Capstone Project - Airbnb New user booking

April 26, 2016

1 Analysis

1.1 Data Exploration and Exploratory Visualization

Some data exploration and exploratory visualization will be performed in order to better understand the data I am dealing with in this Kaggle Competition.

In [2]:
```
# Import libraries
import numpy as np
import pandas as pd


import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('whitegrid')

# Math
from math import floor

%matplotlib inline
```

In [3]:
```
# Loading data in Memory
country_data = pd.read_csv("../data/countries.csv")
gender_data = pd.read_csv("../data/age_gender_bkts.csv")

# train data / test data
train_data = pd.read_csv("../data/train_users_2.csv")
target = train_data['country_destination']
test_data = pd.read_csv("../data/test_users.csv")
```

In [8]:
```
# Some useful constants
n_train_data = len(train_data)
n_test_data = len(test_data)
print("#training samples: {}".format(n_train_data))
```

```
#training samples: 213451
```

In [4]:
```
# summary statistics of destination countries in this dataset and their locations
country_data.head()
```

Out[4]:
```
  country_destination  lat_destination  lng_destination  distance_km  \
0                  AU       -26.853388       133.275160   15297.7440
1                  CA        62.393303       -96.818146    2828.1333
2                  DE        51.165707        10.452764    7879.5680
```

```
3                  ES        39.896027        -2.487694    7730.7240
4                  FR        46.232193         2.209667    7682.9450

   destination_km2 destination_language   language_levenshtein_distance
0        7741220.0                  eng                            0.00
1        9984670.0                  eng                            0.00
2         357022.0                  deu                           72.61
3         505370.0                  spa                           92.25
4         643801.0                  fra                           92.06
```

In [5]:
```python
#  summary statistics of users' age group, gender, country of destination
gender_data.head()
```

Out[5]:
```
  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 [6]:
```python
# What are the train data like?
train_data.head()
```

Out[6]:
```
           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
```

- Some data samples are presented in the previous table.
- Some features might need some cleaning
- Age (a lot of them are NaN and wrong values)

- Dates - We'll need to parse them and transform them into some other features (seasons, years, ...)

Some statistics about the provided features and dataset

- 15 features.
- Mix of continuous and discrete features (age, timestamp, categorical...).
- Size of training set: 213451 instances.
- 12 classes: NDF, US, other, FR, IT, GB, ES, CA, DE, NL, AU, PT

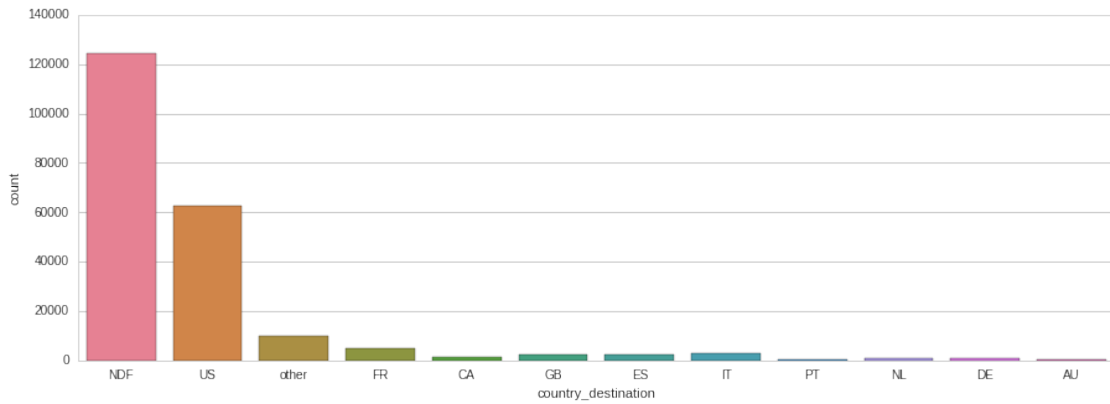
Here is a complete description of the provided features

- id: user id (sequence of characters and digits)
- date_account_created: the date of account creation, format "YYYY-mm-dd" (eg. 2010-06-28)
- timestamp_first_active: timestamp of the first activity, note that it can be earlier than date_account_created or date_first_booking because a user can search before signing up (integer, eg. 20090319043255)
- date_first_booking: date of first booking, format "YYYY-mm-dd"
- gender: categorical (MALE, FEMALE, OTHER, unknown)
- age: discrete variable (from 1 to 2014 with NaNs)
- signup_method: categorical variable (facebook, google, basic, ...)
- signup_flow: the page a user came to signup up from, categorical variable (0 to 5)
- language: international language preference, categorical variable (eg. en)
- affiliate_channel: what kind of paid marketing, categorical variable (eg. seo, channel, ...)
- affiliate_provider: where the marketing is e.g. google, craigslist, other, categorical variable (eg. direct, google, ...)
- first_affiliate_tracked: whats the first marketing the user interacted with before the signing up, categorical variable
- signup_app: categorical variable (eg. Web)
- first_device_type: categorical variable (eg. Mac Desktop, Windows Desktop, ...)
- first_browser: categorical variable (eg. Chrome, Safari,...)
- country_destination: this is the target variable you are to predict (14 classes)

In [9]:
```python
# Let's have a look at the training data
fig, (axis1) = plt.subplots(1,1,figsize=(15,5))
sns.countplot(x='country_destination', data=train_data, palette="husl", ax=axis1)

