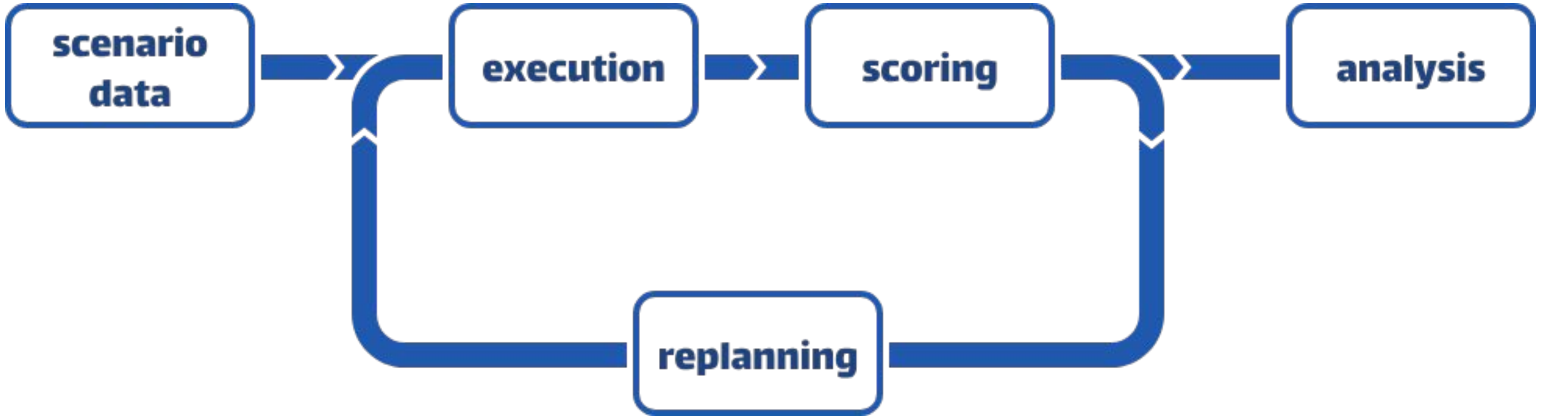
Agent-Based Modeling of Heterogeneous Travel Preferences with MATSim

Christian Rakow | MUM 2025 | 13.06.2025

Travel Preferences are Heterogenous

Common Approaches to Mode Choice Modeling in MATSim

- **Standard iterative process**



- **Direct integration of choice models**
  - By using the *discrete_mode_choice* contrib by Sebastian Hörl
  - Replaces the standard MATSim scoring
  - Plans are generated according to probabilities given by estimated MNL

Multinomial Logit (MNL)

- Both approaches relate to the classical multinomial logit model
- With utility (or score) of person *n* for alternative *i* :

$$U_{ni} = \beta x_{ni} + \varepsilon_{ni} \qquad \varepsilon_{ni} \sim \text{iid extreme value}$$

- β being the coefficients of the choice model or scoring (performing, marginalUtilityOfMoney, marginalUtilityOfDistance, etc…)

- These β are fixed, i.e. every individual has the same valuation
  - There are some exceptions (multiple subpopulations, price dependent scoring)

- In reality individuals have different preferences

Mixed logit (MXL)

- Modeling random taste variations is well understood in discrete choice theory
- Mixed logit model allows for β to vary across each decision maker

$$U_{ni} = \beta_n x_{ni} + \varepsilon_{ni}$$

with

ε_{ni} ~ iid extreme value

$$\beta_n \sim f(\beta|\theta)$$

- β are distributed according to some mixing distribution
- Fits very naturally to the agent-based approach
  - Every agent's preferences are one realization of β

Agenda

1 Evaluating mode choice in MATSim

2 Baseline (without taste preferences)

3 MNL and MXL choice model estimation

4 MATSim model with heterogeneity

VERKEHRSSYSTEMPLANUNG
VERKEHRSTELEMATIK
TU BERLIN

How to evaluate model performance?

- Log-Likelihood
  - Used in many domains: Choice models, Classifiers, LLMs, etc.
  - Maximizing the likelihood is equivalent to minimizing the distance between predicted choice probabilities and observed choices

