Learning, Information and Risk in User Adjustment Processes: Role of Behavior Experiments

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DADDY-0: Day-to day dynamics in transportation networks
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OUTLINE

1. Origins: “le plus ça change”
2. Why Conduct Experiments?
3. Early Commuter Behavior Experiments
4. ATIS Simulators and Experiments
5. Experimental Economics and Route Choice Games
6. Prediction Markets
7. Issues in Experimental Games
8. Risk in Learning Models
9. Route Choice Mechanisms
10. Experiments: Effect of Learning on System Dynamics
11. Concluding Remarks
STABILITY and USER ADJUSTMENT PROCESSES

- An equilibrium would be just an extreme state of rare occurrence if it were not stable— that is, if there were no forces which tended to restore equilibrium as soon as small deviations from it occurred.

- Besides this stability “in the small” one may consider stability “in the large”— that is, the ability of the system to reach an equilibrium from any initial position.

- This latter type of stability is interesting not only because it concerns the capacity of the system to reach a new equilibrium position after some big change, but also because one may want to use an analogue of the adjustment process as a method of computing an equilibrium solution by successive approximations.

from page 70, section 3.3. Stability
Beckmann, McGuire and Winsten (1956)
Studies in the Economics of Transportation
The study of stability hinges ultimately on the question of how road users adjust themselves to changes— that is, how they adapt the extent of their travel by road and their choice of routes to varying traffic conditions. This, however, is one of the big unknowns of road-user behavior, so at the present stage only conjectures are possible.

Through a simple and plausible model one can get a rough picture of the minimum of conditions that must be met in order that the adjustment process should converge.

These road users who have or can obtain adequate knowledge of the traffic conditions, even if not by first-hand experience, choose a route which is optimal at the transportation cost of the last period and set their demand for transportation at levels corresponding to the average costs of trips during the last period.

from page 70, section 3.3.1 Adjustments of Road Users
Consider simple network; known link performance functions;

One O-D pair, connected by two paths

Known constant demand rate $q_{AC}$
Day 1

Assume users act on day $t+1$ according to costs prevailing on day $t$

Day 2

Assume users act on day $t+1$ according to costs prevailing on day $t$

OSCILLATIONS...
\[ X_1 = q_{AC} \]

\[ X_2 = \alpha q_{AC} \]

\[ X_1 = (1 - \alpha)q_{AC} \]

Assume only fraction \( \alpha \) of users act on day \( t+1 \) according to costs prevailing on day \( t \)

and so on…
Using $\alpha = 1/5$

Solution may diverge, oscillate, or possibly approach convergence, depending on parameters of the problem and fraction $\alpha$. Relates problem to classical cobweb pattern in supply-demand equilibration.

**BMW discuss intuitively how equilibrium might be approached, with $\alpha$ decreasing as difference in route costs narrows; adaptive behavior.**
• Suggest concept for *day-to-day learning model*; instead of Markovian assumption (knowledge only of previous day’s experience),
...*some weight may be given to experience of the more remote past, especially where oscillations have already been experienced.* (p. 75)

This work has influenced, directly and indirectly, a fascinating body of work on adjustment processes, day-to-day dynamics and associated system properties, disequilibrium and tatonnement approaches, including:

Horowitz (1984); Mahmassani, Herman and coworkers (1985-2003); Cantarella and Cascetta (1993, several); Friesz, et al. (1993); Nagurney and Zhang (1993, several); Watling (1999); Peeta (2002), Chen and Mahmassani (2004)...

→ Many important results and properties, valuable insight
• R. Chen and Mahmassani (2004)

Bayesian framework for updating travel time perceptions

Trigger Mechanisms: travel time difference threshold vs. periodic

Stopping Rules: based on user confidence (perceived travel time variance)

Heterogeneous Users: selectivity, information

![LOW Threshold](image1)

![HIGH Threshold](image2)
The study of stability hinges ultimately on the question of how road users adjust themselves to changes— that is, how they adapt the extent of their travel by road and their choice of routes to varying traffic conditions. This, however, is one of the big unknowns of road-user behavior, so at the present stage only conjectures are possible. (p.70)

NEED FOR EMPIRICAL BASIS FOR THESE MODELS OF USER BEHAVIOR

LARGE AND GROWING BODY OF LABORATORY EXPERIMENTS; focus on experimental study of system dynamics and user decision processes; early experiments of Mahmassani and Herman (1984-1989); Iida et al. (1990)

CONSIDERABLE INTEREST FROM ITS COMMUNITY and EXPERIMENTAL ECONOMISTS (e.g. 2001 workshop on route choice dynamics organized by Prof. R. Selten in Bonn; Schrekenburg; Helbing...; ongoing efforts at TU-Delft, Napoli, Central Florida)
HIERARCHY OF APPROACHES TO STUDY COMPLEX SYSTEMS

Mahmassani and Herman (1987)

1. Formulate analytical models of idealized situations,
   – to derive basic insight about major elements of the problem.

2. Computer simulations of more realistic situations under assumed behavior and interaction rules,
   – to capture the effect of interactions that are beyond the tractability of simplifies idealizations.

