
# *Airbnb Data Analysis and predicting the destination country for a new user*

*4th Sept 2020*

## *OVERVIEW:*

Airbnb is a renowned American vacation rental online marketplace which offers arrangements for lodging, primarily homestays or tourism experiences. It has a wide range of options to choose from 34000+ cities around 190 countries.

## *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()
```

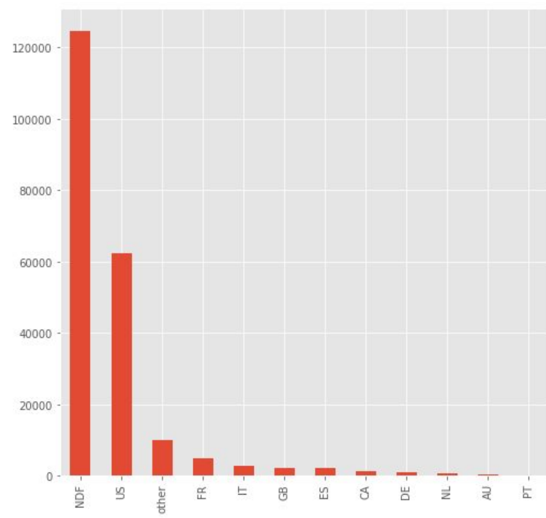
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10567737 entries, 0 to 10567736
Data columns (total 6 columns):
user_id          object
action           object
action_type      object
action_detail    object
device_type      object
secs_elapsed     float64
dtypes: float64(1), object(5)
memory usage: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

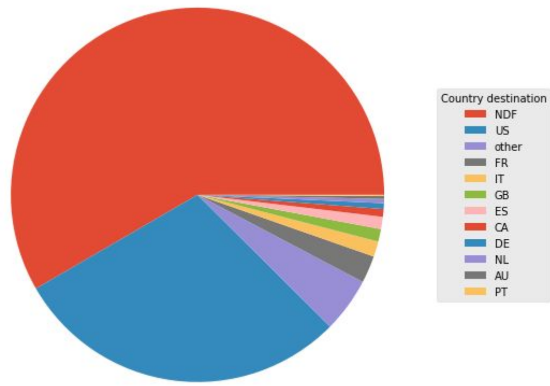
## Countries data

