MODELING PREFERENCES ONLINE

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Abstract: The search for an online product that matches e-shoppers' needs and preferences can be frustrating and time-consuming. Browsing large lists arranged in tree-like structures demands focused attention from e-shoppers. Keyword search often results in either too many useless items (low precision) or few or none useful ones (low recall). This can cause potential buyers to seek another seller or choose to go in person to a store. This paper introduces the SPOT (Stated Preference Ontology Targeted) methodology to model e-shoppers' decision-making processes and use them to refine a search and show products and services that meet their preferences. SPOT combines probabilistic theory on discrete choices, the theory of stated preferences, and knowledge modeling (i.e. ontologies). The probabilistic theory on discrete choices coupled with e-shoppers' stated preferences data allow us to unveil parameters e-shoppers would employ to reach a decision of choice related to a given product or service. Those parameters are used to rebuild the decision process and evaluate alternatives to select candidate products that are more likely to match e-shoppers' choices. We use a synthetic example to demonstrate how our approach distinguishes from currently used methods for e-commerce.

1 INTRODUCTION

The search for an online product that matches e-shoppers' needs and preferences can be frustrating and time-consuming. Information about products and suppliers is usually accessed from database servers using either list browsing or keyword search. However, the amount of information available in those databases has substantially increased the cognitive effort required for e-shoppers to make their choices. Browsing large lists, arranged in tree-like structures can be time consuming, while keyword search often results in too many useless items and too few actually useful (or none) being returned. Thus, instead of facilitating the choice (and the sale), the Internet makes the e-shopper's choice decision-making process more difficult. Such difficulty is frustrating and is detrimental to online sales.

Addressing customers' needs is crucial for e-commerce. E-commerce systems should be able to facilitate the customers' choice process by offering alternatives that are more likely to satisfy their preferences. This would generate less frustration and potentially increase revenues, service level and customer's satisfaction.

Personalization is an approach that uses characteristics of individual users to select information to be searched and displayed to users (Cotter & Smyth 2000). Recommender systems for e-commerce (e.g., Ardissono & Godoy 2000; Domingue et al. 2002, Burke 2000) address the personalization issue by filtering the amount of non-requested products to be showed to the e-shopper in a given session. Recommender systems can be collaborative, content-based, demographic, utility-based, and knowledge-based (Burke 2002).

Recommender systems are useful when customers do not know exactly what product or service they need, or when the company wants to introduce different products to the user. However, when customers roughly know their needs and the type of product or service to address those needs, the problem is to find the best available online option according to the user's viewpoint. This problem is typically addressed only by utility-based recommender systems (Burke 2002). As a comparison, in a physical store, the shopper would be able to use other senses (e.g. vision, touch) to recognize available products and compare them

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before choosing one, or ask a sales person for advice. On the Internet, however, they have to rely on their decision-making skills and the available information to choose the best option.

This paper proposes the use of the economic theory on discrete choices (Ben-Akiva & Lerman 1985) to help e-shoppers find the best match for their needs from what is available on the Internet. In this sense, it can be categorized as an utility-based recommender. *Our approach is to elicit from e-shoppers how they make choices, build a model of their choice behaviour, and use it to refine the search and show products and services that meet their preferences*.

Discrete choice modeling has been largely used in the transportation field to forecast travel demand from disaggregate data on individual choices (Ben-Akiva & Lerman 1985; Fowkes & Shinghal 2002). For example, it is used to forecast demand by finding the likelihood that a travel mode is chosen given certain characteristics such as travel time, comfort, and headway. The rationale for using discrete choice modeling is that it is a mature methodology to uncover users' decision-making processes without asking them directly.

The mathematical model – Logit is very robust and it is likely that the user's decision-making model found is the best possible (Ben-Akiva & Lerman 1985). Alternative methods (e.g. non-linear) are computationally more complex, more demanding to the user, and their result has been shown to be only marginally better (De Carvalho, M. 1998).

