THE AGE OF INTELLIGENT MANUFACTURING

Wojciech Matusik
MIT

THE DIGITALIZATION OF MANUFCTURING

is transforming how products are designed, made, and sold around the world

Rapid iterations, fast time to market

High mix, personalization, low-volume production

On-demand, distributed manufacturing

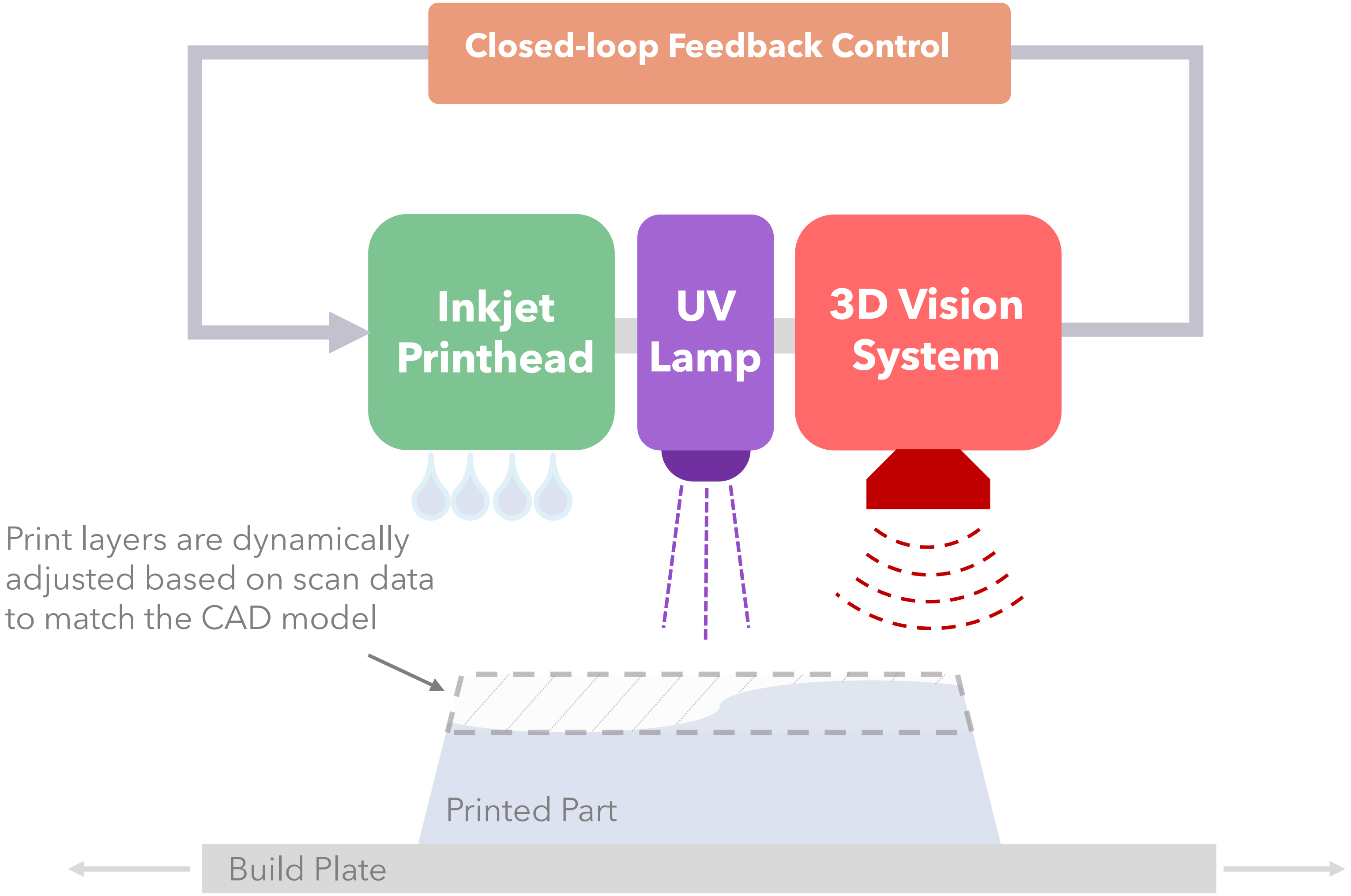
3D printing can enable this paradigm shift

- **DESIGN FREEDOM |** Complex geometries previously impossible
- **PART CONSOLIDATION |** Printing complete products rather than assembling components
- **DISTRIBUTION |** Highly distributed on-demand manufacturing networks

Obstacles: reliability, materials, cost

VCJ

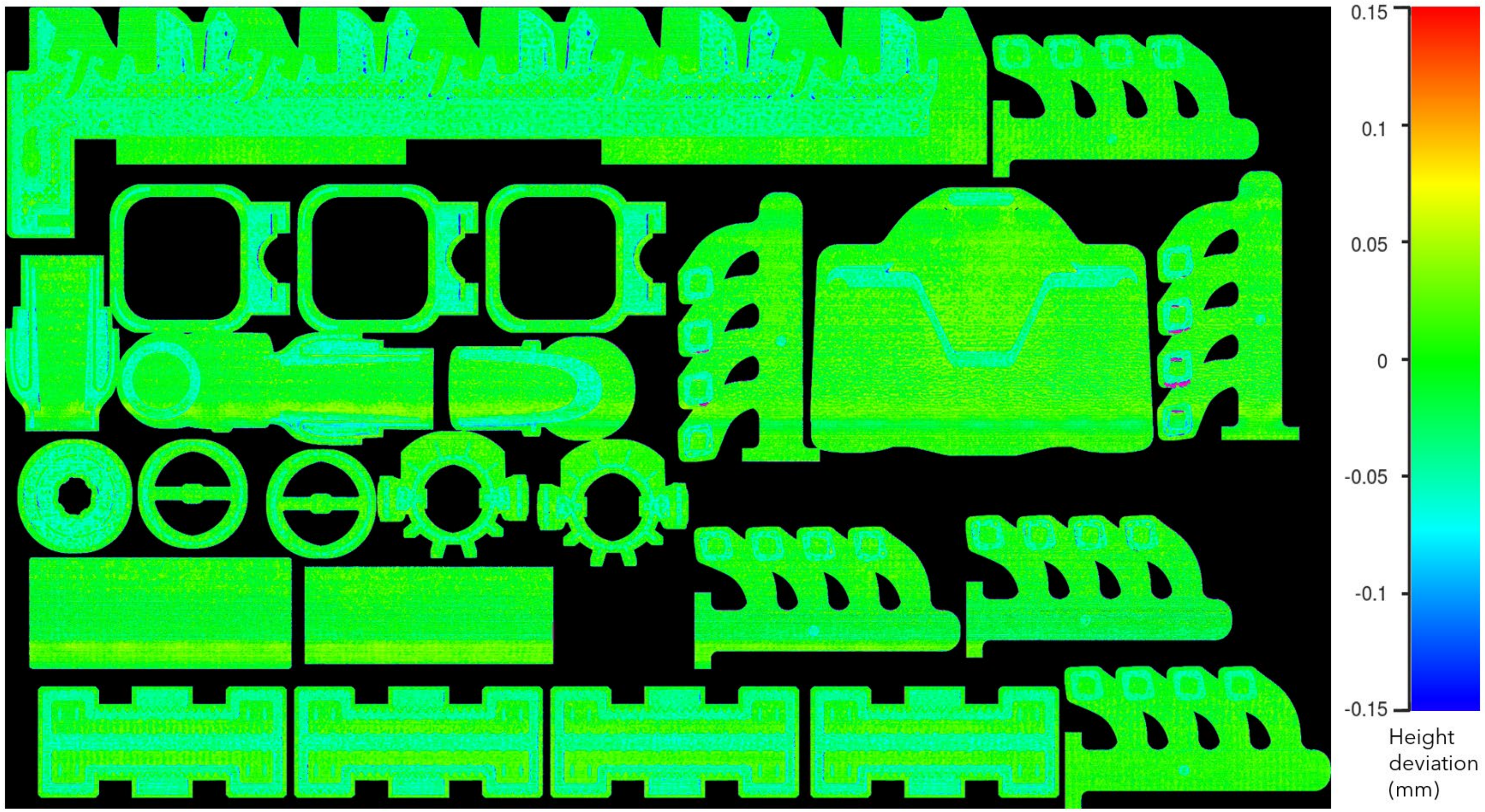
Vision-controlled Jetting



Contactless process **enables the use of high-performance photopolymers.**
First 3D printer to provide closed-loop feedback control of part geometry.

