TransDec: A Data-Driven Framework for Decision-Making in Transportation Systems

Cyrus Shahabi
University of Southern California
Los Angeles, CA 90089-0781
shahabi@usc.edu
http://infolab.usc.edu
OUTLINE

• Motivation: Transportation
• Platform: TransDec
• Traffic Profiles
  – Data Reduction Approach
• Applications: Time-Dependent kNN
• Demonstration
• Future Plans
OUTLINE

- Motivation: Transportation
- Platform: TransDec
- Traffic Profiles
  - Data Reduction Approach
- Applications: Time-Dependent kNN
- Demonstration
- Future Plans
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

GOAL

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

1 Texas Transportation Institute Urban Mobility Report, 2007 data
Traffic Data Lifecycle: Loop Detectors

- Loop Detector: 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 inductance decreases when a car is on top of it.
Single loops can measure:
- Occupancy \((O)\): % of time loop is occupied (had a car on it) per interval
- Volume \((N)\): vehicles per interval
- Speed = \((N \times L) / O\) where \(L\) is a constant proportional to the average length of a car

Slide is courtesy of Prof. Steve Muench
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: Data Aggregator

<table>
<thead>
<tr>
<th>Data Type</th>
<th>Hourly (in KB)</th>
<th>Daily (in KB)</th>
<th>Annual (in KB)</th>
<th>3 Years (in KB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>bus_mta_inv2.xml</td>
<td>0.96</td>
<td>23.00</td>
<td>8,395.00</td>
<td>25,185.00</td>
</tr>
<tr>
<td>bus_mta_rt2.xml</td>
<td>86400</td>
<td>31,950.00</td>
<td>766,800.00</td>
<td>279,882,000.00</td>
</tr>
<tr>
<td>cctv_inv.xml</td>
<td>0.04</td>
<td>2.38</td>
<td>57.00</td>
<td>20,805.00</td>
</tr>
<tr>
<td>cms_inv.xml</td>
<td>0.04</td>
<td>2.17</td>
<td>52.00</td>
<td>18,980.00</td>
</tr>
<tr>
<td>cms_rt.xml</td>
<td>38.40</td>
<td>2,304.00</td>
<td>55,296.00</td>
<td>20,183,040.00</td>
</tr>
<tr>
<td>event_d7.xml</td>
<td>8.80</td>
<td>528.00</td>
<td>12,672.00</td>
<td>4,625,280.00</td>
</tr>
<tr>
<td>rail_mta_inv.xml</td>
<td>0.00</td>
<td>0.04</td>
<td>1.00</td>
<td>365.00</td>
</tr>
<tr>
<td>rail_rt.xml</td>
<td>8.00</td>
<td>480.00</td>
<td>11,520.00</td>
<td>4,204,800.00</td>
</tr>
<tr>
<td>rms_inv.xml</td>
<td>0.60</td>
<td>36.04</td>
<td>865.00</td>
<td>315,725.00</td>
</tr>
<tr>
<td>rms_rt.xml</td>
<td>988.80</td>
<td>59,328.00</td>
<td>1,423,872.00</td>
<td>519,713,280.00</td>
</tr>
<tr>
<td>signal_inv.xml</td>
<td>1.45</td>
<td>87.29</td>
<td>2,095.00</td>
<td>764,675.00</td>
</tr>
<tr>
<td>signal_rt.xml</td>
<td>3,514.67</td>
<td>210,880.00</td>
<td>5,061,120.00</td>
<td>1,847,308,800.00</td>
</tr>
<tr>
<td>tt_d7_inv.xml</td>
<td>0.52</td>
<td>31.08</td>
<td>746.00</td>
<td>272,290.00</td>
</tr>
<tr>
<td>tt_d7_rt.xml</td>
<td>152.00</td>
<td>9,120.00</td>
<td>218,880.00</td>
<td>79,891,200.00</td>
</tr>
<tr>
<td>vds_art_d7_inv.xml</td>
<td>0.08</td>
<td>4.79</td>
<td>115.00</td>
<td>41,975.00</td>
</tr>
<tr>
<td>vds_art_d7_rt.xml</td>
<td>45.00</td>
<td>2,700.00</td>
<td>64,800.00</td>
<td>23,652,000.00</td>
</tr>
<tr>
<td>vds_art_ladot_inv.xml</td>
<td>1.76</td>
<td>105.75</td>
<td>2,538.00</td>
<td>926,370.00</td>
</tr>
<tr>
<td>vds_art_ladot_rt.xml</td>
<td>969.00</td>
<td>58,140.00</td>
<td>1,395,360.00</td>
<td>509,306,400.00</td>
</tr>
<tr>
<td>vds_fr_d7_inv.xml</td>
<td>0.66</td>
<td>39.88</td>
<td>957.00</td>
<td>349,305.00</td>
</tr>
<tr>
<td>vds_fr_d7_rt.xml</td>
<td>722.00</td>
<td>43,320.00</td>
<td>1,039,680.00</td>
<td>379,483,200.00</td>
</tr>
<tr>
<td>Total KB from XML data</td>
<td>6,985.28</td>
<td>419,060.38</td>
<td>10,057,449.00</td>
<td>3,670,968,885.00</td>
</tr>
</tbody>
</table>

