

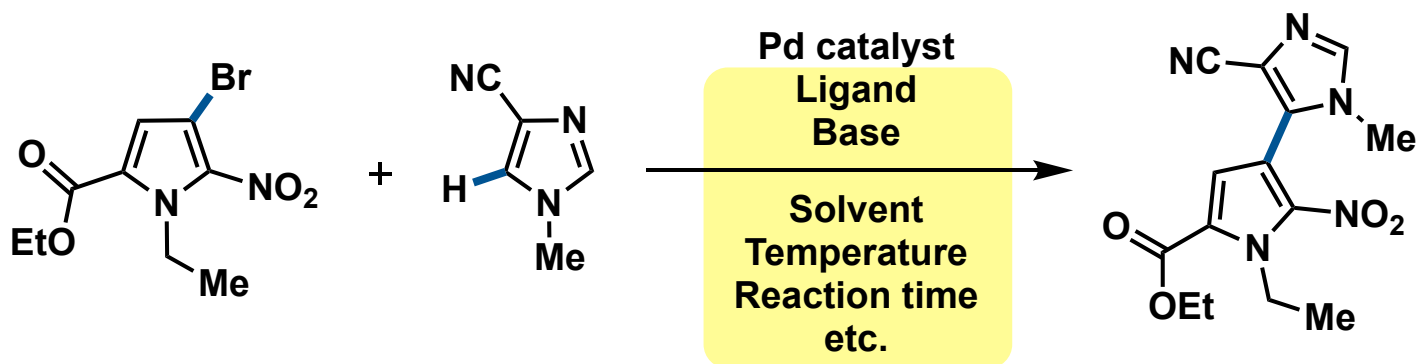
# **Bayesian Optimization for the Exploration of Reaction Conditions**

**Literature seminar**

**M2 Yu Irie**

**2023/9/28 (Thu)**

# Optimization of chemical reaction



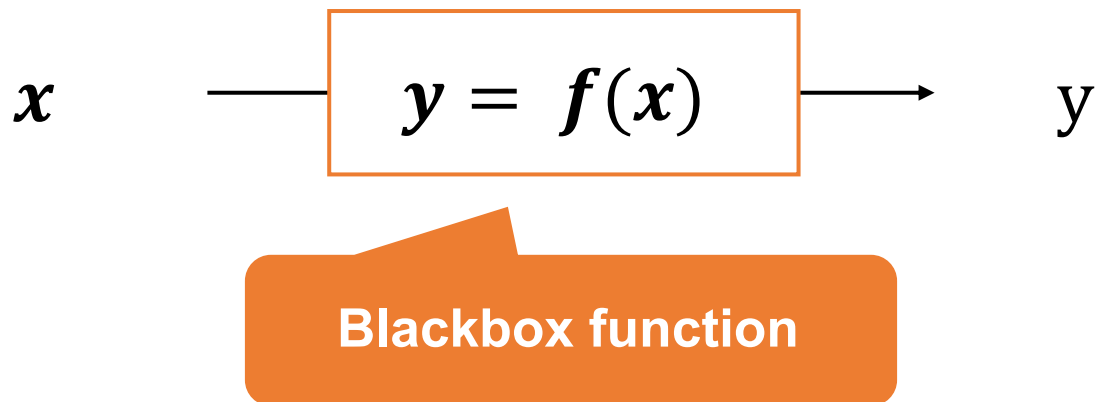
**>10<sup>5</sup> configurations!!**

**In typical laboratory, time and materials are limited...**

- **Scour chemical literature for similar reactions**
  - **Experience**
  - **Mechanistic understanding**

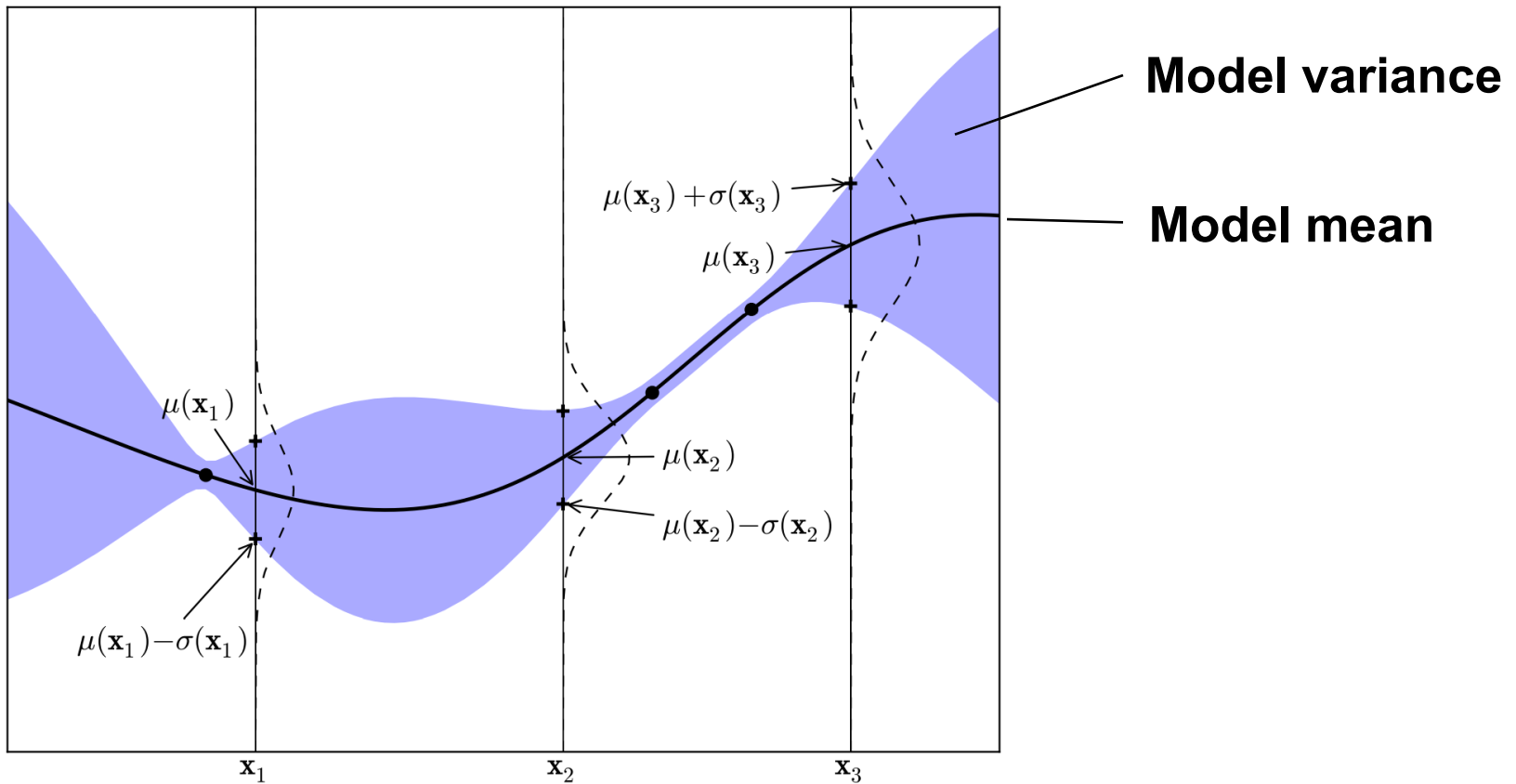
...

# Reaction optimization in machine learning

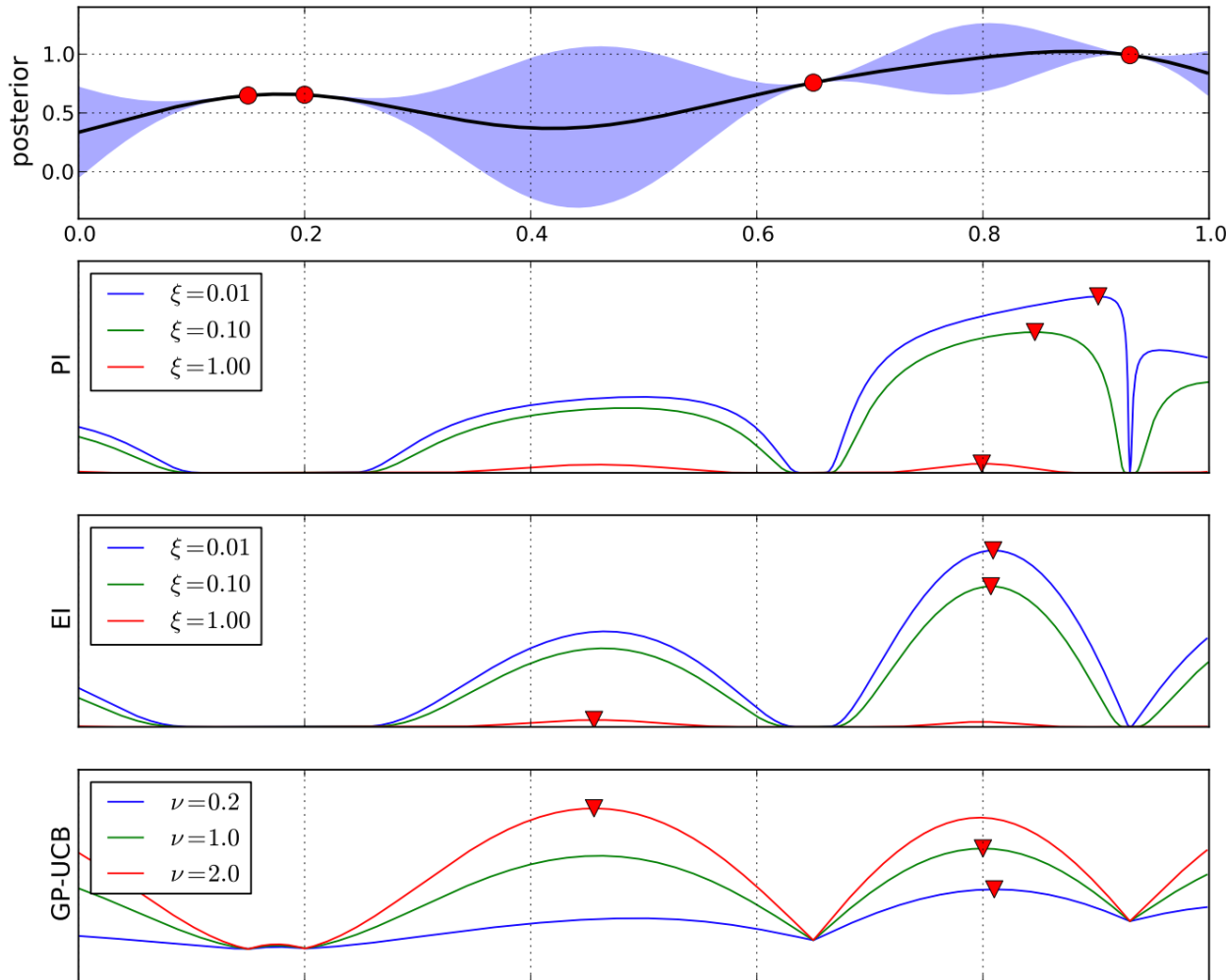


- Automated approaches to algorithm optimization
  - Bayesian optimization
  - ✓ High-quality configurations in fewer evaluations

