

# Using attention to model long-term dependencies in occupancy behavior



Tackling Climate Change with Machine Learning workshop at NeurIPS 2020  
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**Max Kleinebrahm**

Chair of Energy Economics  
Karlsruhe Institute of Technology  
Karlsruhe, Germany  
*max.kleinebrahm@kit.edu*

**Jacopo Torriti**

School of the Built Environment  
University of Reading  
Reading, United Kingdom  
*j.torriti@reading.ac.uk*

**Russell McKenna**

Chair in Energy Transition  
University of Aberdeen  
Aberdeen, United Kingdom  
*russell.mckenna@abdn.ac.uk*

**Armin Ardone**

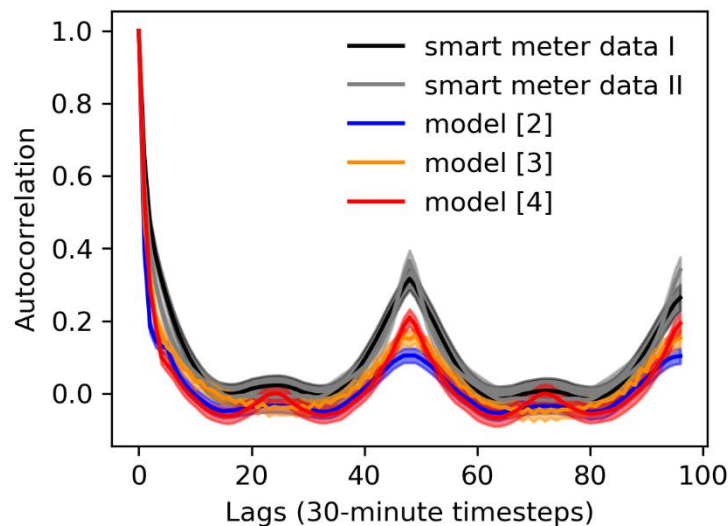
Chair of Energy Economics  
Karlsruhe Institute of Technology  
Karlsruhe, Germany  
*armin.ardone@kit.edu*

**Wolf Fichtner**

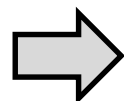
Chair of Energy Economics  
Karlsruhe Institute of Technology  
Karlsruhe, Germany  
*wolf.fichtner@kit.edu*

# Motivation & objective

Why is it important to capture long-term behavioral dependencies in occupant behavior models to tackle climate change?

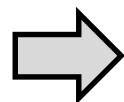


- Occupant behavior has a significant impact on the dynamics of household energy consumption [1]
- Existing studies try to simulate occupant behavior to explain aggregated energy demand [2,3,4]

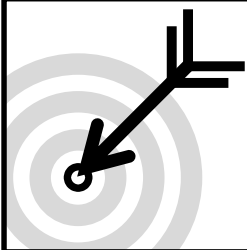


**Low quality individual occupant activity schedules**

- Decarbonisation of domestic energy demand (electricity, heat, mobility)
- New technologies: heat pumps, electric vehicles, batteries,...



