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Articles

Predicting the spatiotemporal legality of on-street parking using open data and machine learning

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ABSTRACT

Searchin… ecially in highly p… et parking is often a c… and parking lots. How… e search process … ata-driven framew… on-street park… a and human … street, census t… achine learning … best with the minimum … ith the highest … four spatial

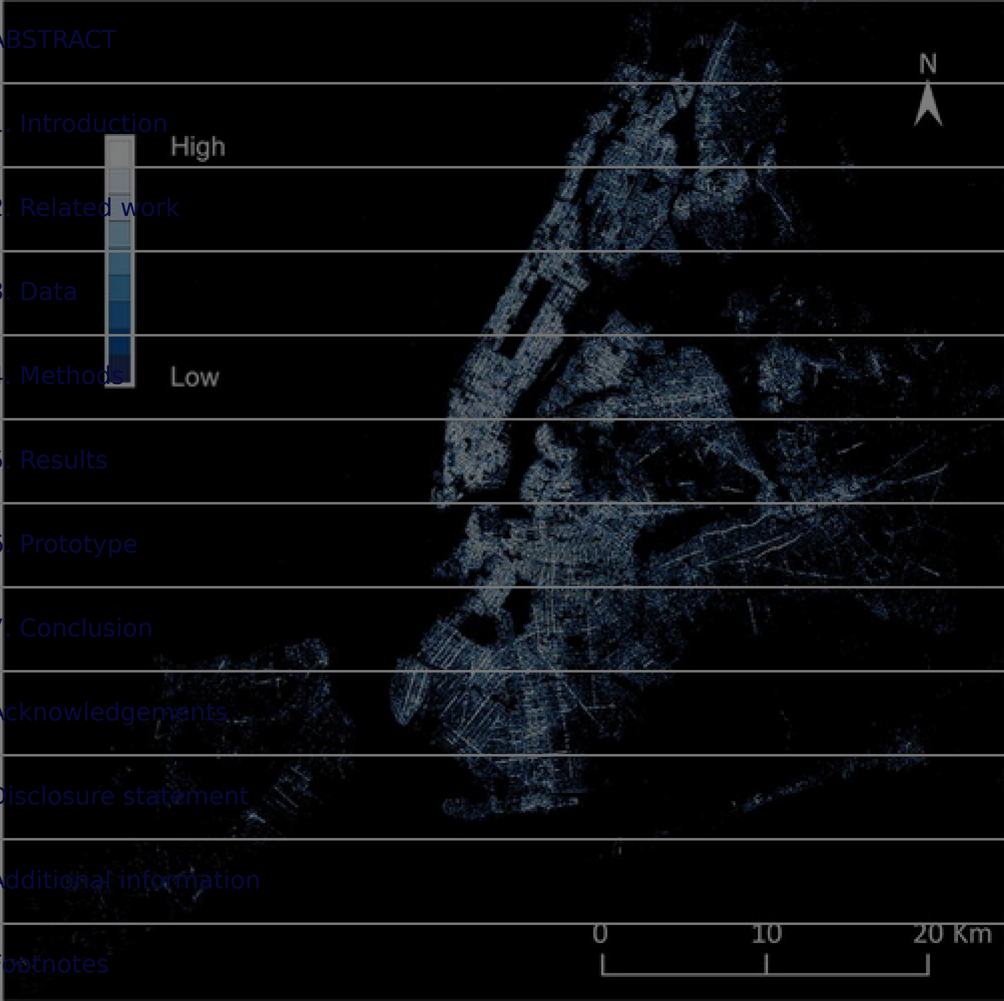
retail stores, health-care services, accommodation and food services are positively associated with the number of parking violation tickets.

KEYWORDS: Open data data fusion machine learning urban computing

1. Introduction

Parking is an important element in the transportation system and plays an important role in people's travel decisions. Parking availability information and pricing can influence people's departure and arrival time, travel mode choices, and activity duration. Almost all U.S. cities have minimum parking requirements for each type of land use, which determines the minimum number of parking spaces that should be provided by land developers. Most on-street parking is free or underpriced compared to garages and parking lots and therefore it is often over-demanded. This makes searching for a parking spot in metropolitan areas a great challenge comparable to the Hunger Games, especially in highly populated areas such as downtown districts, job centres, etc. First, the supply and demand of parking spaces is unbalanced with the increasing number of vehicles but limited parking facilities in urban areas. Second, the urbanization process is accelerating in most metropolitan areas and attracting more job opportunities, human flows, business and social activities. These popular destinations together with underpriced parking generates more travel demand and parking needs. Third, parking availability and legality are highly variable spatially and temporally.

Figure 1. ... ation tickets in the Ne...



