Modeling Driving Decisions with Latent Plans

Charisma Choudhury

Traffic Flow Webinar

4th June, 2010

Outline

- Introduction
- Modeling framework
- Case studies
  - Freeway (motorway)
    - lane changing
    - merging
  - Urban
    - intersection lane choice
    - arterial lane changing
- Conclusions

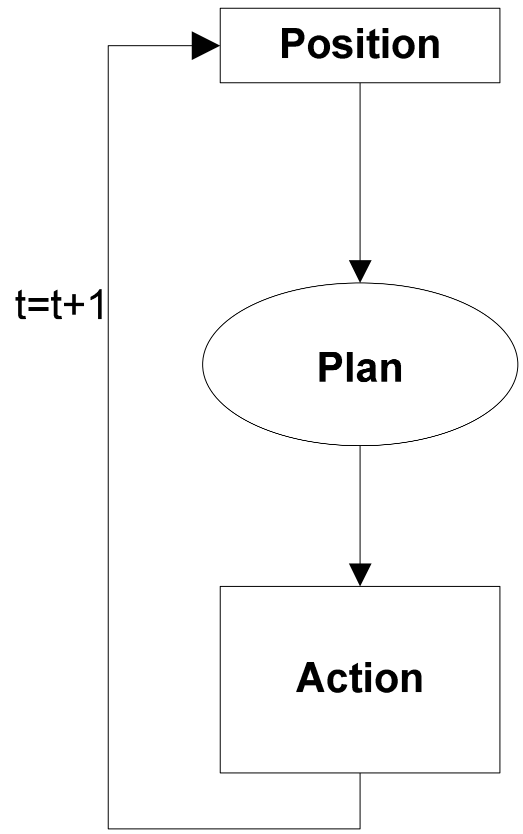
Introduction

Background

- Traffic simulation
  - Analyze congestion management strategies
- Microscopic traffic simulation
  - Mimic individual drivers
  - Key element: driving behavior models
    - acceleration, lane changing, gap acceptance, route choice
- State-of-the-art simulation tools
  - Do not adequately model high levels of traffic congestion
  - Attributed to myopic representation of driving behavior

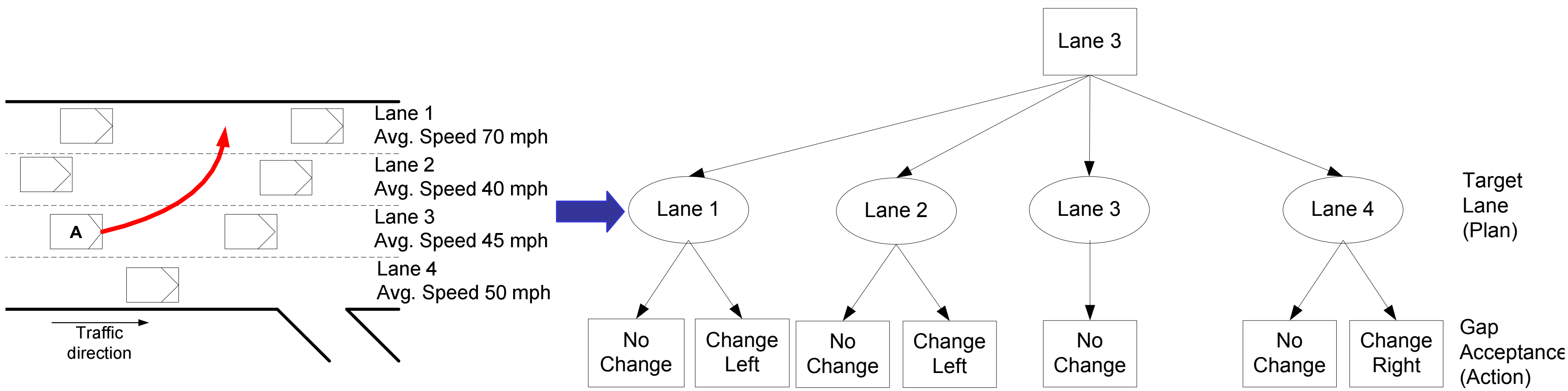
Driving Behavior

- Drivers often plan before they act
  - Plans: targets/tactics
  - Actions: maneuvers
- Plans are unobserved (latent)
- Only actions observed
- Choice set of action can differ with the selected plan



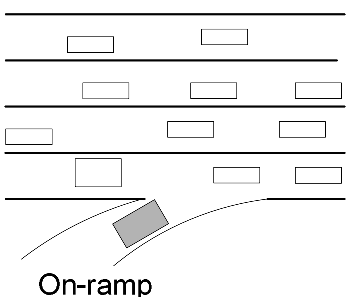
Example 1: Lane changing

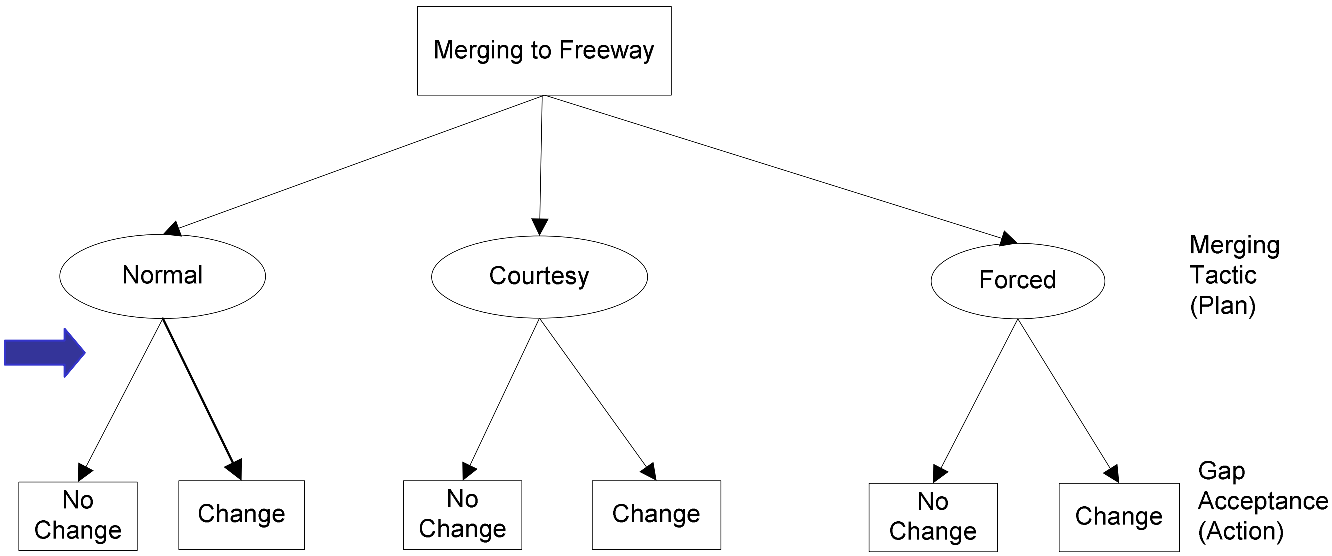
- Maneuver to the target lane may not be possible
  - Plan: target lane
  - Action: gap acceptance



