

# Modeling the Characteristics of Airport Travelers

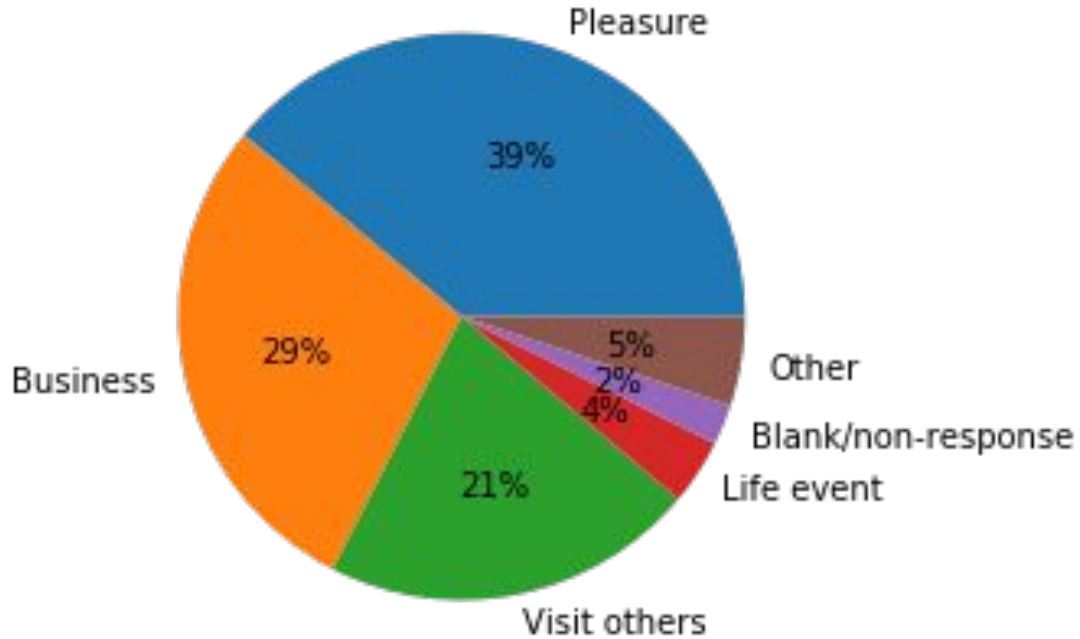
Melanie Malinas

Springboard Data Science Career Track

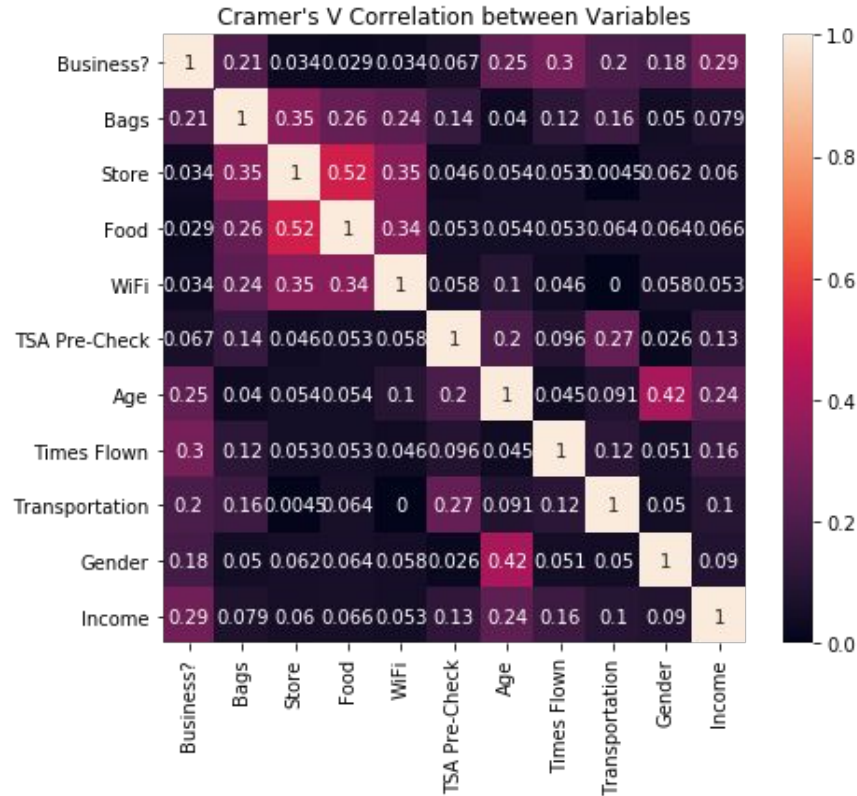