3. **Laboratory experiments**
   – enable observation of behavior under controlled conditions, with a limited number of subjects.

4. Field experiments and/or demonstration projects,
   – to observe the performance of the system and associated user behavior in actual operation.
WHY CONDUCT EXPERIMENTS?

• Complex dynamics and collective effects are essential aspects of the system under consideration, making joint measurement in the real world considerably complicated or costly.

• Situations or policies of interest are not available in the real world (e.g. new technologies), or may be mutually inconsistent in the same system.

• Control for extraneous factors is desired.

• Understanding of dynamics and learning processes is of concern.
Our Scope Today

• Use of experiments and gaming situations to study travel and activity behavior, for the purpose of understanding and modeling the underlying decision, judgment and learning processes, and/or exploring the collective properties resulting from the interaction of multiple decision agents in a transportation context.

• Specifically targeted at methods where
  (1) respondents engage in a repeated game situation, in an iterative, interactive process; and
  (2) respondents experience some kind of payoff as a consequence of the response provided.
  (3) Outcome or payoff experienced by a subject depends specifically on the decision/response supplied by that subject, individually or in interaction with those of other respondents.
KEY ELEMENTS OF EXPERIMENTS

1. A DECISION SITUATION

2. EXPERIMENTAL TASK(S) FOR SUBJECTS TO PERFORM

3. AN INTERACTION BOX --→ DETERMINES PAYOFFS GIVEN DECISIONS

4. A CURRENCY (for Payoff, may be accumulated/traded in experimental economics, given initial allocation; key difference w. transportation simulation games)

5. FEEDBACK MECHANISM (CONTENT, TIMING, DISPLAY…)

6. STOPPING RULE: PRE-DETERMINED NUMBER OF ITERATIONS vs. STATE-DEPENDENT
Subject i

i +1

Subject I

DECISIONS

PAYOFF$

INTERACTIONS

OUTCOMES
KEY ELEMENTS OF EXPERIMENTS

1. A DECISION SITUATION

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COMMUTER BEHAVIOR EXPERIMENTS
THE EARLY EXPERIMENTS (1984-88):

Interaction of user decisions and traffic system dynamics
GENERAL EXPERIMENTAL PROCEDURE

Describe setting (commuting corridor)

USER DECISIONS

Departure time, Route
n = 1,...,N, day t

MACROPARTICLE TRAFFIC SIMULATOR

Arrival Times

Feedback, day t-1

Set t = t+1
COMMUTING CONTEXT
THE EXPERIMENTS

• Experiment 1: 100 subjects
  – Single route corridor ➔ departure time only;
  – Feedback: individual perf. only (limited info)

• Experiment 2: 100 subjects
  – Same as 1; feedback on overall system performance (full info)

• Experiment 3: 200 subjects
  - Two routes: not identical
  - Two information availability groups: full vs. limited
  - More congestion
Day-to-Day Evolution of Fraction of Users Who Switch Departure Time or Route in Sector 2 (all three experiments)
Day-to-Day Evolution of Fraction of Users Who Switch Departure Time or Route in Sector 5 (all three experiments)
Comparison of Average Steady State Performance of Each Sector Under the First Two Experiments
Comparison of Average Performance of the Two Information Availability Groups at the Final State (average over last four days) in Each Sector in the Third Experiment.

It was also noted that FULL INFO group in Experiment 3 was switching less (on average) than LIMITED INFO group.
Behavioral Mechanism

Day-to-day Switching of Departure Time

Boundedly-rational search for acceptable arrival time

Indifference Band for Schedule Delay (viz PAT)
  Asymmetric: early vs. late
  Varies across users (socio-demographics)
  Dynamically varying
    - with experience: short-term vs. long term
    - with information availability
Day-to-day Evolution of Percent of Users Switching Departure Time and Percent Switching Route
EXPERIMENT 3

Day-to-day Evolution of Percent of Users Switching Both Route and Departure Time and Percent Switching Only One
Relation Between Indifference Bands of Departure Time and for Route Switching for Early Arrivals.

If \( SD_{i,t} \leq IBD_{i,t} \) \( \Rightarrow \) Keep both \( DT_{i,t} \) and \( R_{i,t} \)
If \( IBD_{i,t} < SD_{i,t} \leq IBR_{i,t} \) \( \Rightarrow \) Switch \( DT_{i,t} \) only
If \( SD_{i,t} > IBR_{i,t} \) \( \Rightarrow \) Switch both \( DT_{i,t} \) and \( R_{i,t} \)

Note: \( SD_{i,t} \) is the schedule delay of user \( i \) on day \( t \).
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<th>N*</th>
<th>Mean</th>
<th>Variance</th>
<th>Likelihood Ratio</th>
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NOTE: Only 2 people switched route on Day 27, precluding calibration.

*Standard error of parameter estimate is in parentheses.
**DT denotes the indifference band governing departure time switching only (IBDT).
***R denotes the indifference band governing route switching, usually accompanied by departure time switching (IBR).

N denotes the number of observations.
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</table>

†Standard error of parameter estimate is in parentheses.
*N denotes the number of observations
**DT denotes the indifference band governing departure time switching only (IBDT)
***R denotes the indifference band governing route switching, usually accompanied by departure time switching (IBR).
Concluding activities

- Calibrated *joint model of route and departure time switching*, for both early and late arrivals, that captures state dependence and heterogeneity.

