Identifying Parking Demand Hotspots and Predicting Rate Surge Using Machine Learning

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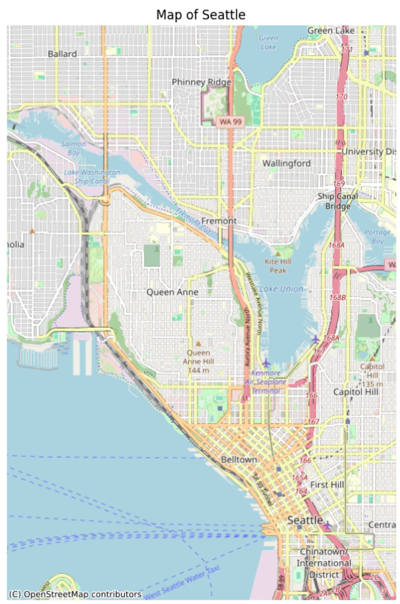

Figure 1. Geographic Scope of Parking Data Analysis in Seattle

Abstract

The growing challenge of parking in dense urban areas necessitates a targeted approach to identify and analyze regions with significant parking demand. This study examines Seattle's historical parking data to illuminate these high-demand zones and project potential future trends in parking requirements. Our goal is to support urban planners in optimizing parking infrastructure, help businesses choose prime locations based on parking accessibility, and aid residents navigate parking availability more efficiently. Employing a blend of k-means clustering, data mining, neural networks ———-, and spatial analysis, we dissect the multifaceted nature of parking patterns. Our data-driven approach harnesses diverse datasets, harmonizing them through advanced machine-learning techniques to derive actionable insights. The implications of this study extend beyond the immediate remit of urban congestion, offering a template for other metropolises grappling with similar challenges. This paper not only contributes to the discourse on urban parking management but also serves as a strategic tool for stakeholders aiming to mitigate the perennial urban challenge of parking inadequacy.

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CCS Concepts: • **Applied computing** → **Transportation, Urban planning**; • **Information systems** → **Data mining, Spatial clustering**; • **Computing methodologies** → **Machine learning**.

Keywords: Urban parking analysis, Spatial clustering, K-means clustering, Variogram analysis, Decision Tree classifier, Logistic Regression, Polynomial Regression, K Nearest Neighbours, Naive Bayes , Neural Networks

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1 INTRODUCTION AND BACKGROUND

The optimal use of land and management of parking are crucial in the context of urban planning for several reasons. Ineffective land use planning and parking mismanagement can lead to a shortage of parking space, high parking tariffs, and traffic congestion, all of which are common everyday parking problems in urban areas. The improper allocation of land for parking facilities can result in an imbalance between parking supply and demand, exacerbating the parking problem in cities [1]. Low parking availability can significantly impact traffic and congestion in urban areas. Evidence suggests that a mismatch between parking supply and demand in denser regions can exacerbate traffic congestion [2]. Peak times in various areas such as early mornings and evenings in residential areas, breakfast, lunch and dinner times around commercial areas, local events around the city lead to parking saturation. When drivers are unable to find parking spots, they cruise along the street further slowing down the traffic on the road and thereby increasing congestion. This behavior not only impacts mobility around the area but also contributes to air and noise pollution and excess greenhouse gas emissions [3].

The assessment of existing parking areas or spaces involves the analysis of various parking characteristics to determine their adequacy and efficiency. This analysis provides valuable insights into the duration of parking space occupancy, as well as data related to accumulation, duration, occupancy, and parking turnover, which are essential for informing and supporting the decision-making process [4]. Parking demand and supply, parking rates, occupancy, and predicting pricing surges can help policymakers establish a baseline for comparative analysis to evaluate the relationships between these characteristics. This could aid the implementation of better parking management and information systems, better parking policies and optimized parking infrastructure.

1.1 Related Research

Previous research has demonstrated the significance of predicting parking occupancy and analyzing parking demand patterns. Various studies have been conducted addressing different aspects of managing parking demand and urban mobility.

The review article by Parmar[4] presents a comprehensive review of models and studies on the parking system. It addresses aspects such as parking characteristics, demand evaluation, driver's parking choice behavior, and the development of demand models considering various factors. The study finds that implementing policies that restrict private vehicle traffic in urban areas, enhancing public transit systems play pivotal roles in mitigating traffic congestion and promoting sustainable urban mobility. Gomari[5] presented an unsupervised approach that employs a two-part clustering analysis - agglomerative clustering on the temporal trend of parking dynamics and a two-stage DBSCAN – K-means clustering on the parking duration information to capture the temporal trend of parking dynamics and parking duration information. This method provided the joint probability of parking purpose by duration and quadkey category.

Provoost[6] focuses on using predictive models based on Neural Networks and Random Forest to predict parking occupancy rates and space availability. The study leverages Web of Things in collecting data via parking and traffic sensors nodes. The study found that their proposed model performed better than the state of the art related work under their study, and the most significant factor in predicting parking occupancy was the historical occupancy rate, with traffic flows around the city being the next important predictive variable. Wong[7] provides a comprehensive overview of the diverse range of parking challenges, aiming to enhance the understanding of parking demand and its implications for urban traffic conditions.

1.2 Problem Statement

Using spatial analysis and parking occupancy data, this study identifies parking demand hotspots in urban areas. The research analyzes the data to pinpoint areas with high parking demand, with the objective of assisting city planners in prioritizing infrastructure development and parking management initiatives. The information derived from this analysis is valuable for city planners to manage parking resources effectively, for businesses to select optimal locations based on parking availability, and residents who can plan their travel based on parking availability. The study addresses the following key questions:

1. Where are the parking demand hotspots located?
2. What are the factors contributing to high parking demand in these areas?
3. How can this information be used to inform infrastructure development and parking management decisions?

1.3 Data Sourcing and Description

The dataset for this study was created by consolidating data from the following sources:

1. **Parking Dataset:** The parking data was obtained from the "The Paid Parking Occupancy 2015 (Archived)"

dataset available on The City of Seattle's Open Data portal. [8]. This dataset provides on-street paid parking occupancy data which includes occupancy datetime, number of transactions that have paid at a specific date and time on a blockface, blockface details such as name and side of the street. Additionally, the dataset contains information such as the parking time limit category, parking space count, paid parking area, paid parking subarea, paid parking rate, parking category, latitude, and longitude.
2. **Weather Data:** The hourly weather data for Seattle for the year 2015 was sourced from VisualCrossing weather API[9]. Research demonstrates that incorporating traffic speed and weather information can significantly improve the prediction performance, particularly in business areas and recreational locations.[10]
3. **Geographical Map Data:** The geographical map data was sourced from OpenStreetMap, a free and open-source mapping platform. [11]. Openstreetmap was used to determine class and type for each parking slot based on the location parameters - latitude and longitude.

These data sources were instrumental in conducting the analysis and deriving the findings presented in this research. The utilization of publicly available data sources ensures transparency and reproducibility in the study, allowing for the validation and further exploration of the research outcomes. Additionally, the statistical summary of paid parking rates by KMeans cluster, as presented in Table 1, provides a quantitative analysis of the parking data, which serves as the foundation for our predictive models and further economic analysis.

Table 1. Descriptive Statistics for Paid Parking Rates of Parking lot clusters

Cluster	Mean	Std	Min	25%	50%	75%	Max
0	1.87258	0.35	1.0	1.5	2.0	2.0	3.0
1	1.00000	0.00	1.0	1.0	1.0	1.0	1.0
2	1.85902	0.48	1.5	1.5	1.5	2.5	4.0
3	1.31579	0.47	1.0	1.0	1.0	2.0	2.0
4	3.19094	0.85	1.5	2.5	3.5	4.0	4.0
5	2.98241	0.88	1.5	2.0	3.0	3.5	4.0
6	1.50000	0.00	1.5	1.5	1.5	1.5	1.5
7	2.04117	0.69	1.0	1.0	2.5	2.5	2.5
8	1.50000	0.00	1.5	1.5	1.5	1.5	1.5
9	3.76060	0.50	1.5	4.0	4.0	4.0	4.0

2 METHODOLOGY

This study adopted a three-step research methodology for modeling the Parking lot network:

1. Predicting Parking Rate using various ML classifiers
2. Spatial Clustering for Hotspot Identification
3. Mapping Network Analysis metrics to Department of Transportation

2.1 Predicting Parking Rate using various machine learning classifiers

The dataset was first refined for predicting parking rates by performing meticulous feature engineering and exploratory data analysis. The study commenced with data preprocessing to remove any missing values and duplicates, thus preserving data integrity. To quantify the influence of location, we calculated each parking spot's distance from downtown Seattle and classified zones into 'residential', 'commercial', and 'mixed-use' categories based on their characteristics. The dataset was streamlined by removing extraneous columns and encapsulated weather influences through a binary 'rain' indicator.

The study applied LabelEncoder to categorical variables such as 'class', 'SideOfStreet', and 'ParkingCategory' for numerical conversion, facilitating their use in machine learning algorithms. Outliers were visualized and removed from key numerical features like 'PaidOccupancy' and 'DistanceFromDowntown' using interquartile range methods. To address class imbalance, a RandomUnderSampler was utilized, ensuring a uniform distribution across different parking demand levels. The data was then standardized to nullify the variance disparity among features. Subsequently, a Principal Component Analysis (PCA) reduced the feature space, improving model efficiency and reducing multicollinearity, as confirmed by a lower condition number. This multi-faceted preprocessing approach was critical to distill the dataset down to the most impactful predictors for accurate hotspot identification.

The covariance matrix suggested a substantial variation in the magnitude of the relationships, while the correlation matrix highlighted both strong and weak linear associations among the variables, with `'DistanceFromDowntown'` showing a significant positive correlation with `'PaidOccupancy'`, indicating its potential impact on parking behavior.

In this study, we employ a range of machine learning classifiers to predict parking rates accurately. Leveraging a diverse set of algorithms, including polynomial regression, decision tree classification, logistic regression, naive Bayes classification, and random forest, we explore their suitability for modeling parking rate prediction. By systematically evaluating these classifiers using established performance metrics such as accuracy, precision, recall, F1-score, and ROC curves, we determine the most effective model for forecasting parking rates. Our methodology involves hyperparameter tuning, cross-validation, and extensive model evaluation, ultimately providing valuable insights for optimizing parking management and infrastructure planning while contributing to the broader field of predictive analytics for urban planning and transportation.

Table 2. Network Analysis Metrics

Metric	Description
K means Cluster	This is a label derived from the K-Means clustering algorithm applied to our geospatial data. The algorithm partitions the city into k distinct non-overlapping clusters based on the geographic coordinates (latitude and longitude) of parking spots. Each cluster represents a group of parking spots that are close to each other. In our case, we chose the number of clusters (k) as 10, aiming to capture the diverse geographic distribution of parking spots across the city.
Eigen Centrality	EigenCentrality, or eigenvector centrality, measures the influence of a node within a network. In our scenario, this could help identify parking spots that are influential due to their location and connectivity to other high-demand parking spots.[12]
Distance Based Centrality	We define this as a proxy measure based on the paid parking rates, assuming that higher rates are indicative of central or popular locations. In our data, this meant that spots with higher rates were considered more central.
Time Based Centrality	This is the inverse of the paid parking rates, assuming that higher rates correlate with lower waiting or parking time, indicating higher demand and thus higher centrality. In our study, this provided a means to factor in the dynamic nature of parking spot popularity over time.

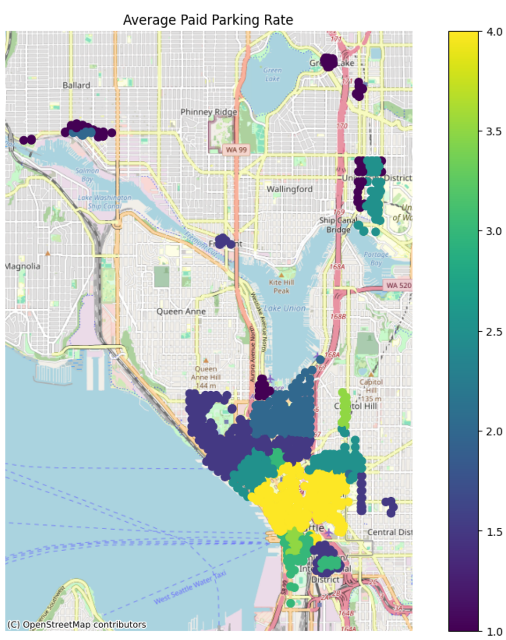

Figure 2. Daily Parking Rate Dynamics on January 15, 2015

2.2 Spatial Clustering for Hotspot Identification

The spatial distribution of parking spots within the urban landscape was analyzed using K-Means clustering, a method that partitions the area into distinct zones based on the geolocation of parking spots and parking rate. This segmentation yielded ten distinct clusters, as shown in Figure 3, each representing a grouping of parking spots based on proximity.

The K-Means algorithm, known for its efficiency in partitioning datasets into 10 distinct non-overlapping subgroups, was utilized to dissect the urban area into clusters based on parking spot locations. This partitioning enabled the identification of hotspots with varying parking demand levels.

In our exploration of urban parking patterns, we focus on how parking rates fluctuate throughout the day across different city zones. To start, we adjusted the geographic data to a common scale, ensuring that no single feature skewed our analysis. Using the KMeans clustering technique, we grouped parking spots into ten clusters, each representing a unique part of the city based on proximity.

We then tracked the average parking rates for each cluster at different hours, revealing the ebb and flow of parking demand. The resulting plot showcased these trends, offering a clear, visual narrative of when and where parking demand peaks. This approach highlighted areas with consistent demand as well as those with more dynamic pricing, informing city planners and residents alike about the rhythm of urban life as reflected in parking patterns.

We kickstarted our analysis by employing Python's Geopandas and PySAL libraries to spatially orient parking data within the city's fabric. This initial step involved curating a GeoDataFrame, providing us with a canvas to plot the latitudinal and longitudinal intricacies of parking spots and their rates. With the spatial weight matrix at our disposal, we moved on to scrutinize the parking rates' spatial distribution through variogram analysis, pinpointing how parking costs fluctuate with distance from the bustling city center.

The culmination of our methodology rests on a delicate balance of statistical rigor and geospatial precision, setting

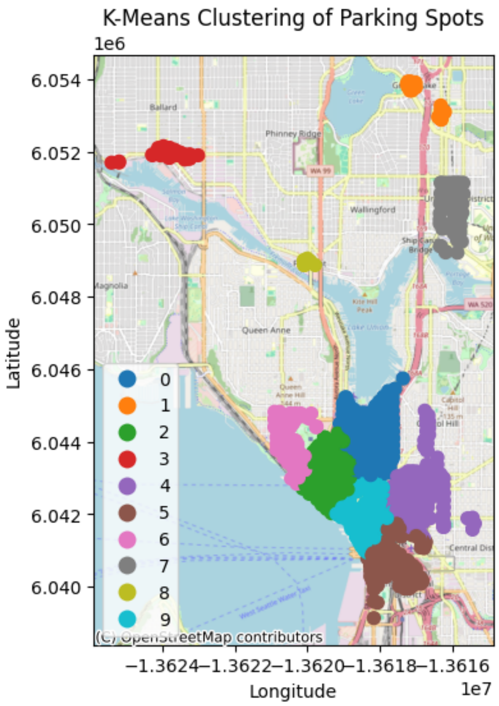

Figure 3. KMeans Clustering of Parking Spots in Seattle

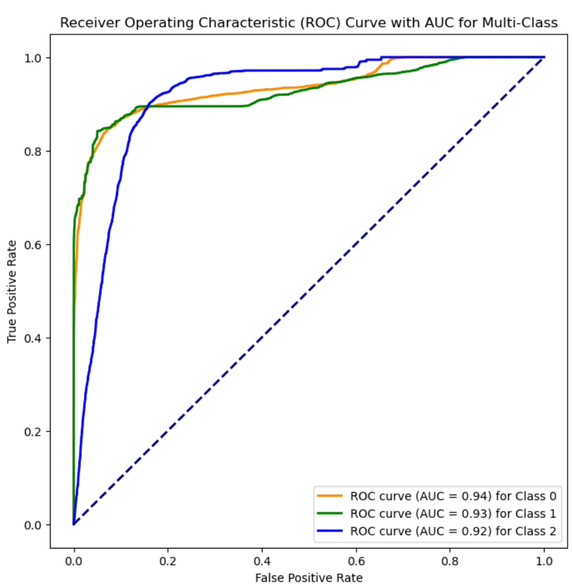

Figure 4. Naive Bayes ROC Curve with AUC for multi class

the stage for policymakers to sculpt a more navigable urban parking landscape.

3 RESULTS

3.1 Classification Analysis

The analysis conducted using various machine learning classifiers demonstrated significant findings in the context of urban parking demand.

The polynomial regression model, with a degree of 3, accounted for non-linear relationships and yielded a high R-squared value of 0.890, indicating a strong fit to the data. This suggests that the model can explain a substantial proportion of the variance in parking demand, which city planners could leverage to make informed decisions on infrastructure development. The F-statistic is significant, suggesting that the model's predictive capabilities are reliable. The Mean Squared Error (MSE) of 0.1104 reflects the average squared difference between the observed actual outturns and the predictions by the model. A lower MSE indicates that the model predicts with higher accuracy, which is beneficial for making precise recommendations for urban planning.

The Decision Tree classifier achieved an accuracy of approximately 84%, with balanced precision and recall metrics across the classes. The high precision and recall for Class 0 and Class 1 suggest that the Decision Tree classifier is effective in identifying areas with low to moderate parking demand. However, the model is particularly adept at identifying high-demand areas (Class 2) with a recall of 0.85, indicating that it can correctly identify most of the high-demand parking hotspots.

Similarly, Logistic Regression and Gaussian NB models yielded comparable accuracy levels, indicating that simpler models could also effectively identify high-demand parking zones. This is particularly useful for city planners when simplicity and interpretability of the model are as important as its predictive performance. The Naive Bayes classifier, with hyperparameter var smoothing set to 1e-06, has been evaluated for its effectiveness in identifying parking demand hotspots. The Receiver Operating Characteristic (ROC) curve for the Naive Bayes classifier from Figure 4 displayed an AUC of 0.94 for Class 0, 0.93 for Class 1, and 0.92 for Class 2, reflecting a high true positive rate with minimal false positives for all classes.

The high recall for high-demand hotspots is particularly beneficial for city planners as it ensures that areas most in need of intervention are likely to be identified, allowing for targeted and effective management of urban parking resources.

The Random Forest model stood out with an accuracy of 92.73%, suggesting that an ensemble approach is more robust for this problem. The high accuracy indicates that Random Forest could be an excellent tool for city planners to predict parking demand hotspots with greater confidence.

The Logistic Regression model achieved an overall testing accuracy of 0.83. The precision, recall, and F1-score indicate a reliable performance across all classes, with a particularly strong precision for Class 1.

Overall, the machine learning classifiers provided a nuanced understanding of parking demand, allowing for a data-driven approach to urban planning and the allocation of city resources. The study's findings could guide targeted interventions to enhance parking availability and manage citywide traffic congestion effectively.

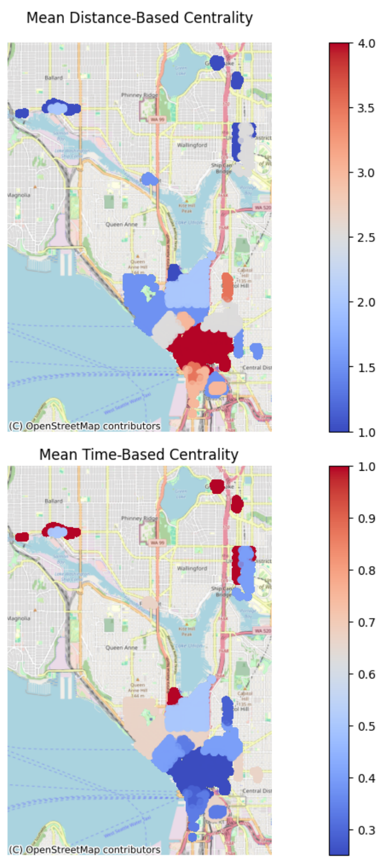

Figure 5. Geospatial Distribution of Parking Centrality in Seattle

3.2 Clustering analysis

Upon closer examination of the clusters, variance in average paid parking rates was observed, suggesting the presence of areas with different parking pricing dynamics. Cluster 4 and Cluster 9, in particular, exhibited higher average rates at 3.19 and 3.76, respectively, indicating these areas have a higher demand for parking or are located in premium zones. Conversely, Cluster 1 and Cluster 3 demonstrated lower average rates, potentially reflecting areas with lower demand or more abundant parking availability.

The clustering analysis provides an insightful overview of parking rate distribution across the city:

1. Cluster 0 (Average Rate: 1.87) and Cluster 2 (Average Rate: 1.86) show moderately high parking rates, suggesting these could be areas of consistent but not peak demand.
2. Clusters 1 and 3, with average rates of 1.00 and 1.32, respectively, could indicate zones where parking is more readily available or less in demand.
3. Clusters 4 and 9 stand out as the zones with the highest parking rates, which may be influenced by proximity to key commercial areas or limited parking space availability, marking them as high-demand hotspots.
4. Cluster 5 (Average Rate: 2.98) also shows an elevated parking rate, suggesting it is a zone of significant parking activity, potentially influenced by occasional events or specific times of the day.
5. Clusters 6, 7, and 8 present average rates of 1.50, 2.04, and 1.50, respectively, indicating these are zones with varying degrees of demand.

The "Time Dynamics within KMeans Clusters" plot indicates the variation in the average paid parking rate across different times of the day for each of the identified clusters. Observing the plot, you can infer the following:

1. Stability and Variability: Some clusters (like Cluster 4) show a stable parking rate throughout the day, indicating a consistent demand or pricing policy. In contrast, other clusters (like Cluster 1 and Cluster 9) show more variability, suggesting fluctuating demand or a dynamic pricing model.
2. Peak and Off-Peak Hours: Clusters like 3 and 9 exhibit clear peak hours with higher parking rates, likely corresponding with business hours or periods of high activity. This can be correlated with commercial areas or regions with significant daytime traffic.
3. Cluster Differentiation: The plot differentiates the clusters based on their average parking rates and the pattern of change over the day. For example, Cluster 0 maintains a higher rate throughout the day, whereas Cluster 8 has a lower, more consistent rate.
4. Potential Anomalies: Sudden spikes or dips (as seen in Clusters 1, 3, and 9) may represent anomalies or special events that affect parking rates.

4 DISCUSSION

We discuss these observations, considering factors such as the proximity to points of interest, urban density, traffic patterns, and policy implications. These visual and analytical insights can guide recommendations for parking management, urban planning, and further research directions, including:

- **Exploration of Cause and Effect:** Investigate why certain clusters have specific time dynamics and what urban characteristics or policies might be influencing these patterns.

Table 3. Summary of Earnings Data per Parking lot in each Cluster

Index	Monthly Earnings	Longitude	Latitude	Street	Suburb
0	25758.72	-122.34835	47.621348	Fairview Avenue North	Belltown
1	20893.92	-122.321868	47.678364	Weedin Place Northeast	Green Lake
2	32976.07	-122.345492	47.615655	3rd Avenue	Belltown
3	34912.54	-122.384985	47.668754	Northwest Market Street	Ballard
4	96291.96	-122.322706	47.612309	Seneca Street	First Hill
5	87276.15	-122.328581	47.600614	South Washington Street	Chinatown District
6	29358.60	-122.354500	47.620350	Harrison Street	Belltown
7	65820.73	-122.314545	47.659303	Brooklyn Avenue Northeast	University District
8	54384.32	-122.350571	47.650771	North 35th Street	Fremont
9	107048.89	-122.336319	47.608516	Union Street	Belltown

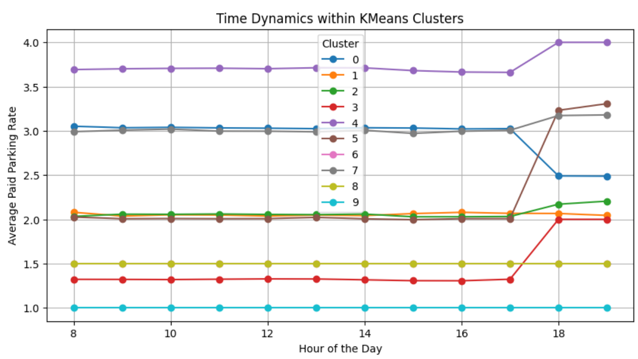

Figure 6. Time Dynamics of Parking Rates within KMeans Clusters

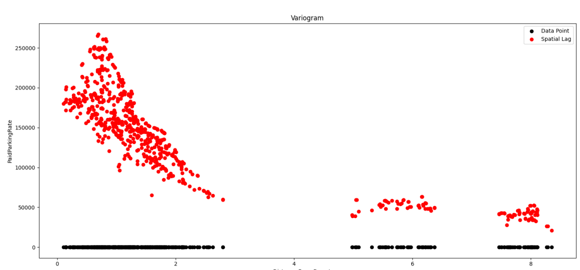

Figure 7. Variogram Analysis of Parking Rates Relative to Downtown Seattle

- **Policy Development:** Use these insights to suggest dynamic pricing policies or targeted infrastructure improvements in areas with high demand variability.
- **Integration with Urban Planning:** Recommend ways these findings can be integrated with broader urban planning initiatives, such as developing public transport options in high-demand areas to alleviate parking pressure.

Incorporating machine learning techniques, particularly Random Forest models, into parking rate prediction offers transformative potential for urban development and policy. By accurately forecasting parking demand, city planners can devise targeted infrastructure strategies and implement dynamic pricing to maximize space and ease congestion. This analytical capability benefits businesses in selecting prime locations, enhances residents' daily planning, and informs real estate trends. Thus, leveraging predictive analytics stands to not only streamline parking management but also significantly improve urban living standards across multiple dimensions. The "K-Means Clustering of Parking Spots" map visualizes the geographic distribution of these clusters, with the color coding corresponding to the cluster each parking spot belongs to. This spatial representation can help in identifying geographic patterns and correlations with urban features.

The analysis revealed distinct patterns of parking demand across the city. Clusters with high mean distance-based centrality scores were predominantly located in the central business district, signifying areas where parking lots are densely packed and uniformly accessible. The time-based centrality heatmaps, on the other hand, unveiled regions where the demand for parking is likely more time-sensitive, possibly due to higher turnover rates and closer proximity to high-traffic venues.

For city planners, the identified hotspots signal areas where the development of new parking infrastructure could alleviate congestion and meet the rising demand. This is particularly pertinent in clusters with high centrality scores, where strategic placement of additional parking facilities could significantly enhance the overall accessibility of the area. Businesses, especially those reliant on customer access to parking, can leverage these findings to scout for optimal locations. Establishing operations in proximity to high-demand parking hotspots could translate to increased foot traffic and revenue.

For residents, understanding the landscape of parking demand facilitates better travel planning. Those residing or working in areas with limited parking availability may opt for alternative transport methods or adjust their schedules to align with the ebbs and flows of parking space occupancy. Furthermore, our study underscores the potential of integrating network analysis with traditional geospatial methods to inform urban infrastructure development.

4.1 Economical Analysis

The intricate balance between urban dynamics and parking infrastructure is vividly reflected in our economic analysis of parking clusters. Cluster 4, nestled in the commercially vibrant First Hill, and Cluster 9, in the densely populated Belltown, emerge as fiscal forerunners. Their robust earnings from parking underscore a high demand for accessible parking in areas thriving with economic activity. Conversely, Clusters 1 and 6, despite their strategic locations near Green Lake and the Belltown corridor, report more modest revenues. This disparity suggests a potential overcapacity of parking or a commendable adoption of alternative transport methods by the local populace. These economic insights lay the groundwork for strategic urban planning and infrastructure development. Policymakers and city planners might find these findings particularly useful for crafting nuanced parking solutions tailored to each neighborhood's unique rhythm and flow.

5 CONCLUSIONS

In our study, we applied a robust theoretical framework to the intricate urban fabric of Seattle, dissecting the city's parking infrastructure with a keen eye on spatial distribution and economic implications. Our analysis painted a clear picture of the urban landscape, highlighting the downtown core and Belltown as the most economically vibrant parking hotspots. This contrasted starkly with quieter zones like Green Lake, where lower economic activity from parking suggests either an oversupply or a cultural shift towards alternative transportation modes.

The economic implications of our findings are substantial, providing city planners and policymakers with a strategic blueprint for optimizing parking management. For instance, in high-demand areas, dynamic pricing could be employed as a tool to manage parking turnover effectively, thus maximizing utility and revenue. Conversely, areas with lower demand could benefit from policy interventions aimed at encouraging public transit use, potentially freeing up valuable urban space for alternative uses.

The granularity of our research offers a quantitative lens through which the resilience of Seattle's parking infrastructure can be assessed. By identifying which areas would benefit most from infrastructural investment or policy shifts, decision-makers are equipped with actionable insights to respond proactively to the ever-evolving demands of urban development. As cities worldwide grapple with the challenges of modernization and increasing vehicle density, our study serves as a model for urban analysis, providing a pathway to a more accessible and economically sustainable urban future.

6 AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: Study conception and design: N. Gaddam, V. Kanakamedala; data collection: A. Gaddam, A. Dange; analysis and interpretation of results: N. Gaddam, V. Kanakamedala, A. Dange; draft manuscript preparation N. Gaddam, V. Kanakamedala, A. Dange. All authors reviewed the results and approved the final version of the manuscript.

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