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HUMAN INDUCTIVE BIASES IN DESIGN DECISION MAKING

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ABSTRACT

Designers make information acquisition decisions, such as where to search and when to stop the search. Such decisions are typically made sequentially, such that at every search step designers gain information by learning about the design space. However, when designers begin acquiring information, their decisions are primarily based on their prior knowledge. Prior knowledge influences the initial set of assumptions that designers use to learn about the design space. These assumptions are collectively termed as inductive biases. Identifying such biases can help us better understand how designers use their prior knowledge to solve problems in the light of uncertainty. Thus, in this study, *we identify inductive biases in humans in sequential information acquisition tasks.* To do so, we analyze experimental data from a set of behavioral experiments conducted in the past [1–5]. All of these experiments were designed to study various factors that influence sequential information acquisition behaviors. Across these studies, we identify similar decision making behaviors in the participants in their very first decision to "choose x". We find that their choices of "x" are not uniformly distributed in the design space. Since such experiments are abstractions of real design scenarios, it implies that further contextualization of such experiments would only increase the influence of these biases. Thus, we highlight the need to study the influence of such biases to better understand designer behaviors. We conclude that in the context of Bayesian modeling of designers' behaviors, utilizing the identified inductive biases would enable us to better model designer's priors for design search contexts as compared to using non-informative priors.

Keywords: Inductive Biases, Information Acquisition, Decision-Making, Engineering Design

1 Introduction

Designers engage in information acquisition activities, such as deciding what information to acquire and how to acquire that information while solving engineering design problems [1, 6]. Such activities are typical in design decision making scenarios, where designers need to acquire information about various design alternatives before choosing the best alternative. Moreover, designers need to make inferences based on their information acquisition activities. For example, designers use simplified models and prototypes to make inferences about the expected performance of final designs under true operating conditions. The underlying cognitive activity of generalization, which is pervasive in problem solving and design, is called inductive reasoning [7, 8].

The act of engaging in information acquisition activities itself requires inductive reasoning. For example, deciding the appropriate point in the design space to conduct an experiment for acquiring information requires making inferences. Designers may project the values of the design parameters from previously conducted experiments to make predictions about novel experimental conditions in the face of uncertainty. Moreover, when there is a lack of available experimental evidence in scenarios, such as the very beginning of an information acquisition activity, then designers' decisions are primarily based on their prior knowledge. In other words, when the available evidence is not enough for designers to make a decision, inductive reasoning enables designers to choose the "most probable” alternative [9] and what constitutes as “most probable” is dependent on the prior experiences of an individual.

Prior knowledge influences the initial set of assumptions that designers use to learn about the design space. Such set of assumptions are termed as *inductive biases* [10, 11]. Bias in design literature is typically associated with negative connotations with a focus on “reducing” [12], “overcoming” [13, 14], or “mitigating” [15] their influence. However, for inductive problems, that is, problems where solutions cannot be identified solely based on the available evidence, inductive biases are *required* to achieve solutions [16]. For example, when the design team members can understand teleconference conversations despite frequent audio interruptions, they are using inductive bias to “fill” the interrupted words by making informed guesses about what sentences the speaker may have uttered.

Existing literature on inductive biases has emphasized the positive implications of identifying inductive biases for developing computational models of cognition [11, 17–21]. For engineering design, understanding inductive biases in designers can enable us to develop descriptive models of engineering design processes. Such models can be developed computationally such that they provide decision support to designers in highly uncertain design situations as well as in the early stages of a design process towards supporting creativity and innovation. However, there is a lack of studies in engineering design contexts for understanding inductive biases in designers.

In this study, *we identify inductive biases in humans in sequential information acquisition tasks.* Such tasks are relevant for engineering design scenarios as designers rarely make artifact decisions based solely on the available information in the design brief. Instead, they make several information acquisition decisions such as what information to acquire and when to acquire that information. Such decisions are influenced by a designer’s prior knowledge [1, 22]. Thus, designers engage in inductive reasoning while making information acquisition decisions. To identify inductive biases in information acquisition scenarios, we analyze experimental data from a set of behavioral experiments conducted in the past [1–5]. All of these experiments were designed to study various factors that influence sequential information acquisition behaviors of designers in engineering design contexts.

We describe the information acquisition scenario as follows. Consider a design problem where a designer optimizes a design objective $f(x)$. They control a set of design variables x in a design space $\mathscr{X}$. However, the designer does not explicitly know the mathematical relationship between the design variables x and the design objective $f(x)$. The designer needs to acquire information about the impact of design variables x on the design outcome $f(x)$. Such information can be acquired by sequentially making decisions such as choosing a value of x and conducting experiments (at that x), which incur a certain cost. We assume that the designer updates their state of knowledge of the design space after executing each experiment. Such a scenario is termed as a sequential information acquisition and decision making (SIADM) scenario. In Section 2.1, we summarize previous experiments where human subjects were required to participate in various SIADM scenarios with a specific focus on parametric optimization tasks.

