Explainable Meta Bayesian Optimization with Human Feedback for Scientific Applications like Fusion Energy

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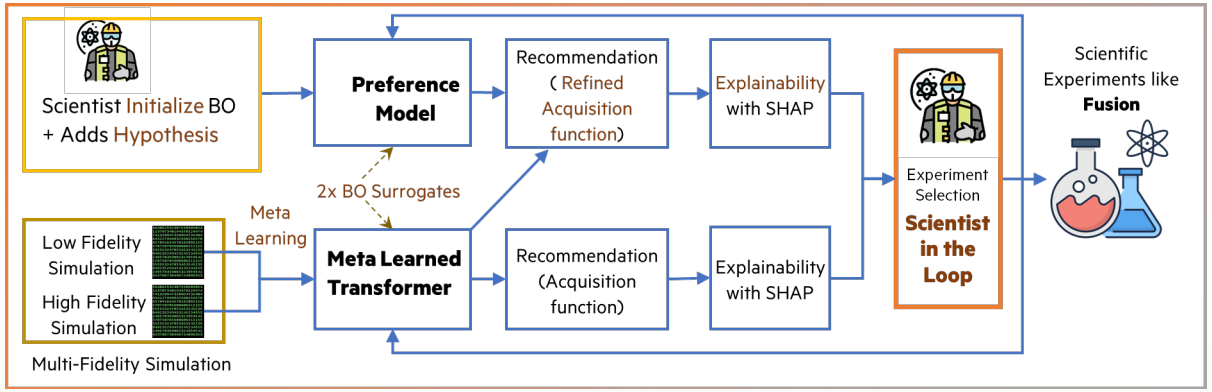

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Challenges with Inertial Confinement Fusion

To produce **1000 megawatts** of electricity for **1 day**

(enough for a major city)

Coal plant

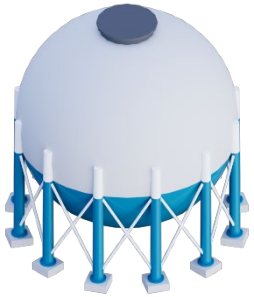
Fuel consumed:

18 million lb coal

80

railroad cars

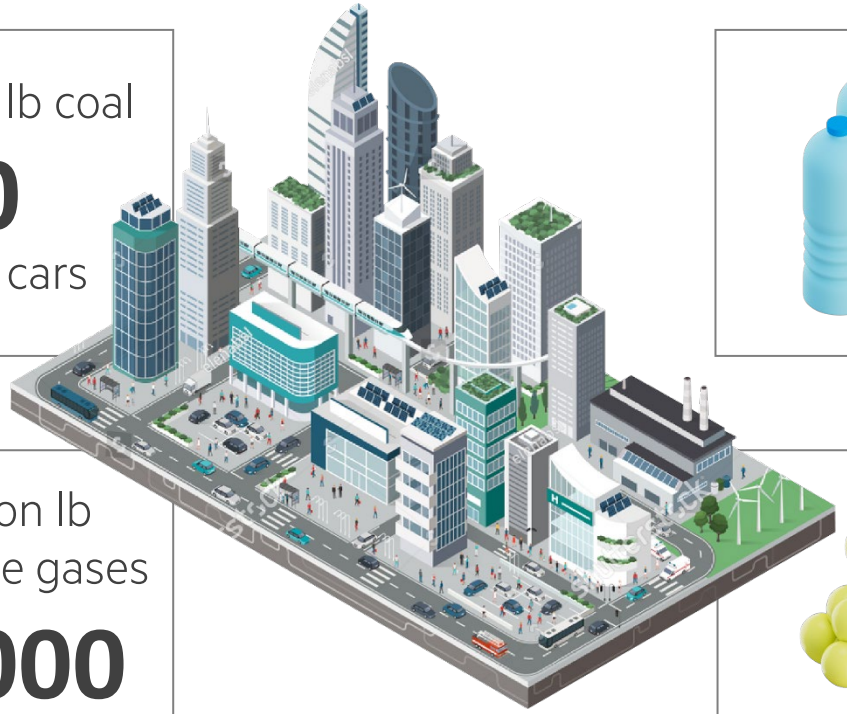
Waste produced:



61 million lb greenhouse gases

28,000

33-foot spheres



Fuel consumed:

1.0 lb D_2, 1.5 lb T_2

3

water bottles

Waste produced:

2.0 lb helium

400

balloons

Deuterium & Tritium

Fusion plant

Data Source: MIT Plasma Science and Fusion Center https://www.youtube.com/watch?v=ft4IhJK4ZTs

