Case-based Reasoning and Dynamic Choice Modeling

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ABSTRACT. *Estimating discrete choices under uncertainty typically rely on assumptions of the Expected Utility Theory. We build on the dynamic choice modeling literature by using a non-linear case-based reasoning approach that is based on cognitive processes and forms expectations by comparing the similarity between past problems and the current problem faced by a decision maker. This study provides a proof of concept of a behavioral model of angler location choice applied to recreational fishers' location choice behavior in Connecticut. We find the case-based decision model does well in explaining the observed data and provides value in explaining dynamic value of attributes.* (JEL C25;Q22;Q50)

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1 Introduction

The random utility model (RUM) is the workhorse of discrete choice analysis in economics, which includes but is not limited to location choice modeling, travel cost analysis, choice experiments, and contingent valuation. RUM spans both revealed choice and stated choice research across most disciplines of economics to explain choice behavior. The explosion in modeling discrete choice behavior and estimating demand from these choices can be traced to the early 1970s, when luminaries such as Daniel McFadden pioneered work in discrete choice modeling and economic choice (McFadden, 1974; Manski, 1977; McFadden, 2001). The stochastic utility models underlying this literature, in practice, usually makes strong assumptions about rationality. When applying these approaches to empirical data, the general practice is to choose models that exhibit high levels of rationality and are linear combinations of explanatory factors, or a reduced form specification.[1] These assumptions are justified in the sense that estimation is easy to compute, the model is consistent with neo-classical theory, and the model is easy to interpret. However, the functional form of the utility and primitives of decision making, is ideally based on the assumptions about how people make a choice (Koppelman, 1981). The present work builds on the dynamic choice framework by introducing a method of estimation based on case-based decision theory (CBDT) to environmental and resource economics.

Expected Utility Theory (EUT) posits that decision makers conceptualize states of the world and assign probabilities to each of those states, updating with Bayes rule. CBDT takes a different approach where knowledge or beliefs of all states of the world are not necessary. Instead, the primitives of CBDT are the ‘problems’, ‘actions’, and ‘results’, which as a triplet are a ‘case’ in CBDT. Information in CBDT enters through the memory of the decision maker which includes past cases. Problems in CBDT are the choice situations that describe the choice being made along with any attributes to the decision problem. CBDT posits that decision makers use the psychological concept of similarity between past problems in memory and the current decision problem to maximize utility. CBDT sums over cases to find the utility of different actions for a given problem, while EUT sums over all state-spaces for each action.

In many decision problems for environmental and natural resource economics, the primitives of EUT may be unnatural to define and difficult to formulate. Take for example a recreational outing to a beach. In EUT, the states of the world include all possible experiences from the trip to a particular beach is a daunting task to define. Further, asking a beach goer what their priors were over each possible outcome and relative states of the world is likely to be unsuccessful. This does not seem like a plausible cognitive description of the decision problem. Further, memory may be defined as the entire cross-sectional choice set which may not be appropriate. CBDT instead supposes that decision-makers under uncertainty ask how similar the trip is to a reference trip, perhaps to other past trips to beaches. When faced with a new decision, the decision-maker's memory is used to form expectations about the utility of a trip to the beach. We can think about many environmental and natural resource decision problems that are similar in complexity to the above example; location choice for recreation (surfing, birders, hiking, fishing) or extractive natural resource decisions (irrigation, forestry, fisheries). For example, we can use the CBDT framework to model crop and irrigation technology choice decisions for farmers where the potential states of the world are difficult to define, yet history and experience may be available to guide the researcher on defining memory.

In our paper, recreational fishers face a location problem of where to go fishing. The EUT relevant state space would need to define all possible distributions of different species of fish and probabilities of catching the target species. This includes all theoretical possibilities as EUT anglers are never surprised by the existence of a state space, rather anglers update priors about the likelihood of them occurring. Then anglers would need to assign utility outcomes to each of these state spaces, a considerable task. CBDT simplifies this task considerably and is a more natural way to formulate the decision problem for an angler. Namely, they draw on experiences to form expectations and use similarity between decision 'problems' to assess the utility of each location under the conditions of the current decision 'problem'.

There are several studies that rely on non-linear utility models to explain behavior in discrete choice literature (Kim et al., 2014; Martínez-Espiñeira, 2006). When choice data exhibit repeated choices studies have introduced state-dependence into the controls (Smith, 2005; Cantillo et al., 2007; Abbott and Wilen, 2010). State dependence is a specific way in which serial correlation is addressed (Heckman, 1981). Like state dependence, CBDT is a dynamic choice framework that maps how past choices influence current choice behavior. The difference between conventional methods used in state dependence literature and our study is that CBDT is context-specific and based on the agent's experience of past trips, the attributes of those trips, the trips' success, and how similar those trips are to the current choice problem.

There are required assumptions when modeling discrete choice with linear additive parameters. First, individual choice is informed by all observations; in other words, an individual's memory is complete with all observable instances of the data. This implicitly relies on the idea that state-spaces are known and calculated by individuals. Second, individuals use rule-based reasoning to make decisions based on the functional form of utility, namely that it is linear and additive in components. The individuals use rules that average the effect of dependent variables on the choice variable across observations. Case-based reasoning posits that individuals take cases from memory and compare the similarity of past problems to the current decision problem to form an expected utility of choices. In other words, individuals reason through analogies to make choices rather than reason through rules. Based on this notion, individuals would expect similar problems to have similar outcomes (Gilboa

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and Schmeidler, 1995). There is support in psychology and economics for case-based reasoning that individuals weigh their own experiences more than other available information which suggests that there are apparent bounds of what is contained in an individual's memory when making decisions, in short, a reasonable constraint on human choice (Shepard, 1987; Pape and Kurtz, 2013; Bleichrodt et al., 2017). Individuals may use rule-based reasoning or case-based reasoning or a combination of the two in practice. Only careful inspection of observed choice can illuminate the decision process.

The implications for employing the case-based reasoning framework on discrete choice questions are twofold. First, if the data generating process that creates choice data is different from the model used, we will be more likely to suffer in out-of-sample prediction. A model consistent with what we know about choice behavior should be better at predicting out-of-sample which are of particular importance to policy (i.e., climate change scenarios, hypothetical scenarios, location closures).[2] Second, using the wrong model for inference on choices will impair our estimates for welfare. Therefore, a model that incorporates what we know about the psychology of choice and explains the data well is likely to provide a better measure of demand. Other researchers also make the argument that welfare analysis should be based on our understanding of the behavioral processes that generate the data (Cerigioni, 2021; Rubinstein and Salant, 2012; Manzini and Mariotti, 2014).

