FACULTY OF ENGINEERING AND ARCHITECTURE

DEPARTMENT OF INFORMATION TECHNOLOGY
RESEARCH GROUP: SUMOLAB

Bayesian active learning for electromagnetic structure design

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Introduction

Design of modern electromagnetic and electronic circuits is a complex task

- Tradeoffs between conflicting design requirements
- Physical effects such as reflection, crosstalk and propagation delays

Computer Aided Design (CAD) is essential

- Systems with high bandwidth and complexity

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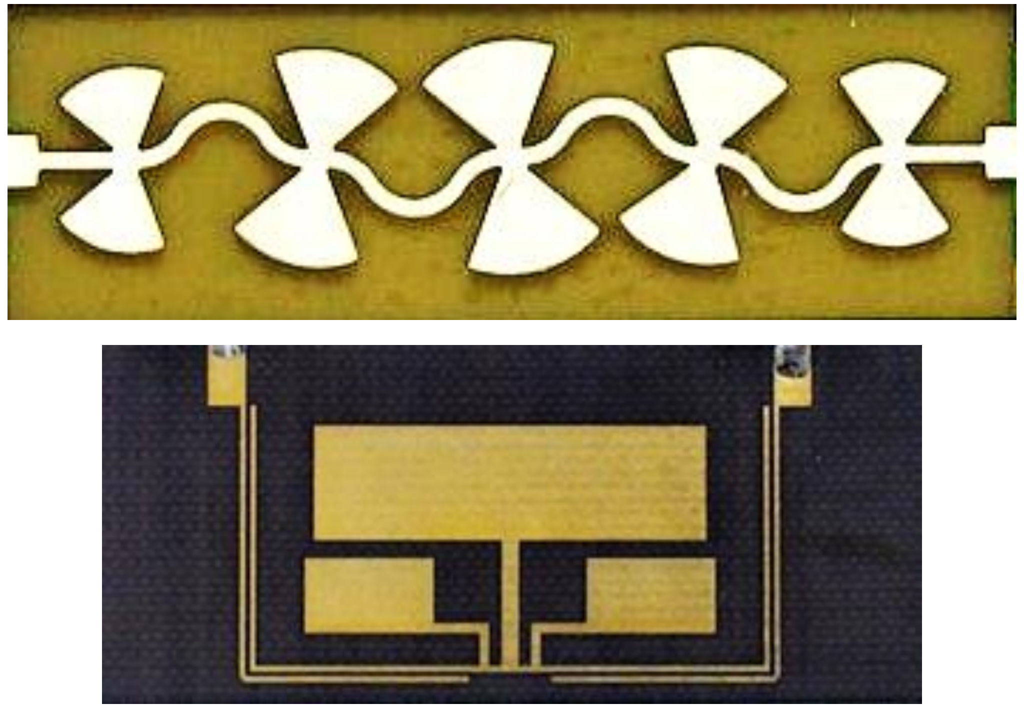
Expensive!

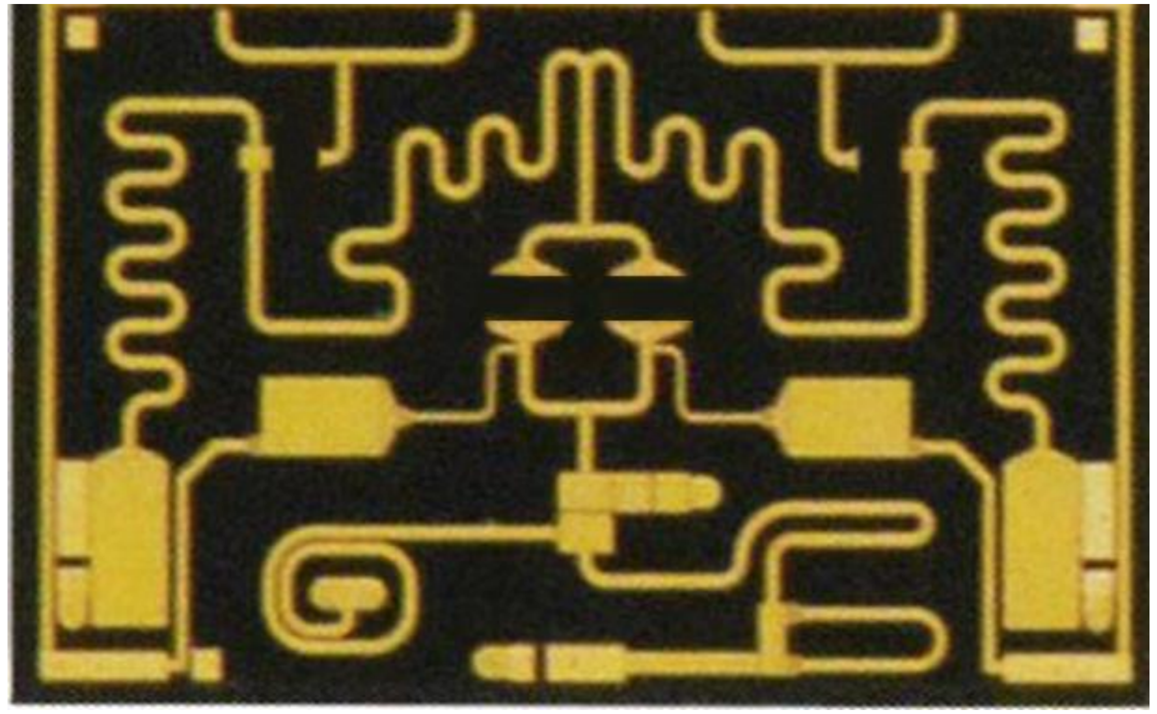
Introduction

Example: RF linear and passive distributed devices

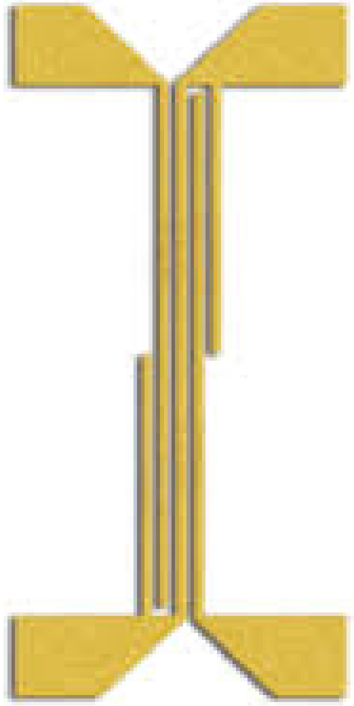
Distributed filters



Matching networks



Couplers



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Example: RF linear and passive distributed devices

- Defined by several geometrical or electrical parameters

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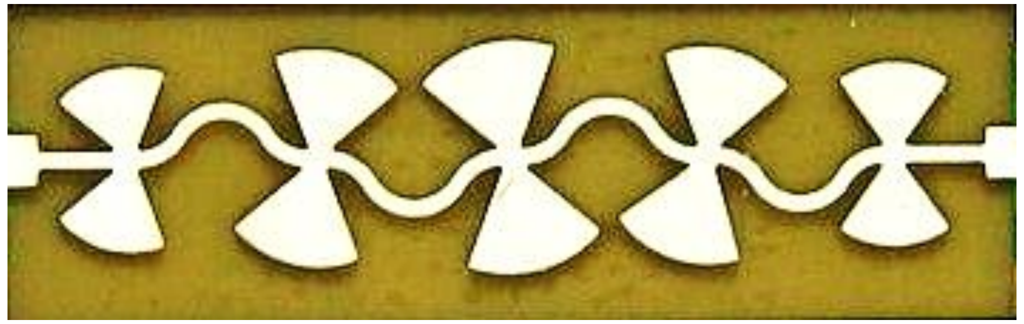

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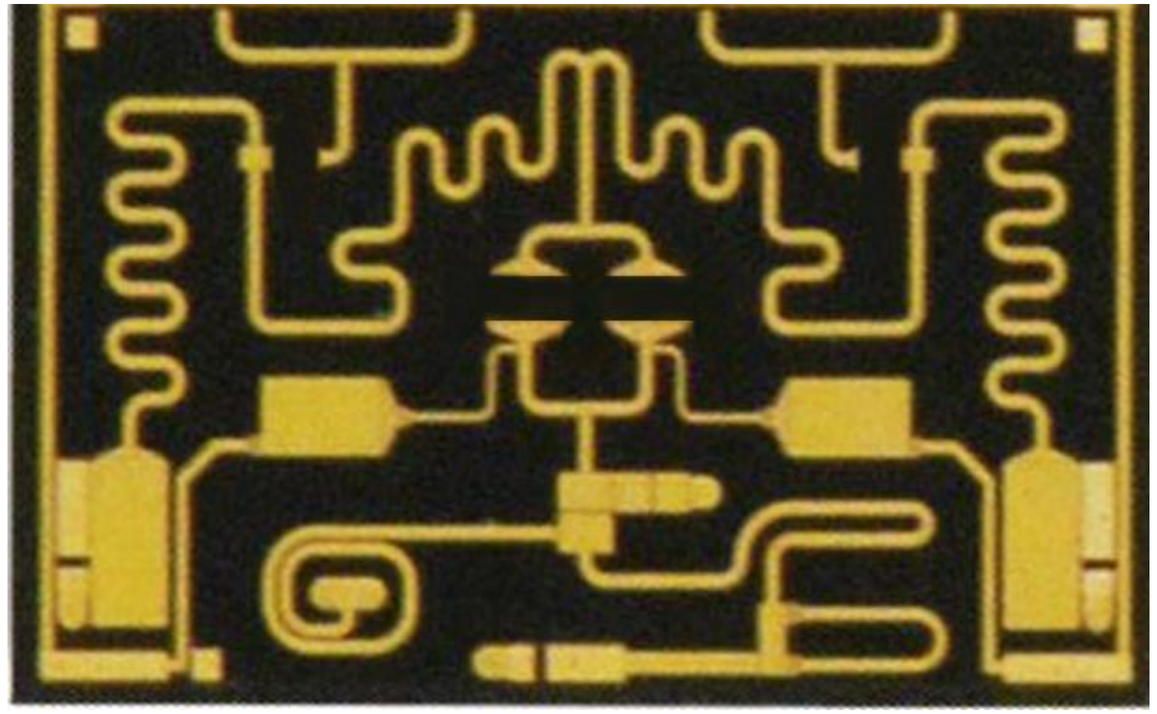

