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DESIGN OF EXPERIMENTS FOR LEARNING PERSONALIZED VISUAL PREFERENCES OF OCCUPANTS IN PRIVATE OFFICES

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ABSTRACT

This paper presents an online data-driven methodology which actively queries a new occupant for learning their personalized visual preferences. Preference is governed by a latent preference relation equivalent to a scalar utility function (the higher the utility, the higher the preference for that state). Information about occupant's preferences is available via pairwise - comparison queries (duels between two different states). We model our uncertainty about the utility via a Gaussian Process (GP) prior and the probability of the winner of each duel by means of a Bernoulli likelihood. This generalized preference model is then used in conjunction with pure exploration acquisition function to drive the elicitation process by actively selecting new queries to pose to the occupant. In this paper, an experimental framework is introduced which focusses on actively selecting new duels to learn the structure of utility everywhere in the state space with fewest possible queries. We illustrate the benefits of our framework by showing that these frameworks need drastically fewer duels for inferring the structure of underlying latent utility function as opposed to randomized data collection. In future, we are going to develop new frameworks which would help us in actively selecting new duels to infer the state with maximum utility function value (focusing on inferring the just the state with maximum utility function value rather than inferring it everywhere). We are also going to use these newly developed frameworks for sequential design of experiments to infer the preferences of new occupants working inside private offices.

1. INTRODUCTION

Commercial buildings are one of the largest energy consuming sectors (6.5% of total energy consumption) in the United States. According to Commercial Buildings Energy Consumption Survey (CBECS), 17% of all electricity consumed in United States' commercial buildings is for lighting, making it the largest end use of electricity. From previous literature, it is seen that occupants' actions have significant impact upon lighting-energy use in these buildings (Gilani et al., 2018). Sadeghi et al. (2017) showed that occupants usually perform these actions so as to adapt their visual environment in response to an external discomfort stimuli (e.g., lowering the window shades when it is too bright, raising the window shades when it is dark or to improve the view, switching on electric lights when it gets too dark.) Occupants tend to interact with building systems in a way that is convenient to them rather than being energy-conserving. Such adaptive behaviors are stochastic in nature and can negatively influence building energy use (Gunay et al., 2014). In order to address these negative effects of occupants' actions on building energy use, building systems with which the occupants interact (e.g. window shades, electric lighting, thermostats.) have been automated in many applications.

Conservative window shades and electric lighting control systems tend to employ hard constraints on the set point values to account for individual variability, avoid occupant complaints and try to maintain acceptable comfort standards for the majority of the occupants (Guo et al., 2010). However, Xiong et al. (2018) observed that while preventing glare conditions is essential, achieving general visual comfort conditions does not translate into satisfaction with the visual environment (or optimal visual preference conditions). Visual comfort conditions vary from person to person, a fact which suggests that a systematic procedure to quantify personalized preferences is needed.

Consequently, researchers have acknowledged these issues and have argued that instead of trying to maintain uniform indoor visual conditions, blinds and lighting automation systems should incorporate adaptive algorithms able to learn preferences of individual occupants.
In this paper, our objective is to develop an adaptive preference elicitation framework for inferring personalized visual preferences of individual occupants working in private offices. Our model explicitly encodes the evident hypothesis that different occupants prefer different visual conditions. We hypothesize that occupant's preference for one state of the room over another is governed by a latent (hidden) scalar utility function (Fishburn, 1970). Our newly developed framework allows us to infer the structure of this utility which can only be queried through pairwise-comparisons (duels). This framework sequentially selects new duels with the highest uncertainty associated with the predictions. We call this pure exploration approach. This paper is organized as follows. In section 2, we introduce the methodology that we follow to design experiments for learning the preferences of occupants. In section 3, we illustrate the benefits of the proposed framework compared to randomized data collection approach. In section 4, we conclude with some discussion and future lines of research.

2. METHODOLOGY

2.1 Preference Elicitation Scheme

The statement that visual state x of the room is preferred to x' can simply be expressed as an inequality relation $u(x) > u(x')$, and $u(\cdot)$ is a latent utility function. For example, a particular occupant may prefer vertical illuminance value of 500 lx (x) over 1000 lx (x'). Consequently, $u(500\text{ lx}) > u(1000\text{ lx})$. The preference elicitation problem is that given a new occupant, we want to determine (or elicit) what the occupant's preferences are by asking a small number of queries/questions to them. Put simply, we try to address the question "how can we learn occupants' preferences without requiring unnecessary or excessive efforts from them?" In this paper, we focus on pairwise-comparison queries (duels) for eliciting preferences since they are known to have low cognitive load (Conitzer, 2007). Our design of experiments (preference elicitation) scheme proceeds as follows:

1. An occupant walks inside the room and is exposed to visual state x. This state can be defined by features such as vertical illuminance, shade position, luminance ratio, etc. For this paper, we are just going to consider a 1D feature space (vertical illuminance) to illustrate our results.
2. After 10 minutes, we change the state of the room to a new state x'.
3. In the middle of 10-minute set, we ask the occupant which state does the occupant prefers.
4. If the occupant prefers the previous state, we consider the previous state as the winner of the duel and record discrete variable y as 0. If the occupant prefers the current state, then we consider the current state as the winner of the duel and record discrete variable y as 1.
5. Based on the response, we update $u(\cdot)$ accordingly.
6. Using the new estimate of $u(\cdot)$, we select the next state x_{new} for querying (asking questions). We repeat this process until a stopping criterion is met.

