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Abstract

The **goal** of this study is to understand how designers make design decisions. A designer in the engineering design process makes the following decisions to find the best design in design space :

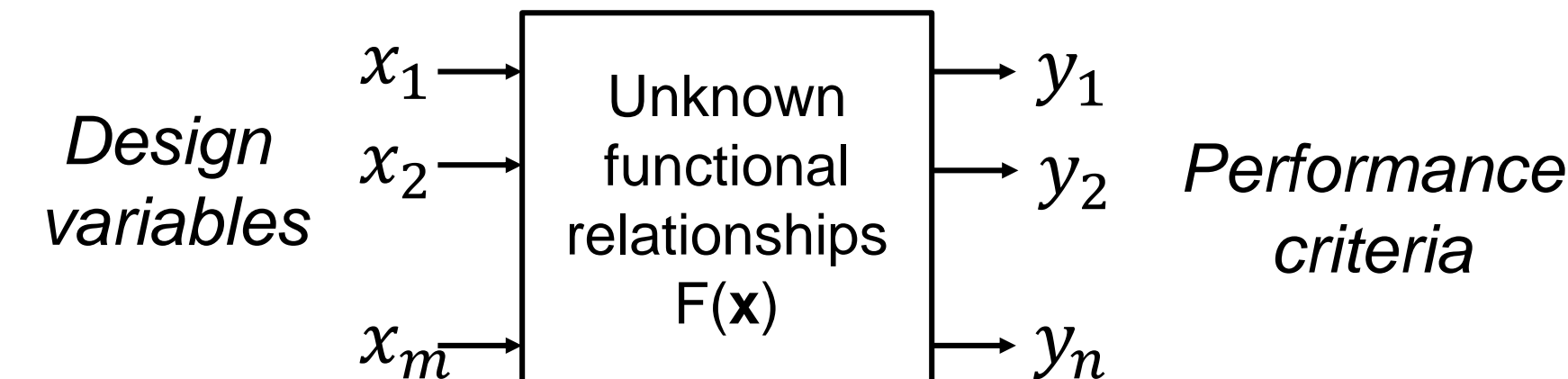
- i. selecting designs for performance evaluation,
- ii. choosing information sources,
- iii. deciding when to stop design evaluations.

Our **approach** consists of i) evidence collection using a behavioral experiment, ii) formulating simple cue-based and judgment-based models of decisions, and iii) running Bayesian model comparison on the experimental data.

The **results** suggest that subjects use simple cue-strategies over judgement-based strategies which are affected by budget available for design evaluations.

