



No More Cruisin' for Parking: Targeted Information and Incentives via Spatio-Temporal Analysis and Bandits

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Motivation



Research Objectives

1. Identify locations where parking demand is similar to allow for targeted advertisement and incentives.
2. Design algorithms to match incentives and ad campaigns to locations and user groups within them.

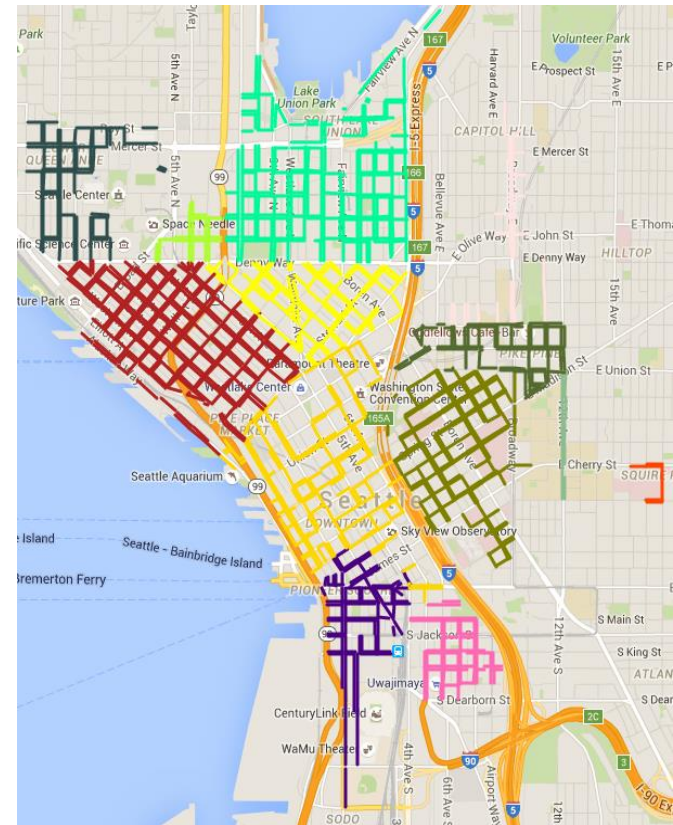


Data Overview

- * Open data from the Seattle Department of Transportation
- * Estimate the occupancy at block i at time k :

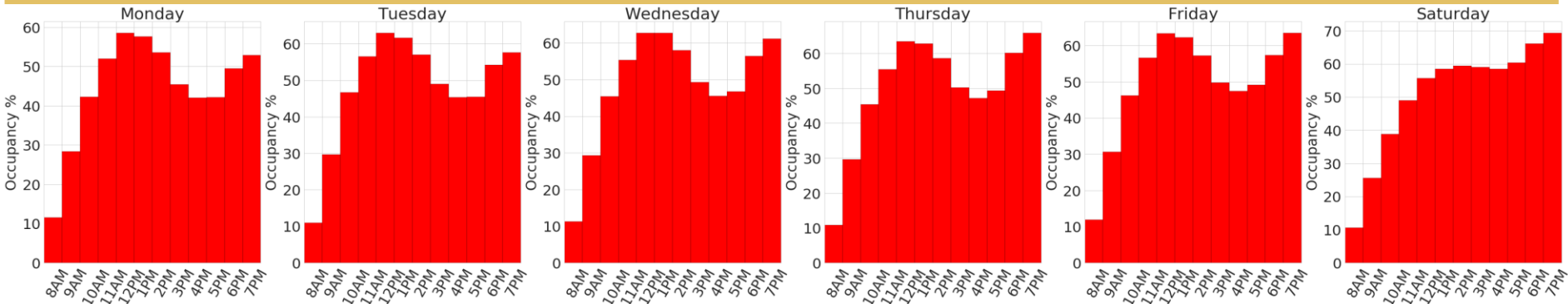
$$Occupancy_i[k] = \frac{Active\ Transactions_i[k]}{Supply_i[k]}$$

- * Experiments in Belltown neighborhood using occupancy data from March 1st, 2016 – July 30th, 2016.

