

****Airbnb New User Bookings**

- **Problem statement:**

Airbnb New User Booking is a kaggle challenge to predict which country a user is likely to book as his or her travel destination based on the data which the user has entered themselves when creating the account or based on the past travels. We need to predict 5 travel destinations for each user. This is a multiclass classification problem i.e how probable a user is going to all the 5 destinations rather than just one.

- **objective:**

To predict the top 5 travel destinations in decreasing order of their relevance

- **Dataset--**

- **train_users.csv** There are 16 features for describing each user in the dataset:
 - ID
 - Date_account_created
 - Timestamp_first_active
 - Date_first_booking
 - Gender
 - Age
 - Signup_method
 - Signup_flow
 - Language
 - First_affiliate_tracked
 - Affiliate_channel
 - Affiliate_provider
 - Signup_app
 - First_device_type
 - Country_destination
- **Sessions.csv**
 - User_id
 - Action
 - Action_type
 - Action_detail
 - Device_type
 - Secs_elapsed
- **Age_Gender_Bkts.csv**
 - Age_bucket
 - Country_destination
 - Gender
 - Population in thousands
 - Year
- **Countries.csv**
 - Country_destination
 - Lat_destination

- Lng_destination
- Distance_km
- Distance_km2
- Destination_language
- Language_levensthein_distance

```
In [1]: import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import scipy.stats as stats
```

- The first step here will be load all the given data into a dataframe to extract all the basic information such as the variations in the values, null values, size of the data, etc.

Age_Gender

```
In [2]: # used pandas to read the the csv file using the read_csv function which is store
df_age = pd.read_csv('age_gender_bkts.csv/age_gender_bkts.csv')
```

```
In [3]: #df_age is a dataframe and we use head function to display the top 5 rows of the
df_age.head()
```

Out[3]:

	age_bucket	country_destination	gender	population_in_thousands	year
0	100+	AU	male	1.0	2015.0
1	95-99	AU	male	9.0	2015.0
2	90-94	AU	male	47.0	2015.0
3	85-89	AU	male	118.0	2015.0
4	80-84	AU	male	199.0	2015.0

```
In [4]: #Check for null values
df_age[df_age['year'].isnull()]
```

Out[4]:

age_bucket	country_destination	gender	population_in_thousands	year
------------	---------------------	--------	-------------------------	------

- From the above cell it is clear that there is no null values present in this feature.
- Now we will deal the age feature here 100+ will be converted to into a bucket and then the buckets will be converted into their mean values as it will increase the versatality as it may be needed for categorical features.

In [5]: *value of 100+ and other values are in bucket form we use the apply function of pandas. In this case, as we are using lambda function to perform our calculation to save space link- https://www.kaggle.com/ashishpatel26/airbnb-rental-data*

```
df_age['age_bucket'].apply(lambda x: '100-104' if x == '100+' else x)
```

In [6]: df_age.head()

Out[6]:

	age_bucket	country_destination	gender	population_in_thousands	year
0	100-104	AU	male	1.0	2015.0
1	95-99	AU	male	9.0	2015.0
2	90-94	AU	male	47.0	2015.0
3	85-89	AU	male	118.0	2015.0
4	80-84	AU	male	199.0	2015.0

In [7]: *#we are calculating the mean age of the age_bucket*

```
df_age['mean_age'] = df_age['age_bucket'].apply(lambda x: (int(x.split('-')[0])) + 5)
```

In [8]: df_age.head()

Out[8]:

	age_bucket	country_destination	gender	population_in_thousands	year	mean_age
0	100-104	AU	male	1.0	2015.0	102.0
1	95-99	AU	male	9.0	2015.0	97.0
2	90-94	AU	male	47.0	2015.0	92.0
3	85-89	AU	male	118.0	2015.0	87.0
4	80-84	AU	male	199.0	2015.0	82.0

In [9]: *# this displays the unique value of the feature column 'year'*

```
df_age['year'].unique()
```

Out[9]: array([2015.])

There is only one year value which doesn't add much information about the data available. So this column can be removed

In [10]: *#since there isn't any variation in the value so we are dropping the particular column*

```
df_age.drop('year', axis=1, inplace=True)
```

In [11]: *#unique values of the feature column 'country_destination'*

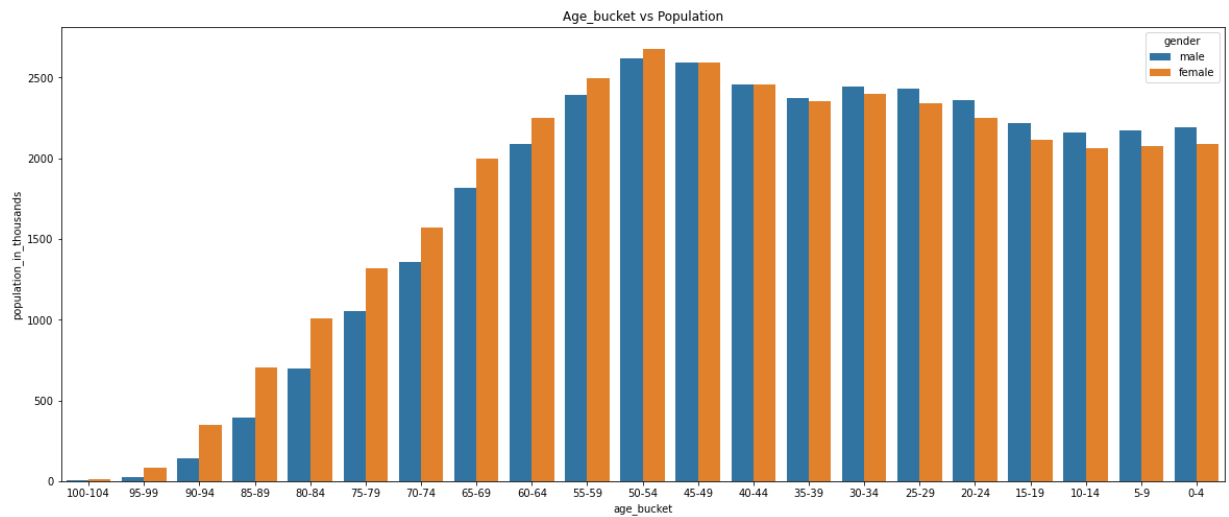
```
df_age['country_destination'].unique()
```

Out[11]: array(['AU', 'CA', 'DE', 'ES', 'FR', 'GB', 'IT', 'NL', 'PT', 'US'],
dtype=object)

The number of countries represented here are very less and very less value can be drawn from this so let us get some more insight from the following plots

```
In [12]: # seaborn barplot - Link-https://seaborn.pydata.org/generated/seaborn.barplot.html
# default arguments - seaborn.barplot(x=None, y=None, hue=None, data=None, order=
plt.figure(figsize=(20,8))
sns.barplot(x='age_bucket',y='population_in_thousands',hue='gender',data=df_age,c
plt.title('Age_bucket vs Population')
```

Out[12]: Text(0.5, 1.0, 'Age_bucket vs Population')

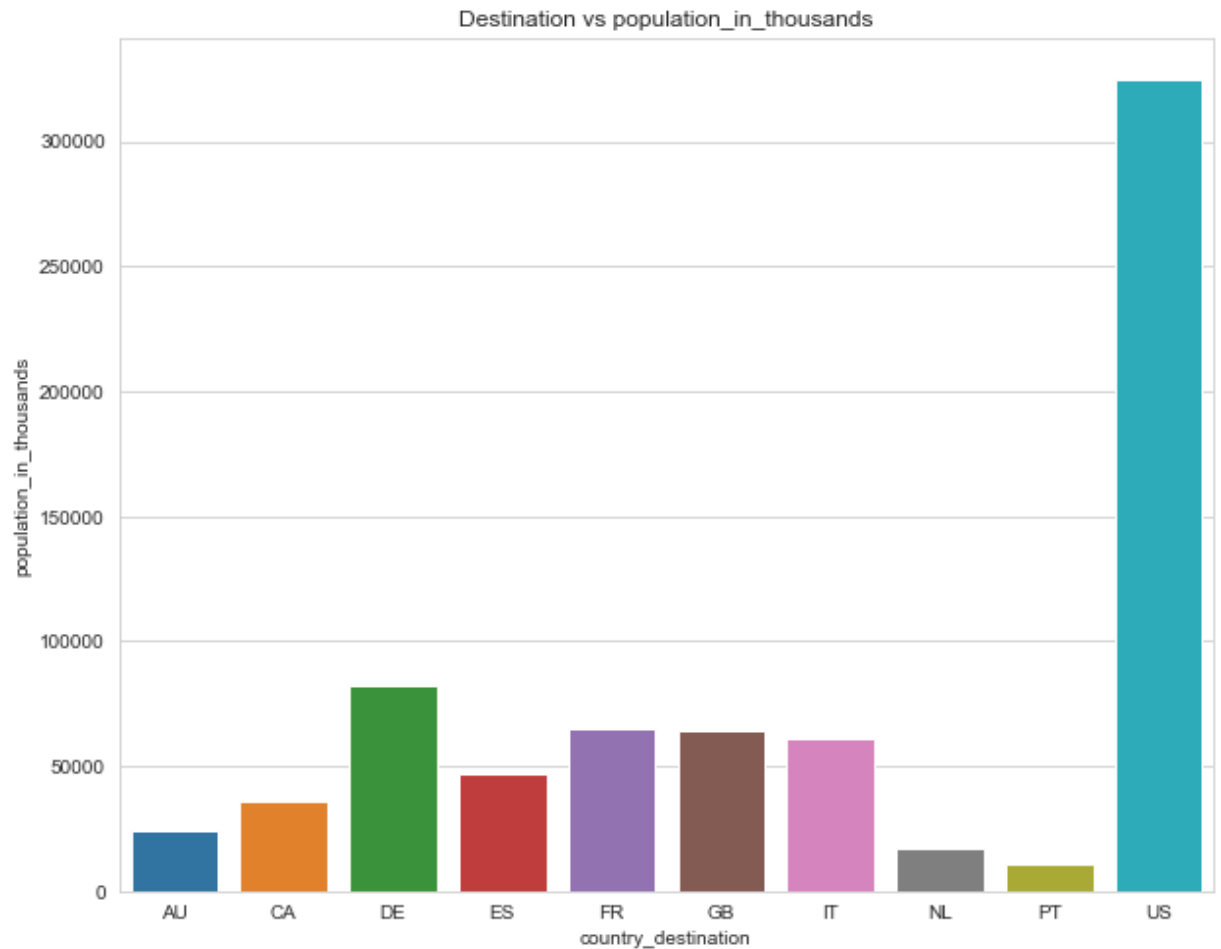


Observations:

- The age group between 50-54 and 45-49 form the largest groups
- male to female ration is pretty even for the middle aged and the younger population but tends to be more skewed as the age bucket values increase i.e women tend to live longer than men.

```
In [13]: # seaborn barplot - Link-https://seaborn.pydata.org/generated/seaborn.barplot.html
# default arguments - seaborn.barplot(x=None, y=None, hue=None, data=None, order=
#with sns.set_style we are controlling the figure aesthetics more here- https://se
sns.set_style('whitegrid')
plt.figure(figsize=(10,8))
# we are grouping the data based on the country destination Link- https://www.gee
df = df_age.groupby('country_destination')['population_in_thousands'].sum()
sns.barplot(x=df.index,y=df)
plt.title('Destination vs population_in_thousands')
```

Out[13]: Text(0.5, 1.0, 'Destination vs population_in_thousands')



It is very clear from the above graph that US is the most populated destination countries and the remaining countries have a population of less than 100 million.

