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Interpretable ML for Transportation Mode Prediction Using Smartphone Travel Diaries

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MOTIVATION

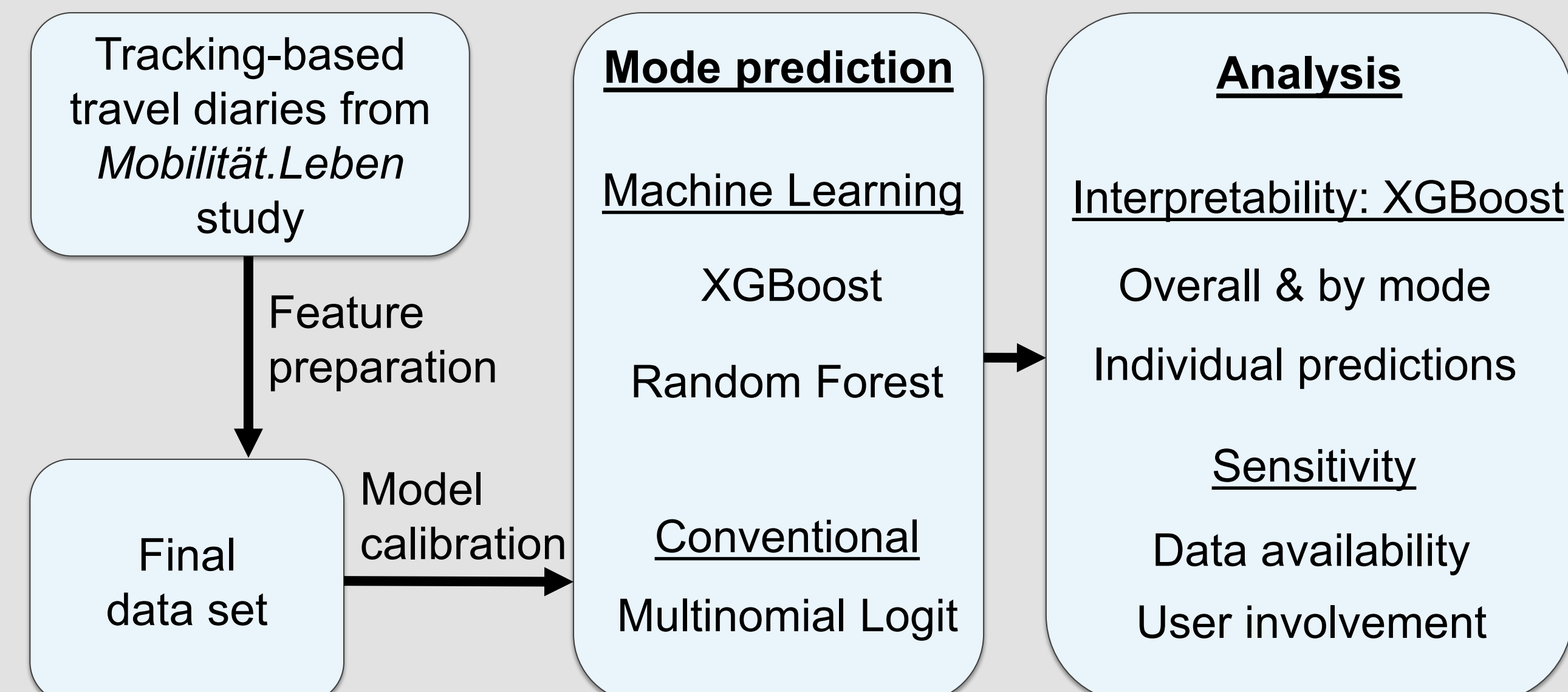
Machine learning for mode prediction on tracking-based travel diaries

- Previously, ML-based mode prediction was only done for survey-based travel diaries
- Tracking-based travel diaries stem from GPS-recordings