- Specified models of *departure time adjustment*, conditional upon decision to switch; includes model of travel time learning and prediction by commuters [route choice, given switch, trivial in two-route corridor].

- Experiment results validated with two-week *diary surveys of actual commuters* in Austin and Dallas:
  - Less dynamic fluctuation in system performance than experiments.
  - Day-to-day variation in actual systems not only dependent on traffic conditions and experience, but also activity patterns (trip chaining), which is not constant for commuters ➔ extended boundedly-rational model to incorporate activity chaining.
  - Behavioral mechanisms developed on basis of laboratory experiments provided good explanation of observed behavior: same model specification, correct signs, but different coefficient magnitudes.
ROLE OF EXPERIMENTS

- Develop insights into behavioral processes
- Develop model specifications
- Learn about
  - Direction (sign) of effects of different attributes
  - Significance of main effects and interactions
  - Relative magnitudes

CONCERN

- External validity
  - Previous experience suggests very good potential to transfer insights, specification and relative magnitudes to real world
  - However, actual parameter values may vary (site specific)

Role of operational tests, in tandem with laboratory experiments, to develop more definitive basis of behavioral knowledge to support ATIS design and deployment.
Role and effect of real-time information on individual decision processes and system dynamics
MOTIVATION

Importance of modeling and understanding tripmaker behavior under real-time information

- ATIS design, deployment and evaluation
- ITS impacts assessment (e.g. congestion alleviation)
- Demand modeling and forecasting applications
- Critical for network performance analysis and state prediction
Travel Simulators for ATIS Behavioral Studies

- Excellent compromise between stated and revealed preferences
- Places participant in simulated choice situation
- Fidelity depends on realism of stimulus and consistency between response and stimulus
Computer-based Interactive Simulators for Study of User Response to ATIS

- University of Leeds (IGOR, VLADIMIR…) [Bonsall et al.]
- University of Texas at Austin [Mahmassani et al.]
- Allen et al.
- Univ. of California at Davis [Jovanis et al.]
- Univ. of California at Irvine (FASTCARS) [McNally et al.]
- Massachusetts Institute of Technology [Koutsopoulos et al.]
OVERVIEW OF RESEARCH METHODOLOGY

- **Observational Framework**
  - Dynamic interactive multi-user travel behavior simulator

- **Empirical Analysis**
  - Perform quasi-experimental design to investigate factors of interest
  - Conduct large scale experiments with actual commuters
  - Build mathematical models of observed choices

- **Modeling Framework**
  - Dynamic Kernel Logit (DKL) formulation / MNP formulation
  - Calibration by iterative Monte-Carlo simulation and non-linear optimization
EXPERIMENTAL DESCRIPTION

• Commuting corridor with common destination in CBD

• Task
  ♦ Reach Workplace in CBD by 8:00 a.m.

• Trip-Choices
  ♦ En-route path choice, Day-to-day Departure time choice

• ATIS information
  ♦ Trip-time, traffic jam message, congestion information, feedback
Central Business District

Day = 1  Time = 7:10 AM

Please select a highway to enter.

Time: 24.1  12.7  11.8
(min)

Legend
Node .........................
Uncongested Link .......
Mild Congestion .......
Moderate Congestion ...
Severe Congestion .......

Hwy-1  Hwy-2  Hwy-3
55mph  45mph  35mph
TIME = 07:45 AM

Please select your next link.

```
[Diagram showing a network of roads with options 1, 2, 3]
```

Legend

- Node: ......................
- Uncongested Link: ....
- Mild Congestion: ......
- Moderate Congestion
- Severe Congestion ...
EXPERIMENTAL TREATMENTS (Experiment ATIS II)

• Nature of ATIS Information:
  ♦ Descriptive, Prescriptive

• Information Type:
  ♦ Prevailing, Predicted, Perturbed
  ♦ Differential Prevailing, Differential Predicted
  ♦ Random

• Feedback:
  ♦ own trip experience
  ♦ recommended path (path with least trip-time at each decision node)
  ♦ best path (ex-post, least trip-time path for the chosen departure time)
En-route and Pre-trip

ROUTE SWITCHING BEHAVIOR: Heterogeneity and Unobserved Structural Effects

- Implement DKL framework with empirical simulator-based (ATIS II) data to analyze:
  - Heterogeneity
  - Unobserved time-dependent effects
  - Role of ATIS information strategy
COMPLIANCE UNDER VARIOUS ATIS STRATEGIES

• Compliance increases with better information quality
  • accuracy, reliability

• Costs and benefits influence compliance
  • switching cost, and trip time saving

• Adverse experience reduces compliance
  • stuck, trip-time variability

• Range of compliance behaviors under various strategies
  • greater compliance with prescriptive information
  • providing feedback on recommended/best path increases compliance
  • higher compliance with complete information than partial, random information
Day-to-day

DEPARTURE TIME ADJUSTMENT:
Comparison of alternative behavioral adjustment mechanisms

