3 ACTIVITY-BASED MODELING OF TRAVEL DEMAND

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3.1 Introduction and Scope

Since the beginning of civilization, the viability and economic success of communities have been, to a major extent, determined by the efficiency of the transportation infrastructure. To make informed transportation infrastructure planning decisions, planners and engineers have to be able to forecast the response of transportation demand to changes in the attributes of the transportation system and changes in the attributes of the people using the transportation system. Travel demand models are used for this purpose; specifically, travel demand models are used to predict travel characteristics and usage of transport services under alternative socio-economic scenarios, and for alternative transport service and land-use configurations.

The need for realistic representations of behavior in travel demand modeling is well acknowledged in the literature. This need is particularly acute today as emphasis shifts from evaluating long-term investment-based capital improvement strategies to understanding travel behavior responses to shorter-term congestion management policies such as alternate work schedules, telecommuting, and congestion-pricing. The result has been an increasing realization in the field that the traditional *statistically-oriented* trip-based modeling approach to travel demand analysis needs to be replaced by a more *behaviorally-oriented* activity-based modeling approach. The next two sections discuss the basic concepts of the trip-based and the activity-based approaches to travel demand analysis.

The Trip-Based Approach

The trip based approach uses individual trips as the unit of analysis and usually includes four sequential steps. The first, trip generation, step involves the estimation of the number of home-based and non-home based person-trips produced from, and attracted to, each zone in the study area. The second, trip distribution, step determines the trip-interchanges (*i.e.*, number of trips from each zone to each other zone). The third, mode choice, step splits the person-trips between each pair of zones by travel mode obtaining both the number of vehicle trips and number of transit trips between zones. The fourth, assignment, step assigns the vehicle trips to the roadway network to obtain link volumes and travel times and the person trips to the transit network. Time-of-day of trips is either not modeled or is modeled in only a limited way, in the trip-based approach. Most commonly, time is introduced by applying time-of-day factors to 24-

hour travel volumes at the end of the traffic assignment step or at the end of the trip generation step.

A fundamental conceptual problem with the trip-based approach is the use of trips as the unit of analysis. Separate models are developed for home-based trips and non-home based trips, without consideration of dependence among such trips. Further, the organization (scheduling) of trips is not considered; that is, there is no distinction between home-based trips made as part of a single-stop sojourn from home and those made as part of a multiple-stop sojourn from home. Similarly, there is no distinction between non-home based trips made during the morning commute, evening commute, from work, and as part of pursuing multiple stops in a single sojourn from home. Thus, the organization of trips and the resulting inter-relationship in the attributes of multiple trips is ignored in all steps of the trip-based method. This is difficult to justify from a behavioral standpoint. It is unlikely that households will determine the number of home-based trips and the number of non-home based trips separately. Rather, the needs of the households are likely to be translated into a certain number of total activity stops by purpose followed by (or jointly with) decisions regarding how the stops are best organized. Similarly, the location of a stop in a multistop sojourn (or tour) is likely to be affected by the location of other stops on the tour. Such multistop tours are becoming increasingly prevalent (see Gordon *et al*., 1988; Lockwood and Demetsky, 1994) and ignoring them in travel analysis means *"discarding an element that is doubtless important in the individual's organization of time and space"* (Hanson, 1980). Also, in a multistop tour from home consisting of, say, a grocery shopping stop and a social visit, the trip-based approach fails to recognize that the travel mode for all three trips (home to shop, shop to visit, and visit to home) will be the same. The travel mode chosen will depend on various characteristics of all three trips (and not any one single trip) and, consequently, these trips cannot be studied independently.

The behavioral inadequacy of the trip-based approach, and the consequent limitations of the approach in evaluating demand management policies, has led to the emergence of the activity-based approach to demand analysis.

The Activity-Based Approach

The activity-based approach to travel demand analysis views travel as a derived demand; derived from the need to pursue activities distributed in space (see Jones *et al*., 1990 or Axhausen and Gärling, 1992). The approach adopts a holistic framework that recognizes the complex interactions in activity and travel behavior. The conceptual appeal of this approach originates from the realization that the need and desire to participate in activities is more basic than the travel that some of these participations may entail. By placing primary emphasis on activity participation and focusing on sequences or patterns of activity behavior (using the whole day or longer periods of time as the unit of analysis), such an approach can address congestion-management issues through an examination of how people modify their activity participations (for example, will individuals substitute more out-of-home activities for in-home activities in the evening if they arrived early from work due to a work-schedule change?).

The shift to an activity-based paradigm has also received an impetus because of the increased information demands placed on travel models by the 1990 Clean Air Act Amendments (CAAAs). These amendments require the inclusion of transportation control measures (TCMs) in transportation improvement programs for MPOs in heavily polluted non-attainment areas and, by state law, for all non-attainment areas in California. Some TCMs, such as HOV lanes and transit extensions, can be represented in the existing modeling framework; however, non-capital improvement measures such as ridesharing incentives, congestion pricing and employer-based demand management schemes can not be so readily represented (Deakin, Harvey and Skabardonis, Inc. 1993, Chapter 2). The ability to model both individual activity behavior and interpersonal linkages between individuals, a core element of activity modeling, is required for the analysis of such TCM proposals. The CAAAs also require travel demand models to provide (for the purpose of forecasting mobile emission levels) link flows at a high level of resolution along the time dimension (for example, every 30 minutes or an hour as opposed to peak-period and off-peak period link flows) and also to provide the number of new vehicle trips (*i.e.*, cold starts) which begin during each time period. Because of the simplistic, "individual-trip" focus of the trip-based models, they are not well-equipped to respond to these new requirements (see Cambridge Systematics, Inc., 1994; Chapter 5). Since the activity-based approach adopts a richer, more holistic approach with detailed representation of the temporal dimension, it is better suited to respond to the new requirements.

The activity-based approach requires time-use survey data for analysis and estimation. A time-use survey entails the collection of data regarding all activities (in-home and out-of-home) pursued by individuals over the course of a day (or multiple days). Travel constitutes the medium for transporting oneself between spatially dis-located activity participations. The examination of both in-home and out-of-home activities facilitates an understanding of how individuals substitute out-of-home activities for in-home activities (or vice-versa) in response to changing travel conditions. This, in turn, translates to an understanding of when trips are generated or suppressed.