Country Statistics

```
In [14]: df_country = pd.read_csv("countries.csv/countries.csv")
```

```
In [15]: # displays the top 5 rows of the dataframe.
df_country.head()
```

Out[15]:

	country_destination	lat_destination	lng_destination	distance_km	destination_km2	destination_la
0	AU	-26.853388	133.275160	15297.7440	7741220.0	
1	CA	62.393303	-96.818146	2828.1333	9984670.0	
2	DE	51.165707	10.452764	7879.5680	357022.0	
3	ES	39.896027	-2.487694	7730.7240	505370.0	
4	FR	46.232193	2.209667	7682.9450	643801.0	

```
In [16]: # this displays the entire dataframe
df_country
```

Out[16]:

	country_destination	lat_destination	lng_destination	distance_km	destination_km2	destination_la
0	AU	-26.853388	133.275160	15297.7440	7741220.0	
1	CA	62.393303	-96.818146	2828.1333	9984670.0	
2	DE	51.165707	10.452764	7879.5680	357022.0	
3	ES	39.896027	-2.487694	7730.7240	505370.0	
4	FR	46.232193	2.209667	7682.9450	643801.0	
5	GB	54.633220	-3.432277	6883.6590	243610.0	
6	IT	41.873990	12.564167	8636.6310	301340.0	
7	NL	52.133057	5.295250	7524.3203	41543.0	
8	PT	39.553444	-7.839319	7355.2534	92090.0	
9	US	36.966427	-95.844030	0.0000	9826675.0	

```
In [17]: #Displays the unique values of the country_destination feature
df_country['country_destination'].unique()
```

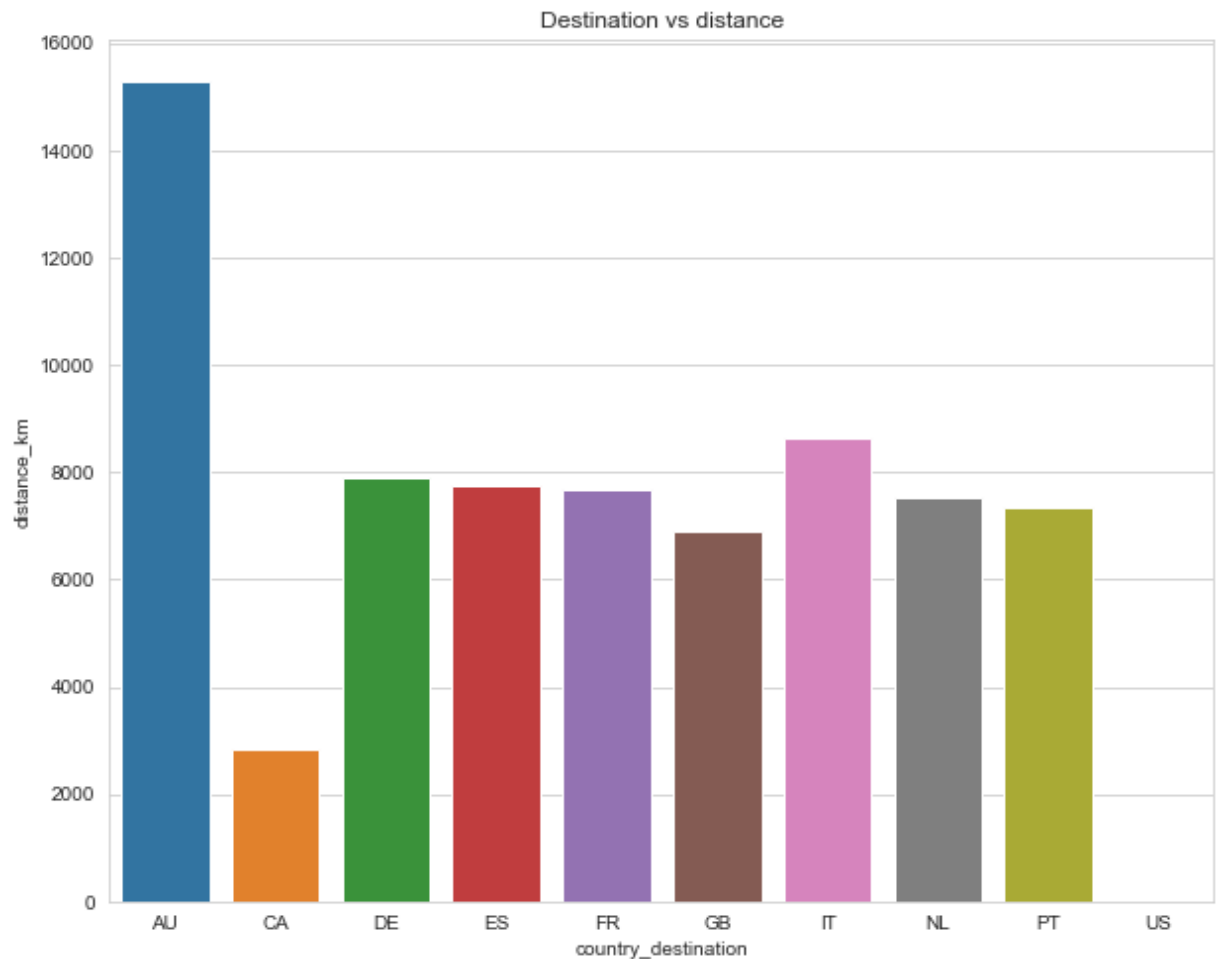
```
Out[17]: array(['AU', 'CA', 'DE', 'ES', 'FR', 'GB', 'IT', 'NL', 'PT', 'US'],
              dtype=object)
```

```
In [18]: #Series.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)
#Return a Series containing counts of unique values.
#Link-https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.Series.value_counts.html
df_train['country_destination'].value_counts()
df_country['country_destination'].value_counts()
```

```
Out[18]: DE      1
FR      1
PT      1
ES      1
AU      1
GB      1
NL      1
US      1
CA      1
IT      1
Name: country_destination, dtype: int64
```

```
In [19]: # seaborn barplot - link-https://seaborn.pydata.org/generated/seaborn.barplot.html
# default arguments - seaborn.barplot(x=None, y=None, hue=None, data=None, order=
#with sns.set_style we are controlling the figure asthetics more here- https://se
sns.set_style('whitegrid')
plt.figure(figsize=(10,8))
sns.barplot(x='country_destination',y='distance_km',data=df_country)
plt.title('Destination vs distance')
```

Out[19]: Text(0.5, 1.0, 'Destination vs distance')



Bar chart describes the distance of the destination country distance from the source country(country from where the booking was done)

To get a better understanding of the corelation between a popularity of a country and language and distance from the origin of booking to its size we will be using a joint plot.

```
In [20]: df_train = pd.read_csv('train_users_2.csv/train_users_2.csv')
```


In [21]: `df_train.head()`

Out[21]:

	id	date_account_created	timestamp_first_active	date_first_booking	gender	age	s
0	gxn3p5htnn	2010-06-28	20090319043255	NaN	unknown-	NaN	
1	820tgsjq7	2011-05-25	20090523174809	NaN	MALE	38.0	
2	4ft3gnwmtx	2010-09-28	20090609231247	2010-08-02	FEMALE	56.0	
3	bjlt8pjhuk	2011-12-05	20091031060129	2012-09-08	FEMALE	42.0	
4	87mebub9p4	2010-09-14	20091208061105	2010-02-18	unknown-	41.0	

In [22]: `Series.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)`
 Return a Series containing counts of unique values.
[Link-https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.Series.value_counts.html](https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.Series.value_counts.html)
`df_train['country_destination'].value_counts()`

Out[22]:

NDF	124543
US	62376
other	10094
FR	5023
IT	2835
GB	2324
ES	2249
CA	1428
DE	1061
NL	762
AU	539
PT	217

Name: country_destination, dtype: int64

In [23]: `df_train[df_train['country_destination'] != 'NDF' & (df_train['country_destination'] != 'other')]`

In [24]: `#Here in the following three cells creating a data frame by taking the values of 'distance_km' and setting the 'country_destination' as the index.`
`dest_dist = df_country['distance_km']`
`dest_dist.index = df_country['country_destination']`

In [25]: `language_difference = df_country['language_levenshtein_distance']`
`language_difference.index = df_country['country_destination']`

In [26]: `destination_area = df_country['destination_km2']`
`destination_area.index = df_country['country_destination']`

```
In [27]: # We are concatenating the dataframes created above using the concat fucntion of
#Link-https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.concat.ht
df_distplot = pd.concat([popularity,dest_dist,language_difference,destination_area])
df_distplot.columns=['popular','dest_dist','language_difference','destination_area']
```

```
In [28]: df_distplot.head()
```

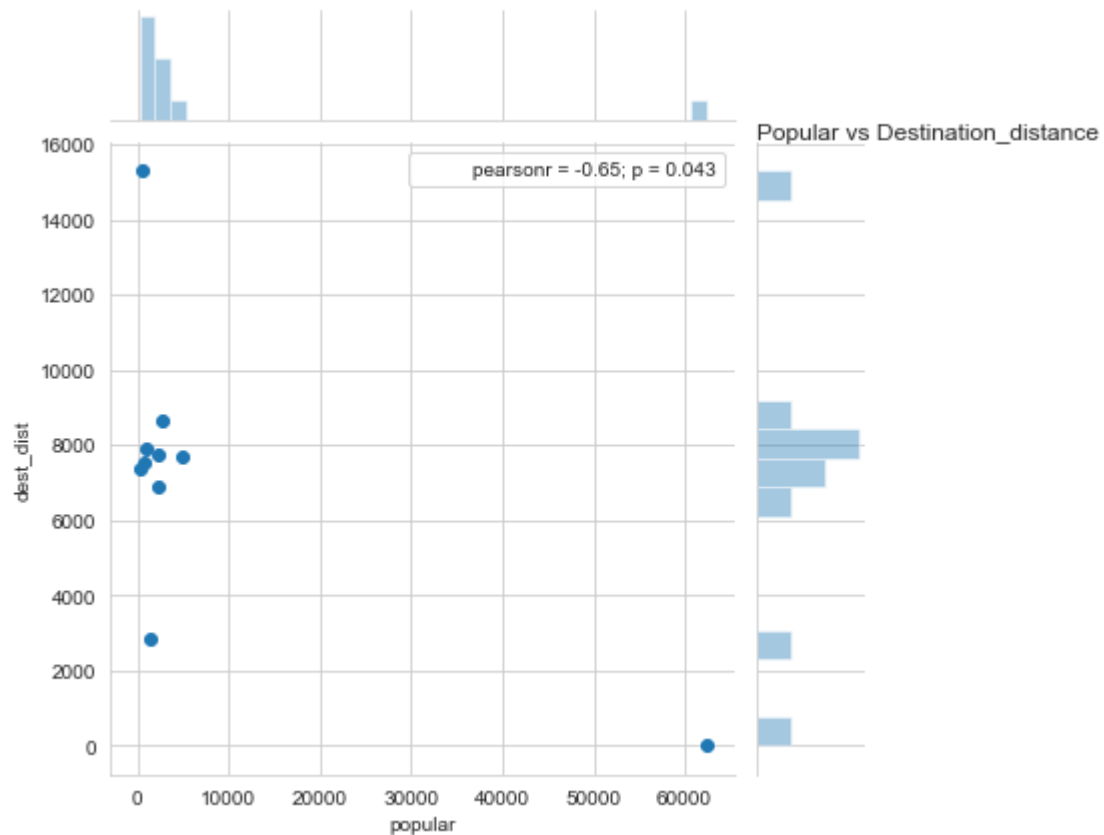
Out[28]:

	popular	dest_dist	language_difference	destination_area
US	62376	0.000	0.00	9826675.0
FR	5023	7682.945	92.06	643801.0
IT	2835	8636.631	89.40	301340.0
GB	2324	6883.659	0.00	243610.0
ES	2249	7730.724	92.25	505370.0

```
In [32]: #seaborn.jointplot(x, y, data=None, kind='scatter', stat_func=None, color=None, h
#Draw a plot of two variables with bivariate and univariate graphs.
#This function provides a convenient interface to the JointGrid class, with sever
#Read more - Link-https://seaborn.pydata.org/generated/seaborn.jointplot.html
j = sns.jointplot(x='popular',y='dest_dist',data=df_distplot)
j.annotate(stats.pearsonr)
plt.title('Popular vs Destination_distance',pad=2.0,loc='left')
plt.show()
```

