Online Computation of Fastest Path in Time-Dependent Spatial Networks

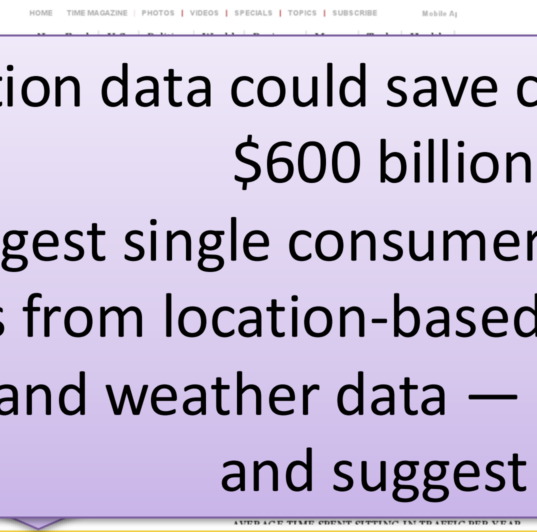
Instructor: Cyrus Shahabi

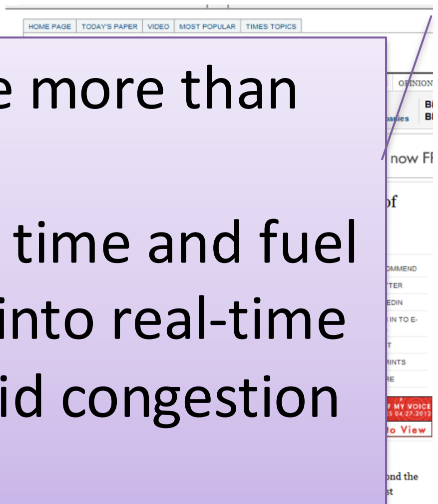
Cost of Traffic Congestion

Traffic congestion is a **$121 billion annual drain** on the U.S. economy[1]:

- 5.5 billion lost hours
- 2.9 billion gallons of wasted fuel
- Travelers had to allow for 60 minutes to make a trip that takes 20 minutes in light traffic.

[1] Texas Transportation Institute Urban Mobility Report, 2012 data





Location data could save consumers worldwide more than $600 billion annually by 2020.
The biggest single consumer benefit will be from time and fuel savings from location-based services — tapping into real-time traffic and weather data — that help drivers avoid congestion and suggest alternative routes.

Intelligent Transportation

PROBLEM

- Traffic congestion is a **$87.2 billion annual drain** on the U.S. economy[1]:
  - 4.2 billion lost hours (one work week for every traveler)[1]
  - 2.8 billion gallons of wasted fuel (three weeks worth of gas for every traveler)[1]

[1] Texas Transportation Institute Urban Mobility Report, 2007 data

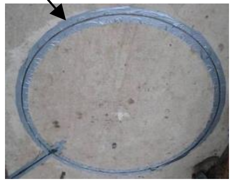
GOAL

- To improve the performance of the surface transportation network through:
  - Capturing real-time data from infrastructure and vehicles
  - Developing data-driven solutions to improve mobility by leveraging optimization opportunities (e.g., path planning for commuter groups)

Traffic Data Lifecycle

- **Loop Detectors**
  - Most commonly used traffic sensors
  - The data is collected in Detector Cabinet and relayed to the service provider
  - Provide two data fields: volume (count) and occupancy (% time a vehicle is over the sensor)

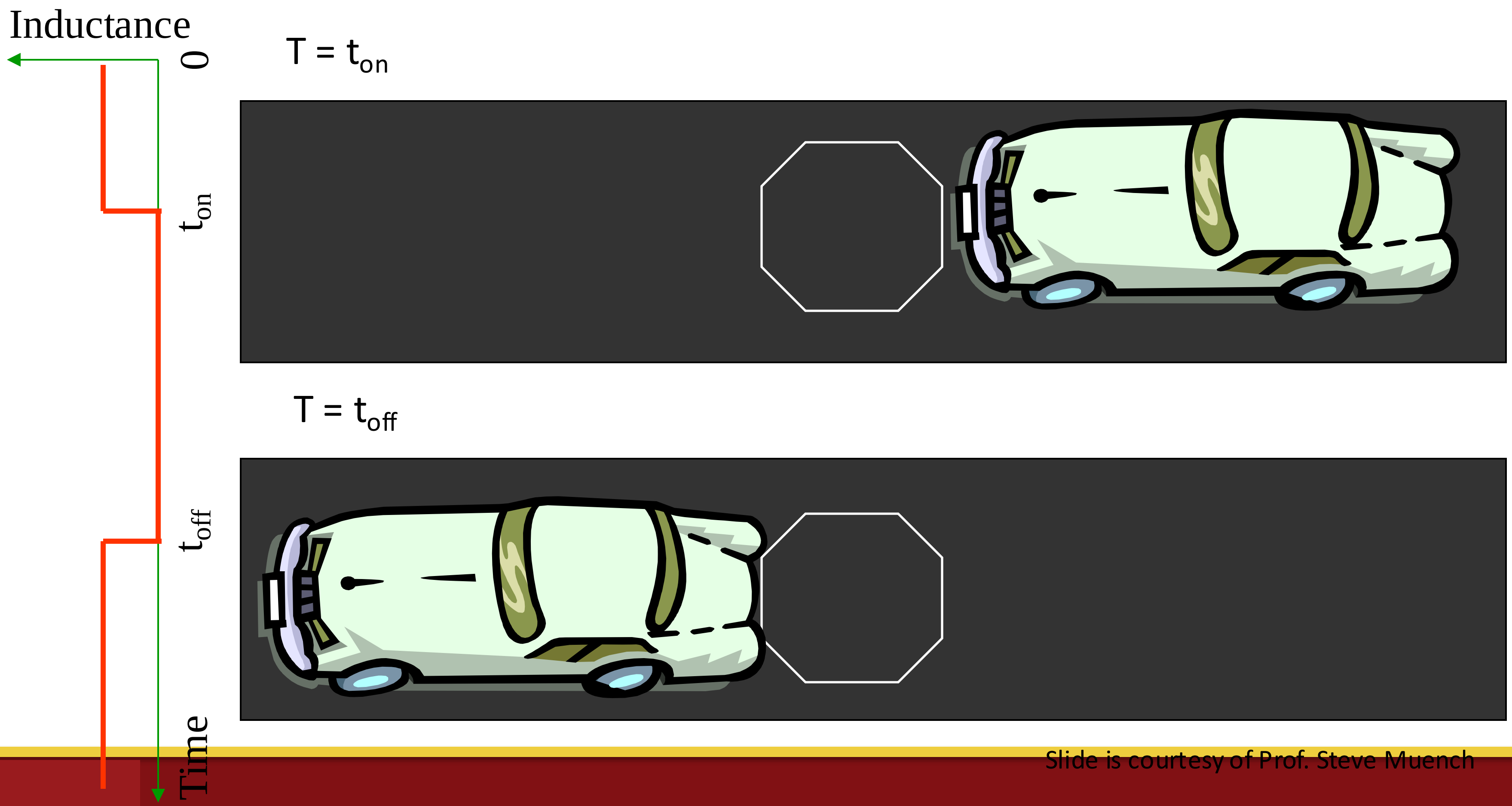
Loop Detector



Detector Cabinet

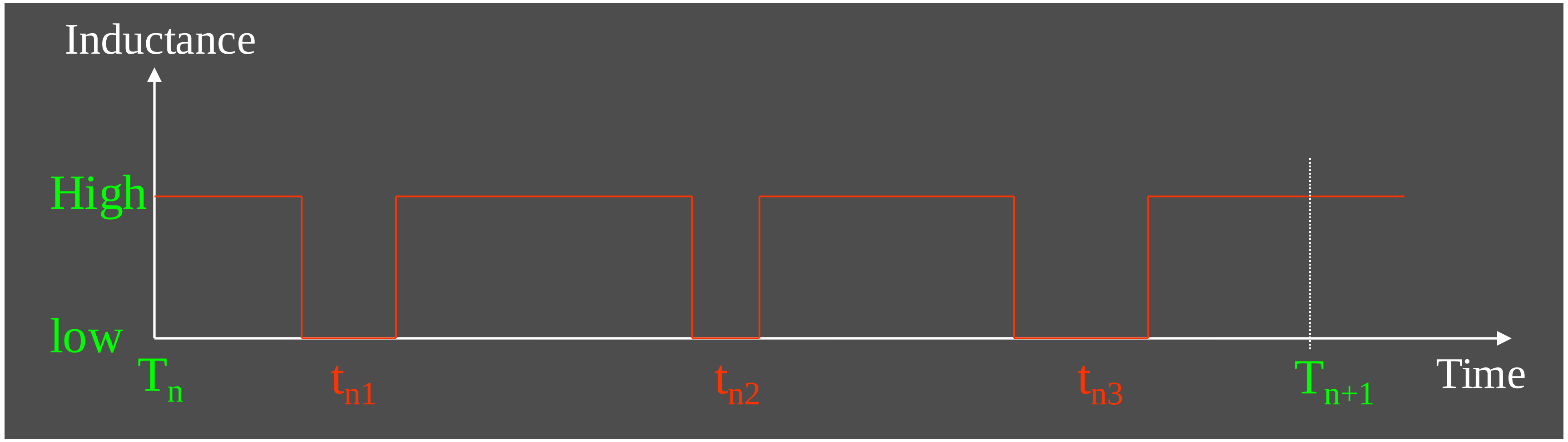
Traffic Data Lifecycle: Loop Detectors

Loop inductance decreases when a car is on top of it.



Slide is courtesy of Prof. Steve Muench

Traffic Data Lifecycle: Loop Detectors



- **Single loops can measure:**
  - **Occupancy (*O*): % of time loop is occupied (had a car on it) per interval**
  - **Volume (*N*): vehicles per interval**
  - **Speed = (N*L)/O where L is a constant proportional to the average length of a car**

Traffic Data Lifecycle: Data Aggregator

RIITS (Regional Integration of Intelligent Transportation Systems)

- A data network affiliated with Los Angeles County Metropolitan Transportation Authority (Metro)
- Collects and serves data from Caltrans, City of Los Angeles Department of Transportation (LADOT), California Highway Patrol (CHP), Long Beach Transit (LBT), Foothill Transit (FHT) and Metro

http://www.riits.net/

Traffic Data Lifecycle

A BIGDATA Problem: V³

Variety (gps, video, loop sensor, events)

Data Type				Hourly (in KB)	Daily (in KB)	Annual (in KB)	3 Years (in KB)
bus_mta_inv2.xml	[illegible]	[illegible]	[illegible]	0.96	23.00	8,395.00	25,185.00
bus_mta_rt2.xml	1065	120	532.50	31,950.00	766,800.00	279,882,000.00	839,646,000.00
cctv_inv.xml	57	86400	0.04	2.38	57.00	20,805.00	62,415.00
cms_inv.xml	52	86400	0.04	2.17	52.00	18,980.00	56,940.00
cms_rt.xml	48	75	38.40	2,304.00	55,296.00	20,183,040.00	60,549,120.00
event_d7.xml	11	75	8.80	528.00	12,672.00	4,625,280.00	13,875,840.00
rail_mta_inv.xml	1	86400	0.00	0.04	1.00	365.00	1,095.00
rail_rt.xml	8	60	8.00	480.00	11,520.00	4,204,800.00	12,614,400.00
rms_inv.xml	865	86400	0.60	36.04	865.00	315,725.00	947,175.00
rms_rt.xml	1236	75	988.80	59,328.00	1,423,872.00	519,713,280.00	1,559,139,840.00
signal_inv.xml	2095	86400	1.45	87.29	2,095.00	764,675.00	2,294,025.00
signal_rt.xml	2636	45	3,514.67	210,880.00	5,061,120.00	1,847,308,800.00	5,541,926,400.00
tt_d7_inv.xml	746	86400	0.52	31.08	746.00	272,290.00	816,870.00
tt_d7_rt.xml	152	60	152.00	9,120.00	218,880.00	79,891,200.00	239,673,600.00
vds_art_d7_inv.xml	115	86400	0.08	4.79	115.00	[illegible]	[illegible]
vds_art_d7_rt.xml	45	60	45.00	2,700.00	64,800.00	[illegible]	[illegible]
vds_art_ladot_inv.xml	2538	86400	1.76	105.75	2,538.00	926,370.00	2,779,110.00
vds_art_ladot_rt.xml	969	60	969.00	58,140.00	1,395,360.00	509,306,400.00	1,527,919,200.00
vds_fr_d7_inv.xml	957	86400	0.66	39.88	957.00	349,305.00	1,047,915.00
vds_fr_d7_rt.xml	361	30	722.00	43,320.00	1,039,680.00	379,483,200.00	1,138,449,600.00
Total KB from XML data	**13980**	**864660**	**6,985.28**	[illegible]	[illegible]	[illegible]	**11,012,906,655.00**

Velocity

Volume

ADMS:
An Exclusive Contract w LA-Metro

Input Traffic Data → Data Processing → Storage → Analysis &Visualization

Highway (4500+ sensors)

Arterial (4700 + **9500 sensors**)

Bus & Rail (2000+ buses)

Event (~400 per day)

Ramp meter

CMS

46 MB/min

StreamInsight

26 MB/min

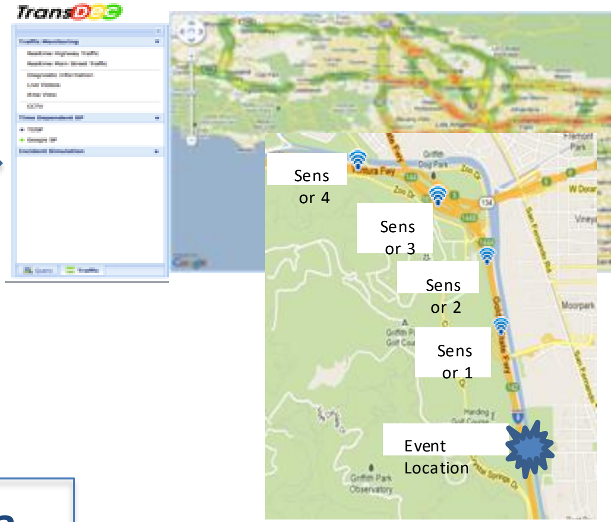
11 TB/Year

ORACLE DATABASE 11g

Spark

Lightning-Fast Cluster Computing

Transit Ridership Data	Inrix Probe Data
4years of ~1M rows	1 year of 400M rows
Truck (WIM) Data	
3 years of 10M rows	

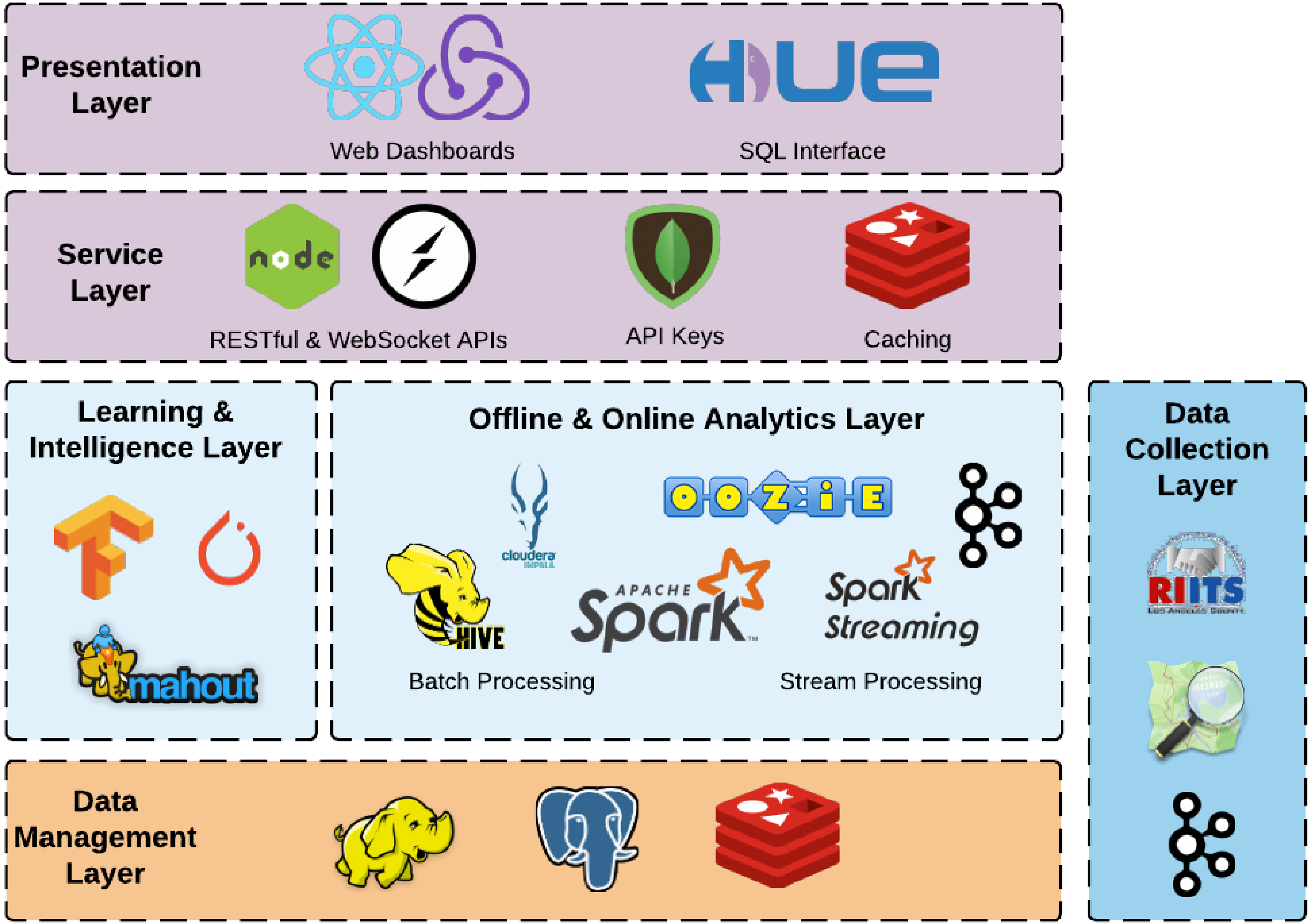


E.g., Traffic Forecasting (ICDM'13, KDD 16, SDM'17, ICLR'18)

ADMSv2: The Architecture

- Decomposed into layers
  - Isolated
  - Independent
- Open-source Frameworks
  - Modern
  - Set-up anywhere

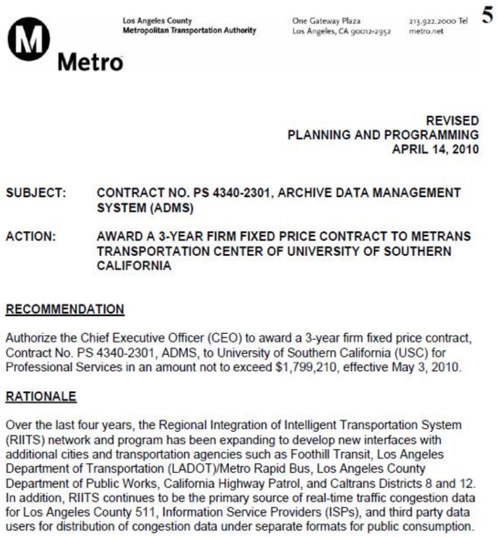
Chrysovalantis Anastasiou, Jianfa Lin, Chaoyang He, Yao-Yi Chiang, Cyrus Shahabi:
ADMSv2: A Modern Architecture for Transportation Data Management and Analysis. ARIC@SIGSPATIAL 2019: 25-28



ADMS Longevity

2011 ADMS RFP (Awarded to USC)	2011-2015 ADMS Developed (Research/Prototype by USC)	2015-2016 ADMS Extension (Awarded to USC)	2016-2019 ADMS Production (Awarded to Parsons/USC Tech Transfer of ADMS)

2019-2024
ADMS Operation & Maintenance



Los Angeles County Metropolitan Transportation Authority

One Gateway Plaza Los Angeles, CA 90012-2952

213.922.2000 Tel metro.net

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Metro

REVISED
PLANNING AND PROGRAMMING
APRIL 14, 2010

SUBJECT: CONTRACT NO. PS 4340-2301, ARCHIVE DATA MANAGEMENT SYSTEM (ADMS)

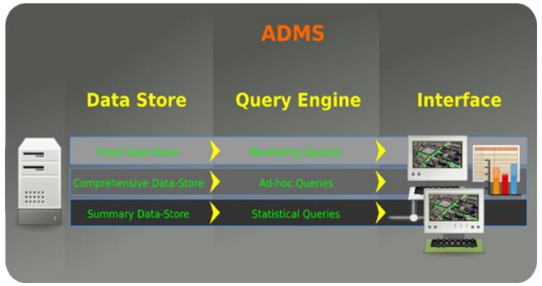
ACTION: AWARD A 3-YEAR FIRM FIXED PRICE CONTRACT TO METRANS TRANSPORTATION CENTER OF UNIVERSITY OF SOUTHERN CALIFORNIA

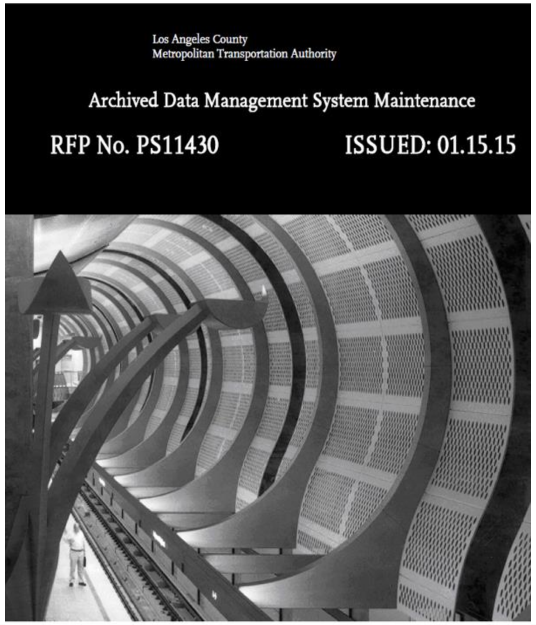
RECOMMENDATION

Authorize the Chief Executive Officer (CEO) to award a 3-year firm fixed price contract, Contract No. PS 4340-2301, ADMS, to University of Southern California (USC) for Professional Services in an amount not to exceed $1,799,210, effective May 3, 2010.