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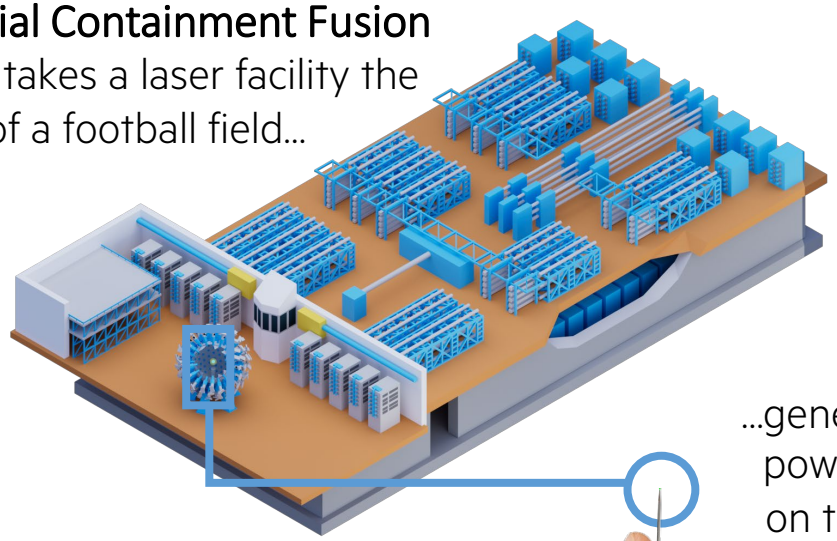
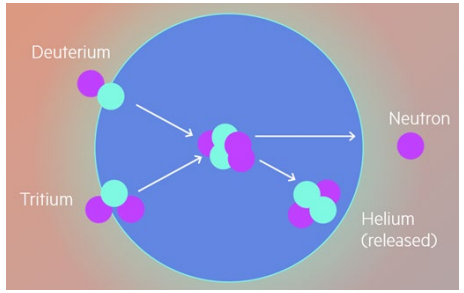
Fusion is the energy source in the sun and stars, and it is Challenging

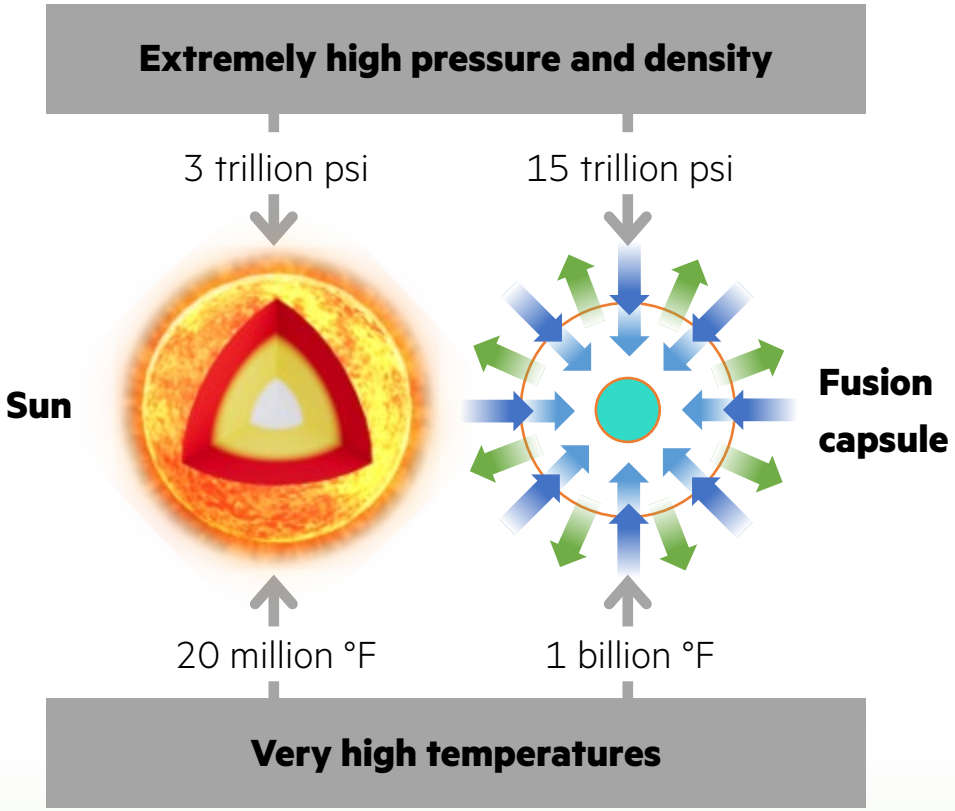
On Earth, nuclear fusion via **Inertial Containment Fusion (ICF)** takes a laser facility the size of a football field…



…generating enough laser power to fire at a **tiny payload** on the end of a pin.