It is important to note that administrating time-use surveys is similar to administrating household travel surveys, except for collection of in-home as well as out-of-home activities. The information elicited from respondents is a little more extensive in time-use surveys compared to travel surveys, but experience suggests that the respondent burden or response rates are not significantly different between time-use and travel surveys (see Lawton and Pas, 1996 for an extensive discussion).

The activity-based approach does require more careful and extensive preparation of data to construct entire "sequences" of activities and travel. On the other hand, such intensive scrutiny of data helps identify data inconsistencies which might go unchecked in the trip-based approach (for example, there might be "gaps" in an individual's travel diary because of non-reporting of several trips; these will be identified during data preparation for activity analysis, but may not be identified in the trip-based approach since it highlights individual trips and not the sequence between trips and activities).

The rest of this chapter focuses on the activity-based approach to travel demand forecasting. The next section traces the history of research on activity analysis. Section 3.3 presents an overview of the modeling methods being used in activity-travel analysis. Section 3.4 discusses how activity-based travel research has been influencing travel demand analysis. Section 3.5 concludes the chapter by identifying important future research topics in the activity analysis area.

3.2 History of Research on Activity Analysis

The seminal works by Chapin (1971), Hagerstrand (1970) and Cullen and Godson (1975) form the basis for much of the research on activity analysis. Chapin (1971) proposed a motivational framework in which societal constraints and inherent individual motivations interact to shape revealed activity participation patterns. Hagerstrand (1970), on the other hand, emphasized the constraints imposed by the spatial distribution of opportunities for activity participation and temporal considerations on individual activity participation decisions, thus laying the foundation for what is now commonly referred to as the space-time "prism". Cullen and Godson (1975) argued that the spatial and temporal constraints identified by Hagerstrand are fundamentally characterized by varying degrees of rigidity (or flexibility). They undertook extensive empirical analysis to indicate that temporal constraints are more rigid than spatial constraints and that the rigidity of temporal constraints is closely related to activity type of participation (with more temporal rigidity associated with work-related activities compared to leisure activities).

Activity-based travel research has received much attention and seen considerable progress since these early studies. In the following review, we will use the term "activity episode" to refer to a discrete activity participation. The term "activity" refers to a collection of episodes of the same type or purpose over some time unit (say a day or a week). The review is undertaken in two categories. The first category focuses on participation decisions associated with a single activity episode. The second category examines individual decisions regarding activity episode patterns (that is, multiple activity episodes and their sequencing).

Single Activity Episode Participation

The studies in this section focus on the participation of individuals in single activity episodes, along with one or more accompanying characteristics of the episode such as duration, location, or time window of participation. The effect of household interdependencies on individual activity choice is represented in these models in the form of simple measures such as presence of working spouse, number of adults, and household structure.

Damm (1980) developed a multivariate daily model of participation and duration in out-of-home non-work activities (no distinction between activity types is made). He partitions the day into five periods based on the work schedule and introduces interdependence in activity participation and duration among time periods using variables which measure the "time spent in other periods". Temporal constraints are represented in the model in the form of variables like duration of work, flexibility of work hours and time spent in other periods. Spatial fixity of work place (an indicator of whether the individual has a fixed work location or not), accessibility, years lived at residence and presence of driver's license are defined to represent spatial constraints. Other socio-economic variables are included to represent the influence of lifecycle (eg., number of children), potential allocation process (eg., work status of spouse), and other familial responsibilities on individual activity participation.

Van der Hoorn (1983) developed an activity episode model for the choice of activity type and location of the episode. The three available locations in his analysis are "at home", "in town" and "outside town" (the term "town" representing the area of residence). Separate logit models are proposed for each previous location, each of five person groups, and for the workweek and weekend. Activity episode choice is regarded as being conditional on the location of the previous activity episode, but not on the activity type performed at the previous location. Location choice is dependent on the previous location and on the next activity episode. The restrictions imposed by external constraints and mandatory activities are taken into account while defining the choice set of available activities and locations.

Hirsh et al. (1986) developed a dynamic theory of weekly activity behavior and modified it suitably to model shopping activity in Israel. They recognized the benefit of studying activities on the basis of a weekly cycle rather than on a daily period. The attributes used in the model are similar to the ones used by Damm and van der Hoorn.

Mannering and his colleagues (Mannering *et al*., 1994, Kim *et al*., 1993) analyzed home-stay duration between successive participations in out-of-home activity episodes. Bhat (1996a) and Neimeier and Morita (1996), on the other hand, formulated and estimated models for the duration of out-of-home activity episodes. The results from these studies suggest that the socio-demographics of the individual's household and the individual (such as household size, income earnings, age, sex, *etc.*), and the work schedule characteristics of the individual, have a substantial effect on the duration of home-stay and out-of-home activity episodes. All the duration studies listed above use a hazard-based duration structure in their analyses.

Activity Episode Pattern Analysis

In this section, we review studies which examine activity episode patterns (*i.e.*, multiple activity episodes and their sequence). Some of these studies focus only on activity episode scheduling and consider the generation of activity episodes and their attributes as exogenous inputs. Such studies are reviewed in the next section. Other studies analyze both activity episode generation and scheduling, and these are reviewed in the subsequent section.

Activity Episode Scheduling A fundamental tenet of the activity episode scheduling approach to the analysis of activity/travel patterns is that travel decisions are driven by the collection of activities that form an agenda for individual participation. Travel patterns are viewed as arising from a more fundamental activity scheduling process. Activity scheduling is affected by spatial/temporal constraints of travel, specifications of precedence among activities, requirements to be with other family members at particular times and places (coupling constraints), and available individual transportation supply environment (the allocation of activities between household members that shapes the activity agenda of each individual and the allocation of household transportation supply between members is presumed to be exogenous in these studies).

Activity episode scheduling models generally take the structure of a computerized production system which comprises a set of rules in the form of condition-action pairs (see Newell and Simon, 1972). Studies in the psychology field suggest that a production system is consistent with the way in which humans perceive, appraise, and respond to spatial and aspatial information within the context of limited-information processing ability (Gärling *et al*., 1994).

One of the earliest scheduling models was CARLA, developed by the Oxford University Transport Studies Unit (Clarke 1986). This model uses the list of activities to be scheduled and their durations to produce all feasible activity patterns in response to a change in the travel environment (for example, transit service improvements or cuts). It does so through the use of a branch-and-bound based combinatorial algorithm which reorganizes a given activity program and selects only those patterns which are feasible in terms of spatio-temporal and inter-personal constraints.

