BREAKING THROUGH THE TRAFFIC CONGESTION: ASYNCHRONOUS TIME SERIES DATA INTEGRATION AND XGBOOST FOR ACCURATE TRAFFIC DENSITY PREDICTION

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1 ABSTRACT
Rapid urbanization has resulted in increased traffic congestion, making accurate traffic density prediction crucial for sustainable urban mobility strategies. This paper proposes a novel methodology that integrates asynchronous time series data from diverse sources to develop accurate traffic density prediction. A case study on OpenDataBCN demonstrates the effectiveness of this approach using an XGBoost model, based on geographical coordinates and timestamp differences. The integration of data from different sources enhances the richness and granularity of information available for analysis, uncovering previously hidden patterns and relationships. The XGBoost model shows superior prediction accuracy and novel insights, highlighting the potential of this methodology for sustainable and efficient urban mobility solutions. This approach can also be useful for developing simulation tools for city traffic data generation and analysis. By promoting the effective utilization of open data platforms and advanced machine learning techniques, this novel approach offers a new paradigm for addressing the challenges of urban mobility in a data-driven manner.

2 INTRODUCTION
In recent years, the rapid urbanization and growth of cities have led to an increase in traffic congestion, posing significant challenges for urban planners and transportation authorities (Aluko 2019). The ability to accurately predict traffic density is crucial for effective traffic management and the development of sustainable urban mobility strategies. With the proliferation of open data platforms, such as OpenDataBCN (de Barcelona 2020) in Barcelona, there is an unprecedented opportunity to leverage vast amounts of heterogeneous data sources to develop accurate traffic prediction models. However, the integration of these diverse data sources, particularly those with asynchronous time series and varying geographical coordinates, remains a significant challenge. This paper aims to address this challenge by proposing a novel methodology for the asynchronous join of time series data based on geographical coordinates and timestamp differences, enabling the incorporation of previously unavailable information for improved traffic density prediction (Garcia, Peyman, Serrat, and Xhafa 2023).
The key contribution of this paper lies in the development of an innovative data integration technique that allows for the seamless combination of asynchronous time series data from various sources, enhancing the richness and granularity of the information available for analysis. By leveraging the wealth of open data provided by OpenDataBCN, this methodology demonstrates the potential of open data platforms in facilitating data-driven decision-making and fostering a more comprehensive understanding of urban dynamics. Furthermore, the integration of these diverse data sources enables the identification of previously hidden patterns and relationships, contributing to the improvement of traffic density prediction accuracy.

To evaluate the effectiveness of this data integration approach, we employ the end-to-end tree boosting system XGBoost (Chen and Guestrin 2016) model to analyze the resulting time series data for predicting traffic density in Barcelona. XGBoost is a powerful machine learning algorithm that has demonstrated exceptional performance in various prediction tasks, making it a suitable choice for this study. Through extensive experimentation and validation, we demonstrate the superiority of our proposed methodology in terms of prediction accuracy and the ability to uncover novel insights from the integrated data.

In conclusion, this paper presents a novel approach to the asynchronous join of time series data based on geographical coordinates and timestamp differences, enabling the effective utilization of open data platforms such as OpenDataBCN for improved traffic density prediction. By harnessing the richness of open data and advanced machine learning techniques, we contribute to the ongoing efforts to make urban data more understandable and profitable for the general public, ultimately promoting more sustainable and efficient urban mobility solutions.

3 DATA SEMANTIC ENRICHMENT MODEL AND IMPLEMENTATION

3.1 Model

In this section, we provide a detailed description of the model used to associate an initial set of values with the closest available measurements based on geographical proximity and minimum difference in timestamps while considering the availability of additional data (Garcia, Peyman, Serrat, and Xhafa 2023). This model is designed to provide an accurate representation of the predefined conditions in different sections of a city, based on the closest measurements available. In the following section, we describe the model in detail, including the inputs, outputs, and the development of the data enrichment process.

