Development of Activity-based Modelling Leveraging Novel Deep Learning Methods

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Introduction

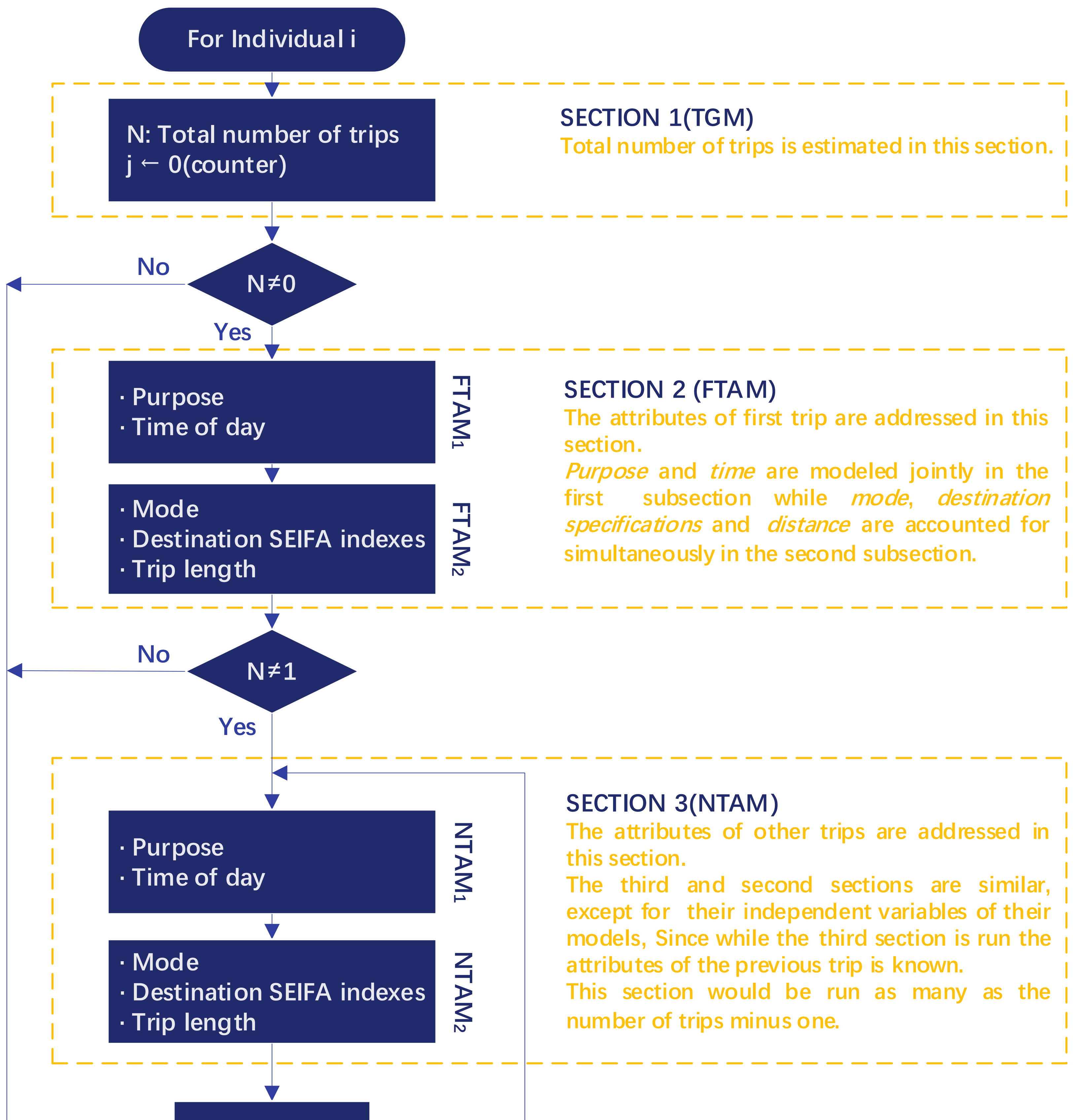
Urban transportation demands a nuanced approach for effective policy-making and planning. The shift towards Activity-Based Modelling (ABM) addresses this by leveraging granular individual-level travel activity data[1]. Its significance lies in fostering detailed urban planning due to its disaggregated nature[2]. However, a deeper understanding of fundamental travel behavior remains a challenge. While deep learning offers potential in unveiling intricate patterns, our preliminary research adopts a different route. We introduce a framework utilizing the Random Forest model, encapsulating the behavioral advantages and policy sensitivity of ABM, while ensuring swift computational processing. Serving as a foundational benchmark, this approach paves the way for the eventual integration of advanced deep-learning techniques into ABM.