Recker et al. (1986a, 1986b) developed another scheduling model called STARCHILD. Their model partitions the daily scheduling process into two stages. In the first stage (also referred to as the pre-travel stage), the individual decides on a planned activity episode schedule based on a pre-determined directory of activities and their duration, location and time window for participation. STARCHILD models the selection of a planned activity program by generating distinct non-inferior patterns using combinatorics and then applying a logit choice model to establish the pattern choice with highest utility. The assignment of a utility value to each pattern is a function of the amount of time in the pattern associated with activity participation, wait time and travel time. The planned activity episode schedule is continuously revised and updated in the second dynamic scheduling stage circumstances or new activity demands. More recently, Recker (1995a) has extended the STARCHILD approach to include a mathematical programming formulation for the choice of an activity-travel pattern from several possible patterns.

Gärling *et al*. (1989) proposed yet another activity scheduling model labeled SCHEDULER. This computational model assumes the presence of a long term calendar (an agenda of activity episodes with duration, appointment details and preference) at the start of any time period. A small set of episodes with high priority are selected from this long term "calendar" and stored in a short term calendar as the subset of episodes to be executed in the short-run. This activity subset is sequenced, and activity locations determined based on a "distance-minimizing" heuristic procedure (see Axhausen and

Gärling for a detailed review). SMASH (Ettema *et al.*, 1993) is a development of the SCHEDULER framework in which heuristic scheduling rules are specified and tested.

A more recent scheduling model is the adaptation simulation system labeled AMOS (for Activity-MObility Simulator) developed by Kitamura *et al.* (1996) to examine the short-term responses to Transportation Control Measures (TCMs). The model takes an observed daily activity-travel pattern of an individual (baseline pattern) and determines an adaption choice (for example, do nothing, change mode, change departure time, *etc.*) to a TCM using a response option generator.

Activity Episode Generation and Scheduling The studies reviewed in this section attempt to capture individual activity/travel patterns by focusing on the mechanism by which individual activities are generated and sequenced.

Kitamura (1983) studied episode sequencing and the tendencies or preferences in the formation of the set of activities to be pursued. A sequential history dependent approach is taken (sequential in that the probability of a given set of activities being chosen and pursued in a particular order is represented by a set of sequential and conditional probabilities). He found a consistent hierarchical order in sequencing episodes (with the less-flexible activities being pursued earlier). Kitamura and Kermanshah (1983) adopted the same sequential view in their extension of the above study to include the time dimension of activity choice. Adler and Ben Akiva (1979) examined inter-trip linkages from a simultaneous decision perspective, *i.e*, on the premise that the individual plans and pre-determines her/his daily travel schedule. The choice alternatives in this approach are entire daily patterns. However, the daily patterns are described by rather simple aggregate measures such as the mode used in travel and number of tours in the pattern. Golob (1986) also used a simultaneous decision approach, though his focus was on trip-chains or tours rather than daily patterns. The spatial and temporal dimensions are suppressed in this analysis. A set of different types of trip-chains are identified and modeled as dependent variables. A multivariate statistical technique (non-linear canonical correlation analysis) is employed for the analysis. Other studies of inter-trip linkage are Kitamura (1984), Nishii et al (1988) and O'Kelly & Miller (1984).

More recently, Ben-Akiva and Bowman (1994) have estimated a utility-based choice model of daily activity schedule of individuals that comprises a nested logit model of activity pattern choices (*i.e.*, purposes, priorities and structure of the day's activities and travel) and tour choices (mode choice, destination choice of stops in tours, and departure time from home and from the "primary" activity in tour). Similar efforts by Wen and Koppelman (1997, 1999) include generation and allocation of maintenance stops and automobiles to household members but excludes mode and destination choice. In contrast to the utility-maximizing discrete choice formulations of Ben-Akiva and Bowman and Wen and Koppelman, Vause (1997) proposes the use of a rule-based mechanism to restrict the number of activity-related choices available to an individual as well as for choice selection from the restricted choice set. Vause emphasizes the need to avoid the use of a single choice strategy in modeling and advances the use of the rule-based mechanism as a method to simulate different choice strategies (such as satisfaction, dominance, lexicographic and utility) within the same operational framework.

Vaughn, Speckman and Pas (Vaughn *et al*, 1997, and Speckman *et al*, 1997) developed a statistical approach to generate a set of baseline household activity patterns including the number and type of each activity episode and its duration, the number of home-based and work/school-based tours and start and end times for tours for a synthetic population represented by a continuous path through space and time. The statistical (as opposed to behavioral) basis of this approach raises questions about its use in prediction. However, it could provide initial travel-activity patterns for input to adaptive modeling systems such as SMASH and AMOS.

The studies of episode patterns discussed thus far either do not model the temporal dimension of episodes or assume broad time periods in the analysis. More recently, two approaches have been proposed to model activity episode generation and scheduling within the context of a continuous time domain. The first is the Prism-Constrained Activity-Travel Simulator proposed by Kitamura and Fujii, 1998 and the other is the Comprehensive Activity-Travel Generation for Workers (CATGW) model system proposed by Bhat and Singh (1999). These two studies are discussed in section 4.2 under the heading of "Emergence of Comprehensive Activity-based Travel Demand Models".

3.3 Modeling Methods in Activity-Travel Analysis

The methods used in activity-based travel analysis include discrete choice models as well as other methods that accommodate non-discrete variables in activity modeling. The latter methods have emerged more recently because of the need to model travel as part of a larger (and holistic) activity-travel pattern and involve relatively non-traditional (in the travel analysis field) methodologies such as duration analysis and limited-dependent variable models. In this section, we discuss these various methods. The material here is drawn liberally from Bhat (1997a), though in a substantially condensed form.

Discrete Choice Models

The multinomial logit (MNL) model has been the most widely used structure for modeling discrete choices in travel behavior analysis. The random components of the utilities of the different alternatives in the MNL model are assumed to be independent and identically distributed (IID) with a type I extreme-value (or Gumbel) distribution (McFadden, 1973). The MNL model also maintains an assumption of homogeneity in responsiveness to attributes of alternatives across individuals (*i.e.*, an assumption of response homogeneity). Finally, the MNL model also maintains an assumption that the error variance-covariance structure of the alternatives is identical across individuals (*i.e.*, an assumption of error variance-covariance homogeneity). The three assumptions together lead to the simple and elegant closed-form mathematical structure of the MNL. However, these assumptions also leave the MNL model saddled with the "independence of irrelevant alternatives" (IIA) property at the individual level (Ben-Akiva and Lerman, 1985). In the next three sections, we will discuss generalizations of the MNL structure along each of the three dimensions mentioned above: a) Relaxation of the IID (across alternatives) error structure, b) Relaxation of response homogeneity, and c) Relaxation of the error variance-covariance structure homogeneity. While we discuss each of the dimensions separately, one can combine extensions across different dimensions to formulate several more generalized and richer structures.

