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Interpretable ML for Mode Choice Modeling on Tracking-based Revealed Preference Data

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MOTIVATION

Machine learning for mode choice modelling on tracking-based RP data

- Previously ML-based mode choice modelling was only done for survey-based RP data
- Tracking-based RP data stems from GPS-recordings

Explore the model interpretability

- It is crucial to understand the factors affecting mode choice

IDEA

Tracking-based revealed preference data (TRP) *Mobilität.Leben*

Feature preparation

Final data set

Model calibration

Mode choice models

Machine Learning
XGBoost
Random Forest

Conventional
Multinomial Logit

Analysis

Interpretability: XGBoost
Overall & by mode
Individual predictions

Sensitivity
Data availability
User involvement

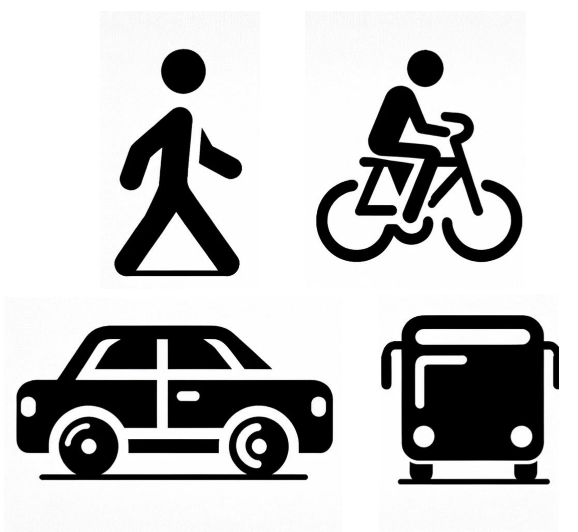
METHODOLOGY

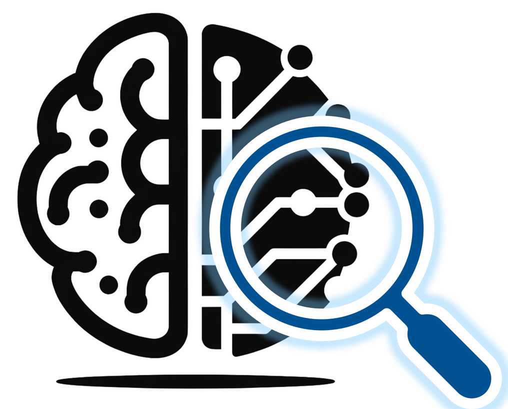
Models
XGBoost and Random Forest are consistently the best models for stated-preference data in literature. Hence, we test these on tracking-based data.

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.

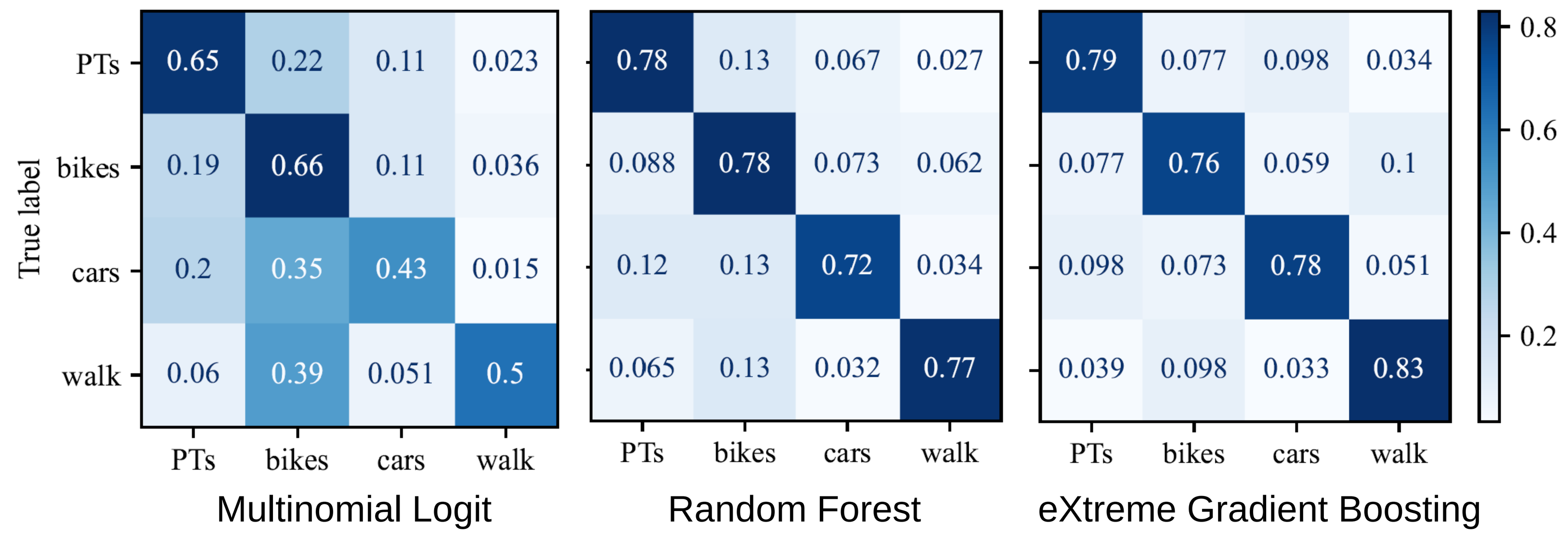
Semi-passive travel diaries: users validate and correct the draft travel diaries, which are automatically generated from the tracking data.

