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Zero-Iteration Manufacturing

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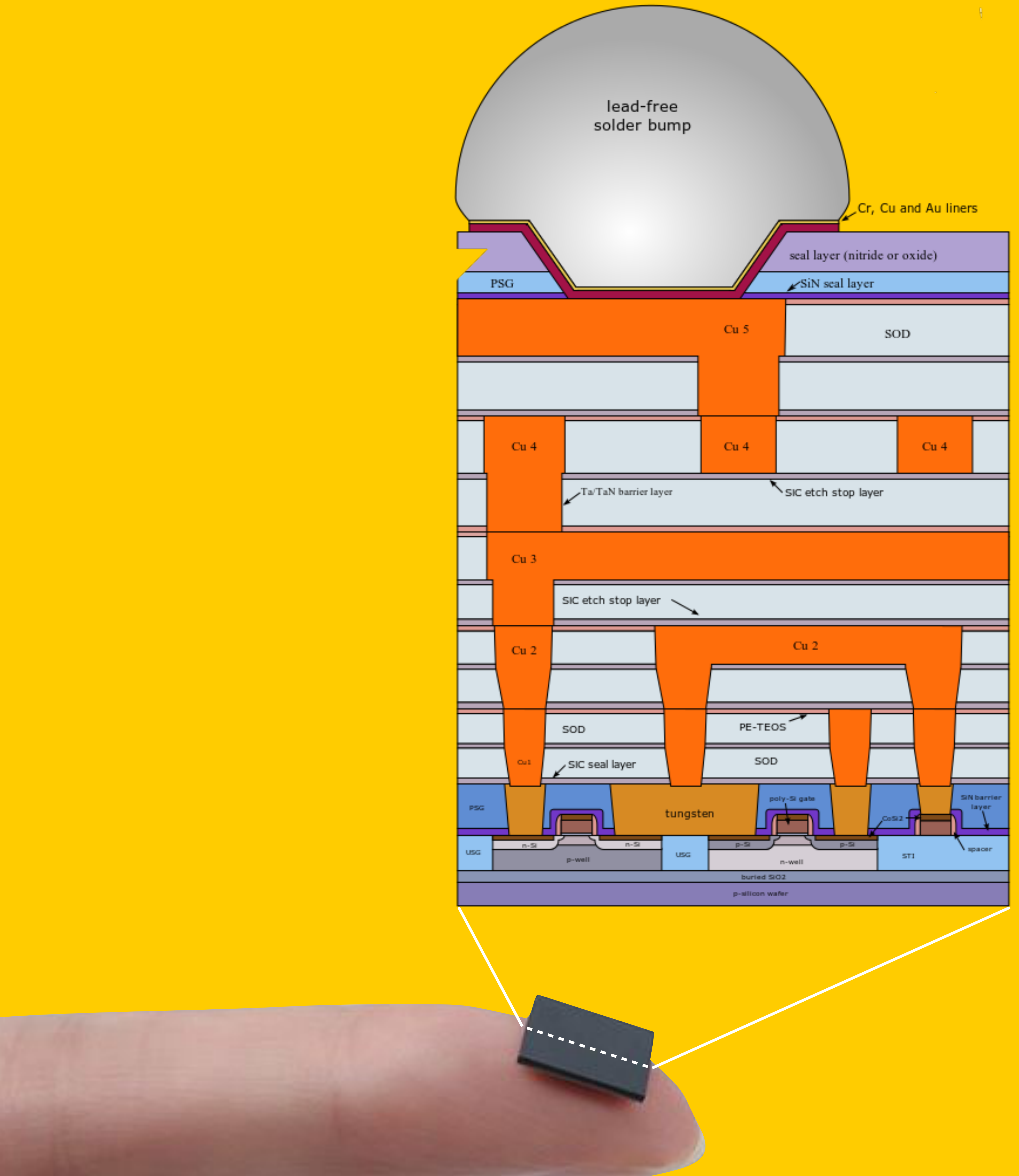
Increasing Complexity in Semiconductors

