A Reliable Travel Time Prediction System with Sparsely Distributed Detectors

Ph.D. Dissertation Proposal

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Outline

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  - The proposed hybrid model
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Introduction

- Travel times (completed and en-route trips) are crucial information for an Advanced Traveler Information System (ATIS)
- Travel time prediction is a challenging task due to the impacts of
  - Geometric features
  - Traffic patterns
  - Availability of detection system, and
  - Nonrecurrent congestion (for example, incidents), etc.

Introduction (cont’d)

- Issues Associated with Existing Models and Systems:
  - High system costs
    - Densely distributed detectors (i.e., 0.5-mile apart)
    - Accurate speed detection
    - Recurrent measurement on travel times

      Coifman et al. (2002, 2003), van Lint et al. (2003), Liu et al. (2006)
  - Reliability
    - Missing or delayed data
    - Nonrecurrent congestions (for example, incidents)

Features of A Cost-efficient and Reliable Travel Time Prediction System

- Required input variables should be obtainable from sparsely distributed traffic detectors
- Take advantage of some actual travel times from the field, but not rely on a large number of such data.
- Be capable of operating under non-recurrent congestion or data-missing conditions and effectively dealing with related issues during real-time operations.

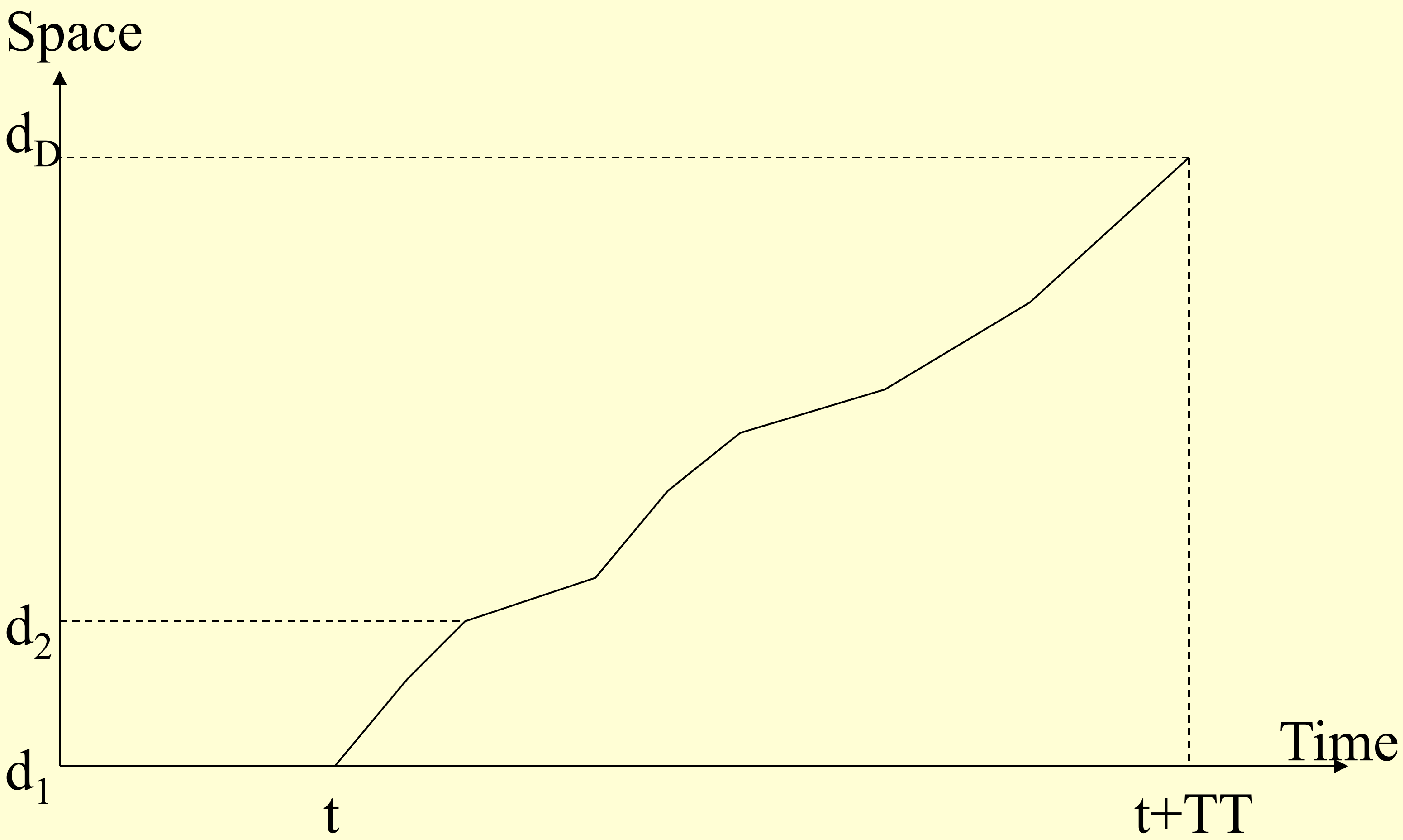
Research Objectives

- Develop a travel time estimation module
  - Reliable estimates of completed trips
  - Under all types of recurrent traffic patterns
  - With sparsely distributed traffic detectors
- Construct a travel time prediction module
  - For freeway segments
  - Large detector spacing
  - Historical travel times and traffic patterns

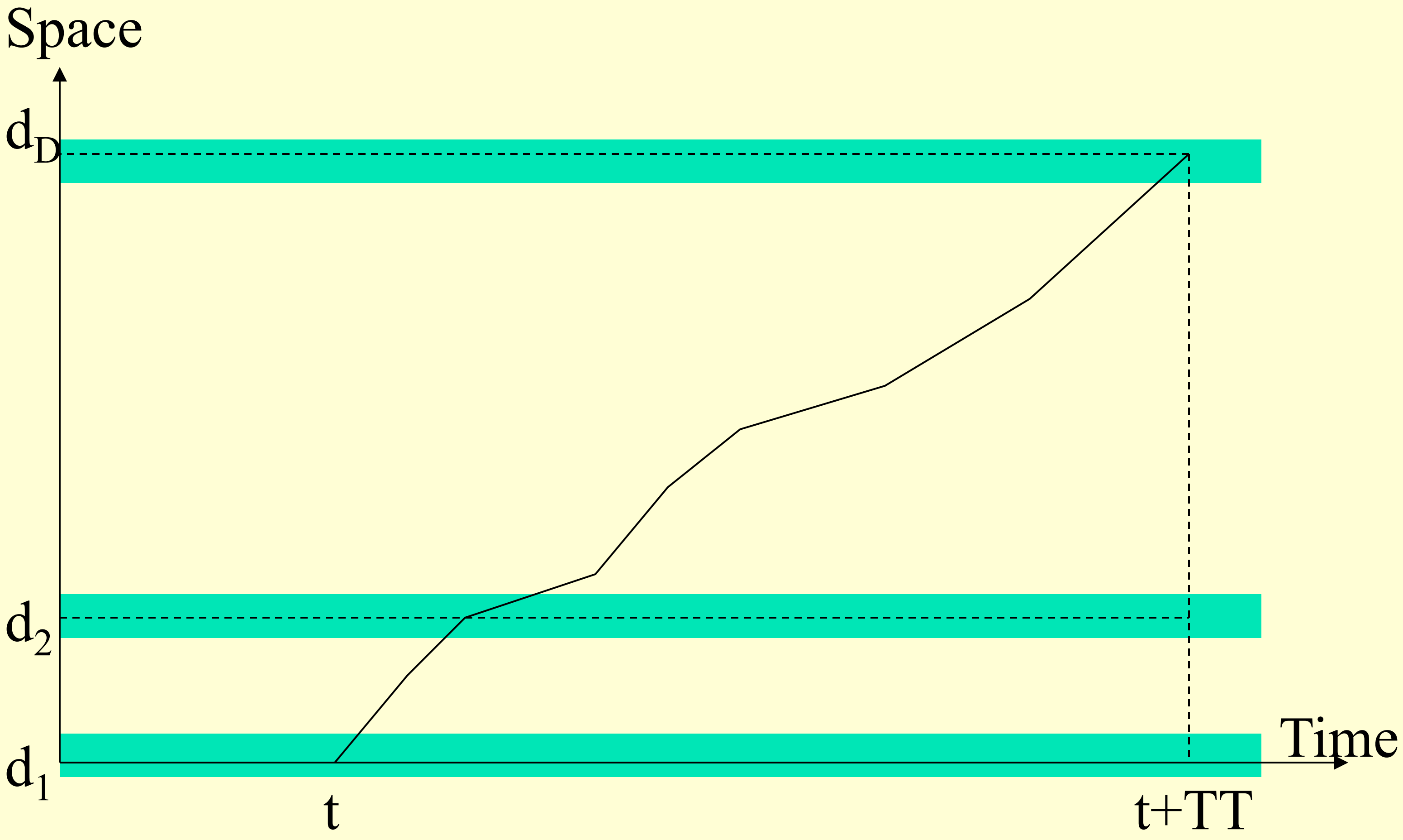
Research Objectives (cont’d)