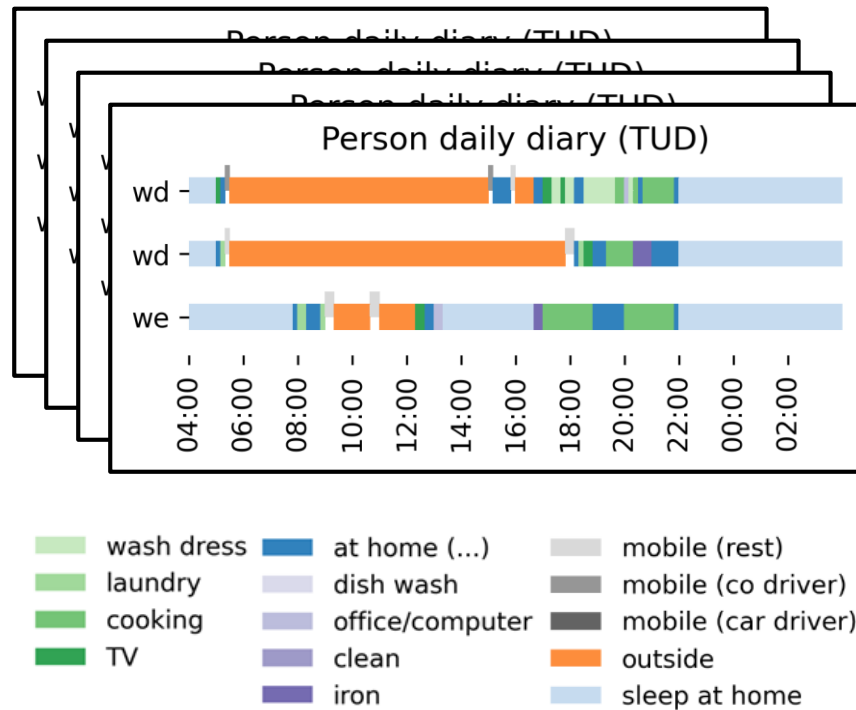
**Flexibility potential**



Representing long-term dependencies in occupant behavior models in order to generate high quality synthetic activity schedules