Example 2: Freeway Merging

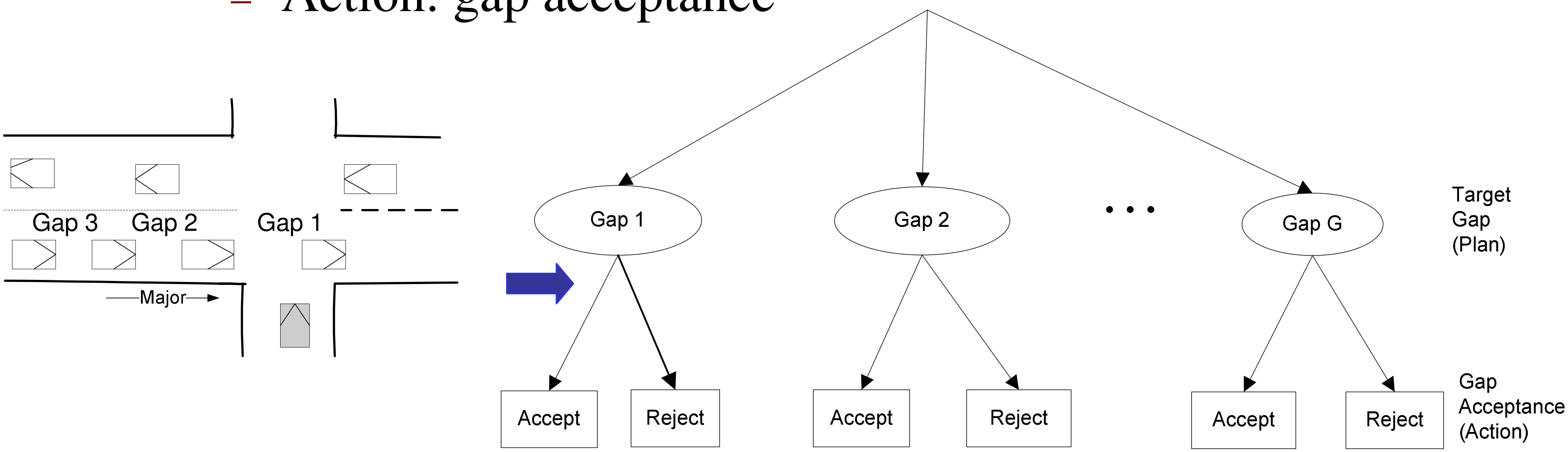
- Chosen tactic may not be continued
  - Plan: merging tactic/mechanism
  - Action: gap acceptance





Example 3: Unsignalized Intersections

- Initially selected target gap may not be acceptable
  - Plan: target gap
  - Action: gap acceptance



Existing Models

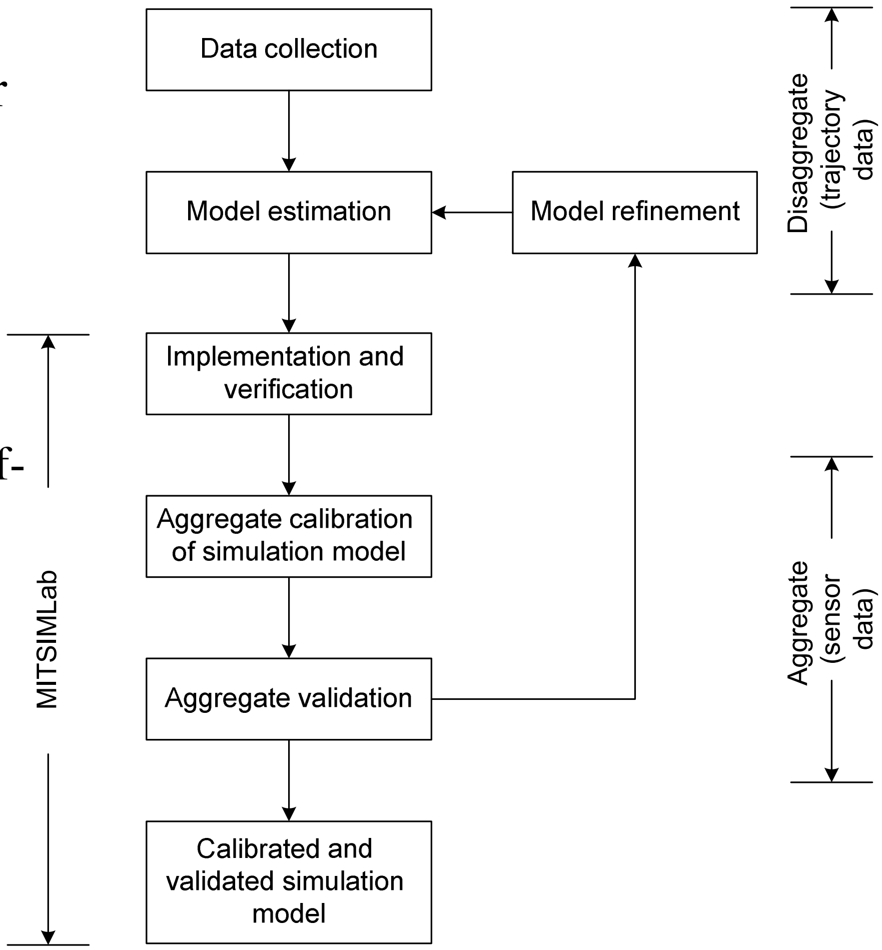
- Latent plans not modeled explicitly
  - Reactive behavior
    - decision of drivers based on present conditions
  - Instantaneous change in decision
    - ignores effect of past plans
    - no state-dependence
  - Myopic behavior
    - ignores anticipation of future conditions

Motivation

- Ignoring latent plans may result in
  - Unrealistic traffic flow characteristics
  - Overestimation of congestion
- Effect more pronounced in congested and incident affected traffic situations

Methodology

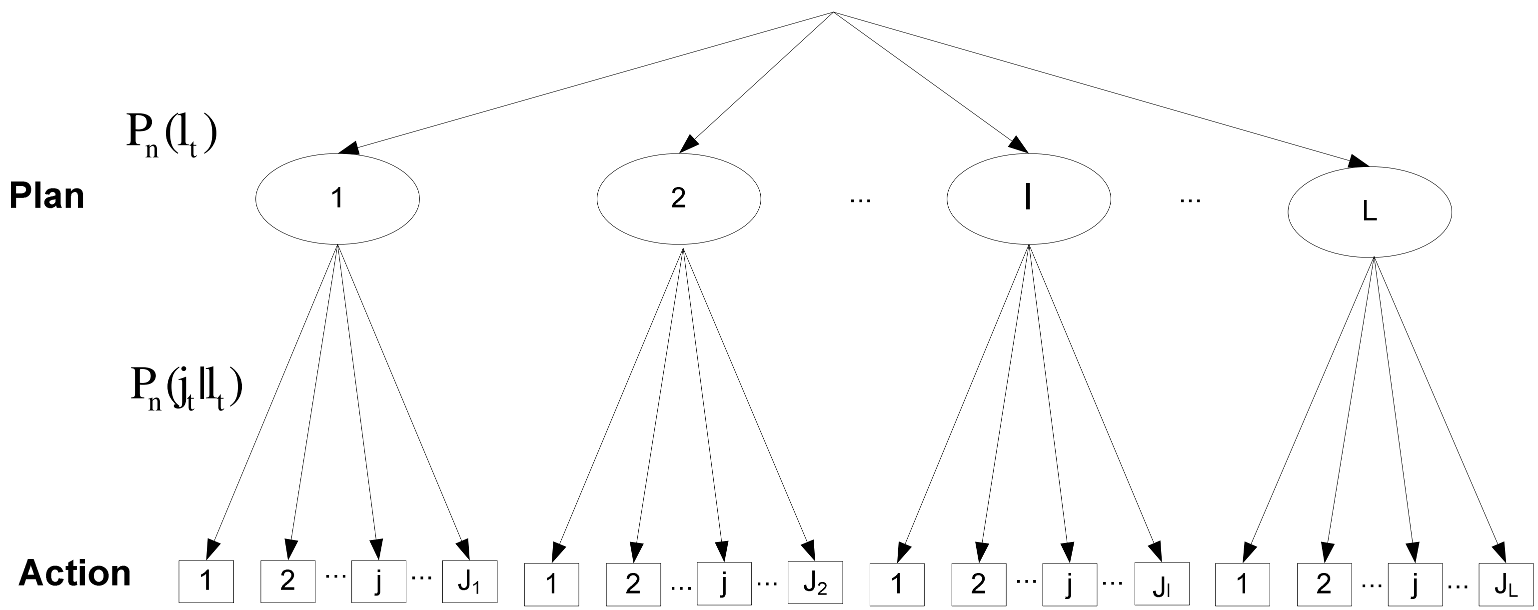
- Objective:
  - Formulate driving behavior models with latent plans
- Approach:
  - Model estimation
    - detailed trajectory data
    - comparison of goodness-of-fit against 'reduced form' models with no latent plans
  - Model validation
    - within MITSIMLab
    - aggregate data