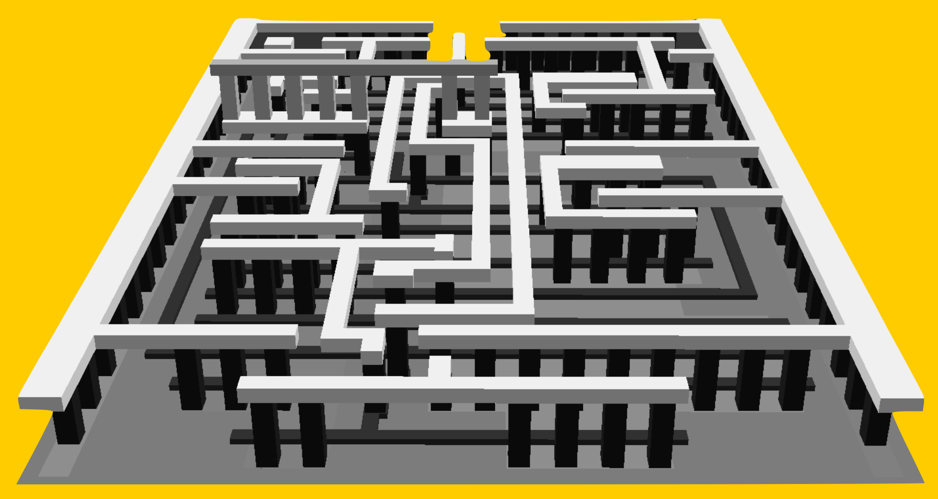


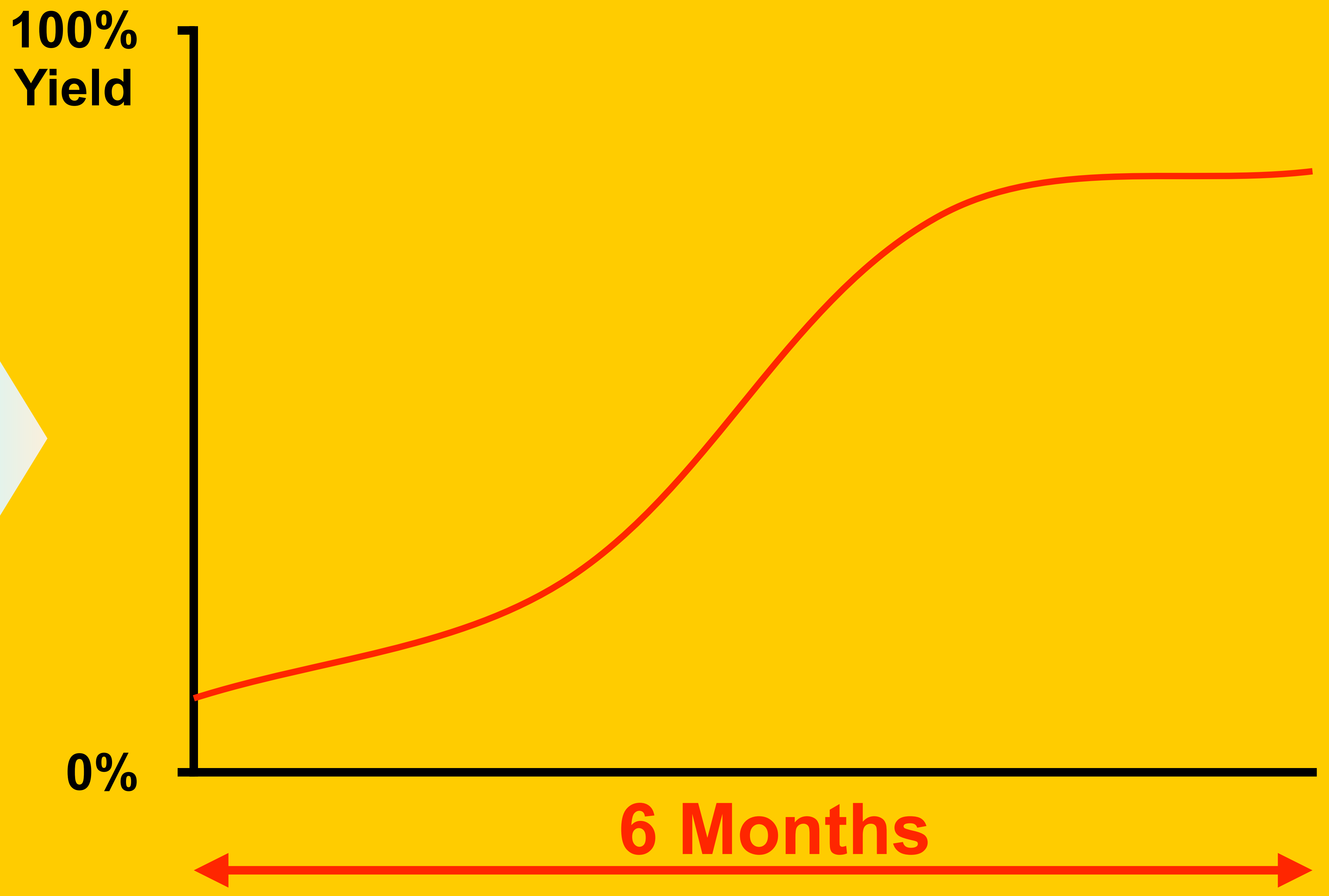
Hundreds of production steps

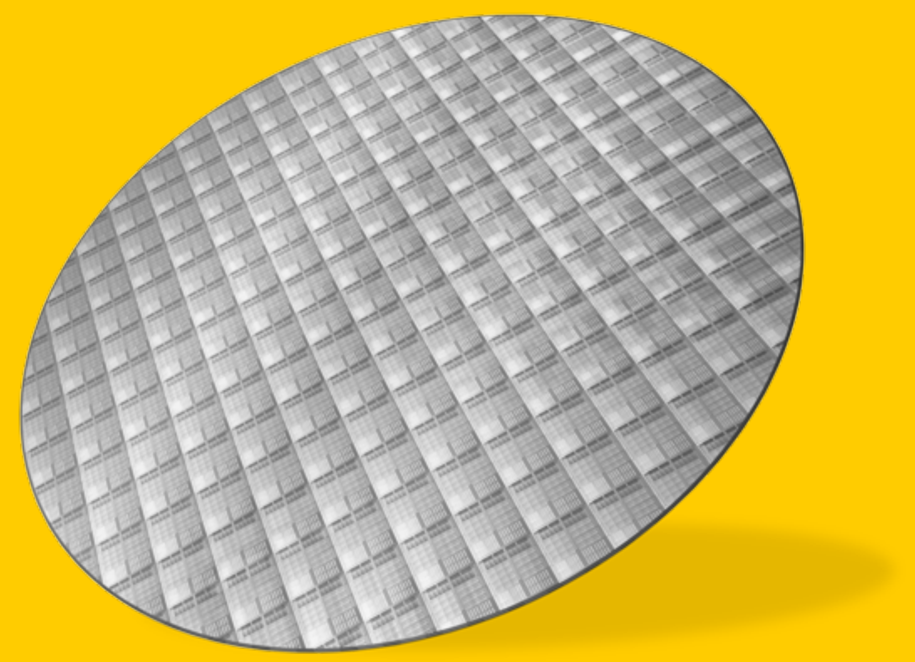
Thousands of process parameters

Billions of transistors/chip

Slow Ramp-Up Hurting Profitability







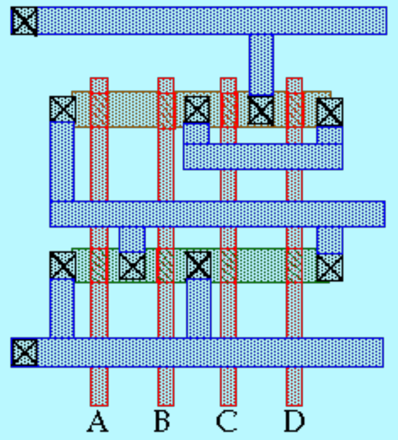
Finalized Design

Ramp-Up
(Trial & Error)

Volume Production

Minimizing Trial & Error With AI

Analogous data
from previous chips



Synthetic data
from physics simulation

Federated Transfer Learning

Perfect Recipes
for entire production flow

Potential Value: $30 million /factory/year

Highlights

Works In Data-Scarce Early Production

Transfer learning and synthetic data enable accurate models even with little production data.

Privacy-Preserving

With decentralized machine learning, data is not aggregated in one single silo.

Self-Perfecting Models

Automated machine learning can continuously refine models during process drifts and process shifts.

Transfer Learning

When adding a new tool to an existing fleet, replacing a reaction chamber, or producing derivative chip products, currently there's the need to build new models from scratch, even though existing or physics-based models already exist.