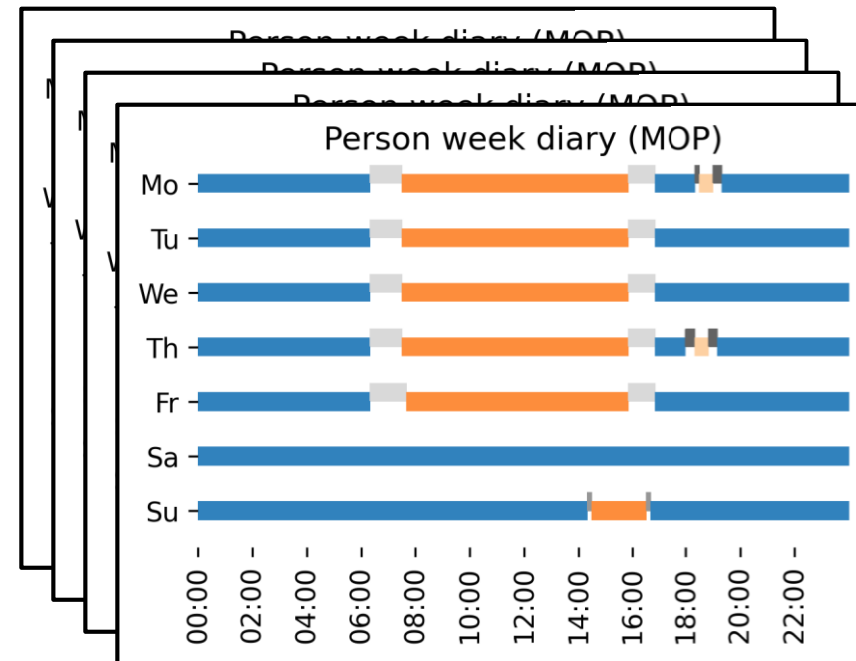
# Input data

## Activity data



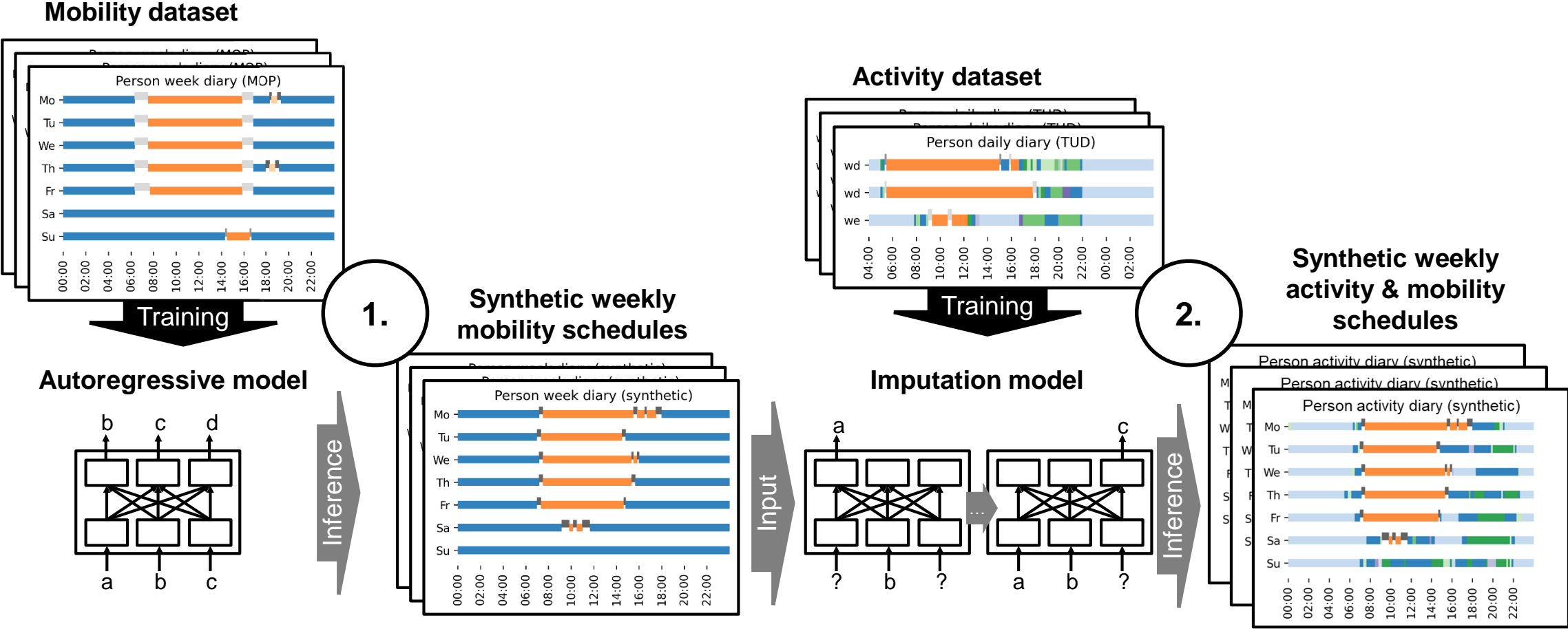
- National representative samples (30 countries)
- Highly differentiated states of activity
- Information about two to three individual days
