

Breakthroughs in data driven materials design

EP14153898.3; US 2014/177578; GB1302743.8

EP14161255.6; US 2014/223465; GB1307533.8

EP14161529.4; US 2014/224885; GB1307535.3

EP14157622.3; amendment to US 2013/0052077 A1; GB1408536.9

Acta Materialia **61**, 3378 (2013)

Intermetallics **48**, 62 (2014)

Phys. Rev. B **90**, 184302 (2014)

Samsung GRO 2013

Theory of Condensed Matter Group, Department of Physics

Materials design using machine learning

Experimental data

First principles calc

Physical models



The screenshot shows the MAGE software interface. At the top, there are buttons for 'Optimize', 'Iteration', 'Probability 0.000', and 'Stagnation'. The status is 'Waiting'. Below this, there are two main panels: 'Specification' and 'Composition'.

Specification

Property	Value	Error	Target
Density kg/m ³	1051.15 ±	1.90	< 1330.00
Cost \$/mol	193.78 ±	0.27	< 400.00
Band gap min eV	2.66 ±	0.00	> 2.45
Efficacy photopic %	37.39 ±	0.25	> 41.00
Efficacy s (blue) %	78.69 ±	0.39	> 70.00
Carrier density	1.50 ±	0.01	> 0.41
Band gap max eV	2.66 ±	0.00	< 2.95
Direct band gap	1.00 ±	0.00	> 0.80
Scissor operator	1.87 ±	0.00	> 0.00

Composition

Element	Conc	Element	Conc	Element	Conc
N	0.500	Al	0.000	P	0.000
Ga	0.375	As	0.000	In	0.125
Sb	0.000	Bi	0.000		



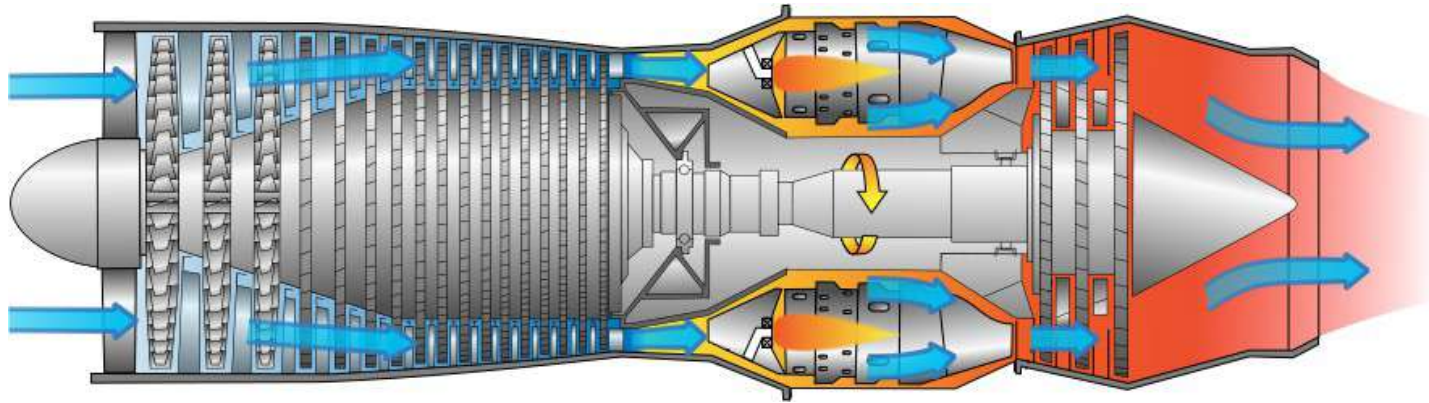
Alloys

Semiconductors

NCM battery

Oil discovery

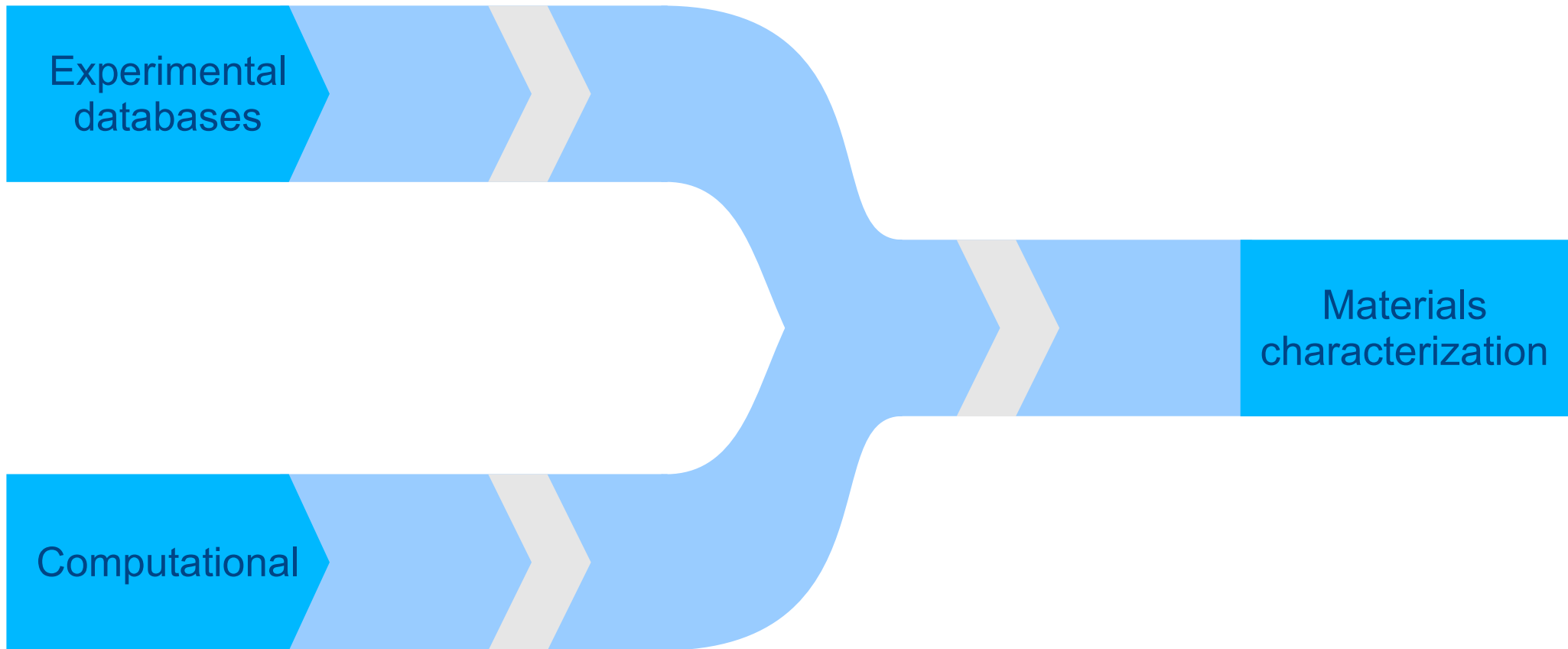
Schematic of a jet engine



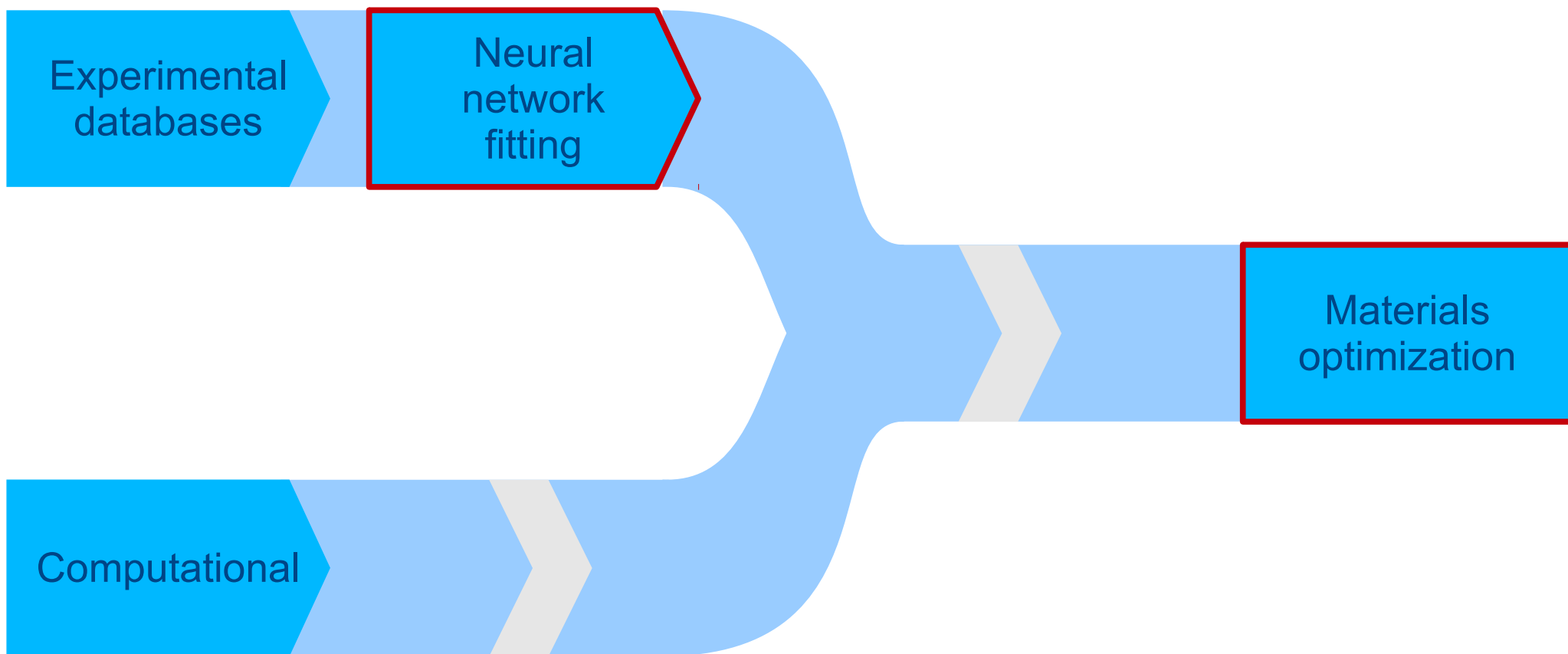
Designing a new alloy – what is required?



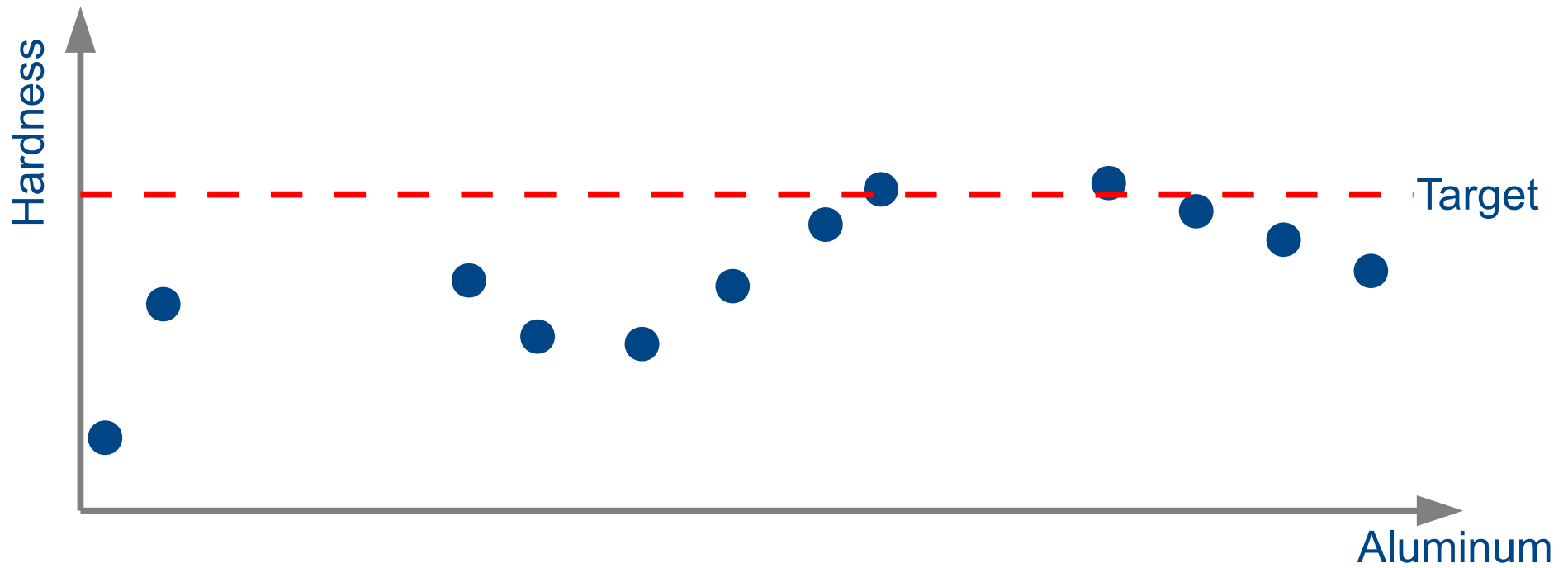
Materials design pipeline



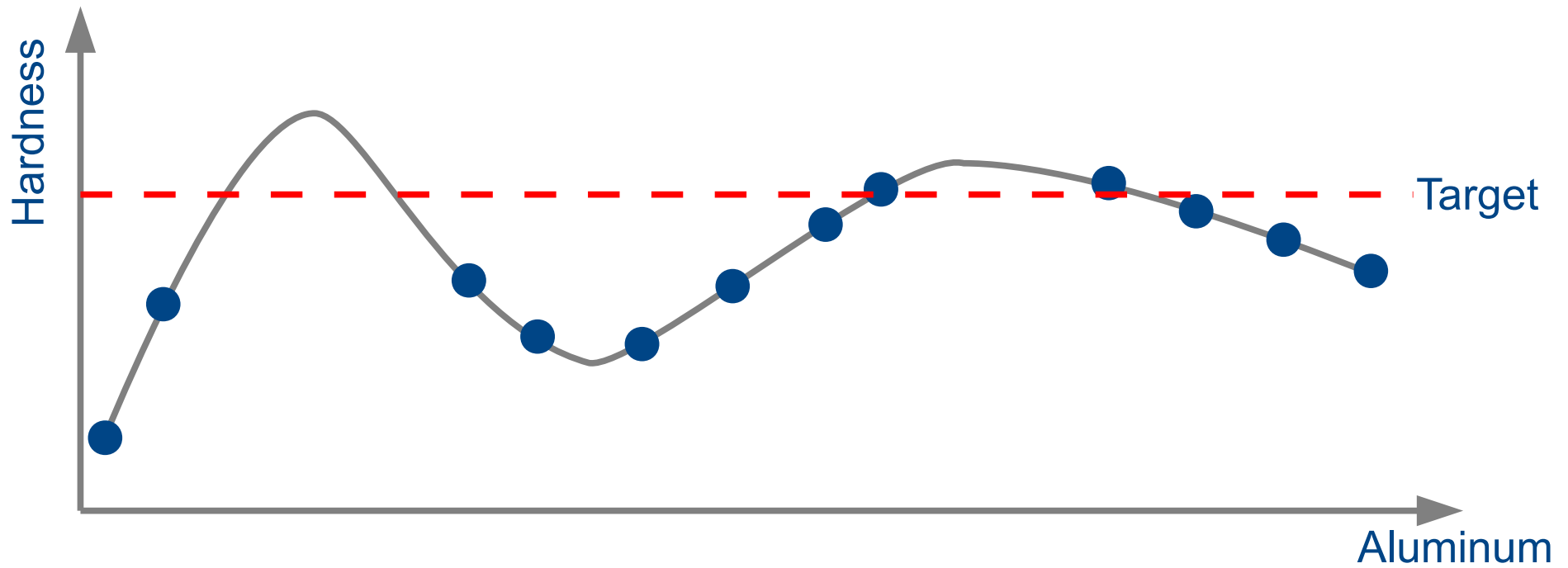
Two new tools in the materials design pipeline