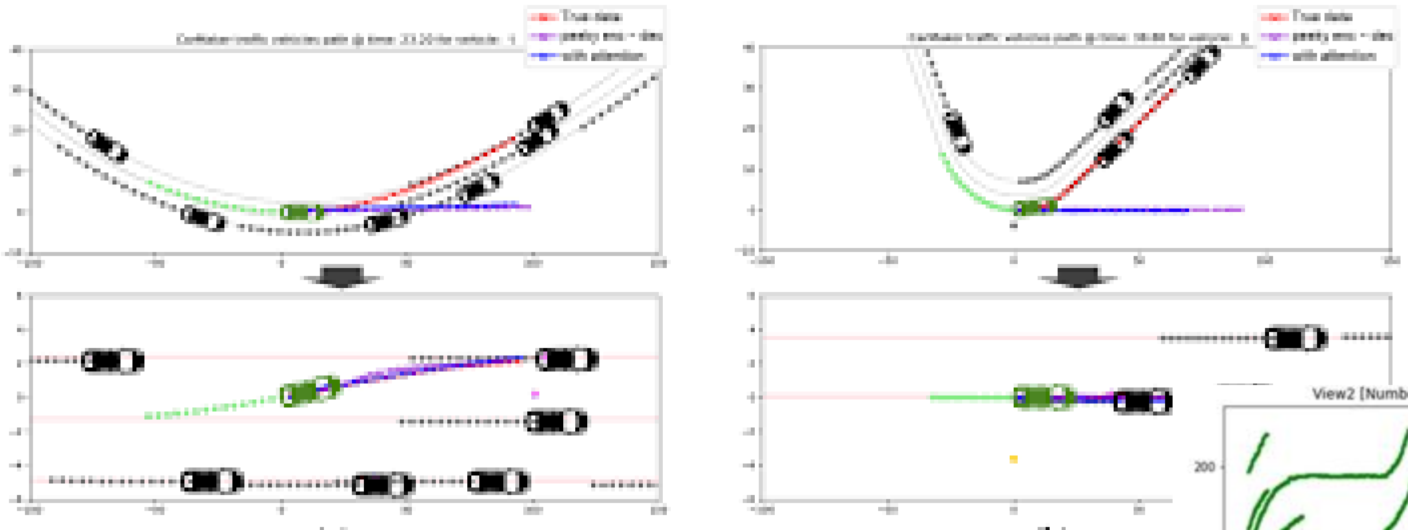
RATIONALE

Over the last four years, the Regional Integration of Intelligent Transportation System (RIITS) network and program has been expanding to develop new interfaces with additional cities and transportation agencies such as Foothill Transit, Los Angeles Department of Transportation (LADOT)/Metro Rapid Bus, Los Angeles County Department of Public Works, California Highway Patrol, and Caltrans Districts 8 and 12. In addition, RIITS continues to be the primary source of real-time traffic congestion data for Los Angeles County 511, Information Service Providers (ISPs), and third party data users for distribution of congestion data under separate formats for public consumption.

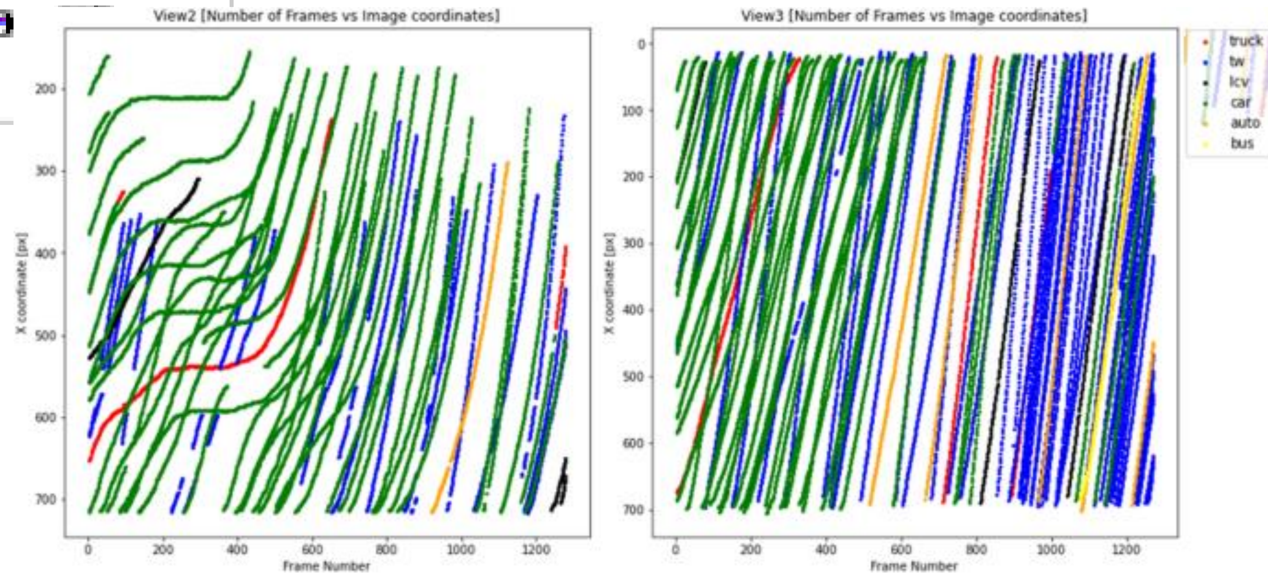




Where does the traffic data currently come from?



(a) (b)



Outline

- Distance Computation
- Motivation
- Related Work
- Time-dependent A* Search
- Experimental Evaluation

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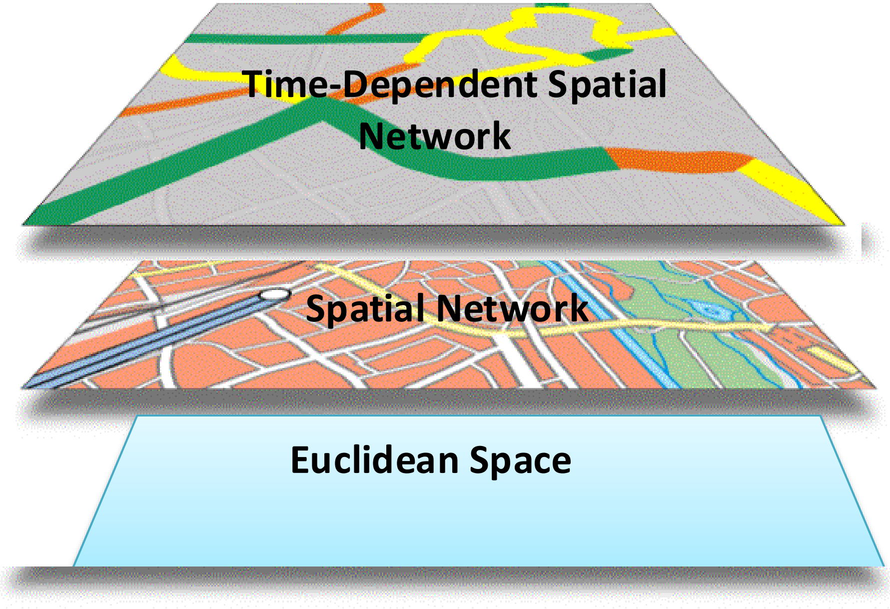
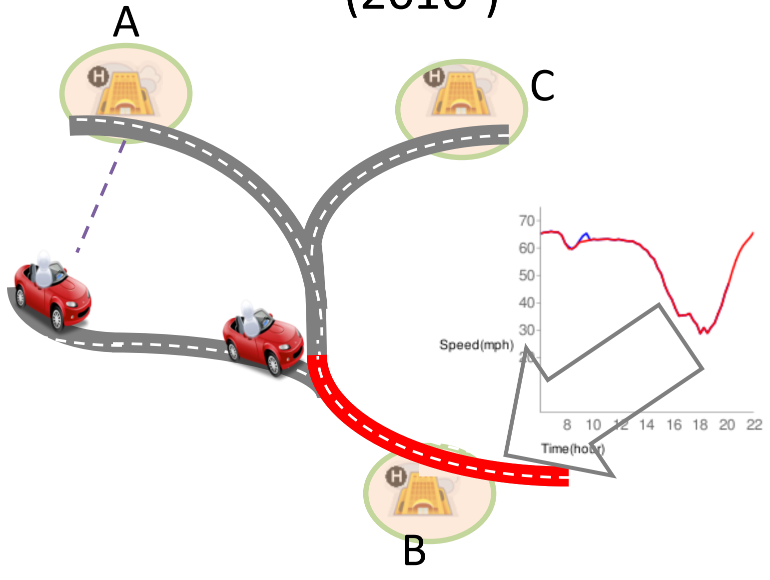
Distance Computation



Time-Dependent Spatial Network (2010-)

Spatial Networks (2003-2010)

Euclidean Space (1995-2003)

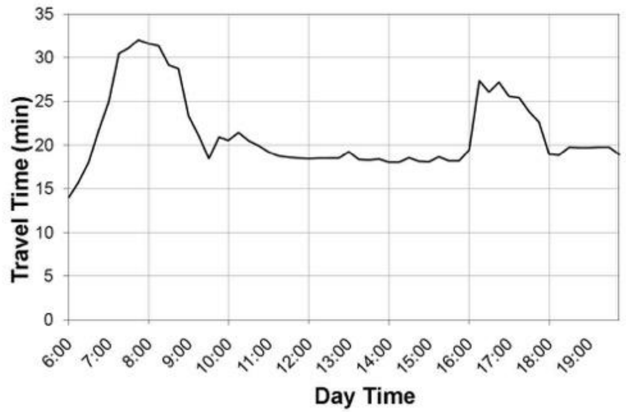


Edge weights change with time

Edge weights are constant

Problem Definition

- Given a time-dependent spatial network where edge weights are function of time



*Source **s** and Destination **d***

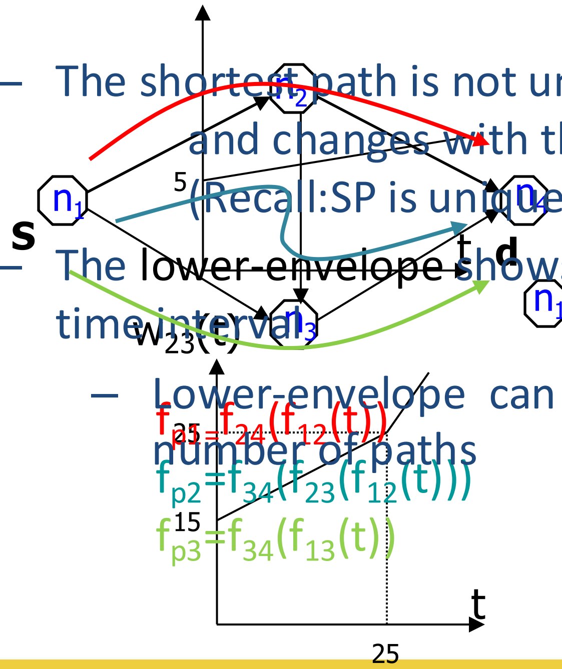
Time-dependent Fastest Path (TDFP)

TDFP (s, d, t_s) with respect to s, d and query time t_s finds *minimum travel time path* among all paths between s and d

Challenge: Too big of a graph to find optimal path in real-time
Typical Approach, Pre-computation, doesn't work

Challenges

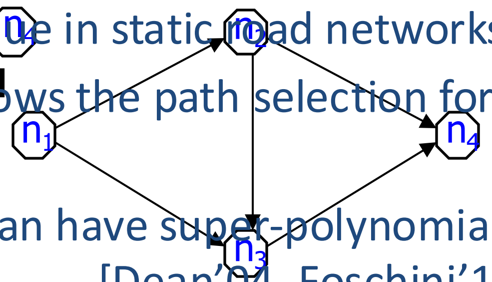
- Is Pre-computation feasible?
  - Compute and store all distance values between all pairs of nodes
  - The shortest path is not unique in TD-RN and changes with the departure time. (Recall:SP is unique in static road networks).
  - The lower-envelope shows the path selection for each time interval.
    - Lower-envelope can have super-polynomial number of paths [Dean'04, Foschini'11]

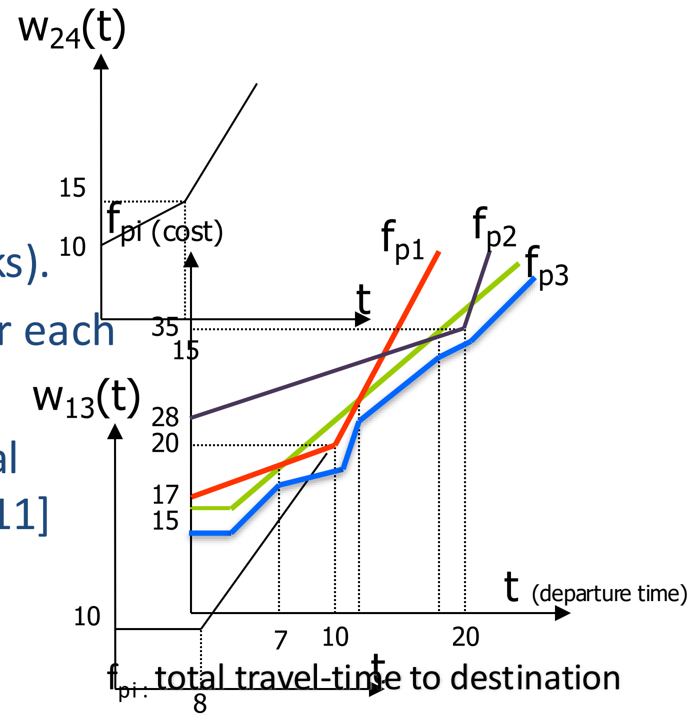


$f_{p1}=f_{24}(f_{12}(t))$

$f_{p2}=f_{34}(f_{23}(f_{12}(t)))$

$f_{p3}=f_{34}(f_{13}(t))$





f_{pi}: total travel-time to destination

Outline

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- Experimental Evaluation

Related Work

Spatial Database

↓

Shortest Path

↓

Static Road Network | TD-Road Network

- Dijkstra [Numerische Mathematik 1959] — GraphHopper & Valhalla & pgRouting (all w/ bi-directional)
- A* [Hart, Nilsson & Raphael [Trans SSC 1968] — GraphHopper & Valhalla & pgRouting (all w/ bi-directional)

Precomputation:

- Geometric speed-up techniques for finding SP, [Wagner et al.,ESA'03]
- Engineering fast route planning algorithms, [Sanders et al., WEA'07]
- Hierarchical routing in RN, [Geisberger et al., WEA'08, Sanders ESA'06] — GraphHopper (w/ bi-directional)
- SILC: Scalable network distance browsing [Samet et al., SIGMOD'08]
- Distance oracles for spatial networks [Sankaranarayan et al., TKDE'10]
- TEDI: Efficient Shortest Path Query Answering on Graphs [Wei, SIGMOD'11]
- Tiled routing (Valhalla) – No research paper (https://valhalla.readthedocs.io/en/latest/mjolnir/why_tiles/) — Valhalla

Related Work

Spatial Database

↓

Shortest Path

↓

Static Road Network | TD-Road Network

- Cooke & Halsey [JMAA'66]
- Dreyfus [OR'69] (Dijkstra Variant)   Valhalla (unidirectional only)
- Orda and Rom, [JACM'90] (Bellman F.)

Precomputation:

Inefficient: high storage cost and long precomputation time

- Time-dependent SHARC [Delling et al., ESA'09]
- Time-dependent Contraction Hierarchies [Batz et al. ALENEX'08]
- Time-dependent ALT [Delling & Wagner, WEA'07]
- Distributed Time-dependent *CH* [Kieritz et al., SEA'10]
- Core Routing on Dynamic TD RN [Delling et. al, INFORMS'11]

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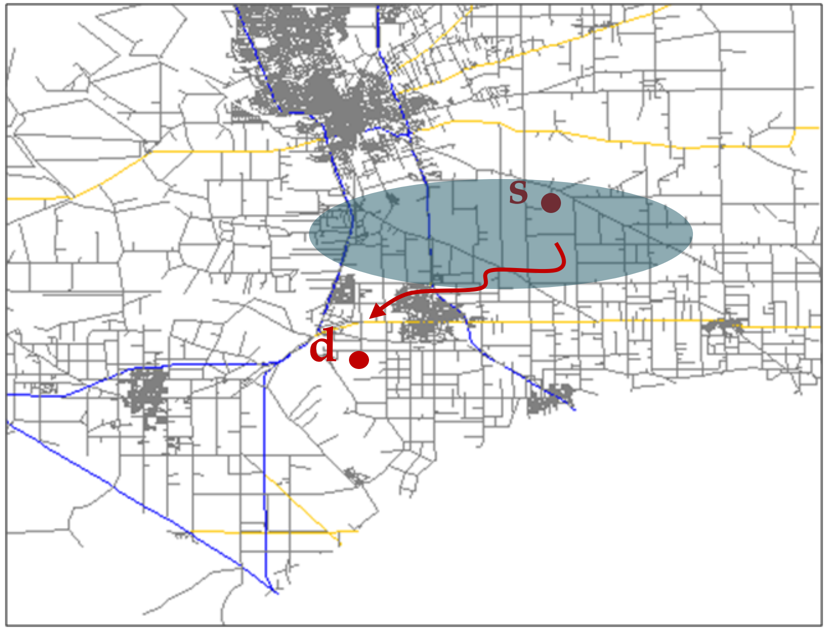
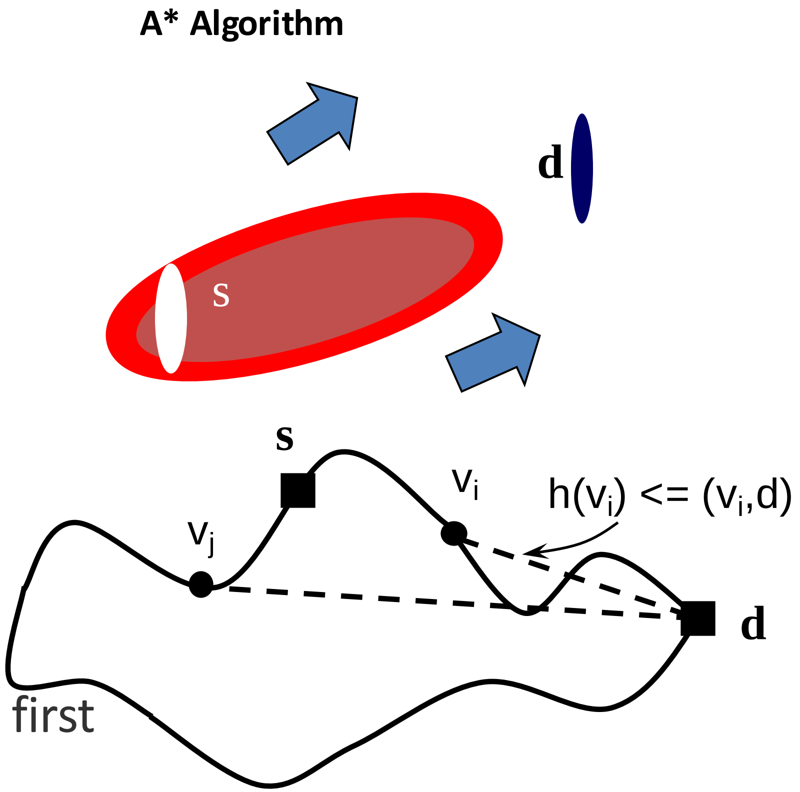
Preliminaries: Static Network

- Dijkstra vs. A*



Problem: 48% of network nodes are scanned



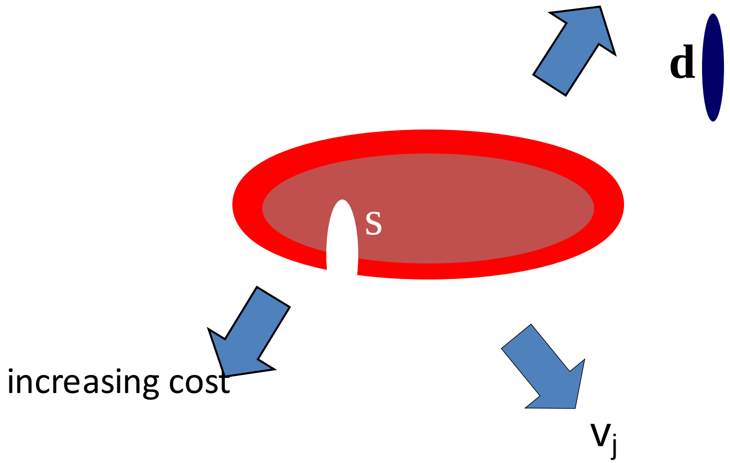
Dijkstra: since $(S,v_j) < (S,v_i)$, expand v_j first

A*: since $(s,v_i)+h(v_i) < (s, v_j)+h(v_j)$, expand v_i first

Optimality Condition: $h(v_i)$ should not overestimate the actual distance between v_i and d.

