Spatial Big Data & Smart Urban Transportation

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Thanks: Sponsors: NSF, USDOD, NASA, USDOT, USDOE, Ford URP, IBM, Microsoft, …
UMN: Center for Transportation Studies, Spatial Computing Group students
Outline

• Background
  – Patial Big Data
  – Spatial Computing Audience: Niche => Everyone

• Transportation Projects
  – 1992: Advanced Traveler Information System
  – 2003: Evacuation Route Planning
  – 2012: Eco-Routing
  – 2015: On-demand Transportation Brokers

• Conclusions
Spatial Computing

- Transformed our lives through understanding spaces and places
  - Ex.: localization, navigation, site selection, precision agriculture, ...
  - Examples: spatial context, situation assessment (distribution, patterns), ...

- Companies and technologies used in spatial computing:
  - ArcGIS
  - Google Earth
  - SaTScan
  - OGC
  - OpenStreetMap
  - Oracle Spatial
  - Ushahidi
  - IBM Smarter Planet
  - Pokémon GO
The study estimates that the use of personal location data could save consumers worldwide more than $600 billion annually by 2020. Computers determine users’ whereabouts by tracking their mobile devices, like cellphones. The study cites smartphone location services including Foursquare and Loopt, for locating friends, and ones for finding nearby stores and restaurants.

But the biggest single consumer benefit, the study says, is going to come 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. The location tracking, McKinsey says, will work either from drivers’ mobile phones or GPS systems in cars.

New Ways to Exploit Raw Data May Bring Surge of Innovation, a Study Says
Outline

• Background
• Transportation Projects
  – 1992: Advanced Traveler Information System (or Location Based Services)
  – 2003: Evacuation Route Planning
  – 2012: Eco-Routing
  – 2015: On-demand Transportation Brokers
• Conclusions
ATIS or Location Based Services

- **Location**: Where am I? (street address, <latitude, longitude>)
- **Directory**:
  - What is around me?
  - Where is the nearest clinic (or ambulance)?
- **Routes**: What is the shortest path to reach there?
Models: Spatial Graphs & Flow Networks

- Ex.: Roadmaps, Electric grid, Supply chains, ...
- Graphs: Nodes, Edges, Routes, ...
- Flow networks: Capacity constrain
- Operations:
  - Geo-code, Map-matching, ...
  - Connectivity, shortest path, nearest neighbor
  - Logistics: Site selection, Allocation, Max-flow, ...

Graph Data for UMN Campus
Courtesy: Bing

<table>
<thead>
<tr>
<th>Nodes</th>
<th>Edges</th>
</tr>
</thead>
<tbody>
<tr>
<td>NID</td>
<td>EID</td>
</tr>
<tr>
<td>N1</td>
<td>E1</td>
</tr>
<tr>
<td>N2</td>
<td>E2</td>
</tr>
<tr>
<td>N3</td>
<td>E3</td>
</tr>
<tr>
<td>N4</td>
<td>E4</td>
</tr>
<tr>
<td>N5</td>
<td>E5</td>
</tr>
<tr>
<td>N6</td>
<td>E6</td>
</tr>
<tr>
<td>N7</td>
<td>E7</td>
</tr>
<tr>
<td>N8</td>
<td>E8</td>
</tr>
<tr>
<td>N9</td>
<td>...</td>
</tr>
</tbody>
</table>
Advanced Traveller Information Systems

**Evacuation Route Planning**

- Parallelize Range Queries
- Shortest Paths
- Storing graphs in disk blocks

- Only in old plan
- Only in new plan
- In both plans
• Background
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Next Generation Navigation Services

- Eco-Routing
- Best start time
- Road-capacity aware, e.g., evacuation route planning

Why UPS trucks (almost) never turn left - CNN.com

www.cnn.com/2017/02/16/world/ups-trucks-no-left-turns/

Feb 23, 2017 - Left-hand turns are dangerous and wasteful, data shows. By avoiding them, UPS saves 10 million gallons of fuel each year. ... pedestrians than right ones, according to data collected by New
Routing Challenges: Lagrangian Frame of Reference

Q? What is the cost of Path <A,C,D> with start-time t=1? Is it 3 or 4?