C:\Users\user\Anaconda3\envs\tf-gpu\lib\site-packages\seaborn\axisgrid.py:1840:
UserWarning: JointGrid annotation is deprecated and will be removed in a future
release.

warnings.warn(UserWarning(msg))

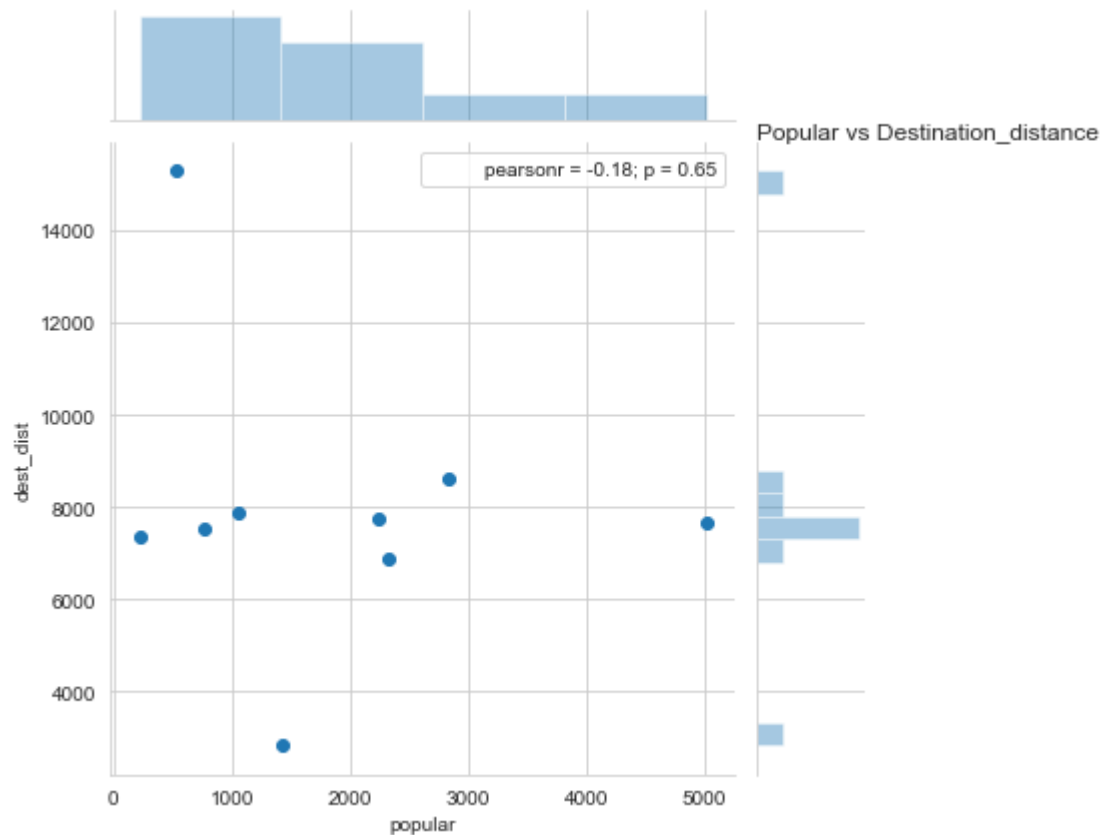


The correlation coefficient here is -ve which shows people tend to choose US i.e their home country than travel abroad i.e many travelers don't want to go far off.

```
In [33]: #seaborn.jointplot(x, y, data=None, kind='scatter', stat_func=None, color=None, h
#Draw a plot of two variables with bivariate and univariate graphs.
#This function provides a convenient interface to the JointGrid class, with sever
#Read more - Link-https://seaborn.pydata.org/generated/seaborn.jointplot.html
j = sns.jointplot(x='popular',y='dest_dist',data=df_distplot.drop('US'))
j.annotate(stats.pearsonr)
plt.title('Popular vs Destination_distance',pad=2.0,loc='left')
plt.show()
```

C:\Users\user\Anaconda3\envs\tf-gpu\lib\site-packages\seaborn\axisgrid.py:1840:
UserWarning: JointGrid annotation is deprecated and will be removed in a future
release.

warnings.warn(UserWarning(msg))

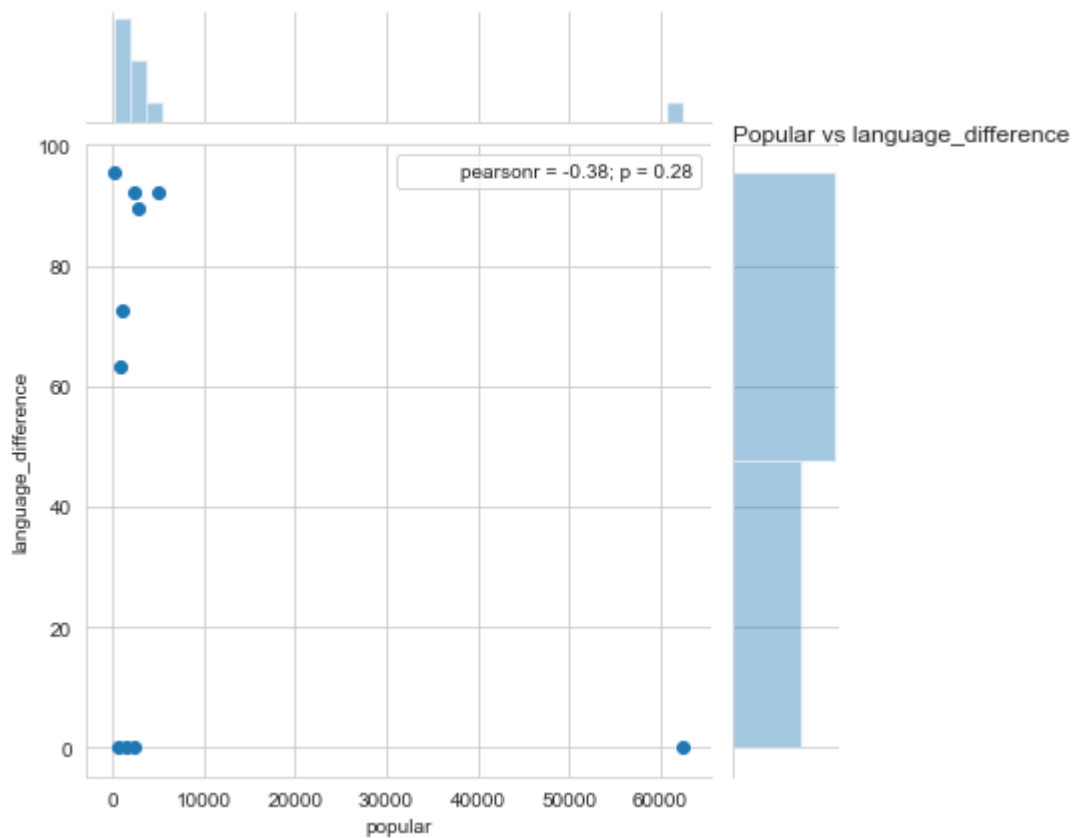


The correlation value has improved but still the users heavily travel close to their country of origin

```
In [34]: #seaborn.jointplot(x, y, data=None, kind='scatter', stat_func=None, color=None, h
#Draw a plot of two variables with bivariate and univariate graphs.
#This function provides a convenient interface to the JointGrid class, with sever
#Read more - Link-https://seaborn.pydata.org/generated/seaborn.jointplot.html
j = sns.jointplot(x='popular',y='language_difference',data=df_distplot)
j.annotate(stats.pearsonr)
plt.title('Popular vs language_difference',pad=2.0,loc='left')
plt.show()
```

C:\Users\user\Anaconda3\envs\tf-gpu\lib\site-packages\seaborn\axisgrid.py:1840:
UserWarning: JointGrid annotation is deprecated and will be removed in a future
release.

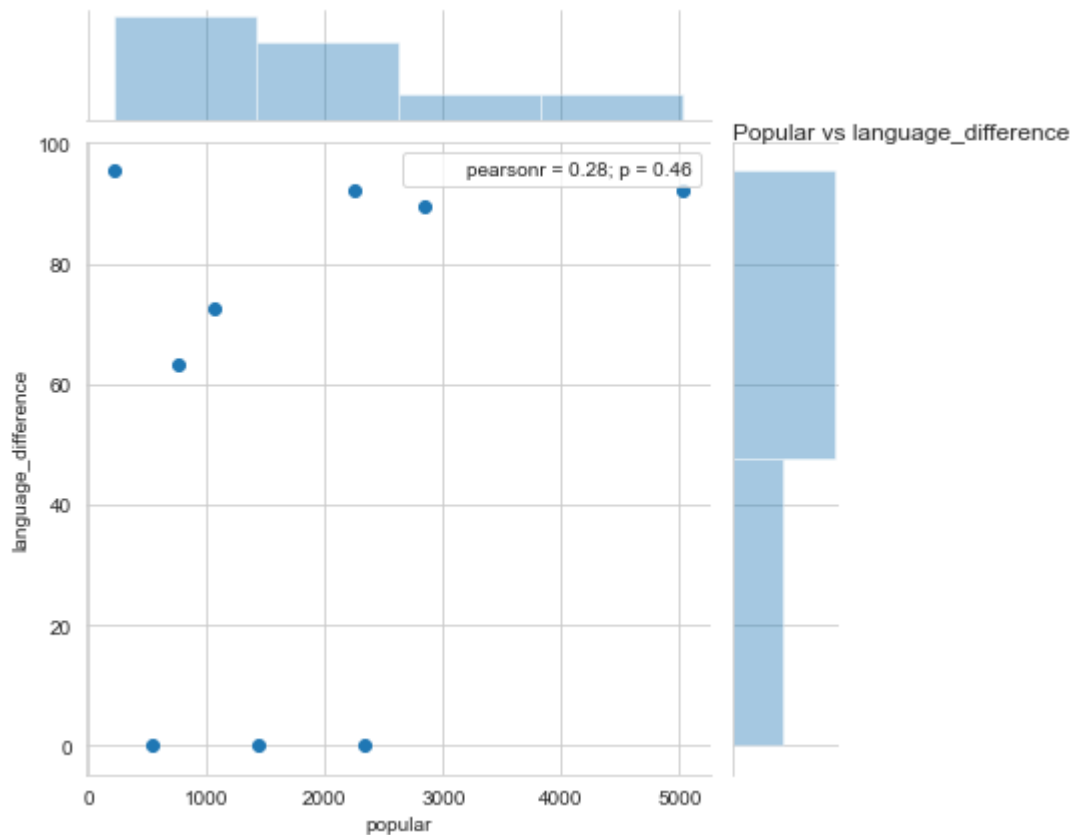
warnings.warn(UserWarning(msg))



```
In [35]: #seaborn.jointplot(x, y, data=None, kind='scatter', stat_func=None, color=None, h
#Draw a plot of two variables with bivariate and univariate graphs.
#This function provides a convenient interface to the JointGrid class, with sever
#Read more - Link-https://seaborn.pydata.org/generated/seaborn.jointplot.html
j = sns.jointplot(x='popular',y='language_difference',data=df_distplot.drop('US'))
j.annotate(stats.pearsonr)
plt.title('Popular vs language_difference',pad=2.0,loc='left')
plt.show()
```

C:\Users\user\Anaconda3\envs\tf-gpu\lib\site-packages\seaborn\axisgrid.py:1840:
UserWarning: JointGrid annotation is deprecated and will be removed in a future
release.

warnings.warn(UserWarning(msg))