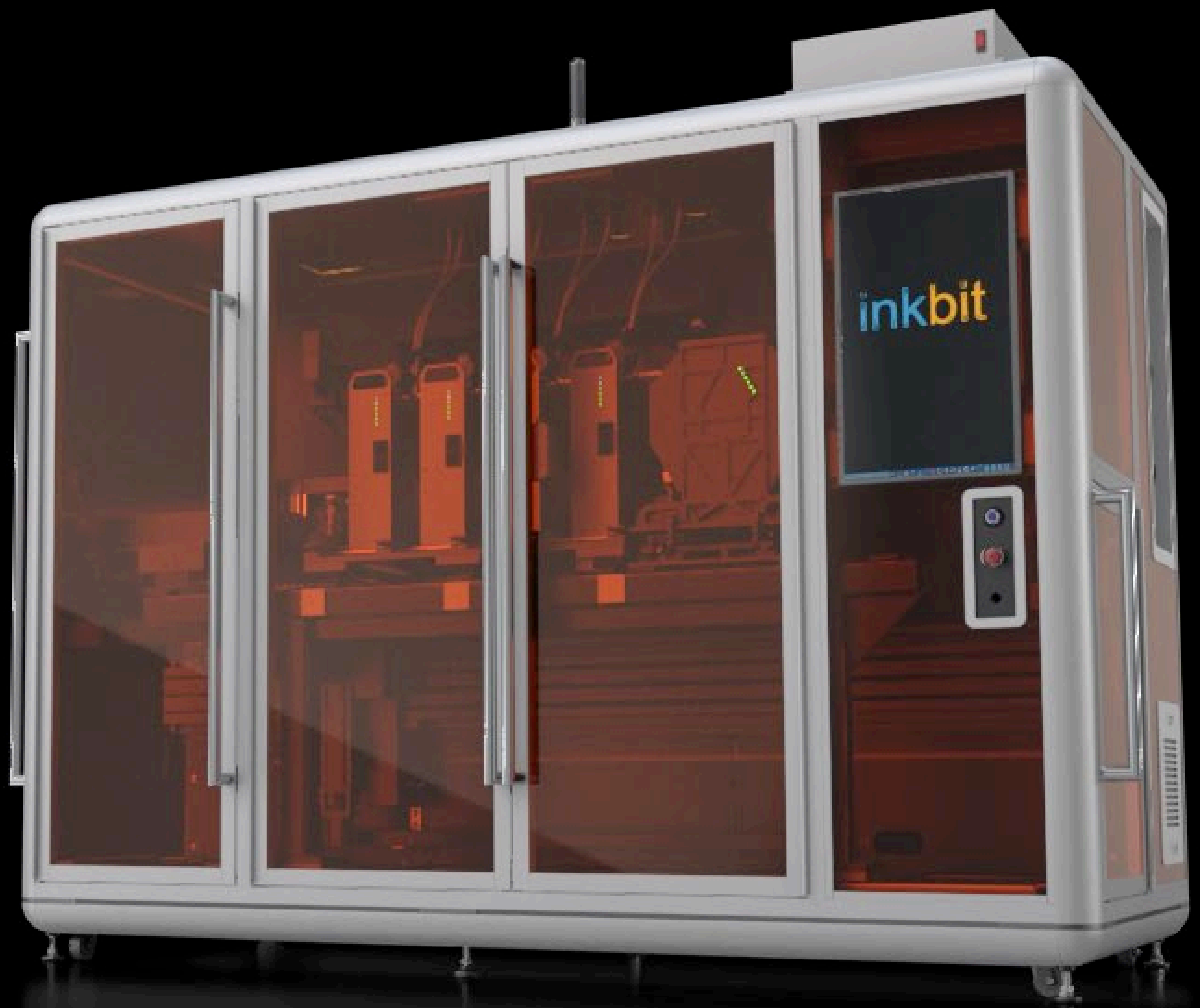
inkbit

High-resolution 3D scan data of every printed layer



~+/- 50 µm driven by scan system

Typical 3D scan of a printed layer



inkbit

Unlocking 3D printing production at scale

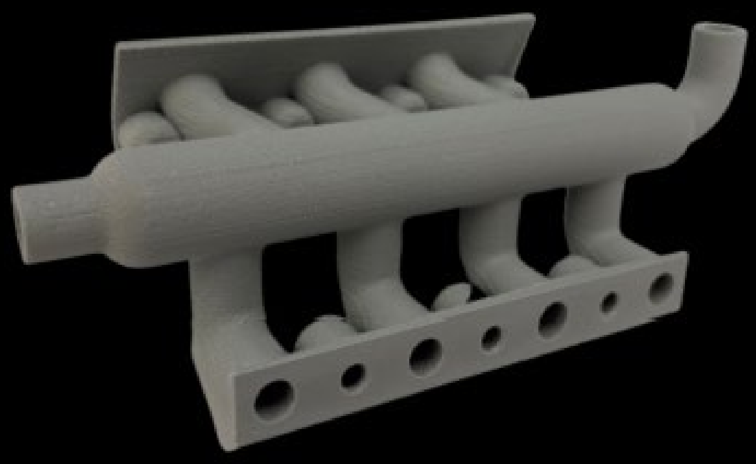
High throughput

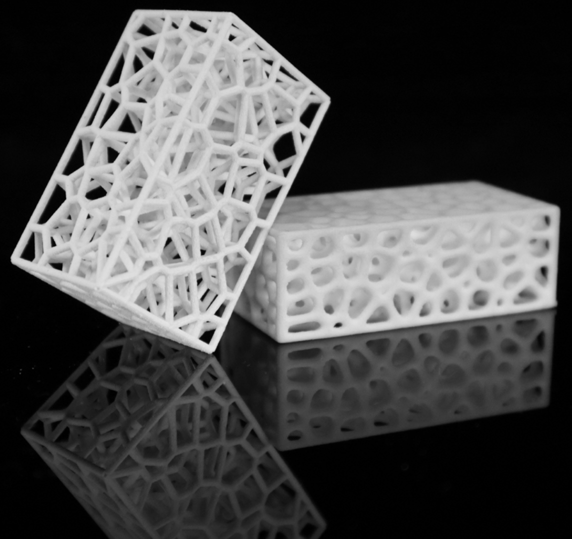
Low labor

High-performance materials

Fine feature resolution

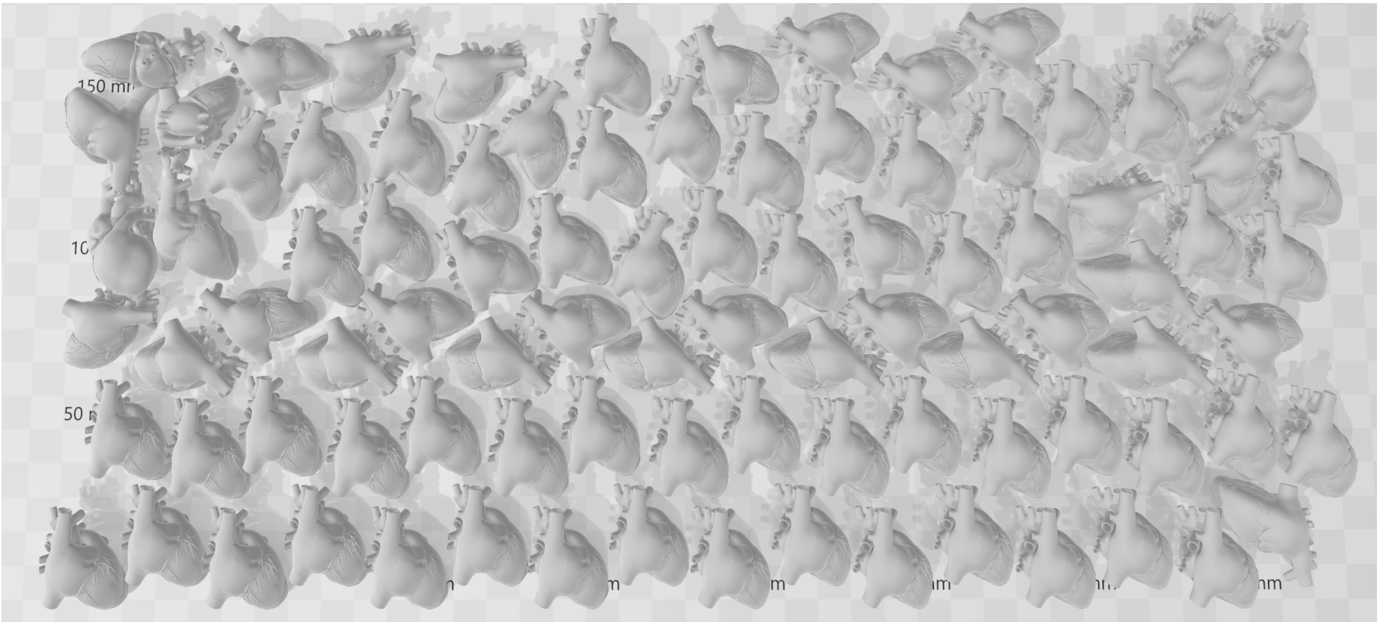
Multi-material capability



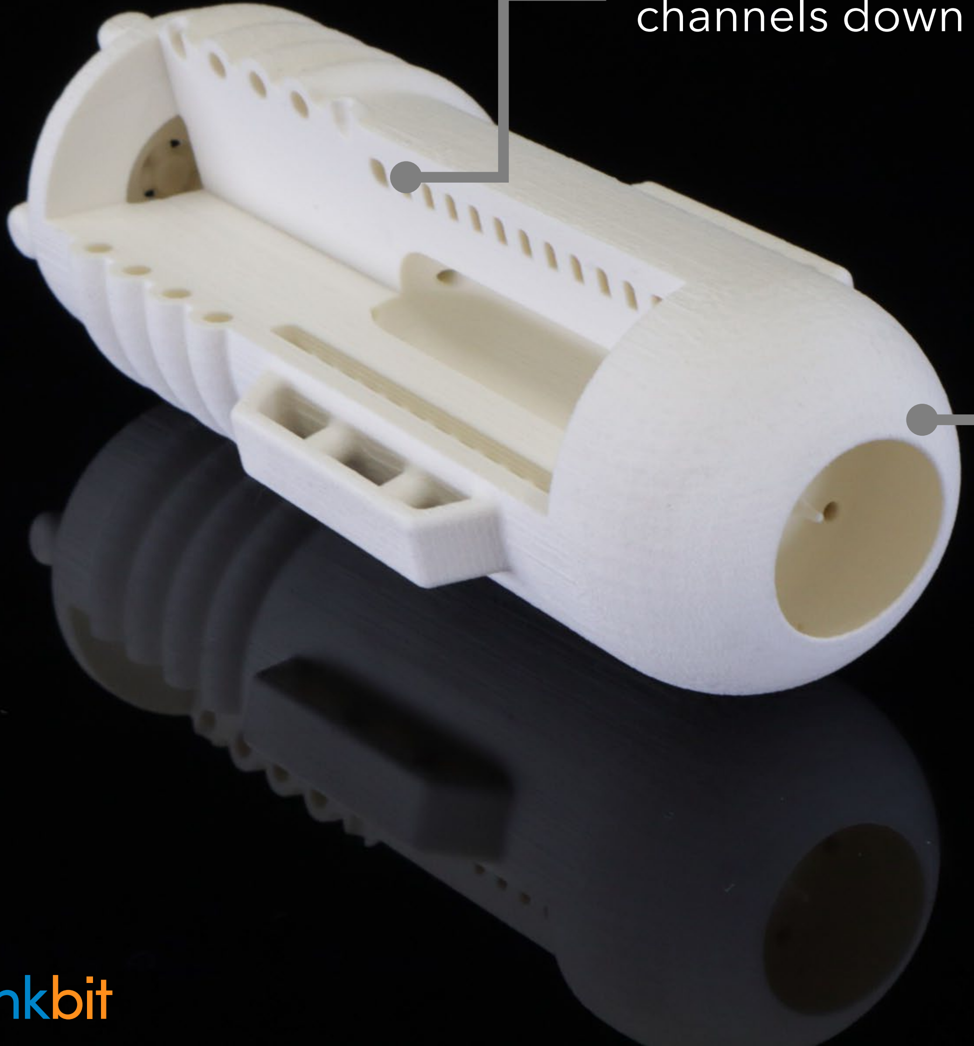


Production Run Example

Dimensions (mm)	36 x 25 x 22
Parts per build	117
Time to print one batch	1.25 h
Number of parts produced by one machine per year	700,000
Material	Elastomeric Thiolene



Fine features in soft elastomers

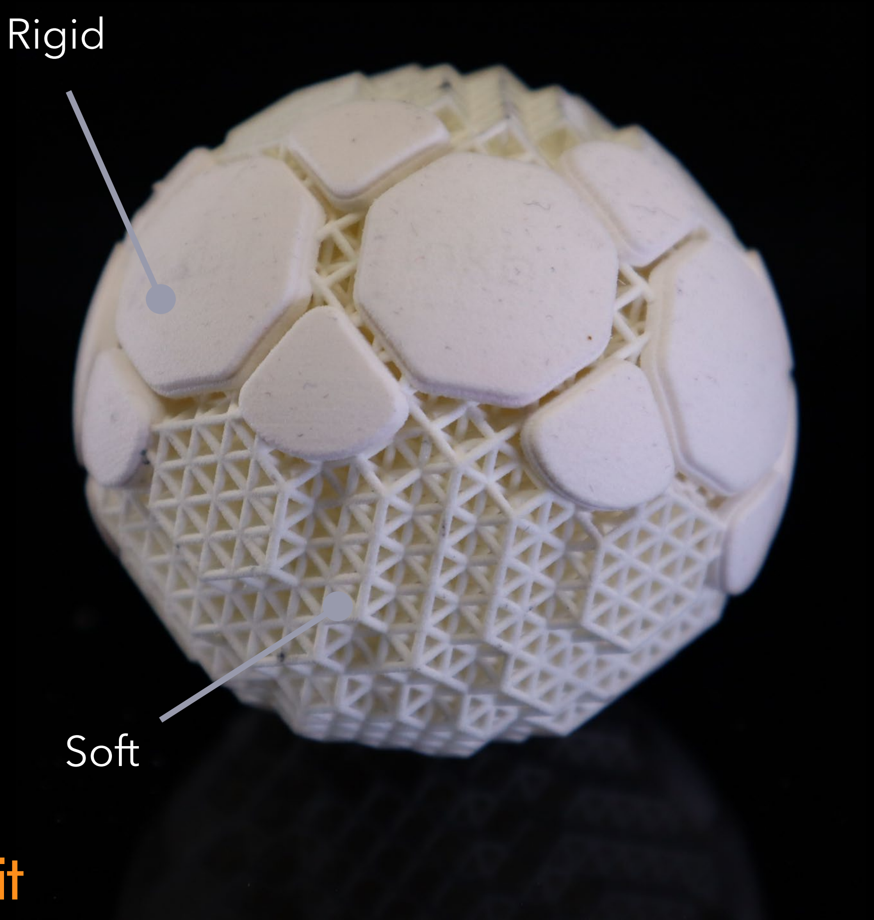


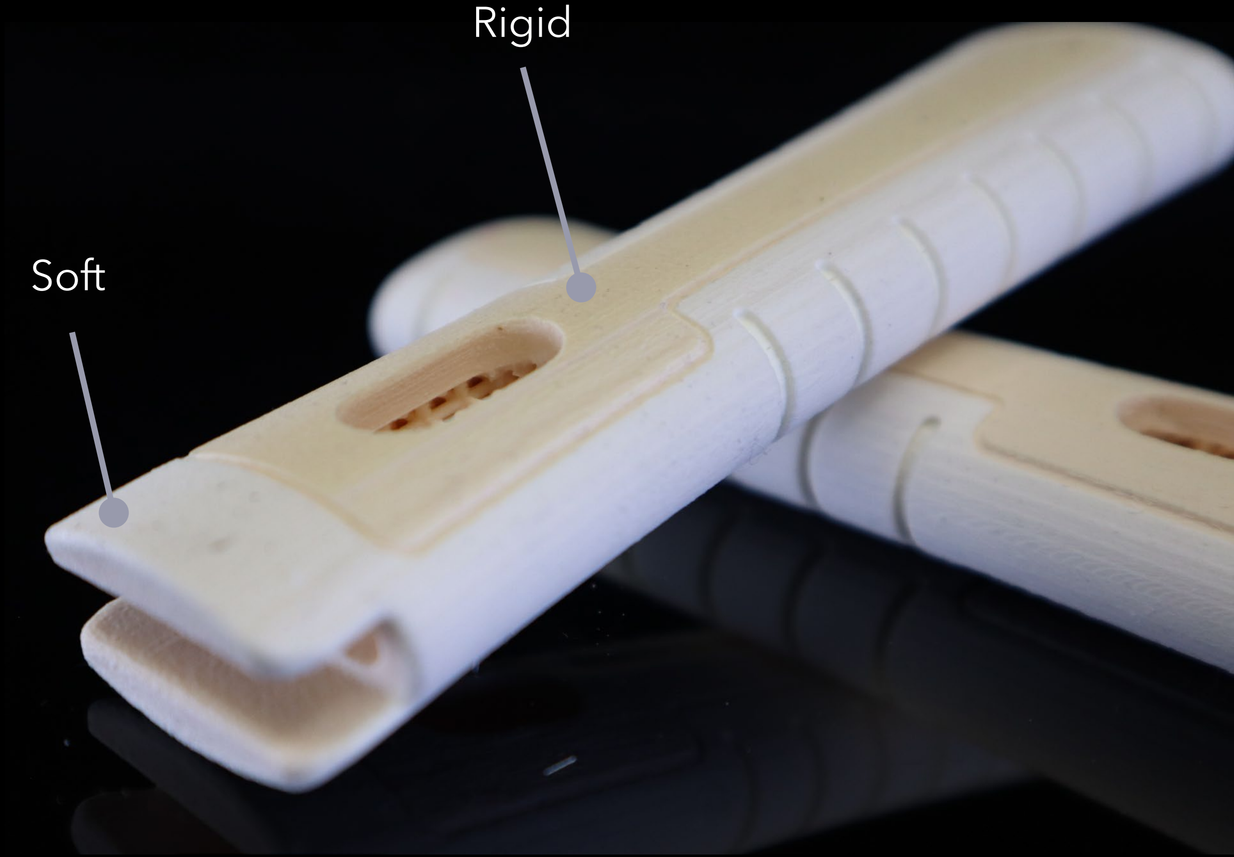
Long and narrow internal conformal channels down to 500 µm in diameter

