Explainable AI for Urban Land Cover Classification Using Mobile Application Traffic Data

Song Gao

GeoDS Lab, Department of Geography, University of Wisconsin-Madison, USA

Email: song.gao@wisc.edu

Abstract. This research explores the use of mobile application traffic data to interpret urban land cover classification using explainable machine learning methods. The experiments using a high-resolution mobile service traffic data in Paris, France show that the hourly downlink traffic of Microsoft Office, Netflix, and Uber together with the XGBoost model can accurately classify land cover types and the SHAP values help interpret instance-level feature importance and their spatial patterns.

Keywords. Explainable GeoAI, LBS, Location Big Data

1. Introduction

Explainable AI methods have been applied in geospatial analysis such that human can understand how machine learning models use the input features to make predictions in geographical phenomenon. Common methods include tree-based explanations, game theory-based explanations, local surrogate models, and so on (Xing & Sieber 2023). In the studies of location-based services, McKenzie et al. (2015) used the information gain to understand global feature importance of temporal check-ins for points-of-interest (POI) classification. However, less attention has been paid to spatial-explicit local explanations (i.e., individual predictions and their spatial patterns). This research aims to explore what kinds of mobile service features (as proxies of human activities) are critical for interpreting urban land cover classification in different regions of cities.

2. Datasets and Preprocessing

Mobile application traffic data: In this research, we employ a high spatiotemporal resolution of service-level mobile traffic dataset in Paris, France (Martínez-Durive et al. 2023), which provides time series of the uplink and downlink traffic generated by 68 mobile applications (e.g., Instagram, Facebook, Netflix, YouTube, Microsoft Office, Google Maps, Uber, etc.) at each 100×100 m^2 grid/tile every 15 minutes. Figure 1 shows the spatial distributions of hourly downlink service traffic of “Microsoft Office” in urban area of Paris on a typical workday (March 18, 2019).

Urban land cover data: We employ the Corine Land Cover (CLC) 2018 dataset produced by the Copernicus Land Monitoring Service and coordinated by the European Environment Agency, which provides high-resolution (100×100 m^2) and thematically detailed information on land cover across Europe (Büttner 2014). The dataset contains 44 land cover classes in the hierarchical 3-level CLC nomenclature and there

Published in “Proceedings of the 18th International Conference on Location Based Services (LBS 2023)”, edited by Haosheng Huang, Nico Van de Weghe and Georg Gartner, LBS 2023, 20-22 November 2023 Ghent, Belgium.

This contribution underwent single-blind peer review based on the paper.
https://doi.org/10.34726/5739

are 19 classes in the study area (as shown in Figure **2** and Table **1**). The land cover layer is further spatially joined to the mobile data service grids layer to create a unified time-series data frame for downstream explainable machine learning tasks.

