Applying Machine Learning to Model Freight Vehicle Type Choice

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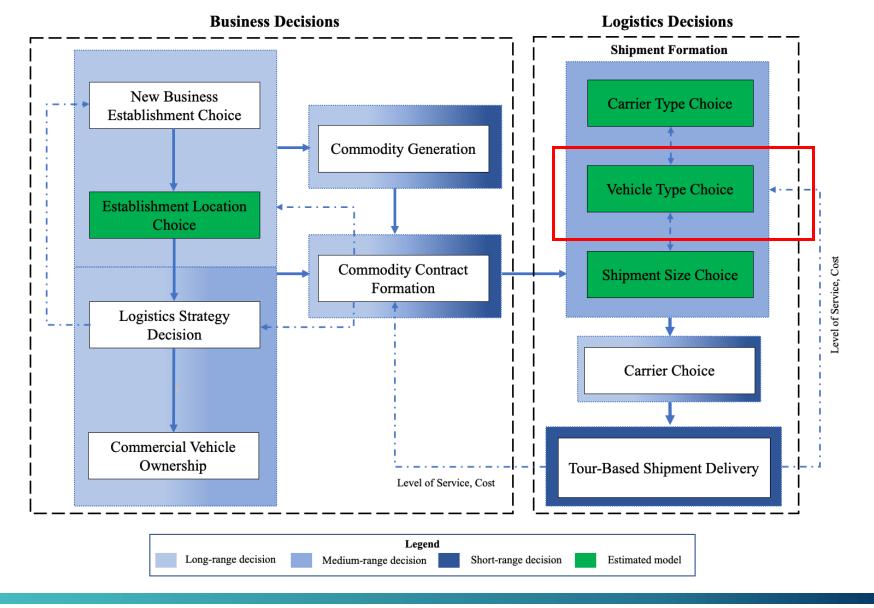
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City Logistics for the Urban Economy





Freight Business and Logistics Decisions Simulation Framework







Freight Mode v/s Vehicle Type

- > Mode Choice:
 - Road, rail, air, water
 - Most relevant for inter-city, statewide, and national level studies
- > Vehicle Type Choice:
 - Road-based mode: Passenger car, trucks, vans, etc.
 - Most relevant for city or metropolitan area level studies



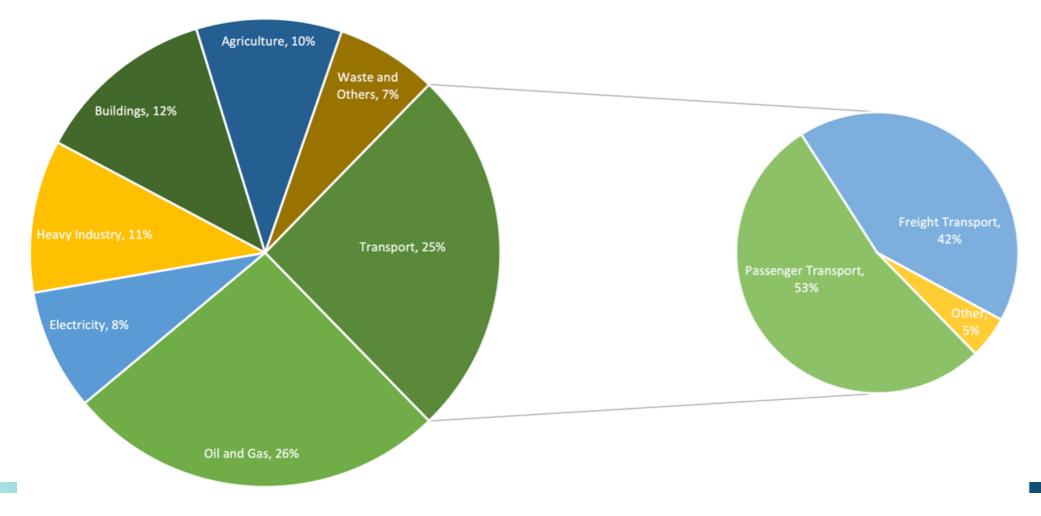
Background and Motivation

- Freight flows have been increasing in Canada.
 - 16.7% increase in freight shipments from 2011 to 2017 (Statistics Canada 2020)
- Economic development of regions
- Global competitiveness of industries
- Changing trends in supply chain and logistics
- Major contribution to greenhouse gas emissions!





