Planning and Action in a Model of Choice

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Outline

- Introduction
- Modeling framework
- Applications
  - Driving behavior
  - Route choice
  - Mode choice
- Conclusion
Introduction
Motivation

- People often plan before they act
  - Plans can be short-term (e.g. target lane), medium-term (e.g. replace an old car) or long-term (e.g. move closer to work)

- Actions depend on the plans
  - Actions can be changing lane, purchasing a new car or moving to a new house

- Plans are often unobserved (latent)

- Supported by behavioral research
Theory of Planned Behavior (Ajzen, 1991)

- Intentions and behavioral control affect behavior

Car Replacement (Marell et al., 1995)

Economy, Innovations, Socio demographics, Environmental concern

Owned Automobiles

Aspiration Level

Comparison

Goal Setting

REPLACEMENT INTENTION

Search

Replacement

Commitment
(DellaVigna and Malmendier, 2006)

- Paying Not to Go to the Gym – overconfidence about future self-control

<table>
<thead>
<tr>
<th>GOAL</th>
<th>COMMITMENT</th>
<th>OUTCOME</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lose a Few Pounds</td>
<td>Monthly Contract</td>
<td>• Pay $17.3 per visit</td>
</tr>
<tr>
<td></td>
<td>Annual Contract</td>
<td>• Go 4.0 times per month</td>
</tr>
<tr>
<td></td>
<td>No Commitment</td>
<td>• Pay $15.2 per visit</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Go 4.4 times per month</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Pay $10-$12 per visit</td>
</tr>
</tbody>
</table>

Gambling (Andrade and Iyer, 2007)

- During planning stage, underestimated negative feelings after a loss

Why Represent Planning in Choice Models?

- Behavioral realism and dynamics
- Policy intervention
Behavioral Realism and Dynamics

- Incorporating plans to improve model performance
- Plans evolve over time
  - Situational constraints
  - Contextual changes
  - Past experiences
- Plans explain timing of actions
- Plans capture temporal dependence
Policy Intervention

- To affect outcomes, need to intervene during planning
  - Information affects route choice
  - Fuel tax affects residential choice
Modeling Framework

Two-Layer Decision Hierarchy

- Choice of plan (targets/tactics): \( l \)
- Choice of action (maneuver/execution): \( j \)
Action Choice Model

- Probability of action $j$:

$$P( j | v ) = \sum_{l} P( j | l, v ) P( l | v )$$

where,

- $j = \text{action}$
- $l = \text{plan}$
- $v = \text{individual specific factor (e.g. aggressiveness)}$
Dynamic Behavior

- Modeling a sequence of plans and actions
- Plans may depend on previous plans (inertia) and past actions (experience)
  - State-dependence

- $l_t =$ plan at time $t$
- $j_t =$ action at time $t$
Dynamic Behavior (cont.)

\[ t = t+1 \]

![Diagram showing the dynamic behavior with nodes and arrows representing the plan and action stages.](image-url)
Dynamic Behavior (cont.)

- Probability of selecting plan \( l \) at time \( t \) (conditional on past plans and actions):
  \[
P(l_t \mid l_{1:t-1}, \nu, j_{1:t-1})
  \]

- Probability of action \( j \) at time \( t \) (conditional on current plan and past plans and actions):
  \[
P(j_t \mid l_{1:t}, \nu, j_{1:t-1})
  \]

where,

\( j_t \) = action at time \( t \)
\( l_t \) = plan at time \( t \)
1:t = 1,2,\ldots,t
Dynamic Behavior (cont.)

- Joint probability of a sequence of plan and actions may be too complex.
- Number of possible sequences of plans is $|L|^T$
  where $|L|$ = number of possible plans.
- Simplified using Hidden Markov Model (HMM).
Hidden Markov Model Assumptions

- Current action only depends on current plan
  \[ P(j_t | l_{1:t}, \nu, j_{1:t-1}) = P(j_t | l_t, \nu) \]

- Current plan only depends on previous plan
  \[ P(l_t | l_{1:t-1}, \nu, j_{1:t-1}) = P(l_t | l_{t-1}, \nu, j_{1:t-1}) \]
HMM Plan Action Model

- The joint probability of the plan and action at time $t$ (conditional on the past)

$$P(j_t \mid l_t, \nu)P(l_t \mid l_{t-1}, \nu, j_{1:t-1})$$

- The joint probability of a sequence of plans and actions

$$\prod_{t=1}^{T} P(j_t \mid l_t, \nu)P(l_t \mid l_{t-1}, \nu, j_{1:t-1})$$
**Probability of a Sequence of Actions**

\[
P(j_1, \ldots, j_T \mid l_0, \nu) = \sum_{(l_1, \ldots, l_T)} \prod_{t=1}^{T} P(j_t \mid l_t, \nu) P(l_t \mid l_{t-1}, \nu, j_{1:t-1})
\]

\[
= \sum_{l_T} P(j_T \mid l_T, \nu) \sum_{l_{T-1}} P(l_T \mid l_{T-1}, \nu, j_{1:T-1}) P(j_{T-1} \mid l_{T-1}, \nu) \cdots
\]

\[
= \sum_{l_1} P(l_2 \mid l_1, \nu, j_1) P(j_1 \mid l_1, \nu) P(l_1 \mid l_0, \nu)
\]

- Can be calculated recursively
- Number of summations reduced from \(|L|^T\) to \(|L|^T\) by the HMM assumptions
  where \(|L|\) = number of possible plans
Applications

- Driving behavior
- Route choice
- Mode choice
1. Driving Behavior
Freeway Lane Changing (Choudhury et al., 2007)

Freeway Lane Changing (cont.)