- Integrate a missing data estimation module
  - To deal with various missing data and delay patterns
- Calibrate an incident detection module
  - Switch the travel time prediction system to a different mode (i.e., display delay warnings instead of predicted travel times) when an incident has been detected.

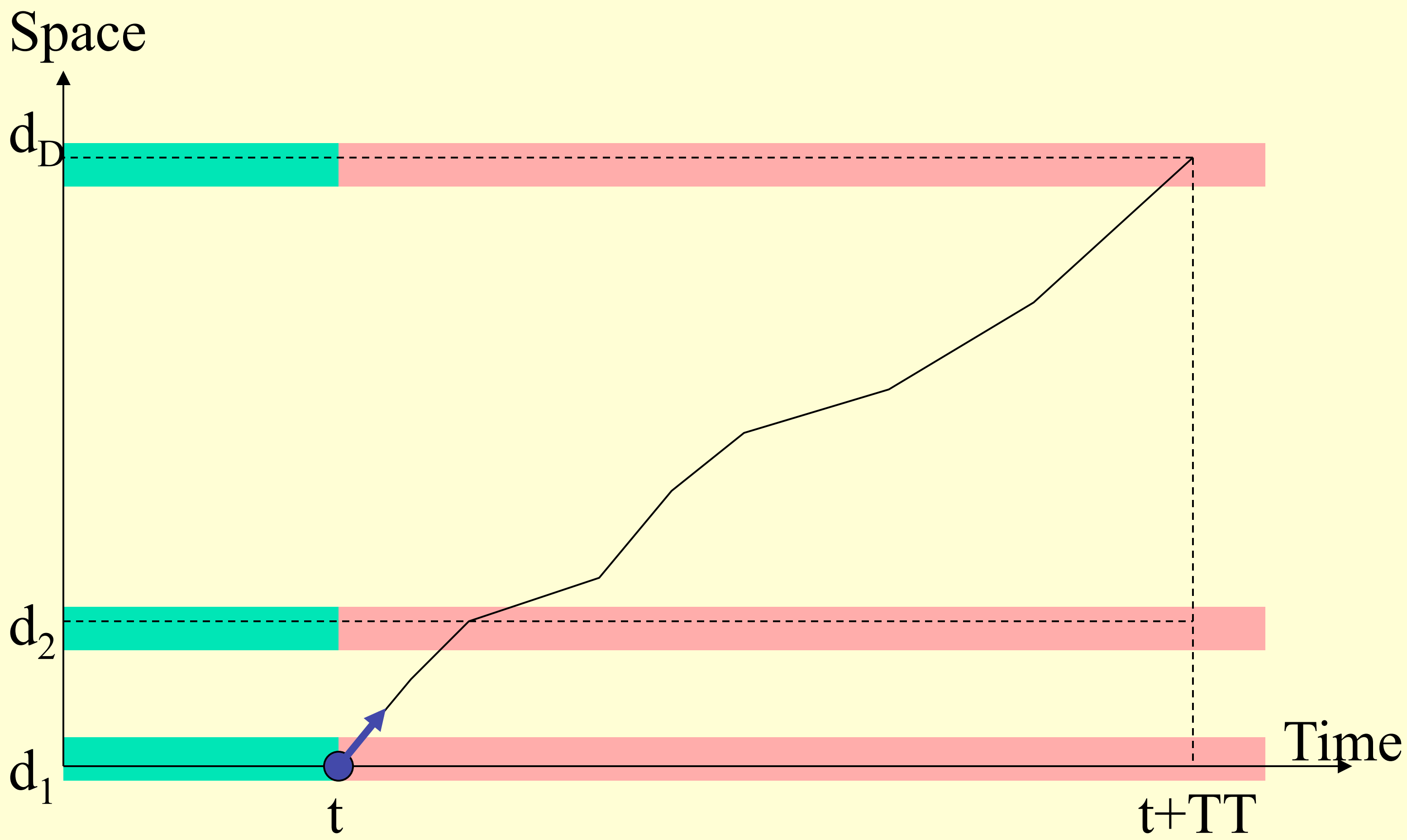
T.T. Estimation vs. Prediction



T.T. Estimation



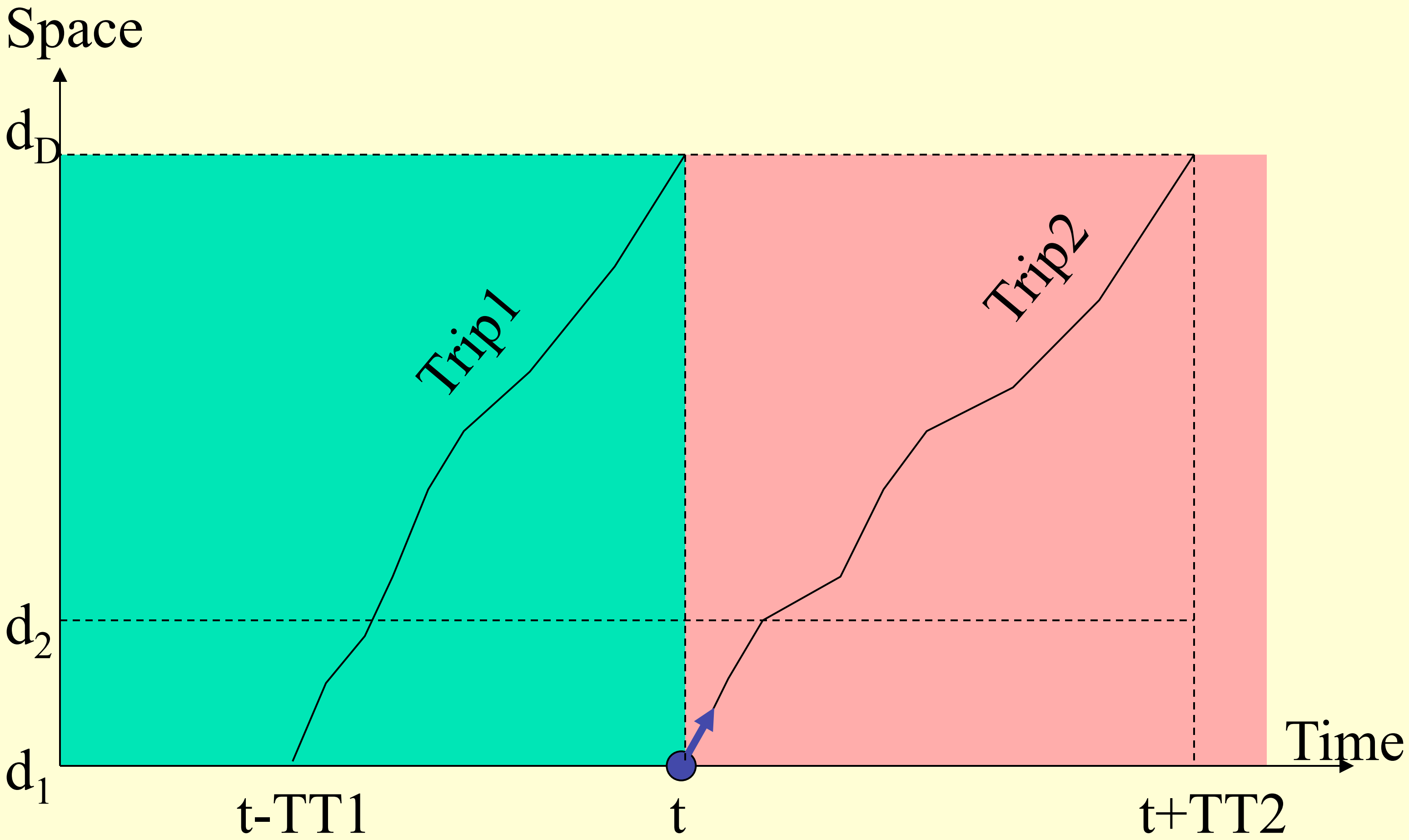
T.T. Prediction

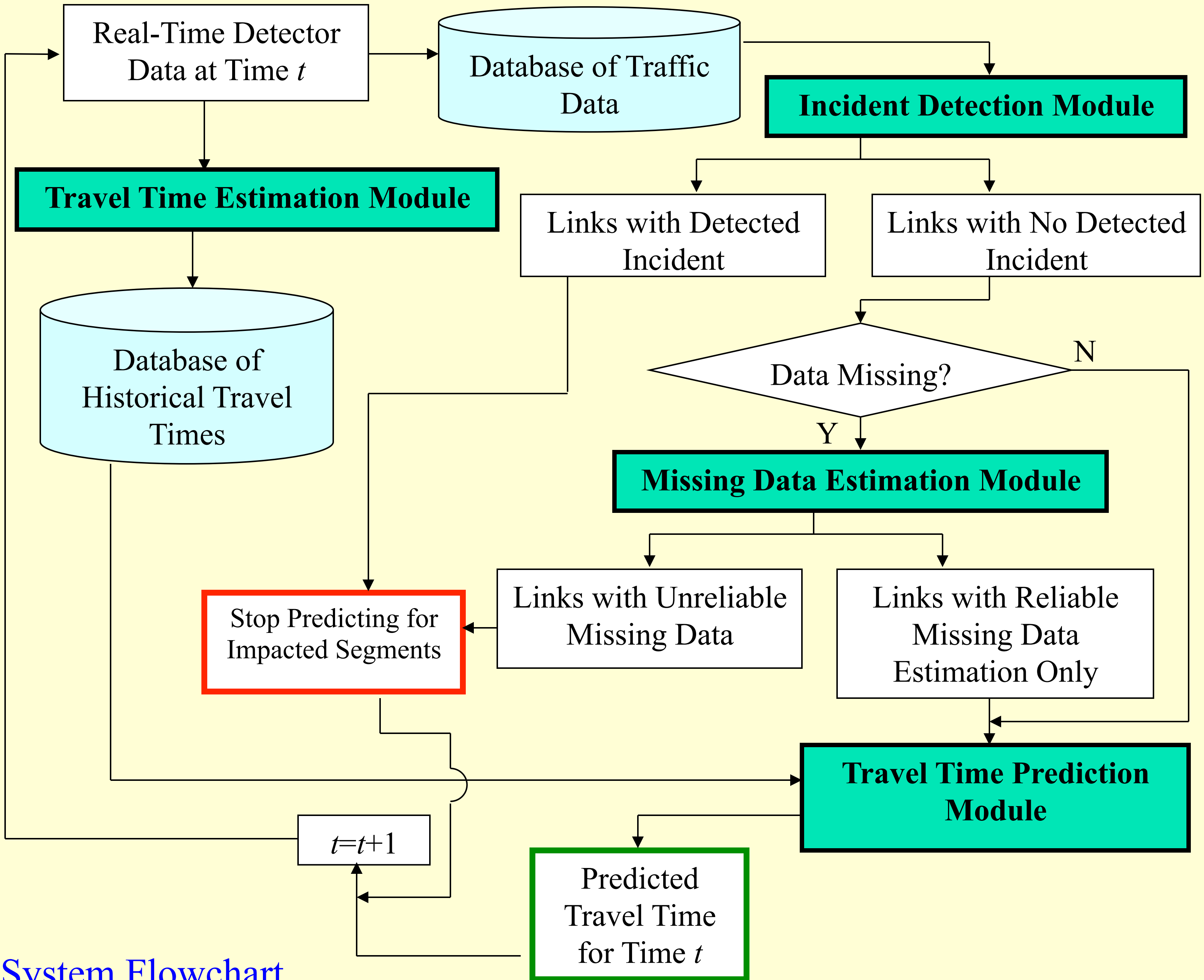


Existing Travel Time Prediction Systems

- Example systems
  - Houston, TX; Atlanta, GA; Chicago, IL; and Seattle, WA, etc.
- Almost all real-world systems use current detected traffic conditions as the prediction of the future
  - Completed trips instead of en-route trips
  - Big difference

Completed Trips vs. En-route Trips





System Flowchart

Literature Review

- Travel Time Estimation
  - Flow-based models
  - Vehicle identification approaches
  - Trajectory-based models

Limitations of Flow-based Models

- Reliability of detector data
  - Detection errors (volume drifting) vary over time and space
- Traffic patterns
