BUSINESS REQUEST/GOALS:

- Predicting where the new user will book their first travel experience has a great value.
- 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, understand what factors would encourage them to engage more deeply and better forecast demand and many more.

WHO CARES ABOUT THIS ?

- Knowing where a new user will book their first travel experience is of great value to Airbnb.
- As a new user getting a personalised treatment is of great value.

DATA COLLECTION AND WRANGLING:

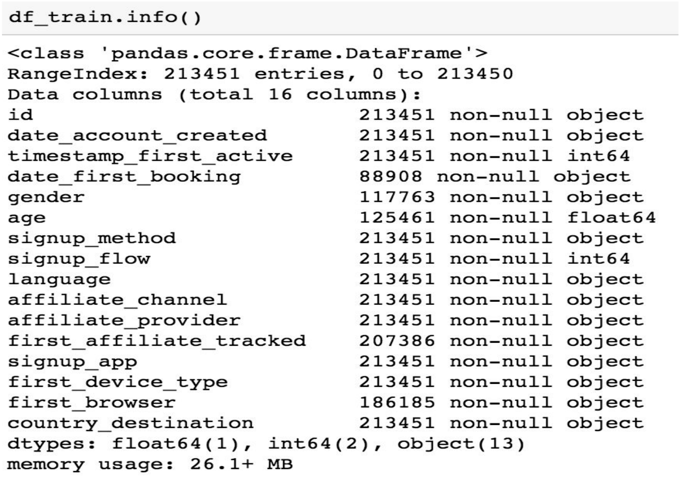
- The data is collected from Kaggle. Ref Data
- Data mainly comprises demographics information, web session records of the user and some summary statistics.
- Most of the data is clean.
- 'US', 'FR', 'CA', 'GB', 'ES', 'IT', 'PT', 'NL','DE', 'AU', 'NDF' are possible destination countries(classes of target 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

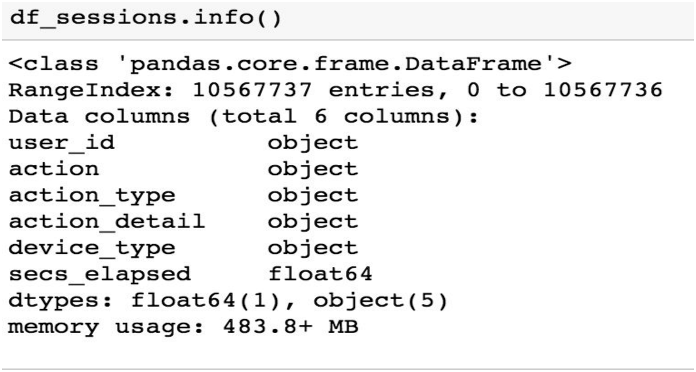
Train data



```
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
```

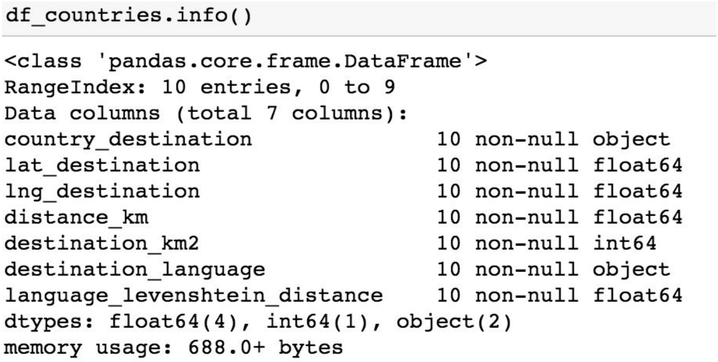
Session data



```
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
```