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On-street parking is often a cost-effective choice compared to parking facilities such as garages and parking lots. However, limited space and complex parking regulation rules make the search process very difficult. Moreover, there is almost no real-time information about available on-street parking spots and it is legal or illegal to park. Even if the driver is a local resident, compound parking rules can still surprise the driver and gen … les, proximit … ain time periods. … ket cost cities in … kets generate … 3. Figure 1 show … ts over the two … ets without overlayi … ets in NYC. The Man … n-street parking … derstand the spatiote … l reliable

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machine learning models to predict the spatiotemporal legality of on-street parking using NYC open data[2].

Another important aspect that needs attention when analysing the point-based parking violation data is the scale effect and the modified area unit problem (MAUP). The scale effect may cause variations in statistical results among different spatial aggregation levels and MAUP affects results when point-based measures are spatially aggregated into different zoning configurations (Openshaw 1984; Fotheringham and Wong 1991). How much detail a machine learning model needs while still producing an acceptable error rate is worth of exploration. To this end, we propose a data-driven framework for understanding and predicting the spatiotemporal legality of on-street parking by training machine learning models using the NYC parking tickets open data. And four types of spatial analysis units (i.e. point, street, census tract, and grid) are used to examine the impact of spatial aggregation scale in machine learning predictive models.

The remainder of the paper is organized as follows. First, in Section 2, we present the literature review on parking availability prediction studies in transportation and computer sciences. Then, in Section 3, we introduce the datasets and preprocessing steps in order to feed the data into machine learning models. In Section 4, we formulate the problem into regression and classification approaches, and briefly introduce a set of machine learning models used in this study. In Section 5, we test our framework at different spatial scales and compare the model performance. In Section 6, we show the designed Web prototype for exploring the parking legality information in NYC. Finally, we conclude this work with some considerations on the potential of this work for ... on 7.

2. Rela...

Parking ... bility and park... nd mode choice (... at parking in the U.S. ... avel and creates i... her active travel m... eated by cruising ... anagement balance the parking demand and supply (Litman 2018). With better parking information provided, drivers can enhance their parking decision-making and prevents parking overflow from one place to another (Caicedo, Blazquez, and Miranda 2012).

There have been many research efforts towards improving the search efficiency for an available parking space given its impact on driving time, traffic, and even air pollution (Teodorović and Panta 2006). One study found that 30% of the average traffic cruising in investigated areas was actually caused by searching for parking, with an average search time of 8.1 min (Shoup 2006). Google AI research team developed a logistic regression model to predict parking difficulty (e.g. limited parking or easy) by utilizing anonymous aggregated trajectory information from mobile users who opt to share their location data (Cook, Li, and Kumar 2017). They used grids as a spatial unit for training the model. Using this, Google launched a new feature for the Google Maps App across 25 US cities that offers predictions about parking difficulty close to users' destination. There also have been studies focused on detecting the availability of parking spaces either using instrument parking infrastructure with special sensors (Chatman and Manville 2014) as well as using crowd-sensing solutions (Chen, Santos-Neto, and Ripeanu 2012; Zheng, Rajasegarar, and Leckie 2015; Pflügler et al. 2016; Bock, Attanasio, and Di Martino 2017), but both types of studies rely on the existence of predefined parking spaces or the development of mobile applications such as PhonePark, iPark, and UPDetector (Xu et al. 2013; Yang, Fantini, and Jensen 2013; Ma, Wolfson, and Xu. 2014). This study focuses on determining the legality of a parking space at a given time and day and the location at different spatial scales by utilizing machine learning algorithms and using publicly available parking violation ticket informat … arking using machine … aining. Some ef … -vector regressi … 2017). With these m … es while requi … dies.

Utilizing … nce is quickly … me tiresome tasks, su … knowledge discover … Mao et al. 2018; H … landslide modelling, and groundwater studies (Naghibi, Pourghasemi, and Dixon 2016). In this study, we examine the importance of spatial resolution when incorporating spatial data with machine learning. At the time of writing, machine learning models examining the spatial heterogeneity at different spatial resolutions are still an emerging study area (Lu et al. 2018; Yang et al. 2019). Such research incorporates Tobler's First Law of Geography (Tobler 1970) and the scale effect, which is to say that more detailed spatial resolution should provide more related features and likely produce less error than less detailed spatial resolutions. The idea that a machine learning model is able to provide these predictions at all is Tobler's First Law of Geography in practice, and potentially transferable according to the Third Law of Geography which focuses one the similarity of geographic configuration of locations in spatial predictions (Zhu et al. 2018). By examining different spatial resolutions or at aggregating into different spatial analysis units, we provide insights into how much detail a machine learning model needs while still producing an acceptable error rate.

3. Data

3.1. Parking violation tickets open data

As mentioned above, we downloaded over 10.8 million parking violation tickets generated in NYC in the fiscal year 2017 and 11.7 million in fiscal year 2018 from the NYC Open Data platform. Each ticket contains information including a summons number, violation code, street address, ticketing time, vehicle plate, etc.

