Impact of atypical events on transportation demand

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Planning

1. Objectives
2. Literature review
3. Case study
4. Methods
5. Results
6. Limitations & conclusion
1. Objectives

- Understanding the impact of atypical events on transportation demand
- Understanding the role of each mode within a multimodal transport system, by comparing their response to various events
2. Literature review
Factors influencing short term travel demand

Meteorology:
- **Cyclists** are affected by weather from previous 3 hours
- **Public transport** is little affected by weather
- **Taxi** demand increases with rain, but the impact of snow is insignificant

Activities:
- During **traditional festivals** in Xi’an (China), subway demand increases by 19%

Subway service disruption:
- After a 10 minutes disruption, 34% of users look for an alternative mode
- 17% of users choose public transit as an alternative mode

Vancouver, Montréal (Gallop et al., 2012; Miranda-Moreno et Nosal, 2011)
Chicago, Pays-bas (Guo et al., 2007; Sabir, 2011; Stover et McCormack, 2012)
New York City (Kamga et al., 2013)
Xi’an, Chine (Tao et al., 2014)
Toronto (Lin, 2017)
3. Case study

- Study area: Montreal
- Modes: bikesharing, taxi, subway, bus
- Level: overall system
- Spatial aggregation: subway station surroundings (800m network distance)
- Period: working days from 2015 to 2017
3. Case study

• Study area: Montreal
• Modes: bikesharing, taxi, subway, bus
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• Spatial aggregation: subway station surroundings (800m network distance)
• Period: working days from 2015 to 2017
3. Data

Data sources

<table>
<thead>
<tr>
<th>Data</th>
<th>Objects</th>
<th>Data collection</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Transcational data</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bikesharing</td>
<td>16M transactions</td>
<td>continuous</td>
<td>Bixi (operator)</td>
</tr>
<tr>
<td>Taxi</td>
<td>11M rides</td>
<td>continuous</td>
<td>Taxi Diamond (25% of fleet)</td>
</tr>
<tr>
<td>Subway</td>
<td>747M smart card validations</td>
<td>continuous</td>
<td>Montreal Transport Authority</td>
</tr>
<tr>
<td>Bus</td>
<td>1,2B smart card validations</td>
<td>continuous</td>
<td>Montreal Transport Authority</td>
</tr>
<tr>
<td><strong>Events data</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weather</td>
<td>26K hourly data and 1,096 daily data</td>
<td>Hourly &amp; daily</td>
<td>Environment Canada</td>
</tr>
<tr>
<td>Activities</td>
<td>1,772 activities near subway stations</td>
<td>Before activities</td>
<td>Montreal Transport Authority</td>
</tr>
<tr>
<td>Service disruptions</td>
<td>3,051 subway service disruptions</td>
<td>Continuous</td>
<td>Montreal Transport Authority</td>
</tr>
</tbody>
</table>
3. Data integration challenges

Different spatial contexts

Solution: Aggregate by subway station surrounding

Varying data collection interval (continuous, hourly, daily)

Solution: Aggregate data by hour

Demand is of a different order of magnitude for modes and stations

Solution: normalize demand by mode and station
4. Method

Objective: generalised additive model (GAM)

Methodology:
1. Demand normalization
2. Data fusion
3. Variable selection
4. Model calibration

\[ i_{n, a, s} = \frac{d_{n, a, s}}{m_{a, s}} \]

\[ m_{a, s} = \frac{1}{n_a} \sum_{h=1}^{n_a} d_{h, a, s} \]

\[ i_{n, a, s} = \frac{d_{n, a, s}}{m_{a, s}} \]

\( h \): time period
\( a \): year
\( s \): subway station
\( n_a \): nb time periods