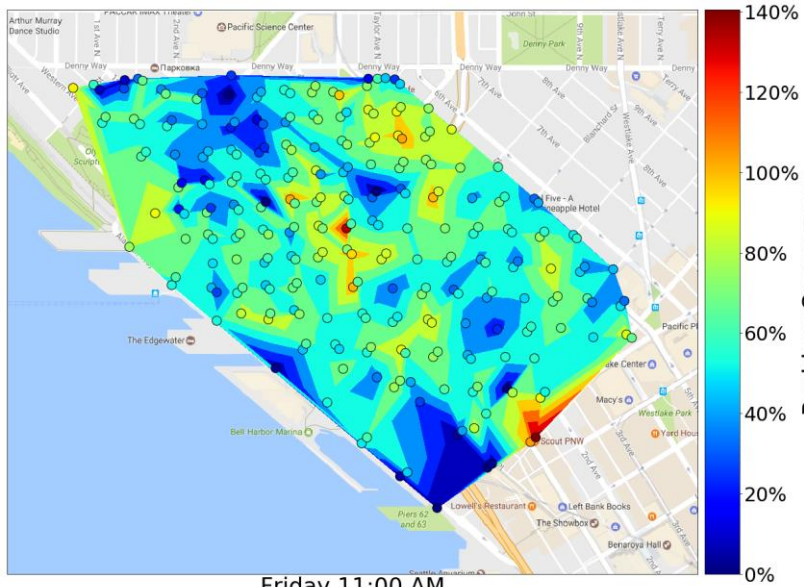


Map of Seattle Paid Parking

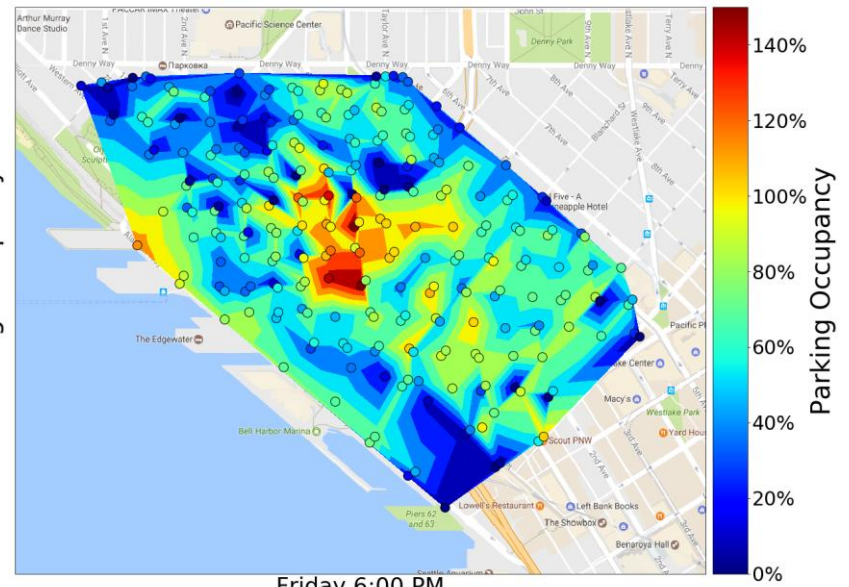
Data Overview



Daily Occupancy Profiles in Belltown



Friday 11:00 AM



Friday 6:00 PM

Contours of Average Occupancy in Belltown from March 1st, 2016 – July 30th, 2016

Gaussian Mixture Model Approach

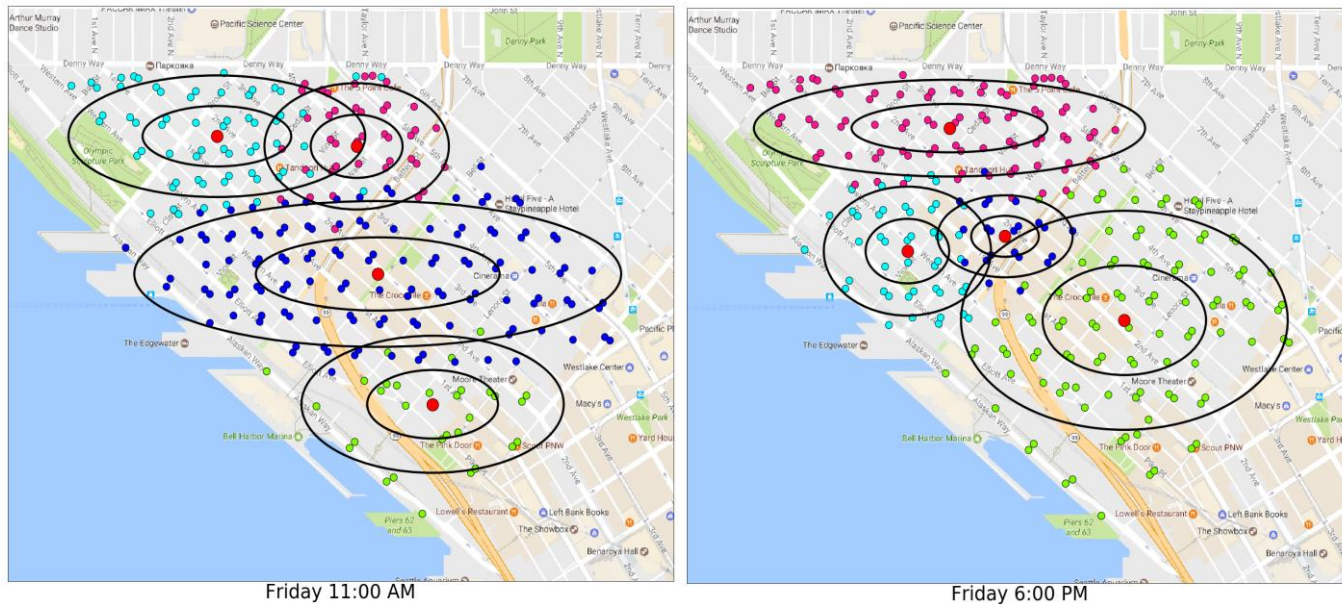
- * Gaussian mixture model (GMM) considering both spatial and occupancy information.
- * At a given time, we consider a sample in our dataset to be a block-face i represented by a vector:

$$x_i = [x_{i,latitude}, x_{i,longitude}, x_{i,occupancy}]$$

- * Expectation Maximization to maximize the log likelihood of the data.

Gaussian Mixture Model Insights

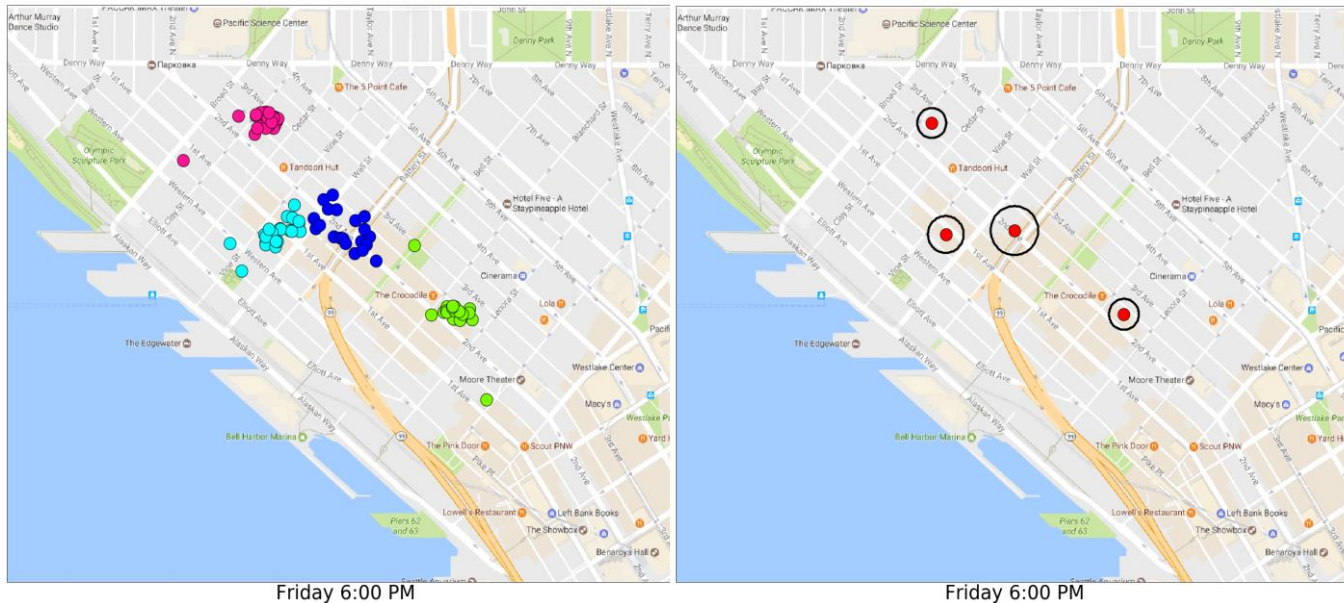
1. The model that is fit depends on the day of week and time of day.
2. Parking behavior is consistent over time.
3. We can find separable locations with similar demand.