Thin walls down to 400 µm

- Shore 25A durometer
- 200% elongation at break
- 1.3 MPa tensile strength

The system can print different materials at the same time





Key capabilities

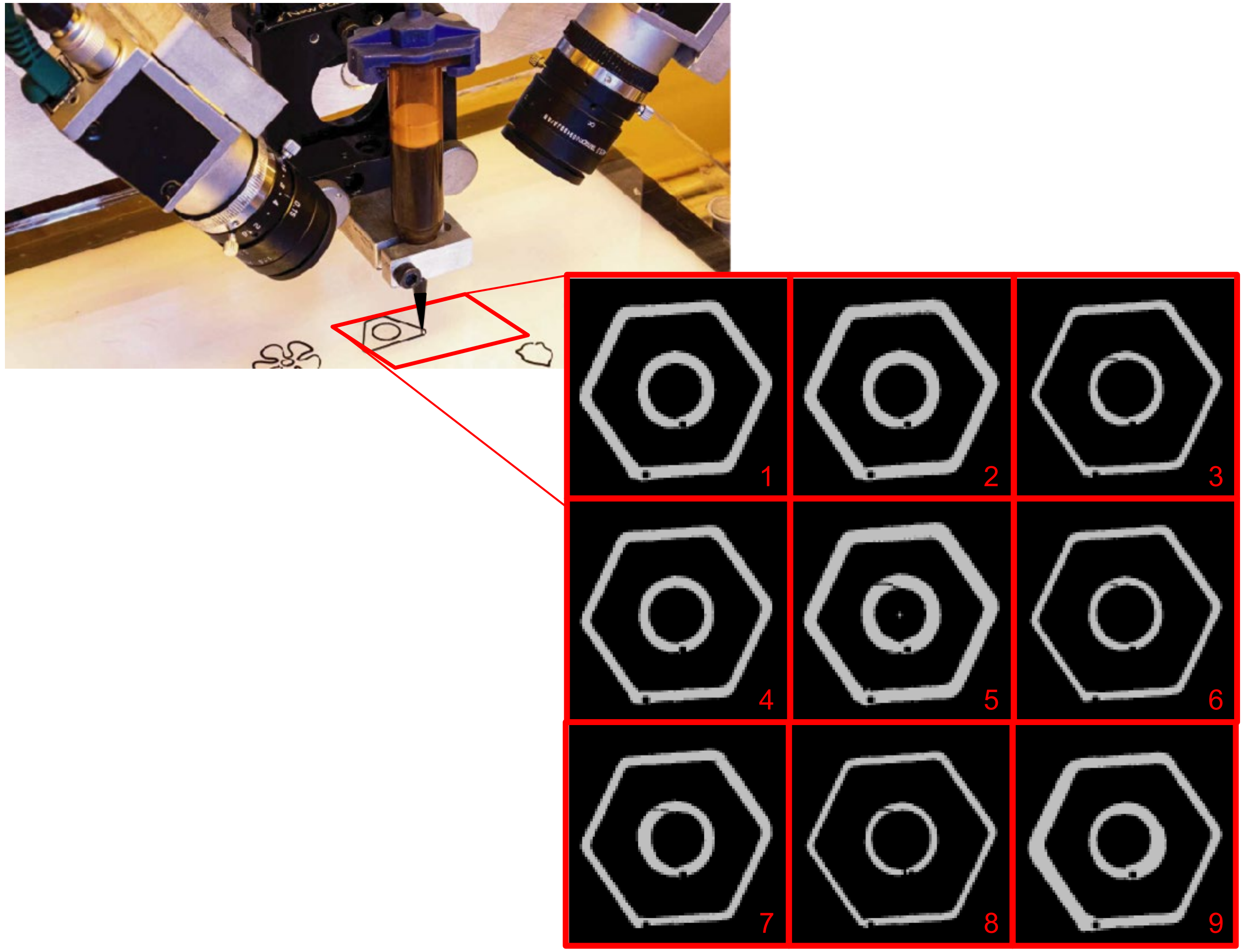
Dimensional accuracy

Functional material properties

Production-scale capabilities

Learning to Control for Manufacturing

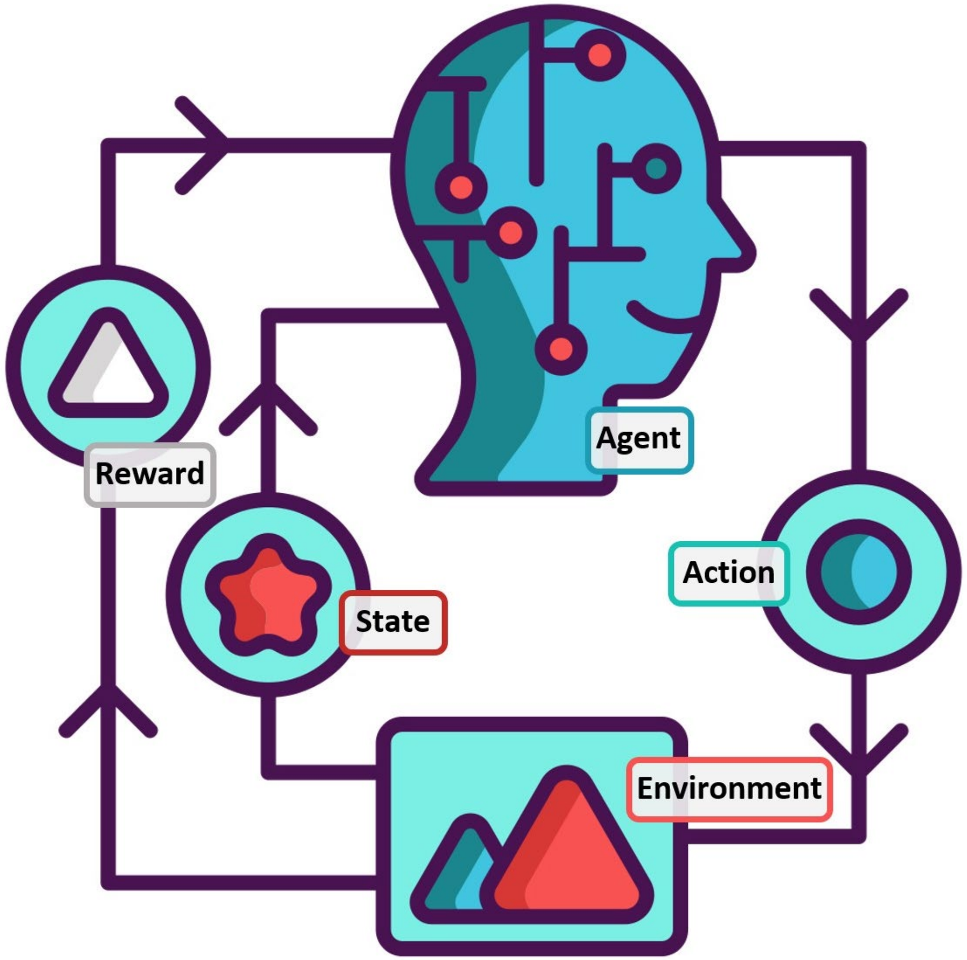
- **AM is prone to random changes in materials and process**
- **AM lacks closed-loop control limiting accuracy**
- **Controllers are hand designed and use no (or limited) sensing**



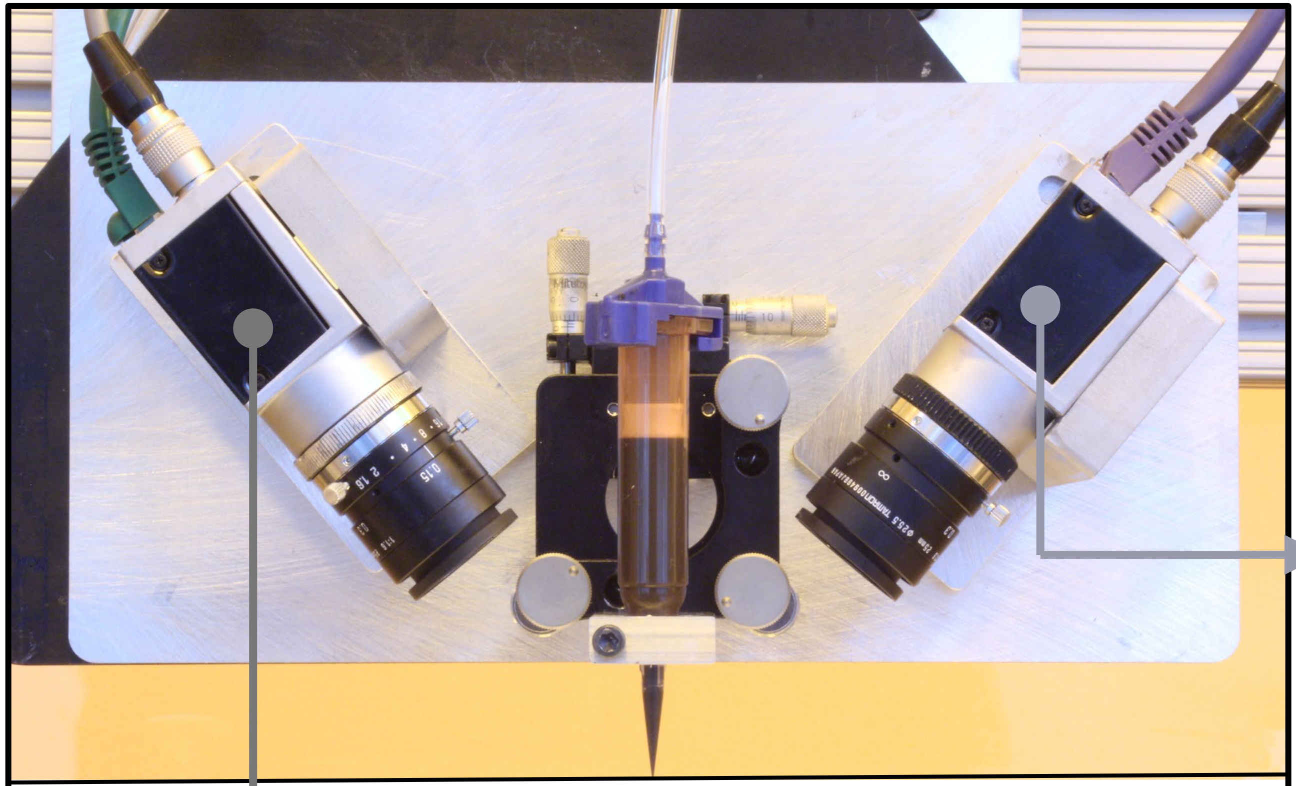
Random Variation

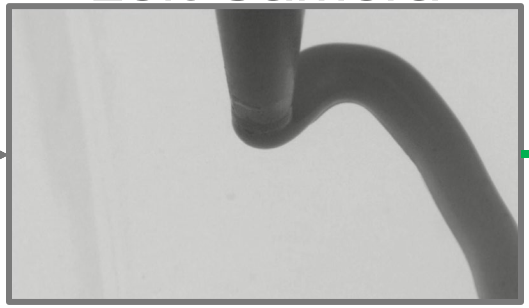
Learning to Control for Manufacturing

- **Reinforcement learning (RL) emerges as a promising methods to optimize control in robotics**
- **RL requires real-time observations/sensing of the environment**
- **RL requires lots of training data (e.g., 100K experiments)**
- **High-performance RL controllers can beat human-designed controllers**