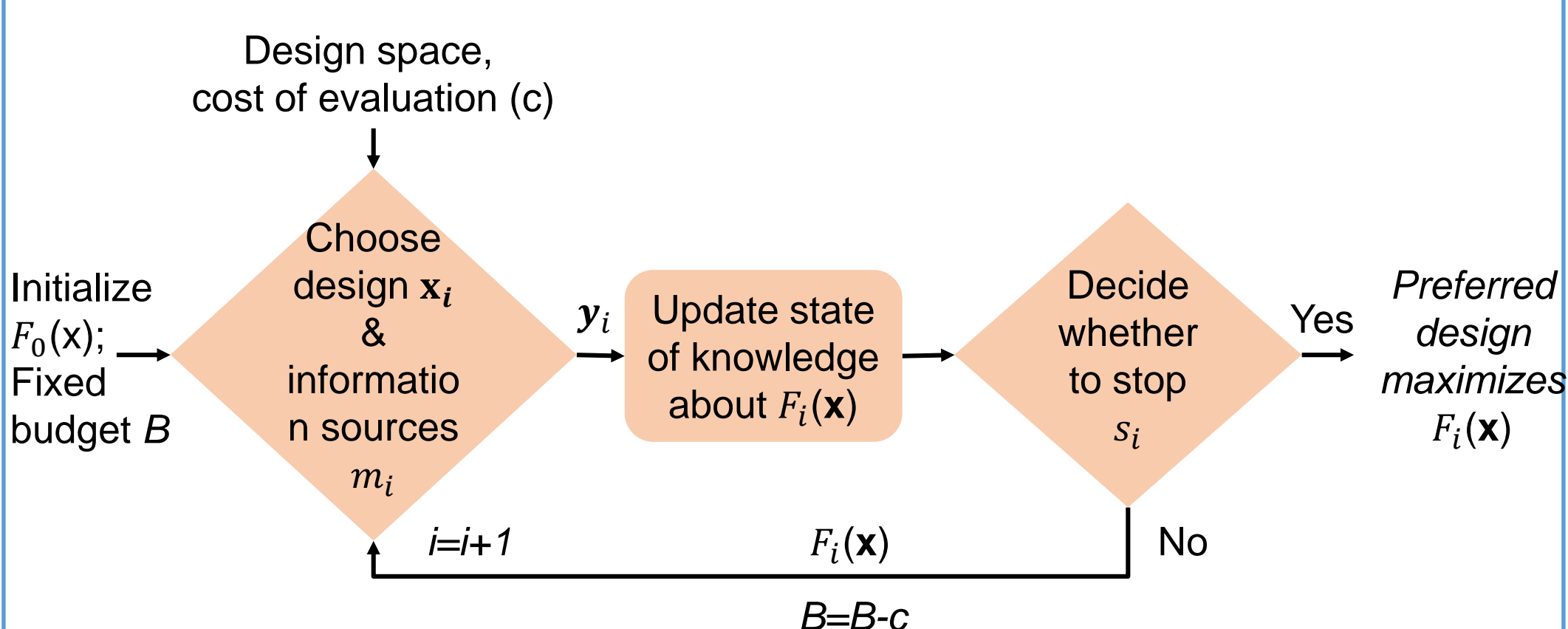
Introduction

The design problem is assumed to have known design parameters and performance criteria, but uncertain mapping between the two.



The nature of design problem.

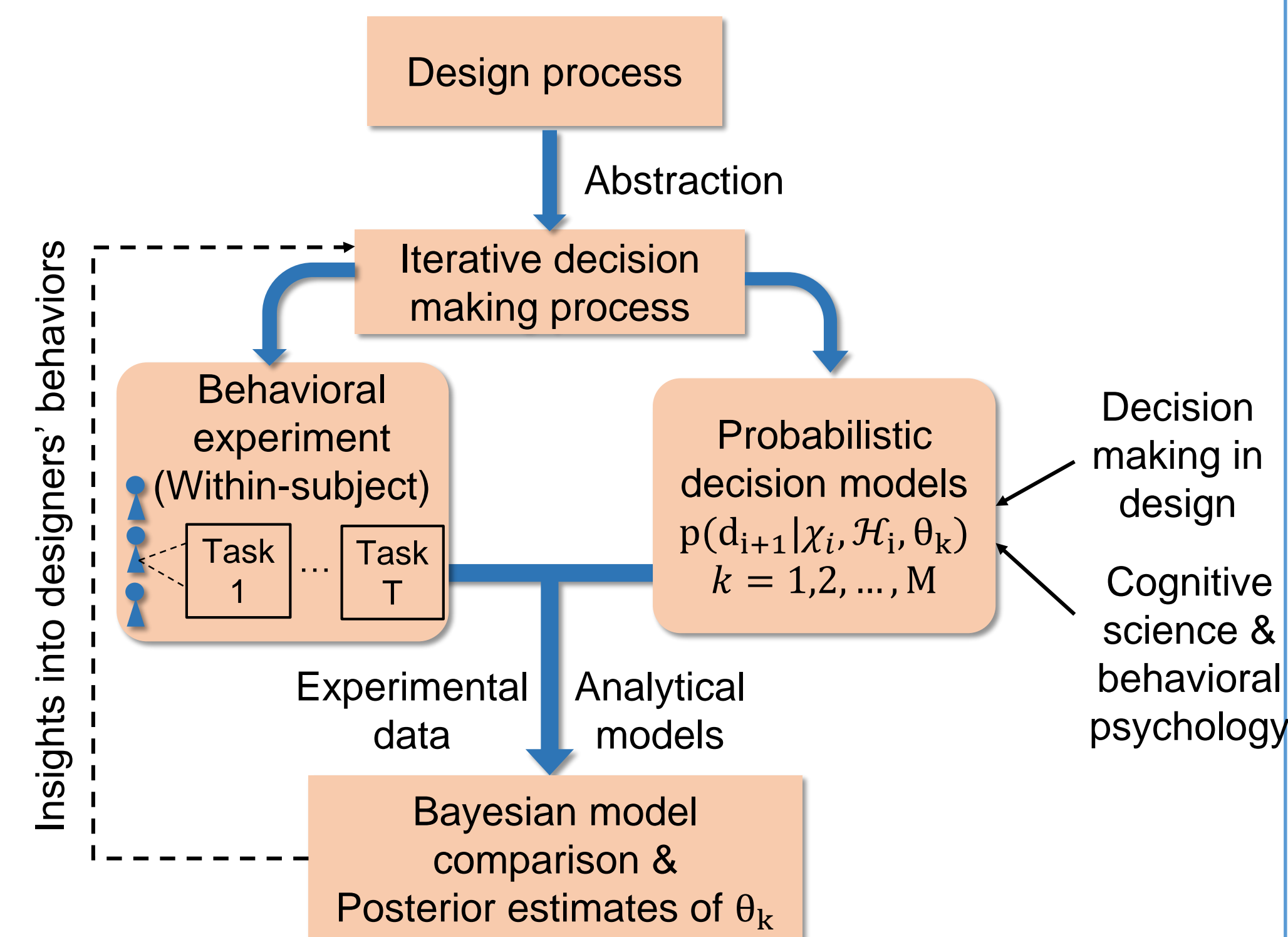
The designer's objective is to find \mathbf{x} that maximizes unknown function $F(\mathbf{x})$ through multiple performance evaluations. In such case, the design process is viewed as iterative decision making process under uncertainty.