Relaxation of the IID (Across Alternatives) Error Structure The rigid inter-alternative substitution pattern of the multinomial logit model can be relaxed by removing, fully or partially, the IID assumption on the random components of the utilities of the different alternatives. The IID assumption can be relaxed in one of three ways: a) allowing the random components to be correlated while maintaining the assumption that they are identically distributed (identical, but non-independent random components), b) allowing the random components to be non-identically distributed (different variances), but maintaining the independence assumption (non-identical, but independent random components), and c) allowing the random components to be non-identical and non-independent (non-identical, non-independent random components). Each of these alternatives is discussed below.

Identical, Non-Independent Random Components The distribution of the random components in models which use identical, non-independent random components can be specified to be either normal or type I extreme value. Discrete choice literature has mostly used the type I extreme value distribution since it nests the multinomial logit and results in closed-form expressions for the choice probabilities.

The models with the type I extreme value error distribution belong to the Generalized Extreme Value (GEV) class of random utility-maximizing models. Five model structures have been formulated and applied within the GEV class. These are: the Nested Logit (NL) model, the Paired Combinatorial Logit (PCL) model, the cross-nested logit (CNL) model, the Ordered GEV (OGEV) model, and the Multinomial Logit-Ordered GEV (MNL-OGEV) model.

The nested logit (NL) model permits covariance in random components among subsets (or nests) of alternatives (each alternative can be assigned to one and only one nest). Alternatives in a nest exhibit an identical degree of increased sensitivity relative to alternatives not in the nest (Williams, 1977, Daly and Zachary, 1978, Daganzo and Kusnic, 1993).

The paired combinatorial logit (PCL) model initially proposed by Chu (1989) and recently examined in detail by Koppelman and Wen (1996) generalizes, in concept, the nested logit model by allowing differential correlation between each pair of alternatives. While the nested logit model is not nested within the PCL structure, an appropriate constrained PCL closely approximates the nested logit model.

Another generalization of the nested logit model is the cross-nested logit (CNL) model of Vovsha (1996). In this model, an alternative need not be exclusively assigned to one nest as in the nested logit structure. Instead, each alternative can be probabilistically assigned to multiple nests. Vovsha proposes a heuristic procedure for estimation of the CNL model.

The ordered GEV model was developed by Small (1987) to accommodate correlation among the unobserved random utility components of alternatives close together along a natural ordering implied by the choice variable (examples of such ordered choice variables might include car ownership, departure time of trips, *etc.*).

The MNL-OGEV model formulated by Bhat (1998b) generalizes the nested logit model by allowing adjacent alternatives within a nest to be correlated in their unobserved components.

The advantage of all the GEV models discussed above is that they allow partial relaxations of the independence assumption among alternative error terms while maintaining closed-form expressions for the choice probabilities. The problem with these models is that they are consistent with utility maximization only under rather strict (and often empirically violated) restrictions on the dissimilarity parameters. The origin of these restrictions can be traced back to the requirement that the variance of the joint alternatives be identical.

Non-Identical, Independently Distributed Random Components The concept that heteroscedasticity in alternative error terms (i.e., independent, but not identically distributed error terms) relaxes the IIA assumption is not new (see Daganzo, 1979), but has received little (if any) attention in travel demand modeling and other fields. Four models have been proposed which allow non-identical random components. The first is the negative exponential model of Daganzo (1979), the second is the heteroscedastic multinomial logit (HMNL) model of Swait and Stacey (1996), the third is the oddball alternative model of Recker (1995b) and the fourth is the heteroscedastic extreme-value (HEV) model of Bhat (1995).

Daganzo (1979) used independent negative exponential distributions with different variances for the random error components to develop a closed-form discrete choice model which does not have the IIA property. His model has not seen much application since it requires that the perceived utility of any alternative not exceed an upper bound.

Swait and Stacey (1996) allowed heteroscedasticity by specifying the variance of the alternative error terms to be functions of observed alternative characteristics. The error terms themselves are assumed to be type I extreme-value. The scale parameter θ_i characterizing the variance of each alternative i is written as $\theta_i = \exp(\beta' z_i)$, where z_i is a vector of attributes associated with alternative i and β is a corresponding vector of parameters to be estimated. The resulting model has a closed-form structure.

Recker (1995b) proposed the oddball alternative model which permits the random utility variance of one "oddball" alternative to be larger than the random utility variances of other alternatives. This situation might occur because of attributes which define the utility of the oddball alternative, but are undefined for other alternatives. Then, random variation in the attributes that are defined only for the oddball alternative will generate increased variance in the overall random component of the oddball alternative relative to others.

Bhat (1995) formulated the heteroscedastic extreme-value (HEV) model which assumes that the alternative error terms are distributed with a type I extreme value distribution. The variance of the alternative error terms are allowed to be different across all alternatives (with the normalization that the error terms of one of the alternatives has a scale parameter of one for identification). Bhat develops an efficient Gauss-Laguerre quadrature technique to approximate the one-dimensional integral in the choice probabilities of the HEV model. The reader is referred to Hensher (1998a; 1998b) and Hensher *et al*. (1999) for applications of the HEV model to estimation from revealed and stated preference data.

The advantage of the heteroscedastic class of models discussed above is that they allow a flexible cross-elasticity structure among alternatives than many of the GEV models discussed earlier. Specifically, the models (except the oddball model) permit differential cross-elasticities among all pairs of alternatives. The limitation (relative to the GEV models) is that the choice probabilities do not have a closed-form analytical expression in the HEV model.

Non-Identical, Non-Independent Random Components Models with non-identical, non-independent random components use one of two general structures: the first is an error-components structure and the second is the general multinomial probit (MNP) structure.

