

Leveraging AI and robotics to accelerate inorganic materials synthesis

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Al and robotics are here...





Chatbots galore







Al and robotics are here...





Chatbots galore









And cute (or creepy) robots











And cute (or creepy) robots





Early examples are promising!





Photocatalysts





Solution synthesis

$2 H_2 O \rightarrow 2 H_2 + O_2$ Water splitting



Early examples are promising!



The mobile chemist handles the vials and does sample transfer



Customized stations handle the finer tasks (weighing, mixing, *etc*.)







Early examples are promising!

Idea Generation

The AI Scientist: Towards Fully Automated Open-Ended Scientific Discovery

Chris Lu^{1,2,*}, **Cong Lu**^{3,4,*}, **Robert Tjarko Lange**^{1,*}, **Jakob Foerster**^{2,†}, **Jeff Clune**^{3,4,5,†} **and David Ha**^{1,†} *Equal Contribution, ¹Sakana AI, ²FLAIR, University of Oxford, ³University of British Columbia, ⁴Vector Institute, ⁵Canada CIFAR AI Chair, [†]Equal Advising

Experiment Iteration

Paper Write-Up

Manuscript

Template

Text Δ via

LLM & aider

Manuscript

LLM Paper

Reviewing

Here, the "experiments" involve writing code, training models, *etc*.







How about for (inorganic) materials science?







Building block

Repeated *many*

times in 3-D to form a crystal







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From discovery to commercialization still takes 10-20 years







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Success stories in materials discovery







Cuprate oxides led to **high-***T*_c **superconductivity**

1990

Sr₂RuO₄

2000

1995

🗖 LaOFeP

2010

2015

2020

2005

UBe₁₃ UPt₃

1985

CeCu₂Si₂

1980

1940

1900



🔶 liq. He

Success stories in materials discovery





Cuprate oxides led to high-T_c superconductivity







Success stories in materials discovery





Discovered in 2007, not yet (successfully) commercialized...

Garnet-type Li₇La₃Zr₂O₁₂ for solid-state electrolytes







Computational materials design has come a long way!



Density functional theory (DFT) can be used to screen for promising materials



Crystal structure



Computational materials design has come a long way!



And more recently... Machine learning Potentials (MLPs) are coming online







Result: more and more **databases of computed materials** are becoming available



155,000 materials



1.22 million materials





3.5 million materials





Computational materials design has come a long way!



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A grad student can synthesize a "handful" of samples each day



Even more time is needed to **characterize** them







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Computations do not tell us how to make a material





A grad student can synthesize a "handful" of samples each day

Even more time is needed to characterize them

Can automation help alleviate this problem?

Most initial synthesis attempts will fail!

Computations do not tell us how to make a material





There are many approaches to make inorganic materials





High-temperature (solid-state)



Low-temperature (solution-based)

Substrate

Deposition (thin films)









Long been the workhorse for inorganic materials synthesis...but remains stubbornly **difficult to automate in a versatile way**

High-temperature (solid-state)



The basics of solid-state synthesis









Even this "simple" technique has limitations





- Starting precursors often react to give **unwanted byproducts/impurities**
- This can result in **zero target yield**, which is **difficult to optimize!**





Closing the loop for autonomous materials synthesis









Closing the loop for autonomous materials synthesis







The A-Lab: three robotic stations in cooperation



Precursor preparation

Heating station

Characterization







The hardware team







N. J. Szymanski, B. Rendy, Y. Fei, et al., Nature (2023).





The A-Lab: a video demo



Precursor preparation





How to interpret the XRD patterns that A-Lab produces?





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A review of X-ray diffraction (XRD) for crystalline materials





2θ



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A review of X-ray diffraction (XRD) for crystalline materials

These patterns act as **"fingerprints"** for materials.

But how do we know what they'll look like?





Forward problem is easy, but reverse problem is hard





- XRD pattern is **not unique**
- Multi-phase mixtures are common
- Experimental artifacts modify peaks



Forward problem is easy, but reverse problem is hard





- XRD pattern is **not unique**
- Multi-phase mixtures are common
- **Experimental artifacts** modify peaks

These can all be **simulated** and fed to an ML model as training data



Neural networks + physics-informed data augmentation





N. J. Szymanski et al., Chem. Mater (2021).



Tests show that ML outperforms traditional methods





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Tests show that ML outperforms traditional methods









If the experiment failed, what should A-Lab do next?