pd.DataFrame({'country_destination_percent' : target.value_counts() * 100 / n_train_data})
```

Out[9]:

	country_destination_percent
NDF	58.347349
US	29.222632
other	4.728954
FR	2.353233
IT	1.328174
GB	1.088774
ES	1.053638
CA	0.669006
DE	0.497070
NL	0.356991
AU	0.252517
PT	0.101663



The data suggest that

- 58% of the new users do not make any booking.
- 30% book in the US
- 5% are other

It seems that americans tend to prefer traveling in their own country rather than traveling abroad.

1.2 Benchmark

In order to assess our model's performances, some benchmarks are required.

1.2.1 Sample submission Benchmark 1

The first idea that comes to mind is to create a classifier that outputs only NDF as predictions. It should provide a simple benchmark for our next iterations. Below is the code used to generate this simple benchmark and writes it in a CSV file so that it can be submitted to Kaggle.

```
def df_submission(ids, f):
    ids_result = []  # list of ids
    cts = []         # list of countries
    for i in range(len(ids)):
        idx = ids[i]
        ids_result += [idx] * 5
        cts += f(i)
    return pd.DataFrame(np.column_stack((ids_result, cts)),
                        columns=['id', 'country'])


def generate_benchmark1_submission(df_train, target, ids):
    df_sub = df_submission(ids, lambda i: ['NDF'])
    df_sub.to_csv(SUBMISSION_PATH + 'benchmark1.csv', index=False)
    return df_sub
```

The NDCG@5 score is: **0.68411** (from Kaggle's scorer)

1.2.2 Sample submission Benchmark 2

The second benchmark that can be used to assess our model's performance is the following: Always predict the 5 top country destinations sorted by frequencies (see previous table). * NDF * US * other * FR * IT

Here is the code for generating this benchmark and saving it into a csv file:

```
def generate_benchmark2_submission(df_train, target, ids):
    prediction = target.value_counts().index.tolist()[:5]
    df_sub = df_submission(ids, lambda i: prediction)
    df_sub.to_csv(SUBMISSION_PATH + 'benchmark2.csv', index=False)
    return df_sub
```

The NDCG@5 score is: **0.85670** (from Kaggle's scorer)

1.2.3 Best entry on this competition

The current best entry is scored **0.88697** in the leaderboard. It is relatively close to the sample submission benchmark 2 (score difference of **0.03**).

1.2.4 Goal

The goal of this project is to create a model that is in between the sample submission benchmark 2 and the best entry in the competition. It means that my model's score should be in the range [**0.85670, 0.88697**]

1.3 Age

In this section, I will explore and discuss the age data.

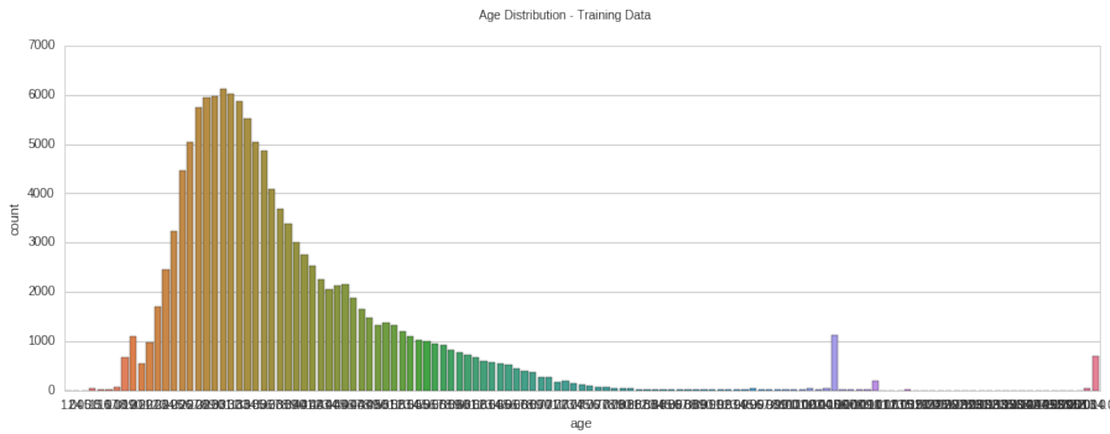
```
In [149]: # Age exploration
          age = train_data['age'].dropna() # A lot of NaN -> fix it with ML?
          real_age = age[(age >= 5) & (age <= 95)] # A lot of outliers
          print(real_age.describe())

