

PreGIS: a platform for urban parking analysis and management

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Abstract

The *PreGIS* project goal is to contribute to a better understanding and management of the urban parking dynamics through the development and experimentation of meaningful tools and models. We have succeeded in developing a web platform prototype and services that will help smart city managers tackle the complex issue of urban parking management and occupancy prediction. Several machine learning algorithms and prediction models have also been implemented and connected to data provided by the sensors. The current API specification is made as an open system, easily expandable in the future, to other partners or other types of relevant information. First analyses and observations performed with the platform, are very inspiring. In addition, feedback of professionals gives us a strong motivation to pursue the development of this ongoing project for other metrics (fraud and turnover rate) or different use cases (dynamic pricing, law enforcement).

Keywords

Parking occupancy rate, visualization, machine learning, predictions, sensors, urban mobility

1. Introduction

Urban parking is an essential component, for the mobility component of any smart city. Recent studies indicate that 30% of urban traffic is generated by people looking for a free parking slot ([1],[2]). This useless traffic is leading to nuisances with a significant impact on environment, economy and citizen's well-being. So, the optimization of the parking capital of a city should be a key objective for any medium or large smart city sustainability.

As drivers proved to be attached to individual freedom, hopes to reduce the vehicle fleet significantly by incentive measures have been disappointed. The rise of electric cars, in the next few years, might help to mitigate some of the issues (noise, pollution). However, it will not lower the economic impact due to wasted time, nor the driver anxiety to find an available parking slot. It might even become more acute as charging time management will add a new constraint to the system.

Extra spaces cannot be generated easily in a city. So, parking places have to be considered as a finite resource. Consequently, their usage must be optimized by driving end-users towards a "best usage" policy. This strategy has already been implemented, tested, and recently extended in San Francisco "SFpark Project" [3], where 28'000 on-street parking meters implement a "demand-responsive pricing" policy. The main achieved benefits are an average parking price lowering, a decreased parking search time (-43%), a decreased distance traveled (-30%), and increased local business sales (+15%).

The *PreGIS* project aims to develop a generic and portable solution to assist the parking managers to make good decisions. The solution should propose three tools for (i) The city's parking status analysis thanks to field sensors and other data sources, (ii) The prediction of the parking status evolution in a

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near future, (iii) The simulation of the parking status given specific conditions (day, event, weather, ...) according to well-chosen management parameters.

To achieve the previously mentioned objectives, PreGIS does rely on the knowledge of academic research and development teams (HEPIA, HE-Arc) for the machine learning, complex data visualization, urban modeling and UX. It also relies on the parking business expertise of the external partners² (IEM, FdP, OCT, SITG), whose cooperation will be essential for the prototype experiment in Geneva.

From the very broad project roadmap that was defined, we choose as input data types the *parking payment rate*, and *parking occupancy rates*. Additional information types (fraud rate, weather, traffic, events) are not yet connected to the system nor used by the models. Although some of them were made available recently, this decision helped to complete the first proof of concept that we present here. Besides it also led to a system more compatible with other cities

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2. PreGIS scope, tools and functionalities

An efficient parking management should favor the capability of as many drivers as possible to take advantage of the available parking slots of a city. To achieve this objective, we believe that the management decisions should rely on quantitative and measurable parameters: turnover rate (τ_{rotation}), fraud rate (τ_{fraud}), and occupancy rate (τ_{occ}). These rates are linked and while the first should be maximized, the second minimized, the last one must be carefully balanced.

Although the precise measurement of these parameters for every single parking slot is out of reach, with PreGIS we are building a prototype platform to explore their behavior, develop prediction models, and in the future analyze the parking management decisions impact. We present here the visualization platform and prediction engines for the spatial interpolation to fill the gaps on the map (parking without sensors), and the temporal prediction (next hour parking prognosis).

In "The high cost of free parking" [4], D.Shoup pointed out the direct relationship between the occupancy rate of on-street parking and significant urban quality metrics (retail shops income, time loss, pollution,). Theory and experiments agree towards the fact that there is an optimum occupancy rate around 85%.