The error-components structure partitions the overall error into two components: one component which allows the random components to be non-identical and non-independent, and the other component which is specified to be independent and identically distributed across alternatives. In particular, consider the following utility function for alternative i:

$$\begin{aligned} U_i &= V_i + \zeta_i \\ &= V_i + \mu' z_i + \epsilon_i \end{aligned} \tag{1}$$

where V_i and ζ_i are the systematic and random components of utility, and ζ_i is further partitioned into two components, $\mu' z_i$ and ϵ_i. z_i is a vector of observed data associated with alternative i, μ is a random vector with zero mean and density $g(\mu \mid \Sigma)$, Σ is the variance-covariance matrix of the vector μ, and ϵ_i is independently and identically standard distributed across alternatives with density function f(.). The component $\mu' z_i$ induces heteroscedasticity and correlation across unobserved utility components of the alternatives (see Train, 1995). While different distributional assumptions might be made regarding f(.) and g(.), it is typical to assume a standard type I extreme value for f(.), and a normal distribution for g(.). This results in a error-components model with a logit kernel. On the other hand, if a standard normal distribution is used for f(.), the result is a error-components probit model. Both these structures will involve integrals in the choice probability expressions which do not have a closed-form solution. The estimation of these models is achieved using logit simulators (in the first case) or probit simulators (in the second case). Different and very general patterns of heteroscedasticity and correlation in unobserved components among alternatives can be generated by appropriate specification of the μ and z_i vectors (see Bhat, 1998c, Ben-Akiva and Bolduc, 1996 and Brownstone and Train, 1999).

The general multinomial probit (MNP) structure does not partition the error terms, and estimates (subject to certain identification considerations) the variance-covariance matrix of the overall random components among the different alternatives (see Bunch and Kitamura, 1990; Lam, 1991; and Lam and Mahmassani, 1991). However, McFadden and Train (1996) have shown that the error-components formulation can approximate a multinomial probit formulation as closely as one needs it to. Further, the error-components models can be estimated using simulators which are conceptually simple, easy to program and inherently faster than simulators for the MNP model (see Brownstone and Train, 1999).

Relaxation of Response Homogeneity The standard multinomial logit, and other models which relax the IID assumption across alternatives, typically assume that the response parameters determining the sensitivity to attributes of the alternatives are the same across individuals in the population. However, if such an assumption is imposed when there is response heterogeneity, the result is biased and inconsistent parameter and choice probability estimates (see Chamberlain, 1980).

Response heterogeneity may be accommodated in one of two ways. In the first approach, the varying coefficients approach, the coefficients on alternative attributes are allowed to vary across individuals while maintaining a single utility function. In the second approach, the segmentation approach, individuals are assigned to segments based on their personal/trip characteristics, and a separate utility function is estimated for each segment. Each of these approaches is discussed next.

Varying Coefficients Approach Consider the utility U_{qi} that an individual q associates with alternative i and write it as:

$$U_{qi} = \alpha_i + \delta_i' z_q + \epsilon_{qi} + \eta_q' x_{qi} \tag{2}$$

where α_i is an individual-invariant bias constant, z_q is a vector of observed individual characteristics, δ_i is a vector of parameters to be estimated, ϵ_{qi} is a random term representing idiosyncracies in preferences, and η_q is a vector representing the responsiveness of individual q to a corresponding vector of alternative-associated variables x_{qi}. The ϵ_{qi} terms may be specified to have any of the structures discussed in Section 3.2. Conditional on η_q and the assumption regarding the ϵ_{qi} terms, the form of the conditional choice probabilities can be developed. The unconditional choice probabilities corresponding to the conditional choice probabilities will depend on the response heterogeneity specification adopted for the η_q vector. A general heterogeneity specification involves allowing each element η_{qk} of the vector η_q to vary across individuals based on observed as well as unobserved individual characteristics: $\eta_{qk} = \pm\exp(\gamma_k + \beta_k' w_{qk} + v_{qk})$, where w_{qk} is a vector of relevant observed individual characteristics and v_{qk} is a term representing random taste variation across individuals with the same observed characteristics w_{qk}. The exponential form is used to ensure the appropriate sign on the response coefficients: a '+' sign is applied for a non-negative response coefficient and the '-' sign is applied for a non-positive response coefficient. v_{qk} is typically assumed to be normally distributed. The random response specification does not exhibit the restrictive independence from irrelevant alternatives (IIA) property even if the IID error assumption across alternatives of the MNL is maintained (see Bhat, 1998d).

Segmentation Approaches Two segmentation approaches may be identified depending on whether the assignment of individuals to segments is exogenous (deterministic) or endogenous (probabilistic).

The exogenous segmentation approach to capturing heterogeneity assumes the existence of a fixed, finite number of mutually-exclusive market segments (each individual can belong to one and only one segment). The segmentation is based on one or two key socio-demographic variables (sex, income, *etc*.). Within each segment, all individuals are assumed to have *identical* preferences and identical sensitivities to level-of-service variables (*i.e.*, the same utility function). Typically, very few (one or two) demographic variables are used for segmentation. The advantage of the exogenous segmentation approach is that it is easy to implement. The disadvantage is that its practicality comes at the expense of suppressing potentially higher-order interaction effects of the segmentation variables on response to alternative attributes.

The endogenous market segmentation approach attempts to accommodate heterogeneity in a practical manner not by suppressing higher-order interaction effects of segmentation variables (on response to alternative attributes), but by reducing the dimensionality of the segment-space. Each segment, however, is allowed to be characterized by a large number of segmentation variables. Individuals are assigned to segments in a probabilistic fashion based on the segmentation variables. Since this approach identifies segments without requiring a multi-way partition of data as in the exogenous market segmentation method, it allows the use of many segmentation variables in practice and, therefore, facilitates incorporation of the full order of interaction effects of the segmentation variables on preference and sensitivity to alternative attributes (see Bhat, 1997b and Gopinath and Ben-Akiva, 1995).

Relaxation of Error Variance-Covariance Structure Homogeneity The assumption of error variance-covariance structure homogeneity across individuals can be relaxed either by a) allowing the variance components to vary across individuals (variance relaxation), b) allowing the covariance components to vary across individuals (covariance relaxation), or c) allowing both variance and covariance components to vary across individuals (variance-covariance relaxation).

