The role of bounded rationality in travel choice behavior and implications for transport modeling

Theo Arentze

Urban Planning group
Eindhoven University of Technology,
The Netherlands
Predicting people’s response to policies is notoriously difficult.
Travel demand models

Micro simulation models

Activity-based models

Daily activity-patterns

Trip records

OD trip matrix

Dynamic/static traffic simulation/assignment models

New model development started in early nineties

Models are now making the transition to practice
Outline of my presentation

• Brief review of activity-based modeling
  • objectives, approach and new developments

• Bounded rationality in travel behavior
  • human biases
  • towards dynamic models

• New modeling approaches
  • habitual behavior and spatial search
  • learning and wellbeing
Why activity-based modeling?

- New demands from transport planning and policy making
  - Switch in focus to travel demand measures
  - Importance of temporal factors (flexible work hours) and task combination
  - Integration of policies: land-use and transport planning
  - More comprehensive evaluation of policies
## Activity-based versus trip-based approach

<table>
<thead>
<tr>
<th>Trip-based</th>
<th>Activity-based</th>
</tr>
</thead>
<tbody>
<tr>
<td>Focus is on trips</td>
<td>Focus is on activities</td>
</tr>
<tr>
<td>Unit is a trip</td>
<td>Unit is a day</td>
</tr>
<tr>
<td>Space-time constraints ignored</td>
<td>Space-time constraints taken into account</td>
</tr>
<tr>
<td>Low resolution time and place</td>
<td>High resolution time and place</td>
</tr>
<tr>
<td>Decision unit is individual</td>
<td>Decision unit is household</td>
</tr>
<tr>
<td>Predicts when, where, transport mode</td>
<td>Predicts which activities, when, where, for how long, trip-chaining and transport mode</td>
</tr>
</tbody>
</table>
Albatross example of an activity-based model

- Rule-based
- Continuous time scale
- Within household-interaction
- Space-time constraints
- National level
- Computation time
  - 10% of population – 2.1 million agents
  - More than 4000 postcode areas
  - Around 8 hours computation time on a standard PC
Albatross example of an activity-based model

Albatross abroad
- Feathers – Belgium
- Under development
  - Seoul
  - Indonesie

Model is static – time span is one day
New developments in activity-based modeling

- From static to dynamic models
  - expand time frame from one day to multiple days
  - include life trajectories and long-term mobility decisions

- Include social networks and social interactions
  - social influence in decision making
  - group decision making – negotiation

- New survey methods and data sources
  - tracking of movements with GPS or mobile phone positioning
  - social media – big data
Incorporating bounded rationality in models of travel demand
Time is ripe

- Cumulative evidence from psychology and behavioral economics
  - See recent book of Daniel Kahneman (2011) – Thinking, Fast and Slow

- Human biases are well documented and tools for data collection and modeling available

- Modern survey technologies facilitate a move from one-day to multiple days data collection

- Wide use of smart phones allows new in-situ data collection methods
Aspects of bounded rationality

Biases are well-documented

Sensitivity to losses
Over responding to peak experiences
Sticking with habits
Impact of emotion
Memory distortions
Limited search and effort

Accounting for biases requires a change from static to dynamic modeling and involves all 4 areas
A model with bounded rationality

Learning & judgment model predicts how an individual learns and makes judgments about risks based on experiences.
A model with bounded rationality

Learning & judgment

Evaluation & decision

Search & info acquisition

Needs and resources

Environment (social and physical)

Mobility patterns & subjective wellbeing

Limited search

Search-and-information-acquisition model predicts the search for alternatives and formation of choice-sets
A model with bounded rationality

The evaluation-and-decision making model, given the choice-sets and judgments of risks, predicts an individual’s choices.
The model of subjective-wellbeing predicts an individual’s satisfaction with the (transport and location) options he has.
Habitual behavior and spatial search
Habitual behavior

• Over time individuals develop particular routines for implementing their activities
• A routine has the form of a script that defines
  – departure time
  – location (destination)
  – duration
  – where from (origin – trip chaining)
  – main transport mode
  – route
• For each activity there may be multiple scripts - alternative ways of implementing an activity
• In habitual mode, individuals select the scripts that best fit the current needs and constraints
### Habitual behavior

#### Example of an agent’s set of scripts

<table>
<thead>
<tr>
<th>Activity</th>
<th>Start time</th>
<th>Location</th>
<th>Duration</th>
<th>Where from</th>
<th>Mode</th>
<th>Route</th>
</tr>
</thead>
<tbody>
<tr>
<td>work</td>
<td>7 am</td>
<td>TUe</td>
<td>8 hours</td>
<td>Home</td>
<td>Walk - Train</td>
<td>local train</td>
</tr>
<tr>
<td>work</td>
<td>8 am</td>
<td>TUe</td>
<td>8 hours</td>
<td>Home</td>
<td>Car</td>
<td>highway</td>
</tr>
<tr>
<td>work</td>
<td>7.45 am</td>
<td>TUe</td>
<td>8 hours</td>
<td>Home</td>
<td>Car</td>
<td>local route</td>
</tr>
<tr>
<td>groceries</td>
<td>morning</td>
<td>Aldi</td>
<td>20 min.</td>
<td>Home</td>
<td>Car</td>
<td>shortest</td>
</tr>
<tr>
<td>groceries</td>
<td>lunch-break</td>
<td>AH</td>
<td>10 min.</td>
<td>Work place</td>
<td>Walk</td>
<td>shortest</td>
</tr>
<tr>
<td>groceries</td>
<td>early afternoon</td>
<td>Market</td>
<td>30 min.</td>
<td>Home</td>
<td>Walk</td>
<td>shortest</td>
</tr>
</tbody>
</table>

... ... ...

| touring -walk  | 7 am       | Neighborh. | 20      | Home       | Walk      | -                |
| touring -walk  | afternoon  | Wood 1     | 2 hours | Home       | Car       | via Reusel       |
| touring -walk  | afternoon  | Wood 2     | 1 hour  | Home       | Car       | via Oisterwijk   |

Alternative ways to implement the work activity – referred to as Scripts
Habitual behavior

Utility of a script

$$U_i(d, t, m, l, T) = v_i(d, t, l) \cdot f_i(T) + U^R(d, t, m, l)$$

Activity component  Travel component

Decision rule

– consider the scripts that meet the following condition

$$U_i(S) > c_d \cdot T(S)$$

Threshold constr.