Design as iterative decision making process under uncertainty.

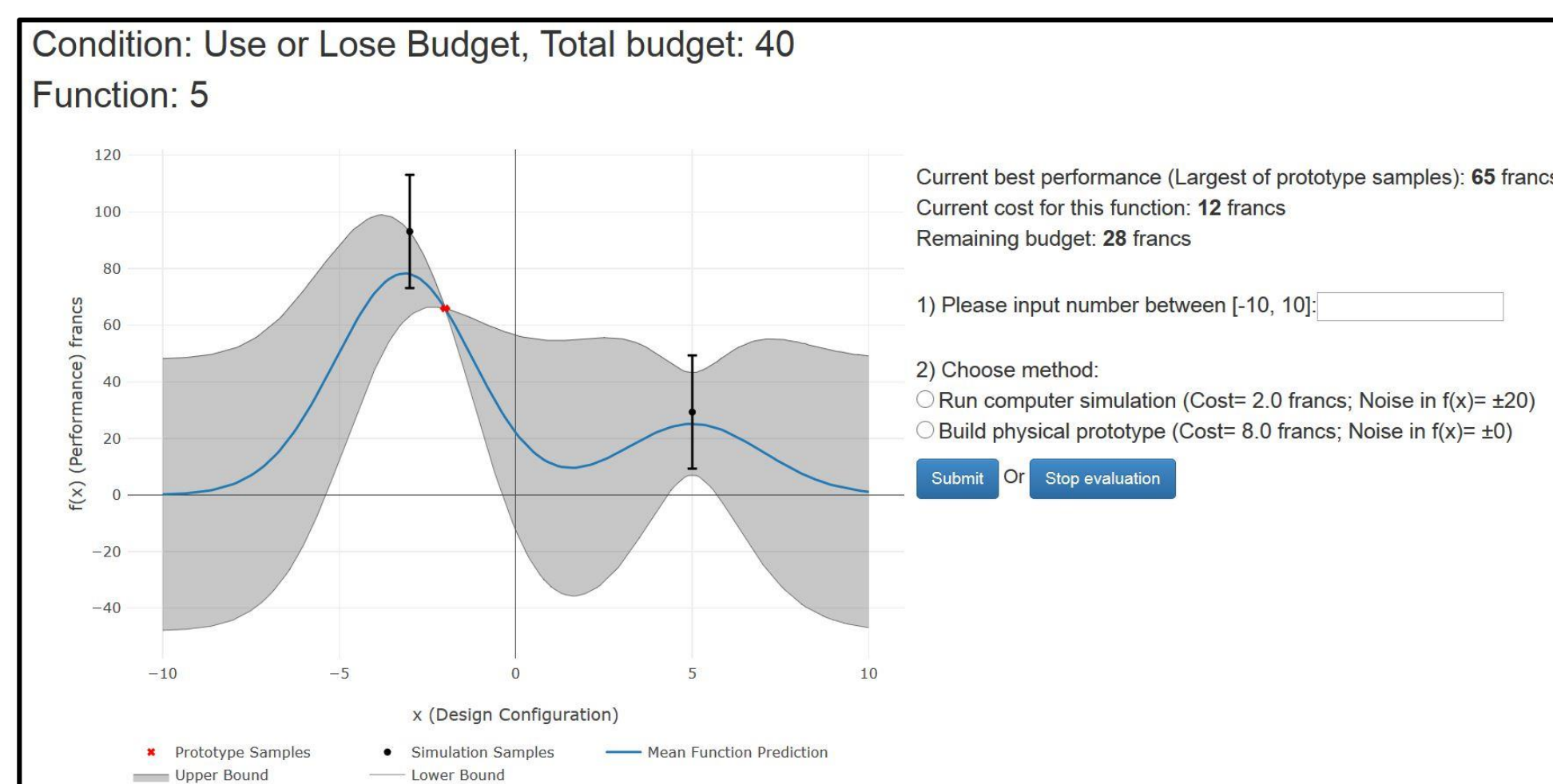
RQ: Which descriptive models provide the best description of designer's sequential decisions in engineering design?