```
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
```

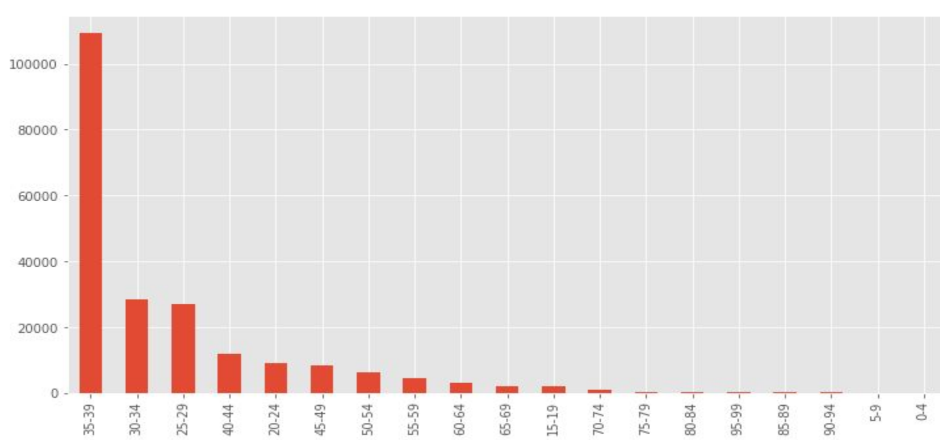
- ***Distribution of destination countries:***




- 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 bookings:***

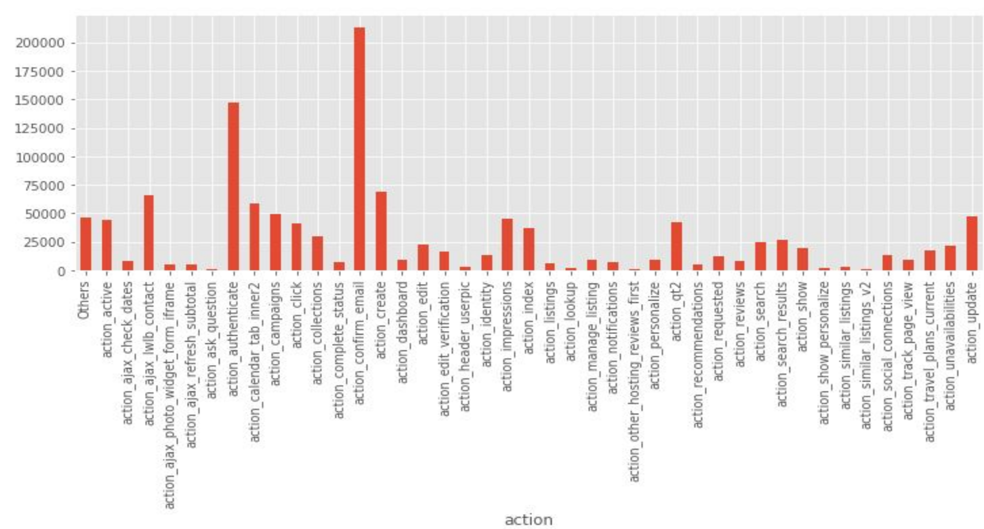


- Most users belong to the age bucket 35-39. Also,there is a lot of variance in booking count as age bucket varies.

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

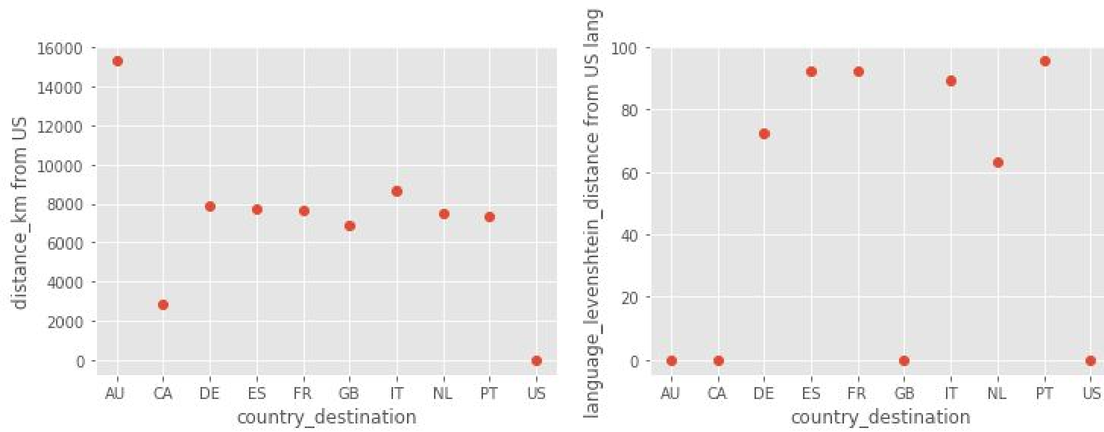

- Mid year(ie May, June) seems to have relatively higher first time bookings.

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



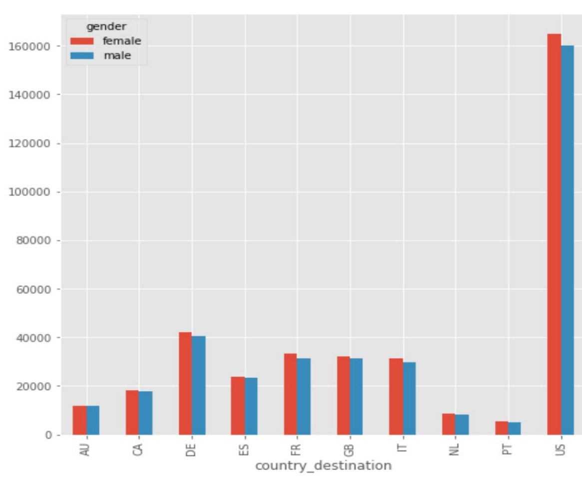
