Teaching Freight Mode Choice Models New Tricks Using Interpretable Machine Learning Methods

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Research Question and Objectives

Why combine machine-learning (ML) and discrete choice models?

- Conventional discrete choice models:
  - Theory-driven and provide clear subject-matter interpretations.
  - Widely used in understanding the travel behavior of passenger and freight and support policy making.
  - Lacking efficient and systematic way to identify non-linear and interactive effects.
- Machine-learning (ML) methods:
  - Often provide better out-of-sample accuracy, but hard to extrapolate.
  - Often capture complex and non-linear relationship among the data.
  - Recently become interpretable and transparent applying SHapley Additive exPlanations (SHAP).

Research goal:

- Develop a multinomial logit (MNL) model for freight mode choice using the insights from ML models.
- Showcase how interpretable ML methods help enhance the performance of MNL models and deepen our understanding of freight mode choice.

Proposed Workflow

Develop freight mode choice models for Austin

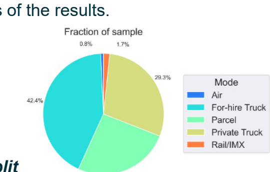
- Using 2017 Commodity Flow Survey (CFS) data (sample size = 247,073).
- For-hire truck (base), private truck, air, parcel, and rail + intermodal truck/rail (rail/IMX).

Compare the performance of two approaches:

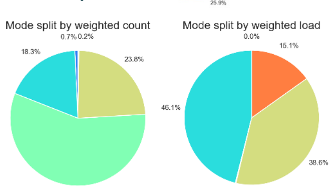
- A conventional logit model approach
  - Baseline MNL models (**'bMNL'**) with mostly linear specifications.
- A machine-learning (**ML**) guided approach
  - Advances MNL model ('**aMNL**') using ML and SHAP interpretations.

Investigate the results in two aspects:

- Accuracy measures of predicted mode choice.
- Interpretations of the results.



Austin mode split



Interpretable Machine-learning Results

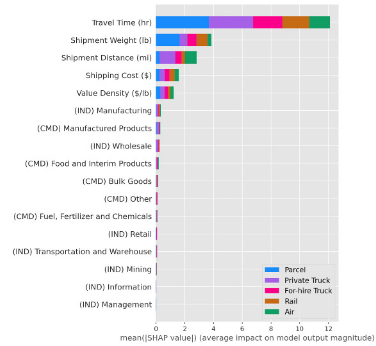
Machine-learning models overview:

- Select ML methods that are
  - Suitable for resolving nonlinear relationships in mode choice models.
  - Seamless connection with SHAP TreeExplainer.

Selected methods:

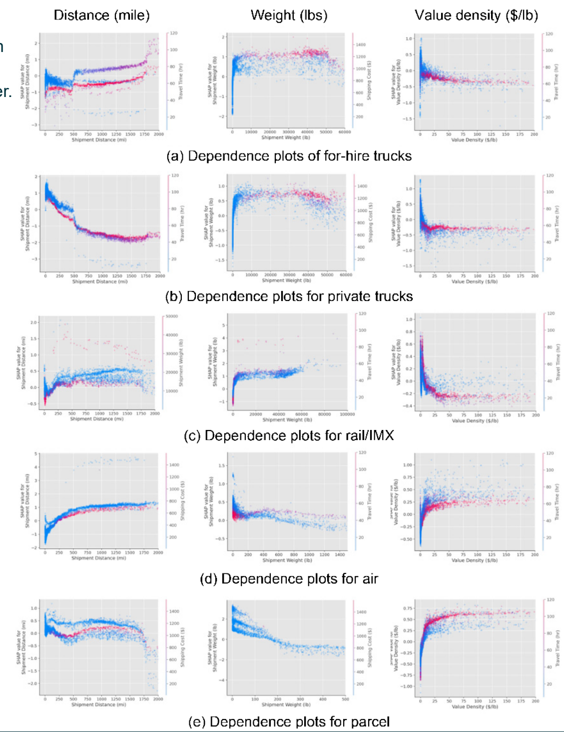
- **Random forest (RF):** builds a large collection of de-correlated trees and then averages them.
- **Boosting Trees:** combines the outputs of many "weak" classifiers to produce a powerful "committee".
  - **XGBoost:** a scalable ML system for tree boosting.
  - **CatBoost:** specialize in categorical data.

SHAP feature importance (CatBoost)



**CMD – Commodity; IND - Industry*

SHAP dependence plots (CatBoost)



(a) Dependence plots of for-hire trucks

(b) Dependence plots for private trucks

(c) Dependence plots for rail/IMX

(d) Dependence plots for air

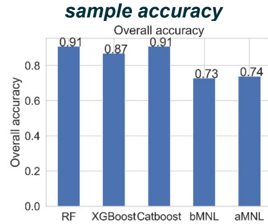
(e) Dependence plots for parcel

Performance Comparison

Out-of-sample accuracy of mode choice models:

- RF and CatBoost have the highest accuracy, followed by XGBoost.
- Tree-based MLs outperform the MNL models.
- aMNL model has higher accuracy than bMNL.