- This study: German TUD [5]

## Mobility data



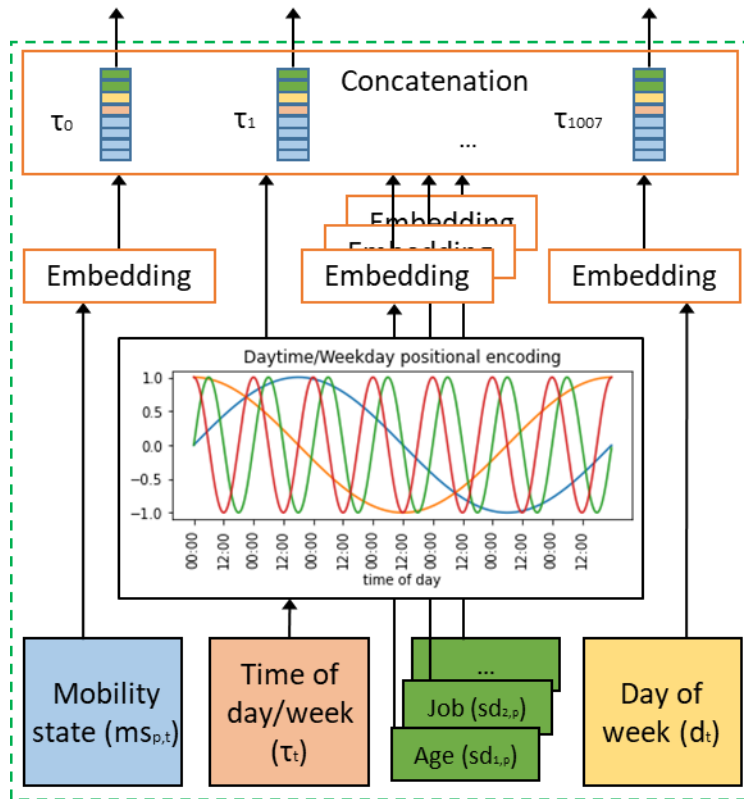
- National representative samples (DE, UK, ...)
- Longitudinal mobility study
- Information about mobility patterns over one week
- This study: German Mobility Panel (MOP) [6]