Several studies in the economics literature show that CBDT performs well in explaining empirical data. Ossadnik et al. (2013) conduct a repeated choice experiment where individuals' choice behavior was assessed based on an urn ball experiment using Maximin Decision Criteria, Reinforcement Learning Model, and CBDT. The results revealed that CBDT explains the experimental data better than a maximin decision criteria model or a reinforcement learning model. Guilfoos and Pape (2016) and Guilfoos and Pape (2020) finds that CBDT explains experimental game theory behavior well in prisoner's dilemma and mixed strategy equilibria games. Both Pape and Kurtz (2013) and Kinjo and Sugawara (2016) show that CBDT explains data well with respect to human classification learning and viewing decisions of Japanese TV dramas, respectively. Case-based decision theory predicts decisions well in several empirical settings. However, this theory has never been applied in non-market valuation studies or location choice modeling, and welfare implications have not yet been explored. Further, CBDT has not been adapted to empirical applications in dynamic choice environments, except for Guilfoos and Pape (2020) and Pape and Kurtz (2013). Our paper builds on the estimation methods presented in Guilfoos and Pape (2020) and applies CBDT to a dynamic empirical application on observed choices outside a laboratory setting.

Location choice behavior is important for environmental policy and management. It reveals preferences for attributes and can illuminate important policy choices for non-market goods. We apply CBDT to a recreational fishers location choice data set. Recreational fishers, unlike commercial, have varying motivations such as spending time with friends and family, catching a trophy fish, deriving

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aesthetic pleasure, catching a target species, and so on (Rubio et al., 2014). Research on choice behavior of recreational fishers is essential as this activity contributes a value addition of 38.7 billion dollars, generating more than 472 thousand employment opportunities and provides 24.3 billion dollars as annual income in the United States as of the year 2016.[3] As a result, the conservation of fishing locations and maintaining an adequate level of fish populations to sustain recreational fishing is an essential economic incentive to the nation. Fisheries management strives to conserve fishing areas, protect marine life, avoid fish stock depletion, and administers policy changes that may cause unintended consequences, especially in the behavior and distribution of recreational anglers (Pauly et al., 2005). However, choices made by fishers are dependent on numerous factors, some of which are uncertain and unobservable to the researcher (Holland, 2008). Therefore, a clear understanding of site selection behavior enables us to design effective regulatory measures and understand how fishermen respond to management policies (Cinti et al., 2010).

This work provides a proof of concept for CBDT in location choice modeling. We find that CBDT and the state dependence model both appear to fit the recreational fishing location choice data well. In sample goodness of fit favors the state dependence model and out of sample goodness if fit favors CBDT. Sometimes the goodness of fit is close between the two models. When investigating model differences by species, it appears that heterogeneity of choice behavior between species may be responsible for the good performance of the state dependence model using in sample goodness of fit. The importance of goodness of fit is in identifying likely patterns of behavior and understanding the data generating process.

Using simulations we show that there may be significant deviations of measures of willingness to pay when applying a linear model if the underlying data generating process is consistent with CBDT. A linear model consistently overstates willingness to pay for the catch of a preferred species, which is statistically different from the 'true' parameters and can be overstated by up to 35%. Further, a CBDT model is consistent with the psychological mechanisms for choice, which may be why the data may appear to fit the CBDT framework slightly better. It is our contention that models which can match known mechanisms for choice may provide a better basis to make inferences about welfare, which appears to be true in other behavioral economic models, such as loss aversion or present biased choices (Thaler, 2016) .

2 Rule-based and Case-based Reasoning in Location Choice

To clarify the differences between rule-based reasoning and case-based reasoning (reasoning by analogy), we provide an example of both. Suppose an individual is interested in purchasing a boat and is deciding which boat satisfies her demand for certain attributes (size, color, style) while

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constrained by a budget. A rule-based decision would reason "I want to buy a boat and boats cost $1,000 per additional foot of length", while reasoning by analogy would reason "my friend's boat cost $20,000 and I want to buy a boat of the same size and characteristics, so it should cost a similar amount". The predictions of rule-based reasoning and case-based reasoning could be similar, but the processes differ in the decision making mechanisms. In location choice modeling, reasoning by analogy is intuitive, as agents choose to visit locations similar to past locations that generated high levels of utility. The same reasoning might present itself negatively as well; "we had a horrible time at Beach A, and Beach Z is very similar to Beach A, so we will not visit Beach Z." Case-based reasoning can also fit into the random utility model, though CBDT suggests a specific functional form and draws its inference through the concept of memory (Guilfoos and Pape, 2020). CBDT is a close relative of reinforcement learning, which draws on similar psychological support (Gilboa et al., 2007; Shepard, 1987; Guilfoos and Pape, 2016, 2020).

CBDT was introduced in Gilboa and Schmeidler (1995). This decision theory captures the thinking process of a decision maker based on the similarity of circumstances. The CBDT framework could be useful for exploring environmental and natural resource economics issues because it provides a framework to estimate welfare for new hypothetical location choices without complete knowledge and assignment of probabilities for all state-spaces. For example, a new public park, the restoration of fishing ground, or other conservation initiatives can change the set of possible locations in the choice set. This theory hypothesizes that decision makers rely on stored memory, experience, and reasoning by analogy to choose whether to visit locations and how they derive value from that choice.

How a resource user chooses a location to visit is difficult to know and construct (Hess et al., 2018). For example, fishers seem to qualitatively assess alternative locations to visit based on intuition and experience. Ethnographic interviews conducted by Holland (2008) show that fishers' choice behavior often does not conform to the assumptions of expected utility. Some of the anecdotal findings include that safe and consistent returns were preferred over maximum fishing catch. However, as with other location choice modeling, fishing location research has relied on LA models. The paper by Bockstael and Opaluch (1983) was one of the first to incorporate uncertainty in fisher's choice model via RUM. Mistiaen and Strand (2000) use a mixed multinomial logistic model to understand the short-run heterogeneous risk preferences in fishing choice behavior. Similarly, several other studies also use LA models to examine fisher behavior when it comes to location choice preferences (Ran et al., 2011; Mistiaen and Strand, 2000; Smith, 2005).

The recreational fishing literature focuses on collecting all attributes that could potentially influence behavior such as cost to travel to the fishing site, fishing quality, water quality, congestion in the site, expected catch, and site history (Train, 1998; Rubio et al., 2014; Morey et al., 1991). We propose to characterize the same attributes through similarity from past experiences to generate expectations and form utility, much like reinforcement learning, where individuals choose locations based on expectations formed through case-based reasoning.

3 Methods

This section describes the methods to estimate both the LA and CBDT models using a random utility model framework. We discuss the model components, the stochastic choice rule, and how to apply the models to the data set.