          # % of NaNs
          percentage_age_NaN = train_data['age'].isnull().sum() * 100 / real_age.describe()['count']
          print("% of NaN entries: {0:.1f}%".format(percentage_age_NaN))
```

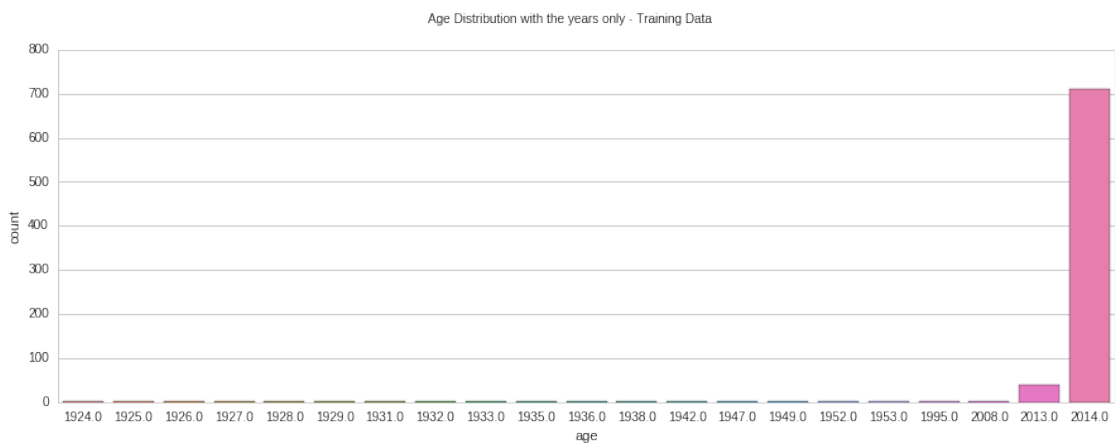
```
count    123011.000000
mean         36.501142
std          11.585328
min           5.000000
25%          28.000000
50%          34.000000
75%          42.000000
max          95.000000
Name: age, dtype: float64
% of NaN entries: 71.5%
```

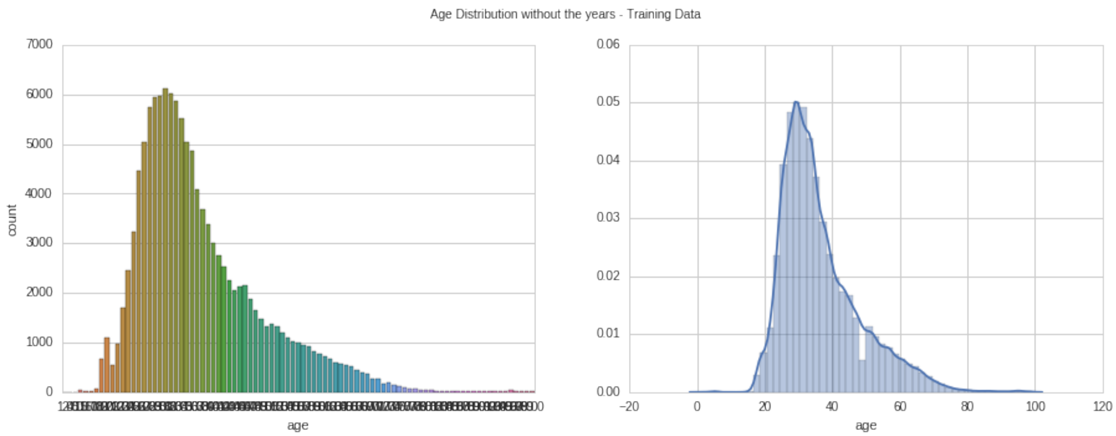
```
In [201]: # Exploring the Age Distribution

          # Training Data
          fig, (axis1) = plt.subplots(1,1,figsize=(15,5))
          fig.suptitle('Age Distribution - Training Data')
          sns.countplot(x='age', data=train_data, palette="husl", ax=axis1)

          # Removing the age values
          fig, (axis1) = plt.subplots(1,1,figsize=(15,5))
          fig.suptitle('Age Distribution with the years only - Training Data')
          sns.countplot(x='age', data=train_data[train_data['age'] > 300], palette="husl", ax=axis1)

          # Removing the year values
          fig, (axis1,axis2) = plt.subplots(1,2,figsize=(15,5))
```

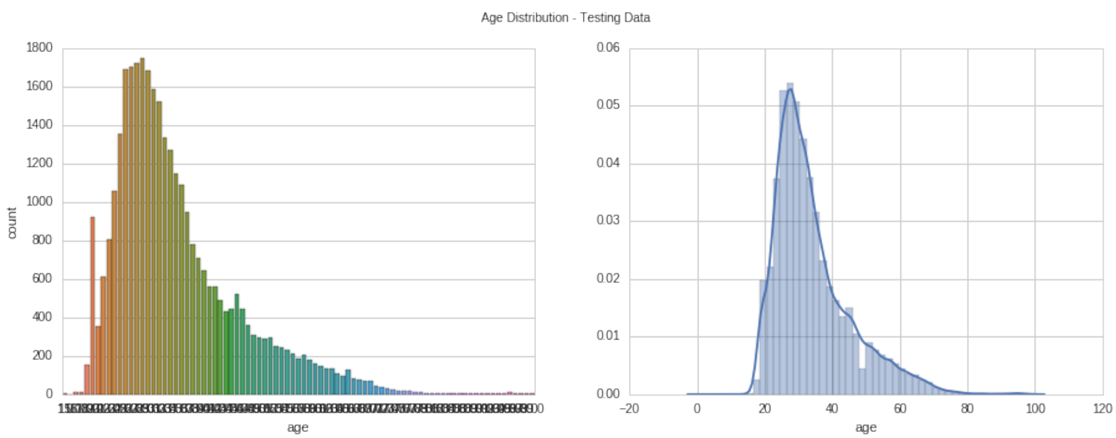
```
fig.suptitle('Age Distribution without the years - Training Data')
sns.countplot(x='age', data=train_data[train_data['age'] < 100], palette="husl", ax=axis1)
sns.distplot(train_data[train_data['age'] < 100]['age'], ax=axis2)