### Heterogeneous (gps, video, loop sensor, events)

### Continuous

### Large

**Total KB from XML data**: 11,012,906,655.00
Requirement (by Metropolitan Transportation Authority) – Archive Data Management System (ADMS)
Technical Challenges of ADMS

- **Data Integration** to handle Data Heterogeneity
- **In-Memory Storage** to handle Data Dynamics
- **Data Indexing** to handle Data Size
- **Data Summarization** for multi-resolution pre-aggregation
OUTLINE

• Motivation: Transportation
• Platform: TransDec
  • Traffic Profiles
    – Data Reduction Approach
• Applications: Time-Dependent kNN
• Demonstration
• Future Plans
TransDec Mission

A data-driven tool that enables on-the-fly spatio-temporal querying, analysis and planning for transportation networks.
Traffic Sensors (currently)

- Currently provided by RIITS
  - Real-time Highway Congestion
  - Real-time Arterial Congestion

- Total of **6300 sensors** (1800 sensors in 18 highways and 4500 in main streets) covering 3000 miles

- Update rate: every **1 minute**
  - Daily 9.1 million rows, **800MB** of data
Current System Architecture

RIITS

Sensory Data

Oracle

Microsoft StreamInsight

Google Maps mash-up
Current System Architecture
[VLDB2010-demo]
• Motivation: Transportation
• Platform: TransDec
• Traffic Profiles
  – Data Reduction Approach
• Applications: Time-Dependent kNN
• Demonstration
• Future Plans
Large Dataset: Should we store everything?

- Can current Database systems answer historic queries in a reasonable time?
  
  “What was the average speed in I-10 during summer 2009 from 4:00-5:00 pm?”

- Lack of methods with short response time

- Can knowledge of Traffic Data help us to reduce data?

Response Time for the indexed table containing data of one year: 58 Seconds!
Data Reduction Approach

- Instead of storing the whole data in DB, store the sketches in memory
- Principal component Analysis (PCA): a mathematical approach for analyzing correlated data
- Components are found using singular value decomposition $\text{COV}(X) = U S V^T$
- A number of components with great influence selected as coordinates
- Representing data using new coordinates
PCA for Traffic Data

- Results for a sensor in I-10 for 5 consecutive days in Summer 2009

- A small number of components hold the major variance in data

- High data compression rate
  - 98% for highway data
• Extra short response time
  – 1 millisecond (compare to 58 sec.)

• Highly accurate for Traffic Data
  – MSE for same query: $10^{-4}$ Mph

• Finding hidden patterns
  – The Two major components in I-10
  – There are less traffic patterns in I-210 compared to I-10
OUTLINE

• Motivation: Transportation
• Platform: TransDec
• Traffic Profiles
  – Data Reduction Approach
• Applications: Time-Dependent kNN
• Demonstration
• Future Plans
• KNN Search Past and Present
• Motivation
• Related Work
• Time-Dependent Spatial Network
• TD-kNN Search Approaches
  – Time-Expanded Networks
  – Incremental Network Expansion
  – Indexing Time-Dependent Networks
• Conclusion
KNN Search Past and Present

- **Spatial Network**
- **Time-Dependent Spatial Network**
- **Euclidean Space**

Edge weights are constant

Edge weights change over time
Outline

• KNN Search Past and Present
• Motivation
• Related Work
• Time-Dependent Spatial Network
• TD-kNN Search Approaches
  – Time-Expanded Networks
  – Incremental Network Expansion
  – Indexing Time-Dependent Networks
• Conclusion
Motivation

• Existing kNN research and commercial systems
  – Find shortest path based on the constant edge weights.
• In Real-world
  – The weight of an edge is a function of time, i.e., time-dependent.
  – Arrival-time to an edge determines the travel-time on that edge.
  – Change in travel-time is significant and continuous not abrupt.