- Action 'confirm_email' and 'authenticate' has the highest mean secsElapsed in a user session.

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



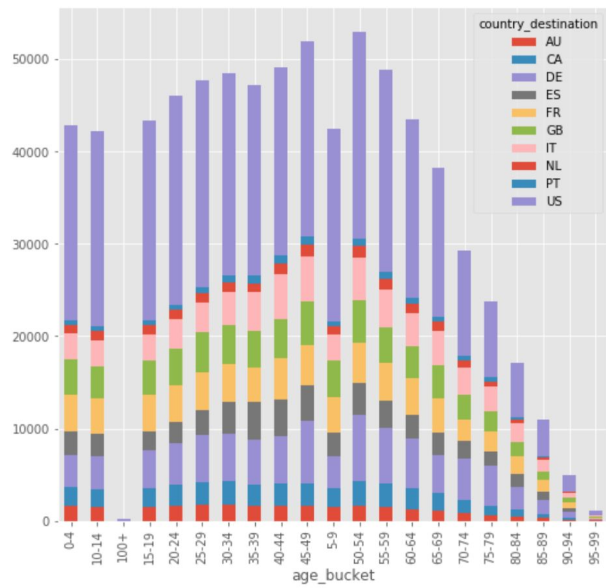

  - From plot 1, AU looks farest from the US in km distance.ES, FR, PT have the highest language_levenshtein_distance i.e these languages have the highest difference score from US english.

  - ***Demographic information of cities***



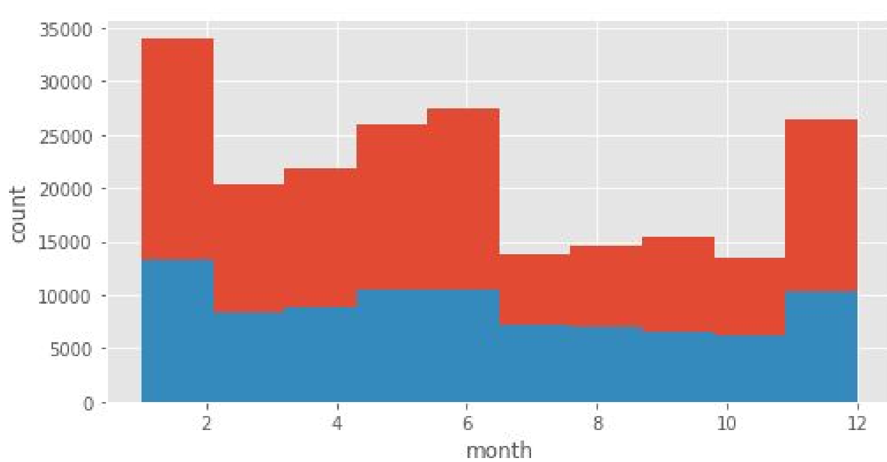
- The US seems to have the highest population, also female population is higher compared to male for all destination countries.

- ***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.