Modeling Framework

Framework

- Two-layer decision hierarchy
  - Choice of plan (targets/tactics): *l*
  - Choice of action (maneuver/execution): *j*



Latent Plan Model

- Probability of observing an action at time *t* by individual *n*:

$$P_n\left(j_t \mid \upsilon_n\right) = \sum_l P_n\left(j_t \middle| l_t, \upsilon_n\right) P_n\left(l_t \mid \upsilon_n\right)$$

where,

j_t = *action at time t*

l_t = *plan at time t*

υ_n = *individual specific random term (e.g. aggressiveness)*

Latent Plan Model (cont)

- Probability of observing the sequence of actions by individual *n*:

$$P_n(j_1, j_2, \ldots, j_T \mid \upsilon_n) = \prod_T \sum_l P_n(j_t \mid l_t, \upsilon_n) P_n(l_t \mid \upsilon_n)$$

$$where,\ T = total\ observations\ of\ the\ individual$$

- Assumption: plans and actions of an individual *n* independent over time (conditional on υ_n)

Likelihood of the Trajectory

- Unconditional probabilities of a sequence of actions:

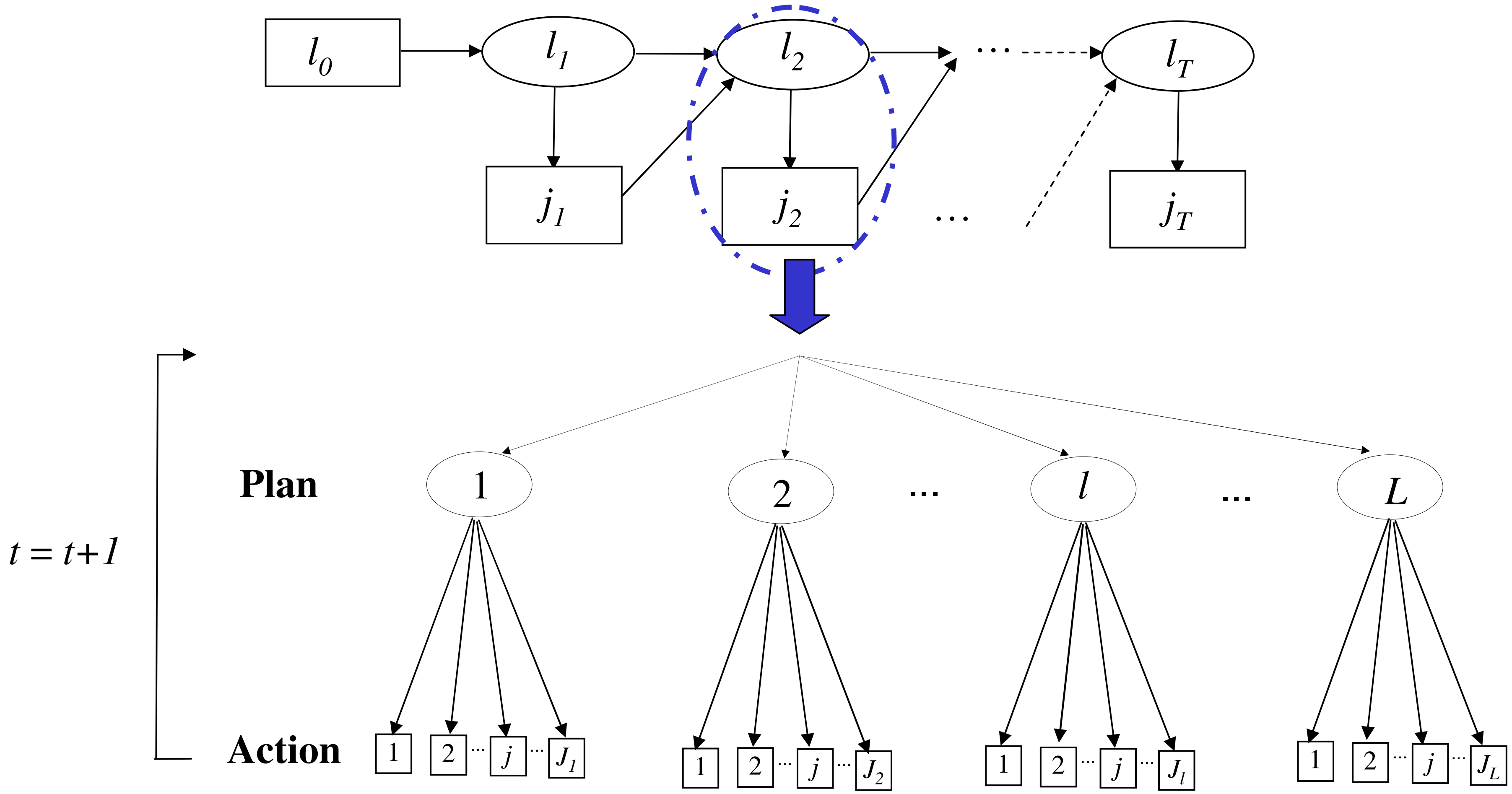
$$P_n(j_1, j_2, \ldots, j_T) = \int_{\upsilon} \prod_{T} \sum_{l} P_n(j_t | l_t, \upsilon_n) P_n(l_t | \upsilon_n) f(\upsilon) d\upsilon$$

- Choice of plan $\left[P_n(l_t | \upsilon_n) \right]$ and choice of action conditional on plan $\left[P_n(j_t | l_t, \upsilon_n) \right]$ can be based on utility maximization:
  - Utility of plan may include expected utility from the action resulting from the execution of the plan

Dynamic Behavior

- Plans may change or evolve
  - Situational constraints
  - Contextual changes
- Plans may depend on previous plans (inertia) and past actions (experience)
  - State-dependence

Dynamic Behavior (cont)



Dynamic Behavior (cont)

- State dependence makes the problem intractable for long trajectories
- Hidden Markov Model (HMM) used to make the problem tractable
  - Current action only depends on current plan
  - Current plan only depends on previous plan and previous action

