THE NATURE OF TRAVEL DECISION-MAKING

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Travel decision-making is described in behavioral terms, and an alternative to conventional travel forecasting is suggested. Two issues are considered. The first is the order of travel decision-making. The second is the interaction of travel decisions. This paper defines the order of travel decision-making with expected utility theory, and it describes the interaction of travel decisions with dynamic programming. The resulting travel model is based on theories of decision-making and is unique in this respect.

•TRANSPORTATION planning has been dominated by engineering and economics throughout its brief history. As a result, conventional travel forecasting neglects the human element in intraurban trip-making. It is possible to improve travel forecasting by first defining the nature of travel decision-making and then applying the result to travel demand modeling. That is the purpose of this study.

Two issues are addressed: In what order are travel decisions made, and in what way do travel decisions interact? The literature on decision-making under uncertainty provides an answer to the first question. And the literature on dynamic decision-making provides an answer to the second. These answers lay the foundation for a unique travel demand model based on current theories of human behavior. This model is proposed as a practical alternative to existing travel demand models.

THE APPEAL OF SEQUENTIAL TRAVEL MODELS

In a recent paper, Brand (4) described alternative methods of travel demand modeling. His alternatives included sequential and simultaneous models. This paper is limited to sequential travel models for two reasons. First, they are more efficient than simultaneous models because the number of travel options (each of which must be evaluated) increases multiplicatively when decisions are combined. Two departure times for each of two modes, each with 10 alternative routes to 10 destinations, translate into 400 ($2 \times 2 \times 10 \times 10$) travel options for each origin in a simultaneous travel model. With literally hundreds of origins and additional times, modes, routes, and destinations, simultaneous travel demand models become unwieldy. Second, travel decisions are apt to be made sequentially rather than simultaneously. The multitude of options available to travelers forces them to simplify the decision-making process. They do this by making sequential decisions, thereby greatly reducing the number of travel options they must consider. Just as travel demand is modeled sequentially in response to the limitations of the digital computer, so may travelers simplify the decision-making process in response to their own limitations. Arguments of this nature are persuasive enough to justify the present emphasis on sequential travel models. Simultaneous travel models and the empirical choice between simultaneous and sequential models will be the subject of future research.

EXPECTED UTILITY THEORY APPLIED TO TRAVEL DECISION-MAKING

Conventional travel forecasting assumes that travelers choose a time of departure, a destination, a mode, and a route in that order. In some travel models, the choice of mode precedes the choice of destination, but the order is always predefined and invariant. This can be criticized on two counts. First, the conventional order is based on neither theory nor observation. It would certainly be fortunate if the conventional order proved to be correct. Second, it is likely that the order of travel decision-making depends on the available alternatives and thus varies with the situation. Any model that assumes a fixed order of travel decision-making cannot consistently reproduce the decision-making process. The following discussion is motivated by these concerns.

The order of travel decision-making has been ignored in the literature with the exception of a paper by Brand (4). Brand suggests several alternative methods of ordering travel decisions: order based on (a) information, decision-making proceeds from the most informed to the least informed decisions; (b) adjustment, decision-making proceeds from the least easily adjusted to the most easily adjusted decisions; and (c) timing, decision-making proceeds from the latest to the earliest decisions in time (that is, the logical order of decisions runs counter to their sequence in time).

It is not possible to choose among the three methods with the limited evidence available [see Feger and Feger (12) and Tate and Howell (23)]. Fortunately, no choice is necessary because a single theory incorporates them all. This theory is well established empirically and ranks among the foremost theories of decision-making under uncertainty.

Few subjects in psychology have received more attention than decision-making under uncertainty. Two reviews of this subject are noteworthy. Edwards (9) provides a useful introduction to the subject. Luce and Suppes (16) go into much greater detail. Readers who desire additional information should consult these reviews.

A prominent theory of decision-making under uncertainty, expected utility theory, defines the order of travel decision-making. Expected utility theory states that decision-makers, when faced with uncertainty, make decisions that maximize their expected utility. That is, they select the option with the greatest expected utility, where the expected utility of an option is given by

$$EU = \sum_{n} u_i p_i \tag{1}$$

where

u_i = utility of outcome i,
p_i = probability that outcome i will occur, and
n = number of possible outcomes.