<table>
<thead>
<tr>
<th>timestamp</th>
<th>mode</th>
<th>station</th>
<th>departures</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015-04-27 16:00</td>
<td>bikesharing</td>
<td>Bonaventure</td>
<td>59</td>
</tr>
<tr>
<td>2015-04-27 16:00</td>
<td>bikesharing</td>
<td>Viau</td>
<td>2</td>
</tr>
<tr>
<td>2015-04-27 16:00</td>
<td>bikesharing</td>
<td>McGill</td>
<td>142</td>
</tr>
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<tr>
<td>2015-04-27 16:00</td>
<td>bikesharing</td>
<td>Bonaventure</td>
<td>1,02</td>
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<td>2015-04-27 16:00</td>
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<td>Viau</td>
<td>0,88</td>
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<tr>
<td>2015-04-27 16:00</td>
<td>bikesharing</td>
<td>McGill</td>
<td>1,08</td>
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<td>...</td>
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</tbody>
</table>
Model equation

\[
\ln(\text{intensity}) = \beta_0 + \beta_1 \text{rain} + \beta_2 \text{wind} + f_1(\text{temperature}) + f_2(\text{disrupt.}) + \sum_{i=1}^{10} \alpha_i \text{activity}_i + \sum_{i=1}^{7} \gamma_i \text{period}_i + \epsilon
\]
\[
\ln(\text{intensity}) = \beta_0 + \beta_1 \text{rain} + \beta_2 \text{wind} + f_1(\text{temperature}) + f_2(\text{disrupt.}) + \sum_{i=1}^{10} \alpha_i \text{activity}_i + \sum_{i=1}^{7} \gamma_i \text{perio}de_i + \epsilon
\]

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>intercept</td>
<td>0.443*</td>
</tr>
<tr>
<td>rain</td>
<td>-0.072*</td>
</tr>
<tr>
<td>wind</td>
<td>-0.001*</td>
</tr>
<tr>
<td>temperature</td>
<td>spline</td>
</tr>
<tr>
<td>disruption</td>
<td>spline</td>
</tr>
<tr>
<td>activities</td>
<td>-</td>
</tr>
<tr>
<td>6am</td>
<td>0.303*</td>
</tr>
<tr>
<td>7am</td>
<td>0.090*</td>
</tr>
<tr>
<td>8am</td>
<td>0.405*</td>
</tr>
<tr>
<td>9am</td>
<td>0.077*</td>
</tr>
<tr>
<td>10 – 11am</td>
<td>-0.101*</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
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</tbody>
</table>

*Significant at a 95% level
\[ \ln(\text{intensity}) = \beta_0 + \beta_1 \text{rain} + \beta_2 \text{wind} + f_1(\text{temperature}) + f_2(\text{disrupt.}) + \sum_{i=1}^{10} \alpha_i \text{activity}_i + \sum_{i=1}^{7} \gamma_i \text{period}_i + \epsilon \]
Temperature variable

Intensity variation with temperature

Intensity variation

Temperature (°C)

mode
- bike
- bus
- subway
- taxi
Subway service disruptions

\[
\ln(\text{intensity}) = \beta_0 + \beta_1 \text{rain} + \beta_2 \text{wind} + f_1(\text{temperature}) + f_2(\text{disrupt.}) + \sum_{i=1}^{10} \alpha_i \text{activity}_i + \sum_{i=1}^{7} \gamma_i \text{periode}_i + \epsilon
\]

Smoothing spline
Subway service disruptions

Intensity variation as a function of service disruption duration

![Intensity variation graph](image-url)
ln(intensity) = β₀ + β₁ rain + β₂ wind + f₁(temperature) + f₂(disrupt.) + ∑_{i=1}^{10} αᵢ activityᵢ + ∑_{i=1}^{7} γᵢ periodᵢ + ε

Activities

Intensity variation

Activity types

Mode
- bike
- bus
- subway
- taxi
Different models for every station
Rain variable

Intensity variation of bikesharing in the presence of rain (1 hour of rain)
6. Limitations

Data limitations:
• No unique id to follow users throughout all modes
• Unknown boarding location for bus
• Only the subway station where the disruption originates is known

Method limitations:
• Station neighborhood areas overlap so trips can be counted multiple times
• Availability of bicycles at bikesharing stations not considered
• Impact of events might differ according to season or time of day
6. Conclusion

Applications:
- Contribute to demand forecasting models
- Dynamic adjustment of supply according to demand

Perspectives:
- Analyse other modes of transportation
- Analyse arrivals
- Test other station neighborhood definitions
- Compare with time series models
Thanks!

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References


