Milestone report

BUSINESS REQUEST/GOALS:

- Airbnb has a wide range of options to choose from 34000+ cities around 190 countries for lodging, primarily homestay or tourism experience.
- Predicting where the new user will book their first travel experience has a great value.
- Having such insights or information can help Airbnb share more personalised content with the community, decrease the average time for first booking, understand how a user engages with the service, what factors would encourage them to engage more deeply and better forecast demand and many more.

WHO CARES ABOUT THIS ?

- Airbnb is keen on knowing where the new user will book their first travel experience.
- As a new user getting a personalised treatment is of great value.

DATA COLLECTION AND WRANGLING:

- The data is collected from Kaggle. Ref [Data]
- Data mainly comprises demographics information, web session records of the user and some summary statistics.
- Most of the data is clean.
- 'US', 'FR', 'CA', 'GB', 'ES', 'IT', 'PT', 'NL','DE', 'AU', 'NDF' are possible destination countries(target variable)
- Timings are transformed to datetime formats.
- Missing values are transformed to np.NAN.
- Some outliers were observed, like in user age which were replaced by mean age.

EXPLORATORY DATA ANALYSIS SUMMARY

Ref script: EDA

- We majorly have the following datasets.
  - Train,sessions and countries.
- Quick glance of data

Train data

```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 213451 entries, 0 to 213450
Data columns (total 16 columns):
id                         213451 non-null object
date_account_created       213451 non-null object
timestamp_first_active     213451 non-null int64
date_first_booking         88908 non-null object
gender                     117763 non-null object
age                        125461 non-null float64
signup_method              213451 non-null object
signup_flow                213451 non-null int64
language                   213451 non-null object
affiliate_channel          213451 non-null object
affiliate_provider         213451 non-null object
first_affiliate_tracked    207386 non-null object
signup_app                 213451 non-null object
first_device_type          213451 non-null object
first_browser              186185 non-null object
country_destination        213451 non-null object
dtypes: float64(1), int64(2), object(13)
memory usage: 26.1+ MB
```

Session data

```
df_sessions.info()
```

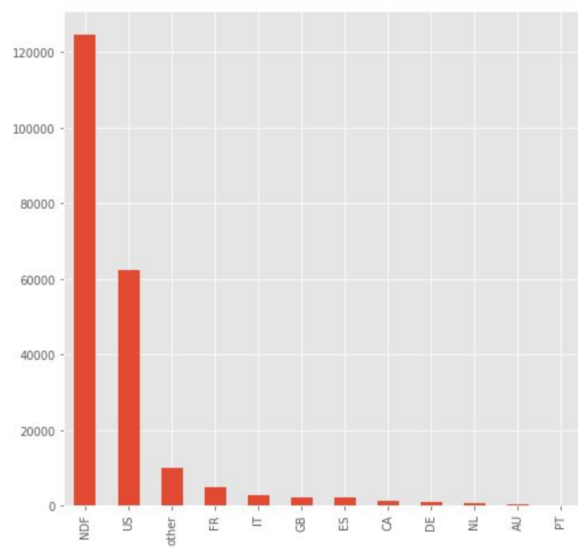
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10567737 entries, 0 to 10567736
Data columns (total 6 columns):
user_id          object
action           object
action_type      object
action_detail    object
device_type      object
secs_elapsed     float64
dtypes: float64(1), object(5)
memory usage: 483.8+ MB
```

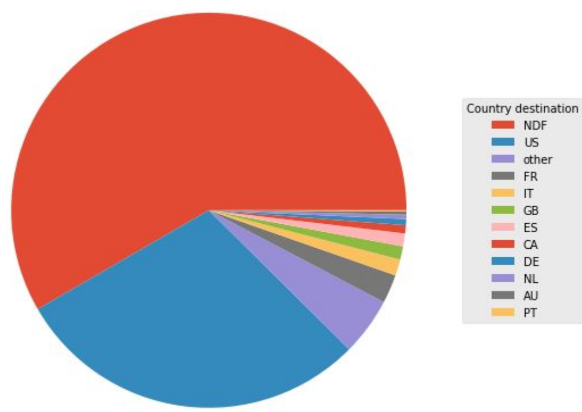
Countries data