# Testing Data
fig, (axis1, axis2) = plt.subplots(1,2,figsize=(15,5))
fig.suptitle('Age Distribution - Testing Data')
sns.countplot(x='age', data=test_data[test_data['age'] < 100], palette="husl", ax=axis1)
sns.distplot(test_data[test_data['age'] < 100]['age'], ax=axis2)

# cut age values into ranges
fig, (axis1) = plt.subplots(1,1,figsize=(15,5))
fig.suptitle('Age ranges and country destinations')
train_data['age_range'] = pd.cut(train_data["age"], [0, 20, 40, 60, 80, 100])
sns.countplot(x="age_range",hue="country_destination", data=train_data[train_data['country_des
```

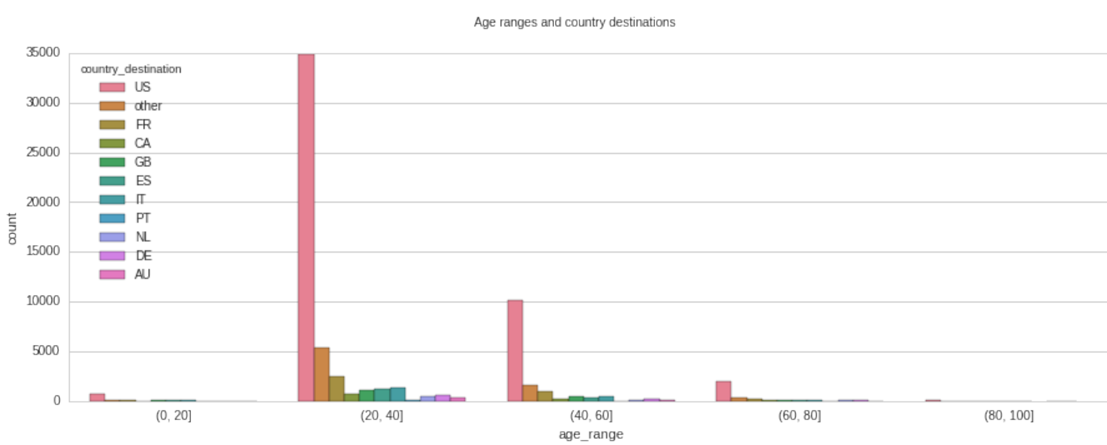
Out[201]: <matplotlib.axes._subplots.AxesSubplot at 0x7f2902496210>











I notice that the age data is malformed

- Sometimes it is an age and sometimes a year date,

- Some values do not make much sense: age <= 5, age >= 95,
- There are a lot of NaN values meaning that these people did not fill out this form input.

Some thoughts on the data * The age distribution seems close to a **Poisson distribution**, * Training and testing data follow the same distribution for age. Which is very important for the training and predicting. * I will need to clean up the data by transforming years