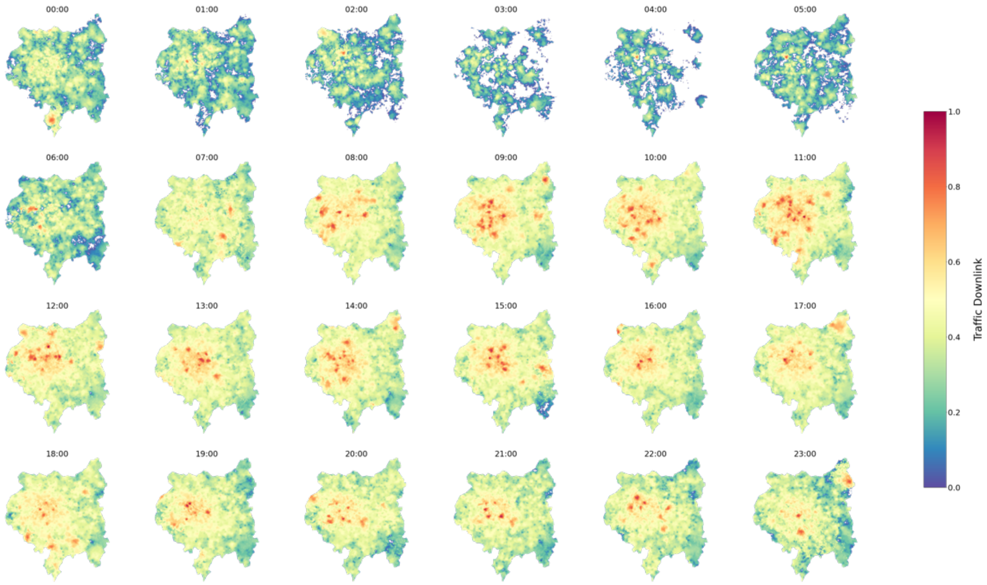

Figure 1. The spatial distributions of hourly downlink traffic of the Microsoft Office service.

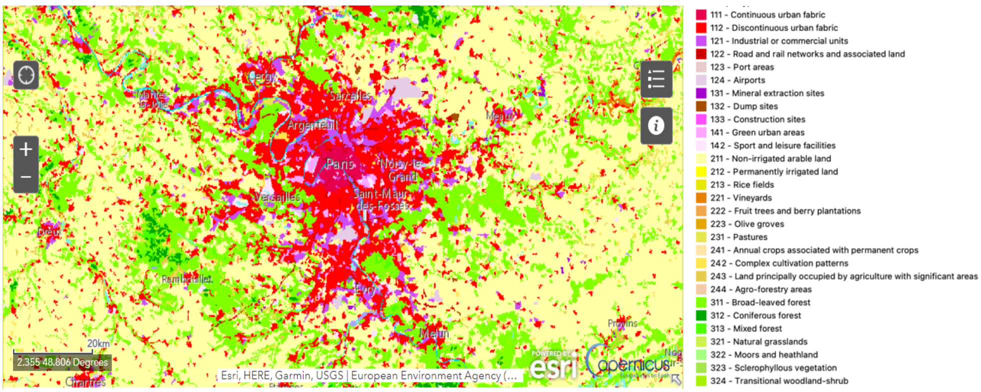

Figure 2. The spatial distributions of Corine Land Cover classes in Paris.

Table 1. Top-10 land cover classes and their distribution percentage in the study area.

Land Cover Type	**Percent (%)**	**Land Cover Type**	**Percent (%)**
Discontinuous urban fabric	52.4	Industrial or commercial units	12.7
Continuous urban fabric	11.3	Green urban areas	6.0
Broad-leaved forest	5.1	Sport and leisure facilities	2.8
Airports	2.5	Road and rail networks	2.0
Non-irrigated arable land	1.7	Water courses	1.0

3. Methods

3.1. Machine Learning Models

In this research, we employ the following machine learning models for land cover multiclass classification based on the unified time-series data of mobile service traffic introduced in Section 2.

XGBoost: is a regularized gradient boosting learning method for optimizing the ensemble of decision-trees and reducing the model overfitting. The "XGBClassifier" is trained for multiclass classification with the softmax objective and 300 gradient boosted trees with the max depth of 5.

Multi-Layer Perceptron (MLP): is a feedforward artificial neural network. We use a MLP classifier with two hidden layers of 100 fully connected neurons with a rectified linear activation function and a learning rate of 0.001.

Transformer: is a deep neural network that uses self-attention mechanisms to draw global dependencies in sequence modeling (Vaswani et al. 2017). We design a multi-head transformer neural network with 40k parameters for the time series land cover multiclass classification in this research.