$$\sum_{n=1}^{N} \sum_{i=1}^{K} y_{ni} \log(P_{ni}(\beta))$$

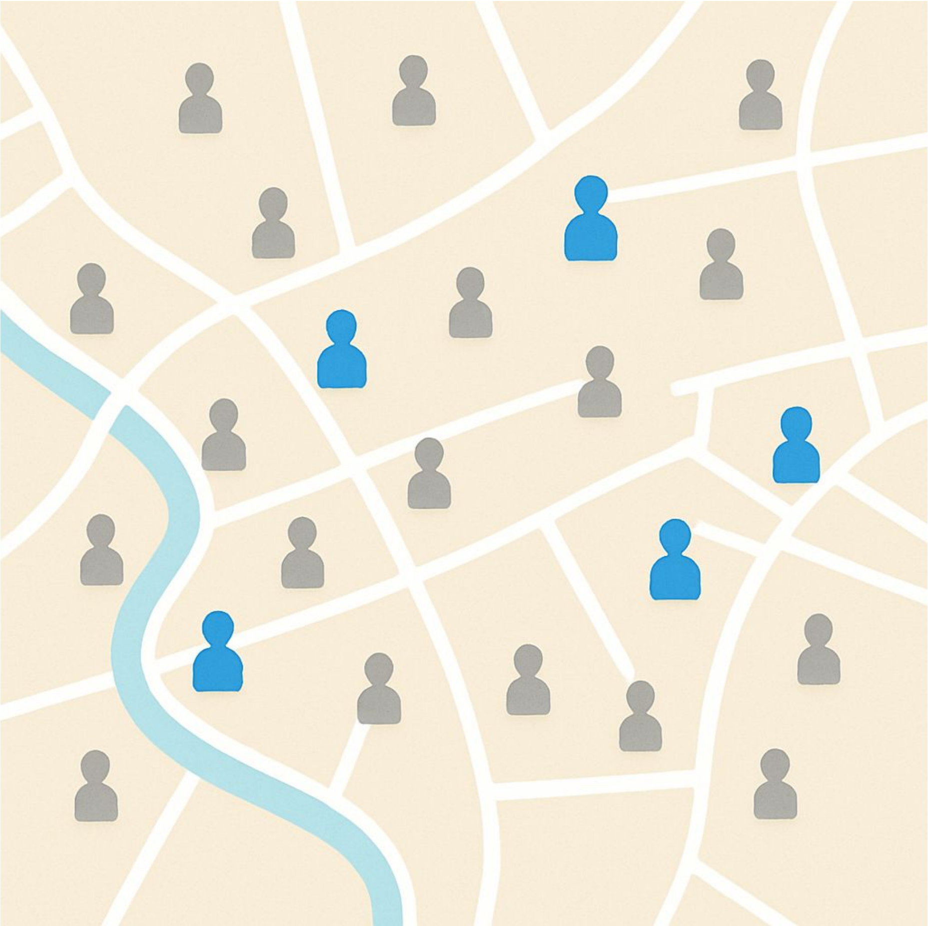
- Simulated Likelihood
  - For MXL it becomes more complex because β are not fixed
  - Probabilities are approximated with a large number of random draws

$$\hat{P}_{ni} \approx \frac{1}{S} \sum_{s=1}^{S} P_{ni}(\beta^{(s)})$$

- The same idea can be applied to a MATSim model
  - But, ground truth is needed!

Reference Population

- Most models consist of **synthetic** agents
  - They replicate statistical properties and correlations
  - But we don’t know their choices
- For validation we need **"Digital Twins"** of real persons
  - They face the same choice situations as the real-world individuals they are meant to represent
  - They replicate not just demographic attributes, but also the same circumstances of the real individuals
- Requires survey or observed data specific to model area
- Enables validation of predicted vs. actual choices
  - Simulated log-likelihood
  - Accuracy, Recall, Precision, etc.

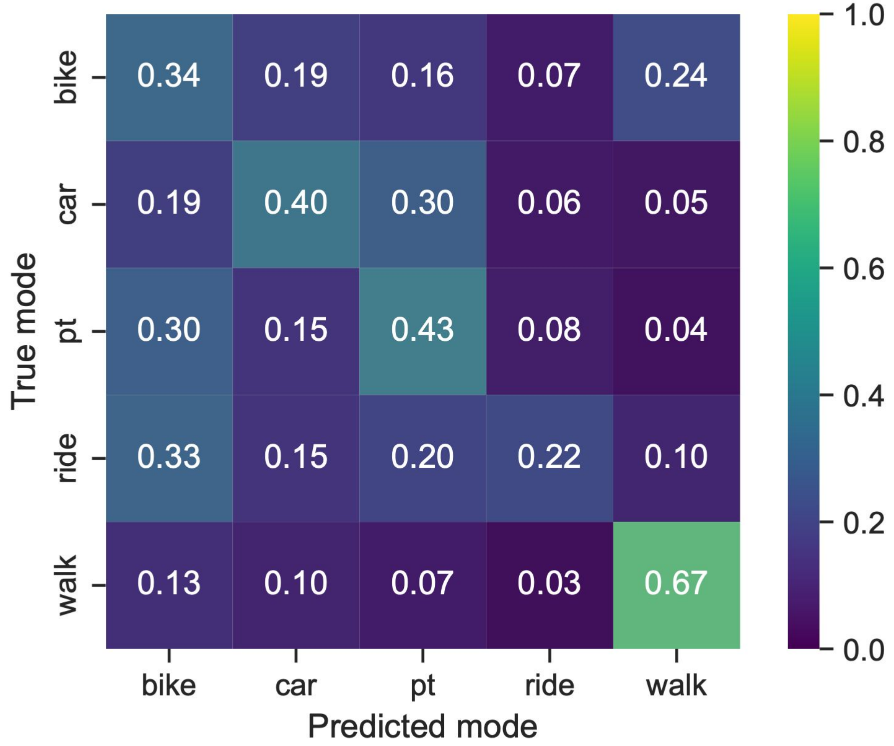


Evaluation (Baseline)