Variance Relaxation Swait and Adamowicz (1996) formulate a heteroscedastic multinomial logit (HMNL) model that allows the variance of alternatives to vary across individuals based on attributes characterizing the individual and her/his environment (the variance, however, does not vary across alternatives). The motivation for such a model is that individuals with the same deterministic utility for an alternative may have different abilities to accurately perceive the overall utility offered by the alternative. The HMNL model has exactly the same structure as the heteroscedastic model described earlier in this section, though the motivations for their development are different. McMillen (1995) also proposes a heteroscedastic model in the context of spatial choice and Gliebe *et al* (1998) incorporated heteroscedastic scaling into the PCL model for stochastic route choice.

Covariance Relaxation Bhat (1997c) develops a nested logit model that allows heterogeneity across individuals in the magnitude of covariance among alternatives in a nest. The heterogeneity is incorporated by specifying the logsum (dissimilarity) parameter(s) in the nested logit model to be a deterministic function of individual-related characteristics. The model is applied to intercity mode choice analysis, where such heterogeneity may be likely to occur.

The author is not aware of any study that allows both variance and covariance components to vary across individuals (variance-covariance relaxation), though in concept the extension involves combining the variance and covariance relaxations discussed earlier.

Hazard Duration Models

Hazard-based duration models are ideally suited to modeling duration data. Such models focus on an end-of-duration occurrence (such as end of shopping activity participation) given that the duration has lasted to some specified time (Hensher and Mannering, 1994). This concept of conditional probability of "failure" or termination of activity duration recognizes the dynamics of duration; that is, it recognizes that the likelihood of ending a shopping activity participation depends on the length of elapsed time since start of the activity.

Hazard-based duration models are being increasingly used to model duration time in activity analysis. To include an examination of covariates which affect duration time, most studies use a proportional hazard model which operates on the assumption that covariates act multiplicatively on some underlying or baseline hazard.

Two important methodological issues in the proportional hazard model are a) the distributional assumptions regarding duration (equivalently, the distributional assumptions regarding the baseline hazard) and b) the assumptions about unobserved heterogeneity (*i.e.*, unobserved differences in duration across people). We discuss each of these issues in next two sections. A comprehensive review of the extension of the simple univariate duration model to include multiple duration processes, multiple spells from the same individual, and related issues may be found in Bhat (1997a).

Baseline Hazard Distribution The distribution of the hazard may be assumed to be one of many parametric forms or may be assumed to be nonparametric. Common parametric forms include the exponential, Weibull, log-logistic, gamma, and log-normal distributions. Different parametric forms imply different assumptions regarding duration dependence. For example, the *exponential* distribution implies no duration dependence; that is, the time to "failure" is not related to the time elapsed. The *Weibull* distribution generalizes the exponential distribution and allows for monotonically increasing or decreasing duration dependence. The form of the duration dependence is based on a parameter that indicates whether there is positive duration dependence (implying that the longer the time has elapsed since start of the duration, the more likely it is to exit the duration soon), negative duration dependence (implying that the longer the time has elapsed since start of the duration, the less likely it is to exit the duration soon), or no duration dependence (which is the exponential case). The *log-logistic* distribution allows a non-monotonic hazard function.

The choice of the distributional form for the hazard function may be made on theoretical grounds. However, a serious problem with the parametric approach is that it inconsistently estimates the baseline hazard and the covariate effects when the assumed parametric form is incorrect (Meyer, 1990). The advantage of using a nonparametric form is that even when a particular parametric form is appropriate, the resulting estimates are consistent and the loss of efficiency (resulting from disregarding information about the hazard's distribution) may not be substantial.

Most studies of duration to date have made an *a priori* assumption of a parametric hazard. The most relevant duration studies for activity-travel modeling include a) the homestay duration models for commuters (*i.e.*, the time between coming home from work and leaving home for another out-of-home activity participation) of Mannering *et al.* (1992) and Hamed and Mannering (1993), b) the sex-differentiated shopping duration models of Niemeier and Morita (1996), c) the shopping activity duration during the evening work-to-home commute of Bhat (1996a), and d) the delay duration model for border crossings by Paselk and Mannering (1993). These studies have been reviewed in greater detail by Pas (1997).

Unobserved Heterogeneity Unobserved heterogeneity arises when unobserved factors (*i.e.*, those not captured by the covariate effects) influence durations. It is well-established now that failure to control for unobserved heterogeneity can produce severe bias in the nature of duration dependence and the estimates of the covariate effects (Heckman and Singer, 1984).

The standard procedure used to control for unobserved heterogeneity is the random effects estimator. This involves specification of a distribution for the unobserved heterogeneity (across individuals) in the population. Two general approaches may be used to specify the distribution of unobserved heterogeneity. One approach is to use a parametric distribution such as a gamma distribution or a normal distribution (most earlier research has used a gamma distribution). The problem with the parametric approach is that there is seldom any justification for choosing a particular distribution; further, the consequence of a choice of an incorrect distribution on the consistency of the model estimates can be severe (see Heckman and Singer, 1984). A second approach to specifying the distribution of unobserved heterogeneity is to use a nonparametric representation for the distribution and to estimate the distribution empirically from the data. This is achieved by approximating the underlying unknown heterogeneity distribution by a finite number of support points and estimating the location and associated probability masses of these support points. The nonparametric approach enables consistent estimation since it does not impose a prior probability distribution.

Application of duration models in the transportation field have, for the most part, ignored unobserved heterogeneity (but see Bhat, 1996a and Hensher, 1994).

Limited-Dependent Variable Models

Limited-dependent variable models encompass a wide variety of structures. In this section, we will focus on inter-related discrete and non-discrete variable systems. The non-discrete variable can take several forms. However, the three most interesting cases in the context of travel and activity modeling are the continuous, ordinal, and grouped forms. Further, the structure for the discrete/ordinal and discrete/grouped variable systems are very similar; so we will examine limited-dependent variable systems under two headings: discrete/continuous and discrete/ordinal models.

Discrete/Continuous Models Hamed and Mannering (1993) use the discrete/continuous model framework to model activity type choice, travel time duration to the activity, and activity duration. Barnard and Hensher (1992) estimate a discrete/continuous model of shopping destination choice and retail expenditure. They use Lee's (1983) transformation method for polychotomous choice situations with non-normal error distributions in the choice model. Bhat (1998e) has also used Lee's method for discrete/continuous models, but extends the method to jointly estimate a polychotomous discrete choice and two continuous choices.