Capstone 1



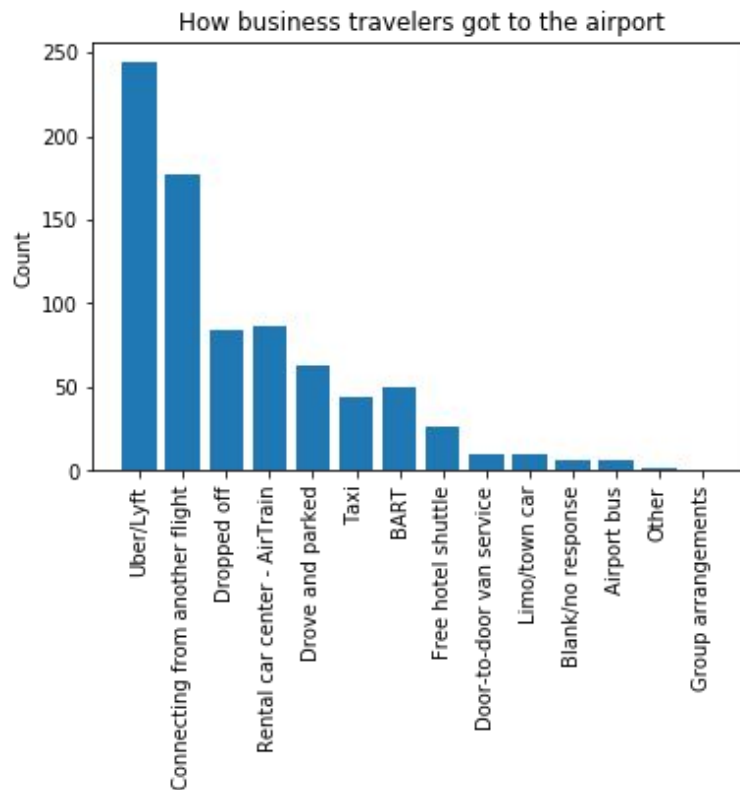
# Types of SFO travelers



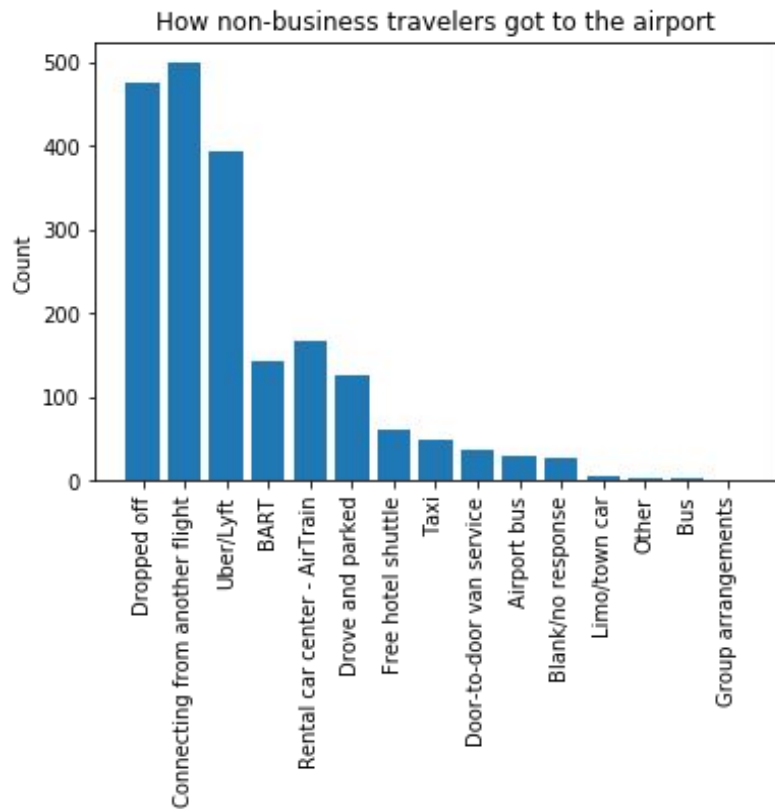
# Categorical correlations between variables