- Maximum utility rule
- Two stage decision rule
- Ordered response adjustment mechanism
- Sequential Greedy Search
COGNITIVE DECISION PROCESSES

UNDERLYING COMMUTER BEHAVIOR DYNAMICS

• Learning
  • discriminative and trial and error learning
  • role of memory
  • attentional factors

• Perception and attitudinal factors
  • margin (12%) added to accommodate uncertainty
  • attitudes towards trip time savings and congestion affect choice

• Judgment of information quality
  • predicted - highest, random - lowest

• Updating perceptions
  • reported information weighted more than past perception in random treatment
  • weights: 2/3 (sequential case) to 8/9 (random evolution)
OVERALL CONCLUSIONS (ATIS EXPERIMENTS)

• Significant effect of network loading magnitude and day-to-day variation
• User behavior varies with ATIS information strategies
• Effect of information depends on network conditions encountered
• Nature of linkage between route and departure time choice varies with information type
• Structural and dynamic effects observed in commuter behavior: heterogeneity, state-dependence, correlations, habit persistence
• Younger respondents more sensitive to information type, LOS measures
• Best path not always chosen - role of search cost, implementation cost, habit, cognitive constraints etc.
• Evidence of cognitive and decision processes: learning, perception, judgment, updating, adjustment Heuristic mechanisms and strategies in day-to-day adjustments
  – compliance and inertia - route choice
  – sequential greedy search - departure time
• User choice behavior may not lead to User Equilibrium flows
Experimental economics is the use of experimental methods to evaluate theoretical predictions of economic behaviour. It uses controlled, scientifically-designed experiments to test economic theories under laboratory conditions. Typical empirical research is limited by the fact that only a subset of the set of all possible influences affect (or can be observed to be affecting) economic decision making; therefore, the ability to control for certain influences is limited or non-existent. With experiments, economists can fix some inputs and measure the effects of other inputs in a way that allows ceteris-paribus comparisons.

Wikipedia (http://www.answers.com/topic/experimental-techniques)
Experimental Method Precepts

1. Use real monetary payoffs to “incentivize” subjects; payoffs should be designed so as to induce the same behavioral response as the experienced consequences in a natural context.

2. Publish complete experimental instructions.

3. Do not use deception, considerable debate; experimental evidence suggests that deception (false consequences to deny participants monetary payoffs) leads to unreliable responses and loss of goodwill.

4. Avoid introducing specific, concrete context keep the decision context stylized and generic, and hence transferable and generalizable.
Experimental Economics and Route Choice Games

- simple route choice experiments with the following elements:
  - (1) a simplified two-route context;
  - (2) idealized pay-off functions that relate the number of people choosing a route to the payoff, reflecting congestion effects;
  - (3) multiple subjects interacting simultaneously through virtual environment;
  - (4) a large number of iterations;
  - (5) different experimental treatments corresponding to varying information availability/feedback levels.
QUESTIONS ADDRESSED

• Understand the dynamic properties of the system, with particular focus on convergence:
  – Does convergence occur?
  – What does it converge to? (properties of steady-state, e.g. is it an equilibrium, what kind of equilibrium…)
  – Does it converge to the same state? (uniqueness)
  – Is it stable?
  – Convergence path, and factors that affect convergence

• Uncover individual choice mechanisms, decision rules and heuristics underlying user behavior;

• Examine potential impact of certain policies or effect of different factors on the decisions of individuals, as well as on properties of the system; e.g. effect of information systems, disruptions, new policies, etc…
Recent Route Choice Experiments

- Selten, Schreckenberg et al. (2004): two routes, 16 players at a time; linear payoffs, two information treatments (own route vs. both routes) 200 iterations each game:
  - No perfect convergence (fluctuations persist, less so with full info), but trends towards Nash Equilibrium
  - Direct responders vs. contrarians
Recent Route Choice Experiments (ctd.)

• Helbing (2004): multi-person interactive route choice game, two routes:
  – chaotic behavior, failure to converge, and turbulence —i.e. changing behavior after periods of stationarity.
  – results confirm earlier finding of Mahmassani and Stephan (1988) that experiments with more people tend to be more chaotic and take longer to converge.

• Rapoport et al. (2005) report on experimental verification of the well-known Braess Paradox in a simple network route choice game.
Recent Route Choice Experiments (ctd.)

- Denant-Boemont and Petiot (2003): assess the value of information to tripmakers in a mode and route choice situation; involves participants in the purchase of information as one of the experimental tasks (in addition to the mode and route decisions).
  - players buy information when the variance in payoffs for the route choice is high
  - players follow different strategies as the game evolves, from relying on external information initially to relying increasingly on one’s own experience (as such experience is accumulated).

  - claim of consistency with a Nash equilibrium is not strongly evident in the reported data.
VIRTUAL INFORMATION MARKETS

• “Information markets generally involve the trading of state-contingent securities. If these markets are large enough and properly designed, they can be more accurate than other techniques for extracting diffuse information, such as surveys and opinions polls.”
  (Chen, Fine and Huberman (2003))

• E.g. Iowa Election Option Markets
VIRTUAL INFORMATION MARKETS

• Problems with information markets:
  – information traps (Camerer and Weigelt, 1991; Noth, et al., 1999),
  – illiquidity (Sunder, 1992),
  – manipulation (Forsythe and Lundholm, 1990; Noth and Weber, 1998), and
  – lack of equilibrium (Anderson and Holt, 1997; Scharfstein and Stein, 1990).