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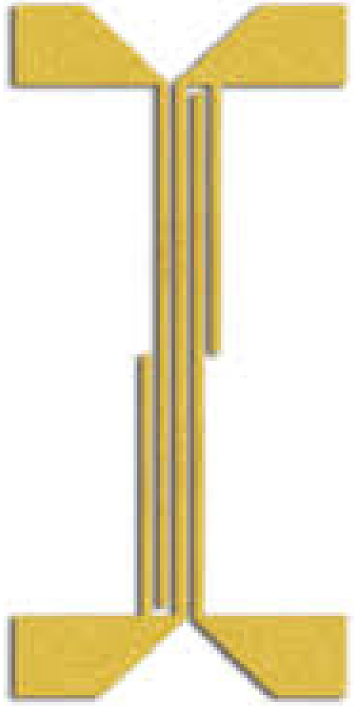
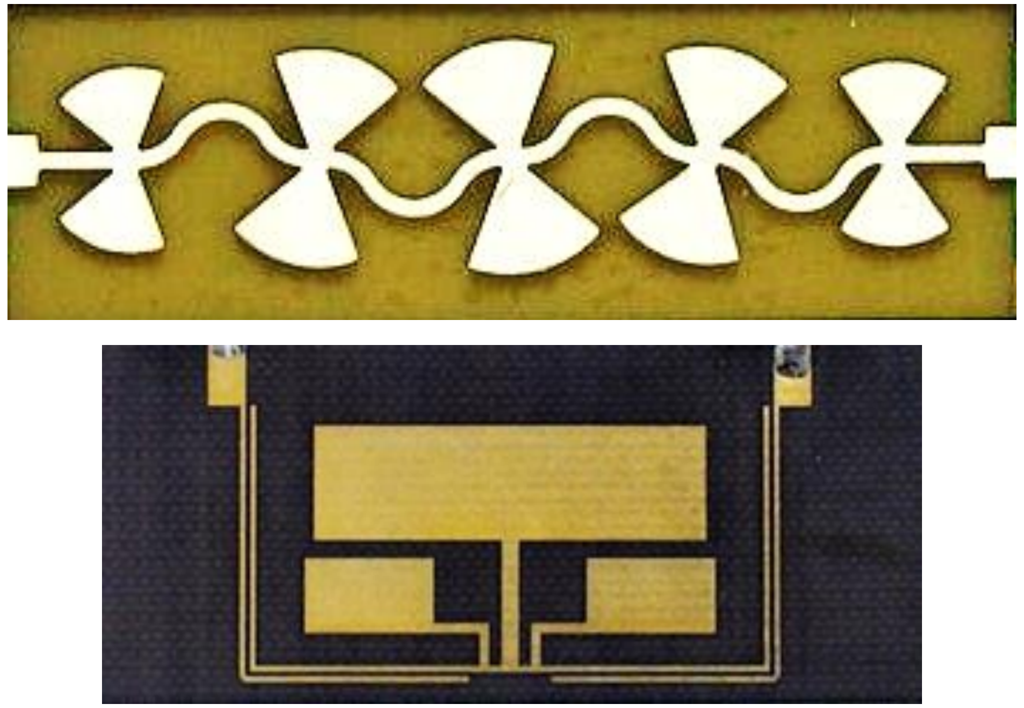


Introduction

Example: RF linear and passive distributed devices

- Defined by several geometrical or electrical parameters
- For each combination of design parameters
  - Time-expensive electromagnetic simulations

Distributed filters



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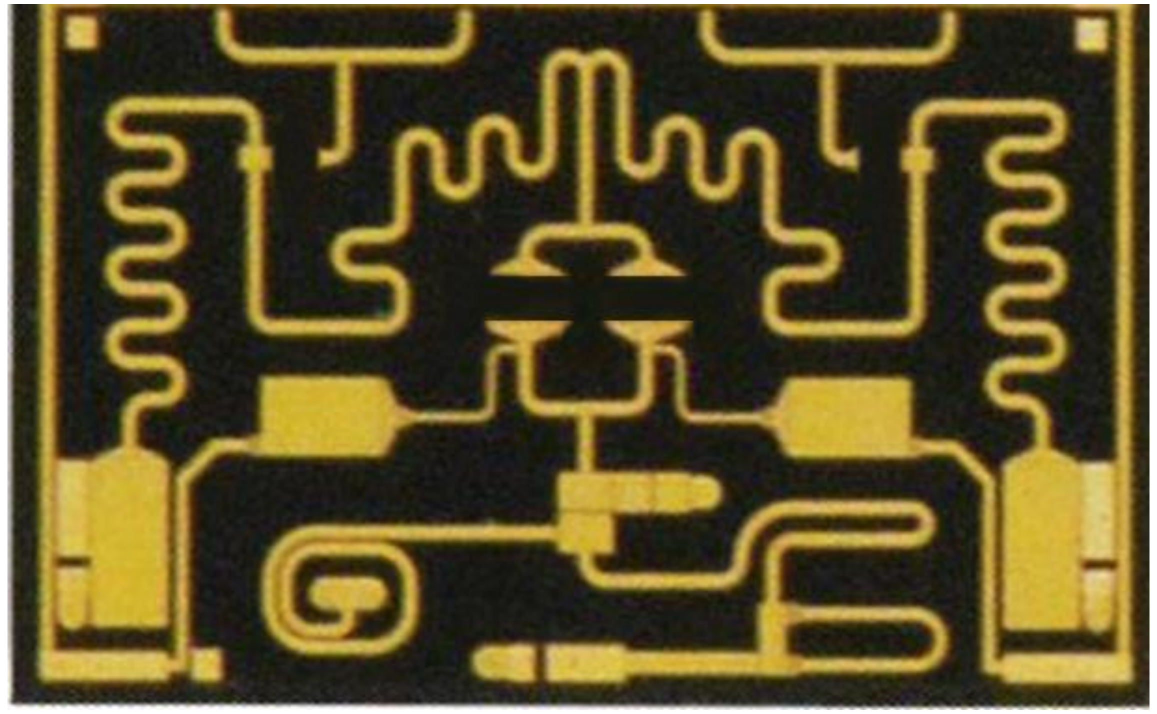

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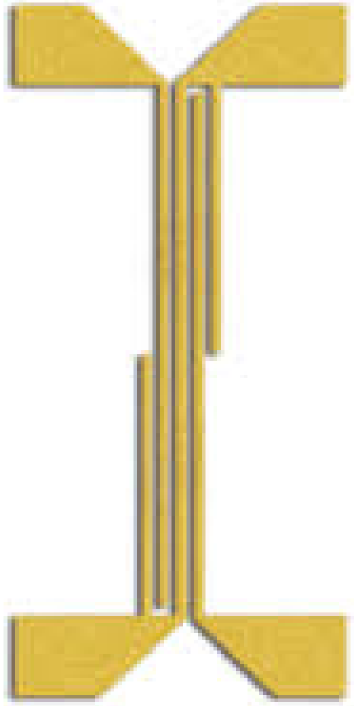

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Example: RF linear and passive distributed elements

- The design process requires to perform many simulations
  - Design space exploration, optimization, uncertainty quantification

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  - Design space exploration, optimization, uncertainty quantification

Infeasible!

Introduction

Idea

- Identifying designs satisfying suitable criteria (application-dependent)
- With a limited number of expensive simulations

The desired design solutions form the ***target region***

This can:

1. Reduce the complexity of the design problem
2. Give insight on the system under study

Introduction

This work:

- Introduces a new methodology for target region identification
- Demonstrates its usefulness by design of a low pass filter
- Provides a PCA based bounding box to describe the target region

Outline

- Goal
- Methodology
- Results and discussion
- Conclusion

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Goal

Find

$$A \coloneqq \{x \in \chi \mid a < f(x) < b\}$$

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Goal

Find

Design space

Expensive simulator

$$A := \{x \in \chi \mid a < f(x) < b\}$$

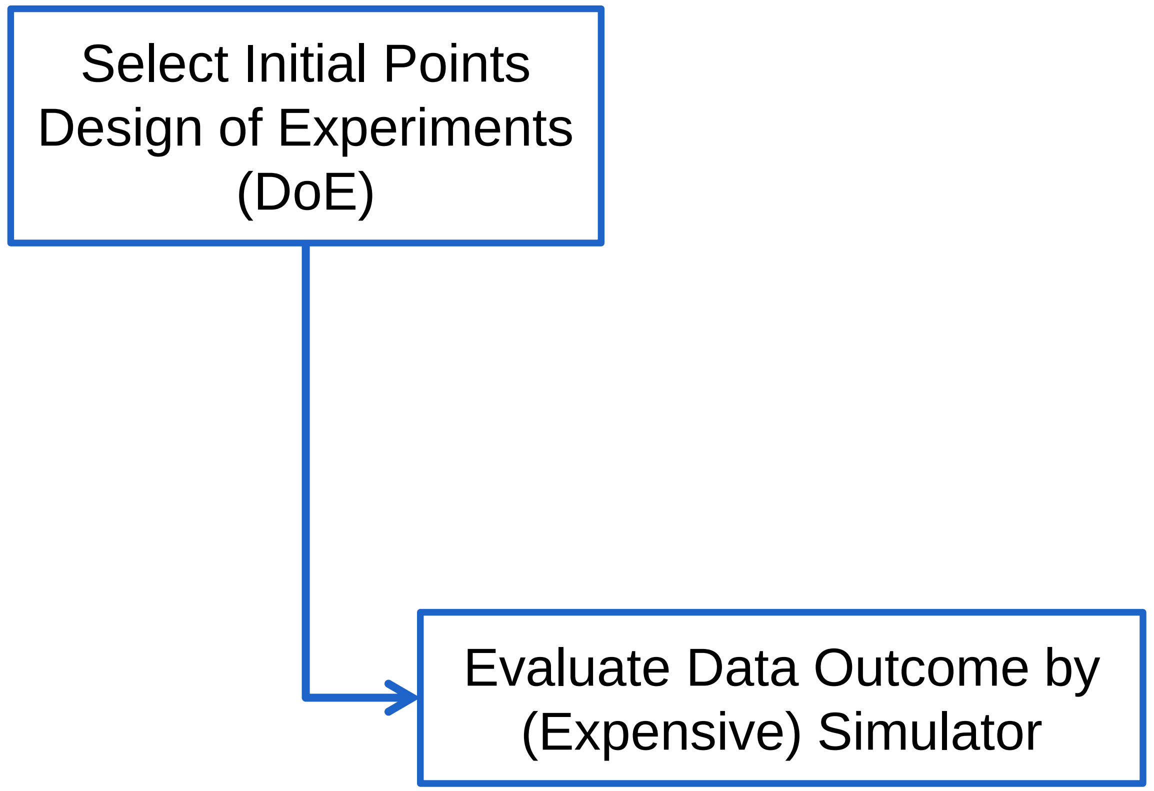
Target region

Design parameters

Methodology

Select Initial Points
Design of Experiments
(DoE)