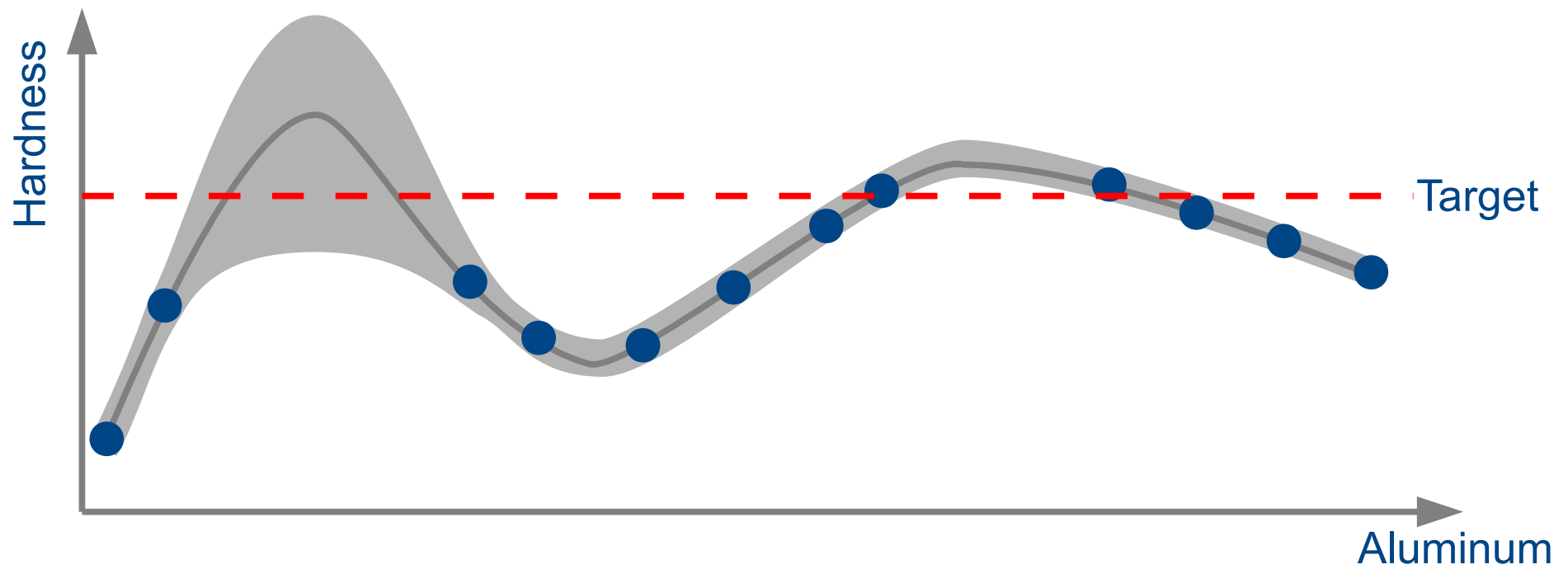
Neural network fitting & optimization



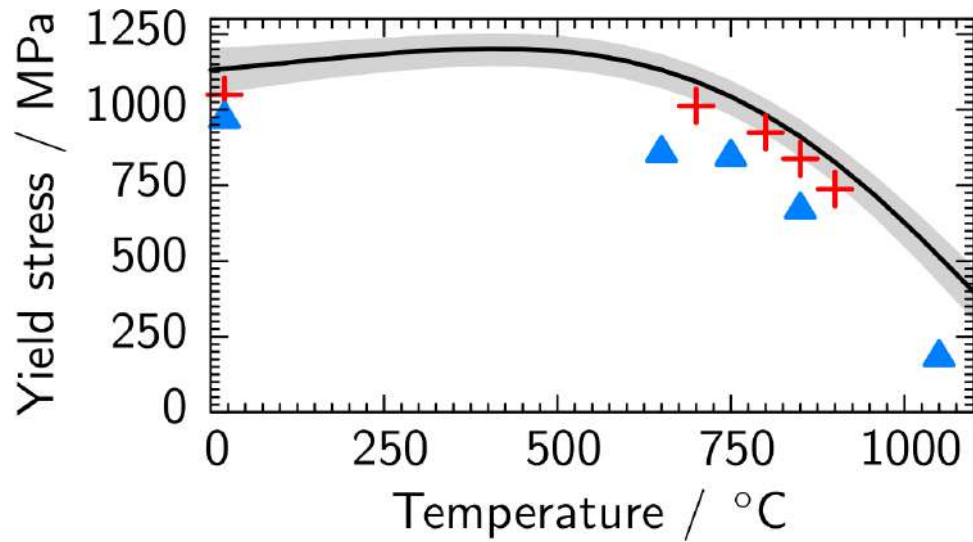
Neural network fitting & optimization



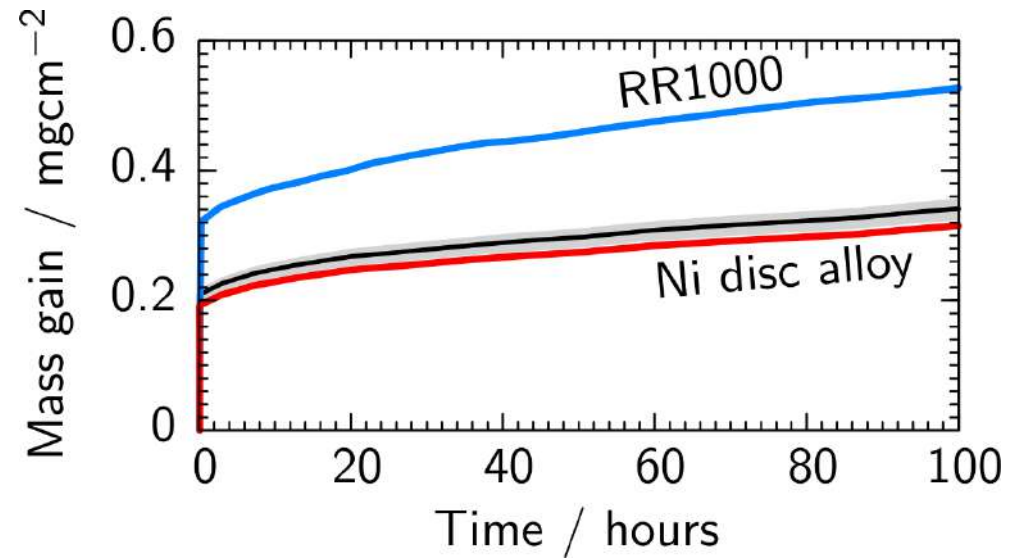
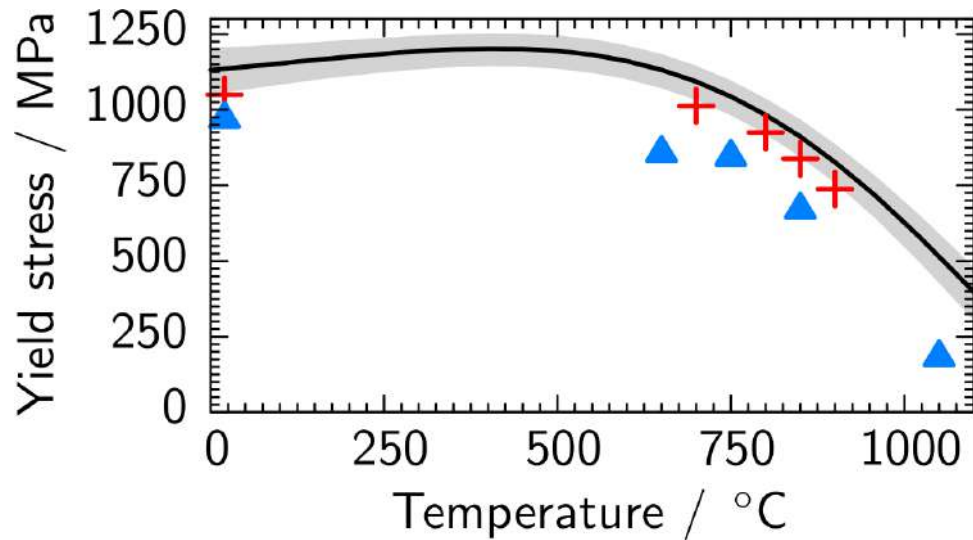
Neural network fitting & optimization



Experimental verification of a Ni-base superalloy



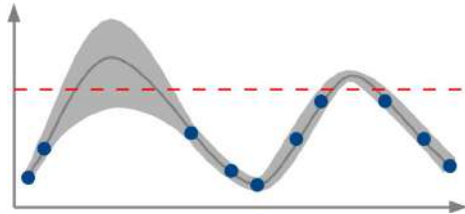
Experimental verification of a Ni-base superalloy