Research Approach



Behavioral experiment

We operationalize the iterative decision making process through the function optimization task.



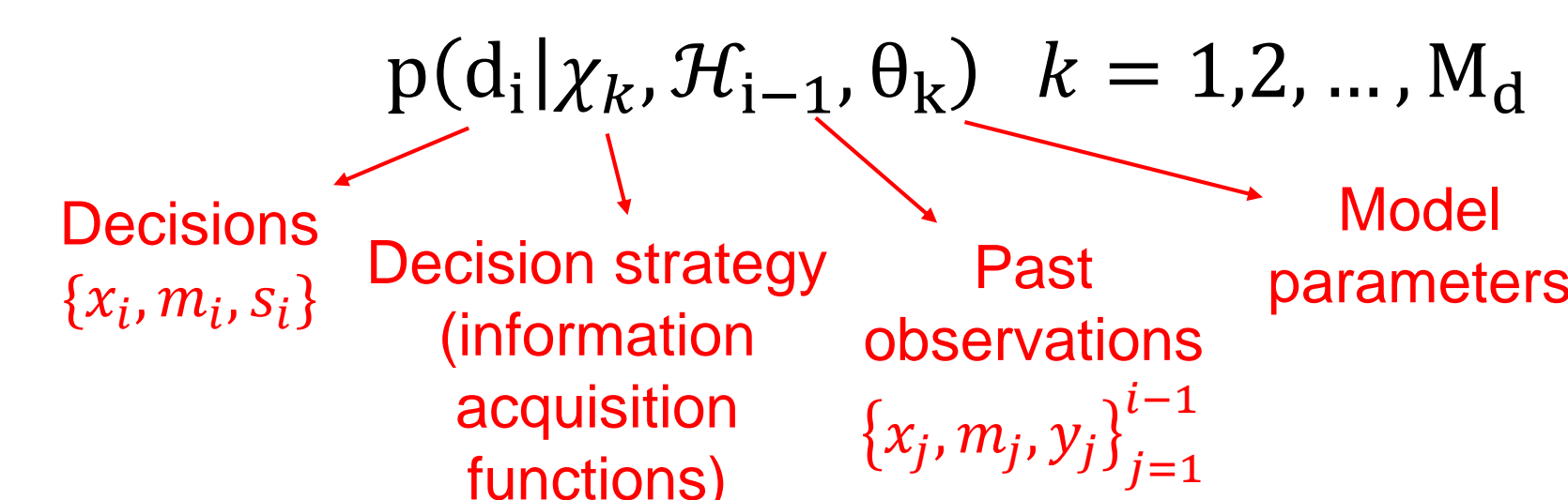
User interface designed using oTree [2].

		Fixed Budget		
		20	40	60
Payment Incentives	Use or Lose Budget	3 funcs	3 funcs	3 funcs
	Save Remaining Budget	3 funcs	3 funcs	3 funcs

Experiment design

- 63 undergraduate students as subjects
- Controlled for order effects, wealth effects, and selection bias