Now that we have a cleaner and well engineered data set we can move to predictive modelling of the rating ,

## *PREDICTIVE MODELING FOR CLASSIFICATION OF DESTINATION COUNTRIES:*

Before modeling, let's perform feature selection and remove redundancy.

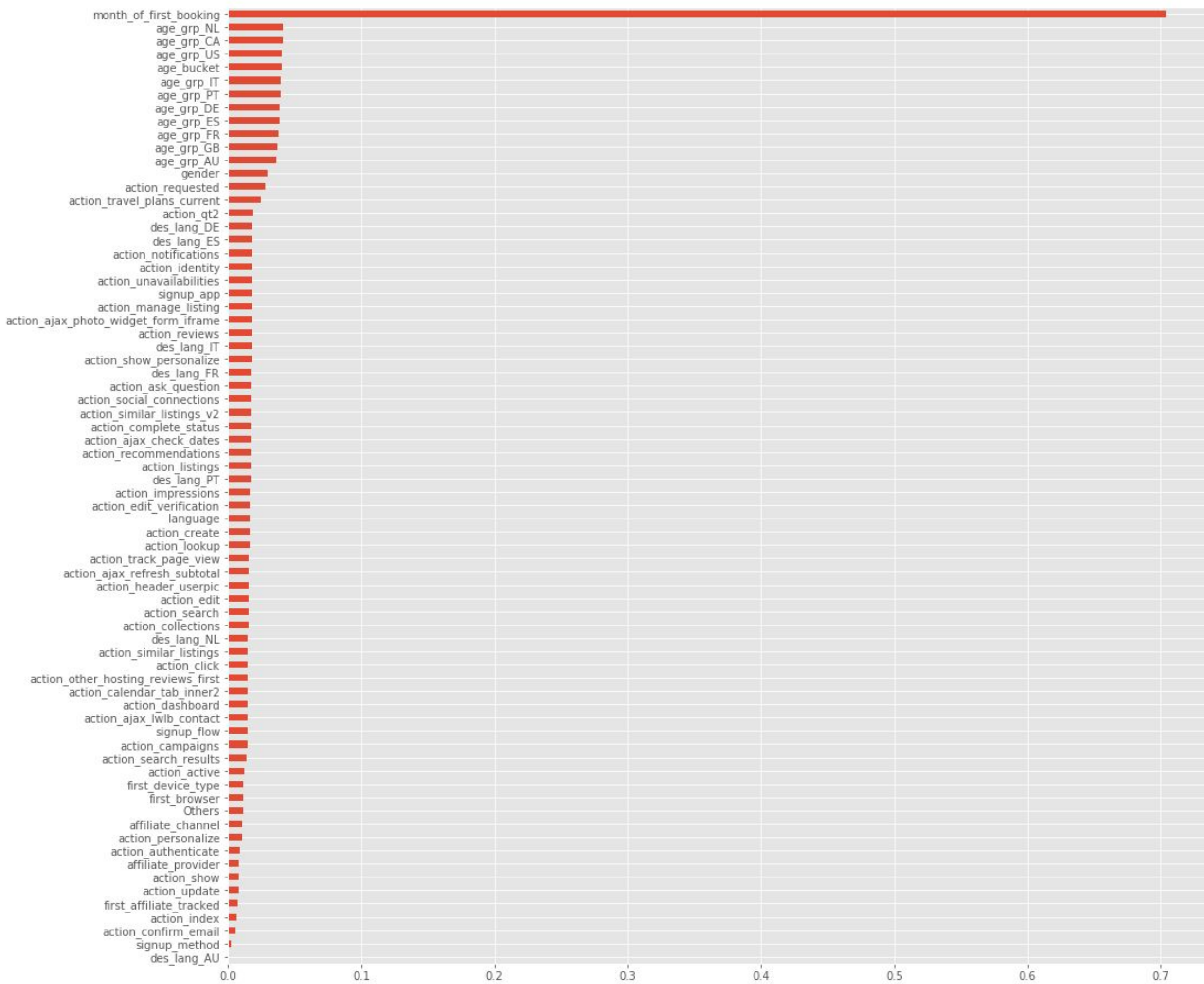
- ***Features Selection based on Mutual information***(Ref script modeling)

  Mutual Information is the measure of dependence between two discrete random variables. In this context, it is a measure of dependence between two features, higher the number more is the dependence.

Before getting the mutual info, we remove quasi constants and duplicate features.

