

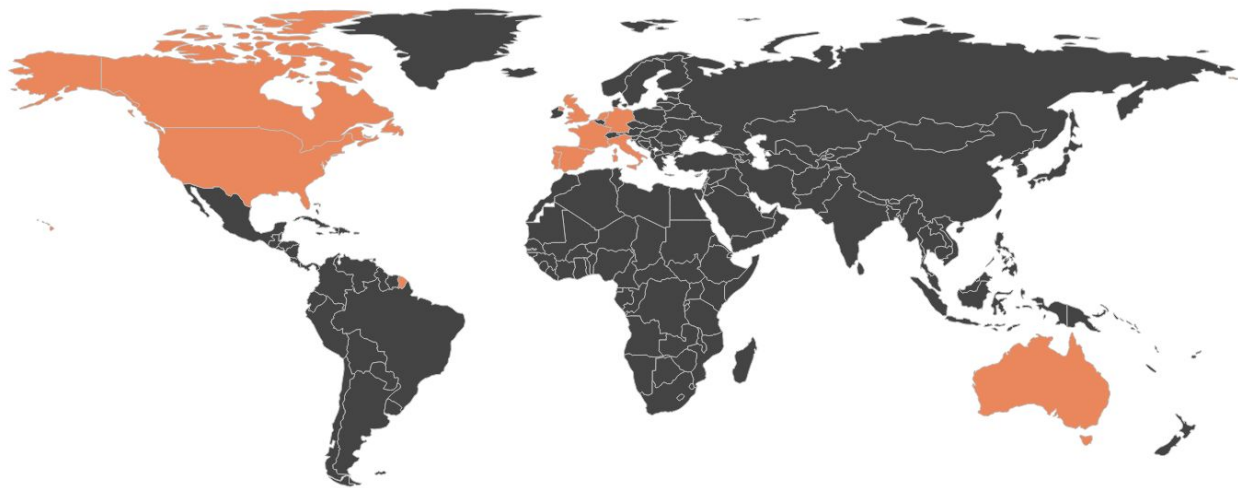
Airbnb New User Bookings



Rob Castellano, Zi Jin, Yannick Kimmel, Michael Winfield

Introduction

- I. Goal of our project
- II. The data
- III. Insights into the data
- IV. Our strategy
 - A. Feature engineering
 - B. Stacking
 - C. Feature importance
- V. Results
- VI. Conclusions



Goals

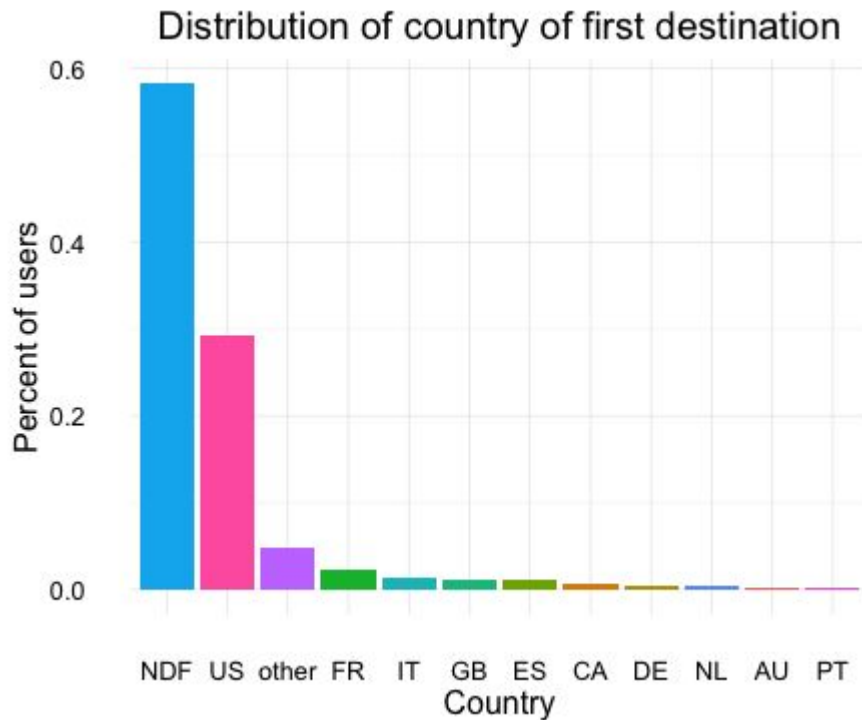
- Kaggle competition hosted by Airbnb, ending Feb 2016.
- Goal: Predict the country of a new user's first destination. This can include not booking (NDF).
- The competition allowed by the submission of five suggestions for each user.
- The competition was graded on normalized discounted cumulative gain (NDCG), which measures the performance of a recommendation system based on the relevance of the recommended entries.