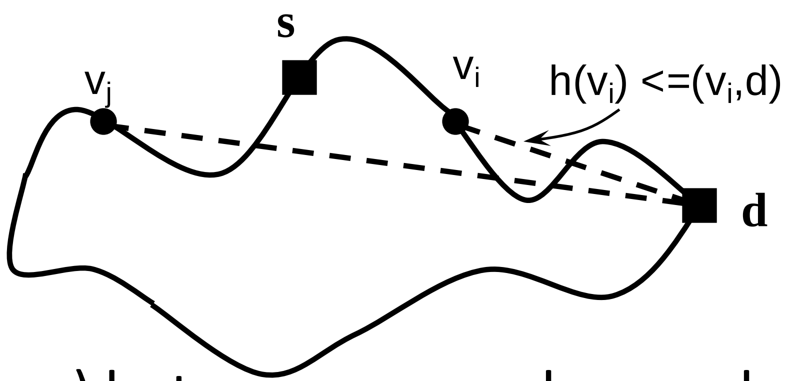
Preliminaries: Time-Dependent Network

- The time-dependent shortest path problem can be solved by modifying Dijkstra Algorithm **[Dreyfus'69]**
  - **Greedy Algorithm:** Starting from s, the network nodes reachable from s in every direction are visited in order of their ***arrival-time***



Time-dependent A* Search

- **Challenge:** Finding heuristic function $h(v_i,d) <= D(v_i,d,t)$ in TD Networks



- The distance (travel-time) between any node v_i and d changes in Time-dependent Road Networks
- $h(v_i,d)$ also needs to be time-dependent

Time-dependent A* Search (Naïve Approach)

- **Naïve Heuristic Function:**

$$\frac{D_{EUC}(v_i, d)}{\max(speed)}$$

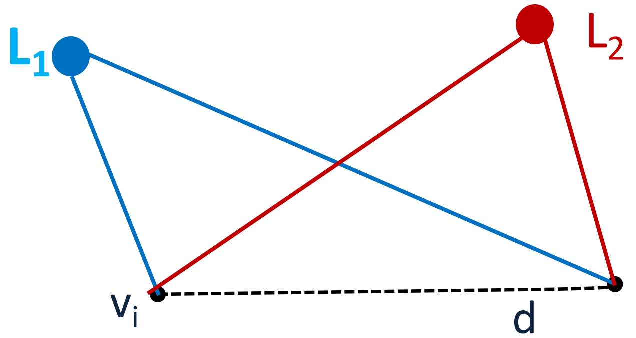
Euclidean distance between v and d divided by the maximum speed among the edges

  - Guaranteed to be a lower-bound as the distance between v and d is never overestimated
  - Problem: It is a very loose bound, hence yields insignificant performance improvement

Chabini & Shan [Trans ITS'02]

Time-dependent A* Search

- **ALT- A* with Landmark and Triangular Inequality:** Originally proposed to accelerate fastest path computation in static road networks **[WEA'09]**



$dist(v_i,d) \geq dist(L_1,d) - dist(L_1,v_i)$

$dist(v_i,d) \geq dist(L_2,v_i) - dist(L_2,d)$

$h(v_i,d) = \max\{(dist(L_1,d) - dist(L_1,v_i)), (dist(L_2,v_i) - dist(L_2,d))\}$

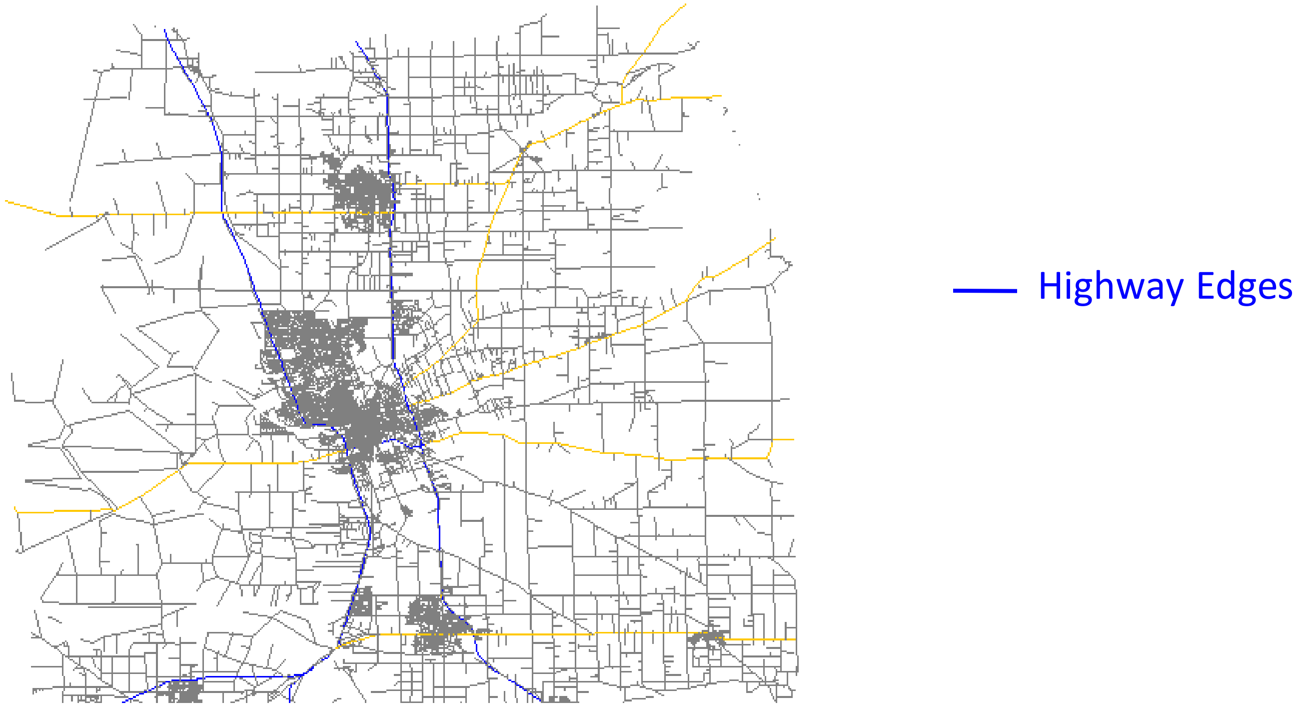
- Landmark selection is difficult and relies on assumptions
- The size of the search space is severely affected by the location of landmarks [Potamias'09]
- So far no optimal strategy (NP-Hard) with respect to landmark selection and random queries has been found [Potamias'09]
- Space inefficient: need to store precomputed distances from each node to each landmark

Time-dependent A* Search

- Goal:
  - Find a $h(v_i)$ that will never overestimate the time-dependent travel-time between v_i and d. This is necessary for Exact results
  - $h(v_i)$ should be as close as possible to actual distances for Efficient processing of fastest path computation
- Approach:
  - **Step 1:** Partition the road network into non-overlapping partitions **(Offline)**
  - **Step 2:** Precompute $h(v_i)$ using distances in and between the non-overlapping partitions **(Offline)**

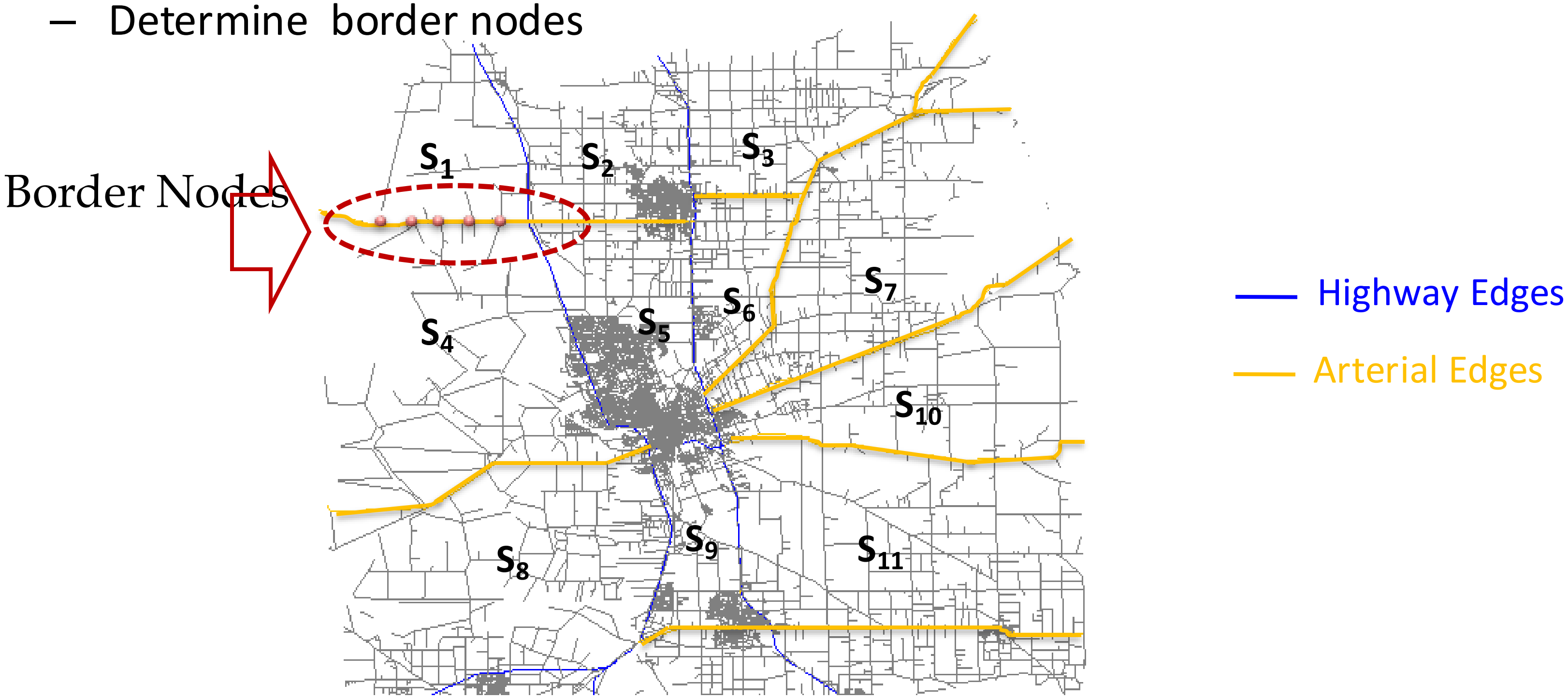
Time-dependent A* Search (Our Approach)

- **Step 1: Partition** the road network using network hierarchies
  - Partition the road network to highways (highest level)



Time-dependent A* Search

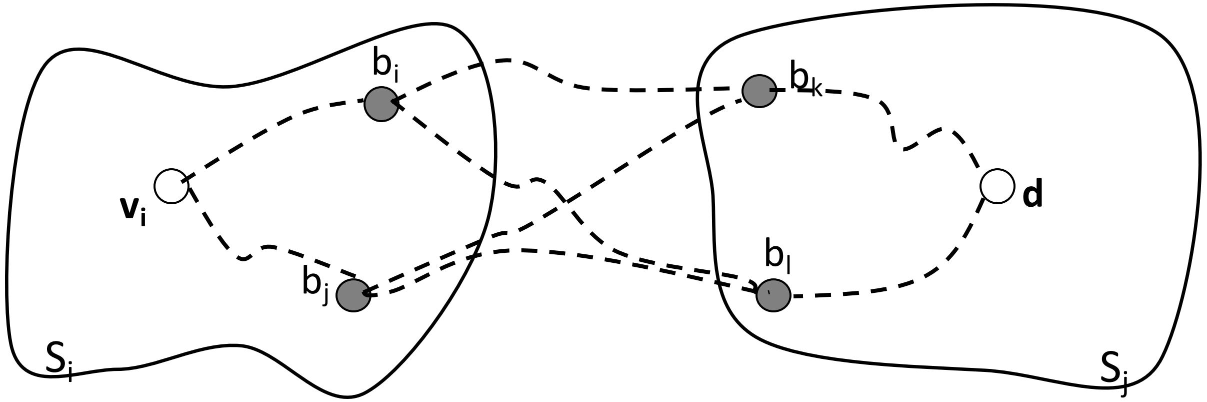
- **Step 1: Partition** the road network using network hierarchies
  - Partition the road network using highest level roads (i.e., highways)
  - Partition each partition using lover level road network (i.e., arterials)
  - Determine border nodes



Our algorithm yields correct results with all non-overlapping partitioning algorithms

Time-dependent A* Search

- **Step 2:** Compute **intra and inter distance labels**
  - **Intra:** fastest path in Lower-bound Graph G_ (where edge weights are travel-time, i.e., fastest speed) from each node v_i to border nodes and border nodes to v_i
  - **Inter :** fastest path in Lower-bound Graph G_ between border nodes

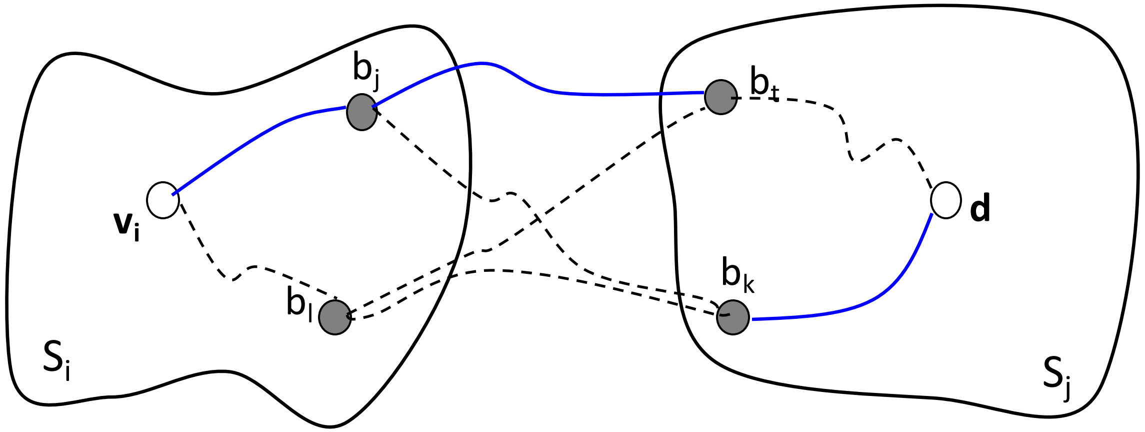


- Only store the minimum of node-to-border, border-to-border, and border-to-node travel times

$$LTT(v_i, b_i) = \arg\min(LTT(v_i, b_i), LTT(v_i, b_j))$$
$$LTT(b_l, d) = \arg\min(LTT(b_k, d), LTT(b_l, d))$$
$$LTT(b_i, b_k) = \arg\min(LTT(b_i, b_k), LTT(b_i, b_l), LTT(b_j, b_k), LTT(b_j, b_l))$$

Time-dependent A* Search

- **Lemma:** $h(v_i,d)$ based on intra and inter distance labels is lower-bound of $TDFP(v_i,d,t)$:



- **Proof:** $h(v_i,d) <= TDFP(v_i,d,t_{vi})$

$$LTT(v_i,b_i) \le TDFP(v_i,b_i,t_{vi}),\ LTT(b_i,b_t) \le TDFP(b_i,b_t,t_{bi}),$$

$$LTT(b_k,d) \le TDFP(b_k,d,t_{bk})$$

$$h(v_i,d) = LTT(v_i,b_i) + LTT(b_i,b_t) + LTT(b_k,d) \le TDFP(v_i,d,t_{vi})$$

Time-dependent A* Search

- **Low Storage Overhead**
  - Only partition, node-to-border and border-to-node information is added to each node v_i
  - Border-to-border information is a small fraction of the all network

Node	Partition	Node-to-Border	Border-to-Node
n_1	S_1	b_1,5	b_1,7
n_2	S_1	b_2,6	b_3,4
….	….	….	….
n_{41}	S_9	b_{17},3	b_{15},6
n_n	S_k	$b_{u,}$,x	b_v,y

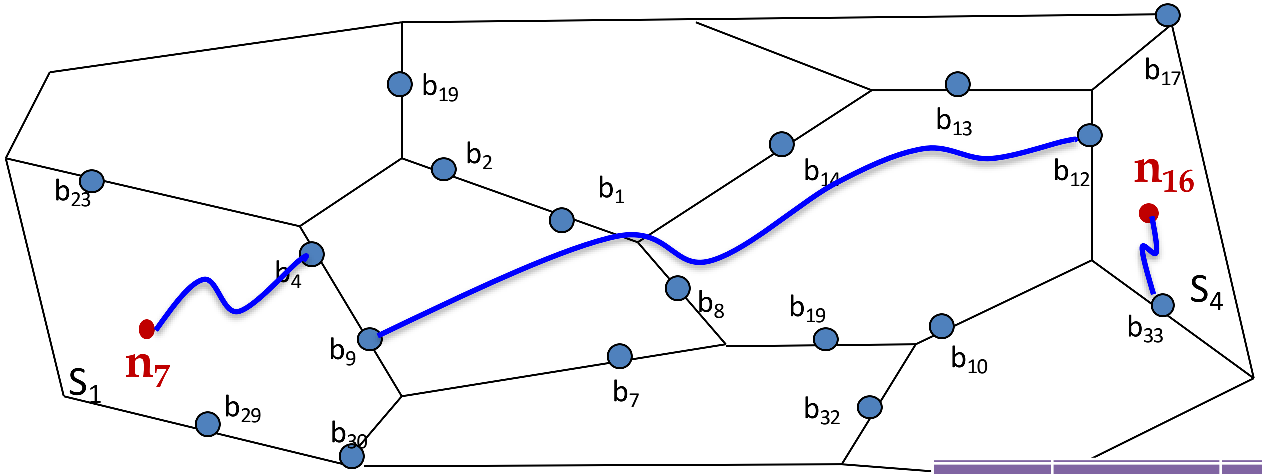
Node-to-Border (Intra)

Border	Border	Distance	Partition
b_1	b_3	14	$S_{1,}S_4$
b_1	b_{41}	18	$S_{1,}$S3
b_1	b_{15}	12	$S_{4,}S_1$
….	….	….	
b_n	b_k	…..	

Border-to-Border (Inter)

Time-dependent A* Search

- **Fast $h(v_i,d)$ computation**
  - $h(v_i,d)$ is computed by simple table look-ups (nanoseconds)



- **Efficient updates** $h(n_7,d) = 6+18+5$
  - Distance labels are only updated if lower-bound distances changed

Node	Partition	Node-to-Border	Border-to-Node
n_6	S_1	b_{23},5	b_{23},7
n_7	S_1	b_4,6	b_9,4
….	….	….	….
n_{16}	**S_4**	b_{17},3	**b_{33},5**
n_n	S_k	b_u,x	b_v,y

Time-dependent A* Search

- Can we further improve the performance of unidirectional TD A* search?

Bidirectional Time-dependent A* Search

Outline

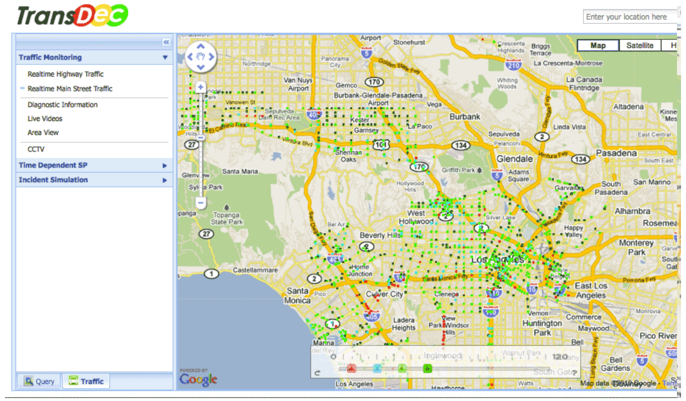
- Distance Computation
- Motivation
- Related Work
- Time-dependent A* Search
- Experimental Evaluation

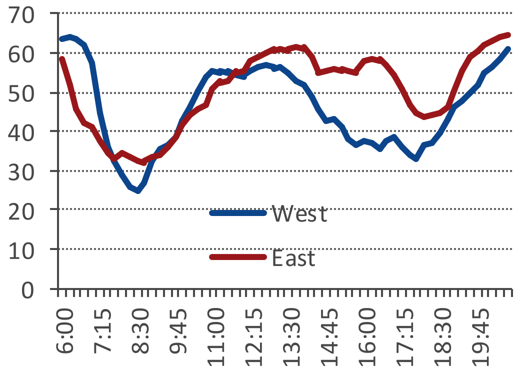
Experimental Evaluation

- **Road Network Dataset**
  (obtained from Navteq)
  - Los Angeles (LA) Network with 304,162 nodes
  - California (CA) Network with 1,965,300 nodes

- **Time-dependent Network Data**
  (obtained from ADMS)
  - LA Metro, Price School of Public Policy and IMSC
  - 6500 Sensors on freeways and arterials in LA
    - 1 sensor/reading per minute
    - Collecting and archiving past 2 years

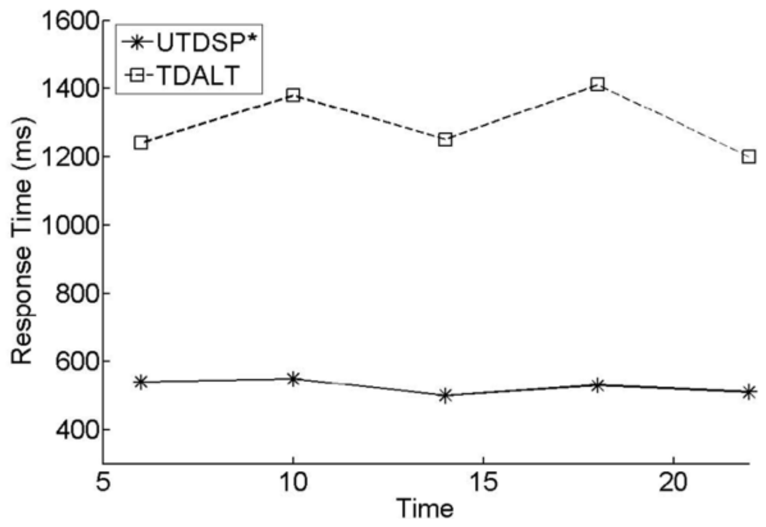
- **Experimental Setup:**
  - A server with 2.7 GHz Pent. Duo Core Proc. and 12GB RAM
  - Source, destination and departure time t_s are determined uniformly at random
  - Average results computed from 1000 random s-d queries





Experimental Evaluation

- **Comparison with TD-ALT**
  – TD-ALT: Determine 64 landmarks based on maxCover (best known landmark selection algorithm)
  – TDFP: Divide CA network to 64 partitions



Derived from 1000 random s-d queries

Response Time:

– TD-ALT very loose bounds based on the randomly selected *s and d, and hence the large search* space.