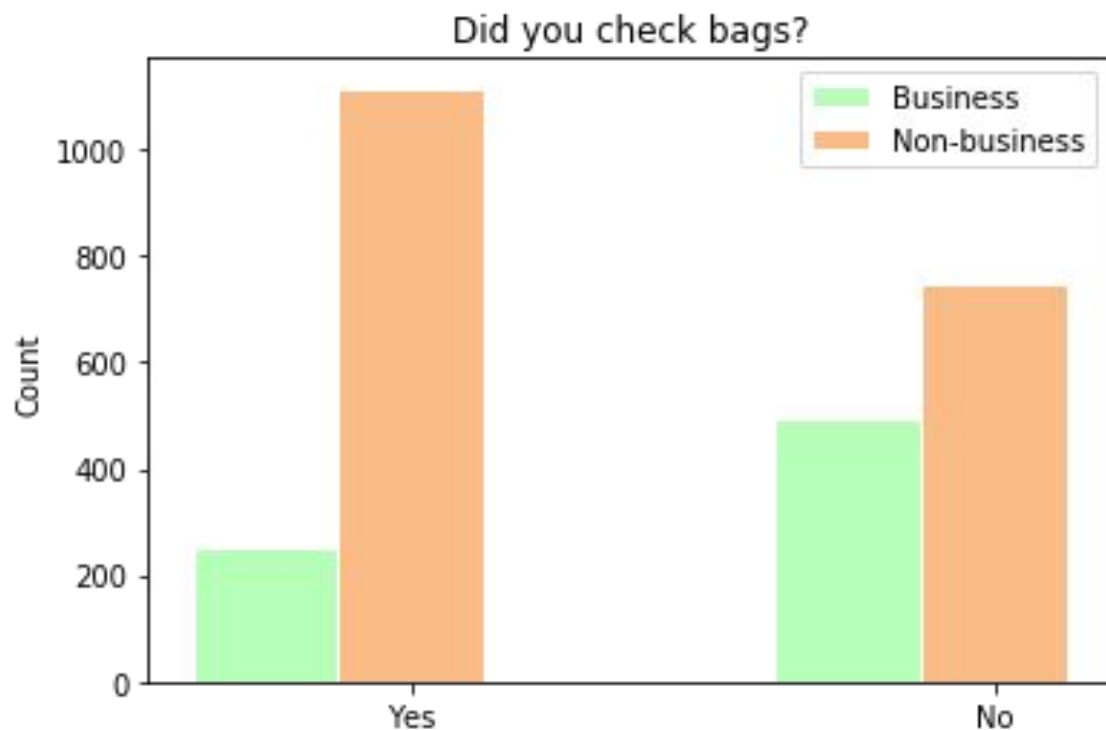
# How business travelers got to the airport