Snapshots of a Graph

<table>
<thead>
<tr>
<th>Path</th>
<th>T = 0</th>
<th>T = 1</th>
<th>T = 2</th>
<th>T = 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;A,C,D&gt;</td>
<td>4</td>
<td>3</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>&lt;A,B,D&gt;</td>
<td>6</td>
<td>4</td>
<td>4</td>
<td>3</td>
</tr>
</tbody>
</table>

Lagrangian Graph

Representations of (Spatio-)temporal Networks

(1) **Snapshot Model** [Guting 04]

Node: \( N_i \)  
Edge: Travel time

(2) **Time Expanded Graph (TEG)** [Ford 65]

Attributes aggregated over edges and nodes.

(3) **Time Aggregated Graph (TAG)** [Our Approach]

Features aggregated over edges and nodes.

- Holdover Edge
- Transfer Edges

Edge: \( [m_1, \ldots, m_T] \)  
\( m_i \)- travel time at \( t = i \)
TAG vs. TEG: Storage Cost Comparison

Trend: TAG better than TEG on storage overhead!

<table>
<thead>
<tr>
<th>Dataset</th>
<th># Nodes</th>
<th># Edges</th>
</tr>
</thead>
<tbody>
<tr>
<td>(MPLS -1/2)</td>
<td>111</td>
<td>287</td>
</tr>
<tr>
<td>(MPLS -1 mi)</td>
<td>277</td>
<td>674</td>
</tr>
<tr>
<td>(MPLS - 2 mi)</td>
<td>562</td>
<td>1443</td>
</tr>
<tr>
<td>(MPLS - 3 mi)</td>
<td>786</td>
<td>2106</td>
</tr>
</tbody>
</table>
Routing Algorithms - Challenges

Find the shortest path travel time from N1 to N5 for start time $t = 1$.

<table>
<thead>
<tr>
<th></th>
<th>N1</th>
<th>N2</th>
<th>N3</th>
<th>N4</th>
<th>N5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>✗</td>
<td>∞</td>
<td>∞</td>
<td>∞</td>
<td>∞</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>✗</td>
<td>3</td>
<td>∞</td>
<td>∞</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>2</td>
<td>✗</td>
<td>3</td>
<td>∞</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>✗</td>
<td>∞</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>8</td>
</tr>
</tbody>
</table>

Dijkstra’s algo.: Reaches N5 at $t=8$.

Optimal path: Reach N4 at $t=3$;
Wait for $t=4$;
Reach N5 at $t=6$
Total time = 5

Total time = 7
Routing Algorithms – Alternate Semantics

Finding the shortest path from N1 to N5..

Start at t=1:
Shortest Path is N1-N3-N4-N5;
Travel time is 6 units.

Start at t=3:
Shortest Path is N1-N2-N4-N5;
Travel time is 4 units.

Fixed Start Time Shortest Path

Least Travel Time (Best Start Time)

Shortest Path is dependent on start time!!
TAG Classification

Future

Predictable

Unpredictable

Ranking of alternate routes

Static

Stationary

Non-stationary

- N1
- N2
- N3
- N4
- N5

[2,2,2,2,2] [3,3,3,3,3] [3,3,3,3,3] [2,2,2,2,2] [1,1,1,1,1]

[2,3,4,5,6] [2,3,4,5,6] [2,3,4,5,6] [2,3,4,5,6] [2,3,4,5,6]

[3,4,5,6,7] [3,4,5,6,7] [3,4,5,6,7] [3,4,5,6,7] [3,4,5,6,7]

[1,1,1,1,1] [1,1,1,1,1] [1,1,1,1,1] [1,1,1,1,1] [1,1,1,1,1]
**Spatio-temporal Graphs: Computational Challenges**