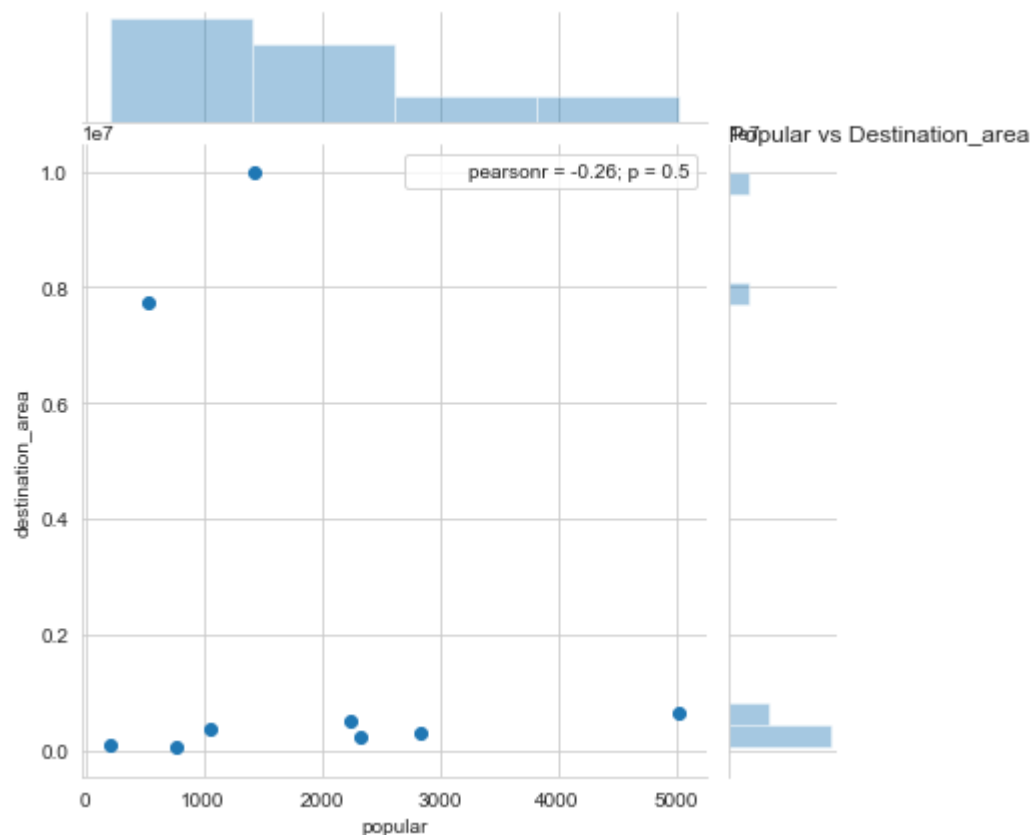
The above two graphs show the correlation between difference of the language of the destination

country and the language of the source country(English). If we remove US as the destination people tend to prefer non english speaking countries

```
In [38]: #seaborn.jointplot(x, y, data=None, kind='scatter', stat_func=None, color=None,
#Draw a plot of two variables with bivariate and univariate graphs.
#This function provides a convenient interface to the JointGrid class, with several
#Read more - Link-https://seaborn.pydata.org/generated/seaborn.jointplot.html
j = sns.jointplot(x='popular',y='destination_area',data=df_distplot.drop('US'))
j.annotate(stats.pearsonr)
plt.title('Popular vs Destination_area',pad=2.0,loc='left')
plt.show()
```

C:\Users\user\Anaconda3\envs\tf-gpu\lib\site-packages\seaborn\axisgrid.py:1840: UserWarning: JointGrid annotation is deprecated and will be removed in a future release.

warnings.warn(UserWarning(msg))



There is a negative correlation here which means people tend to prefer smaller countries and most of the european countries are smaller in size than than non US english speaking countries.

EDA OF Train and Test Users

```
In [39]: print(df_train.head())
print(df_train.shape)
```

```

      id date_account_created  timestamp_first_active  date_first_booking
\
0  gxn3p5htnn          2010-06-28          20090319043255              NaN
1  820tgsjxq7          2011-05-25          20090523174809              NaN
2  4ft3gnwmtx          2010-09-28          20090609231247          2010-08-02
3  bjjt8pjhuk          2011-12-05          20091031060129          2012-09-08
4  87mebub9p4          2010-09-14          20091208061105          2010-02-18

      gender  age  signup_method  signup_flow  language  affiliate_channel  \
0  -unknown-  NaN      facebook           0         en          direct
1      MALE  38.0      facebook           0         en              seo
2      FEMALE  56.0         basic           3         en          direct
3      FEMALE  42.0      facebook           0         en          direct
4  -unknown-  41.0         basic           0         en          direct

      affiliate_provider  first_affiliate_tracked  signup_app  first_device_type  \
0              direct          untracked          Web          Mac Desktop
1             google          untracked          Web          Mac Desktop
2              direct          untracked          Web      Windows Desktop
3              direct          untracked          Web          Mac Desktop
4              direct          untracked          Web          Mac Desktop

      first_browser  country_destination
0          Chrome              NDF
1          Chrome              NDF
2             IE              US
3          Firefox          other
4          Chrome              US
(213451, 16)
```

```
In [40]: df_test = pd.read_csv('test_users.csv/test_users.csv')
```

```
In [41]: # displaying the unique values of the feature column 'date_first_booking'
df_test['date_first_booking'].unique()
```

```
Out[41]: array([nan])
```

from the above analysis we come to the conclusion that the column `date_first_booking` doesn't add much value so we can drop it as the test set doesn't have it.

```
In [42]: #dropping the column 'date_first_booking'
df_train.drop('date_first_booking',axis=1,inplace=True)
```


In [43]: `df_train.head(10)`

Out[43]:

	id	date_account_created	timestamp_first_active	gender	age	signup_method	sign
0	gxn3p5htnn	2010-06-28	20090319043255	unknown-	NaN	facebook	
1	820tgsjxq7	2011-05-25	20090523174809	MALE	38.0	facebook	
2	4ft3gnwmtx	2010-09-28	20090609231247	FEMALE	56.0	basic	
3	bjijt8pjhuk	2011-12-05	20091031060129	FEMALE	42.0	facebook	
4	87mebub9p4	2010-09-14	20091208061105	unknown-	41.0	basic	
5	osr2jwljor	2010-01-01	20100101215619	unknown-	NaN	basic	
6	lsw9q7uk0j	2010-01-02	20100102012558	FEMALE	46.0	basic	
7	0d01nltbrs	2010-01-03	20100103191905	FEMALE	47.0	basic	
8	a1vcnhxeij	2010-01-04	20100104004211	FEMALE	50.0	basic	
9	6uh8zyj2gn	2010-01-04	20100104023758	unknown-	46.0	basic	

In [44]:

```
#Series.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)
#Return a Series containing counts of unique values.
#Link-https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.Series.value_counts.html
df_train['country_destination'].value_counts()
```

Out[44]:

NDF	124543
US	62376
other	10094
FR	5023
IT	2835
GB	2324
ES	2249
CA	1428
DE	1061
NL	762
AU	539
PT	217

Name: country_destination, dtype: int64

```
In [45]: #checking the null values
df_train.isnull().sum()
```

```
Out[45]: id                                0
date_account_created                      0
timestamp_first_active                    0
gender                                    0
age                                       87990
signup_method                             0
signup_flow                              0
language                                 0
affiliate_channel                         0
affiliate_provider                        0
first_affiliate_tracked                   6065
signup_app                               0
first_device_type                         0
first_browser                             0
country_destination                       0
dtype: int64
```

```
In [46]: # displaying the unique values of the gender column
df_train['gender'].unique()
```

```
Out[46]: array(['-unknown-', 'MALE', 'FEMALE', 'OTHER'], dtype=object)
```

```
In [47]: #displaying the unique values of the country_destination column
df_train['country_destination'].unique()
```

```
Out[47]: array(['NDF', 'US', 'other', 'FR', 'CA', 'GB', 'ES', 'IT', 'PT', 'NL',
                'DE', 'AU'], dtype=object)
```

```
In [48]: # displaying the unique values of the first_browser column
df_train['first_browser'].unique()
```

```
Out[48]: array(['Chrome', 'IE', 'Firefox', 'Safari', '-unknown-', 'Mobile Safari',
                'Chrome Mobile', 'RockMelt', 'Chromium', 'Android Browser',
                'AOL Explorer', 'Palm Pre web browser', 'Mobile Firefox', 'Opera',
                'TenFourFox', 'IE Mobile', 'Apple Mail', 'Silk', 'Camino', 'Arora',
                'BlackBerry Browser', 'SeaMonkey', 'Iron', 'Sogou Explorer',
                'IceWeasel', 'Opera Mini', 'SiteKiosk', 'Maxthon',
                'Kindle Browser', 'CoolNovo', 'Conkeror', 'wOSBrowser',
                'Google Earth', 'Crazy Browser', 'Mozilla', 'OmniWeb',
                'PS Vita browser', 'NetNewsWire', 'CometBird', 'Comodo Dragon',
                'Flock', 'Pale Moon', 'Avant Browser', 'Opera Mobile',
                'Yandex.Browser', 'TheWorld Browser', 'SlimBrowser', 'Epic',
                'Stainless', 'Googlebot', 'Outlook 2007', 'IceDragon'],
                dtype=object)
```

```
In [49]: #Replacing the unknown variable with the nan value.
df_train.first_browser.replace("-unknown-", np.nan, inplace=True)
df_train.gender.replace("-unknown-", np.nan, inplace=True)
```

```
In [50]: #Pandas describe() is used to view some basic statistical details like percentile  
#Link -https://www.geeksforgeeks.org/python-pandas-dataframe-describe-method/  
df_train.gender.describe()
```

```
Out[50]: count      117763  
unique         3  
top      FEMALE  
freq       63041  
Name: gender, dtype: object
```

```
In [51]: #Pandas describe() is used to view some basic statistical details like percentile  
#Link -https://www.geeksforgeeks.org/python-pandas-dataframe-describe-method/  
df_train.age.describe()
```

```
Out[51]: count      125461.000000  
mean         49.668335  
std        155.666612  
min          1.000000  
25%         28.000000  
50%         34.000000  
75%         43.000000  
max        2014.000000  
Name: age, dtype: float64
```

```
In [53]: #Pandas DataFrame.loc attribute access a group of rows and columns by label(s) or  
#Link-https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame  
df_train.loc[df_train['age']>1000]['age'].describe()
```

```
Out[53]: count      779.000000  
mean      2011.097561  
std        14.718288  
min      1924.000000  
25%      2014.000000  
50%      2014.000000  
75%      2014.000000  
max      2014.000000  
Name: age, dtype: float64
```

```
In [54]: # since the age has very high values of 1000+ and other values which are very high  
# to reduce the maximum age which otherwise looked like a typo error.  
# In the apply function we are using lambda function to perform our calculation  
df_train['age'] = df_train['age'].apply(lambda x: 2015 - x if x > 1000 else x)
```

```
In [55]: #Pandas describe() is used to view some basic statistical details like percentile  
#Link -https://www.geeksforgeeks.org/python-pandas-dataframe-describe-method/  
df_train.age.describe()
```

```
Out[55]: count    125461.000000  
mean         37.205458  
std          14.209255  
min           1.000000  
25%          28.000000  
50%          34.000000  
75%          43.000000  
max         150.000000  
Name: age, dtype: float64
```

```
In [56]: #Pandas DataFrame.loc attribute access a group of rows and columns by Label(s) or  
#Link-https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame  
df_train.loc[df_train['age']<18]['age'].describe()
```