Background and Motivation





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Background and Motivation

- Implications on quality of life of urban residents
 - Noise pollution
 - Traffic congestion
 - Safety impacts
 - Parking problems
 - Pavement damage



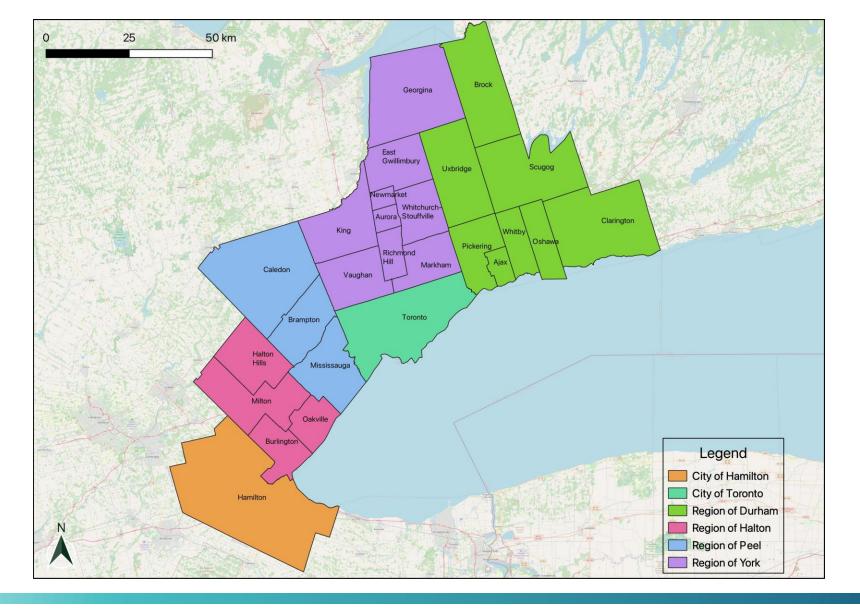


Study Objectives

- Study the factors behind freight vehicle type choice
- Comparison of discrete choice with machine learning methods
 - Discrete choice: Multinomial and mixed logit model
 - Machine learning: Random Forest



Study Area





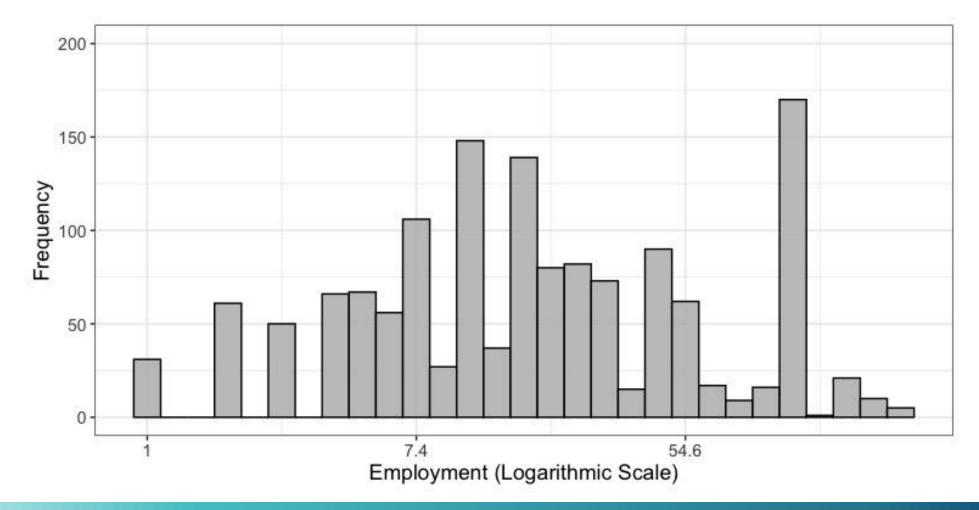


Data Source

- Commercial Travel Survey
 - Region of Peel (2006/07), Region of Durham (2010), Toronto Area (2012)
- Outbound Shipments
 - > 1,439 shipments
 - ➤ 385 firms
- Explanatory Variables
 - Industry type, commodity type
 - Shipment origin and destination (cities)
 - Employment and shipment weight