For the very first experiment in a SIADM scenario, a designer needs to decide at what x they should acquire information with insufficient information of the design space. The designer does not know the mapping between design variables x and the design performance $f(x)$. Thus, the designer needs to rely on their prior knowledge and use inductive reasoning to instantiate the first experiment by choosing design variables x from a range of possible values in a design space.

Without any prior knowledge, a rational strategy to choose the first set of design variables x would be to pick them from a uniform distribution and conduct the experiment in the design space. Thus, a non-informative prior to model such a decision would seem reasonable [23]. However, in order to model designer behaviors, there lies a need to investigate how designers choose the values of their design variables. Do they assign equal probabilities (use a non-informative prior), or do they use inductive biases to preferentially choose among various alternatives? Moreover, there lies a need to investigate whether these decisions are similar across a group of participants or not. Thus, we analyze the very first decisions of the human subjects in our previously conducted behavioral experiments in the context of SIADM scenarios.

The remainder of this paper is organized as follows. In Section 2, we describe the experimental data and the analysis procedure used to identify inductive biases. In Section 3, we report our observations from the experimental data analysis. In Section 4, we use inductive reasoning to hypothesize about the inductive biases that designers use in sequential information acquisition and decision making based on the observations described in Section 3. We conclude in Section 5 by discussing the future work to test the formulated hypotheses towards incorporating inductive biases in computational models of designer behaviors.

2 The Study

In this section, we summarize the past SIADM experimental studies, their similarities and differences in experimental design, the experimental data sets, and the data analysis procedure utilized for identifying inductive biases.

2.1 Summary of Previously Conducted Sequential Information Acquisition Experiments

Table 1 lists the various experimental studies analyzed in this paper to identify inductive biases. These studies are summarized in the following.

TABLE 1: List of Experiments, Design Space Range, Experimental Notes, and Corresponding Labels

Number	Name	Number of Unique Participants	Design Space Range	Experimental Notes	Labels for the experiment
1	Function Minimization Experiment [2]	44	$-100 \leq X \leq 100$	The research objective was to study the influence of cost on SIADM. Participants' objective was to **minimize** the function.	FMinE
2	The Fidelity Experiment [4]	63	$-10 \leq X \leq 10$	The research objective was to study the influence of model fidelity on SIADM. Participants' objective was to **maximize** the function.	FDE
3	The Track Design Experiment [1]	44	$0 \leq X \leq \infty$	The research objective was to study the influence of domain knowledge on SIADM. Participants' objective was to **maximize** the function.	TDE
4	The Function Maximization Experiment [1]	0 (Same pool as that of TDE)	$0 \leq X \leq \infty$	The research objective was to study the influence of domain knowledge on SIADM. Participants' objective was to **maximize** the function.	FMaxE
5	The Opponent-specific Information Experiment [3]	36	$350 \leq X \leq 1000$	The research objective was to study the influence of opponents on Strategic SIADM. Participants' objective was to **maximize** the function.	OppE
6	The Function Complexity Experiment [5]	28	$-10 \leq X \leq 10$	The research objective was to study the influence of function complexity and cost on SIADM. Participants' objective was to **minimize** the function.	FCE

2.1.1 The Function Minimization Experiment

The Function Minimization Experiment [2] was designed to study the influence of the cost of information acquisition on a participant's SIADM process. Participants made sequential decisions to find the *minimum* of a randomly generated convex function. The design space range was $\mathscr{X} = [-100, 100]$. The function minimum was designed to lie in range of $-70 \leq x_{min} \leq 70$.

2.1.2 The Fidelity Experiment

The Fidelity Experiment [4] was designed to study the influence of budget and uncertainty of information sources during information acquisition on a participant's SIADM process. Participants made sequential decisions to find the *maximum* of a randomly sampled function from a Gaussian Process [24] with the hyperparameters, lengthscale $l = 2$ and variance $\sigma = 600$. The design space range was $\mathscr{X} = [-10, 10]$. The function maximum could lie anywhere in the design space.

2.1.3 The Track Design Experiment

The Track Design Experiment [1] was designed to study the influence of domain knowledge and problem framing on a participant's SIADM process. Participants made sequential decisions to find the *maximum* of a randomly generated convex function. The design space range was $\mathscr{X} = [0, \infty)$. The feasible function maximum could lie in the range $\mathscr{X} = [280, 480]$.