Airbnb Kaggle Dataset

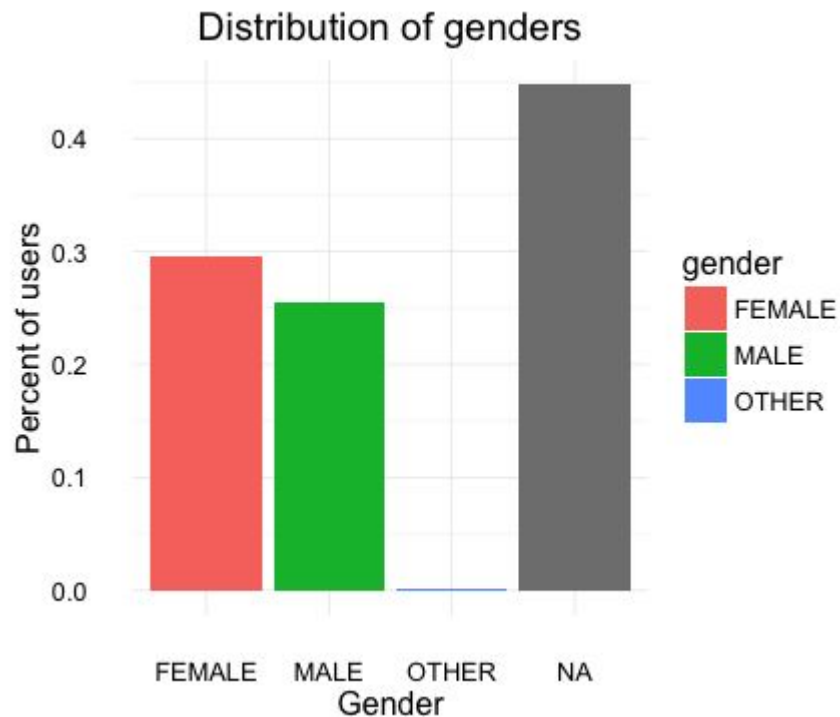
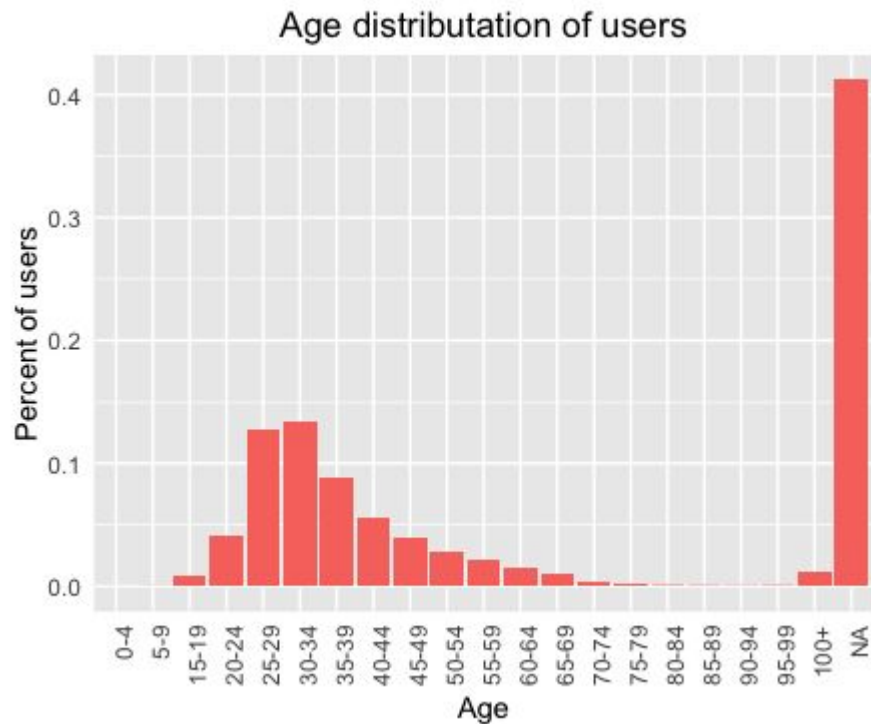
The Airbnb Kaggle dataset consisted of:

- **User information:** Unique ID, age, gender, web browser, avenue in which the user accessed AirBnB, country destination, timestamp of first activity, account created, and first booking.
- **Browser session data:** Unique ID, action type, and time elapsed.
- Training set: 200,000 users--Jan 2010 to Jun 2014
Test set: 60,000 users--July 2014 to Sep 2014

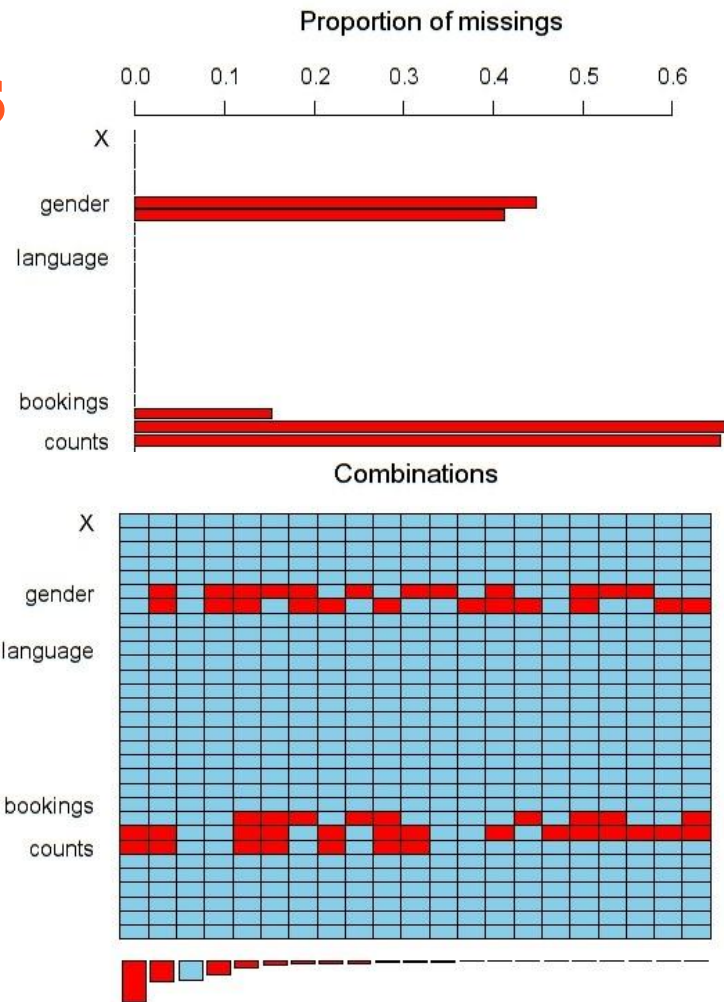
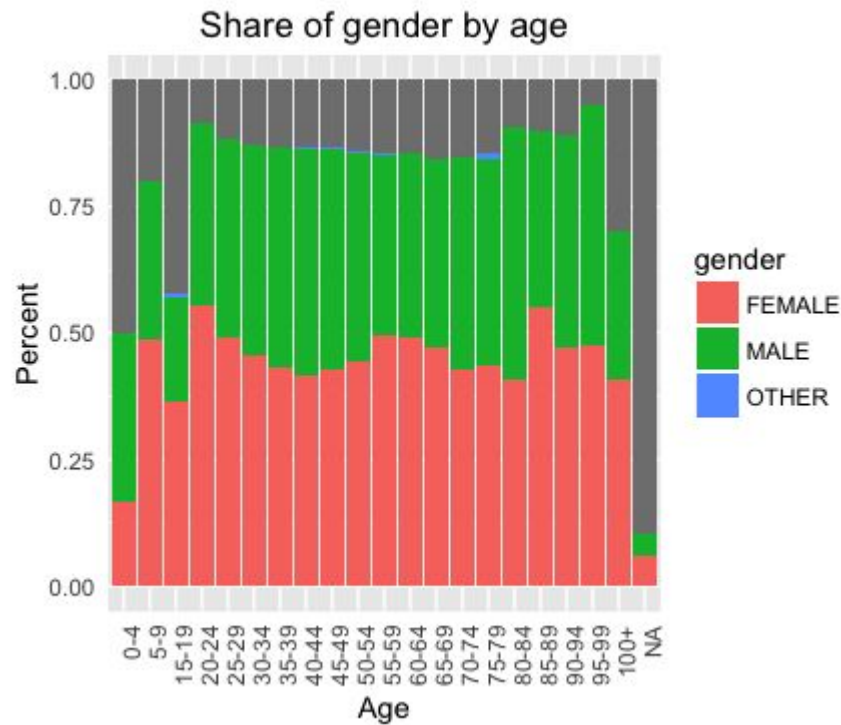
Airbnb User Booking Behavior