  - Require uniformly distributed traffic across all lanes
- Geometric features
  - Cannot model ramp impact

Limitations of Vehicle Identification Approach

- Traffic patterns
  - Lane-based approach, therefore requires low lane changing rate
  - Requires uniform traffic conditions across lanes
- Geometric features
  - May not fit geometric changes, such as lane drop and lane addition
- System cost
  - High. Require new hardware or high bandwidth
- Reliability
  - Low detection resolution under high speed
  - Reduced accuracy under low light (video-based)

Limitations of Existing Trajectory-based Models

- Assumes constant traffic-propagation speed
- May not perform well on long links
  - currently all studies are based on detectors less than 0.5-mile apart
- Requires reliable speed measurement
  - Not available from most traffic detectors

A Hybrid Travel Time Estimation Model with Sparsely Distributed Detectors

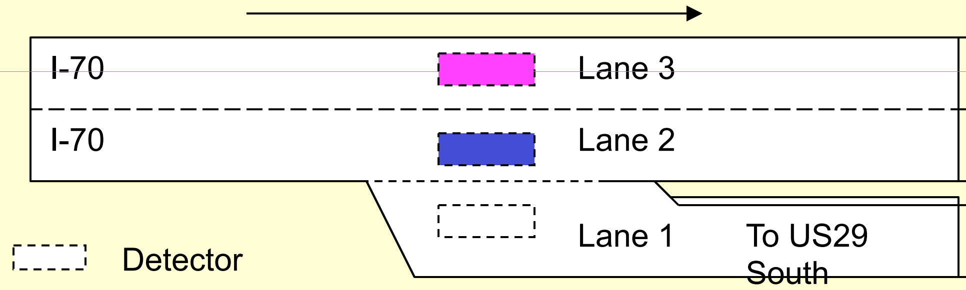
- A Clustered Linear Regression Model as the main model
  - For traffic scenarios that have sufficient field observations
- An Enhanced Trajectory-based Model as the supplemental model
  - For other scenarios