• These phenomena associated primarily with SMALL MARKETS
VIRTUAL INFORMATION MARKETS

• Berg and Rietz (2003), who run the widely-acclaimed Iowa Election Markets, believe that the
  – information and forecasts produced by such large virtual prediction markets can play an important role in decision support systems that address decision situations whose outcomes depend on events predicted through the markets.
  – They illustrate how such markets could be used to obtain conditional predictions, given the occurrence of specific events, e.g. likelihood of a candidate winning conditional on a specific opponent (Berg and Rietz, 2003).
DIRECTIONS FOR CONTINUING RESEARCH
SUBSTANTIVE QUESTIONS

• Understanding day to day evolution

• Effect of information on activity and travel patterns

• Dynamics in activity and travel patterns

• Uncovering decision and learning mechanisms and heuristics (non-utility maximization behaviors)

• LEARNING, LEARNING, JUDGMENT…

• Role of prediction within experiments, and use of experiment results for prediction of behaviors and policy outcomes
CONCERNS AND ISSUES

• Heisenberg Principle– can we observe human particles in a game situation without unduly biasing/influencing their behavior?
• Experimental Economics: Can Money Buy Love?
• Simplicity vs. clutter
• Simple rules, simplistic conclusions?
• External Validity
DIRECTIONS FOR FUTURE RESEARCH

METHODOLOGICAL OPPORTUNITIES

• Virtual Field Experiments: Field Experiments, Virtually—as opposed to laboratory methods

• Measurement opportunities: mobile communication, the cell phone promise, 3G, etc… WHEN ALREADY?

• Adaptive experiments—learning from respondent behavior, and adjusting system behavior accordingly (e.g. through intelligent adaptive bots)
Learning and Risk Attitudes in Route Choice Dynamics

R. Chen and Mahmassani (2009)

• Route choice and switching decisions are made in light of updated perceived travel times and uncertainty.
• Understanding route choice and switching requires an understanding of both individual learning process and risk attitudes.
Past studies on travel time uncertainty have focused on:

- i) Role of perceived uncertainty on route switching
  - Mahmassani and Liu 1999
  - Nakayama et al. 1999
  - Srinivasan and Mahmassani 2000, 2004
  - Avineri and Prashker 2003, 2005

- ii) Risk in the context of travel time reliability
  - Abkowitz, 1981
  - Noland and Small 1995; Noland et al. 1998
  - Ettema et al. 2005

- iii) Role of risk attitudes on route choice
  - de Palma and Picard 2005
  - Chancelier et al. 2006
  - Bogers 2009

Past studies on travel time learning have examined the:

- i) Integration of past, current, and exogenous information
  - Horowitz 1984
  - Mahmassani and Chang 1987
  - Ben-Akiva et al. 1991
  - Chorus et al. 2005+

- ii) Travel time updating process
  - Kaysi 1991
  - Jha et al. 1998
  - Chen and Mahmassani 2002

- iii) Feedback effects of congestion on system properties
  - Mahmassani 1984
  - Helbing et al. 2003
Background (continued)

• However these studies do not address one or more of the following issues:
  – Time-varying parameters reflecting individual perception
  – Heterogeneous users, different user classes/market segments
  – Effects of the interdependency of route choices over time (congestion)
  – Connection between perceived uncertainty and risk attitudes and its aggregate effects in traffic systems (where travel time savings are dependent on the decisions of all users).
  – Joint effects of congestion and activity scheduling
Research Objectives

• Model risk attitudes and learning processes and examine their effect on the dynamic properties of traffic systems.

• Simulation experiments are conducted to examine the effect of learning processes and risk attitudes on:
  
  – (i) travel time perceptions over time, including the degree of uncertainty
  – (ii) risk attitudes and perceptions of uncertainty over time
  – (iii) relationship of the latent attributes described in (i) and (ii) on traffic flow evolution and other dynamic system properties, particularly convergence
Modeling Framework

\[ \tau^u \]

Updated Travel Times (in memory)

Updated Travel Time
Experienced Travel Time
Weighted Travel Time (Experienced and Updated)

Perceived Travel Times
Prospect Theory

Indifference Thresholds
Maximum Prospect

Route Switching/Choice Mechanism

Risk Perception Mechanism

Experienced Travel Times

Learning Mechanism

N=number of experienced travel times not yet used for updating

Traffic Flows

Traffic Network

Bayesian Learning
Reinforcement Learning
Belief Learning

Selected Route
Modeling Framework (continued)

Model Components

• **Learning Mechanisms**
  – Reinforcement Learning
  – Belief Learning
  – Bayesian Learning

• **Perceived Travel Times**
  – Updated Travel Time
  – Experienced Travel Time
  – Weighted Travel Time (Updated and Experienced)
Modeling Framework (continued)