- Currently in Lane 3
  - Lane 1: No Change, Change Left
  - Lane 2: No Change, Change Left
  - Lane 3: No Change
  - Lane 4: No Change, Change Right

Target Lane (Plan)
Gap Acceptance (Action)
Freeway Lane Changing (cont.)

Estimation and Validation

- Estimated with vehicle trajectory data from I-395, VA
- Validated with data from I-80, CA
  - Unlimited access HOV lane
- Additional independent validation in AIMSUN, PARAMICS and VISSIM(ngsim.fhwa.gov)
Freeway Lane Changing (cont.)

Estimation and Validation (cont.)

Vehicle lane distributions
2. Routing Policy Choice (Gao, Frejinger, and Ben-Akiva, 2008)

- Captures *en route* adaptation to traffic information
- Defined for a network with random travel times
- Mapping from node, time, and traffic information to decisions on next links
- Example:
  - (home, 8:00am, Light congestion on highway) -> Highway
  - (home, 8:00am, Heavy congestion on highway) -> Arterial
- Transit strategy is a special case of routing policy
  - Multiple transit lines serve the same destination
  - Board the train that arrives first
  - A mapping from random train arrivals to decision on which line to take

Model Framework

- **Plan**: Routing policy (mapping from network conditions to next nodes)
- **Action**: Path

![Diagram showing routing policies and paths](attachment:image.png)
Model Framework (cont.)

- Routing policy $l$ is latent (plan)
  - Only the path $j$ that is actually taken is observed (action)
- Information $r$ depends on
  - A distinctive realization of all random link travel times.
  - Known to the modeler through archived monitoring data.
  - Unknown to the traveler before the trip.
Model Framework (cont.)

\[ P(j \mid r) = \sum_{l \in G} P(l)P(j \mid l, r) \]

- \( P(j \mid r) \): Probability of observing path \( j \) with information \( r \)
- \( G \): Choice set of routing policies
- \( P(l) \): Routing policy choice model
- \( P(j \mid l, r) \): Binary variable
  
  (1 if policy \( l \) is realized as path \( j \) with information \( r \);
  0 otherwise)

- Choice of action given plan, \( P(j \mid l, r) \), is deterministic
3. Mode Choice (Abou-Zeid and Ben-Akiva, 2009)

- **Plan**: intended usage of different modes (commuting pattern intentions)
- **Action**: car or public transportation (PT)
MIT Study

- Experiment requiring temporary change of commute mode (from car to PT)
- Data collected:
  - 1 month pre-treatment
  - 1 month post-treatment
    - Plan: intended frequency of commuting by car and PT
  - 2 months post-treatment
    - Car or PT
<table>
<thead>
<tr>
<th>PT Plan</th>
<th>Action</th>
<th>Car</th>
<th>PT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than once a month</td>
<td></td>
<td>19</td>
<td></td>
</tr>
<tr>
<td>Once a month</td>
<td></td>
<td>11</td>
<td></td>
</tr>
<tr>
<td>2-3 times per month</td>
<td></td>
<td>13</td>
<td></td>
</tr>
<tr>
<td>Once a week</td>
<td></td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>2-3 times per week</td>
<td></td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>4+ times per week</td>
<td></td>
<td></td>
<td>14</td>
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</tbody>
</table>
Intrinsic utility
$(\Delta U_{Car-PT})$

Latent plan
$(l^*_{Car}, l^*_{PT})$

Action
$(y_{Car}, y_{PT})$

Happiness
$(h_{Car}, h_{PT})$

Observed plan
$(l_{Car}, l_{PT})$
MIT Study
Estimation Results

\[ \Delta U = \beta_1 (ln(Time_{Car}) - ln(Time_{PT})) + \beta_2 (Cost_{Car}/Income - Cost_{PT}/Income) + \varepsilon; \quad \varepsilon \sim N(0,1) \]

**Reduced Form Model**

\[
y = \begin{cases} 
  Car & \text{if } \beta_0 + \Delta U_d + \mu \eta \geq 0 \\
  PT & \text{otherwise} 
\end{cases}
\]

\[ \eta \sim \text{Logistic}(0,1) \]

Choice Log-Likelihood = -37.8

**Plan-Action Model**

\[
y = \begin{cases} 
  Car & \text{if } \beta_0 + l^* + \mu \eta \geq 0 \\
  PT & \text{otherwise} 
\end{cases}
\]

\[ l^* = \Delta U_d \]

\[ l = \lambda l^* + \nu; \quad \nu \sim N(0, \sigma_v^2) \]

Choice Log-Likelihood = -37.2
Conclusion

- Extension of choice models to include planning
- More realistic and better performance compared to models without plans
- Dynamic microsimulation of plans and actions predicts timing of choices