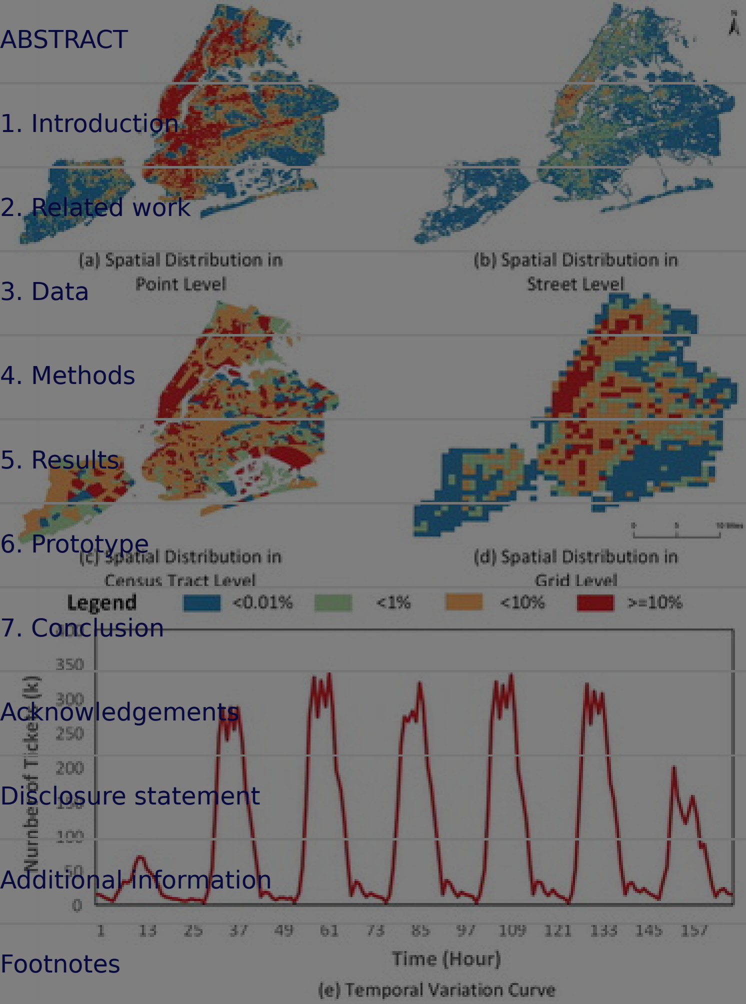
3.2. Po

In order … ed with more parking … tail stores, health-c … er 137,000 point … e[3]. The POIs are fi … em (NAICS) two-digi … ased on the NAICS tw … ng Oil and Gas Extr … Wholesale Trade 42 … 49), Scientific Tech 54, Administrative Support and Waste 56, Educational Services 61, Health Care and Social Assistance 62, Arts & Entertainment & Recreation 71, Accommodation & Food Services 72, Other Services 81, Public Administration 92. In addition, the category of Parking Lots and Garages (NAICS Code: 812,930) is treated as a separate POI category since it is directly related to parking activity. This gives a total of 24 categories of POIs at the root level of categorization as part of model features (See Figure 5 in detail).

3.3. Human mobility patterns

In addition to the static spatial distribution of POIs information, we also retrieved the fine-resolution visit patterns of all POIs from the aforementioned SafeGraph database which covers dynamic human mobility patterns of millions of anonymous smartphone users. For each POI, the records of aggregated visitor patterns illustrate the number of unique visitors and the number of total visits to each venue during the specified time window, which could reflect the attractiveness of each venue. The mean hourly visits over a week were recorded as a 168-dimensional vector to show the dynamic stream of visit patterns. If a visitor stays for multiple hours, a visit will be shown in each hour during which the visitor stayed.

Figure 2. The spatial distribution of parking violation tickets at four spatial scales and the temporal variation curves of tickets.



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3.4. Data preprocessing

In this study, we discretized the study area into four spatial scales (point level, street level, census tract level, and 1 km grid level) and the time into 168 hourly slots (7 days of a week ∗ 24 h of a day) to capture the snapshots of the legality of street parking. To perform … coordinates of each … API. Then, since we … hat were more tha… e number of tickets a… h time slot.

At th… j), the time of da… n(j,h,d) was used as … spatiote… ength stlen, street ty… characte… s follows: [

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features were more complex. At these levels, we not only considered their spatiotemporal characteristics pj, th, and td, their street attributes with the summation of street length sum_st_len and street area sum_st_area, but also considered the dynamic human mobility patterns and the POI distributions in the corresponding spatial unit. The POI data were aggregated to each spatial unit and represented as 24 features. In addition, the number of visits observed in the specified unit sum_visitj, the number of unique visitors sum_visitorj, the number of visits of corresponding to the time of day visit(j,h) and the number of visits of corresponding to the day of week visit(j,d) were added to model the human mobility patterns. Thus, the training features can be represented as follows: [pj, th, td, sum_st_len, sum_st_area, POI1, ⋯, POI24, sum_visitj, sum_visitorj, visit(j,h), visit(j,d)]. Table 1 shows the number of samples at each spatial scale and the ratio of positive and negative cases for parking legality classification (See Section 5.3 for more details).

