

Introduction

Previous Research:

- In-store shopping: 20% of all trips.
- On-line shopping:
 - Complements in-store shopping?
 - Supplements in-store shopping?
 - Modifies in-store shopping? (e.g., induces trips that are otherwise unmade).
- Who are online-shoppers?
 - Younger people
 - Highly educated
 - Higher income
 - Tech savvy
 - Active transport users

Past studies:

- Smaller scales.
- Non-probability samples.
- Older surveys, did not show the current trends.

Research Questions:

- Can internet and technology usage predict the demand for online shopping?
- What are the other predictors of the online shopping tendency?

Methods

Split into training set (80%) and test set (20%).
Applied random forest and gradient boosting (classification).

Procedure:

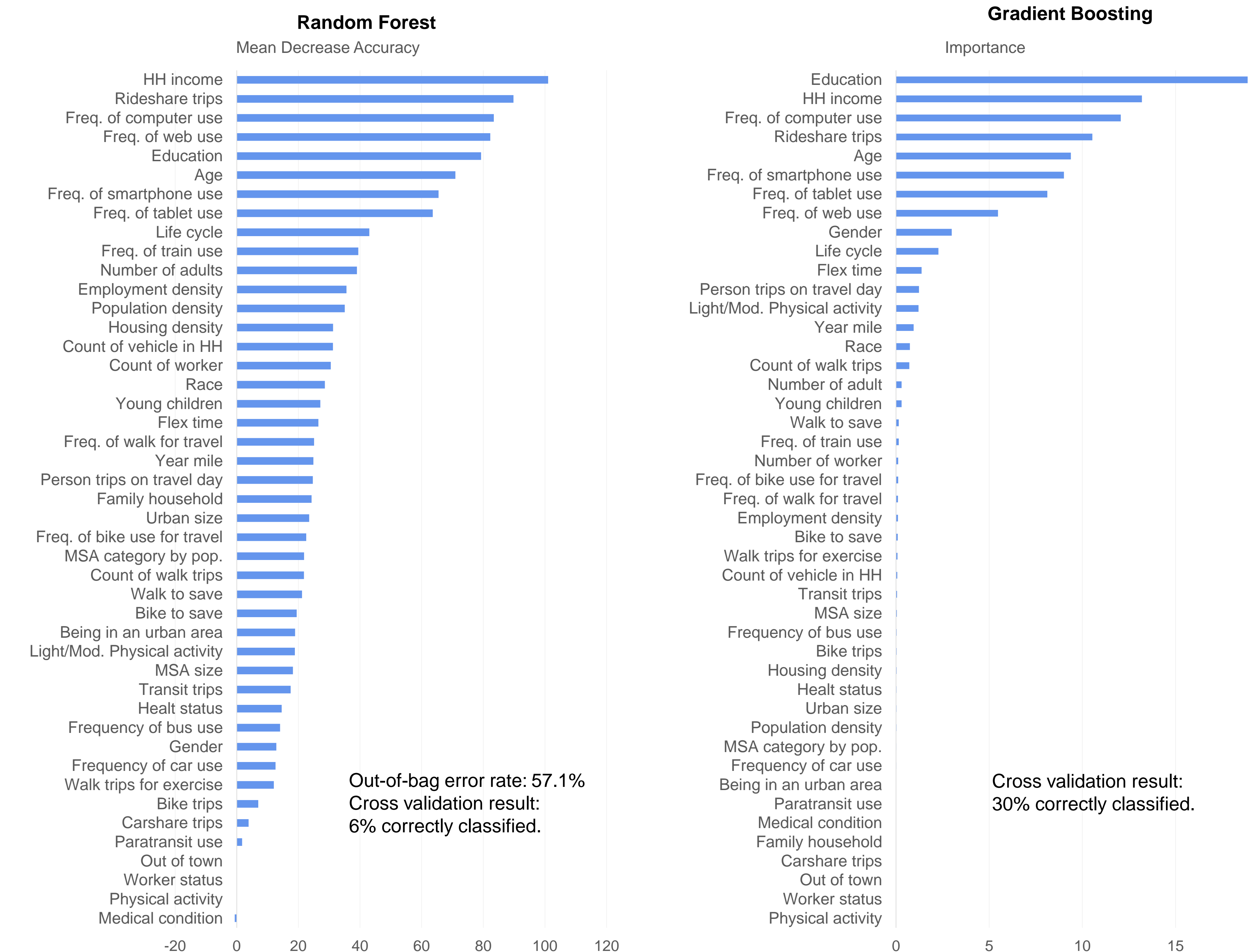
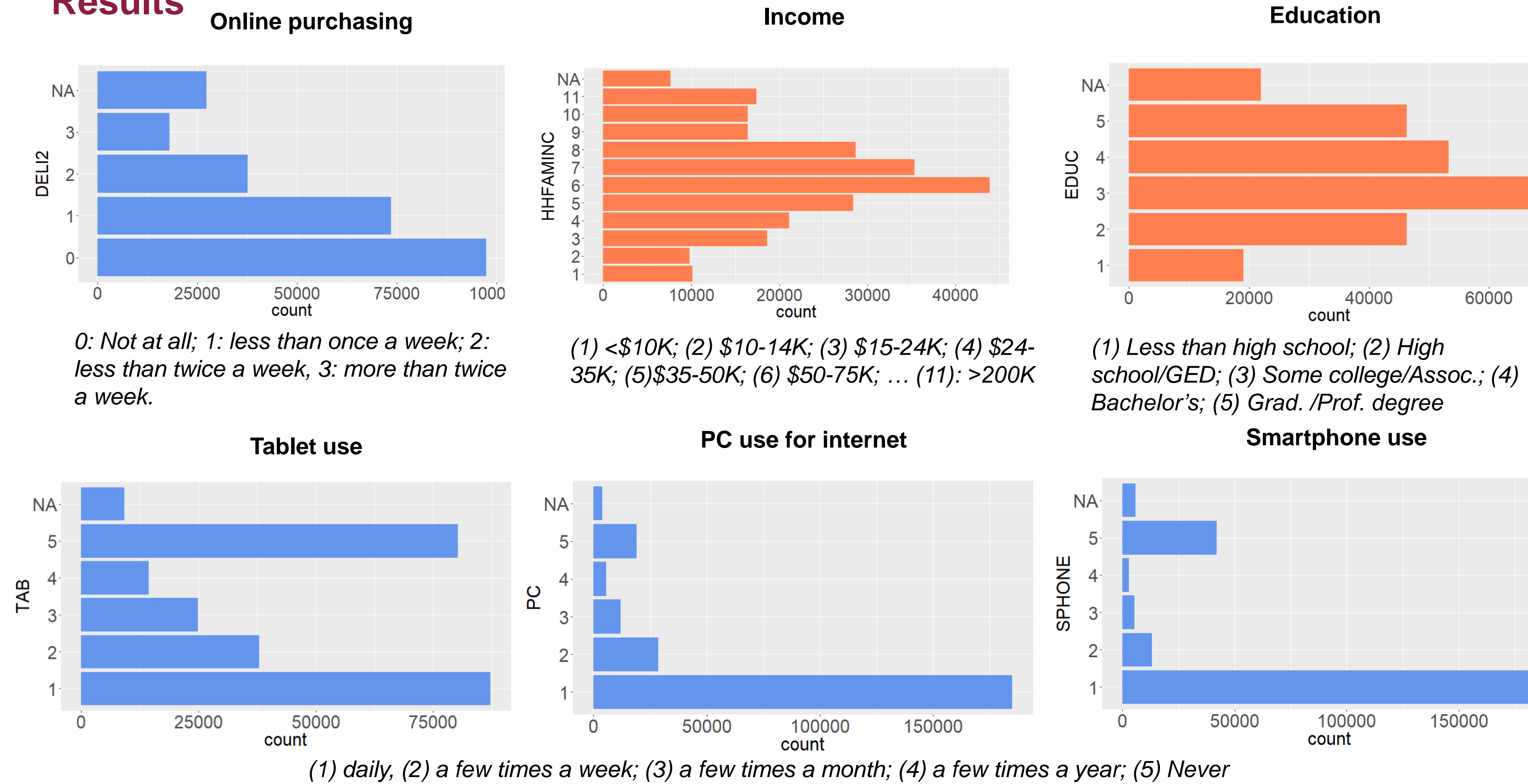
- Grew 5,000 decision trees from subsamples of the training sets.
- Averaged the probability (or took the major vote) to get the final results.
- Performed cross validation.