```
df_countries.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 7 columns):
country_destination              10 non-null object
lat_destination                  10 non-null float64
lng_destination                  10 non-null float64
distance_km                      10 non-null float64
destination_km2                  10 non-null int64
destination_language             10 non-null object
language_levenshtein_distance    10 non-null float64
dtypes: float64(4), int64(1), object(2)
memory usage: 688.0+ bytes
```

- ***Distribution of destination countries:***

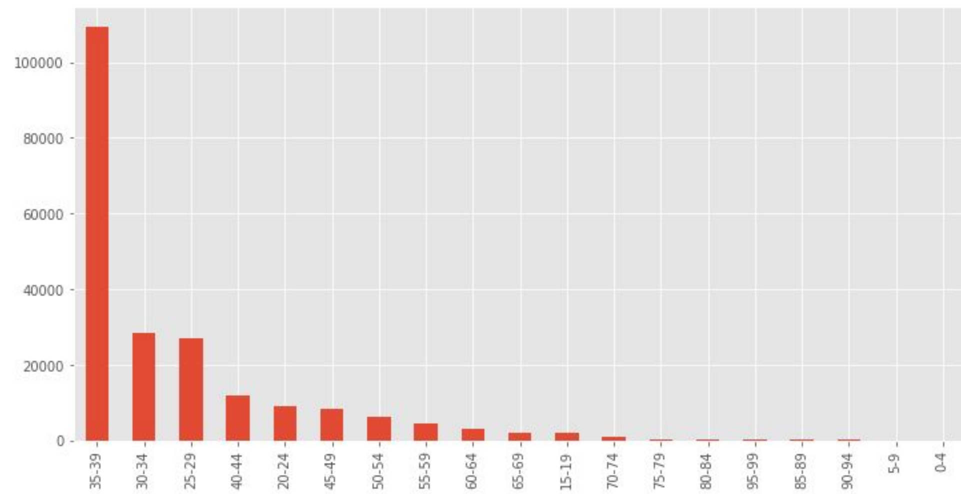




Most of the users land up doing no bookings.

US is the destination country for most of the users, could be because all user data are from people of US which also implies that most users do bookings within the country.

- ***Age group with max bookings:***

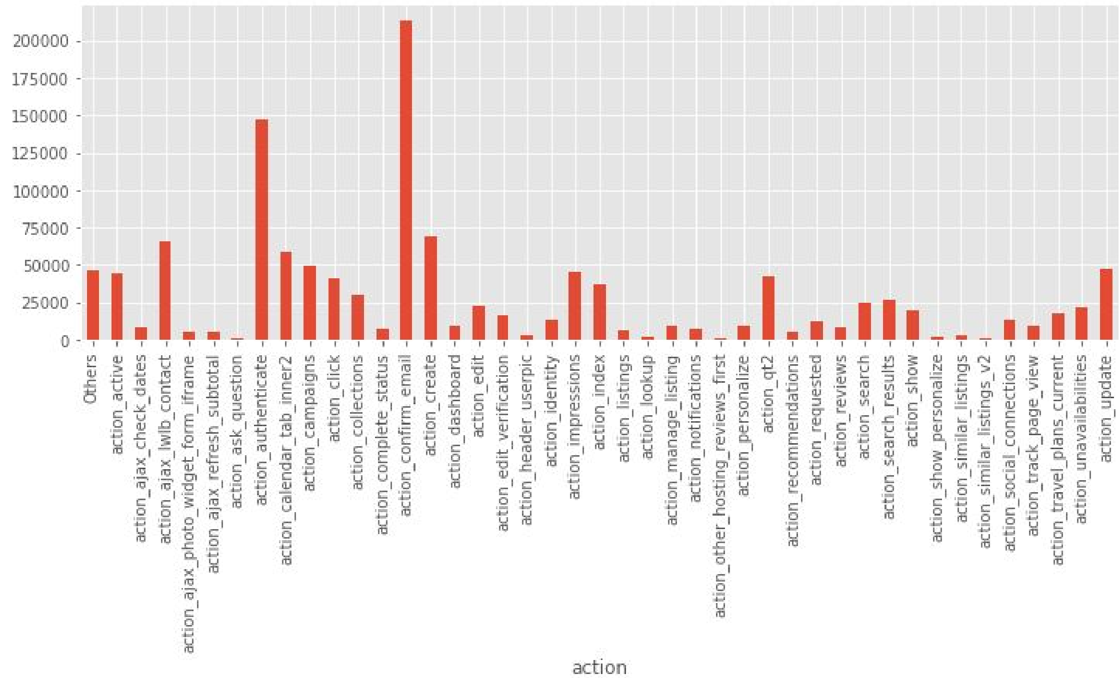


Most users belong to the age bucket 35-39. Also,there is a lot of variance in booking count as age bucket varies.

- ***Age group with max bookings:***

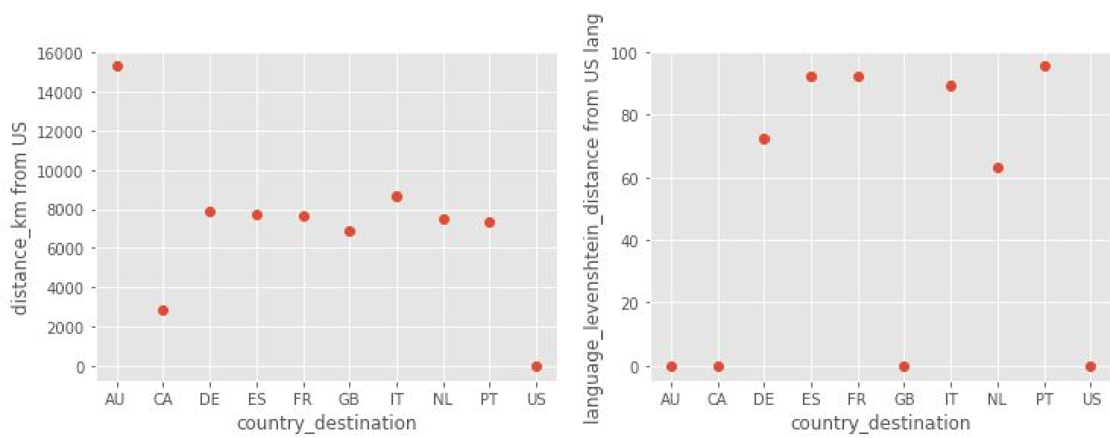
Mid year(ie May, June) seems to have relatively higher first time bookings.

- ***User session action having highest time elapsed:***



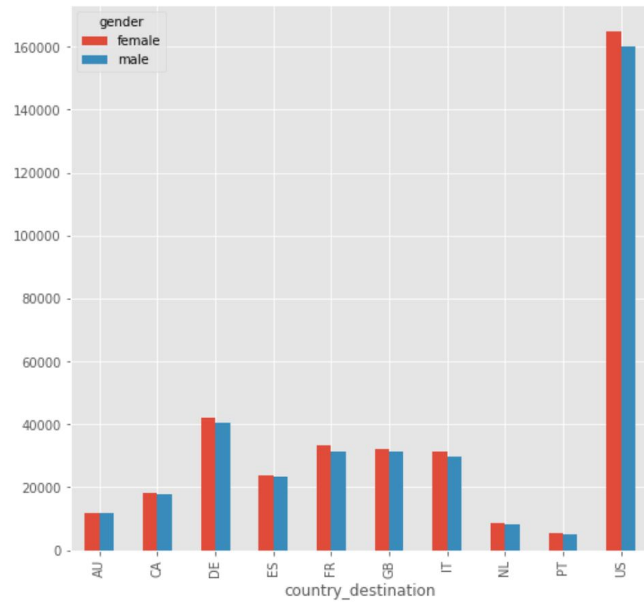
Action 'confirm_email' and 'authenticate' has the highest mean secsElapsed in a user session.

- ***Language difference and km distance for a US user:***