Explore the model interpretability

- It is crucial to understand the factors affecting mode choice

IDEA



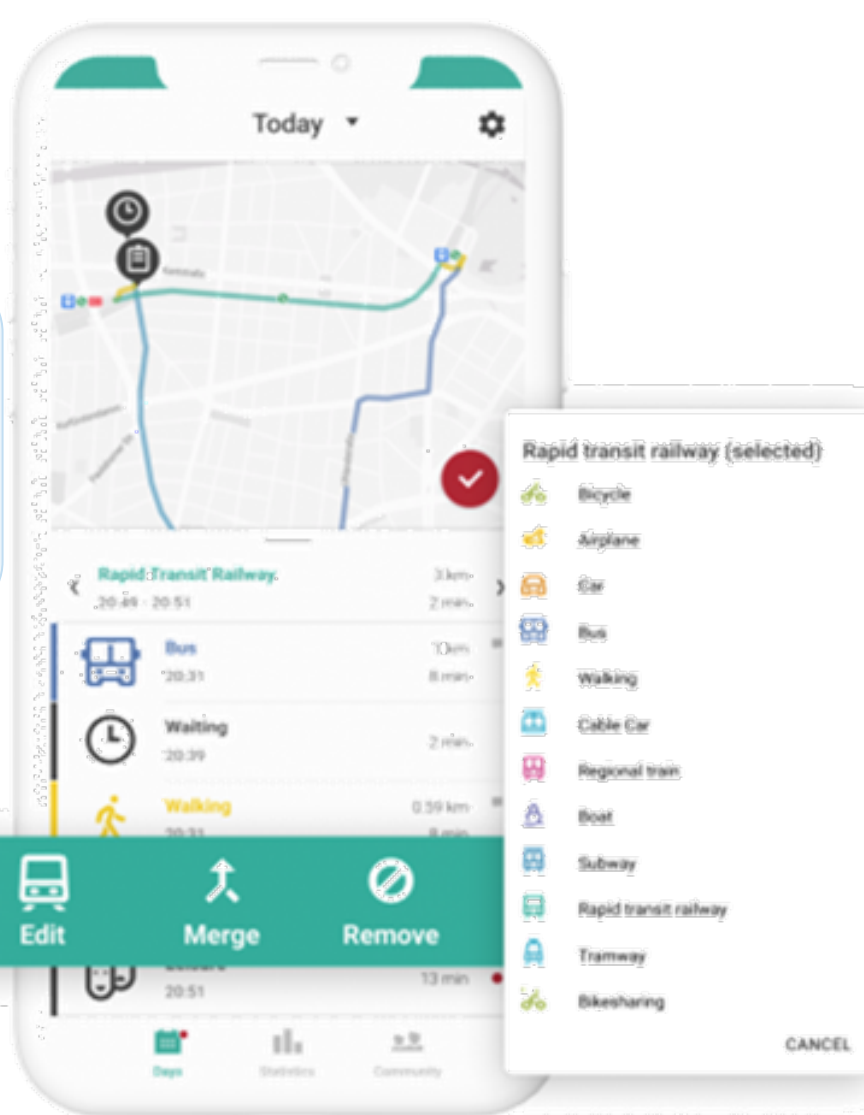
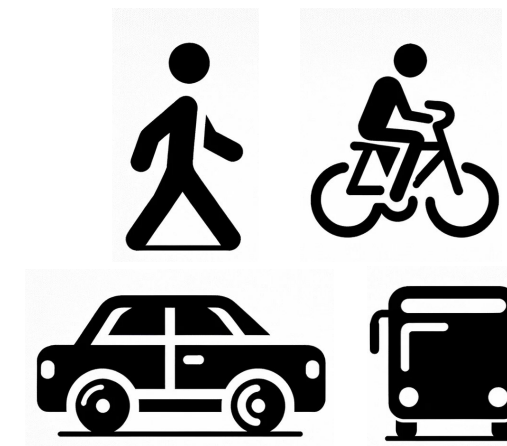
METHODOLOGY

Models: XGBoost and Random Forest (RF) are consistently the best models for survey-based travel diaries in literature. Hence, we test these on tracking-based data.