In an ignited capsule, pressure and temperature are **higher than in the center of the sun**



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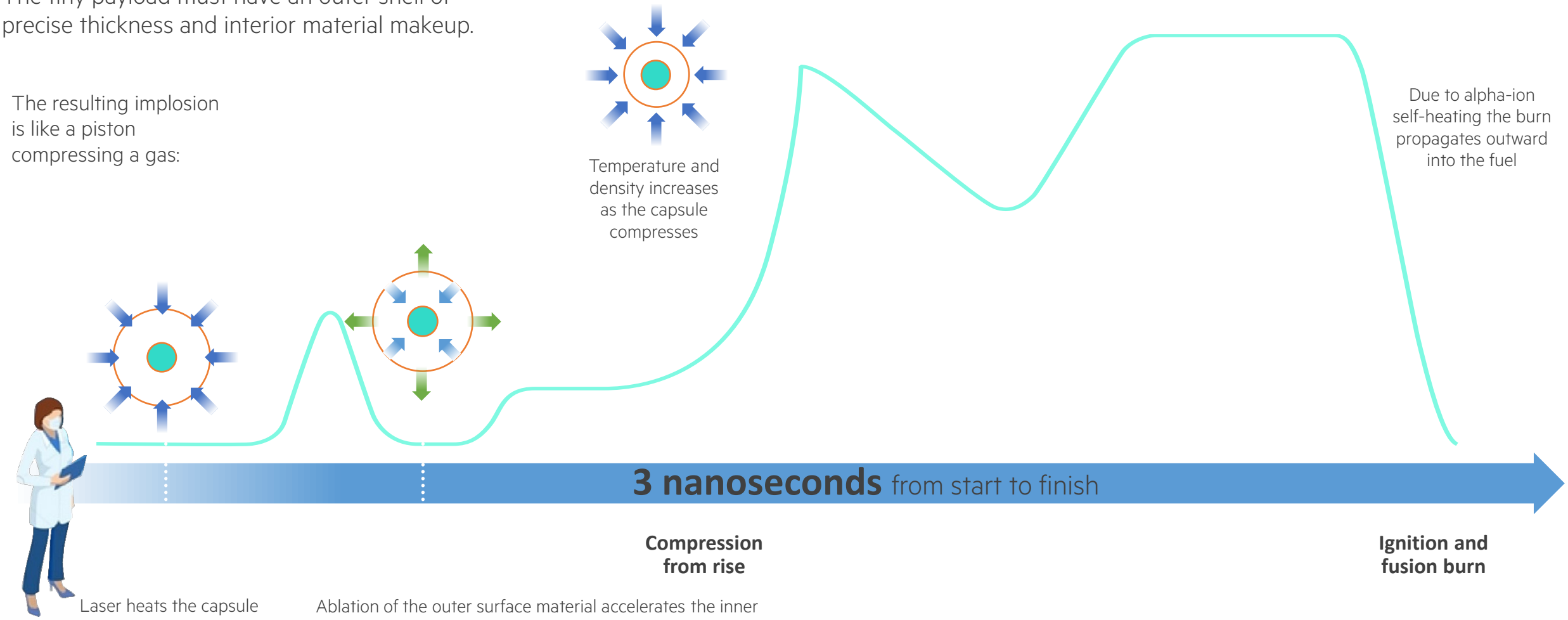
Challenges with Inertial Confinement Fusion

The tiny payload must have an outer shell of precise thickness and interior material makeup.

The resulting implosion is like a piston compressing a gas:



Laser heats the capsule surface increasing the pressure

Ablation of the outer surface material accelerates the inner part of the capsule inwards launching strong rocket-like shocks in the fuel which propagates through the DT gas