Methodology



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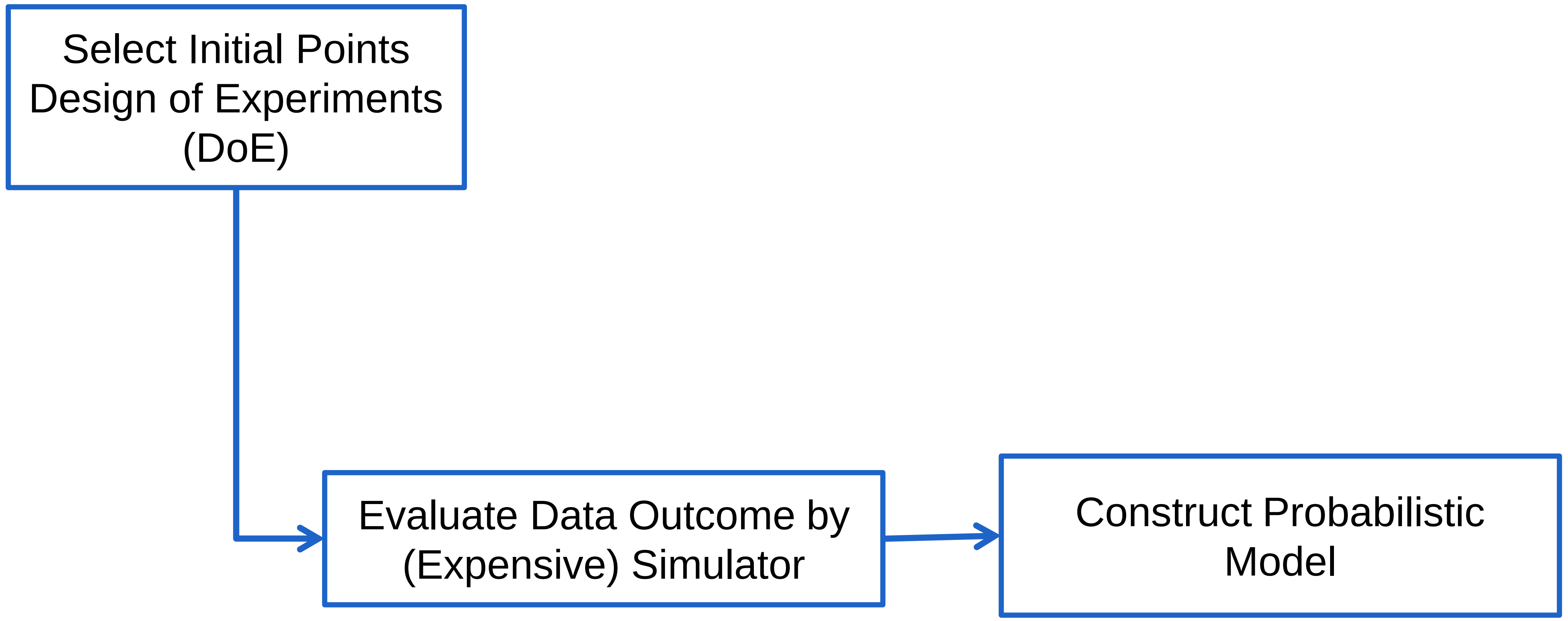

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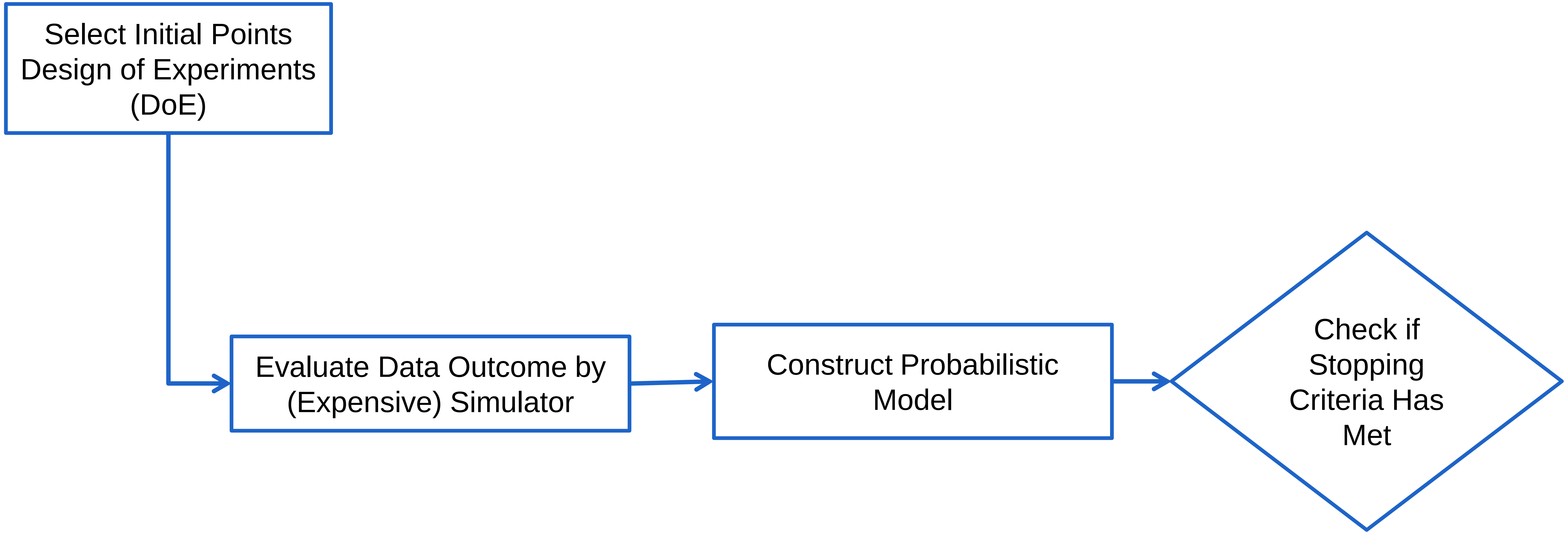

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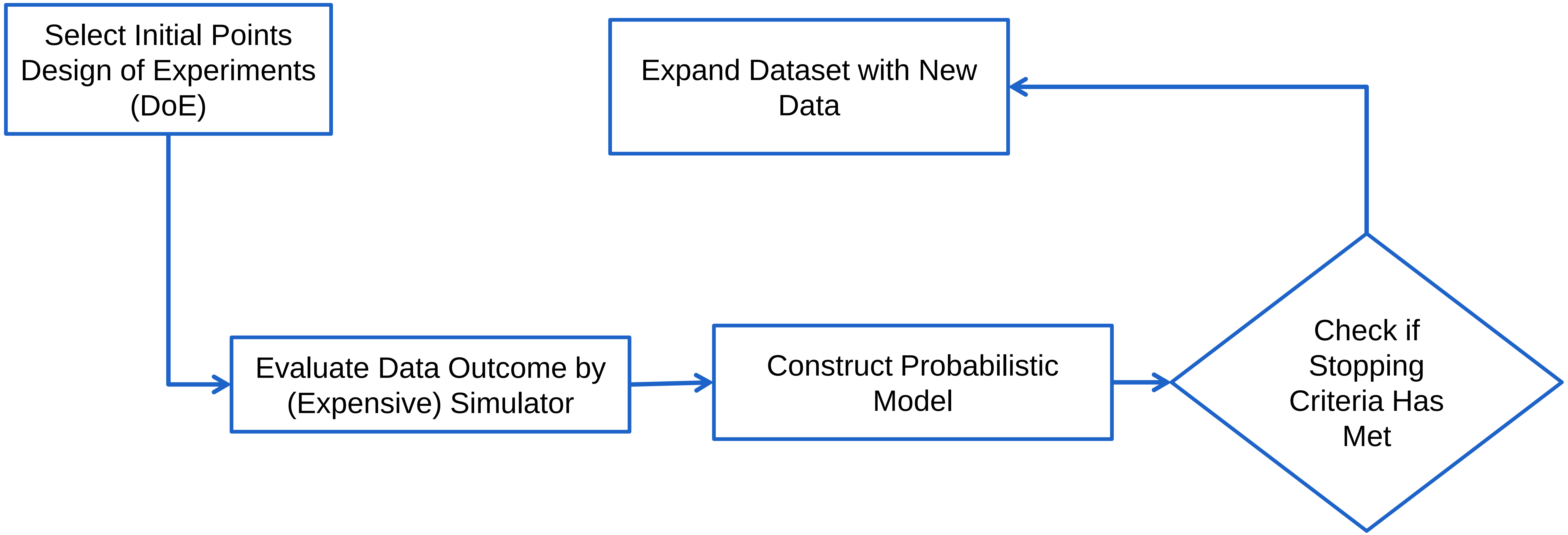

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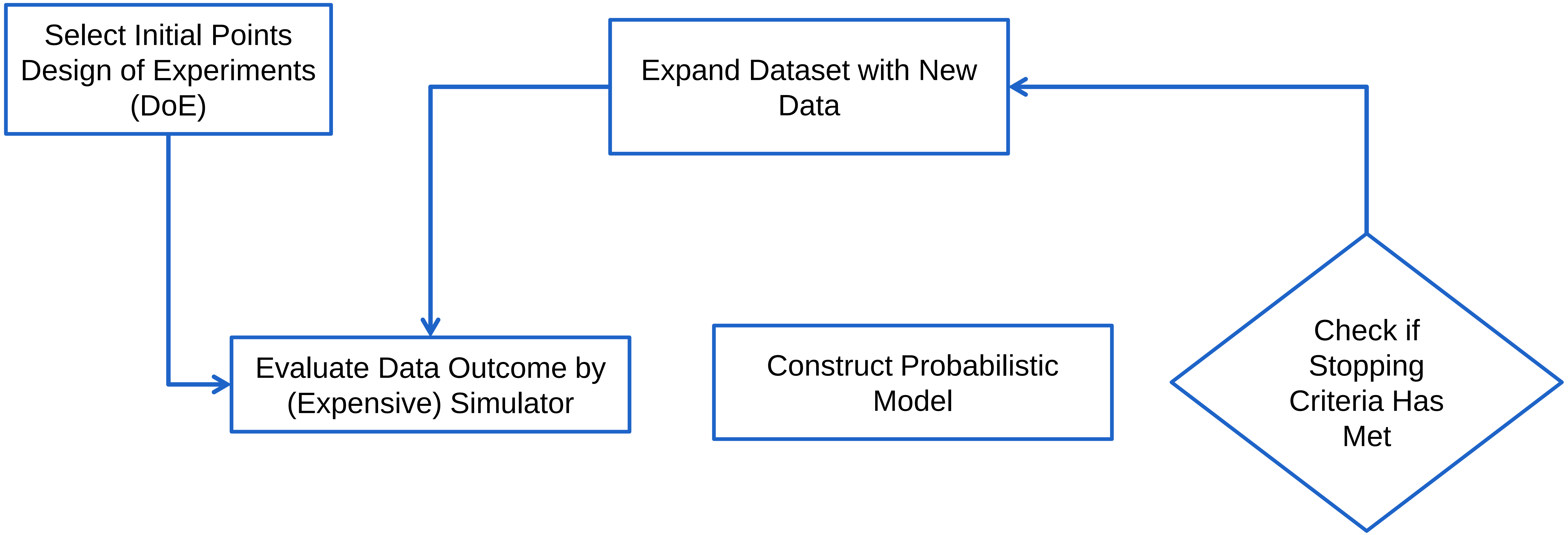