Consider a decision-maker with several options. His first option has two possible outcomes. One outcome has a utility of 10 and occurs 40 percent of the time, and the other has a utility of 5 and occurs 60 percent of the time. From Eq. 1, the expected utility of this option is 7 ($10 \times 0.4 + 5 \times 0.6$). The decision-maker will choose this option only if his other options offer less expected utility.

Travel decision-making necessarily involves uncertainty if it is a sequential process. This is true even if individual travel decisions are made under certainty because future decisions are unknown. For example, if their first travel decision is the choice of departure time, travelers' neglect of destinations, modes, and routes introduces uncertainty into decision-making. Only after all travel decisions are made can the choice of departure time be evaluated with certainty.

Travel decision-making is comparable to gambling. Each decision represents a gamble. It is assumed that travelers evaluate all four travel decisions and make the decision with the greatest expected utility; then they reevaluate the remaining travel decisions and make the decision with the greatest expected utility. This continues until they have made all travel decisions.

Travelers are assumed to have complete knowledge of alternative departure times, destinations, modes, and routes. Individual decisions are therefore made under certainty, and the following equation applies (15, 22):

$$p_i = u_i \Big/ \sum_{n} u_i \tag{2}$$

where p_i is the probability that alternative i will be chosen, u_i is the utility of alternative i, and the summation is taken over all n alternatives.

Combining Eqs. 1 and 2 gives an expected utility of

$$EU = \sum_n u_i^2 \Big/ \sum_n u_i \tag{3}$$

Equation 3 defines the order of travel decision-making. Let us assume that a departure time and destination have been chosen already. Either a mode is chosen next and then a route or vice versa. It will be shown that the order of travel decision-making depends on (a) the number of alternative modes and routes and (b) the similarity of alternative modes and routes. Consider the following examples.

In the first example, there are more alternative routes than modes, but alternative modes and routes are equally similar. The utility of mode and route pairs is

$$\begin{aligned}
M_1R_1 &= 11 = R_1M_1\\
M_1R_2 &= 8 = R_2M_1\\
M_1R_3 &= 5 = R_3M_1\\
M_2T_1 &= 7 = R_1M_2\\
M_2R_2 &= 4 = R_2M_2\\
M_2R_3 &= 1 = R_3M_2
\end{aligned}$$

M_1 refers to mode 1, M_2 to mode 2, R_1 to route 1, and so on. The expected utility of travel is 7.50 if the choice of mode precedes the choice of route and 7.46 if the choice of route precedes the choice of mode. These values are obtained from Eq. 3 by first calculating the expected utility prior to the last decision and then the expected utility prior to the next to last decision. This indicates that travel decisions with few alternatives are made before travel decisions with many alternatives.

In the next example, alternative routes are more similar than alternative modes, but the number of alternative modes and routes is the same. The utility of mode and route pairs is

$$\begin{aligned}
M_1R_1 &= 10 = R_1M_1\\
M_1R_2 &= 8 = R_2M_1\\
M_2R_1 &= 4 = R_1M_2\\
M_2R_2 &= 2 = R_2M_2
\end{aligned}$$

The expected utility of travel is 7.56 if the choice of mode precedes the choice of route and 7.62 if the choice of route precedes the choice of mode. This indicates that travel decisions with similar alternatives are made before travel decisions with dissimilar alternatives.

The conclusions of the last two paragraphs may surprise readers. Intuitively, decisions with many dissimilar alternatives should precede decisions with few similar alternatives. Yet these examples indicate that the reverse is true. There is nothing inconsistent about this. Just as the expected utility of travel is calculated by evaluating the last decision first and just as Brand's third method of ordering travel decisions assumes that the logical order of decisions runs counter to their sequence in time, travel decision-making may begin with the last travel decision and work backward.