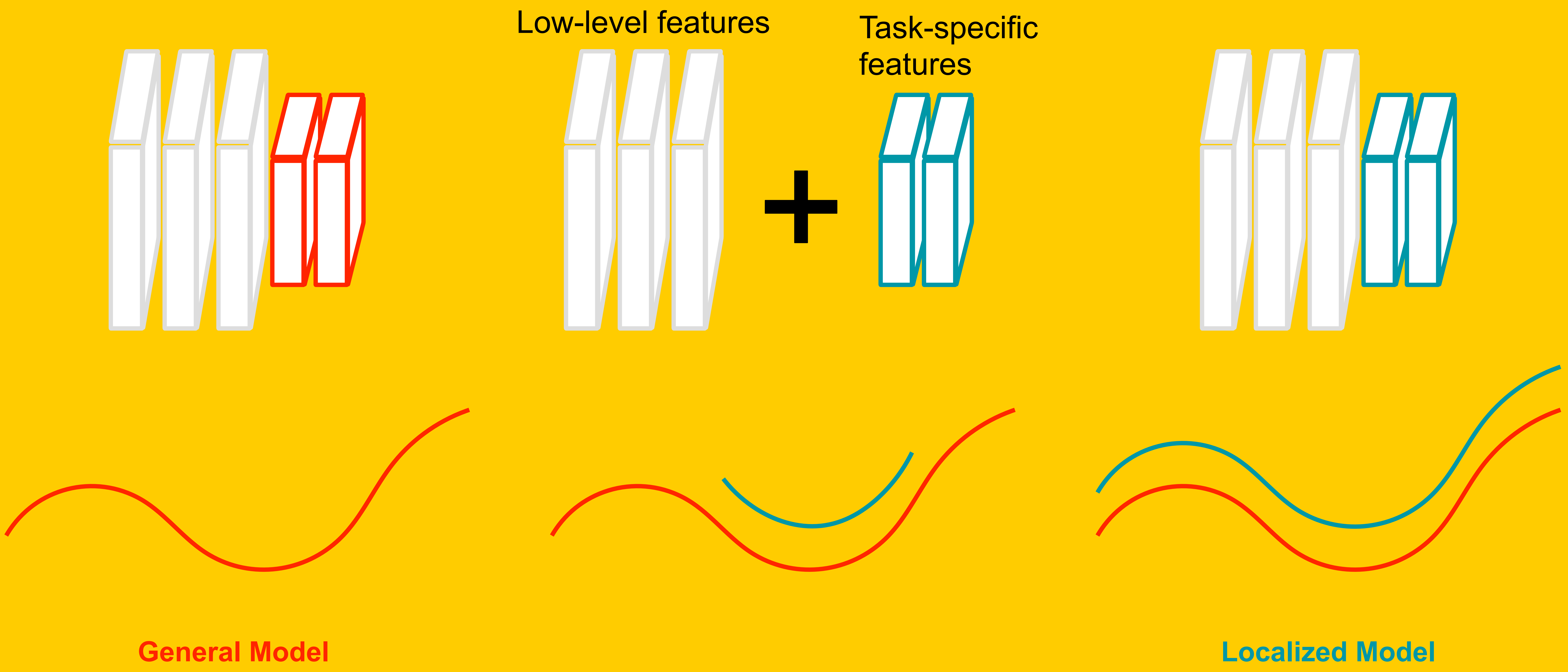
In the beginning of new tool/ chamber usage or ramp-up of new chip, there's often very little production data available. However, these information can provide task-specific insights to help build the localized model.

By transferring the low-level features from the General Model and incorporating task-specific features, the new Localized Model can work beyond its initial limited data range, enabling virtual experimentation with much wider sets of parameters.