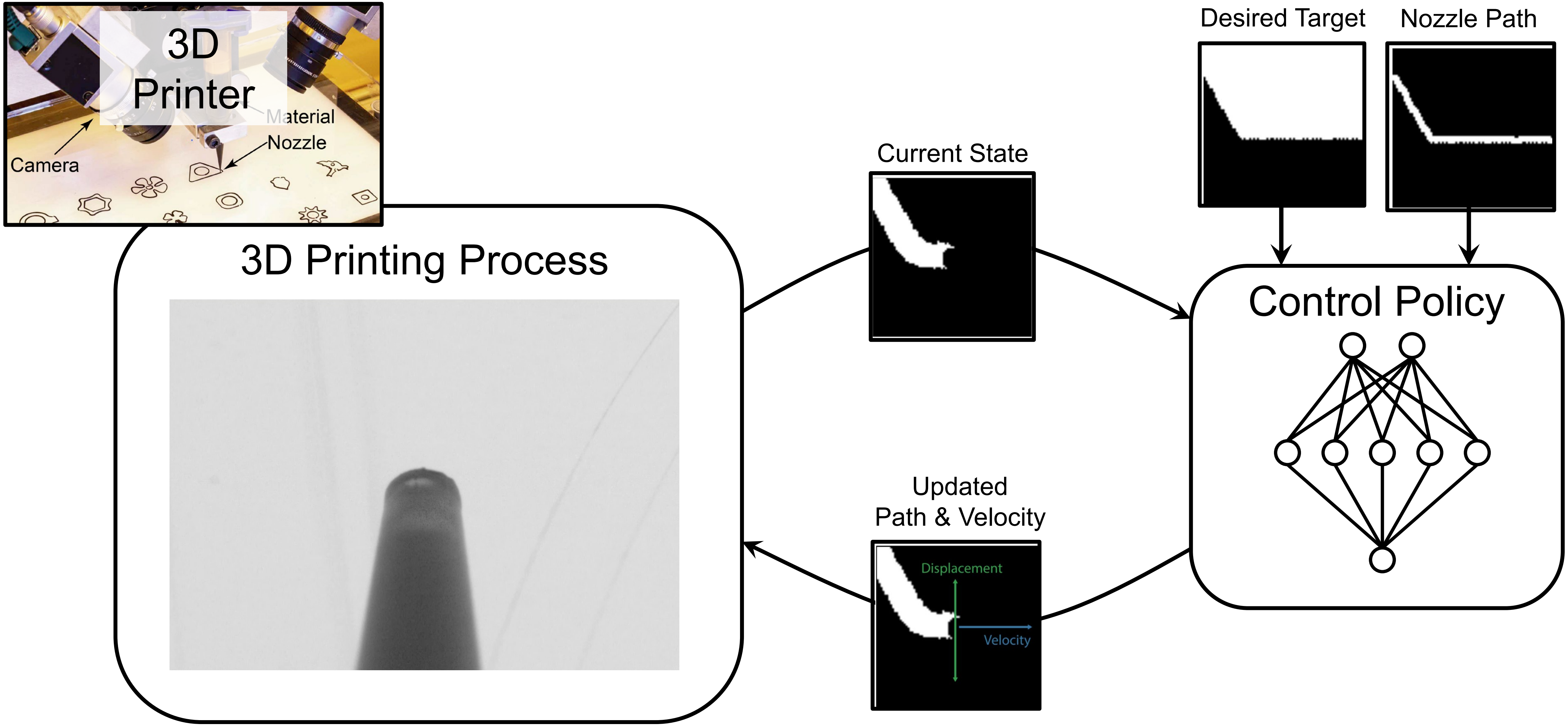


Machine Vision Sensing for AM



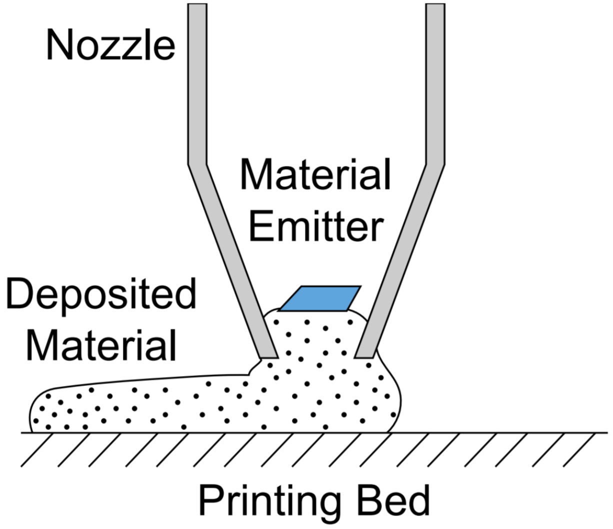


AM System with Control Policy

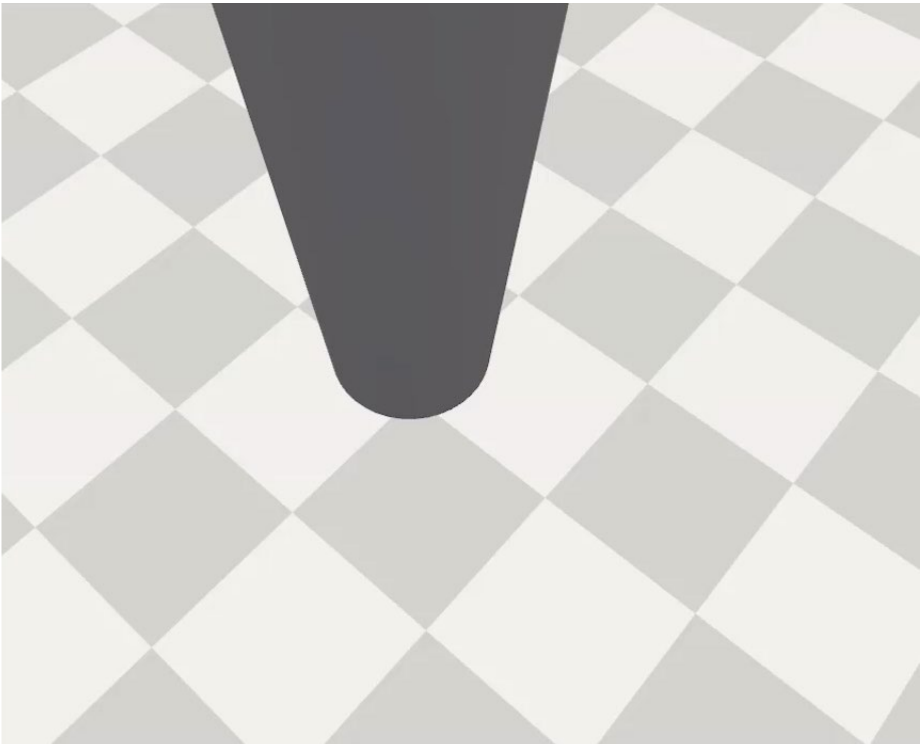


Simulation of the Material Deposition Process

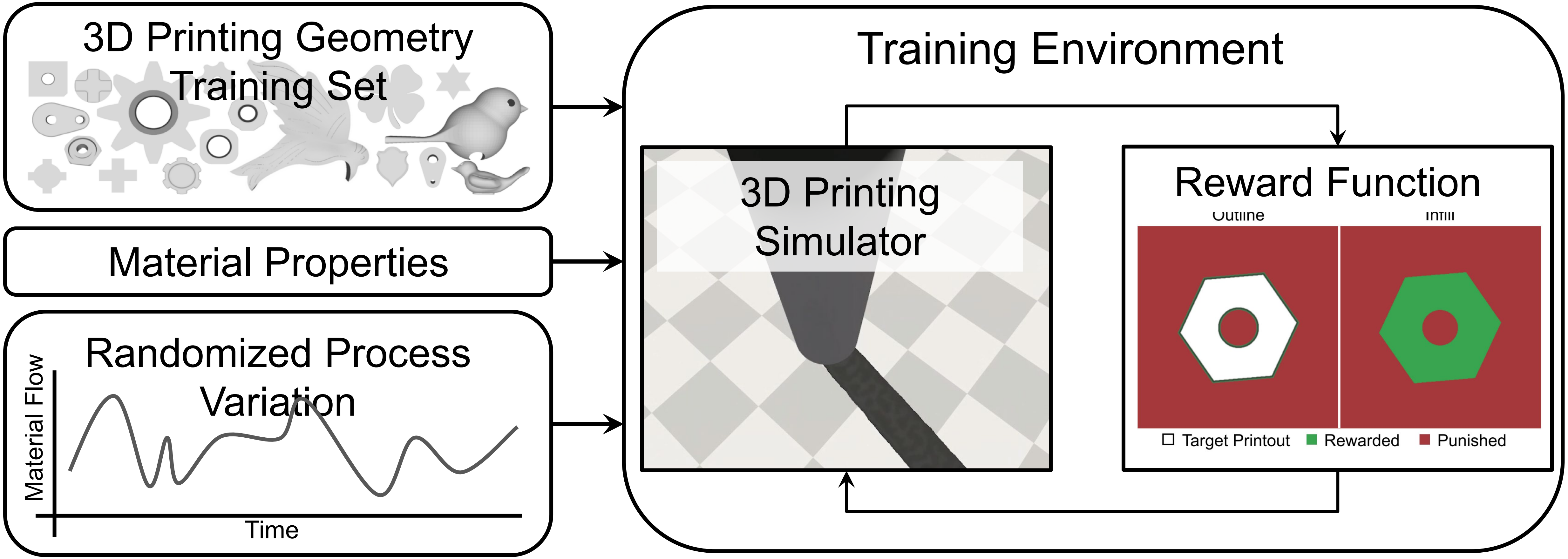
- **3D printer simulation**
  - Particle based simulation
  - Simulates in real-time
  - Easily parallelizable making training possible in short period of time.