2.1.4 The Function Maximization Experiment

The Function Maximization Experiment [1] was designed to study the influence of domain knowledge and problem framing on a participant's SIADM process. It is mathematically the same optimization problem as that in the Track Design Experiment. Participants made sequential decisions to find the *maximum* of a randomly generated convex function. The design space range was $\mathscr{X} = [0, \infty)$. The feasible function maximum could lie in the range $\mathscr{X} = [280, 480]$.

2.1.5 The Opponent-specific Information Experiment

The Opponent-specific Information Experiment [3] was designed to study the influence of the opponent's historical performance information on a participant's SIADM process. Participants not only made sequential decisions to find the *maximum* of a randomly generated convex function but also decided when to stop. The problem statement is the same as that of the track design experiment. The difference is that individuals competed against an opponent to win, as opposed to winning based on their sole performance. The design space range was $\mathscr{X} = [350, 1000]$. The function maximum could lie anywhere in the design space.

2.1.6 The Function Complexity Experiment

The Function Complexity Experiment [5] was designed to study the influence of information acquisition cost and task complexity on a participant's SIADM process. Participants not only made sequential decisions to find the *minimum* of a randomly sampled polynomial function (degree $2, 3,$ or 4), but also decided when to stop. The design space range was $\mathscr{X} = [-10, 10]$. The function maximum could lie anywhere in the design space.

2.1.7 Similarities and Differences Across the Experiments

Concerning similarities, all the experiments are controlled behavioral experiments. All the experiments were conducted in context of a SIADM design scenario.

Concerning major differences across the experiments, we list them in the following.

1. Participants were aware of the design space range in all the experiments except the Track Design and the Function Maximization Experiments.
2. Participants were able to visualize their search history graphically and textually in all the experiments except the Track Design and the Function Maximization Experiments.
3. Only the Track Design Experiment was conducted in a domain-dependent context, whereas the other experiments were domain-independent SIADM problems.
4. The Fidelity Experiment provided participants with a visualization of the uncertainty of the objective function based on a Gaussian Process formulation of the objective functions.
5. The Fidelity Experiment, the Function Minimization Experiment, the Function Complexity Experiment, and the Opponent-specific Information Experiment had a cost associated with the information acquisition search step such that the participants had to decide when to stop their search. Whereas, the other experiments, namely, the track design experiment, and the function maximization experiment, were designed such that participants' efforts were fixed.
6. The Track Design Experiment, the Function Maximization Experiment, and the Opponent-specific Information Experiment were designed such that participants were provided with an initial search data at a fixed point in the design space. The rest of the experiments did not provide an initial data point to the participants.

2.1.8 The Datasets All the experimental datasets are comprised of ordered pairs (x_i, y_i) of participant's search decisions x at each search step i and the corresponding objective function achievement y at that step for every design search problem. The datasets also consist of the details of the function optimum, the best performance of the participants, and the control condition for every SIADM problem presented to the participants.

2.2 Data Analysis

The goal of the data analysis procedure is to identify patterns of search behaviors across various experimental datasets towards understanding inductive biases. To do so, we analyze the first (x_1, y_1), and second (x_2, y_2) search step decisions of the participants in the datasets. We plot histograms of the first search point x_1 across all the participants in a given experimental condition to identify whether participants explore the design space uniformly or not. To understand their information processing behaviors, we also plot participants' second search point (x_2) relative to their first search data (x_1, y_1).

For some experiments initial data (x_0, y_0) for every SIADM problem at some fixed point in the design space was provided (refer to Section 2.1.7). For those experiments, we plot the first search point (x_1) the participants choose relative to the initial data (x_0, y_0) in the design space. Such plots were compared across all the experiments, including the experiments where an initial data point was not provided. For comparisons with experiments without an initial data point, we considered the first chosen search point (x_1) as if it were the initial data point provided to the participants. To choose a fixed value of x_1 (considered as x_0), we chose the point in the sub-range of the design space that had the highest frequency based on the decision data of the participants. Then, the second search point (x_2) was plotted relative to the highest frequency first search point to investigate whether the search behaviors are similar across these experiments.

3 Observations

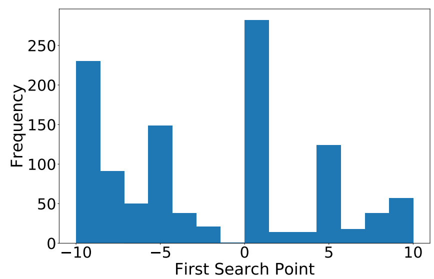
By plotting the search decision data (x, y) of the participants across various experiments, we observe the following.