2.2 Likelihood Model

Assume that N duels have been performed so far. The resulting dataset is then given as:

$$D_{\mathrm{N}} = \{([\mathbf{x}_i, \mathbf{x}_{i+1}], y_i)\ ;\ i = 1, \ldots, \mathrm{N}\}\,, \tag{1}$$

where $\mathbf{x} \in \mathbb{R}^{\mathrm{d}}$ is the feature vector defining the state of the room x and d is the number of features used for that purpose. For each duel $[\mathbf{x}, \mathbf{x}']$, the obtained feedback is a binary return $y \in \{0, 1\}$ representing which of the two state is preferred. Furthermore, the state $\mathbf{x}_{i+1}$ is shared between two duels: duel i and duel $i + 1$. An example of this type of pairwise comparison data is shown in Table. 1. In the given, 1000 lx state is shared between duels 1 and 2 and 2000 lx state between 2 and 3. In a nutshell, for N duels, we are going to observe $(\mathrm{N} + 1)$ states.

Table 1: Example of 1D (Vertical Illuminance) Pairwise Comparison Data

Previous state ($\mathbf{x}$)	**Current state ($\mathbf{x}'$)**	**Response variable (y)**
500 lx	1000 lx	1
1000 lx	2000 lx	0
2000 lx	700 lx	1

The key hypothesis of this paper is that there is a latent utility function value associated with each training example which preserves the preference relations observed in the dataset. More specifically, for each duel $[\mathbf{x}, \mathbf{x}']$, the probability of the current state $\mathbf{x}'$ being preferred over previous state $\mathbf{x}$, defined as the "preference probability", is given as:

$$p(y = 1 \mid [\mathbf{x}, \mathbf{x}'], u(\cdot)) = \Phi\big(u(\mathbf{x}') - u(\mathbf{x})\big), \tag{2}$$

where $\Phi(\cdot)$ is the Probit function which is given as: $\Phi(\mathrm{z}) = \int_{-\infty}^{z} \mathcal{N}(\gamma|0,1)d\gamma$. The probability density $\mathcal{N}(\cdot\,|0,1)$ represents a univariate normal density with mean equal to 0 and standard deviation equal to 1. Similarly, we have an expression for the probability of previous state $\mathbf{x}$ being preferred over current state $\mathbf{x}'$ which is given as: $p(y = 0 \mid [\mathbf{x}, \mathbf{x}'], u(\cdot)) = 1 - p(y = 1 \mid [\mathbf{x}, \mathbf{x}'],\ u(\cdot))$. Note that, for any duel $[\mathbf{x}, \mathbf{x}']$ in which current state is preferred over previous state $(u(\mathbf{x}') > u(\mathbf{x}))$, the expression $\Phi\big(u(\mathbf{x}') - u(\mathbf{x})\big)$ will always be greater than 0.5. Furthermore, assuming that occupant's preference relationships are conditionally independent given the latent utility function values, the conditional data-likelihood is given as:

$$p(D_N|u(\cdot)) = \prod_{i=1}^{N} p(y_i|[\mathbf{x}_i, \mathbf{x}_{i+1}], u(\cdot)) \ . \tag{3}$$

In the above discussion about the likelihood function, we have not provided any form, order or shape to describe the utility function $u(\cdot)$, but instead referred to this utility as an abstract function. In the coming section, Gaussian process model is introduced which formulates our beliefs about the utility function.

2.3 Gaussian Process Prior

Throughout this paper we follow a Bayesian methodology. We model our belief about latent utility function $u(\cdot)$ as a probability measure over function space using a Gaussian process (GP) and update this belief based on the duels data we observe. A GP defines a probability measure on the space of utility functions such that any finite collection of function values follows a multivariate Gaussian distribution. GPs use and properties are extensively reviewed by Rasmussen & Williams (2006). Mathematically, we write $u(\cdot) \sim \mathcal{GP}(m(\cdot), k(\cdot,\cdot))$, where $m(\cdot)$ is the mean function assumed to be equal to 0 in our model and $k(\cdot,\cdot)$ is the covariance function. Due to the Bayesian non-parametric nature of GPs, we get a powerful/expressive model of the occupant's utility function and can incorporate the evidence (i.e. responses of the occupant to our queries) in a structured manner. The joint multivariate normal distribution over the utility function values at all the observed states $\mathbf{X} = \{\mathbf{x}_i|\ i = 1, \dots, \mathrm{N}+1\}$ of the duels data D_{N}, denoted by vector $\mathbf{u} = \big(u(\mathbf{x}_1), u(\mathbf{x}_2), \dots, u(\mathbf{x}_{\mathrm{N}}), u(\mathbf{x}_{\mathrm{N}+1})\big)$**,** is given as:

$$\begin{pmatrix} u(\mathbf{x}_1) \\ \vdots \\ u(\mathbf{x}_{\mathrm{N}+1}) \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ \vdots \\ 0 \end{pmatrix}, \begin{pmatrix} k(\mathbf{x}_1, \mathbf{x}_1) & \dots & k(\mathbf{x}_1, \mathbf{x}_{\mathrm{N}+1}) \\ \vdots & \ddots & \vdots \\ k(\mathbf{x}_{\mathrm{N}+1}, \mathbf{x}_1) & \dots & k(\mathbf{x}_{\mathrm{N}+1}, \mathbf{x}_{\mathrm{N}+1}) \end{pmatrix}\right), \tag{4}$$

