fluid Phase Equilibria 501, 112259 (2019)

Materials & Design 168, 107644 (2019)

Computational Materials Science 147, 176 (2018)

Physical Review Applied 12, 034024 (2019)

Matter 1, 219 (2019)

Scripta Materialia 146, 82 (2018)

Materials & Design 131, 358 (2017)

Prospects for the future



Alchemite™, a full stack machine learning solution to **merge** sparse data, including computational simulations and experimental data

Design battery cathode materials with longer life

Embedded battery management software

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Demo	https://app.intellegens.ai/steel_optimise
Papers	https://www.intellegens.ai/paper.html