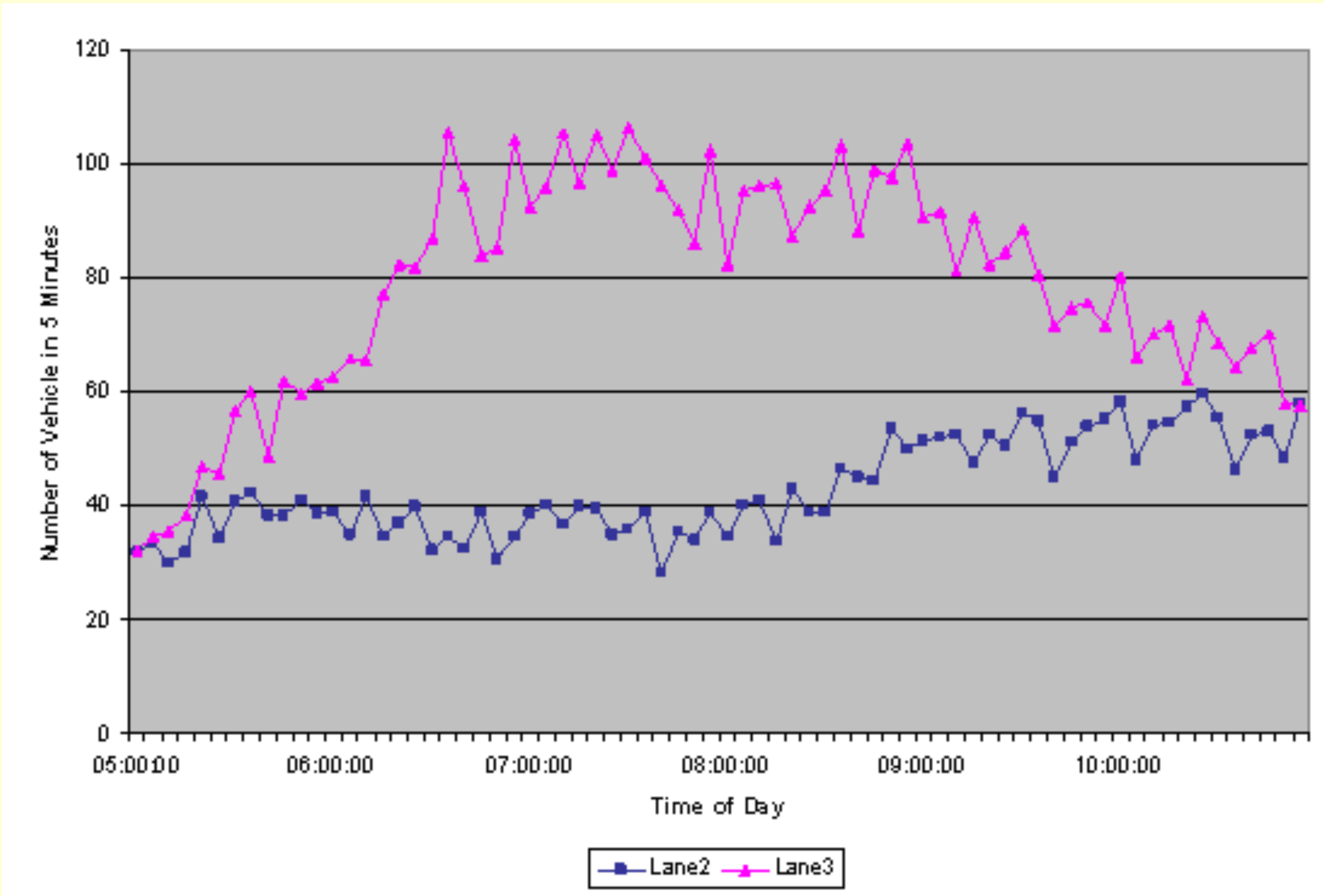
Clustered Linear Regression Model

- Travel times may be constrained in a range under one identified traffic scenario
  - For example, the travel time cannot be free-flow travel time when congestion is being observed at one detector
- Assume a linear relation between the travel time under one traffic scenario with traffic variables from pre-determined critical lanes

Critical Lanes

- Those lanes that directly contribute to estimate the average travel speed of through traffic
- May include both mainline lanes and ramp lanes
- From both upstream and downstream detector locations


I-70
Lane 3
I-70
Lane 2
Lane 1
To US29 South
Detector


120
100
80
60
40
20
0
Number of Vehicle in 5 Minutes
05:00:00
06:00:00
07:00:00
08:00:00
09:00:00
10:00:00
Time of Day
Lane2
Lane3

Model Formulation of the Clustered Linear Regression Model

$$\tau_d(t) = \sum_{la \in \mathbf{CLT}^{\mathbf{d}}_{d,d+1}(p)} b^{T,p}_{d,la} \frac{o_{d,la}(t, \gamma^d_p \boldsymbol{\tau}^E_d(p))}{v_{d,la}(t, \gamma^d_p \boldsymbol{\tau}^E_d(p))} + \sum_{la \in \mathbf{CLR}^{\mathbf{d}}_{d,d+1}(p)} b^{R,p}_{d,la} \frac{o_{d,la}(t, \gamma^d_p \boldsymbol{\tau}^E_d(p))}{v_{d,la}(t, \gamma^d_p \boldsymbol{\tau}^E_d(p))}$$

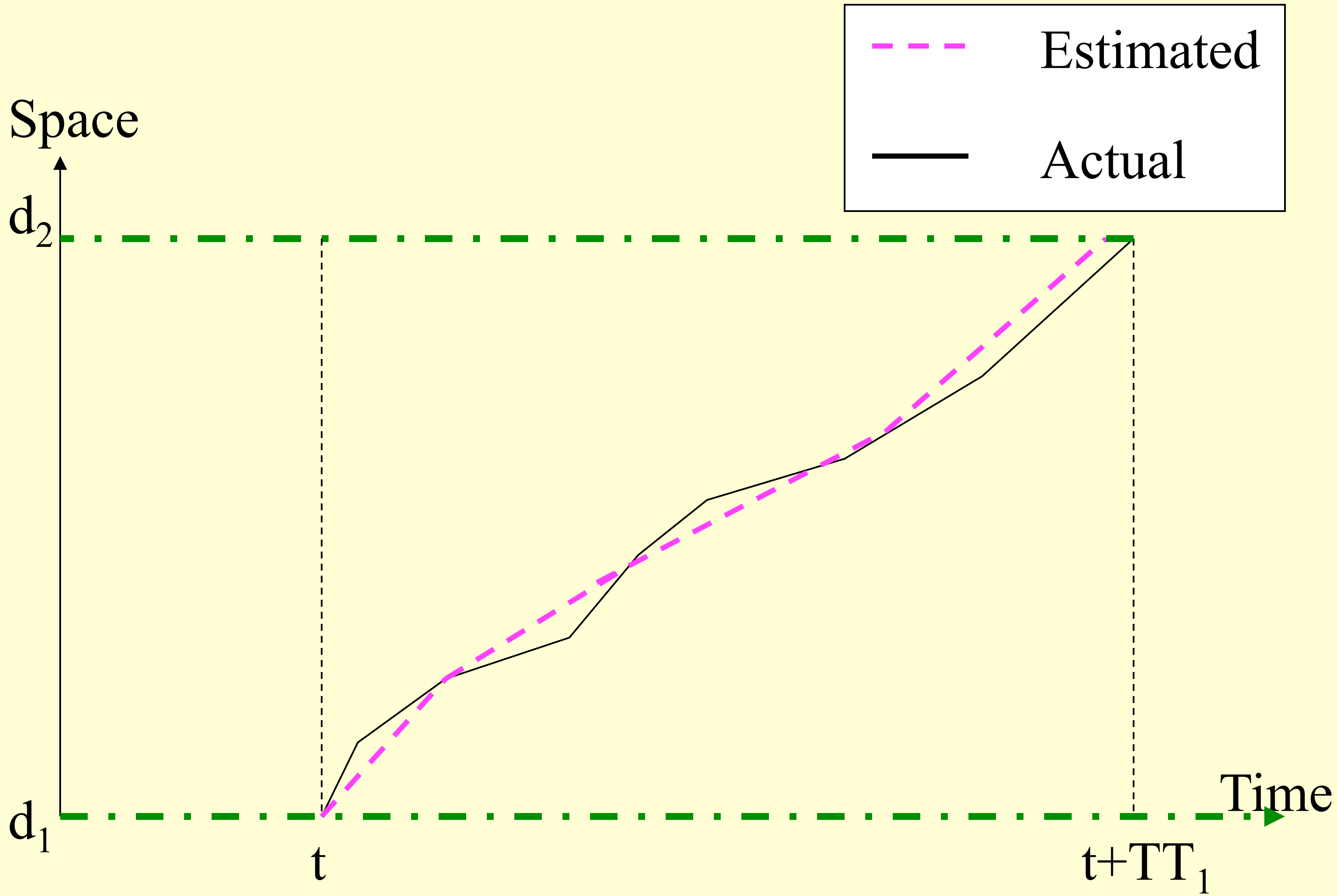
$$+ \sum_{la \in \mathbf{CLT}^{\mathbf{d+1}}_{d,d+1}(p)} b^{T,p}_{d+1,la} \frac{o_{d,la}(t + \gamma^d_p \boldsymbol{\tau}^E_d(p), (1-\gamma^d_p)\boldsymbol{\tau}^E_d(p))}{v_{d,la}(t + \gamma^d_p \boldsymbol{\tau}^E_d(p), (1-\gamma^d_p)\boldsymbol{\tau}^E_d(p))}$$