- OpenBerlin v6.4 (3% sample)
  - No taste preferences
- Berlin travel diary data used as ground truth
- 12 Simulation runs with different random seed

Metric	
Observations	9745
Log-Likelihood	−43144
Accuracy	0.480
Cohen's Kappa	0.320
F1 Score (macro avg.)	0.412
Precision (macro avg.)	0.415
Recall (macro avg.)	0.414

- Accuracy comparable with that of an MNL model
- e.g. Dahmen et al. *Interpretable Machine Learning for Mode Choice Modeling on Tracking-Based Revealed Preference Data*

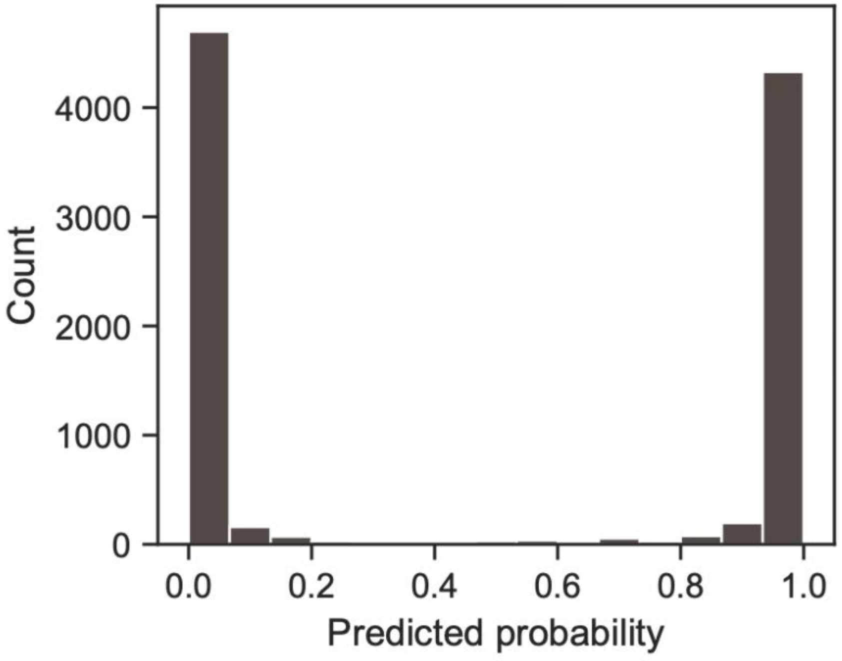


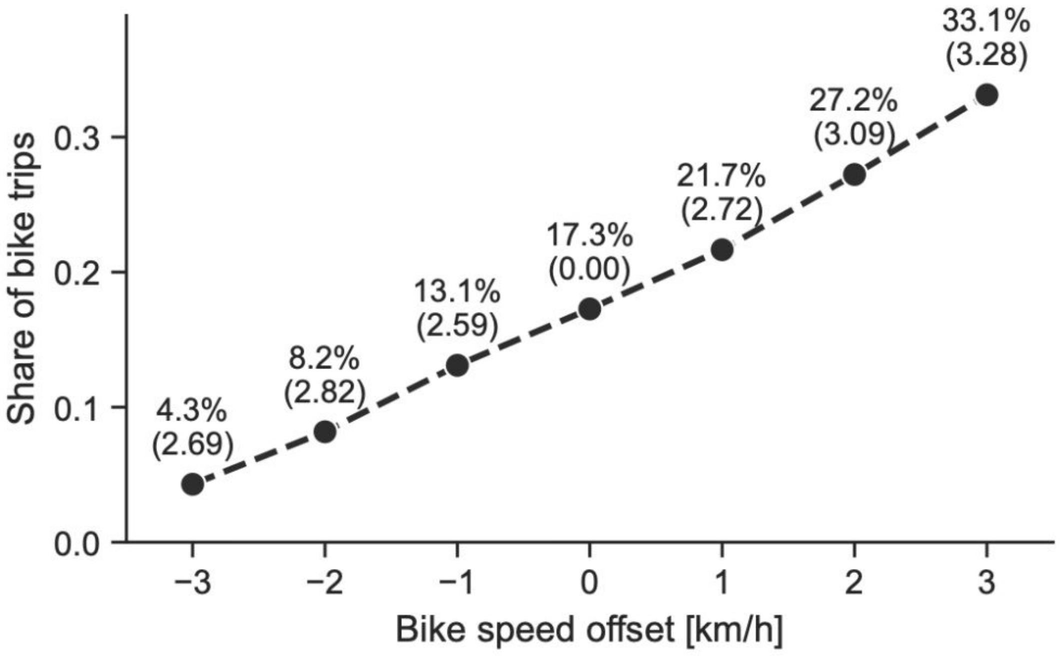
Mode	Precision	Recall	F1 Score
bike	0.286	0.344	0.312
car	0.341	0.396	0.366
pt	0.505	0.432	0.466
ride	0.179	0.223	0.199
walk	0.765	0.674	0.717