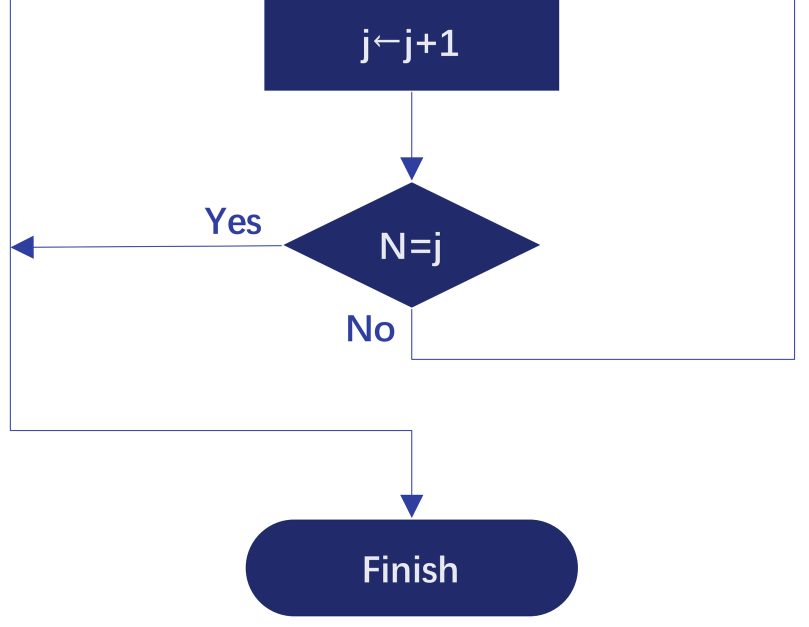
Objectives

Comprehensive Modeling with Efficiency: Design a framework incorporating five interconnected Random Forest models, aiming to capture the full spectrum of trip attributes while prioritizing computational efficiency.
Assessing Model Precision: Examine the Out of Bag (OOB) error rates across the five models to ensure and showcase satisfactory prediction accuracy. A higher OOB rate indicates a lower accuracy.
Understanding Feature Contribution: Leverage the variable importance feature in Random Forest to reveal the significance of each attribute in predictions, thereby highlighting the behavioral advantage and policy responsiveness embedded within Activity-Based Modelling (ABM).

$$\mathrm{OOBErrorRate} = \frac{1}{n}\sum_{i=1}^{n} I(y_i \neq \hat{y}_i) \qquad \mathrm{VI}(X_j) = \frac{1}{N}\sum_{i=1}^{N}[e^*(T_i,T_j) - e(T_i,T_j)]$$

Main Framework





By implementing this framework, it is assumed that:

- People consider their future and past trips while deciding about their current trip
- The decisions on the purpose and the time of day are made prior to the decisions on other trip attributes.

Data

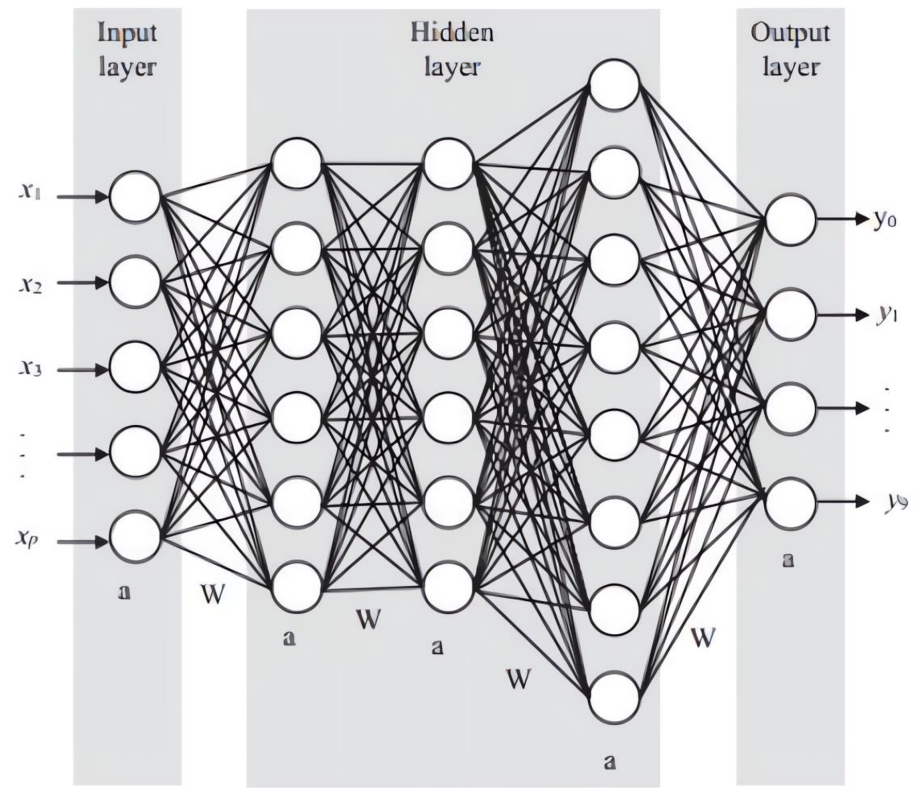
Two major sources of data are used in this study:

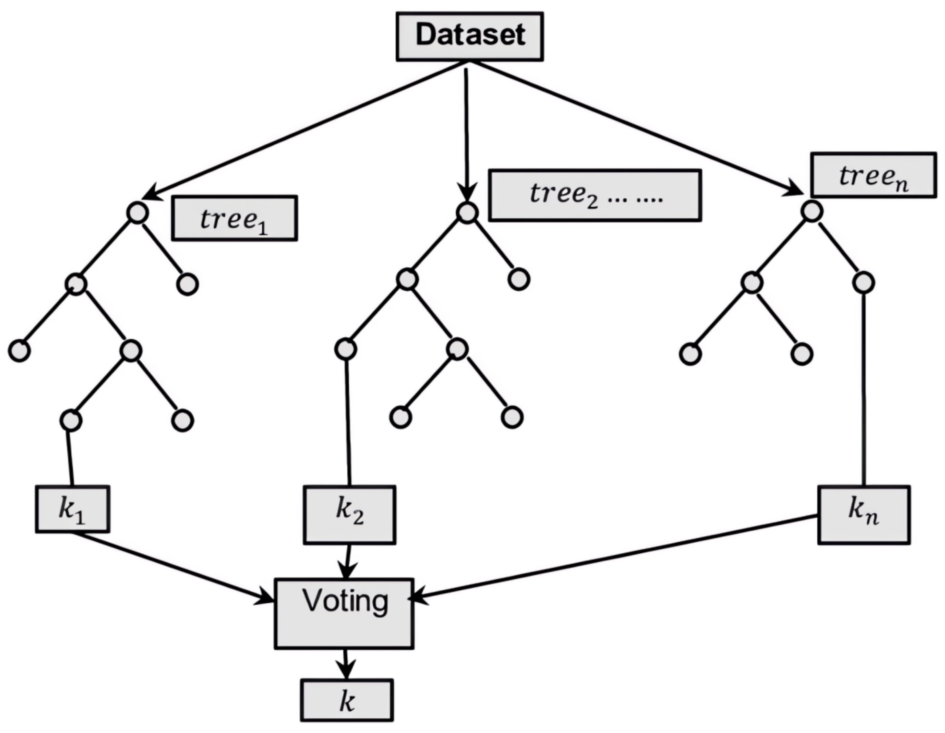
Year 2011 Household Survey Data from Victorian Integrated Survey of Travel and Activities (VISTA): Individual and trip level data to develop the 5 models

Year 2011 Socio-Economic Indexes for Areas (SEIFA) data from Australian Bureau of Statistics (ABS): Integrated into VISTA for revealing destination specifications.