Model Components

• *Risk Mechanism*
  – Prospect Theory

• *Route Switching/Choice Mechanism*
  – Prospect Theory
  – Travel Time Indifference Thresholds
Modeling Framework

\[ \tau^u \]

- Updated Travel Times (in memory)
- Learning Mechanism
- Risk Perception Mechanism
- Route Switching/Choice Mechanism
- Traffic Network

- Experienced Travel Times
- \( T_1, T_2, ..., T_N \)

Bayesian Learning
Reinforcement Learning
Belief Learning
Learning Mechanisms

• Reinforcement Learning

\[ T_1^{-}, T_2^{+}, T_3^{-}, \ldots, T_{N_e}^{-} \] \quad \rightarrow \quad \text{Experienced Travel Times that yield a Travel Time “Gain” from a reference time}

\[ T_1^{-}, T_3^{-}, \ldots, T_{N_e}^{-} \] \quad \text{not Integrated into Memory}

Experienced Travel Times

\[ \tau^u_{post} = \left[ \frac{\phi \cdot C_{prior}}{\phi \cdot C_{prior} + C_{N_e}} \right] \cdot \left( \tau^u_{prior} \right) + \left[ \frac{C_{N_e}}{\phi \cdot C_{prior} + C_{N_e}} \right] \cdot \left( T_{N_e}^{-} \right) \]

\( \phi \): weight on past experiences

\( C_{prior} \): number of times route is chosen in previous choices, and results in a travel time gain

\( C_{N_e} \): number of times route is chosen during period \( N_e \), and results in a travel time gain

\( N_e \): number of days since previous update
Learning Mechanisms (ctd.)

• Belief Learning

\[ \begin{align*}
T_1^i, T_2^i, T_3^i, \ldots, T_{N_e}^i & \quad \cdots \quad T_1^{le}, T_2^{le}, T_3^{le}, \ldots, T_{N_e}^{le} \\
\text{Experienced Travel Times} \quad & \text{not Integrated into Memory} \\
I_e: \text{ set of individuals who selected the same route in period } N_e
\end{align*} \]

\[ \tau_{\text{post}}^u = \left[ \frac{\phi \cdot C_{\text{prior},I_e}}{\phi \cdot C_{\text{prior},I_e} + C_{N_e,I_e}} \right] \cdot \left( T_{\text{prior}}^u + \frac{C_{N_e,I_e}}{\phi \cdot C_{\text{prior},I_e} + C_{N_e,I_e}} \right) \cdot \left( T_{N_e,I_e}^u \right) \]

\[ \phi: \text{ weight on past experiences} \]
\[ C_{\text{prior},I_e}: \text{ number of times route is chosen in previous choices, across } I_e \]
\[ C_{N_e,I_e}: \text{ number of times route is chosen during period } N_e, \text{ across } I_e \]
\[ N_e: \text{ number of days since previous update} \]
Learning Mechanisms (continued)

• Bayesian Learning

\[ T_1, T_2, T_3, \ldots, T_{Ne} \]

Experienced Travel Times not Integrated into Memory

\[ \begin{align*}
\tau_{post, u}^u &= \left[ \frac{1}{\sigma_{prior, u}^2} \right] \cdot \left( \tau_{prior}^u \right) + \left[ \frac{N}{\sigma_e^2} \right] \cdot \left( T_e^c \right) \\
\sigma_{post, u}^2 &= \frac{\sigma_{prior, u}^2 \cdot \sigma_e^2}{\sigma_e^2 + N \cdot \sigma_{prior, u}^2}
\end{align*} \]
Risk Perception

Mechanism

Modeling Framework

Updated Travel Times
Experienced Travel Time
Weighted Travel Time (Experienced and Updated)

$\tau^u$

Updated Travel Times (in memory)

TP Perceived Travel Times

Bayesian Learning
Reinforcement Learning
Belief Learning

Learning Mechanism

Risk Perception Mechanism

Route Switching/Choice Mechanism

T1, T2, ..., TN

Experienced Travel Times

Traffic Network
Perceived Travel Time

- Route choice and switching decisions are made on the basis of perceived travel times.

- Both the updated travel time and the experienced travel times affect the perceived travel time.

  - Updated Travel Time (in memory)

\[ TT_p = \tau_{i,k}^u \]
Perceived Travel Time (continued)

– Experienced Travel Time

\[ TT_p = \begin{cases} \tau_{i,k}^\prime & \text{if updating occurred on iteration } n \\ \Gamma_{i,k}^{e,n} & \text{otherwise} \end{cases} \]

– Weighted Travel Time (Updated and Experienced)

\[ TT_p = \begin{cases} \tau_{i,k}^\prime & \text{if updating occurred on iteration } n \\ \phi(\tau_{i,k}^\prime) + (1 - \phi)\Gamma_{i,k}^{e,n} & \text{otherwise} \end{cases} \]
Modeling Framework

\[ \tau^u \]

- **Updated Travel Times (in memory)**
  - Updated Travel Time
  - Experienced Travel Time
  - Weighted Travel Time (Experienced and Updated)

- **Learning Mechanism**
  - T1, T2, ..., TN
  - Experienced Travel Times

- **Risk Perception Mechanism**
  - \( T_p \) Perceived Travel Times
  - Prospect Theory