**Ranking changes over time**

Violates stationary assumption in Dynamic Programming

<table>
<thead>
<tr>
<th>Time</th>
<th>Preferred Routes</th>
</tr>
</thead>
<tbody>
<tr>
<td>7:30am</td>
<td>Via Hiawatha</td>
</tr>
<tr>
<td>8:30am</td>
<td>Via Hiawatha</td>
</tr>
<tr>
<td>9:30am</td>
<td>via 35W</td>
</tr>
<tr>
<td>10:30am</td>
<td>via 35W</td>
</tr>
</tbody>
</table>

**Waits, Non FIFO Behavior**

Violate assumption of Dijkstra/A*

<table>
<thead>
<tr>
<th>Time</th>
<th>Route</th>
<th>Flight Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>8:30am</td>
<td>via Detroit</td>
<td>6 hrs 31 mlns</td>
</tr>
<tr>
<td>9:10am</td>
<td>direct flight</td>
<td>2 hrs 51 mlns</td>
</tr>
<tr>
<td>11:00am</td>
<td>via Memphis</td>
<td>4 hrs 38 mlns</td>
</tr>
<tr>
<td>11:30am</td>
<td>via Atlanta</td>
<td>6 hrs 28 mlns</td>
</tr>
<tr>
<td>2:30pm</td>
<td>direct flight</td>
<td>2 hrs 51 mlns</td>
</tr>
</tbody>
</table>

*Flights between Minneapolis and Austin (TX)

**Details:** A Critical-Time-Point Approach to All-Start-Time Lagrangian Shortest Paths: A Summary of Results, (w/ V. Gunturi et al.), Proc. Intl. Symp. on Spatial and Temporal Databases, Springer LNCS 6849, 2011. Complete results accepted for the IEEE Transactions on Knowledge and Data Engineering.
Routing in ST Networks: Scalable Methods

Predictable Future

Stationary

Dijkstra’s, A*….

Non-stationary

Special case (FIFO)

TEG: LP, Label-correcting

Unpredictable Future

General Case

TAG: Transform to Stationary TAG

travel times → arrival times at end node → Min. arrival time series

Non-stationary TAG

Stationary TAG
TAG Transformations: Decomposition

Motivation: Simplify analysis, e.g. change in snapshot property, e.g. central node, ...

Result is a collection of Stationary TAG.

Dynamic programming may be used within each sub-TAG!
Spatial Big Data driven Route Preference

Spatially oriented datasets exceeding capacity of current routing systems

- Due to Volume, Velocity (Update-rate) and, Variety

NSF
Sample Engine Sub-System Measurement Data

Engine Sub-system Measurements from Metro-Transit Buses in Twin-Cities

Sample Engine Variables:
- GPS Speed and Position
- Vehicle Load
- Engine and Heater Fuel Flow
- Exhaust Temp and Mass Flow
- Intake Temp And Mass Flow
- Engine Torque and RPM
- Engine Coolant Temp
- Odometer
- 
- 
- 
- 
- ....measurements on 20 engine variables
Sample Patterns in the Data

- Mined temporal signatures of engine variables which are highly associated elevated NOx

<table>
<thead>
<tr>
<th>ID</th>
<th>NWC Pattern C</th>
<th>$K_{C,W_N} (2)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>${w_0, w_0, w_0, w_1, w_2}$</td>
<td>21.57</td>
</tr>
<tr>
<td>2</td>
<td>Engine RPM: ${s_1, s_2, s_3, s_3, s_3}$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Engine power: ${r_5, r_5, r_5, r_5, r_5}$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Wheel speed: ${w_0, w_0, w_0, w_0, w_0}$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Acceleration: ${a_{16}, a_{16}, a_{17}, a_{17}, a_{17}}$</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Engine RPM: ${s_1, s_1, s_2, s_3, s_3}$</td>
<td>16.28</td>
</tr>
<tr>
<td></td>
<td>Engine power: ${r_5, r_5, r_5, r_5}$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Wheel speed: ${w_1, w_0, w_0, w_0, w_0}$</td>
<td>17.15</td>
</tr>
</tbody>
</table>
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- Eco-Routing
- Best start time
- Road-capacity aware