Table 1. The number of samples at different spatial scales and the ratio of positive and negative cases for parking legality classification.

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Figure 2 shows the spatial distributions of georeferenced parking violation tickets at four scales and their temporal variation curve of the summation of tickets. The figure of point level data was derived using kernel density estimation, and the other three

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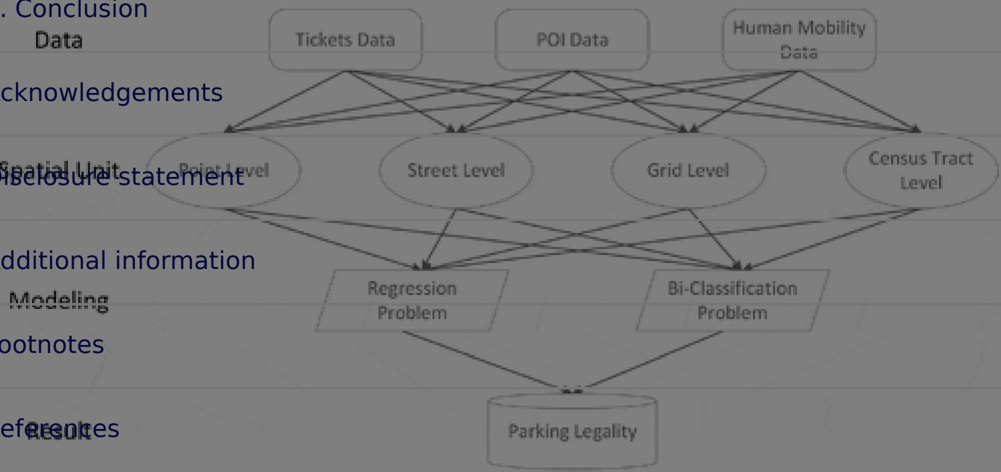
4. Met

In this section, we provide the details of our proposed framework to understand and predict the parking legality. In this framework, we approach the parking legality prediction as a regression problem to predict the number of parking violation tickets given a location and time, and as a binary classification problem to interpret parking legality. To this end, a series of machine learning models are trained in four spatial scales with processed datasets that are mentioned in the previous section. The architecture of our proposed framework is shown in Figure 3.

Figure 3. The proposed parking legality predictive framework using multi-source data and machine learning.



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4.1. Prediction of parking violation counts

To investigate the impact of the spatial scale on different regression models, we selected the following six machine learning models for this study:

MLR: Mu ... tween two or more ... uation to the obse

SVM: Su ... gh-dime ... dicted based on th

Decision ... a model that predicts ... rred from the data

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Random Forest: The random forest (RF) constructs a multitude of decision trees and outputs the results by computing the mean of the predictions of each individual tree (Breiman 2001). RF is trained on different parts of the same training set, with the goal of reducing the variance.

GBRT: The gradient boosted regression trees (GBRT) use a gradient boosting method to construct a set of decision trees as base learners and outputs the result by computing the sum of the base learners (Friedman 2001). XGboost uses a more regularized model formalization to control over-fitting issue and thus is chosen in this study (Chen and Guestrin 2016).

DNN: Deep neural network (DNN) is a multi-hidden-layer artificial neural network whose artificial neurons can respond to a surrounding unit within a portion of the coverage (Goodfellow, Bengio, and Courville 2016). As shown in Figure 4, we constructed a DNN architecture consisting of four fully connected dense layers with reclinear activation functions and two dropout layers with a 0.5 rate to regularize the DNN and improve the generalization error. The output layer uses a linear activation function for regression and a sigmoid activation function to produce a probability between 0 and 1 for binary classification using a threshold of 0.5. The mean square error (MSE) is used as the loss function for regression training while the cross-entropy is used for classifier training.

Figure 4. The multilayer architecture of deep neural network used in this study.

Evaluati … aining the models a … ation.

MSE=1N …

Where yi′ is the number of observed parking violation tickets at the location i, yi is the corresponding predicted value, and N is the number of fed data into each model.

4.2. Prediction of parking legality

In addition to interpreting parking legality as a regression problem by estimating the number of violation tickets, it can also be interpreted as a binary classification problem of whether the corresponding time and place can be legally parked by analysing the historical parking violation ticket information. Therefore, a specified location and time with at least one ticket is marked as 'positive case' (i.e. the machine learning binary classification when the number of tickets ≥1) to represent 'Risky Parking' and the others will be marked as 'negative case' (i.e. the number = 0 and no ticket issued) to represent 'Legal Parking'. In addition to the aforementioned SVM, random forest, and DNN machine learning approaches that can also be used for the classification problem, four additional classification models are used in this study:

KNN: k-nearest neighbours algorithm (KNN) classifies an object by a vote of its neighbours, with the object being assigned to the most common class among its k nearest neighbours in feature space (Cover and Hart et al. 1967).