**Input**

Let $C$ be the set of sections of the city, and let $T$ be the set of timestamps. For each section $c \in C$, let $D_c$ be a dataset of initial values for $c$ at different timestamps $t \in T$. Let $S$ be a set of geographic locations associated with each dataset $D_c$. For each timestamp $t \in T$, let $M_t$ be a set of measurements taken at different locations $s \in S_t$ at time $t$. Each measurement $m \in M_t$ has a geographic location $s_m$ and a timestamp $t_m$, and may be associated with additional data $D'_m$ that is available only at $s_m$.

**Output**

For each section $c \in C$ and timestamp $t \in T$, find the closest measurement $m_{c,t}$ in $M_t$ to the initial values dataset $D_c$ based on both geographical proximity and minimum difference on timestamps. If additional data $D'_m$ is available for $m_{c,t}$, associate it with the corresponding initial dataset value in $D_c$.

**Semantic Data Model**

For each section $c \in C$ and timestamp $t \in T$, we can compute the closest measurement $m_{c,t}$ in $M_t$ as follows:

**STEP 1.** Compute the geographic distances $d(s, D_c)$ between each location $s \in S$ associated with $D_c$ and each location $s' \in S_t$ in $M_t$:

$$d(s, D_c) = \min_{s' \in S_t} \{\text{distance}(s, s')\},$$

where $\text{distance}(s, s')$ is the geographical distance between $s$ and $s'$. 

STEP 2. Find the measurement \( m_{c,t} \) that minimizes the sum of the geographic distance and the absolute time difference with \( D_c \):

\[
m_{c,t} = \arg \min_{m \in M} \left\{ d(s_m, D_c) + \left| \min_{m' \in M} \{|t_m - t_{m'}| - t\} \right| \right\}.
\]  

(2)

In other words, we find the measurement \( m \) in \( M \) that has the minimum sum of geographic distance with \( D_c \) and the absolute time difference with the closest measurement in \( M_t \) to \( t \). The closest measurement in \( M_t \) to \( t \) is obtained by computing the minimum time difference between all pairs of measurements in \( M_t \).

STEP 3. If additional data \( D'_m \) is available for \( m_{c,t} \), associate it with the corresponding initial set value in \( D_c \):

\[
\text{initial set}(c,t) = \begin{cases} 
(\text{initial set}(c,t), \text{value}(m_{c,t})) & \text{if } D'_m \neq \emptyset \text{ for } m_{c,t}, \\
(\text{initial set}(c,t), \text{value}(m_{c,t}), D'_m) & \text{otherwise.}
\end{cases}
\]

(3)

In other words, if additional data is not available for \( m_{c,t} \), we simply associate the initial dataset value from the closest measurement in \( M_t \) to \( D_c \). Otherwise, we associate both the initial set value and the additional data \( D'_m \).

3.2 Computational Complexity

We denote \( n \) as the number of rows in the initial dataset input variable and \( m \) as the number of rows in the extra dataset input variable. Since the initial definition of the algorithm contains nested loops that search for the closest measuring station and timestamp for each point in the initial dataset, the computational complexity is defined as \( O(n^3) \). This means that the running time increases significantly as the size of the dataset grows.

The proposed model has a for loop that iterates over every point in the initial dataset, which has a size proportional to \( n \). For each point, the function must calculate the distance to every point in the extra dataset, which has a size proportional to \( m \). The calculation of normalized distances between the initial point and every point in the extra dataset has a time complexity of \( O(m) \), as it must loop over every point in the extra dataset. Similarly, the normalization of the timestamps has a time complexity of \( O(m) \) as it also must loop over every point in the extra dataset. After normalization, the function must combine the two measures into a single distance value for each point in the extra dataset. This operation has a time complexity of \( O(m) \) as it involves element-wise addition of two arrays of length \( m \). Finally, the function must find the point in the extra dataset that has the minimum combined distance from the current initial point. This operation has a time complexity of \( O(m) \) as it must loop over every point in the extra dataset to find the minimum distance.