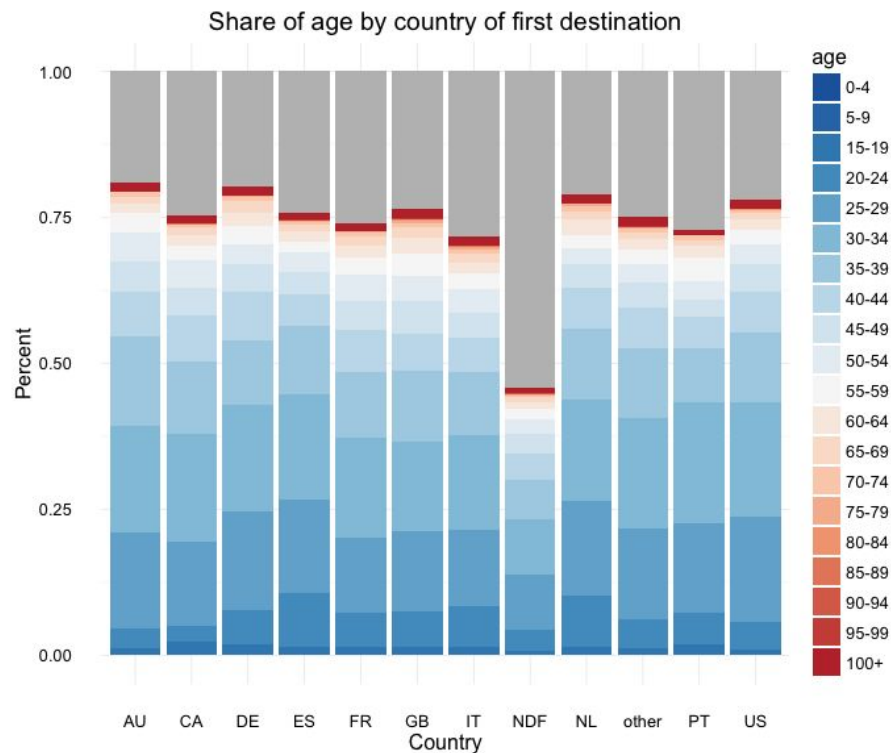
User demographics



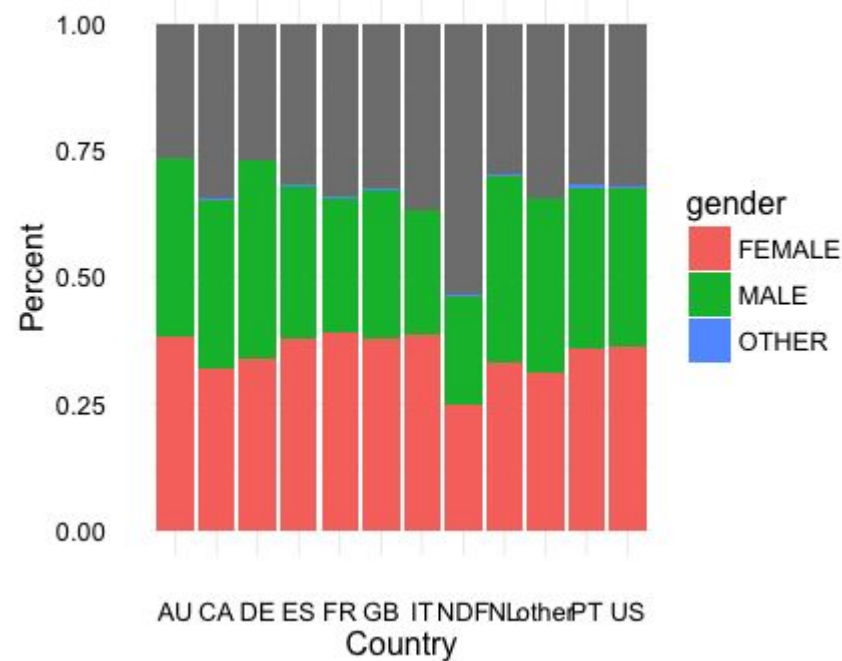
Age/Gender Missingness