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Change in Gibbs free energy provides a driving force for each reaction step:

 $\Delta G = \Delta H - T \Delta S$









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Change in Gibbs free energy provides a driving force for each reaction step:

 $\Delta \boldsymbol{G} = \Delta \boldsymbol{H} - \boldsymbol{T} \Delta \boldsymbol{S}$

A "good" reaction pathway has large ΔG at the target-forming step







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Autonomous Reaction Route Optimization With Solid-State Synthesis

N. J. Szymanski^{*}, P. Nevatia^{*}, et al., Nat. Commun. (2023).









ΔG is the **change in the Gibbs free energy** for the precursors to react and form the target

N. J. Szymanski^{*}, P. Nevatia^{*}, et al., Nat. Commun. (2023).























Closing the loop...Does it work?







Initial test case: synthesizing DFT-stable compounds



155,000 materials

We selected **58 compounds** that are stable in air





The Materials Project

		Ex	plore N	lateria	ls	Ac	Advanced Search Syntax											
¹ H	↓ by Elements •						Ja-0					×			search		2 He	
³ Li	⁴ Be												⁶ C	7 N	⁸ 0	⁹ F	10 Ne	
11 Na	12 Mg												¹⁴ Si	15 P	16 S	17 Cl	¹⁸ Ar	
19 K	20 Ca	21 Sc	22 Ti	23 V	24 Cr	25 Mn	26 Fe	27 Co	28 Ni	29 Cu	30 Zn	31 Ga	32 Ge	33 As	³⁴ Se	35 Br	36 Kr	
37 Rb	38 Sr	39 Y	40 Zr	41 Nb	42 Mo	43 Tc	44 Ru	45 Rh	46 Pd	47 Ag	48 Cd	49 In	50 Sn	51 Sb	52 Te	⁵³	⁵⁴ Xe	
55 Cs	56 Ba	57-71 La-Lu	72 Hf	⁷³ Ta	⁷⁴	75 Re	76 Os	77 Ir	78 Pt	79 Au	80 Hg	81 Tl	⁸² Pb	83 Bi	⁸⁴ Po	85 At	86 Rn	
87 Fr	88 Ra	89-103 Ac-Lr	¹⁰⁴ Rf	¹⁰⁵ Db	¹⁰⁶ Sg	107 Bh	¹⁰⁸ Hs	¹⁰⁹ Mt	110 Ds	111 Rg	112 Cn							
		57 La	58 Ce	59 Pr	60 Nd	61 Pm	62 Sm	63 Eu	64 Gd	65 Tb	66 Dy	67 Ho	68 Er	69 Tm	70 Yb	71 Lu		
		89 Ac	90 Th	91 Pa	92 U	93 Np	94 Pu	95 Am	96 Cm	97 Bk	98 Cf	99 Es	100 Fm	¹⁰¹ Md	¹⁰² No	103 LT		



Ran **3 weeks** of targeted syntheses in the A-Lab



N. J. Szymanski, B. Rendy, Y. Fei, et al., Nature (2023).



Initial test case: synthesizing DFT-stable compounds



71% success per target 41/58 targets

A high success rate per target demonstrates the connection between DFT-calculated stability and synthesizability



A much lower success rate per recipe demonstrates how challenging synthesis can be... even for stable materials!



Initial test case: synthesizing DFT-stable compounds



71% success per target 41/58 targets 130/355 recipes 37% success per recipe

A high success rate per target demonstrates the connection between DFT-calculated stability and synthesizability

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Again, does it work? Yes, but with limitations...







Characterization remains challenging,

and some of these materials contain impurities that are difficult to identify

Not a good fit!





Again, does it work? Yes, but with limitations...







Human experts to the rescue!

Manual analysis leads to a much better fit

Ag impurities are present... More optimization needed!

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In progress: incorporating additional characterization



In the loop: SEM/EDS

This can give information regarding **composition homogeneity**, but the results are limited in their precision





Out of the loop: ICP-MS

Provides more **precise composition**, but is also more difficult to automate





Many more opportunities for automation exist!







Many more opportunities for automation exist!





There is still quite a **disconnect between academia and industry** here

 \rightarrow Room for collaboration! Educate us on what is important to you \odot





Acknowledgements





UCB, LBNL

















UMN



Google