# Gaussian process

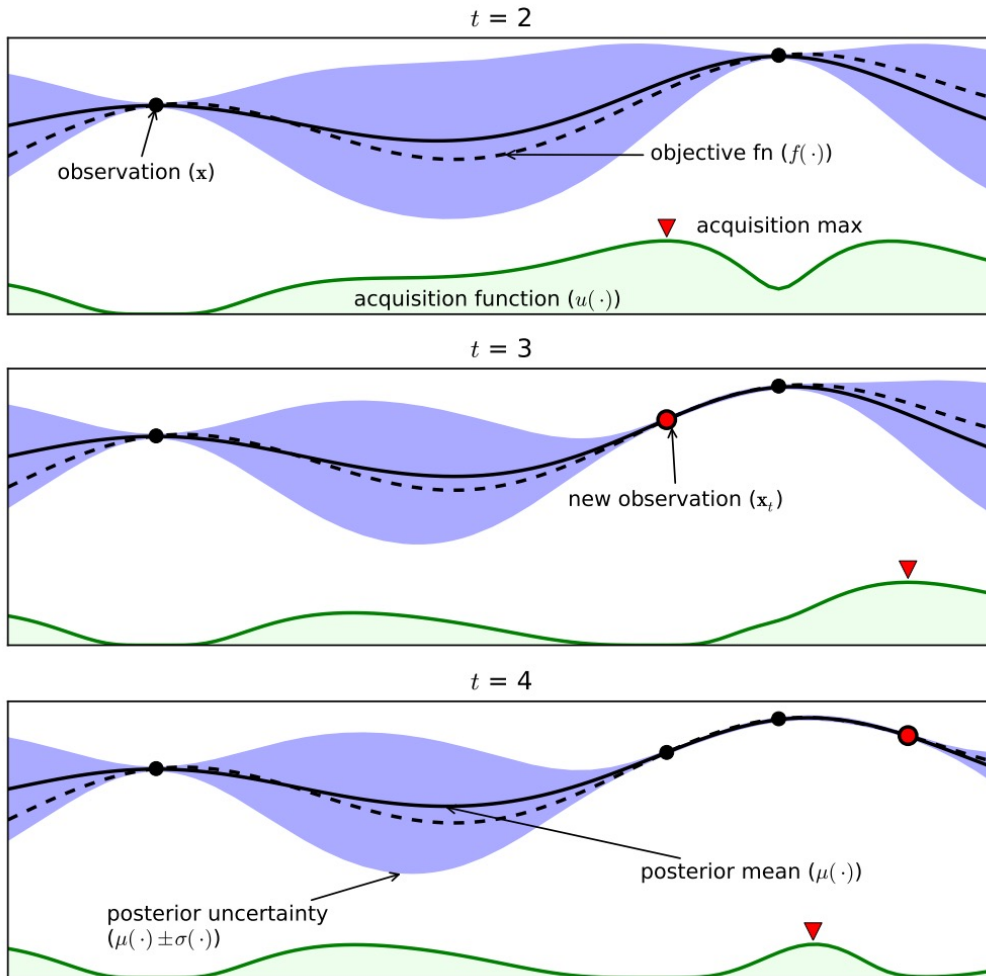


# Acquisition function



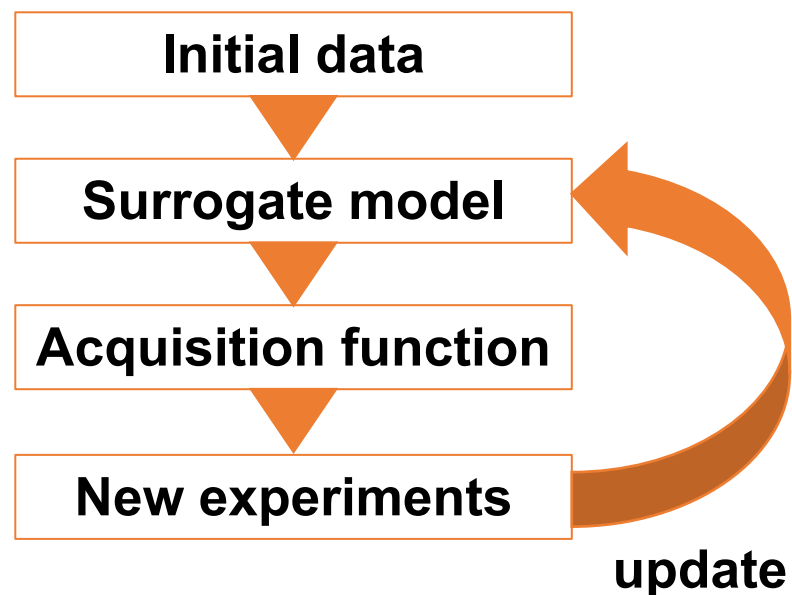
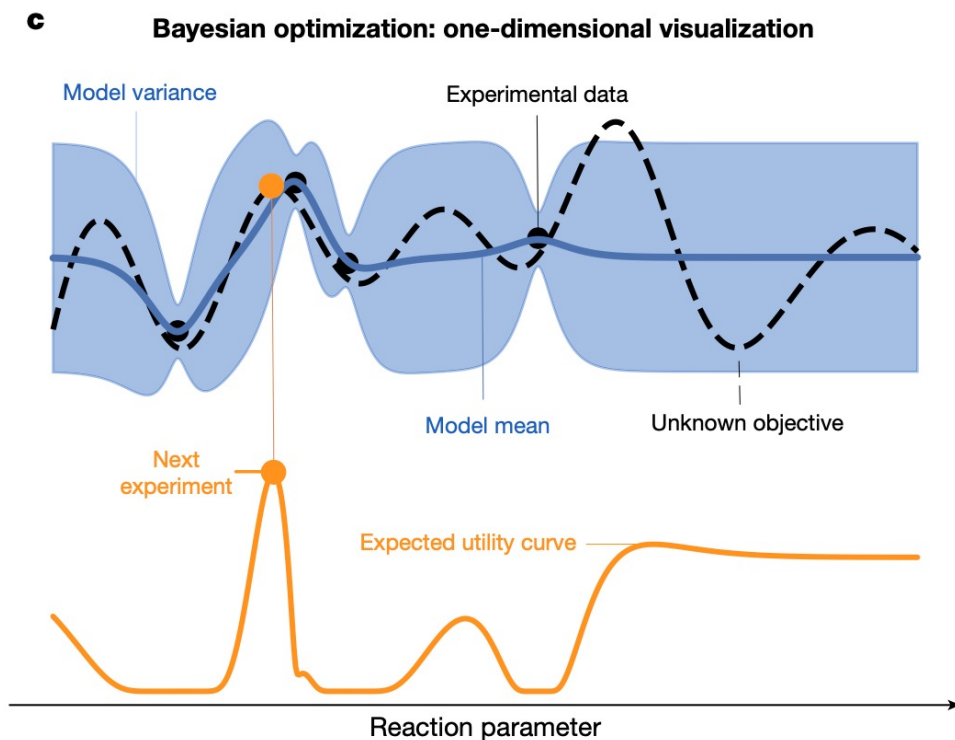
**Exploitation  
vs.  
Exploration**

# Bayesian optimization



- ✓ Find the objective function
- ✓ Uncertainty is gradually minimized
- ✓ Where to observe next is determined automatically

# Bayesian optimization



- Application to diverse search spaces
- Selection of multiple experiments in parallel
- Optimization of chemical processes

# Table of contents

---

- 1. BO as a tool for reaction optimization**
  - 1. Introduction**
  - 2. Model optimization**
  - 3. Performance benchmarking (BO vs. chemists) and Applications**
- 2. Optimizing BO to find general reaction conditions**
  - 1. Introduction**
  - 2. Data-guided down-selection, experiments and model optimization**
  - 3. Optimization and quantification**
- 3. Summary**



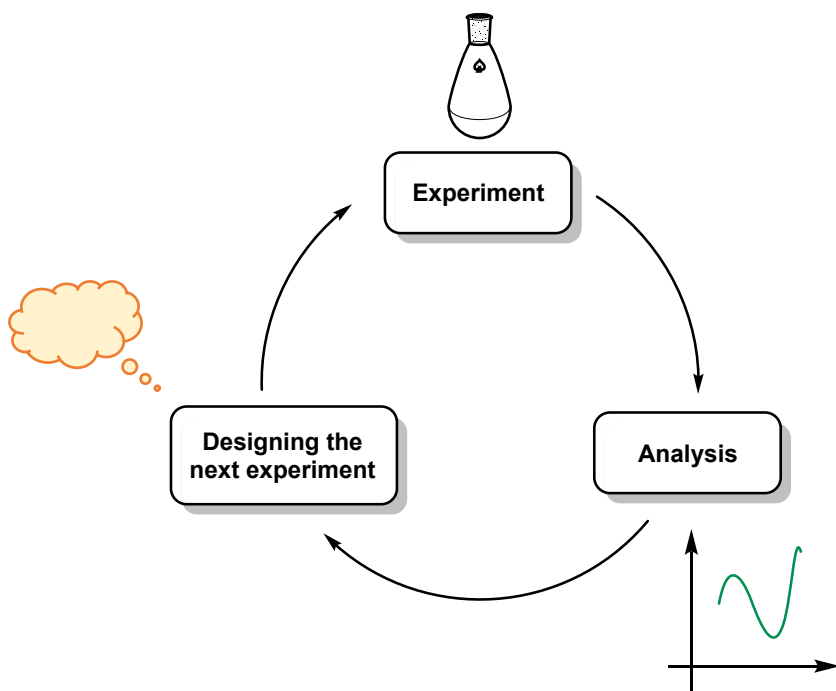
# Table of contents

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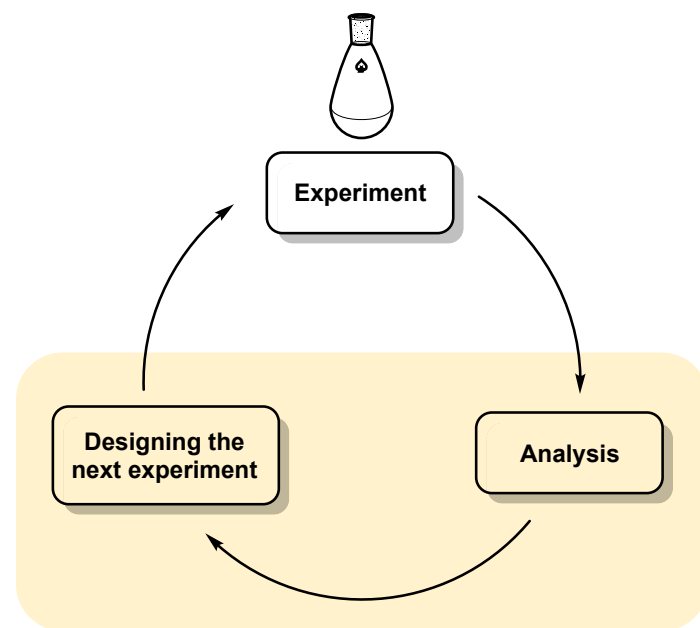
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  - 1. Introduction**
  2. Model optimization
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  2. Data-guided down-selection, experiments and model optimization
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# Application to chemical reactions

## Conventional reaction optimization



## ➤ Acceleration of the optimization of synthetic reactions



## Bayesian optimization (BO)

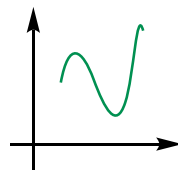
B. J. Shields, J. Stevens, J. Li, M. Parasram, F. Damani, J. I. M. Alvarado, J. M. Janey, R. P. Adams, A. G. Doyle, *Nature* **2021**, *590*, 89–96.

# Application to chemical reactions

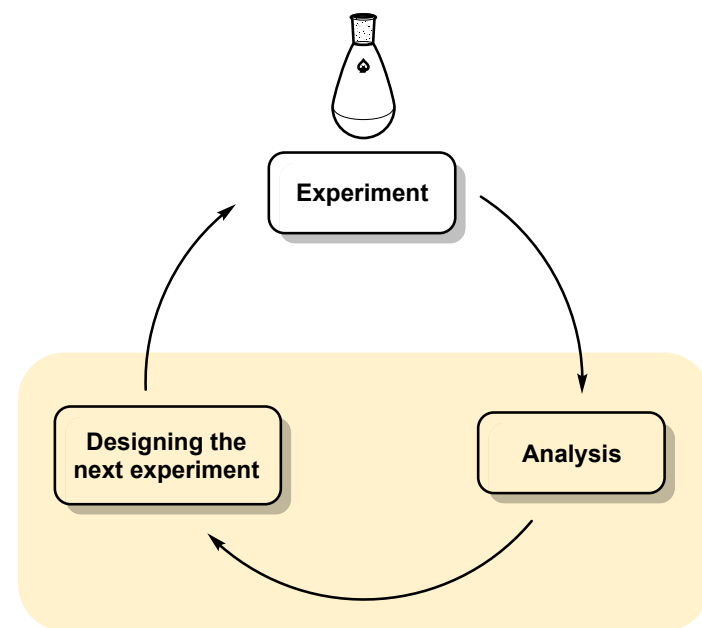
1. Application to typical batch chemistry
2. General-purpose software platforms
3. Systematic comparisons to the performance of chemists

Designing the next experiment

Analysis



➤ Acceleration of the optimization of synthetic reactions



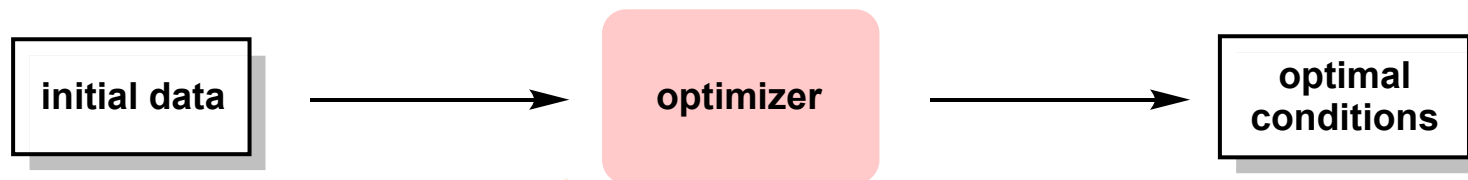
**Bayesian optimization (BO)**

# Table of contents

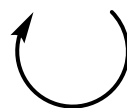
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  1. Introduction
  - 2. Model optimization**
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# Tuning of the algorithm components



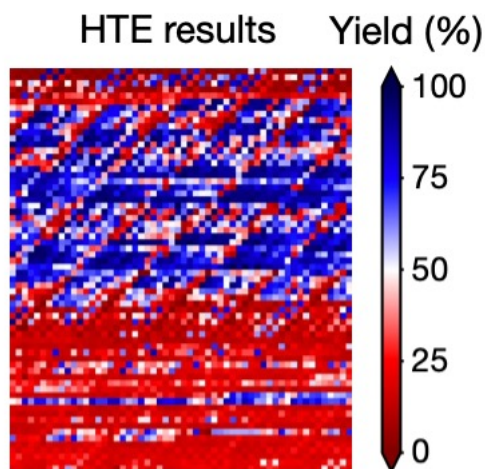
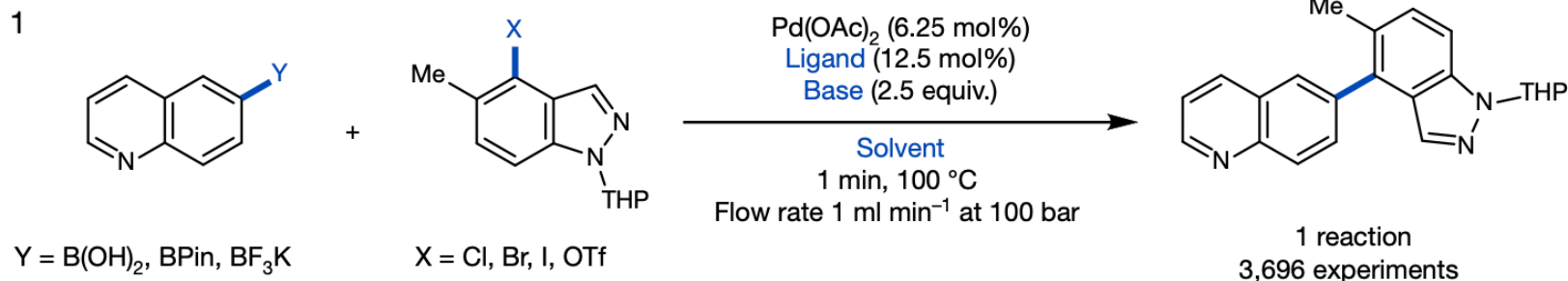
- ✓ Good average performance
- ✓ Outcomes with low variance with respect to the initial data



