

Big Data Analytics for CPS: A Parking Management and **Congestion Reduction Case Study**

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'echnology





Motivation

- Congestion in cities can be reduced by a more efficient use of parking infrastructure
- * Inefficient use of parking is costly to urban centers:
 - Past studies have shown that 30%-50% of peak traffic in city centers is people cruising for parking¹
- * Adopting 'smart' technologies is a potentially lucrative solution:
 - Total market for smart parking in North America and Europe was \$7 billion in 2014 and set to grow to \$43 billion by 2025²
- Seattle Department of Transportation (SDOT) has asked us to come up with control schemes using data and technology to increase revenues and reduce congestion in the city center



¹Millard-Ball, Weinberger, Hampshire (2014) ²Barua (2015)

Problem Statement

- * Working with SDOT we aim to:
 - * Gain insights from Seattle's extensive parking data
 - * Build accurate data-driven models of parking to develop ways to use established parking infrastructure in urban centers more efficiently
 - Propose methods to achieve SDOT's desired level of 70%-90% occupancy.
 - * Occupancy is defined as the time average of the fraction of occupied spots divided by the total number of spots¹.

$$Occupancy = \frac{1}{T} \int_{0}^{T} \frac{Occupied \ spots(t)}{Total \ spots(t)} dt$$



Seattle Parking Data

- * We have obtained street-parking data from SDOT. It includes:
 - * Geographical positions of pay-stations and the number of parking spots per blockface, where a blockface is one side of a city block
 - * 5 years of Pay Station transactions (~45.5 million transactions)
 - * This includes: pay-station identifier, time of transaction, the amount paid, and the duration paid for
 - Note: we only have pay-station level granularity in the data
 - * 2 years of Pay-by-Phone transactions (~800,000 transactions)
 - * This includes: pay-station identifier, time of transaction, the amount paid, and the duration paid for
 - * Note: no user identifying information
 - * Yearly manual survey of Parking Spots from years 2012-2014
 - * One day per year of manually recorded parking transactions including: pay-station identifier, number of cars parked on a blockface at a given time, supply of parking spaces on a blockface at a given time



Initial Insights from SDOT Data

* Parking accounts for \$37.2 million in revenue in 2013 and 2014

* Steady increase in Pay-By-Phone Transactions since its inception



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Initial Insights from SDOT Data

- A first pass at the data was to look at the load on a blockface over time to identify any meaningful trends in the data
 - * We define the load on a blockface *i* at time *k* as the number of cars parked on *i* at time *k* divided by the total number of available parking spots on *i*

 $Load_i[k] = \frac{Occupied \ spots_i[k]}{Total \ spots_i[k]}$

* Since we only know the arrival time of a car on a blockface *i* and an upper limit to the duration of its stay, we approximated the load on *i* over time by the following equation:

$$Load_{i}[k] = \frac{n_{i} * Load_{i}[k-1] + Arrivals_{i}[k] - Departures_{i}[k]}{n_{i}}$$

Where: - n_i is the maximum number of available parking spots on blockface *i* -Arrivals_i[k] is the number of new cars parked on blockface *i* at time k -Departures_i[k] is the number of cars leaving blockface *i* at time k



Initial Insights from SDOT Data

Results from load calculations:

- Parking in Seattle is well below its full capacity
- Different areas have different parking profiles
- * 50% mean occupancy over all blockfaces between 10 am and 4 pm in Seattle
 - occupancy is the time average of the load



Future Work: Modeling Parking

- Building on this preliminary analysis, we aim to build a spatio-temporal model of parking in the city
- Past work in parking modeling in cities has relied on instrumenting a limited number of parking spots and measuring the total number of spaces available at a given time and the exact length of stay^{1.}
- * Modeling occupancy in Seattle is challenging due to:
 - * The lack of the "ground truth".
 - * The lack of key data that would make construction of a deterministic model possible.
 - i.e. exact duration of parking session per transaction, number of available parking spots per blockface on a given day, the total number of cars looking for parking (not just cars that successfully parked)



Future Work: Modeling Parking

- Model parking on the blockface level as a M/G/n queue with arrivals modeled as a Poisson Process within time intervals
 - * Each blockface *i* has:
 - * parameter λ_{ik} : the rate of arrival of new cars during period k. This rate is constant during a period, but varies over different periods. We can estimate λ_{ik} from the data¹²
 - * A prior distribution for the duration of a parking session drawn from the data
 - n servers representing the n available parking spots on the blockface



Future Work: Modeling Parking

- * Benefits of modeling parking as a queue:
 - * Each block is parameterized by its arrival rate, a distribution for service times, and the number of spots
 - * Model is easily scaled up to larger granularities
- * Design questions:
 - * How to deal with new arrivals once the queue is at capacity
 - * Blocking, push to neighboring queue, etc.
- * Model verification:
 - * SF-Park Dataset which has the "ground truth" data
 - * SDOT's yearly manual survey of parking spots



Further Directions

- * Use the parking model to:
 - * Evaluate the difference between the public's optimal consumption of parking resources and the city's
 - * Develop incentive schemes to push consumers towards equilibriums that are efficient from the perspective of the city and the consumer
 - * Find optimal locations for new parking infrastructure
 - * Inferring impact of inefficient parking usage on traffic congestion
 - * Look at ways to maximize revenue for SDOT





Questions?

