Why Americans Travel: Predicting Trip Purpose from the National Household Travel Survey

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Abstract

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1. Introduction

Americans are in constant transit, utilizing the national interstate and highway system to travel various distances. Whether commuting to work, taking vacations, visiting friends and family, transporting goods and services, or engaging in commerce, people are constantly moving. Understanding U.S. travel patterns provides essential insights into a wide range of fields including environmental protection resource allocation, urban planning, and economic trends. This research aims to understand the motivation behind American travel based on trip specifics. Specifically, we seek to predict the purpose of trips in order to understand the connection between travel details and purpose for travel.

A wide variety of industries and stakeholders are interested in understanding travel habits and the usage of American transportation networks, particularly after the disruption of the COVID-19 pandemic that began in 2020. Research applications include: pedestrian studies, bicycle studies, environmental impact, energy consumption, health, public pollcy, transit planning, understanding emerging travel modes, and identifying special population groups (Administration 2023). Lu and Giuliano studied the travel habits of different income and race groups across the pandemic, finding that lower income and ethnic minority groups con-

tinued to travel for work and shopping purposes. Their model using trip purpose indicated that higher-income and White populations were able to limit travel according to government restrictions, likely due to their higher resources and increased ability to work from home (Lu and Giuliano 2023). Paul's dissertation studies the vehicle-sharing its equity impacts, finding that trip purpose is a significant predictor for whether private vehicles are being shared (Paul 2023).

While extensive research has been conducted into the implications of American travel habits on equity, environment, policy, and more, little research has been done on predicting *why* a person traveled based on trip-level data, without knowing the final destination. Our research aims to fill this gap by understanding the purpose of travel without geospatial information. This modeling task importantly protects individual privacy because it includes no GPS data on travel. Using travel data such as trip length, trip timing, and demographics to predict trip purpose can be useful for understanding why Americans are in transit at a given moment. This could be useful in guiding policy decisions, informing traffic patterns, improving public transportation routes, and address socioeconomic disparities in transit.

2. Methods

2.1. Data

As a federally funded agency, the Department of Transportation's Federal Highway Administration (FHWA) seeks to understand how Americans are using the national highway system. Since 1969, the FHWA has regularly conducted the National Highway Travel Survey (NHTS) in order to collect detailed data on the travel habits of Americans and their usage of federal transit networks (Federal Highway Administration 2022a). From January 2022 through January 2023, the FHWA conducted the 2022 NHTS, receiving responses from 7,893 households (Federal Highway Administration 2022b). Survey data includes in-depth information regarding each household member's travel habits across the past 30 days, detailing individual demographic information; household-level demographic information; purpose, location, duration, and mode of transportation for recent travel; and vehicle information (Federal Highway Administration 2022a).

For our research, we chose to utilize the individual demographic information, called the `person` data, along with the trip specific data, called the `trip` data. These two data sources contained 85 predictors that were unique for each observation. We selected these table because 1) 85 predictors was more than sufficient for modeling, and 2) the household and vehicle level data was shared across different observation, creating potential obfuscation in modeling.

2.2. Preprocessing

To prepare the data for modeling, we conducting a thorough cleansing process using `tidyverse` that included creating human-readable variable names and removing missing or incomplete observations. The final data set was a joined combination between person-level data and trip-level data. After joining, all unique identifier variables and flag variables were removed from the data.

Next, a correlation analysis was conducted to prevent autocorrelation or multicollinearity between variables. An analysis revealed that three variables had correlations over 0.2 with the target variable and were somewhat related in content to the target variable (>0.2). In order to build a more robust model, these three variables, `why_trip`, `trip_purpose_old_schema`, and `reason_for_travel_to` were removed.