3.1 Observation 1: Bisection Approach for Sequential Search

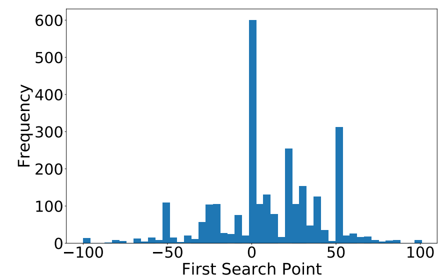
From experimental data, we find that participants predominantly follow a bisection approach for their first decision to "choose x" in SIADM problems when information about the design space is given. Figure 1 illustrates the histograms of the first search point x_1 for all the experiments. None of the histograms illustrate a uniform distribution.

We observe that the first search point x_1 is chosen around the midpoint of the design space range in the Fidelity Experiment (midpoint= 0), Function Minimization Experiment (midpoint= 0), Function Complexity Experiment (midpoint= 0), and Opponent-specific Information Experiment (midpoint= 675). In these experiments, participants were aware of the design space range. Moreover, we observe that for the Track Design Experiment and the Function Maximization Experiment, where participants were not aware of the design space range, their decisions are not uniformly distributed.

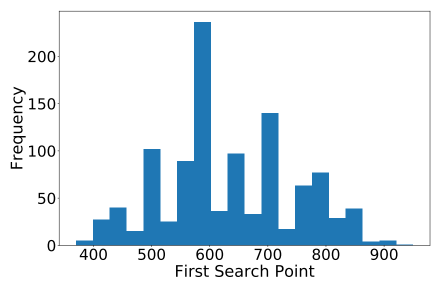
Since the design space range for TDE and FMaxE are $0 \leq X \leq \infty$, a theoretical midpoint for the range does not exist. However, we note that participants' decisions are anchored around 401, which was the initial data point given to the participants in both the experiments. We further discuss anchoring effects in Section 3.2. We also checked for the influence of the experimental interface design on the search behaviors. Specifically, we investigated the possibility that perhaps participants were only able to observe a range of $0 \leq X \leq 800$ in TDE and FMaxE experimental interface screen such that they searched around the midpoint= 400. However, participants were able to observe a range of $0 \leq X \leq 1000$ on the screen. This range is used to plot Figure 1d and Figure 1e. We also had a couple of data points at $x > 20000$, which are omitted in the FMaxE histogram for clarity in the Figure 1e. Such searches



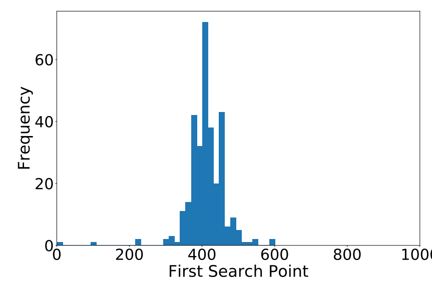
(a) Fidelity Experiment



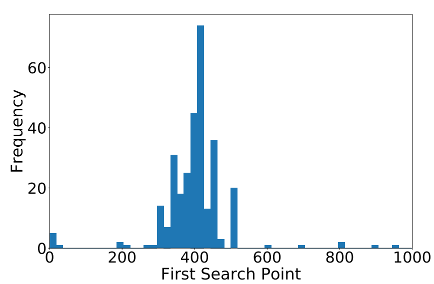
(b) Function Minimization Experiment



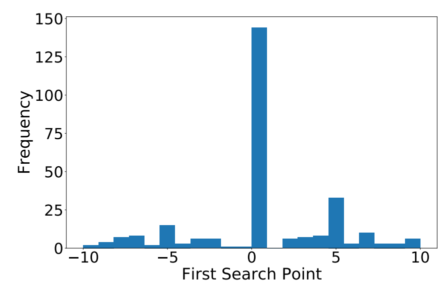
(c) Opponent-specific Information Experiment



(d) Track Design Experiment



(e) Function Maximization Experiment



(f) Function Complexity Experiment

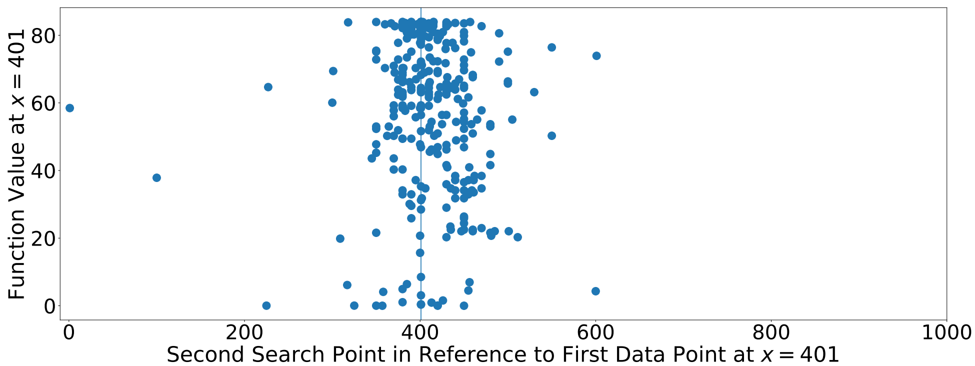
FIGURE 1: Histograms of the frequency of the first search point x_1 chosen by the participants in the experiments.