Probabilistic decision models

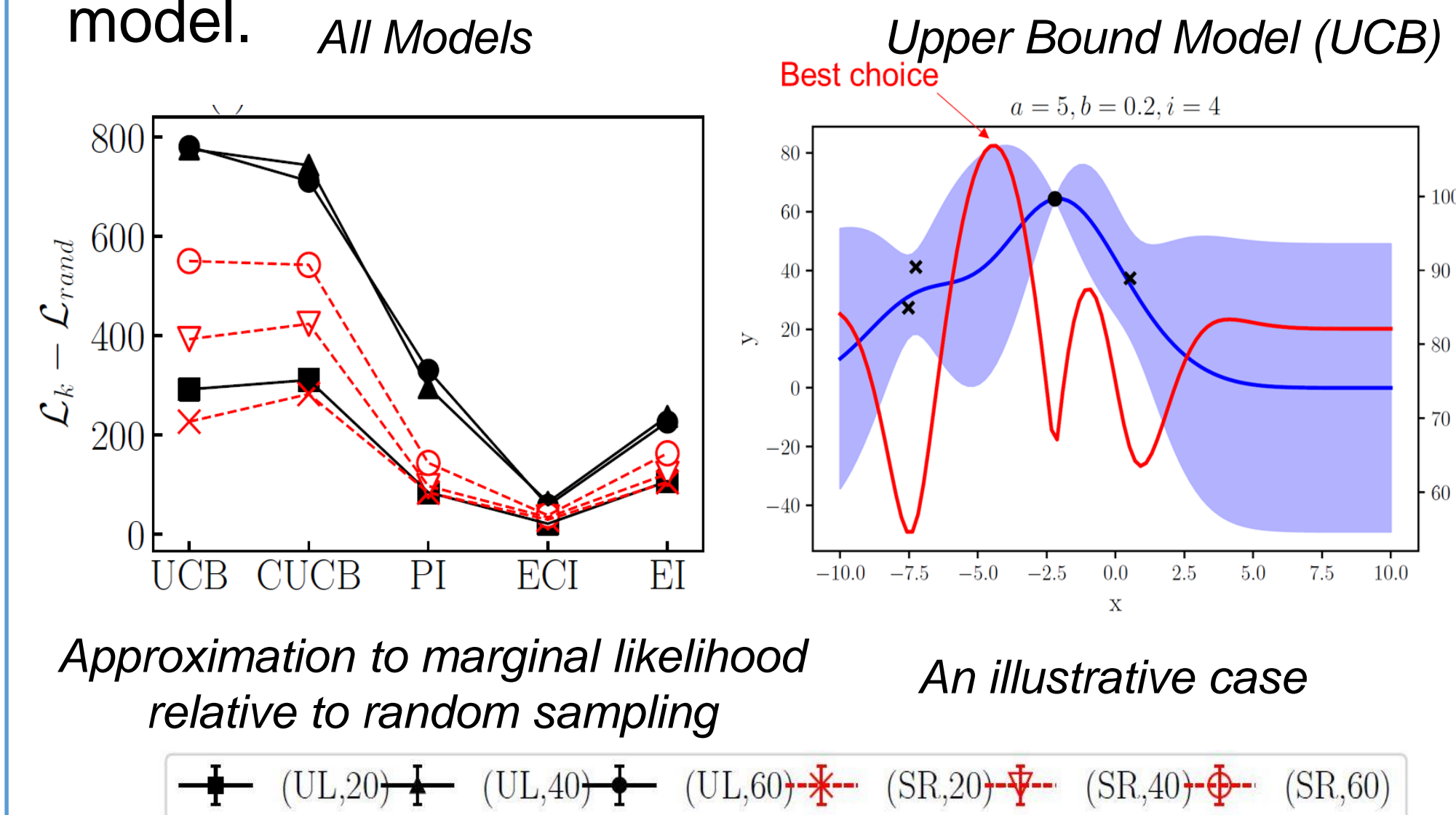


Cue-based strategies	Judgement-based strategies
<ol style="list-style-type: none"> 1. Use fixed no. of low fidelity information sources and fixed no. of high fidelity sources. 2. Stop after exhausting x% of the fixed budget. 3. Evaluate the set of equally spaced designs. 	<ol style="list-style-type: none"> 1. Stop when expectation of improvement is small. 2. Stop after it appears that the maximum performance is found. 3. Use high fidelity info. source when performance peak appears.