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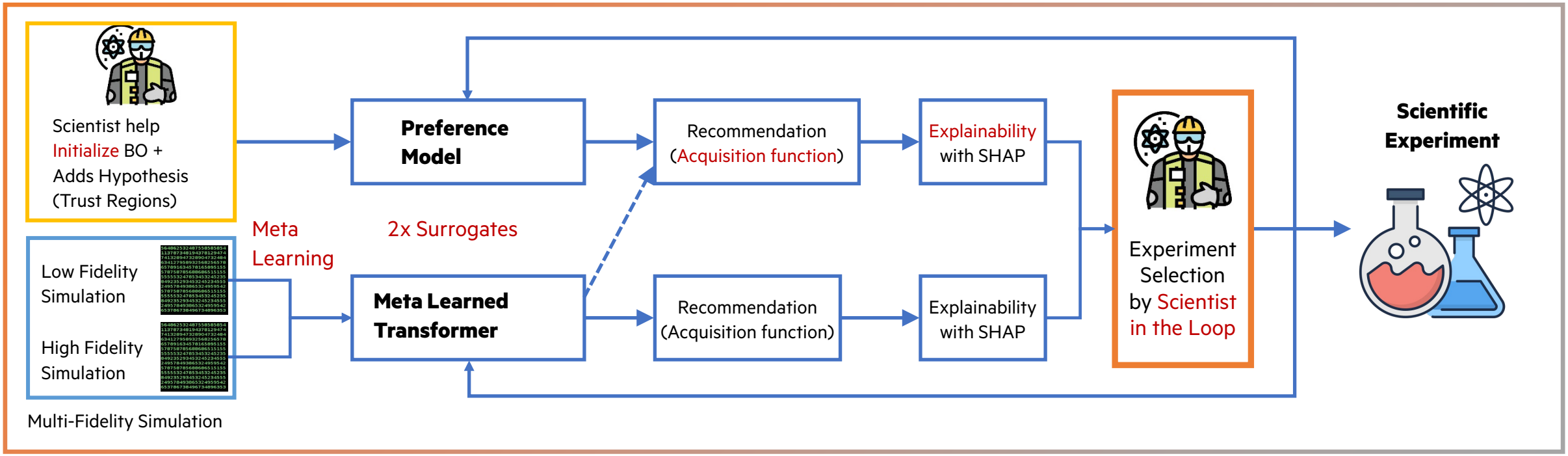
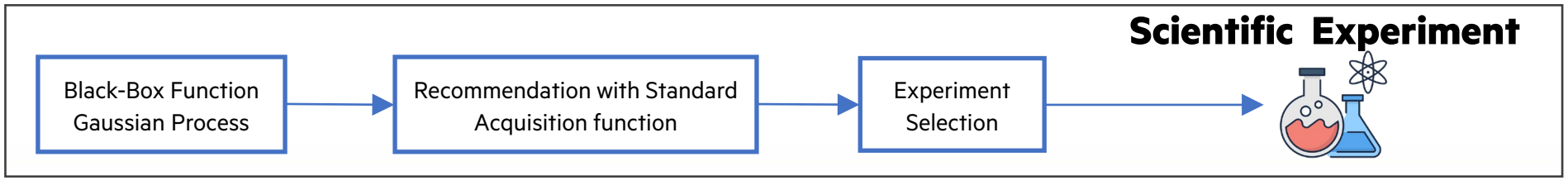
Scientist-in-the-Loop Explainable Optimization with Meta-Learning



Explainable Scientist in the Loop Optimization with Meta Learning from Multi-Fidelity Simulation



Standard Bayesian Optimization – how it has been done

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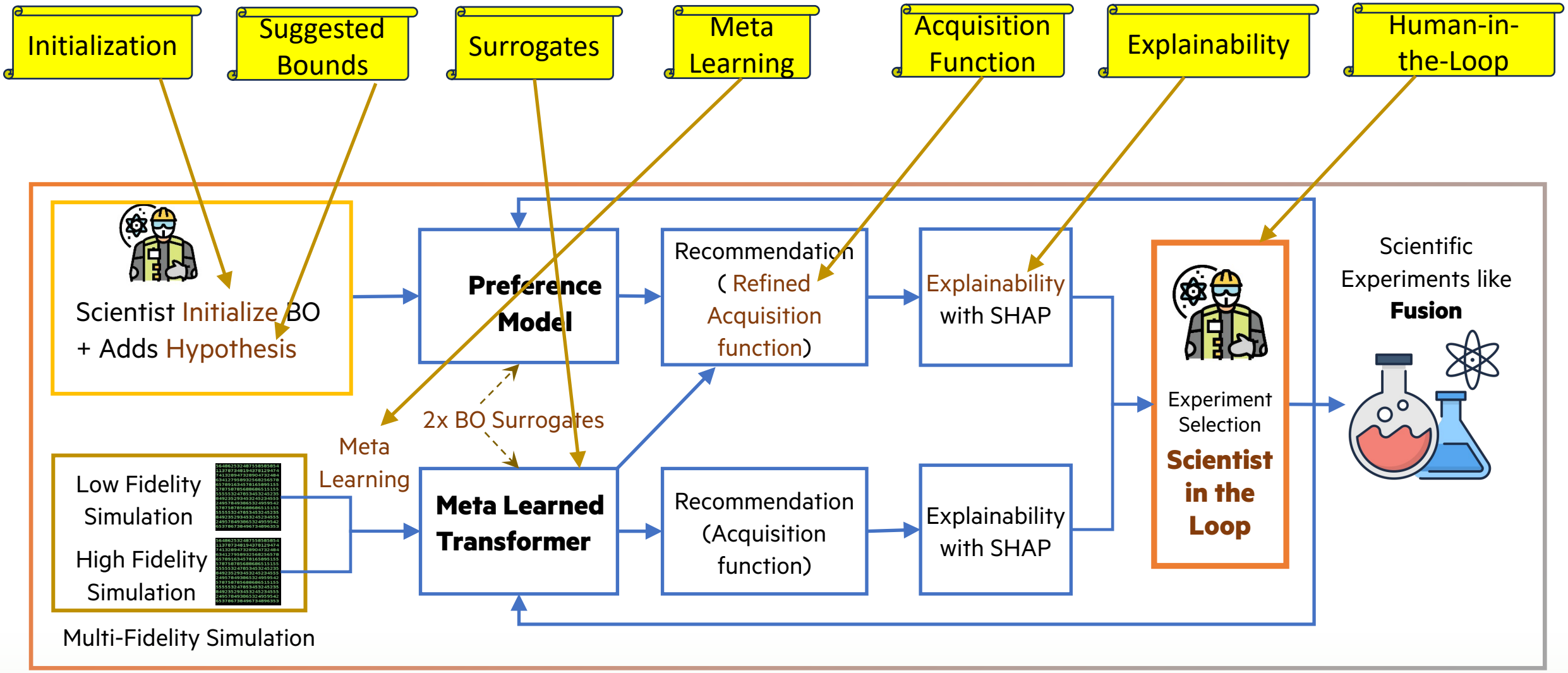
Refinements to Bayesian Optimization for very high sample efficiency