3.1 Random Utility Theory

In random utility theory, an individual decision maker faced with a finite choice set K assigns a utility value to each choice ($U_1, U_2, ..., U_K$) depending on a vector of individual-specific, time-specific, and alternative specific characteristics denoted as X. The decision rule behind this framework hypothesizes that the decision maker would choose an alternative $j \in K$ where the utility derived from j is the maximum possible utility from the given choice set (McFadden, 2001; McFadden and Train, 2000). The probability of choosing the alternative j is given in equation 1:

$$\Pr(j|K,X) : \Pr\left(U_j > U_i\right) \; for \; all \; i \neq j \; \in K \tag{1}$$

The random utility function U_j is the utility attained by the decision maker given the vector of attributes influencing her decision. This utility is a combination of both deterministic as well as stochastic components, $U_j\left((X;\theta), \epsilon_j\right)$. The deterministic component contains the observed vector of attributes, X, and θ is the parameter vector. ϵ_j, is the random component of utility. The unobserved portion is assumed to be independently and identically distributed (iid). Utility is then expressed in equation 2:

$$U_{nj} = f(X,\beta) + \epsilon_{nj}, \tag{2}$$

where U_{nj} is the utility function for the n^{th} individual choosing the alternative j.

The functional form of utility could take many forms. The linear additive version takes information about the decision maker and site characteristics and uses equation 3 to model location choice. We refer to this model as the LA RUM.

$$f(X,\beta) = \sum_{i=1}^{I} \beta_i X_i. \tag{3}$$

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3.2 Case-based Decision Theory

In this section, we demonstrate how CBDT characterizes the deterministic part of the RUM. CBDT is a behavioral model of decision making that we incorporate into the random utility modeling approach. This theory measures utility by incorporating the similarity between the current scenario and scenarios in memory, which are called cases. According to CBDT, every individual has a memory (M), which stores a set of cases (C). Each case is a combination of a set of problems (P), a set of actions (A) taken to resolve this problem, and the subsequent set of outcomes or results (R) obtained from applying the action to the problem. CBDT assumes that individuals refer to their memory of cases and form expectations based on the weighted similarity of past cases and the current problem. A similarity function weighs the similarity between the current problem (p) and past problems (q). Past problems, q, need not be drawn from the decision maker's own experience. These memories could be drawn from outside observations, or they could be hypothetical constructs. The expected utility is a combination of the cases in memory and the results of those cases, weighed by the similarity function. Another component considered in case-based decision theory is the aspiration level (H). Aspiration denotes the satisficing amount of utility the individual pursues. A combination of the above components, that is, the similarity function, utility function, and aspiration level, provides the case-based utility of an individual (Gilboa and Schmeidler, 1995).

In the recreational fisheries context, M is the set of fishing trips stored in the fisher's memory. The problem, P, is defined as each fishing trip's attributes, such as weather conditions, travel cost, or day of the week of the trip. The action, A, is the chosen fishing location of the fisher. The result, R, is a binary indicator variable equal to one when the fisher catches his target species and equal to zero otherwise.[4] The aspiration level, H, for the fisher is the satisficing level of utility derived from his fishing trip. According to this model, the weighted similarity index between past (q) and current problems (p) of the fisherman and results of past trips will form their expectations of utility.

The psychology literature provides surprisingly specific guidance on the form of a similarity function and measures of distance between information in the definition of the problem. Shepard (1987) argues that a specific psychological function that generalizes distances in conditions that can be invariant to monotonic transformations is desirable. He further argues that this generalization is consistent with a general law of how any similarity between stimuli can be experienced by individuals. His work suggests an exponential decay similarity function with Euclidean distance as an approximation of the general invariant monotonic function that generalizes between stimuli. Shepard further argues that these measures have an evolutionary basis and are found to be consistent with the learning data. While any similarity function that is decreasing in distance measures in practice could be applied to the data, we choose one that psychology has suggested emerges from the generalized learning responses from stimuli. This function establishes the resemblance between past problems and the decision maker's

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current problem. As per CBDT, each fisherman will have a set of cases stored in her memory, which she will refer to, when making current decisions. The similarity function is given in equation 4.

$$s(w,p,q) = \frac{1}{\exp\left(d(w,p,q)\right)}, \tag{4}$$

where *w* is the estimated weight between a vector of information from the current case (*p*) and past case (*q*) and where d(.) denotes a distance metric between elements of *p* and *q*. The greater the resemblance between information in the two cases, the greater the estimated weight given to past case.

The consequent case-based utility (CBU) function is given in equation 5.

$$CBU_{ijq} = \sum_{ijq \in M} s(w,p,q)[U(r) - H] \tag{5}$$

In the above equation, the case-based utility for individual *i* for location choice *j*, includes the similarity function *s(w,p,q)*, the utility function, *U(r)*, which denotes the utility derived from the result, *r*, and *H* which is the Aspiration level. We have constrained the aspiration level to be zero because identification is confounded when estimating the initial attractions to locations and the aspiration level jointly.[5] *M* denotes the level of memory the individual has that includes all the cases involved with the chosen alternative *j*. The case-based utility is then measured by taking the summation of the similarity function, weighted by the difference between *U(r)* and *H* (Guilfoos and Pape, 2016). The maximum likelihood estimation procedure estimates the most probable parameters to obtain the observed data.

3.2.1 Distance Measures

The approximation of similarity and distance measures that Shepard (1987) suggests is the functional form we have used in equations 4 and 6, which uses a Euclidean distance measure (Shepard, 1987; Nosofsky, 1992). The suggested approximation also works with a "city-block" distance function (Shepard, 1964, 1987; Aulet and Lourenco, 2021), which we also estimate. The distance function that follows the euclidean distance metric ($d(w,p,q)_E$) is given equation 6.

$$d(w,p,q)_E = \sqrt{\sum_{v=1}^{n} w_v (p_v - q_v)^2} \tag{6}$$

In the above equation, *v* denotes the explanatory variables used in the model. This similarity functional form was used in Pape and Kurtz (2013) to describe data from a human classification learning problem experiment. Guilfoos and Pape (2020) also used the same functional form in mixed strategy equilibria games and found that it performed well in describing the data from those experiments. The other measure of distance used in psychology is called the city-block distance, given in equation 7.

$$d(w,p,q)_C = \sum_{v=1}^{n} w_v |(p_v - q_v)| \tag{7}$$

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3.3 State Dependence Model

The conceptual understanding of state dependence as per Heckman (1981) is the influence of an individual's past experience on their current decisions. The typical method to incorporate state dependence is to linearly add proxy variables that capture individual past experience to the utility function. In order to evaluate the general performance of CBDT, we estimate a model that is often used in the state dependence literature. Similar to Guadagni and Little (1983) and Keane (1997), variables that are serially correlated measures of individual past choices are included as controls in this model.