Discrete/Ordinal Models Bhat and Koppelman (1993) estimate a discrete/grouped system of employment status (represented by a binary flag indicating whether or not an individual is employed) and annual income earnings. Observed income earnings in their data is in grouped form (*i.e.*, observed only in grouped categories such as < 20,000, 20,000-39,999, 40,000-59,999, *etc.*). Since it is likely that people who are employed are also likely to be the people who can earn higher incomes, the two variables are modeled jointly.

Bhat (1997d) has recently developed a <u>joint</u> model of polychotomous work mode choice and number of non-work activity stops during the work commute (*i.e.*, the total number of non-work stops made during the morning home-to-work commute and evening work-to-home commute). The joint model provides an improved basis to evaluate the effect on peak-period traffic congestion of conventional policy measures such as ridesharing improvements and solo-auto use dis-incentives.

3.4 Results of Activity-Travel Analysis

The substantial literature on activity-travel studies precludes a discussion of the results of individual studies. Instead, in this section, we discuss how activity-based travel research has and is influencing travel demand modeling.

Better Specification of Travel Demand Models

The insights obtained from activity-based research has enabled the incorporation of measures of complex behavior in a simple, albeit valuable way in travel choice models. Beggan (1988) used simple descriptors of travel-activity behavior such as the number of stops made during the work tour and the number of tours made during the work day as independent variables and found that even these simplified descriptors had a significant influence on mode-choice to work. Damm (1980) used various descriptors of lifecycle, temporal constraints, spatial constraints, interaction between time periods and interaction between household members in a nested logit model to estimate the participation and duration in discretionary activities. Goulias *et al*. (1989), Bhat *et al.* (1999) and Felendorf *et al*. (1997) recognize the inter-relationships among home-based and non-home based trips in a sojourn from home or from work and develop methods that can be used not only to generate trips but also to determine their placement within the larger daily activity-travel pattern of individuals. Purvis and his colleagues (Purvis *et al*., 1996) at the Metropolitan Transportation Commission (MTC) of the San Francisco Bay area introduced the notion of time constraints by using work travel time as an explanatory variable in their traditional non-work trip generation model.

Clearly, one way that activity-based research is influencing (and has influenced) travel demand modeling is through incremental improvements to trip-based planning methods.

Emergence of comprehensive Activity-Based Travel Forecasting Models

As indicated earlier in the section on activity episode generation and scheduling, two approaches have been recently proposed to model the entire diary activity-travel pattern of individuals within the context of a continuous time domain. The first is the Prism-Constrained Activity-Travel Simulator proposed by Kitamura and Fujii, 1998 and the other is the Comprehensive Activity-Travel Generation for Workers (CATGW) model system proposed by Bhat and Singh (1999).

PCATS divides the day (or any other unit of time) into two types of periods: "open" periods and "blocked" periods. "Open" periods represent times of day when an individual has the option of traveling and engaging in "flexible" activities. "Blocked" periods represent times when an individual is committed to performing "fixed" activities. PCATS then attempts to "fill" the open periods based on a space-time prism of activities contained within the open period. PCATS uses a sequential structure for generation of the activity episodes and associated attributes (activity type, activity duration, activity location, and mode choice) within the "open" period (thus, the unit of analysis in PCATS is the individual activity).

The CATGW framework is based on the fixity of two temporal points in a worker's continuous daily time domain. The two fixed points correspond to the arrival time of an individual at work and the departure time of an individual from work. The day is divided into four different patterns: before morning commute pattern, work commute pattern, midday pattern, and post home-arrival pattern. Within each of the before work, midday and post home-arrival patterns, several tours may be present. A tour is a circuit that begins at home and ends at home for the before work and post home-arrival patterns and is a circuit that begins at work and ends at work for the midday pattern. Further, each tour within the before work, midday and post home-arrival patterns may comprise several activity episodes. Similarly, the morning commute and evening commute components of the work commute pattern may also comprise several activity episodes. The modeling representation for the entire daily activity-travel pattern is based on a descriptive analysis of actual survey data from two metropolitan areas in the U.S. The suite of models in the modeling representation can be used for generation of synthetic baseline patterns as well as to evaluate the effect of Transportation Control Measures (TCMs). The models have been applied to evaluate the potential effect of TCMs on stop-making and cold starts in the Boston Metropolitan area.

Study of Important Policy Issues

The study of policy issues is improved and/or made possible by the activity-based approach. Demand management strategies that attempt to suppress or spread traffic peaks need to be designed based on the effect of these measures on re-scheduling of activities and household interactions. For example, a change in work schedule to an early departure from work may lead to increased trip-making at the evening because of the additional time available to participate in out-of-home activities. If some of this travel is undertaken during the same time as the PM peak-period travel, the extent of congestion alleviation projected by traditional models will not be realized (see Jones et al., 1990). In fact, from an air quality standpoint, Bhat (1998a) illustrates that an early departure from work would lead to more cold starts because of the increased activity durations of evening commute stops resulting from more time availability. Similarly, improvements in high-occupancy vehicle modes or peak period pricing measures are likely to have a rather small impact on the mode choice of individuals who make stops during the commute. The activity-based approach would recognize this association, while traditional mode choice models will overestimate the shift to high-occupancy modes, as clearly demonstrated by Bhat (1997d) using actual empirical data. Another example of the advantage of activity-based analysis relative to traditional methods is in the evaluation of the travel impacts of telecommuting. Specifically, displacements of travel (and its associated consequences) to other times of day due to a change in activity patterns caused by adoption of work telecommuting strategies cannot be examined by the narrow trip-based models, but can be examined using activity-based models (see Mokhtarian, 1993).

Improvements in Data Collection Procedures

Activity research has and continues to provide insights into cost-effective methods of collecting data and improving the accuracy of data collection procedures. It also facilitates the development of new data collection techniques that are responsive to current needs. Improvements in the accuracy of conventional data collection procedures due to activity-based research include the employment of a verbal activity recall framework, stated preference techniques, multi-day surveys, longitudinal data collection, pattern reconstruction techniques, and interactive measurement and gaming simulation techniques (see Lawton and Pas, 1996, for a comprehensive resource paper on survey methods associated with activity analysis).

Contributions to Regional and Community Planning

Models with a sound behavioral casual linkage between individual activity patterns and the travel environment will be critical to good regional and community planning. The activity perspective of travel provides a clear picture of the functioning of urban areas (for example, the spatial characteristics of intra-urban labor markets) and has the potential to identify the differential quality of life associated with different segments of the population. For example, some researchers (see Johnston-Anumonwo, 1995; Hanson and Pratt, 1988, 1992; Preston *et al*., 1993; and MacDonald and Peter, 1994) have used the activity analysis framework to study the social and spatial context of information exchange with regard to employment-related decisions. Ferguson and Jones (1990), on the other hand, used the activity-based perspective to identify the special needs of the elderly and disabled in Adelaide and were able to make specific recommendations to improve the mobility of these population groups by identifying the rhythms and timing under which such individuals live.