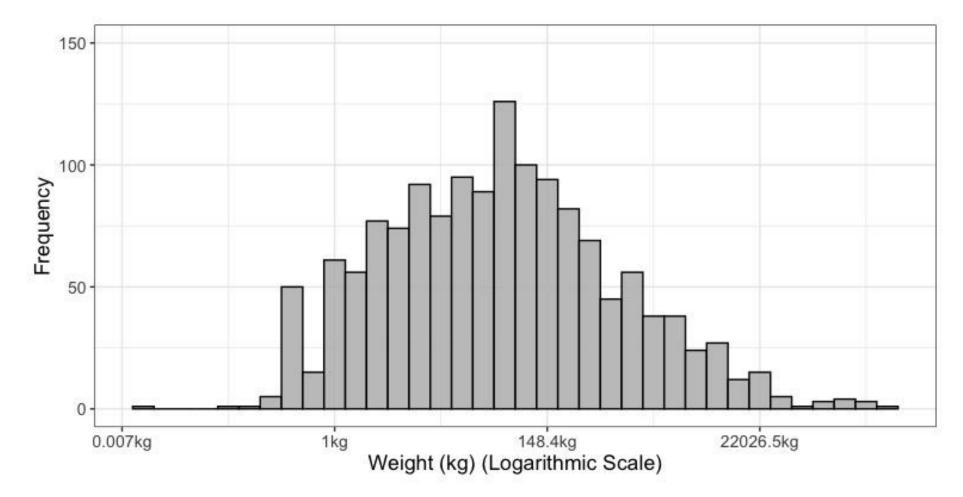
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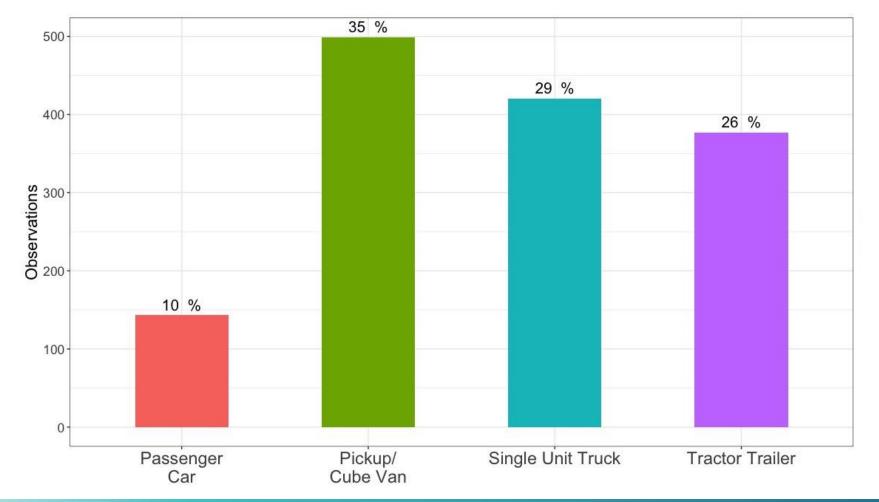
Data Source