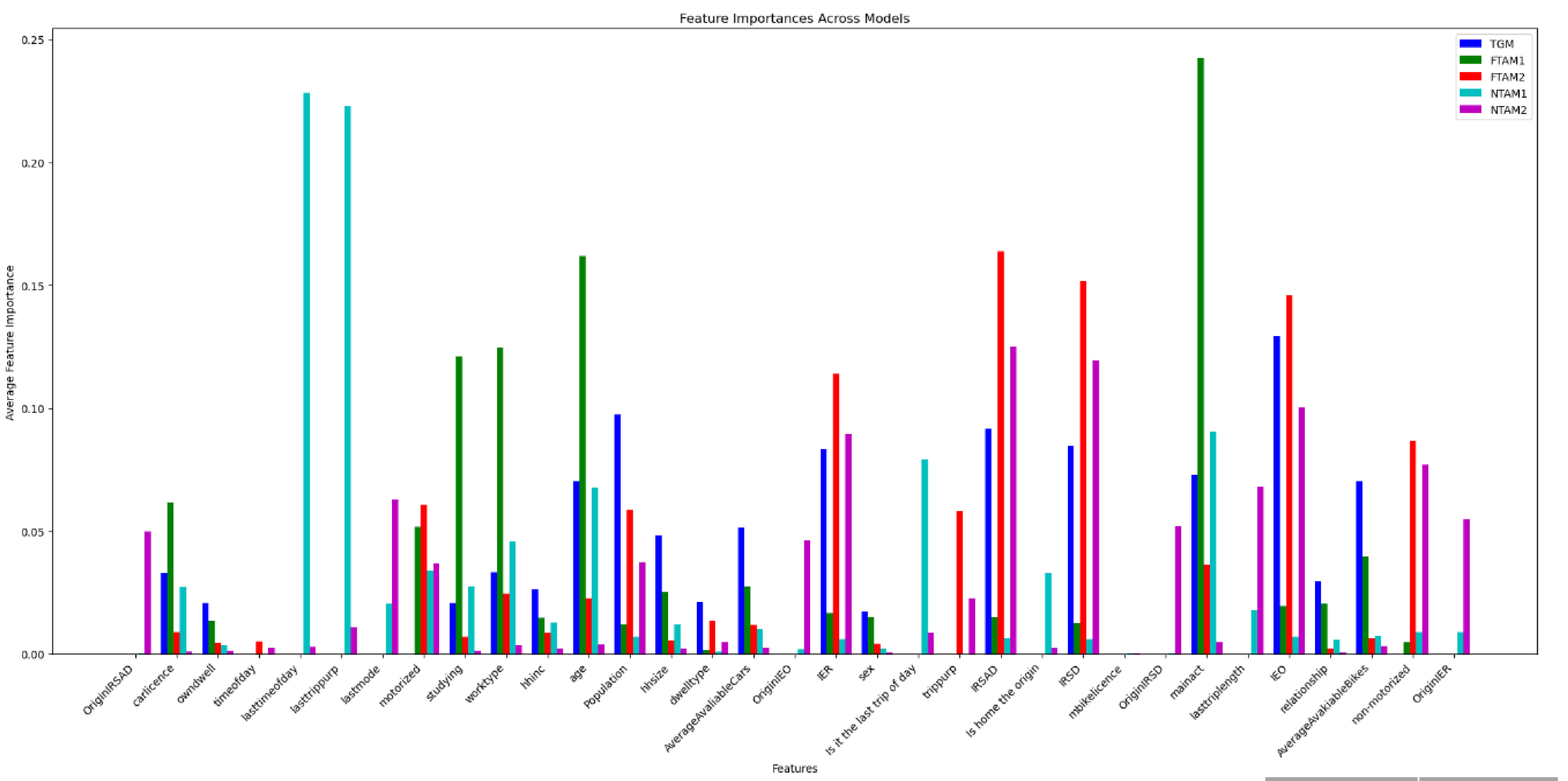
Motivations

Shift to Activity-Based Modelling (ABM): Recognizing the potential of ABM to offer granular, individual-level insights using travel activity data for more precise urban planning.
Limitations of ABM: Despite its detailed nature, ABM struggles with providing a comprehensive understanding of the fundamental travel behaviour patterns.
Promise of Deep Learning: The potential of deep learning techniques to discern intricate patterns and relationships within datasets, enhancing the capability of ABM.
Starting with a Simplified Model: Commencing the research journey with a more accessible Random Forest model to capture some of the key advantages of ABM, serving as an introductory step before diving deeper into complex models.
Computational Efficiency: Developing models that not only capture detailed behavioral patterns but also ensure faster computational processing for practical applications.





Results



•All models consistently rank OriginIRSAD, Studying type, and Gender as low-importance features.
•NTAM1 and NTAM2 show similar patterns in feature importance, hinting at shared underlying structures.
•On the other hand, FTAM1 and FTAM2 exhibit distinct feature importance variations, suggesting diverse data interpretations.
•Notably, the TGM model emphasizes 'carlicence', while 'lasttripmode' and 'motorized trips' are prominent in NTAM models.

Model	OOB Score
TGM	59.3%
FTAM1	54.3%
FTAM2	74.1%
NTAM1	55.7%
NTAM2	74.8%

Controlled Models:
- Minimum of 100 observations per leaf.
- Square root of total variables considered per split.
- 1,000 trees per forest.

Performance:
- OOB results suggest similar accuracy to individual-level demand models.

Training:
- Over 10,000 trips from 3,000 individuals used for training.
- Calibration of all 5 models in the framework took 1-10 minutes each on an i7-13700KF @ 3.40 GHz processor, where the time depends on RF size

Conclusion

- **This study presents a novel demand modelling framework and validates its effectiveness.**
- **The overall accuracy of the framework can be further improved through more nuanced data preprocessing steps.**
- **The framework departs from traditional models by emphasizing individual behaviour in a bottom-up approach.**
- **It offers faster computational speeds compared to activity-based models.**
- **Ideal for smaller regions requiring behavioural demand models with constrained budgets for surveys and model development.**

Acknowledgements / references

[1] Rasouli, S. and H. Timmermans, Activity-Based Models of Travel Demand: Promises,7 Progress and Prospects. International Journal of Urban Sciences, Vol. 18, No. 1, 2014, pp.8 31–60.
[2] Ettema, DF. and HJP. Timmermans, Activity-Based Approaches to Travel Analysis, 1997

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