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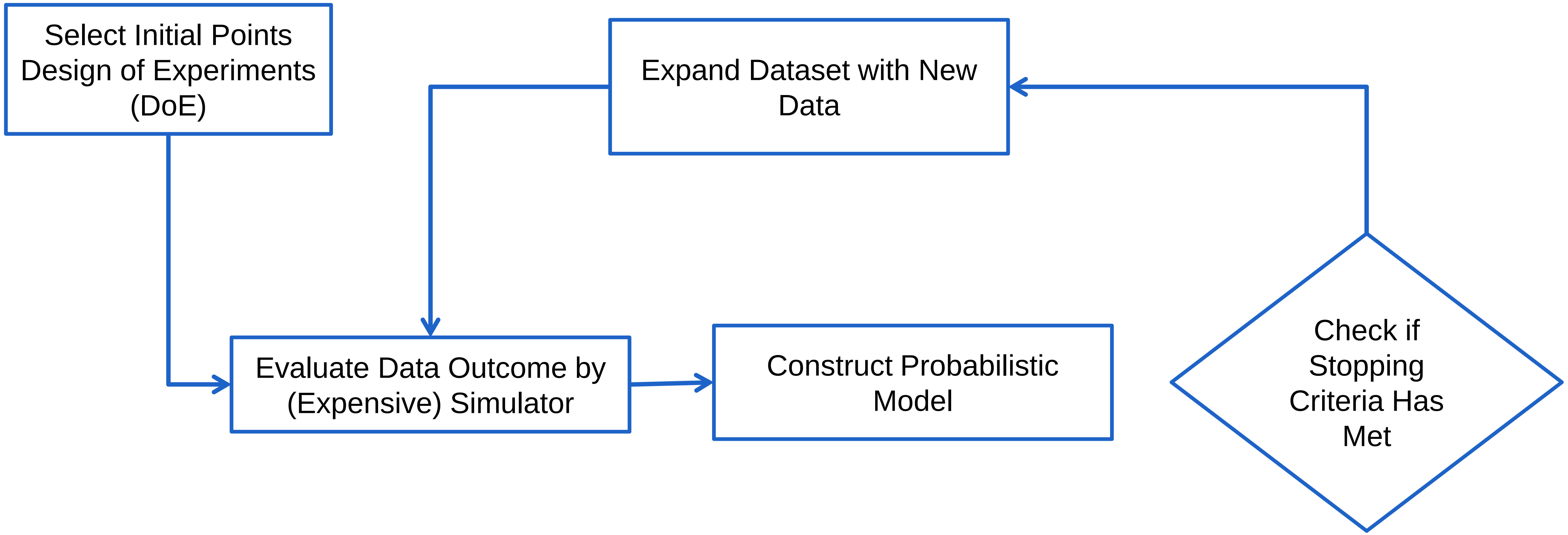

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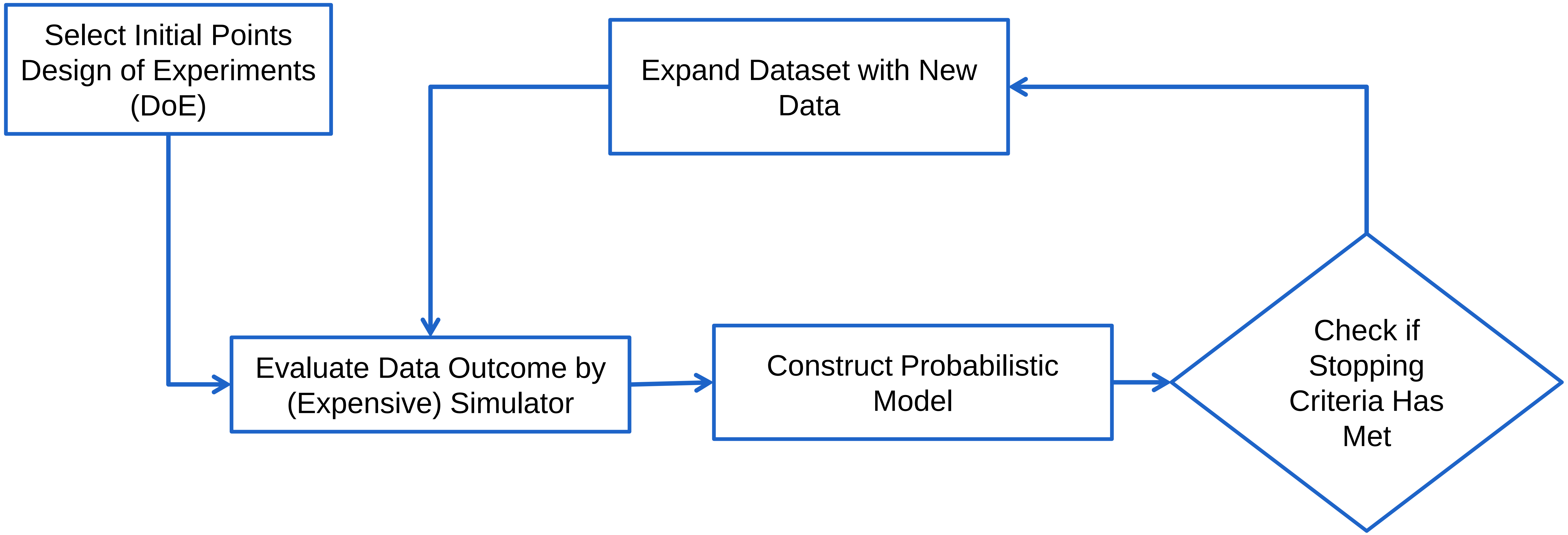

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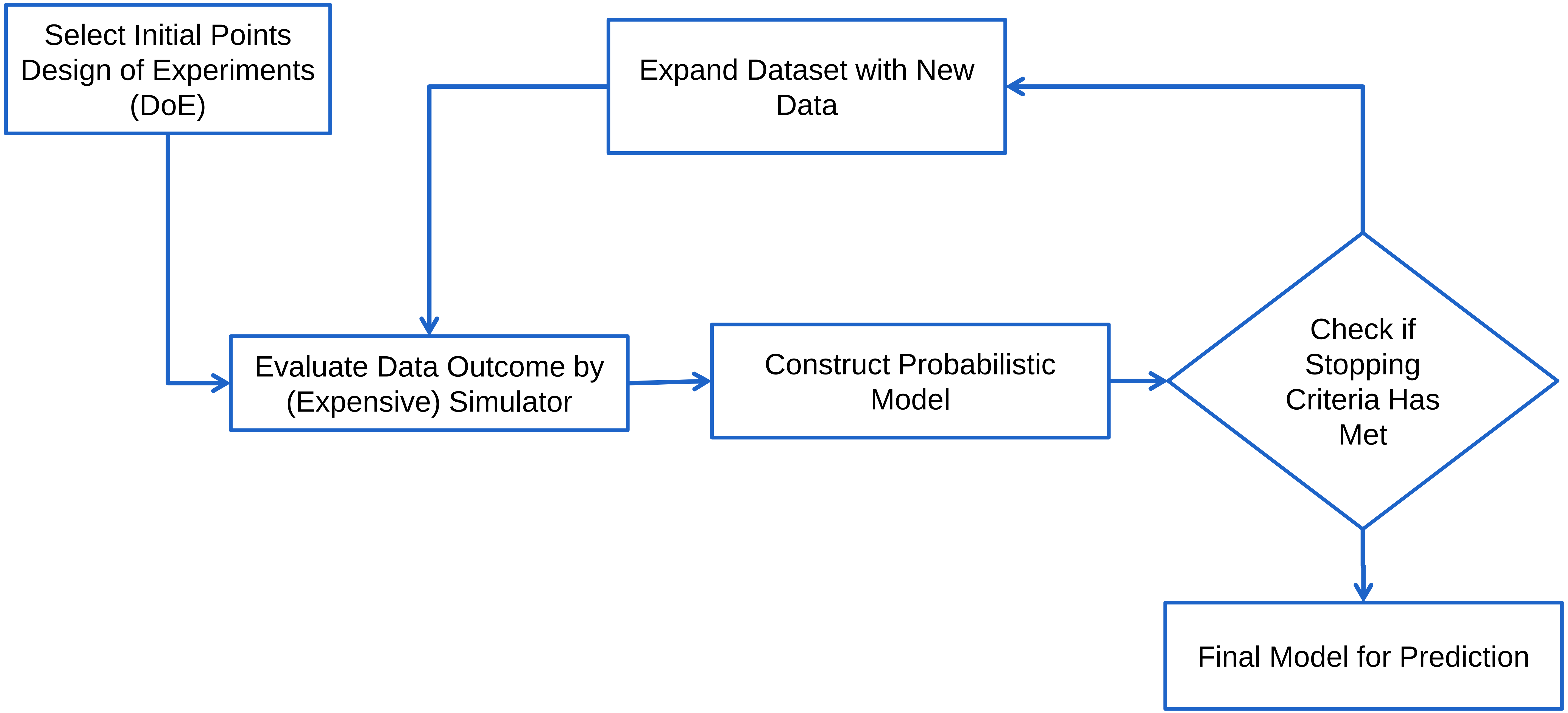

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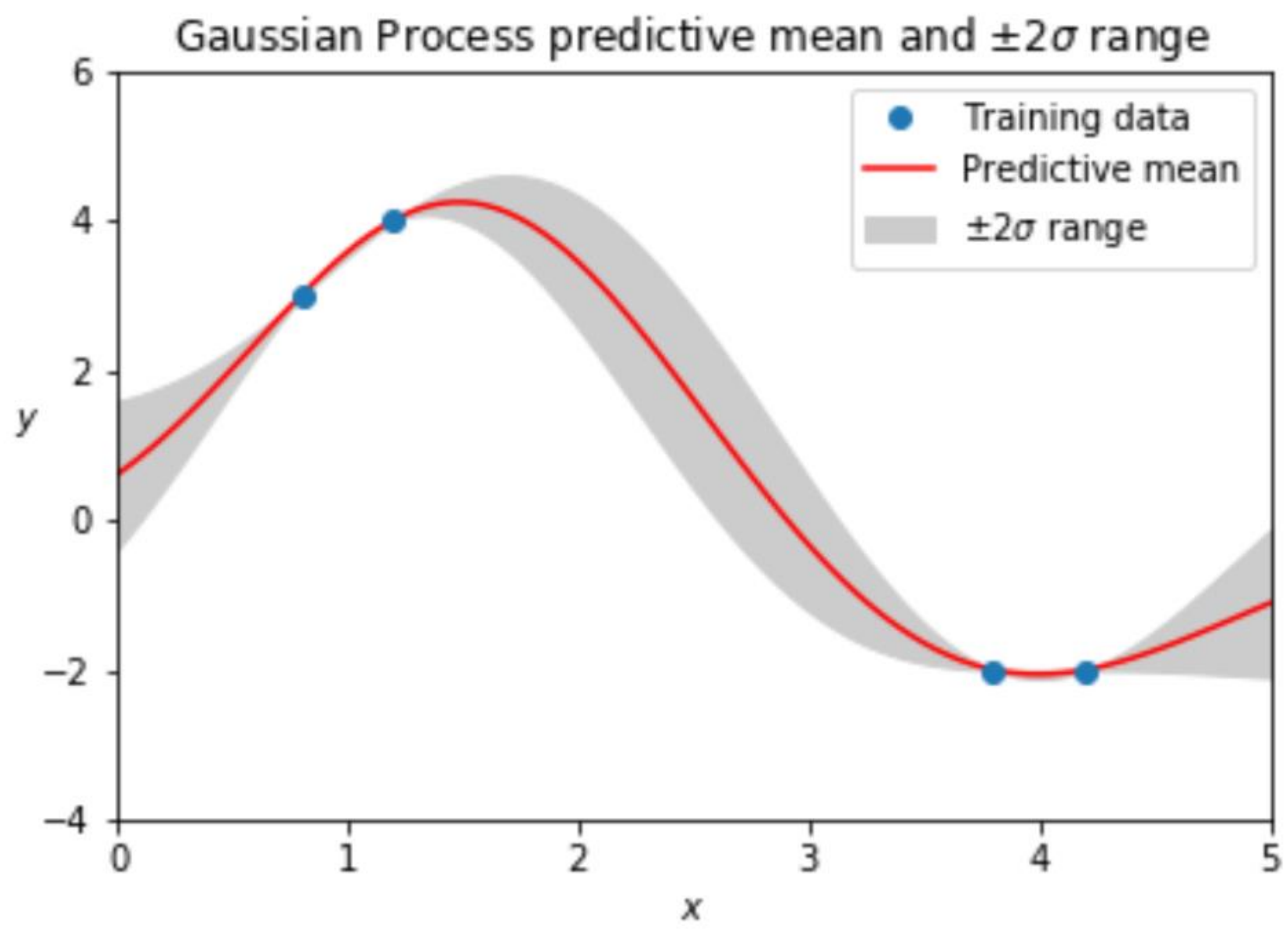
Methodology