General Model

Localized Model

Transfer Learning



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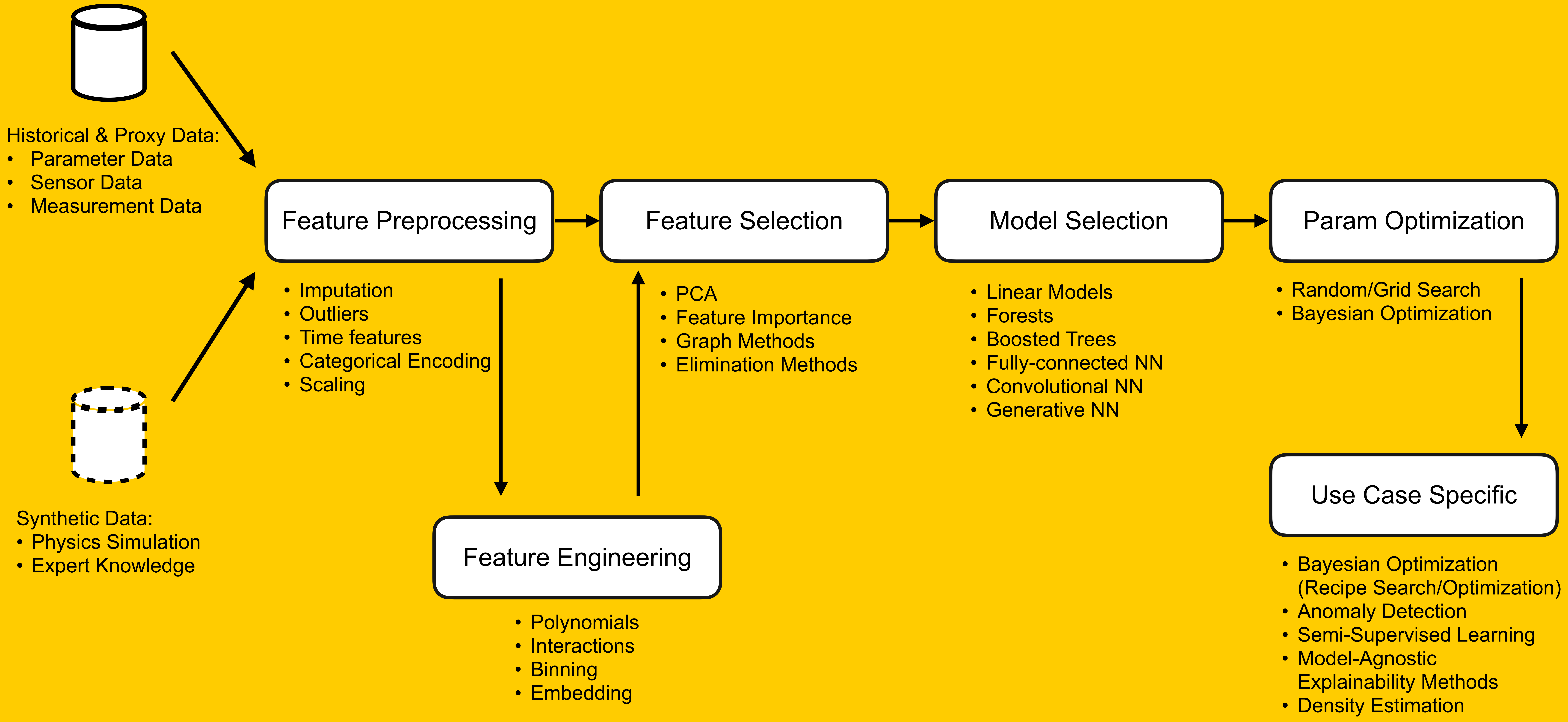
End-To-End AutoML



General Use Cases

Process Modeling & Optimization

- ⬆ Production yield
- ⬇ Material use
- ⬆ Revenue

Production Scheduling

- ⬇ Need for physical measurements
- ⬆ Tool utilization

Design of Experiments

- ⬇ Time-to-market
- ⬆ Cover wider parameter ranges

Case Study: CVD Cost vs. Quality

Problem: A fab wants to reduce material consumption cost for a chemical vapor deposition process while maintaining process quality

Method: Use Conductiv.ai Process Modeling to optimize cost vs. quality

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Case Study: CVD Cost vs. Quality

We input a large dataset with recipe parameters, sensor readings, and metrology data.

Conductiv.ai automatically detects the recipe parameters, and displays their general statistics.

User is able to set the range of extrapolation, to test parameters values outside of initial range.

Parameters

USE	NAME	TYPE	NVALUES	MEAN	STD	MIN	MAX	EXTRAPOLATION MIN	EXTRAPOLATION MAX	COST/UNIT
☑	HE FLOW	num		1829.818	0.058	1829.676	1829.949	1829.649	1829.976	☐
☑	FLOWFACTOR	num		0.917	0.027	0.885	0.95	0.879	0.956	☐
☑	SPACING	num		0.082	0.001	0.08	0.083	0.08	0.083	☐
☑	DEP TIME	num		64.597	2.096	59.61	68.53	58.71799	69.422	☐
☑	DEP TEMP	num		520.727	0.035	520.636	520.906	520.6089	520.933	☐
☑	TOOL	cat	4							☐

* dummy dataset

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Case Study: CVD Cost vs. Quality

The AutoML Engine automatically generates a machine learning model with the most suitable algorithm to predict the target (thickness in this case)

The scores for each algorithm are displayed.