# Model architecture

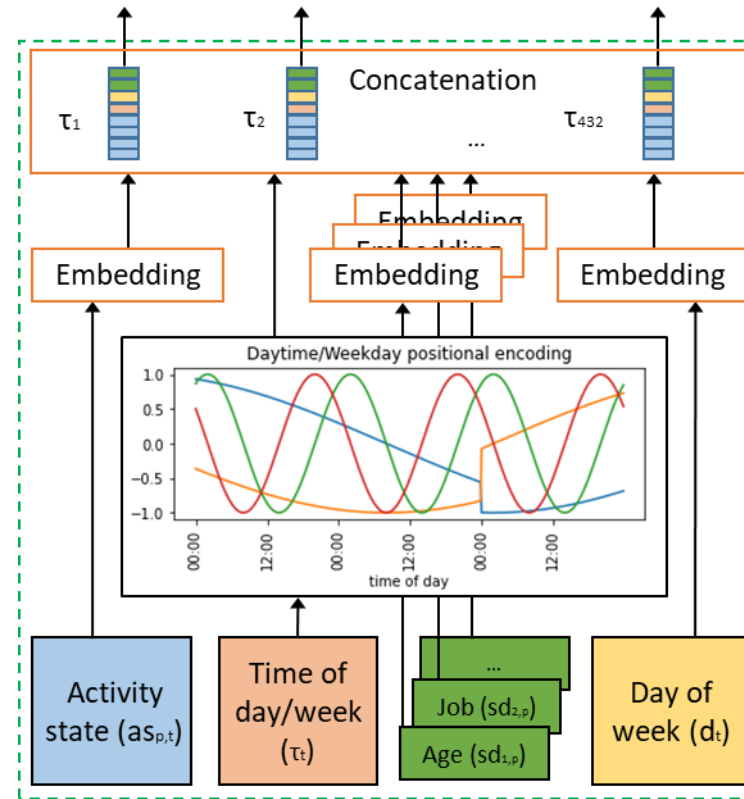


# Input & first layers

a.) Autoregressive model

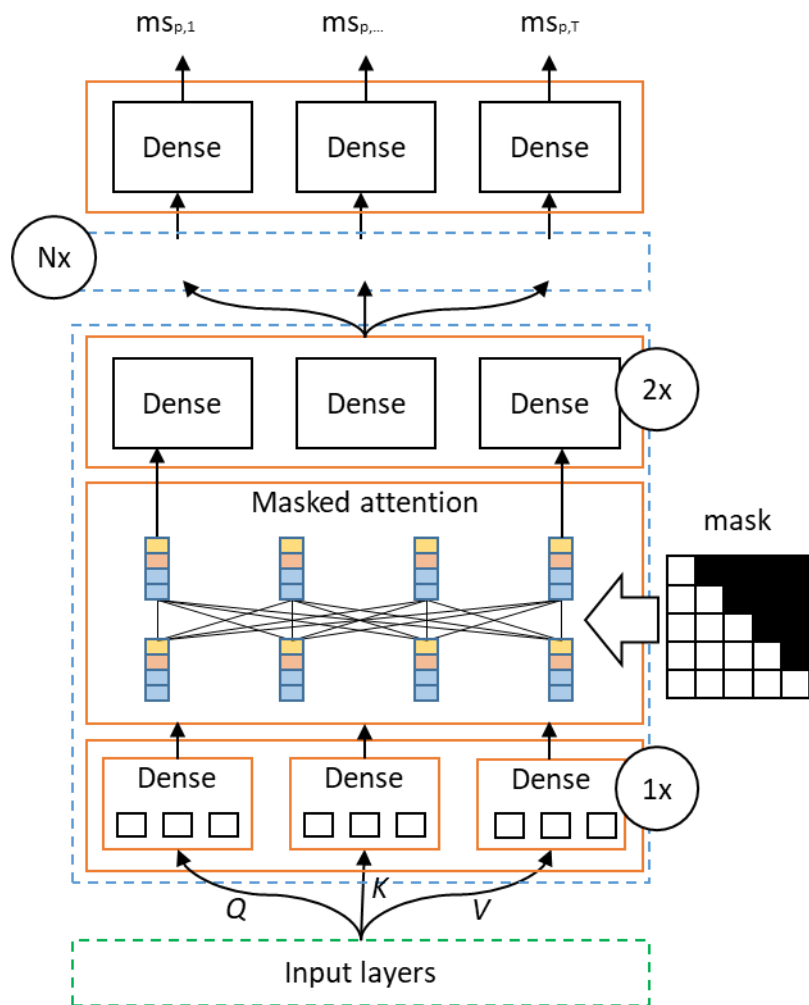


b.) Imputation model

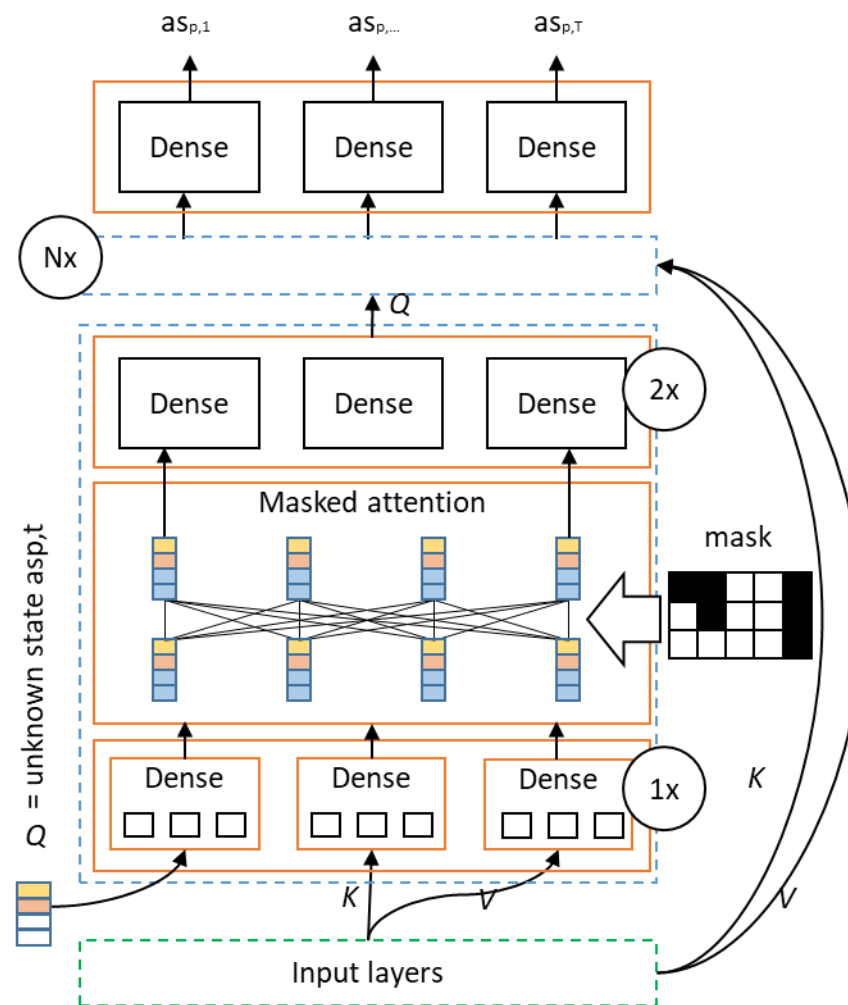


# Autoregressive & imputation model

a.) Autoregressive Transformer