Results

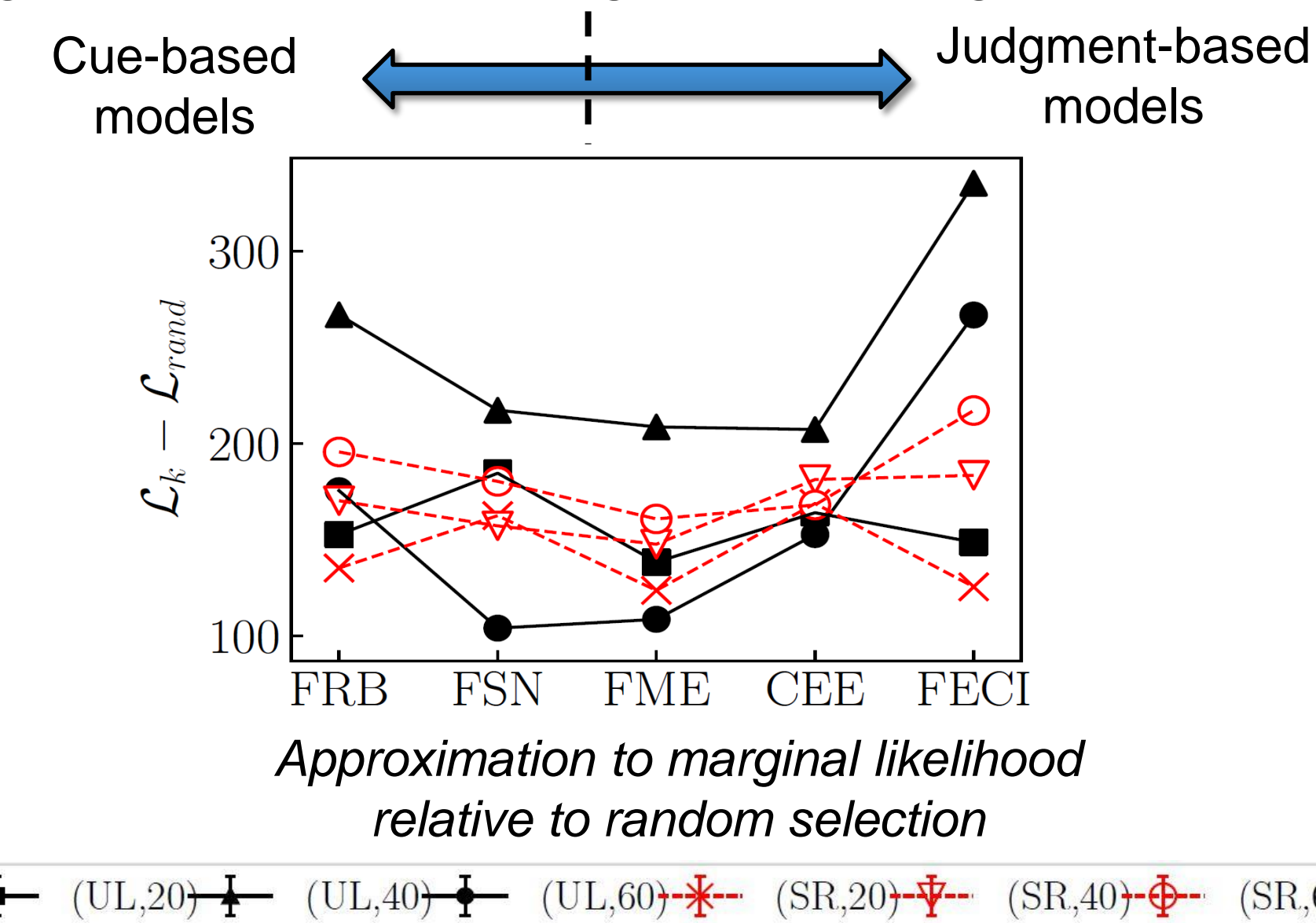
Decision to choose next design \mathbf{x}

The upper confidence bound model based on the cues of predictive uncertainty provide better fit to subjects' decisions than expected utility-based EI model. *All Models*