<table>
<thead>
<tr>
<th>Static</th>
<th>Time-Variant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Which is the shortest travel time path from downtown Minneapolis to airport?</td>
<td>Which is the shortest travel time path from downtown Minneapolis to airport at different times of a work day?</td>
</tr>
<tr>
<td>What is the capacity of Twin-Cities freeway network to evacuate downtown Minneapolis?</td>
<td>What is the capacity of Twin-Cities freeway network to evacuate downtown Minneapolis at different times in a work day?</td>
</tr>
</tbody>
</table>
Societal Challenge: Large Scale Evacuation

Hurricane: Andrews, Rita

- Traffic congestions on all highways
  - e.g. 100-mile congestion (TX)
- Great confusions and chaos

"We packed up Morgan City residents to evacuate in the a.m. on the day that Andrew hit coastal Louisiana, but in early afternoon the majority came back home. The traffic was so bad that they couldn’t get through Lafayette."
Mayor Tim Mott, Morgan City, Louisiana

(http://i49south.com/hurricane.htm)

I-45 out of Houston
(FEMA.gov)
Problem Dimensions

- **Policy Decisions**

- **Computer Science**:
  How to scale up to large roadmaps and populations?

- **(Spatio-temporal) Data Availability**
  - Estimate evacuee population, available transport capacity
  - Pedestrian data: walkway maps, link capacities based on width

- **Traffic Eng.**
  - Link capacity depends on traffic density
  - Modeling traffic control signals, ramp meters, contra-flow, …

- **Evacuee Behavior (Social Science)**
  - Unit of evacuation: Individual or Household
  - Heterogeneity: by physical ability, age, vehicle ownership, language, …
  - How to gain public’s trust in plans? Will they comply?

- **Science**:
  How does one evaluate an evacuation planning system?
Advisory Board

MEMA/Hennepin Co. - Tim Turnbull, Judith Rue
Dakota Co. (MEMA) - David Gisch
Minneapolis Emergency Mgt. - Rocco Forte, Kristi Rollwagen
St. Paul Emergency Mgt. - Tim Butler
Minneapolis Fire - Ulie Seal
DPS HSEM - Kim Ketterhagen, Terri Smith
DPS Special Operations - Kent O’Grady
DPS State Patrol - Mark Peterson

Workshops

Over 100 participants from various local, state and federal govt.
# Workshop Participants

## Federal, State, County, City
- **Gerald Libbe**, Federal Highway Administration (FHWA)
- **Katie Belmore**, Representing Wisconsin Department of Transportation

## Airports
- George Condon, Metropolitan Airports Commission

## Businesses
- **Chris Terzich**, Minnesota Information Sharing and Analysis Center
- **Barry Gorelick**, Minnesota Security Board

## Communications and Public Information
- **Kevin Gutknecht**, Mn/DOT
- **Lucy Kender**, Mn/DOT
- **Andrew Terry**, Mn/DOT

## Dispatch
- Keith Jacobson, Mn/DOT

## Education
- **Bob Fischer**, Minnesota Department of Education
- **Dick Guevremont**, Minnesota Department of Education

## Emergency Management
- **Bruce Wojcik**, Anoka County Emergency Management
- **Tim Walsh**, Carver County Emergency Management
- **Jim Halstrom**, Chisago County Emergency Management
- **David Gisch**, Dakota County Emergency Preparedness
- **Tim O'Laughlin**, Scott County Sheriff – Emergency Management
- **Tim Turnbull**, Hennepin County Emergency Preparedness
- **Judith Rue**, Hennepin County Emergency Preparedness
- **Rocco Forte**, Minneapolis Fire Department – Emergency Preparedness
- **Kristi Rollwagen**, Minneapolis Fire Department – Emergency Preparedness
- **William Hughes**, Ramsey County Emergency Management and Homeland Security
- **Tim Butler**, St. Paul Fire and Safety Services
- **Deb Paige**, Washington County Emergency Management
- **Kim Ketterhagen**, Department of Public Safety (DPS) HSEM
- **Sonia Pitt**, Mn/DOT HSEM
- **Bob Vasek**, Mn/DOT HSEM