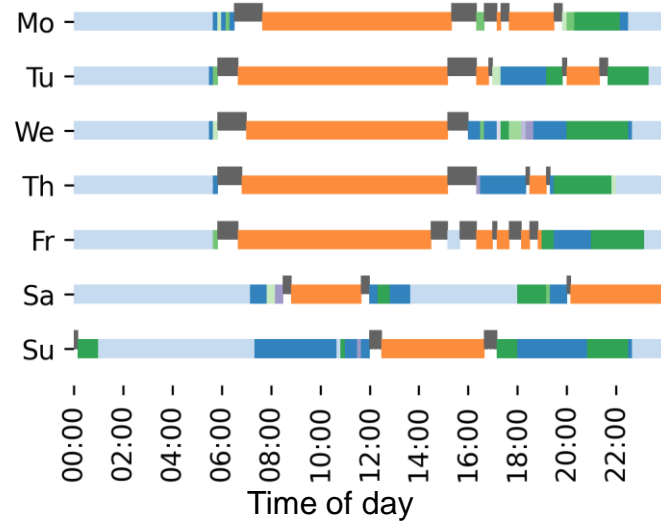


b.) Imputation Transformer

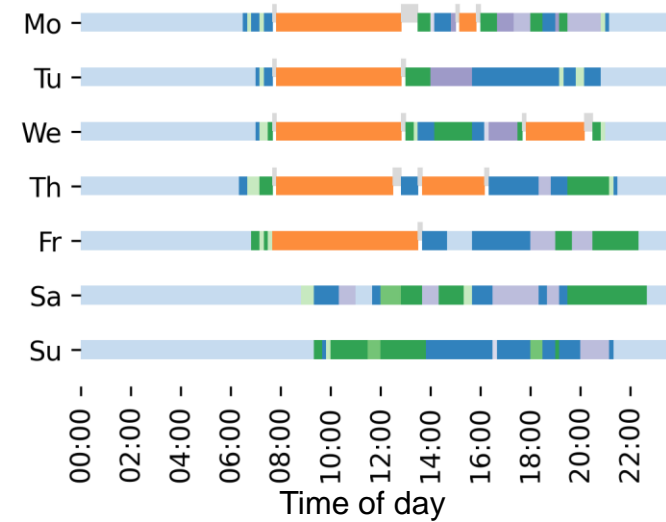


# Exemplary results

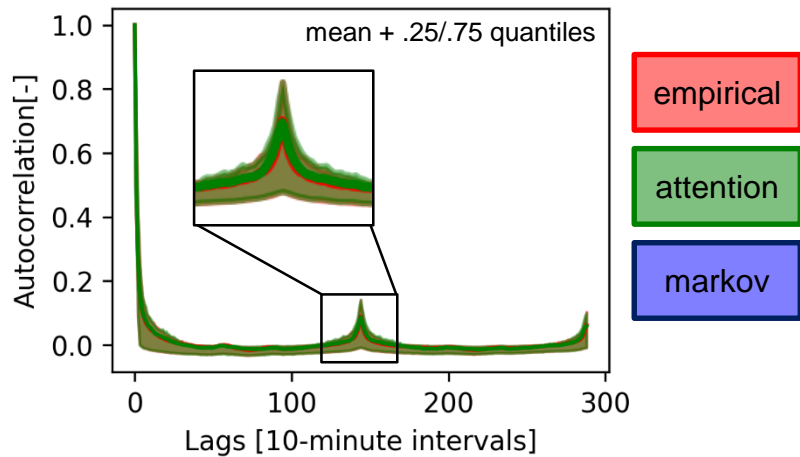
Weekly activity schedule (age: 55, job: full time)



