9^{th} International Conference on Computational Social Science IC^2S^2
July 17-20, 2023, Copenhagen, Denmark

Mobility Rhapsody: Unleashing the Power of Deep Learning and XAI to Decode Urban Flows at City Scale

Keywords: Human Mobility, Human Behavior, Urban Systems, Novel Location Prediction, Mobility Networks

Extended Abstract

In this work, we aim to leverage deep neural networks (NN) and explainable AI tools (XAI) to investigate how human mobility is driven in different temporal settings (e.g., differences between working days and weekends). We carried out the study in 20 different cities around the world. The model we used is inspired by Deep Gravity Model [1] and consists of 4 fully connected networks, each followed by a LeackyReLU activation function and a dropout layer with a probability of 0.3. We trained the model with a learning rate of 0.001. We used RMSprop as the optimizer and we initialized it with a momentum of 0.5. We compare the results obtained by our model to the ones reached by a Gravity model G. The implementation of the Gravity model is available in scikit-mobility. A comparison of the performances of the flow generated by our model (NN) and a Gravity model (G) can be seen in Table 1. In particular, we can see that regardless of the temporal setting (e.g., weekends - WE, weekdays - WD), our model outperforms the selected baseline.

The performances are measured using the Sørensen-Dice index, also called Common Part of Commuters (CPC), which is a well-established measure to compute the similarity between real flows, y^r, and generated flows, y^g:

$$CPC = \frac{2\sum_{i,j} min(y^g(l_i,l_j), y^r(l_i,l_j))}{\sum_{i,j} y^g(l_i,l_j) + \sum_{i,j} y^r(l_i,l_j)} \tag{1}$$

CPC is always positive and contained in the closed interval $(0,1)$ with 1 indicating a perfect match between the generated flows and the ground truth and 0 highlighting bad performance with no overlap.

Then, we use shapely values provided by SHAP [2] to explain the importance of features using mobility flows generated by the models and spot differences in the attractiveness of different geographical features during weekends and weekdays. Using SHAP allows us to, for example, understand the role of restaurants in different temporal settings. In Figure 1, we can see an example of some preliminary results of SHAP values for the city of Barcelona. In the Figure, we can see the feature importance of the geographical features collected using OpenStreetMap, population, and distances. The target of the model is to generate flows that match the ones we collected from Twitter over 2014-2021 (2020 excluded). In Figure 1, on the left, we have the importance of features during weekdays, while on the right, we analyze the weekends. Each point denotes an origin-destination pair, where blue points represent pairs where the feature has a low value and red points pairs with high values. For each variable, these points are randomly distributed along the vertical axis to make overlapping ones visible. The point's position on the horizontal axis represents the feature's Shapely value for that origin-destination pair, that is, whether the feature contributes to increasing or decreasing the generated flow for that pair. The order of the features corresponds to the general importance. While there are not many differences in terms of general importance, the impact on the flow in weekdays over the shops in origin (for example) in comparison to weekends is bigger. This methodology gives us another way to characterize the generation of mobility flows in cities.

	NN (WE)	NN (WD)	G (WE)	G (WD)		NN (WE)	NN (WD)	G (WE)	G (WD)
Barcelona	68.5	68.8	47.6	48.9	**Manila**	69.9	62.3	50.7	50.2
Bogota	64.8	62.4	49.2	49.1	**C. de Mexico**	54.6	55.8	41.8	44.3
Cairo	69.4	63.7	52.7	53.1	**Moscow**	59.8	60.0	42.8	42.9
Chicago	63.2	63.8	51.1	54.3	**New York City**	63.2	57.9	47.4	48.3
Copenhagen	49.8	49.9	41.8	41.5	**Osaka**	58.6	61.1	52.7	53.4
Detroit	62.8	64.8	53.9	51.7	**Paris**	55.3	55.9	47.6	48.0
Istanbul	57.4	53.3	47.2	45.8	**Sao Paulo**	62.7	63.2	50.9	51.2
Jakarta	71.8	68.9	61.3	60.6	**Seattle**	58.2	59.8	44.9	44.9
Los Angeles	66.4	68.1	55.2	55.6	**Stockholm**	59.6	59.5	51.9	51.9
London	62.7	62.7	49.8	49.4	**Tokyo**	57.8	60.2	49.8	49.9

Table 1: Accuracies of Gravity model (G) and our model (NN) during weekends (WE) and weekdays (WD).

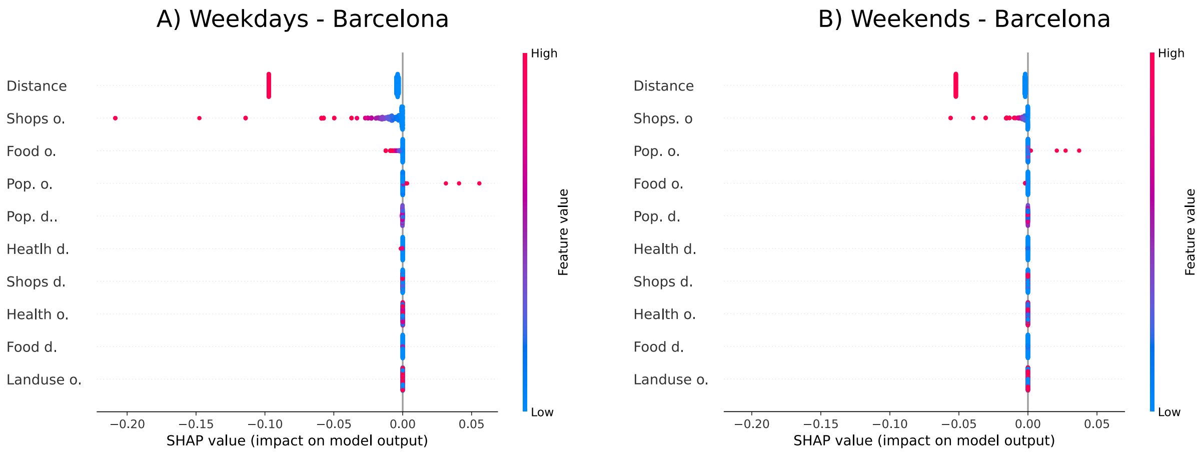

Figure 1: Distribution of Shapely values for all features used for Barcelona on A) Weekdays and B) Weekends.

References

[1] Simini, F., Barlacchi, G., Luca, M. et al. *A Deep Gravity model for mobility flows generation*. Nat Commun **12**, 6576 (2021).

[2] Lundberg, S. M. and Lee, S.-I. *A unified approach to interpreting model predictions*. Advances in Neural Information Processing Systems **30**, 4765–4774 (2017).