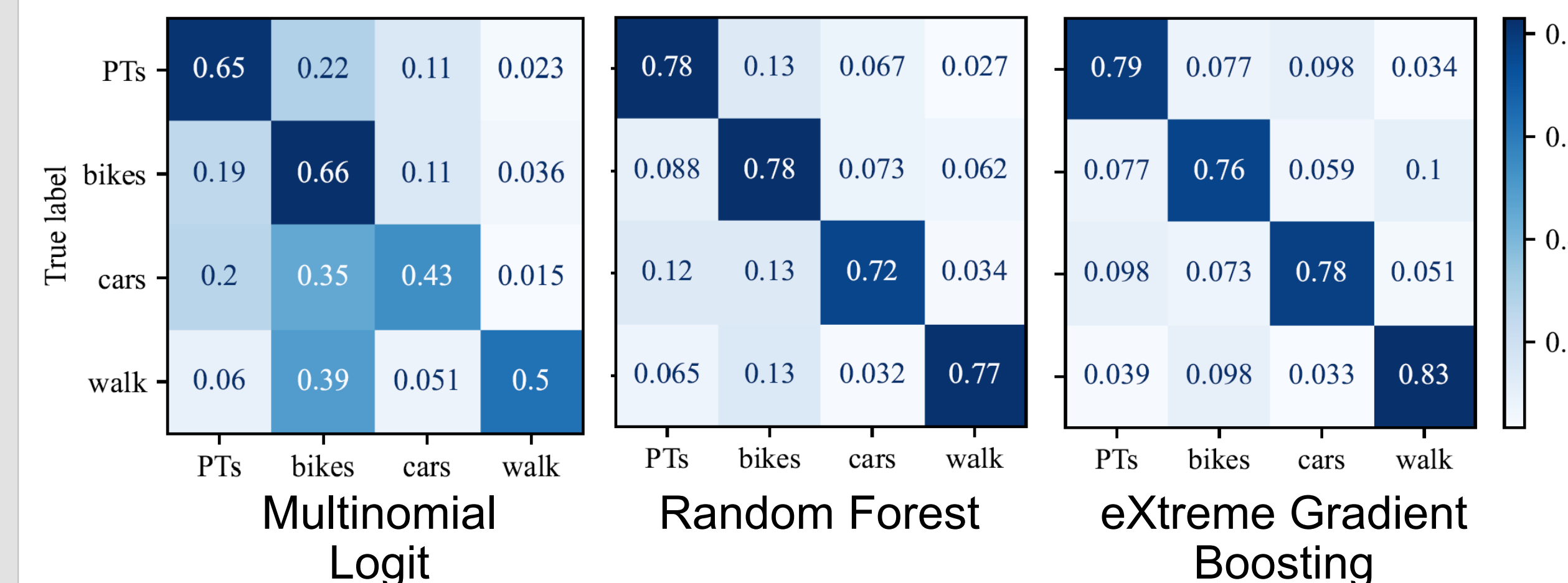
Data source: Mobilität.leben, which is a long-duration (>1 year) semi-passive tracking data set, with a heterogeneous user-base (+1000 participants), most of which live in Munich.

Semi-passive travel diaries: users validate and correct the draft travel diaries, which are automatically generated from tracking data.

Input data: A wide range of features was considered (see Table). Public transport (PT) price considers possession of monthly pass. Time by walking/bike and car cost were removed due to collinearity.



OVERALL RESULTS



The XGBoost and RF outperform the MNL by far, yet XGBoost has best overall accuracy.

SENSITIVITY ANALYSIS

In practice, it is often difficult to obtain a wide range of data.

How much is the model performance impacted when the input data is subject to certain constraints?

E.g., lack of a data type, or when fully-passive instead of semi-passive data is used.