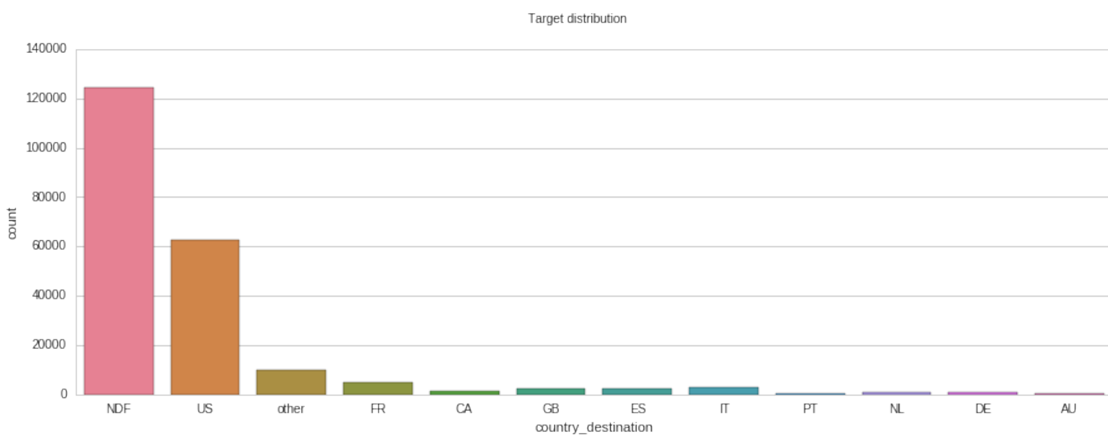
Cleaning the data

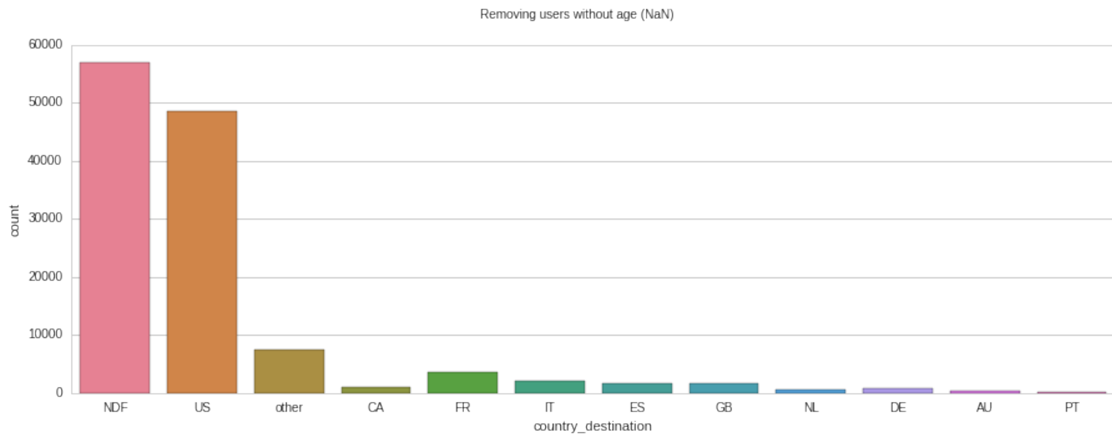
- Set a valid range (x0, x1) where x0 = 15, x1 = 90
- any values between 1915 and 2000 are birth years
- any age outside the valid range is set to NaN

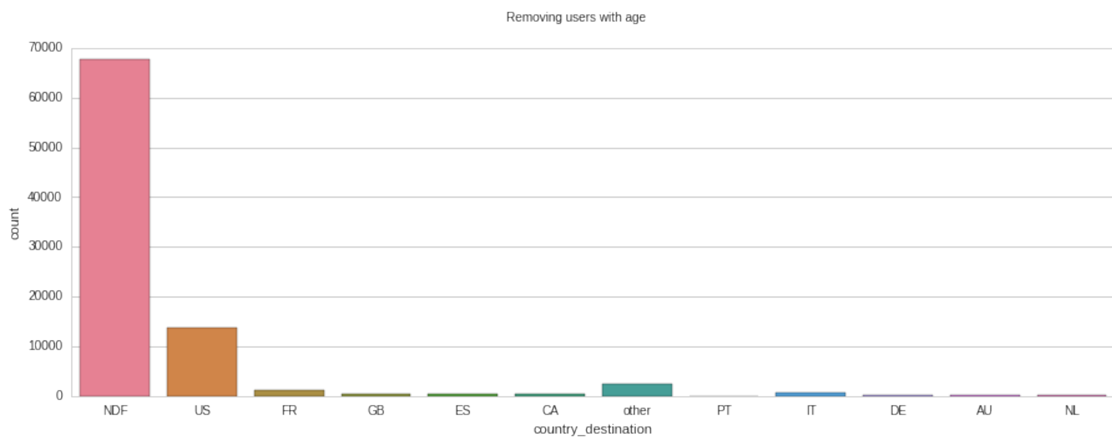
What is the correlation between users not filling their ages and the destination? Let's have a look.

In [151]:
```
# Without changing the target data
fig, (axis1) = plt.subplots(1,1,figsize=(15,5))
fig.suptitle('Target distribution')
sns.countplot(x='country_destination', data=train_data, palette="husl", ax=axis1)

# Removing users without age
fig, (axis1) = plt.subplots(1,1,figsize=(15,5))
fig.suptitle('Removing users without age (NaN)')
sns.countplot(x='country_destination', data=train_data[train_data['age'].notnull()], palette=

# Removing users with age
fig, (axis1) = plt.subplots(1,1,figsize=(15,5))
fig.suptitle('Removing users with age')
sns.countplot(x='country_destination', data=train_data[train_data['age'].isnull()], palette="
```

Out[151]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f290985fa10>
```