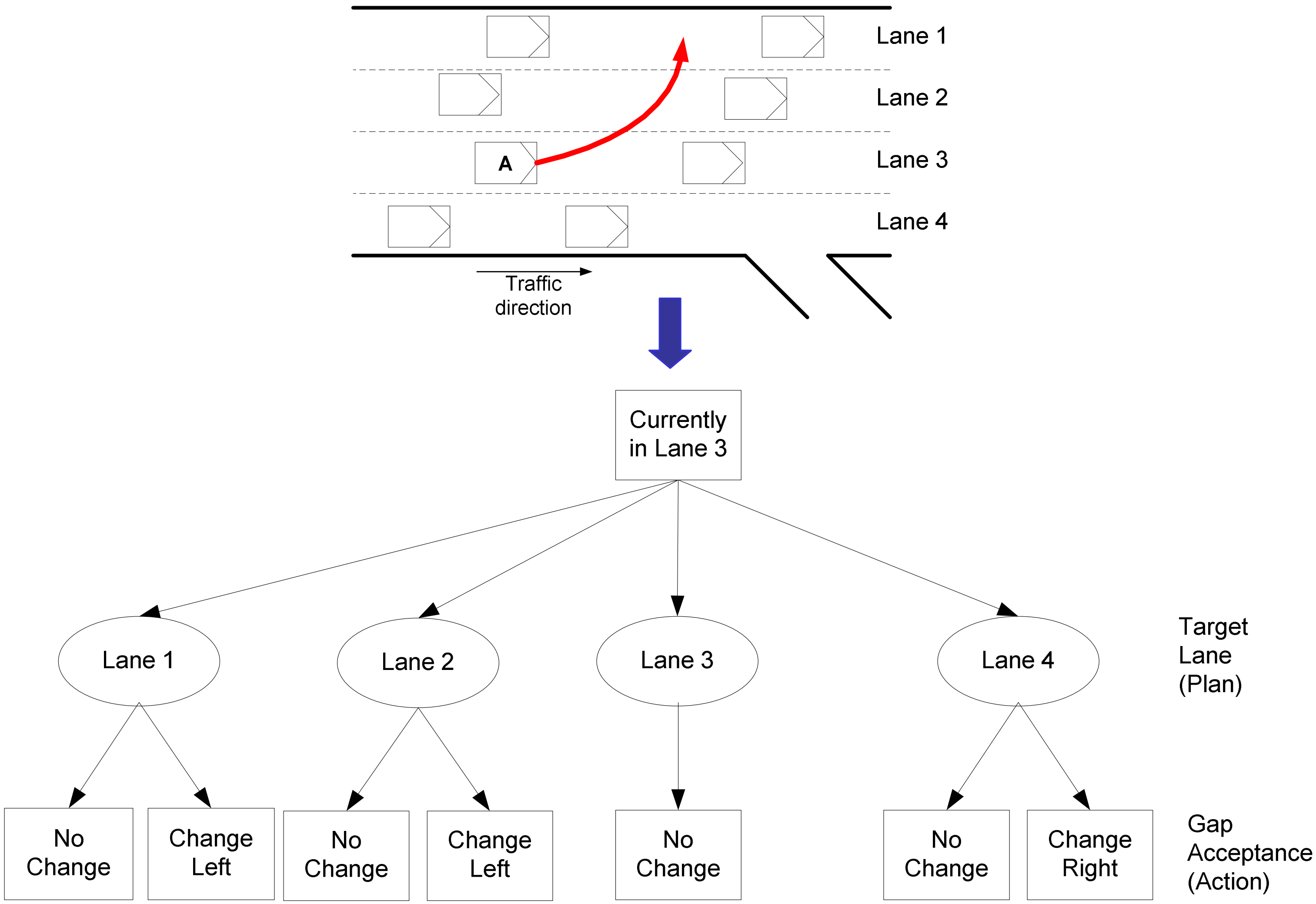
Case Studies

Case Studies

1. Freeway/Motorway
   1.1 Lane changing
   1.2 Merging
2. Arterial
   2.1 Intersection lane choice
   2.2 Mainline lane changing

1.1 Freeway Lane Changing

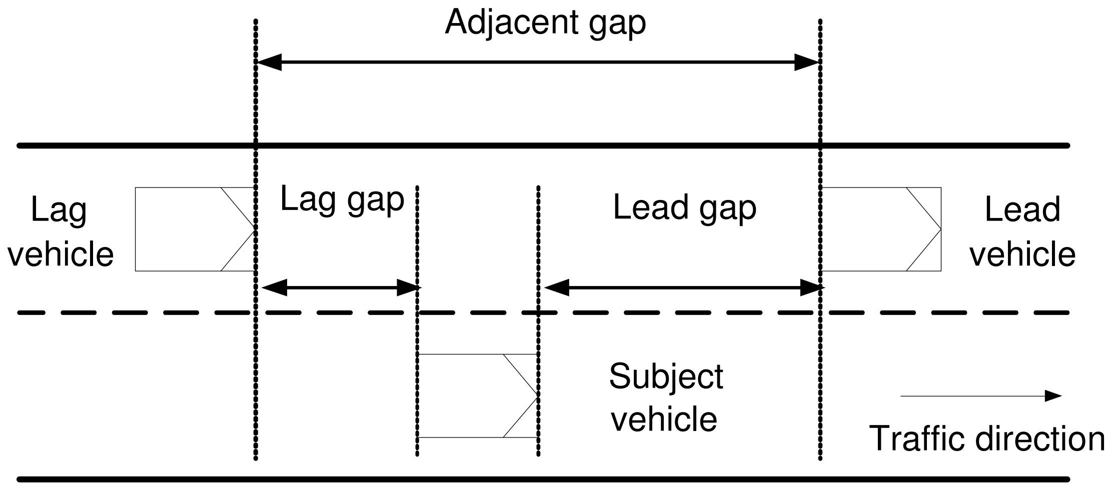
1.1.1 Model Framework



1.1.2 Model Structure

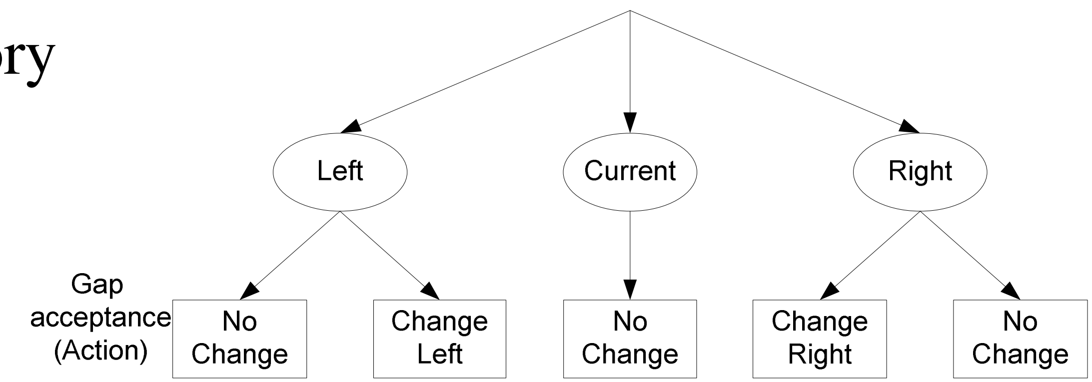
- Lane change executed if both lead and lag gaps are acceptable
  - Acceptable gap:

    available gap $\geq$ critical gap (latent)



1.1.3 Estimation

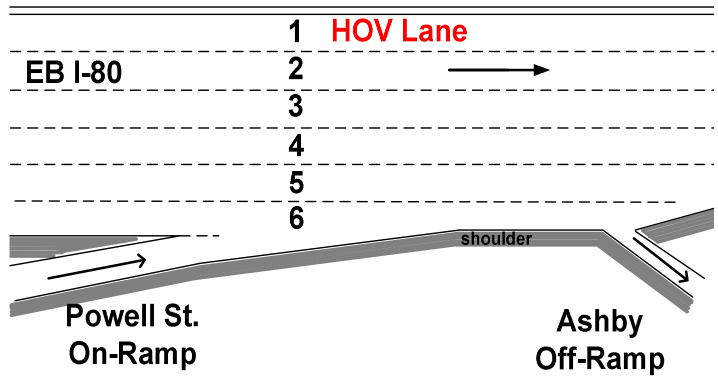
- Estimated with trajectory data from I-395, VA
- Compared with a 'reduced form' model with no latent targets (Toledo 2003)