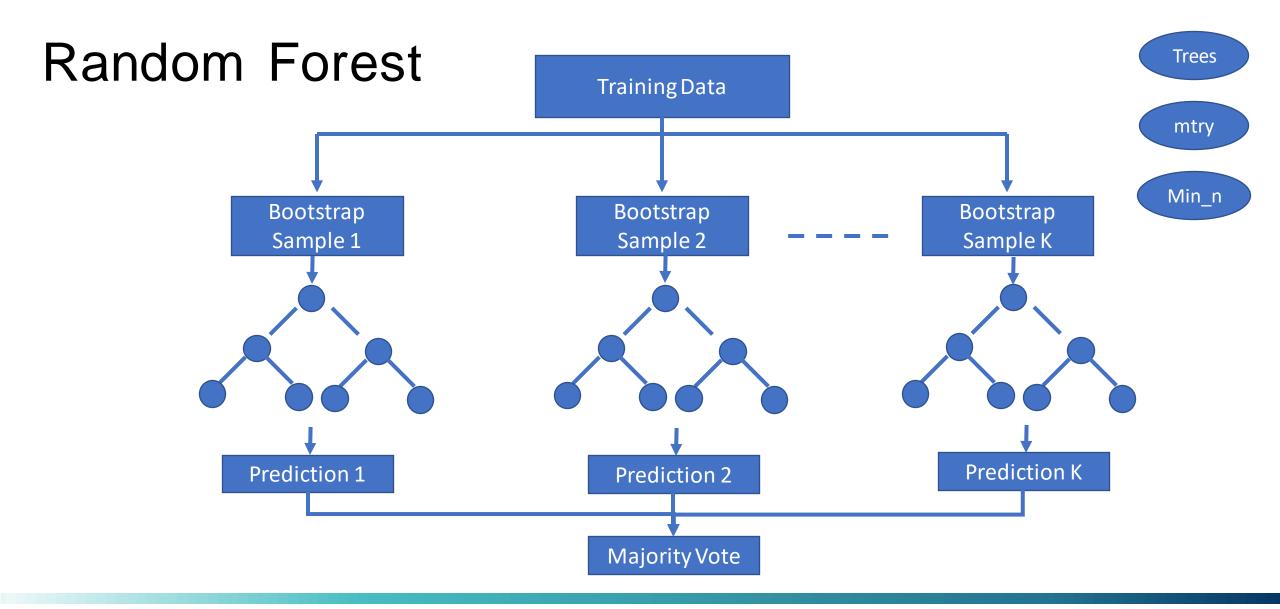


Data Source – Vehicle Types













Random Forest – Variable Importance

- Shapley Additive Explanation (SHAP)
 - To assess the impact of explanatory variables on the model output
 - Comparison of model prediction with and without the variable
 - SHAP value is calculated for every observation
 - Variables are sorted based on the impact
 - Color of the point shows its value
 - Red: high value
 - Blue: low value





Training v/s Testing Data

- Models are developed on training data
 - RF: 10-fold cross validation
- Model prediction accuracy is calculated on testing data
- Training and testing data are divided based on firms
 - Training data: 269 firms with 1114 shipments (70%)
 - Testing data: 116 firms with 325 shipments (30%)