where $\mathcal{N}(\mathbf{0}, \mathbf{K})$ is a multivariate Normal distribution with $\mathbf{0}$ mean and covariance matrix $\mathbf{K}$. As we can see from Eq. (4), GPs are fully specified by covariance function $k(\cdot,\cdot)$. We use the most common squared exponential covariance function to define our GP prior which is given as : $k(\mathbf{x}_i, \mathbf{x}_j) = \nu \exp\Big(\sum_{m=1}^{d} -\frac{1}{2l_m^2}\big(\mathbf{x}_{i,m} - \mathbf{x}_{j,m}\big)^2\Big)$, where d is the number of features used to define the state of the room (in this paper, we are using vertical illuminance to define the state of the room and hence $d = 1$) and $\mathbf{x}_{i,m}$ denotes the m-th element of $\mathbf{x}_i$.We denote the parameters variance ν and length-scales l_m of the covariance kernel (so-called hyper-parameters) by $\boldsymbol{\theta} = (\nu, l_1, l_2 \dots, l_d)$. Following Bayesian modeling approach, we need to place priors over these hyper-parameters $\boldsymbol{\theta}$ such that they reflect our beliefs about them. We assign uninformative prior distribution over ν and l_m:

$$p(\nu|\alpha_1, \beta_1) \sim \mathcal{G}(\alpha_1, \beta_1),$$

and

$$p(l_m|\alpha_2, \beta_2) \sim \mathcal{G}(\alpha_2, \beta_2),$$

where $\mathcal{G}(\alpha, \beta)$ is the probability distribution function (PDF) of Gamma distribution with a shape parameter α and scale parameter β. Here we set parameters $\alpha_1, = 1, \beta_1 = 1, \alpha_2 = 1$ and $\beta_2 = 1$. Now that we have defined GP prior $p(\mathbf{u}|\boldsymbol{\theta})$ (Eq. (4)) and prior over hyper-parameters $p(\boldsymbol{\theta}) = p(\nu|\alpha_1, \beta_1)p(l_m|\alpha_2, \beta_2)$, we condition our model based on the duels data we observe to infer the posterior distribution over the quantities of interests.

2.4 Posterior Distribution

Given a set of pairwise comparison data and prior distribution over latent utility function values, our next task is learning the posterior distribution over utility function values. Using Bayes' rule, we can obtain the posterior distribution as:

$$p(\mathbf{u}, \boldsymbol{\theta}|\mathcal{D}_{\mathrm{N}}) = \frac{p(\mathcal{D}_{\mathrm{N}}|\mathbf{u})p(\mathbf{u}|\boldsymbol{\theta})p(\boldsymbol{\theta})}{p(\mathcal{D}_{\mathrm{N}})}\ . \tag{5}$$

The non-Gaussian nature of the conditional likelihood term (eq. (3)) makes the above integral analytically intractable but it can be approximated via Hamiltonian Monte Carlo (HMC) sampling technique (see Subsection 2.6).

2.5 Prediction

Now that we have quantified our posterior beliefs regarding the utility function values, we shift our attention to predictions of utility function values and the preference probability (see Eq. (2)). We are interested in answering the question, "given a completely new duel $[\mathbf{r}, \mathbf{s}]$, what is the probability of $\mathbf{s}$ being preferred over $\mathbf{r}$ and vice versa?" We call this quantity the "preference probability". The task of inferring preference probabilities is divided into two steps. First, we compute posterior predicted utility function values for these two states. The posterior predictive distribution over utility function values $\mathbf{u}_t = \big(u(\mathbf{r}), u(\mathbf{s})\big)^T$ is given as:

$$p(\mathbf{u}_t|[\mathbf{r}, \mathbf{s}], \mathbf{X}, \mathcal{D}_{\mathrm{N}}) = \int p(\mathbf{u}_t|[\mathbf{r}, \mathbf{s}], \mathbf{X}, \mathbf{u}, \boldsymbol{\theta})p(\mathbf{u}, \boldsymbol{\theta}|\mathcal{D}_{\mathrm{N}})\, d\mathbf{u}d\boldsymbol{\theta}, \tag{6}$$

where $p(\mathbf{u}, \boldsymbol{\theta}|\mathcal{D}_{\mathrm{N}})$ is the joint posterior distribution and conditional prior $p(\mathbf{u}_t|[\mathbf{r}, \mathbf{s}], \mathbf{X}, \mathbf{u}, \boldsymbol{\theta})$ is given as:

$$p(\mathbf{u}_t|[\mathbf{r}, \mathbf{s}], \mathbf{X}, \mathbf{u}, \boldsymbol{\theta}) = \ \mathcal{N}(\mathbf{k}_t^T\boldsymbol{\Sigma}^{-1}\mathbf{u}\mathbf{K}_t, \mathbf{K}_t -\ \mathbf{k}_t^T\mathbf{K}^{-1}\mathbf{k}_t),$$

where $\mathbf{k}_t = \begin{pmatrix} k(\mathbf{r}, \mathbf{x}_1),\ k(\mathbf{r}, \mathbf{x}_1), \dots, k(\mathbf{r}, \mathbf{x}_{\mathrm{N}}), k(\mathbf{r}, \mathbf{x}'_{\mathrm{N}}) \\ k(\mathbf{s}, \mathbf{x}_1),\ k(\mathbf{s}, \mathbf{x}_1), \dots, k(\mathbf{s}, \mathbf{x}_{\mathrm{N}}), k(\mathbf{s}, \mathbf{x}'_{\mathrm{N}}) \end{pmatrix}^T$ and $\mathbf{K}_t = \begin{pmatrix} k(\mathbf{r}, \mathbf{r}) & k(\mathbf{r}, \mathbf{s}) \\ k(\mathbf{s}, \mathbf{r}) & k(\mathbf{s}, \mathbf{s}) \end{pmatrix}$. In Eq. (6), the utility function values $\mathbf{u}$ and hyper-parameters $\boldsymbol{\theta}$ are marginalized out. Second, we compute the posterior predicted preference probability distribution as:

$$p(y_t = 1|[\mathbf{r}, \mathbf{s}], D_{\mathrm{N}}) = \int \Phi(u(\mathbf{s}) - u(\mathbf{r})|\mathbf{u}_t)p(\mathbf{u}_t|[\mathbf{r}, \mathbf{s}], \mathbf{X}, \mathcal{D}_{\mathrm{N}})d\mathbf{u}_t\,. \tag{7}$$

In Eq. (7), we marginalize over the new duel's posterior utility function values to infer posterior predicted preference probability.