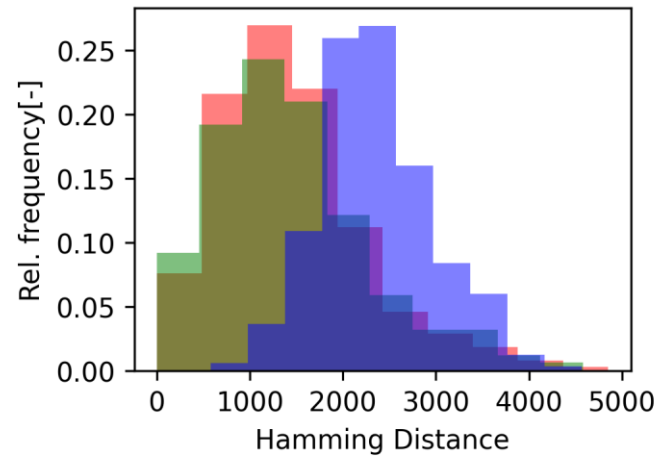
Weekly activity schedule (age: 15, job: student)



State: mobile (driving car)



Hamming distance weekdays



## Visual control:

- Interday dependencies are reproduced
- Behavior of different socio-demographic groups is captured

## Aggregated metrics:

- State probability
- State duration
- State autocorrelation
- Weekly appearances of state
- Hamming distance between weekdays:

$$hd_n = \sum_{d_1=1}^5 \sum_{d_2=1}^5 |\{t \in \{1, \dots, T_d\} | s_{d_1,t} \neq s_{d_2,t}\}| \quad \forall n \in N$$

# Conclusion & outlook & challenges

## Conclusion:

- Attention based models can capture complex long-term dependencies in occupancy behavior
- The diversity in behavior across the entire population and different socio-demographic groups is adequately reproduced by the presented approach
- The approach combines the advantages of two datasets and creates a new high quality synthetic dataset for energy system modelers

## Outlook:

- Individual behavior → household behavior (*challenge*: quadratic memory and time complexity with sequence length)
- Open data → differential privacy (*challenge*: trade off between accuracy and privacy)



Thanks for your ~~attention!~~

$$\text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V!$$

- [1] Koen Steemers and Geun Young Yun. Household energy consumption: A study of the role of occupants. *Building Research & Information*, 37(5-6):625–637, 2009.
- [2] Richardson, Ian; Thomson, Murray; Infield, David; Clifford, Conor (2010): Domestic electricity use. A high-resolution energy demand model. In *Energy and Buildings* 42 (10), pp. 1878–1887. DOI: 10.1016/j.enbuild.2010.05.023.
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- [5] Destatis (2006): Zeitbudgeterhebung: Aktivitäten in Stunden und Minuten nach Geschlecht, Alter und Haushaltstyp. Zeitbudgets - Tabellenband I. 2001/2002. Wiesbaden. Available online at [https://www.statistischebibliothek.de/mir/receive/DEMonografie\\_mods\\_00003054](https://www.statistischebibliothek.de/mir/receive/DEMonografie_mods_00003054).
- [6] Weiß, Christine; Chlond, Bastian; Hilgert, Tim; Vortisch, Peter (2016): Deutsches Mobilitätspanel (MOP) - wissenschaftliche Begleitung und Auswertungen, Bericht 2014/2015. Alltagsmobilität und Fahrleistung, checked on 10/22/2019.