Storage:

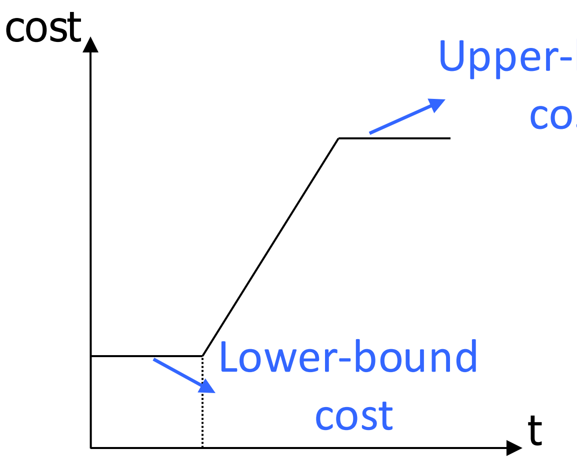
– TD-ALT attaches each node an array of 64 elements. Total Storage = 63 MB for CA

– TDFP attaches each node an array of 2 elements (intra distance labels) and b-to-b. Total Storage=8.5 MB for CA

Time-Dependent KNN (TD-KNN)

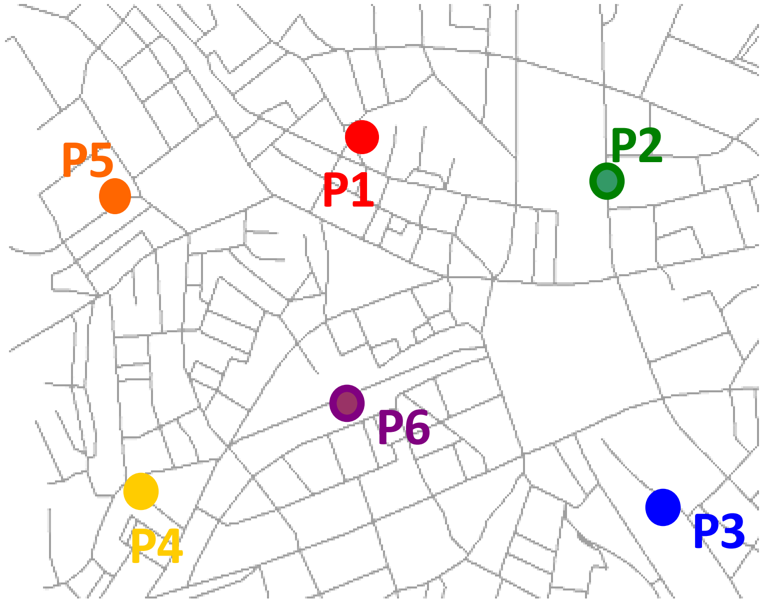
Ugur Demiryurek, Farnoush Banaei-Kashani, and Cyrus Shahabi, Efficient K-Nearest Neighbor Search in Time-Dependent Spatial Networks, 21st International Conference on Database and Expert Systems Applications (DEXA10), Bilbao, Spain, August 2010

Indexing Time-Dependent Spatial Network



Lower-bound travel-time (LTT):
of an edge is traversing that edge with maximum possible speed

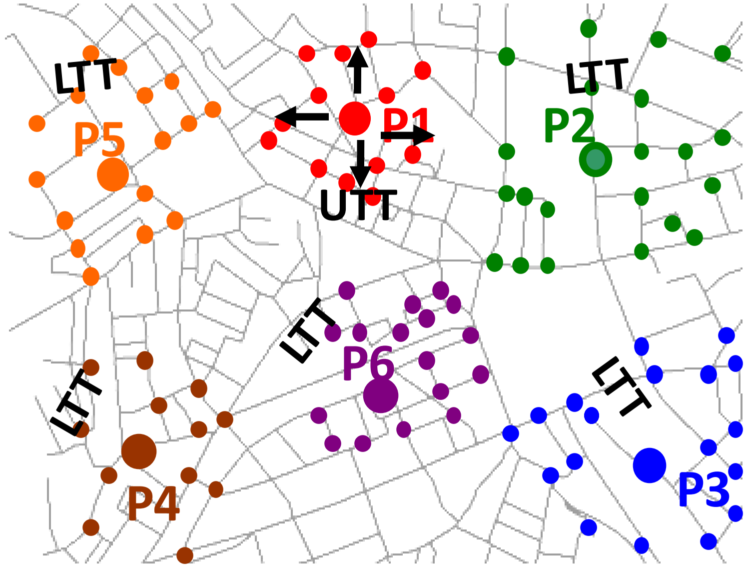
Upper-bound travel-time (UTT):
of an edge is traversing that edge with minimum possible speed



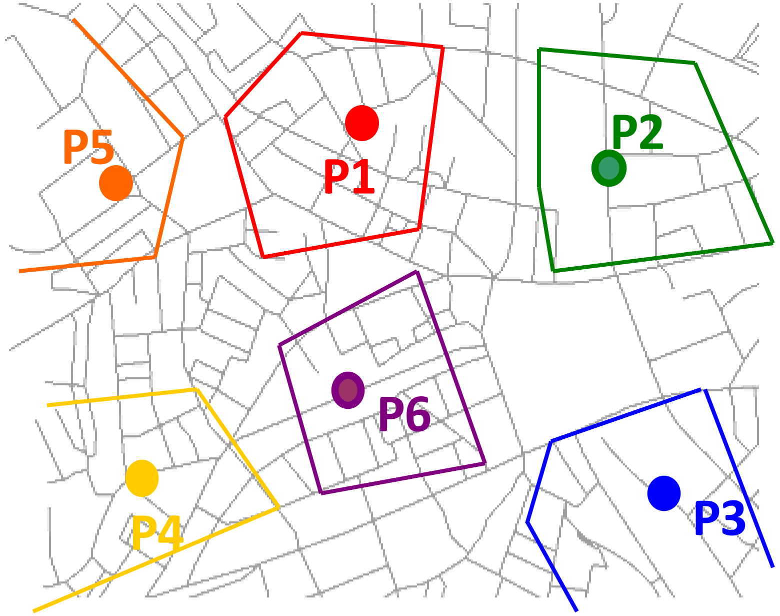
Can we partition the road network based on data objects using LTT and UTT?

Indexing Time-Dependent Spatial Network

❑ Tight Cells (TC)

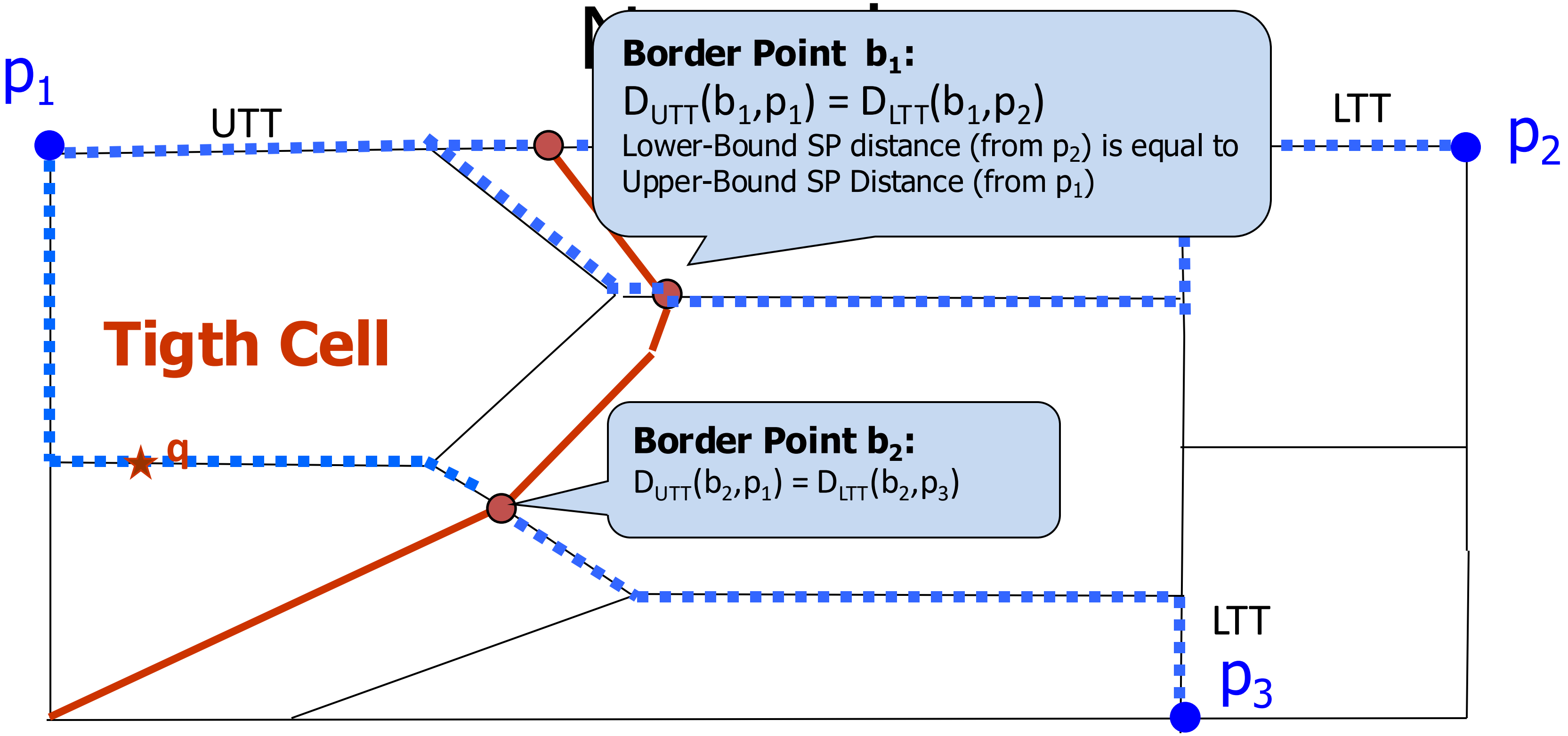


Grow SP trees from each site simultaneously using
UTT for one site and
LTT for the other sites



Repeat the process for all sites and find Tight Cells (TC)

Indexing Time-Dependent Spatial Networks

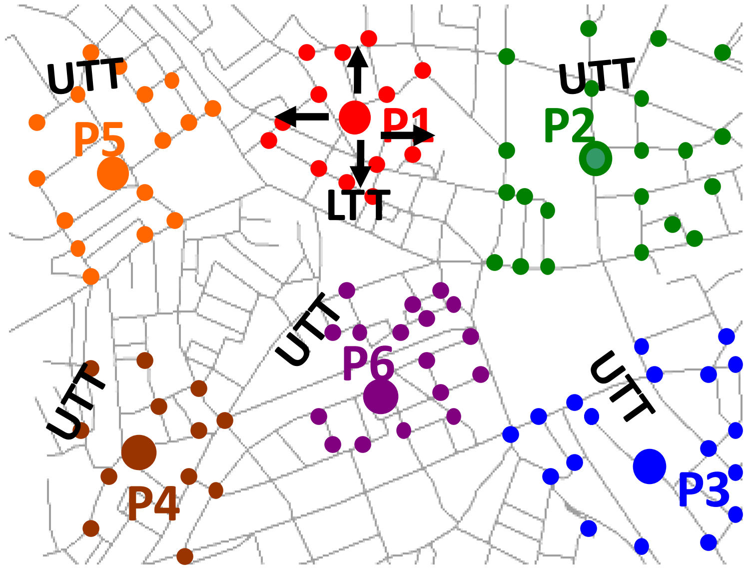


Any query point inside the tight cell of a data object p is guaranteed to have p as its NN.

Proof: $D_{UTT}(q,p1) < D_{LTT}(q,p2)$ If the upper-bound travel time between the query object q and a data object p (e.g., p1) is less than any of the lower-bound travel time from q to any other data object, then that p is the nearest neighbor of q.

Indexing Time-Dependent Spatial Network

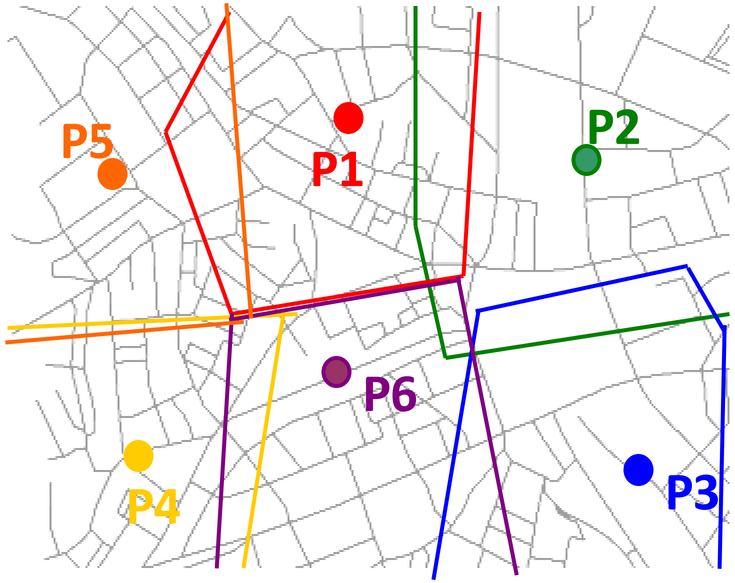
❑ Loose Cells (LC)



Grow SP trees from each site simultaneously using

LTT for one site and

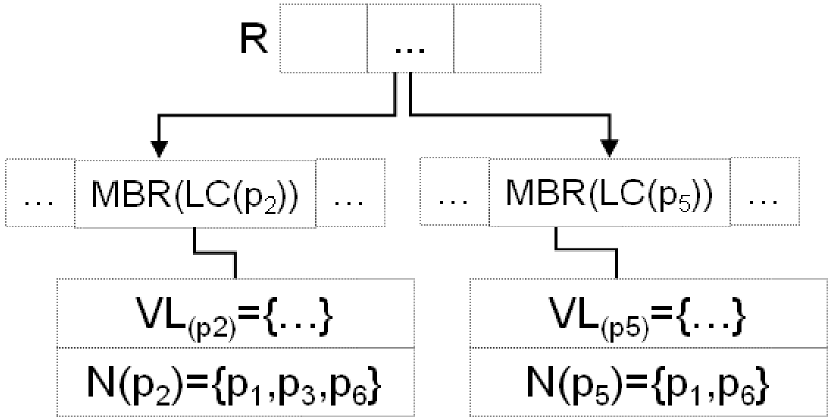
UTT for the other sites

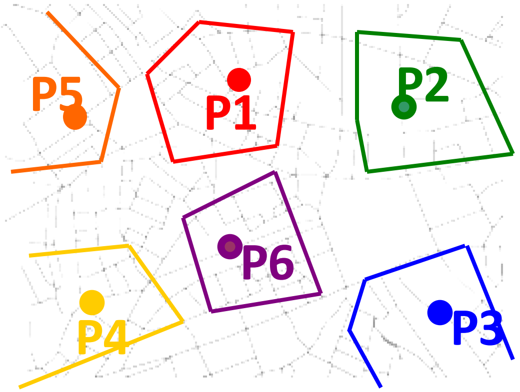


- ❑ Loose Cells cover the entire network.
- ❑ Any query point q outside of the LC of p is guaranteed not to have p as its NN
- ❑ If outside tight cell but inside loose cell, find the overlapping loose cells generators and then Dreyfus (or TD-A*) to decide which of the p's is closer
- ❑ Direct Neighbors e.g., $p_{2=}\{p_1,p_6,p_3\}$

Indexing Time-Dependent Spatial Network

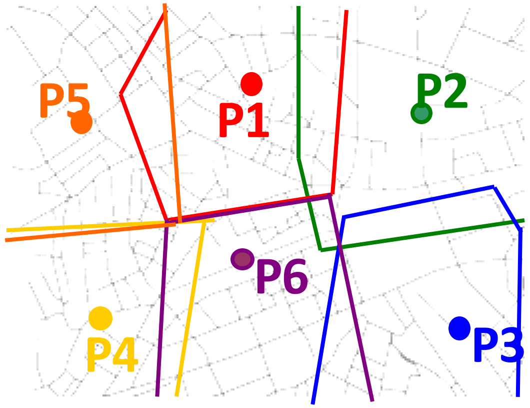
- TC and LC Index





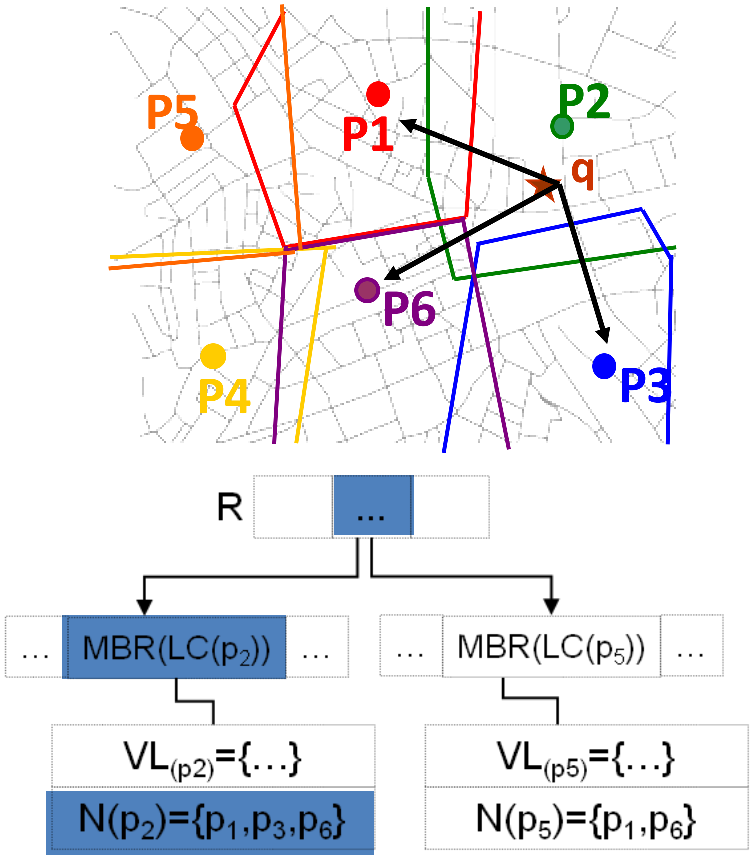
Tight Cells

Loose Cells



Index TCs and LCs with a spatial index (e.g., R-tree, Quad-tree)

Indexing Time-Dependent Spatial Network



Query Processing

- **NN**

  Given the location of q, depth-first search from the TC Index (or LC Index) root to the node that contains q.

- **kNN**

  The second NN must be among the direct neighbors of the first NN. Check the neighbors of the NN

(Section 4.1 for details)

Index Maintenance

- Index Maintenance
  - Edge Weight Update

    Update the index structure **only** when min or max costs change.
  - Data Object Update

    Local update (i.e., only the neighbor cells) when a data-object is added or removed from the system.