Section 2 reviews methods used in this work: discrete choice modeling, stated preference, ontologies, and personalization. The SPOT methodology is described in Section 3, followed by a demonstration that uses statistics-based simulation in Section 4; Section 5 is a discussion and Section 6 concludes.

2 METHODS

2.1 Discrete Choice Theory

The term *choice* refers to the cognitive process of a consumer who, after evaluating the alternatives in a *choice set*, decides to select one of them (Louviere 1988). Discrete choice modeling is a well-known and mature methodology (Ben-Akiva & Lerman 1985) to investigate that process. The main feature of discrete choice data is that the observed response (i.e. the dependent variable) is discrete: the method only determines whether or not customers choose one alternative option.

Discrete choice models can use compensatory or non-compensatory rules. Compensatory models allow offsetting changes in one or more attributes to compensate for a change in a particular attribute (implying simultaneous consideration of all attributes). For instance, a roomier seat can compensate for a higher price in air travel. By contrast, non-compensatory models do not permit trade-offs between attributes; comparisons are made on a sequential consideration of each attribute. The last decision is often based on a compensatory model to compare final options (if more than one). This is the decision-making situation faced by e-shoppers on the Internet.

Discrete choice modeling is based on the economic utility theory for compensatory models with the following four assumptions about the consumer behaviour.

1. Products or services can be represented in vectors of feature-value pairs (attributes), e.g. cost, brand.
2. Customers are optimizers and they compare options based on the value of their attributes.
3. Customers make trade-offs between attributes of a product/service to reach their decision, e.g. in transport service, less comfort can be accepted if the fare is reduced.
4. Customers are maximizers and they always choose the best perceived option within a knowledge domain.

2.2 Stated Preference

Stated Preference (SP) is a technique used to collect data on individual's discrete choices (Pearmain & Kroes 1990). It can be understood as a simulation game where individuals are asked to state their preferences for a set of possible options (i.e. choice set). A choice set is composed of at least two alternatives e.g. a trip can be characterized by the attributes cost and in-vehicle travel time. A choice set would consider the transportation modes car and train, each mode being represented by its respective cost and travel time. The number of choice sets is developed according to the number and levels of attributes to be considered.

The design of a SP collection must consider trade-offs between attributes of the product or service. Respondents should be given choice sets with possible options, but it is not necessary to know exactly which options are available and the exact values of the attributes; the attribute values should be as close to reality as possible. An Internet collection can be designed at runtime (e.g. using the support of a knowledge base).

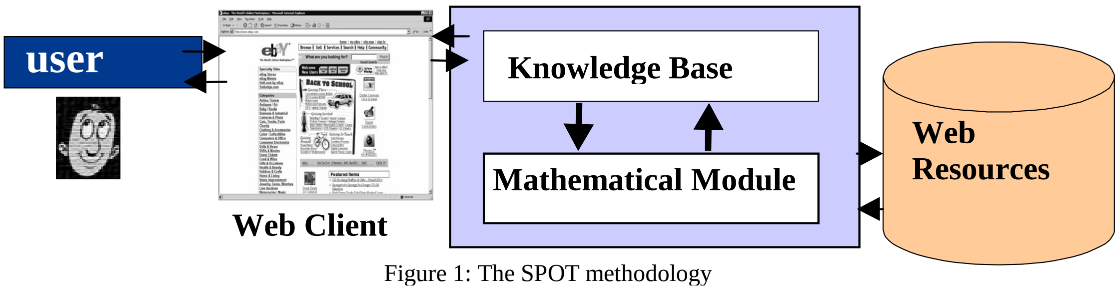

Figure 1: The SPOT methodology

A desired property of a SP collection is orthogonality (zero correlation between attribute values and alternatives), so that separate effects on choices can be estimated, as well as possible interaction effects of their combinations. For the sake of demonstration (Section 4) we are employing a full factorial design that guarantees orthogonality (Kocur et al. 1982). On a real situation, fractional designs have to be employed to reduce the respondents' fatigue. Factorial design provides a way to investigate the interaction effects between attributes, such as price and travel time. To measure all interaction effects one should use a full factorial design, which is a problem that grows exponentially. Fractional factorial designs are employed to reduce dimension and the number of alternatives users have to analyse. In that case, some minor interaction effects are ignored in the experiment.