Comparison of input data scenarios

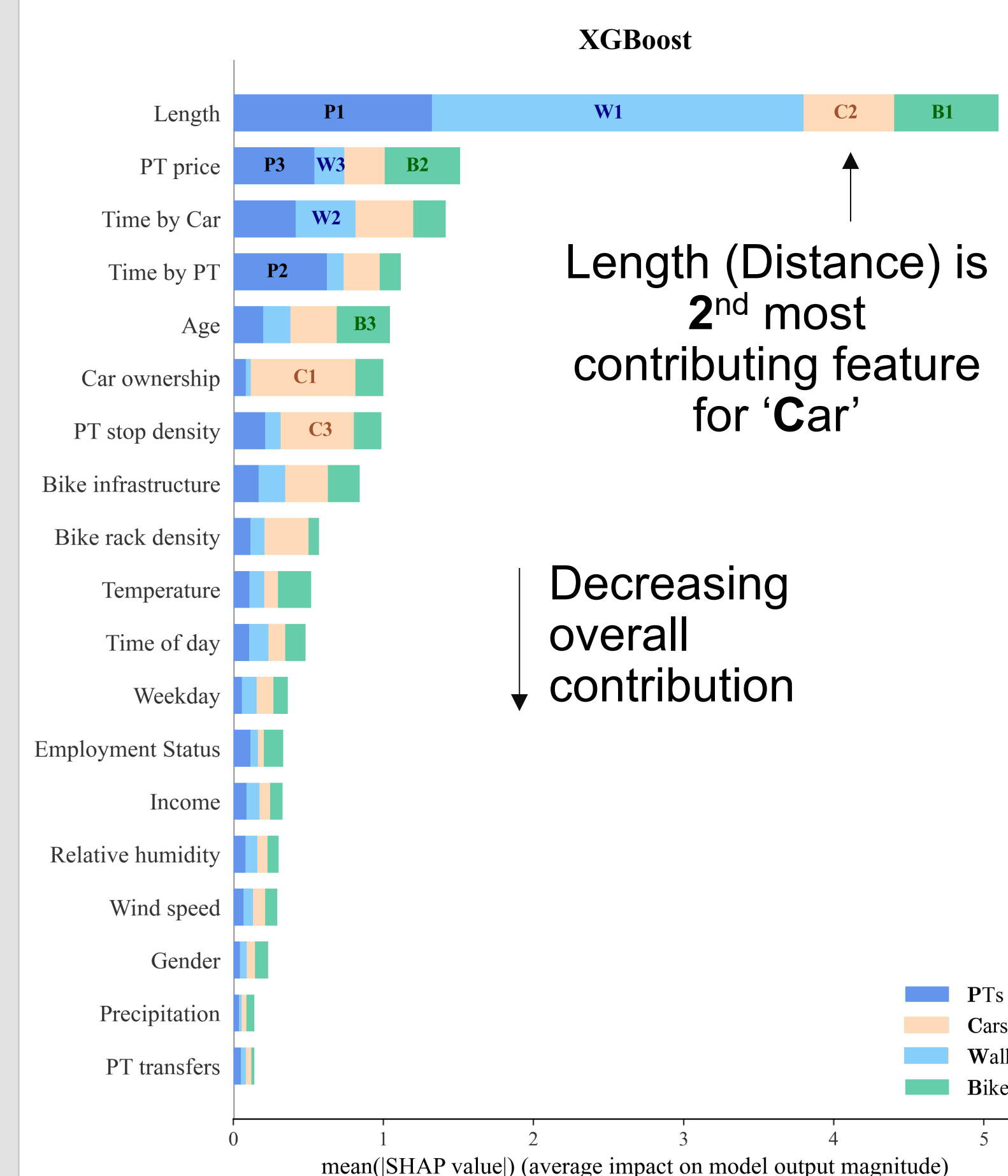
Input data scenario	XGBoost	RF	MNL
Benchmark	79.0	76.3	57.7
No survey based data*	-3.0	-3.1	-0.9
No infrastructure data	-1.6	-1.3	-2.8
No weather data	-0.6	0.8	-0.2
No alternative travel time data	-0.5	0.5	-4.4
Only trip data**	-25.5	-28.3	-11.0
Incl. all collinear features	0.0	-2.6	-3.9
Fully-passive tracking	-2.6	-3.4	-4.1

*(socio-demographic, PT monthly-pass and car ownership)

** (length, time of day, weekday)

INTERPRETABILITY

Overall feature contribution by mode



Length (Distance) is 2nd most contributing feature for 'Car'

Decreasing overall contribution

An in-depth interpretability analysis was performed for the best-performing model.