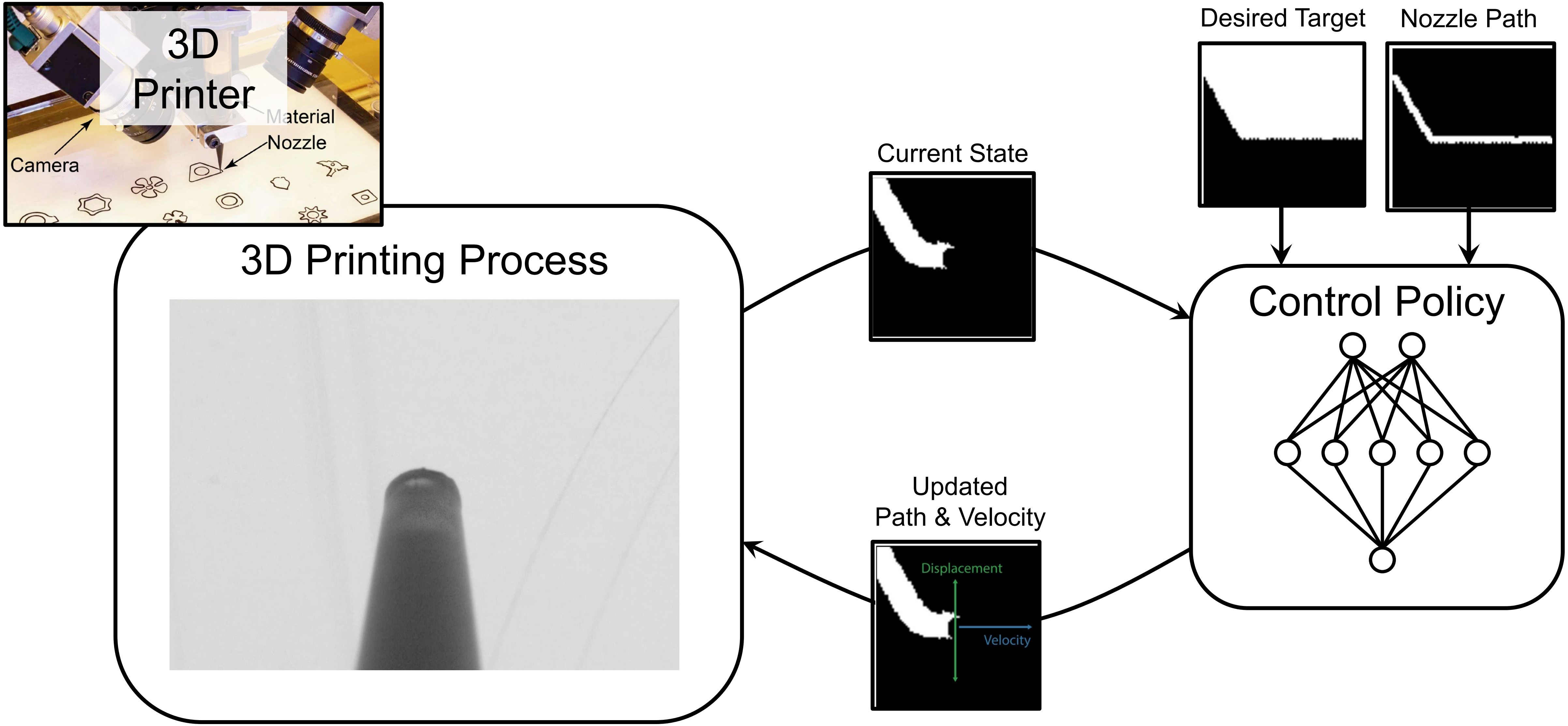
3D Printing Simulation



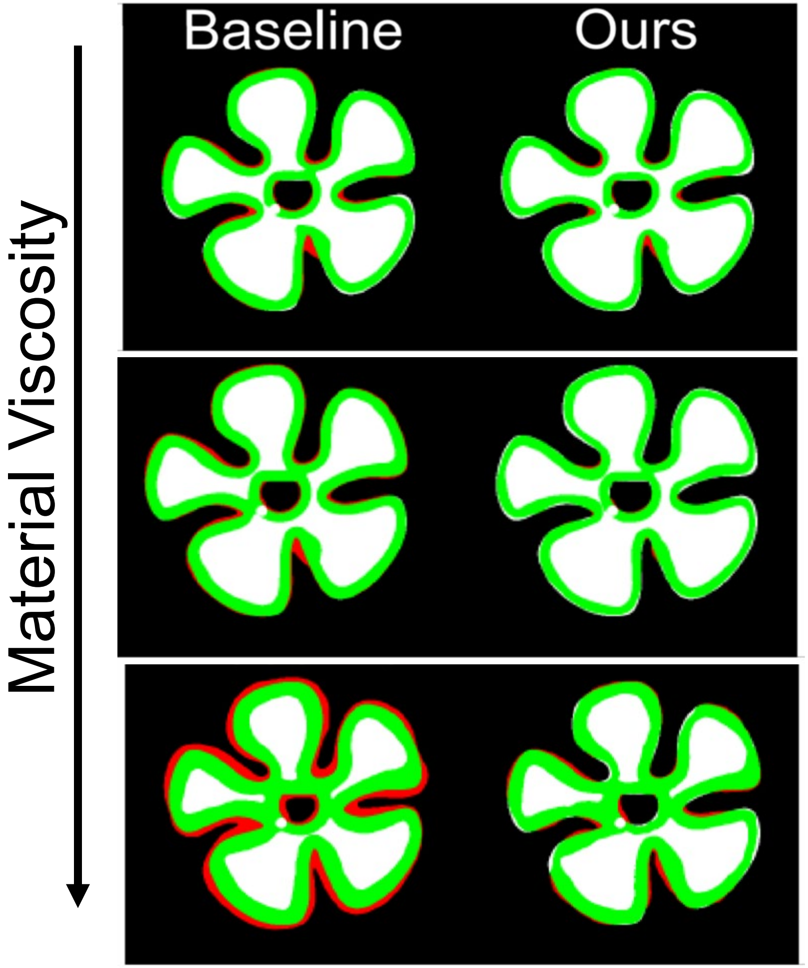
Training Robust Control Policy

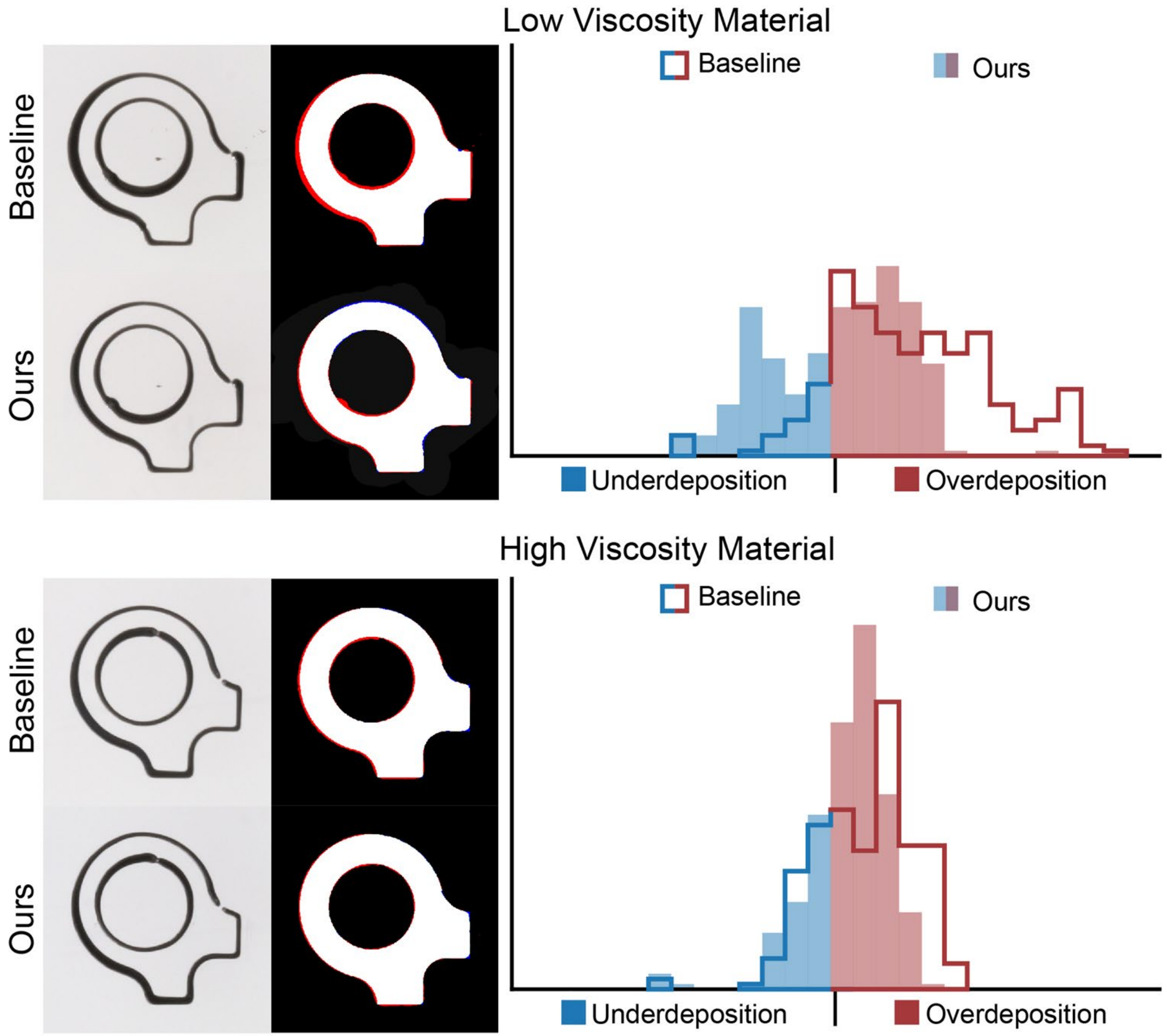


Control Policy Transferred to Real System



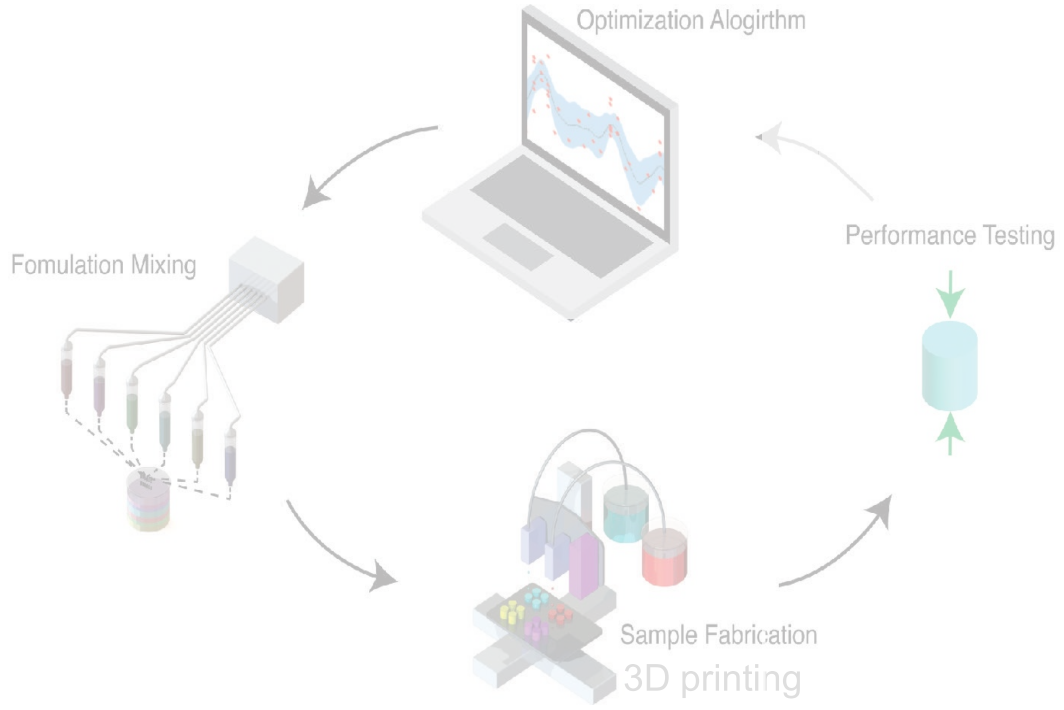
Viscosity Agnostic Control Policy



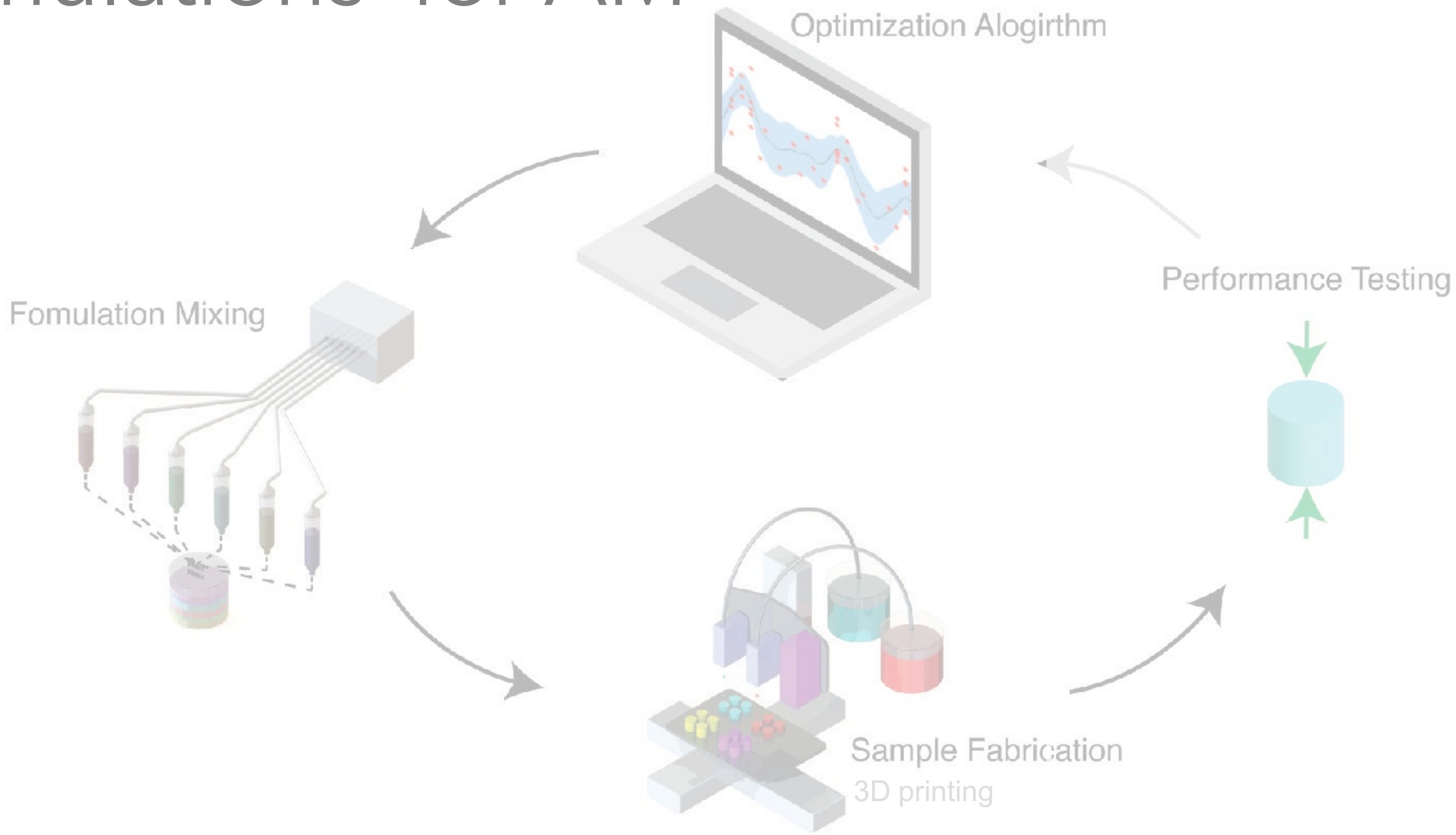


Automated Process Optimization

- **Can we automatically optimize a manufacturing process?**
- **What if numerical simulation does not exist?**
- **How to solve this problem if one can run only limited number of experiments (e.g., 100)?**



Case Study: Optimization of Material Formulations for AM



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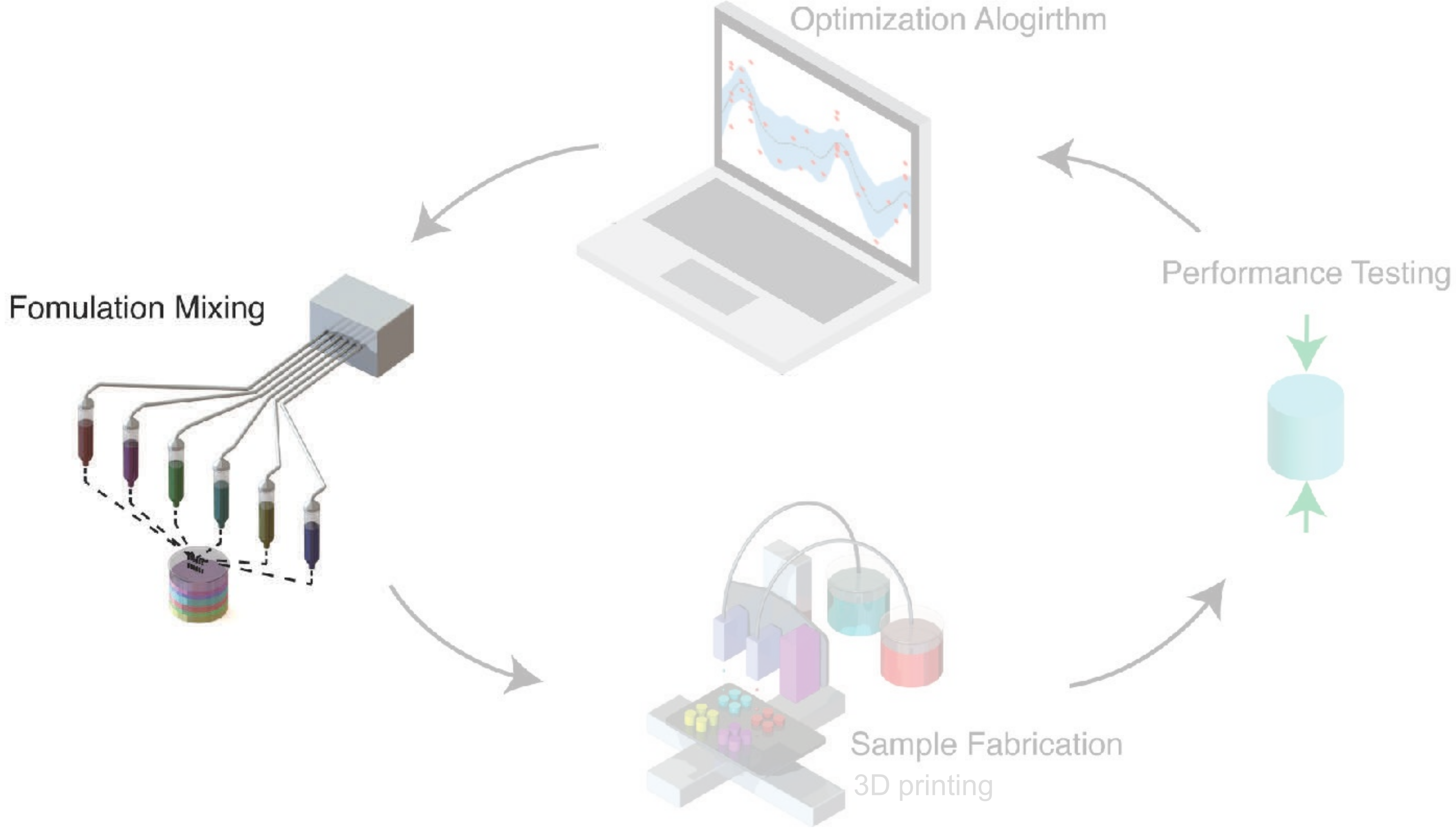