In our proposed approach, customers' stated preference data is used to calibrate a Logit model (Ben-Akiva & Lerman 1985) that will unveil the parameters (weights) that the e-shopper would use to evaluate and choose one online option.

2.3 Logit Modeling

Logit modeling assumes that options are represented by a function (U_i) composed of unobserved variables (β_j), which are somehow associated with characteristics (X_{ij}) of the product (*i*) and a random term (ε)(See Equation 1). The function U might be continuous or not, depending on the type of the attributes. If price is continuous and colour is discontinuous, then a function with both these variables would necessarily be discontinuous at some point. The values of the coefficients are found from data containing trade-offs between attributes that are therefore incorporated into the modeling.

$$U_i = f(\beta_j X_{ij}, \varepsilon) \qquad \text{Equation (1)}$$

The coefficients (β) on the observed characteristics (X_{ij}) in the utility function (U_i) are estimated with an optimization procedure such as Newton-Raphson (Ben-Akiva & Lerman 1985). The exponential behaviour (*e*) is employed to explain predicted probabilities (P_i) of a particular response ("buy" or "not buy") regarding an alternative "i" (See Equation 2) belonging to the choice set with "J" options. Thus, the likelihood that an alternative is chosen is expressed as a function of its attributes and the other options available in the choice set.

$$P_i = \frac{e^{Ui}}{\sum_j e^{U_j}} \qquad \text{Equation (2)}$$

As maximizers, individuals place their preferences in the alternative they recognize as having the highest utility value ($U_i > U_j$). The analyst uses the modeling approach to be able to find the likely coefficients underneath the decision that has determined the choice. Considering that some of the variables influencing the choice might not have been accounted for, a random term is added to the model. In case of Logit, Luce (1959) has shown that the random term is independent and identically distributed according to the Weibull distributions. This means that alternatives are uncorrelated and also independent. We will use this characteristic of the model as the base to create synthetic data and demonstrate our approach (Section 4).

2.4 Web Personalization

Web personalization is concerned with schemes that select the type and quantity of content to be shown to the e-user based on individual profiles. Personalization applications for e-commerce usually show products and services the e-shopper did not ask for, hoping that some of them will catch his or her attention.

Content-based filtering makes recommendations based on comparisons between resources and the user's profile. Results retrieved are based on their similarity to what the e-shopper has previously shown interest. Collaborative filtering selects products or services that are recommended or used by the e-shoppers' peers by identifying groups of users with similar characteristics and interests (Cotter & Smyth 2000).

The approach in this paper can be considered both utility and knowledge-based. Utility-based because it models utilities of an option; knowledge-based because it proposes the use of ontologies for representing knowledge related to online shopping. Ontologies are knowledge models that retain conceptualizations that are explicit, consensual, and conceptual (Gruber 1993). ALICE (Domingue et al. 2002) is an example of an ontology-based recommender system.

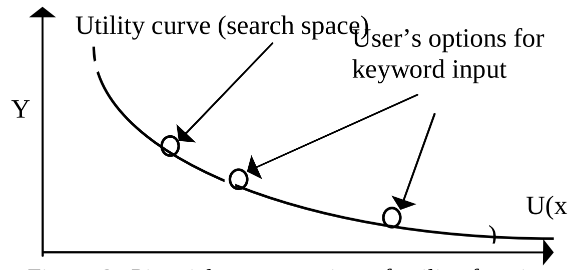

Figure 2: Pictorial representation of utility function (U(*x*))

3 SPOT METHODOLOGY

The Stated Preference Ontology Targeted (SPOT) methodology (Figure 1) for web personalization uses the implicit user's decision function to find the product or service with the highest likelihood of being considered by the e-shopper in a given e-session. While keyword search methods use words to find related information, SPOT uses the individual's decision function (i.e. utility) to search the web space and find appropriate offers. Figure 2 is a pictorial representation of the search space, i.e. data points and extrapolation points. One can understand those points as choice possibilities or products. The approach suggested in this paper builds a user profile based on the individual's utility curve, instead of those based on isolated points whose matching product options might not exist.