Outcome variable: DELIVER (regroup, discrete)

Predictor variables:

- Internet usage (through PC, web, smartphone, tablet)
- Travel patterns and lifestyle (e.g., physically activeness, mode use, trips by modes, car and bike share membership, vehicle ownership).
- Socio-demographic and other variables.

Results



Main Findings

- The use of ridesharing, PC, internet, smartphones, and tablets were among the strongest predictors of online purchasing.
- Household income was the strongest predictor of this tendency in random forest model; education was the strongest predictor in the gradient boosting model.
- Age also played a big role in predicting online shopping frequency.
- Other factors that had smaller effects were gender, life cycle (i.e., household composition), and number of adults in the household.
- Employment density and population density have moderate predictive power, suggesting the role of the built environment on predicting online purchasing.

Implications and Future Directions

- Practitioners can identify a market segmentation of online shoppers in order to predict the online shopping patterns in travel demand models.
- Practitioners can use a predictive online shopping model to estimate potential delivery truck traffic, devise strategies to manage in-store shopping travel demand and modify parking requirement for commercial zones.
- More studies are needed to replicate the results as well as improve the predictive power.
- Other unanswered questions for future studies:
 - The link between online and in-store shopping.
 - Whether online shopping substitutes, complements, or modifies in-store shopping travel and the associated change in VMT.

Selected References

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