It is encouraging that order based on information and order based on adjustment represent special cases of the present theory. Incomplete information about travel alternatives results in uncertainty in decision-making and causes the probabilities of selection to converge. In the limit, if no information is available, the probability of selection is the same for every alternative. This decreases the expected utility of corresponding travel decisions and causes travelers to postpone these decisions until other decisions are made. Order based on information applies in this case. When travel decisions are long-lived, the probabilities of selection are affected, but in this case they tend to diverge rather than converge. It is likely that travelers exercise greater care when they make long-lived decisions, and therefore they select alternatives with maximum utility. This increases the expected utility of long-lived travel decisions and causes travelers to advance these decisions relative to other travel decisions. Order based on adjustment applies in this case.

DYNAMIC PROGRAMMING APPLIED TO TRAVEL DECISION-MAKING

Conventional travel demand models assume that travel decisions are made independently, whereas direct demand travel models assume that travel decisions are fully integrated. It is likely that travel decisions are neither so independent nor so fully integrated as assumed in these models.

In his review of sequential decision-making, Edwards (8) divided sequential decisions into six classes. His sixth class included dynamic decisions of the type made by travelers, which are characterized by the dependence of later decisions on earlier decisions. Because travel decision-making is a dynamic process, the literature on dynamic decision-making applies and a substantial body of knowledge is available. During the 1950s Bellman (2) developed an analytical technique known as dynamic programming. At that time Bellman suggested that dynamic programming could be used to simulate dynamic decision-making. Dynamic programming has since been applied to dynamic decision-making in a variety of theoretical and empirical studies (5, 14).

Several studies have compared the performance of subjects on dynamic decision-making tasks to the results of dynamic programming. Using variations of the Reader's Control Problem to simulate recurrent business decisions, Rapoport and Ray applied dynamic programming to stochastic problems (19), adaptive problems (18), adaptive problems of unknown duration (20), and deterministic problems (21). In all cases dynamic programming adequately described subjects' performance on dynamic decision-making tasks.

Dynamic programming is based on the principle of optimality, which states that the best decision at each stage in the decision-making process is the decision that optimizes the remainder of the process. Dynamic programming therefore begins with the desired objective (a maximum benefit from travel) and works backward through the sequence of decisions to the starting point (the decision to work, shop). Each decision in the sequence is optimized according to a predefined decision rule. A decision-maker can ignore past and future decisions and evaluate his present alternatives with this decision rule.

In many ways, travel decision-making is an ideal problem for dynamic programming. Problems must be divided into stages in dynamic programming. Travel decision-making has four stages—the choice of departure time, destination, mode, and route. Alternative states must be defined at each stage. Alternative departure times, destinations, modes, and routes represent alternative states of the various travel decisions. An objective function must be optimized in some manner. The objective function in travel decision-making is the utility of travel and, of course, it is maximized. Actions and policies must be defined. Choices among alternative departure times, destinations, modes, and routes represent actions, and sets of choices represent policies. Returns on all actions and policies must be evaluated. This presents a problem because no utility accrues in travel until all travel decisions are made. However, it may be possible to associate utility with individual travel decisions. The utility of individual travel decisions will be a function of independent measures of performance (i.e., measures that do not depend on other travel decisions) such as distance between zones in trip distribution, smoothness of ride in modal split, and directness of route in network assignment.

Once the utility of individual decisions is determined, a dynamic programming model can be developed. The following notation is used:

$f_n(a)$ = maximum utility of all remaining travel decisions if alternative a is chosen in the nth decision (= objective function in state a and stage n if decision-making is optimal);

u_{ab} = utility of travel alternative b in the n+1 stage of travel decision-making if travel alternative a was chosen in the nth stage (= the return from the action of choosing state b in stage n+1 when state a was chosen in stage n);

t = alternative departure times;

d = alternative destinations;

m = alternative modes;

r = alternative routes; and

o = state of travelers after travel decision-making.