Apart from CBDT, we estimate two other models for comparison. The first model uses the cross-sectional data to make predictions with a linear additive combination of controls (LA). The second model includes the additional state dependence variables, the weighted average of past location choices nested in the LA model.

$$x_{ijt} = \alpha * x_{ijt-1} + (1 - \alpha) * y_{ijt-1} \tag{8}$$

Equation 8 defines the state dependence variable x_{ijt-1}. The state dependence variable is a dynamic measure of past location choices, where the variable α determines the weight on past choices. The variable *y* equals one for a visit to site *j* at time *t* for individual *i* and zero otherwise. The parameter α acts like a discount factor on past choices, similar to a recency parameter in CBDT, which measures the distance between current choice and past choices in the choice problem. The state dependent variable requires an initial value, which we set equal to zero. The combination of the LA model with all the controls including the state dependent variables, henceforth referred to as the state dependence model (SD), is similar to models from Smith (2005) and Smith and Wilen (2002) in the fisheries literature.

The choice of alpha could be optimized by the researcher, adding another degree of freedom for model choice. In Appendix A, we show a range of alphas and the resulting model goodness of fit measures. We note that the state-dependence model fit does not vary much based on the choice of α. The performance of the state-dependence model is slightly affected by α when using out-of-sample measures. We use α = 0.50 in the main text as it performs well in the out-of-sample tests. Our findings are robust to different values of α.

3.4 Stochastic Choice Rule

A common stochastic choice rule applied in discrete choice modeling literature is the logit response model. The multinomial logistic model is used when the choice set faced by an individual has multiple discrete alternatives (Sellar et al., 1986; Parsons et al., 1999). For instance, recreational fishers have multiple fishing sites in their choice set. The choice probability that a decision maker chooses one of the alternatives, $j \in K$ is given in equation 9.

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$$P_{nj} = \frac{\exp\,(\lambda, U_{nj}(\beta, x_{nj}))}{\sum_{i=1}^{K} \exp\,(\lambda, U_{ni}(\beta, x_{ni}))}, \quad (9)$$

where $U_{nj}(\beta, \mathrm{x}_{\mathrm{nj}})$ is the utility of alternative j for individual n, which is a linear additive function of attributes (x) in the LA model and a summation of utility weighted similarity functions for CBDT. The sensitivity parameter, λ, which is assumed to be one in LA models, are estimated in CBDT. λ is important to the estimation of learning models on laboratory data of discrete choice and is considered in Guilfoos and Pape (2020). As λ approaches zero the data appear to be completely random to the model predictions and as it approaches the model appears to be more deterministic in fitting the data. The above choice rule implies that the probability of a fisherman choosing site j from choice set K, is the exponential of the utility from site j divided by the sum of all of the exponentiated utilities (Ben-Akiva et al., 1985; McFadden, 1974).

An important critique against the multinomial logit choice model is the assumption of Independence of Irrelevant Alternatives (IIA). This assumption implies that the utility from one alternative is solely influenced by individual-specific characteristics which are constant across alternatives (Train, 1998). To counter this limitation and to account for other considerations such as heterogeneity and taste variations, other models such as nested logit, latent class, and mixed multinomial logit are used. Such models rely on location specific variation that involves additional conditions to the multinomial choice probabilities (McFadden, 2001; Ben-Akiva et al., 1997). In this paper, we apply the original multinomial logit choice process to compare the linear additive rule-based model with the case-based reasoning model, CBDT. It is important to note that both models would suffer equally with such limitations.

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4 Welfare Analysis with CBDT

In this section, we discuss welfare within the CBDT framework. Welfare estimation is essential for policy evaluation; therefore, we need to understand how CBDT choice affects our estimates of willingness to pay for goods. An important assumption when measuring welfare in discrete choice models is the interpretation of the cost coefficient as the marginal utility from income. This monetary value is then used to compute the fishers' willingness to pay estimates for a change in site attribute, holding all else constant (McConnell, 1995; Hanemann, 1983).

The theory of welfare valuation is unaffected by CBDT's assumption of a functional form of utility, but there are practical considerations to confront when implementing CBDT. For instance, based on the assumptions we make regarding memory, we need to construct a history of experiences that resemble a representative individual from the data to understand how the payoffs from choices are incorporated into the choice set.

The conditional indirect case-based utility function (CBV) as defined in equation 10.

$$CBU_{ij} = CBV_i\left(y_i - Q_j, x_{ij}\right) + \epsilon \tag{10}$$

where y denotes the income for individual i; Q_j being the attribute for choice j and x denotes other explanatory variables affecting utility. Equation 11, demonstrates how a change in policy that alters the site attribute from Q^0 to Q^1 can be measured:

$$CS_{ij} = \frac{\ln\left[\sum_{j=1}^{J} e^{CBV\left(Q_j^1\right)}\right] - \ln\left[\sum_{j=1}^{J} e^{CBV\left(Q_j^0\right)}\right]}{\frac{\partial CBV_{ij}}{\partial y}} \tag{11}$$

To compute the value of a change of compensating surplus (*CS*) in site attributes we need to make assumptions about all site attributes. Similar to the linear additive form of utility models when variables are held at their means in the numerator of equation 11, in CBDT, we need to make assumptions on the values of variables in the similarity function. When valuing a change in result, like catching a target species of fish, the similarity function is held at some assumed value. On the other hand, when valuing a change in the attribute, Q, in the similarity function, we must consider if the attribute affects the result, (r), as well as the similarity function. The indirect case-based utility as a function of a particular Q is given in equation 12.

$$CBV(Q_j^1) = \frac{1}{exp\sqrt{w_{Q_j^1}\left(p_{Q_j^1} - q_{Q^A}\right)}} u(r|Q_j^1) \tag{12}$$

In CBV, we make assumptions about the past problems in memory, q_Q, either by taking the average distribution of past attributes (Q^A), or by another measure of a representative past. Other possible choices for welfare calculations are calculating welfare for specific populations of memory, or to calculate the distribution of welfare for the sample population. For instance, it may be preferable to assume a specific memory distribution if attempting to obtain the welfare gain or loss for a specific sub-population or type of angler. Assumptions are also required regarding how Q_j^1 affects the result, r. To measure how attributes affect results we need to establish a functional form, as provided in equation 13, that measures the effect of the attributes on the results.

$$r(X) = f(\beta_v, X_v) + \epsilon \tag{13}$$

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We then use the predictions from equation 13 to construct the average result, $r(Q_j^1)$, conditional on attribute Q_j^1 for a particular site j and estimate the location choice model using CBDT as outlined in section 3.2. Lastly, we need a measure of the marginal utility of income, y to interpret the effect of a change in attribute on utility in dollar terms. We hypothesize that the marginal utility of income could be rule-based or case-based. If rule-based, we would typically recover a constant marginal utility of income. However, if case-based, the derivative of CBU with respect to cost (or measure of income) would potentially affect both the result, r, and the comparison to past cases through the estimated weights in the similarity function. The estimates from the location choice model and the predictions from equation 13 are used as inputs into equation 12.