2.1. Data Sources

Three sources of data have been acquired.

- Outdoor parking sensor for on-street *occupancy rate*
- Outdoor parking meters for on street *payment rate*
- Indoor parking *occupancy rate*

The (outdoor) parking *occupancy rates* were gathered by a network of 650 *PrestoSense*^[TM] sensors installed by the Geneva state under the operational control of IEM ltd since 2018. Data was collected automatically (24/7, 365 days/year) providing a complete figure of the parking status of the city. Note that most of the data gathered in 2020 could not be used due to COVID related changes on the streets of Geneva. The individual sensors were split between 15 zones, throughout Geneva, to provide a good panel of different kinds of districts (office, residential, commercial, mixture). The rotation rates also available have not been used yet.

Outdoor parking meters do provide payment events that are summed to compute the payment rate (number of payment/hour). They do not reliably provide the other metrics alone, but are still a good predictor for some of them, or can be used in conjunction with the sensors to provide the *fraud rate*.

² **IEM**: Ingénierie Electronique Monétique; **FdP**: Fondation des Parkings; **OCT**: Office Cantonal des Transports; **SITG**: Système d'Information du Territoire à Genève.

The indoor parking data was not used until now, because of noise that would require time-consuming manual curation. Nonetheless, we expect to clean it and use it in the future as it should be correlated with parking availability outdoors.

2.2. Temporal Prediction Engine

In [5], we presented the architecture and results obtained by an ensemble of transparent models to predict car parking occupancy in one of the 15 zones. The engine successfully predicted the occupancy rate at a sensor location in the future (+14', +30', +60'). An approach with *multi-layer perceptrons* achieved an average *accuracy* exceeding 80% for predictions in the future up to 1hour, outperforming a naïve (history based) or K-NN approach. This prediction is based on the sensor occupancy rate of the previous hour as well as historical data (1 and 2 weeks before).

The prediction is based on three-class classifiers. The three classes correspond to the meaningful categories for a parking *occupancy rate* τ_{occ} : low-occupancy ($\tau_{occ} < 60\%$), average-occupancy ($>60\% \tau_{occ} \leq 90\%$), saturated occupancy ($\tau_{occ} > 90\%$).

In this work, the size of the whole dataset was approximately doubled, with respect to [5]. We selected it between 2018 and 2019, before the Covid-19 pandemic. Overall, we retained over 300000 samples in the training set and about 63000 samples in the testing set, covering the majority of the 2019 last quarter.

The time series in the input are given every two minutes. We tested several lengths, between 40 minutes (20 inputs) and 1440 minutes (720 inputs). Here we present our best results obtained with DIMLP ensembles. Table 1 illustrates the best predictive accuracies obtained in zone “Bd Helvétique” (the same zone reported in [5]). We used several models: SVMs; Decision Trees; and ensembles of DIMLPs. Note that the training of the models was performed ten times with the same training set; after training, the results on the testing set were averaged.

In a second series of experiments, we trained DIMLP ensembles on the entire dataset encompassing all the 15 zones. Note that the new dataset includes more than 4.5 million samples. For a training time-related issue, we limited the time series to 20 and 35 inputs. We illustrate the results in Table 2, with the first row showing a naïve classification rule of choosing the true class provided one week in the past.

DIMLP ensembles are without any doubt more accurate than the naïve decision rule.

Table 1

Average predictive accuracy of different models in the "Bd Helvétique" zone. The input number of the time series related to the occupancy rate is in brackets

	14 minutes	30 minutes	60 minutes
SVM	91.4 % (720)	89.3 % (720)	87.7 % (720)
Decision Trees	91.2 % (100)	88.8 % (720)	86.5 % (720)
DIMLP	91.6 % (400)	89.7 % (720)	87.9 % (720)

Table 2

Average predictive accuracy provided by DIMLP ensembles in 15 zones. The input number of the time series related to the occupancy rate is in brackets