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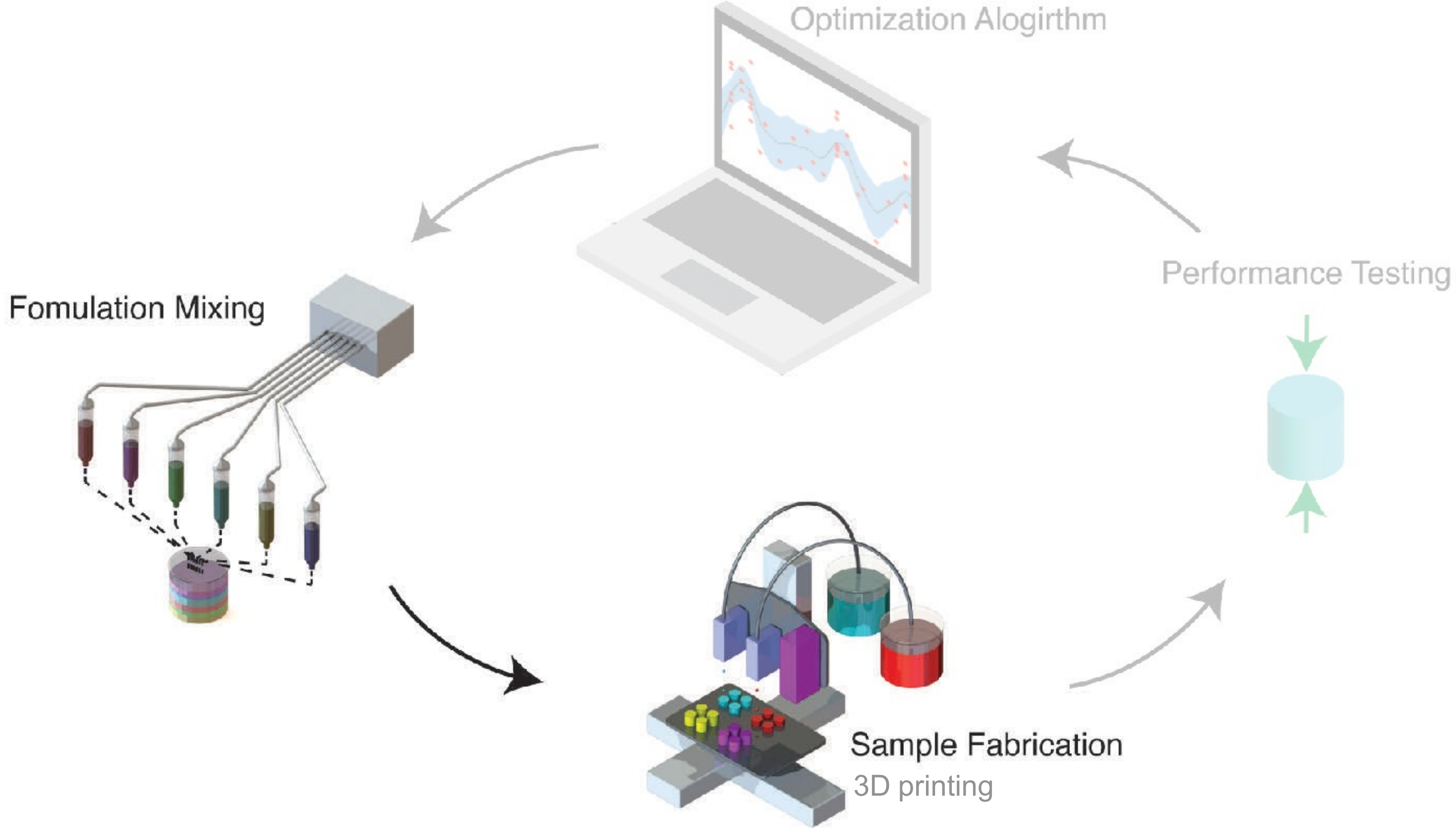

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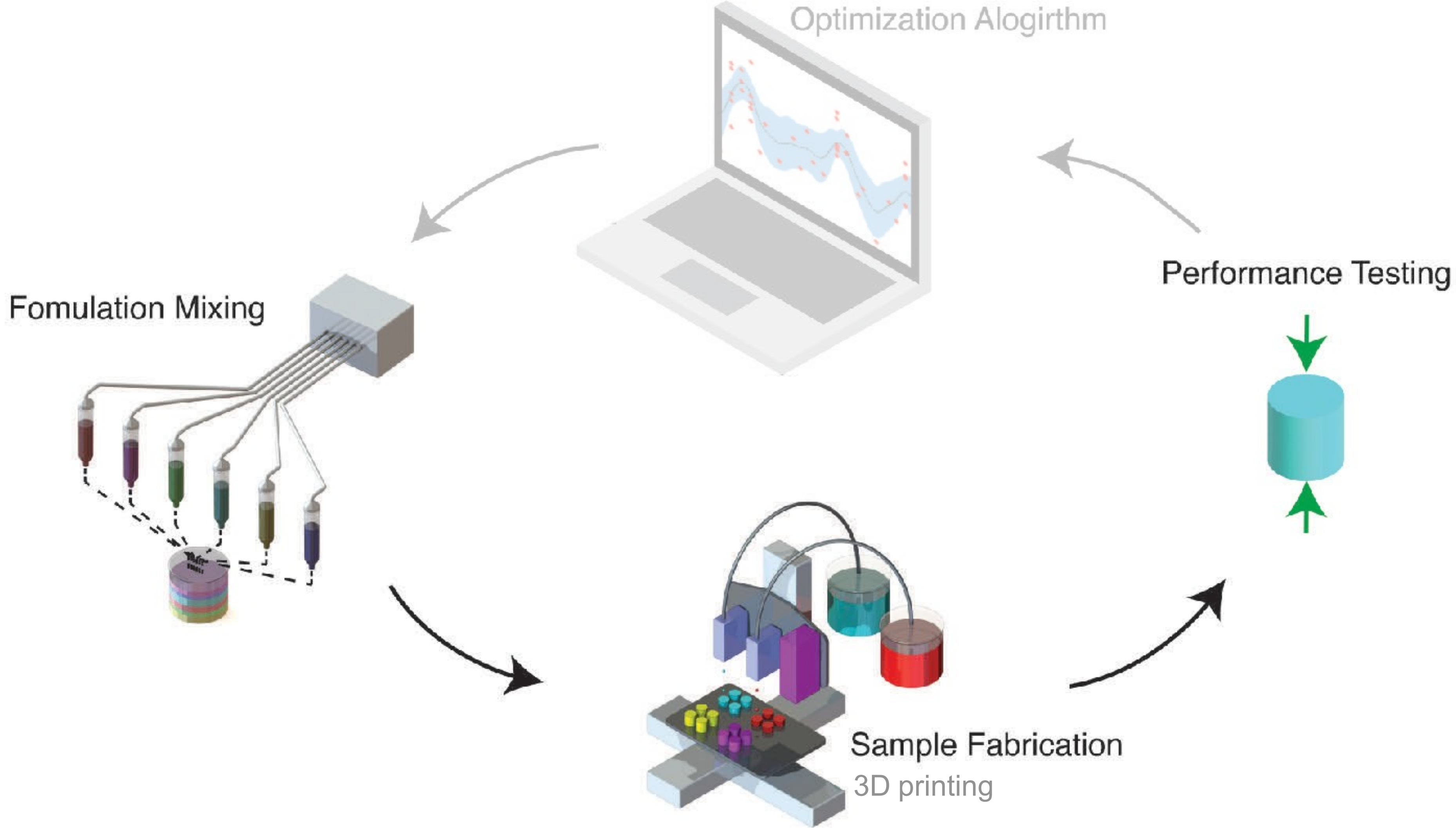

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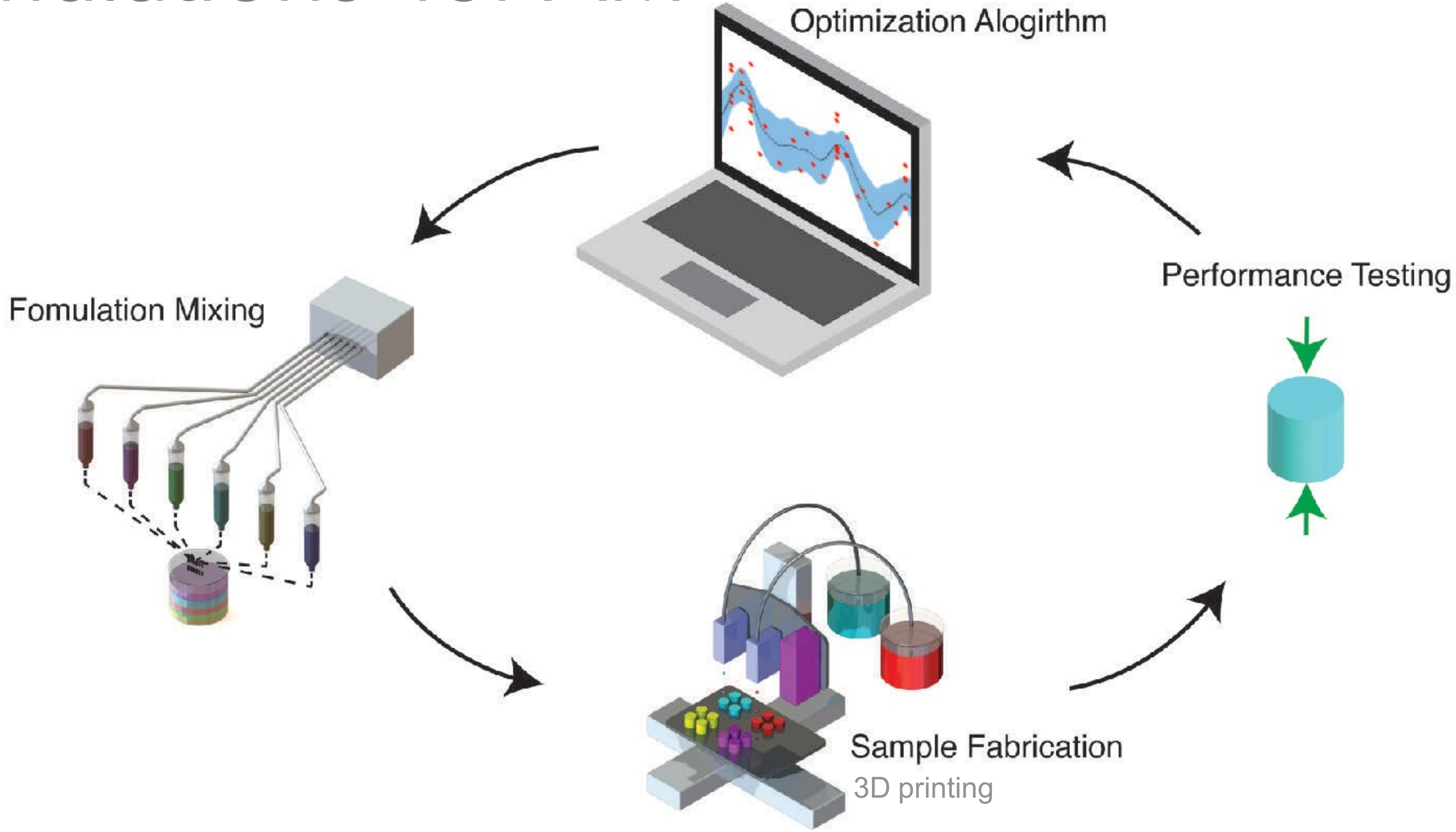
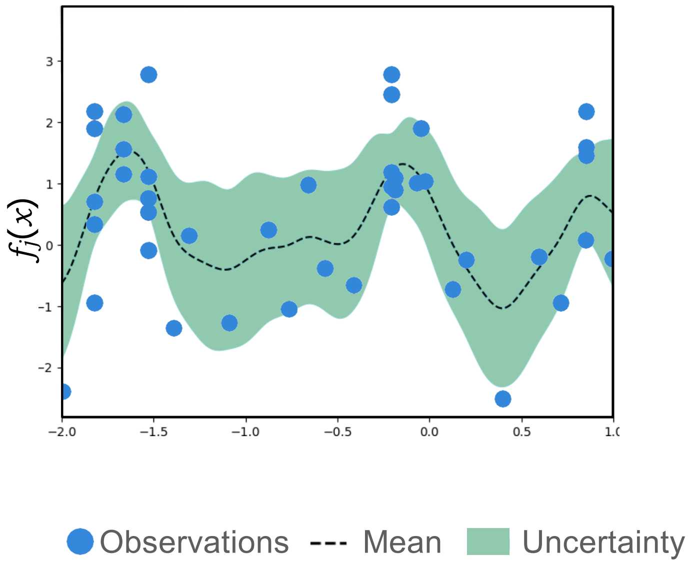