If travel decisions are made in the conventional order (i.e., departure time, destination, mode, and route), the following equations can be derived from the principle of optimality:

$$f_4(r) = \max_{u_{ro}} [u_{ro}]$$

$$f_3(m) = \max_{u_{mr}} [u_{mr} + f_4(r)]$$

$$f_2(d) = \max_{u_{dm}} [u_{dm} + f_3(m)]$$

$$f_1(t) = \max_{u_{td}} [u_{td} + f_2(d)]$$

By way of example, the third equation says that the maximum utility of all remaining travel decisions if destination d is chosen in the second stage of travel decision-making is equal to the maximum value of the sum of the utility of destination d plus the maximum utility of all remaining travel decisions if mode m is chosen in the third stage of travel decision-making. $f_2(d)$ is evaluated for all modes that serve destination d. Modes that do not are ignored. The other equations are analogous.

Dynamic programming identifies the optimal departure time, destination, mode, and route. It does not distribute trips among alternative departure times, destinations, modes, and routes as conventional models do. Distribution is a separate process. Several methods of distribution are available. The most promising is an intervening opportunities approach that assigns a constant fraction of all remaining trips to the best of the remaining travel alternatives (the process is then repeated without this alternative).

The use of dynamic programming to simulate travel decision-making has one major drawback. Dynamic programming simulates optimal decision-making, but travel decision-making is apt to be suboptimal. The issue in travel forecasting is not how travelers should make decisions but how travelers do make decisions. Arriving at the same conclusion (for decision-making in general), Rapoport extended his earlier analysis to include suboptimal decision-making (17). He began by noting that shortcomings of the human memory, the cost of information-gathering and -processing, the inability to plan ahead, the ignorance of interdependencies, and so on limit our ability to make decisions. Decision-making "in non-trivial tasks will, in general, not be optimal." He went on to propose a theory of dynamic decision-making that makes use of programming algorithms. Decision-makers are assumed to plan ahead one, two, or even more decisions in dynamic decision-making tasks. The extent to which they plan ahead depends on their ability and the nature of their tasks. Rapoport described empirical tests of his theory. Subjects' performance on Elithorn's perceptual maze test (10) was compared to the results of three algorithms. The first algorithm assumed that subjects plan ahead one move when choosing among alternative paths through a maze, the second that they plan ahead two moves, and the third that they plan ahead three moves. The performance of many subjects corresponded to one of the three algorithms (particularly to the third one) and varied with the design of the maze. It would appear that planning horizons do vary from individual to individual and from task to task.

If travel decision-making is suboptimal, Rapoport's algorithms can be used in travel forecasting. One algorithm applies to travelers with a planning horizon of one travel decision, another to travelers with a planning horizon of two travel decisions, and a third to travelers with a planning horizon of three travel decisions. (A planning horizon of four travel decisions leads to optimal decision-making.) Algorithms can be chosen by comparing the results of each to the behavior of travelers. The algorithm that best describes the travel behavior of each socioeconomic class can be used in forecasting.

It should be noted that existing travel models correspond to the extremes of travel decision-making. Conventional travel demand models assume that travel decisions are independent of each other. Trip generation, trip distribution, modal split, and network assignment are modeled independently and undertaken sequentially. Each is completed without reference to the others. Conventional travel forecasting corresponds to the simplest type of travel decision-making, where travelers ignore all future decisions. The result of sequential decision-making is identical to that of dynamic decision-making if the planning horizon of travelers is one travel decision. In contrast, direct demand models assume that travel decisions are fully integrated. Trip generation, trip distribution, modal split, and network assignment are combined in a single model. Because all stages are undertaken simultaneously, they are allowed to fully interact and influence each other. Direct demand forecasting corresponds to the most sophisticated type of travel decision-making, where travelers consider all travel decisions simultaneously. The result of simultaneous decision-making is identical to that of dynamic decision-making if the planning horizon of travelers includes all remaining travel decisions. Existing models can describe the extremes of travel decision-making, but only behavioral models can describe travel decision-making in general.

Transportation planning has been dominated by engineering and economics throughout its history. Hopefully, this paper and another by the author (11) have demonstrated the potential of behavioral models in transportation planning. I believe that transportation planning is ready to incorporate psychological theory into its simple economic models.

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