# Stability of travel behavior: Modeling incremental changes of travel demand instead of recreating it from scratch

DALL-E: pedestrian, bike, train and auto as a pencil drawing

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Dr. Rolf Moeckel, Professor of Travel Behavior
Technical University of Munich

Amicalola Falls
State Park, Georgia
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# Stability of Travel Behavior

# Stability of travel behavior

Travel behavior may differ a lot from day to day (Raux et al. 2016, Hanson 1988, Huff et al. 1986)
Travel behavior is rather stable from year to year (McCarthy 1982, Kitamura 1987, Jones 1988, Cui et al. 2014)

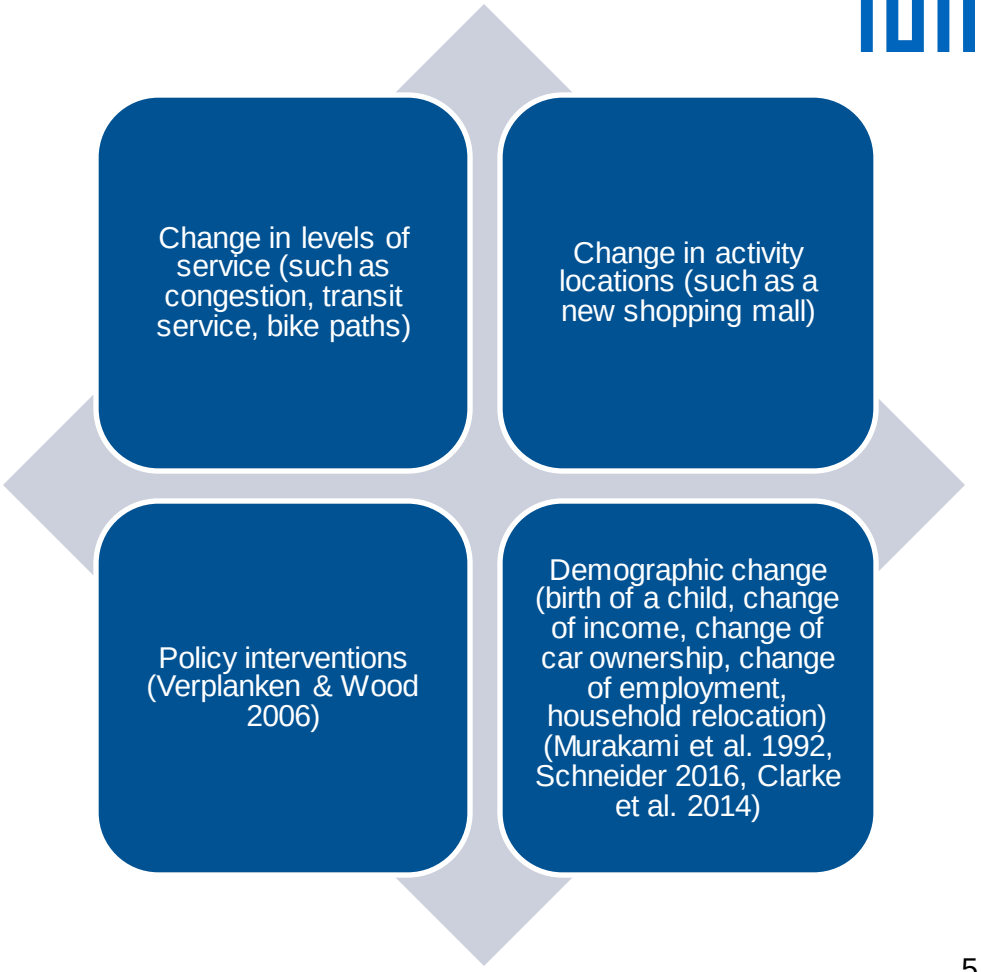
To a large degree, travel behavior is driven by habitual choices that do not change often (Gärling & Axhausen 2003).