5 Data

We use data from Connecticut recreational fishers to test the empirical fit of each model. The data used in this study was obtained from the Volunteer Angler Survey Program (VAS) provided by the Connecticut Department of Energy and Environmental Protection (DEEP).[6] Fishing trip and catch information are recorded in survey logbooks by anglers voluntarily. The survey logbooks are provided to each angler participant, and anglers are encouraged to send back in the completed logbooks via mail. Weather data is obtained from the NOAA's (National Oceanic and Atmospheric Administration) National Centers for Environmental Information (NCEI)[7] and joined to the trip data by day of the trip.

After accounting for missing values, the VAS data received has a total of 3,182 day trip records taken by 51 survey participants from the year 2013 to 2016. A concern with location choice data is the potential for a selection problem of who goes fishing or which anglers choose to report trips. This would need to incorporate a first-stage estimate to model the selection process, and using a CBDT framework to model the data generating process of site selection as a second-stage. Since the selection of our data is based on voluntary participation it may very well have a selection bias which may interact with a travel cost coefficient; yet the model comparisons of the second-stage are still valid comparisons as all models in our paper use the same sample.

The area assigned to recreational anglers in Connecticut is appropriated into six area codes. Each three-digit area code denotes an area of the Long Island Sound defined by NOAA[8]. Figure 1 (Map of Long Island Sound) presents the areas used in this study as recorded in the Fishing Vessel Trip Report. The trip report also contains the species caught, the number of fish caught, and each catch's weight and size. Observations recorded from the Long Island Sound but not noted on the map have been grouped into a sixth area denoted as *other*. The smallest unit of observation for location is the area codes used in our definition of location. Fishing sites may be aggregated, which could create aggregation bias (Parsons

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and Needelman, 1992). Though all models would suffer from aggregation bias and it should not affect model selection criteria.

The variables in this data set are work day, if a trip is taken on a weekday, the month and year of the trip, daily average wind speed, daily average temperature, daily average precipitation, angler id, fishing hours on trip, and trip mode (type of boat or if the shore). The variables described are used to derive the key variables commonly used in fisheries literature (McConnell et al., 1995; Hunt, 2005; Timmins and Murdock, 2007). The derived key variables of interest are *site congestion*, *expected catch rate*, *site history*, and *period*. The summary statistics of the same are included in Table 1.

5.1 Expected Catch Rate

The expected catch represents the expected payout received in terms of fish caught per unit effort from each site. We construct this variable based on multiple attributes of the trip. It is estimated using the number of anglers, fishing hours, area, trip mode, weather variables, workday, year, and month. This predicted measure for catch rate is estimated using a Poisson process model, an approach popularized by McConnell et al. (1995). Further details and estimated results of the Poisson process model are reported in Appendix B.

Weather is an important aspect of recreation behavior (Chan and Wichman 2020; Dundas and von Haefen 2020). Weather can affect an angler's decision to go fishing on a particular day and which location to visit through expected catch. In our work, we use weather as an input to expected catch. Aspects of weather and climate (wind speed, temperature, and precipitation) are used to define expected catch for an area. We define trace precipation for weather with the average daily precipitation is less than 0.005 inches. Weather can also shift behavior due to climate change, though we do not model all of these behaviors in this work. Other adaptations anglers make to adjust to climate change may include shifting the time of day to fish to adjust to extreme temperatures (Dundas and von Haefen 2020).

5.2 Indexing Memory

In case-based decision theory, each case in the decision maker's memory, which are previous fishing trips in this study, is chronologically ordered and indexed using a variable we call period. This variable is a constructed variable which equals the accumulated number of trips an angler takes. Period is a measure of recency in CBDT. A relatively recent case may have a more considerable influence in the decision making process than an older case. To account for this, we include period in the model as an attribute. In the LA model this variable acts as a proxy for individual fishing experience within our sample size.

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5.3 Site Congestion

The variable site congestion refers to the number of other fishers encountered during the fishing trip. The effect of congestion as a site attribute is important when modeling location choice preferences. The standard hypothesis is that congestion initially acts as a proxy for the popularity of the site. However, beyond a certain degree, it is considered less desirable and acts as a disutility in the site choice model (Timmins and Murdock, 2007). In this study, congestion is the individual share of total fishing trips taken the previous year in the same month in the same location. The share of a participant in proportion to the number of site visitors measures the likelihood of running into others on a trip to a particular location. In this method, we presume that fishers formed expectations regarding the congestion of a site while they were making the site choice decision. Therefore, we use the fisher's previous visitation experience in that site to measure congestion. The share of each individual across total site visitors gives us an insight into how much site space they occupy as well as the frequency of encountering another fisher (Schuhmann and Schwabe, 2004). A smaller individual share implies more congestion at the specific site. Also, considering the year before reduces the limitations of recall memory and the same month is used to account for the seasonal nature of this recreational activity (Kolstoe et al., 2018).

The construction of site congestion is based on the anglers in our dataset which acts as a proxy for actual congestion. This variable therefore may contain measurement error in the variation between the actual measure due to anglers that did not report their day trips.

5.4 Site History

The familiarity of the site is another attribute that may affect its utility. Site history is a binary indicator for whether the chosen site was visited in the previous period by the same individual. This measure is a direct way to capture the incidence of repeat visitation and its importance in site selection.

5.5 CBDT Variables

In the CBDT model, we use the variables period, site congestion, site history, and expected catch rate to define the problem, (P). The result (R), or payout, is a binary indicator of whether the targeted species was caught on the trip. This result is a proxy for actual utility received on a trip as that is not observable. The set of actions (A) are the fishing area locations.

6 Model Goodness of Fit Comparison

The in-sample quantitative fit of LA, CBDT, and SD models are compared using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). When comparing the

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information criteria for the estimated results, a relatively smaller AIC or BIC value means that the model has better goodness of fit (Atkinson, 1981).