## Fire
- **Gary Sigfrinius**, Forest Lake Fire Department

## Health
- **Debran Ehret**, Minnesota Department of Health

## Hospitals
- **Dan O’Laughlin**, Metropolitan Hospital Compact

## Human Services
- **Glenn Olson**, Minnesota Department of Human Services

## Law Enforcement
- **Brian Johnson**, Hennepin County Sheriff
- **Jack Nelson**, Metro Transit Police Department
- **David Indrehus**, Metro Transit Police Department
- **Otto Wagenpfeil**, Minneapolis Police Department
- **Kent O'Grady**, Minnesota State Patrol
- **Mark Peterson**, Minnesota State Patrol
- **Chuck Walarius**, Minnesota State Patrol
- **Douglas Biehn**, Ramsey County Sheriff’s Office
- **Mike Morehead**, St. Paul Police

## Maintenance and Operations
- **Beverly Farraher**, Mn/DOT
- **Gary Workman**, Mn/DOT
- **Robert Wryk**, Mn/DOT

## Military
- **Daniel Berg**, Marine Safety Office St. Louis Planning Division

## Planning
- **Connie Kozlak**, MetCouncil

## Public Works
- **Bill Cordell**, Wright County
- **Jim Gates**, City of Bloomington
- **Jim Grube**, Hennepin County
- **Bob Winter**, Mn/DOT
- **Klara Fabry**, City of Minneapolis
- **Mark Kennedy**, City of Minneapolis
- **Gary Erickson**, Hennepin County
- **Dan Schacht**, Ramsey County

## Safety
- **Thomas Cherney**, Minnesota Department of Public Safety
- **Doug Thies**, Mn/DOT

## Security
- **Paul Pettit**, Transportation Security Administration

## Transit
- **Dana Rude**, Metro Mobility
- **Steve McLaird**, MetroTransit
- **Christy Bailly**, MetroTransit
- **David Simoneau**, SouthWest Metro Transit

## Traffic
- **Thomas Bowlin**, City of Bloomington
- **Jon Wertjes**, City of Minneapolis
- **Bernie Arseneau**, Mn/DOT
- **Amr Jabr**, Mn/DOT
- **Eil Kwon**, Mn/DOT
- **Paul St. Martin**, City of St. Paul

## Trucking
- **John Hausladen**, Minnesota Trucking Association

## University
- **Dan JohnsonPowers**, University of Minnesota Emergency Management

## Volunteer Organizations
- **Gene Borochoff**, Minnesota Volunteer Organization active in Disaster
Computational Problem: Evacuation Route Planning

**Given**
- Number of evacuees and their initial locations
- Evacuation destinations
- A transportation network, a directed graph $G = (\text{Nodes, Edges})$ with
  - Travel time for each edge
  - Capacity constraint for each edge and node

**Output**
- Evacuation plan = a set of origin-destination routes & schedule

**Objective**
- Minimize evacuation time

**Constraints**
- (Spatio-temporal) Data Feasibility
- Computational Scalability to large population and geographies
- (Societal) Application Domain Interpretability and value
  - Transportation Network Capacity $\ll$ Number of evacuees
Spatio-temporal Data Feasibility

• (Spatio-temporal) Data Feasibility
  • Is it doable with available geographic dataset?
  • Does it require new geo-datasets, surveys, mapping efforts?

• Digital Road Maps
  • Are Navteq, OpenStreetMap digital roadmaps adequate?
  • Capacity constraints: TP+ (Tranplan) has major roads

• Evacuee Population
  • Is Census Data adequate? Timely?
  • Day-time population – employment, school, tourist, events, …
  • Location-aware Smart-phones estimate real-time population
Computational Feasibility

Computational Scalability to large population and geographies

Is it computable in reasonable time with current hardware, software?