Workdays are more stable than non-workdays, travel time is more stable than trips (Schlich & Axhausen 2003)

Source: hhagedorn on https://qimby.net/

# Change of travel behavior

Change in travel behavior is typically driven by one (or more) of the following:



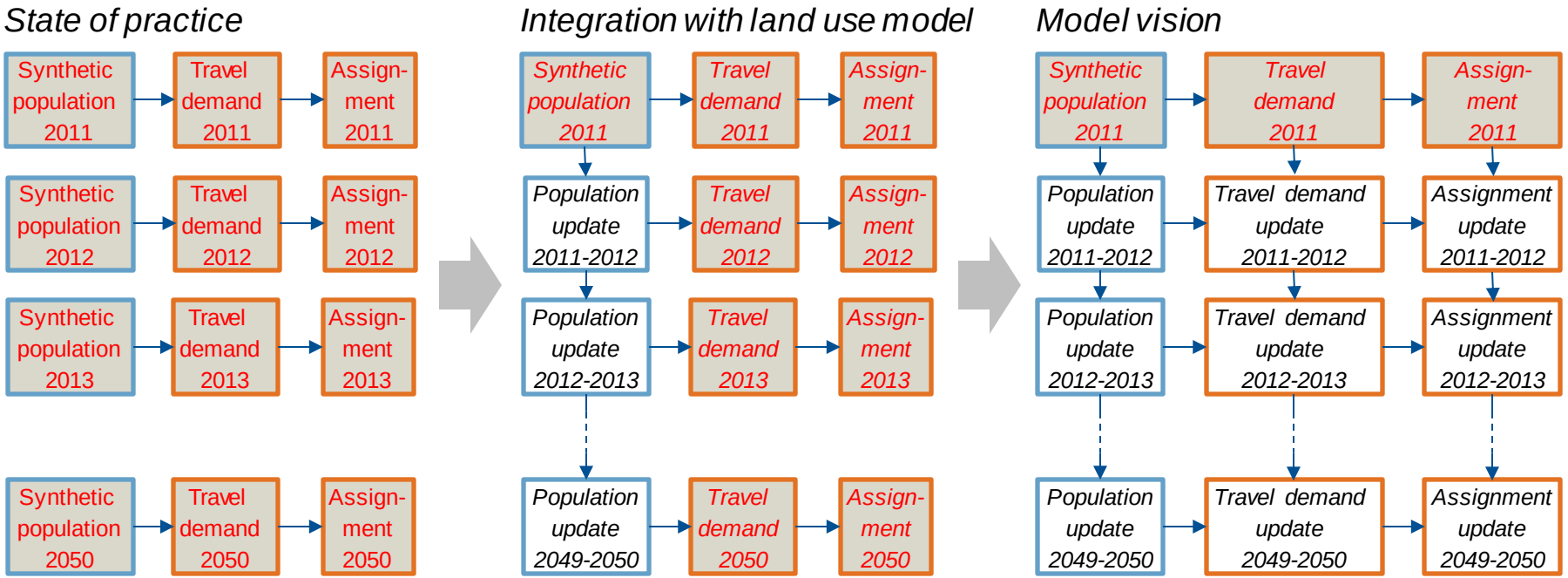

For most households, such changes are rare.

# Study Rationale

# Research rationale

- Most transport models **recreate travel behavior from scratch** each time the model runs.
- When testing a policy scenario (such as opening a new road), travel choice are created from scratch the next time the model runs, **ignoring habitual behavior**.
- In **land use modeling**, we have long overcome recreating populations from scratch every simulation period (Waddell 2002). It is time to do the same in transport modeling.

# Vision of model evolution



# Panel data and travel behavior change

# Panel survey data

- The German mobility panel survey collected week-long travel diaries from 1994 to 2023, where the same household was interviewed three years in a row
- Almost 2,000 household interviewed per year

| Kohorte | Jahr | 2017 abs. | 2017 % | 2018 abs. | 2018 % | 2019 abs. | 2019 % | 2020 abs. | 2020 % | 2021 abs. | 2021 % |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 2017 | HH | 806 | 100% | 618 | 77% | 539 | 87% | | | | |
| | P | 1.391 | 100% | 1.061 | 76% | 911 | 86% | | | | |
| 2018 | HH | | | 744 | 100% | 596 | 80% | 544 | 91% | | |
| | P | | | 1.264 | 100% | 1.009 | 80% | 895 | 89% | | |
| 2019 | HH | | | | | 718 | 100% | 591 | 82% | 513 | 87% |
| | P | | | | | 1.271 | 100% | 1.030 | 81% | 866 | 84% |
| 2020 | HH | | | | | | | 828 | 100% | 659 | 80% |
| | P | | | | | | | 1.536 | 100% | 1.205 | 78% |
| 2021 | HH | | | | | | | | | 668 | 100% |
| | P | | | | | | | | | 1.176 | 100% |
| Gesamt | HH | | | | | 1.853 | | 1.963 | | 1.840 | |
| | P | | | | | 3.191 | | 3.461 | | 3.247 | |