Age & Gender on Country Destination

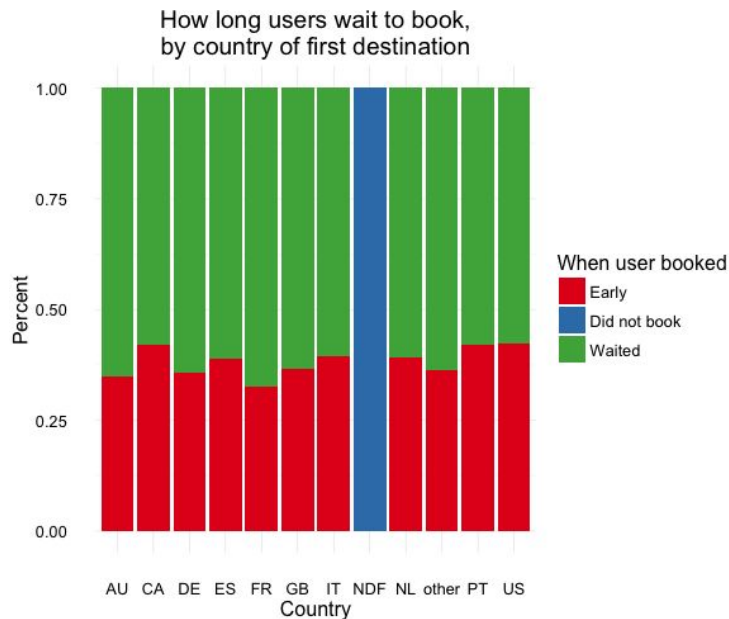
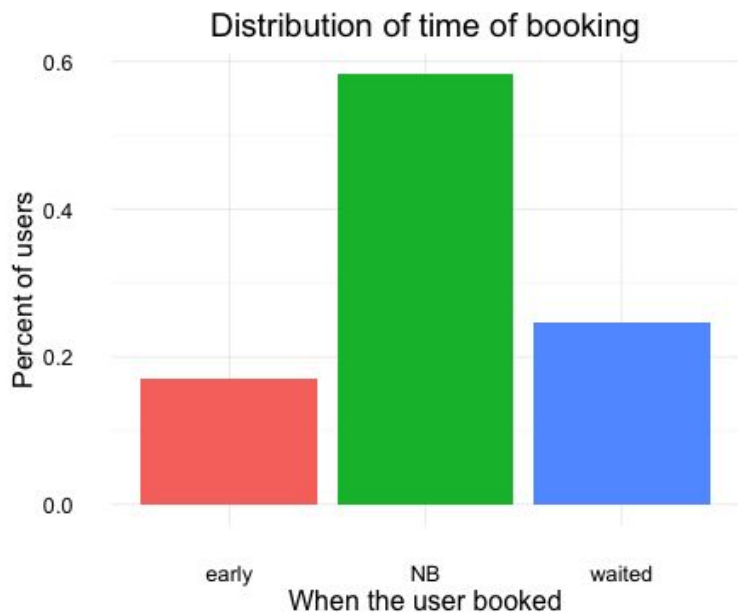