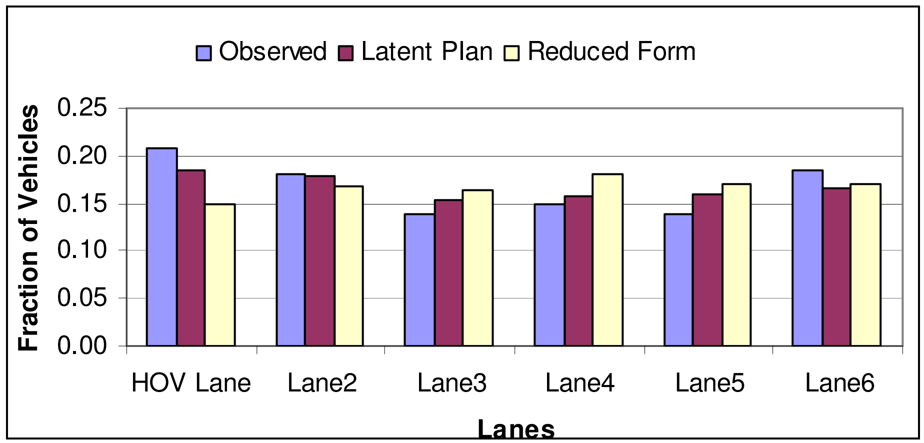
Statistic	Reduced Form Model	Latent Plan Model
Log likelihood value	-888.78	-875.81
Number of parameters (K)	26	31
Akaike information criteria (AIC)	-914.78	-906.81
Adjusted rho-bar square ($\bar{\rho}^2$)	0.362	0.368

1.1.4 Validation

- Data from I-80, CA
  - Unlimited access HOV lane



- Additional independent validation in AIMSUN, PARAMICS and VISSIM[1]



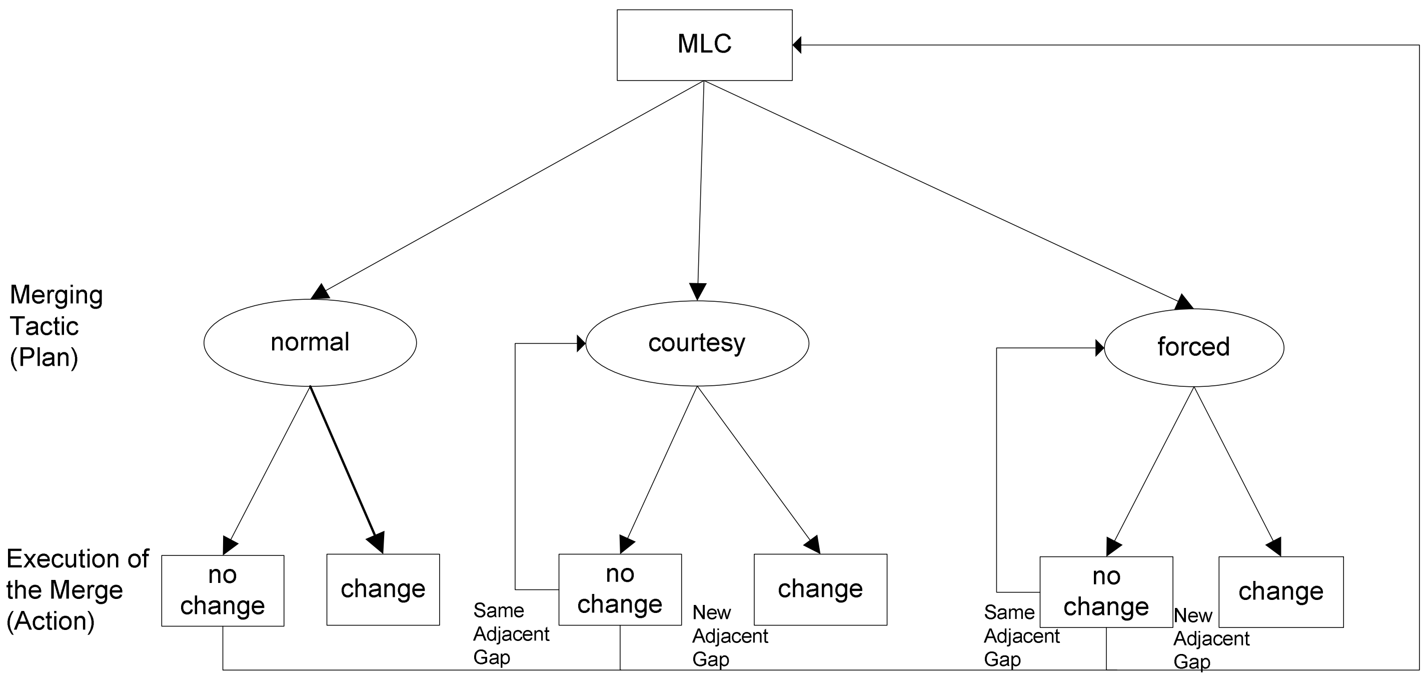
Vehicle lane distributions

[1]http://ngsim.fhwa.gov

1.2 Freeway Merging

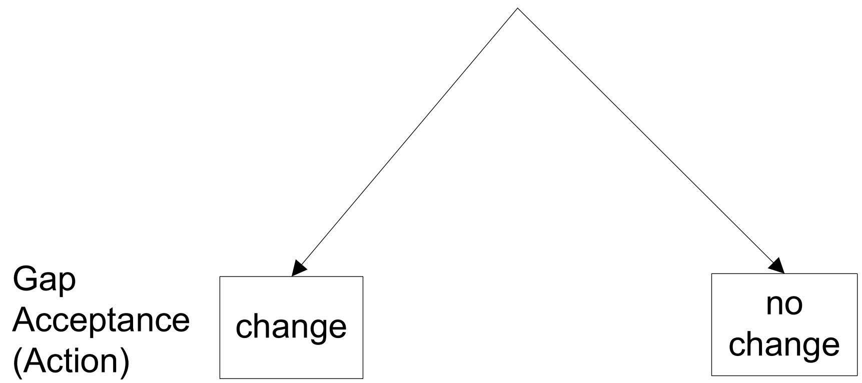
1.2.1 Model Framework

- Lane changing tactics
  - **Normal** - Adjacent gaps acceptable
  - **Courtesy** - Lag vehicle decelerates voluntarily
  - **Forced** - Lag vehicle forced to decelerate



1.2.3 Estimation

- Estimated with trajectory data from I-80, CA
- Compared with a ‘reduced form’ model with no latent tactics (Lee 2006)