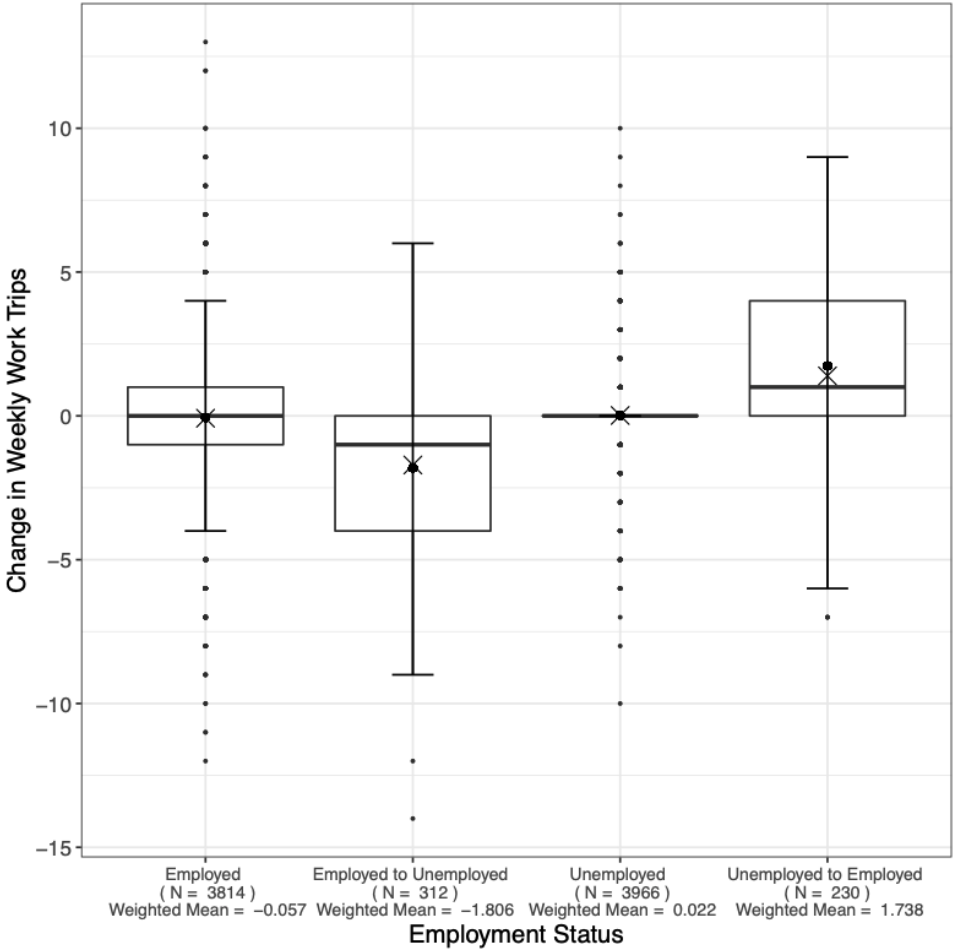
KIT Quelle: Deutsches Mobilitätspanel

# Live events studies

1. change in employment status of a person
2. change in household size
3. change in household income
4. birth of a new child
5. change in household car ownership
6. household relocation