Multi-Objective Bayesian Optimization

Surrogate model

Fit GPs for each objective f_j

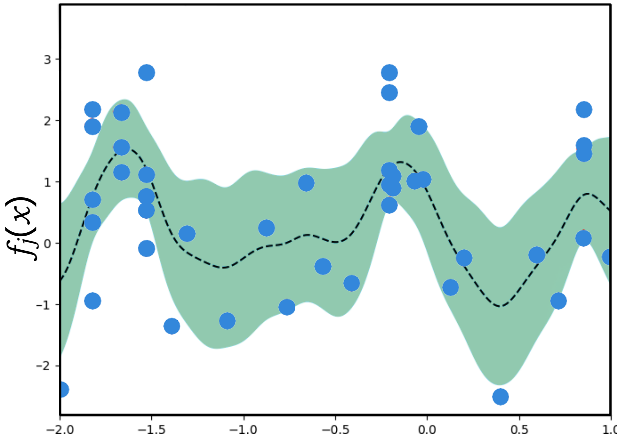


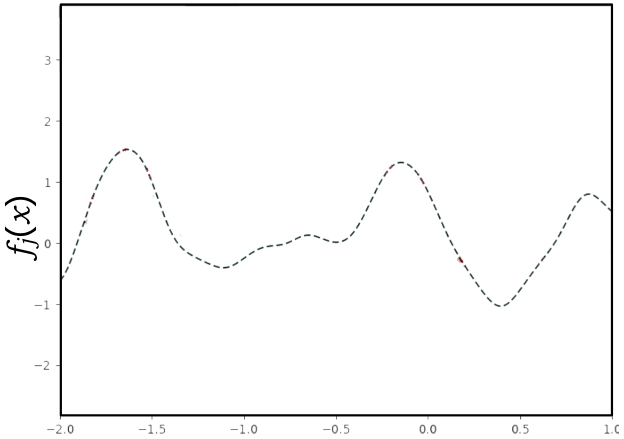
Multi-Objective Bayesian Optimization

Surrogate model → Acquisition function

Fit GPs for each objective f_j

Approximate functions f_j from mean of GPs





Observations --- Mean Uncertainty

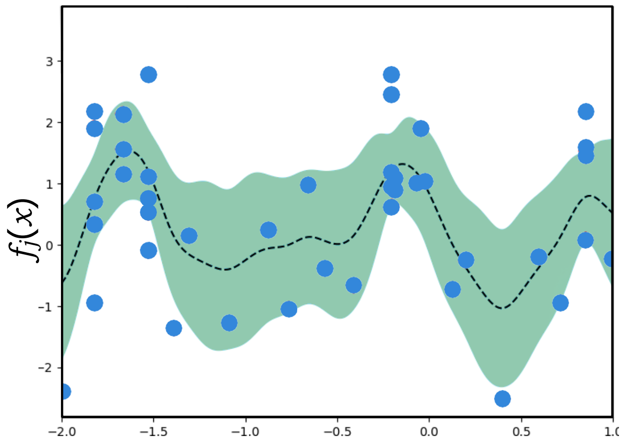
Multi-Objective Bayesian Optimization

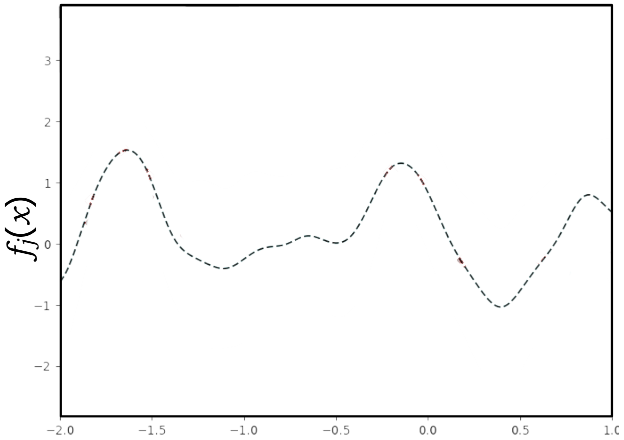
Surrogate model → **Acquisition function** → **Multi-objective solver**

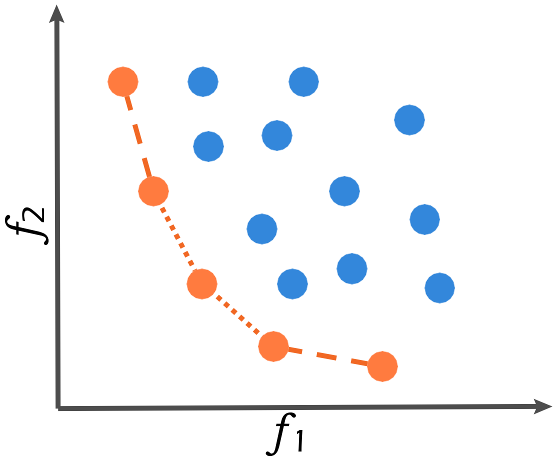
Fit GPs for each objective f_j

Approximate functions f_j from mean of GPs

Approximate Pareto set and front over all f_j







Observations --- Mean Uncertainty

Observations Pareto front

Multi-Objective Bayesian Optimization

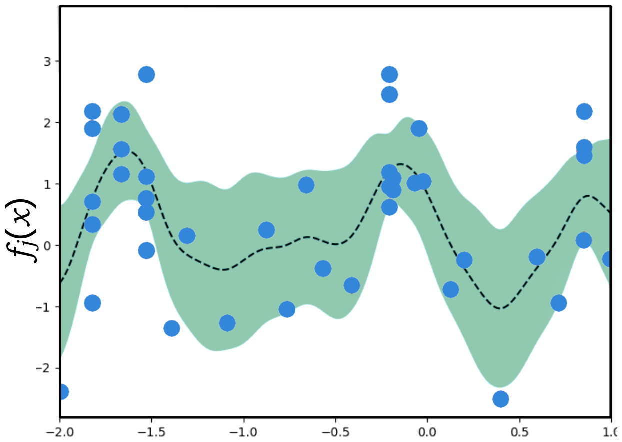
Surrogate model → Acquisition function → Multi-objective solver → Selection

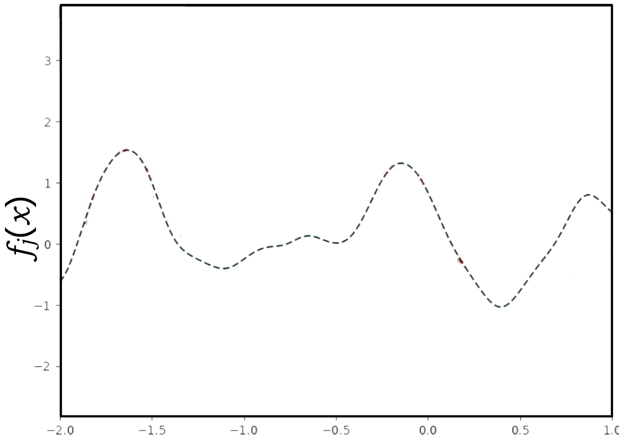
Fit GPs for each objective f_j

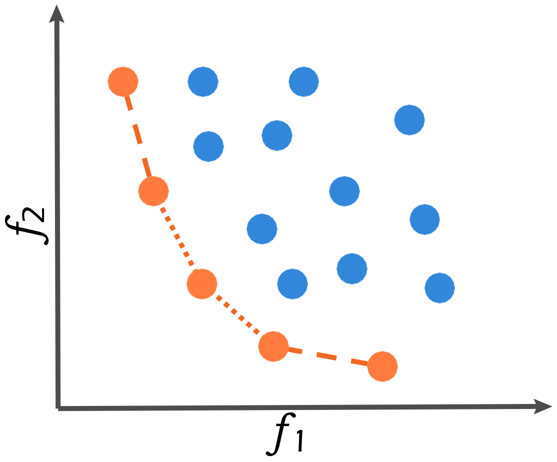
Approximate functions f_j from mean of GPs

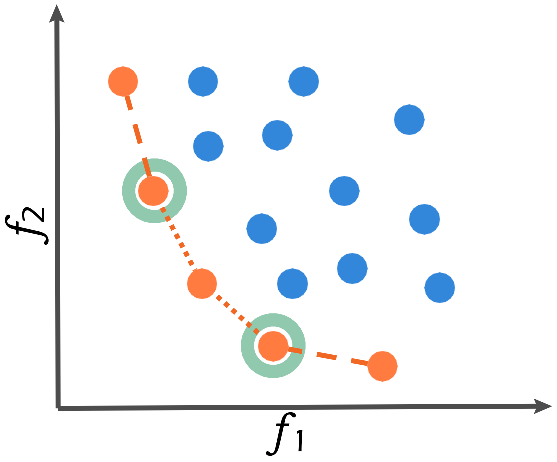
Approximate Pareto set and front over all f_j

Propose a batch of points to evaluate next







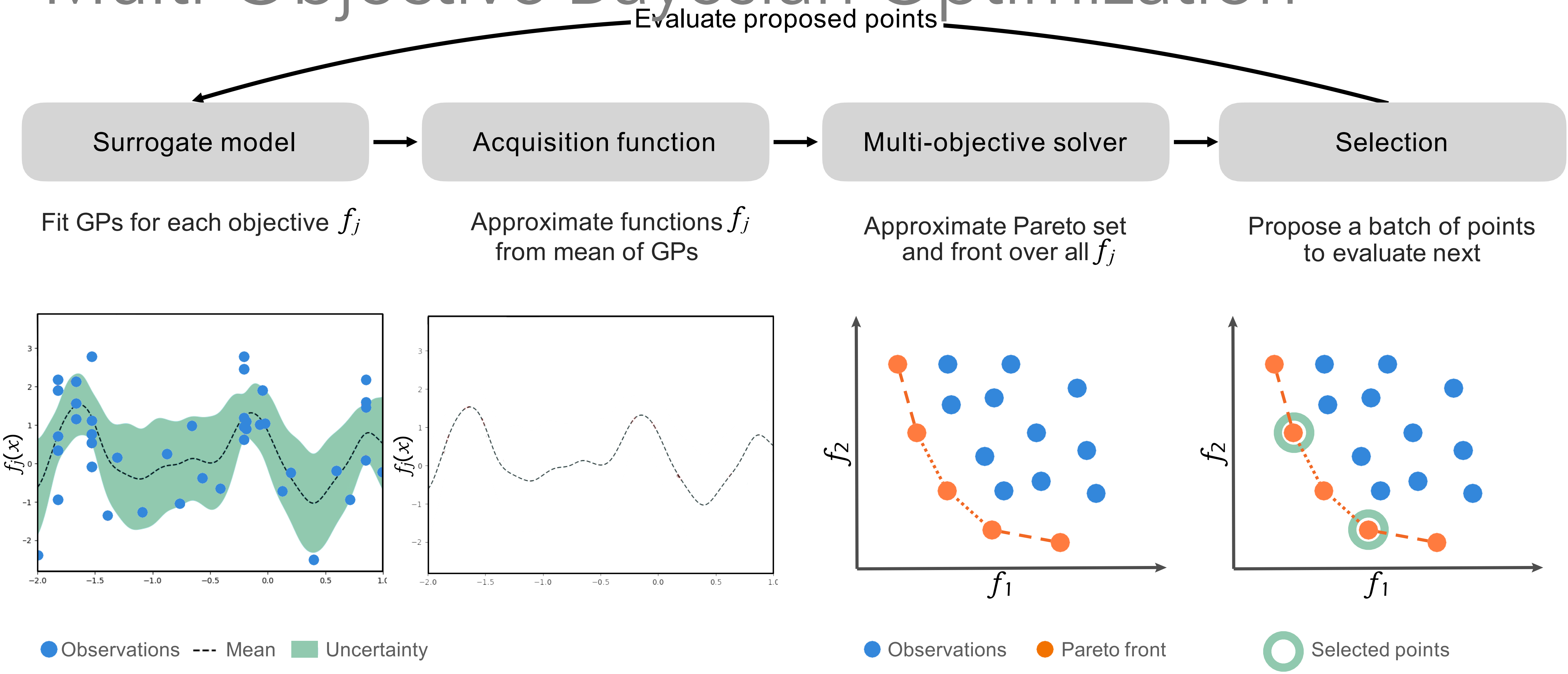


Observations --- Mean Uncertainty

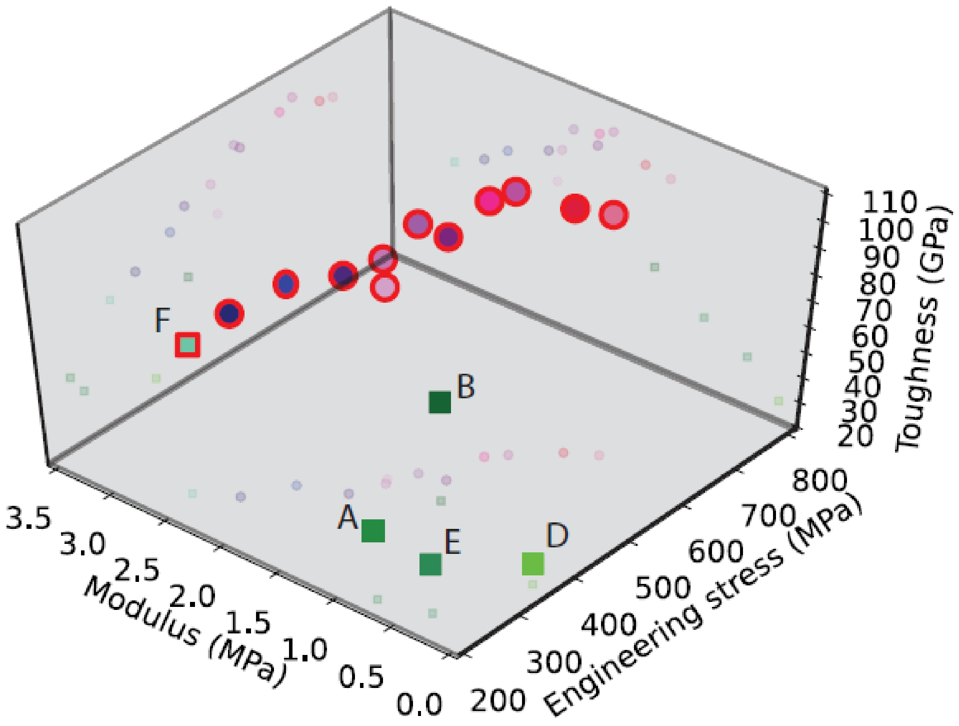
Observations Pareto front

Selected points

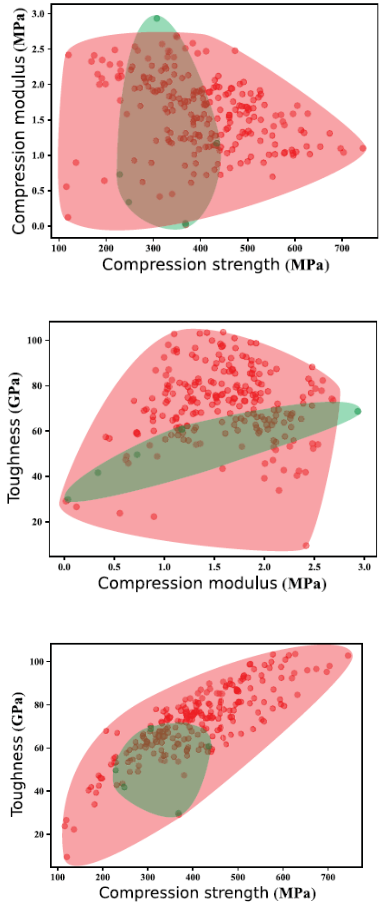
Multi-Objective Bayesian Optimization



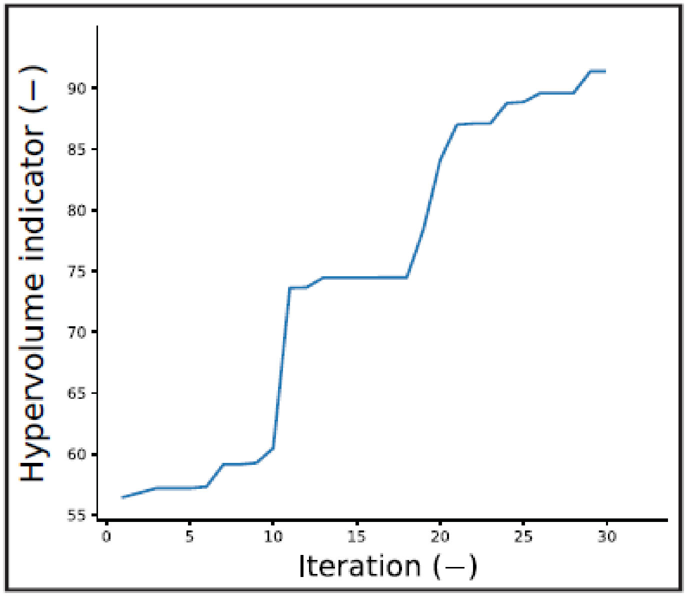
Results



A
B
D
E
F
Modulus (MPa)
3.5 3.0 2.5 2.0 1.5 1.0 0.5 0.0
Engineering stress (MPa)
200 300 400 500 600 700 800
Toughness (GPa)
20 30 40 50 60 70 80 90 100 110