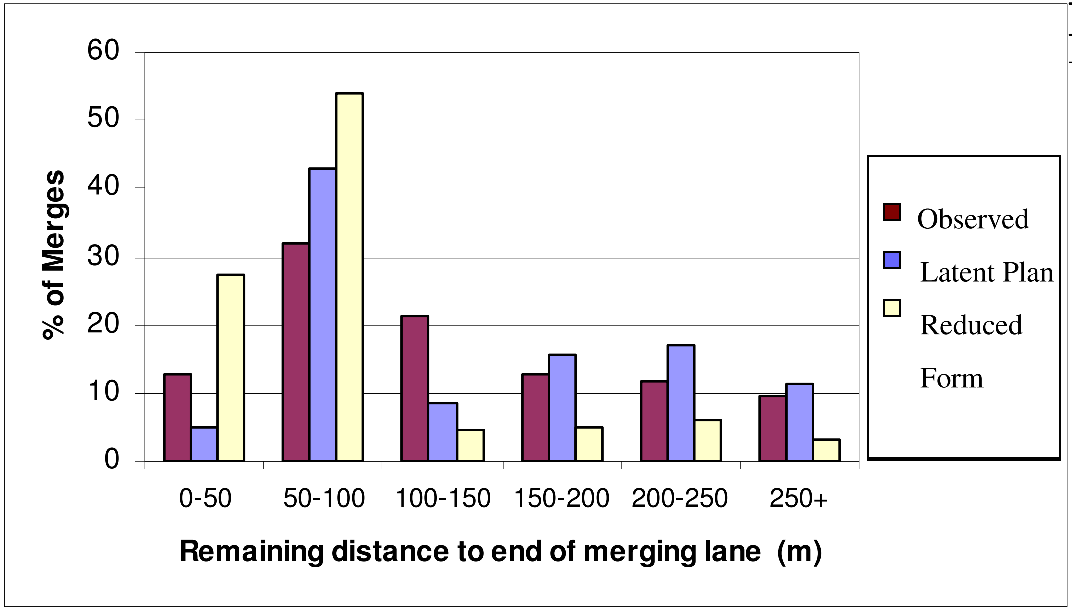


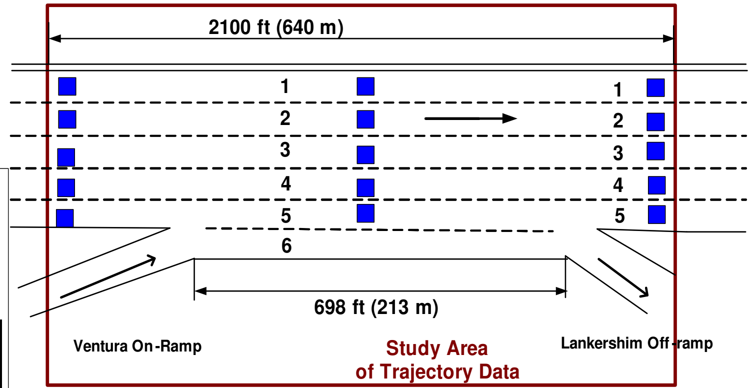
Statistic	Reduced Form Model	Latent Plan Model
Log likelihood value	-1639.69	-1609.65
Number of parameters (K)	17	42
Akaike information criteria (AIC)	-1622.69	-1567.65
Adjusted rho-bar square ($\bar{\rho}^2$)	0.87	0.88

1.2.4 Validation

- Data from US101 interchange in Los Angeles

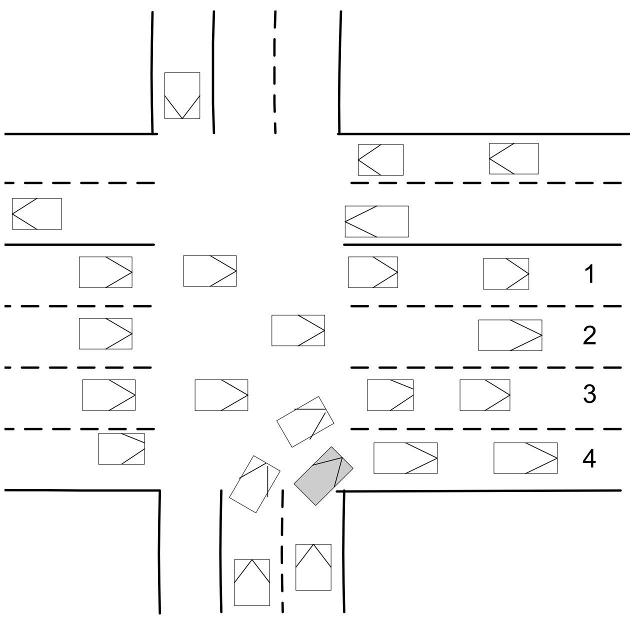
Lane change location distributions

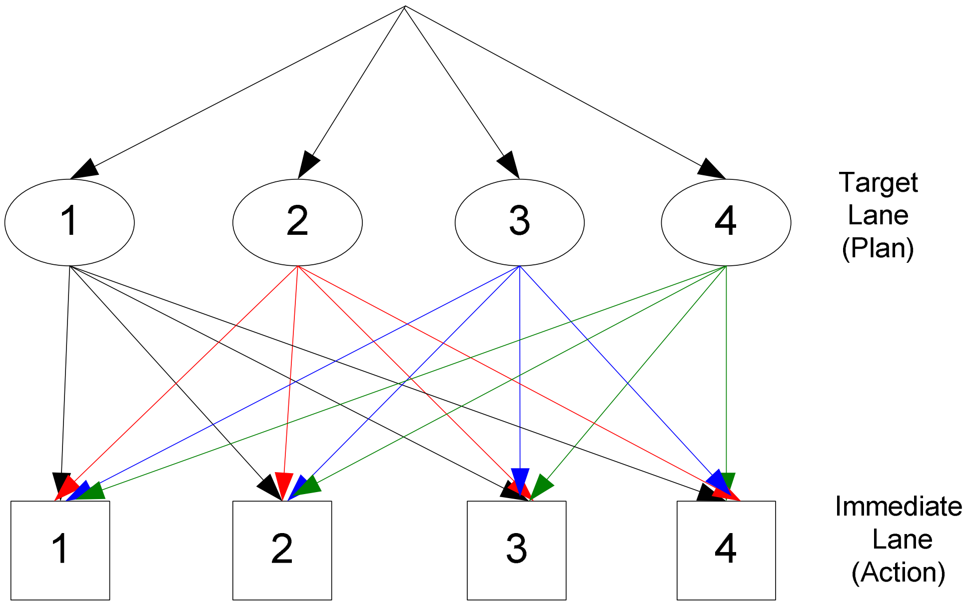




2.1 Arterial Intersection Lane Choice

2.1.1 Model Framework



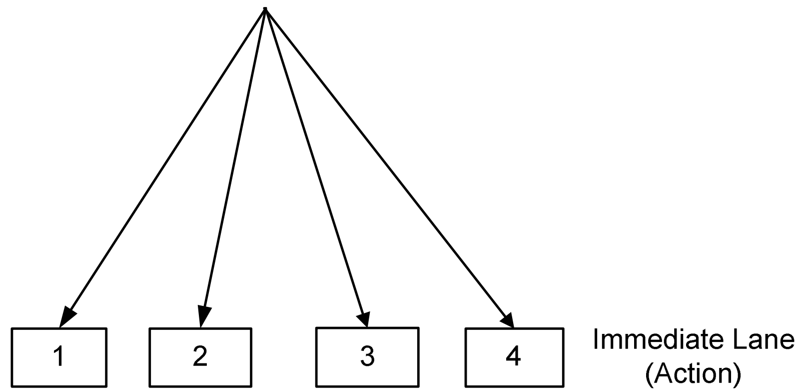


2.1.2 Model Structure

- Target lane attributes include:
  - Anticipated delay
    - Depends on ‘plan-ahead’ of the driver
    - ‘Myopic drivers’ vs. ‘Drivers who plan-ahead’
  - Expected maximum utility from immediate lane choice
- Immediate lane attributes include:
  - Current position of the driver
  - Neighborhood variables

2.1.3 Estimation

- Estimated with trajectory data collected from Lankershim Boulevard, CA
- Compared with a 'reduced form' model with no latent target