$$+ \sum_{la \in \mathbf{CLR}^{\mathbf{d+1}}_{d,d+1}(p)} b^{R,p}_{d+1,la} \frac{o_{d,la}(t + \gamma^d_p \boldsymbol{\tau}^E_d(p), (1-\gamma^d_p)\boldsymbol{\tau}^E_d(p))}{v_{d,la}(t + \gamma^d_p \boldsymbol{\tau}^E_d(p), (1-\gamma^d_p)\boldsymbol{\tau}^E_d(p))} + b^{0,p}_d$$

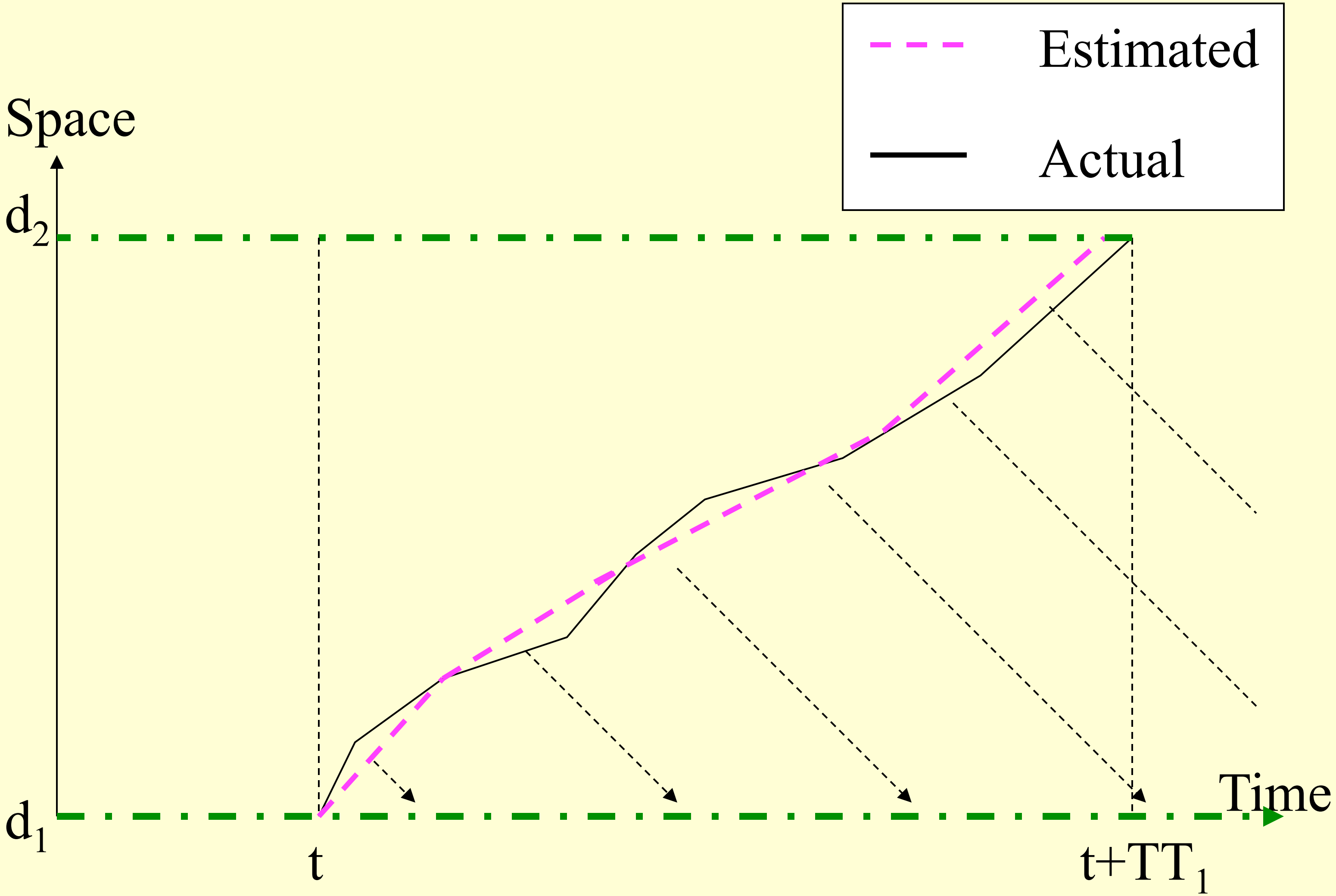
An Enhanced Trajectory-based Model

- Combines and enhances two types of trajectory estimation:
  - Traffic propagation relations when the vehicle is close to one detector
  - An enhanced piecewise linear-speed-based model when the vehicle is far from both detectors
- Does not require speed in input variables
  - Estimate the occupancy first, then use occupancy-speed relation to estimate the vehicle's speed