Input data
A wide range of features was considered (see Table). 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.

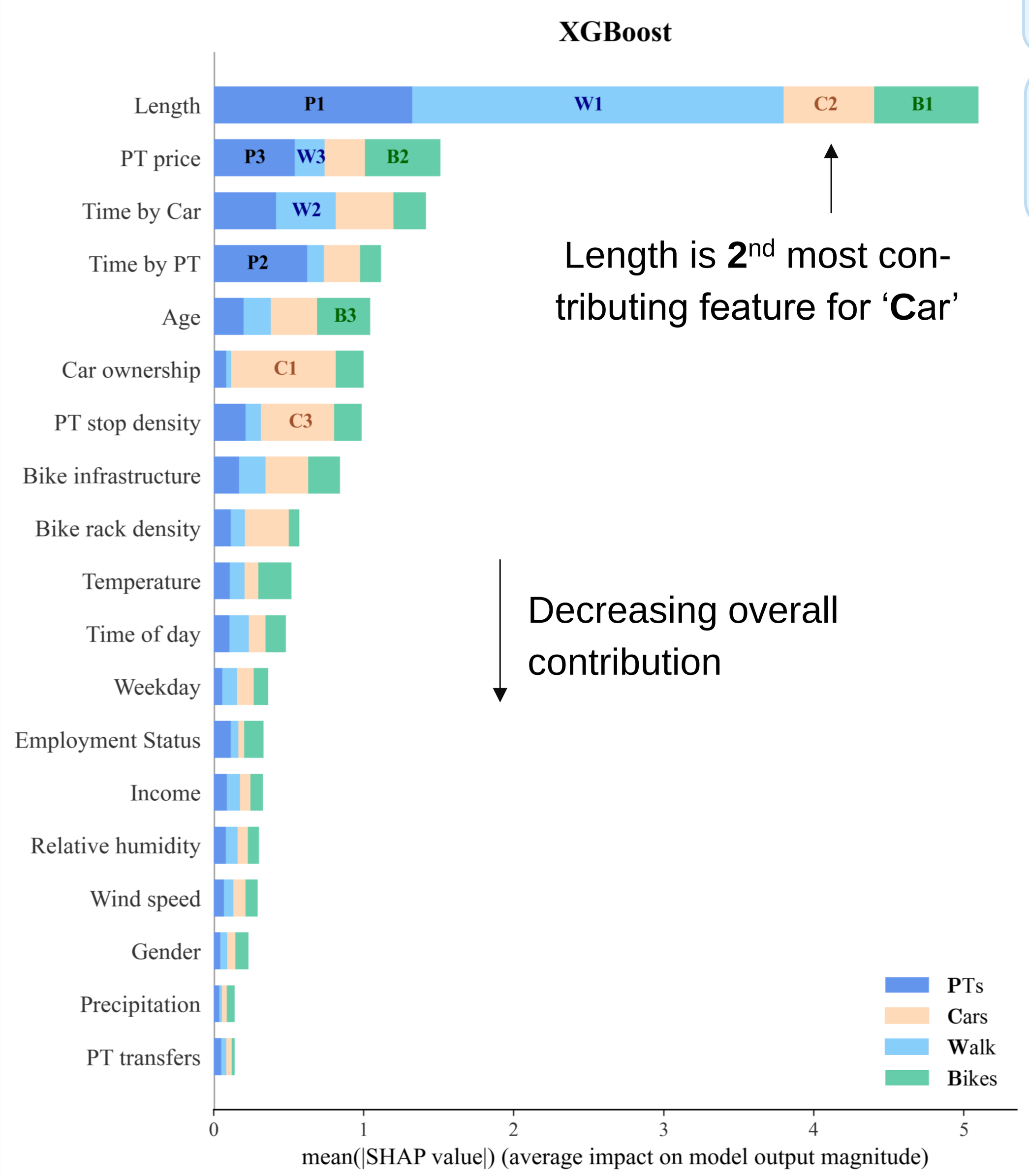
Comparison of input data scenarios

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



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

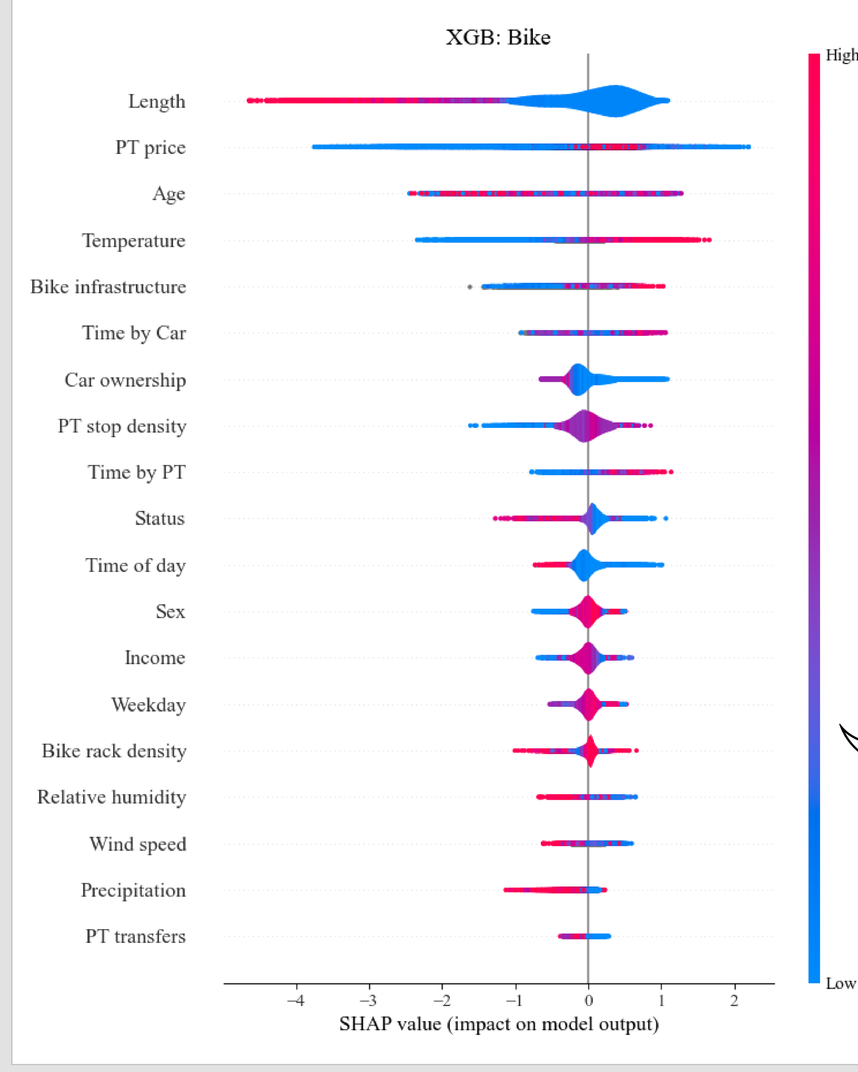
SHAP values measure the relative contribution of a feature to the model output [1].

Features considered in each model

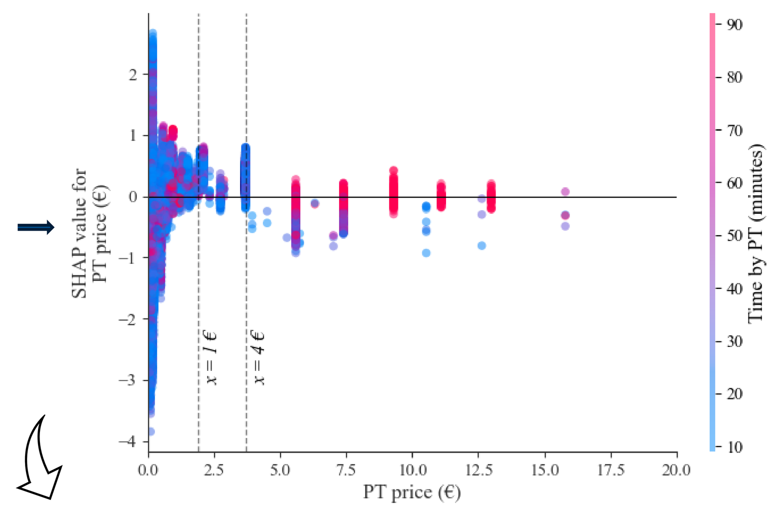
Group	Feature	Example
Socio-demo-graphic	Age	32 years
	Income	0
	Employment status	1
	Gender	1
	Car ownership	0
Weather	Precipitation	2 mm
	Temperature	16 °C
	Rel. humidity	82 %
	Wind speed	1.5 m/s
Estimated travel time & cost	Time by car	17min
	Time by PT	34 min
	PT transfers	1
	PT cost	5.6 €
Trip information	Length	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 more in depth, we can 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 can 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

Contact & Download

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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.