Therefore, the total time complexity of the proposed function is \( O(nm^2) \). This is because for every point in the initial dataset, the function must perform \( O(m^2) \) calculations to find the point in the extra dataset with the minimum distance. Any other computational improvement had to be discarded since the complexity of the possible geographical references could not be supported by the definition of the implementation.

In terms of space complexity, the function creates a new dataset to store the output, which has a size proportional to \( n \). Additionally, the function creates a spatial index for the extra dataset, which has a size proportional to \( m \). With this, we can state that the total space complexity of the function is \( O(n + m) \).

4 CASE STUDY: FROM TIME SERIES DATA TO SEMANTICALLY ENRICHED DATA

The growth of urban areas has brought about a significant increase in the number of vehicles on the roads, resulting in an unprecedented level of traffic congestion. As a result, it has become increasingly important for city planners and transportation authorities to gain insights into traffic patterns and trends, in order to
optimize traffic flow and reduce congestion. In this case study, we explore the use of an algorithm for associating traffic density values with measurements and additional data, as a means of moving from time series data to semantically enriched data. By applying this algorithm to a real-world dataset, we aim to demonstrate the potential of this approach in improving the accuracy and reliability of traffic analysis, and supporting the development of more effective traffic management strategies.

### 4.1 Preprocessing, feature engineering and standardization

A preprocessing method is defined with the ultimate goal of standardization and interoperability, with the adoption of time and space filters, and it involves several key steps (see processing workflow in Figure 1).

![Preprocessing flow diagram](image)

**Figure 1:** Preprocessing flow diagram designed for the use case

In the first step, the user selects a dataset of interest from the Open Data Barcelona portal, specifying a specific time and geographic range. Subsequently, built-in methods request the data through an API, returning the raw dataset in its original form. It is important to emphasize that each chosen dataset requires a unique preprocessing and cleaning method due to the differences in data sources and structures.

To ensure the necessary treatment for each dataset, we have developed a modular approach that involves the removal of invalid and redundant data, identification and elimination of duplicate entries, and standardization of geographical and temporal properties. Special emphasis is given to generating GeoPandasDataframes with geometries derived from the coordinates provided in the original data, which can be Points, Linestrings, or Polygons, depending on the nature of the data. Moreover, after cleaning and standardizing the data, we restructure the initial dataset to ensure that the data is presented in a consistent format for further analysis.

Finally, this method employs built-in predefinitions of different sections of the city to extract the selected period and section of data chosen by the user. This facilitates targeted analysis of specific neighborhoods, streets, and other relevant city subdivisions. In summary, the proposed preprocessing method plays a crucial role in enabling the analysis of Open Data Barcelona datasets by providing clean and standardized data that is readily available for further exploration and analysis.

### 4.2 Open Data Barcelona data selection and geographic sections definition

We present the datasets included in the case study for the asynchronous join process. The table includes information on the number of different geographical locations contained in each dataset, their geographic definition, and the type of information that can be retrieved from them. Additionally, the estimated update
rate and periodicity in which the data is updated according to what Open Data Barcelona states in each dataset metadata.

- Traffic Density: Traffic Density values and Initial Locations in a categorical internal system (from no traffic to jam). Updated every 15 minutes (when there is data available) and collected from 534 sections of streets defined in the city map of Barcelona.
- Pollutants: Eight pollution sensors coordinates (points) spread out on Barcelona city that detect different pollutants every hour (when there is data available). For this case, carbon monoxide measured in \( mg/m^3 \), nitrogen monoxide measured in \( \mu g/m^3 \) and black carbon concentration measured in \( \mu g/m^3 \).