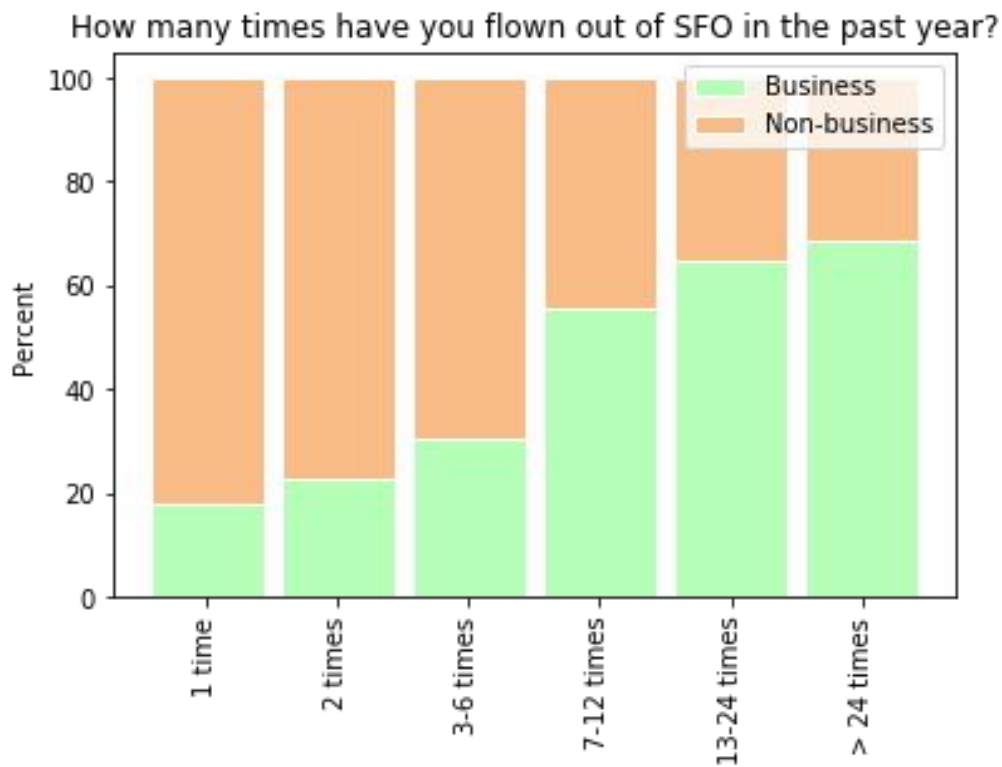
# How non-business travelers got to the airport



