Analyzing the impact of fare-free public transport policies on crowding patterns at stations using crowdsensing data

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Introduction

- Understanding the potential impact of fully or partially fare-free PT (FFPT) policies on crowding patterns
- Heterogeneous impacts of PT pricing policies among PT stations
- Emerging crowdsensing data have wide coverage and fine resolution in spatial and temporal dimensions

Contributions

- Methodological framework leveraging wide-coverage PT station busyness data for demand pattern analysis
- Evaluating the 9-Euro ticket experiment in Germany using opportunistic data

Three-step busyness-based evaluation

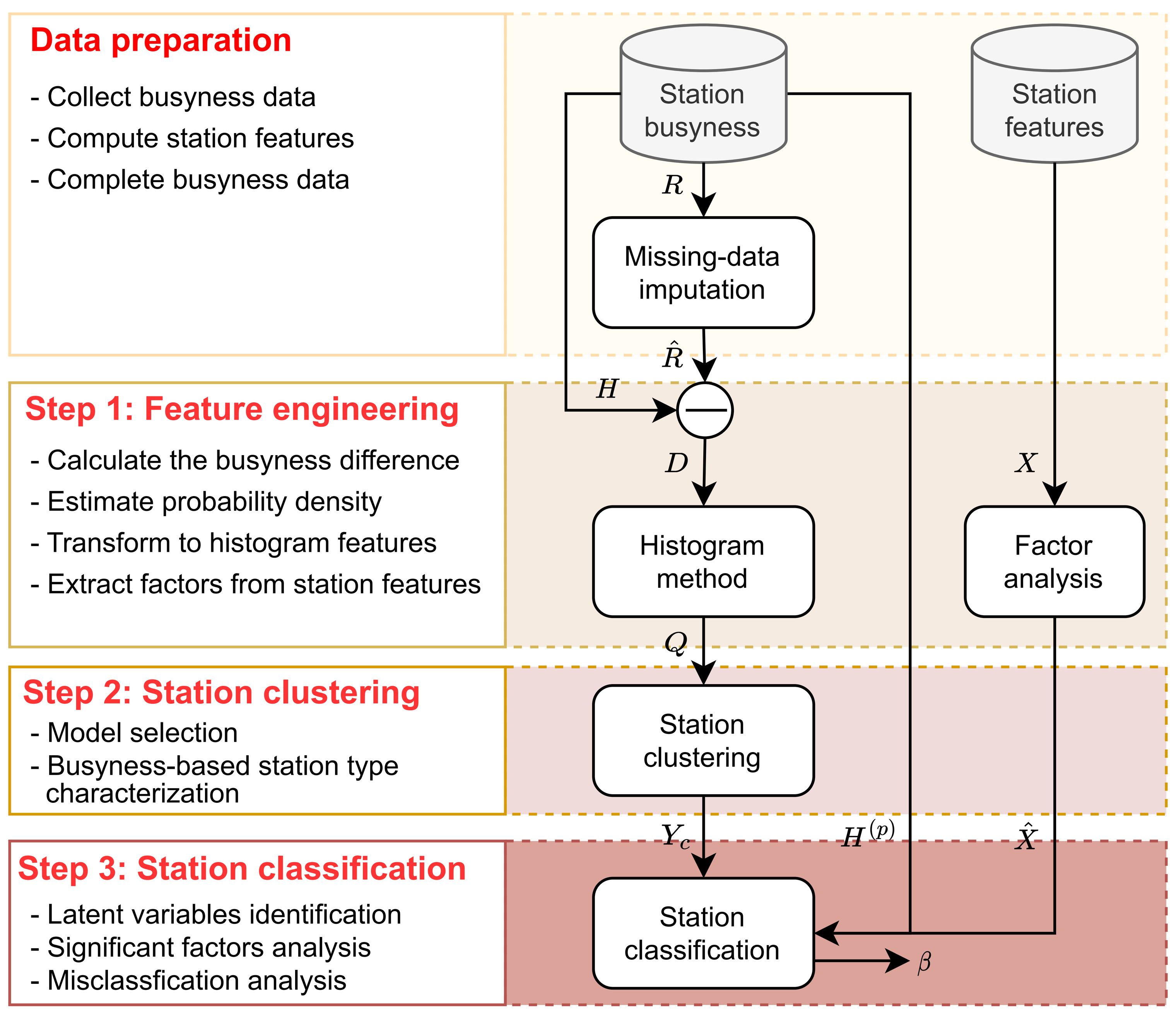

Figure 1. Three-step busyness-based evaluation framework for public transport policies.