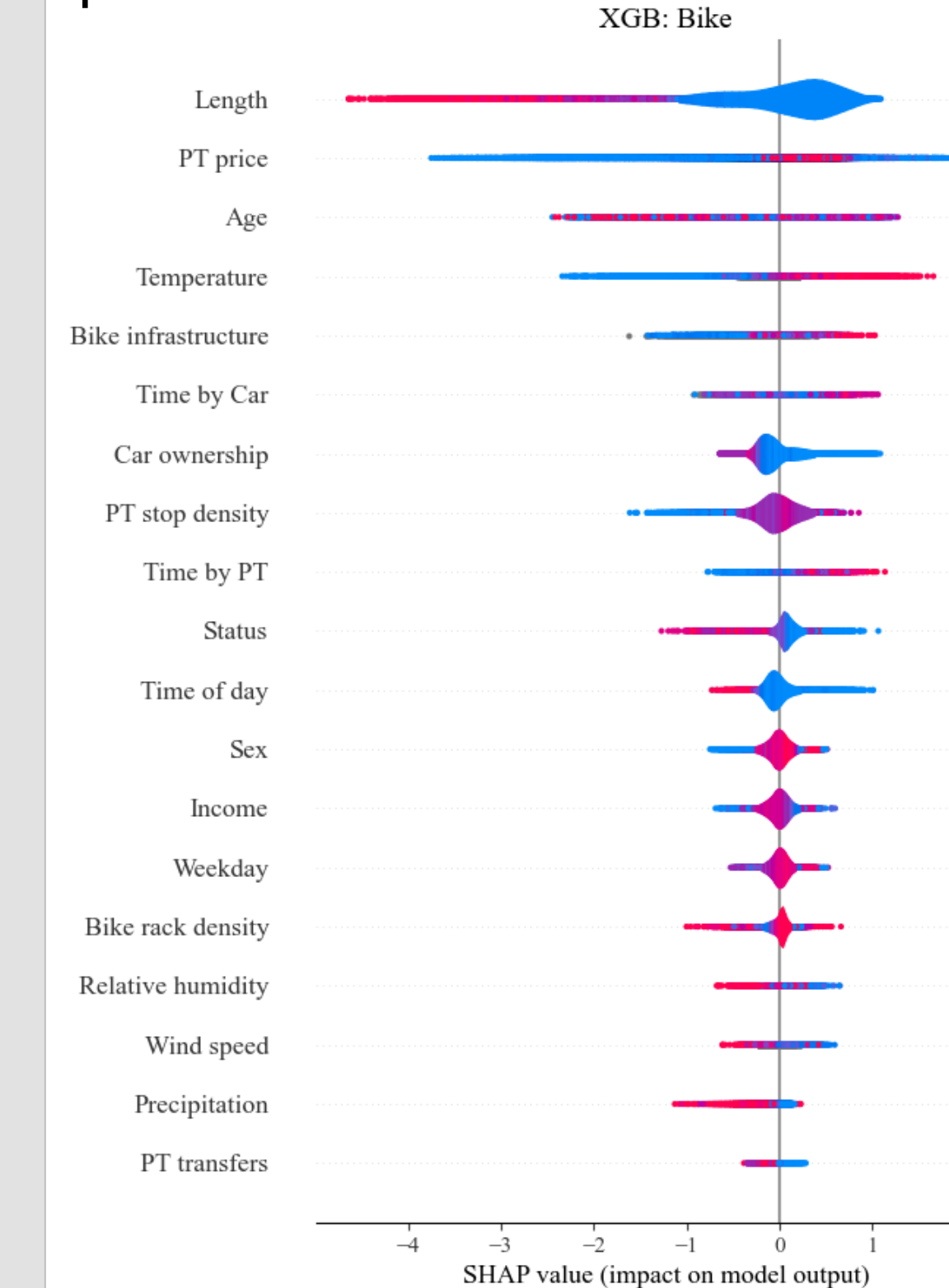
SHAP values measure the relative contribution of a feature to the model output [1].