Reaction optimizations with different **random** initial starting data



# Training data used to select BO parameters

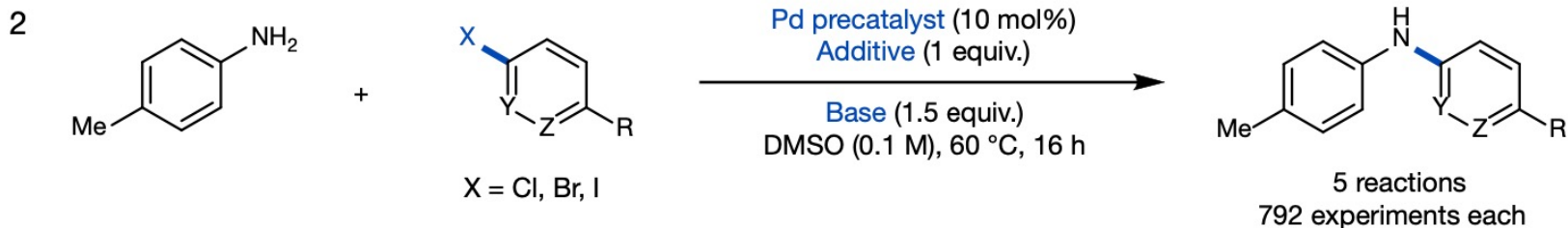


➤ **Published results of HTE (High Throughput Experiments) of 6 reactions in total were used for model optimization.**

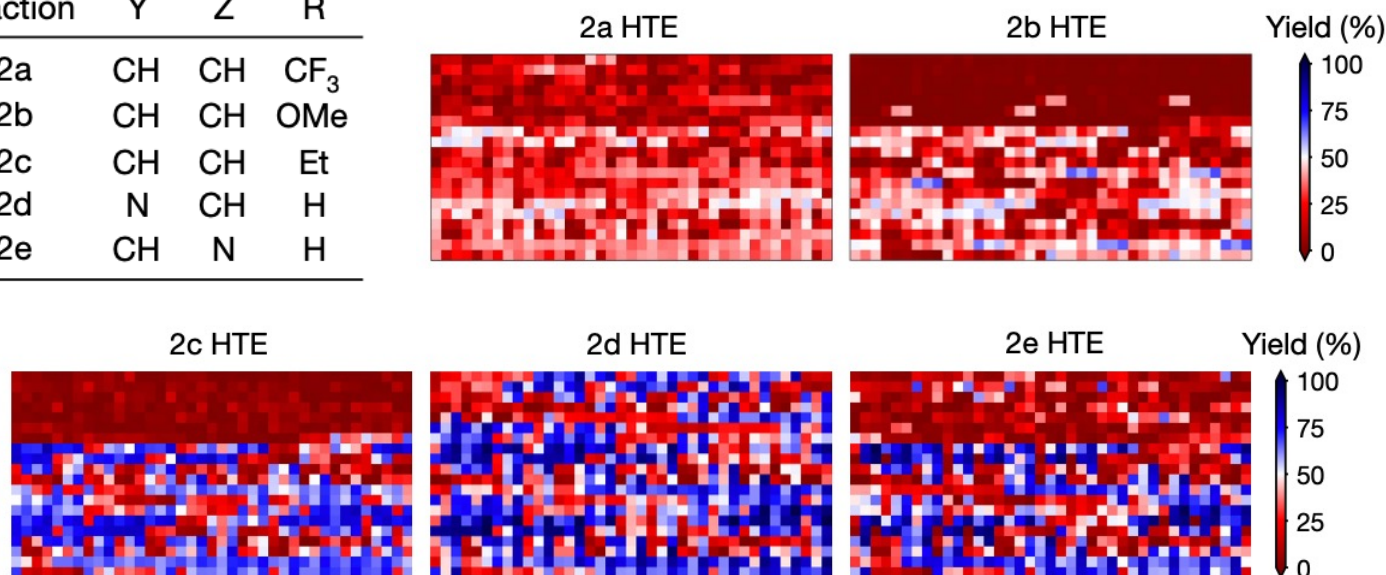
P. Richardson, N. W. Sach, *et al.* *Science* **2018**, 359, 429–434.

R. P. Adams, A. G. Doyle, *et al.* *Nature* **2021**, 590, 89–96.

# Training data used to select BO parameters

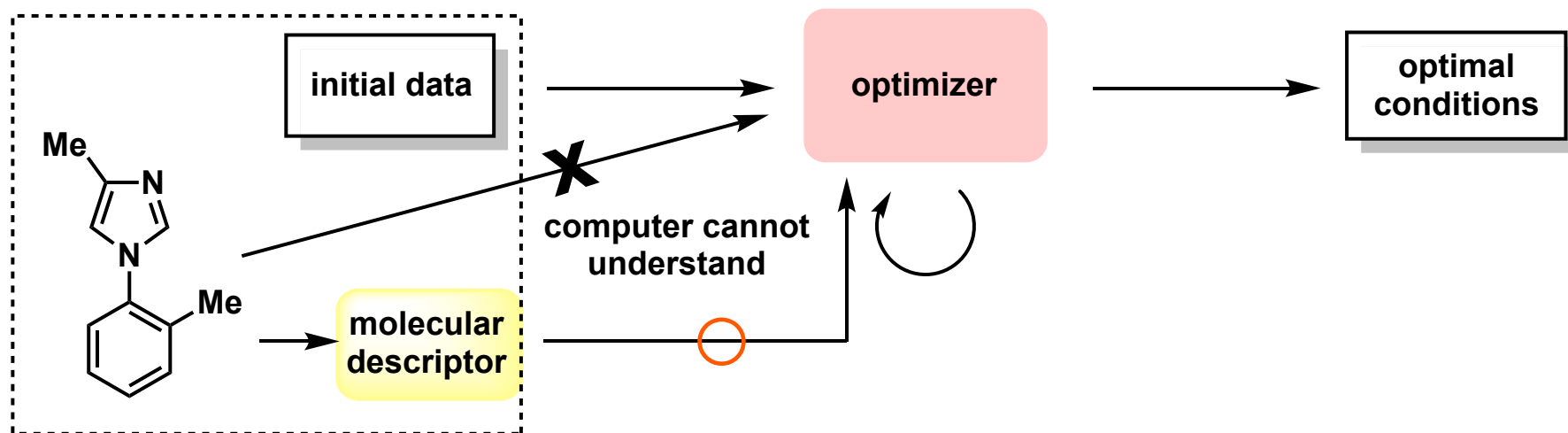


Reaction	Y	Z	R
2a	CH	CH	CF <sub>3</sub>
2b	CH	CH	OMe
2c	CH	CH	Et
2d	N	CH	H
2e	CH	N	H



S. D. Dreher, A. G. Doyle, *et al.* *Science* **2018**, 360, 186–190.  
R. P. Adams, A. G. Doyle, *et al.* *Nature* **2021**, 590, 89–96.

# Selection of descriptors

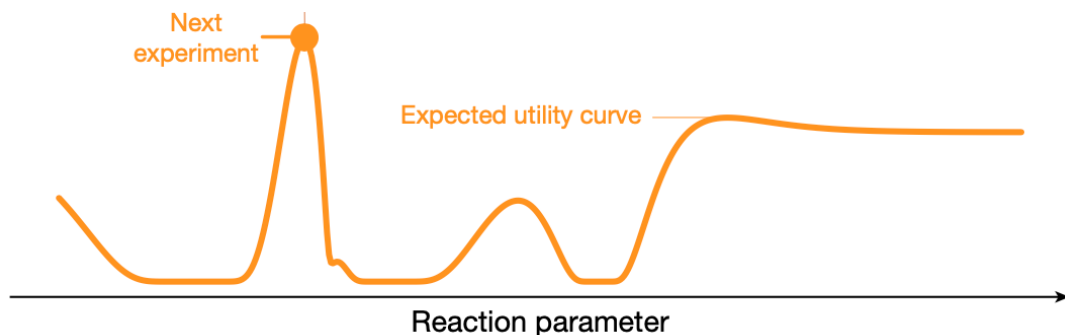


In this report, **Density Functional Theory Descriptors** was the best.

Contains: global (e.g. LUMO energy and dipole moment)/  
local (e.g. atomic NMR shift and charge for labeled atoms)  
electronic and global steric (e.g. molar volume) descriptors etc.

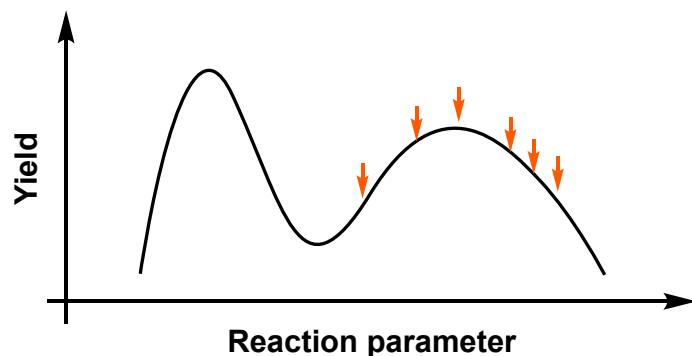


# Optimization of an acquisition function



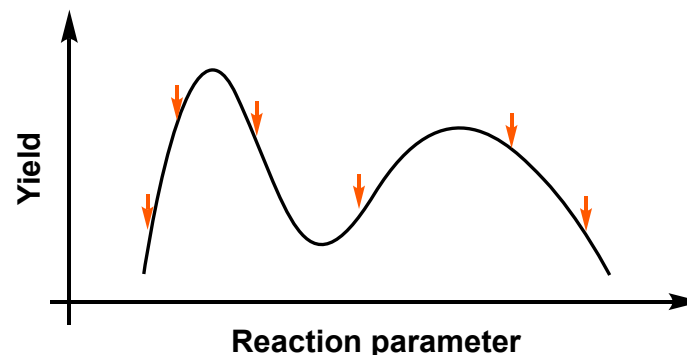
- ✓ utilization of both information and uncertainty to drive optimization

## ➤ Pure exploitation



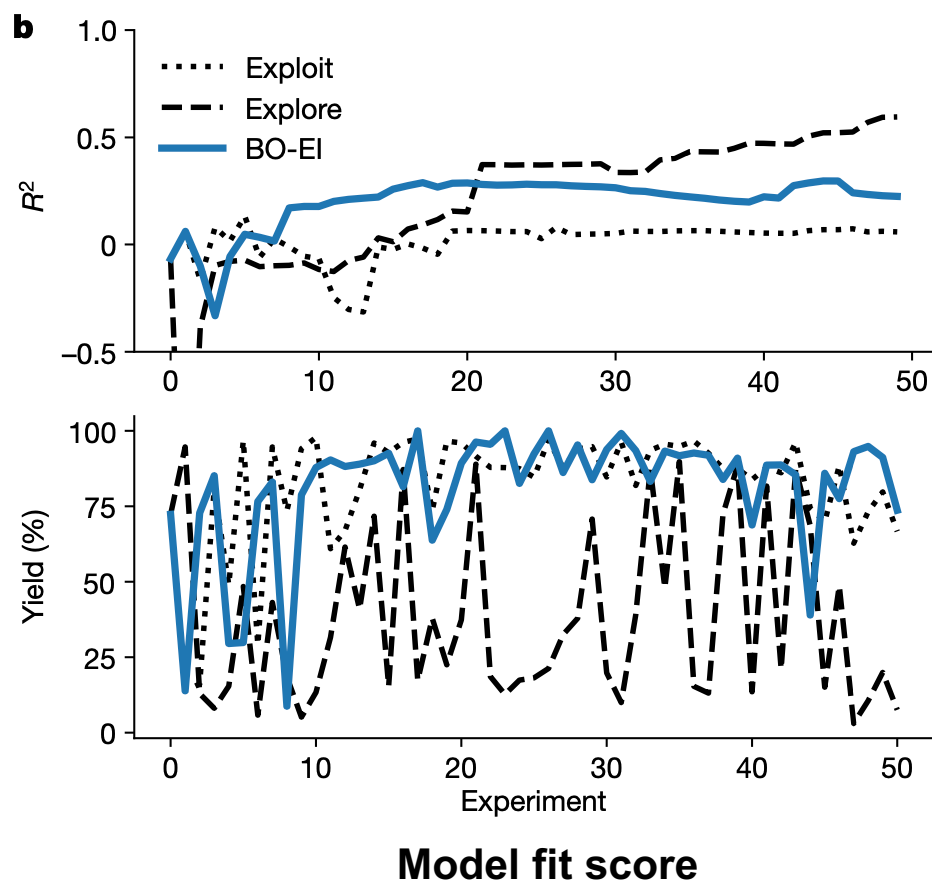
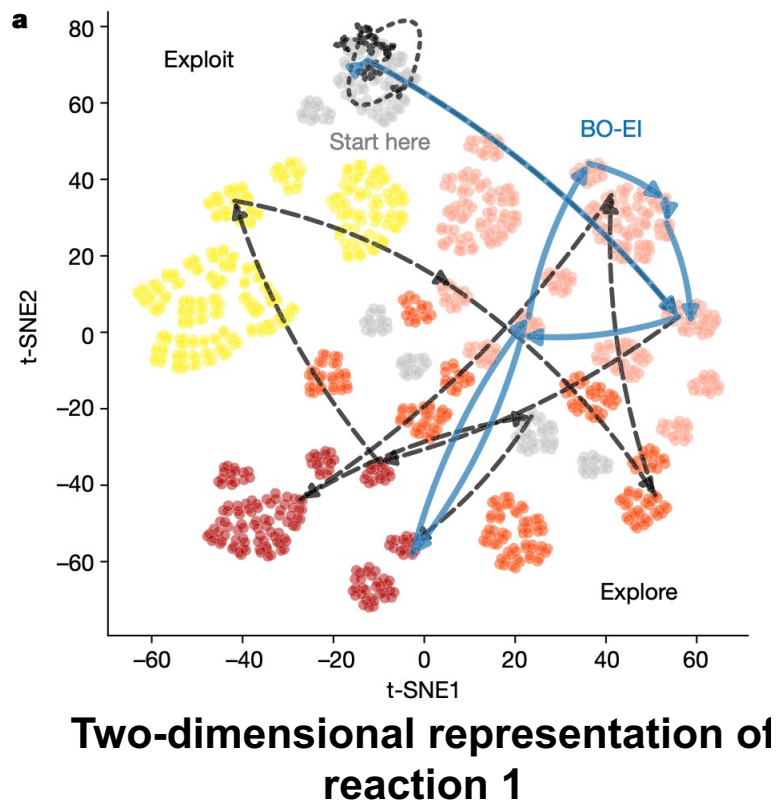
- Could become trapped in local maxima