VERKEHRSSYSTEMPLANUNG
VERKEHRSTELEMATIK
TU BERLIN

Elasticities (Baseline)

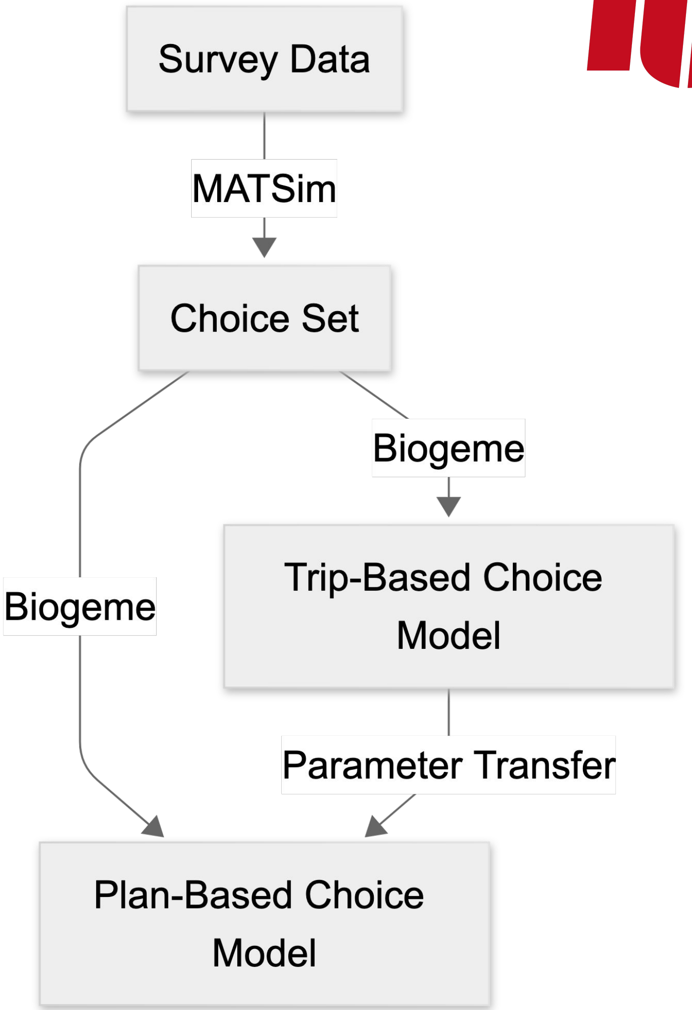
- The model is overconfident: Most predictions are near 1 or 0
- The elasticities are very high (here for cycling speed)
- Agents have no preferences → They quickly switch mode when utility tips in favor of a different mode





Parameter Estimation

- Based on Daily Travel Diary (SrV 2018)
  - Revealed preference data (RP)
- Choice set is calculated using MATSim
- Limitations
  - Attributes of the unselected alternatives are not known
  - Spatial accuracy is limited due to privacy preservation
- Stated preference (SP) data is not available for the model area
- Methodology could work with either RP or SP data
- Biogeme used for estimation



Trip-based Choice Model (MNL)

$$U_{m,j} = \beta_{\mathrm{ASC},m} + \beta_{\mathrm{time}} \cdot x_{\mathrm{travelTime},m} - x_{\mathrm{ptTransfers}} + \beta_{\mathrm{money}} \cdot \zeta_{\mathrm{income},j} \left(\beta_{\mathrm{fixedCost}} \cdot x_{\mathrm{fixedCost},m} + x_{\mathrm{distanceCost},m}\right)$$

where the estimated parameters are:

- $\beta_{\mathrm{ASC},m}$ is the alternative-specific constant for mode m
- β_{time} is the base value of time (in utils)
- β_{money} is the marginal utility of money
- $\beta_{\mathrm{fixedCost}}$ is the price perception of fixed costs
- $\zeta_{\mathrm{income},j}$ is an interaction term for the income and perception of costs:

$$\zeta_{\mathrm{income},j} = \left(\frac{1942}{x_{\mathrm{income},j}}\right)^{\lambda_{\mathrm{income}}}$$