2.6 Training and Sampling

We make use of Python's GPflow 0.4.0 package (Matthews et al., 2017) to sample from the joint posterior distribution over utility function and hyper-parameters $p(\mathbf{u}, \boldsymbol{\theta}|\mathcal{D}_{\mathrm{N}})$ (see Eq.(5)) via HMC sampling (Duane et al., 1987). Using these joint posterior samples $\big(\mathbf{u}^{(j)}, \boldsymbol{\theta}^{(j)}|\mathcal{D}_{\mathrm{N}}\big) \backsim p(\mathbf{u}, \boldsymbol{\theta}|\mathcal{D}_{\mathrm{N}}), j = 1, 2, \dots, \mathrm{S} = 2000$,we approximate the posterior predictive utility function values for new room states (Sec. 2.5) as:

$$p(\mathbf{u}_t|[\mathbf{r}, \mathbf{s}], \mathbf{X}, \mathcal{D}_{\mathrm{N}})\ \approx \frac{1}{\mathrm{S}} \sum_{j=1}^{\mathrm{S}} p\big(\mathbf{u}_t\big|[\mathbf{r}, \mathbf{s}], \mathbf{X}, \mathbf{u}^{(j)}, \boldsymbol{\theta}^{(j)}\big)\,. \tag{8}$$

Similarly, posterior predicted preference probability distribution is given as:

$$p(y_t = 1|[\mathbf{r}, \mathbf{s}], \mathcal{D}_{\mathrm{N}})\ \approx\ \frac{1}{S}\sum_{j=1}^{\mathrm{S}} \Phi\big(u(\mathbf{s})^{(j)} - u(\mathbf{r})^{(j)}\big)\,, \tag{9}$$

where $[u(\mathbf{s})^{(j)}, u(\mathbf{r})^{(j)}$ are posterior utility function values sampled from $p(\mathbf{u}_t|[\mathbf{r}, \mathbf{s}], \mathbf{X}, \mathcal{D}_{\mathrm{N}})$ (Eq.(8)).

2.7 Sequential Learning

We now have all the main components required to set up our preference elicitation framework. Our main objective in this section is to develop a framework which uses previously seen duels data in order to design future experiments (select future queries to elicit/ask the occupants) and to incorporate the information obtained from occupant's responses back into our model in a structured manner. Put simply, in this section, we address the question of "if we had time/budget to elicit M extra duels from the occupant (in addition to the previously known duels data D_N, how should we do it?" Note that, in our problem, one data point (state) is always shared between two duels (refer to Eq. (1)). Our goal in this section is to model a sequential design of experiments/elicitation policy for selecting the next datapoint for completing the last duel $[\mathbf{x}_{\mathrm{N}+1}, \mathbf{x}_{\mathrm{N}+2}]$ and is given as:

$$\mathbf{x}^{*}_{\mathrm{N}+2} = \arg\max \alpha(\mathbf{x}_{\mathrm{N}+2} | D_{\mathrm{N}}, \boldsymbol{\theta}). \tag{10}$$

We define $\mathbf{x}^{*}_{\mathrm{new}}$ as the ***new datapoint of the last duel (NDLD state)***. $\alpha(\cdot)$ denotes the acquisition function (Brochu et al., 2010) we are going to use. This elicitation framework algorithm is described in Fig. 2. The sequential design of experiments policy help us to converge to the true global utility with as few queries to the occupant as possible. For inferring the true global utility (and thereby the true preference probability), we propose to use the pure exploration (PE) acquisition function. For simplicity in writing equations, in the coming part of this Sub-section, we drop the dependency of all quantities on the hyper-parameters $\boldsymbol{\theta}$ and observed states $\mathbf{X}$.

We make use of PE acquisition function for inferring true preference probabilities/global utility function values with as few queries to the occupant as possible. We want to be more confident in our predictions about preference probabilities. Being Bayesian, this means that we want to minimize the uncertainty (variance) associated with our predicted (posterior) preference probabilities. The more we explore the states space, the lower will be the uncertainty associated with our predictions, i.e. our model will become more and more confident in its predictions. PE searches the state for which we are most uncertain about the probability of the outcome, i.e., it has the highest variance for $\Phi\big(u(\mathbf{x}_{\mathrm{N}+2}) - u(\mathbf{x}_{\mathrm{N}+1})\big)$, which is the result of transforming out epistemic uncertainty about $u(\cdot)$, modeled by a GP, through the probit function. PE can be carried out by maximizing:

$$\alpha_{\mathrm{PE}}(\mathbf{x}_{\mathrm{N}+2} | D_{\mathrm{N}}) = \mathbb{V}\big[\Phi\big(u(\mathbf{x}_{\mathrm{N}+2}) - u(\mathbf{x}_{\mathrm{N}+1})\big) \big| [\mathbf{x}_{\mathrm{N}+1}, \mathbf{x}_{\mathrm{N}+2}], D_{\mathrm{N}}\big], \tag{11}$$