highlight that participants were able to explore in the design space range such that $x > 1000$. However, their search patterns were not at a perceived "midpoint" neither were they uniformly distributed. Thus, we concluded that participants were anchored to the initial data point for the FMaxE and TDE experiments.

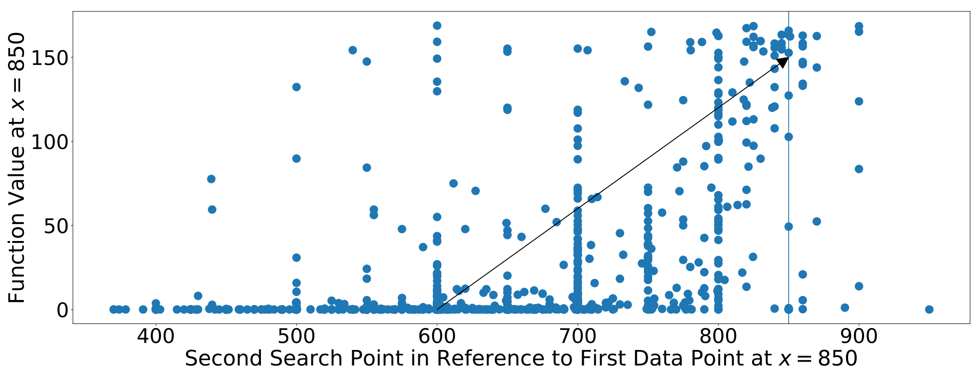
3.2 Observation 2: Exploitation instead of Exploration

As discussed in Section 2.1.7, in some of the experiments, the participants were provided with an initial data point. These experiments are the Track Design Experiment, the Function Maximization Experiment, and the Opponent-specific Information Experiment. For these experiments, we plot the scatter plots, as shown in Figure 2. We plot all the first search decisions (x_1) with the observed initial function value (y_0) pairwise (x_1, y_0). We do so to investigate whether participants search decision at x_1 was influenced by the value of the objective function y_0 for the initial data point x_0.

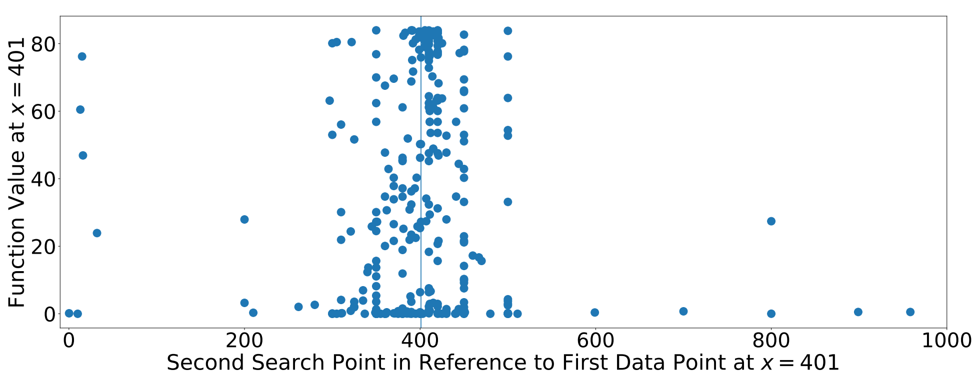
We find that as the y_0 value increases, the first search decisions x_1 are closer to the x_0 position of the initial data point (given that participants were required to maximize the objective). In other words, the plot highlights the anchoring of the first decision point with respect to the initial data point as the initial data point's objective function value increases. We note that the participants were not aware of the maximum achievable value of the function objective. Thus, there is not sufficient evidence from the initial data point that they are close to the maximum or not. Consider Figure 2b, where we observe that the participants search closer to $x_0 = 850$ when function value is greater than 100. This implies that participants tend to



(a) Track Design Experiment: Initial data is given at $x = 401$. As the initial objective function value data increases, people sample the next search point closer to the initial $x = 401$.