Parameter	Estimate	Rob. std. err.	Rob. t-test*
$\beta_{\mathrm{ASC,car}}$	-2.136	0.044	-48.84
$\beta_{\mathrm{ASC,pt}}$	-0.731	0.026	-28.31
$\beta_{\mathrm{ASC,bike}}$	-1.477	0.023	-64.75
$\beta_{\mathrm{ASC,ride}}$	-2.641	0.034	-77.45
β_{time}	5.501	0.104	52.65
β_{money}	0.397	0.029	13.90
$\beta_{\mathrm{fixedCost}}$	0.269	0.039	6.82
$\lambda_{\mathrm{income}}$	0.276	0.037	7.37
LL(0)			−40804.33
LL(final)			−31093.86
Adj. Rho-square			0.238
Parameters			8
Observations			27732

* All parameters are significant at the 99.9% level (|t| > 3.29).

Plan-based Choice Model (MXL)

The utility of a whole daily plan is specified similar to MATSim's leg scoring function:

$$U_{k,j} = \sum_{m \in \text{modes}} \hat{U}_{m,k,j}$$

with modes being the set of all possible modes (car, pt, ride, bike, walk). $\hat{U}_{m,j}$ is the utility of mode m for plan k and person j, defined as:

$$\begin{aligned}
\hat{U}_{m,k,j} = {} & \hat{\beta}_{\text{ASC},m,k} \cdot x_{\text{usage},m,j,k} \\
& + \left(\beta_{time} + \beta_{\text{travel},m}\right) \cdot x_{travelTime,m,j,k} \\
& - x_{\text{ptTransfers},m,j,k} + \beta_{\text{busLegs}} \cdot x_{\text{busLegs},m,j,k} \\
& + \beta_{\text{money}} \cdot \zeta_{\text{income},j} \left(\beta_{\text{fixedCost}} \cdot x_{\text{used},m,j,k} \cdot x_{\text{fixedCost},m} + x_{\text{distanceCost},m,j,k}\right)
\end{aligned}$$

Plan-based Choice Model Results

- $\hat{\beta}_{\mathrm{ASC},m,k} \sim \mathcal{N}(\beta_{\mathrm{ASC},m}, \sigma_{\mathrm{ASC},m})$ is a normal distributed person-specific ASC, capturing taste heterogeneity in the population
- β_{time} is the value of time (in utils)
- $\beta_{\mathrm{travel},m}$ is the marginal utility of travelling with mode m
- β_{money} is the marginal utility of money
- $\beta_{\mathrm{fixedCost}}$ is the price perception of fixed costs
- β_{busLegs} is the utility per leg of a bus ride
- $\zeta_{\mathrm{income},j}$ interaction term for the income and perception of costs

Parameter	Estimate	Rob. std. err.	Rob. t-test*
$\beta_{\mathrm{ASC,car}}$	-2.357	0.108	-21.89
$\sigma_{\mathrm{ASC,car}}$	1.507	0.112	13.42
$\beta_{\mathrm{ASC,pt}}$	-1.063	0.062	-17.29
$\sigma_{\mathrm{ASC,pt}}$	1.738	0.080	21.85
$\beta_{\mathrm{ASC,bike}}$	-0.693	0.055	-12.58
$\sigma_{\mathrm{ASC,bike}}$	0.880	0.049	17.79
$\beta_{\mathrm{ASC,ride}}$	-5.066	0.230	-22.02
$\sigma_{\mathrm{ASC,ride}}$	2.861	0.153	18.67
β_{busLegs}	-0.164	0.063	-2.59
$\beta_{\mathrm{travel,bike}}$	1.309	0.164	8.01
$\beta_{\mathrm{travel,ride}}$	4.443	0.413	10.76
LL(0)			−25278.78
LL(final)			−17084.51
Adj. Rho-square			0.324
Parameters			11
Observations			8400

* All parameters are significant at the 99% level ($|t| > 2.58$).

VERKEHRSSYSTEMPLANUNG
VERKEHRSTELEMATIK
TU BERLIN

Transfer to MATSim

- The estimated parameters are transferred to MATSim
- Taste Variations need to be generated and enabled in the *scoring* config:

```xml
<module name="scoring">

    <parameterset type="scoringParameters" >
        <param name="subpopulation" value="null" />

        <!-- Other scoring parameters -->

        <parameterset type="modeParams" >
                <!-- Other scoring parameters -->
        </parameterset>

        <parameterset type="tasteVariations" >
            <!-- Exponent for income dependent scoring. Exponent for (global_income / personal_income) ** x.
            <param name="incomeExponent" value="2.0" />

            <!-- List of utility parameters that are loaded from each person. -->
            <param name="variationsOf" value="constant, dailyUtilityConstant" />
         </parameterset>
    </parameterset>
</module>
```