3.2. SHAP Values for Model Interpretability

Then, we utilize the model-agnostic SHAP (SHapley Additive exPlanation) values (Lundberg & Lee 2017), which provide a unified approach to interpreting the above-mentioned machine learning models' performance. The *local explanation* method aims to ensure an explanation function $g(z') \approx f(h_x(z'))$ when $z' \approx x'$, where f is the original prediction model and x' is simplified inputs that can map to the original inputs x through a mapping function $h_x(x')$. The explanation function g is defined as a linear function of binary variables:

$$g(z') = \emptyset_0 + \sum_{i=1}^{M} \emptyset_i z'_i$$

where $z' \in \{0, 1\}^M$, M is the number of simplified input features, $\emptyset_i$ are the Shapley values that measure how much a feature's value changes the model 's prediction with a game-theory sampling strategy. Local explanation methods help interpret the impact of input features on individual predictions (e.g., a single sample data point or a couple of sample data points). There exist different algorithms to compute the SHAP values (Lundberg et al. 2018); here, we apply the *tree-based explainer* for the XGBoost model and the *kernel-based explainer* for the MLP and transformer models to get their corresponding SHAP values using the 'shap' Python package. Furthermore, we perform the spatial analysis to understand the spatial patterns of SHAP values of each feature on specific land cover type predictions.

4. Experiments and Results

In the experiments, we select three mobile data service apps (i.e., Netflix, Microsoft Office, and Uber) due to their popularity and they potentially represent people's stay-at-home, working, and transportation activities in the city. The unified time-series data frame contains the hourly average downlink traffic of these mobile services for each 100x100 m^2 tile/grid of Paris on a typical workday. Therefore, we have 24*3=72 features/attributes and 1 target variable (land cover type) as inputs for all the machine learning models. We then split the data with 80% for model training and 20% for testing. As shown in Table 2, the XGBoost model with accuracy of 0.91 outperforms the MLP and the Transfomer regarding the multiclass land cover classification on the testing data while their mean F1-score (macro) are very close. In the following, we only report the best performing model (XGBoost)'s interpretability.

Figure 3 shows the SHAP value computation results of top-20 most influential features on the type-specific land cover classification using the XGBoost model. Overall, both daytime and night hours of *Microsoft Office* service traffic, midnight *Netflix* and *Uber* traffic have larger magnitude of impact on the classification output of the testing data. However, the effects of those hourly features are different for specific land use type. For instance, the service traffic features "Office 1:00~1:59" has the largest impact on the "Airport" while "Office 9:00~9:59" has the largest impact on the "Industry and Commercial Units". Interestingly, the spatial patterns of SHAP values are also varying. Figure 4 shows the spatial distributions of SHAP values of the selected feratures for the classification of "Continuous Urban Fabric" type. We find that "Office 9:00~9:59" traffic has moderate positive impact across the study area but "Netflix 2:00~2:59" and "Uber 23:00~23:59" traffic have strong distinctive impacts in the urban center (mostly positive) and suburb (most negative) of the city, which demonstrates the spatial heterogeneity of individual feature importance.

Table 2. The comparison of different machine learning models' performance (accuracy and F1-score) on land cover classification for the testing data.

	Testing Accuracy	F1-Score (macro)
XGBoost	0.91	0.80
Multi-Layer Perceptron (MLP)	0.87	0.79
Transformer	0.82	0.76