Out-of-sample predictions for all models are also conducted. For model selection, the out-of-sample procedure is preferred since the in-sample fit can be more easily manipulated by the addition of controls, which may mask how well the underlying model is performing. We use a method of roll-forward samples to estimate out-of-sample fit as measured by log-likelihood. In this approach, a percentage of decision maker's choice data, which comprises of cases ordered chronologically, is used to predict the remaining hold-out sample. We conducted a rolling window selection for out-of-sample fit comparison using 15, 25, 50, 75, and 90 percent of choice data for all models.

Lastly, we use a non-nested model selection test developed by Vuong (1989) to evaluate if the models are statistically different from each other. The Vuong test determines if the CBDT model is the preferred model using in-sample measures.

7 Results

First, we discuss the fit of each of the models considered. Table 2 reports the measures of fitness for the LA, SD, and CBDT models. Using the in-sample goodness of fit, we find that the SD model is the best model by all criteria. CBDT models perform similarly with either a Euclidean distance or city-block distance metric. Despite having thirty parameters more than CBDT, which has ten parameters, the BIC measure for both SD and CBDT model is similar. Therefore, the penalty for parameters from BIC makes the models similar in in-sample goodness of fit. Both dynamic models outperform the LA model, indicating that the dynamic history of behavior is important in this context. We find that model selection using the Vuong non-nested model selection test (Vuong, 1989) favors the SD model and is statistically significant at the 1% level (z-stat = 2.73). We provide the details of the LA model in Appendix C.

The SD and CBDT model both fit the data well. To guard against model overfitting, we compared the out-of-sample goodness of fit for all models. We compare the rolling out-of-sample goodness of fit based on fishers' memory. Table 3 reports the log-likelihood value for all models. CBDT, with both distance metrics, performs better than all other models in general, except for the 50% memory hold out sample. We take this as an indication that the SD model may be overfitting the data and is not as parsimonious as the CBDT model. Given the simpler and more intuitive model performs well in this task, the results suggest CBDT as a model that explains the observed data well.

Next, we discuss the parameters from the CBDT model results. Table 4 contains the coefficient estimates from the CBDT model. The coefficients for "Area i" are relative initial attractions to the stated location areas. These parameters are similar to attractions to strategies that learning rules

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accumulate in behavioral game theory (Guilfoos and Pape, 2020). This initial attraction also serves a role similar to fixed effects in a LA model. Initial attractions to locations and aspiration levels are not separable in estimation and therefore aspiration is left out. In columns 1 through 4 of Table 4, we incrementally add controls to the model of CBDT using the Euclidean distance metric. In column 5 we report the CBDT model using city-block distance metric.

The coefficients in the LA model are log odds ratios; with CBDT the coefficients are the weights, w_v, given to that parameter in the similarity function as specified in equation 6. The weights from the CBDT model, if positive, indicate a degree of similarity between current and past cases. For instance, the estimated weight for site congestion is substantial, positive, and statistically significant. It indicates a high degree of similarity between the congestion level for the current and past locations. The weight for expected catch increases in statistical significance using the city-block distance metric. This means that while model goodness of fit is robust to different distance functions, the interpretation of individual pieces of the definition of the problem are sensitive to the functional form used to define distance. The estimated weight for the variable period accounts for recency. In other words, the similarity weight for period accounts for the temporal distance between the current choice problem and trips that occurred in the past. Trips further in the past are given less weight in forming expectations. All the parameter estimates are logical and intuitive in interpretation. To interpret the relative importance of each weight we must standardize them, which we do in Appendix D using the estimates from column 4 in Table 4. Recency and then congestion appear to play the most important roles in the weight of information of the problem set.

The results estimated until now include all fish species. We check the robustness of our results by analyzing each target species separately, using CBDT and the Euclidean distance metric. Table 5 reports the estimated weights for the top four target species considered by recreational fishermen in our data set. The BIC model selection criteria show CBDT better fits the data than LA for all species. CBDT also has a better fit than the SD model for striped bass, bluefish, and black sea bass but not fluke.

In terms of interpretation, the coefficient for expected catch shows significance for striped bass and fluke. On the other hand, the estimated weight for site congestion is significant, positive, and substantial for all target species, especially for black sea bass. This finding implies that choice location weighs cases in the past with similar congestion very high when constructing location preferences. This finding conforms to the existing literature regarding the importance of including congestion effects when modeling recreational choice behavior (Schuhmann and Schwabe, 2004; Bujosa et al., 2015; Timmins and Murdock, 2007).

Another point of interest is that the goodness of fit seems to favor CBDT in the samples for different species. These results suggest that heterogeneity plays an important role in modeling decisions. The parameters in CBDT are significantly different and CBDT performs better by in-sample fit

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compared to the other models. This shows the importance of heterogeneity by species. Inclusion of interaction terms in the model by species- or species-specific models- may be more appropriate when estimating location choice for anglers.

8 Simulation of Welfare Changes

We use simulated data to demonstrate the errors in estimating welfare when ignoring non-linear aspects of dynamic choice when the data generating process is from a case-based decision maker. We conducted this simulation for two reasons. First, it allows us to add a measure of marginal utility of money, which is lacking from our recreational fishing data. Second, we can run controlled experiments with simulated data varying the relationships between random variables.

The generated discrete choice data follows equation 14, where we index the current period (*t*) to reference past periods (*q*), in memory. Decision maker *i*, considers attributes, *k*, for two locations *j* = [1,2] with a random variable for travel cost, *C*. We use specifications of travel cost data from Melstrom and Lupi (2013) to inform our simulated data. The site attributes (*k*) are expected catch rate (ECR) and site congestion (SC), and the index for time (*period*). Additionally, we assume the error term, ϵ_{ijt}, to be independent and identically distributed and from the logistic function. Following the premise behind CBDT, memory is constructed on the three previous periods, after which the fourth and subsequent periods are forgotten. Memory in this and other empirical work (Pape and Kurtz, 2013; Guilfoos and Pape, 2016; Guilfoos and Pape, 2020) appears to be highly discounted. Using the assumption of only three periods in memory is similar to highly discounting further periods. The result (or reinforcement mechanism) is a binary indicator that equates to one if the fisher caught their preferred species at location *j*, referenced as catch.

$$CBV_{ijq} = \beta_0 + \beta_1 * C_{ijt} + \sum \frac{catch}{e^{\sqrt{\sum w_k \left(p_{kijt} - q_{kijq}\right)^2}}} + \epsilon_{ijt} \tag{14}$$

Descriptive statistics for the parameters and the distributions of random variables are provided in Table 6. Each simulation contains 1000 anglers, over 20 time periods (40,000 observations), and is repeated 500 times. We have left aspiration levels out of our simulation since we did not estimate them in the empirical section. It is worth noting that if included, aspiration levels would shift welfare measures similar to intercept terms from a linear additive model