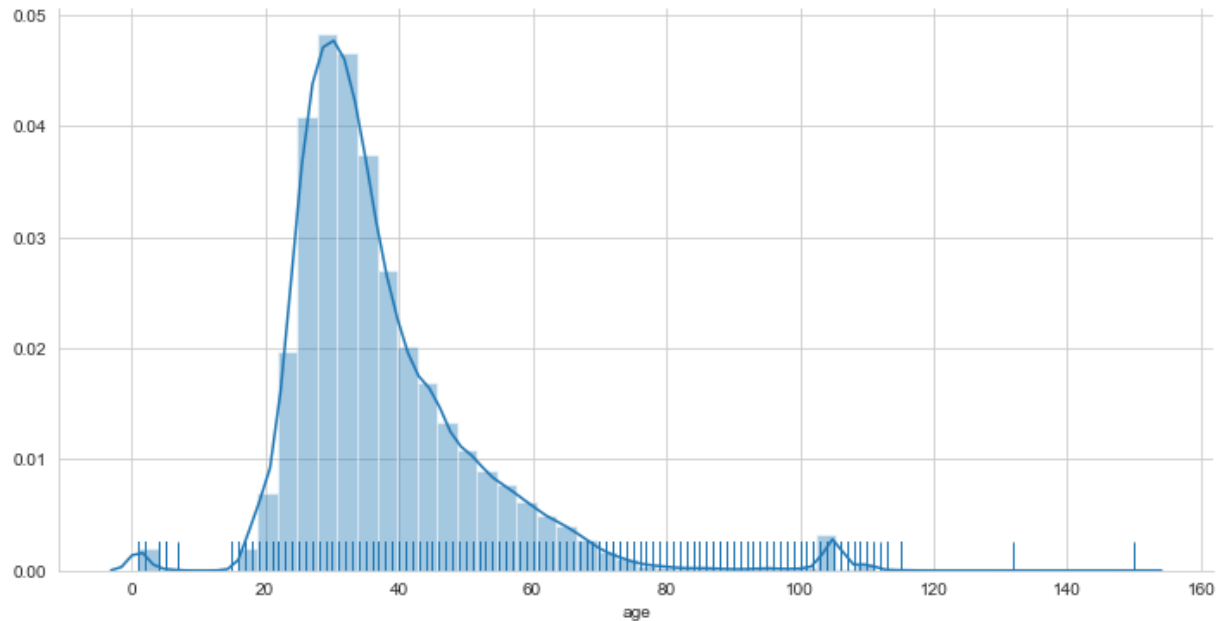
```
Out[56]: count     908.000000  
mean         2.998899  
std          4.899317  
min           1.000000  
25%           1.000000  
50%           1.000000  
75%           1.000000  
max          17.000000  
Name: age, dtype: float64
```

```
In [57]: #Pandas DataFrame.loc attribute access a group of rows and columns by Label(s) or  
#Link-https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame  
  
#Pandas describe() is used to view some basic statistical details like percentile  
#Link -https://www.geeksforgeeks.org/python-pandas-dataframe-describe-method/  
df_train.loc[df_train['age']>100]['age'].describe()
```

```
Out[57]: count      0.0  
mean      NaN  
std      NaN  
min      NaN  
25%      NaN  
50%      NaN  
75%      NaN  
max      NaN  
Name: age, dtype: float64
```

```
In [58]: # Here we are trying to clip off the ages below 18 and above 100 as they don't se  
df_train['age'] = df_train['age'].apply(lambda x: np.nan if (x >100 and x<18) else
```

```
In [59]: #seaborn.distplot(a, bins=None, hist=True, kde=True, rug=False, fit=None, hist_kws=None)
#Flexibly plot a univariate distribution of observations
#Link- https://seaborn.pydata.org/generated/seaborn.distplot.html
plt.figure(figsize=(12,6))
sns.distplot(df_train.age.dropna(),rug=True)
sns.despine()
plt.show()
```

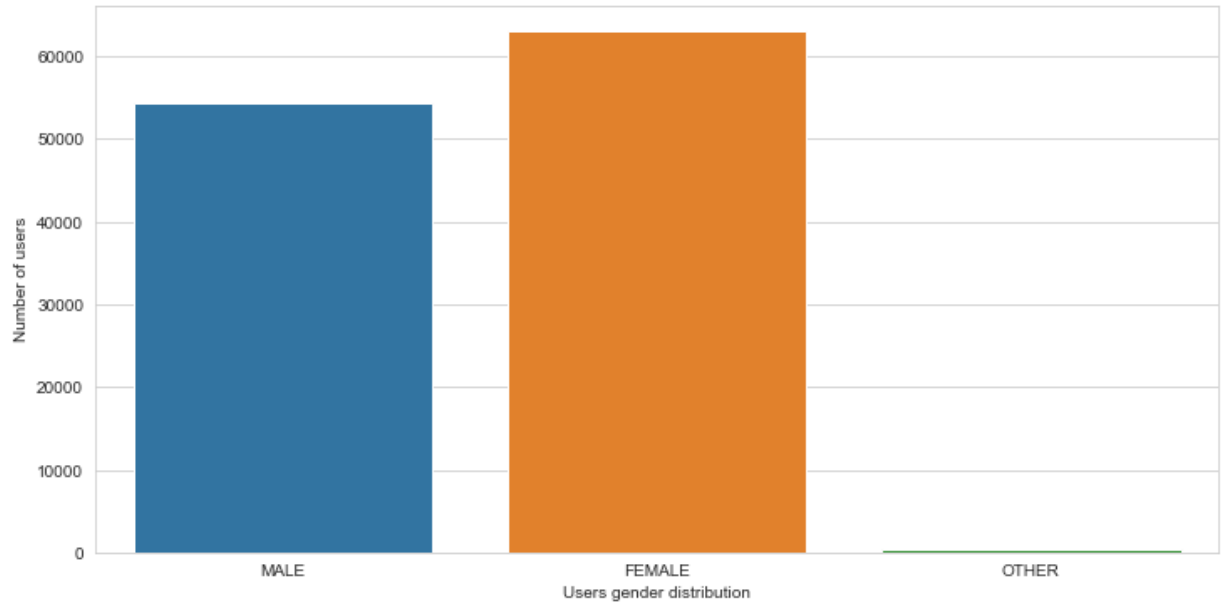


from the above graph it is clearly visible that majority of the users are in the age group of 20-40

User's gender

```
In [29]: #Replacing the unknown variable with the nan value.
df_train.gender.replace("-unknown-", np.nan, inplace=True)
```

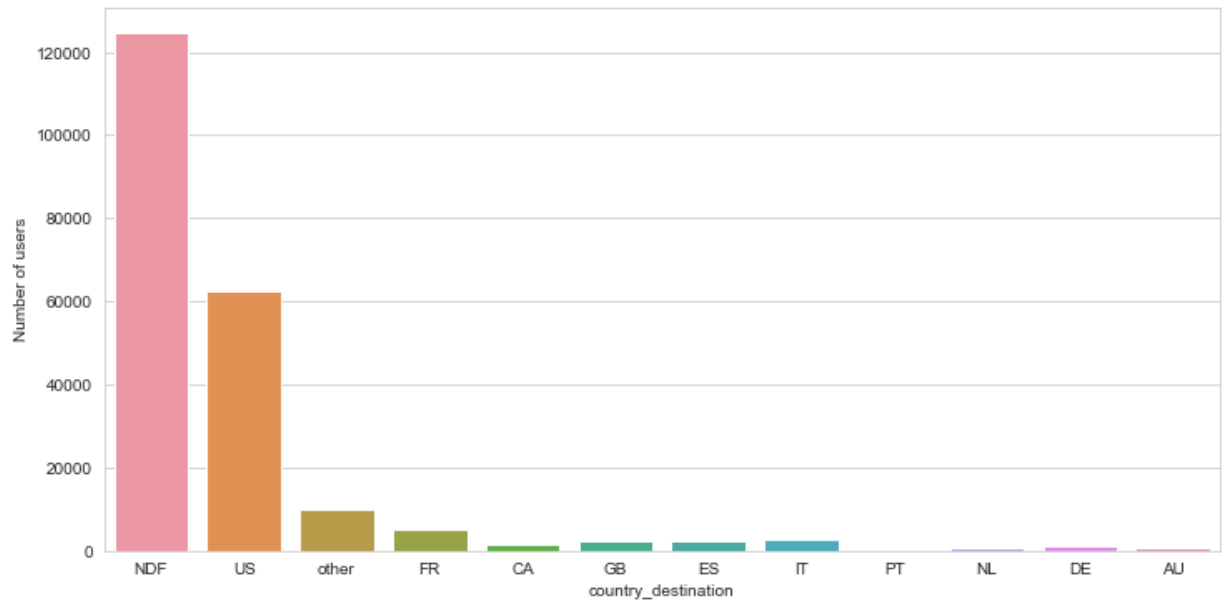
```
In [60]: #seaborn.countplot() method is used to Show the counts of observations in each category
#https://seaborn.pydata.org/generated/seaborn.countplot.html
plt.figure(figsize=(12,6))
sns.countplot(x='gender',data=df_train)
plt.ylabel('Number of users')
plt.xlabel('Users gender distribution')
plt.show()
```



The female count is a bit more than male but not by much

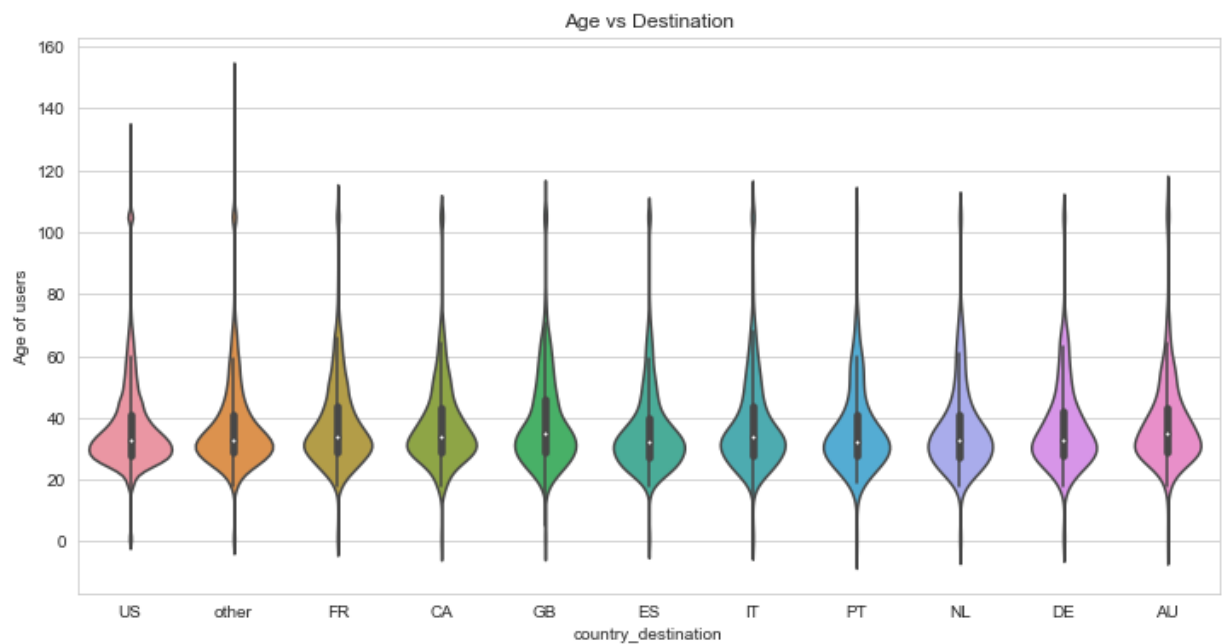
Travel Destination

```
In [61]: #seaborn.countplot() method is used to Show the counts of observations in each category
#https://seaborn.pydata.org/generated/seaborn.countplot.html
plt.figure(figsize=(12,6))
sns.countplot(x='country_destination',data=df_train)
plt.ylabel('Number of users')
plt.xlabel('country_destination')
plt.show()
```