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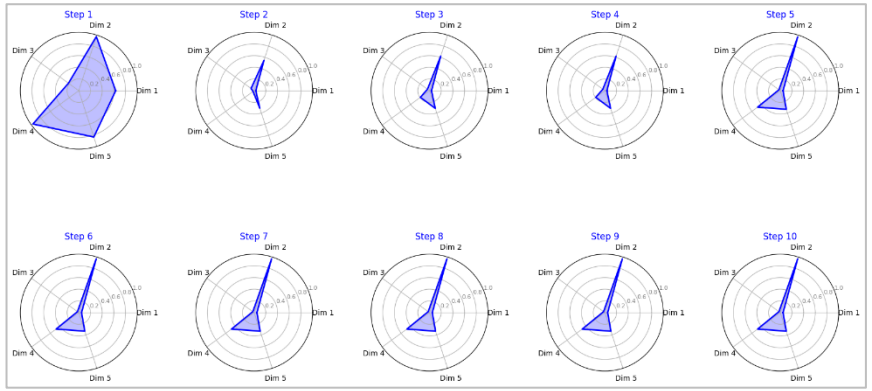
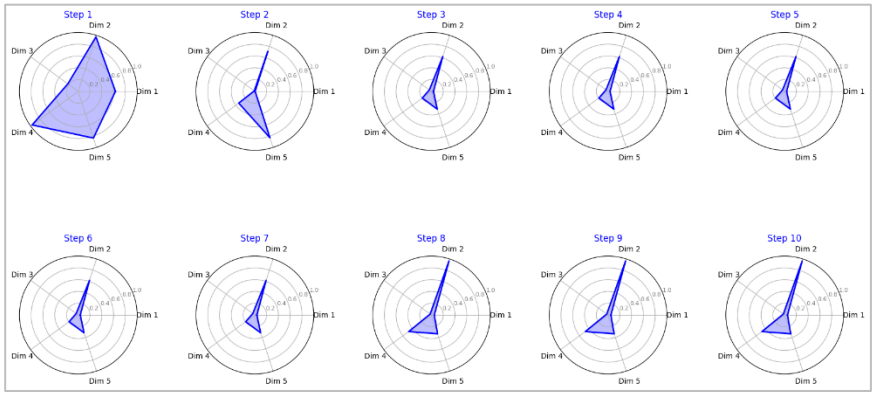
Optimization: Inertial Confinement Fusion with 5 input dimensions