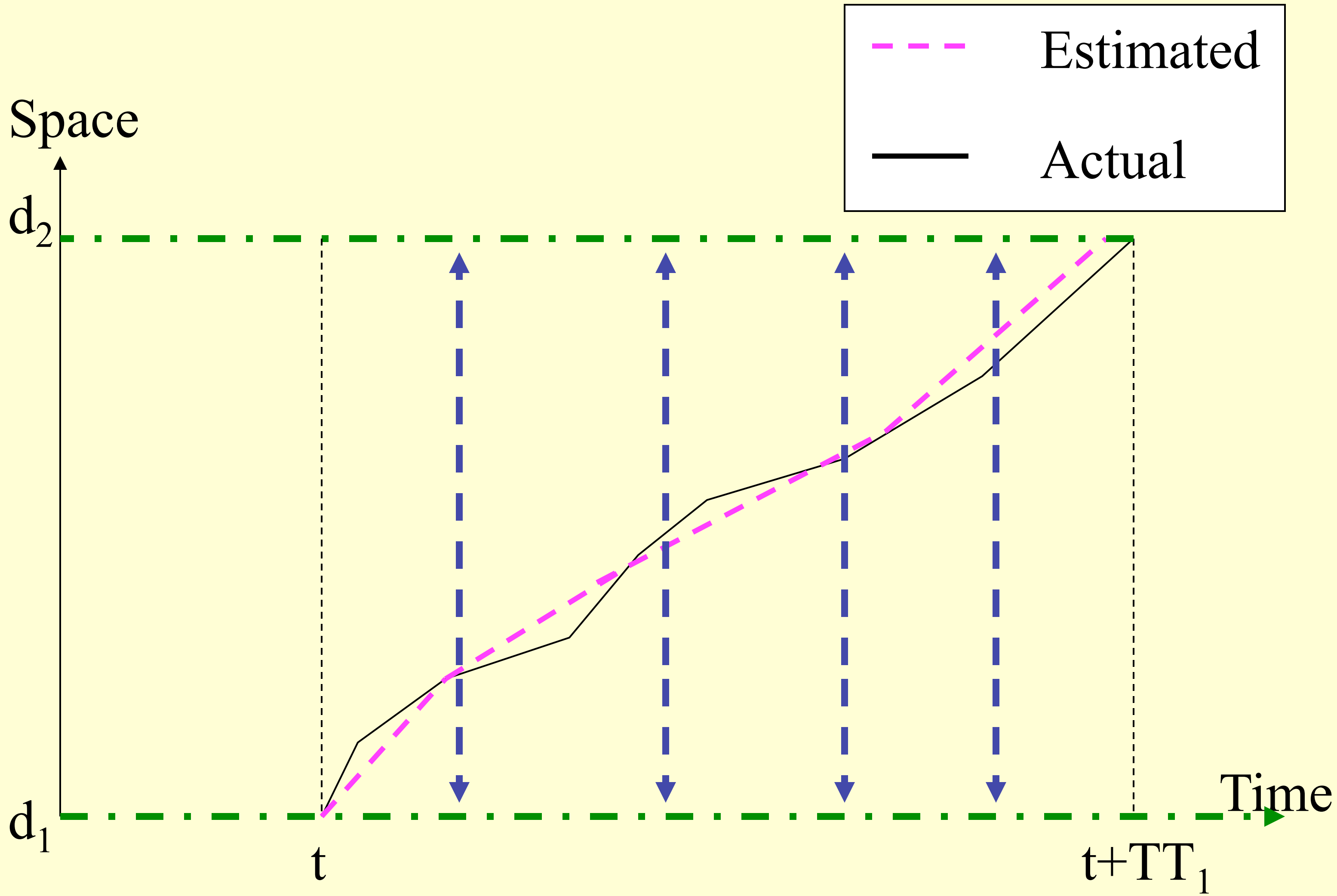
Trajectory-based Method



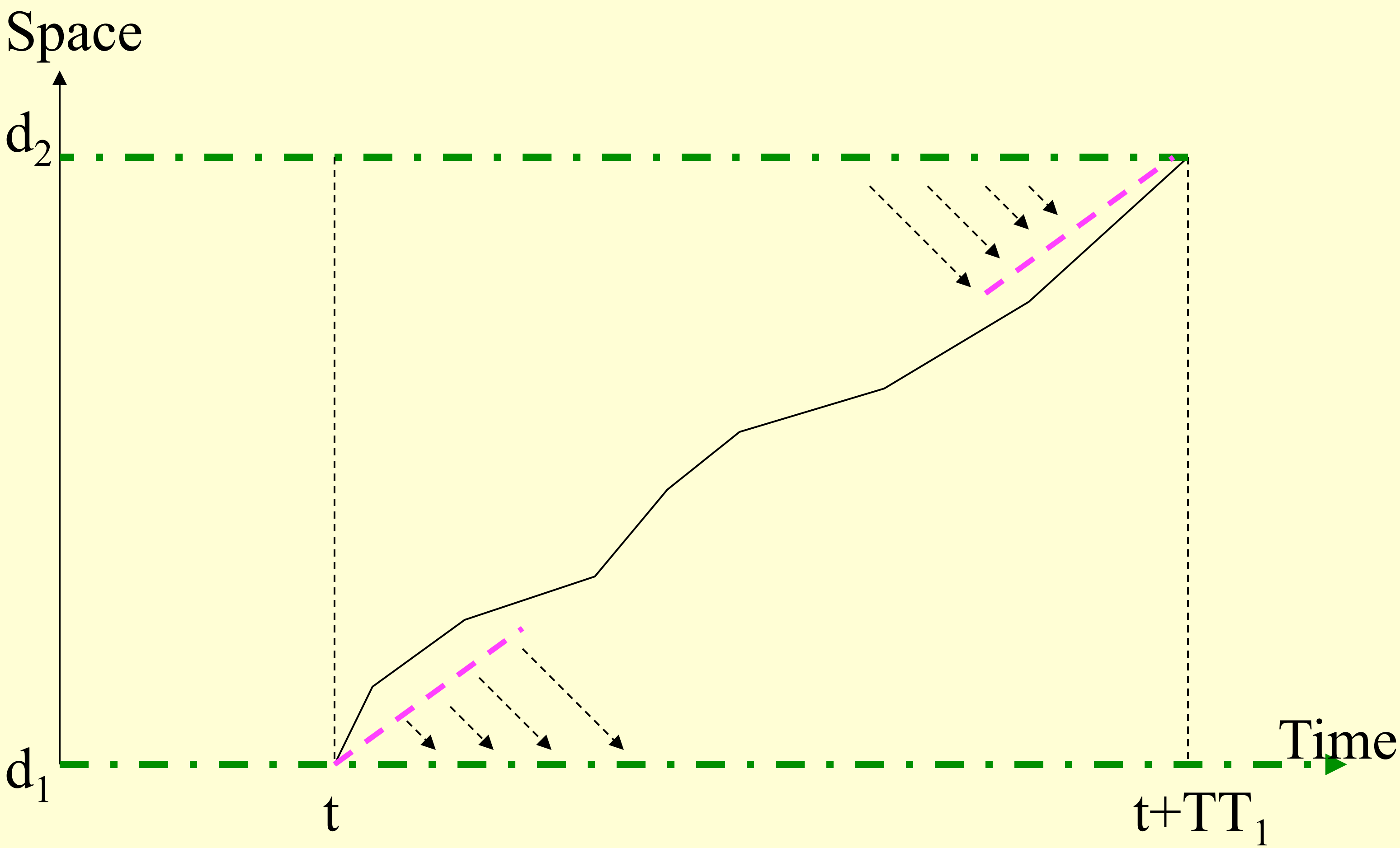
Trajectory-based Method



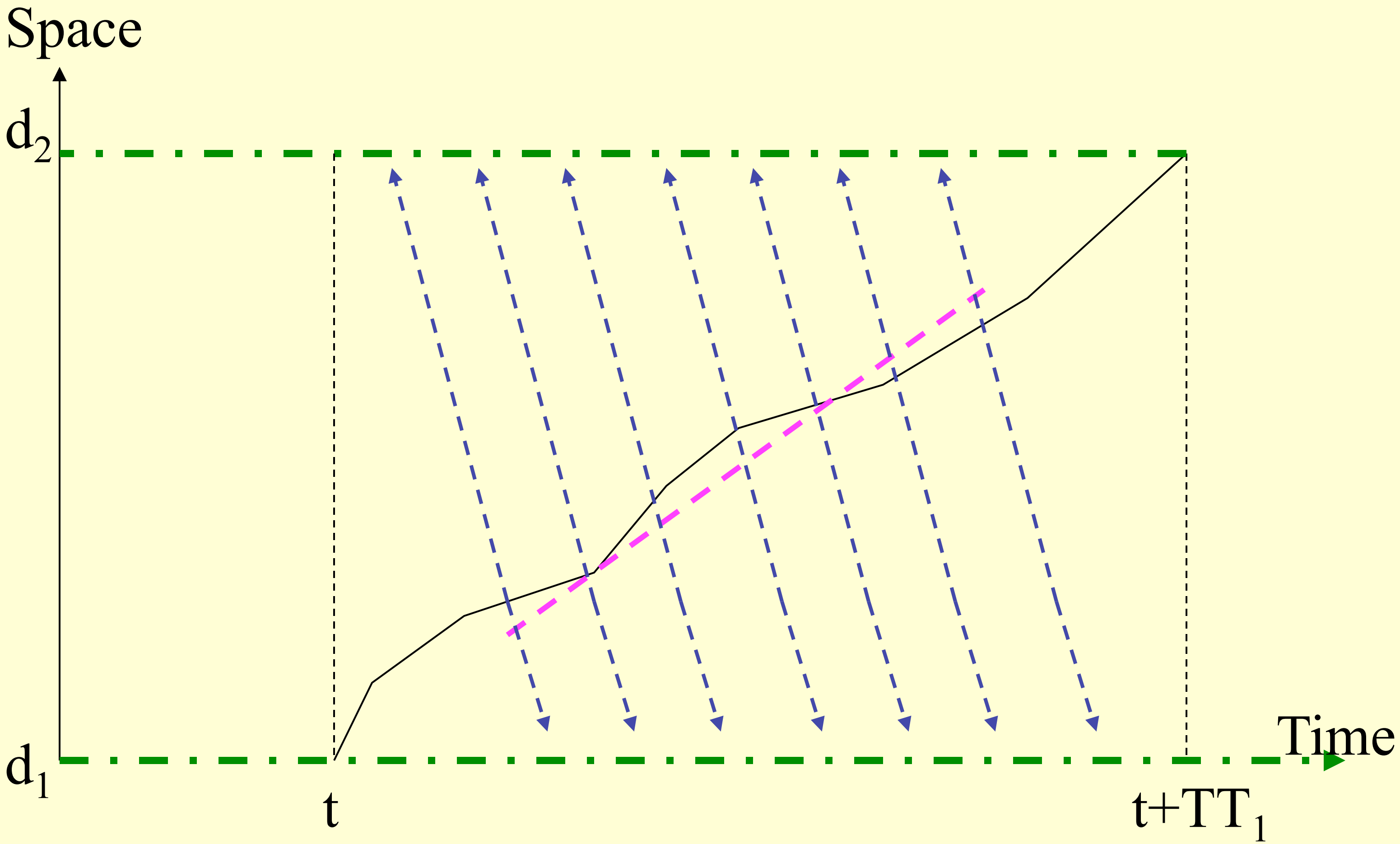
Trajectory-based Method



An Enhanced Trajectory-based Method



An Enhanced Trajectory-based Method



Model Formulation

$$O(x,t)=\begin{cases} o_d\left(t+\dfrac{x-x_d}{u_c^{\max}},\, t+\dfrac{x-x_d}{u_c^{\min}}\right) & \text{, if } x-x_d<\hat{x} \\ o_{d+1}\left(t-\dfrac{x_{d+1}-x}{u_c^{\min}},\, t-\dfrac{x_{d+1}-x}{u_c^{\max}}\right) & \text{, if } x_{d+1}-x<\hat{x} \\ o_d\left(t+\dfrac{\hat{x}-x_d}{u_c^{\max}},\, t+\dfrac{\hat{x}-x_d}{u_c^{\min}}\right) & \\ +\dfrac{(x-x_d-\hat{x})}{\hat{x}} & \text{, otherwise} \\ \times\left(o_{d+1}\left(t-\dfrac{x-(x_{d+1}-\hat{x})}{u_c^{\min}},\, t-\dfrac{x-(x_{d+1}-\hat{x})}{u_c^{\max}}\right)\right. & \\ \left.-o_d\left(t+\dfrac{\hat{x}}{u_c^{\max}},\, t+\dfrac{\hat{x}}{u_c^{\min}}\right)\right) & \end{cases}$$

$$\hat{x}=\begin{cases} \min\left(\dfrac{l_d}{3},\dfrac{1}{3}\text{mi}\right) & \text{, when } l_d\geq 1\text{ mile} \\ \dfrac{l_d}{3} & \text{, otherwise} \end{cases}$$

$$x_d\leq x\leq x_{d+1}$$

$u_c^{\min}$ and $u_c^{\max}$ are the minimum and the maximum traffic propagation speeds.

Model Formation (cont'd)

$$u(x,t) = \begin{cases} u_{free} & , o(x,t) <= o_{free} \\ u_{cong} + (u_{free} - u_{cong})(1 - \dfrac{o(x,t) - o_{free}}{o_{cong} - o_{free}})^{m} & , o_{free} < o(x,t) <= o_{cong} \\ u_{min} + (u_{cong} - u_{min})(1 - \dfrac{o(x,t) - o_{cong}}{o_{max} - o_{cong}})^{n} & , o_{cong} < o(x,t) <= o_{\max} \\ u_{min} & , \text{otherwise} \end{cases}$$