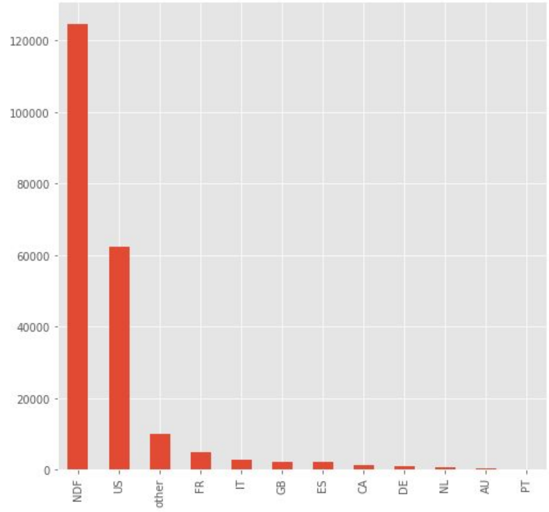
Countries data

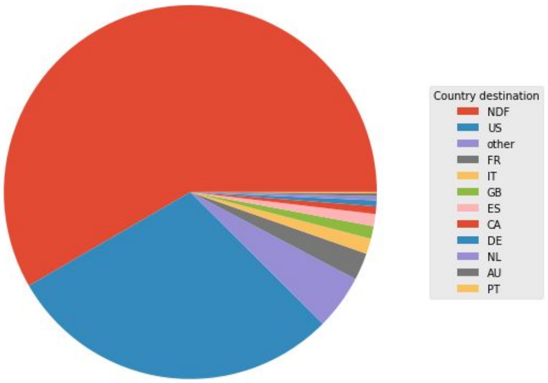


```
df_countries.info()
```

```
<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
```

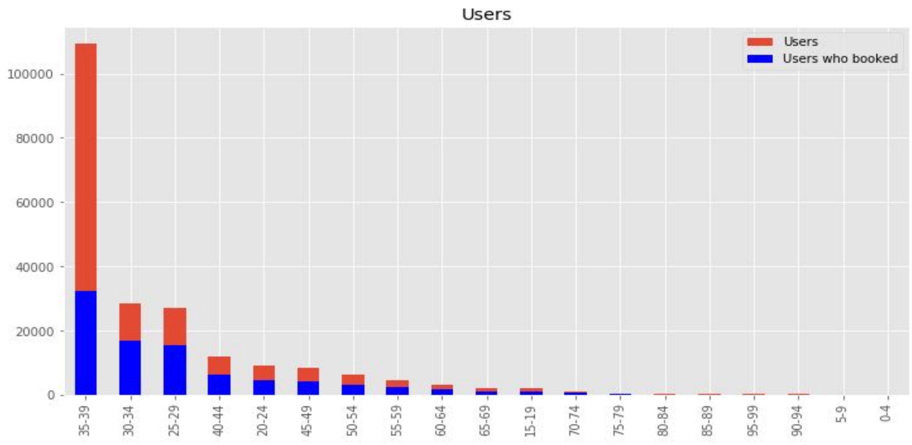
- ***Distribution of destination countries:***





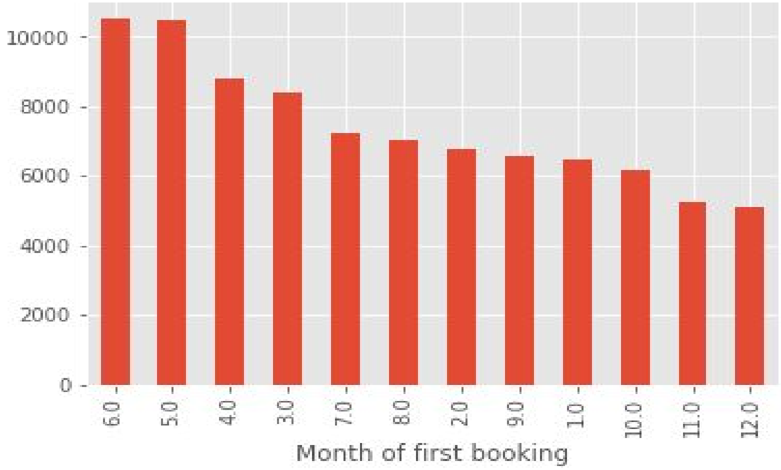
- Most of the users land up doing no bookings(NDF).
- US is the destination country for most of the users, could be because all user data are from people of US which also implies that most users do bookings within the country.
- US and NDF are the most favourable classes making it an imbalance set.