Input variations for successive steps



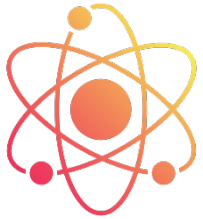
Preference Model + Meta Learning

Input variations for successive steps

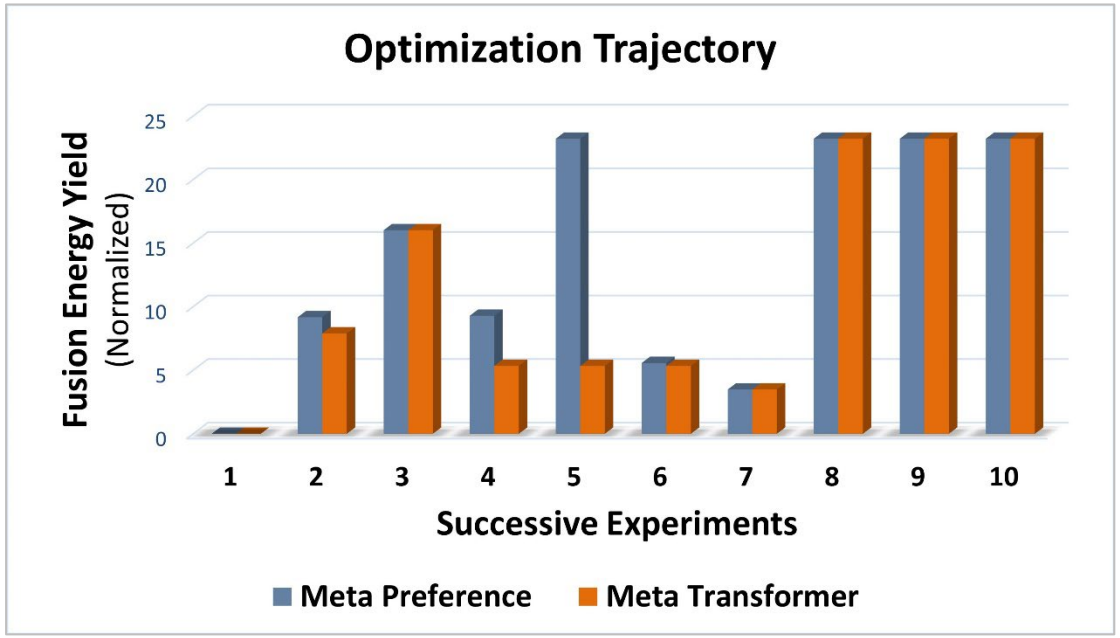


Meta-learned Transformer Surrogate

Scientist In-the-Loop for Experiment Selection



Energy Yield (Simulated)



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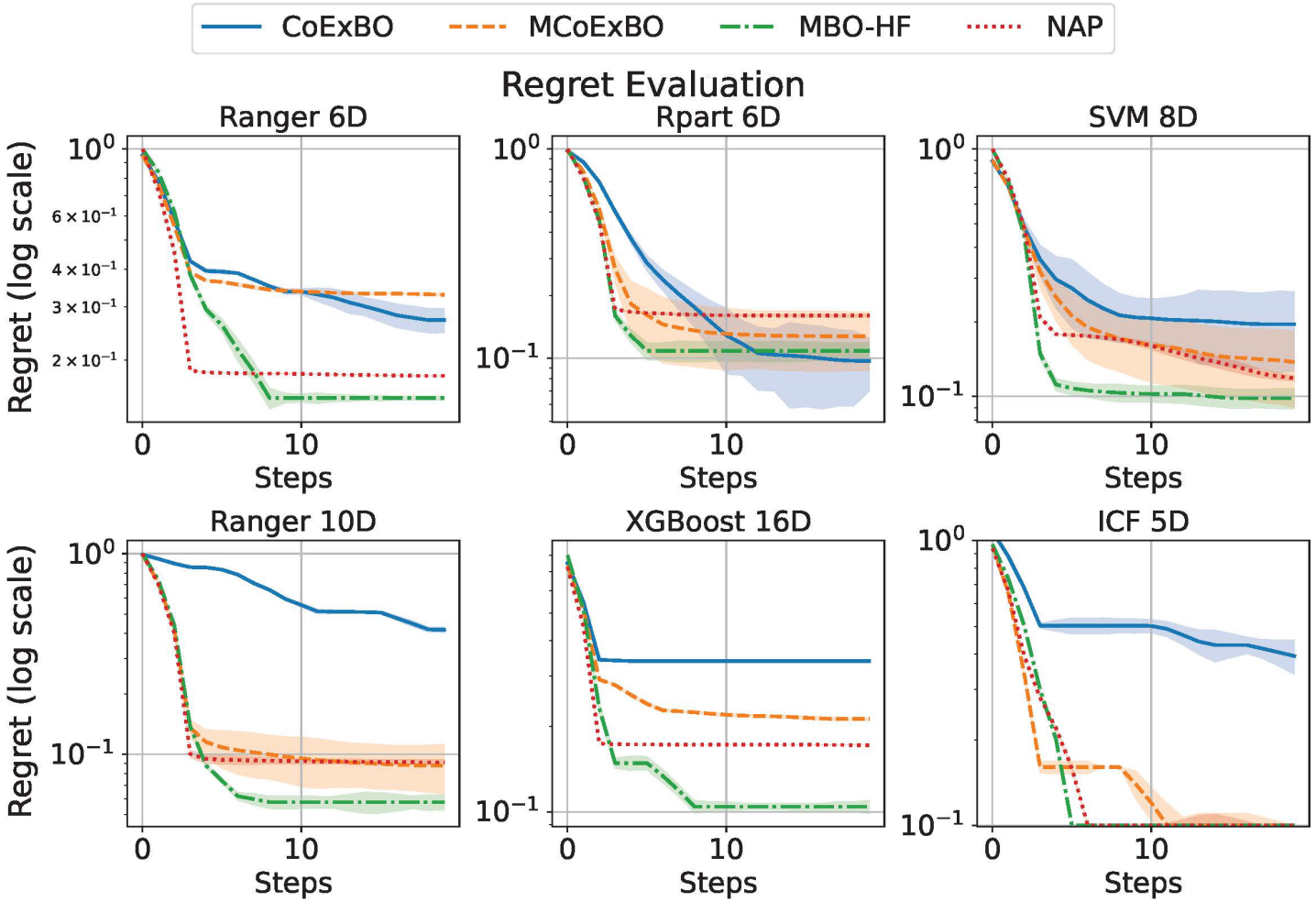
Results: MBO-HF performance