Share of gender by country of first destination



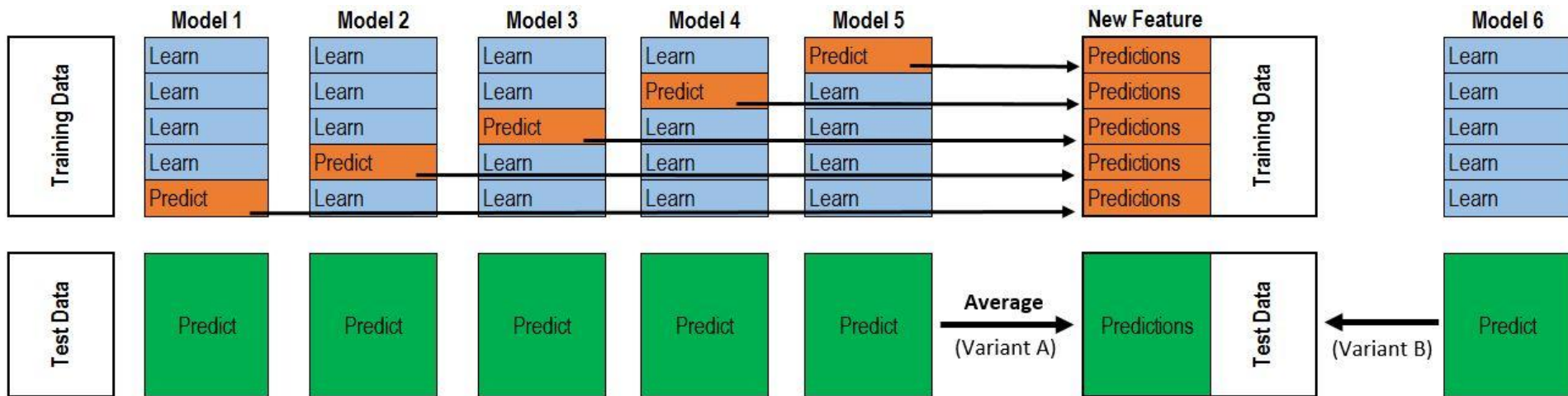
Time variable feature engineering

- *We decided to engineer 3 features based on user booking behavior, specifically the time between the creation of Airbnb accounts, a user's first activity on the website, and their date of first booking.*