Does it require computer science advances?

A. Related Work in Transportation Sc.: Dynamic Traffic Assignment

- Game Theory: Wardrop Equilibrium, e.g. DYNASHMART (FHWA), DYNAMIT(MIT)

**Limitation:** Nice Game Theory, but Extremely high computation time

- Does not scale to medium size networks and populations!

B. Related Work Operations Research: Time-Expanded Graph + Linear Prog.

- Optimal solution, e.g. EVACNET (U. FL), Hoppe and Tardos (Cornell U).

**Limitation:**
- High computational complexity => Does not scale to large problems
- Users need to guess an upper bound on evacuation time
  Inaccurate guess => either no solution or increased computation cost!

<table>
<thead>
<tr>
<th>Number of Nodes</th>
<th>50</th>
<th>500</th>
<th>5,000</th>
<th>50,000</th>
</tr>
</thead>
<tbody>
<tr>
<td>EVACNET Running Time</td>
<td>0.1 min</td>
<td>2.5 min</td>
<td>108 min</td>
<td>&gt; 5 days</td>
</tr>
</tbody>
</table>

C. Computer Science: Capacity Constrained Route Planner

- Extends shortest-path algorithms to honor capacity constraints
- Scales up to to Millions of evacuees over hundreds of square miles
1. Model node capacity and edge capacity as a time series instead of a fixed number.

Time series representation:

For a given node $N_i$:

\[
\text{Available	extunderscore Node	extunderscore Capacity} ( N_i , t ) = \text{Available capacity of node } N_i \text{ at time } t
\]

For a given edge $N_i - N_j$:

\[
\text{Available	extunderscore Edge	extunderscore Capacity} ( N_i - N_j , t ) = \text{Available capacity of edge } N_i - N_j \text{ at time } t
\]

2. Generalize shortest-path algorithm to account for time-variant capacity constraints
Performance Evaluation

Setup: fixed number of evacuees = 5000, fixed number of source nodes = 10 nodes, number of nodes from 50 to 50,000.

- CCRP produces high quality solution, solution quality increases as network size grows.
- Run-time of CCRP is scalable to network size.

Figure 1 Quality of solution

Figure 2 Run-time

<table>
<thead>
<tr>
<th>Number of Nodes</th>
<th>Running Time (second)</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td>CCRP: 0.1, NETFLO: 0.3</td>
</tr>
<tr>
<td>500</td>
<td>CCRP: 1.5, NETFLO: 25.5</td>
</tr>
<tr>
<td>5000</td>
<td>CCRP: 23.1, NETFLO: 962.2</td>
</tr>
<tr>
<td>50000</td>
<td>CCRP: 316.4, NETFLO: 962.2</td>
</tr>
</tbody>
</table>
Contributions

- Computer Science: New algorithm to scale up to metropolitan scenarios
- Transportation Science: Walking first mile speeds up evacuation by factor of 3
- Policy: Increase public trust in evacuation plans

Societal Impact highlighted in Fox TV (KMSP) evening news

A 5-minute video-clip is at http://www.cs.umn.edu/~shekhar/talk/video/fox9_aired_mpg.avi
It highlighted the evacuation route planning work along with its social impact including those on evacuation plan for Minneapolis-St. Paul Twincities.

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• Conclusions
Motivation

• Increasing proliferation of mobile technologies led to emergence of the **on-demand and sharing economies**, with $50+ billion in spending

• Need to investigate a *broker* that leverages real-time commerce opportunities among mobile consumers and service providers
  • How to meet large demand with a fixed supply?
**Basic Concepts**

- **Service Provider**: A provider registered in the system is defined using its location and service rate per hour over the day (e.g., 15 requests per hour).

- **Consumer Request**: A request from a mobile consumer, including the consumer’s current location, max. acceptable travel distance and max. acceptable waiting time before service.