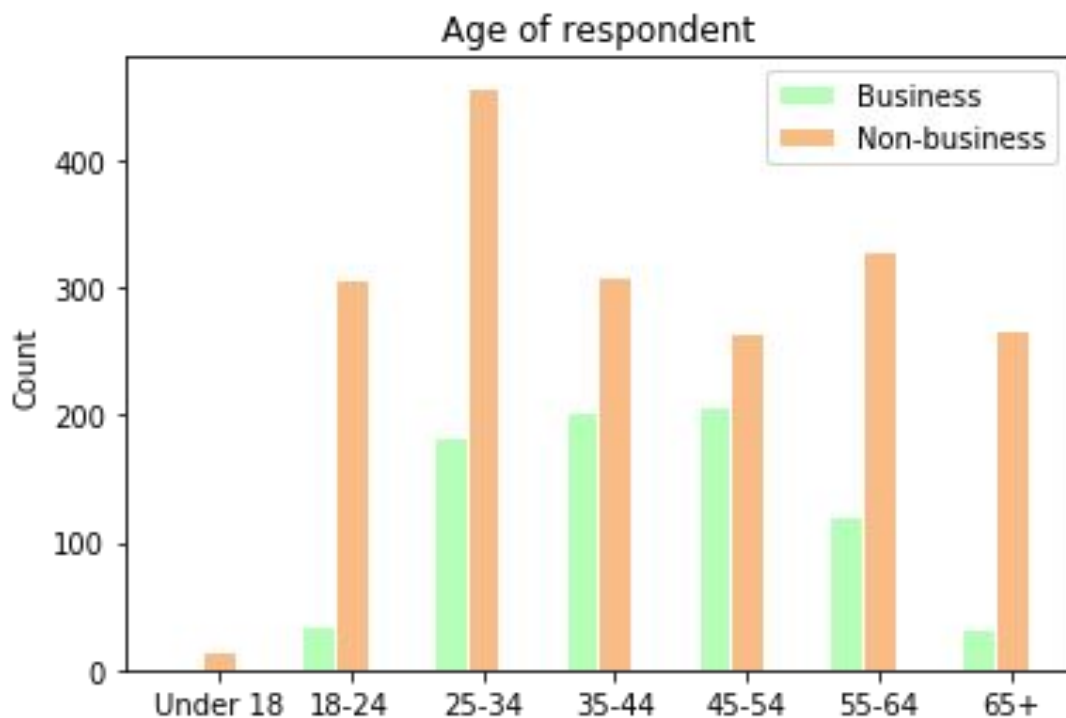
# Checking bags



# Times flown out of SFO

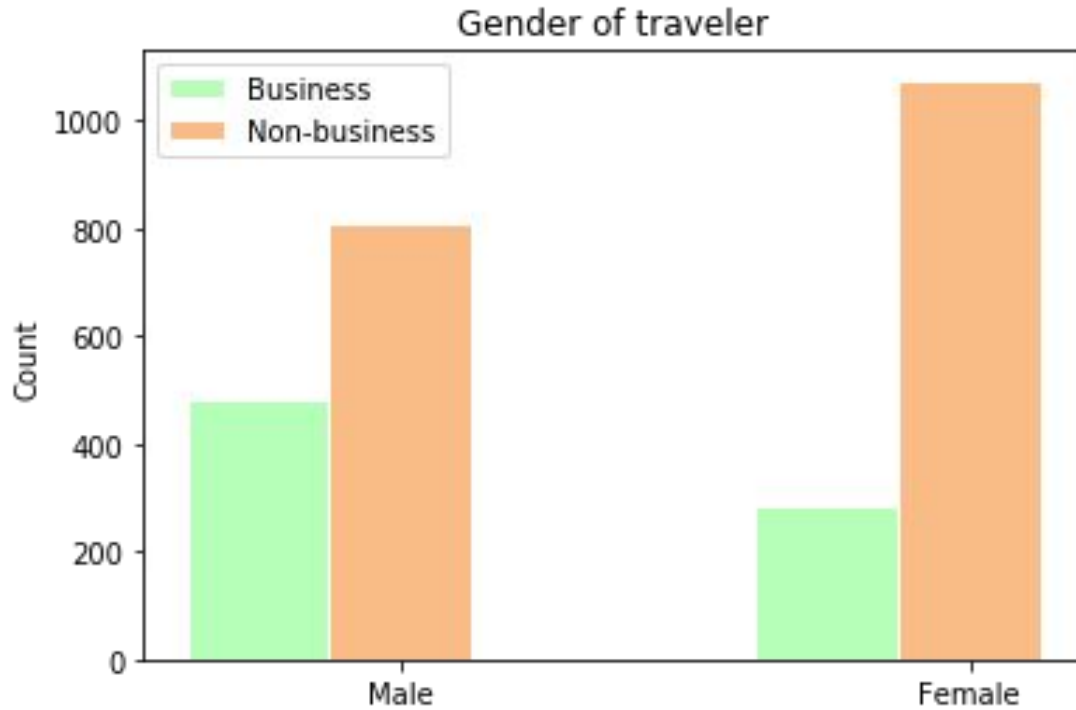


# Age of traveler

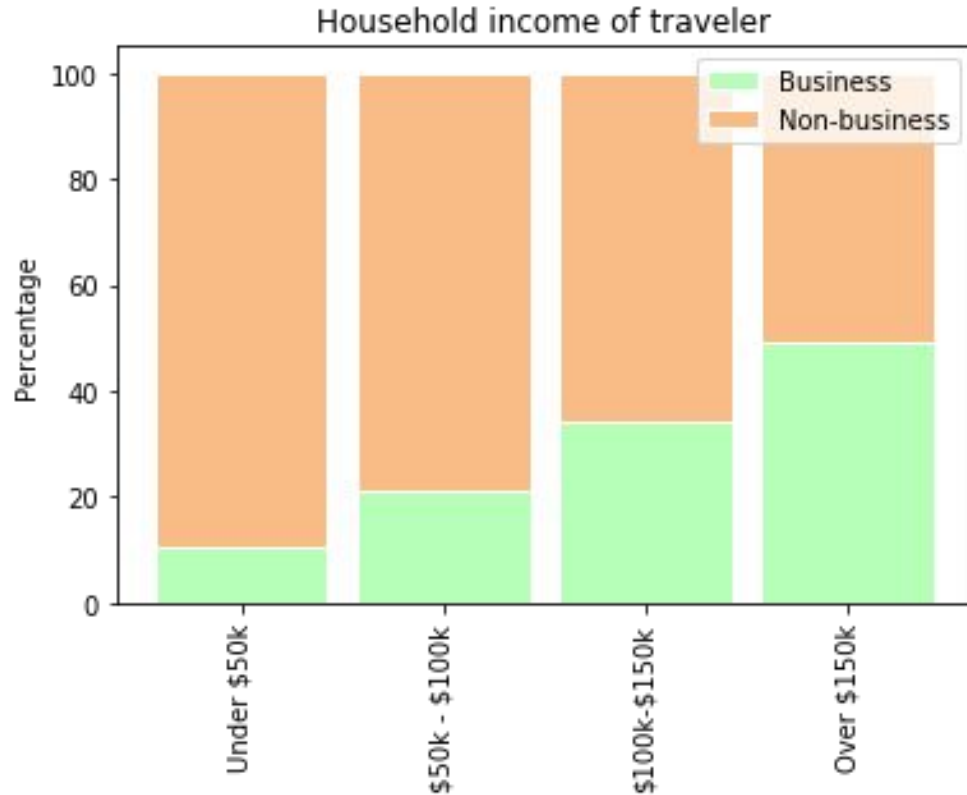




# Gender of traveler



# Household income of traveler



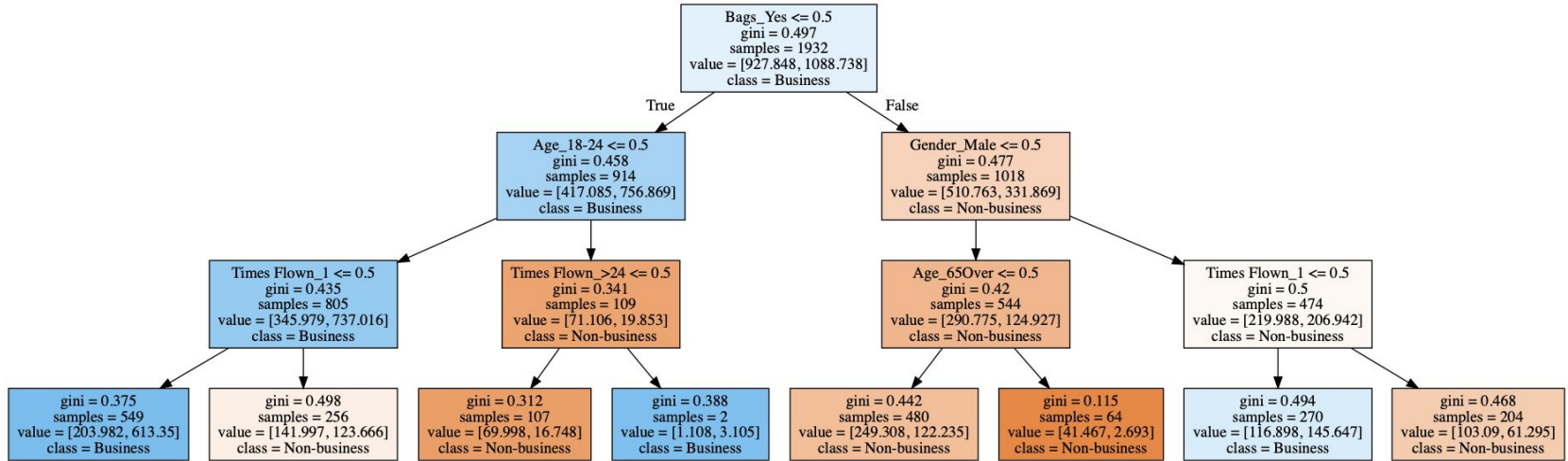
# Business case

- Airline marketing a travel rewards credit card
- Giving deal when checking in at the desk of the airport
  - Features to use: Bags, Age, Gender, Times Flown
- Optimizing F1 score
  - Striking a balance between precision and recall

# Machine learning methods

Method	Precision	Recall	F1 Score
Logistic regression - no class balance	0.54	0.63	<b>0.581</b>
Logistic regression - class balance	0.55	0.61	<b>0.578</b>
Random forests - no class balance	0.59	0.52	<b>0.550</b>
Random forests - class balance	0.61	0.51	<b>0.553</b>
SVM - no class balance	0.66	0.42	<b>0.511</b>
SVM - class balance	0.49	0.64	<b>0.553</b>
Logistic regression - upsampling	0.58	0.60	<b>0.591</b>

# Decision tree visualization



# Conclusions

- It is possible to predict whether someone is a business traveler based only on their gender, age, number of times flown out of SFO, and whether they checked a bag.
- Surprising that logistic regression was the best model and random forests did not do as well
- Usefulness of upsampling
- Assumptions of this project:
  - We did not have info on whether someone used a business credit card to book flight or whether they used a business-related email
- Work may be useful for distinguishing non-obvious business travelers from non-business travelers