*A **surrogate model** is a computationally **cheap** probabilistic model to describe the real problem*

Gaussian Process [1]

$$\mu(\boldsymbol{x}_*) = \mathbb{E}(f_*|\boldsymbol{x}_*, D_n) = k_{*n}^T(K_{nn} + \sigma^2 I)^{-1} y$$

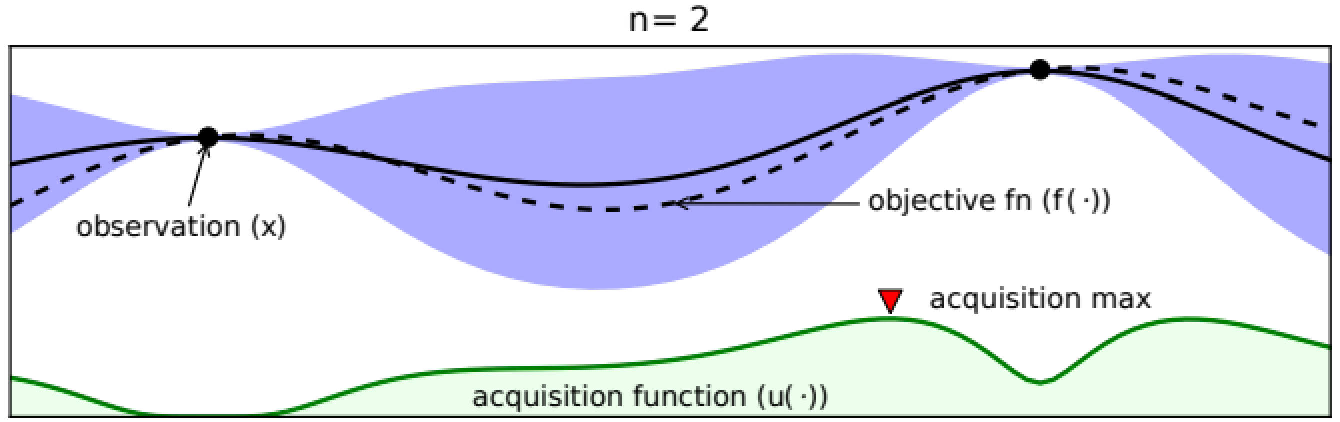
$$\sigma^2(\boldsymbol{x}_*) = \mathbb{V}[f_*|\boldsymbol{x}_*, D_n] = K_{**} - K_{n*}^T(K_{nn} + \sigma^2 I)^{-1} K_{n*}$$



[1] Rasmussen, Carl Edward. "Gaussian processes in machine learning." Summer School on Machine Learning. Springer, Berlin, Heidelberg, 2003.

Methodology

$$\alpha(\boldsymbol{x}) = \mathbb{H}(p(g|D_n)) - \mathbb{E}_{p(f_{\boldsymbol{x}}|D_n,\boldsymbol{x})}\left[\mathbb{H}(p(g|D_n \cup \{\boldsymbol{x}, f_{\boldsymbol{x}}\}))\right]$$



Bayesian Active Learning by Disagreement (BALD) [2]

$$\mathbb{H}(p(f|D_n, \boldsymbol{x})) - \mathbb{H}(p(f|D_n, \boldsymbol{x}, b < f < a))$$
$$= \log\left(\sqrt{2\pi e \sigma^2} Z\right) +$$
$$\frac{1}{2Z}\left[(\alpha - \mu)\mathcal{N}(\mu|\alpha, \sigma^2) - (\beta - \mu)\mathcal{N}(\mu|\beta, \sigma^2)\right]$$

$$Z = \Phi\left[\frac{\beta - \mu(\boldsymbol{x})}{\sigma}\right] - \Phi\left[\frac{\alpha - \mu(\boldsymbol{x})}{\sigma}\right]$$

[2] Houlsby, Neil, et al. "Collaborative Gaussian processes for preference learning." *Advances in neural information processing systems*. 2012
[3] Shahriari, Bobak, et al. "Taking the human out of the loop: A review of Bayesian optimization." Proceedings of the IEEE 104.1 (2015): 148-175.

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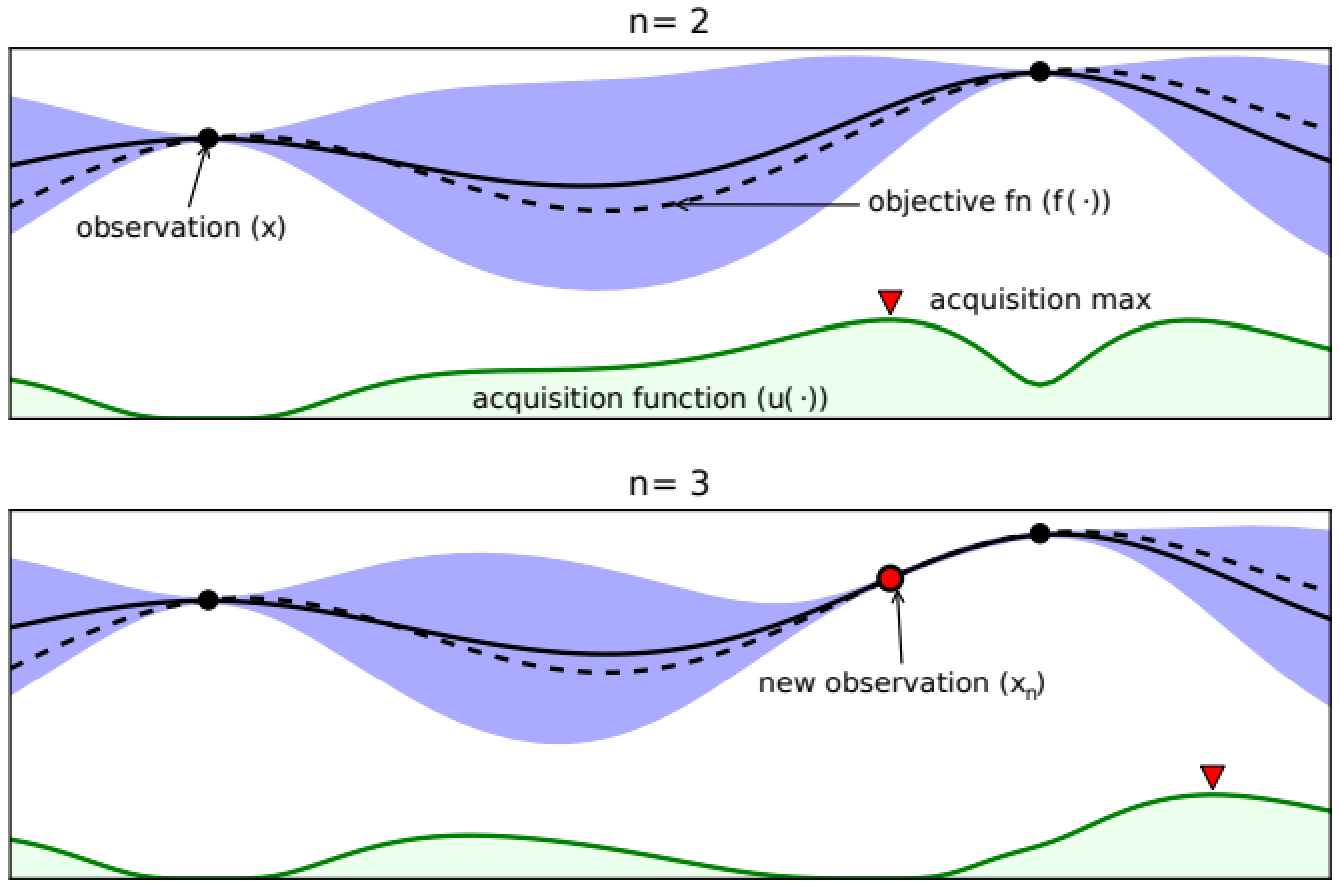