- ***Age group with max users and users who booked:***



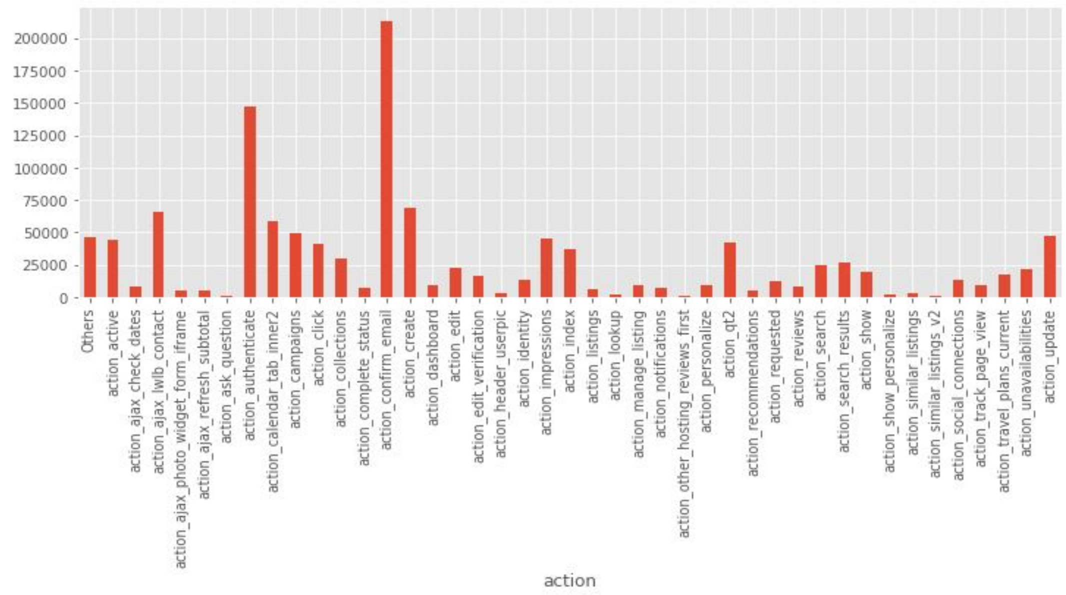
- Most users are from age bucket 35-39.
- There is a lot of variance in count as age bucket varies.
- Age bucket 35-39 has relatively low booking to not booking ratio.
- Users of Age bucket 30-34 and 25-29 has relatively higher booking to Non booking ratio.

- ***Monthly count of first bookings:***



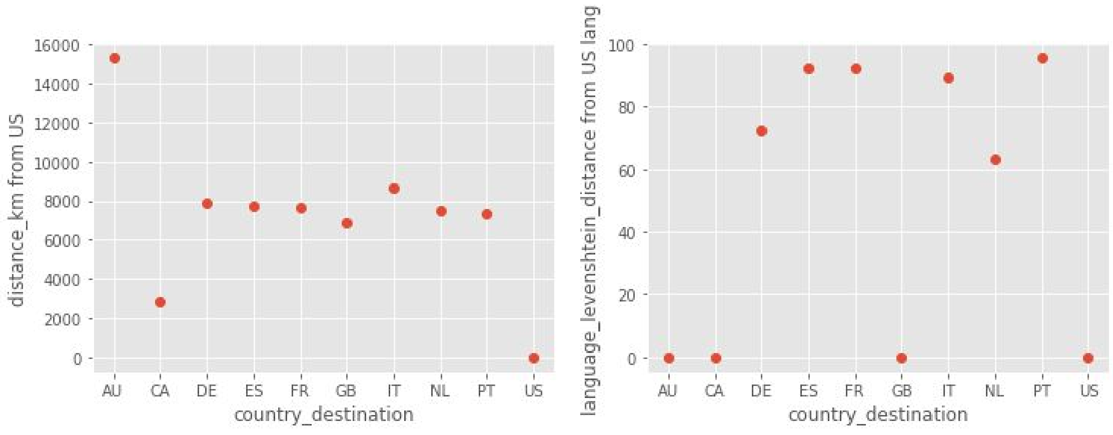
- Mid year(ie May, June) seems to have relatively higher first time bookings.
- Year end has relatively low first bookings.