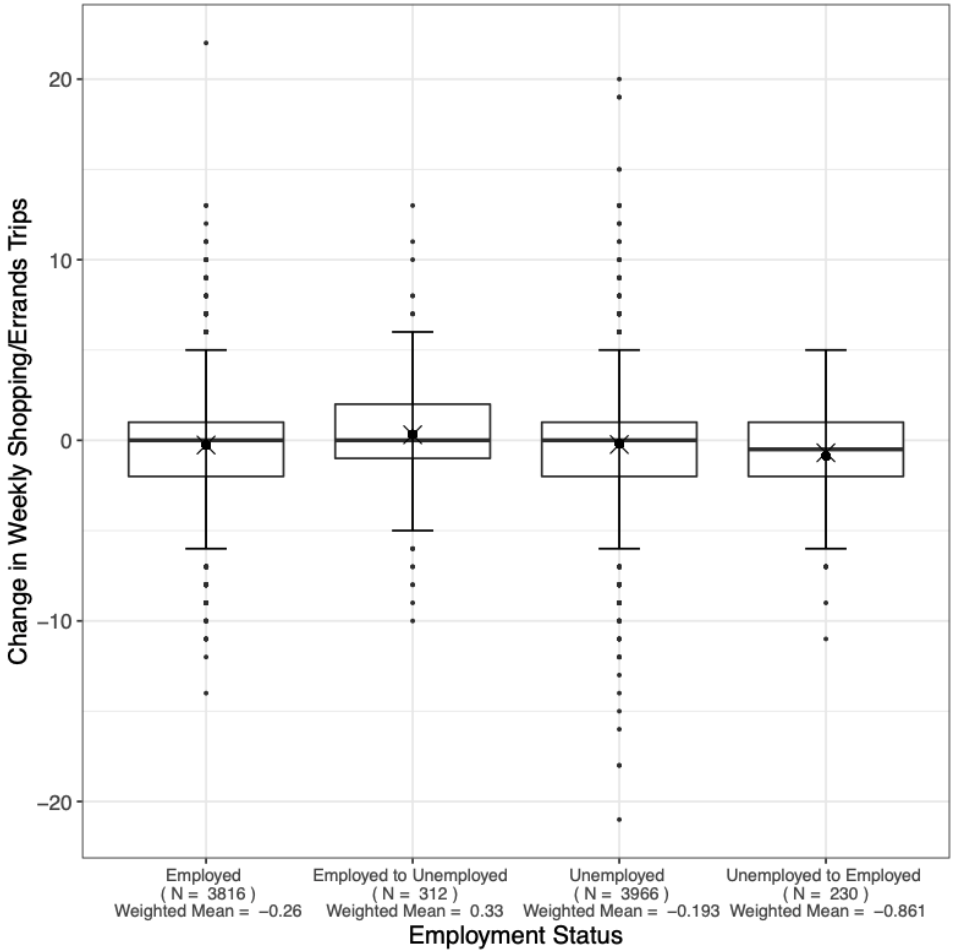
| Number of Life Events | Persons | Proportion |
|---|---|---|
| 0 | 5,404 | 54.8% |
| 1 | 3,275 | 33.2% |
| 2 | 876 | 8.9% |
| 3 | 237 | 2.4% |
| 4 | 56 | 0.6% |
| 5 | 9 | 0.1% |
| 6 | 2 | 0.0% |

Source: Ahmed & Moeckel (2023)




# Change in weekly work trips due to change in employment

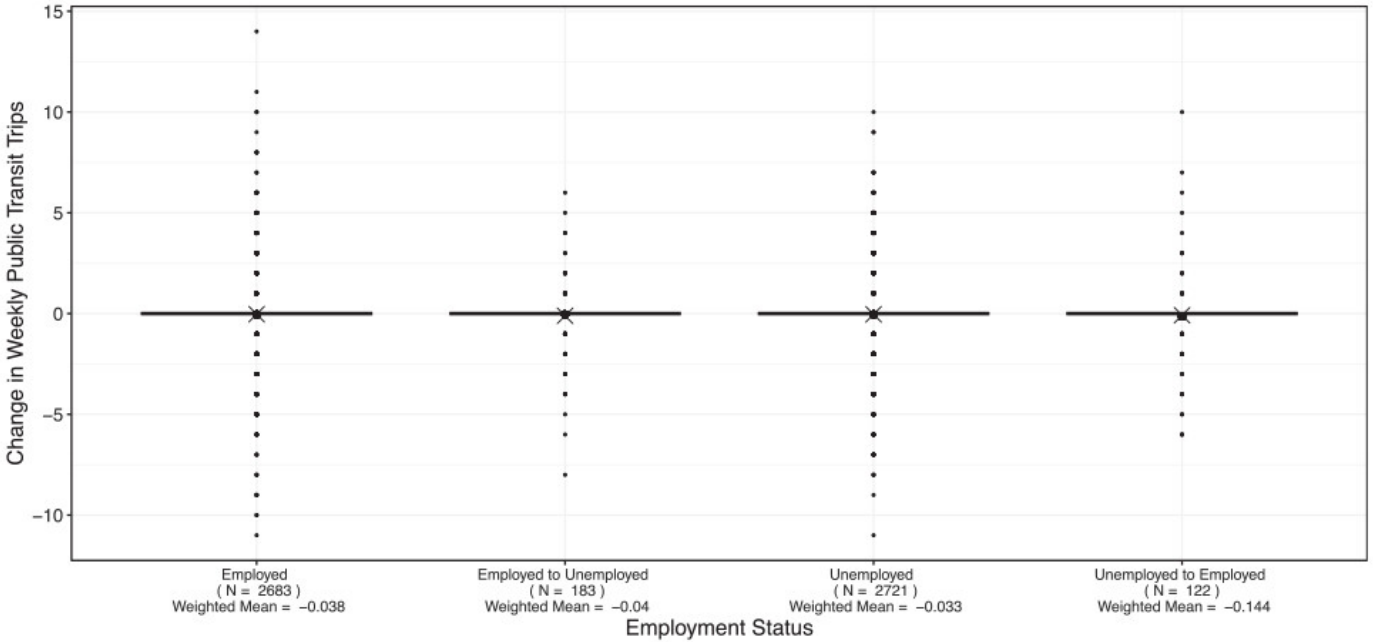
Source: Ahmed & Moeckel (2023)