MBO-HF outperforms baselines on all 6 benchmarks, lower the better. Shaded areas: +/- 1SD. Regrets are normalized.

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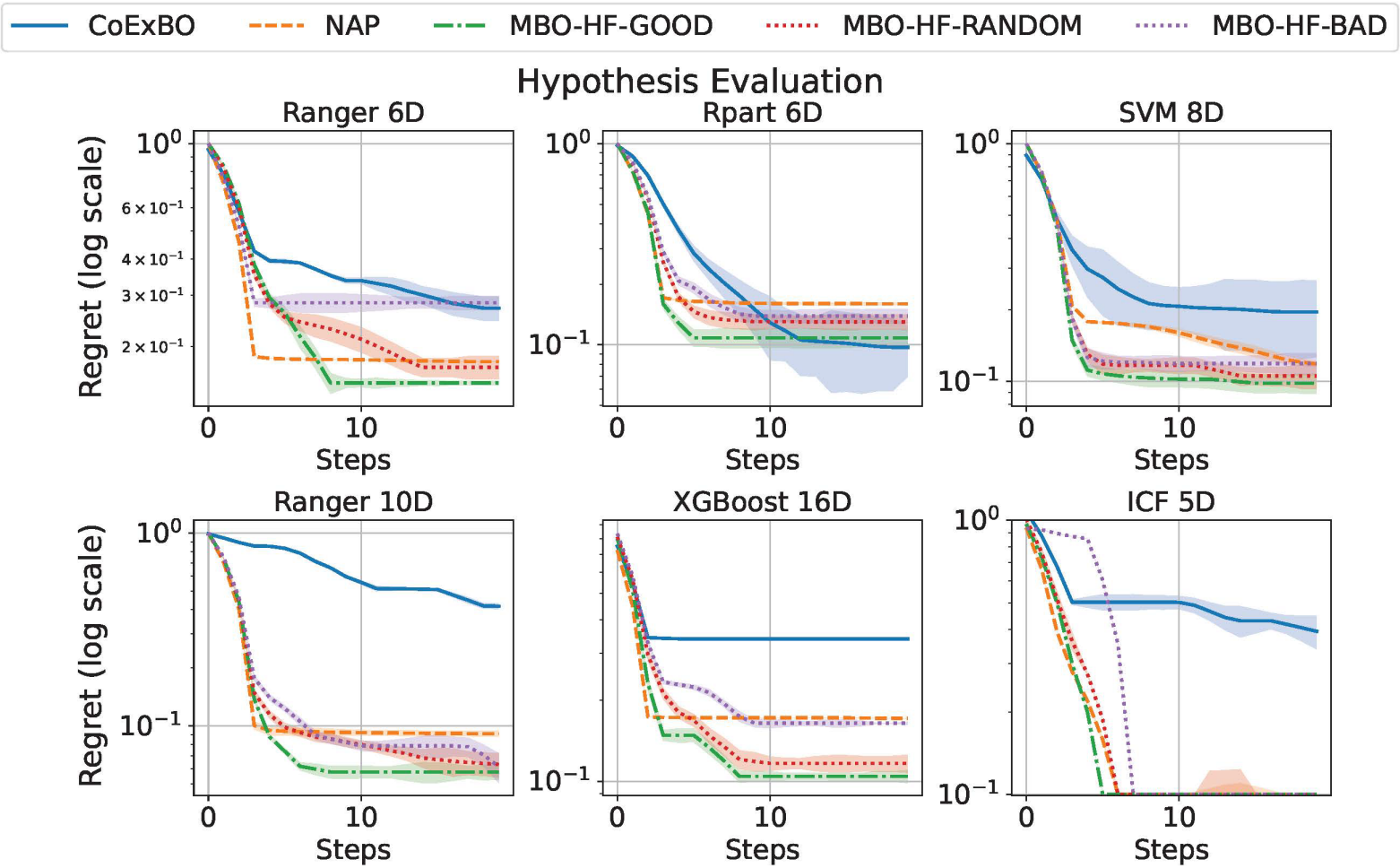
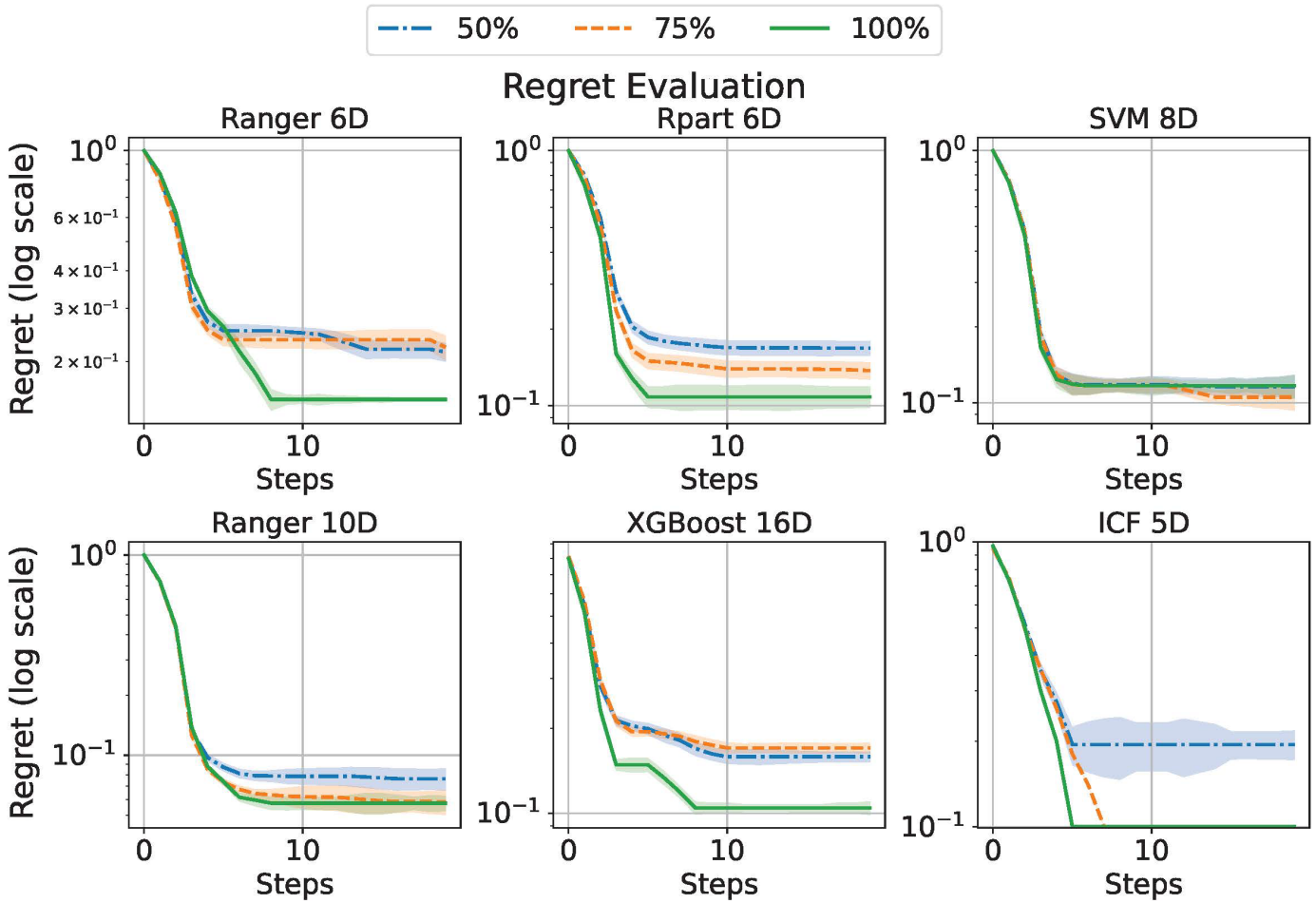
Results: MBO-HF hypothesis evaluation



Comparison of different hypothesis: “Good" best-case, “Bad" worst-case, and Random sampling in preference learning initialization. Shaded areas: +/- 1SD. Regrets normalized.

Results: MBO-HF accuracy evaluation



Results of the comparison between different expert's accuracy percentages. The shaded areas represent a +/- 1SD error. Regrets are normalized.

Climate Change AI

NEURAL INFORMATION PROCESSING SYSTEMS

Thank You

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