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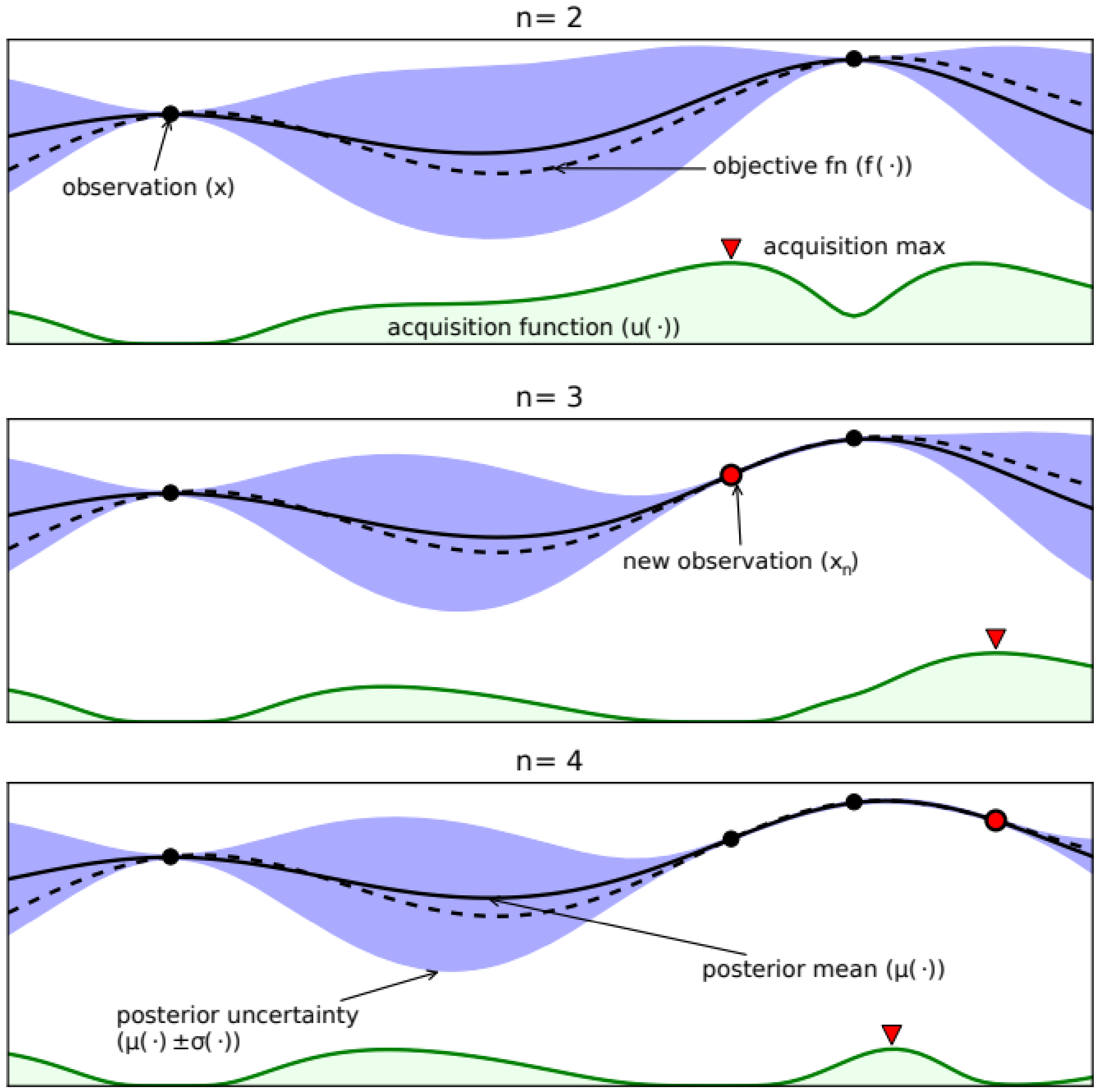

[3]

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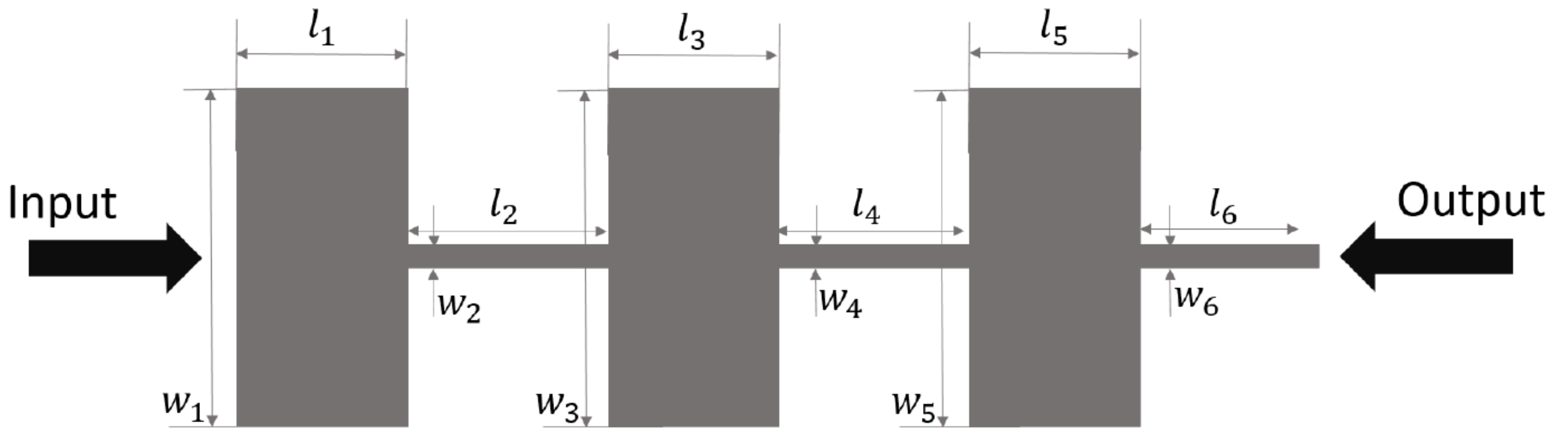
Application: Low Pass Filter Design



Name	Geometry parameter
microstrip lengths	l_1=2.05 mm, l_2=6.63 mm, l_3=7.69 mm, l_4=9.04 mm, l_5=5.63 mm, l_6=2.41 mm
microstrip widths	$w_2 = w_4 = w_6$ =0.428 mm

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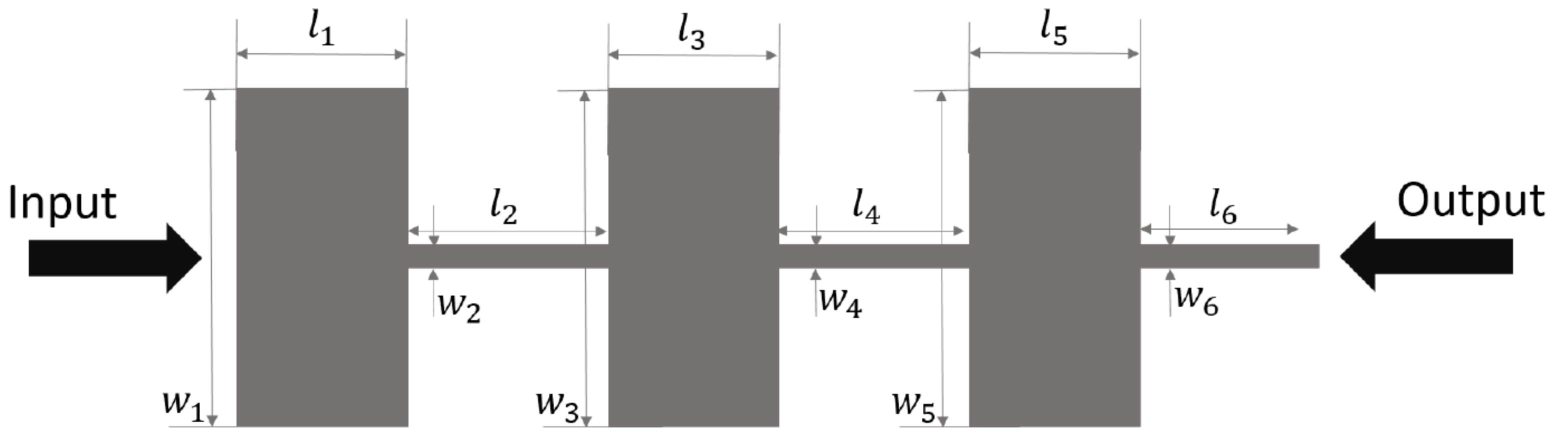

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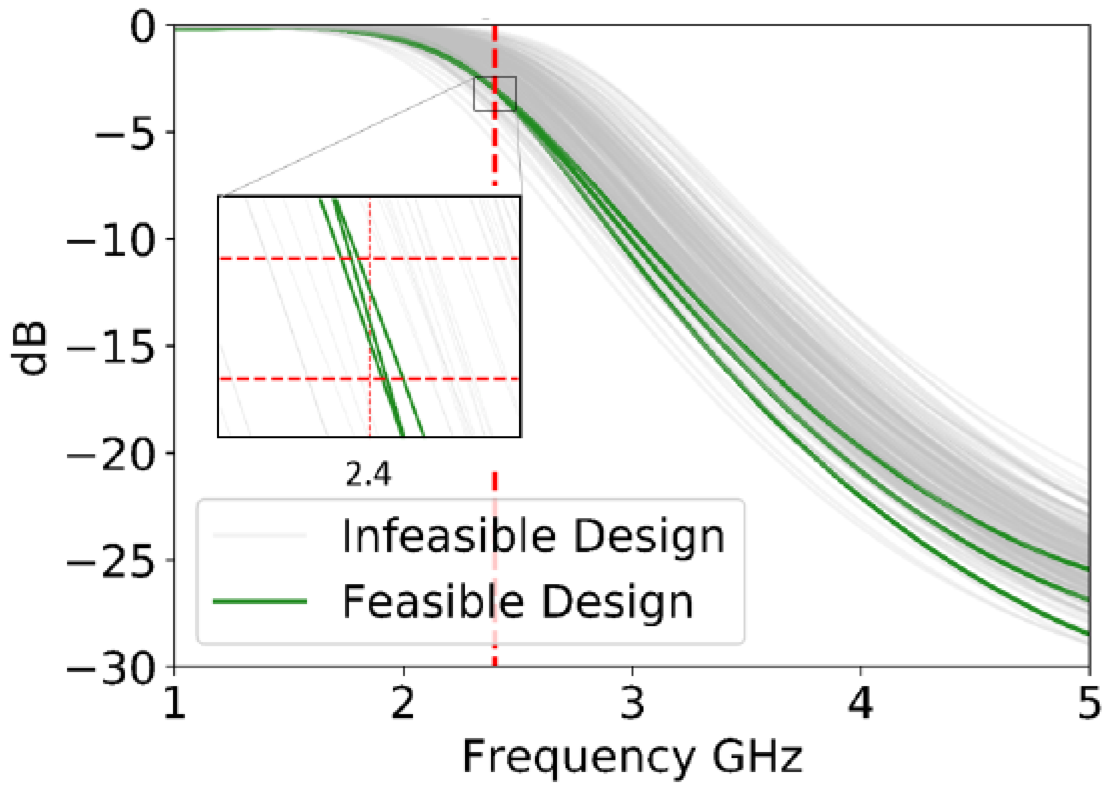
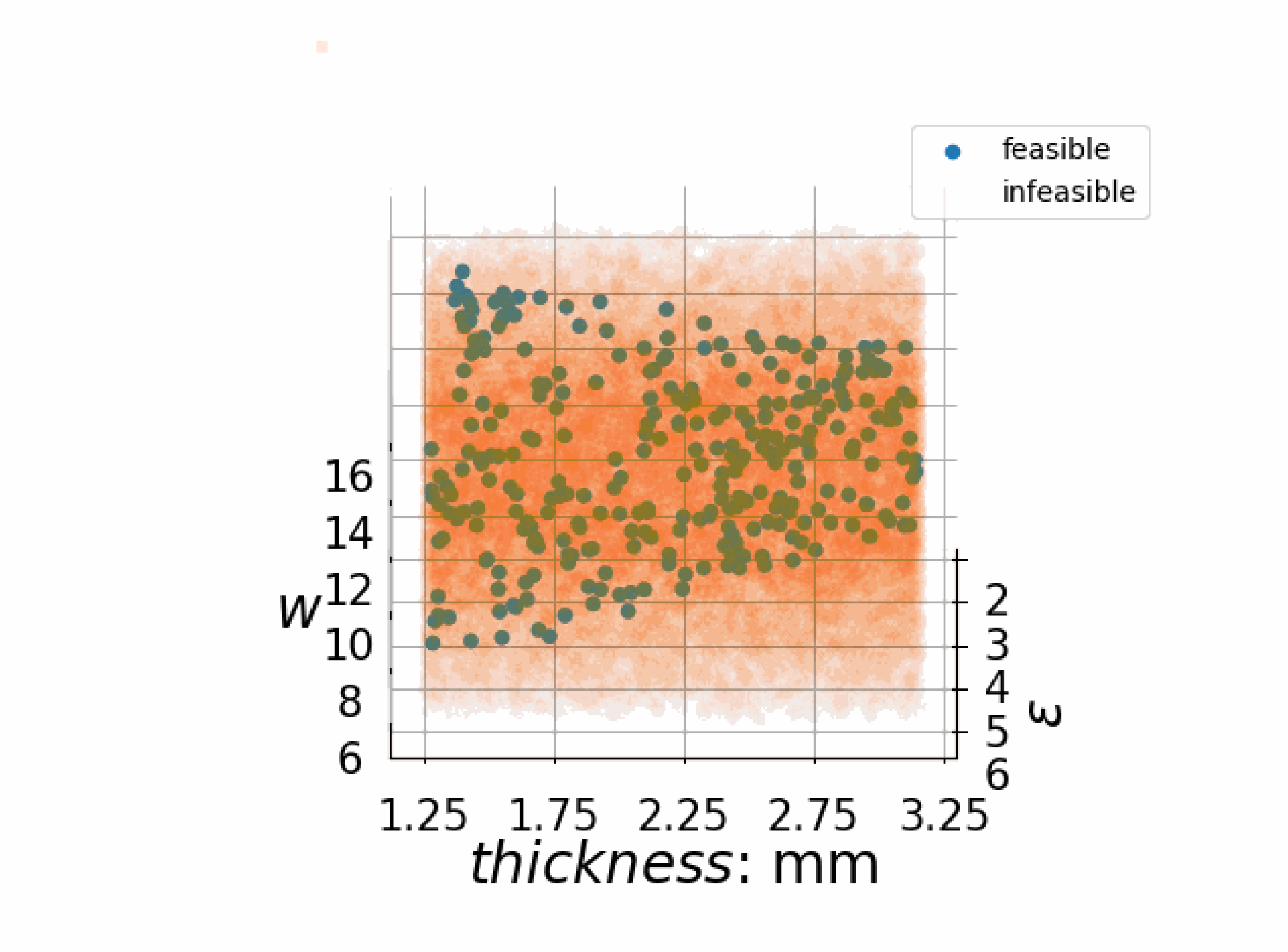
Design Goal:

Find $\left|\, |S_{12}(f_c, \epsilon, h, w_{1,3,5})|_{\text{dB}} + 3\ \text{dB} \,\right| \leq \tau$

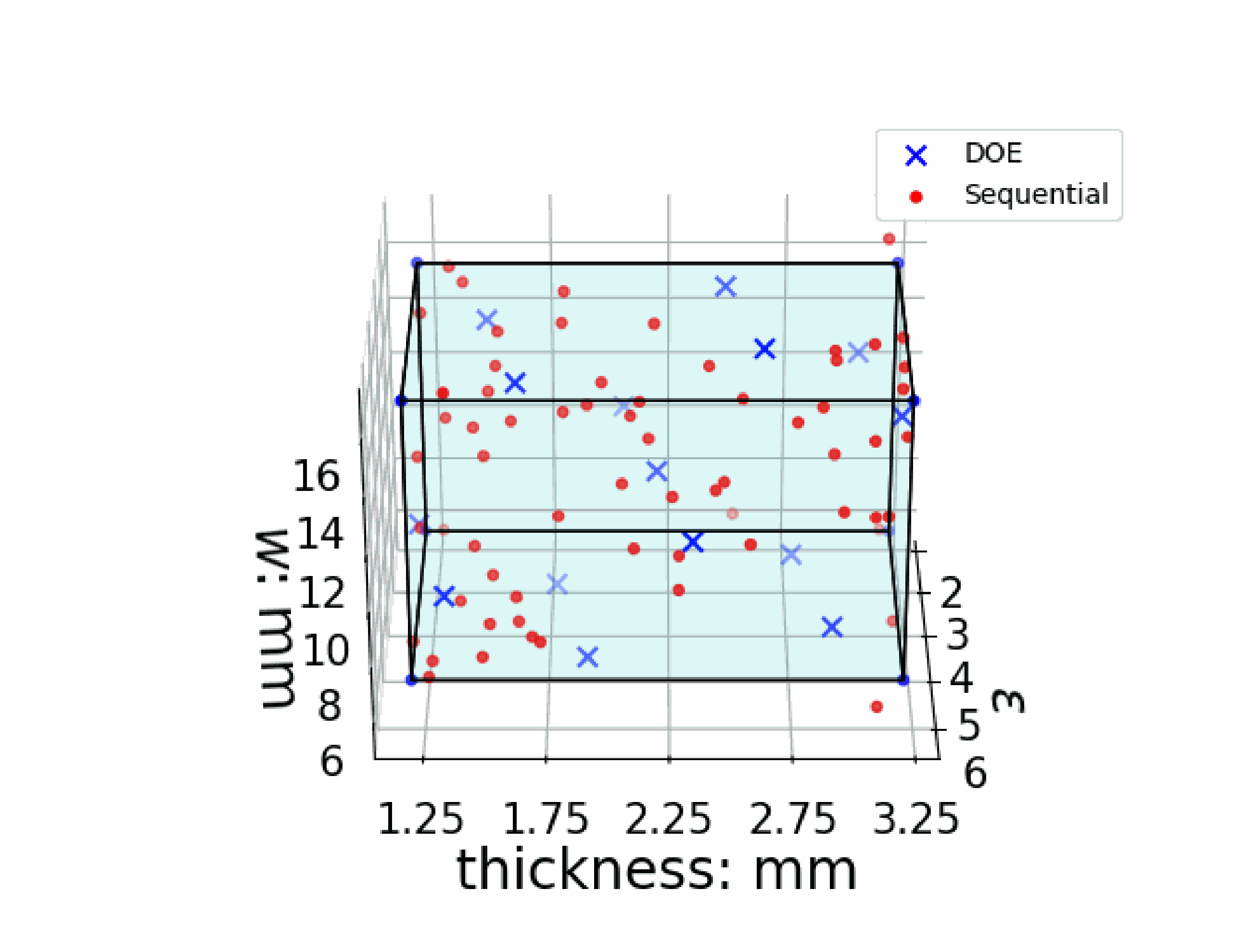
subject to
$\epsilon \in [2.1, 6.3]$, $h \in [1.2, 3.2]$ mm, $w_{1,3,5} \in [5.6, 16.9]$ mm



Results and Discussion

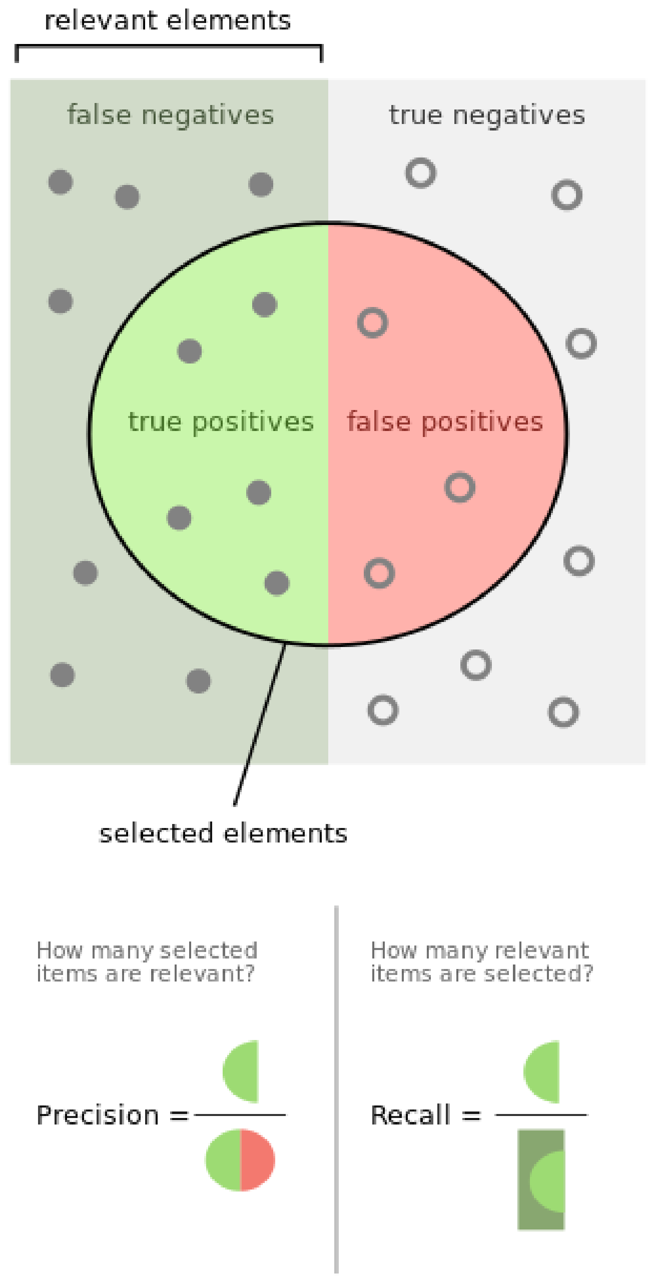


Real target region found by simulation
(**50000** samples generated by Latin Hypercube sampling)