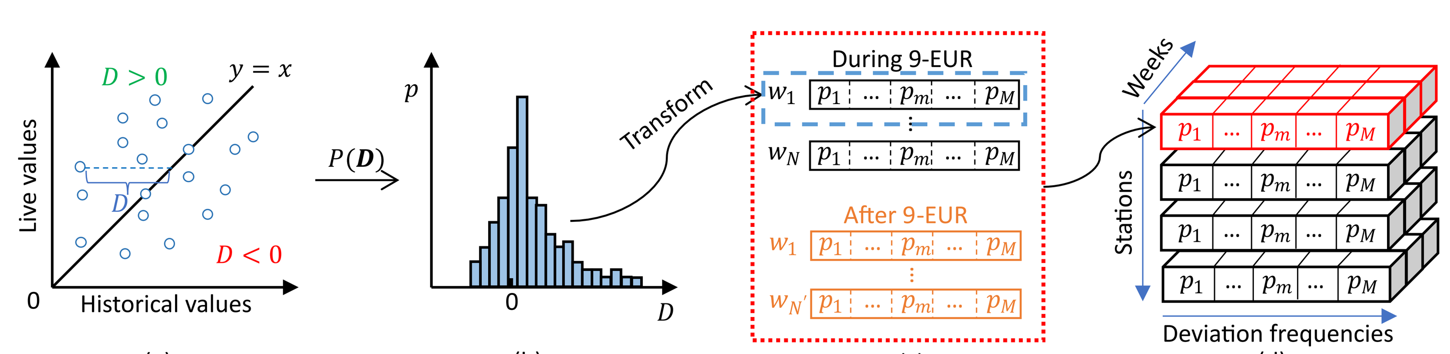

Figure 2. Feature engineering based on the histogram method.

Case study and data

German federal government introduced "9-EUR Ticket":

- Partially FFPT
- From June 1 to August 31, 2022
- Nationwide policy (natural experiment)
- Valid on all regional, local, and urban PT services

Google's Popular time (GPT) data is collected (every two hours) for 2,134 railway stations at different phases of the policy.