```
from sklearn.feature_selection import VarianceThreshold, mutual_info_classif
from sklearn.feature_selection import SelectKBest, SelectPercentile
```

Sklearn.feature_selection module provides mutual_info_classif for getting mutual info.




From the plot we see, the month_of_first_booking has the highest mutual information value.

Next ,we select the best features keeping a threshold of 10 percentile.

Now that we have a reduced optimal feature set we can start modeling the data and attempt the classification problem.

To start with  lets try some decision trees models,

***Random Forest Classifier:***

```
clf = RandomForestClassifier(n_estimators=100,random_state=0,n_jobs=1)
clf.fit(X_train,y_train)
```

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=None, max_features='auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=1,
                       oob_score=False, random_state=0, verbose=0,
                       warm_start=False)
```

```
print("accuracy_score",accuracy_score(y_test,y_pred))
```

```
accuracy_score 0.8756480729589606
```

```
print(classification_report(y_test,y_pred))
```

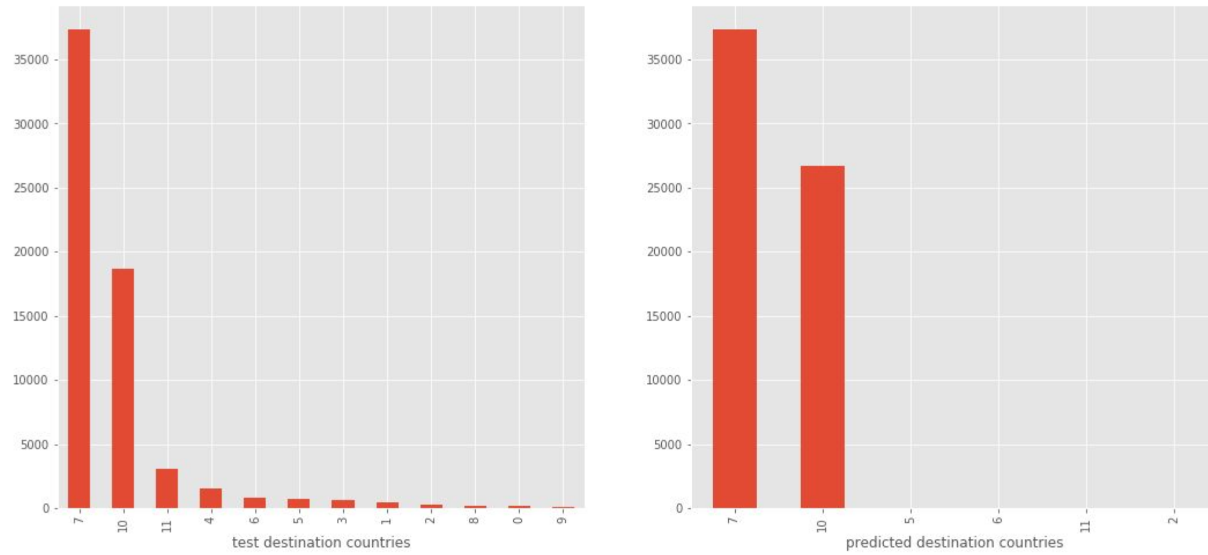
```
              precision    recall  f1-score   support

           0       0.00      0.00      0.00       162
           1       0.00      0.00      0.00       428
           2       0.00      0.00      0.00       318
           3       0.00      0.00      0.00       675
           4       0.00      0.00      0.00      1507
           5       0.00      0.00      0.00       697
           6       0.00      0.00      0.00       851
           7       1.00      1.00      1.00     37363
           8       0.00      0.00      0.00       229
           9       0.00      0.00      0.00        65
          10       0.70      1.00      0.82     18713
          11       0.00      0.00      0.00      3028

    accuracy                           0.88     64036
   macro avg       0.14      0.17      0.15     64036
weighted avg       0.79      0.88      0.82     64036
```

Random classifier gives an accuracy score of 0.875.From the classification report, the majority class 7 and 10 are identified.

Following plot shows comparison of real test and predictions,




Further, hyperparameter tuning using Randomised CV gave an accuracy of **0.875.**

***Neural Networks:***

- Neurals networks take into account interactions between features.
- The hidden layers between the input and output layers capture the interactions or in other words the nodes in the hidden layers represent the aggregation of information at each node and adds to models capability to capture interactions.
- More nodes, more interactions we capture.
- We would be using Keras interface to the Tensorflow Deep learning library.