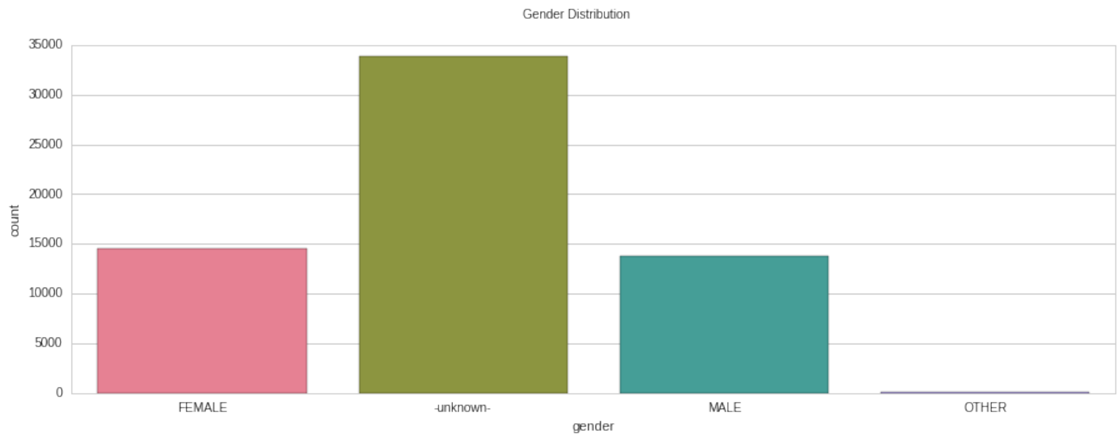


From the plots above, the data suggests that only 25% of users with missing ages book while 55% of users with age book a trip. **NDF** stands for No Destination Found.

1.4 Gender

In [153]:
```
# Gender Exploration
gender = train_data['gender']
gender.value_counts(normalize=True) # How to fix unknown? and OTHER?

fig, (axis1) = plt.subplots(1,1,figsize=(15,5))
fig.suptitle('Gender Distribution')
sns.countplot(x='gender', data=test_data, palette="husl", ax=axis1)
```

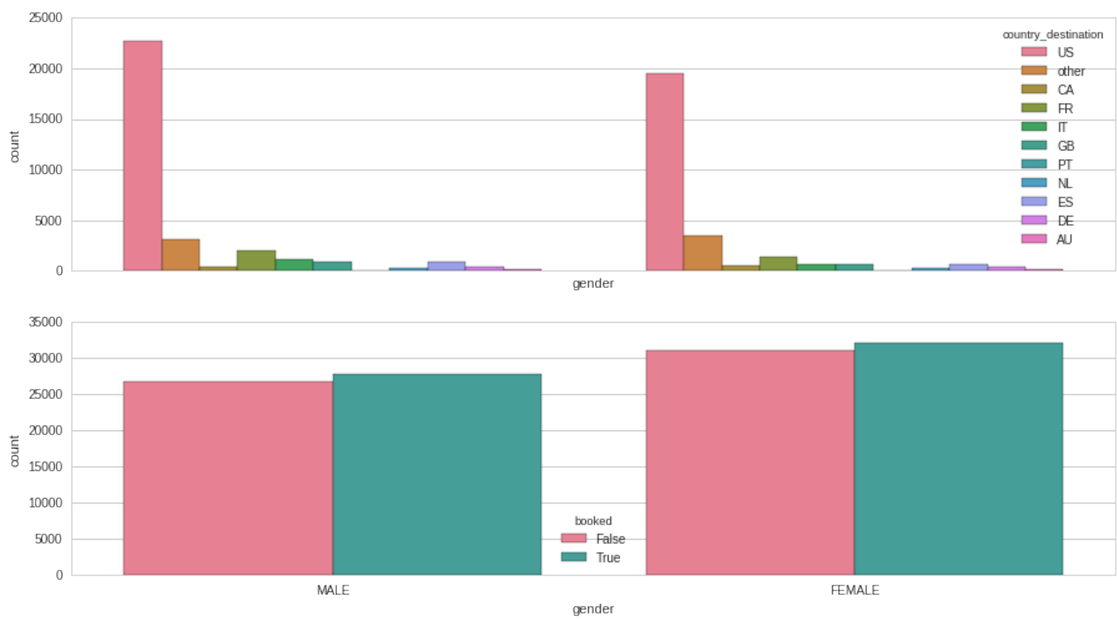
Out[153]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f290b5ee310>
```



This column needs some cleaning by removing the unknown and other.

```
In [154]: # Keeping only
          train_data_clean_gender = train_data.query('["MALE", "FEMALE"] in gender')
          train_data_clean_gender.loc[:, 'booked'] = train_data["country_destination"].apply(lambda x :

          fig, (axis1, axis2) = plt.subplots(2,1,sharex=True,figsize=(15,8))
          sns.countplot(x="gender",hue="country_destination", data=train_data_clean_gender[train_data_c
          sns.countplot(x="gender",hue="booked", data=train_data_clean_gender, palette="husl", ax=axis2
```

```
Out[154]: <matplotlib.axes._subplots.AxesSubplot at 0x7f2909925f90>
```



The data suggests that the gender has no impact on the country destination and if the first destination was booked.