where,

$$\mathbb{V}\big(\big[\Phi\big(u(\mathbf{x}_{\mathrm{N}+2}) - u(\mathbf{x}_{\mathrm{N}+1})\big)\big| [\mathbf{x}_{\mathrm{N}+1}, \mathbf{x}_{\mathrm{N}+2}], D_{\mathrm{N}}\big) = \int Z^2 \, p(u(\mathbf{x}_{\mathrm{N}+2}), u(\mathbf{x}_{\mathrm{N}+1}) | D_{\mathrm{N}}, [\mathbf{x}_{\mathrm{N}+1}, \mathbf{x}_{\mathrm{N}+2}], \boldsymbol{\theta}) \, du(\mathbf{x}_{\mathrm{N}+2}) du(\mathbf{x}_{\mathrm{N}+1}), \tag{12}$$

where $Z = \Big(\Phi\big(u(\mathbf{x}_{\mathrm{N}+2}) - u(\mathbf{x}_{\mathrm{N}+1})\big) - \mathbb{E}\big[\Phi\big(u(\mathbf{x}_{\mathrm{N}+2}) - u(\mathbf{x}_{\mathrm{N}+1})\big)\big]\Big)$ and $\mathbb{E}[\cdot]$ calculates the expectation of the probability density distribution. Note that in the elicitation process driven by PE, duels that have already been queried will have a lower chance of being visited again (since the uncertainty associated with the given duel is low). Since integral in Eq. (12) is intractable, we approximate it using HMC (see Sub section 2.6, Eq. (9)).

Now that we have proposed pure exploration based preference elicitation frameworks, in this section, we are going to validate our framework in terms of its performance. We are going to need some data to test our framework on. Let us formulate a simple 1D example in which we assume that we have an imaginary occupant whose utility for different state values is as shown in the Fig.2. Our job is infer the structure of this utility everywhere in the state space.

<u>Require</u>: Duels dataset $D_{\mathrm{N}} = \{([\mathbf{x}_i, \mathbf{x}_{i+1}], y_i) \,;\, i = 1, \dots, \mathrm{N}\}$ and the budget (remaining evaluations) M.

for $j = 0$ **to** M **do**

1. Fit a GP model using observed data $D_{\mathrm{N}+j}$ and learn utility $u(\cdot) |\, D_{\mathrm{N}+j}$.
2. Compute the acquisition function $\alpha(\cdot)$.
3. Infer NDLD state: $\mathbf{x}^{*}_{\mathrm{N}+2} = \arg\max \alpha(\mathbf{x}_{\mathrm{N}+2} | D_{\mathrm{N}}, \boldsymbol{\theta})$.
4. Query the occupant for duel $[\mathbf{x}_{\mathrm{N}+1}, \mathbf{x}_{\mathrm{N}+2}]$ and obtain $y_{\mathrm{N}+j}$.
5. Augment data: $D_{\mathrm{N}+j+1} = \{D_{\mathrm{N}+j} \cup ([\mathbf{x}_{\mathrm{N}+1}, \mathbf{x}^{*}_{\mathrm{N}+2}], y_{\mathrm{N}+j})\}$.

end for

Fit a GP model to $D_{\mathrm{N}+\mathrm{M}}$ and learn $u(\cdot) |\, D_{\mathrm{N}+\mathrm{M}}$.

Report the learned utility and preference probabilities.

Figure 1: Sequential Design of Experiments Algorithm

3. NUMERICAL RESULTS

3.1 Synthetic Occupant Data Generation

For generating synthetic duels, the set-up is as follows:

1. We assume that the visual state of the room is defined by vertical illuminance feature (1D case).
2. We assume that we have an imaginary occupant working inside a given office whose utility for different states (vertical illuminance values) is as seen in Fig. 2. We want to learn this utility.
3. We assume that we can only query information about this utility function through pairwise comparisons.
4. The outcome (response of the occupant) for a given pairwise comparison is generated as described in section. 3 i.e., the outcome is drawn from a Bernoulli distribution of which the sample probability is computed according to $\Phi\big(u(\mathbf{x}') - u(\mathbf{x})\big)$. Example initial duels generated using utility function in Fig. 3 is shown in Table 2.

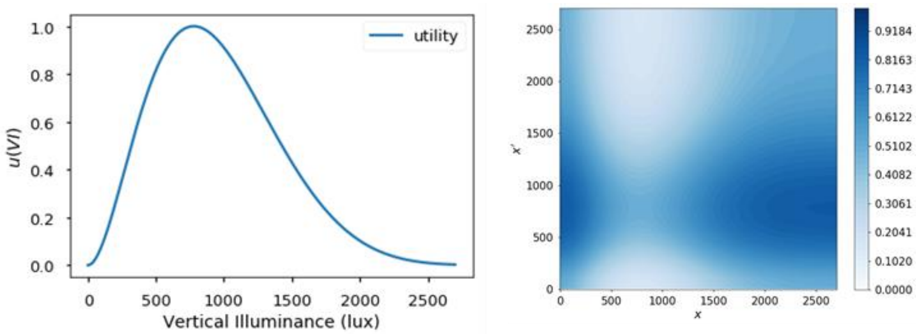

Figure 2: Actual utility function and preference probability contour plots. ***Left:*** Utility function value given vertical illuminance. From this 1D utility plot, we can say that the given imaginary occupant is going to prefer VI = 720 lx over all the other states (VI values). ***Right:*** Preference Probability Contour Plot. This plot shows the probability of state x' being preferred over x.