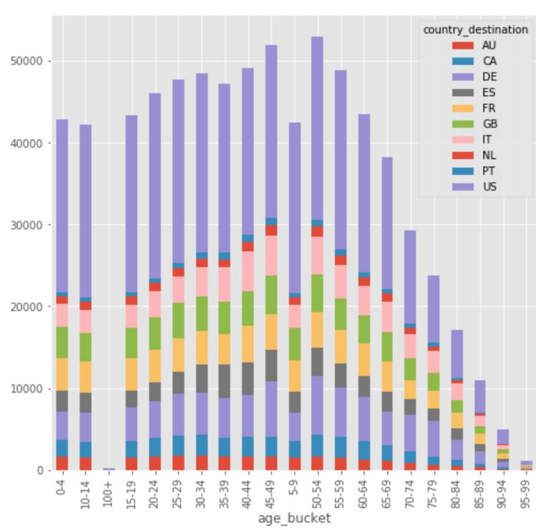
From plot 1, AU looks farest from the US in km distance.ES, FR, PT have the highest language_levenshtein_distance i.e these languages have the highest difference score from US english.

- ***Demographic information of cities***



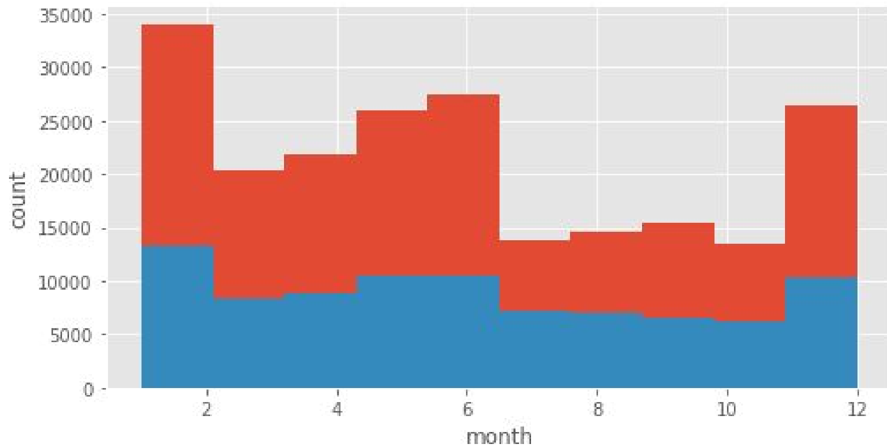
The US seems to have the highest population, also female population is higher compared to male for all destination countries.

- ***Age bucket wise distribution of destination country***



There is no significant variation in the segments with age buckets.

- ***Highest first bookings and accounts created***



From the plot, we see that the shapes of accounts created and first bookings are quite similar, December and January have the maximum count.

DATA PREPROCESSING AND FEATURE ENGINEERING:

As a part of data preprocessing and feature engineering following steps were performed.

- Datetime format transformations.
- Extracting important features from datetime like month were added as separate features.
- Less frequent categories considering a threshold were transformed to single categories like 'Others'.
- Grouping and aggregations.
- Dropping redundant columns.
- Joining eg. Session data was joined with train data.
- Age to Age_group transformation.
- Adding features like user language, age group preferences from the demographics information of the destination countries.