4.3 Computational Results

In this section, we present the computational results obtained from using the methodologies and implementations discussed in this study, to merge the selected data into a homogeneous time series for the different street sections in Barcelona, keeping the original objective of providing a comprehensive view of the traffic data in Barcelona and presenting a unified time series data.

Combining data from different sources provides a broader perspective of the city’s traffic and helps in identifying trends and patterns that may not have been apparent in individual datasets, as shown in Figure 2. The resulting time series provides a valuable resource for analyzing and understanding the traffic patterns in Barcelona. For example, correlations between certain pollution levels and areas of the city that are more prone to traffic congestion can now be evaluated, along with tracking changes in traffic patterns over time based on the availability of other methods of public transportation.

One significant advantage of the proposed methodology is that it enables the application of more advanced analysis methods like windowed cross-correlation (Boker, Xu, Rotondo, and King 2002), a time
series analysis technique used to identify correlations and time lags between different time series data points. With this kind of tools now available, users can identify time lags between two time series that came from different sources.

5 Extreme Gradient Boosting Model Comparison

Extreme Gradient Boosting (Chen and Guestrin 2016) (XGBoost) is a scalable machine learning method for tree gradient boosting. XGBoost is a powerful machine learning algorithm that excels in dealing with high-dimensional, sparse, and structured data, making it a suited choice for predicting traffic density expressed as categories of different density. In addition, XGBoost can handle missing values and has the ability to identify and prioritize the most informative features, which is useful for feature selection (Alsahaf, Petkov, Shenoy, and Azzopardi 2022).

Following similar gradient boosting methods, XGBoost creates a mathematical structure that extracts a prediction \( y_i \) out of the given \( x_i \). In particular, XGBoost generates an ensemble \( \mathcal{F} = \{ f(x) = w_q(x) \} (q : \mathbb{R}^m \rightarrow T, w \in \mathbb{R}^T) \) of K-Classification and Regression Trees (CART) where \( f_k \) corresponds to every tree \( q \) with its own structure, defined as the \( T \) number of leaves and the \( w \) set of leaf weights.

With this structure defined, a \( K \) additive function defines the predicted output as

\[
\hat{y}_i = \phi(x) = \sum_{k=1}^{K} f_k(x_i), \quad f_k \in \mathcal{F}
\]

In this particular case, values such as the geographical location of the section we are evaluating, the moment in time in which the values were taken and other data engineering variables described later are given as data values \( x_i \). Instead of purely classifying into categories like regular decision trees, this model adds the continuous scores extracted from the weights \( w \) out of the given \( x_i \) to optimize it, is expressed with its first and second order gradient statistics \( r_i \) and \( h_i \), respectively, as

\[
\sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t-1)} + f_i(x_i)) + \Omega(f_i)
\]

where \( \hat{y}_i^{(t)} \) is the prediction at that instance and iteration. This implies that \( f_i \) is added greedily following the performance it shows on the optimization instances and iterations.

The objective function, by taking the second-order Taylor expansion of the loss function with respect to \( \hat{y}_i \) to optimize it, is expressed with its first and second order gradient statistics \( g_i \) and \( h_i \), respectively, as

\[
\sum_{i=1}^{n} \left[ l(y_i, \hat{y}_i^{(t-1)} + g_i f_i(x_i) + \frac{1}{2} h_i f_i^2(x_i) \right] + \Omega(f_i)
\]

where \( g_i = \partial_{\hat{y}_i} l(y_i, \hat{y}_i^{(t-1)}) \) and \( h_i = \partial^2_{\hat{y}_i} l(y_i, \hat{y}_i^{(t-1)}) \).
that can be simplified by removing the constant variables to obtain a simplified objective function at the iteration $t$ like

$$\tilde{L}^{(t)} \simeq \sum_{i=1}^{n} \left[ g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \Omega(f_t) \tag{9}$$

that relies the optimization of the function only on $g_i$ and $h_i$.