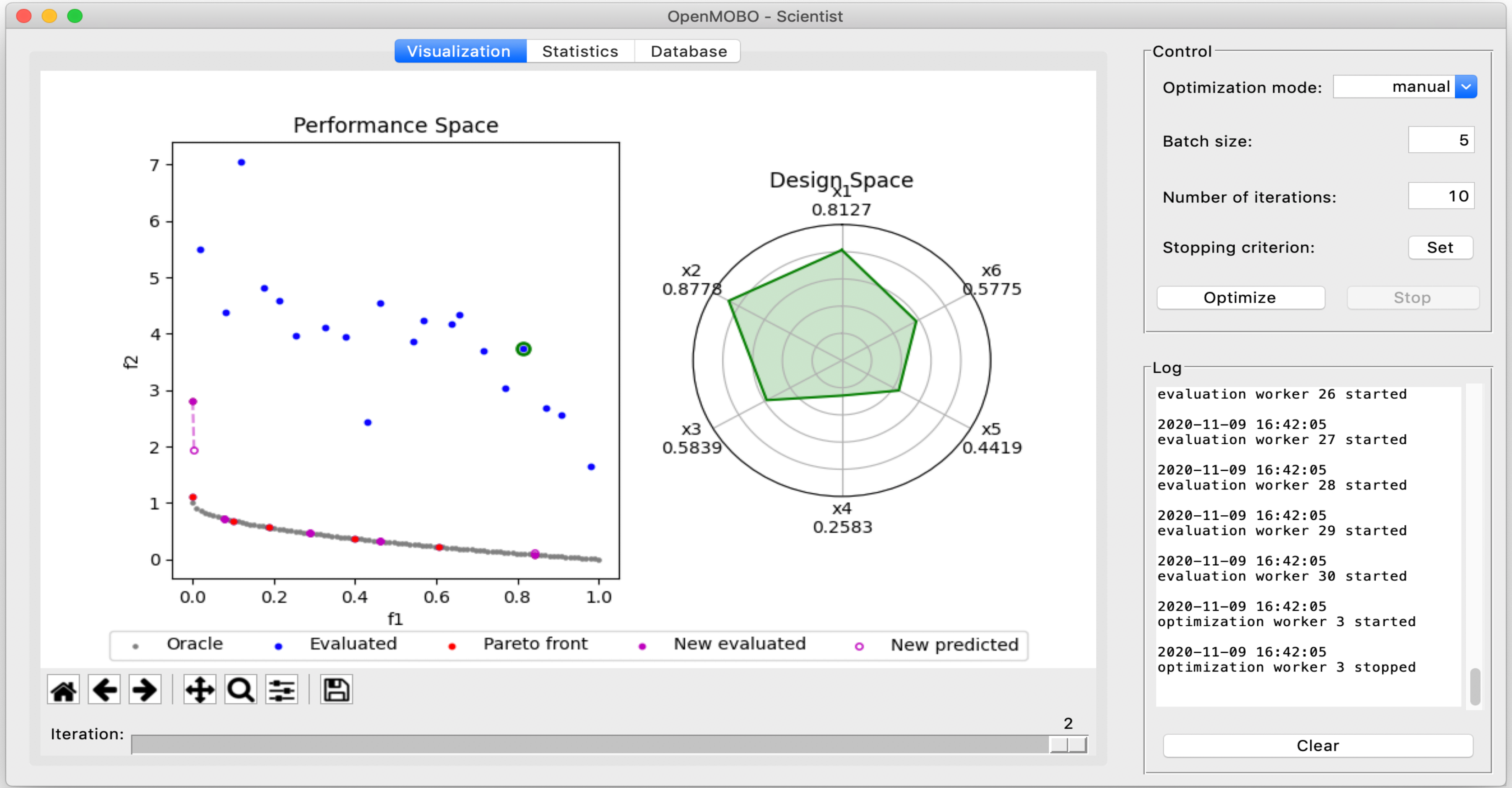


Compression modulus (MPa)
Compression strength (MPa)
Toughness (GPa)
Compression modulus (MPa)
Toughness (GPa)
Compression strength (MPa)



Hypervolume indicator (–)
55 60 65 70 75 80 85 90
0 5 10 15 20 25 30
Iteration (–)

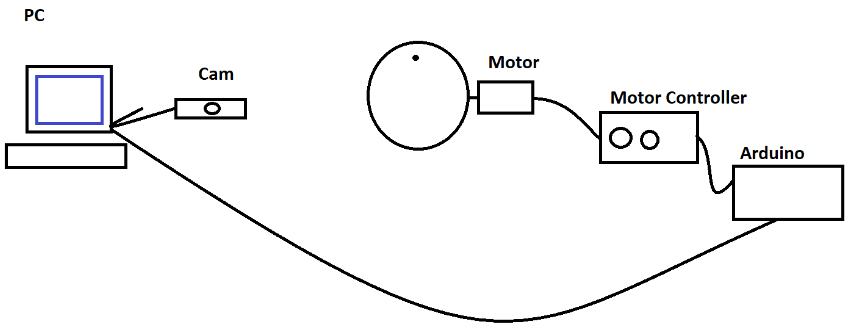
Optimal Experiment Design Platform

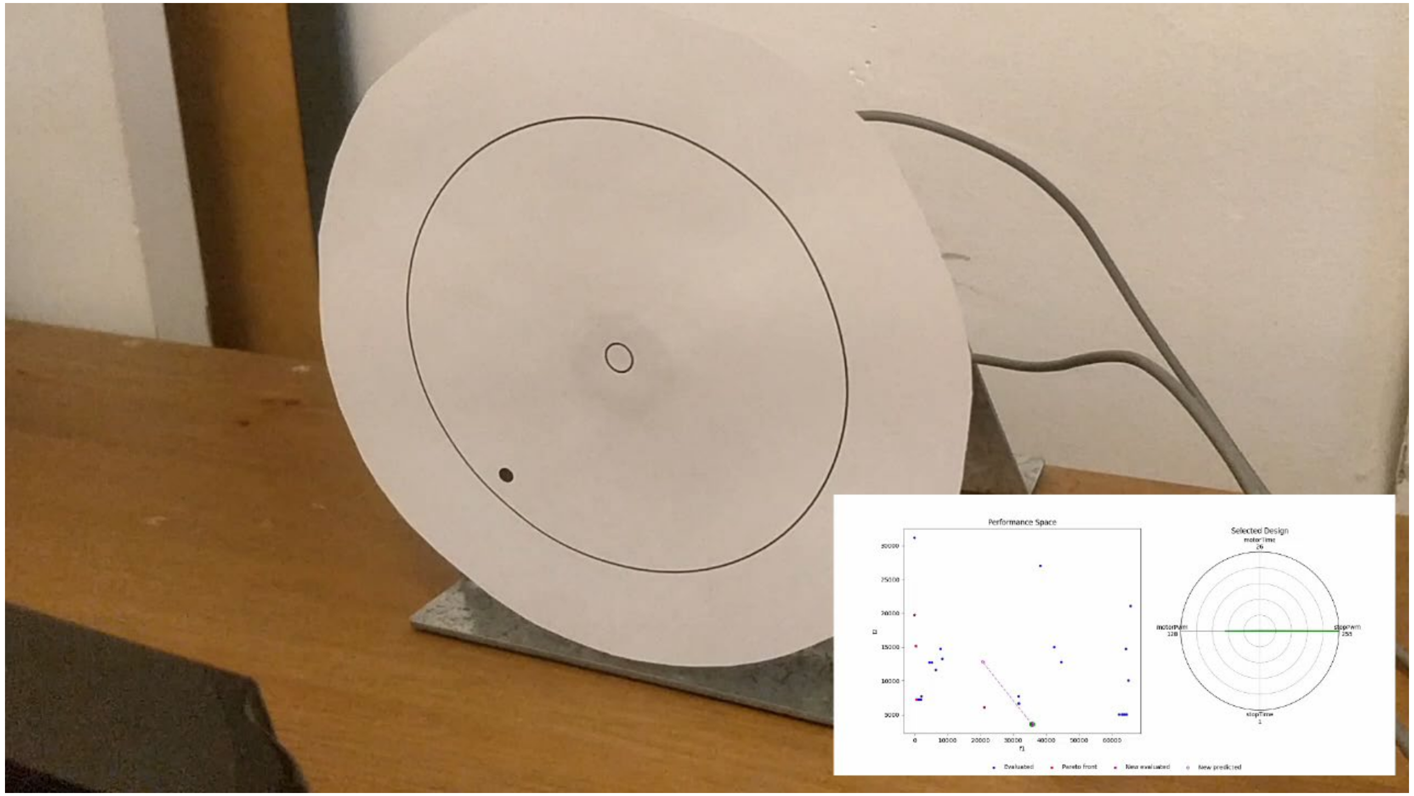


- **Open-source**
- **Easy-to-use GUI**
- **Built-in visualizations**
- **Human-in-the-loop optimization**

https://www.autooed.org/

Example Usage Scenarios

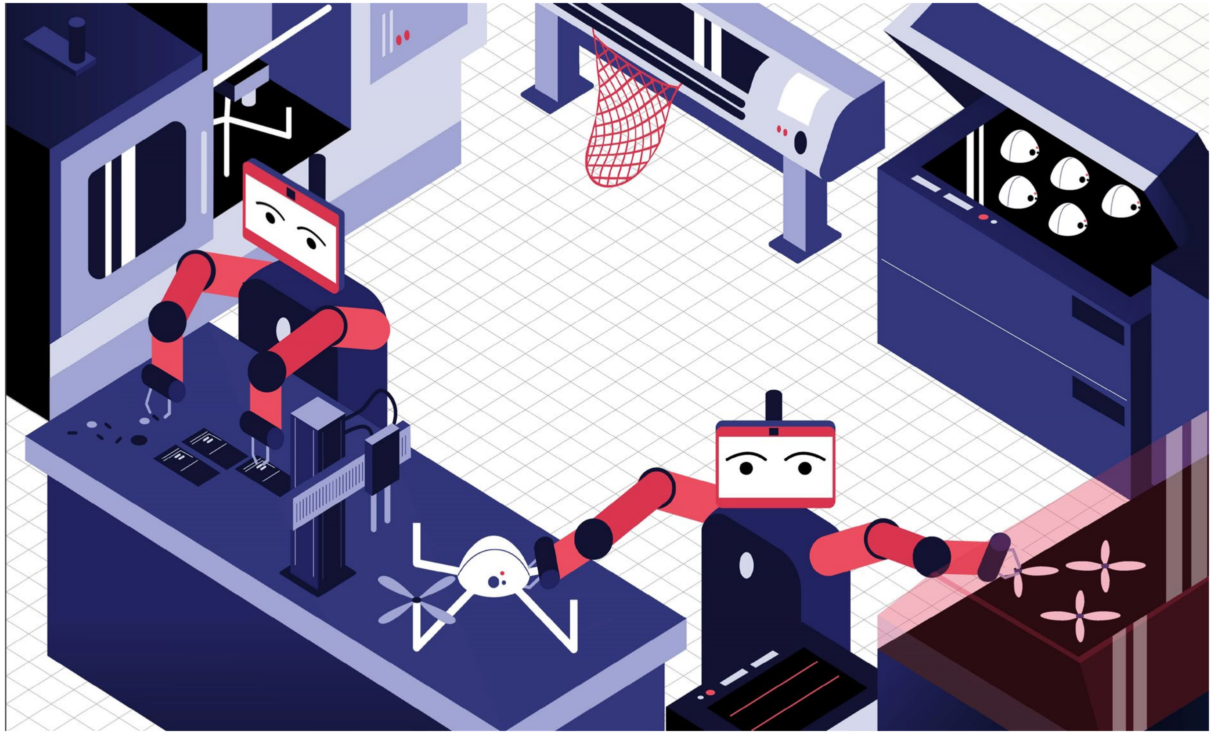




https://www.autooed.org/

The Age of Intelligent Manufacturing

- **Future manufacturing equipment will incorporate sensing (e.g., eyes)**
- **Sensing and simulation will be employed to learn controllers (e.g., brains) to optimize system performance**
- **New blueprint methods are being developed to adapt this workflow for any manufacturing system**



Questions

- **Contact: Wojciech Matusik, wojciech@mit.edu**