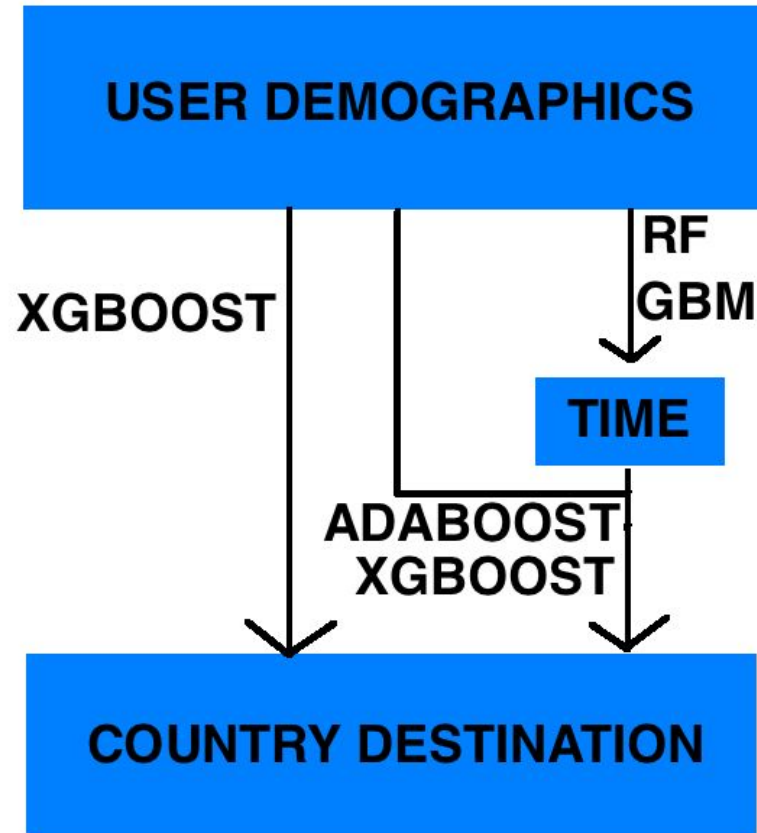


Stacking

- *Out-of-fold predictions of those three features were then added to the training dataset and test dataset through the process of stacking.*