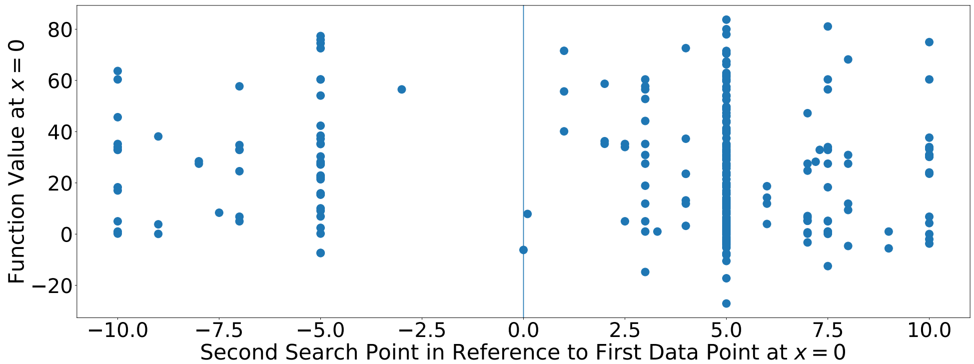


(b) Opponent-specific Information Experiment: Initial data is given at $x = 850$. As the initial objective function value data increases, people sample the next search point closer to the initial $x = 850$.

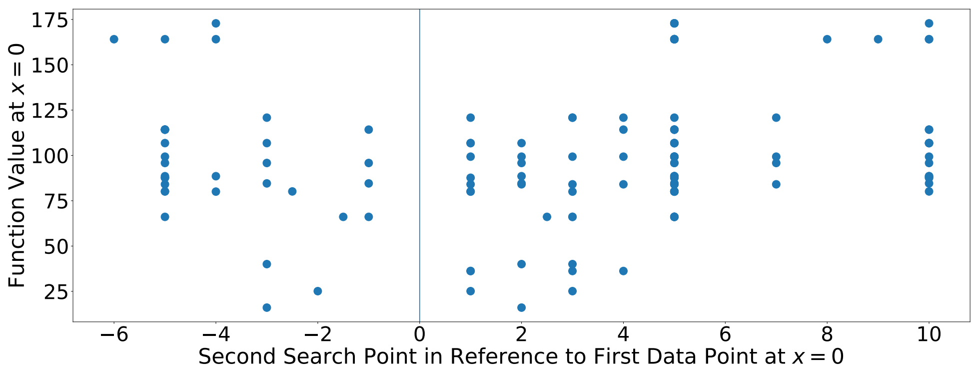


(c) Function Maximization Experiment: Initial data is given at $x = 401$. As the initial objective function value data increases, people sample the next search point closer to the initial $x = 401$.

FIGURE 2: Plots of the experimental data where initial data (x_0, y_0) was provided. We plot a scatter plot all the first search decisions (x_1) with the observed initial function value (y_0) pairwise (x_1, y_0). We do so to highlight that as the y_0 value increases, the first search decision x_1 is closer to the x_0 position of the initial data point. In other words, the plot highlights the anchoring of the first decision point with respect to the initial data point.



(a) Fidelity Experiment: Plot of the x_2 value sampled after observing data at $x_1 = 0$. Each (x_2, y_1) data point corresponds to the x_2 value sampled after observing function value y_1 at $x_1 = 0$. We do not observe anchoring to the initial data point. We observe a "strong" bisection strategy approach for searching the second x.



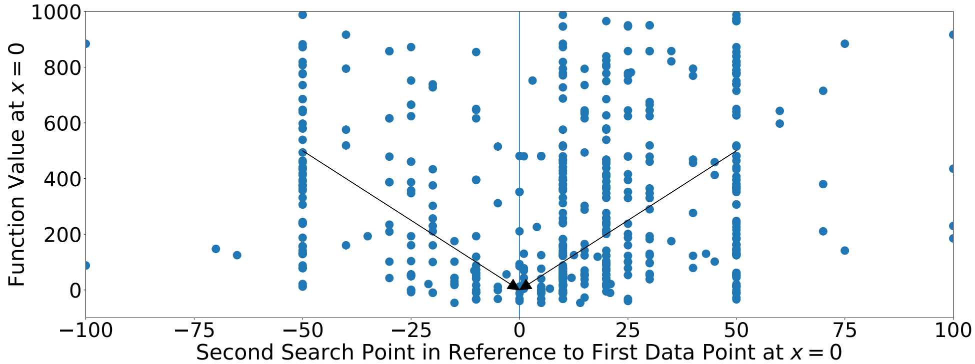
(b) Function Complexity Experiment: Plot of the x_2 value sampled after observing data at $x_1 = 0$. Each (x_2, y_1) data point corresponds to the x_2 value sampled after observing function value y_1 at $x_1 = 0$. We do not observe anchoring to the initial data point.