Once again, the objective function can be expanded, this time through its regularization term $\Omega$, for an instance set $I$ of the leaf $j$ for a given structure $q(x_i)$ as $I_j = \{i | q(x_i) = j\}$

$$\tilde{L}^{(t)} \simeq \sum_{i=1}^{n} \left[ g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \gamma T + \frac{1}{2} \lambda T \sum_{j=1}^{T} w_j^2 \tag{10}$$

so we can find the optimal leaf weight $w_j^*$ of leaf $j$ and the goodness of fit of the overall structure $q(x)$ as

$$w_j^* = - \frac{\sum_{i \in I_j} g_i}{\sum_{i \in I_j} h_i + \lambda} \tag{11}$$

$$\tilde{L}^{(t)}(q) = - \frac{1}{2} \sum_{j=1}^{T} \left( \frac{\sum_{i \in I_j} g_i}{\sum_{i \in I_j} h_i + \lambda} \right)^2 + \gamma T \tag{12}$$

With a greedy algorithm, XGBoost starts from a single leaf and on every iteration a new branch is added to it using Equation (12) as a scoring function to measure the improvement on the general tree structure $q$. With an instance $I = I_L \cup I_R$ where $I_L$ and $I_R$ are the sets of the nodes in each branch after they split, then the possible gain is measured as

$$Gain = \frac{1}{2} \left[ \left( \frac{\sum_{i \in I_L} g_i}{\sum_{i \in I_L} h_i + \lambda} \right)^2 + \left( \frac{\sum_{i \in I_R} g_i}{\sum_{i \in I_R} h_i + \lambda} \right)^2 - \frac{(\sum_{i \in I} g_i)^2}{\sum_{i \in I} h_i + \lambda} \right] - \gamma \tag{13}$$

### 5.1 Evaluation Metrics

**Area Under the ROC curve (AUC)**

The evaluation of this classification system is chosen to be the area under the ROC curve (AUC) with an Over to Rest (OrV) strategy, since it is a very well-known measure of performance for machine learning models. The Over the Rest strategy implies that any missclassification is considered a wrong classification no matter which two classes are being mistaken. With this, we define our AUC method as

$$AUC = \sum_i \{(1 - \beta_i \Delta \alpha ) + \frac{1}{2} [1 - \beta \Delta \alpha] \} \tag{14}$$

where $\alpha$ is the probability of a false positive and $1 - \beta$ the probability of a true positive.

**SHapley Additive Explanations (SHAP)**

SHapley Additive Explanations (SHAP) is a machine learning model interpretation tool based on game theory (Lundberg and Lee 2017). With SHAP, the attribution of every variable to the final output is measured by taking one variable into the model at a time and measuring the expected value of the function of the model’s output. With this changes produced by the addition of each variable, SHAP computes the average contribution by measuring the impact of every possible variable orderings.

The average contribution of the variable $x$ in the model $f$ can be computed as:

$$g(x') = \phi_0 + \sum_{i=1}^{M} \phi_i x'_i \tag{15}$$
where $x' \in \{0, x_i\}^M$ is the number of input variables, and $\phi_i \in \mathbb{R}$.

A single understandable solution is generated with SHAP since three main properties are present:

• Local accuracy: when the function that relates $x$ to $x'$ defined as $h_x(x')$ equals the set of variables $x$, and therefore the approximation of $f$ equals to the output of $f$.
• Missigness: when the values that are missing have no impact on the output of the model, $x'_i = 0 \rightarrow \phi_i = 0$.
• Consistency: if a model changes so that some input’s contribution increases or stays the same, the Shapley value also has to increase or stay the same regardless of the other inputs.

SHAP, and in particular Tree SHAP (Lundberg, Erion, Chen, DeGrave, Prutkin, Nair, Katz, Himmelfarb, Bansal, and Lee 2020), can provide explanations for the impact of variables in tree-based machine learning models such as the one used. Tree SHAP performs an exploration of the model with an input dataset $X$ of size $N \times M$ and produces a matrix of equal size with the SHAP values for every variable on every tuple in $X$. With this values, consistency of explanation in guaranteed for individual predictions, along with an identification of the contribution with a sign indicator.