Alloys discovered

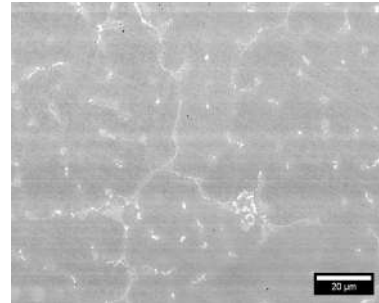
Discovery algorithm

EP14153898.3
US 2014/177578
GB1302743.8



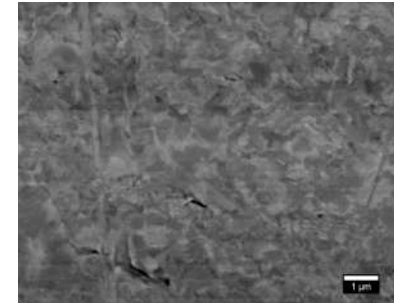
Mo-Hf forging alloy

EP14161255.6
US 2014/223465
GB1307533.8



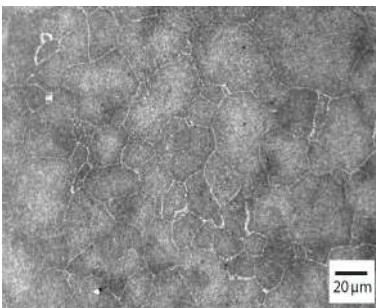
Mo-Nb forging alloy

EP14161529.4
US 2014/224885
GB1307535.3



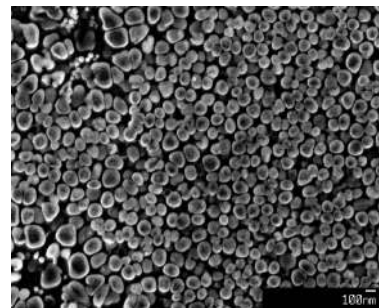
RR1000 grain growth

Acta Materialia, 61, 3378



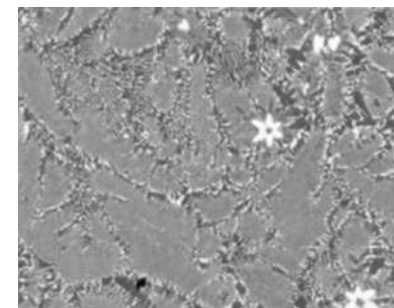
Ni disc alloy

EP14157622.3
US 2013/0052077 A2
GB1408536.9

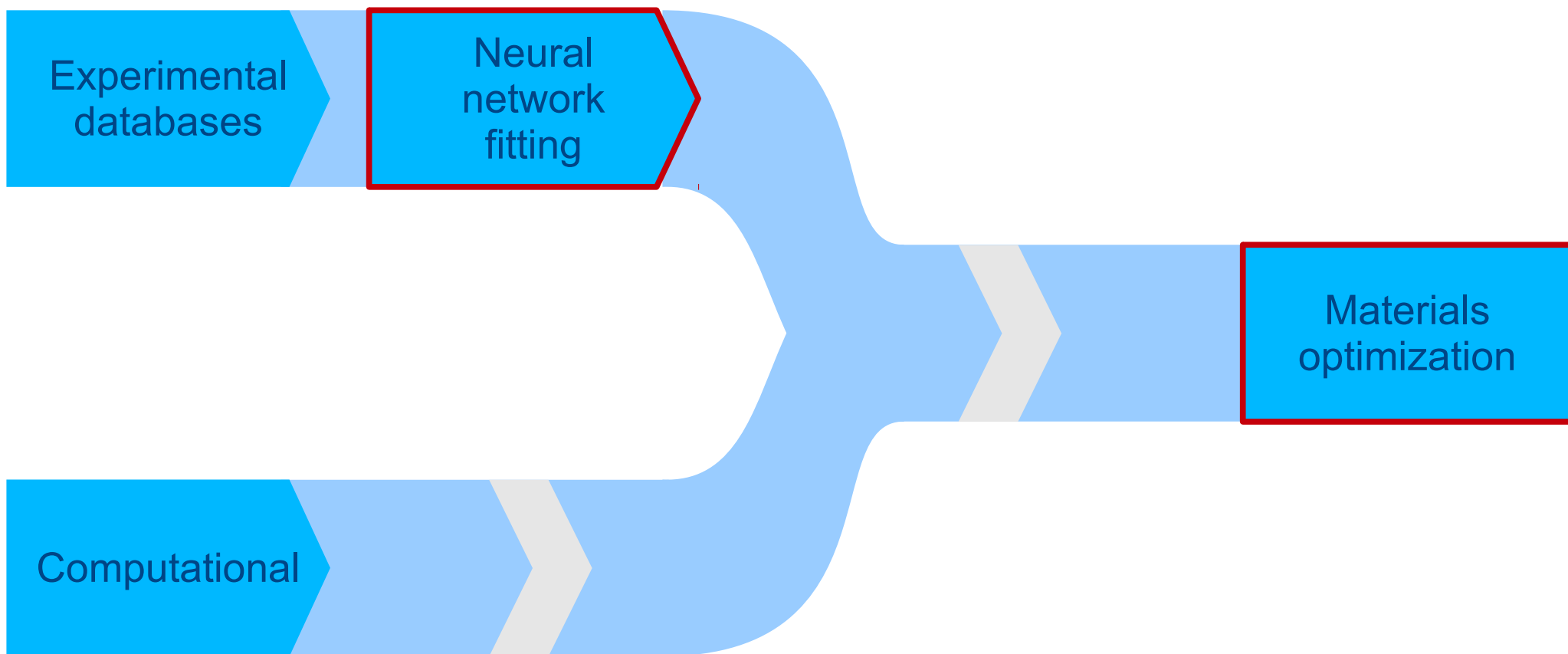


Cr-Cr2Ta alloys

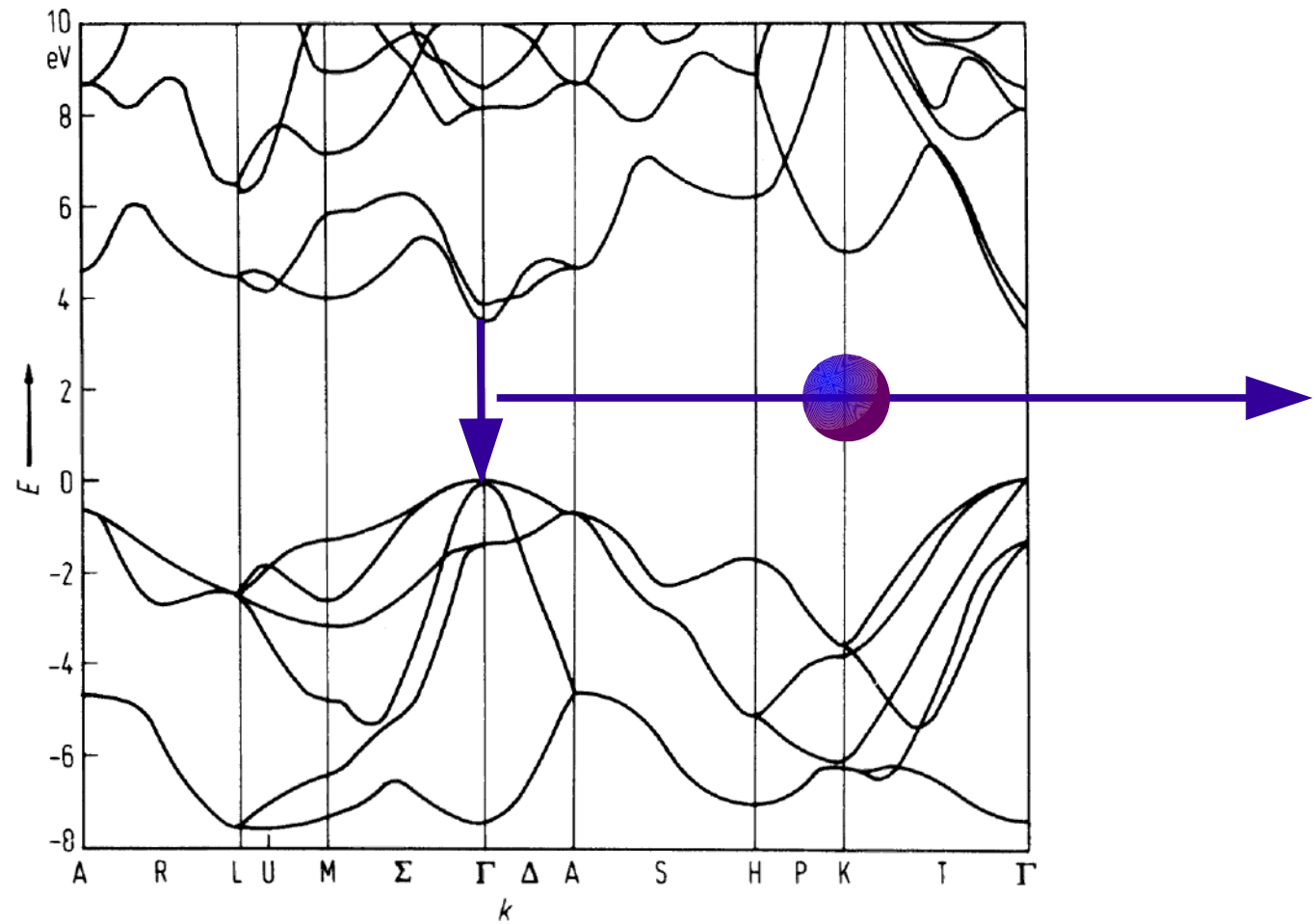
Intermetallics 48, 62



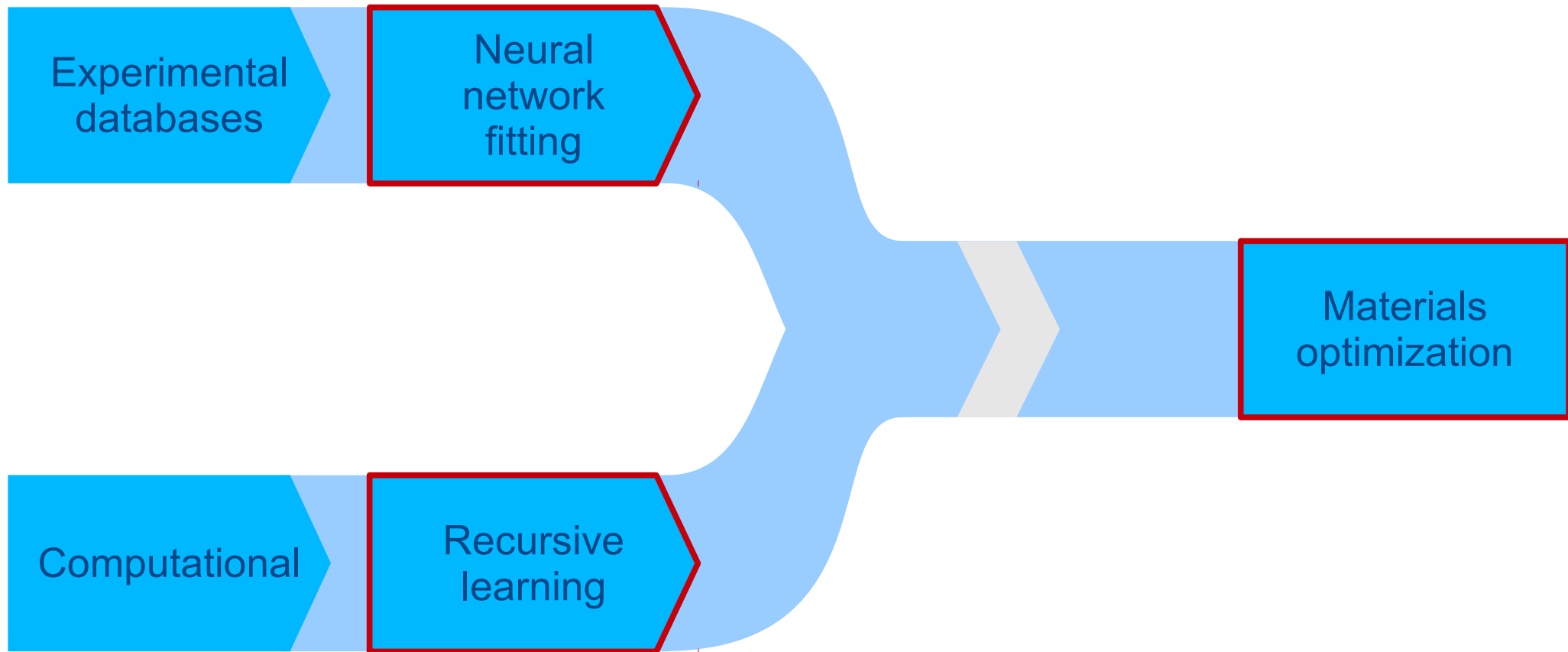
Two new tools in the materials design pipeline



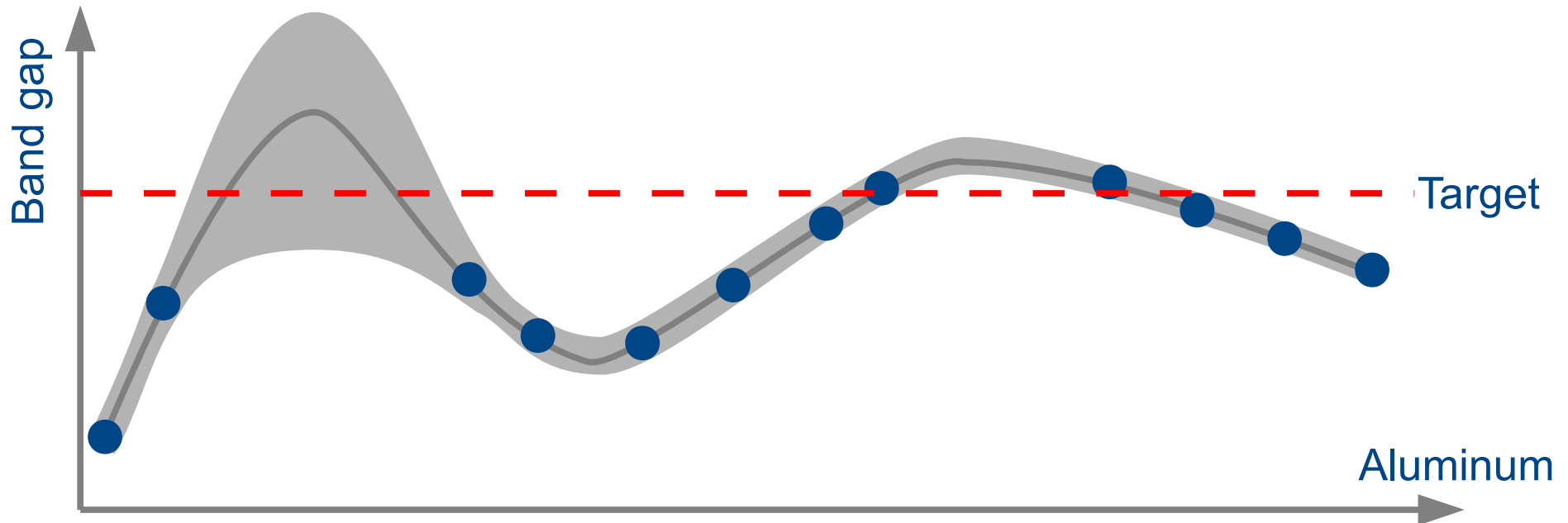
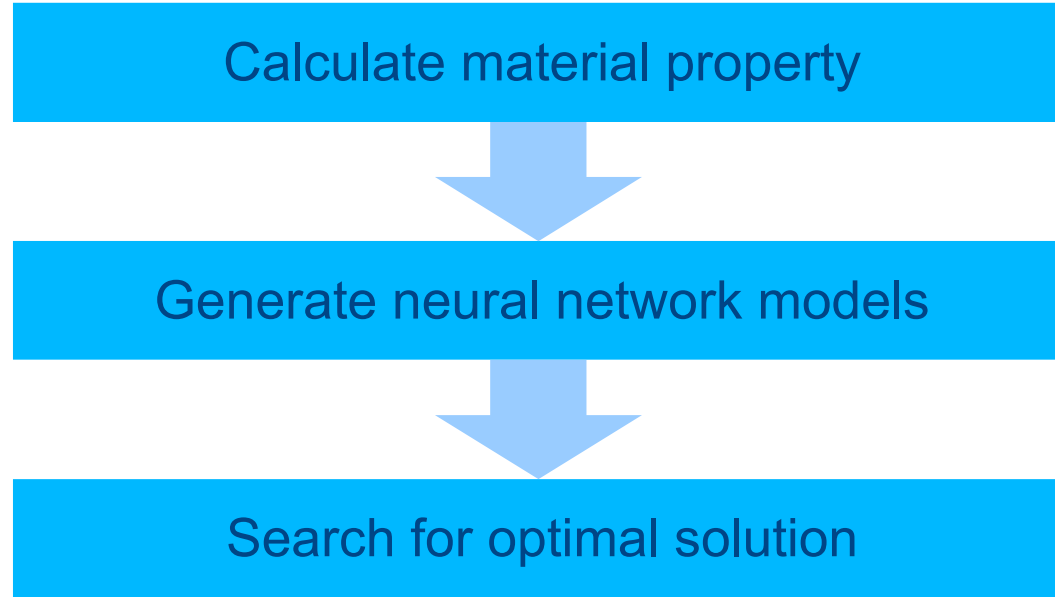
InGaN-base semiconductors for blue LEDs