3.2 Framework in Action

For selecting the NDLD state, the set-up is as follows:

1. The search for NDLD state is performed in a grid of size 40 from min vertical illuminance value of 1 lx to maximum vertical illuminance value of 2700 lx.
2. Each elicitation process starts with 2 initial (randomly selected) duels and a total budget of 100 duels (for random-search) and 100 duels (for PE search) are run.
3. The PE framework vs. randomized data collection in action is shown in Fig. 3.

As we can see from Fig. 3 (top 3 rows, right columns), pure exploration approach is searching through the whole space of allowed vertical illuminance values (the duels are selected in such a way that they are far apart from each other in the search space). Elicitation in such a manner (PE) helps to decrease the uncertainty associated with predicted preference probabilities and thereby helps to converge to the true utility of the occupant in the smallest possible number of duels.

Table 2: Example of initial duels data generated using utility function shown in Fig. 3.

Previous state ($\mathbf{x}$)	**Current state ($\mathbf{x}'$)**	**Actual Preference Probability (p)**	**Response of the Imaginary Occupant (p)**
TRIAL 1			
495.9	606.12	0.549	1
606.12	275.51	0.302	0
TRIAL 2			
2038.77	2369.38	0.473	0
2369.38	661.22	0.829	1
TRIAL 3			
2204.08	826.53	0.83	1
826.53	2479.59	0.163	0

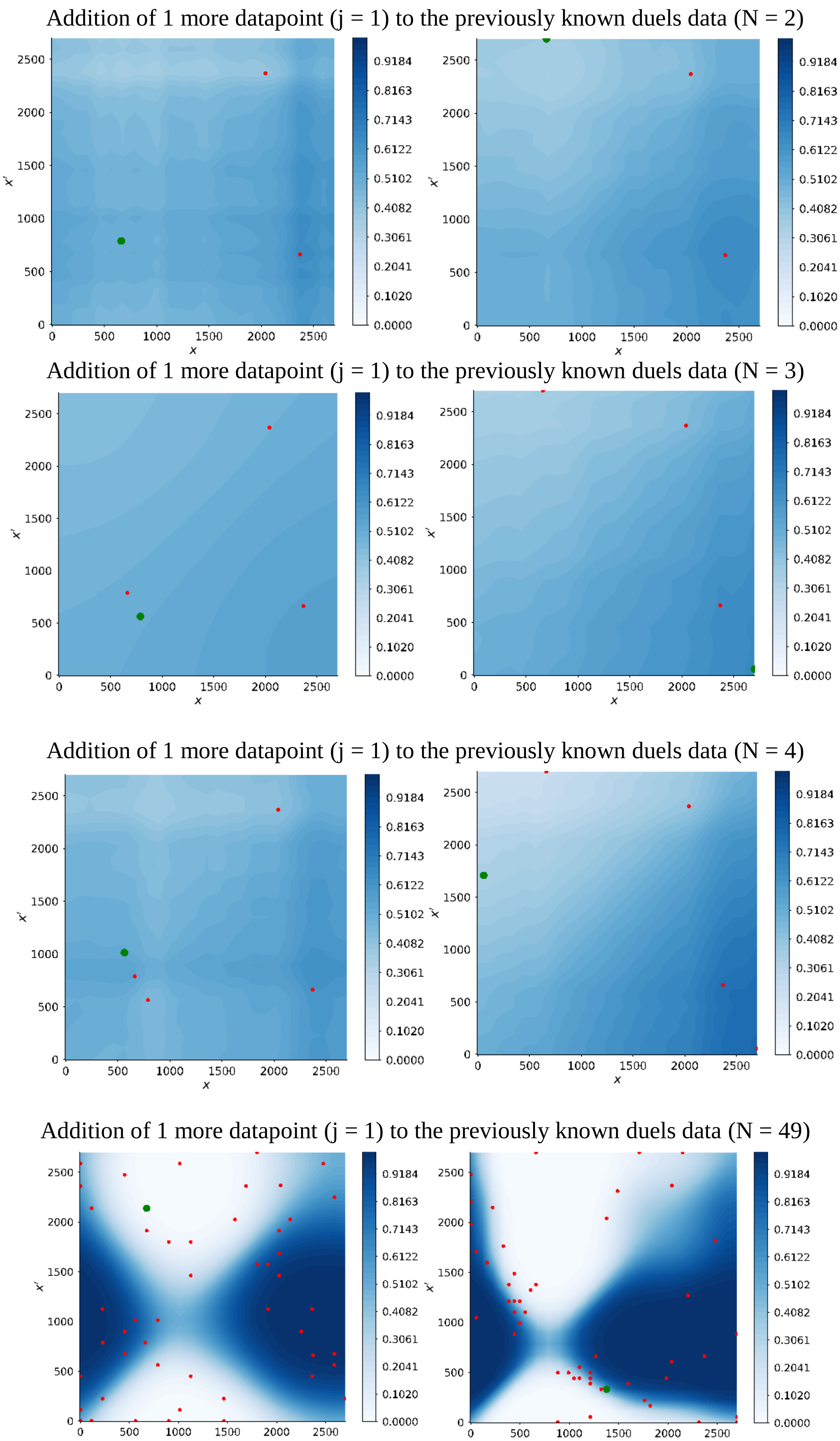

Figure 3 Random Search (left) vs. Pure Exploration (right) preference elicitation: selection of next data point (denoted by green circles) when we know previous duel values (denoted by red circles).