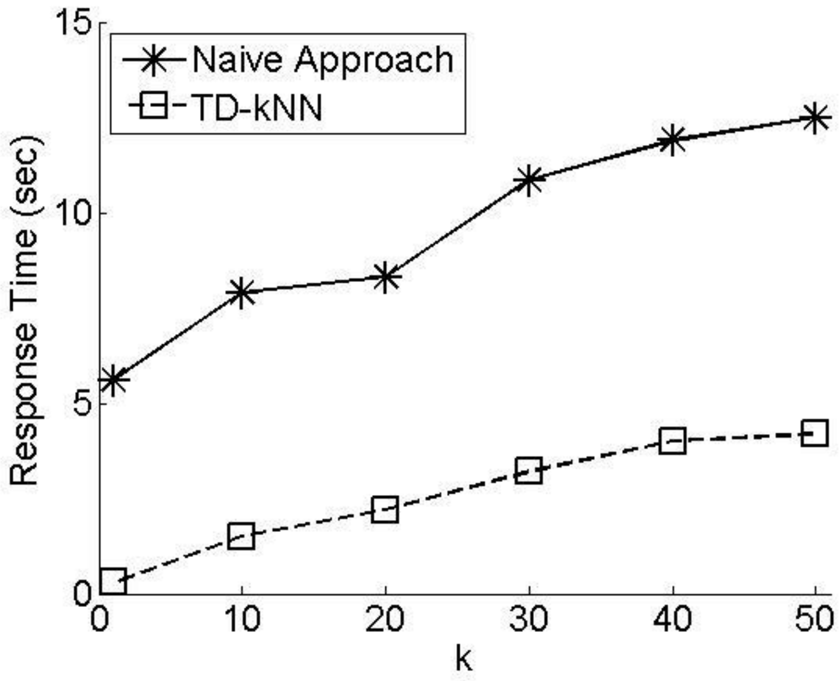
    (Section 4.2 for details)

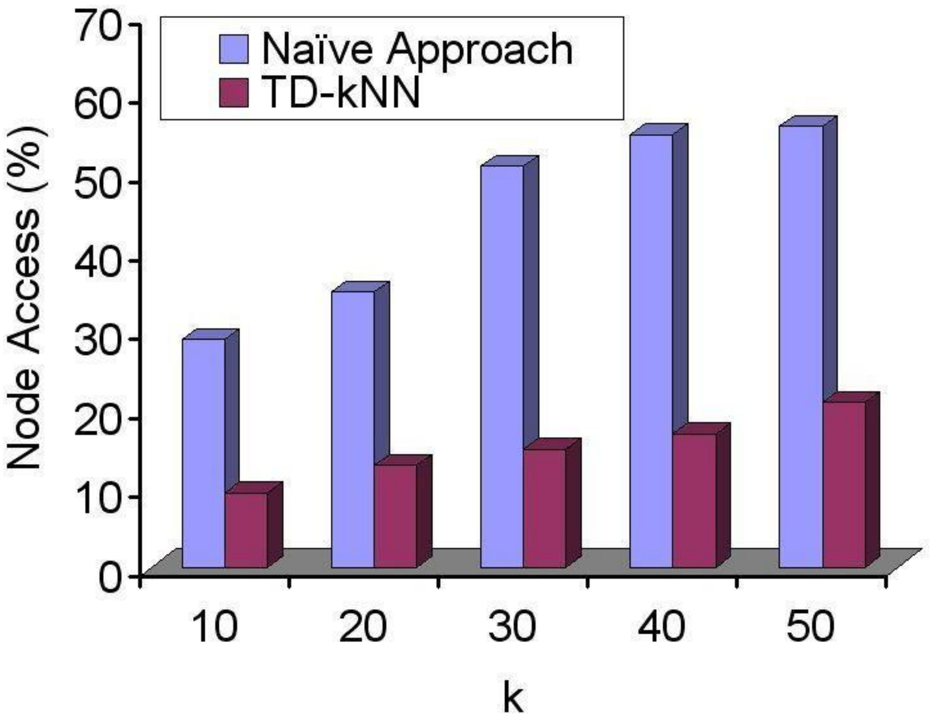
Indexing Time-Dependent Spatial Network

- Pros
  - Provides exact results
  - Localize the NNs and minimize the need for time-dependent SP calculation
  - Scalable and efficient for large set of query and data objects, and large networks
- Cons

Experimental Results

Naïve Approach= INE with Dreyfus's Dijkstra





k vs Response Time

k vs Network Node Access

USC Viterbi
School of Engineering
Integrated Media Systems Center

More

Future: Traffic Forecasting

Applications

Conclusion & Acknowledgement

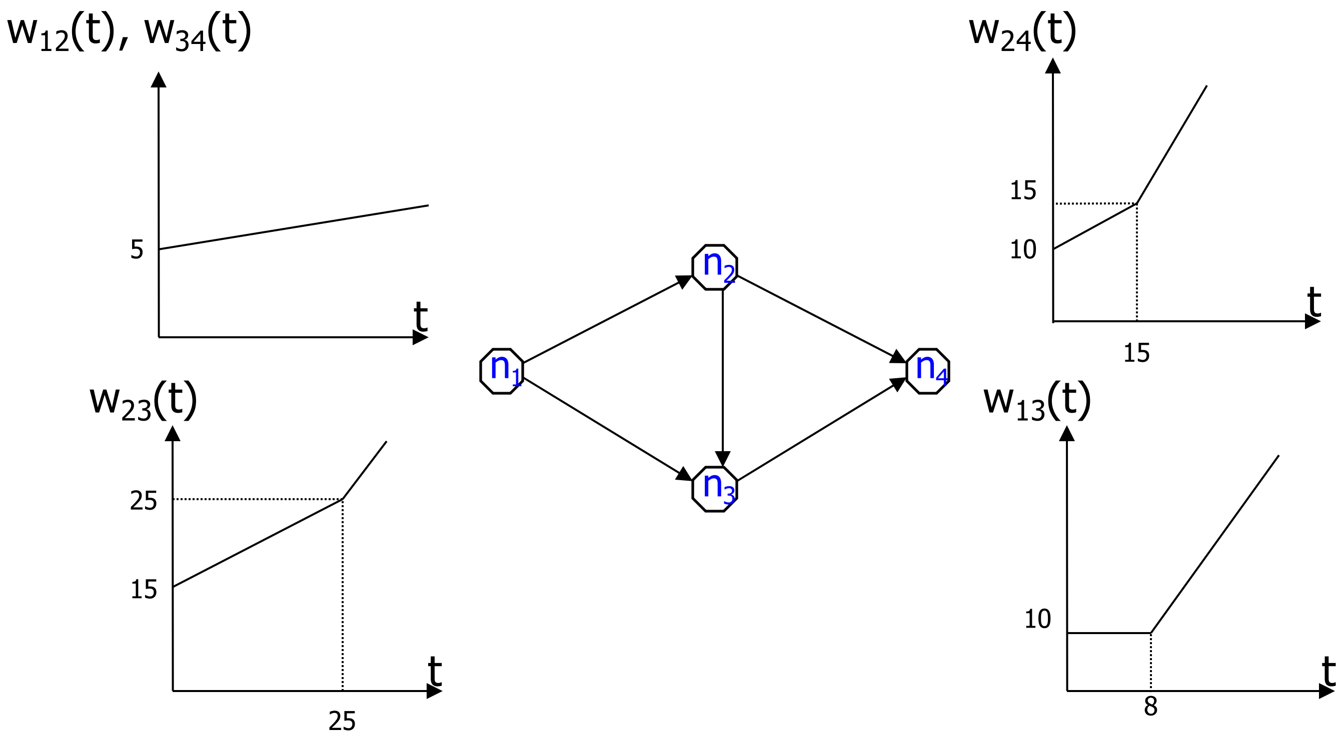
More

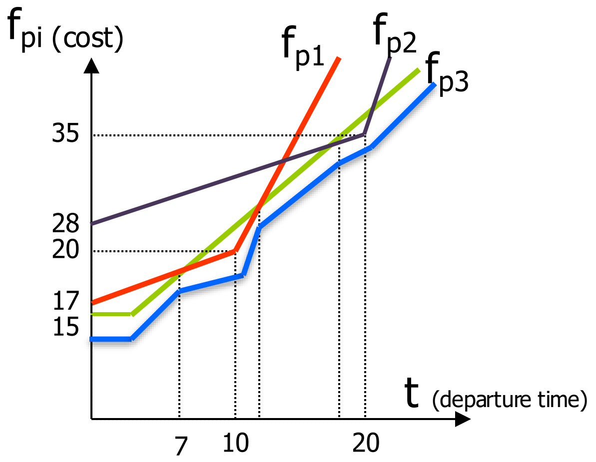
Future: Traffic Forecasting

Applications

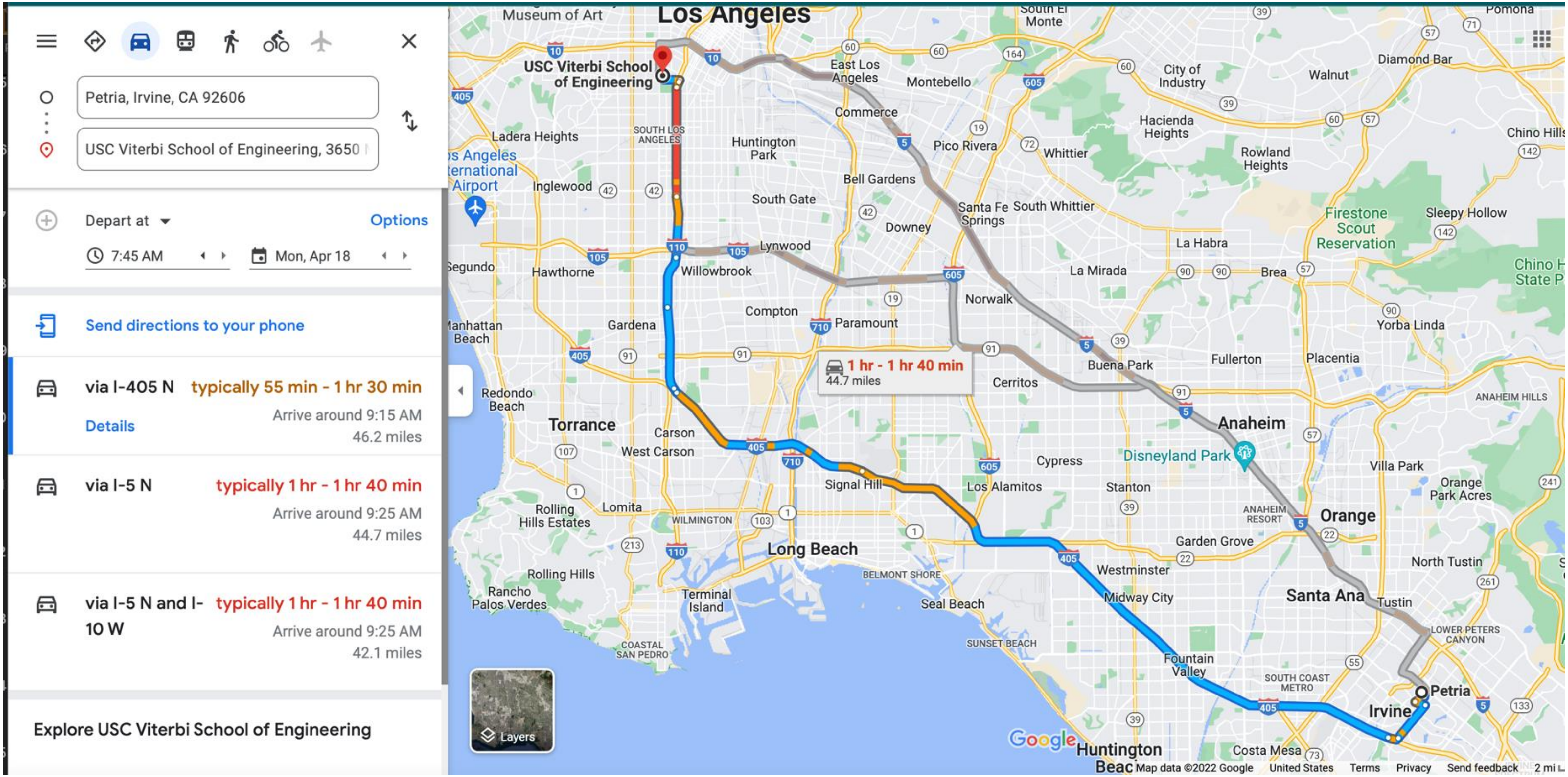
Conclusion & Acknowledgement

Where does the weight come from?





f_{pi}: total travel-time to destination



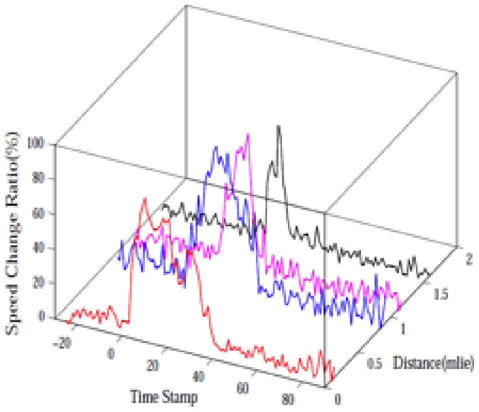
Petria, Irvine, CA 92606
USC Viterbi School of Engineering, 3650
Depart at
Options
7:45 AM
Mon, Apr 18
Send directions to your phone
via I-405 N
typically 55 min - 1 hr 30 min
Details
Arrive around 9:15 AM
46.2 miles
via I-5 N
typically 1 hr - 1 hr 40 min
Arrive around 9:25 AM
44.7 miles
via I-5 N and I-10 W
typically 1 hr - 1 hr 40 min
Arrive around 9:25 AM
42.1 miles
Explore USC Viterbi School of Engineering
Los Angeles
USC Viterbi School of Engineering
1 hr - 1 hr 40 min
44.7 miles
Long Beach
Torrance
Anaheim
Santa Ana
Irvine
Petria
Huntington Beach
Disneyland Park
Layers
Map data ©2022 Google
United States
Terms
Privacy
Send feedback
2 mi