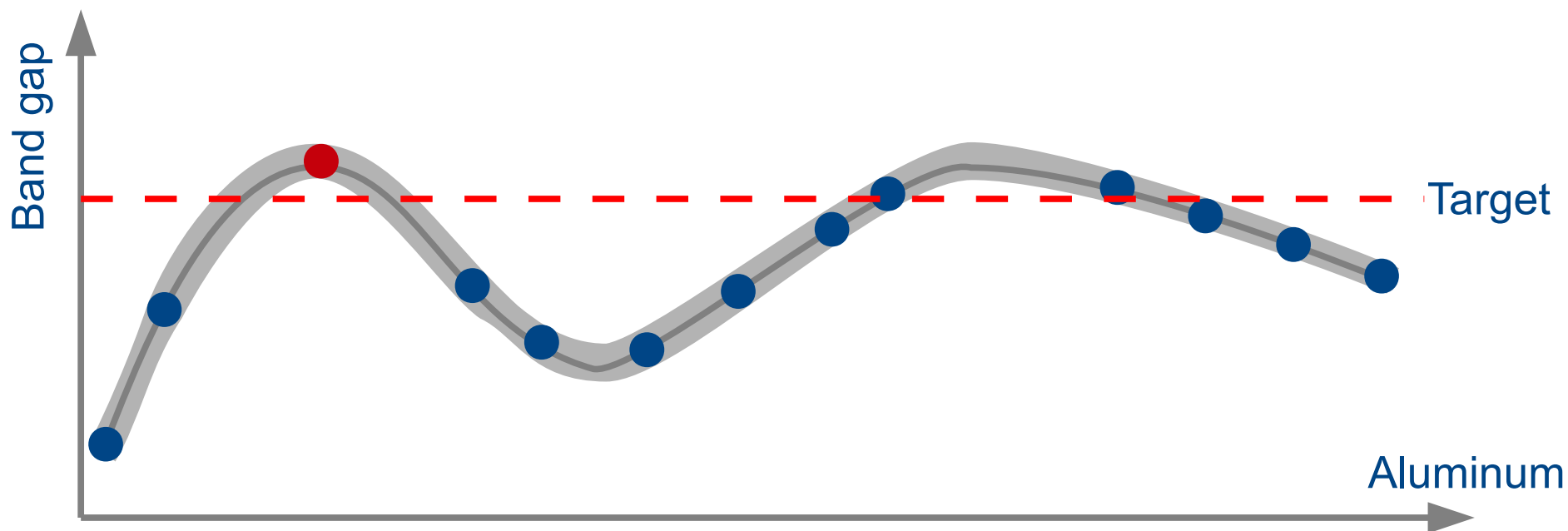
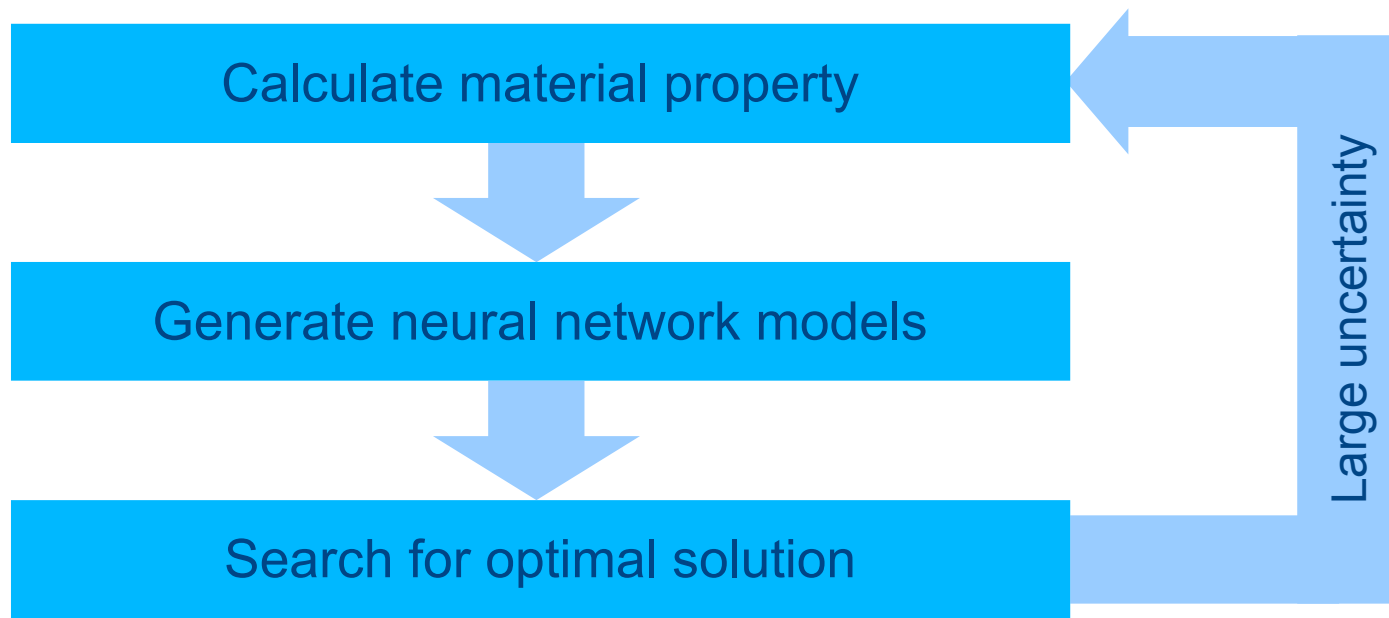
Three new tools in the materials design pipeline