Models

MODEL	FINISHED	DATASET	PARAMETERS	TARGET	ALGORITHM	AGGREGATED ERROR		
3	yes	test	HE FLOW FLOWFACTOR SPACING DEP TIME DEP TEMP TOOL	THICKNESS	SVR GradientBoostingRegressor RandomForestRegressor MLPRegressor AdaBoostRegressor Ridge Lasso	0.613 0.632 0.633 0.65 0.675 0.839 0.839	select	delete

* dummy dataset

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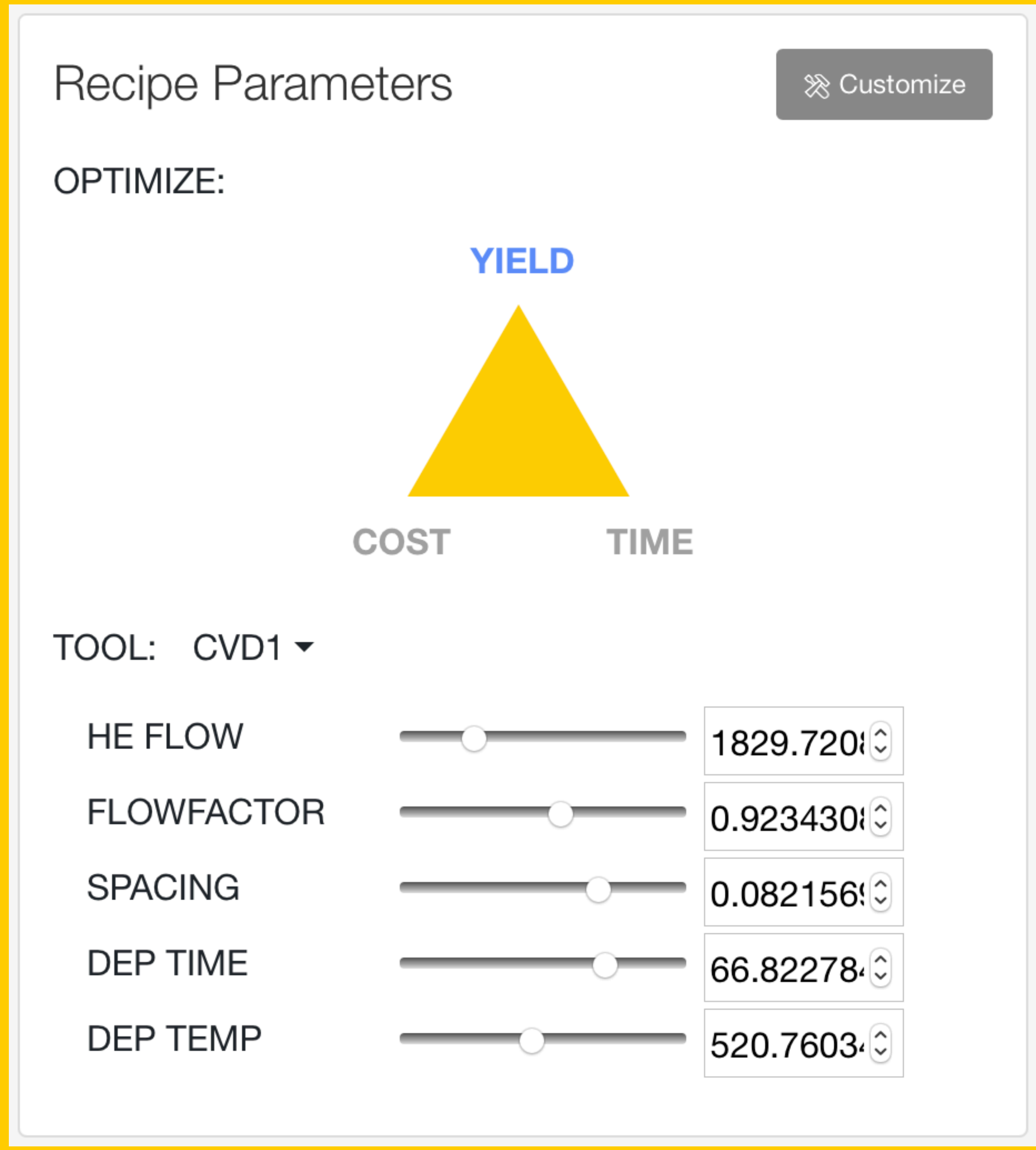
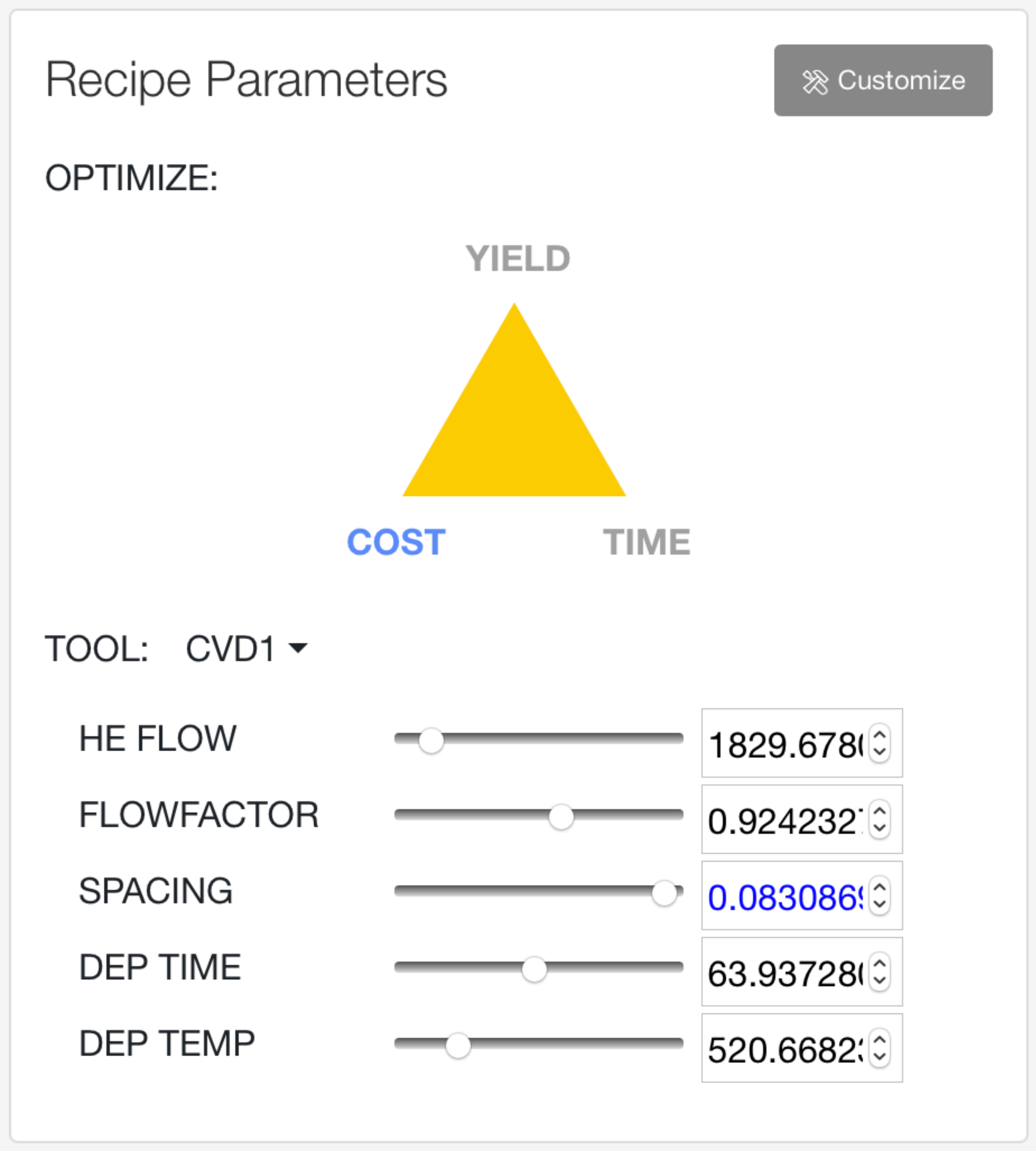
Case Study: CVD Cost vs. Quality

Using the model selected, the software automatically determines the best recipe parameters based on selected criteria.