3.3 Evaluation Methodology

For framework evaluation, the set-up is as follows:

1. Each algorithm is run for 3 times (trials) with different initial duels (same for both random search and pure exploration elicitation) and we report the average performance across all trials.
2. For evaluating the performance of PE vs randomized data collection, hit rate accuracy (HRA), normalized Euclidean distance (NED), normalized variance in posterior preference probability samples (NVAR) and out-of-sample deviance (OSD) performance metrics (Sub-section 3.3) are considered. These metrics are evaluated on 200 testing duels data $D_{\text{test}} = \left\{\left([\mathbf{t}_k, \mathbf{t'}_k], y^{(k)}_{\text{actual}}\right) |\ k = 1, \ldots, \mathrm{T}\,; \mathrm{T} = 200\right\}$ (which are different from the duels data on which the model is trained).

3.4 Performance Metrics

Performance is evaluated on testing duels given as: $D_{\text{test}} = \left\{\left([\mathbf{t}_k, \mathbf{t'}_k], y^{(k)}_{\text{actual}}\right) |\ k = 1, \ldots, \mathrm{T}\,; \mathrm{T} = 200\right\}$. Definitions of different performance metrics used for evaluating elicitation frameworks are given below:

6.3.1 Hit-Rate Accuracy (HRA)

HRA is used as a statistical measure of how well a binary classification model correctly identifies or excludes a condition. Put simply, HRA is defined as the average chance of correct prediction. Higher the value of HRA, the better the elicitation framework is. In our case, HRA is given as:

$$\text{HRA} = 1 - \frac{\sum_{k=1}^{\mathrm{T}} \left| y^{(k)}_{\text{pred}} - y^{(k)}{}_{\text{actual}} \right|}{\mathrm{T}}, \tag{13}$$

where $y^{(k)}_{\text{pred}} = 1$ if $p^{(k)}_{\text{mean}}$ i.e. $\mathbb{E}[p(y_k = 1|D_{\mathrm{N}}, [\mathbf{t}_k, \mathbf{t}_k'])] >$ 0.5 and 0 otherwise.

6.3.2 Normalized Euclidean Distance (NED)

NED between two vectors gives a measure of "similarity" between the two vectors. In our, we calculate the Euclidean distance between predicted preference probability and actual preferences in the test set and divide it by the number of test data points T. The lower the value of NED metric, the better the given framework and vice versa. It is given as:

$$\text{NED} = \frac{1}{\mathrm{T}} \sqrt{\sum_{k=1}^{\mathrm{T}} \left(p^{(k)}_{\text{mean}} - y^{(k)}_{\text{actual}}\right)^2}, \tag{14}$$

where $p^{(k)}_{\text{mean}} = \mathbb{E}[p(y_k = 1|D_{\mathrm{N}}, [\mathbf{t}_k, \mathbf{t}_k'], \boldsymbol{\theta})]$.

6.3.3 Normalized Variance in Posterior Preference Probabilities (NVAR)

Variance gives a measure of how much uncertainty there is, in our predictions. The lower the value of NVAR, the better the given framework and vice versa. It is given as:

$$\text{NVAR} = \frac{1}{\mathrm{T}} \left(\sum_{k=1}^{\mathrm{T}} p^{(k)}_{\text{var}}\right), \tag{15}$$

where $p^{(k)}_{\text{var}} = \mathbb{V}[p(y_k|D_{\mathrm{N}}, [\mathbf{t}_k, \mathbf{t}_k'])]$.

6.3.3 Out of Sample Deviance (OSD)

In information theory literature, deviance is introduced as a principled way to measure distance of different models' predictive distributions (let's say model *a* and model *b*) from that of the target (true) distribution (*c*). The lower the value of OSD, the better the given framework and vice versa. In our case, it is defined as:

$$\text{OSD} = -2 \times \frac{1}{T} \sum_{k=1}^{T} \log(\mathbb{E}[p(y_k|D_N, [\mathbf{t}_k, \mathbf{t}_k'], \boldsymbol{\theta})]). \tag{16}$$

Fig. 4 shows the performance of PE approach against randomized data collection (as we add more and more duels). The results are consistent across all the four performance metrics plot, that is, pure exploration approach has consistently been proven better than randomized data collection.