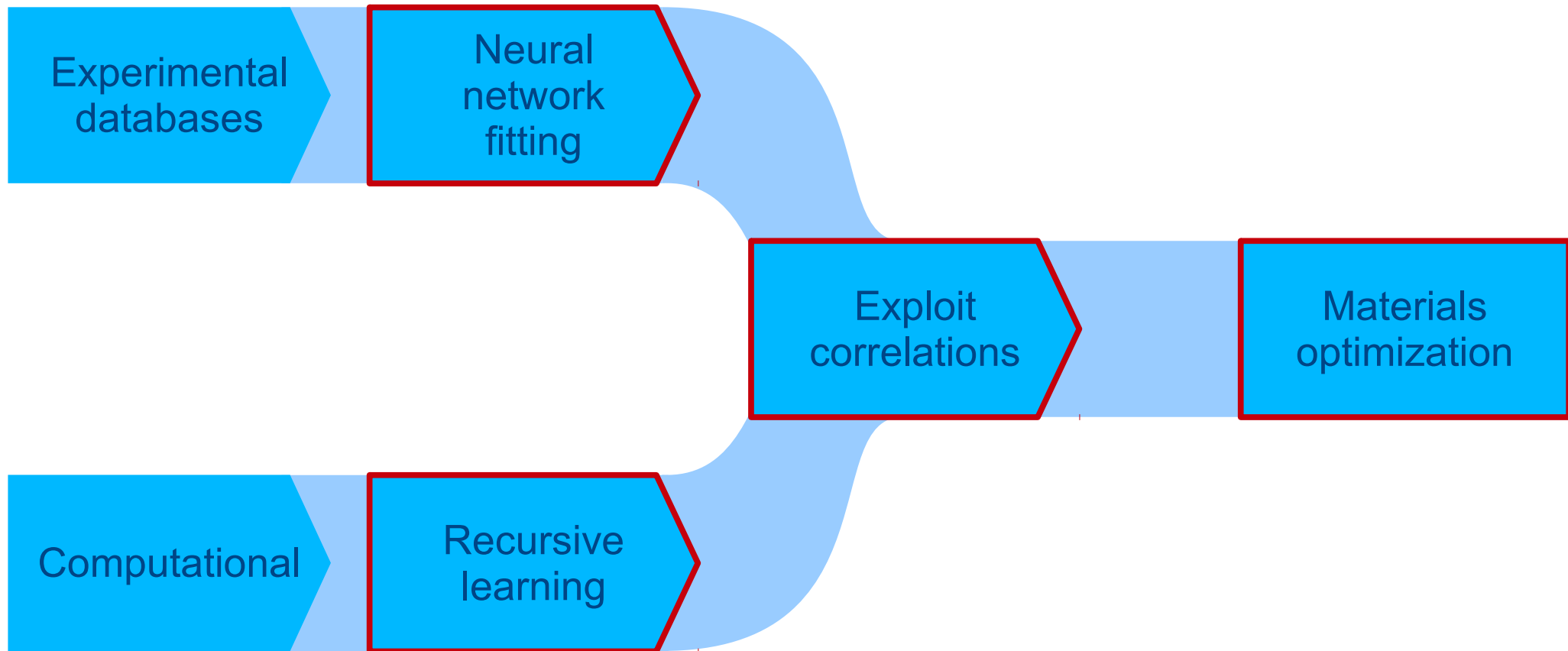
Recursive learning in neural networks



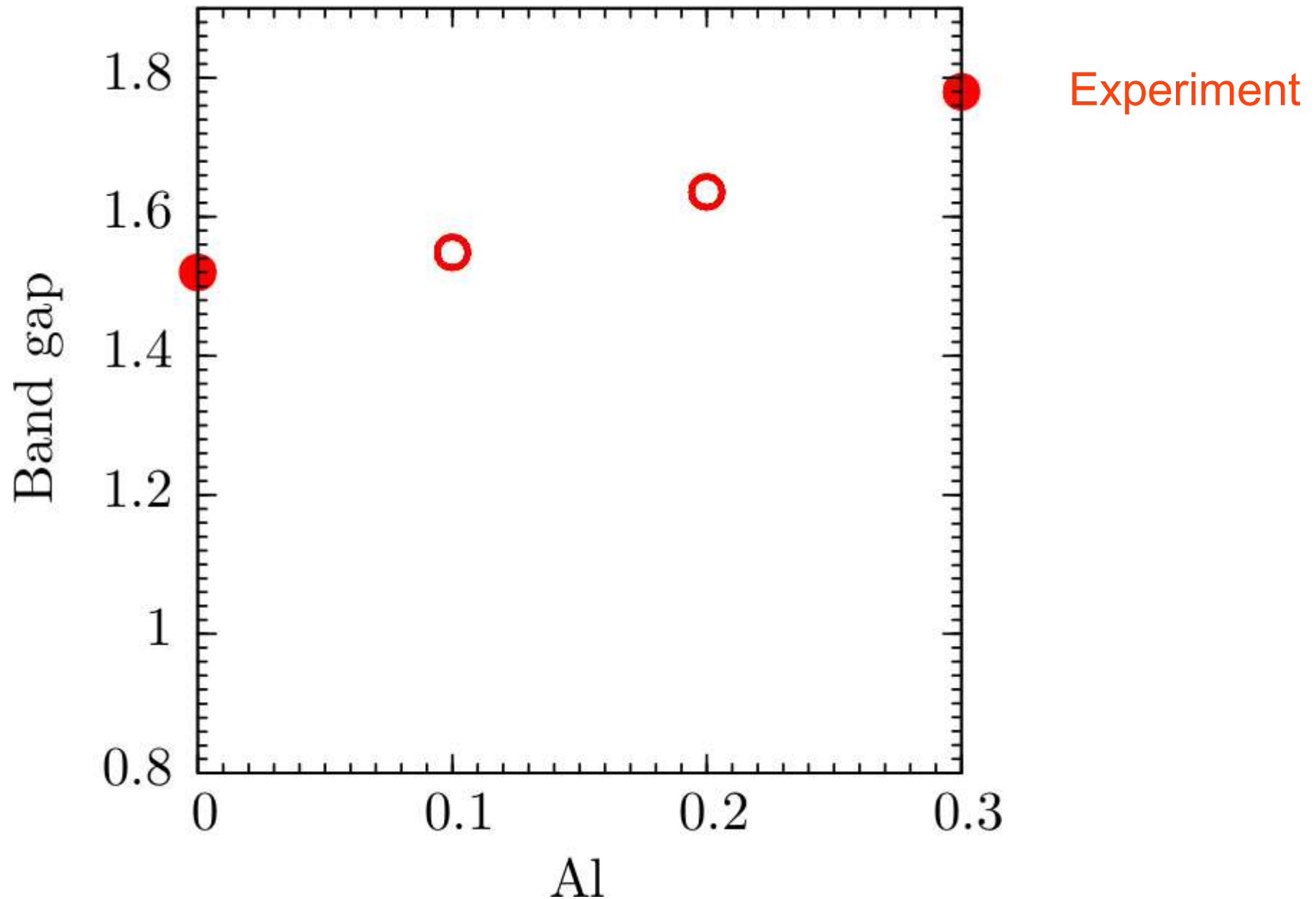
Recursive learning in neural networks



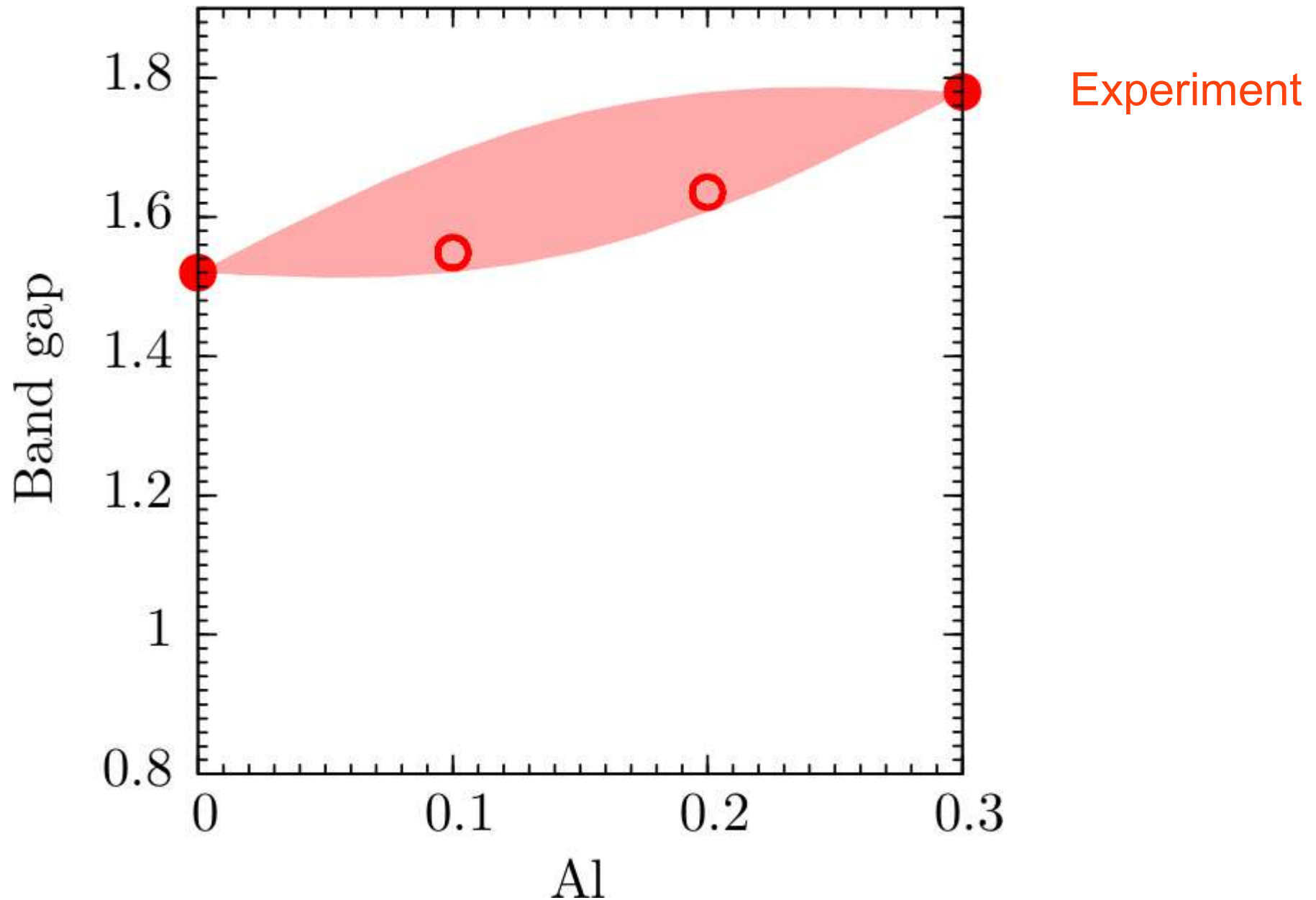
Four new tools in the materials design pipeline



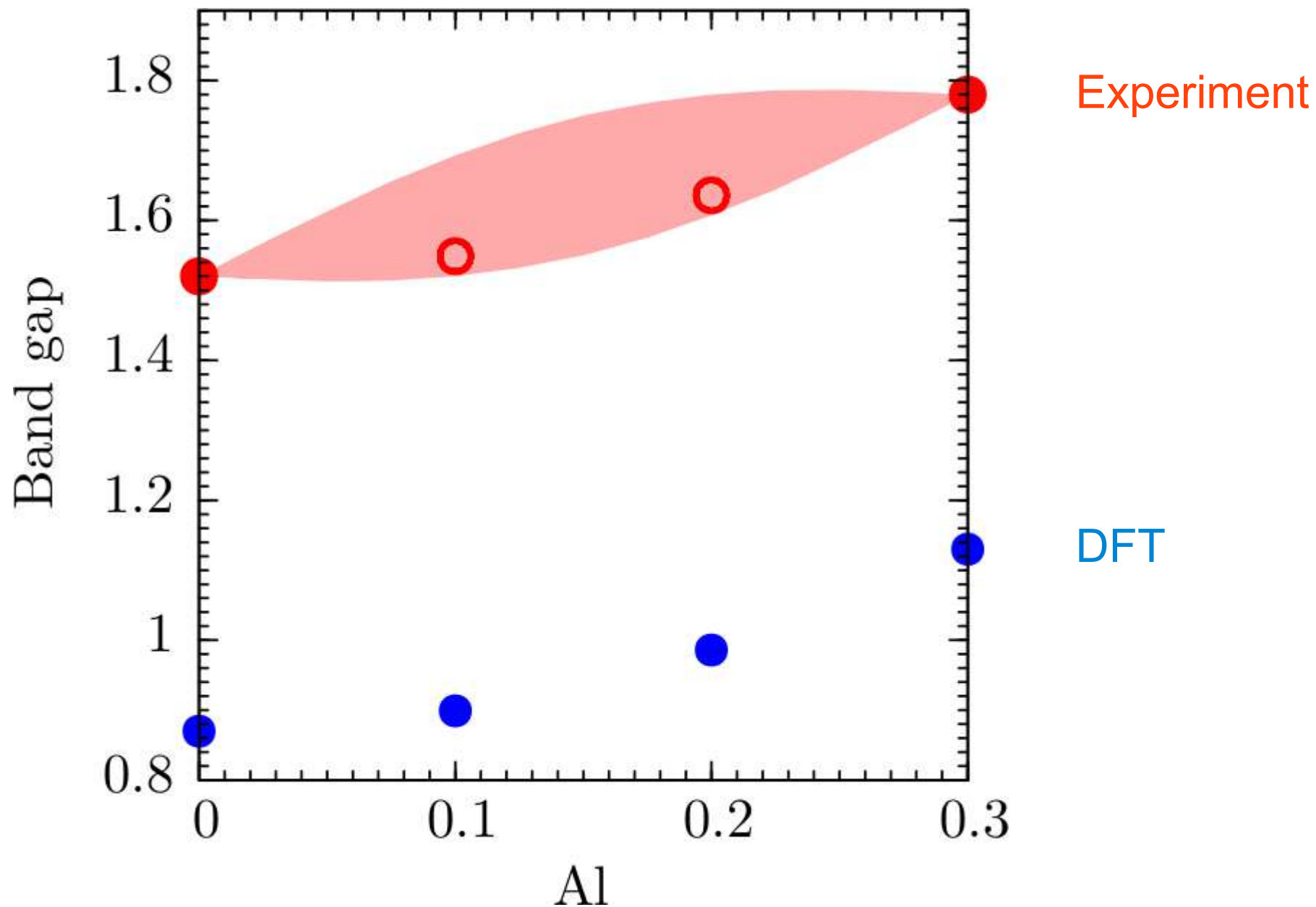
InGaN-base semiconductors: exploiting correlations



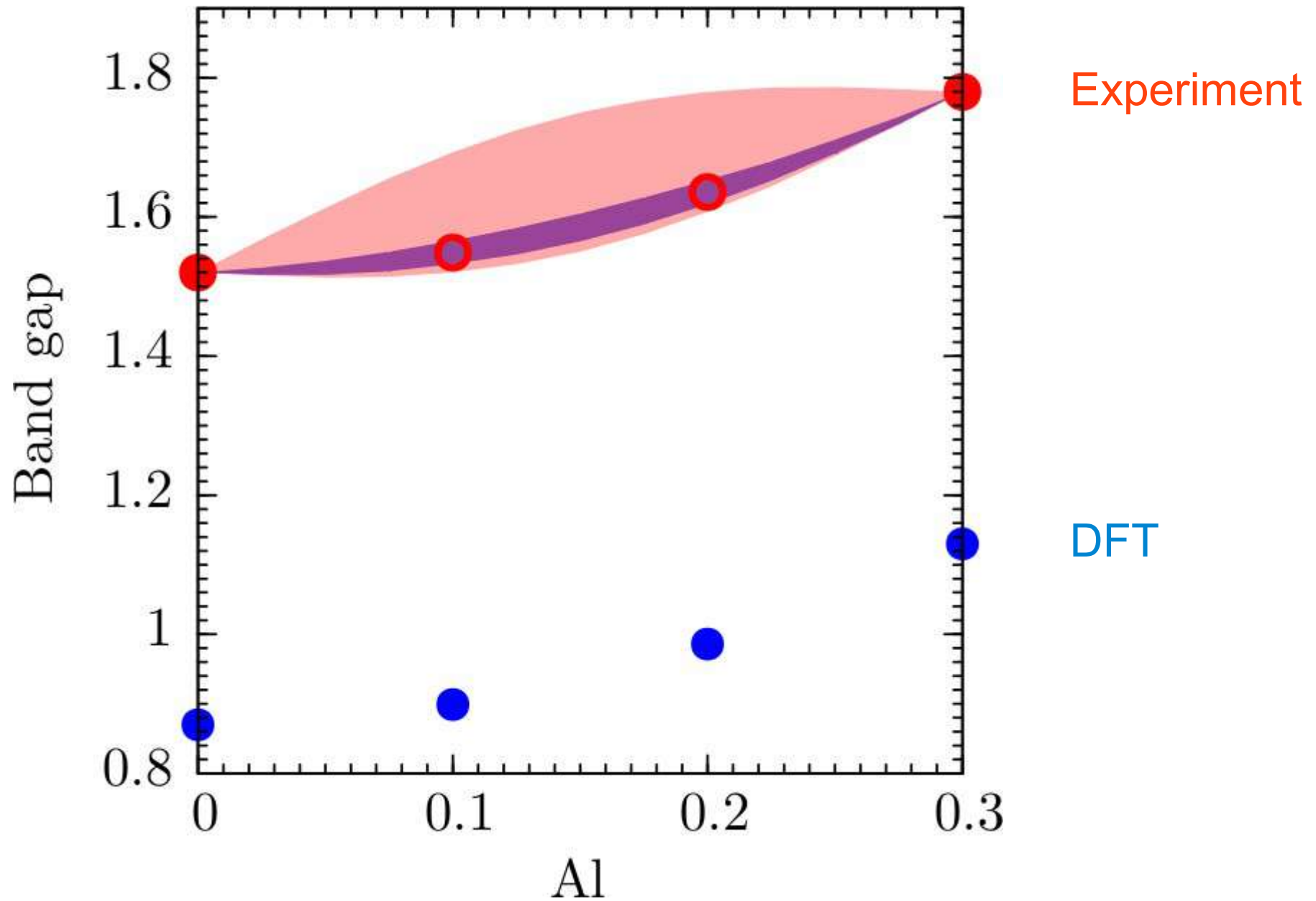
InGaN-base semiconductors: exploiting correlations



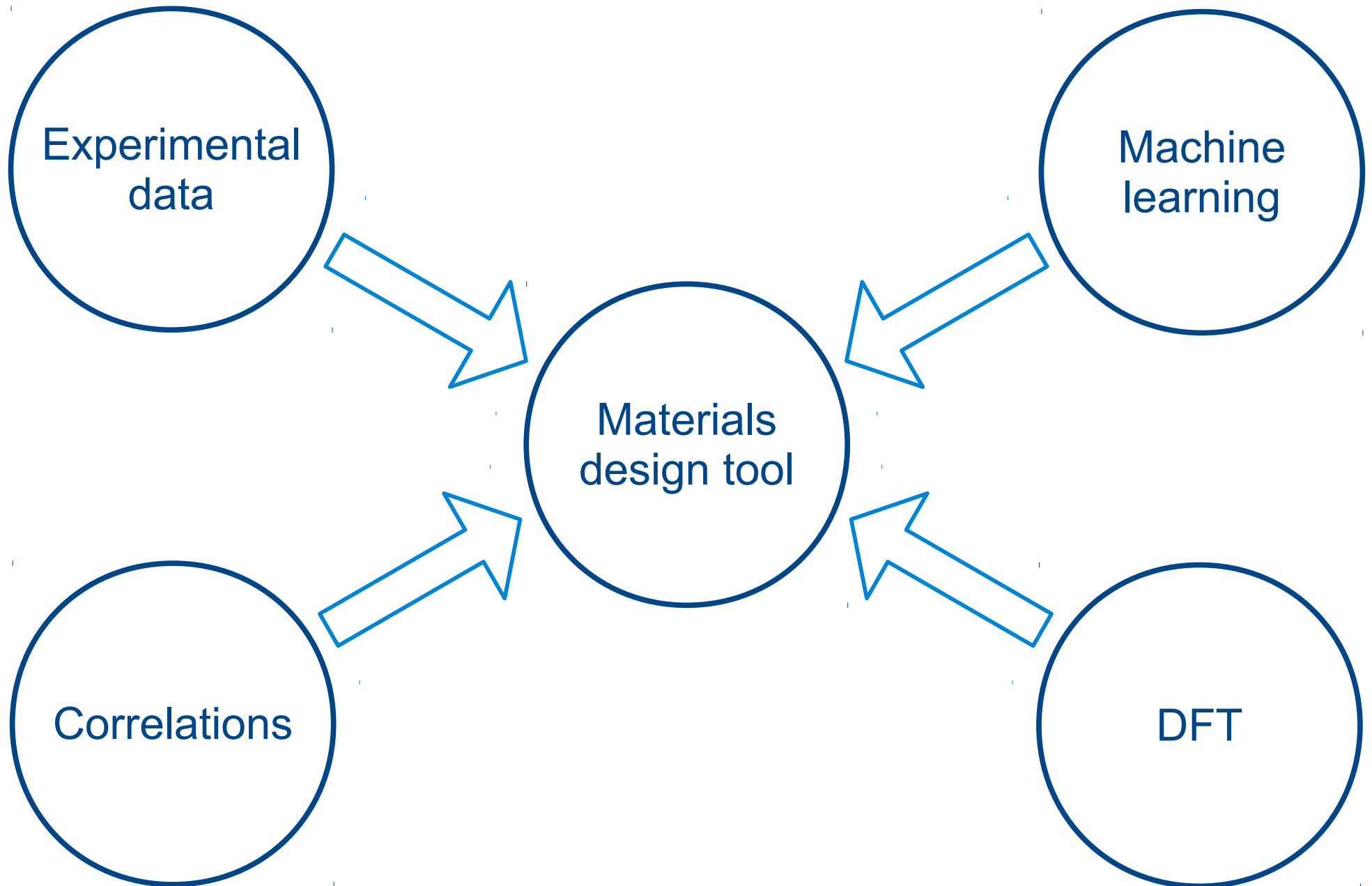
InGaN-base semiconductors: exploiting correlations