# Change in weekly shopping trips due to change in employment

Source: Ahmed & Moeckel (2023)

# No explanatory power for number of transit trips




Source: Ahmed & Moeckel (2023)

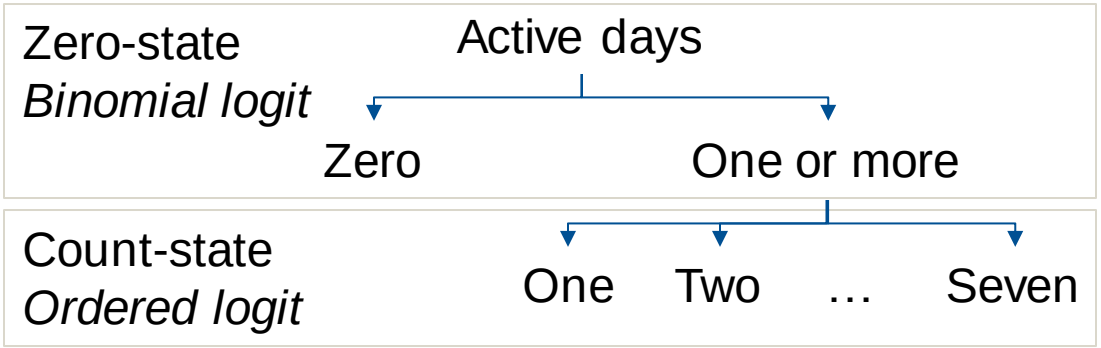
# Analysis of life events

**Becoming employed or unemployed** trigger the **highest differences** on mandatory active days and slight variations in discretionary active days

Active days are rather **stable for unemployed** (95%), employed (50%) and **students** (60%)

# Machine Learning and Travel Behavior Change

# Econometric models




| Purpose | Model | Traditional | AI-informed |
|---|---|---|---|
| Mandatory | Zero-state | 0.508 | 0.536 |
| | Count-state | 0.559 | 0.565 |
| Discretionary | Zero-state | 0.472 | 0.476 |
| | Count-state | 0.676 | 0.677 |

*Pseudo* $R^2$

# Methodology: machine learning pipeline

**Data split**

1. Training (80%) and testing (20%)
2. Stratified random split
3. Strata based on the distribution of the target variable