  Workflow steps for Keras:

  - Specify Architecture
  - Compile
  - Fit
  - Predict

Further let's start with defining a baseline model,

```
#Set up the model
model_bSGD = Sequential() #base model using SGD optimiser

# Add the first layer
model_bSGD.add(Dense(100, activation='relu', input_shape=(n_cols,)))

# Add the output layer
model_bSGD.add(Dense(target_class, activation='softmax'))

# Compile the model
model_bSGD.compile(optimizer='SGD',
               loss='categorical_crossentropy',
               metrics=['accuracy'])

# Fit the model
model_bSGD.fit(predictors, target, epochs = 5)
```

```
WARNING:tensorflow:From /Users/Anand/anaconda3/lib/python3.7/site-packages/keras/backend/tensorflow_backe
he name tf.global_variables is deprecated. Please use tf.compat.v1.global_variables instead.

Epoch 1/5
149415/149415 [==============================] - 8s 56us/step - loss: 4454283.2270 - accuracy: 0.5831
Epoch 2/5
149415/149415 [==============================] - 8s 56us/step - loss: 1.1734 - accuracy: 0.5835
Epoch 3/5
149415/149415 [==============================] - 10s 64us/step - loss: 1.1679 - accuracy: 0.5835
Epoch 4/5
149415/149415 [==============================] - 9s 63us/step - loss: 1.1659 - accuracy: 0.5835
Epoch 5/5
149415/149415 [==============================] - 8s 53us/step - loss: 1.1650 - accuracy: 0.5835
```