Logistic regression: It uses a logistic function to model the relationship between one dependent binary variable and one or more nominal, ordinal, interval or ratio-level independent variables (Berkson 1944).

Naive Bayes: Naive Bayes is a probabilistic classifier that makes classifications using the Maxi

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$$Recall=\frac{TP}{TP+FN} \quad (4)$$

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

$$F1=\frac{2*Precision*Recall}{Precision+Recall} \quad (6)$$

5. Results

Figure 5. The result of selected variables vs. R-squared at the census tracts level and at the 1 km grid level.

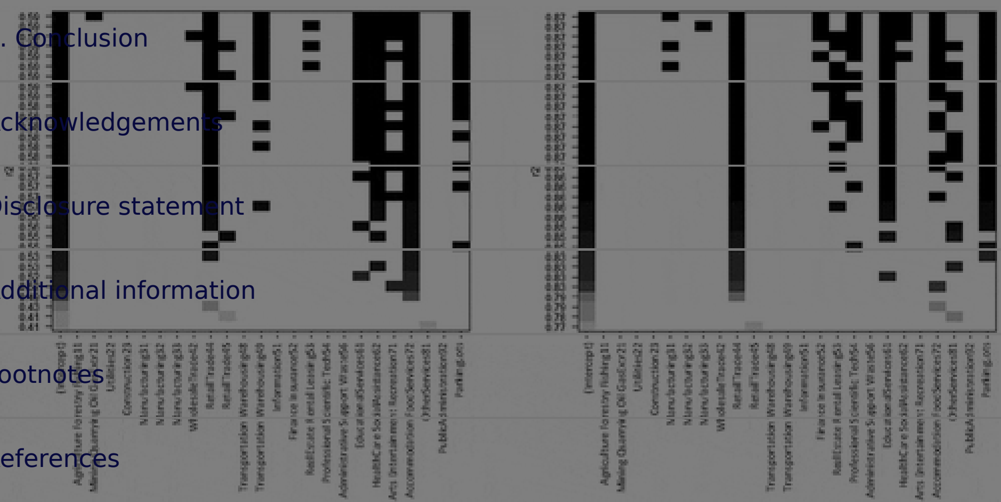

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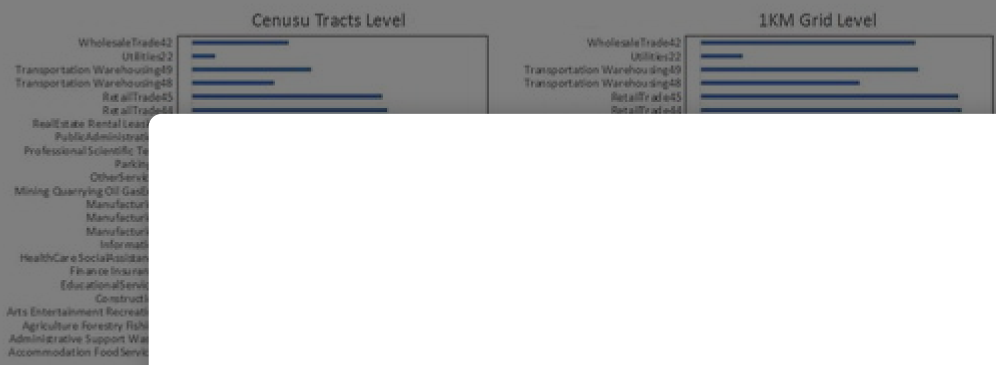
Figure 6. The correlation analysis at the census tract level and the 1 km grid level.



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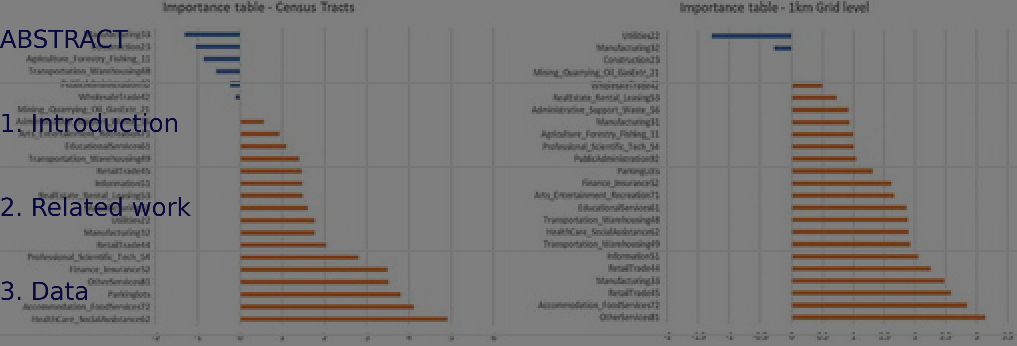

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5.1. Relationship between parking violation and POIs and visit patterns

For POI-based and mobility-based analyses, the POIs mentioned in Section 3 are aggregated to the census tracts level and the 1 km grid level, respectively, to conduct analysis. After the aggregation, for each analysis unit (a census tract or a grid cell) there is a sum of parking tickets and 24 categories of POIs in each unit.