Research: Traffic Forecasting *(Learn & Be Curious)*

Single sensor

Time series analysis

ICDM'2012



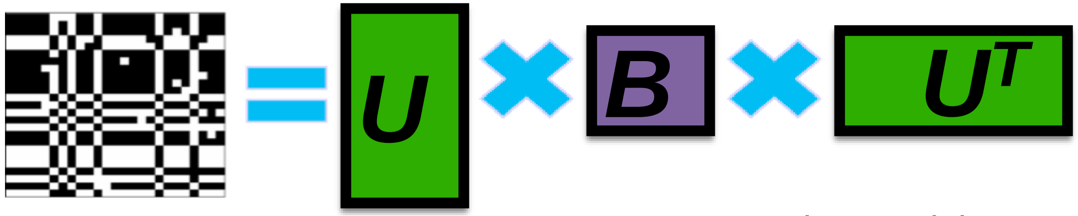
Single sensor

Causality

ICDM'2013

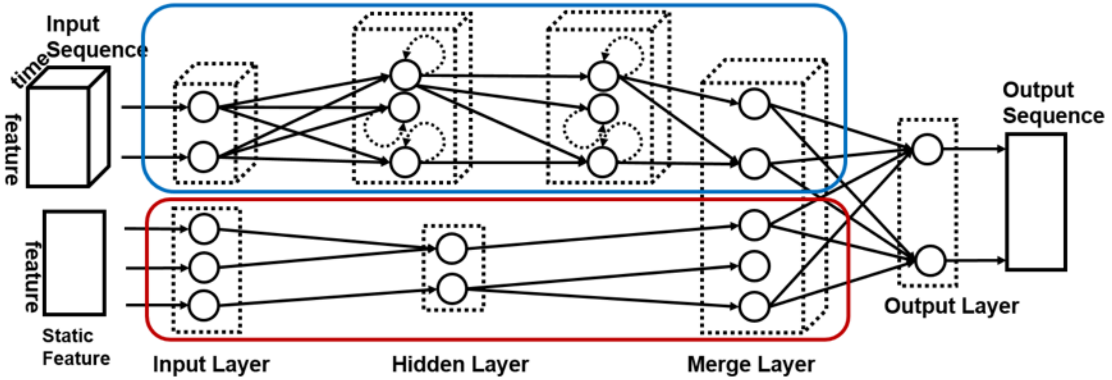
Multi sensor

Latent Space -- *SIGKDD'2016*



Graph matrix: G^{nxn} Latent properties: U^{nxk} and B^{kxk}

Multi sensor Deep Learning *SDM'2017, ICLR'18*



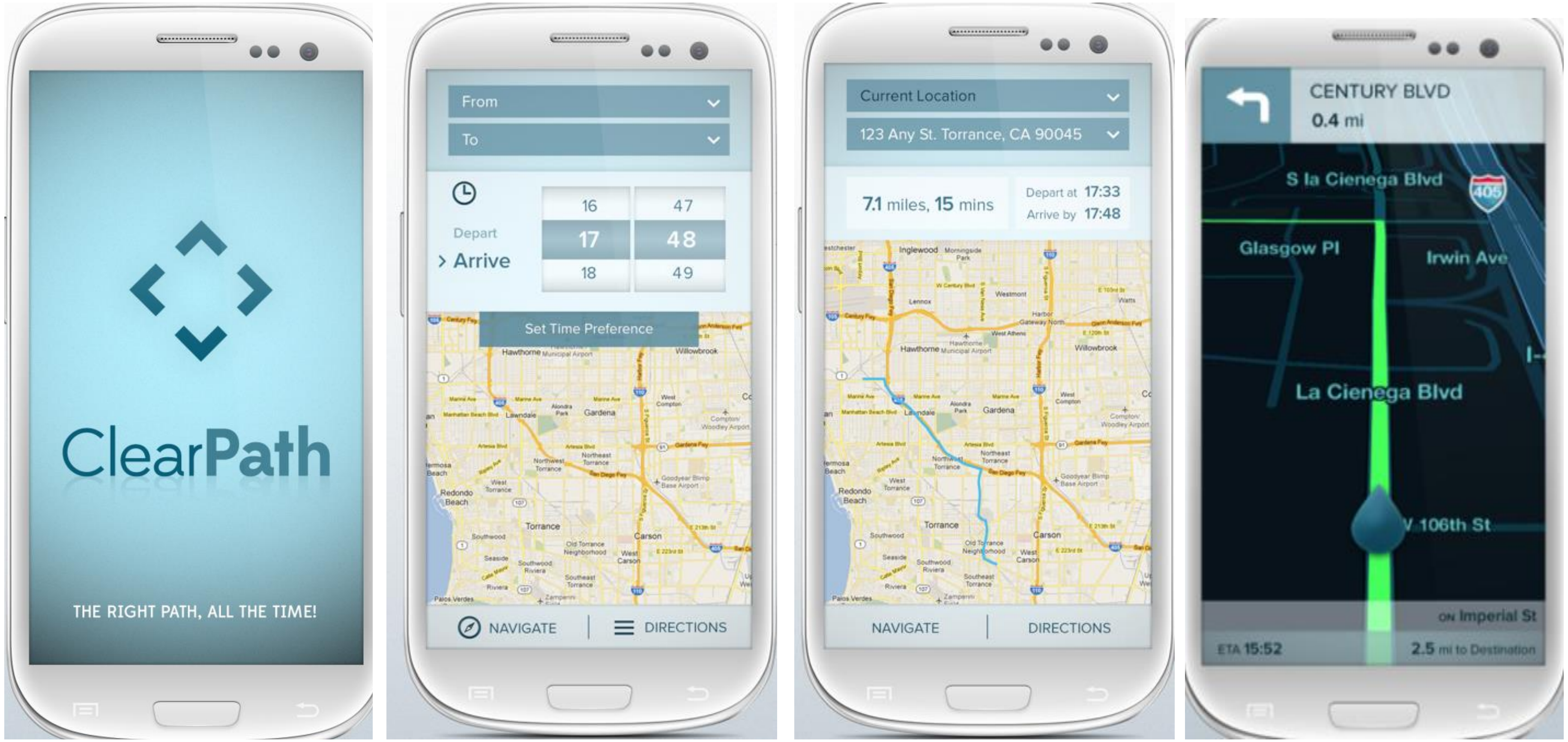
More

Future: Traffic Forecasting

Applications

Conclusion & Acknowledgement

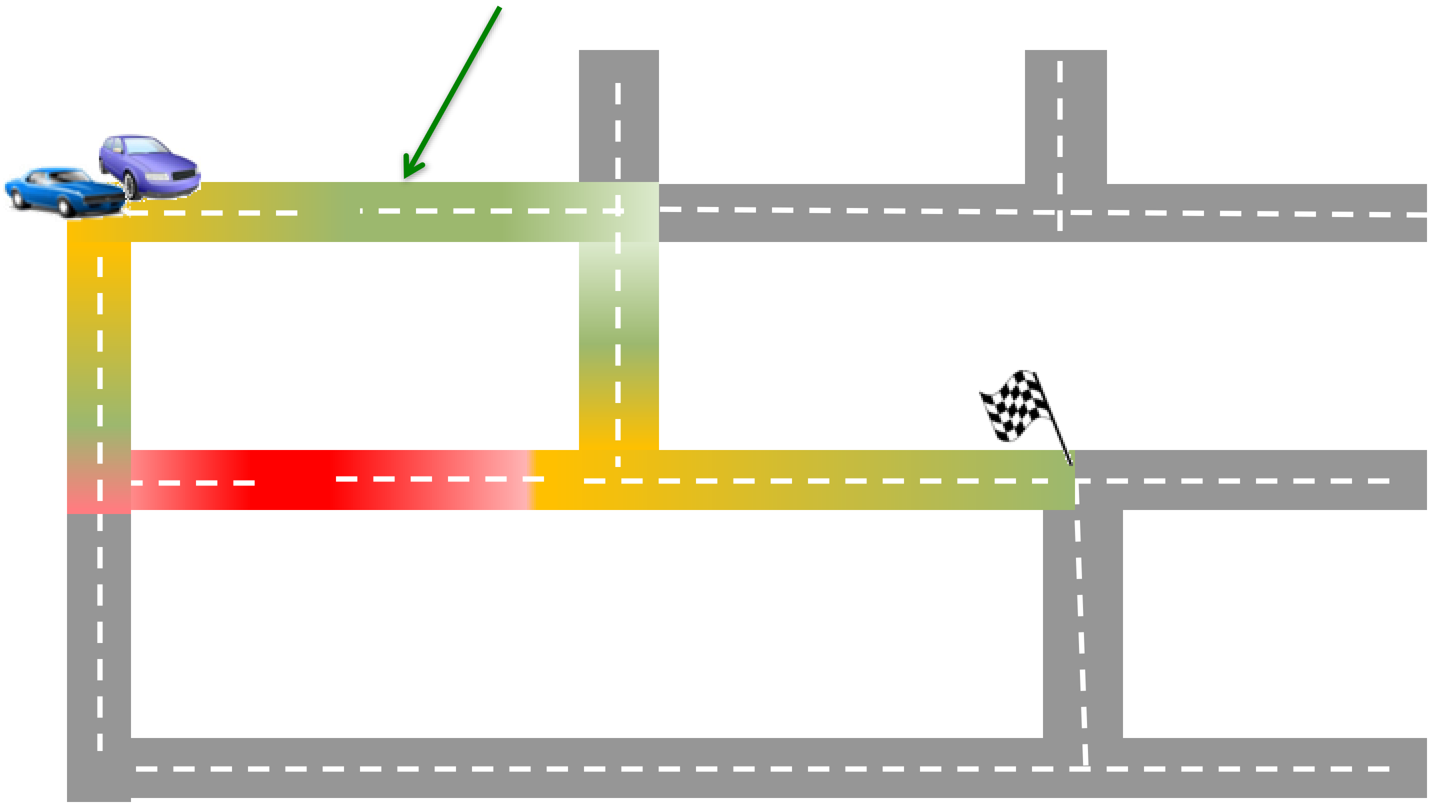
B2C App: ClearPath



Main Differentiator: Predictive Path Planning

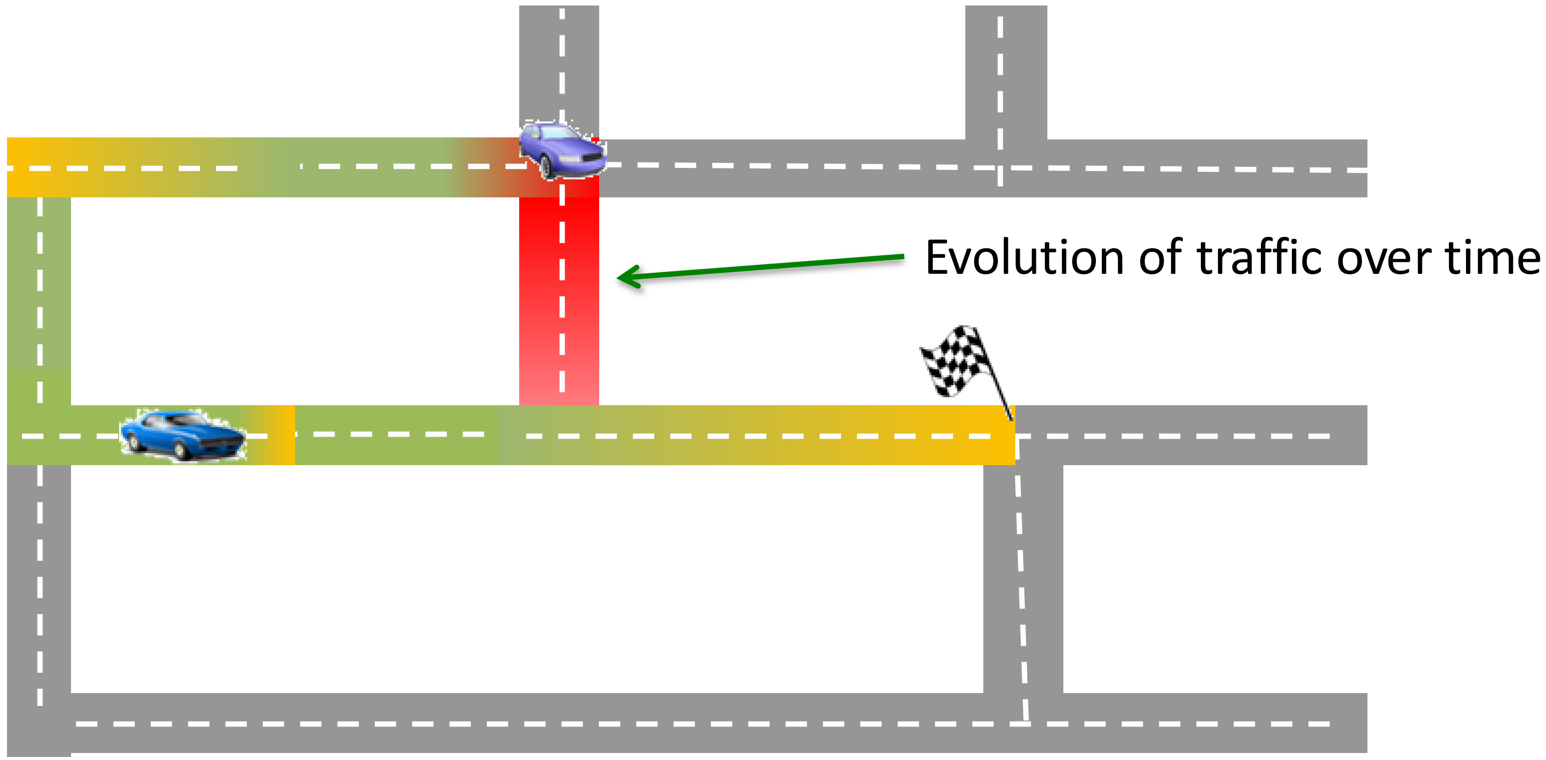
Predictive vs. Real-Time Path-Planning

Best Route based on current conditions



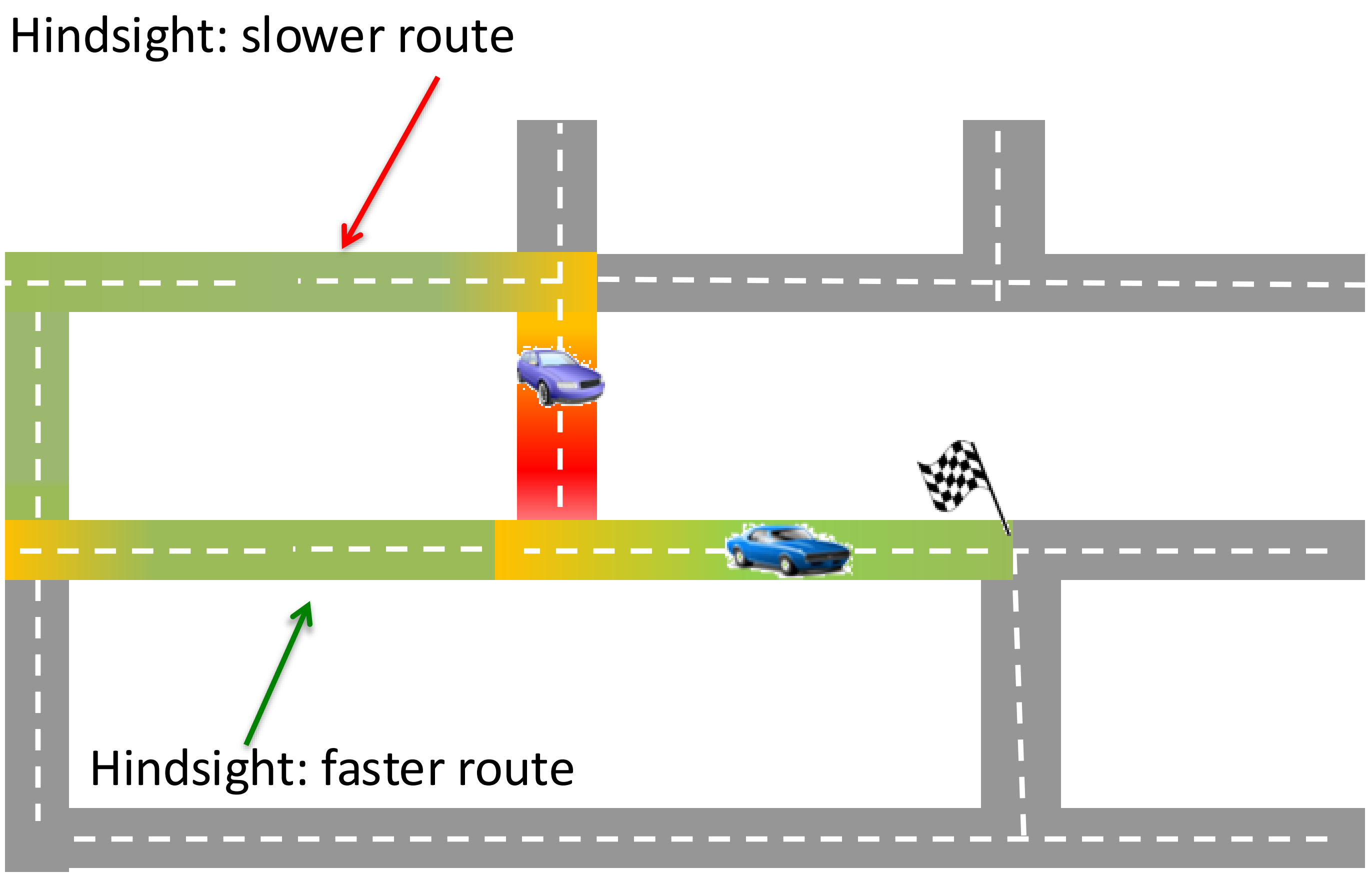
7:10AM

Predictive vs. Real-Time Path-Planning



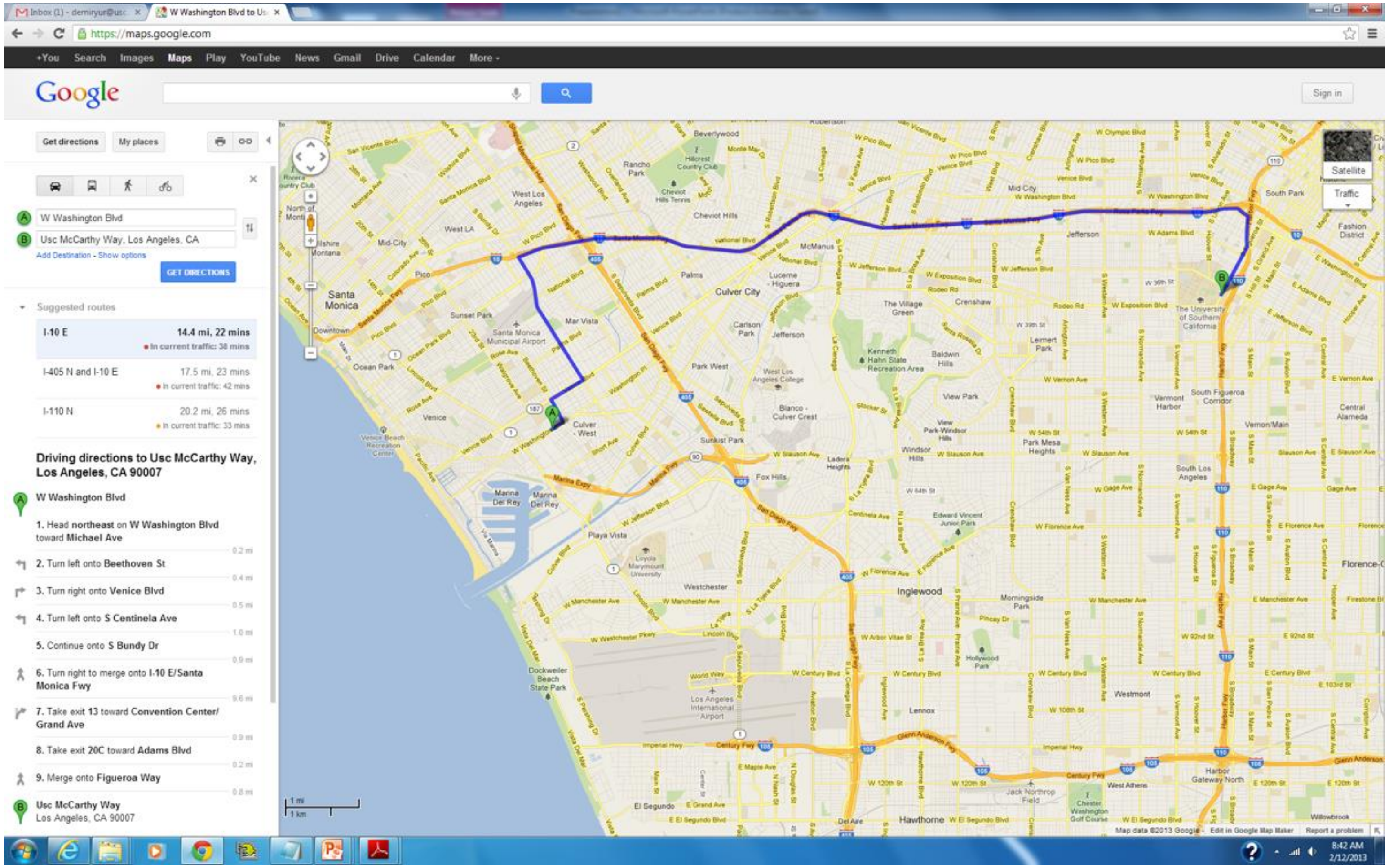
7:15AM

Predictive vs. Real-Time Path-Planning



7:20AM

Google Option #1

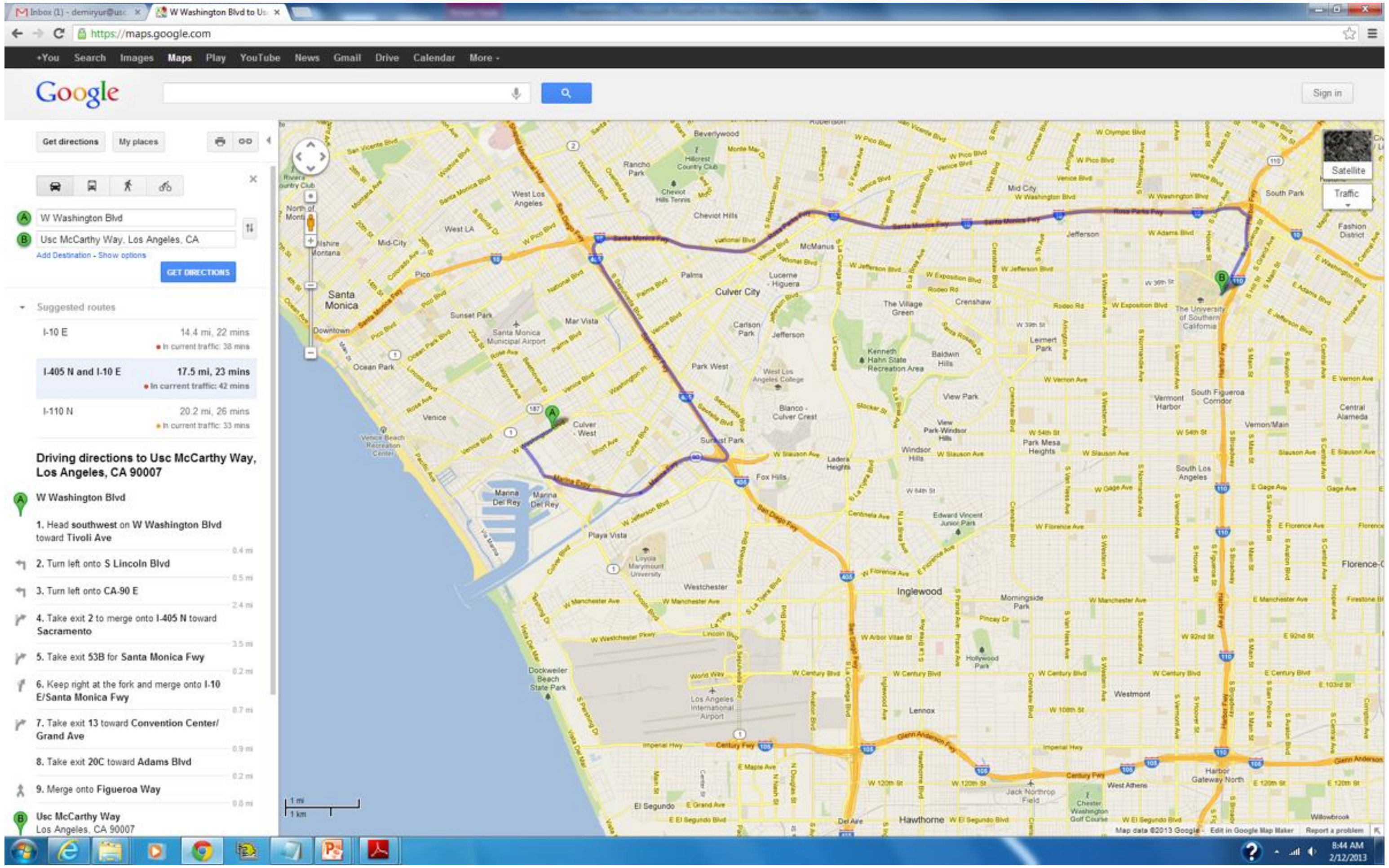


8:00 AM Thursday

Source: W Washington Blvd & Beethoven St

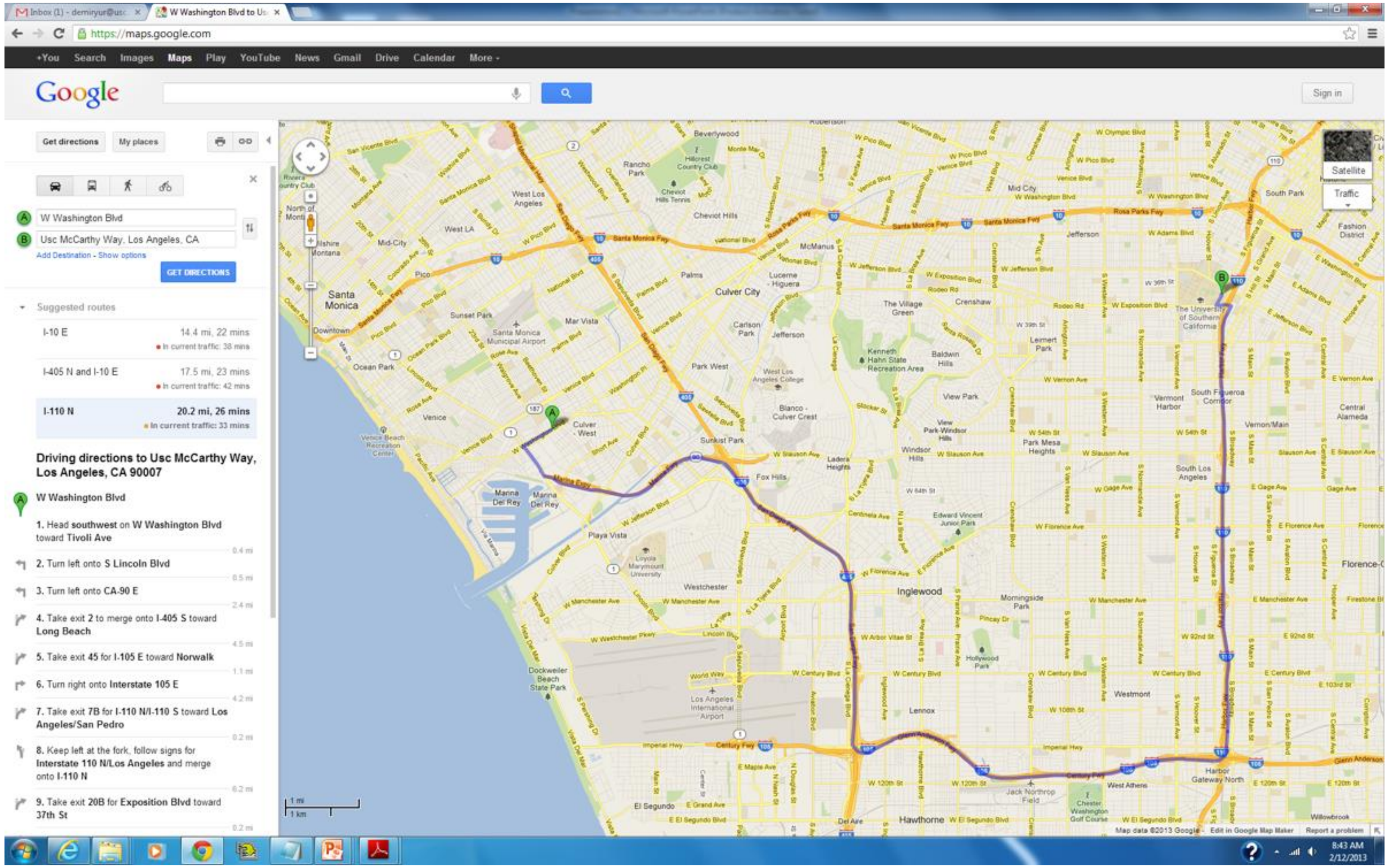
Destination: USC

Google Option #2



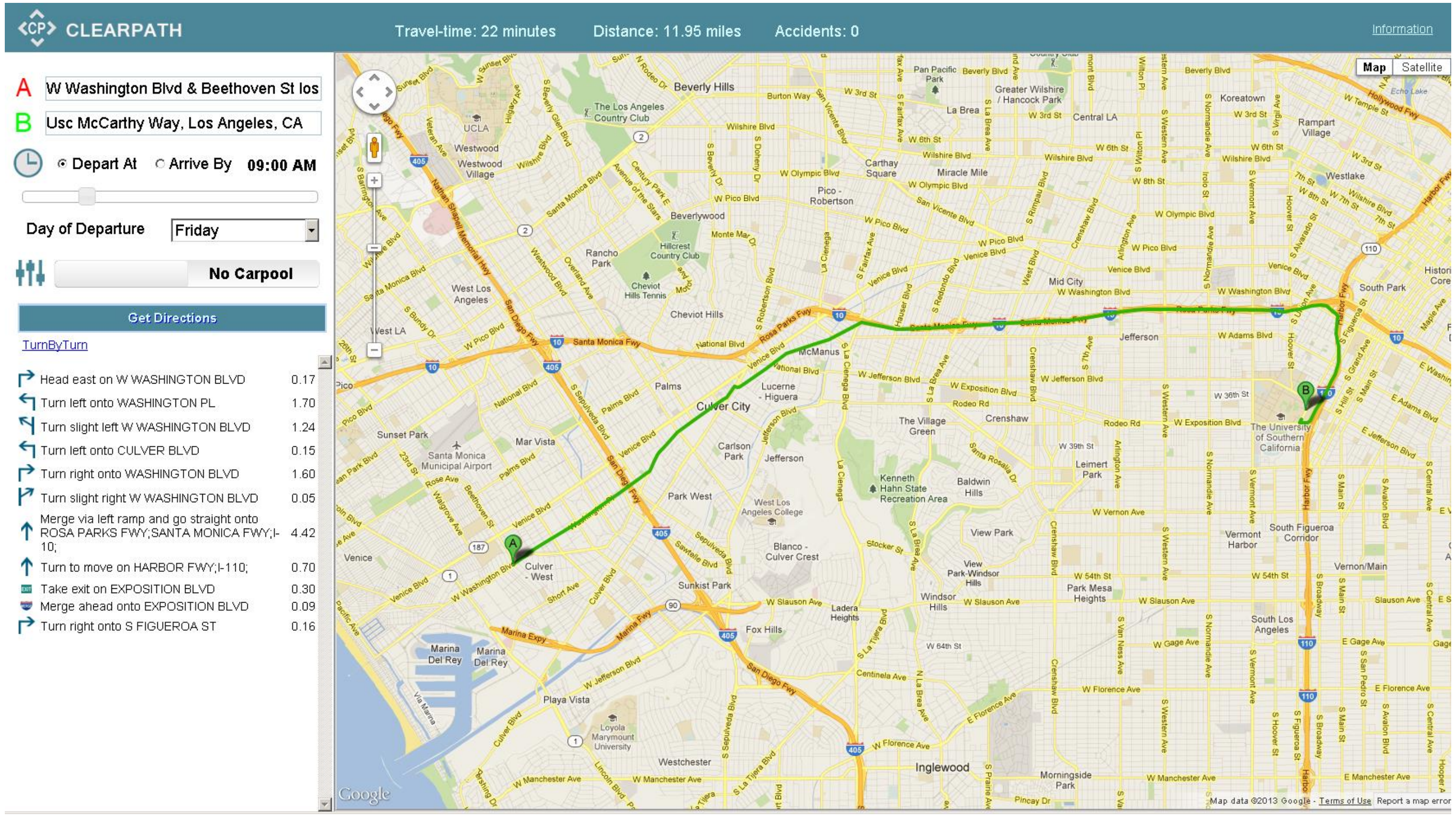
8:00 AM
Thursday
Source: W Washington Blvd & Beethoven St
Destination: USC

Google Option #3



8:00 AM
Thursday
Source: W Washington Blvd & Beethoven St
Destination: USC

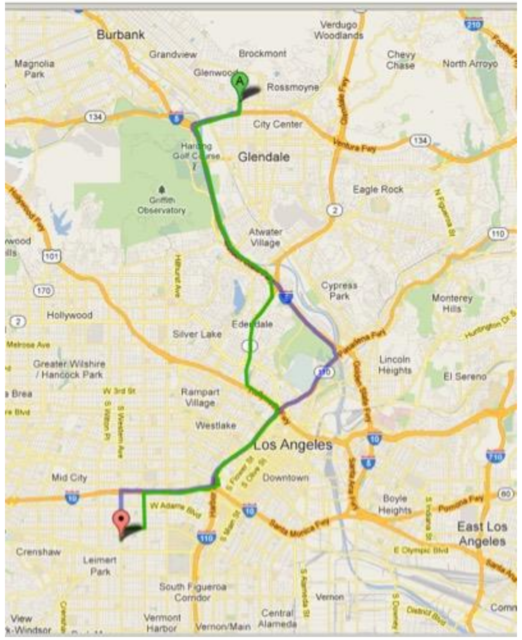
ClearPath



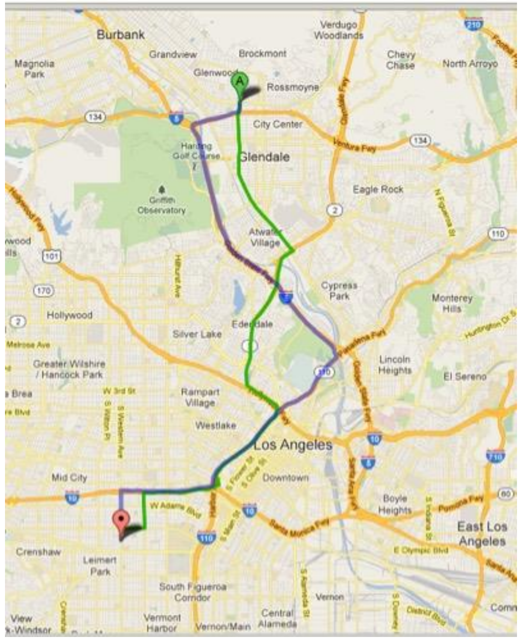
8:00 AM
Thursday
Source: W Washington Blvd & Beethoven St
Destination: USC

Comparisons (Saved Time)

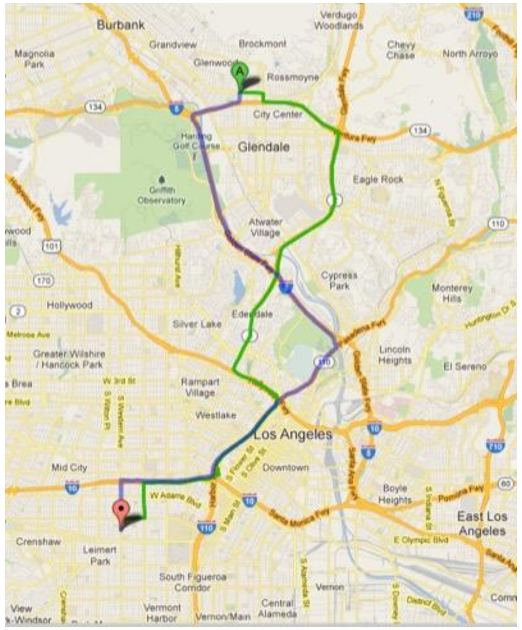
Glendale → USC



6:30 AM
ClearPath:22min
Google:21min, 42min w traffic



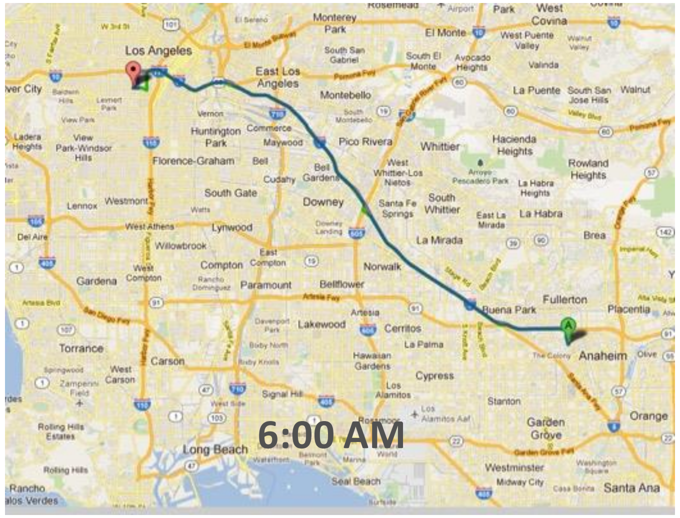
7:15 AM
ClearPath:26min
Google:21min, 42min w traffic

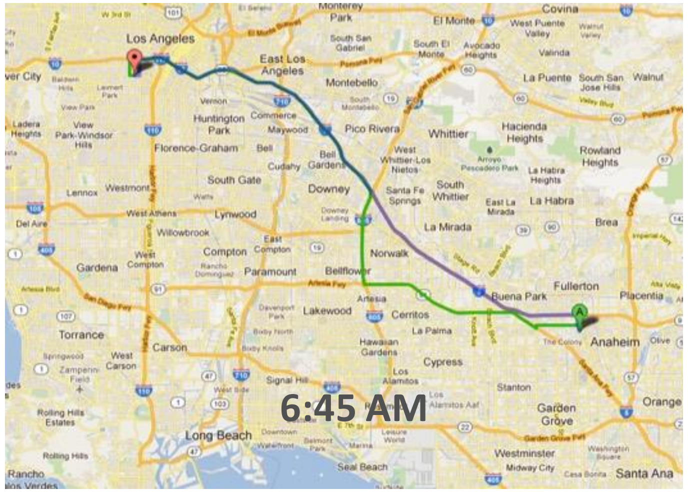


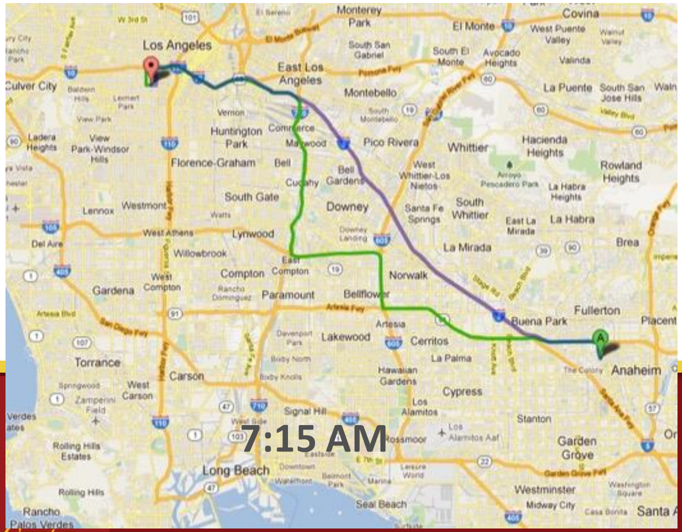
8:30 AM
ClearPath:31min
Google:21min, 42min w traffic

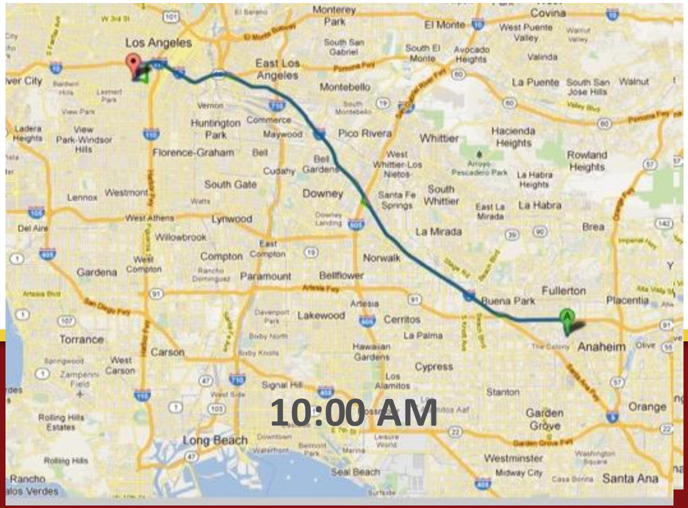
Comparisons (Path Alternatives)

Anaheim → USC



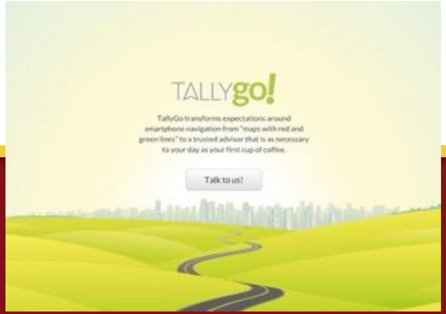


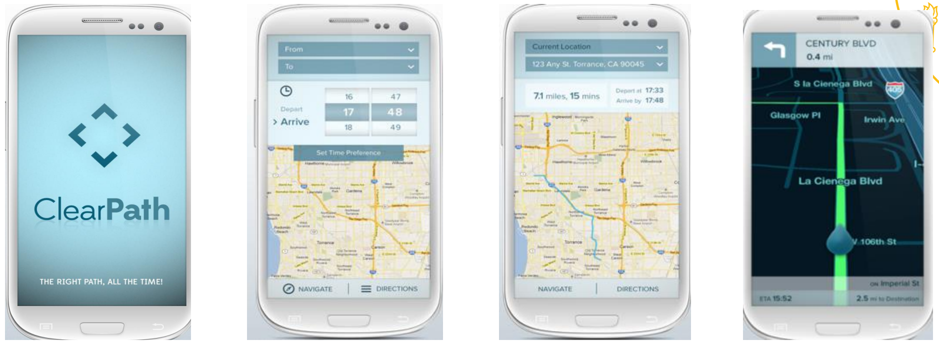




Tech-Transfer -- ClearPath

- IdeasEmpowered 2012 (USC competition)
- Spinoff in 2013
- Licensed technology from USC in Dec. 2014
- Raised $1.2M funding from group of investors
  - 10 Employees
  - Built on state-of-the art infrastructure – Spark, Cassandra