Number of users who did not end up booking any trip is the maximum, the most popular destination which was chosen is US.

```
In [62]: #Violin Plot is a method to visualize the distribution of numerical data of different categories
#The density is mirrored and flipped over and the resulting shape is filled in, c
#Link -https://www.geeksforgeeks.org/violin-plot-for-data-analysis/
plt.figure(figsize=(12,6))
df_withoutNDF = df_train[df_train['country_destination'] != 'NDF']
sns.violinplot(x='country_destination',y='age',data=df_withoutNDF)
plt.xlabel('country_destination')
plt.ylabel('Age of users')
plt.title('Age vs Destination')
plt.show()
```

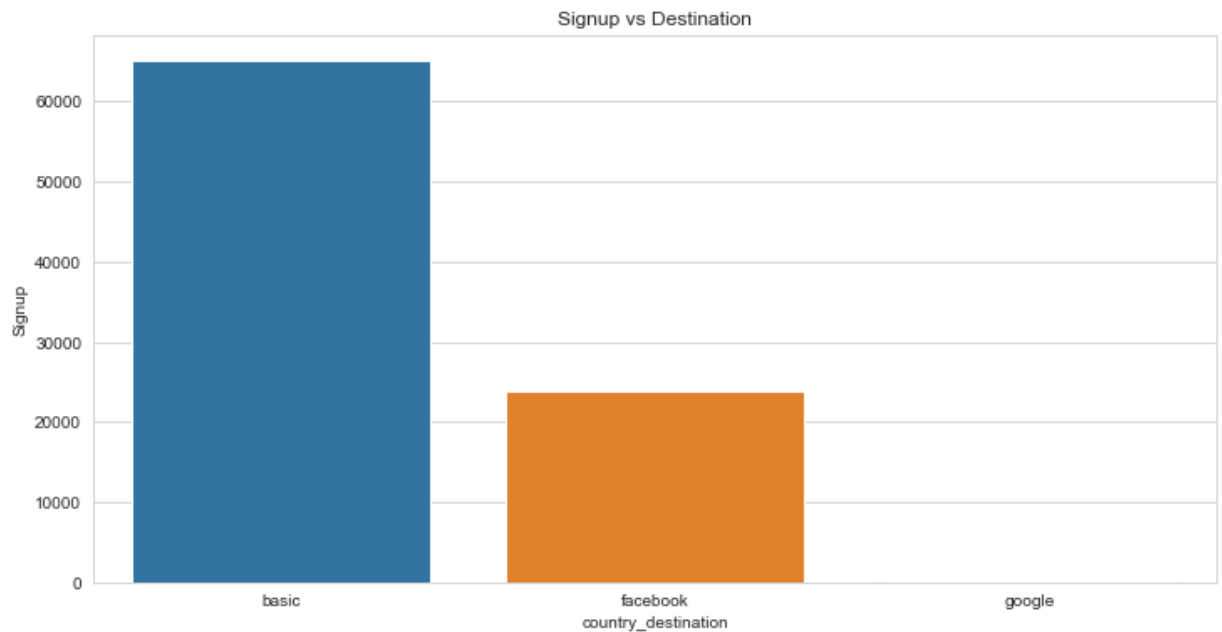


The age difference is not that much when we look at the destinations that are booked, they are pretty evenly spread out.

In [63]: *#seaborn.countplot() method is used to Show the counts of observations in each category*
#https://seaborn.pydata.org/generated/seaborn.countplot.html

```
plt.figure(figsize=(12,6))
plt.figure(figsize=(12,6))
df_withoutNDF = df_train[df_train['country_destination'] != 'NDF']
sns.countplot(x='signup_method', data=df_withoutNDF)
plt.xlabel('country_destination')
plt.ylabel('Signup')
plt.title('Signup vs Destination')
plt.show()
```

<Figure size 864x432 with 0 Axes>



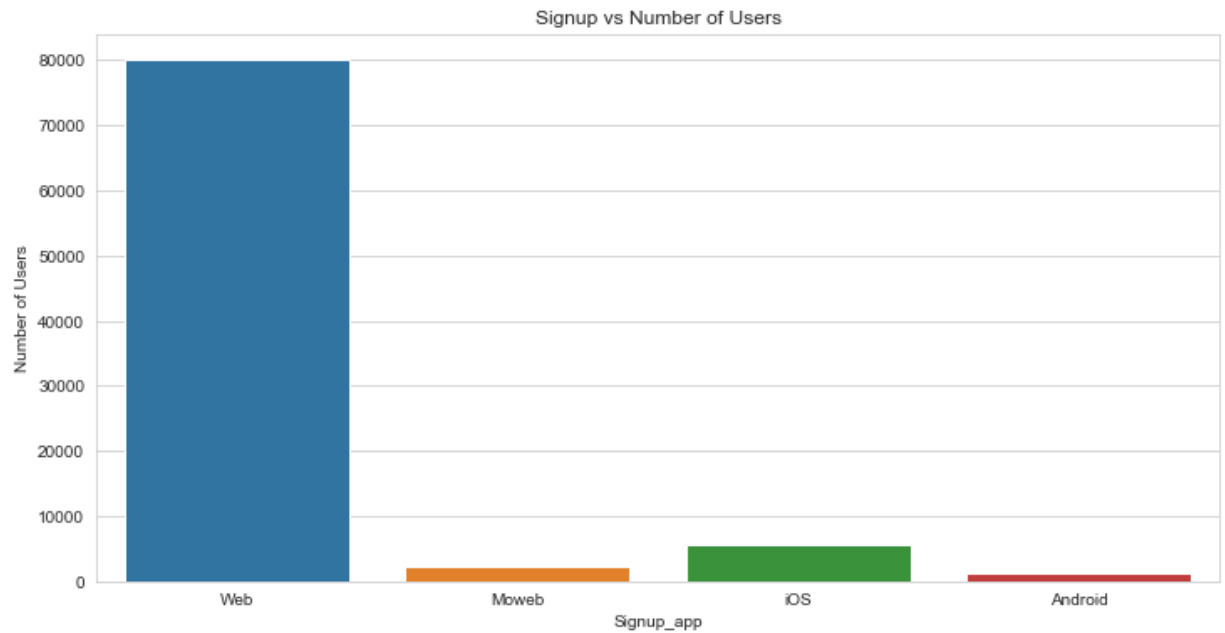
Basic method is the most common method of booking atleast once.

```
In [64]: #seaborn.countplot() method is used to Show the counts of observations in each category
#https://seaborn.pydata.org/generated/seaborn.countplot.html
plt.figure(figsize=(12,6))
df_withoutNDF = df_train[df_train['country_destination'] != 'NDF']
sns.countplot(x='country_destination',data=df_withoutNDF,hue='signup_method')
plt.xlabel('country_destination')
plt.ylabel('Signup')
plt.title('Signup vs Destination')
plt.legend(loc='upper right')
plt.show()
```



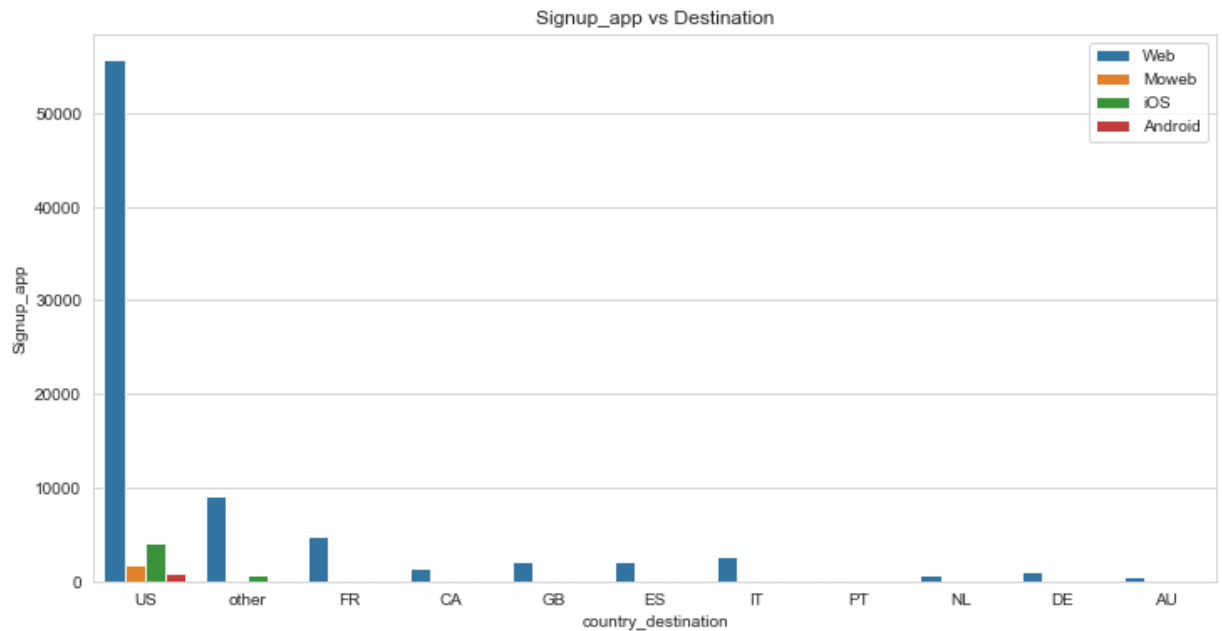
In the above graph we come to a conclusion that the basic email is the most preferred choice of logging into airbnb to book destination

```
In [65]: #seaborn.countplot() method is used to Show the counts of observations in each category
#https://seaborn.pydata.org/generated/seaborn.countplot.html
plt.figure(figsize=(12,6))
df_withoutNDF = df_train[df_train['country_destination'] != 'NDF']
sns.countplot(x='signup_app',data=df_withoutNDF)
plt.xlabel('Signup_app')
plt.ylabel('Number of Users')
plt.title('Signup vs Number of Users')
plt.show()
```



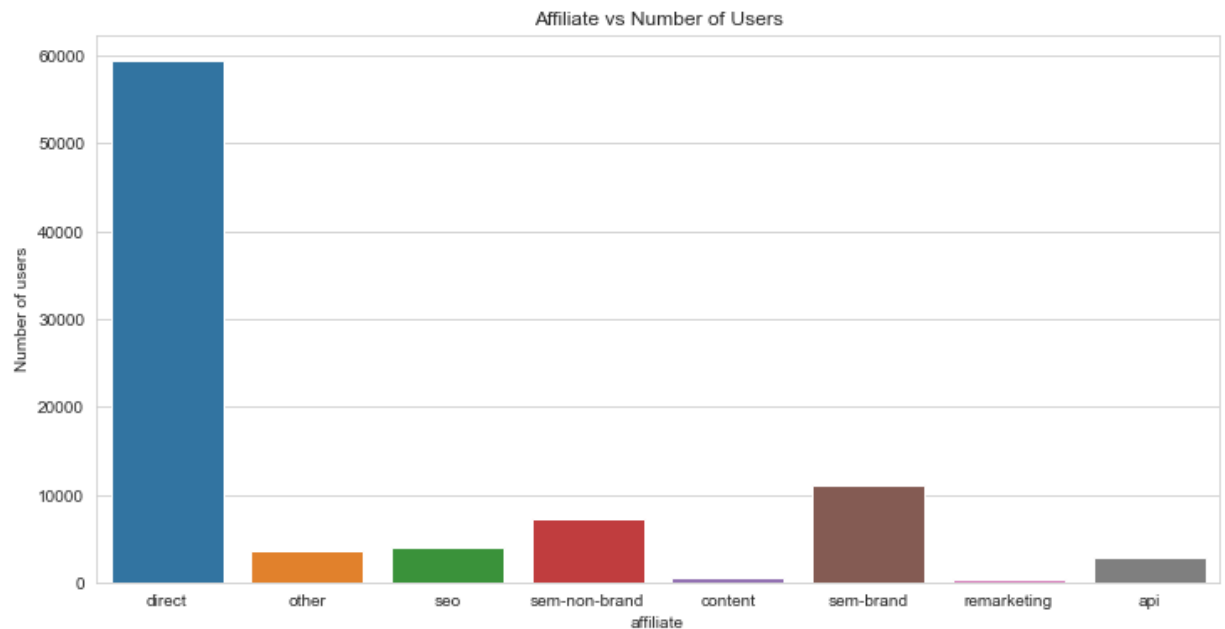
The most preferred way for a user to book is through the web then followed by using an iOS device.

```
In [66]: #seaborn.countplot() method is used to Show the counts of observations in each category
#https://seaborn.pydata.org/generated/seaborn.countplot.html
plt.figure(figsize=(12,6))
df_withoutNDF = df_train[df_train['country_destination'] != 'NDF']
sns.countplot(x='country_destination',data=df_withoutNDF,hue='signup_app')
plt.xlabel('country_destination')
plt.ylabel('Signup_app')
plt.title('Signup_app vs Destination')
plt.legend(loc='upper right')
plt.show()
```



It is clear from the above graph that the users in USA have shown some variation in booking through the app but have majorly used the web to make bookings. The other countries use the web as the only source of booking.