Pictures courtesy: http://www.wfrc.org/cms

Monday travel-time on a segment of I-405 in LA
Time-dependent kNN (TD-kNN)

• Given a query point $q$ and a set of objects $P$, find the $k$ objects in $P$ that are closest to $q$ in time-dependent cost (e.g., travel-time)

• The shortest path from source to candidate hospitals may change depending on the departure-time

• The result of kNN depend on when the query is issued
Outline

• KNN Search Past and Present
• Motivation
• Related Work
• Time-Dependent Spatial Network
• TD-kNN Search Approaches
  – Time-Expanded Networks
  – Incremental Network Expansion
  – Indexing Time-Dependent Networks
• Conclusion
Related Work

Spatial Networks

Shortest Path
- Dijkstra
- A*

kNN Search
- Query processing in SNDB: Papadias et al., [VLDB03]
- Voronoi-based kNN in SNDB: Shahabi et al., [VLDB04]
- CNN queries in RN: Cho et al., [VLDB05]
- CNN monitoring in RN: Mouratidis et al., [VLDB06]
- S-Grid: Huang et al., [SSTD07]
- Scalable network distance browsing: Samet et al., [SIGMOD08]

All kNN approaches are based on precomputation of static SP algorithms.
Related Work

Time-Dependent Spatial Networks

Time-Dependent Shortest Path

Fixed Edge Cost (FC)
- Cook and Halsey, [JMA66] – Dynamic Programming
- Kohler et al., [ESA02]– Time-Expanded Graphs

Variable Edge Cost (VC)
- Dreyfus, [JOR69] – Dijkstra Variant in FIFO
- Harpen, [MMO69]- Non-FIFO, NP Hard
- Orda and Rom, [JACM90] – Bellman Ford Algorithm
- George and Shekhar, [SSTD07]- Time-Aggregated Graphs

- Both of DT and CT algorithms can be extended to address TD-kNN. However, they are either approximate or do not scale.
- Precomputation in time-dependent networks is a big challenge.
Outline

- KNN Search Past and Present
- Motivation
- Related Work
- **Time-Dependent Spatial Network**
- TD-kNN Search Approaches
  - Time-Expanded Networks
  - Incremental Network Expansion
  - Indexing Time-Dependent Networks
- Conclusion
Time-dependent Spatial Network

- \( G(V,E,T) \): For every edge \( e(v_i; v_j) \), there is a cost function \( w_{ij}(t) \) which specifies the cost of traveling from \( v_i \) to \( v_j \) at time \( t \).
- First-In-First-Out (FIFO) Network: Moving objects exit from an edge in the same order as they entered into that edge.
Time-dependent Spatial Network (Cont)

- **Path (s-d) Cost Functions**
  - Composition of edge arrival functions.
  - Arrival-time (and cost) to destination is a function of departure-time from the source.

\[
\begin{align*}
  f_{12}(t_1) &= t_2 \\
  f_{24}(t_2) &= f_{24}(f_{12}(t_1)) \\
  p_1 &= (v_1, v_2, v_4) \\
  f_{p1} &= f_{24}(f_{12}(t)) \\
  p_2 &= (v_1, v_2, v_3, v_4) \\
  f_{p2} &= f_{34}(f_{23}(f_{12}(t))) \\
  p_3 &= (v_1, v_3, v_4) \\
  f_{p3} &= f_{34}(f_{13}(t))
\end{align*}
\]
Path (s-d) Cost Functions
- Shortest path is **not unique** and changes based on the departure time
- The lower-envelope of \( f_p(t) \)
  - Each piece gives the shortest path for the corresponding time-interval
  - Exponential pieces [Dean04] \( \rightarrow \) exponential number of paths

**Pre-computation**
One needs to consider all possible paths (since SP is not unique) between all possible source and destination nodes
Outline

- KNN Search Past and Present
- Motivation
- Related Work
- Time-Dependent Spatial Network
- TD-kNN Search Approaches
  - Time-Expanded Networks
  - Incremental Network Expansion
  - Indexing Time-Dependent Networks
- Conclusion
TD-kNN Approach-1
Time Expanded Networks (TEN)

- Given $G(V,E,T)$, discretize the time domain $T$ into $n$ points of time, and construct $n$ $G(V,E)$ graph. [Koehler02]
TD-kNN Approach-1
Time Expanded Networks (TEN)

- The weight of an edge in TEN is the time difference between the time events associated with its endpoints
- A time-dependent edge cost is represented as a static flow in the corresponding TEN

(a) $t=0$
(b) $t=10$
(c) $t=30$
(d) $t=20$

- Static Network
TD-kNN Approach-1
Time Expanded Networks (TEN)

• Pros
  – Enables time-dependent kNN problem to be solved by applying techniques developed for static networks hence recomputation is possible