## ➤ Pure exploration



- May achieve the best global understanding

# Balancing exploration and exploitation



**Explorer: Better fit, low yield**  
**Exploiter: High yield**

**Balancing**

**Expected improvement**

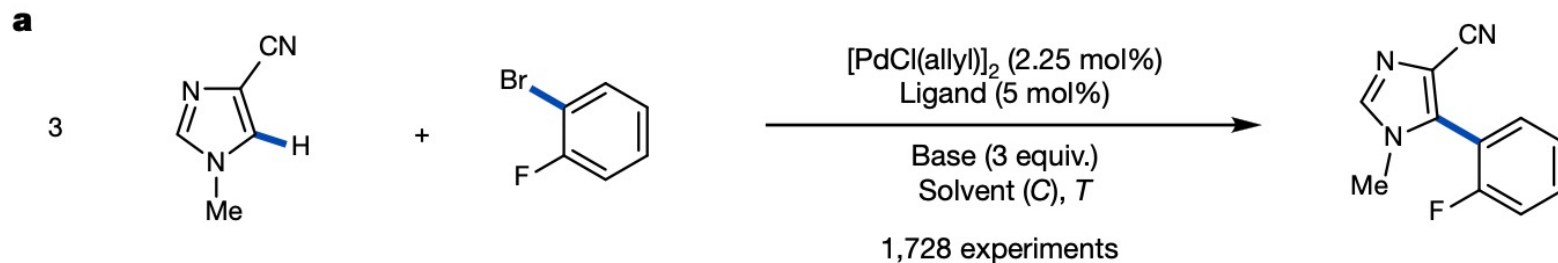
# Table of contents

---

- 1. BO as a tool for reaction optimization**
  1. Introduction
  2. Model optimization
  - 3. Performance benchmarking (BO vs. chemists) and Applications**
2. Optimizing BO to find general reaction conditions
  1. Introduction
  2. Data-guided down-selection, experiments and model optimization
  3. Optimization and quantification
3. Summary

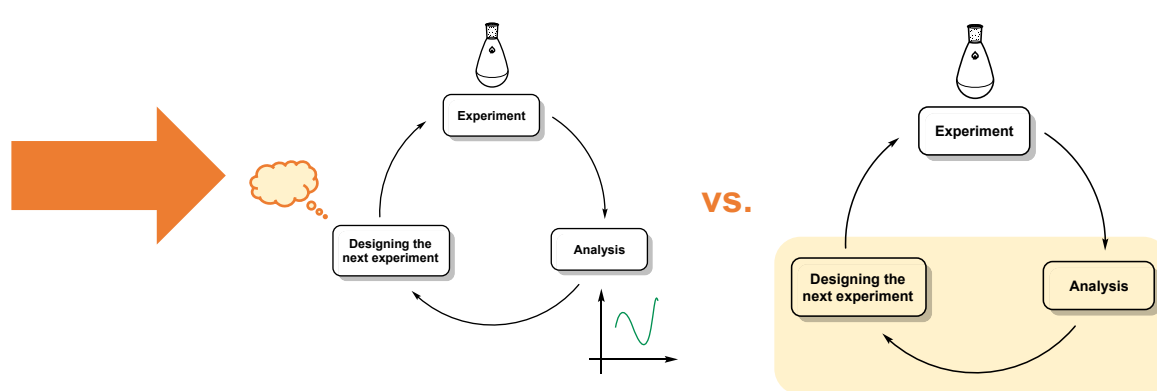
# Test in a new reaction space

## Palladium-catalyzed C–H functionalization



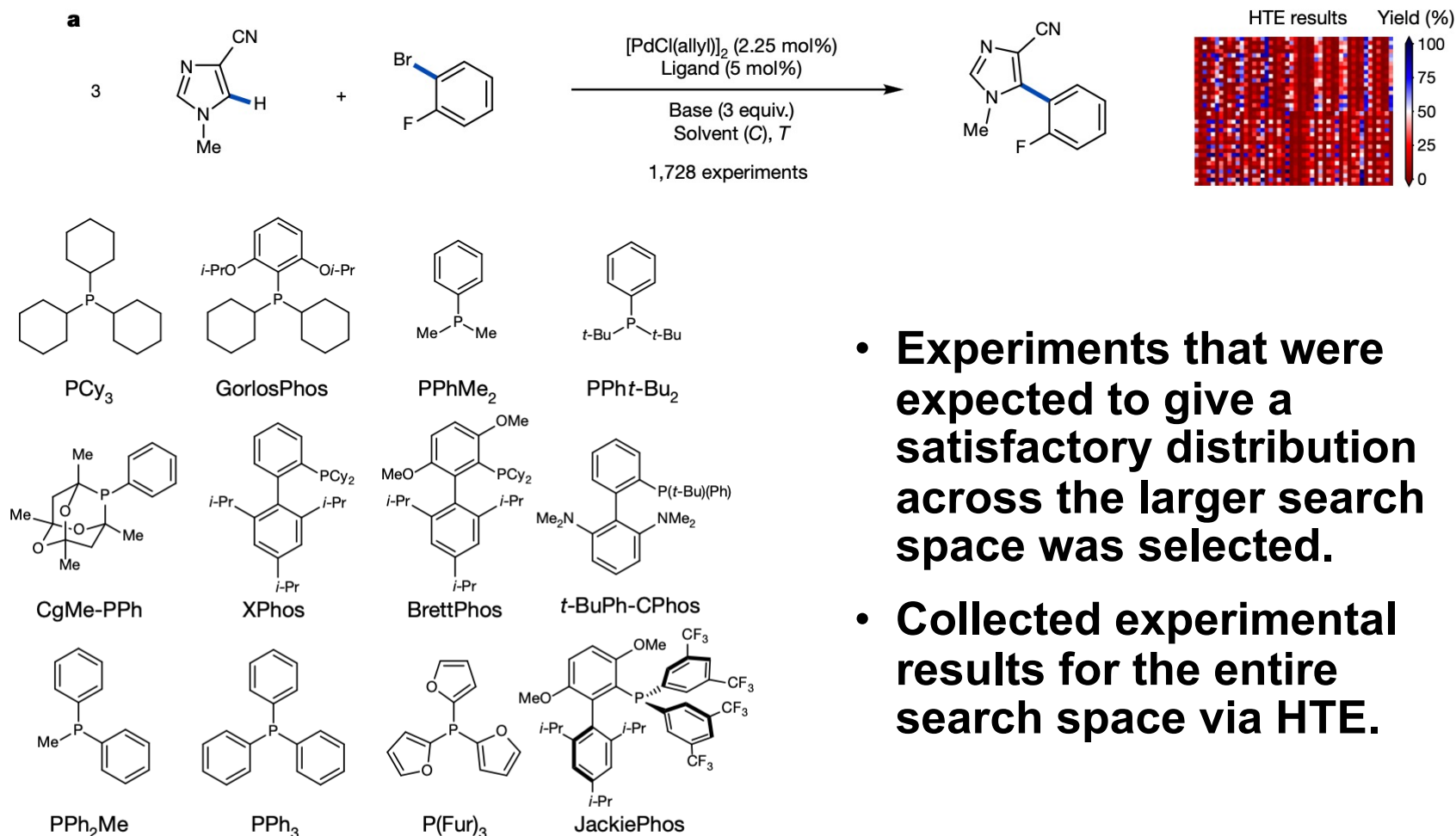
High-throughput experimentation

### Data collection



### Bayesian optimization (BO)

# BO vs. human experts (Data collection)

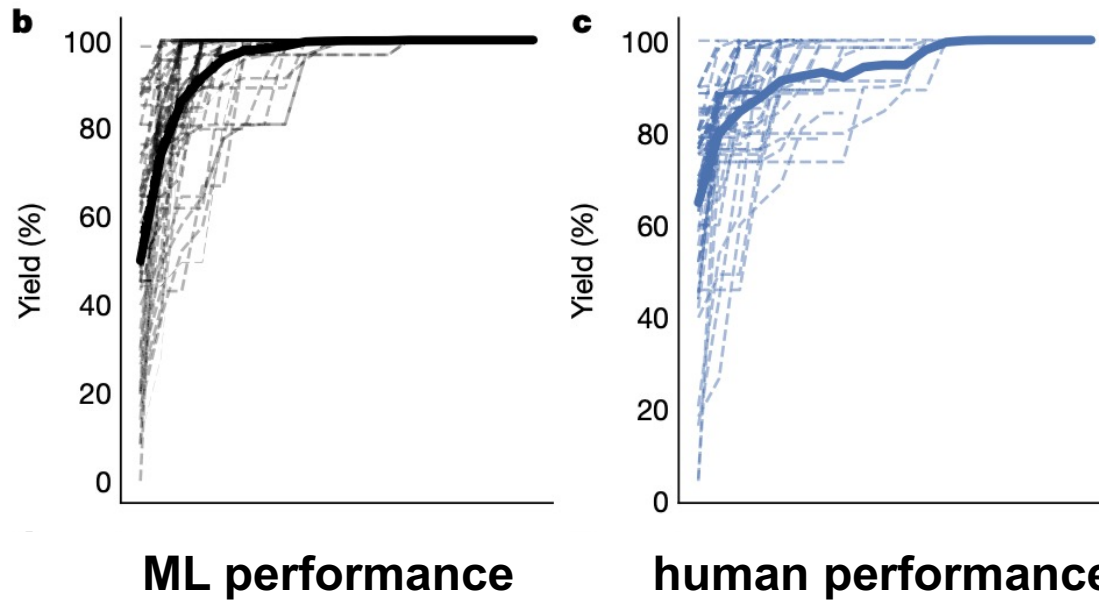


- Experiments that were expected to give a satisfactory distribution across the larger search space was selected.
- Collected experimental results for the entire search space via HTE.

KOAc	CsOAc	BuOAc	BuCN	90	120	0.057	0.153
KOPiv	CsOPiv	<i>p</i> -Xylene	DMAc				
Base		Solvent		T (°C)		C (M)	

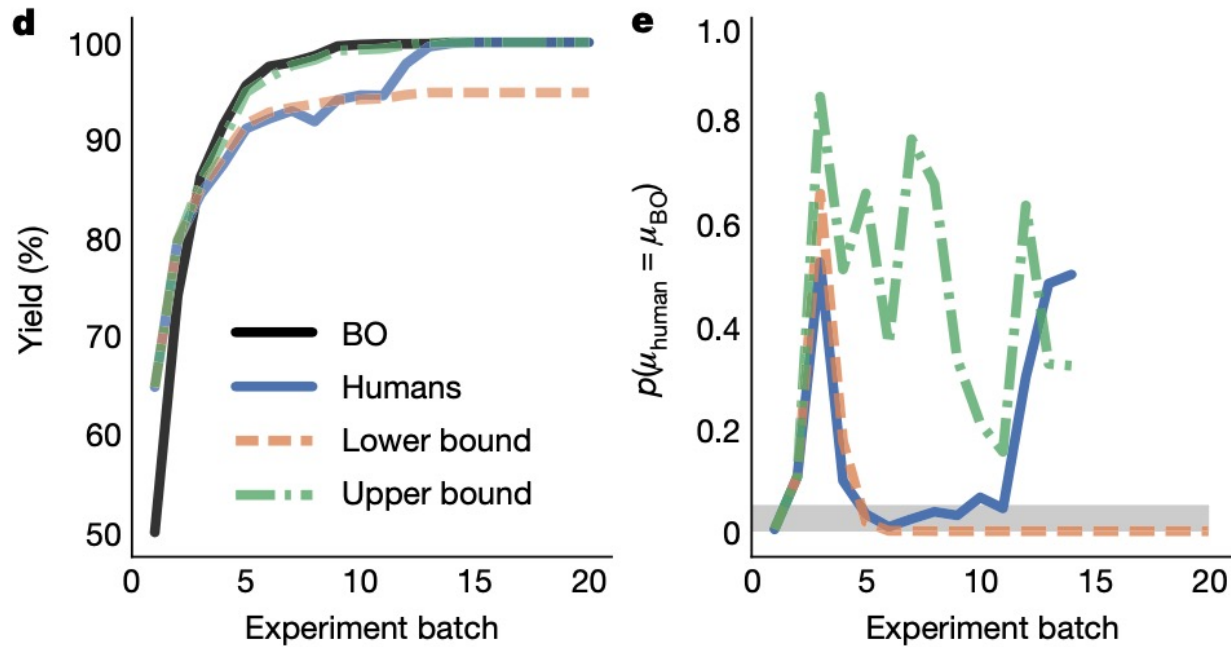
R. P. Adams, A. G. Doyle, *et al.* *Nature* **2021**, 590, 89–96.