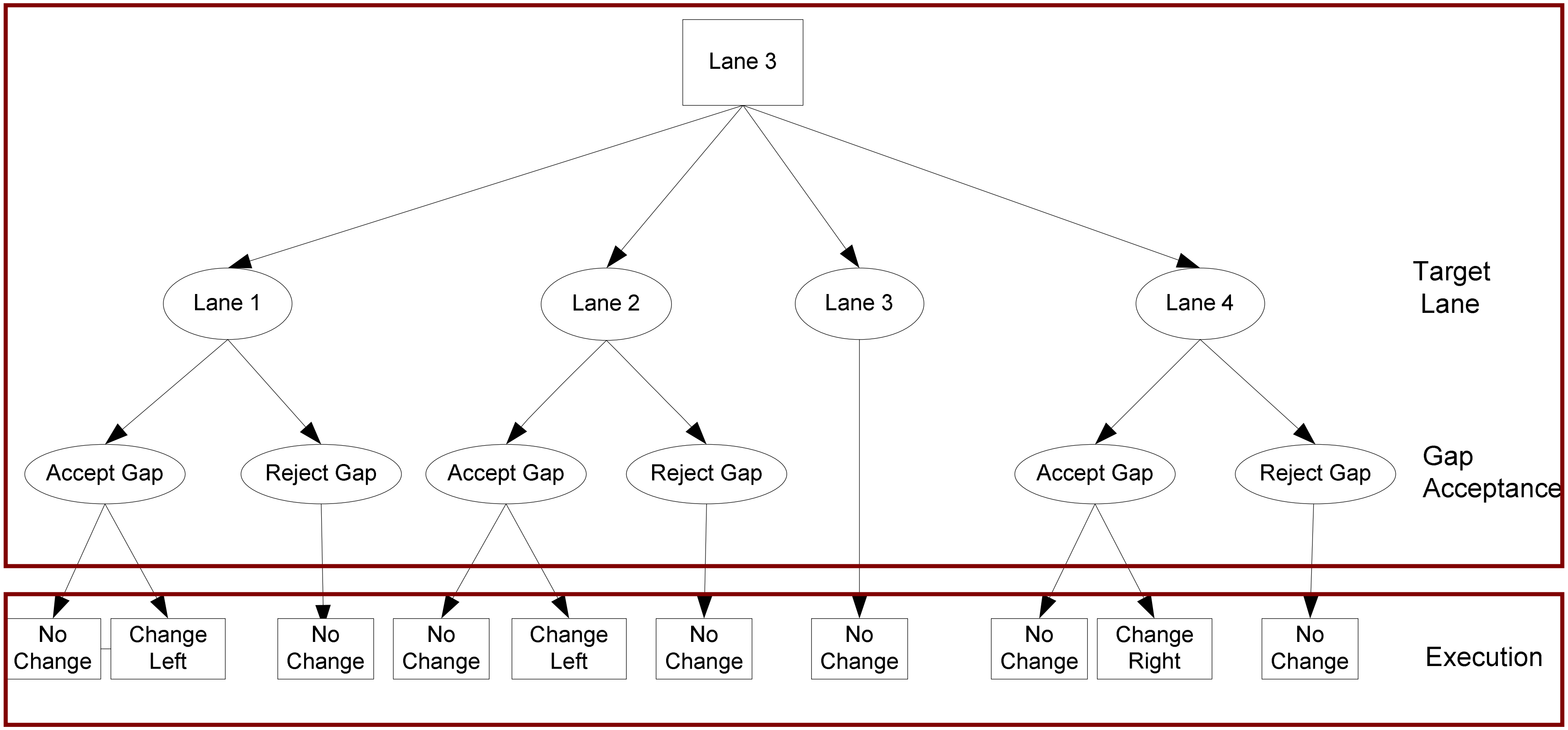


Statistic	Reduced Form Model	Latent Plan Model
Log likelihood value	-2120.4	-2115.8
Number of parameters (K)	18	20
Akaike information criteria (AIC)	-2139.3	-2135.8
Adjusted rho-bar square ($\bar{\rho}^2$)	0.235	0.237

2.2 Mainline Lane Changing

2.2.1 Model Framework

- Similar framework as in freeway lane selection
  - Additional latent level to capture duration of lane changes

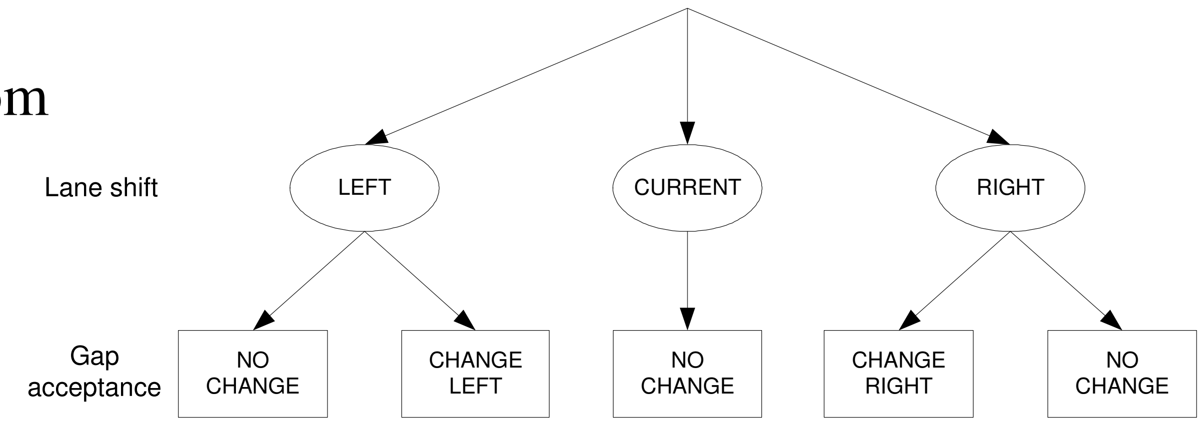


2.2.2 Model Structure

- Path-plan
  - Individual specific continuous distribution of look-ahead/ plan-ahead
- Execution
  - Captures the duration of execution of the lane change
  - Function of speed of the subject vehicle, density etc.

2.2.3 Model Estimation

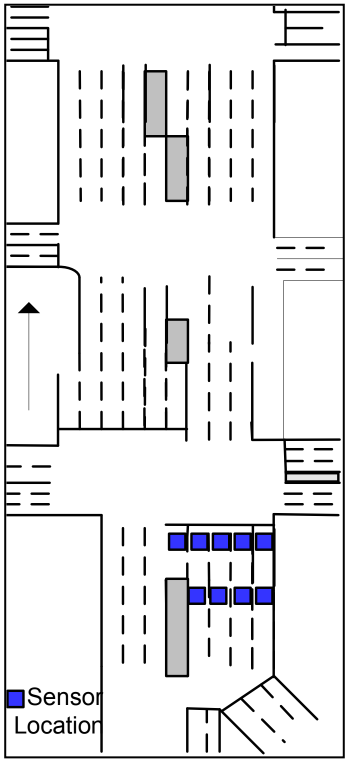
- Estimated with trajectory data from Lankershim Boulevard, CA
- Compared with 'reduced form' model reestimated with the same data

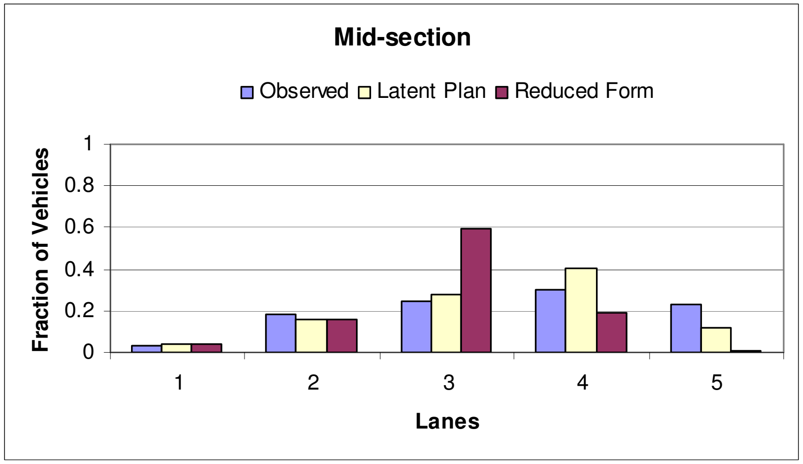


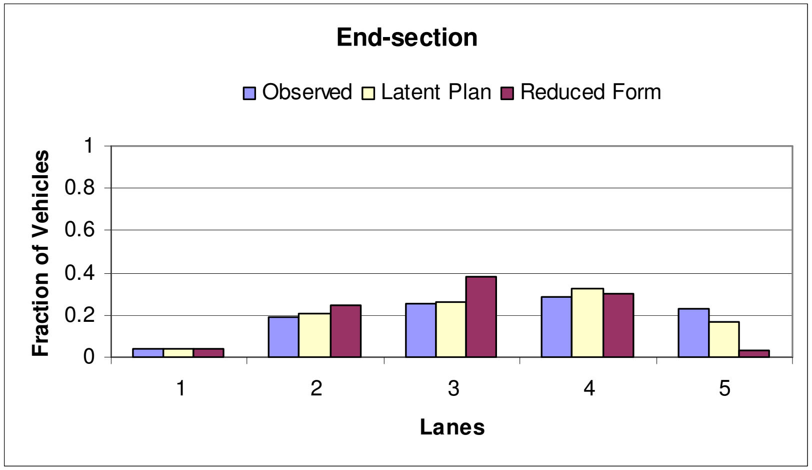
Statistic	Reduced Form Model	Latent Plan Model
Log likelihood value	-1186.9	-1003.6
Number of parameters (K)	17	22
Akaike information criteria (AIC)	-1203.9	-1126.1
Adjusted rho-bar square ($\bar{\rho}^2$)	0.441	0.531