	14 minutes	30 minutes	60 minutes
Naïve	65.5 %	65.6 %	65.7 %
DIMLP (20)	86.2 %	81.7 %	76.9 %
DIMLP (35)	86.3 %	81.9 %	76.7 %

2.3. Spatial Prediction Engine

The methodology used for spatial prediction, was taken from the environmental studies based on machine learning [6]. The common problem is that the ground truth is only available at scarce locations (weather stations in [7], occupancy sensors in PreGIS), often missing where predictions have to be done. Therefore, other spatiotemporal predictors were used in addition to the ground truth (sensor) data

to do predictions at new locations. Besides the latitude and longitude, the most important PreGIS spatiotemporal predictors are the paid parking tickets (correlated to parking usage), the area demography statistics (density of living/working drivers, ...), time of the day, day of the week and day of the year (parking occupancy patterns have a strong seasonality).

The algorithms used to create the model are "Random Forest", and "K-nearest neighbors". The last one appears to give meaningful regression outputs when viewed through PreGIS *ParkingWeatherMap* functionality (Fig.2). This work could be enhanced and extended, as shown in [7] by a *Target-Oriented Variable Selection* algorithm to optimize the use of additional predictors' data (input) in the system.

2.4. Architecture

The PreGIS platform is built using the microservices type architecture. The HTTP protocol is used to communicate between the different services. They are built using the Django Python web framework and the Django REST framework. The APIs follow the REST principle and data is exchanged using the JSON data format.

The user interface consumes the different services and allows the users to interact with the data. It is built as a single page application using *VueJS* as the JavaScript frontend framework along with two libraries: *Vue Router* and *Vuex*. The design and styling of the user interface is made using the *Bootstrap* CSS framework. Most technologies used in the creation of the tool are open source, minus the map service, provided by *Mapbox*.

In order to facilitate the integration of the different API clients in the frontend, a standard was created. This standard specifies the inputs, outputs, response formats and endpoints for the APIs. It was created with scalability in mind so that future implementations can be added.

(Fig.1) shows the workflow of the system from the input data providers (IEM Prestopark), feeding the machine learning engines that will then expose to the visualization frontend the different entities to be displayed: static (measured) metrics, predicted metrics, geometrical entities (parking areas). The UI backend provides authentication and other services to improve the user experience (UX).

The visualization frontend (see next section) offers a platform secure access through authentication and allows the manager to draw specific areas of interest on the map and perform temporal analysis over them. A limited access will be granted for anonymous user to view the current parking status and near future prediction.

Note that some additional source data providers are outside of PreGIS 1.0 scope. They have not yet been connected to the system but their future integration is discussed in section 4.

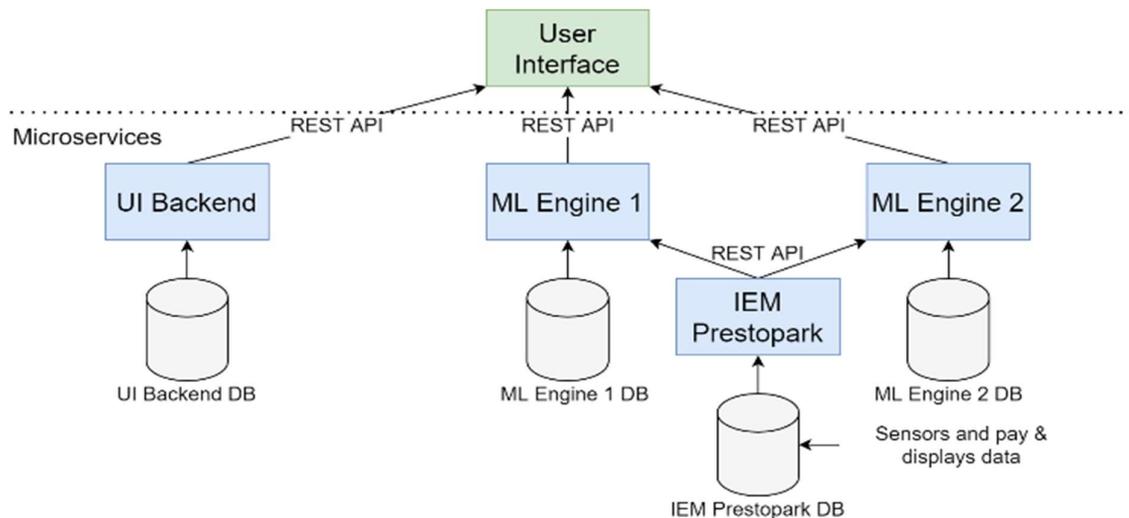


Figure 1: PreGIS components and workflow (v.1.0)