The multi-linear regression is conducted first to obtain an overall relationship between the parking violation and its surrounding environments. Then, the correlation analysis and the importance ranking using the random forest regression method are also implemented to identify critical factors for the parking violation.

5.1.1. Census tracts level

In the census tracts level, when using all 24 categories of POIs to fit the number of parking tickets in the linear regression, an adjust R^2 around 0.59 is obtained. To select the most important variables, an exhaustive search for the best subsets of variables for predictin ... ows the selected ... s changes from 2 t ... g by the model. T ... parking violation ... nal Services, Health ... Parking Lots.

The resu ... random forest re ... ethods are not very ... Accomm ... nce

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increase of parking violation, which may not be intuitive. This might indicate that the current parking lots are still not enough for the parking needs of citizens in New York.

5.1.2. 1 km grid level

At the 1 km grid level, the result of multiple linear regression using all 24 variables is around 0.87, which indicates a good estimation. Figure 5 shows the best subsets of variables for prediction. The frequently selected variables are a little different from the result of the census tracts level, which are Retail Trade, Educational Services, Accommodation and Food Services, and Parking Lots. However, by examining the multicollinearity of different combinations of variables, there always exists high colinearity with the Variance Inflation Factor of over four among variables.

In this case, the results from correlation analysis (Figure 6) and the importance ranking from random forest regression (Figure 7) may be more reliable. The results of the correlation analysis at the 1km grid level are very similar to that of the census tracts level (except for the ParkingLots) where Accommodation and Food Services, Retail Trade and Other Services are the top three most correlated variables to parking ticket numbers. These three factors are also the top three important factors in the importance ranking.

In general, most categories of the POIs will lead to an increase in parking violation, especially when there are accommodation, food, and retail stores. Also, the existence of parking lots cannot prevent the parking violation, which shows that the need for parking lots is still not satisfied at the current stage.

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As show ... ss the four different ... effect. With the decr ... tract to 1 km g ... across all mode ... ith 80% training ... for predictin ... . It shows that the ... st at the 1 km grid ... iven the level, which has a small gap. The results also show that the random forest model works the best with the minimum RMSE and outperforms other competitors by a large margin across all the spatial scales. Note that for the support-vector regression (SVR), we tried different kernel types (e.g. linear, second-degree polynomial, Gaussian RBF) and reported the best model result. The decision tree model built with recursive greedy algorithms ended up with a very complex structure with 36,797 and 13,459 leaf nodes at the census tract level and at the grid level, respectively. XGBoost and DNN are just as good as or better than simple MLR by a small margin at different spatial scales.

Table 2. Prediction of parking violation ticket counts using location and time features with different machine learning models.

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Table 3. Prediction of parking violation ticket counts using all features with different machine learning models.

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In addition, as expected, these machine learning models using all available features (Table 3) achieve a better performance compared with the same model but fed with only
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Figure 8. The learning curves for predicting the number of parking violation tickets with cross-validation at different spatial scales.