– choose the script that maximize $U$

Adaptation rule

Increase threshold if time budget is exceeded
Decrease threshold if time budget is not fully used
Spatial search

- If dissatisfied with current set of scripts then the agent starts exploration

The probability that a location $i$ is discovered is specified as

$$P(i|K) = \frac{\exp(U_i(K) / \tau)}{\sum_{j \in J} \exp(U_j(K) / \tau)}$$

The Boltzmann model

- Attributes considered
- Universal choice set
- Hidden utility for the agent
- Lack of information
  - Limited effort
  - Limited access to info sources

Limited search can be modeled by means of $\tau$
An implementation

Current choice set

Empty?

Y

The profile with max activation level (W)

N

New choice set

Experience based learning

MC: delay

Update:
- Beliefs for delay in c
- Emotional value of this experience
- Experienced utility of this profile
- Awareness-Activation-Emot.Value

Update aspirations

The profile with max expected utility (EUE)

Satisfied?

Y

Habit

N

Exploitation

Satisfied?

Y

The newly discovered

N

Exploration

Long-term satisfied?

N

Become “awake”

Y

Maintain
Effect of memory and emotion on learning and satisfaction

New modeling approaches (2)

How do travelers judge the likelihood of a risky event?

How do travelers judge degree of satisfaction with choice alternatives?
How do travelers judge the likelihood of a risky event?

• This is a relevant question
  • knowing how travelers make likelihood judgements is important for understanding their choice behavior

• Naïve model
  • people count occurrences and store frequency data in memory – their judgments are unbiased

• However, this is not in line with evidence. Two fundamental biases in human likelihood judgements are well-known (Lichtenstein et al., 1978)
Primary bias

• small probabilities are overestimated and large probabilities are underestimated
• this explains why rare events may have a large impact
Secondary bias

- events that are more vividly imagined are overestimated
- this explains why a salient event such as a plane crash tends to have much more impact than a more common event
• **Availability / fluency heuristic**
  - first formulated by Tversky and Kahneman (1973)
  - supported by numerous empirical studies

• **Tversky and Kahneman (1973)**
  - people use a byproduct of memory processes to judge the likelihood of some event
  - that is, the **ease** with which examples of the event can be retrieved from memory is used as criterion
  - the easier examples come to mind the more likely the event is judged to be

• **This heuristic explains the primary and secondary biases** (Hertwig et al. 2005)
• ACT-R cognitive architecture provides a model of memory encoding and retrieval processes (Anderson et al. 2004)

\[ A_{ik} = \ln\left( \sum_{j \in k} (t_{ij})^d \right) \]

\[ Q_{ik} = \frac{A_{ik}}{\sum_j A_{ij}} \]

• This model explains the primary bias
Memory model

- Extension of the ACT-R memory model to account for effect of arousal on memory

\[ A_{ik} = \ln\left( \sum_{j \in k} (t_{ij})^{d(S)} \right) \]

\[ Q_{ik} = \frac{A_{ik}}{\sum_j A_{ij}} \]

- This extended model also explains the secondary bias
How do travelers judge degree of satisfaction with choice alternatives?

• This is a relevant question
  • knowing how travelers arrive at satisfaction judgements is important for understanding subjective wellbeing and habitual behavior

• Naïve model
  • decision utility is the same as experienced utility
    ➢ utilities can be derived from choice behavior

• However, Kahneman (2000) points to known biases:
  • neglect of duration of episodes
  • dominance of end outcome of episodes
  • disproportional impact of peak experiences
• Again, the memory model of ACT-R offers a way to describe this process

\[ A_{ij} = \ln \left( (t_{ij})^{d(S)} \right) \]

\[ U_i = \sum_j A_{ij} \cdot U_{ij} \]

• This model explains the disproportional impact of extreme events on satisfaction
Data collection

- Experience sampling
- Small questionnaire on the smartphone completed on every trip
  - data of the trip (mode, route, purpose, etc.)
  - emotional state of the traveller during the trip (arousal and valence)
  - satisfaction judgement (experienced utility)
- In-situ measurement of affective experiences of travelers (Ettema et al. 2014)

\[
A_{ij} = \ln \left( (t_{ij})^{d(S)} \right)
\]

\[
U_i = \sum_j A_{ij} \cdot U_{ij}
\]
Implications for policy making and modeling

- **Policy making - theory stresses:**
  - importance of reliability of transport services on satisfaction and risk assessment
    - avoid negative peak experiences
  - importance of avoiding losses in the behavior change targeted
    - losses generate negative emotion

- **Transport modeling**
  - the memory-based models of learning and judgement can be incorporated in dynamic travel-demand models
Conclusion

• It was argued that
  • taking bounded rationality into account matters – human biases are well-documented
  • to realize this, static models should be replaced by dynamic models

• I highlighted new modeling approaches in areas of
  • habitual behavior and spatial search
  • learning and wellbeing
Conclusion

• The new approaches are only in its infancy

• New data collection and estimation methods are needed to estimate parameters of
  • habitual behavior and search
  • learning and wellbeing

• New agent-based platforms are needed to develop full-scale applications
Thank you for your attention!