5.2 Experimental Results

In this section, the results of the prediction model, its performance metrics and a variable analysis are described and analysed.

Classes identified on the data

For the purpose of applying this method for parameter importance analysis, we consider the different densities obtained from the original dataset as different classification options following: 0 = very fluid, 1 = fluid, 2 = dense, 3 = very dense, 4 = congestion.

Final dataset

The dataset contains information structured following Table 1 with data from the entire year 2019. We split the dataset in two different sets for the training and test steps of the training and evaluation process. With this, we assign a 70% of the dataset to the training step and we keep the remaining 30% for evaluation of the parameters taken. Finally, data from January to March of 2022 is processed for the final analysis and predictions shown at the model performance section. The last three parameters, marked with * on Table 1, are added on another iteration of the model with the same parameters to compare the impact on the accuracy on the new model.

For the XGBoost, the parameters were tuned with a cross validation tool defined as a grid search with 5 folds, containing different possible configurations for the following parameters within reasonable ranges, as we can see on Table 2.

Model Performance

The Area Under the Curve in Figure 3 shows that the overall performance of the model is highly positive, finding that areas under every ROC are over 80%, even without the addition of the pollution data.

It is worth mentioning that for the extreme cases the initial model performs better on average, adding both a percentage of true positives over 85%, but it presents subtle drop on intermediate classes. This drop gets softened on the model that includes the pollution data, showing the increase on accuracy.

On average, this model presents an accuracy rank of 71.56% for the data of 2019 without the addition of the pollution data. This accuracy increases to 79.65% with the pollution data added as parameters in the model.

Variable Analysis. Shapley Additive Explanations

The importance on average of every variable for every class can be assessed by using Shapley Additive Explanations, a method from cooperative game theory that increase the interpretability of the final output values. Figure 4 shows the model’s impact of the different combinations of variables for each class.
Table 1: Dataset description for the XGBoost model.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Type</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Section ID</td>
<td>Unique identifier of the Barcelona Road sections.</td>
<td>number</td>
<td>1 to 534</td>
</tr>
<tr>
<td>Status</td>
<td>Current traffic status of the section.</td>
<td>number</td>
<td>0 to 4</td>
</tr>
<tr>
<td>FromNorth</td>
<td>Geographic coordinate system Latitude where the section starts (North).</td>
<td>number</td>
<td>2,099 to 2,222</td>
</tr>
<tr>
<td>FromWest</td>
<td>Geographic coordinate system Longitude where the section starts (West).</td>
<td>number</td>
<td>41,338 to 41,450</td>
</tr>
<tr>
<td>ToNorth</td>
<td>Geographic coordinate system Latitude where the section ends (North).</td>
<td>number</td>
<td>2,100 to 2,223</td>
</tr>
<tr>
<td>ToWest</td>
<td>Geographic coordinate system Longitude where the section ends (West).</td>
<td>number</td>
<td>41,338 to 41,449</td>
</tr>
<tr>
<td>DailyHour</td>
<td>Hour of the day when the status was measured.</td>
<td>number</td>
<td>0 to 23</td>
</tr>
<tr>
<td>DailyMinute</td>
<td>Minute of the hour when the status was measured.</td>
<td>number</td>
<td>0 to 60</td>
</tr>
<tr>
<td>Weekday</td>
<td>Day of the week when the status was measured.</td>
<td>number</td>
<td>1 to 7</td>
</tr>
<tr>
<td>DayMonth</td>
<td>Day of the month when the status was measured.</td>
<td>number</td>
<td>1 to 31</td>
</tr>
<tr>
<td>Holiday</td>
<td>Boolean value representing a holiday on the corresponding day.</td>
<td>Boolean</td>
<td>False or True</td>
</tr>
<tr>
<td>*pollution_6</td>
<td>Carbon monoxide density level measured in $mg/m^3$.</td>
<td>number</td>
<td>0.057 to 0.5</td>
</tr>
<tr>
<td>*pollution_7</td>
<td>Nitrogen monoxide density level measured in $µg/m^3$.</td>
<td>number</td>
<td>1 to 41</td>
</tr>
<tr>
<td>*pollution_22</td>
<td>Black carbon density level measured in $µg/m^3$.</td>
<td>number</td>
<td>125.43 to 3183</td>
</tr>
</tbody>
</table>