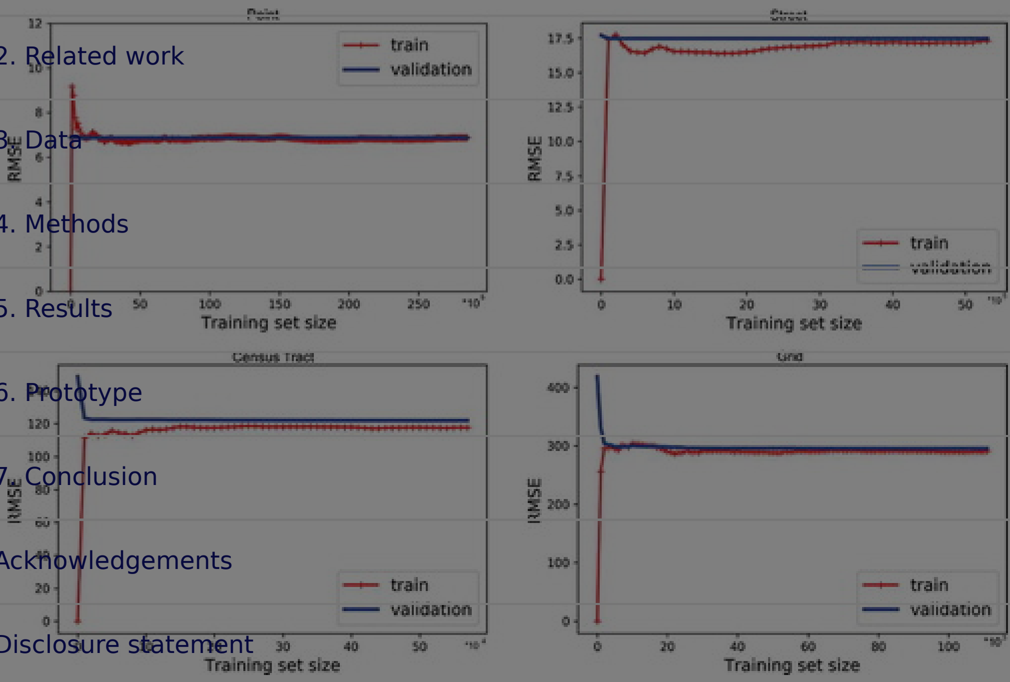

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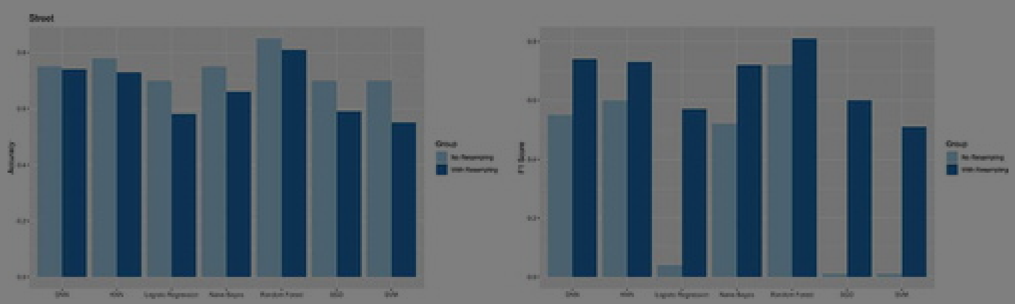
Figure 9. The accuracy and F1-score of different prediction models comparison using imbalanced and balanced samples with resampling process at the street scale.



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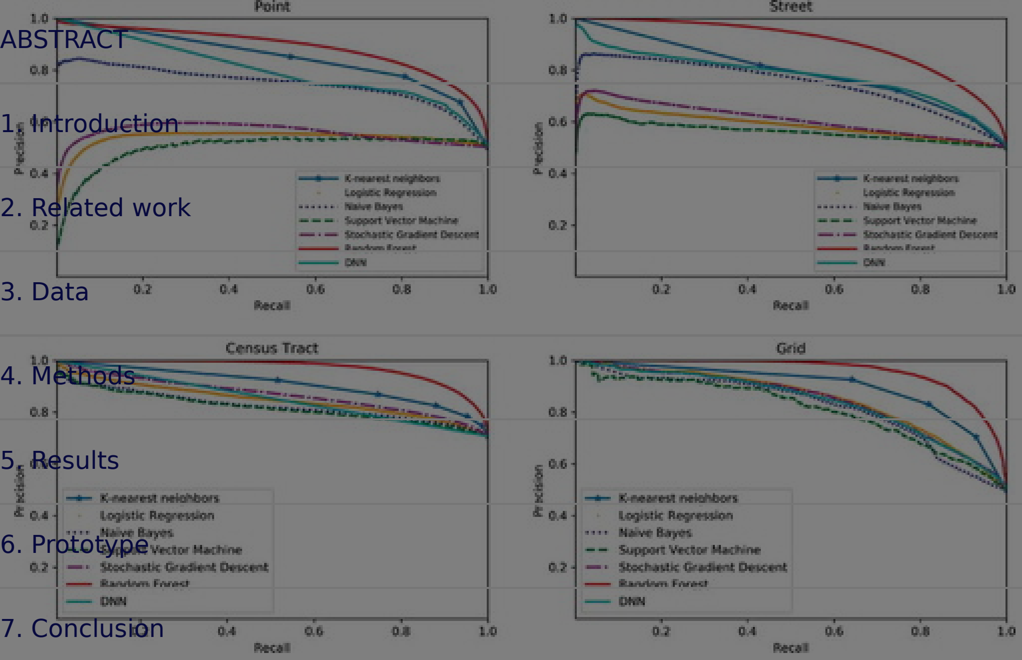

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5.3. Results for prediction of parking legality

Regarding the classification results, as shown in Table 4, random forest outperforms all other models and achieved both high accuracy scores (0.82, 0.85, 0.86, and 0.88) and high F1-scores (0.82, 0.72, 0.90, and 0.88) across all four spatial scales. The KNN and the DNN also perform well and fall behind the random forest by a small margin. Note that we chose k = 3 as the number of nearest neighbours in feature space with regard to the temporal autocorrelation patterns of parking legality over time and its impact on model performance). The autocorrelation coefficient for parking legality with a temporal lag of 3 hours is 0.28, 0.40, 0.38, and 0.55 at the point, street, census tract, and grid levels, respectively. Although the Naive Bayes model gets a good accuracy and F1 scores a … 72), it doesn't … ensus tract level (0. … ue discusse…