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



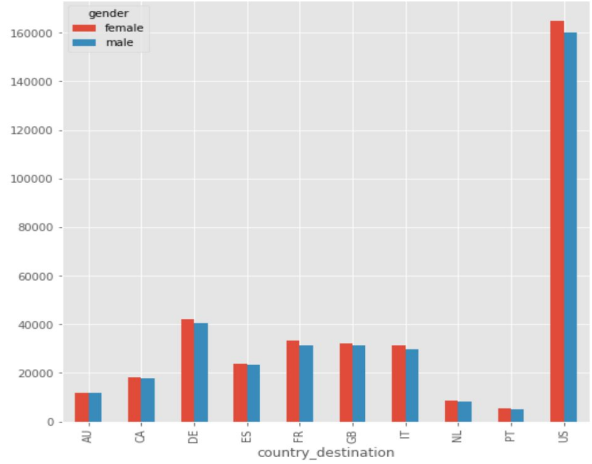
- Action 'confirm_email' and 'authenticate' has the highest mean secsElapsed in a user session.

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



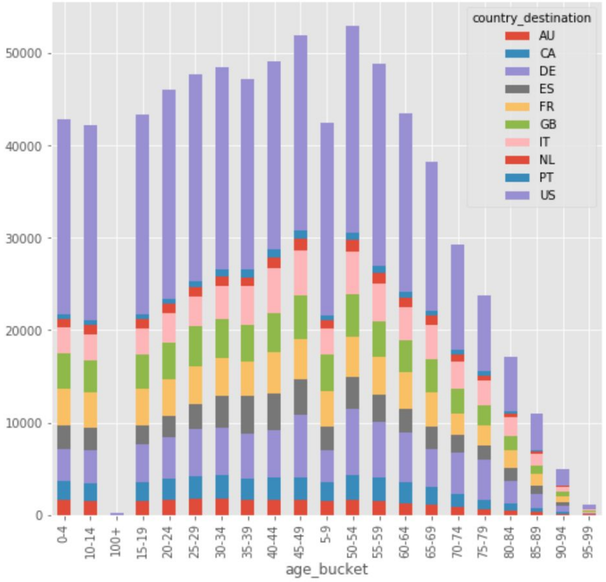
- From plot 1, AU looks farest from the US in km distance.ES, FR, PT have the highest language_levenshtein_distance i.e these languages have the highest difference score from US english.

- ***Demographic information of cities***



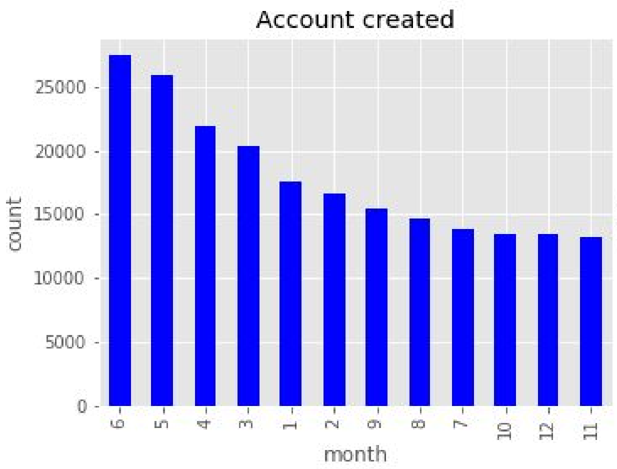
- The US seems to have the highest population, also female population is higher compared to male for all destination countries.

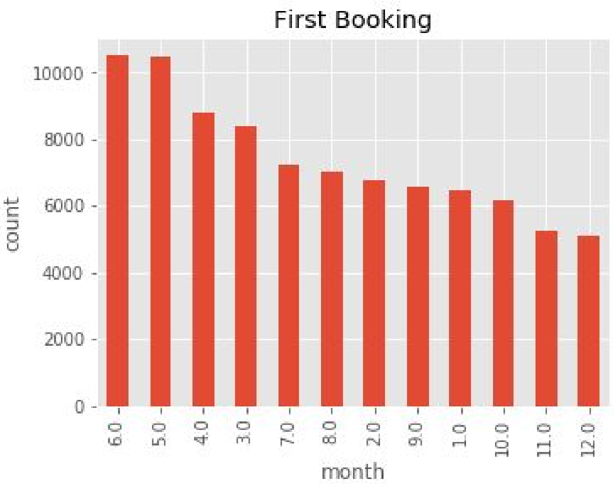
- ***Age bucket wise distribution of destination country***



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

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





- From the plot Shapes of Account created and first bookings over months are almost same.
- First half of the year has the max accounts created.
- June and May are months of highest first bookings.

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.