• Cons
  – High storage: The network size is increased proportional to the number of snapshots (n)
  – Approximate Results: The state of the network between two snapshots is not captured
    • The query time can be between two snapshots $t_1$ and $t_2$ (e.g., $t=12$). However, only the edge weights at $t_1$ or $t_2$ can be used, hence causing errors. The error is accumulated along the path and is unbounded.
TD-kNN Approach-2

Incremental Network Expansion (INE)

- Modified Dijkstra algorithm for time-dependent spatial networks [Dreyfus 69]
  - Analogous to shortest path distances, arrival-time to nodes is used as the labels that form the basis of the greedy algorithm
- Expand the network based on the arrival-time to each node around \( q \) until \( k \) objects are found
TD-kNN Approach-2
Incremental Network Expansion (INE)

• Pros
  – INE provides exact results as compared to TEN

• Cons
  – Slow response time: the overhead of network expansion is very high particularly in large networks with a sparse set of data objects, hence not applicable to online apps
TD-kNN Approach-3
Indexing Time-Dependent Spatial Network [DEXA2010]

- Edge cost function

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

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)

Tight Cells (TC)

Lower-bound cost

Upper-bound cost

cost

t

P1

P2

P3

P4

P5

P6
TD-kNN Approach-3
Indexing Time-Dependent Spatial Network

• Loose Cells (LC)

  - Loose Cells cover the entire network.
  - Any query point $q$ outside of the Loose Cell of $p$ is guaranteed not to have $p$ as its NN.
  - If $q$ is not inside any TC, it must be inside one (or more) LC(s) and the generator of those LCs are the only NN candidates.

Index TCs and LCs with a spatial index (e.g., R-tree, Quad-tree) to expedite the process of finding the tight/loose cell(s) that contain $q$.

Grow SP trees from each site simultaneously using LFT for one site and UFT for the other sites.
TD-kNN Approach-3
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 [DEXA’10]

Naïve Approach = INE with Dreyfus’s Dijkstra

\( k \) vs Response Time

\( k \) vs Network Node Access

\( \text{Naive Approach} \)

\( \text{TD-kNN} \)

Node Access (%)
Outline

• KNN Search Past and Present
• Motivation
• Related Work
• Time-Dependent Spatial Network
• TD-kNN Search Approaches
  – Time-Expanded Networks
  – Incremental Network Expansion
  – Indexing Time-Dependent Networks
• Conclusion
Conclusion

• In real-world edge weights are time-dependent.
  – New techniques needed to extend spatial query processing (such as kNN queries) in RN to a new family of time-dependent query processing solutions.

• Existing approaches (TEN and INE) can be extended to address time-dependent kNN; not efficient and exact.

• Indexing time-dependent network (on TCs and LCs) is an efficient and scalable approach.
• Motivation: Transportation
• Platform: TransDec
• Traffic Profiles
  – Data Reduction Approach
• Applications: Time-Dependent kNN
• Demonstration
• Future Plans
GeoInsight: A framework for spatiotemporal analysis of traffic density

Traffic Heatmaps: Spatiotemporal analysis of traffic congestion in LA
Season: Spring
Day: Monday
**Time: 9:30 AM**

Traffic patterns in north-east direction

*Navigate in time for different Season/Day/Hour traffic pattern visualization*

Season: Spring
Day: Monday
**Time: 5:30 PM**

Traffic patterns in north-east direction
• Motivation: Transportation
• Platform: TransDec
• Traffic Profiles
  – Data Reduction Approach
• Applications: Time-Dependent kNN
• Demonstration
• Future Plans
Future Work

- Data Reduction & Modeling
  - Trying other approaches: Sampling, Wavelets, …
  - Add temporal tags to spatial tags
  - Use models to generate traffic data for un-equipped roads
- Time-dependent shortest path
  - Evaluate the proposed indexing techniques
  - Other spatial queries: RkNN, spatial-skyline, …
- Closed-loop, holistic, real-time transportation optimization
  - Complementing analysis with decision-making and actuation to close the optimization loop
  - Developing scalable optimization solutions that consider the integrated transportation system as a whole
  - Introducing efficient data analysis techniques to enable on-the-fly decision making
References

• 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

• Ugur Demiryurek, Bei Pan, Farnoush Banaei-Kashani, and Cyrus Shahabi, Towards Modeling the Traffic Data on Road Networks, ACMGIS 2009 Workshop on Computational Transportation Science , Seattle, Washington, November 2009


• J. Halpern. *Shortest route with time dependent length of edges and limited delay possibilities*. In MMO, 1969.


Thanks!