# BO vs. human experts (Game results)



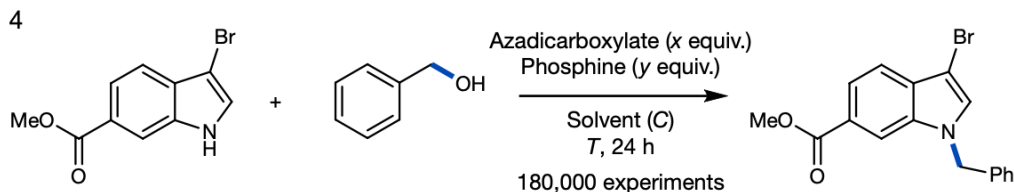
	Optimizer	Humans
Initial choices	random	significantly better selection
Final results	○ (the average performance within three batches of five experiments)	△

# BO vs. human experts (Game results)

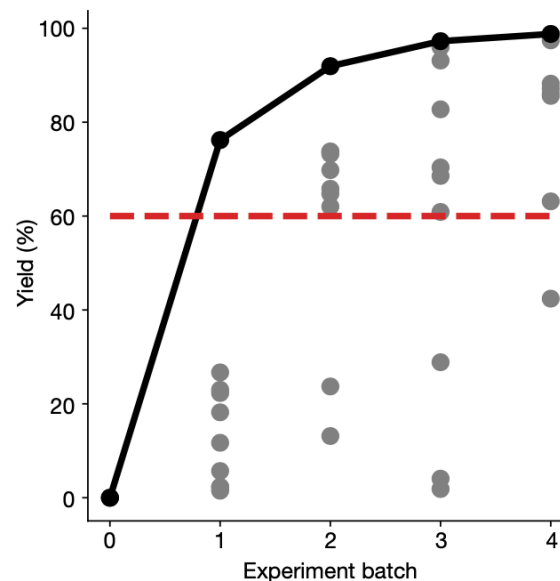
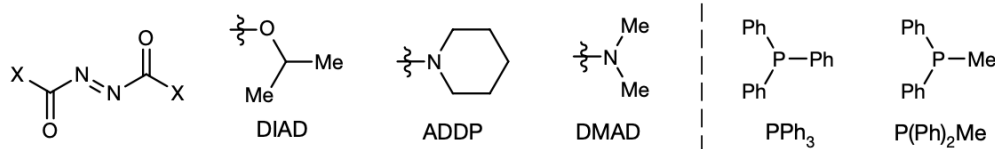


- **Best- and worst-case bounds for average human performance**
  - **Bayesian reaction optimization on average outperformed human experts.**

# Optimization of a Mitsunobu reaction



Entry	AD	x (equiv.)	Phosphine	y (equiv.)	Solvent	C (M)	T (°C)	Yield
1	DIAD	1.1	PPh <sub>3</sub>	1.1	THF	0.1	25	60%
2	ADDP	1.9	P(Ph) <sub>2</sub> Me	1.9	THF	0.2	25	99%
3	DMAD	1.9	P(Ph) <sub>2</sub> Me	1.9	MeCN	0.15	45	99%
4	ADDP	1.9	P(Ph) <sub>2</sub> Me	1.9	THF	0.15	45	99%

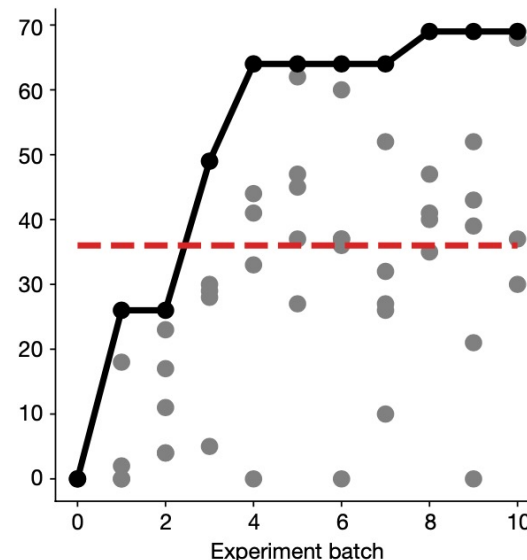
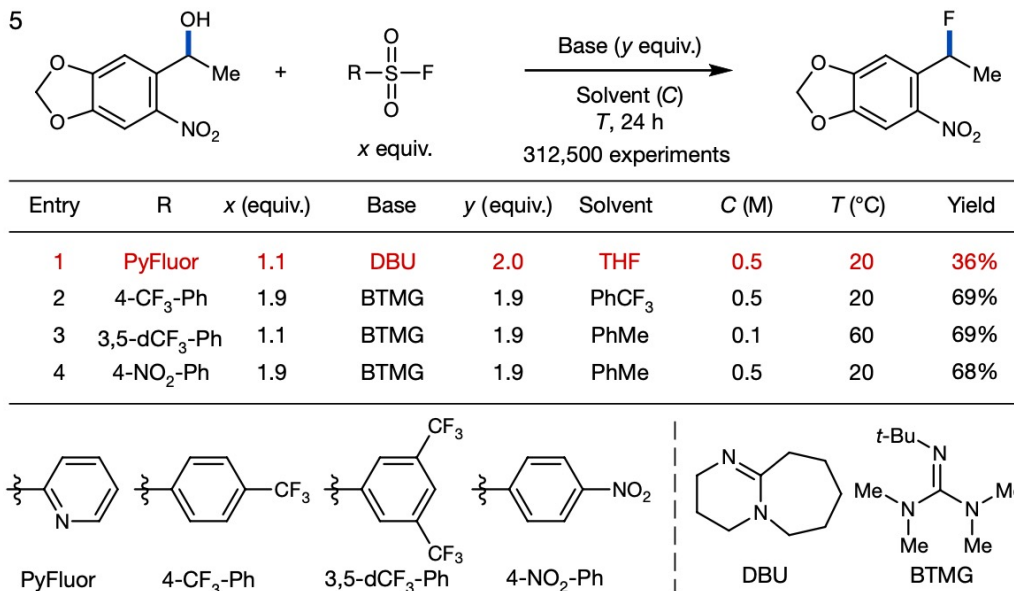


➤ From 180,000 possible configurations in total...

- ✓ The optimizer quickly surpassed the benchmark result.
- ✓ Three distinct sets of reaction conditions (99% yield) were identified in only four rounds of ten experiments.



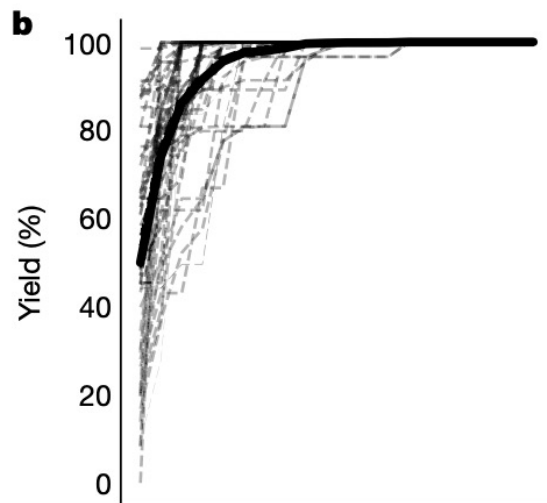
# Optimization of a deoxyfluorination reaction



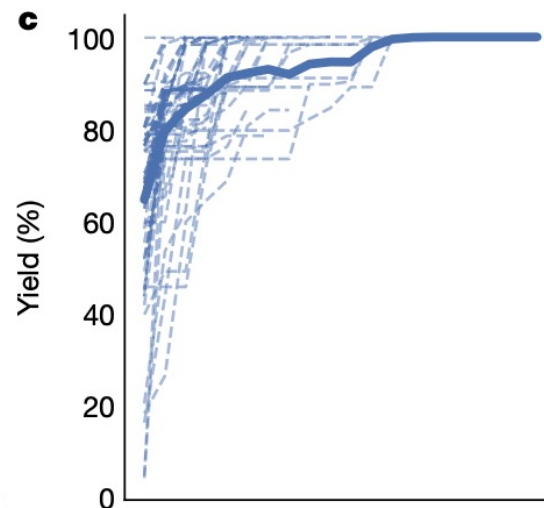
➤ From 312,500 possible configurations in total...

- ✓ The optimizer surpassed the benchmark result within three rounds of five experiments.
- ✓ Reaction conditions that produced TM in 69% yield were identified in ten rounds of experiments.

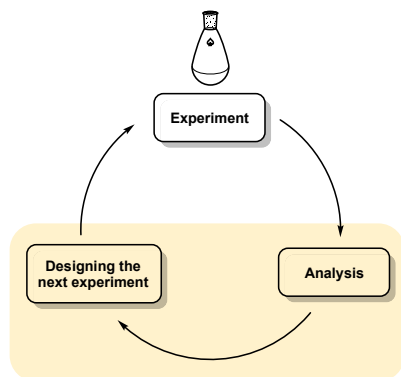
# Short summary



ML performance



human performance



Bayesian  
optimization (BO)

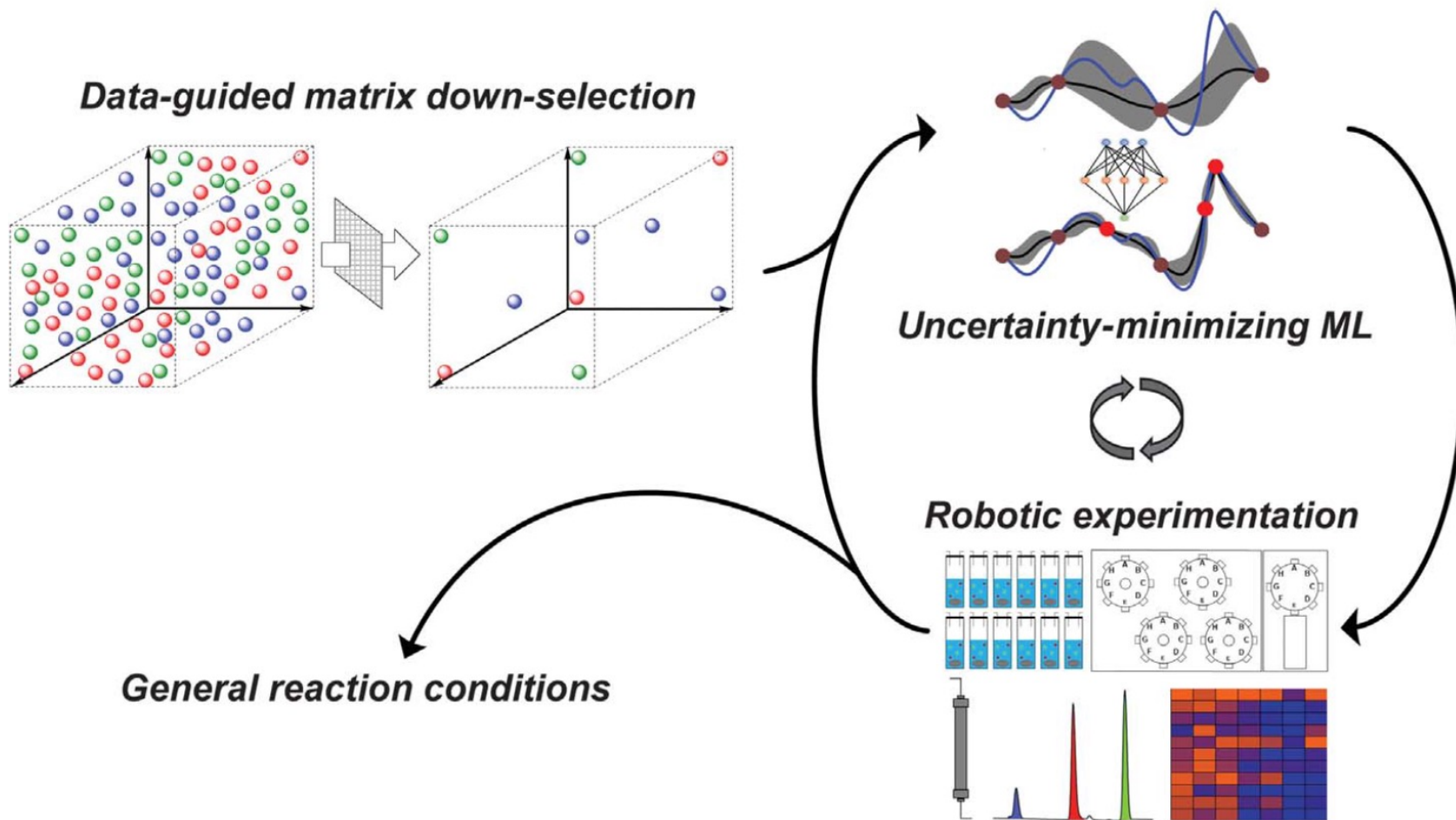
✓ An efficient and solid method to optimize reaction conditions