Number of records: 24,533,298

Table 2: Parameter matrix for XGBoost.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Final value</th>
<th>Cross validation candidates</th>
</tr>
</thead>
<tbody>
<tr>
<td>max_depth</td>
<td>10</td>
<td>5, 7, 9, 10, 11</td>
</tr>
<tr>
<td>eta</td>
<td>0.3</td>
<td>0.1, 0.2, 0.3, 0.4</td>
</tr>
<tr>
<td>gamma</td>
<td>1</td>
<td>0.5, 1, 1.5, 2, 5</td>
</tr>
<tr>
<td>subsample</td>
<td>1</td>
<td>0.6, 0.8, 1</td>
</tr>
<tr>
<td>objective</td>
<td>multi:softmax</td>
<td>-</td>
</tr>
<tr>
<td>num_class</td>
<td>5</td>
<td>-</td>
</tr>
</tbody>
</table>

(a) AUC for the initial XGBoost model. (b) AUC for the XGBoost model with pollution data.

Figure 3: Effects on the AUC after the incorporation of the pollution data.

Interestingly, the analysis revealed that the new pollution index variables were not among the top three most important variables. However, we observed that they still had a positive effect on the model’s classification for each traffic density. This suggests that the new pollution index variables provided valuable information for predicting traffic density, despite not being among the top-ranked variables.

The positive effect of the new pollution index variables on the model’s prediction of traffic density may be due to their ability to capture the impact of pollution on traffic (European Environment Agency 2022). Pollution levels and traffic density are strictly related, as high levels of pollution can be directly linked...
with traffic density, and they can reduce visibility and increase the likelihood of accidents. Furthermore, pollution can affect the health and well-being of individuals living in the area, which can impact their travel patterns and behaviors.

By including the new pollution index variables in the XGBoost model, we were able to capture this important relationship between pollution and traffic density, which contributed to the model’s overall predictive power. Our findings highlight the importance of considering a broad range of variables when developing predictive models for traffic density, as even variables that may not be among the most important can still provide valuable insights and improve the accuracy of the model’s predictions.

Figure 4: Impact on model output by predicted class.
6 CONCLUSIONS

This study presents a novel approach to address this problem by integrating asynchronous time series data from diverse sources to develop a more accurate traffic density prediction. The study used an XGBoost model based on geographical coordinates and timestamp differences to demonstrate the effectiveness of this approach on OpenDataBCN. The integration of data from multiple sources improves the richness and granularity of information available for analysis, revealing previously hidden information that could not be applied without the methodology applied. The XGBoost model demonstrates superior prediction accuracy and indicates the potential of this approach for sustainable and efficient urban mobility solutions. Furthermore, this approach can be useful for generating and analyzing city traffic data through simulation tools. By utilizing open data platforms and advanced machine learning techniques, this novel approach offers a new paradigm for addressing the challenges of urban mobility in a data-driven manner. The XGBoost model developed in this study demonstrates that the addition of pollution parameters to traffic density data using a data enrichment model for asynchronous data improves the precision of the model. This conclusion is supported by the results of the ROC plot, which shows that the model performs better when pollution parameters are included and a SHAP exploration that shows the relative importance that these variables have on the overall model performance.

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AUTHOR BIOGRAPHIES

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