VERKEHRSSYSTEMPLANUNG
VERKEHRSTELEMATIK
TU BERLIN

Usage Example

- The presented functionality has been merged into the MATSim Repo (PR #3855)
- Parameters can be set per person using the provided API:

```java
// In your PopulationUtils class:
Person person = population.getPersons().get(Id.createPersonId("1"));

// Create a map of mode-specific utility parameter variations
Map<String, Map<ModeUtilityParameters.Type, Double>> variations = Map.of(
    "car", Map.of(
        ModeUtilityParameters.Type.constant, -1.0  // -1.0 additional utility for car
    ),
    "pt", Map.of(
        ModeUtilityParameters.Type.constant, 0.5,  // +0.5 utility for PT
        ModeUtilityParameters.Type.marginalUtilityOfDistance_m, -0.0001  // Different distance utility
    )
);

// Set the variations on the person
PersonUtils.setModeTasteVariations(person, variations);
```


VERKEHRSSYSTEMPLANUNG
VERKEHRSTELEMATIK
TU BERLIN

MATSim Results

- Same evaluation methodology as in the base case (12 runs)
  - For every run, different taste variations are sampled

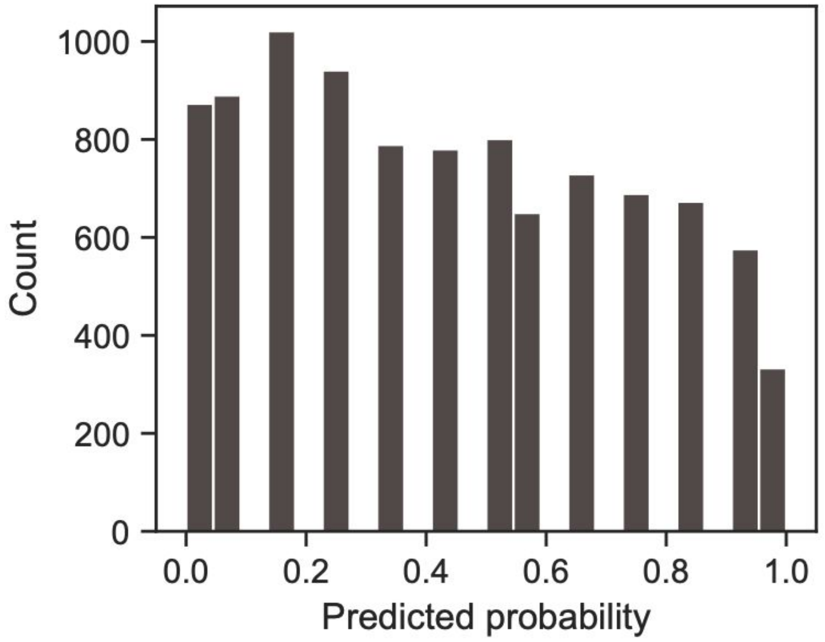
- Log-Likelihood improved from **-43144** to **-15684**
- Accuracy has decreased
  - Accuracy alone is a poor indicator of predictive power (Accuracy paradox)

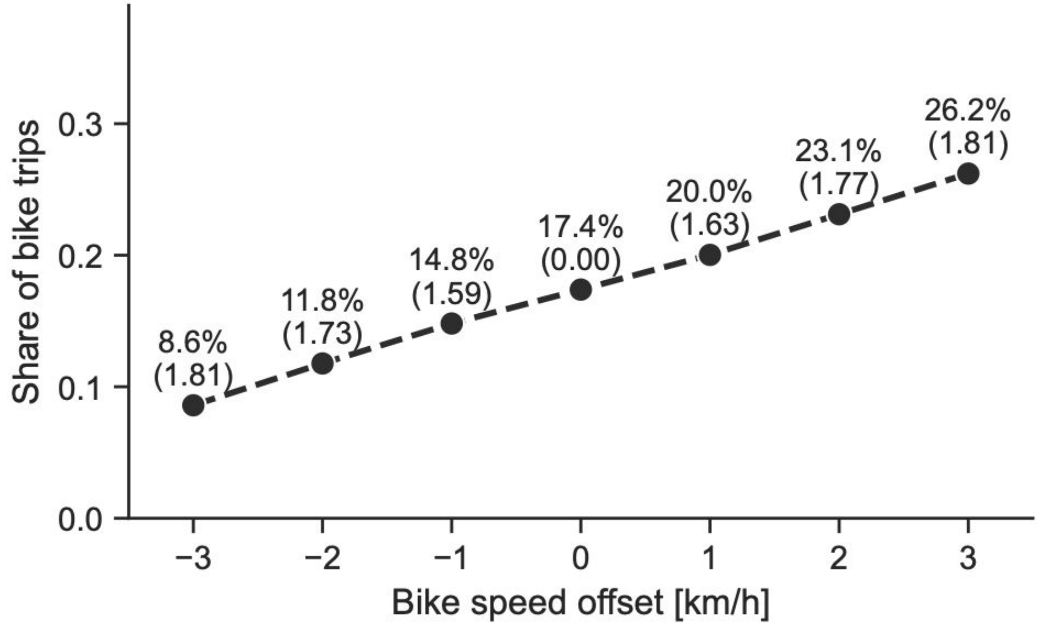
Metric	
Observations	9745
Log-Likelihood	−15684
Accuracy	0.444
Cohen's Kappa	0.267
F1 Score (macro avg.)	0.359
Precision (macro avg.)	0.361
Recall (macro avg.)	0.359