In Table 6, the correlation parameter describes the level of correlation between ECR and C. After each simulation, we use the standard logistic model to estimate the coefficients from equation 15. We then use a Wald test to assess if the recovered coefficients are equal to the ‘real’ coefficients that generated the data. The travel cost coefficient, β_1, and the coefficient on a prior catch at location *j*, β_4, is

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used to assess how the marginal willingness to pay for a target species is estimated. Since we assumed a linear additive cost structure, the 'real' coefficient is equal to -0.065, which is the marginal utility of money. While the marginal increase in the previous period catch is one over the average similarity function from the previous period, 0.517, we can further accumulate the value of all past catches as far back as an individual's memory goes to assess the cumulative effects of catches at a particular location. Willingness to Pay for a site is acquired in the same manner, provided we assume a value for past catches or the expected value of catching the preferred species.

$$CBV_{ijq} = \beta_0 + \beta_1 * C_{ijt} + \beta_2 * ECR_{ijt} + \beta_3 * SC_{ijt} + \beta_4 * Catch_{ij,t-1} + \epsilon_{ijt} \quad (15)$$

The error rate in identifying β_1 is high (100%) with a p-value < 0.05, with a statistical difference in the real cost coefficient and the estimated cost coefficient at close to 100% of the time. The error rate in identifying the marginal value of a previous catch is also high (100%) with a p-value < 0.05. The mode and mean of point estimates for $\hat{\beta}_1$ are systematically lower than the 'true' parameter, which inflates the willingness to pay of any attribute. As the correlation between a random variable within the similarity function and the linear additive part of the data generating process increases, so do the issues with precision around the marginal utility of money and with the bias in the estimated $\hat{\beta}_1$.

The marginal willingness to pay for a preferred species by construction is $7.96. The LA model retrieves between $9.36 and $10.73 with a larger bias with high correlations between random variables. This demonstrates a concern with the bias in welfare when the data generating process is case-based and nonlinear in ways that a linear specification mis-specifies.

This simulation demonstrates that in dynamic processes it is easy to mis-specify the choice data generating mechanism when omitting the dynamic aspect. This is of course a weak empirical test of the importance of case-based decision theory as many types of dynamic data generating mechanisms would also produce results that are different than the linear models would predict. Future work must investigate which theories are consistent with the data, how to structurally estimate known behavior, and to construct tests of validity for the behavioral theories.

9 Discussion and Limitations

We find some support to recommend case-based reasoning to empirical location choice data. First, our results show that CBDT does a good job explaining the data using out-of-sample goodness of fit. CBDT does well in reproducing the choice data across different cutoffs. Replicating the data generating process is of particular concern for the external validity of estimates and welfare estimates when considering non-market valuation.

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There are limitations to the CBDT approach. When applying models to empirical data, the researcher often does not know much about the choice data, such as the experiences that shaped preferences. Therefore, in constituting an individual's memory using CBDT, we may leave out or misconstrue what is in memory or how a particular memory enters into utility. In panel data where repeat observations are available, there is a natural definition of the memory to draw on, the past experience of the decisionmaker. Our framework naturally suggests itself to panel data in which memory can be easily defined. Much of the work done on location choice has used surveys in the past and oftentimes it is not a panel of data. Yet, we imagine that other methods could be used to supplement survey data or cross-sectional data to define memory or history. One potential method is to join cell phone data that gives insight into location choice histories[9]. Another is to develop repeat surveys with more extensive histories, ratings of past trips, or particularly salient experiences. Though domain specific knowledge about information available to decision makers should be used in defining all primitives of the decision problem in empirical applications.

Exploration is another aspect of behavior that may be relevant for angler behavior. In the deterministic formulation of CBDT not reaching a satisficing level of utility leads to more exploration. There are three elements that affect this exploration behavior in our applied setting that differ from this deterministic interpretation. First, we have a stochastic decision process where the exploration may occur randomly. Second, we have few locations in the choice set and estimate initial attractions to each, which may confound preferences for exploration as preferences for the areas. Third, if the coefficient weights in the similarity function are estimated to be negative that would lead to greater exploration or variety-seeking behavior in those attributes of the 'problem'.

One difficulty in measuring how a location choice enters into utility is the 'result' of a particular choice. In our case, we use the catch that a recreational fisher gets as their reward for fishing in a particular location. This is a proxy for actual utility. An ideal data set would be a panel of choice observations where the information set and result is known to the researcher. The lack of a 'result' is a limitation in most travel cost studies. CBDT suggests that this is a vital piece of information that would reinforce choices in a repeated choice setting. In our setting, recreational fishers may be motivated by the number of fish caught, type of fish, size of the fish caught or spending quality time with family. Information about the level of success attained due to a past choice made is an essential determining factor behind how individuals make future decisions. We feel that catching a target species is a good proxy measure of the result, though, in other settings, a measure of success of a choice may be difficult or impossible to know or omitted from survey data.

Another limitation of this study is omitted variables. We lack information about fishers' individual characteristics, such as income, education, and travel cost to the site. While we contend that the omitted variables do not favor one model over the other, a complete set of variables is desirable.

Fisheries economists have applied other models that incorporate alternative specific characteristics into the model. A prospective future application in CBDT accounts for unobserved heterogeneity by allowing parameters to vary across observations. Such a model would be comparable to a latent class or mixed multinomial logistic model.

10 Conclusion

In this study, we find that case-based decision theory explains location choice behavior well. We find in-sample goodness of fit favors a linear additive state dependence model, while the out-of-sample goodness of fit favors CBDT. Using both models, or mixes of behavioral models in investigating empirical choice can only give us more insight into the mechanisms for choice and the importance of information to the decision makers. Building upon the state-dependence literature, our work confirms that dynamic elements in fishery location choice is extremely important.

The compact and parsimonious CBDT model is promising for behavioral modeling of discrete choice data. It may explain data better and adds an element of value in the dynamic importance of information. Further research is needed to better match and collect data for behavioral decision making models such as CBDT. However, we can imagine future surveys' future efforts may capture explicit measures of success of trips and aspiration values. Further work may also find when or if this type of behavioral modeling is needed to understand the observed choice.

Care needs to be taken when considering discrete choice modeling and non-market valuation work. Using simulation data, we demonstrate the reduced form model's potential bias, assuming that the data generating process is case-based.

This work and past empirical work on CBDT (Guilfoos and Pape, 2020; Kahneman, 2003; Gilboa et al., 2007; Bleichrodt et al., 2017; Ossadnik et al., 2013) suggest themselves to other applications outside of location choice modeling. Behavioral modeling is not limited to the functional form of choice but can involve cognition, rationalization, or other psychological aspects of choice. The extension of behavioral modeling, and specifically case-based reason modeling, to other choice settings, may provide more accurate welfare estimates if the models better match our understanding of how people make decisions.