Our target variable had five classes for categorizing the purpose of trips. We assessed the balance of the classes in order to ensure our final model would be unbiased. Seven observations with no data for the target variables were omitted.
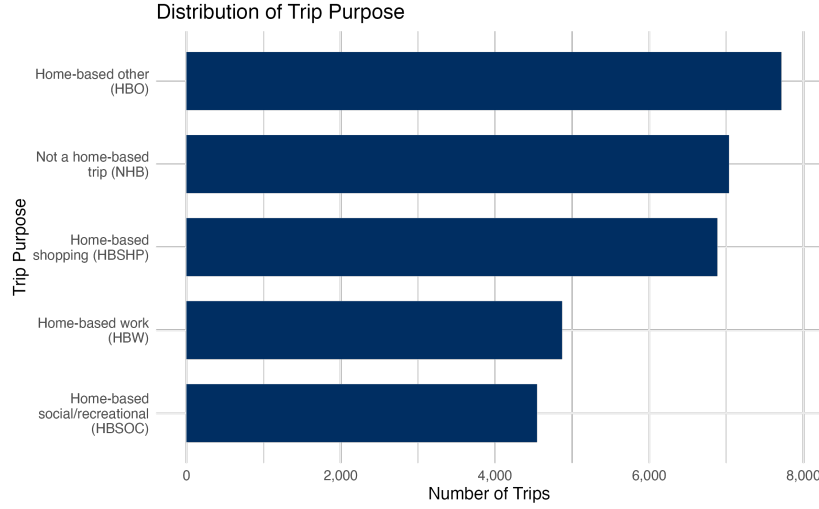

Figure 1: Support of trip purpose, the target variable for modeling.

An analysis of the target variable support shows that the classes are fairly balanced. While there is a distinction between the class sizes, each class has a significantly large sample size to create a fairly unbiased model. Modeling will be assess using balanced metrics in order to verify that final results remain unbiased by class imbalance.

For all modeling, numerical predictors were scaled and centered to normalize predictive influence. Categorical predictors were one-hot encoded, generating binary nomial predictors for each class level. The final cleaned data set of `person` and `trip` data contained 31,050 observations, 71 predictors, and one target variable.

2.3. Statistical Modeling

In order to predict trip purpose using NHTS data, we trained and assessed five different statistical learning model architectures. We aimed to establish a base line model and then test various methods in order to improve the predictive power of the statistical learning. Our goal was to achieve a high predictive accuracy and a high ROC AUC score, creating a model with strong predictive power and balanced results.

All statistical models were trained with 80% of the data, using k-fold cross validation for hypertuning parameters. Models were hypertuned using grid search techniques in order to find the most appropriate hyperparameters. Final results were assessed on the remaining 20%

of the data.

Logistic Regression

In order to establish a base line predictive model, we first trained a logistic regression model on the training data set. The logistic model was trained on 22,356 observations of the data. We utilized 5-fold cross validation to hypertune the models. Hypertuning was utilized for regularization penalty type, regularization penalty value, and optimizer values. We utilized a one-vs-rest strategy to account for the multiclass nature of our data, meaning that each iterations trained 5 versions of the model comparing one target class level with all other classes.

Support Vector Machine

Next, a support vector machine was trained on the training data set to classify the data. The support vector classifier was hypertuned using 5-fold cross validation. The model was hypertuned for the $L2^2$ regularization penalty value and kernel type. All models were training with a one-vs-rest strategy for the multiclass problem. The final model was trained to generate probabilistic predictions using Scikit-learn's `predict_proba()` function and a pairwise coupling strategy.

Neural Network

We designed and trained a neural network to predict trip purposes using `keras`. Extensive hypertuning using 5-fold cross validation included tuning for the optimizer's learning rate, hidden unit size, dropout regularization levels, and activation functions. The final model was a linear deep feed forward multilayer perceptron with 2 hidden layers. Both hidden layers have a hidden size of 64 and utilize sigmoidal activation. After hypertuning, we found that the best model used no regularization, so the dropout level was 0. The output layer uses softmax to output predicted probabilities that the observation belongs in each of the five target classes. The model was trained with a patience level of two epochs and utilized 10% of the training data as a validation set to implement early stopping. The loss function was categorical crossentropy and the optimizer was Adam.

Random Forest

A random forest classifier was utilized to predict trip purpose from the observations. We trained a random forest classifier using 5-fold cross validation to find the best hyperparameters. Hyperparameter search included the maximum depth of branches, minimum number of samples requires to split a leaf, and the number of trees (estimators) in the forest. The best model was selected as the model with the highest accuracy.

XGBoost

Finally, an XGBoost classifier was trained to predict trip purpose from our training data. The XGBoost model was hypertuned for maximum tree depth, learning rate of the optimizer,

number of trees (estimators), the minimum loss reduction required to split a leaf (also called gamma), the subsampling ratio for preventing overfitting, and the subsample size of the columns used by each tree. XGBoost was hypertuned using 3-fold cross validation and a random grid search.

3. Results

What are the results?

4. Discussion

What do the results mean?

5. Conclusion

Conclusion here

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