Travel Time Prediction

- Parametric Models
  - Time series model
  - Linear regression model
  - Kalman Filter model
- Nonparametric models
  - Neural Network model
  - Nearest Neighbor model
  - Kernel model and local regression model

Autoregressive Integrated Moving Average (ARIMA)

- Advantages:
  - Ability to predict a time series data set
  - Good for predicting traffic data (volume, speed, or occupancy) at one detector
- Disadvantages:
  - Focus on the mean value, therefore cannot well predict scenarios that less frequently occur
  - It is hard to model multiple sets of time series data together (for example, multiple series of data from detectors)

Linear Regression Models

- One single linear regression model cannot predict well for all traffic scenarios, therefore multi-model structure is often used:
  - Layered/clustered linear regression model
  - Varying coefficient linear regression model

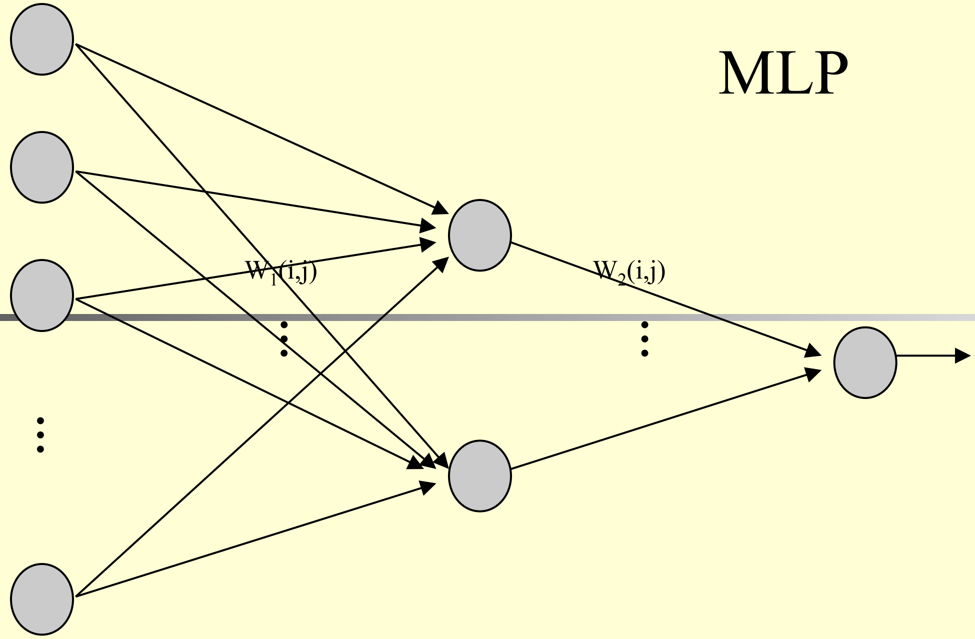
Kalman Filter Model

- Ability to auto-update parameters based on the evaluation of the prediction accuracy of the previous time interval
- Good performance when the true value can be obtained with a short delay (Chien et al., 2002 and 2003)
- May not work well for a prediction system with long travel times (long travel times = long delay for the update process)

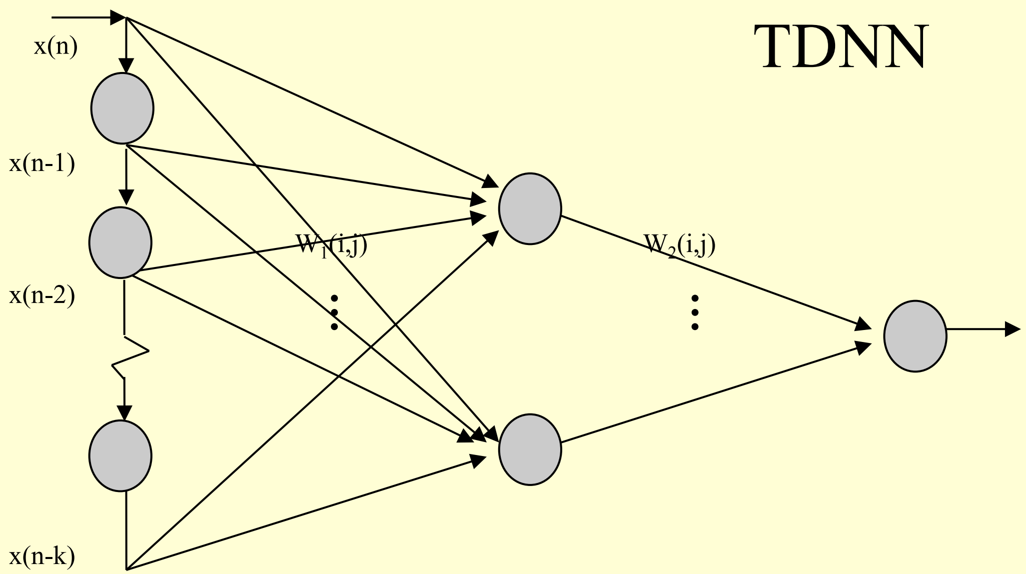
Neural Network Models

- Widely used to predict travel times
- Accurate and robust because of its good ability to recognize patterns
- Multi-layer Perceptron (MLP) and Time Delay Neural Network (TDNN) are mostly seen in the literature
- A large amount of training data