**Feature selection**

1. Lasso regression
2. Ridge regression
3. Without feature selection

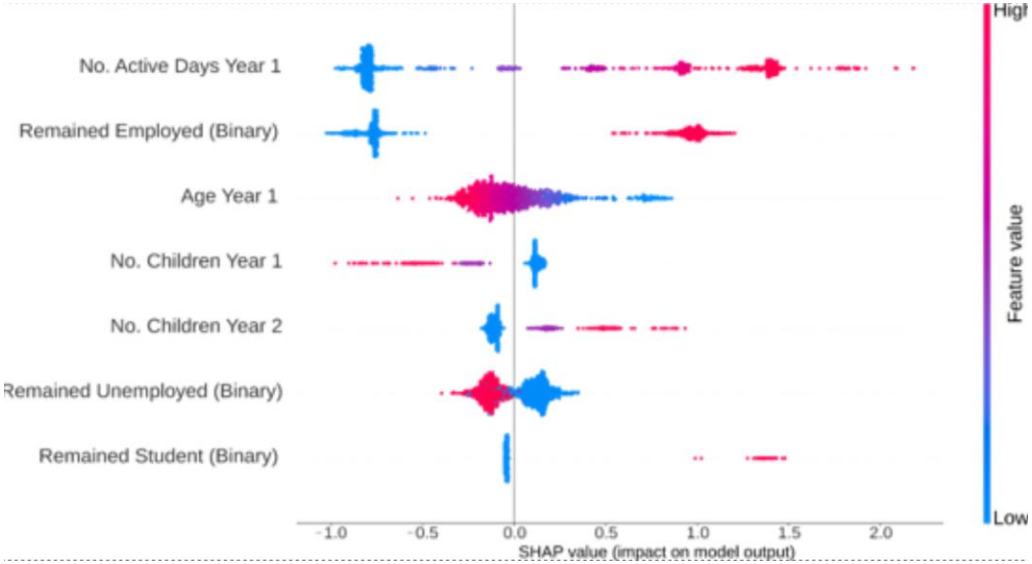
**Regression with hyperparameters**

1. Linear regression
2. Lasso regression
3. Ridge regression
4. Neighbors regression (KNN)
5. Support Vector regression (SVR)
6. Random Forests (RFs)
7. Multi-Layer Perceptrons (MLPs)

| Purpose | Data split | Linear | Lasso | Ridge | KNN | SVR | RFs | MLPs |
|---|---|---|---|---|---|---|---|---|
| Mandatory | Training | 0.743 | 0.756 | 0.756 | 0.740 | 0.740 | **0.843** | 0.751 |
| | Testing | 0.767 | 0.769 | 0.769 | 0.754 | 0.757 | **0.776** | 0.775 |

# AI-interpretability: SHapley Additive exPlanations (SHAP)

- **Stability** on active days is confirmed for both mandatory and discretionary acts
- Individuals who remain employed or studying tend to have more active days with mandatory activities
- **Similar conclusions** are obtained in the **traditional** econometric model

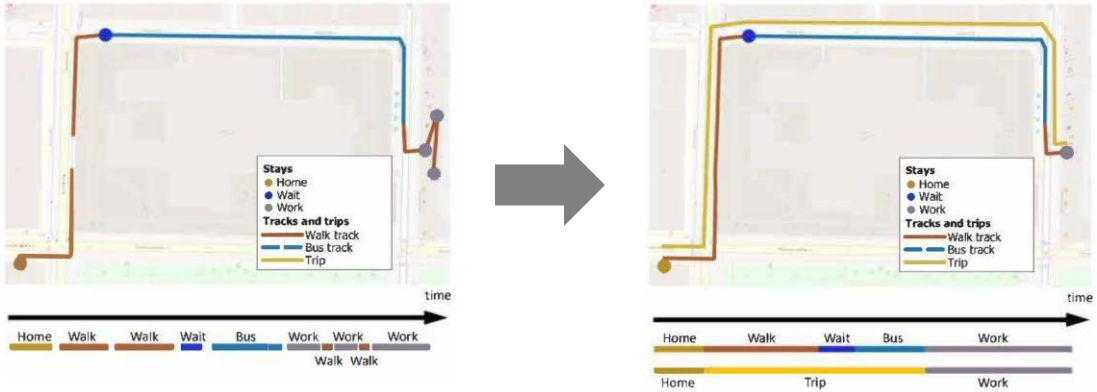



Active days with mandatory activities

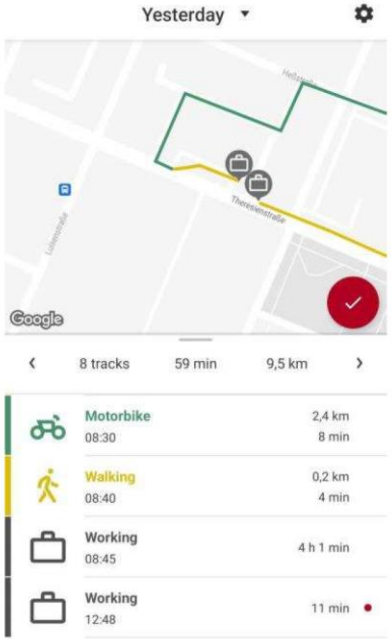
# Mobile Phone Data and Travel Behavior Stability