The core of the methodology is stated preference: the technique employed to collect individual data on discrete choices (i.e. how individuals make decisions). Once enough data is collected, the model is calibrated using Logit modeling. The results are coefficients relating product attribute values and their importance to the users. Those coefficients are then used to rebuild the utility function for each alternative of product available online. Those with the highest likelihood value should be shown to the user. The two main modules in SPOT are the knowledge base and the mathematical module. The knowledge base retains ontologies, (e.g. products, customers' profiles, communities); the mathematical module manipulates algorithms for modeling the discrete choice data, and for analysis of the results.

3.1 Knowledge Base

We are assuming that within the semantic web, products and services will be described using product ontologies. Standards for defining and classifying goods have already been developed, such as ISO 10303 (step) and can be used as the basis of products ontologies. Such ontologies will contain links to web pages of those companies providing the service, and to product attributes that customers might consider important (and therefore use in their decision-making).

The ontology-based recommender system ALICE (Domingue et al. 2002) includes ontologies for customer, products, typical shopping tasks, and the external context. Ontologies are populated as they are linked to the company's databases. Two important ontologies in ALICE are Customers and Products. Customers ontology defines slots about customers (their typology, how they use the product, which attributes are important, etc.). The Product ontology contains information about the product, such as type and attributes.

As product ontologies grow, so does the need for more sophisticated methods to select products to offer to users. The SPOT methodology can be implemented on top of e-commerce systems such as ALICE (ibid) to address the selection problem. E-shoppers' preferences and information about their decision-making processes would be part of the customer's ontology.

Another characteristic of incorporating knowledge bases to e-commerce systems is the potential to systematically discover knowledge from collected data. Kozinets (1999) suggests the identification of true communities of consumption by clustering information on individuals' profiles i.e. gathered in their buying decision-making processes.

4 SYNTHETIC STUDY

We demonstrate our approach using a theoretical example of an online search situation where we compare keyword search with SPOT.

4.1 Methodology

A factorial design was used to gather choice answers for a simulated customer. The full factorial design guarantees that calibration results are significant. Alternative options were built with the purpose of showing how the proposed methodology compares with the traditional database search. The data contains choice sets with three alternatives each, which are evaluated in three attributes (Table 1: Attributes 1, 2, and 3). For instance, a transport option could be characterized by its cost, travel time, and headway. High and low (Table 1) indicate extreme ranges for the options.

Table 1 Attribute levels for the 512 choice scenarios

	Alternative 1		Alternative 2		Alternative 3	
	low	high	low	high	low	high
Attribute 1	30	80	40	100	50	120
Attribute 2	20	45	15	30	10	40
Attribute 3	30	15	60	20	70	30

The synthetic data is created based on a full factorial design so that our simulated customer made 512 hypothetical discrete choices. Of course, in a real situation there are other methods (Fowkes & Shinghal 2002) that can be employed to reduce this number to an acceptable value and still show good calibration performance.

The simulation approach is based on the fact that we *know* the deterministic part of the utility function used by decision makers in a choice situation. The random term is the unknown part of the utility but we know its distribution mean and standard deviation. The total utility for each alternative is found by adding the random term (Weibull distributed) to the deterministic utility component (see Equation 1). A linear function that adds the option attribute values by its respective weight is employed to find the deterministic component. The probabilistic part is simulated using the method of the inverse function. Thus pseudo-random numbers are created according to the inverse of the Weibull probability distribution (Equation 4) and used as the behaviour of our simulated individual regarding his choices. Following is a brief explanation of the Weibull probability distribution as the base to create data that follows Logit assumptions.