- **Route Switching/Choice Mechanism**

- **Traffic Network**

Learning Mechanisms:
- Bayesian Learning
- Reinforcement Learning
- Belief Learning

NO UPDATING
Risk Mechanism

• Prospect Theory

\[
P(T) = \Omega^{\text{gain}} \Phi(T^{\text{gain}}) V(T^{\text{gain}}) + \Omega^{\text{loss}} \Phi(T^{\text{loss}}) V(T^{\text{loss}})
\]

- Weighted Probability of a Travel Time Gain
- Value of a Travel Time Gain
- Weighted Probability of a Travel Time Loss
- Value of a Travel Time Loss
Risk Mechanism (continued)

- Travel Time Value Function

\[ v(\Delta T) = \begin{cases} 
(\Delta T)^\alpha & \text{if } \Delta T \geq 0 \\
-\lambda(-\Delta T)^\alpha & \text{if } \Delta T < 0 
\end{cases} \]

- \( \alpha \) and \( \lambda \) are shape parameters for the value function

- Value function is steeper for losses compared to gains
Risk Mechanism (continued)

• Under Prospect Theory individuals are:

  – i) risk seeking for gains and averse for losses of low probabilities

  – ii) risk averse for gains and seeking for losses of high probability
Risk Mechanisms (continued)

- However, assuming that individuals under-weigh or over-weigh the probability of gains and losses depending on risk attitude:
  - i) risk seekers will under-weigh probabilities of losses and overweigh probabilities of gains
  - ii) risk avoiders will overweigh probabilities of losses and under-weigh probabilities of gains
  - iii) risk neutral individuals will not overweigh or under-weigh any probabilities

- Risk attitudes are reflected in an individual’s probability weighing function for gains and losses.
Risk Mechanism (continued)

• Probability Weighing Function

\[ \Omega(p) = \begin{cases} 
\left(\frac{1-\pi}{\pi}\right) \cdot p & p \leq \pi, 0 \leq \pi \leq 1 \\
\left(\frac{\pi}{1-\pi}\right) \cdot p - \left(\frac{1-2\pi}{1-\pi}\right) & p > \pi, 0 \leq \pi \leq 1 
\end{cases} \]

– \( \pi \) parameter between 0 and 1 that determines the inflection point of the weighing function \( \Omega(p) \)
Risk Mechanism (continued)

- Probability Weighing Function

  - *Risk Seekers*
    \[ \pi^{\text{gain}} \leq 0.5 \quad \pi^{\text{loss}} \geq 0.5 \]
    Overweigh Probability of a Gain               Under-weigh Probability of a Loss

  - *Risk Avoiders*
    \[ \pi^{\text{gain}} \geq 0.5 \quad \pi^{\text{loss}} \leq 0.5 \]
    Under-weigh Probability of a Gain               Overweigh Probability of a Loss
Weighing Functions for a Risk Averse Individual ($\pi^{\text{loss}}=0.25; \pi^{\text{gain}} = 0.75$)
Risk Mechanism (continued)

- Under Prospect Theory the alternative with the greatest "prospect" is chosen

\[ \delta_n = \max \left\{ p_{k,n}, \forall k \in K \right\} \]
Modeling Framework

\[ \tau^u \]

Updated Travel Times (in memory)

Updated Travel Time
Experienced Travel Time
Weighted Travel Time (Experienced and Updated)

Perceived Travel Times
Prospect Theory

Indifference Thresholds
Maximum Prospect

Learning Mechanism

Bayesian Learning
Reinforcement Learning
Belief Learning

Traffic Network

\( T_1, T_2, ..., T_N \)

Experienced Travel Times

Traffic Flows

Route Switching/Choice Mechanism

Selected Route
Route Switching Mechanism

- Travel Time Indifference

\[
\delta_{i,n} = \begin{cases} 
1 & \text{if } \frac{\tau_{i,k}^u - \tau_{i,k}^{u,\text{best}}}{\tau_{i,k}^{u,\text{best}}} \geq \Delta^i \cdot \tau_{i,k}^u, \text{ where } 0 \leq \Delta^i \leq 1 \\
0 & \text{otherwise} 
\end{cases}
\]

- \( \delta_{i,n} \) a variable that takes a value of 1 if the difference between the current and best perceived travel times are acceptable, and 0 otherwise.

- \( \Delta^i \) acceptability threshold for the travel time differences.
Experimental Setup

• Network Used in Experiments

![Network Diagram](attachment:network_diagram.png)
Experimental Setup

- Link Cost Functions

\[
c_l = \begin{cases} 
    t_l^{\text{min}} \left(1 + \frac{b_l f_l}{\text{cap}_l - f_l}\right) & f_l \leq e_l \cdot \text{cap}_l \\
    t_l^{\text{min}} \left(1 + \frac{b_l e_l}{1 - e_l} + b_l \left(\frac{f_l}{\text{cap}_l - e_l}\right)\right) & f_l > e_l \cdot \text{cap}_l 
\end{cases}
\]

- $t_l^{\text{min}} \geq 0$ is the zero flow travel time
- $b_l \geq 0$ defines the slope of the curve
- $\text{cap}_l \geq 0$ is the link capacity
- $0 \leq e_l \leq 1$ defines the under saturation limit
Experimental Factors