InGaN-base semiconductors: exploiting correlations



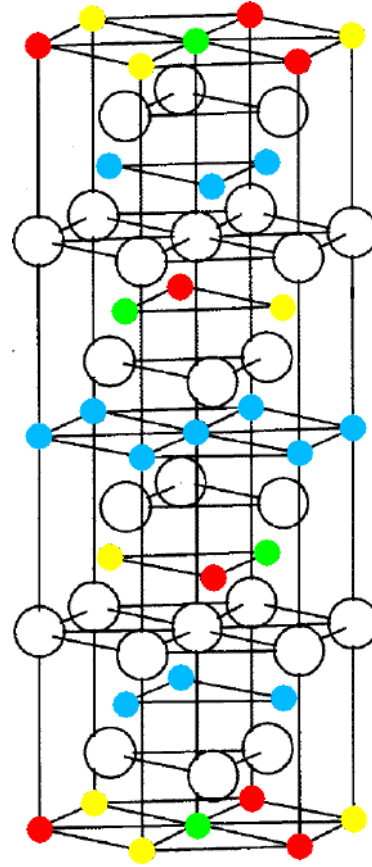
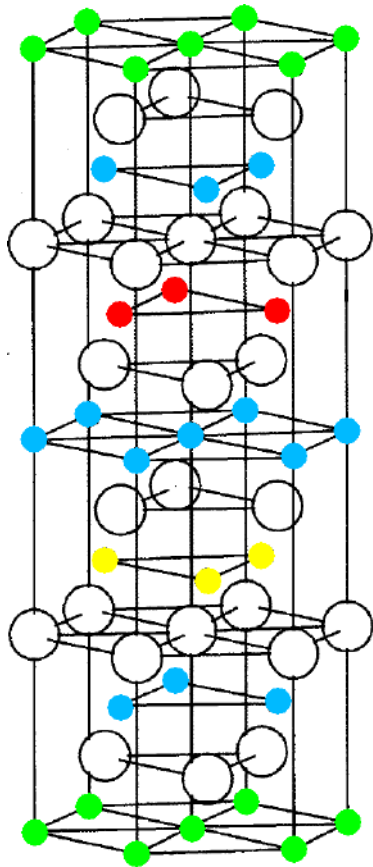
Unification of approaches



Nickel-Cobalt-Manganese (NCM) battery materials

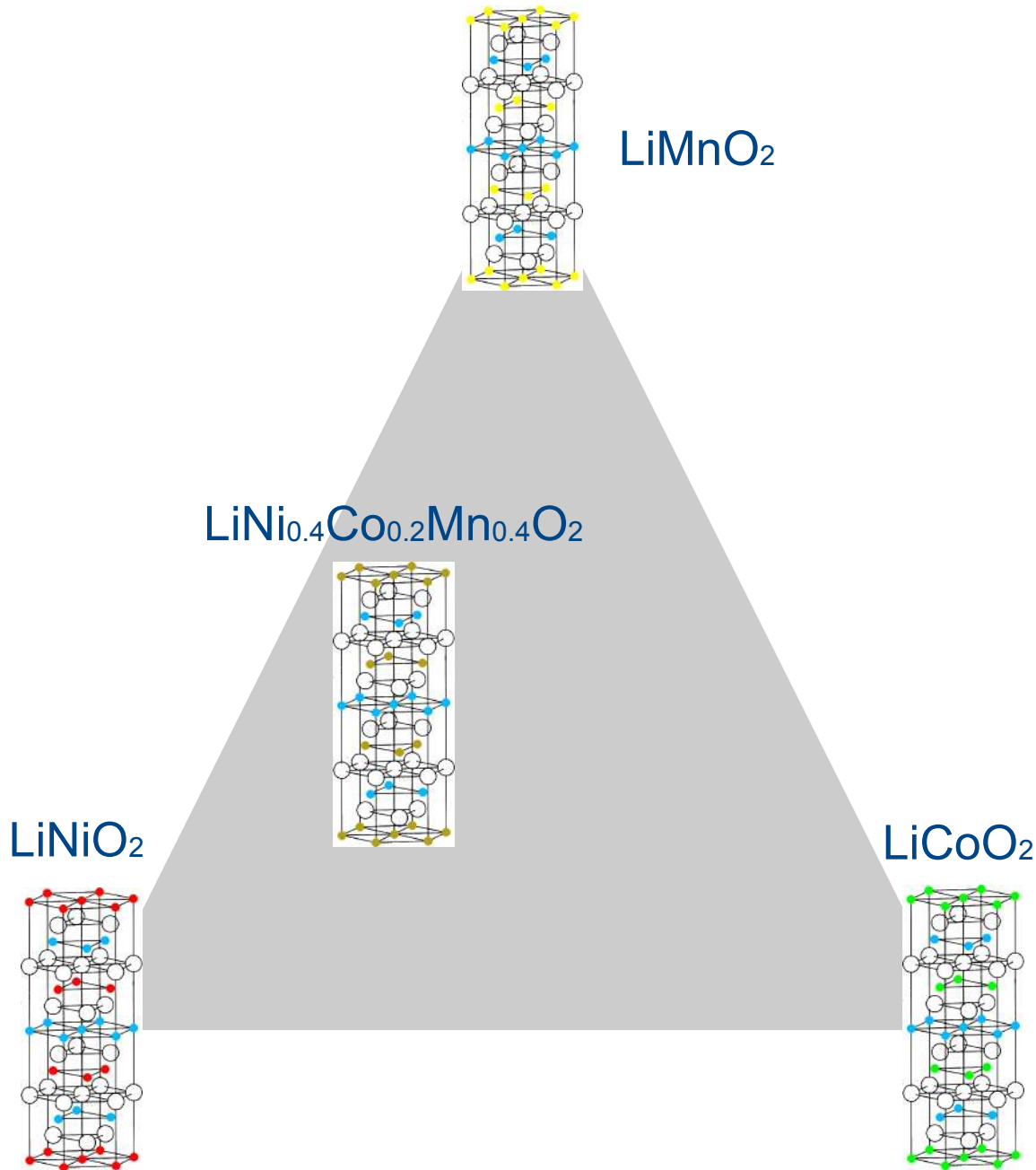


Nickel-Cobalt-Manganese (NCM-424) battery materials



○	O
●	Li
●	Ni
●	Co
●	Mn

Approach: Lego: previous approach

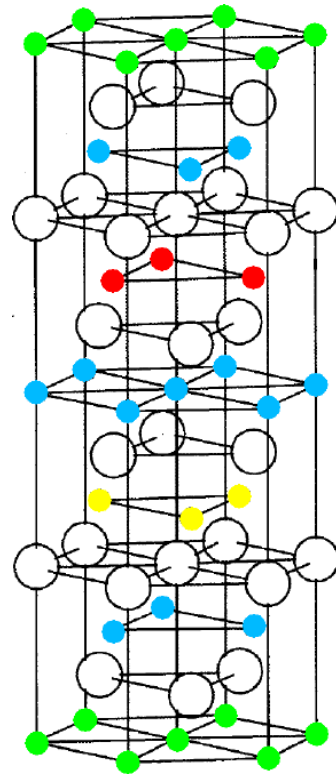


Access any composition

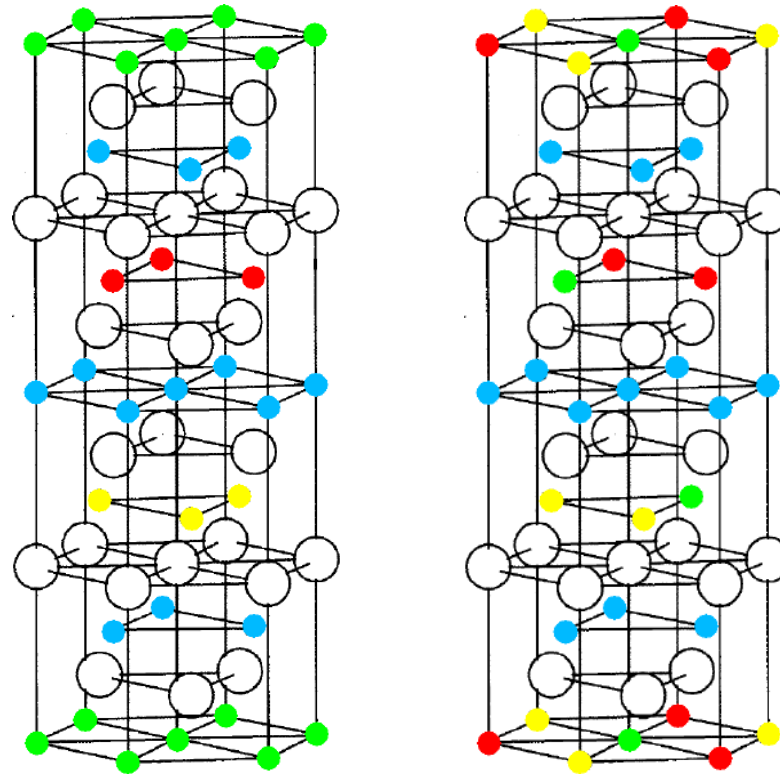
No information on order

No Li migration

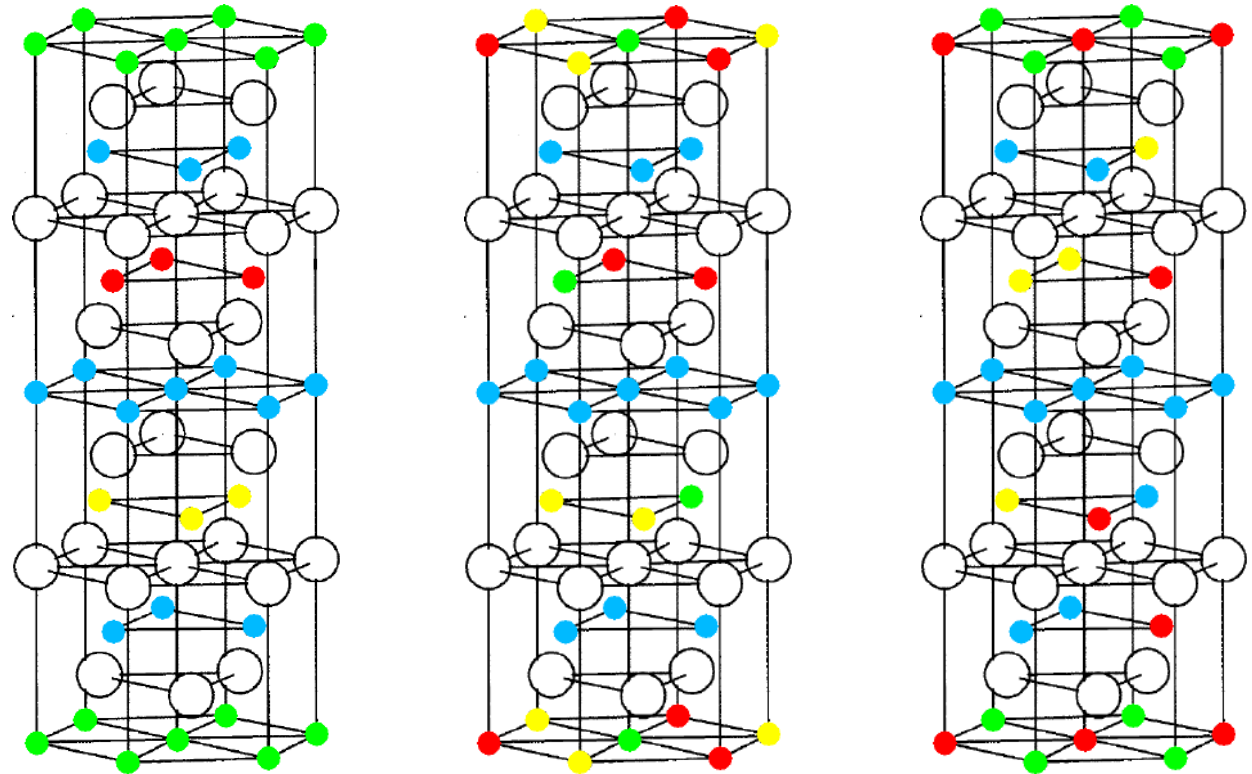
Approach: exhaustive exploration of unit cells



Approach: exhaustive exploration of unit cells



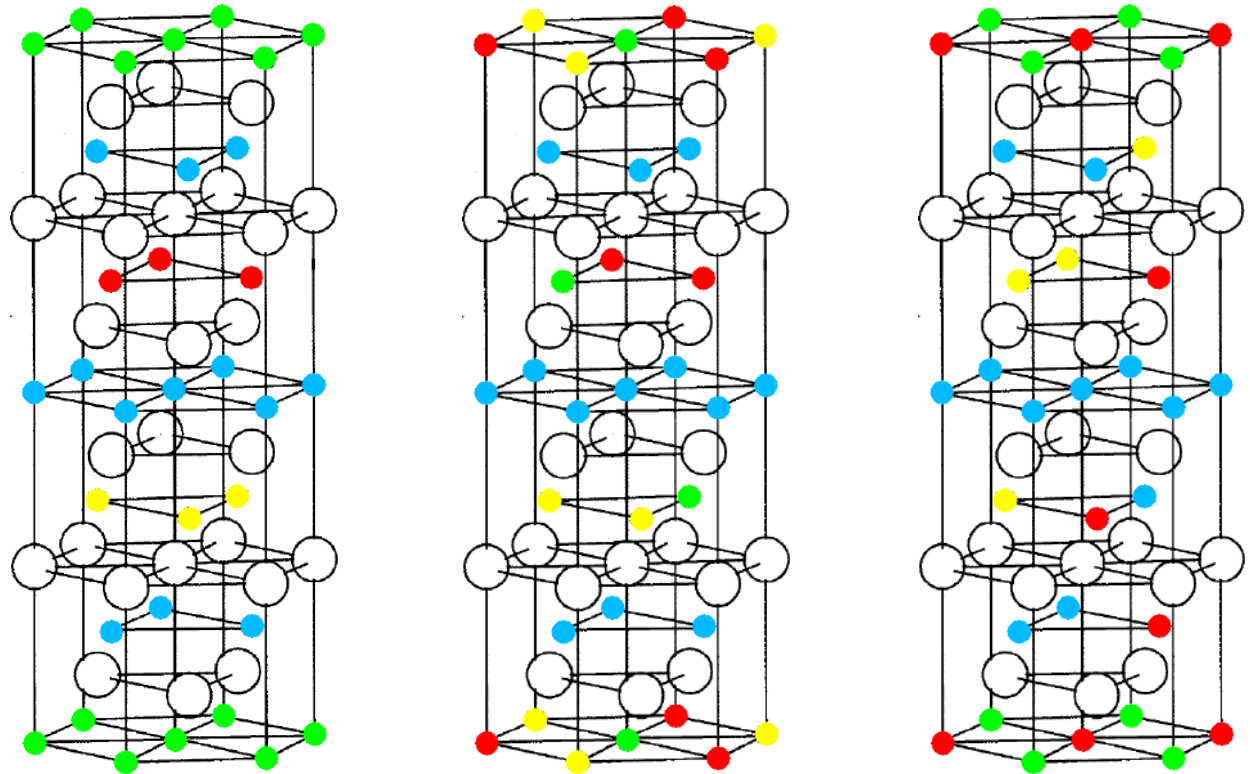
Approach: exhaustive exploration of unit cells



