Plan and Action in a Model of Choice

Moshe Ben-Akiva

Northwestern University

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Outline

• Introduction
• Modeling framework
• Applications
  1. Driving behavior
  2. Route choice
  3. 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)

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 Lyer, 2007)

- During planning stage, underestimated negative feelings after a loss

Why Represent Planning in Choice Models?

• Policy Interventions should be directed to planning step
  – Information affects route choice
  – Fuel tax affects residential choice

• Behavioral Realism
  – Improve model performance

• Dynamics
  – Plans evolve over time (situational constraints, contextual changes, past experiences)
  – Plans explain timing of actions
  – Plans capture temporal dependence
Travel Choice (Hirsh et al., 1986)

- Weekly activity planning - each week is divided into multiple time periods

Modeling Framework
Two-Layer Decision Hierarchy

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

• Probability of action $j$:

$$P( j | \nu ) = \sum_l P( j | l, \nu ) P( l | \nu )$$

where,

$j = \text{action}$

$l = \text{plan}$

$\nu = \text{individual specific factor (e.g. aggressiveness)}$
Dynamic Behavior

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

  - \( l_t = \text{plan at time } t \)
  - \( j_t = \text{action at time } t \)
Dynamic Behavior (cont.)

Plan

Action

$t = t+1$
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):
  \[
P(j_t \mid l_t, \nu, j_{1:t-1})
  \]

where,

\( j_t = \text{action at time } t \)

\( l_t = \text{plan at time } t \)

\( 1:t = 1,2,\ldots,t \)
Dynamic Behavior (cont.)

• Joint probability of a sequence of plans and actions may be too complex

• Number of possible sequences of plans is $|L|^T$
  where $|L| = \text{number of possible plans}$

• Simplified using Hidden Markov Model (HMM)
Hidden Markov Model Assumptions

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

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

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

\[ P \left( j_t \mid l_t, \nu \right) P \left( l_t \mid l_{t-1}, \nu , j_{1:t-1} \right) \]

• The joint probability of a sequence of plan-action

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

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

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

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

- Can be calculated recursively

- Number of elements reduced from \(|L|^T\) to \(|L|T\) by the HMM assumptions

where \(|L| = \text{number of possible plans}\)
Extending the Plan-Action Model

• Motivation:

  Implementation of an action takes time

    – Maneuvering time to execute a lane-change after getting an acceptable gap, moving to a house after purchasing it etc.

• Extension:

  Include implementation of actions as a third layer in the decision hierarchy

• Key advantage:

  Models of planning and action are no longer sensitive to the choice of time interval
Plan-Action-Implementation Model

\[ t = t + 1 \]
Applications

- Driving behavior
- Route choice
- Mode choice
1. Driving Behavior
Arterial Lane Changing (Choudhury et al., 2010)

Lankershim Boulevard, Los Angeles, California

Arterial Lane Changing (cont.)

- Model

  - Additional layer to model the duration/execution of the lane change
Arterial Lane Changing (cont.)

• Methodology
  – Time resolution of the panel data affects the execution model
  – Coefficients of the execution model were estimated along with all other unknown parameters
  – Procedure repeated for multiple datasets extracted from the same video
  – Datasets differ in time resolution (.2 sec, .5 sec, 1 sec and 2 sec)
Arterial Lane Changing (cont.)

- Results
Arterial Lane Changing (cont.)

• Probability of lane change increases with time step

• No significant change in coefficients of target lane choice and gap acceptance levels

• Coefficients of execution level vary linearly with the log of the time step
2. Routing Policy Choice  
(Gao, Frejinger, and Ben-Akiva, 2008)

- *En route* adaptation in response to real-time traffic information
- Network with random travel times
- Mapping from node, time, and traffic information to a decision on the next link
- Example:
  - (home, 8:00am, Light congestion on highway) -> Highway
  - (home, 8:00am, Heavy congestion on highway) -> Arterial

Routing Policy Choice
(Gao, Frejinger, and Ben-Akiva, 2008) (cont.)

- 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](image)
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.)

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

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

• Choice of action given plan, \( P(j | l, r) \), 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)

![Diagram showing mode choice with nodes labeled 1 to L, and branches to Car and 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
### MIT Study

**Plan-Action**

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Car</th>
<th>PT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than once a month</td>
<td>19</td>
<td></td>
</tr>
<tr>
<td>Once a month</td>
<td>11</td>
<td></td>
</tr>
<tr>
<td>2-3 times per month</td>
<td>13</td>
<td></td>
</tr>
<tr>
<td>Once a week</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>2-3 times per week</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>4+ times per week</td>
<td></td>
<td>14</td>
</tr>
</tbody>
</table>
 MIT Study
Model Framework

- Mode choice model framework

Intrinsic utility ($\Delta U$)

Happiness ($h_B$, $h_A$)

Reported plan ($l$)

Action ($y$)
\[ \Delta U = \beta_1 \left( \ln(\text{Time}_{\text{Car}}) - \ln(\text{Time}_{\text{PT}}) \right) + \beta_2 \left( \frac{\text{Cost}_{\text{Car}}}{\text{Income}} - \frac{\text{Cost}_{\text{PT}}}{\text{Income}} \right) + \varepsilon; \quad \varepsilon \sim N(0,1) \]

Reduced Form Model

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

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

Choice Log-Likelihood = -37.8

Plan-Action Model

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

\[ l^* = \Delta U_d \]

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

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