Decomposition of Congestion and Travel Time Reliability into Various Sources Using Link Speed Data

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NATMEC
July 1, 2014
Congestion Pie in PeMS

- PeMS collects many types of raw, detailed data
  - Fixed sensors or link-based
  - Incidents, events
  - Real-time or batch
- Performs many different types of computations
  - Imputes for bad sensors
  - Travel time
  - Spatial measures
- Congestion Pie Computation
  - Breaks down congestion by cause
  - A decomposition model
  - Starts with all congestion, pulls it apart to its components
- Causes of congestion
  - Excess demand
  - Sub-optimal ramp meters
  - Incidents
  - Other (unknown)
Innovation for better mobility

• We generate this for each route
• Allows us to explore, what sort of operational strategies should we pursue for each location?

Congestion Pie by Route

- Reduction
- Demand
- Accidents
- Miscellaneous

5-N 5-S 710-N 710-S
101-N 101-S 105-E 105-W
110-E 110-W 210-E 210-W
405-N 405-S 10-E 10-W

Sub-Optimal Ramp
Excess Demand
Incidents
(35%)
(7%)
(10%)

Innovation for better mobility
Example Investments

10-E
- Sub-Optimal Ramp Metering (57%)
- Incidents (10%)
- Excess Demand (7%)

10-W
- Sub-Optimal Ramp Metering (35%)
- Incidents (45%)
- Excess Demand (9%)

Ramp metering

Freeway service patrol
Current Work on Travel Time Reliability

- Extend congestion pie concepts to travel time reliability
  - Want to quantify the components of travel time reliability at individual freeways
  - Make an “Un-reliability Pie”

- Method:
  - Uses “link speed” data (3rd party data) to compute route travel times
  - Build a linear model of route travel time as a function of different variables (incidents, work zones, weather, etc)
  - Fit the 95th percentile (buffer time) of travel time on same variables

- Application:
  - “For I-5 in LA, with the planning time of 20 min, 10 min are due to incidents, 2 min are due to weather, and the remaining 8 min are due to inadequate base capacity”
  - This suggests that an operational response that reduces impact of incidents by half would improve travel time reliability by 5 min
Model

- Decomposition model
  - We know the total travel time and it’s statistics on a route
  - We know the various events that took place
  - Model travel time as a regression on the input variables
  - Model travel time reliability also as a regression on the input variables

- Input variables that we use:
  - incidents,
  - weather,
  - work zones,
  - special events,
  - and inadequate base capacity or bottlenecks.

- We use 95th percentile travel time as our metric for travel time reliability / variability.
  - Buffer time = 95th percentile of travel time – median travel time
Steps

1. Pick a date range, time period, and corridor:
   1. Date range needs to be homogeneous and long enough for "travel time reliability" to be meaningful. (e.g. weekdays during Q1 2013)
   2. Time period needs to be long enough to include effect of incidents (e.g. AM peak period of 5-10AM)
   3. Corridor needs to be large enough to include effect of incidents (e.g. 10-mile section)

2. Corridor-level aggregation of travel time:
   1. Could use any travel time data source, such as link speed data or loop data.
   2. We use 3rd party speeds

3. Corridor-level aggregation of source factors:
   1. Assemble daily n_crashes, rain, workzone variables.

4. Quantile regression to fit the 95th percentile of travel time on the source variables
   1. The result is tt_95th = b0 + b1*n_crashes + ...

5. Calculation of the contribution of individual sources to the buffer time.

\[
\text{Contribution of Factor } j = \beta_j \bar{x}_j \text{ (min), and}
\]

\[
\% \text{ Contribution of Factor } j = \frac{\beta_j \bar{x}_j}{\text{buffer time}} \times 100 \text{ . (}%.
\]
Example Application to a Route

- Applied to a 30.5-mi section of northbound I-880 in the San Francisco Bay Area, California.
- Data input: non-holiday weekdays for a year, over 3 periods:
  - 7-9AM
  - 11AM-1PM
  - 4-6PM
- The following variables are used:
  - n_crashes: TASAS database
  - rain: precipitation data
  - active work zone: Caltrans
  - special event (Coliseum)
- Use travel times from 3rd party data
Factors: Demand