Decision to choose between low- & high-fidelity information sources

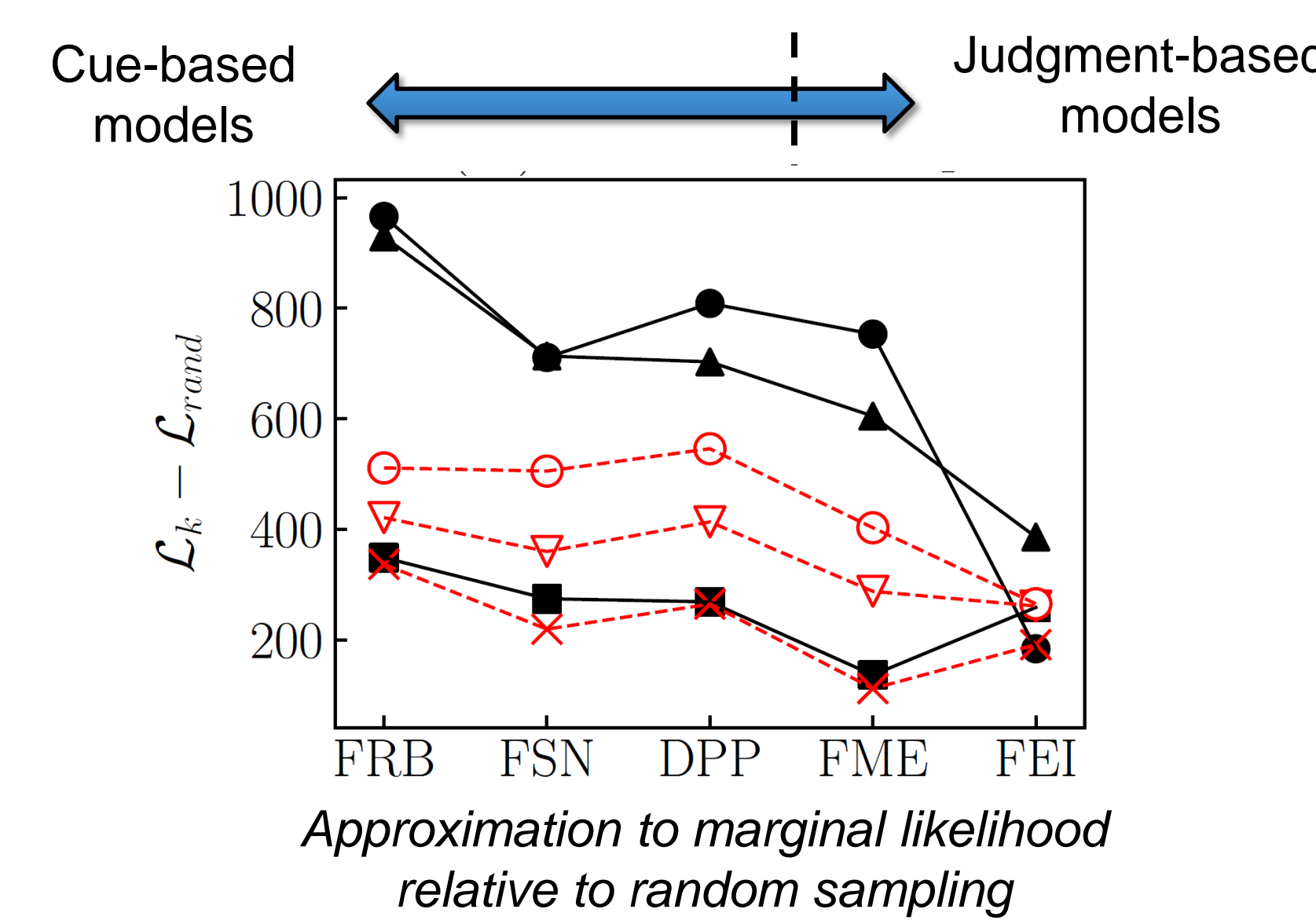
Cue-based models (FSN, FRB) have the highest marginal likelihood at low fixed budget, while judgment-based models (FEI) have the highest marginal likelihood at large fixed budget.



FSN: Fixed Sample Number; FEI: Fixed Expected Cond. Improvement

Decision to stop or not

Stopping after the remaining budget is smaller than a fixed value (FRB model) is the most likely strategy.



FRB: Fixed Remaining Budget; FEI: Fixed Expected Improvement

Discussion

Simple cue-based models are better predictor of subjects' decisions than judgment-based models (some based on the expected utility theory), except for the decision to choose between information sources at large fixed budget. We also cross-validated these results on the test dataset. We observed that the judgment-based models were largely incorrect in predicting decisions to choose next design \mathbf{x} and stopping.

Whether cue-based or judgment-based models are optimal depends upon the domain knowledge and available information specific to the design problem [3]. Regardless, designers can likely be pushed toward using cue-based models by restricting fixed budget for design evaluations or incentivizing to save budget. Inversely, they can likely be pushed to use judgment based-models by increasing the fixed budget available for design evaluations.

These models have many applications including in the specification of designer agents for game-theoretic models of design contests and agent-based models of systems engineering. An accurate quantification of design performance in terms of the designer's strategy is possible to achieve by modeling designers as decision makers following the probabilistic decisions models.

References

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