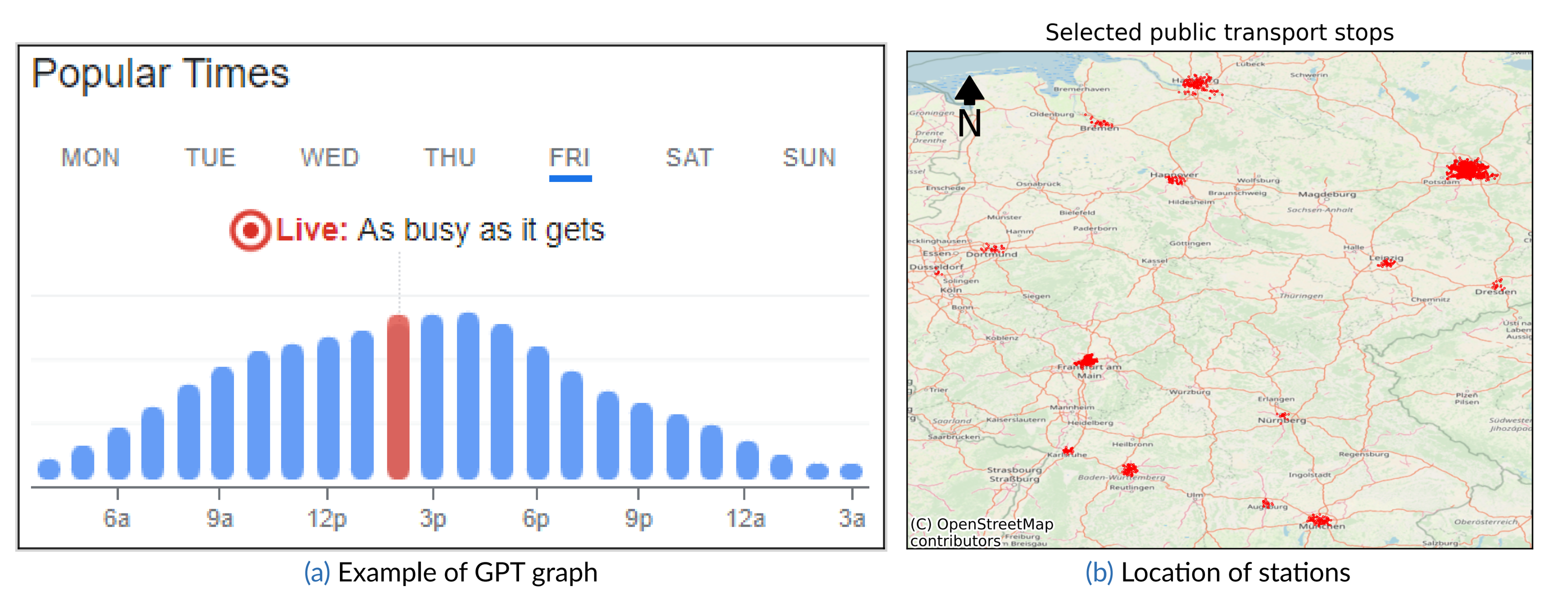

Figure 3. Example of GPT graph and location of selected PT stations.

Station clusters characterization

- **Cluster 1:** unaffected stations (146).
- **Cluster 2:** mildly stimulated (92). Increase $\Rightarrow$ recover slowly
- **Cluster 3:** intensely stimulated (55).
  Increase significantly $\Rightarrow$ reduce immediately