Mode	Precision	Recall	F1 Score
bike	0.259	0.277	0.268
car	0.297	0.346	0.319
pt	0.473	0.465	0.469
ride	0.087	0.081	0.084
walk	0.689	0.624	0.655

Elasticities

- Model is not overconfident anymore
- Elasticities are reduced compared to baseline

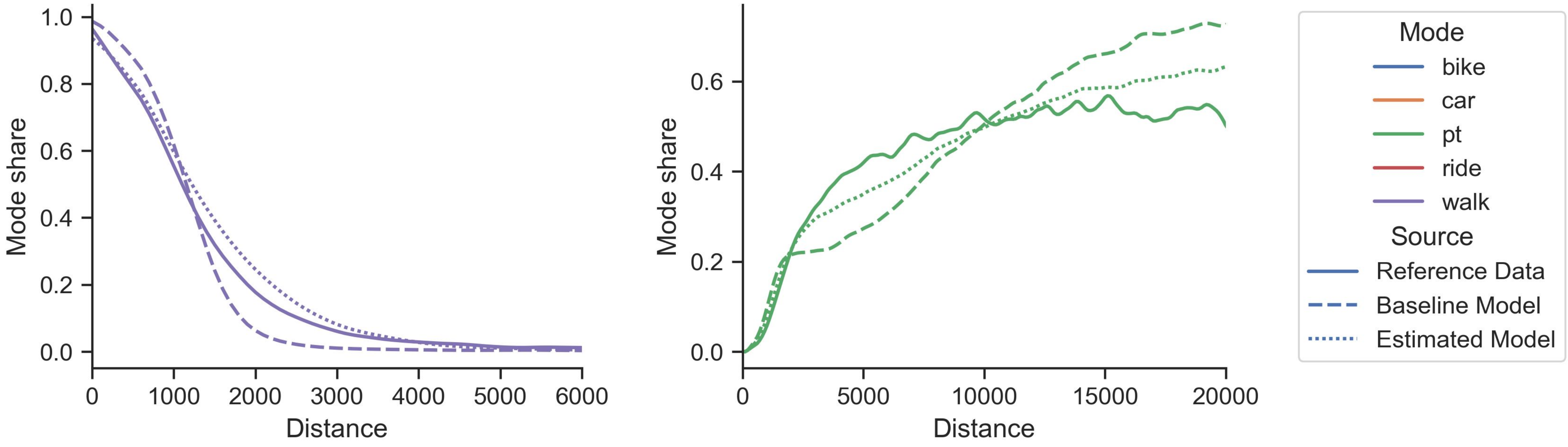




VERKEHRSSYSTEMPLANUNG
VERKEHRSTELEMATIK
TU BERLIN

Modal Distance Distribution

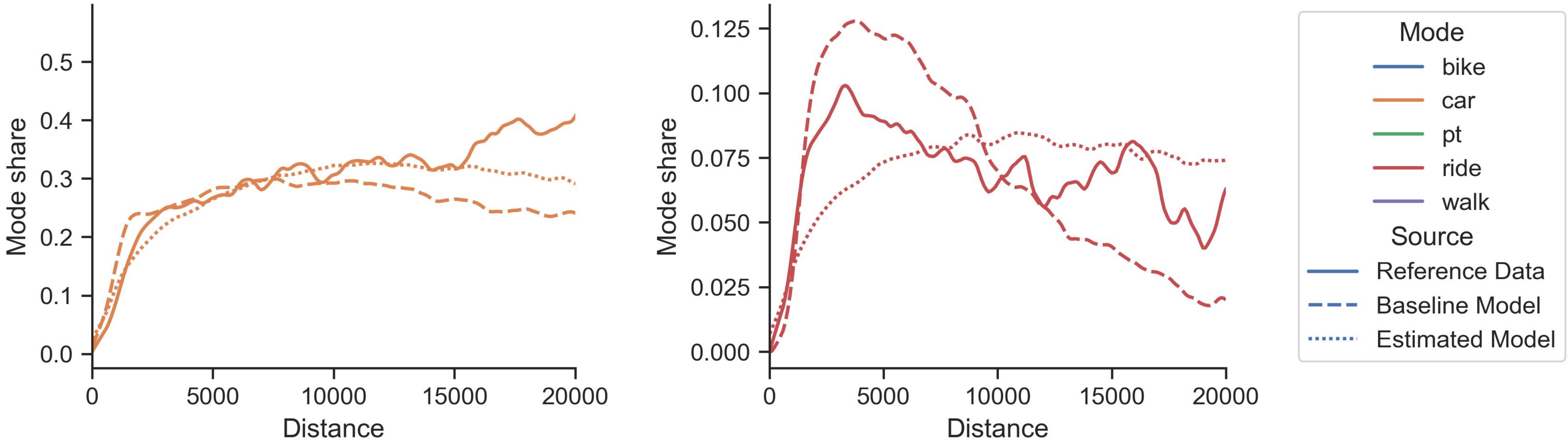
- Improved fit of modal distance distributions
  - People who like walking will also walk longer distances