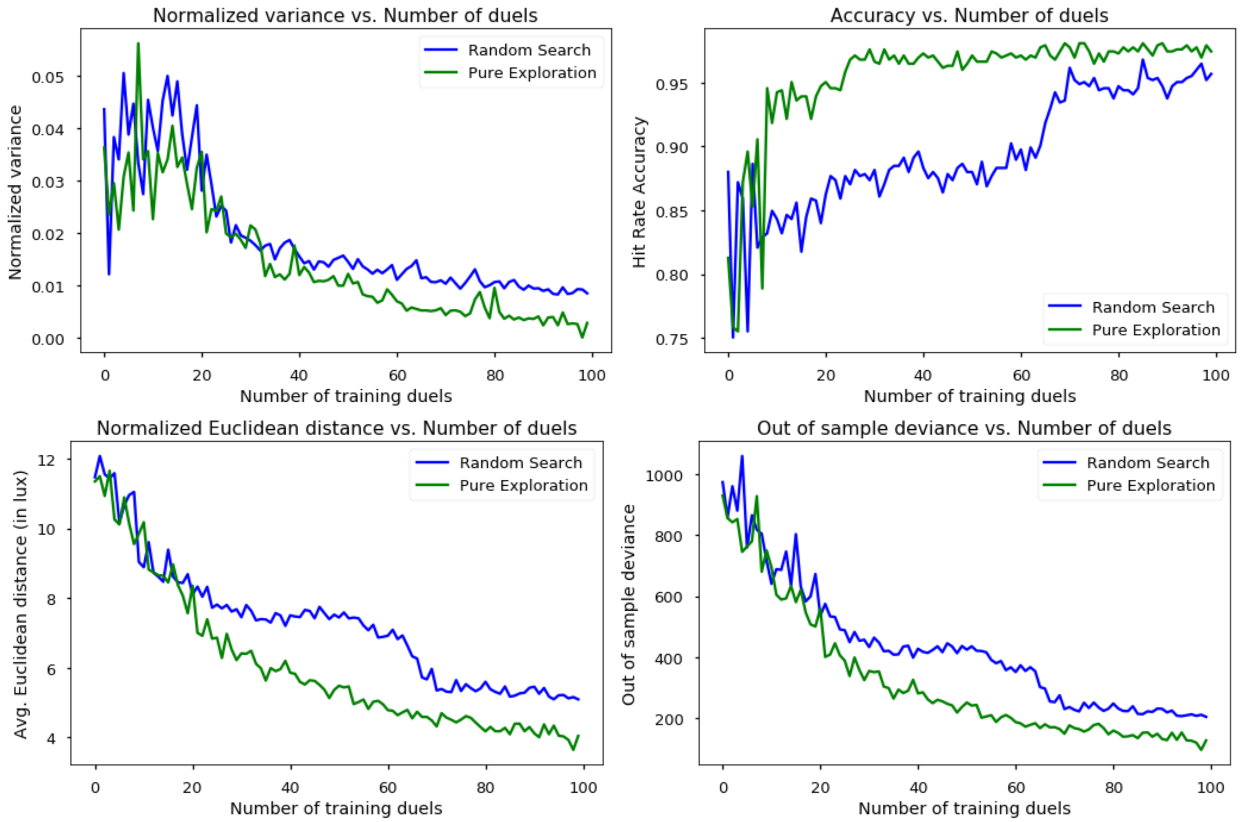

Figure. 4 Comparison of performance (Pure Exploration vs. Random Search).
Top left: mean variance metric; **Top right:** hit rate accuracy metric
Bottom left: average Euclidean distance metric; **Bottom right:** out of sample deviance metric

4. CONCLUSIONS AND FUTURE WORK

In this work we present new design of experiments framework for eliciting the visual preferences of new occupants who are going to work inside private offices. The key concept of this paper is to model latent utility function which governs occupant's preference as a Gaussian Process, which helps us in quantifying the epistemic uncertainty associated with our predictions. This epistemic uncertainty drives our future elicitation efforts. We have proposed new pure exploration based acquisition function. We show that PE approach converges faster to the true utility function values as compared to randomized data collection approach and are therefore less intrusive. In future, using this framework, we are going to design new experiments for learning the preferences of actual occupants working inside these private offices.

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REFERENCES

Brochu, E., Cora, V. M., & De Freitas, N. (2010). A tutorial on Bayesian optimization of expensive cost functions, with application to active user modeling and hierarchical reinforcement learning. *arXiv preprint arXiv:1012.2599*.

Conitzer, V. (2007, May). Eliciting single-peaked preferences using comparison queries. In *Proceedings of the 6th international joint conference on Autonomous agents and multiagent systems* (p. 65). ACM.
Duane, S., Kennedy, A. D., Pendleton, B. J., & Roweth, D. (1987). Hybrid monte carlo. *Physics letters B*, *195*(2), 216-222.
Fishburn, P. C. (1970). *Utility theory for decision making* (No. RAC-R-105). Research analysis corp McLean VA.
González, J., Dai, Z., Damianou, A., & Lawrence, N. D. (2017). Preferential Bayesian Optimization. *arXiv preprint arXiv:1704.03651*.
Gilani, S., O'Brien, W., & Gunay, H. B. (2018). Simulating occupants' impact on building energy performance at different spatial scales. *Building and Environment*, *132*, 327-337.
Gunay, H. B., O'Brien, W., Beausoleil-Morrison, I., & Huchuk, B. (2014). On adaptive occupant-learning window blind and lighting controls. *Building Research & Information*, *42*(6), 739-756.
Guo, X., Tiller, D. K., Henze, G. P., & Waters, C. E. (2010). The performance of occupancy-based lighting control systems: A review. *Lighting Research & Technology*, *42*(4), 415-431.
Matthews, A. G. D. G., van der Wilk, M., Nickson, T., Fujii, K., Boukouvalas, A., León-Villagrá, P. & Hensman, J. (2017). GPflow: A Gaussian process library using TensorFlow. *Journal of Machine Learning Research*, *18*(40), 1-6.
Rasmussen, C. E., & Williams, C. K. (2006). Gaussian processes for machine learning. 2006. *The MIT Press, Cambridge, MA, USA*, *38*, 715-719.
Sadeghi, S. A., Awalgaonkar, N. M., Karava, P., & Bilionis, I. (2017). A Bayesian modeling approach of human interactions with shading and electric lighting systems in private offices. *Energy and Buildings*, *134*, 185-201.
Xiong, J., Tzempelikos, A., Bilionis, I., Awalgaonkar, N. M., Lee, S., Konstantzos, I., & Karava, P. (2018). Inferring personalized visual satisfaction profiles in daylit offices from comparative preferences using a Bayesian approach. *Building and Environment*, *Vol. 138*, 74-88.