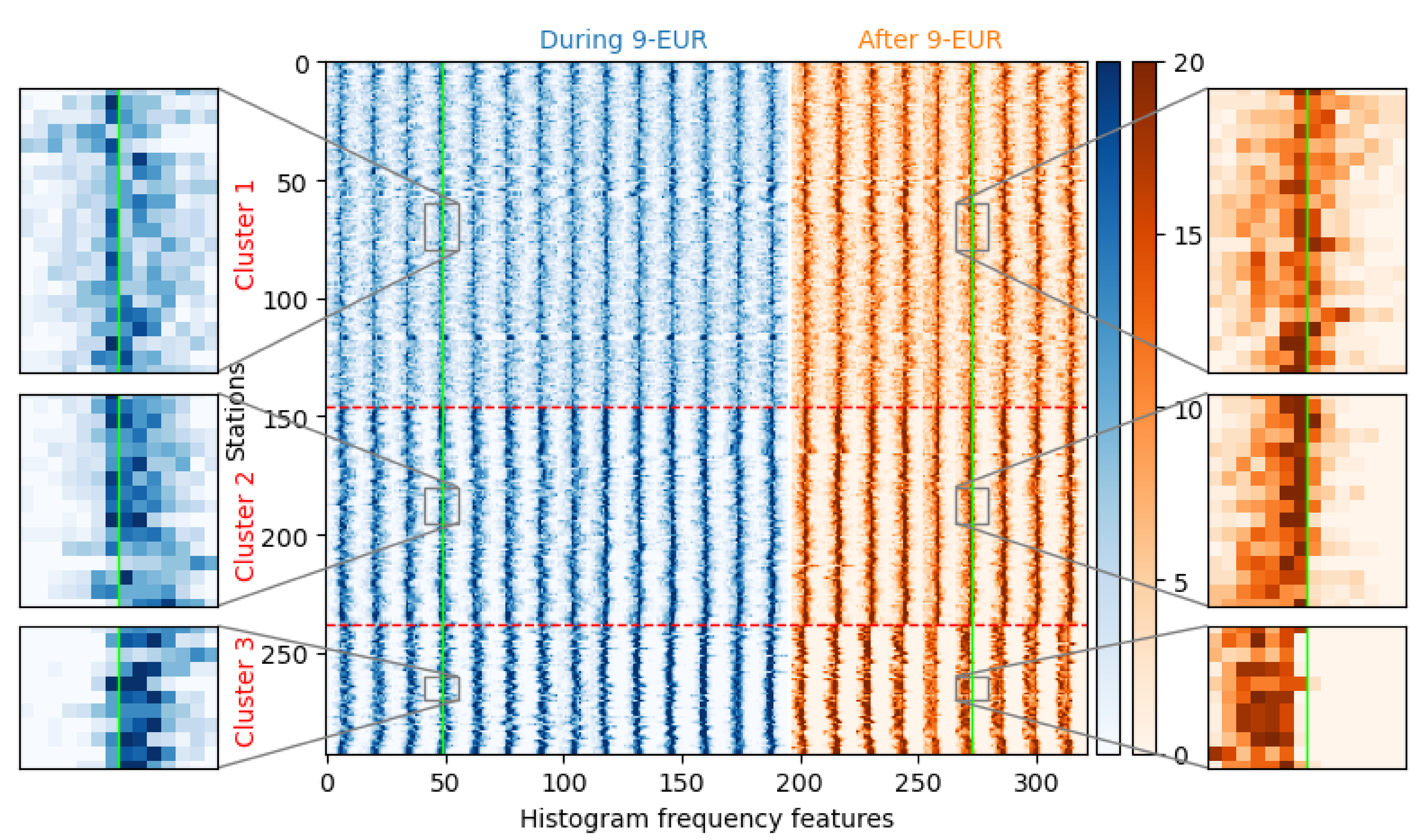

Figure 4. Station clusters based on busyness deviations.

Latent variables extraction

- Factors extracted from crowding patterns represent the demand patterns at different periods of the week. (CP0-10)
- Factors extracted from highly correlated features emphasize the significance of POI, population, and network features. (PPN0-8)

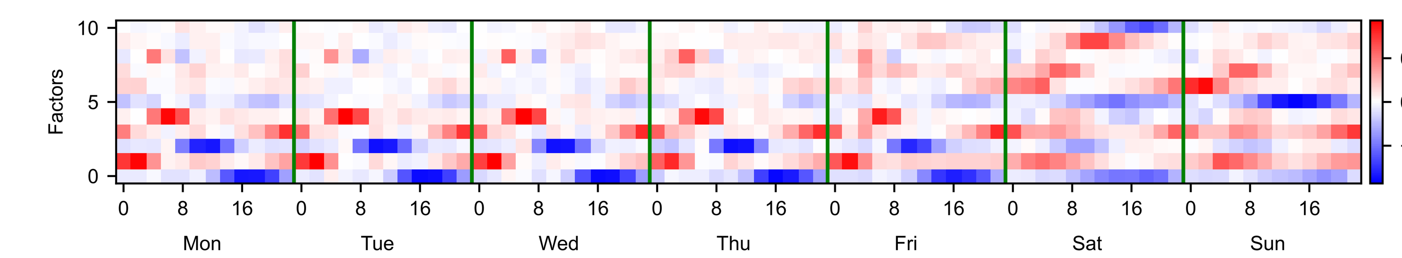

Figure 5. Factors extracted from historical crowding pattern features.

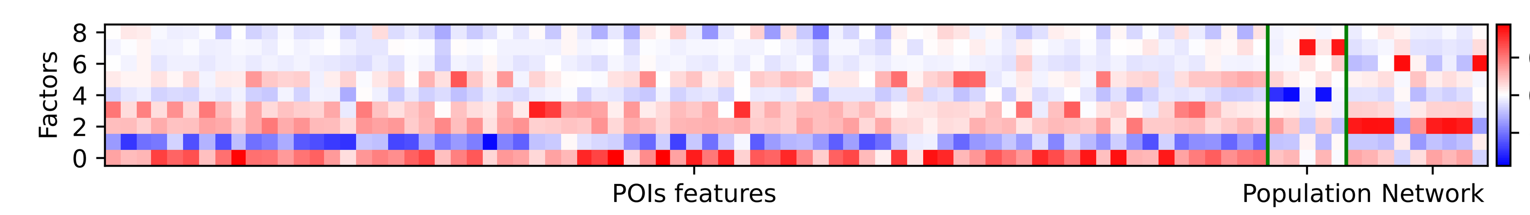

Figure 6. Factors extracted from highly correlated features.

Station classification based on busyness patterns

LightGBM achieves a weighted F1 score of 0.704.

- A strong association between station characteristics and the heterogeneous impact.
- 48.2% of misclassifications predict C2 as C1.