Workflow

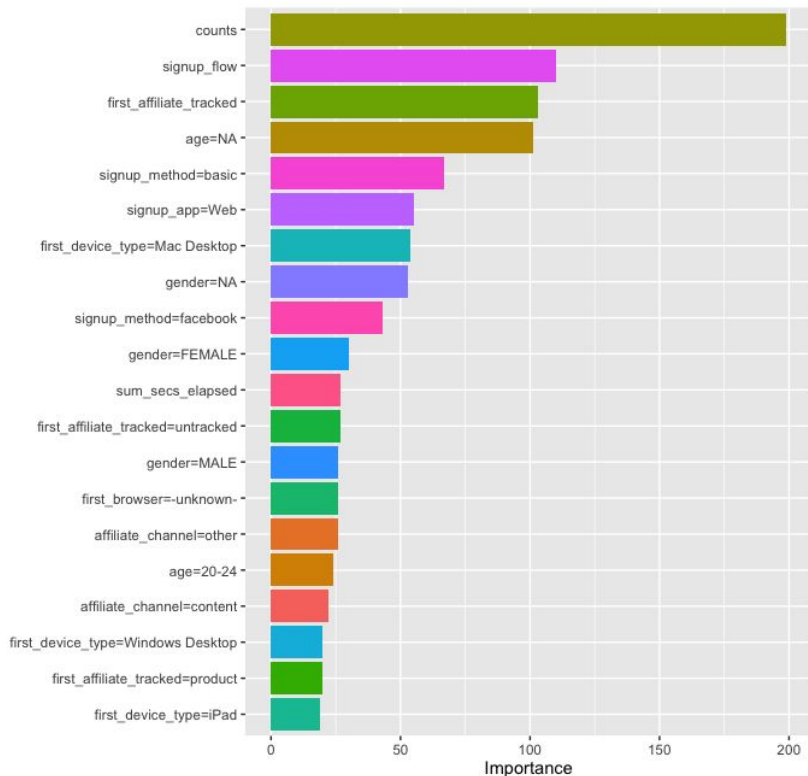


Predicting Country Destination

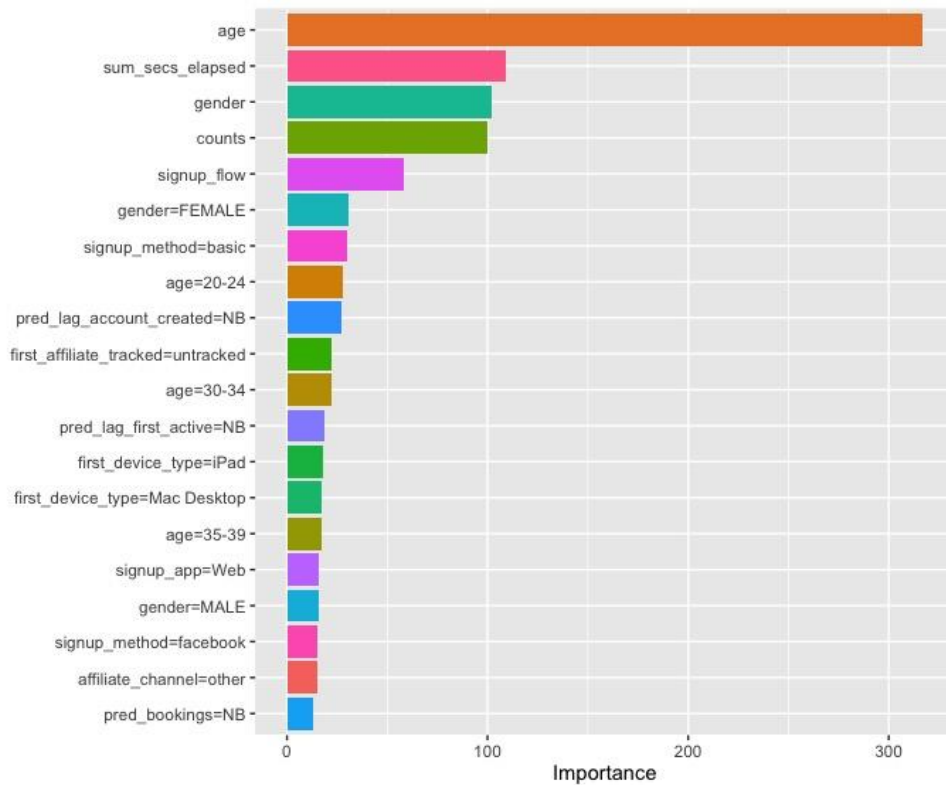
- First choices either NDF or USA.
- Ran grid search cross-validation
- Unstacked:
 - XGBoost -- Improved Kaggle ranking from #1165 to #374 with score of 0.87055
 - Best parameters: learning_rate 0.1, max_depth 0.4, n_estimators: 100
- Stacked:
 - XGBoost -- Kaggle ranking of #1030 with score of 0.86332
 - AdaBoost -- Kaggle ranking of #1028 with score of 0.86445

Variables of importance in XGBoost

Unstacked Model



Stacked Model



Conclusions

1. Performed exploratory data analysis on Airbnb new user information.
2. Wrangled and munged data in Python and R.
3. Used R for visualization and the creation of a Shiny App.
4. Feature engineered time-lag-based variables using Python and R.
5. Fit models (XGBoost/Random Forest/AdaBoost) using Python.
6. Performed predictions on users using XGBoost that ranked at 374 on Kaggle.



Recommendations to Airbnb

- Invest in collecting more demographic data to differentiate country destinations. A possible source includes Facebook (~1/4 users enter through FB).
- Flag users who decline to enter age and gender; such users are more likely to browse without booking.
- Continuously collect browser session activity; such data was helpful for predictions. This data was available only for newer users.

Future Directions

Steps to improve our predictions:

- Optimize tuning parameters for XGBoost on the stacked dataset.
- Stack country of destination predictions to dataset as features to improve predictions.
- Use multiple XGBoost models (stacked or unstacked) and ensemble them.