- From above baseline model setting single layer with

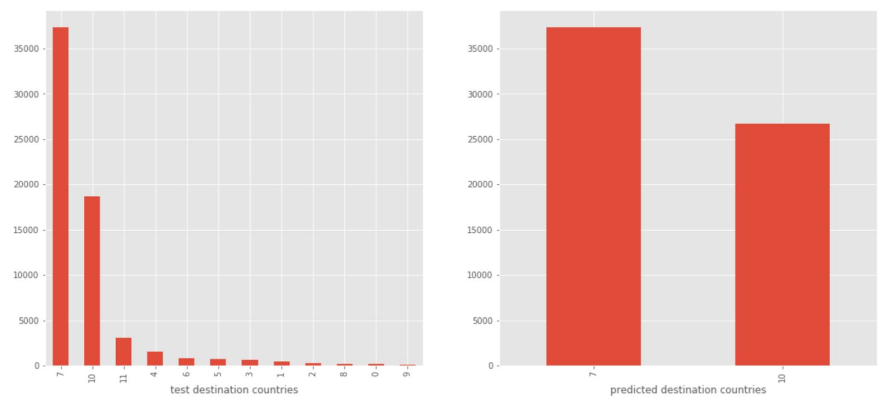
  nodes = 100

  Epoch = 5

  Optimiser = **'SGD'(Stochastic Gradient Descent)**

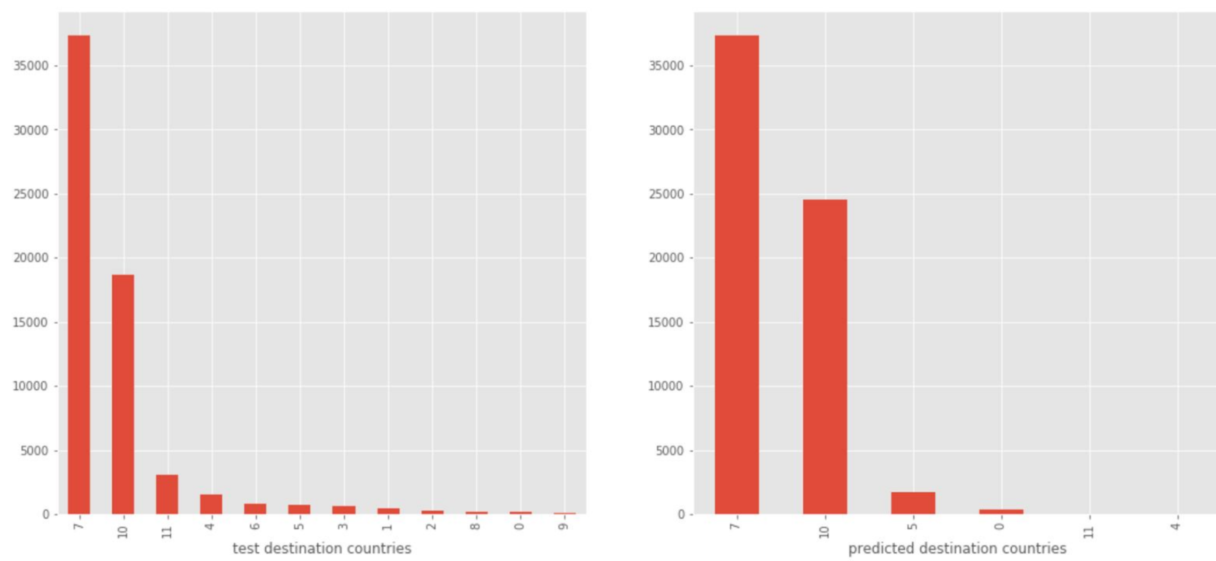
  Activation = **'relu'**

- Results an accuracy of **0.583**

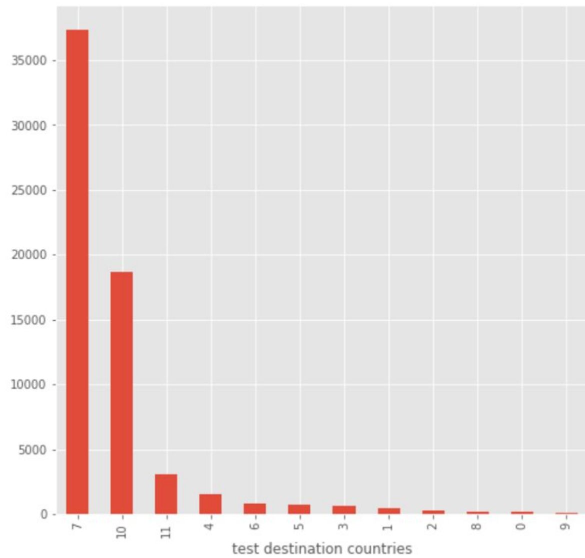


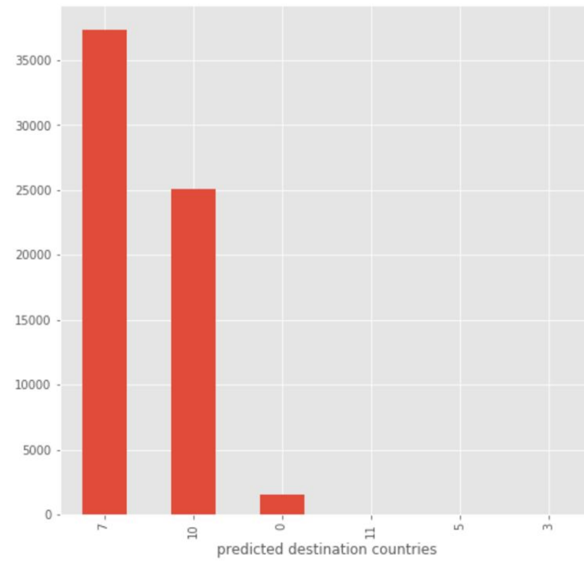

From the above plot comparing the real test data and predictions shows that the major classes 7 and 10 were identified to some extent.

- Further using optimiser ‘**Adam**’ gave slightly better results with accuracy of **0.806** and identification of some rare classes.




- Further Parameter optimisation on Learning rate, epoch, nodes, layers, EarlyStopping and Cross validation gave an validation accuracy of **0.859** along with some rare class identification.




## *Insights from model analysis:*

- As the dataset was imbalanced, and because we wanted this bias in our predictions we did not handle this imbalance and let our model learn it.
- RandomForest classifiers gave a good result, identifying mostly the major classes
- Neural Networks classifier also gave a similar accuracy, but could also identify some of the rare classes.

***Future Development:*** As a part of future development and refinements,

- Would like to include more features and more visualizations using seaborn.