GMM fits on Average Occupancy in Belltown from March 1st, 2016 – July 30th, 2016

Consistency of Parking Behavior

- * GMM fits are similar from week to week at a day of week and time of day.
- * Using a learned model on a new date at the same day of week and time of day, ~90% of block-faces are assigned to the same mixture component.



Spatial Autocorrelation

- * Spatial autocorrelation measure Moran's I:

$$I = \frac{N \sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{W \sum_i (x_i - \bar{x})^2}$$

- * N is the number of block-faces indexed by i and j , x is the occupancy, \bar{x} is the mean of x , w_{ij} is the matrix of spatial weights with 0 along the diagonal, W is the sum of all w_{ij} .
- * Weighting matrix with connections between blocks in the same mixture component given weight 1, and 0 otherwise.
- * 99.6% of the time the p-value for spatial autocorrelation is significant ($< .05$).

Targeted Information and Incentives

- * Targeted information and incentives to induce more socially optimal parking behavior.



- * We can consider the locations we identify as groups of users with similar preferences.
- * The problem becomes selecting the best mechanism to influence behavior in the desired way.

Multi-Arm Bandits

- * Classical multi-arm bandit
 - * Each arm has an expected value and returns a random reward.
- * Multi-arm bandits as a matching problem
 - * Pulling an arm can be viewed as matching a mechanism to a user.
 - * We model the dynamics of the rewards (user types/preferences) as time varying stochastic processes that depend on the offered mechanisms.

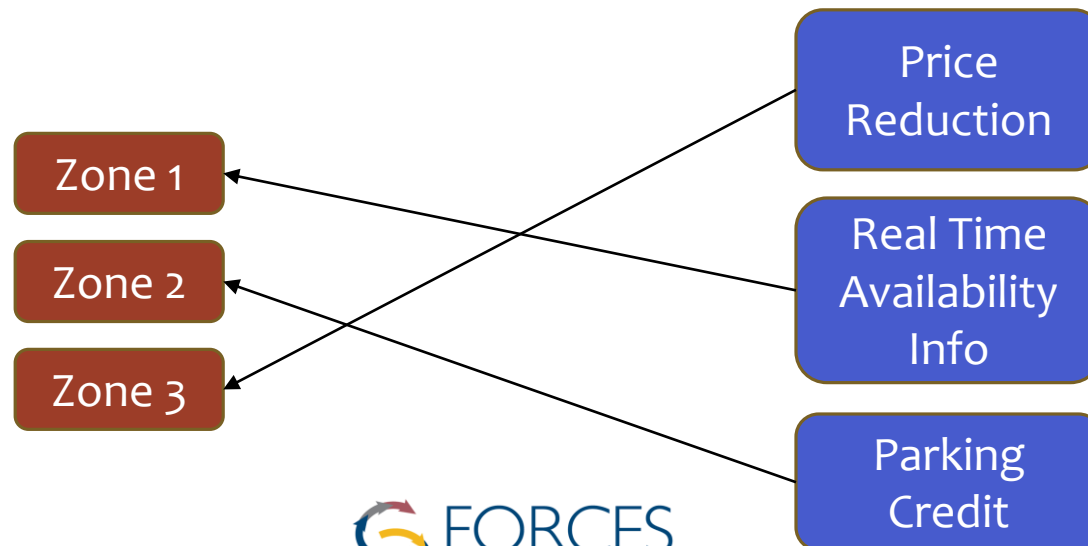


Results

- * Challenging problem due to the dependence between arms.
 - * Single Markovian reward process for all arms.
- * Solution to matching a single user/location to incentives.
 - * Regret bounds on UCB algorithm for expected regret.
- * Targeting human decision makers makes minimizing volatility important.
 - * Regret bounds on UCB algorithm for mean variance risk measure.

An Extension to a Combinatorial Framework

- * Each arm can be viewed as a set of mechanisms being matched to a set of users/locations with evolving preferences.
- * Framework results in a super exponential number of arms, requiring clever methods to solve the problem efficiently.
- * Combinatorial matching framework in parking:



Seattle – A Living Lab

- * Collaboration with the Seattle Department of Transportation (SDOT) allows us to use the city as a testbed for our algorithms.
- * Planning experiments with the SDOT to test our spatio-temporal algorithms together with our multi-arm bandit framework.



- * The SDOT will organize user feedback via surveys.

Future Directions

- * Theoretical extensions by attaining better bounds using time in-homogeneous Markov chain mixing characterizations.
- * Including new risk metrics such as coherent risk measures in multi-arm bandits.
- * Multi-objective multi-arm bandits.

Thank You

Questions?

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