4.1.1 Weibull Probability Distribution

The random part of the utility refers to unknown variables influencing the choice process, from the analyst point of view. For instance, taste variation. Logit modeling is based on the assumption that such random term is Weibull (or Extreme Value) distributed (Luce 1959) as in Equation 3. Therefore, knowing the inverse of the cumulative Weibull distribution function (Equation 4), it is possible to recreate a SP experiment synthetically. This procedure allows one to compare methodologies on the bases of what the answers would be.

$$F(\varepsilon) = e^{-e^{-\mu(\varepsilon-\eta)}} \qquad \text{Equation(3)}$$

Assuming η=0, the inverse of that function (Equation 4) results in a random number (ε) which is Weibull distributed. This number would account for the uncertainties in the modeling a process analysts do not know (though known by the decision-maker).

$$\varepsilon = \frac{-\ln(-\ln(u))}{\mu}, \qquad \mu = \frac{\pi}{\sqrt{6} * \sigma} \qquad \text{Equation(4)}$$

Where u = a uniformly random number; σ = standard deviation; η = location parameter.

Table 2: Calibration results for SP discrete choice data

Likelihood	-176.7801
Rho-Squared	0.6857
N. iterations	7
Coefficients	
Attribute 1	-0.03697 (-9.2)
Attribute 2	-0.03057 (-12)
Attribute 3	-0.03032 (-5.5)

The synthetic data (composed of 512 choice scenarios and the choice) is then used to calibrate a Logit model that reveals the weights the customer used to make the choice. The performance of the calibration is investigated using a well-known econometric test, Rho squared. Results from calibrating our synthetic data are shown in Table 2. Rho squared is quite high and coefficients are significant, as expected (since we are using data that follows Logit modeling).

Table 3: Choice options and respective utility values

Option	Attr. 1	Attr. 2	Attr. 3	Utility*
1	30	20	15	-7.6779
2	30	45	30	-15.7752
3	30	45	30	-15.7752
4	30	45	30	-15.7752
5	30	45	30	-15.7752
6	100	30	20	-13.4744
7	40	15	60	-7.8835
8	120	40	30	-17.574
9	50	10	70	-7.0279
10	50	10	30	-5.8151
11	50	40	70	-16.1989
12	50	40	30	-14.9861

Additionally, coefficients used to create the data could be roughly recovered. Therefore, we are using these coefficients to evaluate the alternative options in Table 3. Observe that in our special case we know the true coefficients employed to create the data. In real situations those coefficients are only known employing a mathematical model. A major advantage of using synthetic data is that we know beforehand the deterministic part of the utility function and the parameters used to create the random part. Then, we can evaluate the results comparing them with the known function used to create the data. The following tables show the results from calibrating the SP synthetic dataset.

4.2 Results

Table 3 shows for each option (1 to 12) their attribute values and their respective utilities. For instance, the values of Attributes 1, 2 and 3 for Option 1, are 30, 20 and 15, respectively. In case of a transport option it could be 30 minutes travel time, 20 minutes waiting time, and price of 15 USD, or nominal values. Table 3 is the database of available options for a searching system.

Given the database of 12 possible choices shown in Table 3, we examine Situation 1 and Situation 2, where we employ respectively keyword search and SPOT. Results are shown in Tables 4 and 5.

Situation 1: The user inputs a keyword that matches at least one of the available options. For instance, value of 40 to Attribute 1.

Table 4: Results for Attribute 1 = 40

Method	Result shown to the user
Keyword search	Alternative 7 (40, 15, 60)
SPOT	Alternatives 9, 10 and 1

Keyword search shows Alternative 7 as its own possible match. SPOT methodology using the value of the utility of all alternatives, would show three results corresponding respectively to 1st, 2nd, and 3rd places.