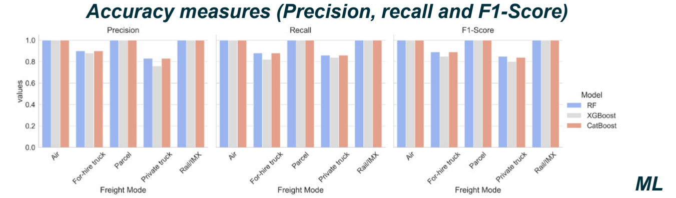
Overall out-of-sample accuracy

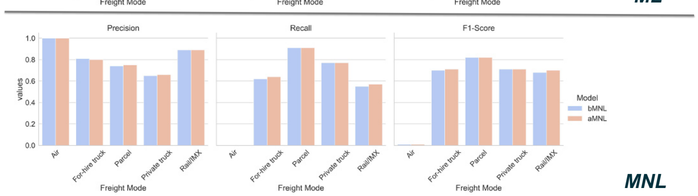


Performance measures (Precision, Recall, F-1 Scores) by mode:

- ML generate accurate predictions for all modes, while the accuracy of the two truck modes are slightly lower.
- MNL models have larger errors for air and rail/IMX, potentially due to low sample size.

Accuracy measures (Precision, recall and F1-Score)





Baseline Multinomial Logit Model

Highlights of bMNL model estimation:

- Results from MNL do not capture the intricate relationship demonstrated in SHAP.
- Low-impact factors (e.g., some industries) may absorb the effects from more influential factors.

Variables	Mode (for-hire truck as the base) Air	Parcel	Private Truck	Rail/IMX
Constant	-5.05***	0.472***	1.395***	-5.49***
Distance (mile)	0.002***	0.001***	-0.005***	-6.1e-5
Value density ($/lb.)	1.4e-5***		-0.001***	
Weight between 150 and 1,500 lbs.	-3.211***			1.798***
Weight between 1,500 and 30,000 lbs.	-3.784***		0.044**	3.352***
Weight between 30,000 and 45,000 lbs.			-0.67***	2.627***
Weight greater than 45,000 lbs.			-1.207***	4.296***
Commodity is bulk		-1.107***	-0.78***	-2.094***
Commodity is fuel, fertilizer or other chemical		-0.77***	-0.338***	-1.296***
Commodity is interim product or food	-0.98***	-1.312***		-3.077***
Commodity is manufactured goods	0.882***		-0.912***	-1.458***
Information industry		0.126**	-0.968***	
Manufacturing industry		0.327***	-0.319***	-0.558***
Management industry		0.325***	0.202*	-2.185***
Retail industry	0.558***	2.459***	1.08***	
Transport and Warehouse industry				-2.311***
Wholesale industry			0.493***	-1.403***
Shipping Costs	-0.001***			
Shipping Time	-0.003***			
Number of parameters	47			
Number of observations	247,073			
Log-likelihood	-157,515			
Adjusted ρ^2	0.567			

*p<0.1, ** p<0.01, *** p<0.001

Advanced Multinomial Logit Model

Highlights of new findings in aMNL model:

- SHAP results help remove nine low-impact factors.
- Binned specifications of distance and value density help reveal nonlinear relationships of mode preferences.

Variables	Mode (for-hire truck as the base) Red cell highlights removed variables in aMNL Air	Parcel	Private Truck	Rail/IMX
Constant	-5.258***	0.237***	1.405***	-6.366***
Distance*(Distance <= 500 miles)	0.004***	0.004***	-0.005***	0.001***
Distance*(Distance > 500 miles)	0.002***	0.001***		
(Distance > 500 miles)		2.220***		0.321*
Value density*(Value density <= $5/lb.)	-0.114*	0.012	0.009	
(Value density > $5/lb.)			-0.301***	
Value density*($5/lb.<Value density<= $25/lb.)	0.039***	0.025***		
(Value density>$25/lb.)	1.557***	0.372***		
Value density*(Value density <= $1/lb.)				-0.223*
Value density*($1/lb.<Value density<= $10/lb.)				0.124***
Weight*(Weight <= 150 lbs.)	-46.389***	-33.591***	2.815***	
Weight between 150 and 1,500 lbs.	-3.329***			
Weight between 1,500 and 30,000 lbs.	-3.619***			2.151***
Weight between 30,000 and 45,000 lbs.			-0.749***	1.606***
Weight greater than 45,000 lbs.			-1.281***	3.232***
Commodity is bulk			-0.732***	-1.273***
Commodity is fuel, fertilizer or other chemical		-0.329***	-0.248***	-0.843***
Commodity is interim product or food	-0.642**	-0.790***	0.144***	-2.681***
Commodity is manufactured goods	0.354***	0.089**	-0.847***	-1.049***
Information industry			-1.111***	
Manufacturing industry		0.155***	-0.375***	0.519***
Management industry				
Retail industry	-1.625***			
Transport and Warehouse industry				
Wholesale industry			0.469***	
Shipping Costs	-0.001***			
Shipping Time	-0.003***			
Number of parameters	51			
Number of observations	247,073			
Log-likelihood	-145,857			
Adjusted ρ^2	0.576			

Findings and Recommendations

- Using insights from SHAP, aMNL's accuracy surpass that of bMNL.
- The estimated aMNL reveals significant and complex relationships that are hidden in bMNL.
- The directions of impacts from aMNL and CatBoost are often aligned.
- Interpretable ML can be a useful tool to enhance the practice of freight behavior analysis and modeling.

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