VERKEHRSSYSTEMPLANUNG
VERKEHRSTELEMATIK
TU BERLIN

Modal Distance Distribution (cont.)

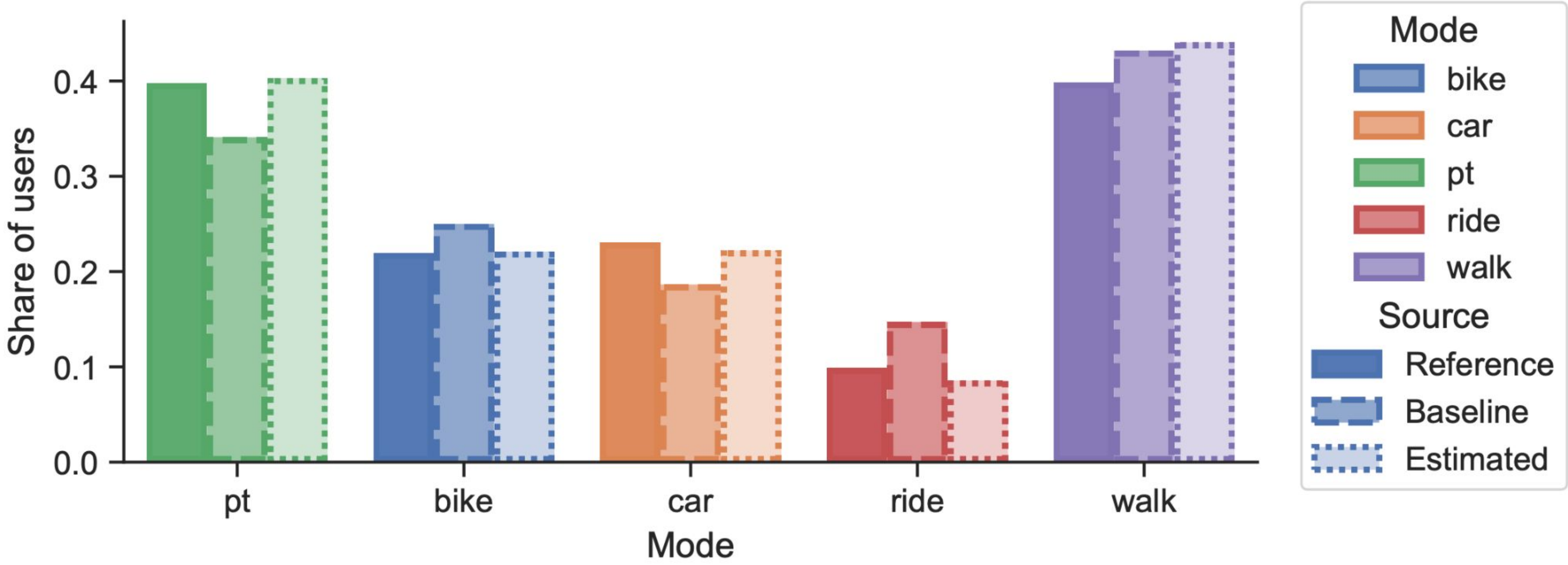
- Ride (passenger) mode does not benefit from this approach
  - Ride usage is due to household structure, availability, time schedule, etc.
  - Not determined by individual preference → utility specification needs to be adapted



VERKEHRSSYSTEMPLANUNG
VERKEHRSTELEMATIK
TU BERLIN

Share of mode users

- Users using a mode at least once per day



Thank you
for your attention!

- Including taste preferences improves model performance
- Validating with real-world data is important
- MXL and ABM fit conceptually well together

Christian Rakow
Simunto GmbH
rakow@simunto.com