Situation 2: The same user inputs a keyword that does not match any of the available options (quite common on the Internet for travel services like car rental). For instance, value of 60 to Attribute 1.

In Situation 2, the keyword search method does not return any possibility. On the other hand, SPOT methodology returns 3 possible alternatives. In this case, we are employing a compensatory model and the three attributes are evaluated at once. However, a non-compensatory model can also be employed to perform a pre-selection of maximum or minimum attribute values. As an example, the user would not accept to pay more than US$ 50 for the trip.

Table 5: Results for Attribute 1 = 60

Method	Result shown to the user
Keyword search	None
SPOT	Alternatives 9, 10 and 1

Given results shown on Table 3, the best choice from the customer decision-process viewpoint would be Option 10 (the highest utility), which is highlighted.

In this theoretical example, we illustrated how using knowledge about the user's decision-making process can improve the quality of the online search results. For instance, in case of Situation 1, only one alternative would be shown to the user (Option 7 in Table 3). This alternative would not even be considered by the user as there are others with higher utility value (Table 3). On the other hand, Situation 2 would show no results to the user; as the criteria do not match any of the alternatives in the database (Table 5). This is quite a common situation in e-commerce sites.

5 DISCUSSION

A recommender system is one that, based on certain criteria, recommends products or services. Current personalization schemes are mainly focused on delivering contents that are either similar to users' profiles (i.e. content-based) or are recommended by their peers (i.e. collaborative). Information on e-shoppers (e.g., history, profile, preferences) is used to feed the personalization scheme. A comprehensive review of recommender systems is given by Burke (2002). Being utility-based, this paper addresses a slightly different problem: *how to help the e-shopper decide between the choices available on the Internet*.

Usually, the information gathered over the Internet from recommender systems is not used for other purposes than to feed the personalization scheme. These schemes do not address ways to improve the company's decision strategies (such as product design), or how it could help the e-shopper's choice decision-making process. Helping the e-shopper in this decisive moment has the potential not only to increase the company's sales but also to improve the knowledge about their customers' values. That is often a strategy used in physical stores where the sales person often has a decisive impact on the choice.

Figure 3 illustrates a real situation of online car rental pictured on a shopbot web page. Shopbot is an e-commerce portal where users have access to different web service providers and can compare their offers as well as buy them. In this web site, the e-shopper begins the search process filling out a form with some parameters (e.g., car size, pick-up day, pick-up location). Those parameters are used to search the server database for available options. Quite often the search is unsuccessful at the first time. There are different reasons for that. For example, the specific supplier may not have branches on the pick-up location, or the requested car size is not available. Eventually, the user has to change the search parameters a couple of times in order to find one offer. When the user finally manages to find some offers, she or he has to reason and decide for one of them or none. It might be the case that by evaluating the choices available, the user considers that all offers are overpriced compared to the prices of the cars and decides not to buy the service. Therefore, instead of hiring a car, the individual might decide to use local public transport, or a taxi service. Note that decision processes vary according to the individual and the situation. Whether the individual is shopping for himself or for a company may change the decision model.

From the perspective of the car rental company, it could be a lost sale. If only the car-rental company new how individuals evaluate the different attributes of the service, they would try to show alternative options from the customer perspective. Maybe showing an offer with a better car would give the correct balance between the price of the car and the rental value.

In the example above, we are assuming that the user evaluates the car rental options considering the price of the vehicle being hired and alternative ways of transport (such as public transport and taxi). Other decision models for this service would consider car-size within an acceptable price-range. In the car rental business, companies are often bounded to specific carmakers. Moreover, they have prices tied to combination offers that force the consumer to purchase at least two services. A web portal offering such car rental services would benefit from the SPOT approach, as it would *always* show options regarded by the user as relevant. With currently used methods, the search usually has to be repeated a couple of times with different keywords before a reasonable option comes up as a result.

