(Other) Smart City Services

Tarek Abdelzaher
Dept. of Computer Science
University of Illinois at Urbana Champaign
Recap

- Sensing in social spaces informs data-centric applications in two ways:
Recap

- Sensing in social spaces informs data-centric applications in two ways:
  - First approach:
    - Statistics
Recap

- Sensing in social spaces informs data-centric applications in two ways:
  - Second approach:

Modeling
Recap

Sensing in social spaces informs applications in two ways:

- **Offers data statistics:**
  - Statistics need a lot of data → Can’t generate statistics if you did not measure.
  - *Example:* report speed of traffic on different streets by multiple cars and empirically compute the average

- **Allows data modeling:**
  - Models allow inferring values of these variables even in places where you did not measure
  - *Example:* generate a model that predicts traffic speed as a function of speed limit, number of lanes, time of day, and day of the week, and weather (dry/rain/etc)
CityDrive: Predicting Traffic Light Schedules

Fuel burned

Energy wasted

Velocity

Slides by Yiran Zhao, Infocomm 2014 (with minor re-formatting)
Smartphone-based Prediction

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Locating Intersections

- Car stops for more than 10 seconds before accelerating? → Intersection

Possible locations of intersections

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Group acceleration vectors with approximately the same direction into one cluster. Each cluster should represent one branch of the intersection.

- Intersections with less than 3 or greater than 5 clusters are removed.
- Intersections with outgoing vectors, are removed.

(a) Invalid intersection
(b) Valid intersection

Slides by Yiran Zhao, Infocomm 2014 (with minor re-formatting)
Linking Intersections

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A vehicle stops and waits for green light. Waiting at time T0.

On detection of acceleration, smartphone records time T1.

On detection of entering another branch, smartphone records time T2.

Smartphone sends \{wait time: (T1-T0); acc. time: (T2-T1); branch: I1,O3; ID\} to the server.

Detect Cycle Length

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Phase Sequence Inference

- Once the traffic signal cycle length $T_c$ is obtained, the sequence of states $\{S_i, i = 1, 2, ..., N\}$ are to be determined.
- Ideally, and typically, there are four states after complete merging:

- And the above four states should happen in sequence:
  $$S_1 \rightarrow S_2 \rightarrow S_3 \rightarrow S_4 \rightarrow S_1...$$
- We give a new name to states that are in sequence and in closed loop: phase.

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Results

- Less getting stuck in red lights

(a) With CityDrive
(b) Without CityDrive

<table>
<thead>
<tr>
<th></th>
<th>With CityDrive</th>
<th>Without CityDrive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy consumption</td>
<td>13.9</td>
<td>33.7</td>
</tr>
<tr>
<td>Number of acceleration</td>
<td>0.09</td>
<td>1.67</td>
</tr>
</tbody>
</table>

Slides by Yiran Zhao, Infocomm 2014 (with minor re-formatting)
Traffic Light Phase Prediction

- Can we predict when the light is going to turn green?

(1) Phase 1 ($S_1$).
(2) Phase 2 ($S_2$).
(3) Phase 3 ($S_3$).
(4) Phase 4 ($S_4$).
(5) Phase 5 ($S_5$).
(6) Phase 6 ($S_6$).
(7) Phase 7 ($S_7$).
(8) Phase 8 ($S_8$).
Traffic Light Timing Prediction

- Maximum likelihood algorithm: reconstructs maximum likelihood estimate of phase durations and sequence given acceleration patterns of vehicles.
Energy Delay Trade-off
Another Example of Modeling

- Understanding urban pollution profiles

(a) Monday–Saturday.  
(b) Sunday.
Measuring Urban Pollution

- 10 sensor nodes on public buses
Selecting Regression Parameters

What factors might impact pollution?

<table>
<thead>
<tr>
<th>Variable [unit]</th>
<th>Variable [unit]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population [inhabitants/ha]</td>
<td>Industry [industry buildings/ha]</td>
</tr>
<tr>
<td>Building height [floor levels/ha]</td>
<td>Heating [oil and gas heatings/ha]</td>
</tr>
<tr>
<td>Terrain elevation [average m/ha]</td>
<td>Road type [busiest road type/ha]</td>
</tr>
<tr>
<td>Distance to next road [m]</td>
<td>Distance to next large road [m]†</td>
</tr>
<tr>
<td>Terrain slope [average degree/ha]</td>
<td>Terrain aspect [average degree/ha]</td>
</tr>
<tr>
<td>Traffic volume [vehicles per day/ha]</td>
<td>Distance to next traffic signal [m]</td>
</tr>
</tbody>
</table>

*Five road types: residential, tertiary, secondary, primary, and freeway.
†Road types classified as large: secondary, primary, and freeway.
Selecting Regression Parameters

- What factors might impact pollution?
Prediction Results

- Measured versus predicted pollution level
Prediction Results

- Quantifying the Error

![Box plot showing RMSE for different temporal map resolutions](image)
Combining Models and Statistics

- Historical measurements
- Environmental conditions and weekday
- Current environmental conditions and weekday
- Real-time measurements
- Data selector
- Model
- Pollution map with high temporal resolution