```
In [169]: train_data['signup_method'].value_counts(normalize=True)
```

```
Out[169]: basic       0.716310
          facebook    0.281132
          google      0.002558
          Name: signup_method, dtype: float64
```

```
In [168]: train_data['first_device_type'].value_counts(normalize=True)
```

```
Out[168]: Mac Desktop           0.419768
          Windows Desktop       0.340668
          iPhone                0.097254
          iPad                  0.067177
          Other/Unknown         0.049974
          Android Phone         0.013132
          Android Tablet        0.006053
          Desktop (Other)       0.005617
          SmartPhone (Other)    0.000356
          Name: first_device_type, dtype: float64
```

```
In [171]: train_data['first_browser'].value_counts(normalize=True)
```

```
Out[171]: Chrome                  0.299108
          Safari                  0.211613
          Firefox                 0.157671
          -unknown-               0.127739
          IE                      0.098702
          Mobile Safari           0.090297
          Chrome Mobile           0.005950
          Android Browser         0.003987
          AOL Explorer            0.001148
          Opera                   0.000881
          Silk                    0.000581
          Chromium                0.000342
          BlackBerry Browser      0.000248
          Maxthon                 0.000216
          IE Mobile               0.000169
          Apple Mail              0.000169
          Sogou Explorer          0.000155
          Mobile Firefox          0.000141
          SiteKiosk               0.000112
          RockMelt                0.000112
          Iron                    0.000080
          IceWeasel               0.000061
          Pale Moon               0.000056
          Yandex.Browser          0.000052
          SeaMonkey               0.000052
          CometBird               0.000052
          Camino                  0.000042
          TenFourFox              0.000037
          wOSBrowser              0.000028
          CoolNovo                0.000028
          Avant Browser           0.000019
          Opera Mini              0.000019
          Mozilla                 0.000014
          Comodo Dragon           0.000009
          Flock                   0.000009
```

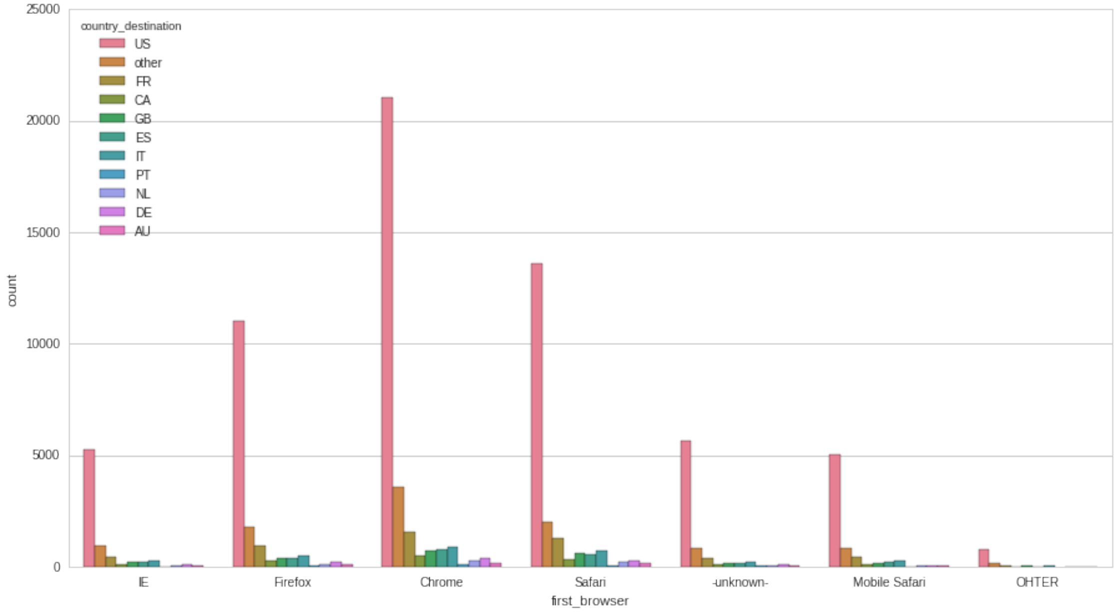
```
Opera Mobile             0.000009
SlimBrowser              0.000009
OmniWeb                  0.000009
Crazy Browser            0.000009
TheWorld Browser         0.000009
PS Vita browser          0.000005
Googlebot                0.000005
IceDragon                0.000005
Stainless                0.000005
Conkeror                 0.000005
Outlook 2007             0.000005
Palm Pre web browser     0.000005
Kindle Browser           0.000005
Epic                     0.000005
Google Earth             0.000005
Arora                    0.000005
NetNewsWire              0.000005
Name: first_browser, dtype: float64
```

Some values are not useful if the frequency is too low. A cleaning step is to remove/change the value if the frequency is under a threshold.