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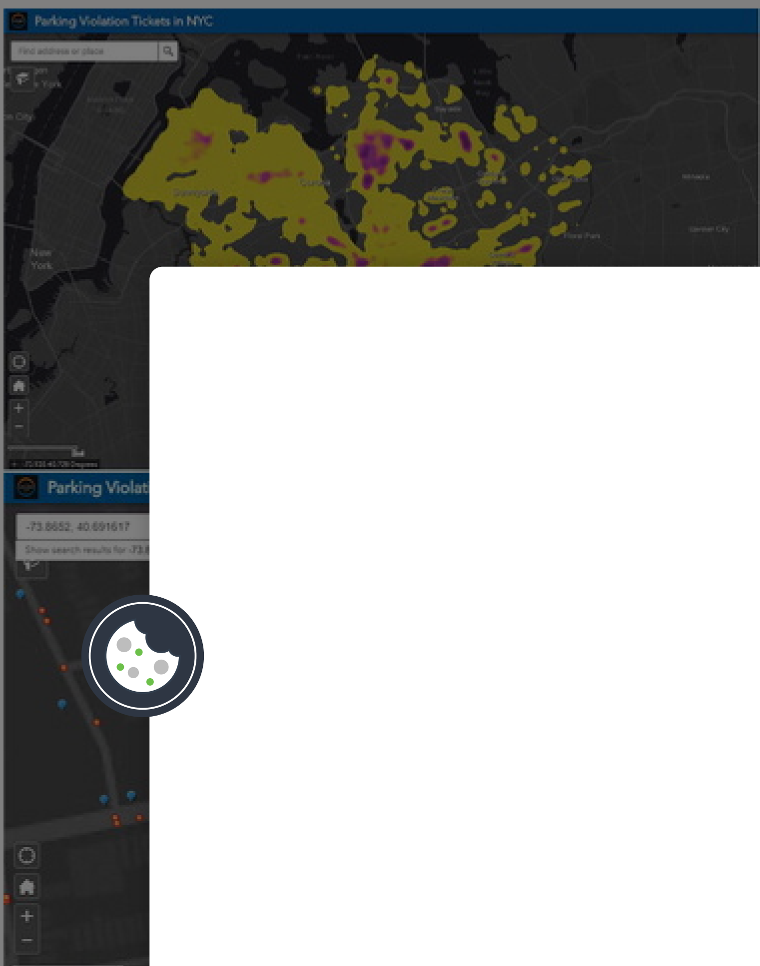
Another important issue requiring attention is the presence of imbalanced training data in practice. In our case, there is a class imbalance between the positive class and the negative class for parking legality. The imbalanced training data can cause the accuracy paradox such that we get excellent accuracy but the accuracy is only reflecting the dominating class distribution. Taking the no-resampling street-level data as an example, as shown in Figure 9, all the models got a high overall accuracy (over 0.7) but relatively low F1-scores, and some of the models (e.g. logistic regression, SVM and SGD) even got close to 0. That is mainly because of the imbalanced training samples between positive (29.7%) and negative (70.3%) classes. Therefore, we resampled the training data with a more balanced distribution for both positives (50%) and negatives (50%). The F1-score increased significantly since we get a better precision and recall performance. Alternatively, one may want to check the detailed precision-recall curves with different recall rates as shown in Figure 10 to compare the model performance especially for highly skewed datasets (Davis and Goadrich 2006). It shows that the random forest outperforms all other models with the highest precision value across different recall rates in parking legality prediction at four spatial scales.

Figure 11. The Web interface of the multi-scale parking legality analysis platform based on Esri Web AppBuilder.



6. Prototype

With regard to the multi-level spatial variation of parking space availability and parking legality, we also worked to design and develop a parking legality Web GIS application by integrating the NYC parking violation open data with statistical analysis at different spatial scales. The machine learning models are encapsulated as web service APIs and deployed using the Flask web framework. As shown in Figure 11, at a large-scale zoom level, it covers huge amount of data points. Thus, it is better to use KDE mapping for exploring the overall spatial patterns of parking legality while checking the detailed parking legality at a specific location with historical parking ticket statistics and violation type information.

7. Conclusion

In this study, we propose a data-driven framework for understanding and predicting the spatiotemporal legality of on-street parking by training a set of machine learning models using the NYC parking violation ticket open data. The models are tested at four types of spatial analysis units (i.e. point, street, census tract, and grid) and the results confirmed the impact of spatial scale in machine learning predictive models. The more

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frequency across space over time may have potential impact on generating the parking violation tickets. With better on-street parking information provided in advance, drivers can enhance their parking decision-making. Our research may offer insights into parking management policy such as parking regulation rules, pricing, and time limitation to balance the parking demand and supply at different spatial scales using open data.

Acknowledgements

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Disclosure statement

No potential conflict of interest was reported by the authors.

Additional information

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