Approach: exhaustive exploration of unit cells

153153000
possible
permutations
=42000 years

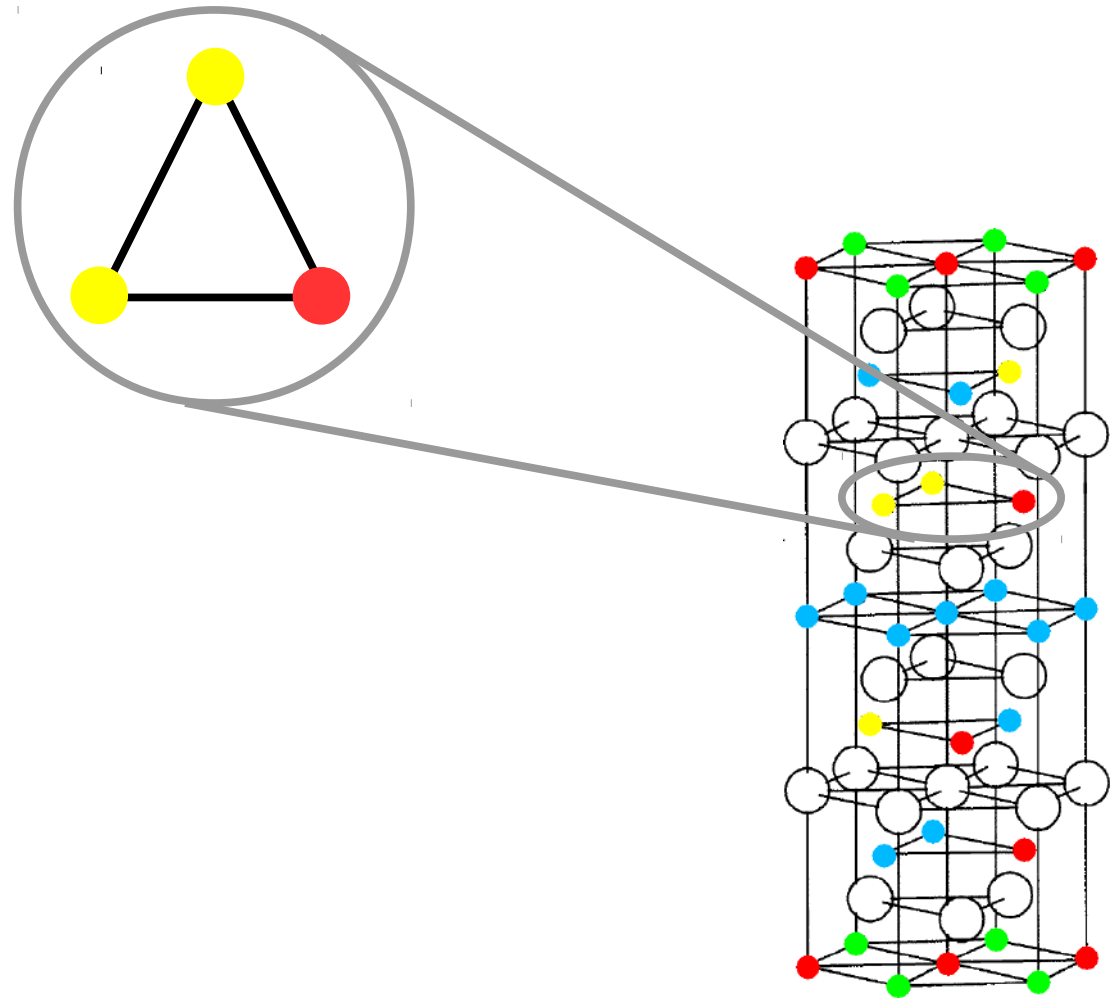
Only examine
order that fits
into the unit cell