FIGURE 3: Plots of the experimental data that do not suggest anchoring bias of the second search decision x_2 with respect to the first search point data (x_1, y_1).

believe that an objective function value of 100 or above is "close enough" to the function optimal such that they tend to exploit around the initial data point $x_0 = 850$. Such an observation is counter-intuitive when compared to the exploration-exploitation strategies where it is assumed that initially when an individual is not aware of the design space, they tend to explore the design space to sequentially acquire information and then in the later stages they tend to exploit the available information to search locally within the design space.

We also compare the experimental data where the initial search point was provided, with the experimental data where initial data was not provided, as discussed in Section 2.2. We find similar anchoring tendencies for the Function Minimization Experiment (where initial data was not provided), as illustrated in Figure 4. We observe that if the function objective value at $x = 0$ is closer to 0, then participants tend to exploit near $x = 0$. This implies that participants believe the function minimum is close to 0. Again, we note that the participants were not aware of the minimum achievable function objective value. Moreover, the function minimum was experimentally designed to assume negative values.

We do not find anchoring tendencies in the Function Complexity and the Fidelity experiment (where initial data was not provided). Figure 3 illustrates the plots of the second search data x_2 with respect to the highest frequency first search point (for frequencies, refer to Figure 1f and Figure 1a). We note that the Function Complexity and the Fidelity experiments were designed with objective functions of higher complexity than the



(a) Function Minimization Experiment: Plot of the x_2 value sampled after observing data at $x_1 = 0$. Each (x_2, y_1) data point corresponds to the x_2 value sampled after observing function value y_1 at $x_1 = 0$. People are anchored to the initial sampled data point in a similar pattern as if they were provided with an initial data point.

FIGURE 4: Plots of the experimental data that suggest anchoring bias of the second search decision with respect to the first search point data.

other experiments where the objective functions were convex. Such knowledge about the nature of the function complexity may have influenced participant behaviors to avoid anchoring early in the design search. This suggests that the problem context and function complexity can influence participants' anchoring behaviors and nudge them to explore further before exploiting.

3.3 Observation 3: Influence of Information about Uncertainty in the Design Space on the Search Decisions

We observe that the histogram from the Fidelity Experiment, as seen in Figure 1a, is different from the rest of the plots in Figure 1, such that participants search at the boundary ($x = -10$) comparably to the midpoint $x = 0$. The Fidelity Experiment was the only experiment where participants were able to visualize a Gaussian Process for the unknown objective function with uncertainty bounds for the predictive function mean. Such visual information stimuli may have nudged participants to explore the design space boundaries where uncertainty is typically high once the midpoint value has been sampled. Such information may have resulted in learning behaviors over repeated game-play such that participants decided to explore at the boundaries in their successive first search decisions. Such an observation suggests that participants' search behaviors are influenced by providing them visual statistics about the function uncertainty.

3.4 Observation 4: Searching Left Half vs. Right Half of a Design Space Range

From the histogram plots in Figure 1, we observed that when the experimental objective was to maximize a given function objective, the first search decisions across all the participants dominated the left half of a known design space range. We also observe that the first search decisions across all the participants dominated the right half of a known design space range when the experimental objective was to minimize a given function objective. For example, in the Fidelity Experiment and the Opponent-Specific Information Experiment, the participants were supposed to *maximize* the unknown function. We observe that in Figures 1a and 1c participants searched greater to *left* of the midpoints 0 and 675 respectively as compared to the right. Similarly, for the Function Minimization and the Function Complexity experiments, the participants were supposed to *minimize* the unknown function. We observe that in Figures 1b and 1f participants searched greater to *right* of the midpoint 0 as compared to the left.

We conjecture a directionality effect where participants' search behaviors sequentially traverse in the positive (or negative) direction of an axis in the design space depending on whether they minimize or maximize a given objective. We do not consider the Function Maximization or the Track Design Experiment as the participants did not know the design space range. Consequently, they were not sharing common knowledge of the design range. Moreover, the experimental problem did not have a theoretical midpoint. We could not compare participants' directionality with respect to their perceived midpoint.

3.5 Observation 5: Choosing Whole Numbers

Across all the experimental data, we also observe that participants prefer searching for the design parameters in whole numbers. Such an observation is consistent with existing literature on bounded rationality [25] that can explain people's preferences towards whole numbers due to the following reasons.

First, it requires a lower effort to not input a decimal point and further digits. Second, participants are not aware of the sensitivity (slope) of the objective function to the variation in the design parameters. Thus, they do not have an incentive to conduct a "fine-grained" search. Third, numbers divisible by 2, 5, and 10 are preferred due to their historical and mathematical context.