3. PreGIS tools and results

In the next figures, we present two visualizations offered by the PreGIS website. In Fig.2, we see the *ParkingWeatherMap* of the pay parking segments in Geneva. They contain ~5'000 park slots. The color scale represents the occupancy rate (green if empty, red if full). The time can be changed with the slider at the bottom to study the evolution over a 24 hours period or for the future 60 minutes with prediction for the end-user. It proved to be useful for assessing the nature of a neighborhood by observing some occupation patterns through the day (define homogeneous clusters in a city), and "feel" problems that can occur, while developing robust prediction algorithms.



Figure 2: *ParkingWeatherMap* of a business area in Geneva at 6AM (left), and 3PM (right) on Monday

In Fig. 3, after drawing on the map a polygon, and specifying a time interval, corresponding measurements and prediction model outputs are fetched and displayed for comparison or analysis. In this plot we did compare the payment rates and occupation rates of a street near the city center over a full week. We can see the day and night pattern clearly through the pay rates (parking is free in Geneva between 6PM and 8AM). The weekend is also visible on the right side with significant occupation and almost no payment. One more interesting point is the trailing of the occupation curves after lowering of payment curves that hint of possible frauds by drivers.

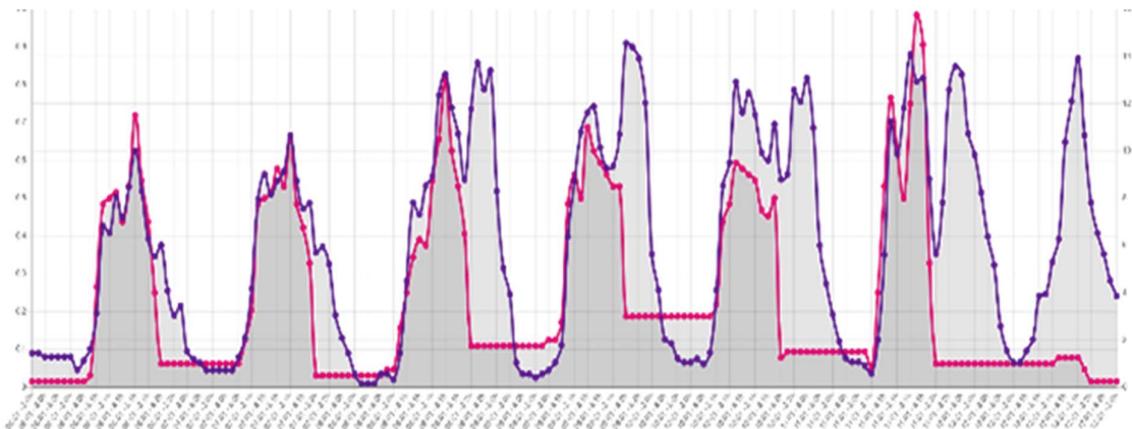


Figure 3: Occupancy rate (purple) and Pay rate (red) over one week at "Rue du Cendrier" (Geneva)

We also use the web application to compare the performance of different prediction algorithms with respect to the ground truth measured by occupancy sensors. As an example of regression predictions, Fig.4 shows the occupancy rates obtained by engines based on K-NN and Random Forest.