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Tables

Variable	Mean	Std Dev	Min	Max
Expected Catch Rate	12.23	11.35	0.43	112.9
Period	100	120	1	502
Site Congestion	0.12	0.15	0	1
Site History (Yes = 1)	0.87	0.33	0	1
Payout	0.69	0.46	0	1

Table 1: Summary Statistics of Key Variables

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	Log-Likelihood	AIC	BIC
Linear Additive Model	-1194.66	2439.32	2590.95
CBDT Euclidean	-928.31	1876.62	1937.28
CBDT City-Block	-922.09	1864.18	1924.84
State Dependence Model	-845.23	1748.45	1924.34

Table 2: Comparison of Model Selection Criteria. Notes: AIC and BIC denote Akaike Information Criteria and Bayesian Information Criteria respectively. In the above model selection criteria, the smallest represents the preferred model.

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`	Percentage of Memory				
	15%	25%	50%	75%	90%
Linear Additive Model	-44247	-6543	-1643	-363	-163
CBDT Euclidean	-961	-805	-447	-207	-85
CBDT City-Block	-934	-788	-432	-209	-86
State Dependence Model	-25081	-7379	-396	-252	-123

Table 3: Out-of-Sample Fit: Log-likelihood Comparison. Notes: In the above model selection criteria, the largest log-likelihood represents the preferred model. Columns represents different percentage of decisionmakers memory used to predict the remaining percentage of choices.

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	Fishing Area as Dependant Variable				
Variables	(1)	(2)	(3)	(4)	(5)
Area 1 (Initial Attraction)	2.99***	0.56***	0.35***	0.29***	0.26***
	(0.38)	(0.09)	(0.06)	(0.05)	(0.05)
Area 2 (Initial Attraction)	-1.23***	-0.24**	-0.21**	-0.18***	-0.16***
	(0.52)	(0.11)	(0.08)	(0.07)	(0.06)
Area 3 (Initial Attraction)	-2.54***	-0.49***	-0.41***	-0.33***	-0.30***
	(0.66)	(0.14)	(0.11)	(0.09)	(0.08)
Area 4 (Initial Attraction)	-3.45***	-0.67***	-0.58***	-0.48***	-0.44***
	(0.78)	(0.16)	(0.13)	(0.10)	(0.10)
Area 5 (Initial Attraction)	5.02***	0.99***	0.64***	0.49***	0.45***
	(0.48)	(0.12)	(0.08)	(0.06)	(0.06)
Sensitivity Parameter (λ)	41.7***	207.9***	267.2***	333.2***	358.05***
	(2.99)	(21.82)	(25.52)	(31.25)	(34.36)
Expected Catch Rate	0.01***	0.02***	0.00*	0.00	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Period		0.068***	0.065***	0.043***	0.20***
		(0.01)	(0.01)	(0.01)	(0.02)
Site Congestion			542.8**	412.2**	10.17***
			(105.8)	(84.8)	(1.39)
Site History (Yes=1)				8.57***	1.60***
				(1.74)	(0.18)
N	3182	3182	3182	3182	3182
AIC	2611.85	2413.51	2041.11	1876.63	1864.18
BIC	2654.31	2462.03	2095.69	1937.28	1924.84

Table 4: Estimated Parameters using CBDT. Notes: The first column lists the site choices and variables used in the model. The respective parameter estimates for the areas, the sensitivity parameter as well as the CBDT weights estimated for each variable for four CBDT models is mentioned in the subsequent columns.The standard error and significance are given parenthesis. ***, ** and * denotes 1 percent, 5 percent and 10 percent significance level. Columns 1 through 4 use Euclidean distance while column 5 used City-Block distance.

	Striped Bass	Blue Fish	Fluke	Sea Bass
(ii) Model Selection Criteria (BIC)				
LA	1387	727	862	506
SD	1053	620	724	434
CBDT	1034	566	739	392
	1848	1027	964	413
(ii) Similarity Weights from CBDT				
Expected Catch Rate	0.003*	0.002	0.008***	0.001
Period	0.054***	0.53***	0.012**	0.12***
Site Congestion	24.14**	71.51**	256.61***	882.9***
Site History	12.67**	1.27*	7.26***	0.08

Table 5: Model Selection & Estimated Weights for Different Target Species. Notes: The four columns represent the top four target species preferred by recreational fishermen in this data set.

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Variable	Description
Period	Takes values from 1 to 20.
Travel Cost (C)	= N(60,20)
Expected Catch Rate (ECR)	= N(2,0.2)
Site Congestion (SG)	= 0.5 + U[0,1]
Catch	= 1 if N(2,0.2) > ECR for sites visited.
Correlation Parameter	In number range from 0 to 0.90
Intercept (β_0)	= 1 for site j=1 and =2 for site j = 2
Travel Cost Coefficient (β_1)	=-0.065
Recency Similarity Coefficient (w_1)	=1
ECR Similarity Coefficient (w_2)	=0.20
SG Similarity Coefficient (w_3)	=0.85

Table 6: Description of Simulated Data

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Figures

Fig 1. Map of Long Island Sound. Caption- This map denotes the areas in our study area, which is restricted to areas 141, 142, 143, 144, 145, and 146.

Notes

1 There is a robust literature on learning models and Markov decision models that do not use these same assumptions. However, these are typically not used in non-market valuation or location choice modeling.

2 Behavioral anomalies can be important to model selection. For instance, if loss framing is important, then a model based on prospect theory may be appropriate and performs better out-of-sample.

3 The website https://www.fisheries.noaa.gov/content/fisheries-economics-united-states-2016

4 There are many possible choices for the result which we explored. These could be the number of fish caught or the weight of the accumulated catch. We find that the target species is a good proxy for the result in this setting.

5 This point is made in Guilfoos and Pape (2020).

6 The website http://www.ct.gov/deep/cwp/view.asp?a=2696&q=322750 provides details about VAS program in Connecticut.

7 The website https://www.ncdc.noaa.gov/ provides details about the NCEI and details about how to obtain weather data and information.

8 The document https://www.greateratlantic.fisheries.noaa.gov/public/nema/apsd/vtr_inst.pdf is the Fishing Vessel Trip Report Reporting Instructions for the Great Atlantic Region provided by NOAA. It provides details about the areas appropriated into grid codes in the New England region.

9 Safegraph or similar data companies could be used to mine data on visitations and potential representative memories for defining the information of the problem. We thank an anonymous reviewer for this suggestion.

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