



# Identifying Parking Demand Hotspots and Predicting Rate Surge

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# URBAN TRANSITIONS 2024

Integrating Urban and Transport Planning,  
Environment and Health for Healthier Urban Living

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Sitges, Barcelona, Spain



**I am happy for you to photograph or  
tweet the slides from my talk**





## ML-driven Parking: From Reactive Management to Predictive Solutions

Why wait to circle for a parking spot in a area?

What if we could predict parking spot availability nearby?



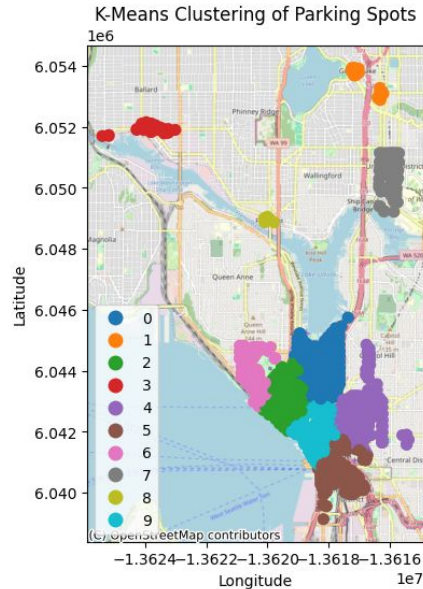
# WHY THE U.S. HAS TOO MUCH PARKING

A glowing neon sign that says "PARK" in a stylized, outlined font. The sign is illuminated with a warm, orange-red light and is set against a dark, textured background. The letters are three-dimensional and have a double-line outline.

# Integrating data science with urban planning

**Predict behavior:**

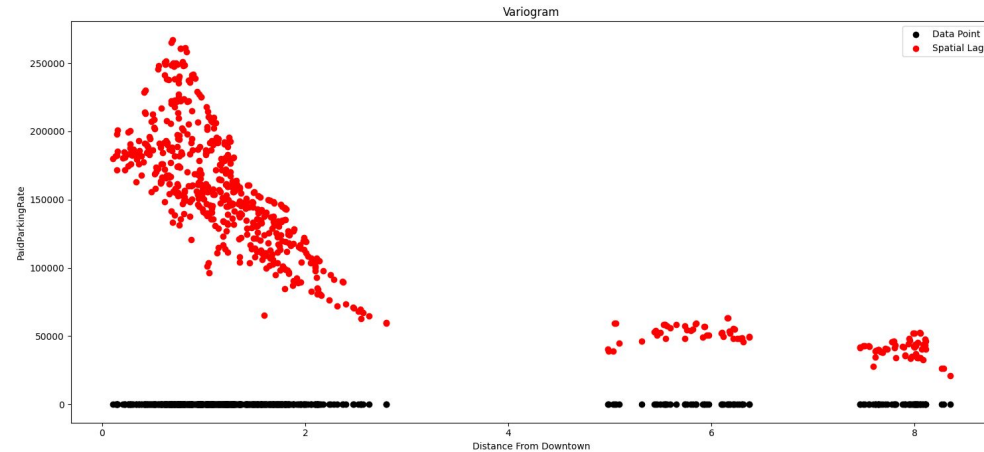
**Where is parking demand highest?**



→ Big data analytics & machine learning

**Optimize resources:**

**How to manage parking efficiently?**



→ Dynamic interventions (smart pricing)

# Data Sources: Building a Comprehensive View

Seattle Open Parking  
Data 2015

Visual Crossing API

Offerings



**Seattle**



**visualcrossing**  
*Weather Data*



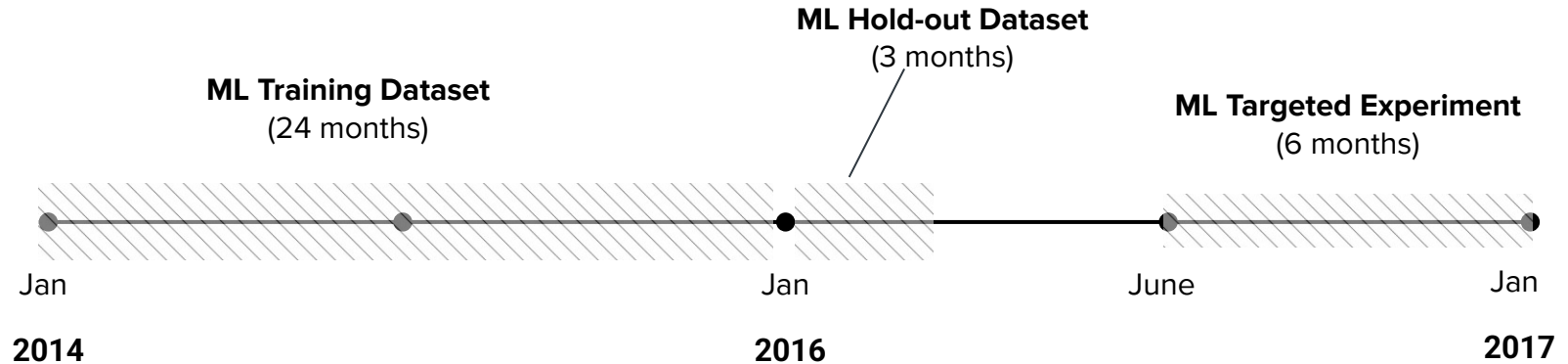
**OpenStreetMap**

# Study Overview and Timeline

- Phase 1: ML Algorithm Development
- Phase 2: Implementation & Analysis

**DESIGNING ML ALGORITHM**

**APPLYING ML ALGORITHM AND EXECUTING EXPERIMENTS**



# Key Findings from ML Models

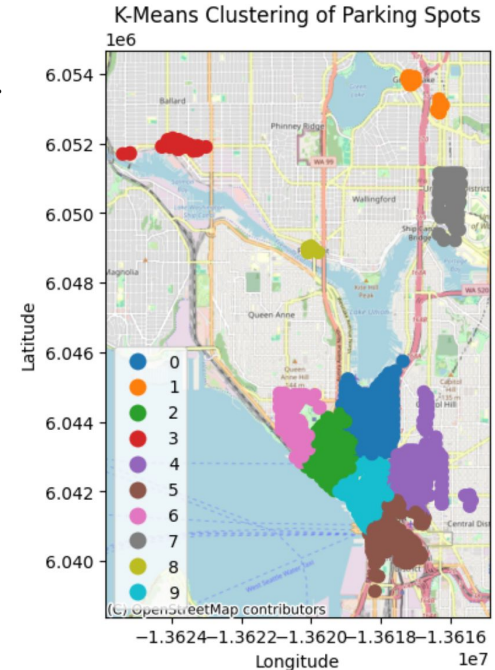
## Identify parking demand hotspots

### K Means Clustering -

To pinpoint areas in Seattle with high and low demand for parking.

High rates in cluster 4 & 9 (Avg rates 3.50\$)

Low demand clusters 1 & 3 (Avg rates 1.20\$)



# Key Findings from ML Models

## Predicting Parking Rate Surges

Forecast rate changes, especially during peak times, to optimize urban parking management.

Model Performance:

- Random Forest: Highest accuracy (92.73%) – effective for rate surge prediction.
- Polynomial Regression: R-squared of 0.89 – captures non-linear demand patterns.
- Decision Tree: 84% accuracy – identifies high demand areas.

These models offer reliable insights for dynamic pricing, congestion management, and targeted urban planning.

# Triage by Impact Level

How do our findings translate to different stakeholder priorities?

## High Priority Areas: Belltown & First Hill Clusters

**Monthly revenue:** \$96K-\$107K | Commercial zones, high-traffic areas, event venues

## Medium Priority Areas: Chinatown & University District

**Monthly revenue:** \$65K-\$87K | Shopping districts, entertainment areas, mixed residential

## Low Priority Areas: Green Lake & Residential Zones

**Monthly revenue:** \$20K-\$35K | Residential areas, low-turnover zones

# Practical Applications

## For City Planners

Dynamic pricing strategies

Infrastructure optimization

Resource allocation

## For Businesses

Location optimization

Customer accessibility

Revenue potential

## For Residents

Real-time availability

Reduced search time

Better urban experience

# Future Research

- Real-Time Data Integration
- Create a user friendly mobile application
- Advanced model optimizations with deep learning models (LSTM's) to capture complex patterns.

# Thank you

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