- **Service Provider Proposition**: A quadruple \((r, p, d, w)\) where:
  - \(r \in\) set of available consumer requests
  - \(p \in\) set of registered service providers
  - \(d\): distance between \(r\) and \(p\)
  - \(w\): waiting time before \(r\) is served by \(p\)

Example: \((C_1, P_1, 2\text{ miles}, 5\text{ min})\)
Problem Definition: On-Demand Spatial Service Propositions

• **Input:**
  – A set $P$ of service providers
  – A set $R$ of consumer requests arriving dynamically
  – A number of required propositions $K$

• **Output:** $K$ service provider(s) propositions for each request

• **Objective:** Maximize number of matched requests

• **Constraints:**
  – Each returned proposition satisfies the consumer’s max. travel distance and waiting time constraints and does not violate the provider’s service rate.

• **Other considerations:**
  – Keeping the eco-system functioning by engaging many service providers
Challenges

- Need to satisfy many conflicting requirements of the broker, consumers and service providers:

- Ratio of demand to supply exhibits spatio-temporal heterogeneity

- Given a number of consumer requests and their candidate propositions at time t, finding the set of K-propositions that maximizes the matching size is an NP-Hard problem[1].
Limitations of Related Work

Keeps provider eco-system alive?

No

Least Travel Cost (LTC)
(ridesharing, spatial crowdsourcing)

Least Location Entropy Priority (LLEP)
(spatial crowdsourcing)

Yes

Proposed work
Least Accepted First (LAF),
Least appearance as Candidate First (LCF)
Proposed Approach

• Proposed a heuristic-based greedy matching algorithm

• Proposed a new category of service provider-centric heuristics:
  – **Least Accepted First (LAF):** Prioritize providers with least number of completed transactions.
    » Balances requests among providers
  – **Least appearance as Candidate First (LCF):** Prioritize providers with least number of occurrences in candidate lists.
    » favors providers in less populated regions, longer service times, and new providers.
**Experimental Setup**

- **Experimental Goal:** How the proposed heuristics compare to related work under different supply-demand scenarios?
- **Datasets:**
  - Simulate a fixed demand-supply ratio for each hour

- LTC: Least Travel Cost
- LLEP” Least Location Entropy Priority

- LAF: Least Accepted First
- LCF: Least appearance as Candidate First

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Simulator</th>
<th>Output statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>supply-demand ratio $s_{dr}$</td>
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<tr>
<td>No. required propositions $K$</td>
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<td></td>
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<tr>
<td>timeout interval length $t_{timeout}$</td>
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<tr>
<td>Range of provider service rates $[r_{min}, r_{max}]$</td>
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<td>Range of max. acceptable travel distance $[d_{min}, d_{max}]$</td>
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<tr>
<td>Range of max. acceptable waiting time $[w_{min}, w_{max}]$</td>
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<td>Grid cell length $l_G$</td>
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</tbody>
</table>
Summary of Experimental Results

- LAF achieved highest average no. of assigned requests/provider & least standard deviation
- For supply ≈ demand, LAF & LCF achieved the highest % of matches
- LAF engaged 100% of providers even when supply >> demand
• **Contributions:**
  – Formally defined the problem of On-demand Spatial Service propositions.
  – Proposed a greedy matching approach with a new category of provider-centric heuristics.
  – Experimental evaluation showed that proposed heuristics can achieve:
    • largest number of matched requests for balanced supply and demand,
    • best balance among providers when supply >> demand.

• **Future Work:**
  – Mobile service providers
  – Provider ratings
  – Profit variation
Conclusions

• Computation cost should not limit your work
  – Big Data
  – Large number of consumers and/or suppliers
  – Big Urban Areas
  – Interactive Response Time

• Midwest Big Data Hub
  – Access to big data & compute hardware and software
  – Workshop on big data platforms

• Transportation Projects
  – 1992: Advanced Traveler Information System
  – 2003: Evacuation Route Planning
  – 2012: Eco-Routing
  – 2015: On-demand Transportation Brokers