Approach: characterize with a local order matrix

$$N_{\text{yellow-yellow}}=1$$

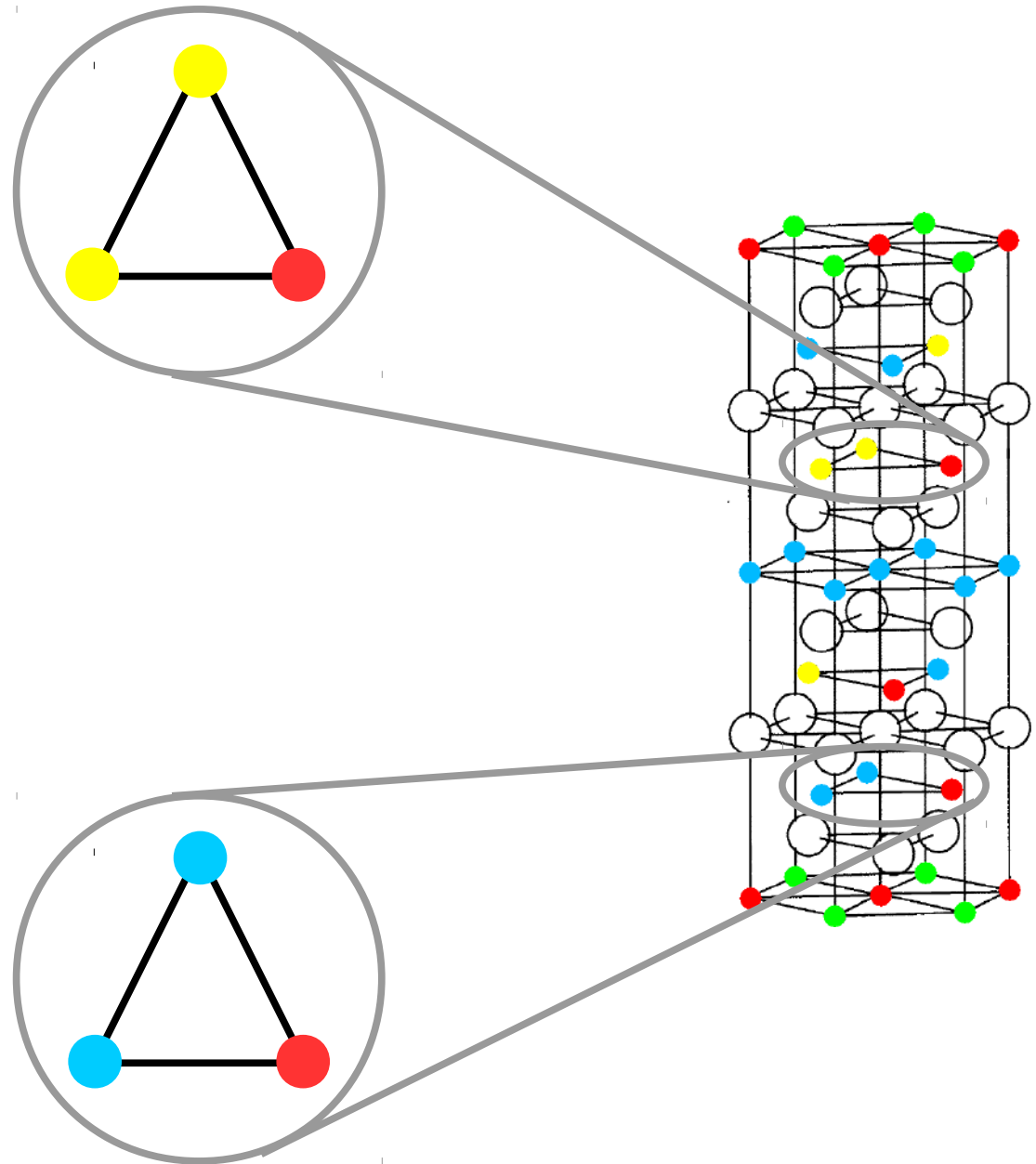
$$N_{\text{yellow-red}}=2$$



Approach: characterize with a local order matrix

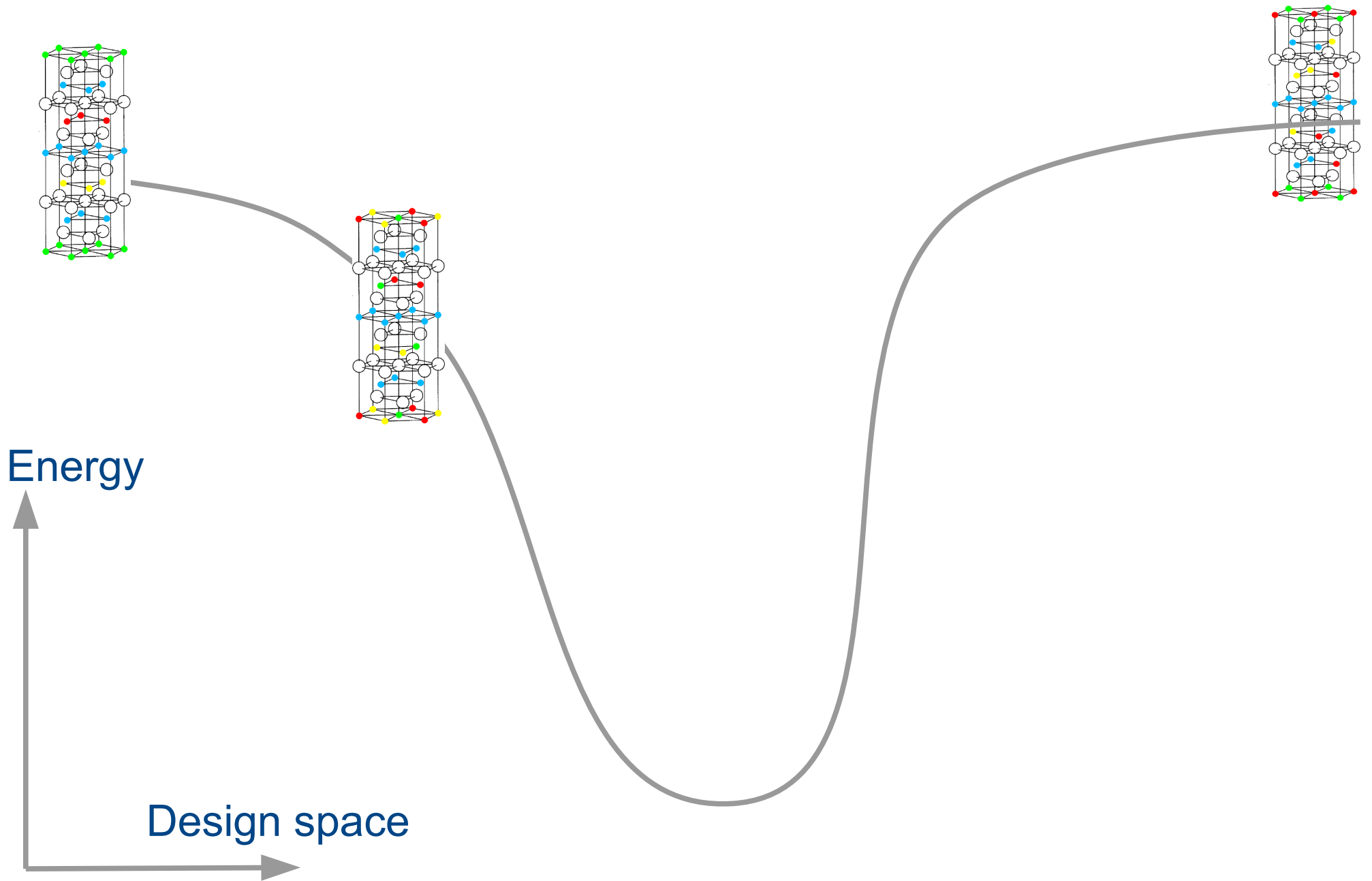
$$N_{\text{yellow-yellow}}=1$$

$$N_{\text{yellow-red}}=2$$

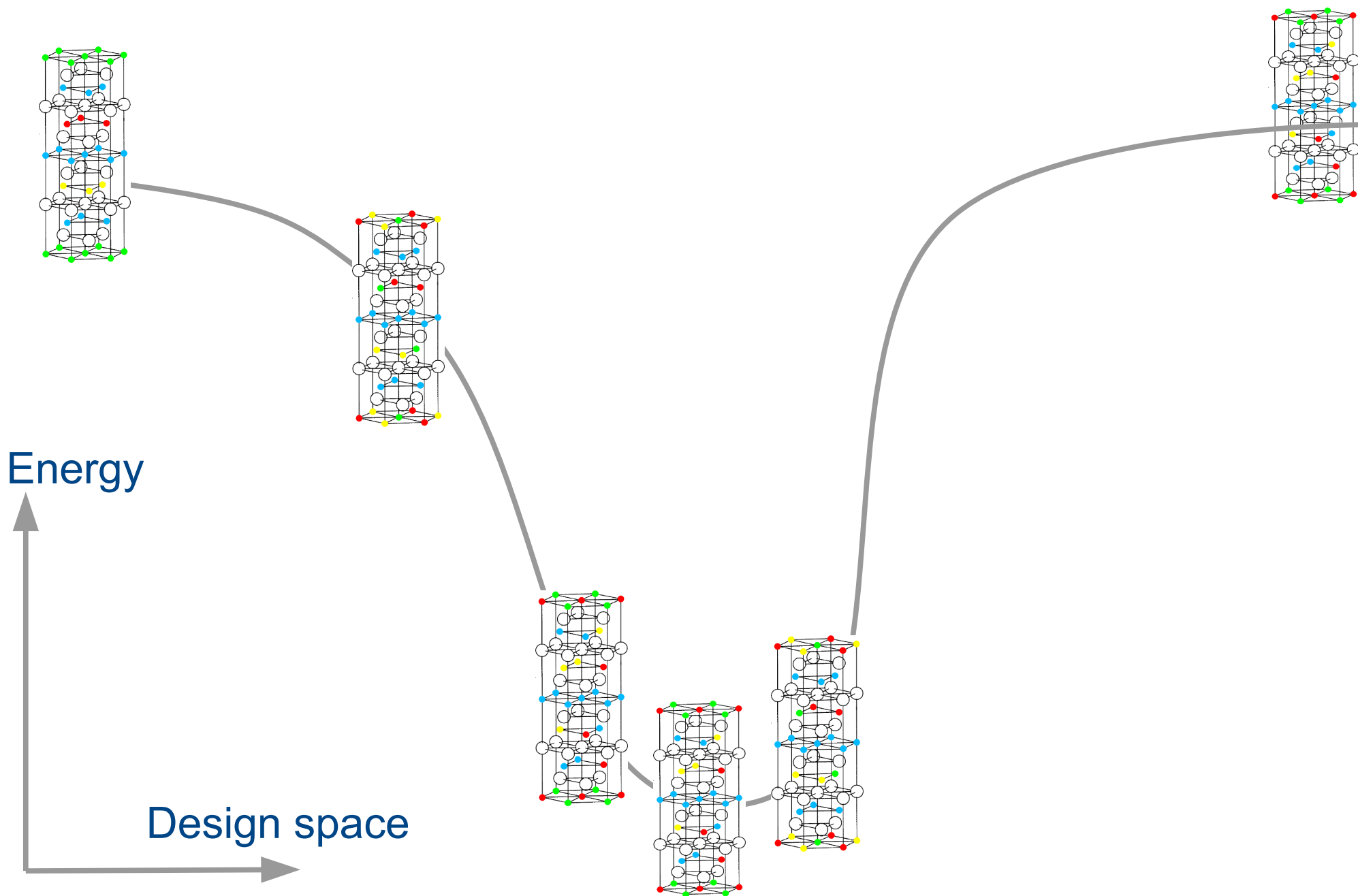


$$N_{\text{red migrate}}=1$$

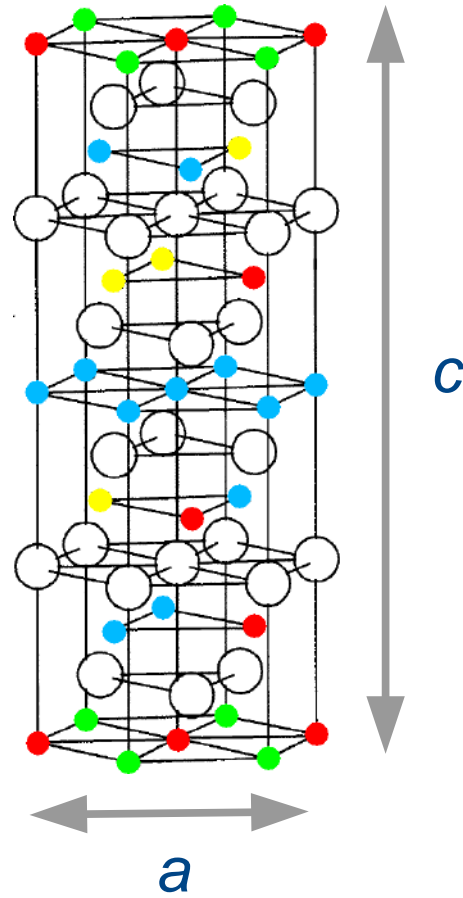
Recursive learning



Recursive learning



Lattice constants



Predictions from the neural network

Structure	a (Å)	c (Å)
LiNi _{0.4} Co _{0.2} Mn _{0.4} O ₂ neural net	2.851	14.269
LiNi _{0.4} Co _{0.2} Mn _{0.4} O ₂ experiment	2.866	14.254

Structure	a (Å)	c (Å)
LiNiO ₂	2.9108	14.1099
LiCoO ₂	2.8473	13.9214
LiMnO ₂	2.7614	14.7740
LiNi _{1/3} Co _{1/3} Mn _{1/3} O ₂ layered	2.8827	14.1067

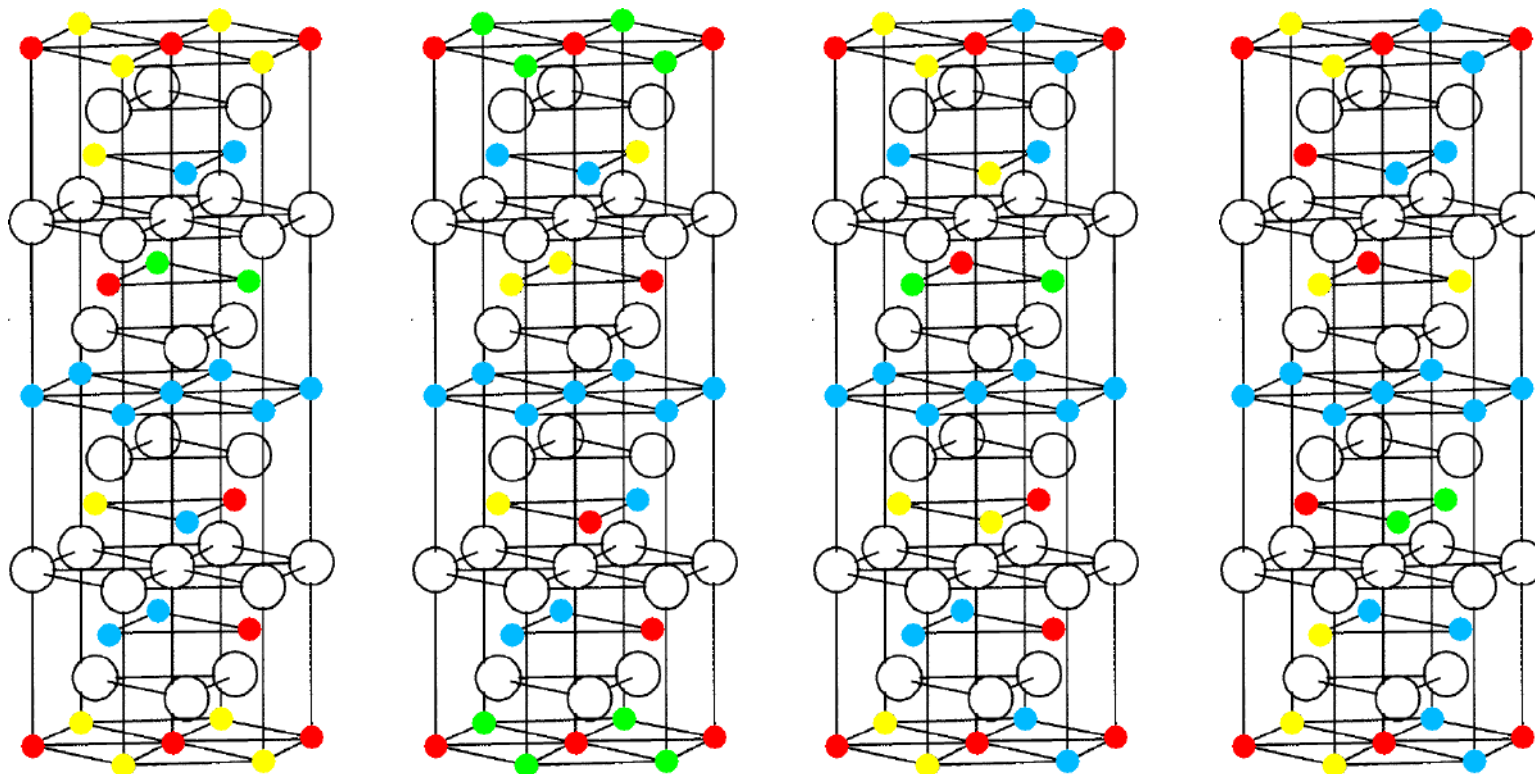
Local order matrix

Matrix element	Optimal	Expected if random
$N_{\text{Co-Co}}$	0.34	0.75
$N_{\text{Ni-Ni}}$	0.16	0.75
$N_{\text{Mn-Mn}}$	0.09	0.75
$N_{\text{Li-Li}}$	0.08	0.75
$N_{\text{Co-Ni}}$	2.5	2.25
$N_{\text{Co-Mn}}$	0.2	2.25
$N_{\text{Ni-Mn}}$	3.4	2.25
$N_{\text{Ni-Li}}$	0.32	2.25
$N_{\text{Co-Li}}$	0.21	2.25
$N_{\text{Mn-Li}}$	1.37	2.25
N_{Ni}	1.82	0
N_{Co}	0.02	0
N_{Mn}	0.01	0

Local order matrix within a single unit cell

Matrix element	Optimal	Achievable in single unit cell
$N_{\text{Co-Co}}$	0.34	1
$N_{\text{Ni-Ni}}$	0.16	0
$N_{\text{Mn-Mn}}$	0.09	1
$N_{\text{Li-Li}}$	0.08	0
$N_{\text{Co-Ni}}$	2.5	2
$N_{\text{Co-Mn}}$	0.2	0
$N_{\text{Ni-Mn}}$	3.4	3
$N_{\text{Ni-Li}}$	0.32	1
$N_{\text{Co-Li}}$	0.21	0
$N_{\text{Mn-Li}}$	1.37	1
N_{Ni}	1.82	1
N_{Co}	0.02	0
N_{Mn}	0.01	1

Four representative unit cells



$E=-18430.0\text{eV}$

$E=-18428.2\text{eV}$

$E=-18428.1\text{eV}$

$E=-18429.0\text{eV}$

Experiment

$a=2.863\text{\AA}$

$a=2.852\text{\AA}$

$a=2.857\text{\AA}$

$a=2.860\text{\AA}$

$a=2.866\text{\AA}$

$c=14.212\text{\AA}$

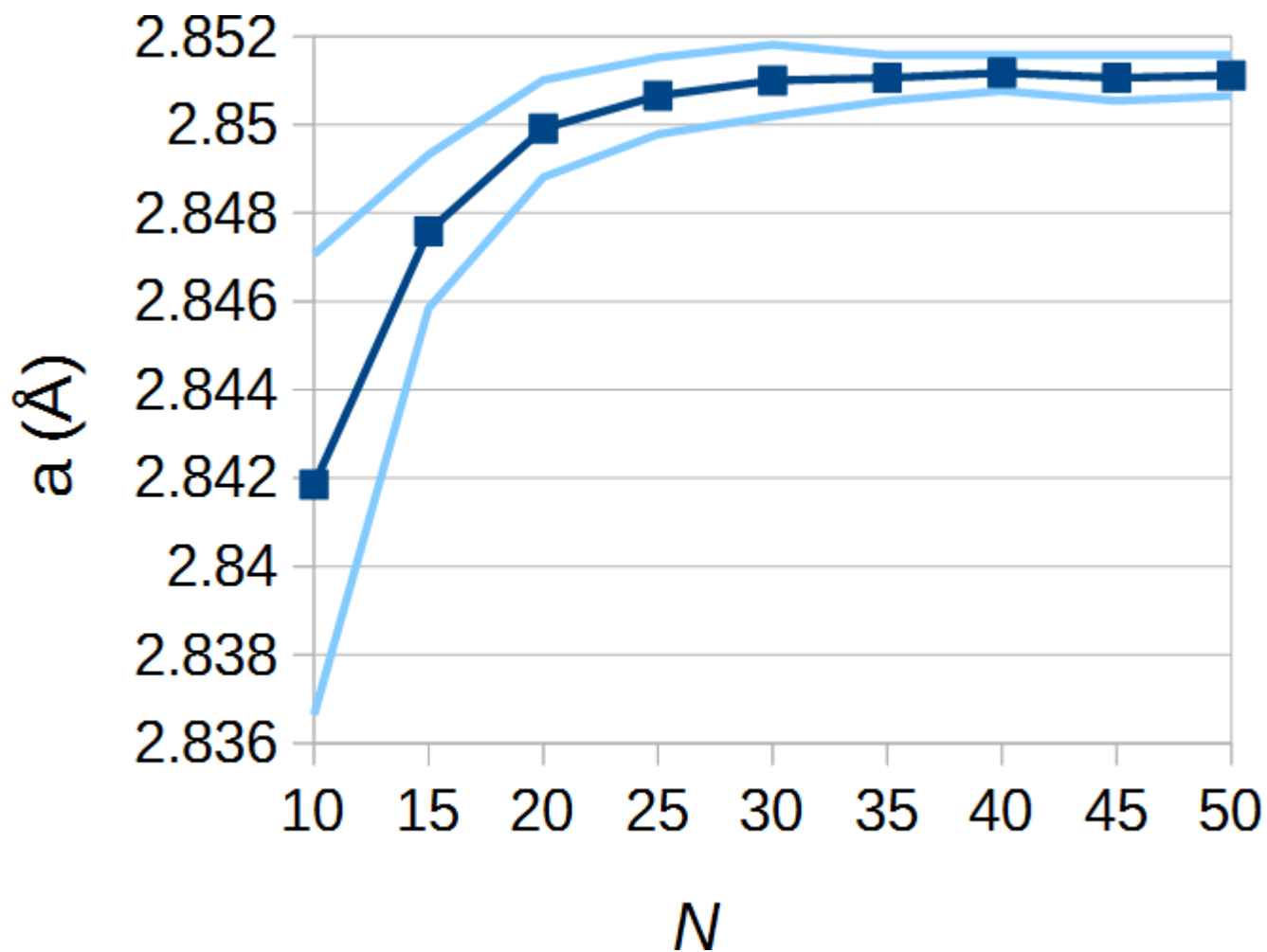
$c=14.274\text{\AA}$

$c=14.254\text{\AA}$

$c=14.221\text{\AA}$

$a=14.254\text{\AA}$

How many calculations are required



Prospects for the future

Test four new tools uniquely unified within a materials design tool to maximize learning from data

Build on these platforms to respond to future GRO and Samsung collaboration needs

Continue high-level interaction with SAIT Europe and SAIT HQ teams to work on most relevant needs and outcomes