3.5 Future directions in Activity-Based Travel Research

The review of activity-based studies in section 3.2 indicates the substantial progress that has been made in recent years. There is no question that there is an increasing realization and awareness of the need to model travel as part of a holistic (and temporally continuous) activity-travel pattern. However, there is still a long way to go in understanding how households and individuals make choices that drive their activity and travel patterns. The objective of this section is to highlight some of the directions that we consider important in activity-based travel analysis.

Inter-Individual Interactions in Activity Behavior

An area that has received limited attention thus far in the activity analysis literature is the interactions among individuals in a household and the effect of such interactions on individual activity episode patterns. Interactions among individuals might take the form of joint participation in certain activities (such as shopping together or engaging in recreational/social activities together), “serve-passenger” and “escort” activities where one individual facilitates and oversees the participation of another in activities (for example, the "soccer mom" phenomenon), and allocation of autos and activities among individuals (especially in multi-adult, one-car households). Such interactions can lead to constraints that may be very important in individual activity/travel responses to changes in the transportation or land-use environment. However, the comprehensive activity analysis frameworks today that model individual activity patterns within a continuous time domain (such as those discussed in section 3.2) do not consider inter-individual interactions. On the other hand, some recent efforts (for example, see Wen and Koppelman, 1999) have focused on inter-individual interactions in activity decisions but have not examined individual activity-travel patterns at a fine level of temporal resolution. Integration of efforts which accommodate inter-individual interactions in activity patterns with efforts that use a continuous time domain is, therefore, likely to be a very fruitful area for further research.

Time-Space Interactions in Activity Behavior

Another area that needs substantial attention in the future is the explicit accommodation of time and space interactions. Most early research in the activity analysis area emphasized the dependence in spatial choices among activities using either semi-Markov processes or discrete-choice models (Horowitz, 1980; Kitamura, 1984; O'Kelly and Miller, 1984; Lerman, 1979). These studies ignored the temporal aspects of activity participation. More recently, some studies have focused on the timing and duration of activities (Ettema *et al*., 1995; Hamed and Mannering, 1993; Bhat, 1996a). But these studies have not examined spatial issues. Thus, though one of the key concepts of the activity-based approach is the time-space interaction, little work has been done toward developing such an integrated modeling approach. Thill and Thomas, 1987, indicated the following in their review of travel behavior research: *"In spite of various devices to account for links between decisions, no study has thus far appropriately restored the simultaneity of intended choices....It is necessary to conceive a framework that combines both temporal and spatial aspects of travel choice and that considers multipurpose multistop behavior as a multidimensional whole"*. This statement remains valid even today. Recent work by Thill and Horowitz (1997a,b), Dijst and Vidakovic (1997), and Bhat (1998a) starts to address this concern, but there is still much work to be done in this area.

In-Home and Out-of-Home Activity Substitution

In-home and out-of-home activities have quite different implications for travel; an in-home episode does not involve travel (for a person already at home), while an out-of-home episode requires travel. Thus, the in-home/out-of-home participation decision has an impact on the generation of trips (see Jones *et al*., 1993). Understanding this substitution is important, particularly at a time when opportunities for entertainment at home are increasing because of the increasing accessibility of households to computers, theater quality audio and video systems, and an almost unlimited choices of movies to view from home. Despite the importance of understanding in-home and out-of-home substitution effects, very few studies have examined this issue (see Kitamura *et al*, 1996, Kraan, 1996 and Bhat, 1998e). And even these studies have examined substitution only in the context of broad activity types (such as discretionary activities, maintenance activities, *etc.*) rather than the more relevant substitution in specific activity types.

One of the impediments to a detailed analysis of in-home and out-of-home substitution has been (until recently) the unavailability of data on in-home activities. From a data collection standpoint, a related complication is the participation of individuals in multiple activities at the same time at home (for example, eating and watching television at the same time). Thus, research is required into how we might collect detailed data on activity type of participation at home and how we might be able to elicit information on multi-activity participation.

Unit of Analysis

The unit of analysis typically used in the activity-based travel models is the weekday. The implicit assumption is that there is little variation in activity-travel patterns across different days of the week. Research focusing even on simple aggregate measures of activity-travel behavior (such as trip frequency, and number and type of stops made during the morning/evening commutes) has indicated quite substantial intrapersonal variability across weekdays (see Pas and Koppelman, 1986; Jou and Mahmassani, 1997). One can therefore expect substantial day-to-day variations when considering entire activity-travel patterns. In addition, the focus on a single weekday does not allow the examination of the interaction in activity participation between weekends and weekdays. Of course, the use of an entire week as the unit of analysis will require the collection of time-use diary data over at least one week. This offers research opportunities for the development of data techniques that can collect time-use data over a week without being prohibitively expensive or appearing excessively intrusive.

The Decision Mechanism

As described earlier in the paper, there have been several previous modeling efforts to generate activity episode patterns. However, we still lack a good understanding of the decision mechanism underlying revealed activity episode patterns. For example, how do households and individuals acquire and assimilate information about their activity/travel environment, is activity-travel behavior pre-planned or is it subject to dynamic adjustment or is there a mixture of these processes, are attributes of activity episodes determined jointly or sequentially, and what objective do individuals follow while determining their scheduling decisions? The main challenge to studying these issues is that the generation and scheduling process that determines the revealed episode patterns can only be understood if additional data on the internal mechanism leading up to revealed episode patterns is collected. Such data are not currently available and again this offers another research opportunity in the area of data collection.

Clearly, there are important theoretical and methodological advances still to be made in the activity-based travel research field. As progress is made on these fronts, we are bound to see more applications of the activity paradigm in travel demand modeling. Some metropolitan planning organizations (MPOs) are already embracing this new paradigm and pursuing efforts to develop comprehensive activity model systems to replace the traditional four-step trip-based methods. Many other MPOs realize the need to switch to an activity-based modeling system in the near future. To conclude, the activity-based approach to travel demand modeling is slowly, but steadily, finding its way into actual practice.

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