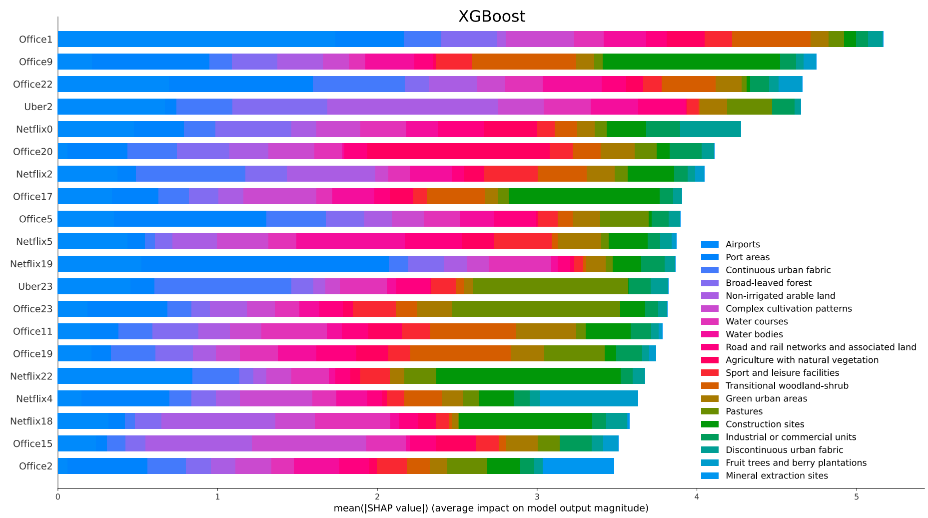

Figure 3. The SHAP values of different features for the XGBoost model.

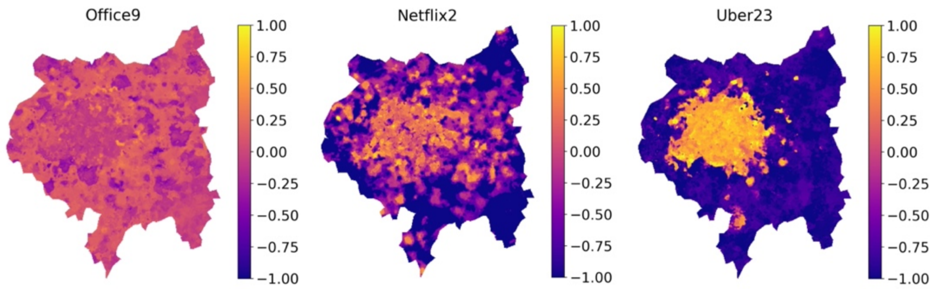

Figure 4. The spatial distributions of SHAP values of the selected feratures.

5. Conclusion

This research utilizes the model-agnostic SHAP values to interpret the instance-level feature impacts of hourly mobile application traffic in the urban land cover classification using machine learning models. The experiments using high-resolution mobile traffic and land cover data in the city of Paris show a promising performance of XGBoost in model accuracy and good interpretability with the selected temporal bands of Microsoft Office, Netflix, and Uber mobile service traffic. The results also demonstrate the spatial heterogeneity of instance-level feature importance in explainable machine learning models. Future work will further explore the interaction effects of different features and on other mobile applications as well as deeper understanding of human-environment interactions from the explainable GeoAI perspective.

References

Büttner, G. (2014). CORINE land cover and land cover change products. In *Land use and land cover mapping in Europe: practices & trends* (pp. 55-74). Springer Netherlands.

Martínez-Durive, O. E., Mishra, S., Ziemlicki, C., Rubrichi, S., Smoreda, Z., & Fiore, M. (2023). The NetMob23 Dataset: A High-resolution Multi-region Service-level Mobile Data Traffic Cartography. *arXiv:2305.06933.*

McKenzie, G., Janowicz, K., Gao, S., Yang, J. A., & Hu, Y. (2015). POI pulse: A multi-granular, semantic signature–based information observatory for the interactive visualization of big geosocial data. *Cartographica: The International Journal for Geographic Information and Geovisualization*, 50(2), 71-85.

Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. *Advances in neural information processing systems*, 30, 1-10.

Lundberg, S. M., Erion, G., Chen, H., DeGrave, A., Prutkin, J. M., Nair, B., ... & Lee, S. I. (2020). From local explanations to global understanding with explainable AI for trees. *Nature Machine Intelligence*, 2(1), 56-67.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). *Attention is all you need. Advances in neural information processing systems*, 30.

Xing, J., & Sieber, R. (2023). The challenges of integrating explainable artificial intelligence into GeoAI. *Transactions in GIS.* 27(3), 626-645.