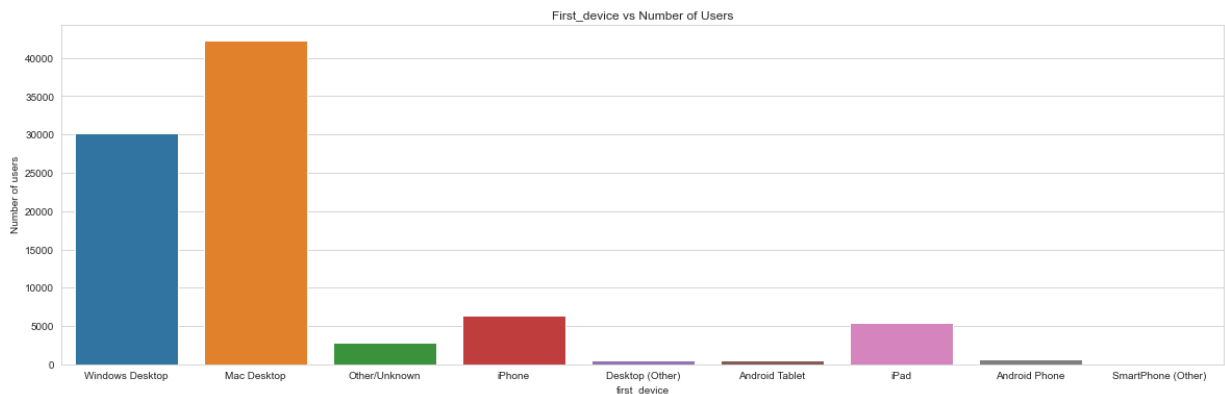
```
In [67]: #seaborn.countplot() method is used to Show the counts of observations in each category
#https://seaborn.pydata.org/generated/seaborn.countplot.html
plt.figure(figsize=(12,6))
df_withoutNDF = df_train[df_train['country_destination'] != 'NDF']
sns.countplot(x='affiliate_channel',data=df_withoutNDF)
plt.xlabel('affiliate')
plt.ylabel('Number of users')
plt.title('Affiliate vs Number of Users')
plt.show()
```



Majority of the users come directly to the web site although some come through the other ads and other channels but the difference is huge.

In [68]: *#seaborn.countplot() method is used to Show the counts of observations in each category*
[#https://seaborn.pydata.org/generated/seaborn.countplot.html](https://seaborn.pydata.org/generated/seaborn.countplot.html)

```
plt.figure(figsize=(20,6))
df_withoutNDF = df_train[df_train['country_destination'] != 'NDF']
sns.countplot(x='first_device_type',data=df_withoutNDF)
plt.xlabel('first_device')
plt.ylabel('Number of users')
plt.title('First_device vs Number of Users')
plt.show()
```



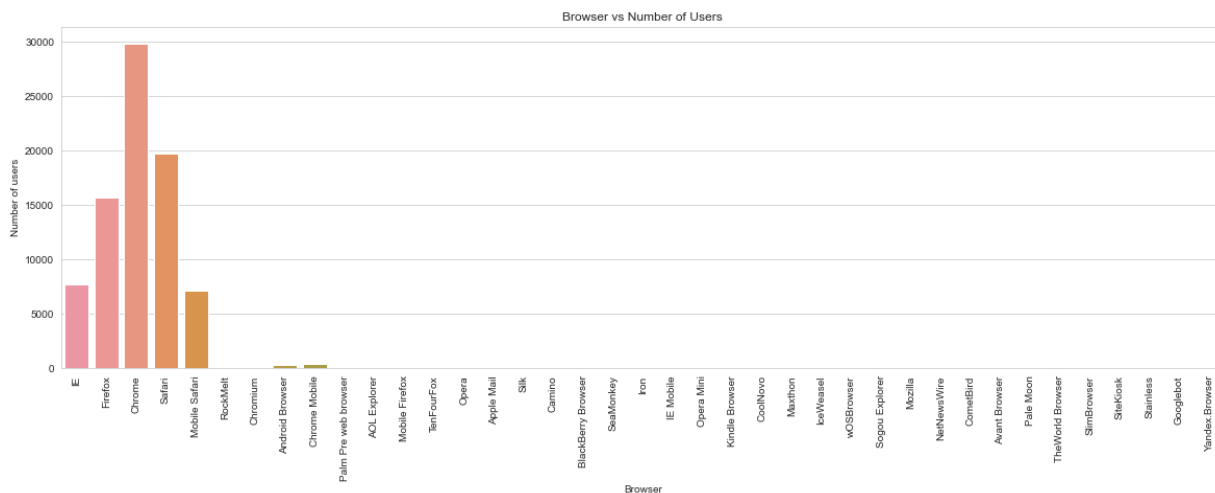
In [69]: *#seaborn.countplot() method is used to Show the counts of observations in each category*
[#https://seaborn.pydata.org/generated/seaborn.countplot.html](https://seaborn.pydata.org/generated/seaborn.countplot.html)

```
plt.figure(figsize=(12,6))
df_withoutNDF = df_train[df_train['country_destination'] != 'NDF']
sns.countplot(x='country_destination',data=df_withoutNDF,hue='first_device_type')
plt.xlabel('country_destination')
plt.ylabel('Number of users')
plt.title('First_device_type vs Destination')
plt.legend(loc='upper right')
plt.show()
```



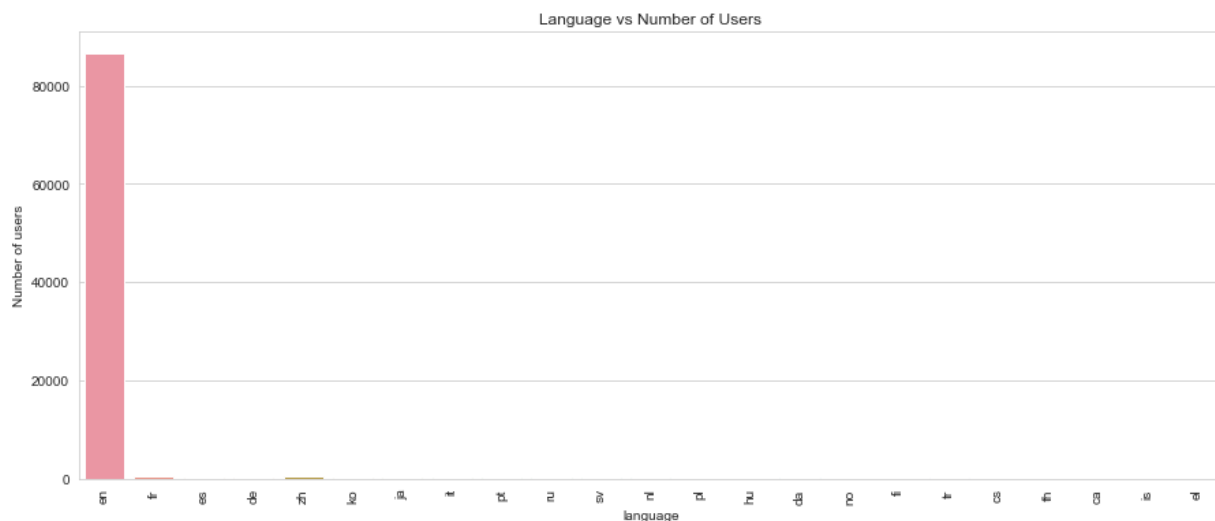
The above two graphs show that Apple devices are primarily the most common devices used by the users to book their travel destination whether it is in the US or any other country

```
In [70]: #seaborn.countplot() method is used to Show the counts of observations in each category
#https://seaborn.pydata.org/generated/seaborn.countplot.html
plt.figure(figsize=(20,6))
df_withoutNDF = df_train[df_train['country_destination'] != 'NDF']
sns.countplot(x='first_browser',data=df_withoutNDF)
plt.xlabel('Browser')
plt.ylabel('Number of users')
plt.title('Browser vs Number of Users')
plt.xticks(rotation=90)
plt.show()
```



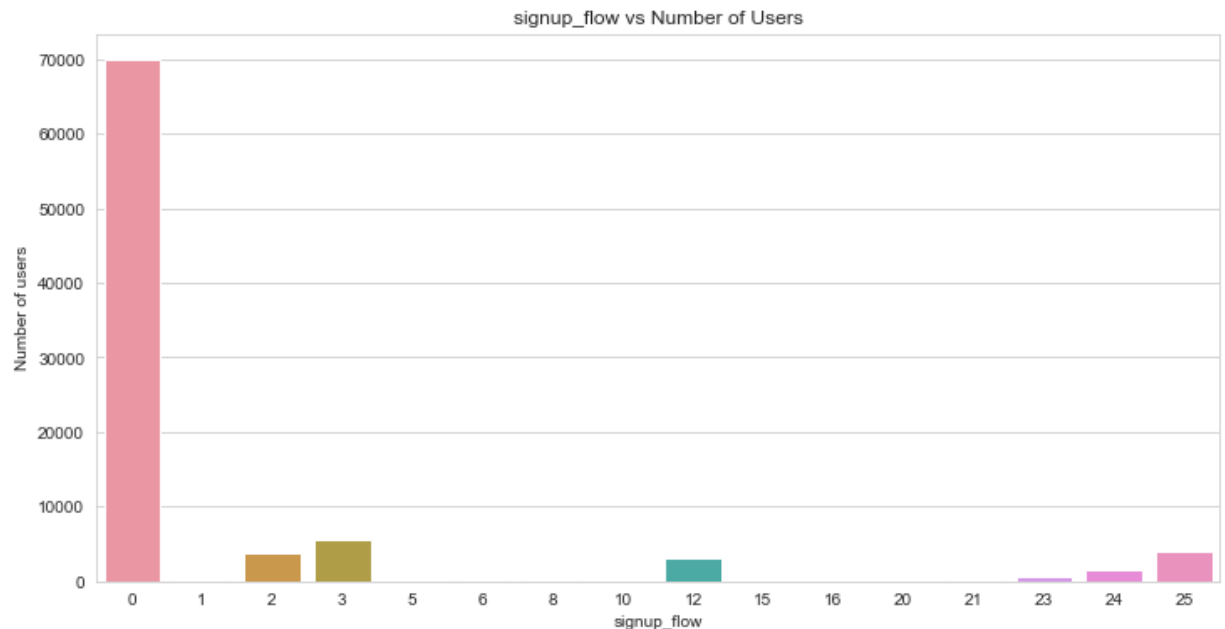
Chrome is the most popular browser used to access the website

```
In [71]: #seaborn.countplot() method is used to Show the counts of observations in each category
#https://seaborn.pydata.org/generated/seaborn.countplot.html
plt.figure(figsize=(15,6))
df_withoutNDF = df_train[df_train['country_destination'] != 'NDF']
sns.countplot(x='language',data=df_withoutNDF)
plt.xlabel('language')
plt.ylabel('Number of users')
plt.title('Language vs Number of Users')
plt.xticks(rotation=90)
plt.show()
```



```
In [72]: #seaborn.countplot() method is used to Show the counts of observations in each category
#https://seaborn.pydata.org/generated/seaborn.countplot.html
plt.figure(figsize=(12,6))
df_withoutNDF = df_train[df_train['country_destination'] != 'NDF']
sns.countplot(x='signup_flow',data=df_withoutNDF)
plt.xlabel('signup_flow')
plt.ylabel('Number of users')
plt.title('signup_flow vs Number of Users')

plt.show()
```



```
In [73]: #Pandas describe() is used to view some basic statistical details like percentile
#Link -https://www.geeksforgeeks.org/python-pandas-dataframe-describe-method/
df_train['signup_flow'].describe()
```

```
Out[73]: count    213451.000000
mean         3.267387
std          7.637707
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max          25.000000
Name: signup_flow, dtype: float64
```

English is the most popular language.