MLP



TDNN



k-Nearest Neighbor Model

- Looks for *k* most similar cases as the current condition from the historical database to come out a prediction
- Requires a fairly large historical database

$$dist_{EUC}(p,q) = \sqrt{\sum_{i=1}^{K} (p_i - q_i)^2}$$

$$dist_{NUW}(p,q) = \sqrt{\sum_{i=1}^{K} w_i (p_i - q_i)^2}$$

Other Nonparametric Models

- Share a common structure
  - A clustering function
  - A kernel function (linear, nonlinear and/or other form) for each cluster
- For example
  - Kernel regression
  - Layered linear regression
  - Time-varying coefficient linear regression

A Hybrid Travel Time Prediction Model

- A *k*-Nearest Neighbor Model as the main model
  - For cases with sufficient good matches in the historical data
- An enhanced time-varying coefficient model as the supplemental model
  - For other cases

k-Nearest Neighbor Model for Travel Time Prediction

- An updated distance function
  - Based on three types of traffic state
- Geometric features
  - Take traffic data from critical lanes only
  - The time range of input data increases with the distance to the origin
- Daily and weekly traffic patterns
  - Varying search window based on historical traffic patterns

Modified Definition of the Distance

$$mdis = \sqrt{\sum_{i=1}^{k} w_i (p_i^* - q_i^*)^2}$$

$$p_i^* = \begin{cases} p_i & \text{, when } TC_d^{l_a}(t, t+\Delta t) = 0 \\ OC_d^{l_a} & \text{, when } TC_d^{l_a}(t, t+\Delta t) = 1 \\ OF_d^{l_a} & \text{, when } TC_d^{l_a}(t, t+\Delta t) = -1 \end{cases}$$

$$q_i^* = \begin{cases} q_i & \text{, when } TC_d^{l_a}(t_h, t_h+\Delta t) = 0 \\ OC_d^{l_a} & \text{, when } TC_d^{l_a}(t_h, t_h+\Delta t) = 1 \\ OF_d^{l_a} & \text{, when } TC_d^{l_a}(t_h, t_h+\Delta t) = -1 \end{cases}$$

Consideration of Traffic Patterns

$$mdis = \sqrt{\sum_{i=1}^{k} w_i (\hat{p}_i - q_i^*)^2}$$

Where

$$\hat{p}_i = \begin{cases} M & \text{, if } |t - t_h| > T_{th}(d, t) \\ p_i^* \times \hat{w} & \text{, otherwise} \end{cases}$$

$$\hat{w} = \begin{cases} 1 & \text{, if } \exists s,\ wk_h \in \boldsymbol{W}_s \text{ and } wk_c \in \boldsymbol{W}_s \ (1 \le s \le \mathrm{S}) \\ M & \text{, otherwise} \end{cases}$$

$$\bigcup_{s=1}^{S} \boldsymbol{W}_s = \{\text{all weekdays}\}$$

M is a very large number.
wk_c and wk_h are weekdays of the current case and the historical case respectively

An Enhanced Time-varying Coefficient Model

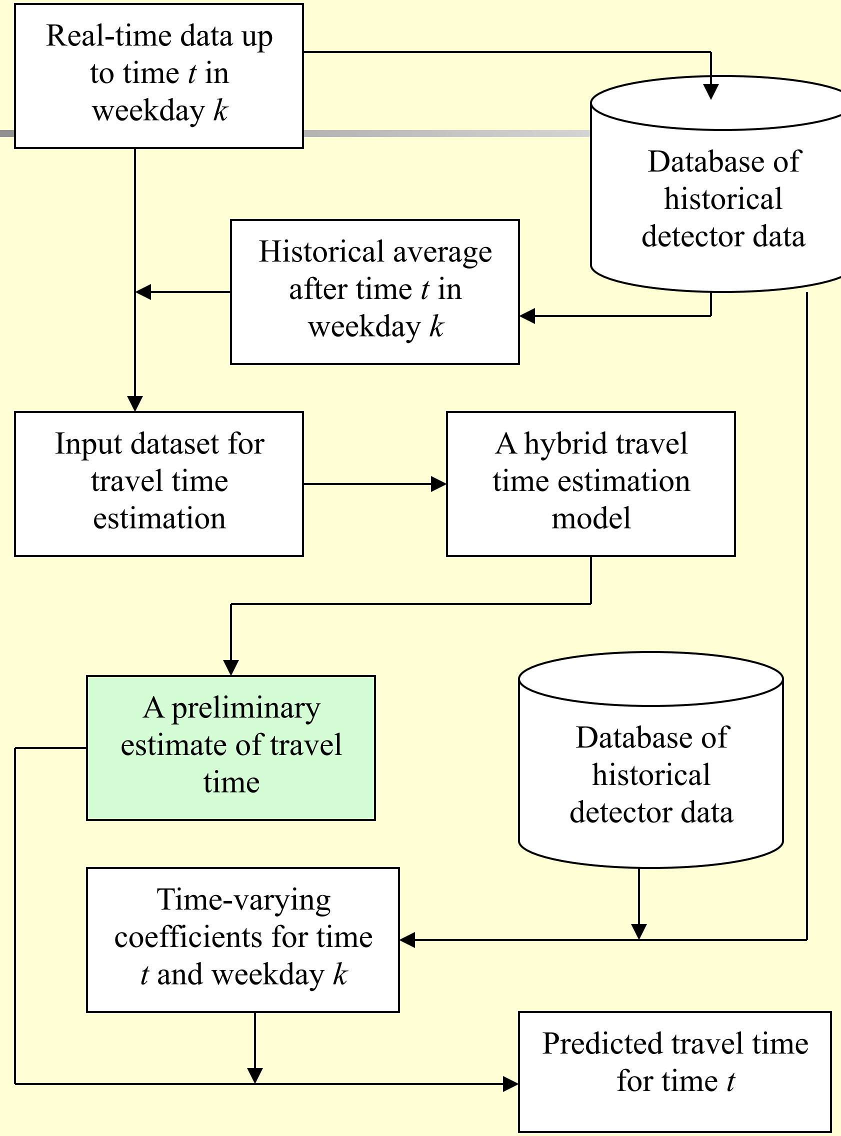
- Same global linear model structure
- Varying coefficients at each time interval
- A linear relation with time-varying coefficients between the predicted travel time and a *status travel time* (a preliminary prediction)

Status Travel Time

- Original form

$$T^*(t,\Delta) = \sum_{d=1}^{D-1} \frac{x_{d+1} - x_d}{v_d(t-\Delta)}$$

Enhanced Status Travel Time for Long Links



Model Formulation

- Consider both daily and weekly traffic patterns

$$T(t) = a_{t_i}^{k}\hat{T}(t) + b_{t_i}^{k}$$

Where *T*(*t*) is the travel time to predict

$a_{t_i}^{k}$ and $b_{t_i}^{k}$ are the weekly time varying coefficients for the t_i^{th} interval of the current weekday, *k*.

Summary

- Completed tasks
  - Perform an in-depth review of literature associated with travel time prediction
  - Develop a modeling framework for a travel time prediction system with sparsely distributed detectors on the freeway
  - Propose a hybrid model for estimating travel times for freeways with sparsely distributed detectors
  - Develop a hybrid model for travel time prediction for freeways with sparsely distributed detectors

On-going Works

- Incorporating a Missing Data Estimation Module to the Travel Time Prediction System
- Developing an Alternative Model Structure for Travel Time Prediction with Neural Network Models
- Developing an Incident Detection Module to Avoid Potential Large Errors under Non-recurrent Congestion
- Numerical Analysis with the Off-line Data for System Demonstration

Thank you!

Any questions?