4 Hypotheses Generation and Discussion

Based on the Observations 1 through 5, we formulate hypotheses about the inductive biases, that is, the set of assumptions or rules, that individuals may use to acquire information in a design space. Such hypotheses are operationalized in a design search context and presented as H1 through H5.

H1 In a design search activity, designers acquire information at the midpoint of a known design space range.
Based on Observation 1, we hypothesize that humans can cognitively divide a given range into equal halves easier than dividing it unequally. Such an aspect of cognition results in an inductive bias for design search activities where designers may be biased to search by bisecting a design range. For design scenarios, such a bias may nudge designers to choose the mean values for the design parameter ranges while conducting experiments to acquire information. Such systematic behaviors can influence the diversity of solutions generated by the participants of a crowdsourcing contest for engineering design scenarios.

H2 In a design search activity, designers anchor themselves to the prior data about the mapping of the design variables and the design quality, irrespective of the uncertainty of knowledge of the design range or the optimality of the design quality.
Based on Observation 2, we hypothesize that humans develop a prior belief about the target values they wish to achieve for a given objective while acquiring information via experimentation. Such beliefs result in an inductive bias such that higher the similarity of the initial experiment outcome to their own belief about the objective achievement, the closer is the next experiment to the initial experiment. In a design context, such a bias has implications for how designers choose to explore the design space. Designers may not be able to produce radical innovations due to the tendency of experimenting incrementally.

H3 Designer's search behaviors can be nudged by providing a visual representation of the design parameter statistics.
Existing literature on information stimuli for decision making discusses how designers' decisions are influenced by the visual representation of information [26]. From Observation 3, we hypothesize that the visual information stimulus provides additional evidence that overcomes designer's inductive bias, such as using a bisection approach (observation 1) by nudging them to search for other alternatives. Such knowledge can enable designers of a crowdsourcing contest to deliberately and purposefully influence the diversity of solutions they can expect by providing the appropriate information stimuli for the design problem.

H4 Designers are biased to explore a design space "directionally" based on whether they are required to maximize or minimize a given objective.
Based on Observation 4, we hypothesize that humans have an inherent directionality while acquiring information which is dependent on the optimization context. If the null of such a hypothesis is rejected, it would have serious implications on the way we computationally model cognition. Currently, a computational optimization algorithm can be used either in a minimization or maximization context by simply switching the mathematical sign. However, from a cognitive standpoint, it may not be trivial. For example, consider the mathematical equation for calculating the expected payoff $\mathscr{E}(\Pi)$ for searching for a solution that yields a reward π. The equation is given as, $\mathscr{E}(\Pi) = \pi * P_{\text{search}} - C$. Where P_{search} is the probability of searching the solution, and C is the cost of searching. For such an equation, humans may optimize the expected payoff differently by maximizing the gross pay $\pi * P_{\text{search}}$ and minimizing the costs C differently.
We note that the implication of Hypothesis 4 is not the same as corroborating existing literature on reward maximization and punishment minimization [27]. For example, Prospect theory [28] discusses how humans assess their losses and gains asymmetrically. The theory focuses on modeling the utility functions of individuals asymmetrically such that it can capture the effect of human behavior towards reward maximization and punishment minimization. However, Hypothesis 4 implies that even if designers have the same utility toward maximizing or minimizing a given objective, the *process* that humans adopt is different towards optimization in maximization versus minimization scenarios.

H5 Designers have an inductive bias to select whole numbers for design parameters in a design search activity.
From Observation 5, we hypothesize that when humans initially explore a search space, they do not conduct a fine-grained search unless they receive additional information or have prior knowledge of the design space. This observation is consistent with existing literature on bounded rationality [25] that explains human decision making based on the limited cognitive resources of individuals. In a design context, such a hypothesis has implications for computational modeling of a designer's information acquisition activity. Computational models may have the resources to conduct a fine-grained search without

prior information. However, to make better predictions about how designers influence the design outcomes, such a bias needs to be accounted for while computationally modeling designer behaviors.

5 Future Work

In this study, we observed the very first decision of human subjects in a SIADM scenario. We investigate such a decision because designers use inductive reasoning to make such a decision. We made five observations about similarities in the first search decision of the participants across various SIADM experimental studies. Based on the observations, we hypothesize the inductive biases that designers use to make their search decisions. The formulated hypotheses need to be tested by conducting design experiments where participants would make decisions on the basis of insufficient data. By testing such hypotheses, we can validate the influences of the inductive biases identified in this study. Such biases need to be incorporated in computational models of designer behaviors to automate design behaviors while solving complex design problems.

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