# Table of contents

---

- 1. BO as a tool for reaction optimization**
  1. Introduction
  2. Model optimization
  3. Performance benchmarking (BO vs. chemists) and Applications
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  - 1. Introduction**
  2. Data-guided down-selection, experiments and model optimization
  3. Optimization and quantification
3. Summary

# Optimization of general reaction conditions

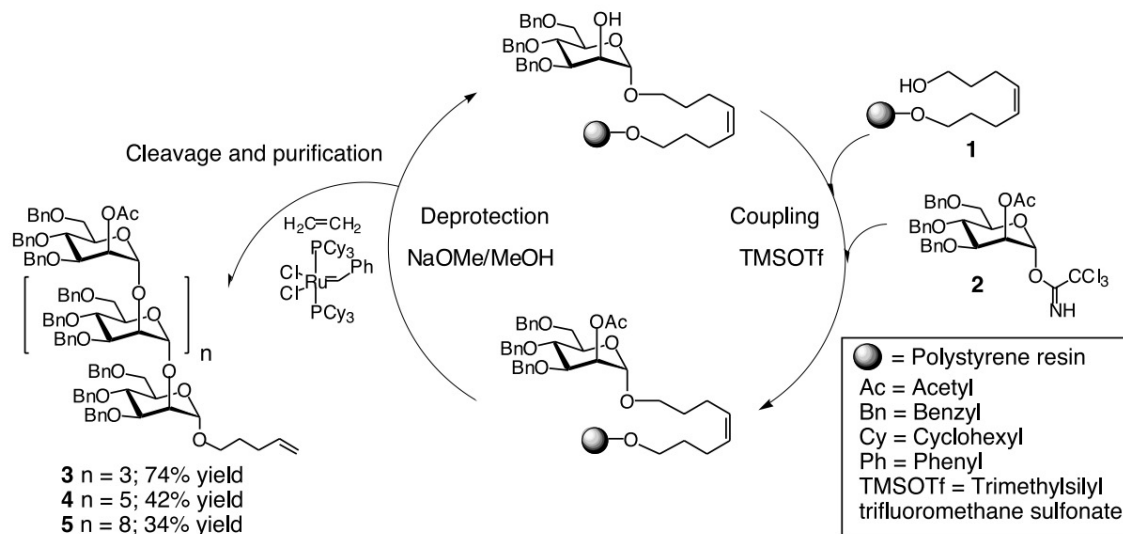


N. H. Angello, V. Rathore, W. Beker, A. Wołos, E. R. Jira, R. Roszak, T. C. Wu, C. M. Schroeder, A. Aspuru-Guzik, B. A. Grzybowski, M. D. Burke, *Science* **2022**, 378, 399–405.

# Importance of general reaction conditions

Automated  
synthesis  
methods for  
peptides, nucleic  
acids, and  
polysaccharides

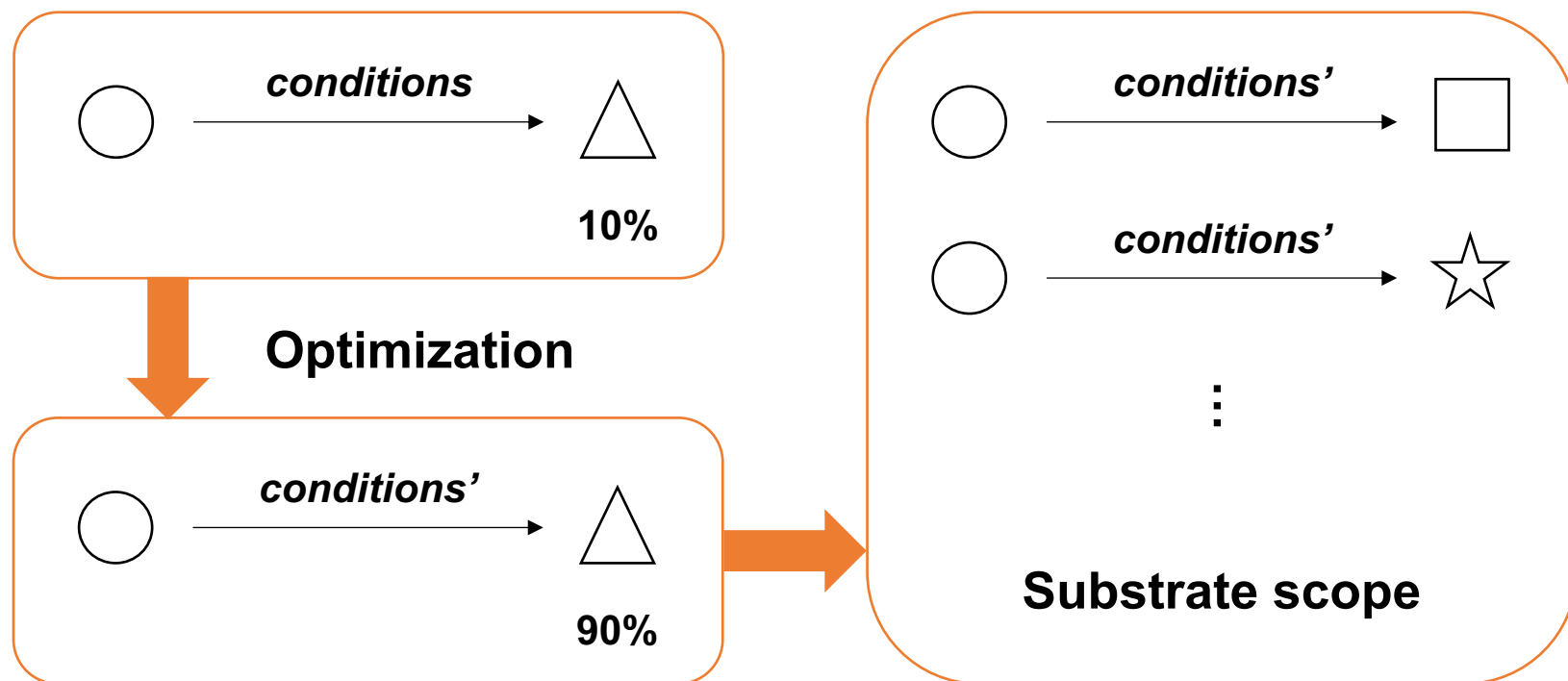
Highly general  
reaction conditions



## Automated oligosaccharide synthesis

P. H. Seeberger, *et al.* *Science* **2001**, 291, 1523–1527.

# Reaction conditions for small organic synthesis

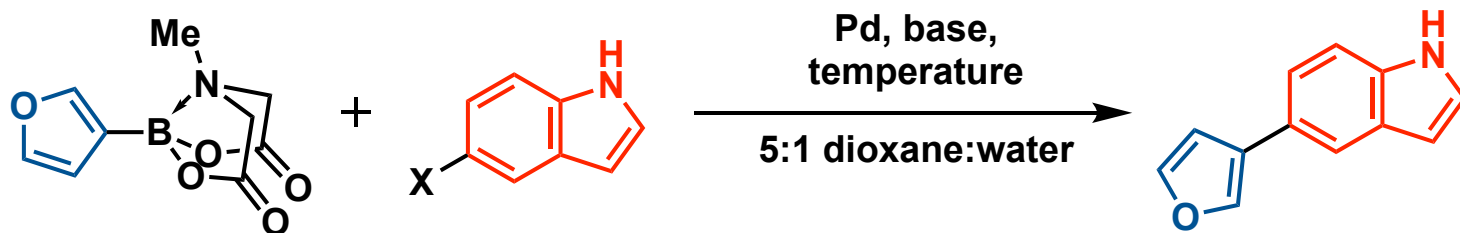


To identify **general** conditions:  
all possible combinations of substrates  
× all possible combinations of reaction conditions

➤ **Difficult to navigate via standard approaches**

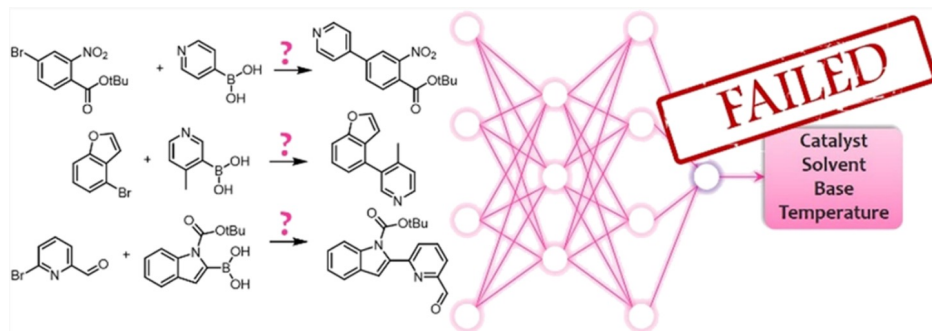
# (Hetero)aryl Suzuki-Miyaura cross-coupling

A promising method to synthesize heteroaryl molecular fragments:  
SMC (Suzuki-Miyaura cross-coupling)

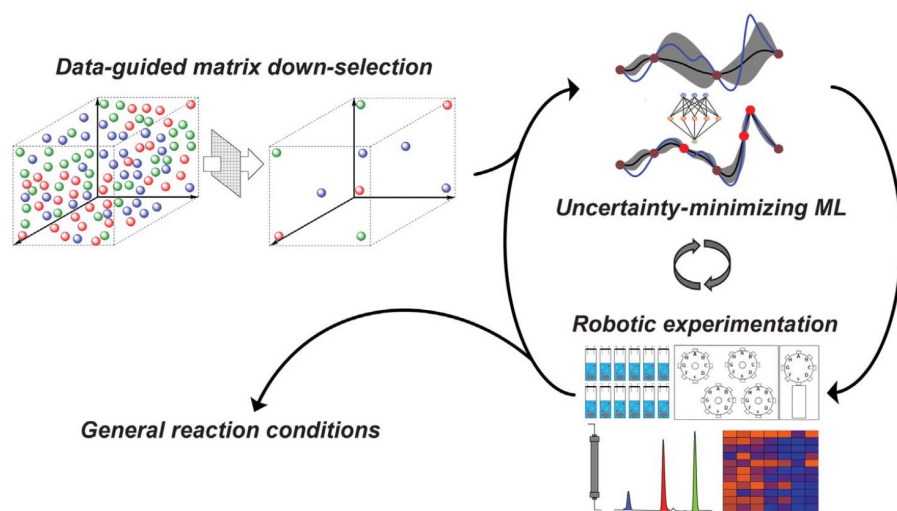


➤ Finding general conditions

- This had been attempted, but failed, to discover them by mining the extensive chemical literature



# Overview of the method



1. **Data-guided matrix down-selection** to render the vast search space tractable
2. **Modified BO** to efficiently drive prediction optimization
3. **Robotic experimentation** to increase throughput, precision, and reproducibility