RMSE [particles/cm²]

- Novel model
- Standard model
The Electric Grid: Yesterday and Today

- One-way limited communication
- One-way power flow
- Centralized generation
- No electric vehicles
- Few sensors and analog control
- Little to no consumer choice
- Reactive maintenance
- Limited usage transparency
The Electric Grid: Yesterday and Today

- Bi-directional and instantaneous communication and metering
- Bi-directional power flow
- Pervasive monitoring and digital control
- Self-monitoring & high visibility
- Many consumer choices

The transition has begun, with peak-demand management (demand response, ILM), and dynamic pricing (e.g. critical peak pricing programs)
Supply-following Loads

### Optimizing
- Energy storage
- Pricing
- CO₂ reduction
- Energy efficiency
- E-car integration

### Intelligent Load Management (ILM)

### Balancing the grid
- Avoid investments in new power plants
- Increase power quality
- Integrate volatile renewable energy
- E-Car charging

### Smart Consumption
**Smart Buildings**

- Two-way communication with utilities
- Proactive energy management / smart consumption
- Energy sources with onsite generation assets
- Storage capacity for added flexibility
- Active carbon management
Why do we need Demand Response?

An oversold or undersold flight is similar to the electrical grid at capacity….

Every Person who gives up their seat is a “Negawatt” and will receive compensation for giving up a seat.

In other words the utility company will pay you to reduce your load during peak demand.
Intelligent Load Management

- Leverages existing BAS equipment to generate cash payments through automated load management

- Allows building operators to participate in Demand Response, Critical Peak Pricing and Smart Grid programs through local utilities

- Balances multiple factors:
  - Corporate standards
  - Efficiency
  - Financial
  - Site conditions

- The technology leader in multi-site load aggregation with **proven financial results**
Example: Siemens Demand-Response System

An event notification is received via a change in event status from the Demand Response Automation Server.

Our Intelligent Software Aggregation Engine acknowledges an event is being called.

Our Aggregation Engine relays signal to onsite communicators and notifies the customer simultaneously.

Within 1 minute of initial dispatch, load begins to ramp down at customer sites.

- Approach facilitates reliable participation in short notice programs.
Demand Response

- How much capacity/flexibility is available to respond to supply variations?
  - A study of HVAC systems
The Dataset

- Examples of dataset measurements
- Data used to build model relating external temp, internal temp, set point, AC power, etc.

<table>
<thead>
<tr>
<th>Data Field</th>
<th>Resolution</th>
<th>Sampling Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature setpoint, $T_{set}(t)$</td>
<td>1 [$^\circ$F]</td>
<td>5 mins</td>
</tr>
<tr>
<td>Internal Temperature, $T_{int}(t)$</td>
<td>1 [$^\circ$F]</td>
<td></td>
</tr>
<tr>
<td>Duty Ratio, $d(t)$</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td>Average Power, $P_{avg}$</td>
<td>0.01 [W]</td>
<td></td>
</tr>
<tr>
<td>External Temperature, $T_{ext}(t)$</td>
<td>0.1 [$^\circ$C]</td>
<td>1 hour</td>
</tr>
<tr>
<td>Solar Insolation, $\phi_{sol}(t)$</td>
<td>0.01 [W/m$^2$]</td>
<td></td>
</tr>
</tbody>
</table>
Model Validation

- Predicting how internal temperature will change in response to large set point changes
Demand Response Potential

- Adapting temperature set point to external supply variations
Demand Response Potential

- Several "What If" Scenarios

<table>
<thead>
<tr>
<th>Case Study</th>
<th>External Temp.</th>
<th>Setpoint Profile</th>
<th>Setpoint Change $\Delta T_{set}^{\text{event}}$</th>
<th>Scenarios</th>
<th>Event Start Hour, $t_{\text{event}}$; [hour of the day]</th>
<th>DR event Duration, $D_{\text{DR}}$; [hours]</th>
</tr>
</thead>
<tbody>
<tr>
<td>CS-1</td>
<td>82°F, Constant</td>
<td>76°F, Constant</td>
<td>2°F, 4°F</td>
<td>A, B, C, D</td>
<td>12, 15, 12, 15</td>
<td>[1.2.3.4] hours</td>
</tr>
<tr>
<td>CS-2</td>
<td>Measured, Thu. 21/06/2012</td>
<td>Avg. Weekday Profile</td>
<td>2°F, 4°F</td>
<td>A, B, C, D</td>
<td>12, 15, 12, 15</td>
<td>[1.2.3.4] hours</td>
</tr>
<tr>
<td>CS-3</td>
<td>Measured, Sun. 17/06/2012</td>
<td>Avg. Weekend Profile</td>
<td>2°F, 4°F</td>
<td>A, B, C, D</td>
<td>12, 15, 12, 15</td>
<td>[1.2.3.4] hours</td>
</tr>
</tbody>
</table>
Impact on Energy Savings

[Graph showing energy savings for CS-2 and CS-3 with different symbols and lines representing different categories A, B, C, and D.]