  - B2C business model (didn't work! Cost of User Acquisition)
- New App in 2015: TALLYgo





Main Differentiator: Predictive Path Planning

BUSINESS & ECONOMY

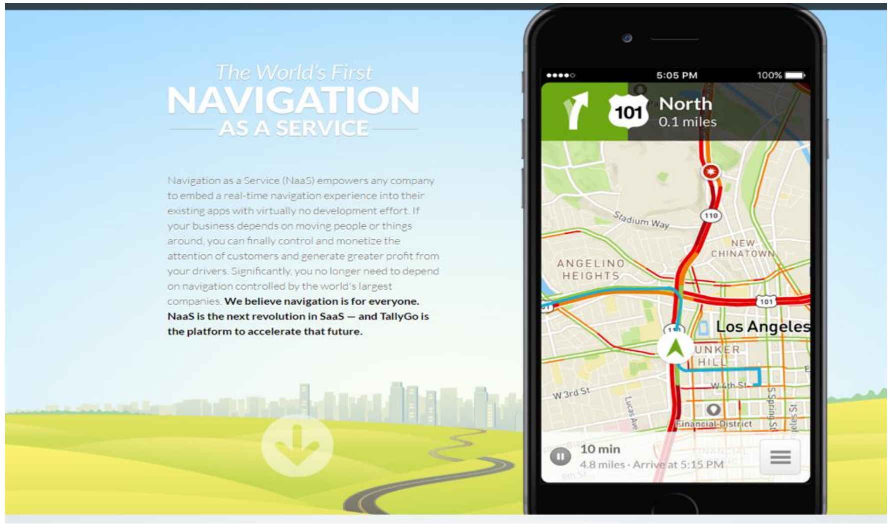
01:37

LA Auto Show 2013: Connected Car Expo unveils apps that bark, predict, navigate

http://www.voanews.com/content/traffic-technology-clearpath/1616682.html

TallyGo Exit *(Disagree & Commit)*

- New business B2B model (API)
  - LAFD Deployment
- Acquired in March 2019



United States Patent and Trademark Office
An Agency of the Department of Commerce

US Patent No. 9,286,793
Traffic prediction using real-world transportation data
March 15, 2016

US Patent No. 8,660,789
Hierarchical & exact fastest path computation in time-dependent spatial networks
February 2014

US Patent No. 8,566,030
Efficient K-nearest neighbor search in time-dependent spatial networks
October 2013

More

Future: Traffic Forecasting

Applications

Conclusion & Acknowledgement

Conclusion

Research

- Accurate traffic prediction
- Fastest-Path computation in time-dependent networks

System Development

- TransDec
- ADMS

Tech-Transfer

- 3 Patents
- Startup

ClearPath
The right path,
all the time!

Acknowledgement

Traffic Congestion:


Balan Sethu Raman, MS


Dan Fay, MS


Prof. Giuliano (School of Policy)


Kali K. Fogel
LA-Metro

Kenneth Coleman
Motorist Services Program Manager at LA-Metro

TransDec:


Ugur Demiryurek


Barak Fishbain


Keivan Hamedaniraja


Afsin Akdogan


Colin Gu


Mohammad Ali, MS

Research:


Penny Pan


F. Banaei-Kashani


A. Ranganathan, IBM


Chetan Gupta, HP Labs

ClearPath:


Hamid Heidary, CEO


CTO


Chris O'Connell, VP Bus Dev


Phil Spivey, Board Member

USC Viterbi School of Engineering
Integrated Media Systems Center

Where did the student go?

- Time-dependent Route Planning + ADMS & Foundry Development

Ugur Demiryurek · 1st
Research Scientist at Apple
Los Angeles, CA

Mohammad Kolahdouzan · 1st
Engineering Manager at Google
Altadena, CA

George Constantinou · 1st
Software Engineer, AWS Lambda at Amazon
Seattle, WA

- Traffic Forecasting

Dingxiong Deng · 1st
Research Scientist at Facebook
San Francisco Bay Area

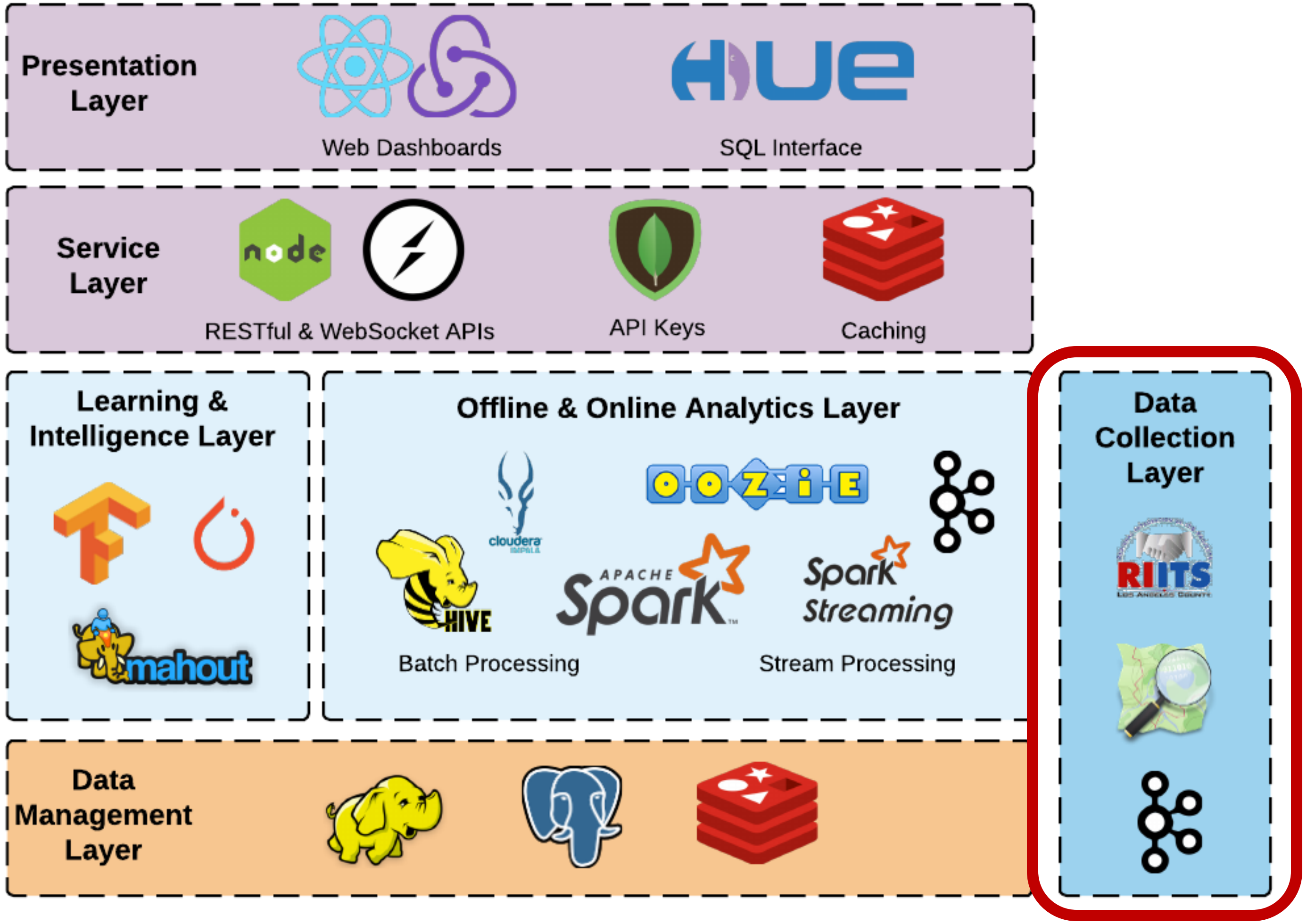
YaGuang Li · 1st
Senior Research Engineer at Google Brain
Mountain View, CA