```
In [190]: def clean_under_threshold(df, column, f, freq_threshold=.001):
              frequencies = df[column].value_counts(normalize=True)
              return apply_on(df, column, lambda x: f(x) if frequencies[x] < freq_threshold else x)

          clean_data_first_browser = clean_under_threshold(train_data, 'first_browser', lambda x: 'OHTE
          print(clean_data_first_browser['first_browser'].value_counts(normalize=True))

          # Plot the first browsers
          fig, (axis1) = plt.subplots(1,1,sharex=True,figsize=(15,8))
          sns.countplot(x="first_browser",hue="country_destination", data=clean_data_first_browser[clea
```

```
Chrome           0.299108
Safari           0.211613
Firefox          0.157671
-unknown-        0.127739
IE               0.098702
Mobile Safari    0.090297
OHTER            0.014870
Name: first_browser, dtype: float64
```

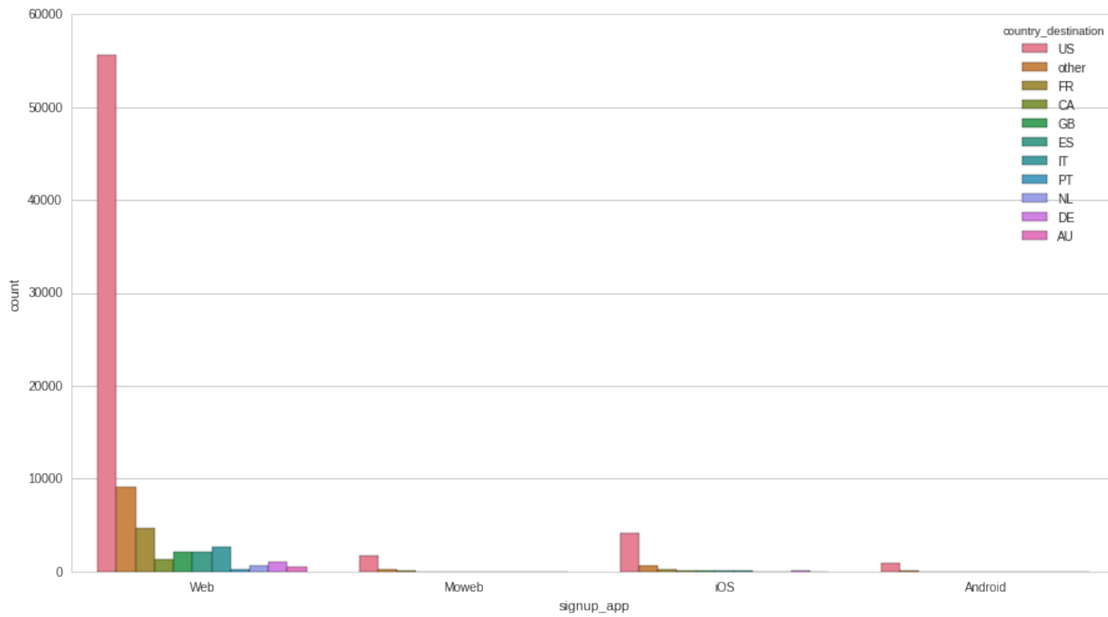
```
Out[190]: <matplotlib.axes._subplots.AxesSubplot at 0x7f2903fa7e50>
```




```
In [188]: print(train_data['signup_app'].value_counts(normalize=True))

          # Plot the signup app
          fig, (axis1) = plt.subplots(1,1,sharex=True,figsize=(15,8))
          sns.countplot(x="signup_app",hue="country_destination", data=train_data[train_data['country_de
```

```
Web         0.856014
iOS         0.089102
Moweb       0.029332
Android     0.025552
Name: signup_app, dtype: float64
```

```
Out[188]: <matplotlib.axes._subplots.AxesSubplot at 0x7f2903efab90>
```



1.5 Algorithms and Techniques

- The trained model will return probabilities for each country destination given a new unseen datapoint. The 5 most likely classes will be used to make a prediction in that order.
- The datasets provided by Kaggle are quite small (they fit in RAM) which makes model training and evaluation simpler since I do not need to use distributed computing or large EC2 instances to handle it.
- Computation will be done on my laptop (at least at the beginning) so that I can iterate faster on the core algorithms and data processing. Later, when hyperparameter tuning is performed, I might need to run it in on an other machine to get it done faster.

With small datasets, batch training can be done and many algorithms can be tested and compared

- SVMs
- Decision Trees
- Naive Bayes
- ...

1.5.1 Cleaning and missing values

The age feature is very messy and some cleaning is needed to make use of it.

- The outliers will be removed,
- The years will be transformed in ages,
- The missing values will be replaced with the collection's mean.

1.5.2 Feature Engineering

The date features need to be transformed to numbers. Some feature engineering is needed to make that transformation. We may want to keep or engineer the following

- Year
- Month
- Day
- Weekday
- Season
- ...

The first step is to use the train_users.csv dataset only. If needed, I'll make use of the sessions.csv and the other csv files.

1.5.3 Data Transformation

Some data transformation will be needed

- Dimensionality reduction (with Principal Componenent Analysis): The training set is not large and the curse of dimensionality can be the root cause for bad performances.
- Data normalization: Some algorithms I want to try require data normalization (SVM and Naive Bayes for instance).

1.5.4 Boosting methods

Some boosting methods will be used to get better scores. I am planning on trying

- Random Forests (Adaboost or Bagging),
- Extreme Gradient Boosting - xgboost - that usually works well on Kaggle competitions.

```
In [ ]:
```