- Experimental Factors Examined

<table>
<thead>
<tr>
<th>Factors Relating to Experiments Considering Risk Attitudes</th>
<th>Factors Common to All Experiments</th>
</tr>
</thead>
<tbody>
<tr>
<td>i) Percentage of Risk Seekers and Avoiders</td>
<td>i) Demand Level (V)</td>
</tr>
<tr>
<td>ii) Risk Avoidance (( \pi^{gain} ) and ( \pi^{loss} ))</td>
<td>ii) Initial Uncertainty (variance - ( \beta ) )</td>
</tr>
<tr>
<td></td>
<td>iii) Perceived Travel Time</td>
</tr>
<tr>
<td></td>
<td>iv) Learning Mechanism</td>
</tr>
</tbody>
</table>
Performance Measures

- Two principal types of descriptors are considered:
  - Day-to-day flow pattern of traffic, in particular convergence.
  - Number of days until convergence.
Simulation Results: Demand Level (V)

- Number of Iterations until Convergence for Different Demand Levels (V)

<table>
<thead>
<tr>
<th></th>
<th>Bayesian</th>
<th>*Reinforcement</th>
<th>Belief</th>
</tr>
</thead>
<tbody>
<tr>
<td>V = 0.75</td>
<td>31</td>
<td>21</td>
<td>4</td>
</tr>
<tr>
<td>V = 1</td>
<td>59</td>
<td>NC</td>
<td>4</td>
</tr>
<tr>
<td>V = 1.5</td>
<td>NC</td>
<td>NC</td>
<td>4</td>
</tr>
<tr>
<td>V = 2</td>
<td>NC</td>
<td>NC</td>
<td>4</td>
</tr>
</tbody>
</table>

– V = demand level

* Note: Under reinforcement learning convergence was assumed reached when day-to-day flows changed within a band of 5 user
Simulation Results: Demand Level (V)

• Under Bayesian and reinforcement learning, as the number of users in the system or demand increases, convergence is more difficult to attain.

• Convergence is quicker to obtain under belief learning compared to Bayesian learning.

• The number of users in the system or demand level does not seem to affect convergence under belief learning.

• Strict convergence under reinforcement learning was difficult to obtain.
Simulation Results: Degree of Risk Aversion ($\pi^{\text{loss}}$)

- Number of iterations until convergence as the mean $\pi^{\text{loss}}$ increases, for different percentages of risk seekers in the population
Simulation Results: Degree of Risk Aversion ($\pi^{\text{loss}}$)

- Under **Bayesian learning**, as the risk attitudes in the population become more extreme ($\pi^{\text{loss}}$ increases), convergence occurs sooner.

- A high number of risk seekers (90%) leads to easier convergence under **Bayesian learning**, compared to a low percentage (10%).

- Under **belief learning**, a high percentage of risk seekers leads to a more difficult convergence, compared to a low percentage (10%).

- No convergence was obtained under **reinforcement learning**.
Simulation Results: Initial Perceived Variance ($\beta$)

- Number of iterations until convergence as the number of risk seeking individuals in the population increases, for different initial perceived variances ($\beta$)
Simulation Results: Initial Perceived Variance ($\beta$)

- Initial perceived variance of travel times seems to have no effect on convergence under Bayesian and belief learning.
- Under Bayesian learning, as the number of risk seeking users increases, convergence appears easier to obtain.
- Under belief learning, as the number of risk seeking users increases, convergence appears more difficult to obtain.
- Convergence is easier to obtain under belief learning compared to Bayesian learning overall.
- No convergence was obtained under reinforcement learning.
Conclusions

- Explicitly considering risk attitudes and their effect on an individual’s perception of uncertainty does influence the convergence of traffic flows in a network.
- The percentage of risk seekers in the population affects the rate of convergence, possibly by affecting the rate of sampling taken by individuals and by adding variability in experienced travel times.
- For Bayesian learning, any mechanism that affects the rate of sampling will affect the rate of convergence.
- For belief learning, users’ risk attitudes seem to have less of an effect on convergence compared to Bayesian and reinforcement learning.
- Belief learning considers experiences of all users, which may serve to lead a system to faster convergence compared to other learning mechanisms.
- Convergence is more difficult to obtain under reinforcement learning, possibly due to the selectivity in sampling of travel times.
- Note: under reinforcement learning, only choices that result in positive payoffs (a decrease in travel time) are used for updating.
- Observation of actual behavior is critically needed to advance our understanding of learning dynamics in transportation systems.
Concluding Comments

• Research to understand day-to-day dynamics of users in traffic systems is alive and well
• Need to move away from simplistic games and experiments towards observationally-supported science
• Valid, operationally useful frameworks and tools are beginning to appear
• Unfortunately, still teaching user community how to do within-day dynamic analysis; day-to-day even more challenging
• The danger of over-promising
• Main use of models: comparative assessment of the differential dynamic properties of various measures and strategies; likelihood of convergence, potential for chaotic behavior
• Move away from focus on final states (comparative states) to understanding evolutionary paths
THANK YOU!