# Data

- Since Summer 2022, the team of Dr. Klaus Bogenberger (TUM) is collecting mobile phone data with MOTIONTAG App
- 3,080 participants in Munich metropolitan area
- Process for detection of legs and stops required:




*Raw data records* *Processed data*



# Research idea

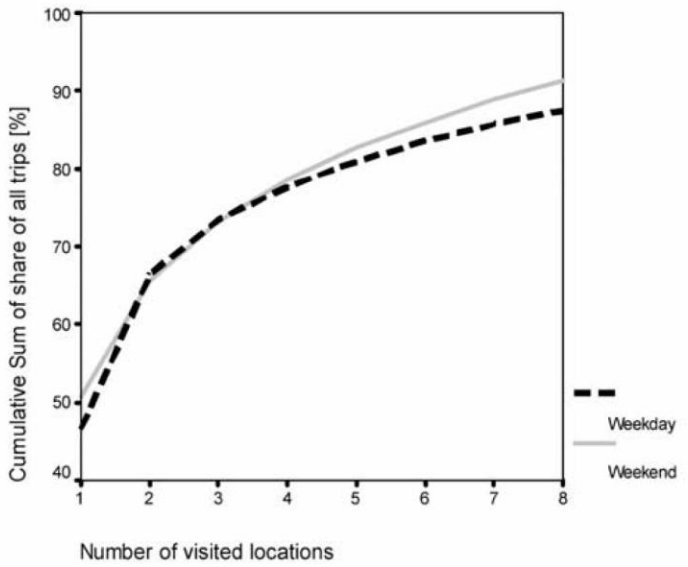
Major strength of data:
Individuals can be traced **over multiple days**

Analyses:

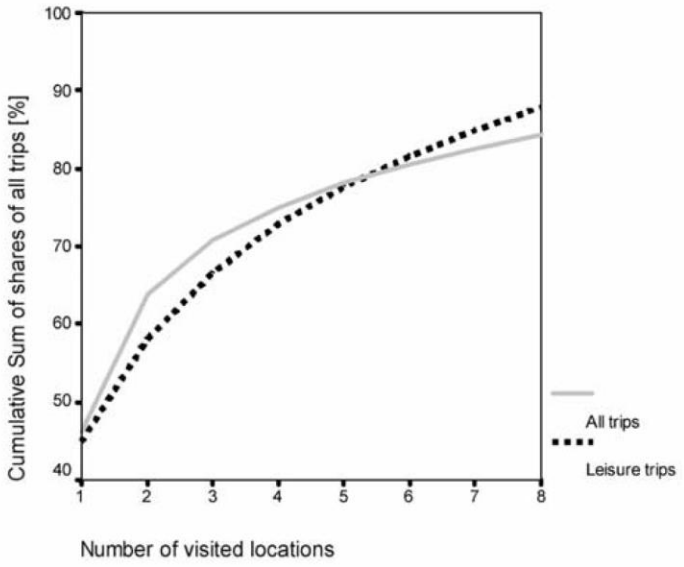
- **How many trips** are made by a participant day after day
- Does the participant repeatedly visit **the same destination**? Several times per day, per week, per month?
- What **time of day** are repeated destinations visited?