2.2.4 Model Validation

- ‘Synthetic’ sensor counts and speeds from Lankershim Boulevard, CA







Vehicle lane distributions

Summary

- Explicit models of latent plan result in:
  - Improved behavioral representation
  - Enhanced explanatory power
  - Better representation of congestion
- Reflected by improvements in:
  - Goodness-of-fit
  - Validation results

Enhancements

- Dimensions of latent plans
  - Lane changing: target gap, acceleration (Choudhury et al. 2009), execution (Ramanujam et al. 2008)
- State-dependency hypotheses
  - Lane changing (Toledo et al. 2008), route choice
- Temporal discounting of anticipated actions
  - Dynamic programming

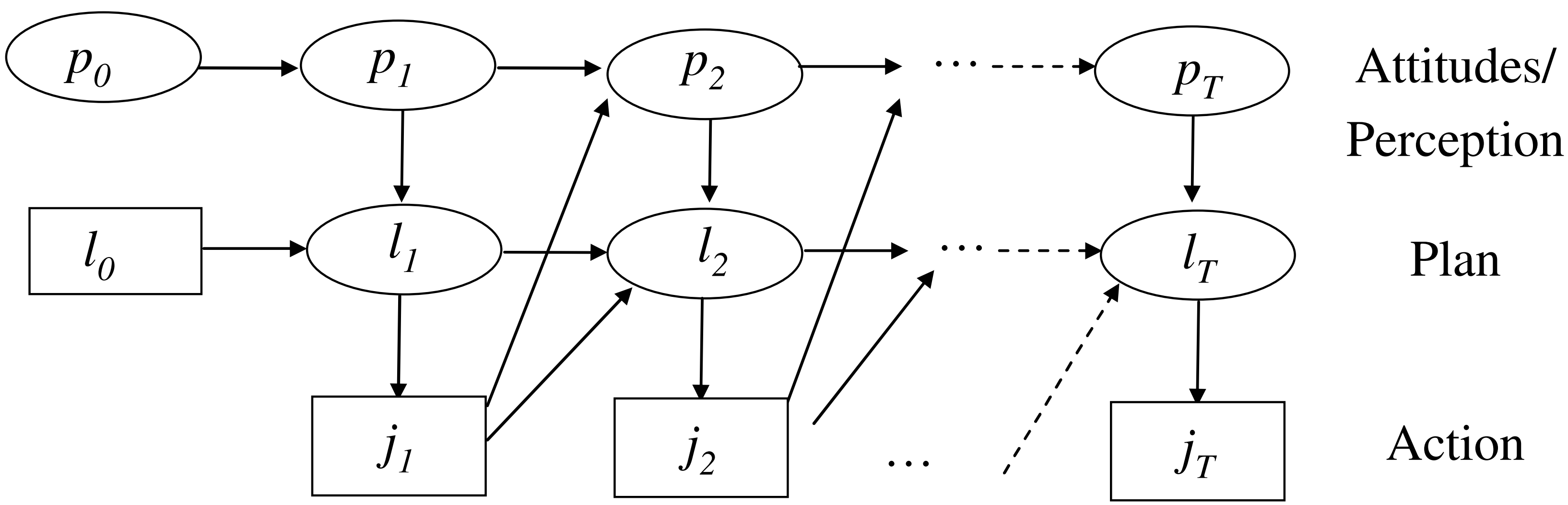
Future Research Directions

- Latent plan methodology applicable in many different contexts
  - Daily activity pattern
    - Final activities are observed
  - Travel behavior
    - Chosen destination, departure time, mode and routes are observed
  - Residential location choice
    - Ultimate choice is observed
  - Auto ownership
    - Data reflects only finally purchased vehicle

Future Research Directions (cont)

- Effect of perceptions and attitudes in latent plans and action choices
- Function of personal traits, mood etc.

Future Research Directions (cont)



- Details:
  - Modeling Driving Decisions with Latent Plans, PhD dissertation, MIT, 2007:

    http//mit.edu/its/publications.html

  - Related Papers:

    http://teacher.buet.ac.bd/cfc
- Questions?
  - cfc@ce.buet.ac.bd

Appendix

Dynamic Behavior (cont)

- Probability of individual n selecting plan l at time t (conditional on past plans and actions):

$$P_n(l_t \mid l_{1:t-1}, \upsilon_n, j_{1:t-1})$$

- Probability of observing an action at time t by individual n (conditional on present plan and past plans and actions):

$$P_n(j_t \mid l_{1:t}, \upsilon_n, j_{1:t-1})$$

j_t = *action at time t*

l_t = *plan at time t*

υ_n = *individual specific random term* (*e.g. aggressiveness*)

$1{:}t=1,2,\ldots,t$

Dynamic Behavior (cont)

- Unconditional probability of observing an action at time *t* by individual *n*:

$$P_n\left(j_t \mid j_{1:t-1}, \upsilon_n\right) = \int_{\upsilon} \sum_{(l_1,\ldots,l_t)} P_n\left(j_t \mid l_{1:t}, j_{1:t-1}, \upsilon_n\right) P_n\left(l_t \mid l_{1:t-1}, j_{1:t-1}, \upsilon_n\right) f(\upsilon)\, d\upsilon$$

- Number of summations $|L|^T$

  where $|L|$ = number of possible plans

- Simplified using Hidden Markov Model (HMM) formulation

HMM Assumptions

- Current action only depends on current plan

$$P_n\left(j_t \middle| l_{1:t}, \upsilon_n, j_{1:t-1}\right) = P_n\left(j_t \middle| l_t, \upsilon_n\right)$$

- Current plan only depends on previous plan and previous action

$$P_n\left(l_t \middle| l_{1:t-1}, \upsilon_n, j_{1:t-1}\right) = P_n\left(l_t \middle| l_{t-1}, \upsilon_n, j_{t-1}\right)$$

- The joint probability of the plan and action at time *t* (conditional on the previous observation):

$$P_n\left(j_t \middle| l_t, \upsilon_n\right) P_n\left(l_t \middle| l_{t-1}, \upsilon_n, j_{t-1}\right)$$

Likelihood of the Trajectory with State-dependence (cont)

- For a sequence of actions:

$$P_n\left(j_1,\ldots,j_T \middle| l_0,\upsilon_n\right)=\sum_{(l_1,\ldots,l_T)}\prod_{t=1}^{T}P_n\left(j_t \middle| l_t,\upsilon_n\right)P_n\left(l_t \middle| l_{t-1},\upsilon_n,j_{t-1}\right)$$

$$=\sum_{l_T}P_n\left(j_T \middle| l_T,\upsilon_n\right)\sum_{l_{T-1}}P_n\left(l_T \middle| l_{T-1},\upsilon_n,j_{T-1}\right)P_n\left(j_{T-1} \middle| l_{T-1},\upsilon_n\right)\ldots$$

$$\sum_{l_1}P_n\left(l_2 \middle| l_1,\upsilon_n,j_1\right)P_n\left(j_1 \middle| l_1,\upsilon_n\right)P_n\left(l_1 \middle| l_0,\upsilon_n\right)$$

  - Can be calculated recursively
  - Number of summations reduced from $|L|^T$ to $|L|T$ where $|L|$ =number of possible plans