➤ **Succeeds in identifying general reaction conditions!**

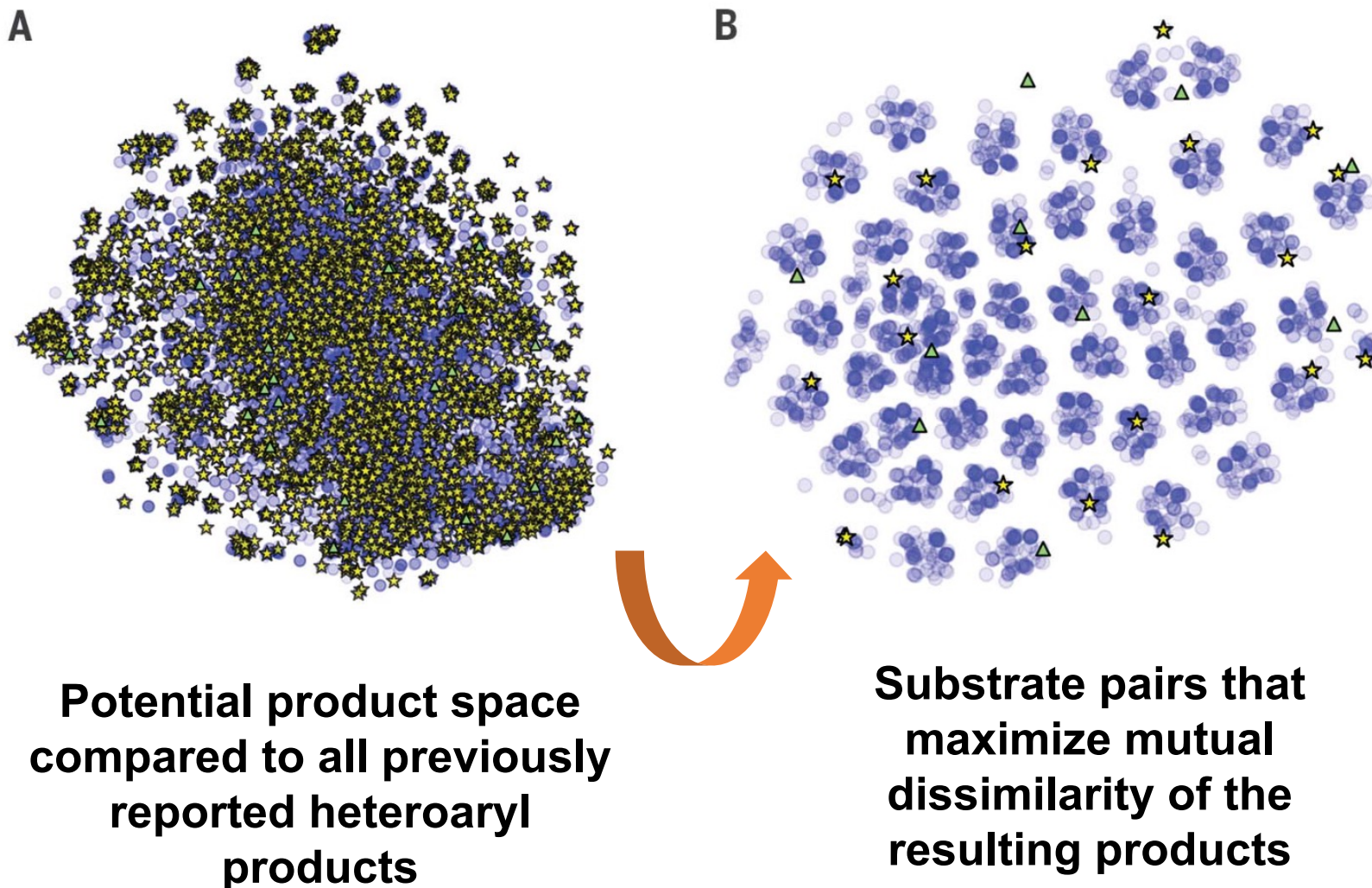


# Table of contents

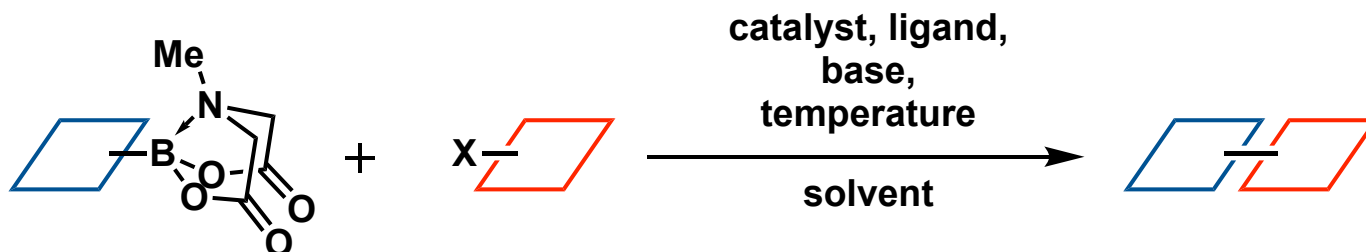
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1. BO as a tool for reaction optimization
  1. Introduction
  2. Model optimization
  3. Performance benchmarking (BO vs. chemists) and Applications
2. **Optimizing BO to find general reaction conditions**
  1. Introduction
  2. **Data-guided down-selection, experiments and model optimization**
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3. Summary

# Data-guided down-selection of substrates



# Data-guided down-selection of conditions



- extent of prior use
- structural diversity
- functional diversity

---

selected conditions	
catalysts	Pd SPhos G <sub>4</sub> , Pd(PPh <sub>3</sub> ) <sub>4</sub> , PdXPhosG <sub>4</sub> , Pd P(tBu) <sub>3</sub> G <sub>4</sub> , Pd PCy <sub>3</sub> G <sub>4</sub> , Pd <sub>2</sub> (dba) <sub>3</sub> , and Pd(dppf)Cl <sub>2</sub>
bases	sodium carbonate and potassium phosphate
temperatures	60° C and 100° C
solvents	dioxane, toluene, and dimethylformamide, all used in 5:1 mixture with water

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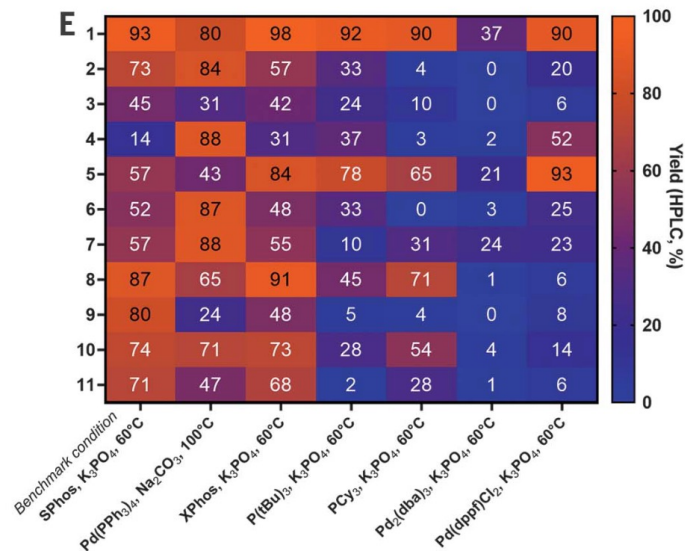
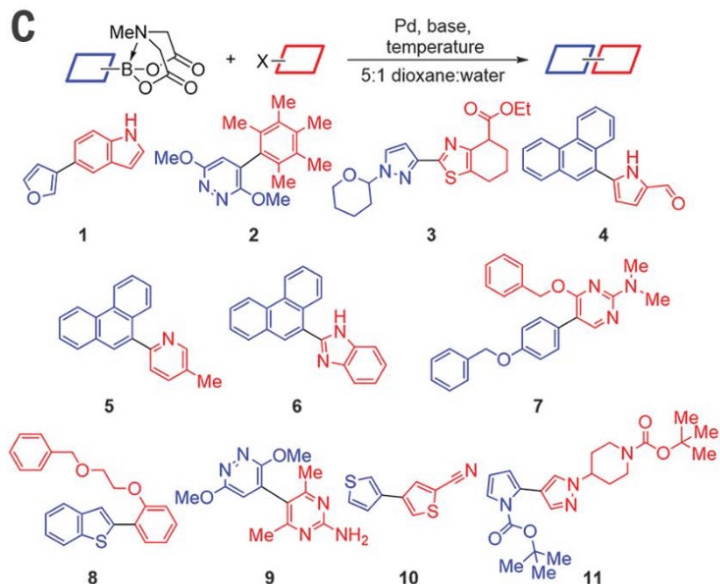
# Robotic system for reaction performance



**When each reaction was repeated twice, the yields exhibited only  $\pm 2\%$  deviation.**

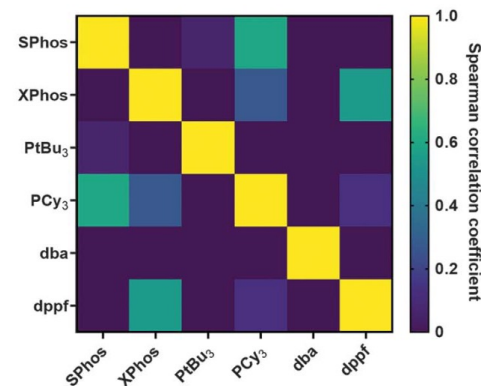
- **One of the key advantages of automated experimentation**

# Seeding experiments



- Catalysts with**
- similar functions
  - poor performance were eliminated.

**528 reactions in total**



# Uncertainty-minimizing ML for generality

- **Aim: to maximize the objective function  $f(c)$**

$$f(c) = \frac{1}{|S|} \sum_{s \in S} y(s, c)$$

**C={c}: the set of possible reaction conditions**

**S = {s}: a set of substrate pairs**

**y(s,c): reaction yield**

- **BO: each experiment performed immediately provides information about the objective function**
- **In this case: determination of  $f(c)$  for given conditions requires experiments with every pair of substrates in the S set**

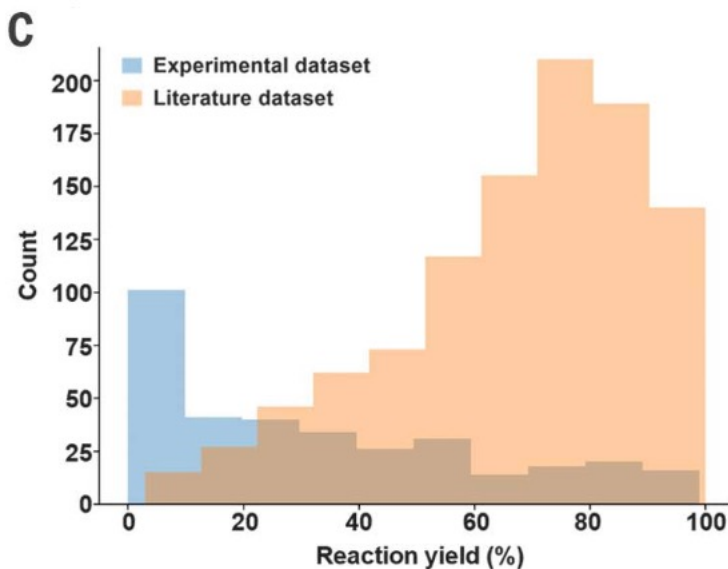
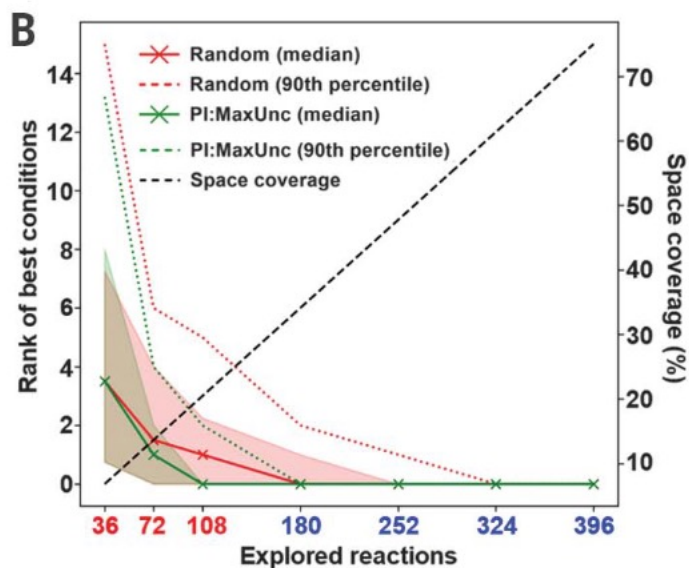
# Table of contents

---

1. BO as a tool for reaction optimization
  1. Introduction
  2. Model optimization
  3. Performance benchmarking (BO vs. chemists) and Applications
- 2. Optimizing BO to find general reaction conditions**
  1. Introduction
  2. Data-guided down-selection, experiments and model optimization
  - 3. Optimization and quantification**
3. Summary



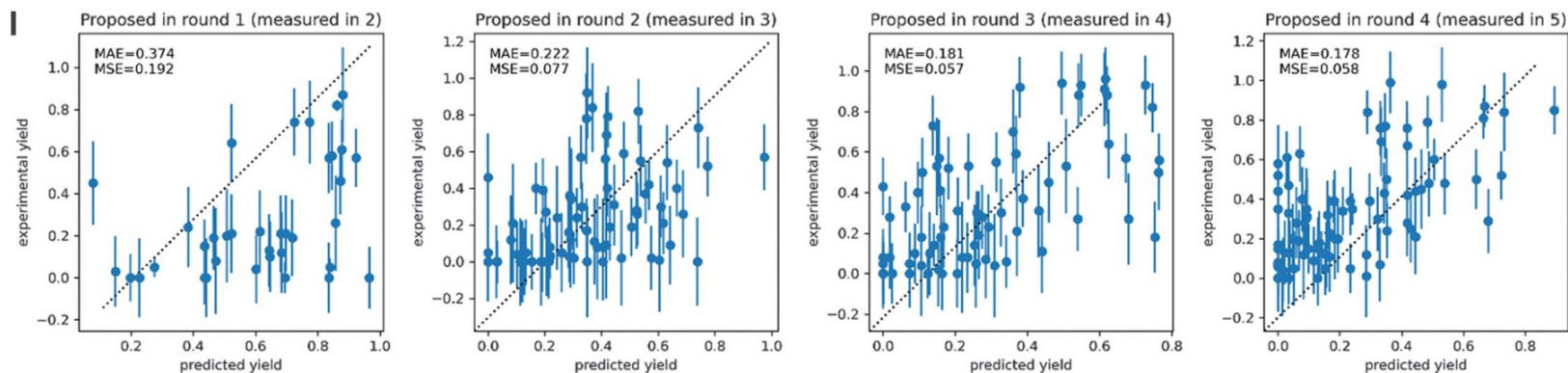
# Advantages found for model-guided research



- ✓ Apparent efficiency compared to random sampling
- ✓ Uniformly distributed yields over the range of possible values