Furthermore, the SPOT methodology is based on knowledge about how customers evaluate product characteristics, e.g. what sort of decision process they perform, which attributes and variables they consider. This is an application with potential to take full advantage of the semantic web infrastructure. It can search semantic information on products (i.e. from products ontology) and service information, and populate ontologies on customers' profile. Although ontologies are seen as the core of the semantic web, actual applications are still in their infancy. An initiative for transforming knowledge about products and services into a world common ontology is ISO 10303, an International Standard for product data representation and exchange. However, there is still need for technologies that enable application systems to exchange and share data about technical products. Their product classification cannot be used as a complete ontology, as the definitions tend to be semantically weak.

6 CONCLUSIONS

The SPOT methodology discussed in this paper uses the evaluation of the online alternatives based on the e-shopper decision process. This personalization scheme will prompt advantageous options that the e-shopper would not find otherwise. The main purpose of SPOT is not to make recommendations on products that users may or may not be interested in. SPOT's main contribution is to help the user with the decision-making on products he needs but have difficulties choosing between the large amounts available on the Internet. This approach has the potential to substantially improve the relevance of the results shown to the e-shopper in an e-commerce session and therefore increase the likelihood of a sale. Even though the user would be anonymous during the session, results from the system allow the company to know the trade-offs individuals make between the characteristics of a product or service and use them to forecast online demand, improve products, etc.

This paper discusses a methodology that uses economic theory on discrete choices to link e-shoppers' decision-making process to available online options. The approach suggested in this paper builds a user profile based on the individual's utility curve, instead of isolated points (the user's criteria) whose options might not exist.

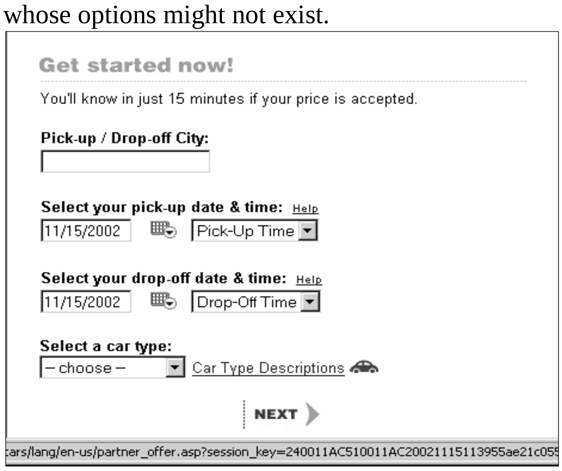

Figure 3: Online car rental shopbots

The main input to the proposed methodology is the discrete choice data, which is collected from interactive Stated Preference "games" that the e-shopper agrees to participate. The data is then used to calibrate a Logit model that will reveal the trade-offs the e-shopper employed in his or her choice decision-making process. Afterwards, these results are employed to search for the available options and calculate their values as the customer himself would. Options with high utility value are then shown to the e-shopper.

The benefits of using the methodology are twofold. First, it has the potential to increase customer satisfaction and therefore the likelihood of sales and revisits. Second, the information on customer's choice decision-making process gives the company insights on how to improve the business (such as product design and sales). The implementation of this methodology requires investigation of the user's decision-making process for each product and the development of friendly interfaces to reduce the time to collect stated preference data online.

The major challenge of implementing SPOT is the data gathering. The approach's input is data from an interactive SP game that demands customers' time. Customers have to be convinced that providing answers to the interactive game will give them a better service. A friendly interface can help overcome this problem by reducing the cognitive effort needed for the task.

Another alternative would be to insert an additional reasoning step and try to match a current e-shopper with a previously recorded decision-making model. This match could be based on similarity (i.e. using case-based reasoning) and would reduce the number of required questions to elicit the e-shopper's preferences.

We should also consider that customers may not be interested in wasting time to take part in a SP game that evaluates low priced products or services. This requires an analysis of the customer's value of time to discover the threshold from which they would be willing to compare options further. As a guideline, the company could employ this methodology only to the most profitable or high priced 20% products, which often represents approximately 80% of the company's profit.

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