Features considered in each model

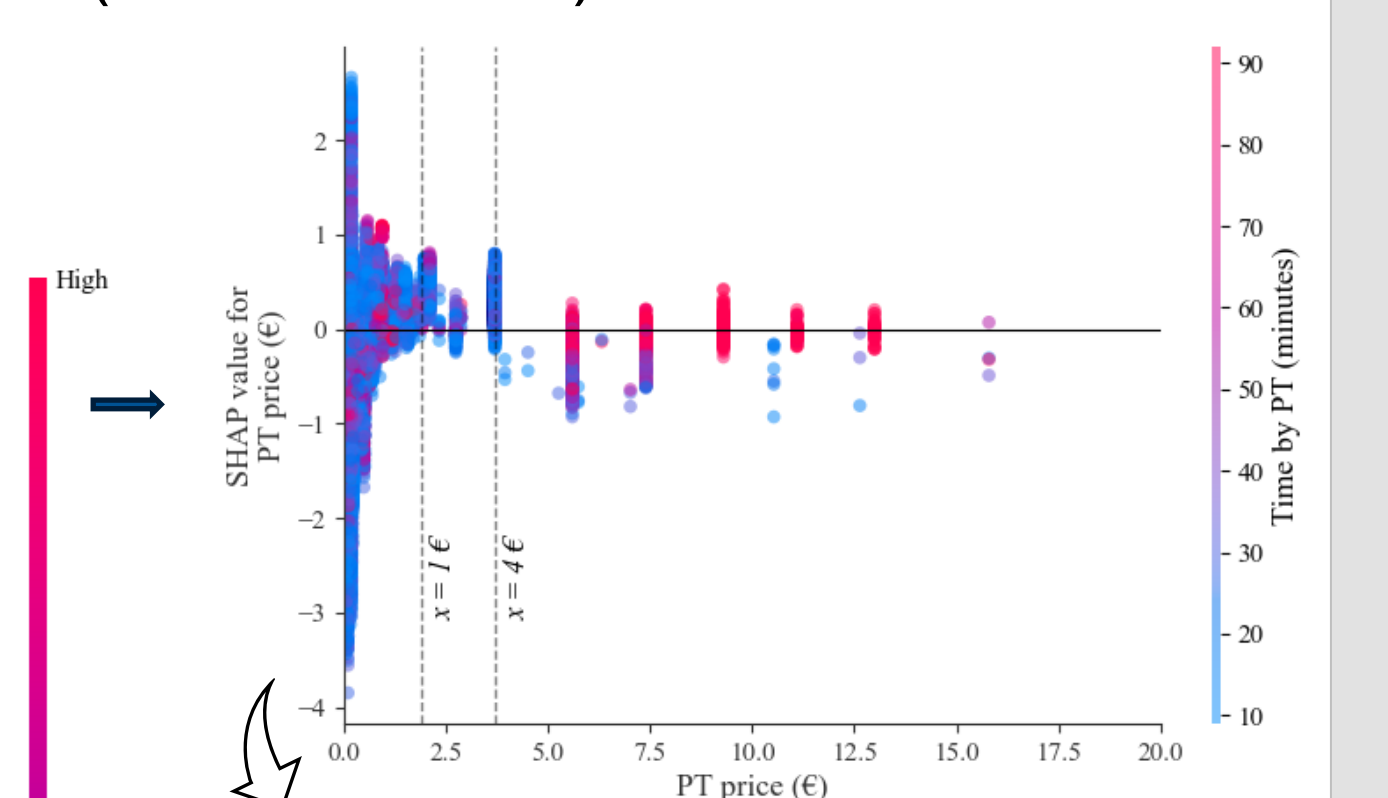
Group	Feature	Example
Socio-demo-graphic	Age	32 years
	Income	0
	Employment status	1
	Gender	1
	Car ownership	0
Weather	Precipitation	2 mm
	Temperature	16 °C
	Rel. humidity	82 %
	Wind speed	1.5 m/s
Estimated travel time & cost	Time by car	17min
	Time by PT	34 min
	PT transfers	1
	PT cost	5.6 €
Trip information	Length (Distance)	8,700 m
	Trip start time	15:00 hr
	Day of week	6
Infrastructure	Bike racks	2
	PT stop density	1
	Bike infra. quality	0.24

Mode-specific interpretability

Contribution of a feature to bike predictions



Dependency plot of PT-price (color: PT time)



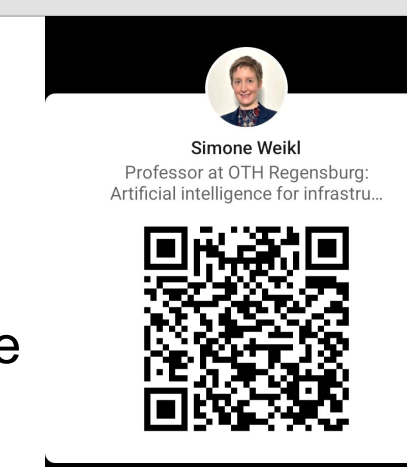
To understand the SHAP values of a feature in depth, we look at a dependency plot. As the PT price rises for short duration PT trips, cycling decreases (negative SHAP values).

For each mode (output class) we plot the distribution of SHAP values for each feature.

E.g., we observe negative SHAP values for low temperatures, indicating that for these the mode "bike" is less likely

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References:
[1] Lundberg, S. M. and S.-I. Lee, A unified approach to interpreting model predictions. Advances in neural information processing systems, Vol. 30, 2017.