User can select the three presets (Yield, Cost, Time), or click on "Customize" to set specific criteria (Yield >85%, Time <60s… etc)

In this case, we chose to optimize for cost.



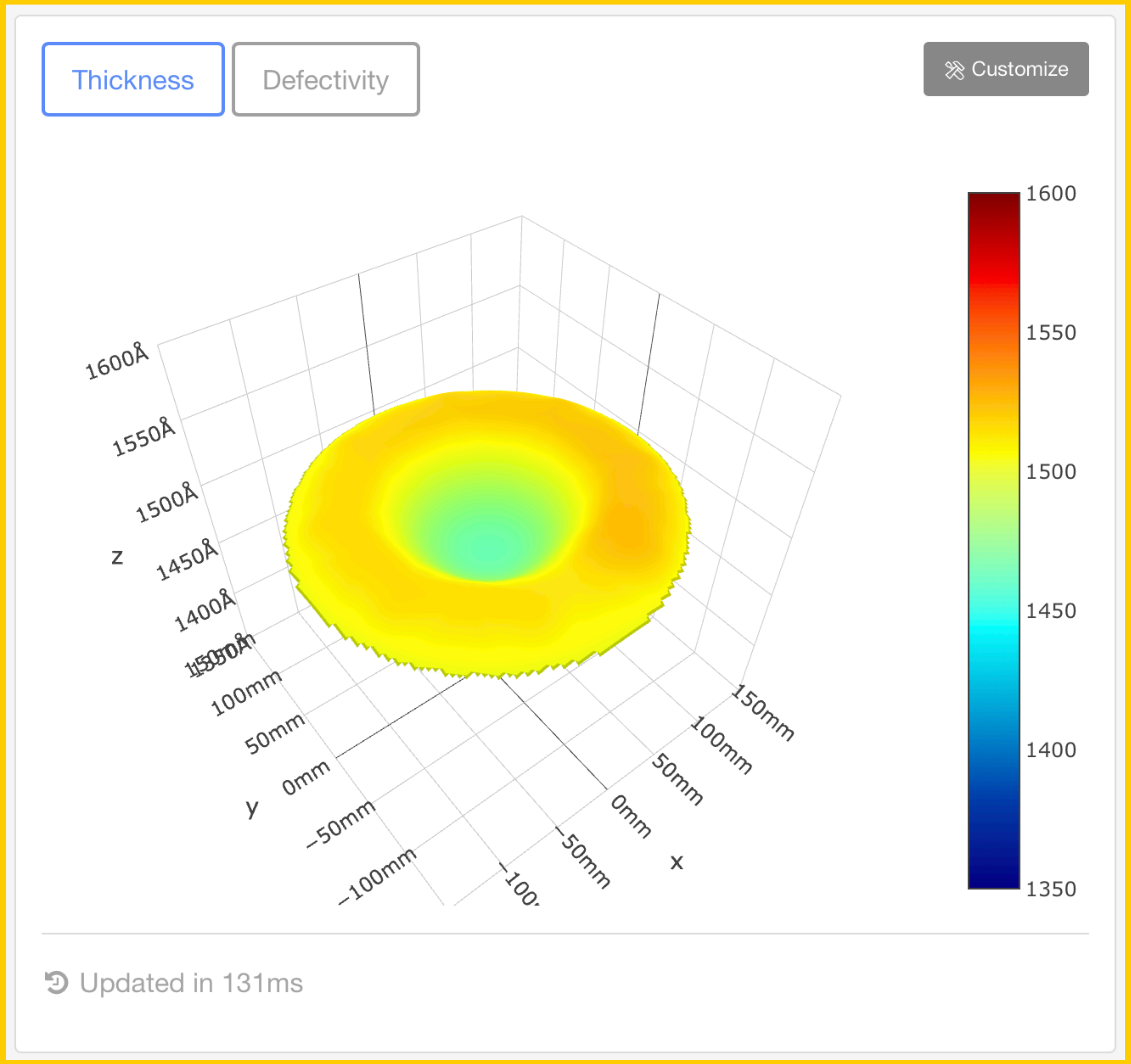


* dummy dataset

Case Study: CVD Cost vs. Quality

After selecting to optimize for cost, a visualization of the wafer's thickness profile is generated dynamically.

When the user is content with the selection, the recipe parameters can be sent directly to the tool.



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