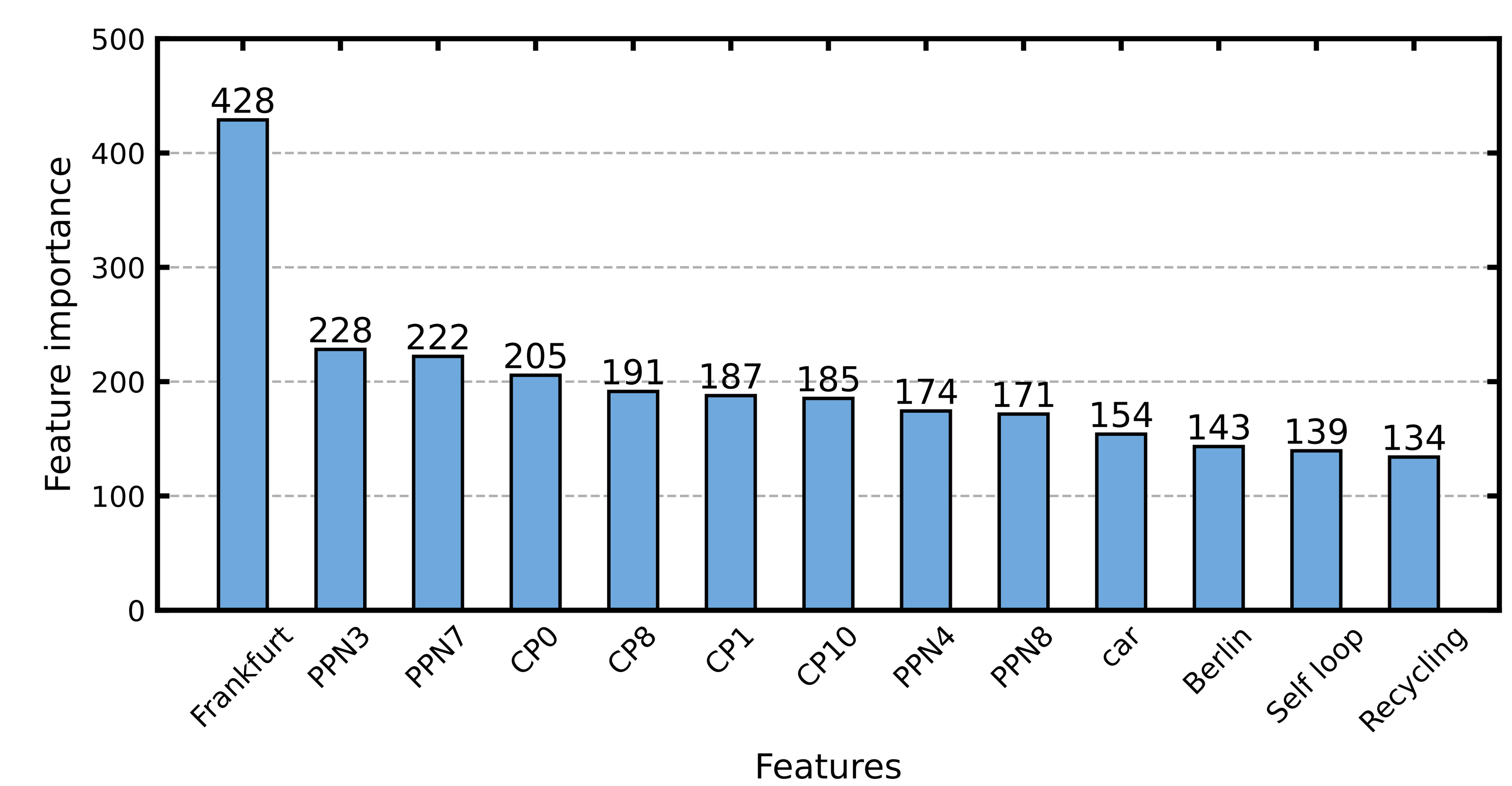

Figure 7. The most important features based on information gain (greater than 100).

Conclusions

- Three business-based station categories are identified
- Station location, nearby activities, population in the station vicinity and neighbors, and demand patterns play a significant role in the crowding pattern changes