Bei (Penny) Pan · 1st
Senior Machine Learning Engineer at Facebook

Rose Yu · 2nd
Assistant Professor at University of California, San Diego - Jacob...
San Diego, CA

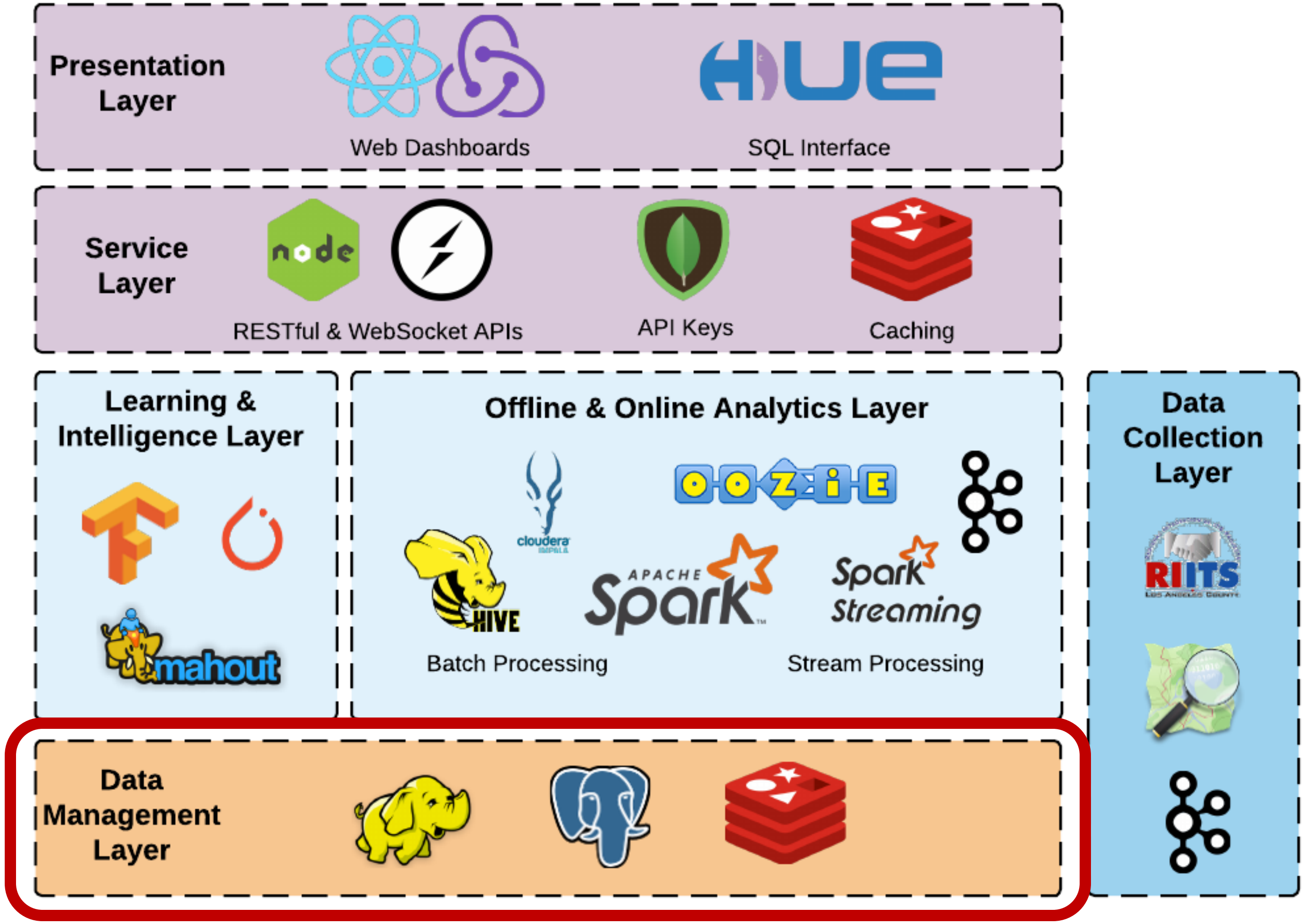
For your reference …

ADMSv2: The Architecture



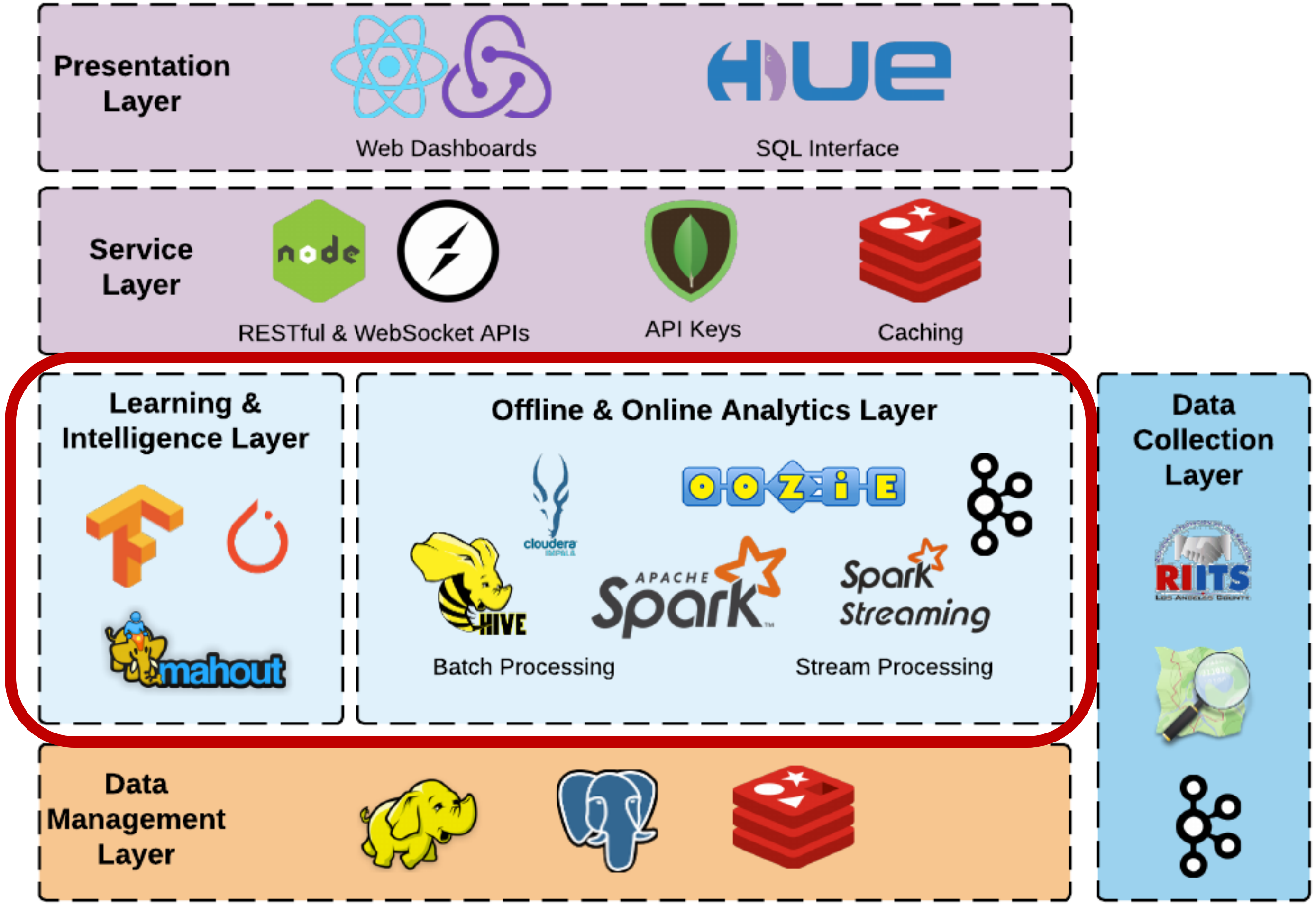
- Micro-services design
  - Independent
  - Isolated
  - Scalable
- Crawls / Consumes data from external data sources
- Pushes data to internal streams
  - Maps to internal data model

ADMSv2: The Architecture



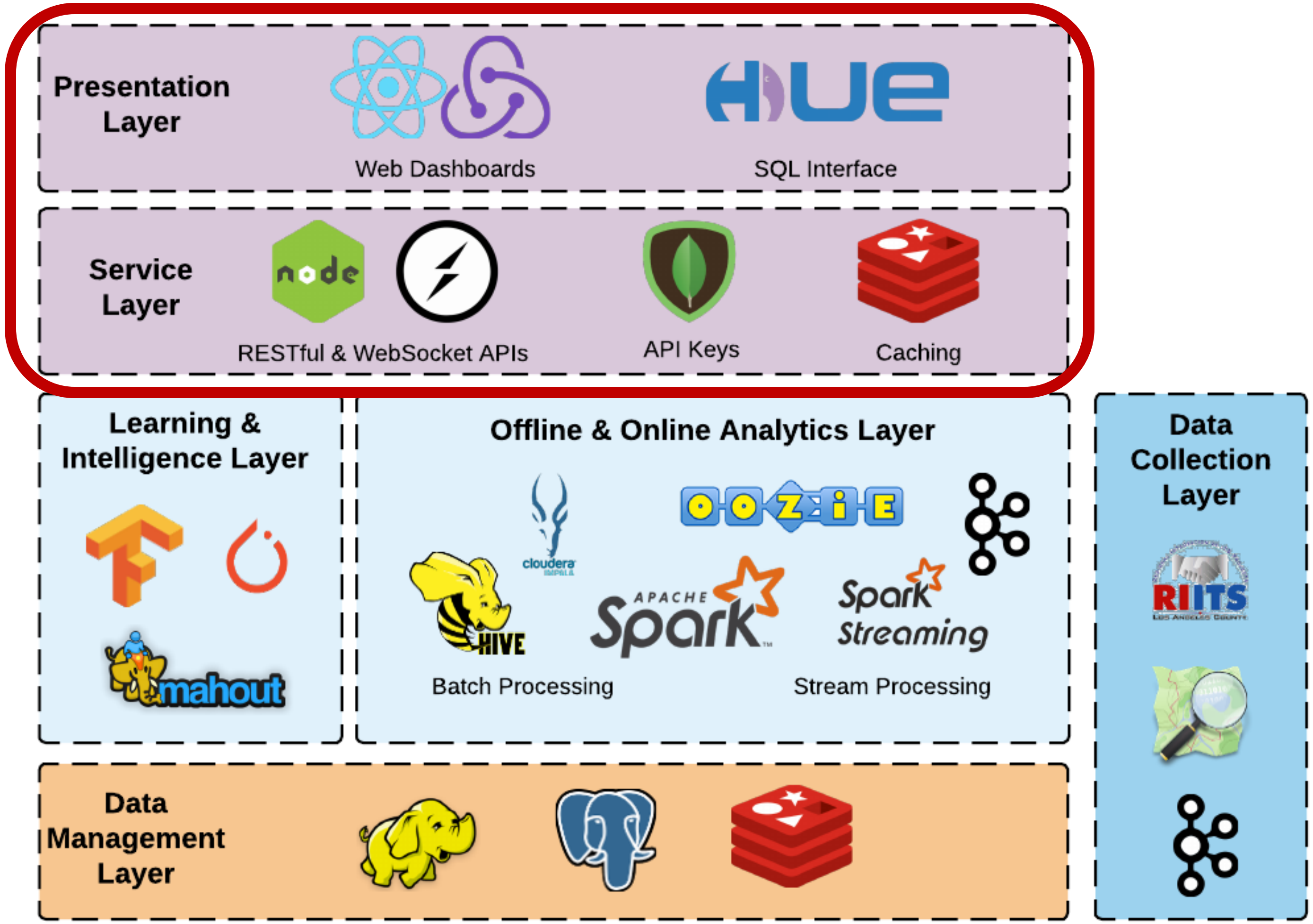
- Specialized data stores
  - Big Data (Hadoop HDFS)
  - Spatial-temporal (PostgreSQL)
  - Caching (Redis)
- Optimize spatial queries with indexes
- Reduce shuffling during distributed processing with spatial partitioning

ADMSv2: The Architecture



- Distributed processing engines
  - Batch (Hive, Impala, Spark)
  - Online/Streaming (Spark)
- Machine Learning Frameworks
  - PyTorch
  - Tensorflow
- High performance for queries that involve large amounts of data
- Easier transformation of training data for ML

ADMSv2: The Architecture



- Dashboards for data dissemination
- Web APIs
- SQL Interface for on-demand complex data processing

Policy- ADMS *(Deliver Results)*

- Collaboration between IMSC and Sol Price School of Public Policy

- Did Expo Line increase transit patronage?
- Did Expo Line impact traffic performance?
- Quasi-experimental design: Before/after and with/without


Los Angeles Times

L.A. Expo Line hasn't reduced co[…] promised, a study finds

USC researchers found that the 8.6-mile Expo Line did accomplish a worthy goal: boosting transit ridership in a dense, car-choked corridor. (Irfan Khan / Los Angeles Times)

By Dan Weikel and Alice Walton · Contact Reporters

NOVEMBER 17, 2015, 4:00 AM

Contrary to predictions used to promote the first phase of the Expo light rail line between downtown and Los Angeles' Westside, a new study has found that the $930-million project has done little to relieve traffic congestion in the area.

USC Viterbi
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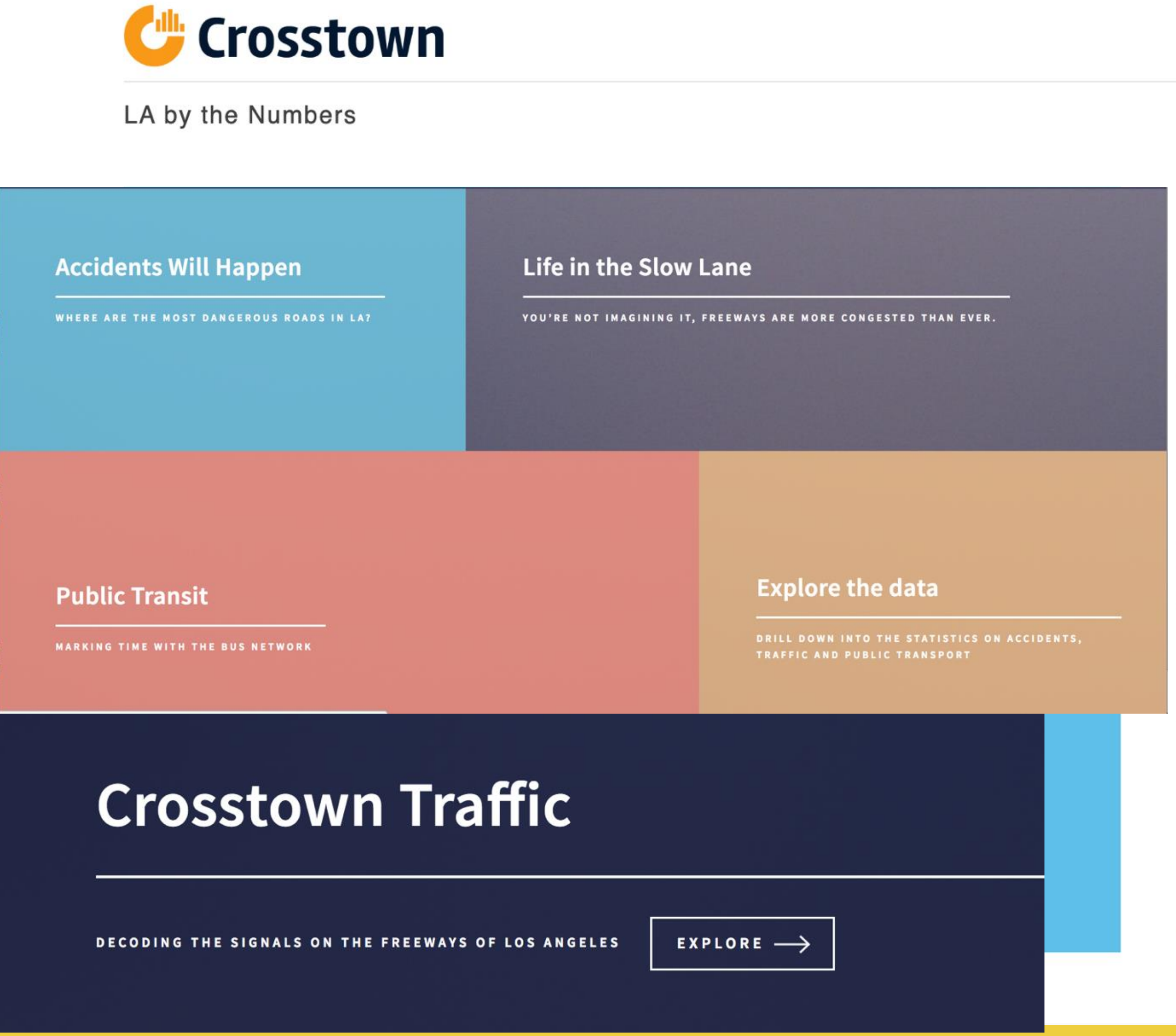
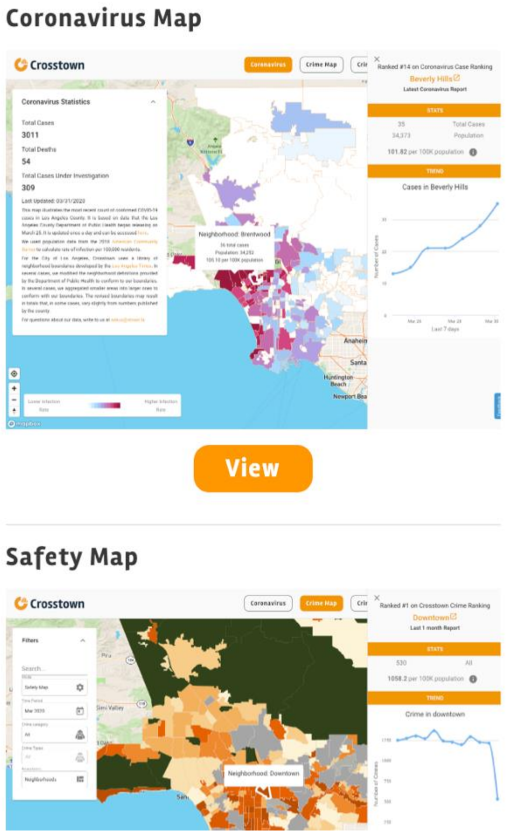
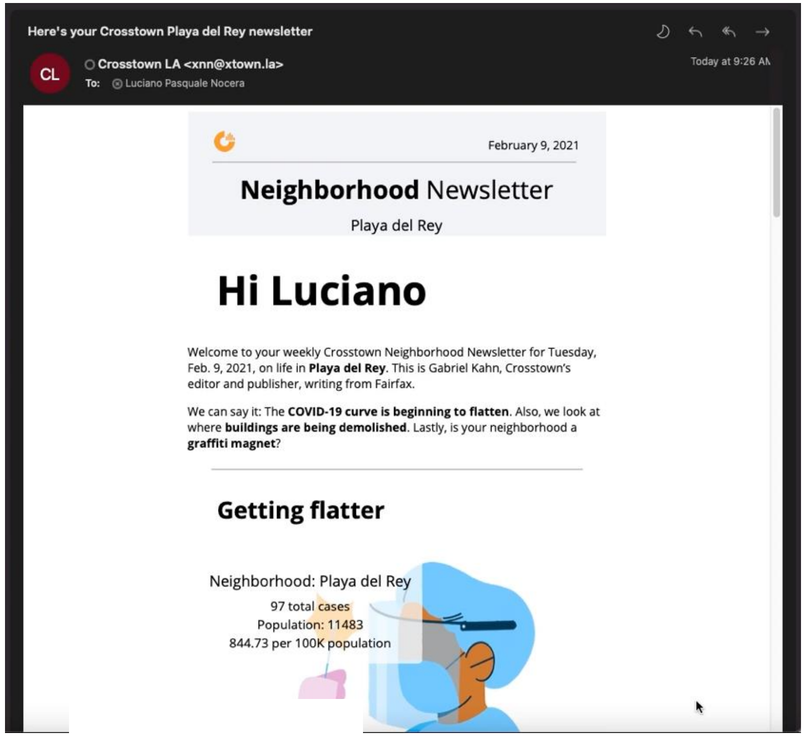
Integrated Media Systems Center

Data Driven Journalism





Crosstown Foundry Newsletter



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http://www.nbclosangeles.com/news/local/USC-Freeway-LA-Traffic-Study_Los-Angeles-416848663.html

ANNENBERG FOUNDATION

Crosstown Foundry Newsletter

- Markdown Template
  - Edit <u>static</u> and <u>dynamic</u> newsletter content
- Mixins (dynamic content)
  - Grammar:

NAME:AGGREGATION:FILTERS

  - JavaScript modules encoding data or data visualizations queried from the Crosstown Databases
  - Localized to specific spatial and temporal extent
- HTML Converter & Linter
  - Validates mixins
  - Renders the markdown in HTML