# Repeated destinations

Weekdays versus weekend



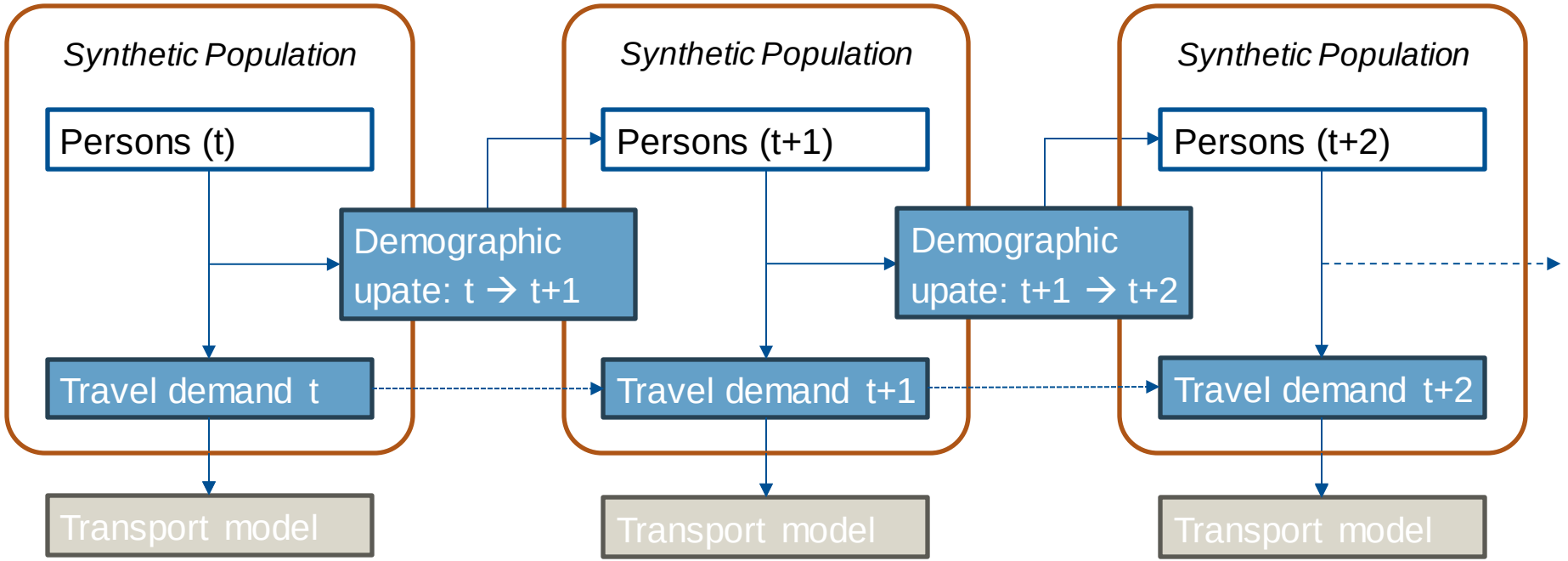

All trips versus leisure trips




Source: Mobidrive survey, Schönfelder & Axhausen (2001)

# Outlook

# Model concept



# Conclusions

- **Day-to-day travel behavior variability** cannot be explained by currently observed data.
- Travel behavior **over weeks is very stable** and should not be reinvented every time the transport model runs.
- Much behavior is **driven by habits** that should not be modeled with tabula-rasa methods.
- It is time for **transport modeling** to catch up with **land use modeling** and adjust travel behavior incrementally, rather than reinventing it from scratch every time the model runs.

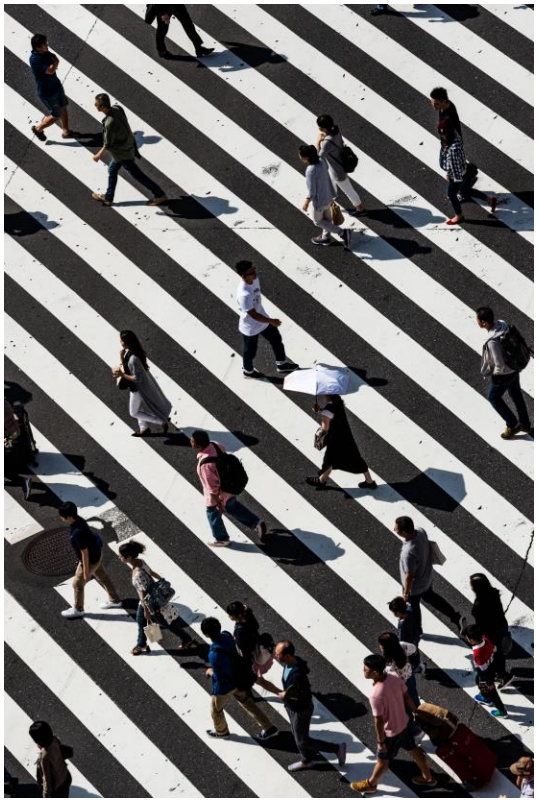


Photo by Ryoji Iwata on Unsplash