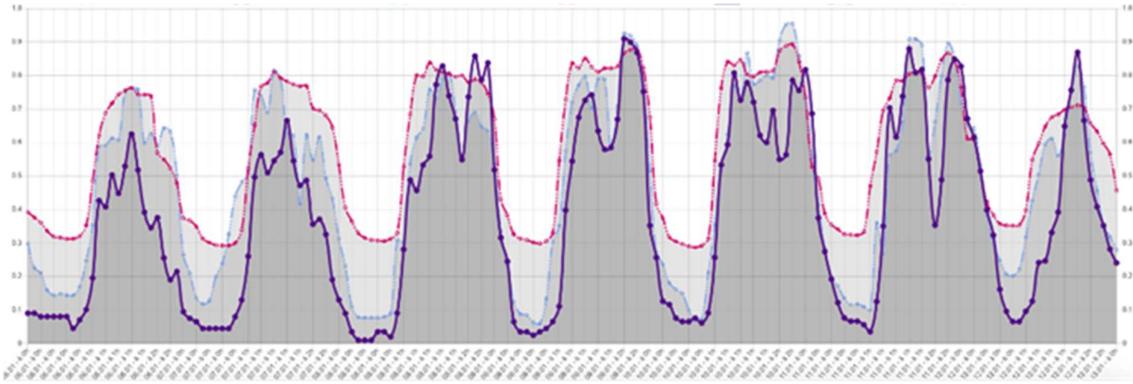


Figure 4: Comparison of two prediction models (red [Random Forest] and blue [K-NN]) with ground truth (purple) at "Quartier des Banques" (Geneva)

4. Follow-up and future developments

A current problem with prototypes based on Machine Learning techniques is the ability to explain their responses. Indeed, the majority of the used models, such as artificial neural networks are considered black-boxes. The DIMLP networks are transparent; hence in future work we will be able to explain why a prediction belongs to a given class. Note that typical responses will involve some time-series variables and other inputs relevant to the predictions. For instance, weather conditions and traffic intensity are not yet accounted for. Consequently, it will be interesting to determine whether they improve the predictions. Furthermore, the output of a neural network can be associated with a probability. Thus, it will be useful to provide a trust factor that will allow the user to have some degree of confidence in the system.

A natural question is whether our current model, trained with over four million samples, is general enough to be transferred to other cities. Perhaps, this is true to some extent. In this case, our current model could be simply tuned with few training iterations to a new location.

The sensors used to calculate the average occupancy rate in a given parking zone allowed us to perform good predictions. Nevertheless, for obvious cost reason, it is unwise to have as many sensors as there are car parks. In preliminary experiments, using half the number of sensors compared to the number of car parks, we found that the degradation of the predictions was small. In the future, we will systematically vary the proportion of sensors to determine how accurate the predictions remain.

Besides the occupancy rate, other metrics can be inferred from the combination of sensors and parking meters, or even *scan cars* [8] when available for the city management. We plan to extend the functionality and predictions proposed by PreGIS to two additional metrics:

- The *fraud rate*, percentage of unlawfully occupied parking slots, should be kept to a minimum. By predicting a fraud map, the law enforcement might optimize the control scheduling, effectively discouraging fraudulent parking usage.
- The *turnover rate*, number of car swaps per hour on a parking slot, is derived from the sensors. It could spot the *sticky cars* that are a real issue for parking management. This would help to optimize the parking duration time limits.

Another crucial question is how to consider our model dynamicity. By dynamicity we mean how to make it evolve over time so that it adapts to the current traffic situation. This situation may be due to one-off events that impact the driver's behavior like for example, the Covid pandemic since March 2020. More common events related to urban development like road rehabilitation work or area reallocation lead to highly dynamic data inputs. Consequently, we should include model updating strategies integrating these new parameters as input data for the training phase. Reiterating a training cycle to refine the predictions should not be constraining for the manager, while periodically allowing a subtle model evolution in order to stick to reality. The strategy to be implemented must respond to this delicate balance.

As the project stands, in addition to the training data used (sensors) we plan to introduce other data types. Among those envisaged, we already mentioned weather conditions and traffic intensity. Socio-demographic aspects could also be considered. One could naively imagine that densely populated centers affect the motorization rate. This motorization rate itself impacts the traffic intensity. It would then be interesting to see how the predictions behave.

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