- Demand drives some of delay
- But a lot of AM delay is due to the recurrent downstream bottleneck from I-580/980/880/80 crunch.
- Much of AM traffic's reliability pie could be ascribed to "demand/capacity".
Factors: Crashes

- Crashes drive some of travel time variability.
- Approximate 95th percentile at each number of crashes is shown.
- 95th percentile quantile regression for AM is: \( y = 46.8 + 1.28 \times n\_crashes \), shown in blue line.
Factors: Weather/Rain

- Rain in California?
- Rain adds somewhat to travel time variability
- But since it rains so little (volume), the effect is small
Factors: Work Zone

- Work zones happen mostly during noon time
- Or in the middle of the night (not shown)
- Hence, these don't affect travel time much
- Which is good management!
Factors: Special Events

- This section of roadways is next to the Oakland Coliseum
- These are concerts, baseball games, events, etc.
- They are rare and but seems to have some effect during PM travel times.
Quantile Regression

Regressing to get 95th percentile
Example of a solution:

**AM**: buffer_time = 46.0 + 1.67 * n_crashes + 6.17 * Rain + 1.02 * Work_zone

**PM**: buffer_time = 39.9 + 1.73 * n_crashes + 7.95 * Rain + 25.7 * Work_zone + 1.27 * Special event

Parameters are found by solving the standard regression optimization problem (need linear programming, though)
## Contributions of Each Factor

<table>
<thead>
<tr>
<th>Source</th>
<th>AM Minutes</th>
<th>AM %</th>
<th>Noon Minutes</th>
<th>Noon %</th>
<th>PM Minutes</th>
<th>PM %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant (capacity, demand fluctuation)</td>
<td>7.2</td>
<td>81.6%</td>
<td>6.52</td>
<td>76.4%</td>
<td>5.03</td>
<td>60.1%</td>
</tr>
<tr>
<td>Traffic Accidents</td>
<td>1.33</td>
<td>15.1%</td>
<td>0.02</td>
<td>0.3%</td>
<td>2.13</td>
<td>25.5%</td>
</tr>
<tr>
<td>Weather</td>
<td>0.25</td>
<td>2.8%</td>
<td>-0.12</td>
<td>-1.4%</td>
<td>0.41</td>
<td>4.9%</td>
</tr>
<tr>
<td>Work zones</td>
<td>0.04</td>
<td>0.5%</td>
<td>1.14</td>
<td>13.4%</td>
<td>0.72</td>
<td>8.6%</td>
</tr>
<tr>
<td>Special events</td>
<td>0</td>
<td>0.0%</td>
<td>0.97</td>
<td>11.4%</td>
<td>0.07</td>
<td>0.9%</td>
</tr>
<tr>
<td>Total Buffer Time</td>
<td>8.82</td>
<td>100.0%</td>
<td>8.53</td>
<td>100.0%</td>
<td>8.37</td>
<td>100.0%</td>
</tr>
<tr>
<td>Median Travel Time</td>
<td>38.82</td>
<td></td>
<td>29.02</td>
<td></td>
<td>34.82</td>
<td></td>
</tr>
<tr>
<td>95th Percentile</td>
<td>47.64</td>
<td></td>
<td>37.55</td>
<td></td>
<td>43.19</td>
<td></td>
</tr>
</tbody>
</table>

The pie charts represent the contributions of each factor for AM, Noon, and PM times.
Discussion/Next Steps

- **Discussion**
  - 99% of work is compiling the reliable source data for each day and each peak hours.
  - Leverages link speed data so it’s applicable in many places.
  - We expect to observe different breakdown of travel time reliability in different regions (e.g. larger weather "slice" in Minnesota compared to large incident "slice" in California).

- **Next Steps**
  - Currently implementing methodology to sit beside regular “congestion pie”
  - Allows for simultaneous reporting on congestion and reliability