# Yields of reactions the model requested



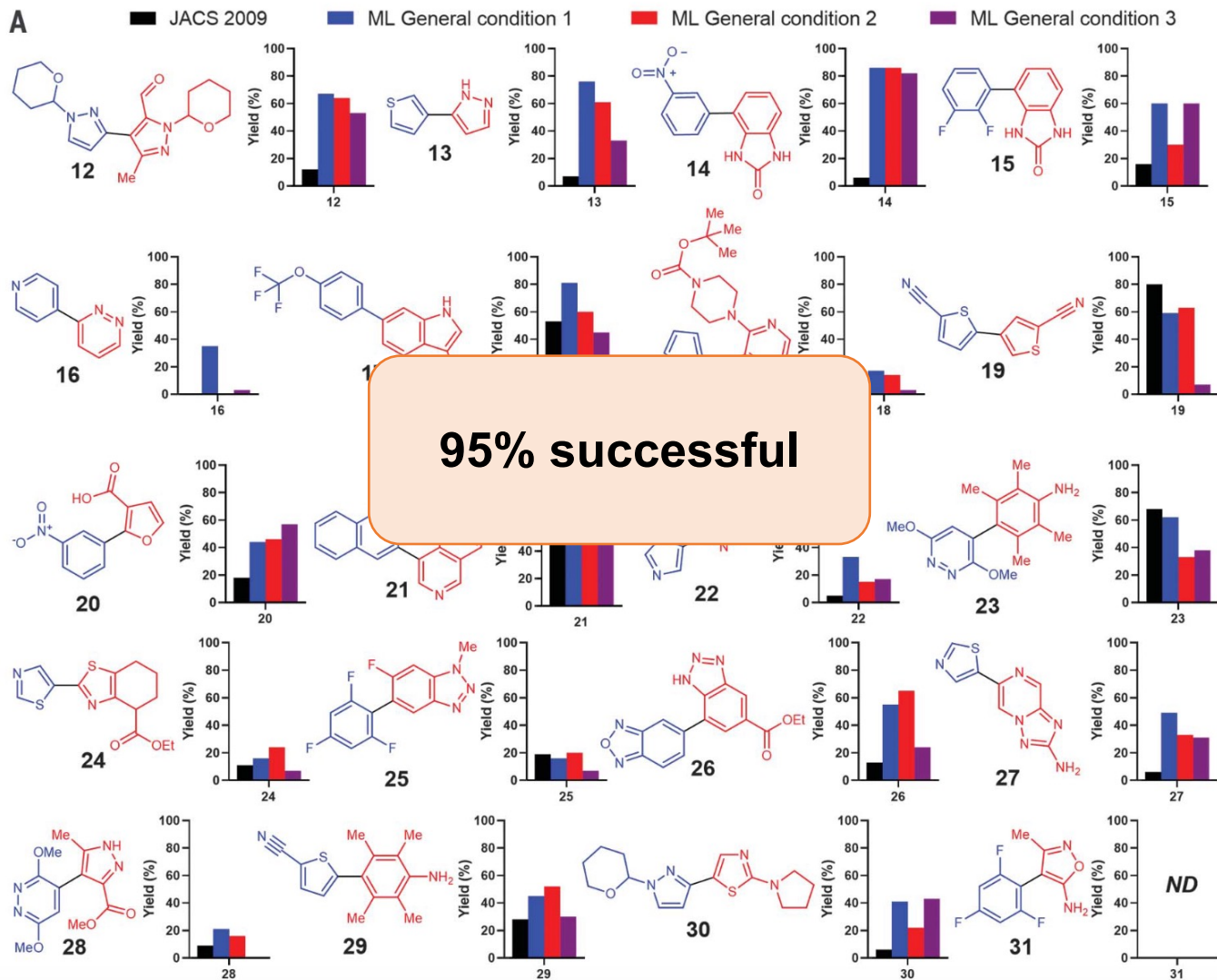
## Exploration of good reactions in the second iteration

- Attention shifted toward the “negative examples”

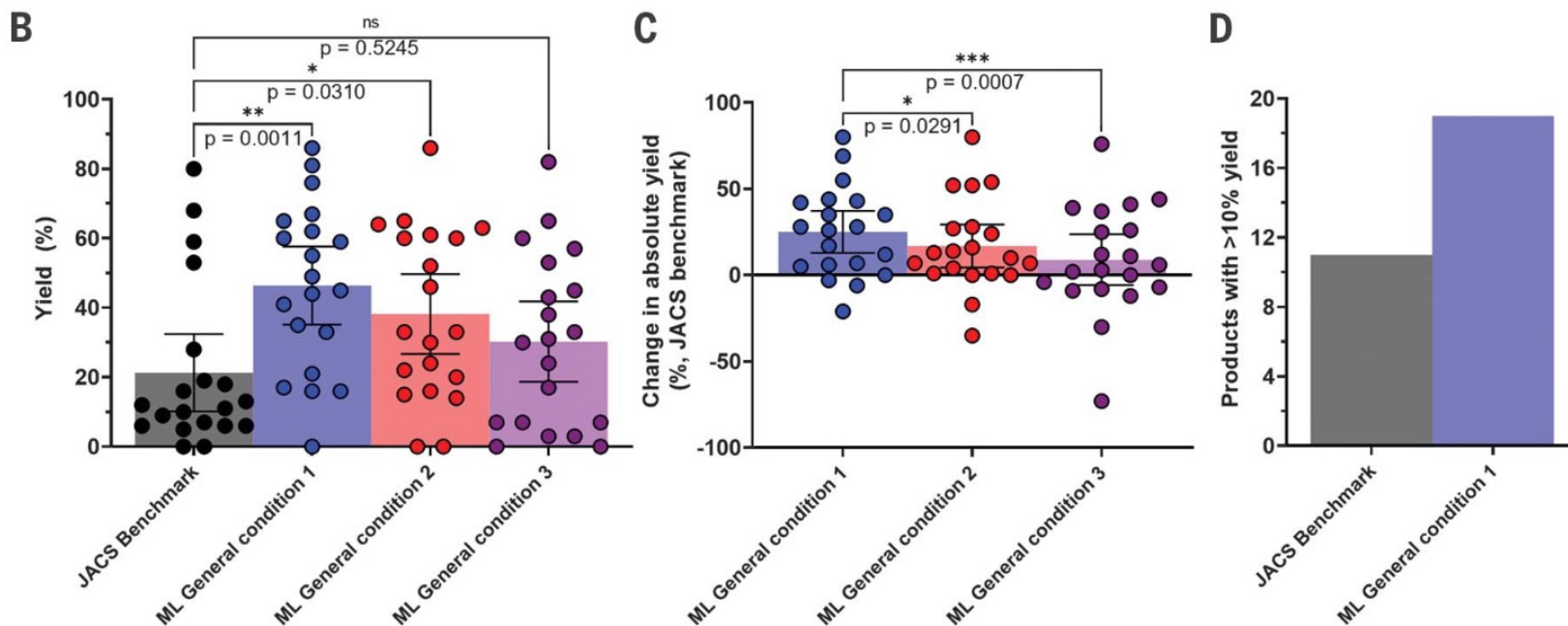
### Findings through the overall analysis:

- Relatively good candidate solutions were identified early
- The model initially tried to look for better-yielding reactions
- More and more attention was dedicated to decreasing the uncertainty of its estimates as the “loop” progressed

# Quantifying generality

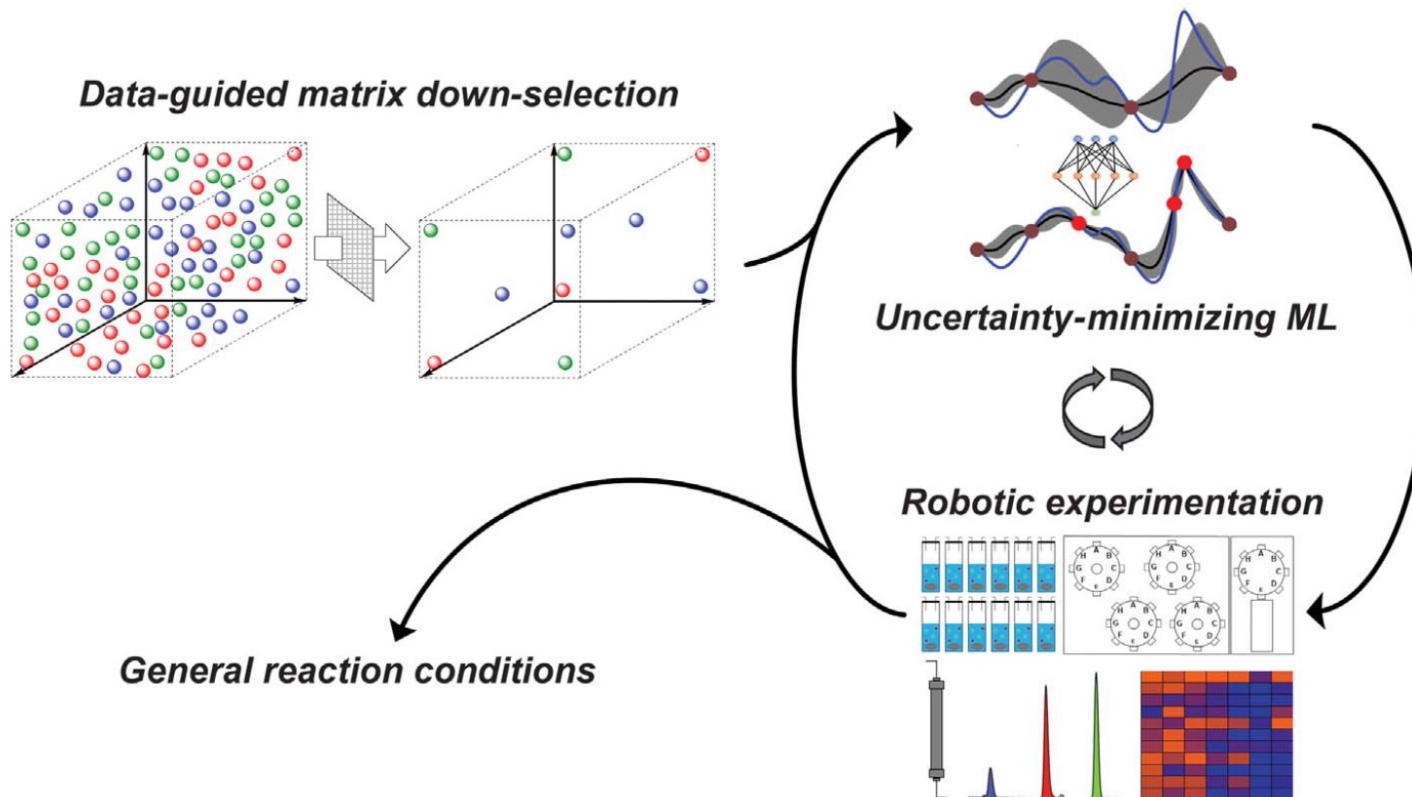


# Comparison with the reported conditions



**ML-discovered general reaction conditions performed substantially better.**

# Short summary



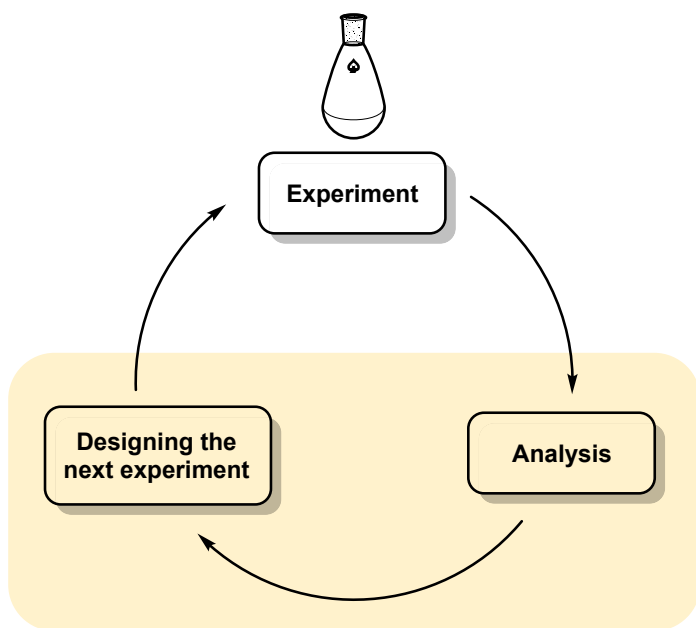
**A nearly impossible challenge of finding general conditions was overcome by ML-assisted approach.**

# Table of contents

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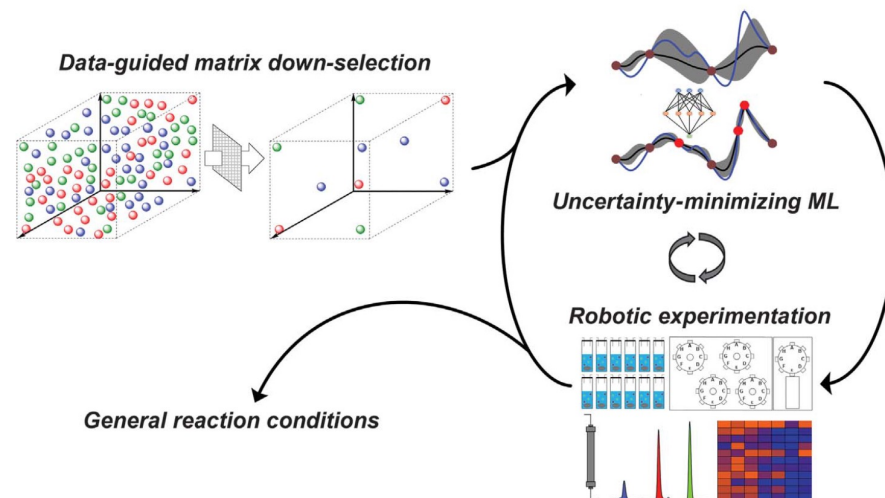
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  1. Introduction
  2. Model optimization
  3. Performance benchmarking (BO vs. chemists) and Applications
2. Optimizing BO to find general reaction conditions
  1. Introduction
  2. Data-guided down-selection, experiments and model optimization
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# Summary



## Bayesian optimization (BO)

- ✓ Optimization of the reaction conditions using certain substrates utilizing BO



- ✓ Further modified ML-assisted method to find general conditions applicable to various substrates