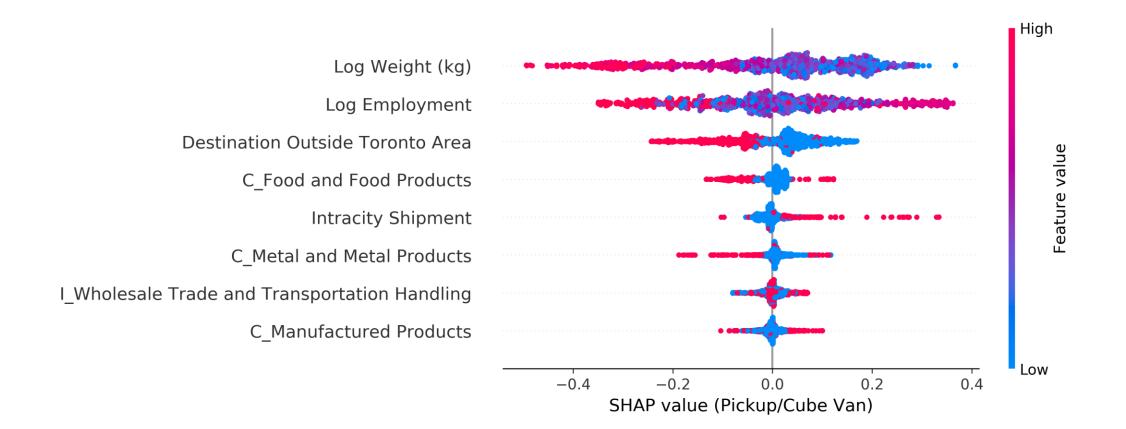




Results

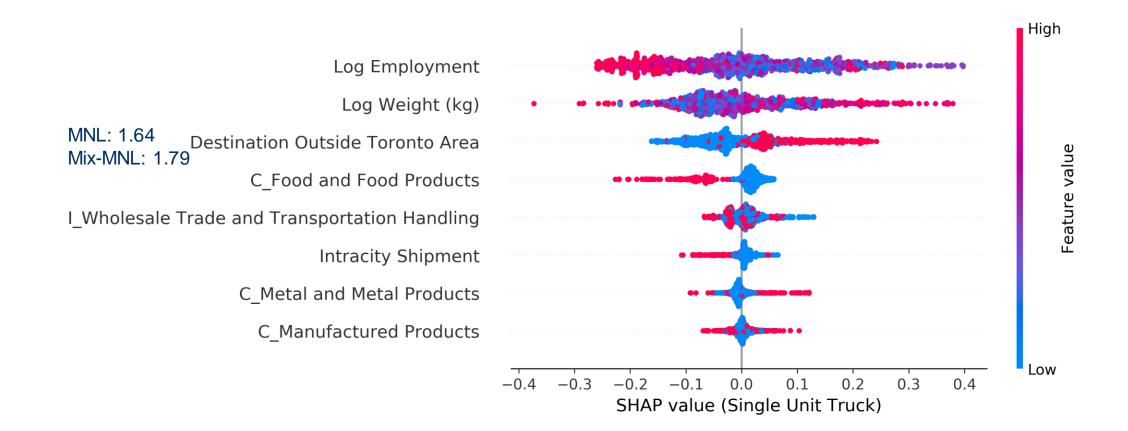






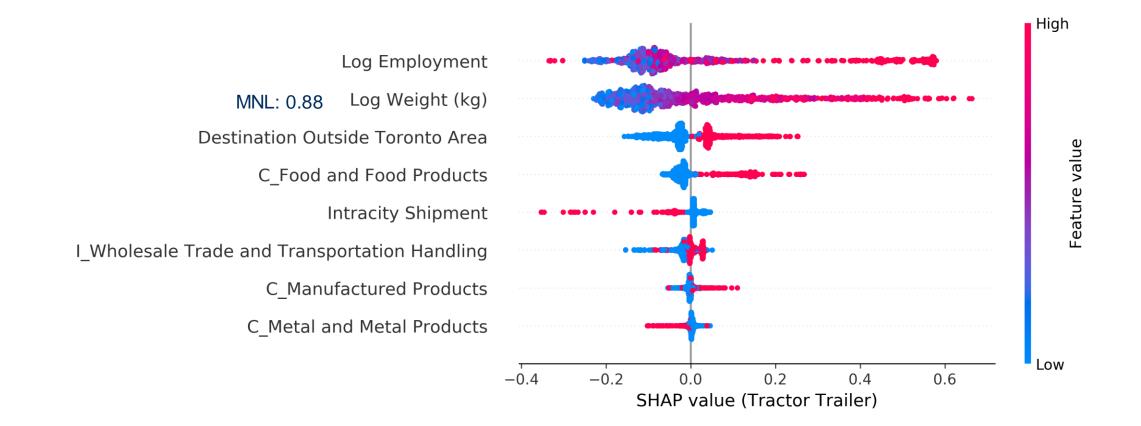






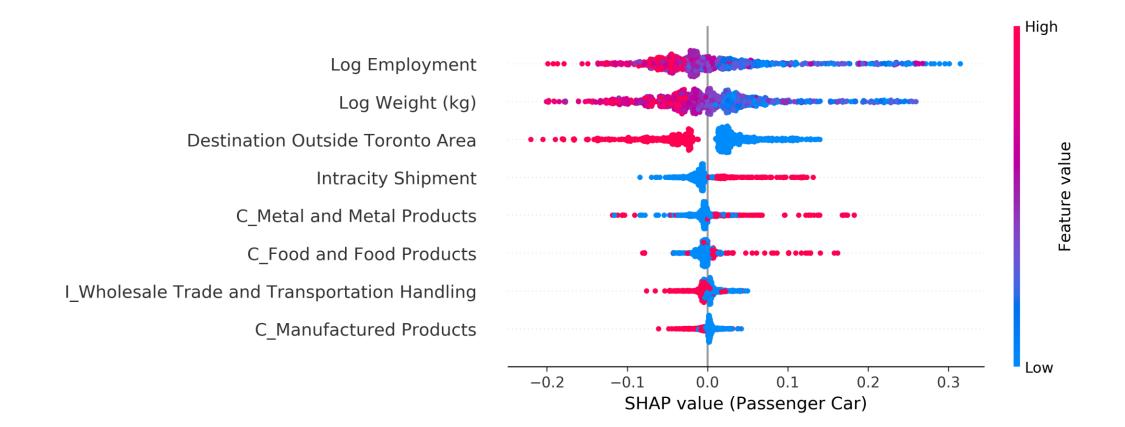














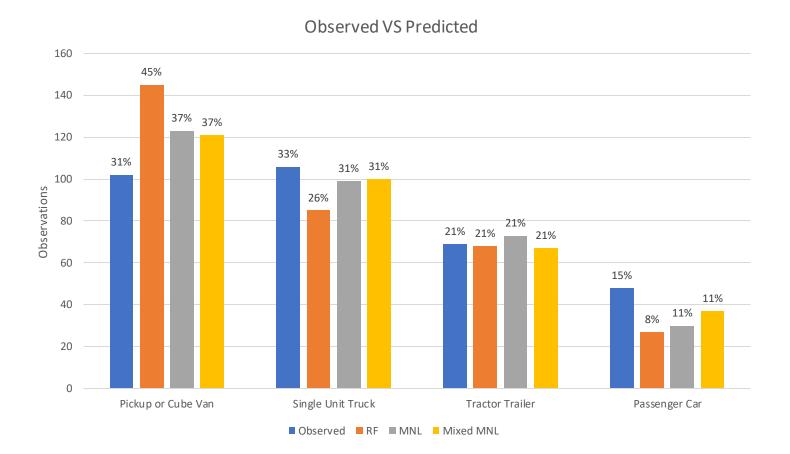


Discrete Choice Methods

- > Larger firms are more likely to use larger vehicles
- > Larger vehicles are more likely to be used for heavier shipments
- > Intracity shipments are more likely to be transported using smaller vehicles
- > Larger vehicles are more likely to be used for shipments destined outside of Toronto Area



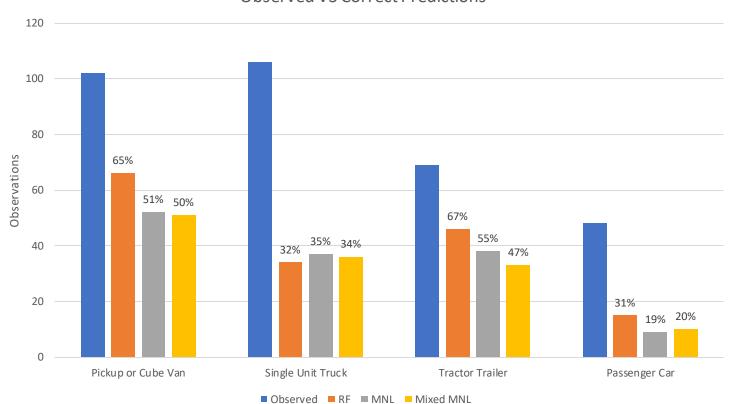
Model Predictions







Prediction Accuracy



Observed VS Correct Predictions





Results Summary

> Overall prediction accuracy

➢ Random Forest: 50%

≻ MNL: 42%

≻ Mix-MNL: 40%





Conclusion

- > Applications in policy analysis
 - Demand for parking facilities
 - Greenhouse gas emissions
 - E-commerce, same-day deliveries





Conclusion

- Freight vehicle type choice is studied using discrete choice and RF methods
- Commercial travel survey data are used to develop models for the Toronto Area
- RF results are interpreted using SHAP based variable importance
- RF model has higher prediction accuracy than DCM





More about this work!

• More details about models and results can be found in:

Ahmed, U., & Roorda, M. J. (2022). Modeling freight vehicle type choice using machine learning and discrete choice methods. Transportation Research Record, 2676(2), 541-552.