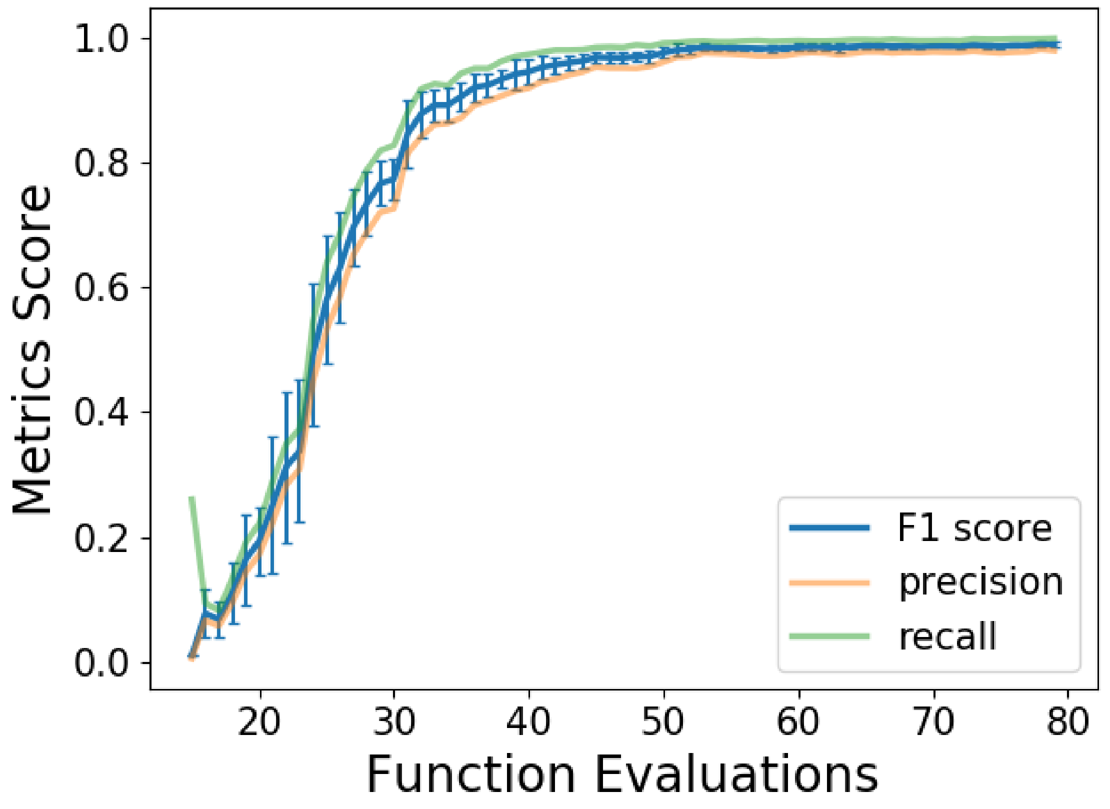


Sequential Active Learning by
Entropy Feasible Search (with only **80** samples)

Results and Discussion



Precision and Recall [4]



Progress Plot of Sequential Sampling
(The experiments is repeated 5 times with error bar shown in the figure)

$$F1 = 2 \cdot \frac{precision \ \cdot recall}{precission + recall}$$

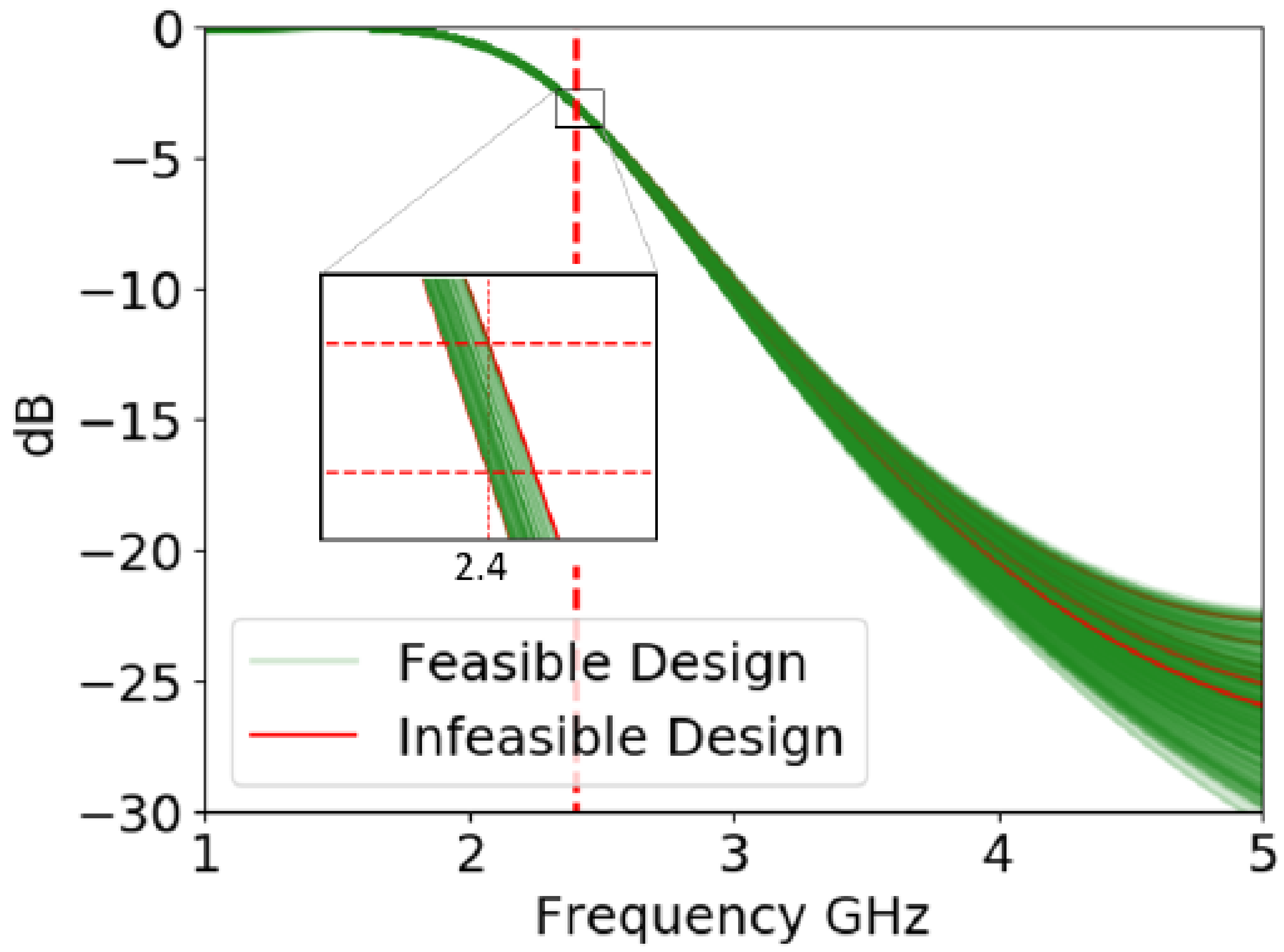
[4] https://en.wikipedia.org/wiki/F1_score

Results and Discussion

We use the **real simulator** to evaluate **323** design configurations predicted feasible by the model.

Only **6** of which are infeasible in reality,

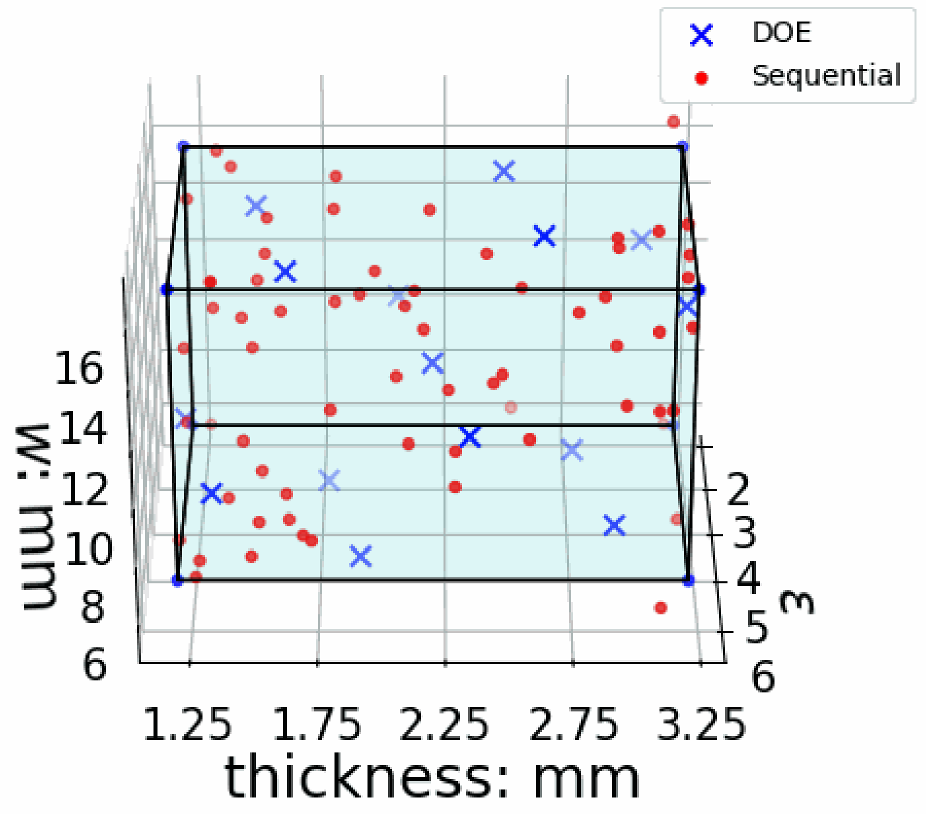
Which means, based on the 323 data points, the ***precision*** of the model is **98.14%**



Results and Discussion

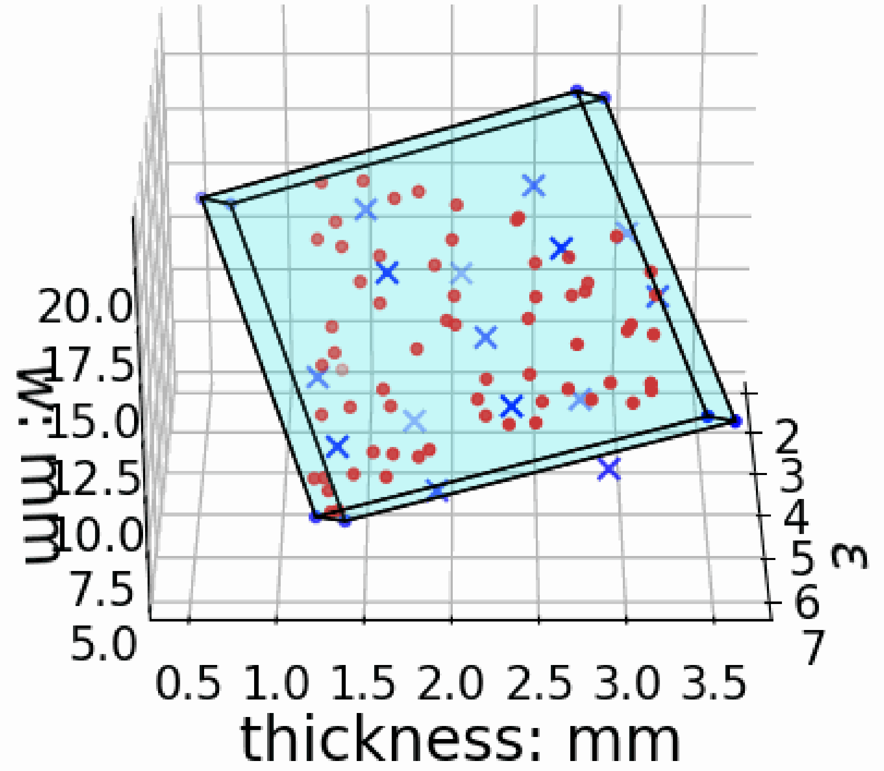
– Feasible region representation

Simple Bounding Box



32% reduction on design space

Principal Component Analysis (PCA)-based approach



85% reduction on design space!

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Conclusion

Our approach:

- Provides a way to generate/identify target regions
- Data efficient

Future work:

- Challenging to not violate constraints
- More compact way to describe target region

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