Dates

- We will visualize how the users will be booking across the year which months there are more bookings etc.


```
In [74]: # this shows all the columns present in the dataframe
df_withoutNDF.columns
```

```
Out[74]: Index(['id', 'date_account_created', 'timestamp_first_active', 'gender', 'age',
               'signup_method', 'signup_flow', 'language', 'affiliate_channel',
               'affiliate_provider', 'first_affiliate_tracked', 'signup_app',
               'first_device_type', 'first_browser', 'country_destination'],
              dtype='object')
```

```
In [75]: #Pandas DataFrame.loc attribute access a group of rows and columns by label(s) or
#Link-https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame
# in this cell we are converting the timestamp value in the correct datetime form
# Link- https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.to_datetime
import pandas as pd
result = df_withoutNDF.loc[:, 'timestamp_first_active']
result = pd.to_datetime(result, infer_datetime_format=True)
```

```
In [76]: df_withoutNDF.head()
```

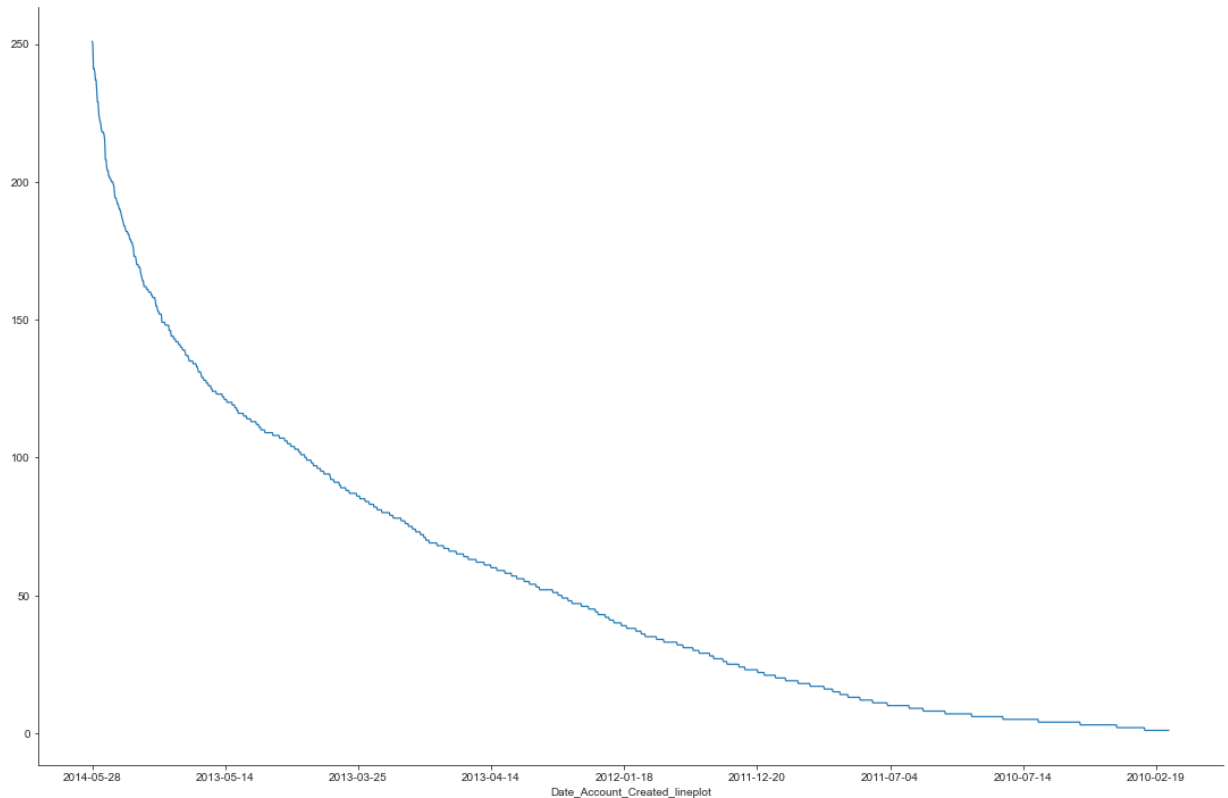
```
Out[76]:
```

	id	date_account_created	timestamp_first_active	gender	age	signup_method	signup_flow
2	4ft3gnwmtx	2010-09-28	20090609231247	FEMALE	56.0	basic	
3	bjlt8pjhuk	2011-12-05	20091031060129	FEMALE	42.0	facebook	
4	87mebub9p4	2010-09-14	20091208061105	NaN	41.0	basic	
5	osr2jwljor	2010-01-01	20100101215619	NaN	NaN	basic	
6	lsw9q7uk0j	2010-01-02	20100102012558	FEMALE	46.0	basic	

```
In [77]: sns.set_style('ticks')
fig,ax = plt.subplots()
fig.set_size_inches(18.7,12.27)
df_withoutNDF.date_account_created.value_counts().plot(kind='line',linewidth=1.2)
plt.xlabel('Date_Account_Created_lineplot')
sns.despine()
```

C:\Users\user\Anaconda3\envs\tf-gpu\lib\site-packages\pandas\plotting_matplotlib\ib\core.py:1192: UserWarning: FixedFormatter should only be used together with FixedLocator

```
ax.set_xticklabels(xticklabels)
```



The user growth has taken up sharply after 2013

Users's Session Data

```
In [78]: session = pd.read_csv("sessions.csv/sessions.csv")
```

```
In [79]: session.columns
```

```
Out[79]: Index(['user_id', 'action', 'action_type', 'action_detail', 'device_type',  
              'secs_elapsed'],  
              dtype='object')
```

```
In [80]: print("The number of unique session ids are:",len(session.user_id.unique()))
```

The number of unique session ids are: 135484

```
In [81]: #Pandas describe() is used to view some basic statistical details like percentile  
#Link -https://www.geeksforgeeks.org/python-pandas-dataframe-describe-method/
```

```
session.action_type.describe()
```

```
Out[81]: count      9441533  
         unique         10  
         top          view  
         freq      3560902  
         Name: action_type, dtype: object
```

```
In [82]: #Pandas describe() is used to view some basic statistical details like percentile  
#Link -https://www.geeksforgeeks.org/python-pandas-dataframe-describe-method/  
session.action.describe()
```

```
Out[82]: count      10488111  
         unique         359  
         top          show  
         freq      2768278  
         Name: action, dtype: object
```

```
In [83]: #Pandas describe() is used to view some basic statistical details like percentile  
#Link -https://www.geeksforgeeks.org/python-pandas-dataframe-describe-method/  
session.action_detail.describe()
```

```
Out[83]: count      9441533  
         unique         155  
         top    view_search_results  
         freq      1776885  
         Name: action_detail, dtype: object
```

```
In [84]: #Series.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)
#Return a Series containing counts of unique values.
#Link-https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.Series.value_counts.html
df_train['country_destination'].value_counts()
session.action_detail.value_counts().head(10)
```

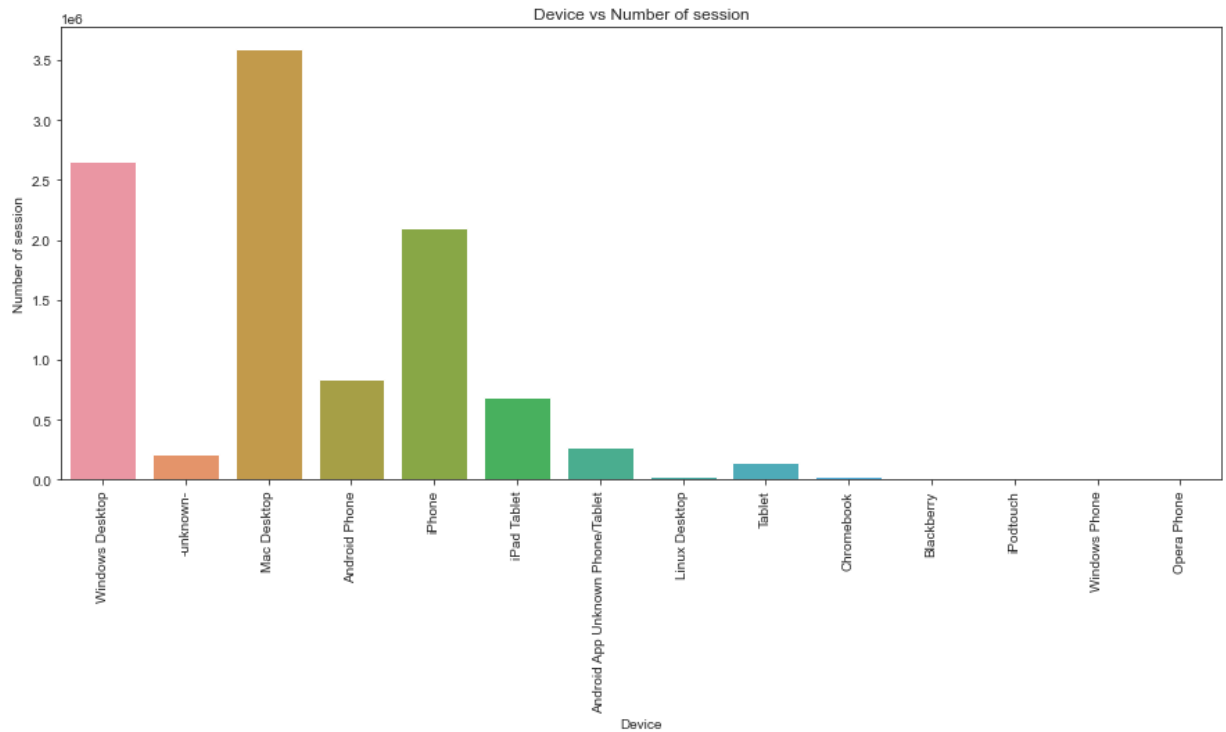
```
Out[84]: view_search_results      1776885
p3                                1376550
-unknown-                        1031141
wishlist_content_update          706824
user_profile                     656839
change_trip_characteristics      487744
similar_listings                 364624
user_social_connections          336799
update_listing                   269779
listing_reviews                  269021
Name: action_detail, dtype: int64
```

```
In [85]: #Series.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)
#Return a Series containing counts of unique values.
#Link-https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.Series.value_counts.html
df_train['country_destination'].value_counts()
session.action.value_counts().head(5)
```

```
Out[85]: show      2768278
index      843699
search_results  725226
personalize   706824
search      536057
Name: action, dtype: int64
```

The most popular action amongst the users is browsing i.e show and the remaining values are kind of similar.

```
In [86]: #seaborn.countplot() method is used to Show the counts of observations in each category
#https://seaborn.pydata.org/generated/seaborn.countplot.html
plt.figure(figsize=(15,6))
sns.countplot(x='device_type',data=session)
plt.xlabel('Device')
plt.ylabel('Number of session')
plt.title('Device vs Number of session')
plt.xticks(rotation=90)
plt.show()
```



As seen from the train and test set EDA it is here from the session data analysis too confirmed that Mac Desktop is most preferred tool to access Airbnb

In []: