Airbnb New User Bookings_ML_DL_Deploy

December 30, 2024

```
==================  Predicting First Booking Destination for Airbnb New Users  ================
```

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

[2]:
```
#df_train after clean and transorm
df_train=pd.read_csv('F://Andalosia//airbnb-recruiting-new-user-bookings//
 ↪data_clean//df_train_1.csv')
df_train.head()
```

[2]:
```
    gender signup_method  signup_flow language affiliate_channel  \
0  Unknown      facebook            0       en            direct
1     MALE      facebook            0       en               seo
2   FEMALE         basic            3       en            direct
3   FEMALE      facebook            0       en            direct
4  Unknown         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  … day_first_active  month_first_active  year_first_active  \
0        Chrome  …               19                   3               2009
1        Chrome  …               23                   5               2009
2            IE  …                9                   6               2009
3       Firefox  …               31                  10               2009
4        Chrome  …                8                  12               2009

   day_first_booking  month_first_booking  year_first_booking  age_group  \
0                 11                    9                2013      26-35
1                 11                    9                2013      36-45
2                  2                    8                2010      56-65
3                  8                    9                2012      36-45
```

```
4               18                 2              2010      36-45

   num_actions  num_devices  total_secs
0         38.0          1.0    874009.0
1         38.0          1.0    874009.0
2         38.0          1.0    874009.0
3         38.0          1.0    874009.0
4         38.0          1.0    874009.0

[5 rows x 24 columns]
```

[3]:

```
#df_train after clean and transorm
df_test=pd.read_csv('F://Andalosia//airbnb-recruiting-new-user-bookings//
 ↪data_clean//df_test_1.csv')
df_test.head()
```

[3]:

```
           id   gender signup_method  signup_flow language affiliate_channel  \
0  5uwns89zht   FEMALE      facebook            0       en            direct
1  jtl0dijy2j  Unknown         basic            0       en            direct
2  xx0ulgorjt  Unknown         basic            0       en            direct
3  6c6puo6ix0  Unknown         basic            0       en            direct
4  czqhjk3yfe  Unknown         basic            0       en            direct

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

   … day_first_active  month_first_active  year_first_active  \
0  …                1                   7               2014
1  …                1                   7               2014
2  …                1                   7               2014
3  …                1                   7               2014
4  …                1                   7               2014

   day_first_booking  month_first_booking  year_first_booking  age_group  \
0                  9                    5                2012      36-45
1                 29                   10                2011      26-35
2                 10                   10                2011      26-35
3                 22                    5                2011      26-35
4                  2                    7                2011      26-35

   num_actions  num_devices  total_secs
0          8.0          2.0    120334.0
1         19.0          2.0    251266.0
```

```
2          58.0           1.0    976722.0
3          11.0           1.0    124148.0
4          19.0           1.0    455170.0

[5 rows x 24 columns]
```

check before work on it

[4]:
```
df_train.shape
```

[4]:
```
(213451, 24)
```

[5]:
```
df_test.shape
```

[5]:
```
(62096, 24)
```

[6]:
```
df_train.isnull().any().any()
```

[6]:
```
False
```

[7]:
```
df_test.isnull().any().any()
```

[7]:
```
False
```

1 Label Encoding

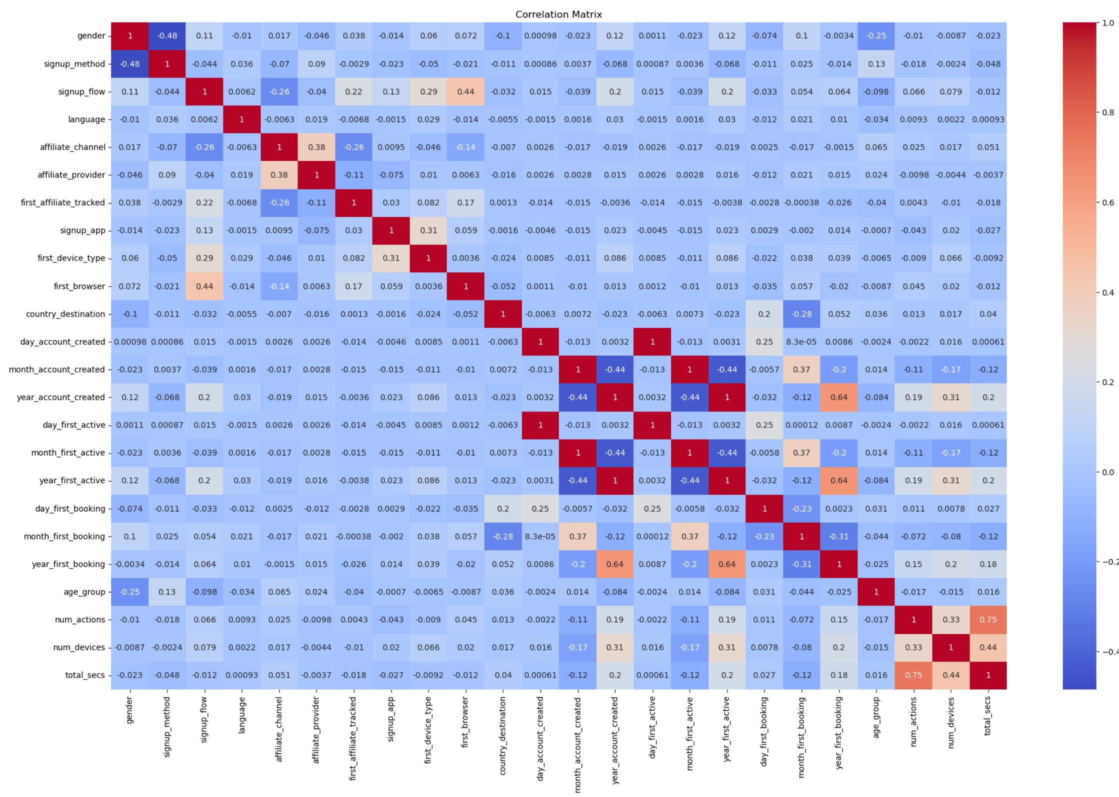
[8]:
```
#i will take a copy 'id' from df_test bec i will use it later
ids = df_test['id'].copy()
df_test = df_test.drop(columns=['id']) # drop id before encoding
```

[9]:
```
from sklearn.preprocessing import LabelEncoder

# initializel Labelencoder
label_encoder = LabelEncoder()

# List of columns to encode
columns_to_encode = ['gender','signup_method', 'language', 'affiliate_channel',␣
 ↪'affiliate_provider',
                     'first_affiliate_tracked', 'signup_app',␣
 ↪'first_device_type',
                     'first_browser', 'age_group']

# Encode columns in df_train and df_test
for column in columns_to_encode:
    # Fit the label encoder on df_train and transform both df_train and df_test
    df_train[column] = label_encoder.fit_transform(df_train[column].astype(str))
    df_test[column] = df_test[column].astype(str).apply(
```

```
        lambda x: label_encoder.transform([x])[0] if x in label_encoder.classes_ else len(label_encoder.classes_))#transform return list so i write [0] to get value from list
```

[10]:
```
df_train['country_destination'] = label_encoder.fit_transform(df_train['country_destination'])#i transform it alone bec it isnot in df_test
```

[11]:
```
plt.figure(figsize=(25, 15))

corr_matrix = df_train.select_dtypes(include='number').corr()#correlation heatmap to show relatioships
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



2 Feature Selection with RandomForest

[12]:
```
X = df_train.drop(columns=['country_destination'])
y = df_train['country_destination']
```

[13]:
```python
from sklearn.ensemble import RandomForestClassifier

model_selection = RandomForestClassifier(random_state=42)
model_selection.fit(X, y)
```

[13]: RandomForestClassifier(random_state=42)

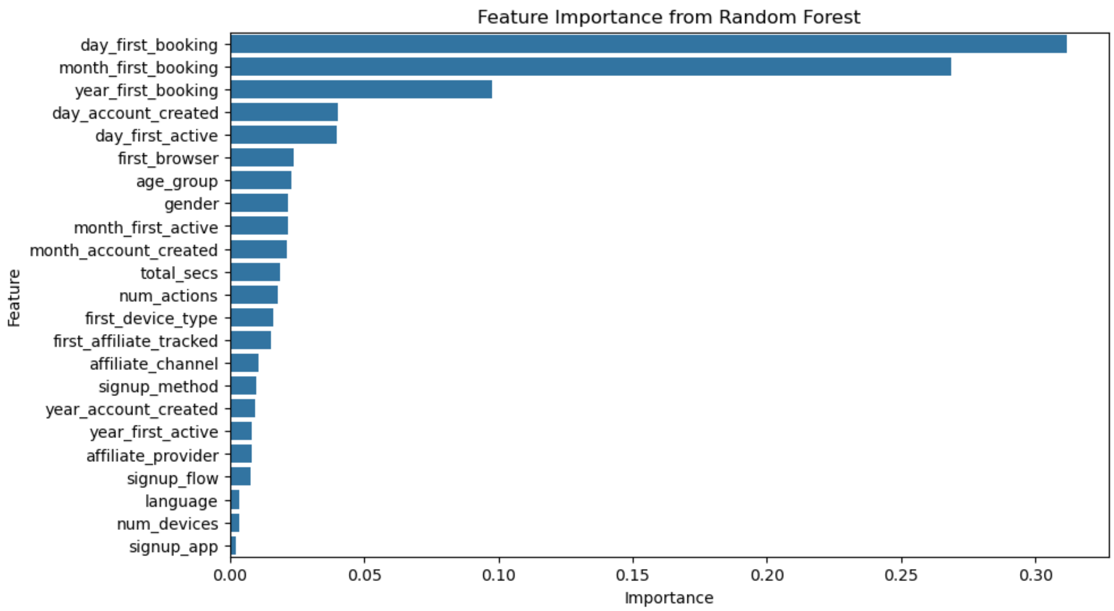
[14]:
```python
features = X.columns

#importances from the model
importances = model_selection.feature_importances_

# Create a DataFrame for easy plotting
feature_importance_df = pd.DataFrame({
    'Feature': features,
    'Importance': importances
})

# Sort the features by importance
feature_importance_df = feature_importance_df.sort_values(by='Importance',␣
 ↪ascending=False)

feature_importance_df
```

[14]:

	Feature	Importance
16	day_first_booking	0.311676
17	month_first_booking	0.268609
18	year_first_booking	0.097579
10	day_account_created	0.040074
13	day_first_active	0.039829
9	first_browser	0.023743
19	age_group	0.022843
0	gender	0.021673
14	month_first_active	0.021627
11	month_account_created	0.021124
22	total_secs	0.018864
20	num_actions	0.017741
8	first_device_type	0.016144
6	first_affiliate_tracked	0.015410
4	affiliate_channel	0.010609
1	signup_method	0.009981
12	year_account_created	0.009568
15	year_first_active	0.008256
5	affiliate_provider	0.008065
2	signup_flow	0.007648
3	language	0.003604
21	num_devices	0.003276

```
7                  signup_app    0.002054
```

[15]:
```python
plt.figure(figsize=(10,6))
sns.barplot(x='Importance', y='Feature', data=feature_importance_df)
plt.title('Feature Importance from Random Forest')
plt.show()
```



[16]:
```python
df_train.columns
```

[16]:
```
Index(['gender', 'signup_method', 'signup_flow', 'language',
       'affiliate_channel', 'affiliate_provider', 'first_affiliate_tracked',
       'signup_app', 'first_device_type', 'first_browser',
       'country_destination', 'day_account_created', 'month_account_created',
       'year_account_created', 'day_first_active', 'month_first_active',
       'year_first_active', 'day_first_booking', 'month_first_booking',
       'year_first_booking', 'age_group', 'num_actions', 'num_devices',
       'total_secs'],
      dtype='object')
```

3 Train - Test -Split

[17]:
```python
X = df_train.
 ↪drop(columns=['country_destination','signup_app','language','num_devices','signup_flow','af
 ↪'month_first_active',
       'year_first_active'])
y = df_train['country_destination']
```

[18]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_train_split, X_val_split, y_train_split, y_val_split =␣
↪train_test_split(X_scaled, y, test_size=0.2, random_state=42)
```

[19]:
```
df_test=df_test.
↪drop(columns=['signup_app','language','num_devices','signup_flow','affiliate_provider','day
↪'month_first_active','year_first_active'])
df_test = scaler.transform(df_test)#i use the same scaler on df_test
```

[20]:
```
city_counts = df_train['country_destination'].value_counts()
print(city_counts)
```

```
country_destination
7     124543
10     62376
11     10094
4       5023
6       2835
5       2324
3       2249
1       1428
2       1061
8        762
0        539
9        217
Name: count, dtype: int64
```

4 XGB

[21]:
```
import xgboost as xgb

model = xgb.XGBClassifier(random_state=42)
model.fit(X_train_split, y_train_split)
```

[21]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
```

```
multi_strategy=None, n_estimators=None, n_jobs=None,
num_parallel_tree=None, objective='multi:softprob', …)
```

5 Predicted Country Destinations with IDs

[22]:
```python
from sklearn.metrics import accuracy_score
import math

y_val_pred = model.predict(X_val_split)
val_accuracy = accuracy_score(y_val_split, y_val_pred)
val_accuracy_percentage = math.ceil(val_accuracy * 100)
print(f"Validation Accuracy: {val_accuracy_percentage}%")
```

```
Validation Accuracy: 88%
```

[23]:
```python
# test_predictions = model.predict(df_test)
country_map = {
    0: 'NDF', 1: 'US', 2: 'other', 3: 'FR', 4: 'CA', 5: 'GB', 6: 'ES', 7: 'IT',
    8: 'PT', 9: 'NL', 10: 'DE', 11: 'AU'
}
```

[24]:
```python
probabilities = model.predict_proba(df_test)
probabilities
```

[24]:
```
array([[3.4286670e-02, 1.6237877e-02, 5.6668208e-03, …, 4.2633494e-04,
        6.0851222e-01, 8.5853785e-02],
       [5.4968479e-03, 3.6489308e-02, 4.7807079e-02, …, 2.2514400e-03,
        5.2430040e-01, 8.0398418e-02],
       [2.8900593e-03, 4.2524107e-02, 1.8318508e-02, …, 2.1790902e-03,
        6.1796999e-01, 9.7465515e-02],
       …,
       [5.6908512e-03, 3.4708884e-02, 5.0816674e-02, …, 3.8081906e-03,
        6.0031527e-01, 9.5301472e-02],
       [3.3315194e-03, 1.9190235e-02, 9.5080230e-03, …, 9.3804271e-04,
        7.7158314e-01, 1.6349578e-02],
       [1.4020243e-03, 7.0327516e-03, 1.8950006e-03, …, 1.2608627e-03,
        9.0473735e-01, 4.9268249e-02]], dtype=float32)
```

[25]:
```python
top_5_predictions = []
for i, user_probs in enumerate(probabilities):
    # Get the top 5 predictions based on the probabilities
    top_5_indices = np.argsort(user_probs)[::-1][:5]  # Sort the probabilities␣
 ↪in descending order and get the top 5
    top_5_countries = [country_map[idx] for idx in top_5_indices]

    # Add the data to the list
    for country in top_5_countries:
```

```python
        top_5_predictions.append({
            'id': ids[i],
            'Predicted_Country_Destination': country
        })

# Convert the list to a DataFrame
top_5_predictions_df = pd.DataFrame(top_5_predictions)

top_5_predictions_df
```

[25]:

```
                id Predicted_Country_Destination
0       5uwns89zht                            DE
1       5uwns89zht                            CA
2       5uwns89zht                            AU
3       5uwns89zht                            FR
4       5uwns89zht                            ES
…            …                           …
310475  9uqfg8txu3                            DE
310476  9uqfg8txu3                            AU
310477  9uqfg8txu3                            CA
310478  9uqfg8txu3                            ES
310479  9uqfg8txu3                            PT

[310480 rows x 2 columns]
```

[26]:

```python
value_counts = top_5_predictions_df['Predicted_Country_Destination'].
 ↪value_counts()

print("Predicted Country Destination Frequency:")
print(value_counts)
```

```
Predicted Country Destination Frequency:
Predicted_Country_Destination
DE       62095
AU       60867
CA       57357
ES       38987
FR       32100
GB       25596
US       15081
PT        7159
other     6051
NDF       3876
NL        1003
IT         308
Name: count, dtype: int64
```

[27]:
```
# from sklearn.metrics import classification_report
# print(classification_report(y_val_split, y_val_pred))
```

6 Evaluating Model Performance with NDCG

NDCG measures how well a model ranks its predictions, giving more importance to placing the correct answers higher in the list. It helps evaluate ranking models, like recommendation systems, where the order of predictions matters, not just whether they are correct or not. The higher the relevant items are ranked, the better the model's performance is considered.

[28]:
```
# LabelBinarizer is appropriate for use with NDCG as it converts categorical␣
↪target labels
from sklearn.preprocessing import LabelBinarizer

label_binarizer = LabelBinarizer()
y_val_encoded = label_binarizer.fit_transform(y_val_split)
```

[29]:
```
from sklearn.metrics import ndcg_score

y_pred_prob = model.predict_proba(X_val_split)  # Predict on validation set
# Calculate the NDCG score
model_score = ndcg_score(
    y_true=y_val_encoded,
    y_score=y_pred_prob,
    k=5,
)

model_score = math.ceil(model_score * 100)
print(f"Model NDCG Score: {model_score}")
```

```
Model NDCG Score: 93
```

7 Grid Search to optimize hyperparameters

[30]:
```
from sklearn.model_selection import GridSearchCV
# from sklearn.linear_model import LogisticRegression
import lightgbm as lgb
from catboost import CatBoostClassifier
from sklearn.ensemble import HistGradientBoostingClassifier


random_forest_model =␣
↪RandomForestClassifier(class_weight='balanced',random_state=42)

xgb_model = xgb.XGBClassifier(objective='multi:softmax',␣
↪num_class=12,random_state=42)
```

```
lgb_model = lgb.LGBMClassifier(is_unbalance=True, objective='multiclass',␣
↪num_class=12,random_state=42)

# logistic_model = LogisticRegression(multi_class='multinomial',␣
↪class_weight='balanced', solver='lbfgs', random_state=42)
hist_gb_model =␣
↪HistGradientBoostingClassifier(loss='log_loss',class_weight='balanced',random_state=42)
catboost_model = CatBoostClassifier(loss_function='MultiClass',␣
↪verbose=0,random_state=42)
```

[31]:
```
# Grids for each model
#  [100, 150, 200, 300]   [ 10, 15, 20]
param_grid_rf = {'n_estimators': [ 200, 300], 'max_depth': [15, 20]}
param_grid_xgb = {'max_depth': [3, 5], 'learning_rate': [0.01, 0.1]}
# [50, 100]
param_grid_lgb = {'n_estimators': [100], 'learning_rate': [0.01, 0.1]}
# param_grid_logistic = {'C': [0.1, 1, 10], 'penalty': ['l2']}
param_grid_catboost = {'depth': [3, 5], 'learning_rate': [0.01], 'iterations':␣
↪[50]}
param_grid_hist_gb = {'max_iter': [200,300], 'learning_rate': [0.01, 0.001],␣
↪'max_depth': [ 7,10]}

# Dictionary of models
models = {
    'random_forest': (random_forest_model, param_grid_rf),
    'xgb': (xgb_model, param_grid_xgb),
    'lightgbm': (lgb_model, param_grid_lgb),
    # 'logistic_regression': (logistic_model, param_grid_logistic),
    'catboost': (catboost_model, param_grid_catboost),
    'hist_gradient_boosting': (hist_gb_model, param_grid_hist_gb),
}
```

[32]:
```
#  GridSearchCV for each model
best_models = {}
for model_name, (model, param_grid) in models.items():
    grid_search = GridSearchCV(model, param_grid, cv=3, scoring='accuracy',␣
↪n_jobs=-1)
    grid_search.fit(X_train_split, y_train_split)
    best_models[model_name] = grid_search.best_estimator_

    print(f"Best parameters for {model_name}: {grid_search.best_params_}")
    print(f"Best score for {model_name}: {grid_search.best_score_}\n")
```

```
Best parameters for random_forest: {'max_depth': 20, 'n_estimators': 300}
Best score for random_forest: 0.8697411571796674
```

```
Best parameters for xgb: {'learning_rate': 0.1, 'max_depth': 5}
Best score for xgb: 0.875228390723823

[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.009030 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 694
[LightGBM] [Info] Number of data points in the train set: 170760, number of used
features: 15
[LightGBM] [Info] Start training from score -5.995925
[LightGBM] [Info] Start training from score -4.997892
[LightGBM] [Info] Start training from score -5.299255
[LightGBM] [Info] Start training from score -4.553584
[LightGBM] [Info] Start training from score -3.750720
[LightGBM] [Info] Start training from score -4.537584
[LightGBM] [Info] Start training from score -4.319159
[LightGBM] [Info] Start training from score -0.538093
[LightGBM] [Info] Start training from score -5.639486
[LightGBM] [Info] Start training from score -6.900520
[LightGBM] [Info] Start training from score -1.231221
[LightGBM] [Info] Start training from score -3.049878
Best parameters for lightgbm: {'learning_rate': 0.01, 'n_estimators': 100}
Best score for lightgbm: 0.8752166783790115

Best parameters for catboost: {'depth': 5, 'iterations': 50, 'learning_rate':
0.01}
Best score for catboost: 0.8738814710705083

Best parameters for hist_gradient_boosting: {'learning_rate': 0.01, 'max_depth':
10, 'max_iter': 300}
Best score for hist_gradient_boosting: 0.6328941204029047
```

==**Prediction**==================

8 XGB algorithm

[33]:
```python
best_xgb_model = best_models['xgb']
best_xgb_model.fit(X_train_split, y_train_split)
```

[33]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.1, max_bin=None,
```

```
                 max_cat_threshold=None, max_cat_to_onehot=None,
                 max_delta_step=None, max_depth=5, max_leaves=None,
                 min_child_weight=None, missing=nan, monotone_constraints=None,
                 multi_strategy=None, n_estimators=None, n_jobs=None, num_class=12,
                 num_parallel_tree=None, …)
```

[34]:
```
y_val_pred_1 = best_xgb_model.predict(X_val_split)
val_accuracy = accuracy_score(y_val_split, y_val_pred_1)
```

[35]:
```
# round the accuracy
val_accuracy_percentage = math.ceil(val_accuracy * 100)
print(f"Validation Accuracy: {val_accuracy_percentage}%")
```

```
Validation Accuracy: 88%
```

9 Predicted Country Destinations with Tunning

[36]:
```
probabilities = best_xgb_model.predict_proba(df_test)

top_5_predictions = []
for i, user_probs in enumerate(probabilities):

    top_5_indices = np.argsort(user_probs)[::-1][:5]
    top_5_countries = [country_map[idx] for idx in top_5_indices]

    for country in top_5_countries:
        top_5_predictions.append({
            'id': ids[i],
            'Predicted_Country_Destination': country
        })

top_5_predictions_df = pd.DataFrame(top_5_predictions)

top_5_predictions_df
```

[36]:

	id	Predicted_Country_Destination
0	5uwns89zht	DE
1	5uwns89zht	CA
2	5uwns89zht	AU
3	5uwns89zht	FR
4	5uwns89zht	ES
…	…	…
310475	9uqfg8txu3	DE
310476	9uqfg8txu3	AU
310477	9uqfg8txu3	CA
310478	9uqfg8txu3	GB
310479	9uqfg8txu3	ES

[310480 rows x 2 columns]

[37]:
```
# Count the frequency of each predicted value
value_counts = top_5_predictions_df['Predicted_Country_Destination'].
↪value_counts()

print("Predicted Country Destination Frequency:")
print(value_counts)
```

```
Predicted Country Destination Frequency:
Predicted_Country_Destination
DE       62096
CA       61757
AU       61295
ES       44795
FR       36737
GB       29845
US        8338
other     2139
PT        2026
NDF       1064
NL         233
IT         155
Name: count, dtype: int64
```

10 NDCG score_Tunning

[38]:
```
y_pred_prob = best_xgb_model.predict_proba(X_val_split)  # Predict on␣
↪validation set
# Calculate the NDCG score
model_1_score = ndcg_score(
    y_true=y_val_encoded,
    y_score=y_pred_prob,
    k=5,

)
import math

model_1_score = math.ceil(model_1_score * 100)
print(f"Model NDCG Score: {model_1_score}")
```

```
Model NDCG Score: 93
```

11 Prediction With SMOTE

[39]:
```python
from imblearn.over_sampling import SMOTE

# SMOTE
smote = SMOTE(random_state=42)
X_train_sm, y_train_sm = smote.fit_resample(X_train_split, y_train_split)

print("before SMOTE:", y_train_split.value_counts())
print("after SMOTE:", y_train_sm.value_counts())
```

```
before SMOTE: country_destination
7     99700
10    49851
11     8088
4      4013
6      2273
5      1827
3      1798
1      1153
2       853
8       607
0       425
9       172
Name: count, dtype: int64
after SMOTE: country_destination
10    99700
7     99700
11    99700
4     99700
3     99700
6     99700
2     99700
5     99700
8     99700
1     99700
9     99700
0     99700
Name: count, dtype: int64
```

[40]:
```python
best_xgb_model_smote = best_models['xgb']
best_xgb_model_smote.fit(X_train_sm, y_train_sm)
```

[40]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
```

```
                 interaction_constraints=None, learning_rate=0.1, max_bin=None,
                 max_cat_threshold=None, max_cat_to_onehot=None,
                 max_delta_step=None, max_depth=5, max_leaves=None,
                 min_child_weight=None, missing=nan, monotone_constraints=None,
                 multi_strategy=None, n_estimators=None, n_jobs=None, num_class=12,
                 num_parallel_tree=None, …)
```

[41]:
```
y_val_pred_smote = best_xgb_model_smote.predict(X_val_split)
val_accuracy_smote = accuracy_score(y_val_split, y_val_pred_smote)
```

[42]:
```
val_accuracy_percentage_smote = math.ceil(val_accuracy_smote * 100)
print(f"Validation Accuracy:{val_accuracy_percentage_smote}%")
```

```
Validation Accuracy:85%
```

[43]:
```
test_predictions_smote = best_xgb_model_smote.predict(df_test)
```

[44]:
```
probabilities = best_xgb_model_smote.predict_proba(df_test)

top_5_predictions = []

for i, user_probs in enumerate(probabilities):
    top_5_indices = np.argsort(user_probs)[::-1][:5]
    top_5_countries = [country_map[idx] for idx in top_5_indices]

    for country in top_5_countries:
        top_5_predictions.append({
            'id': ids[i],
            'Predicted_Country_Destination': country
        })

top_5_predictions_df = pd.DataFrame(top_5_predictions)

top_5_predictions_df
```

[44]:

	id	Predicted_Country_Destination
0	5uwns89zht	DE
1	5uwns89zht	FR
2	5uwns89zht	ES
3	5uwns89zht	GB
4	5uwns89zht	CA
…	…	…
310475	9uqfg8txu3	DE
310476	9uqfg8txu3	GB
310477	9uqfg8txu3	NDF
310478	9uqfg8txu3	US
310479	9uqfg8txu3	CA

```
[310480 rows x 2 columns]
```

[45]:
```
# Count the frequency of each predicted value
value_counts = top_5_predictions_df['Predicted_Country_Destination'].
 ↪value_counts()

print("Predicted Country Destination Frequency:")
print(value_counts)
```

```
Predicted Country Destination Frequency:
Predicted_Country_Destination
DE       61780
CA       44560
ES       31057
GB       30550
FR       28993
PT       23943
US       22952
AU       20306
NL       18472
NDF      17176
other    10615
IT          76
Name: count, dtype: int64
```

[46]:
```
top_5_predictions_df.to_csv('predictions_df_smote.csv', index=False)
```

12 NDCG score_Smote

[47]:
```
y_pred_prob_smote = best_xgb_model_smote.predict_proba(X_val_split)  # Predict␣
 ↪on validation set
# Calculate the NDCG score
model_2_score = ndcg_score(
    y_true=y_val_encoded,
    y_score=y_pred_prob_smote,
    k=5,
)
model_2_score = math.ceil(model_2_score * 100)
print(f"Model NDCG Score: {model_2_score}")
```

```
Model NDCG Score: 91
```

13 Voting Classifier with Multiple Models for Ensemble Learning

[48]:
```
from sklearn.ensemble import VotingClassifier

voting_model = VotingClassifier(
    estimators=[
    ('random_forest', best_models['random_forest']),
    ('xgb', best_models['xgb']),
    ('lightgbm', best_models['lightgbm']),
    ('catboost', best_models['catboost']),
#     ('hist_gradient_boosting', best_models['hist_gradient_boosting']),
], voting='soft', n_jobs=-1)
```

[49]:
```
voting_model.fit(X_train_split, y_train_split)
```

[49]:
```
VotingClassifier(estimators=[('random_forest',
                              RandomForestClassifier(class_weight='balanced',
                                                     max_depth=20,
                                                     n_estimators=300,
                                                     random_state=42)),
                             ('xgb',
                              XGBClassifier(base_score=None, booster=None,
                                            callbacks=None,
                                            colsample_bylevel=None,
                                            colsample_bynode=None,
                                            colsample_bytree=None, device=None,
                                            early_stopping_rounds=None,
                                            enable_categorical=False,
                                            eval_metric=N…
                                            min_child_weight=None, missing=nan,
                                            monotone_constraints=None,
                                            multi_strategy=None,
                                            n_estimators=None, n_jobs=None,
                                            num_class=12,
                                            num_parallel_tree=None, …)),
                             ('lightgbm',
                              LGBMClassifier(is_unbalance=True,
                                             learning_rate=0.01, num_class=12,
                                             objective='multiclass',
                                             random_state=42)),
                             ('catboost',
                              <catboost.core.CatBoostClassifier object at
0x000002082B94B530>)],
                 n_jobs=-1, voting='soft')
```

[50]:
```
y_val_pred_vote = voting_model.predict(X_val_split)
val_accuracy = accuracy_score(y_val_split, y_val_pred_vote)
```

```python
val_accuracy_percentage = math.ceil(val_accuracy * 100)  # rounding up to the␣
↪nearest integer
print(f"Validation Accuracy: {val_accuracy_percentage}%")
```

```
Validation Accuracy: 88%
```

[51]:
```python
probabilities = voting_model.predict_proba(df_test)
top_5_predictions = []
for i, user_probs in enumerate(probabilities):

    top_5_indices = np.argsort(user_probs)[::-1][:5]
    top_5_countries = [country_map[idx] for idx in top_5_indices]

    for country in top_5_countries:
        top_5_predictions.append({
            'id': ids[i],
            'Predicted_Country_Destination': country
        })

top_5_predictions_df = pd.DataFrame(top_5_predictions)

top_5_predictions_df
```

[51]:

	id	Predicted_Country_Destination
0	5uwns89zht	DE
1	5uwns89zht	IT
2	5uwns89zht	AU
3	5uwns89zht	CA
4	5uwns89zht	FR
…	…	…
310475	9uqfg8txu3	DE
310476	9uqfg8txu3	AU
310477	9uqfg8txu3	IT
310478	9uqfg8txu3	CA
310479	9uqfg8txu3	ES

[310480 rows x 2 columns]

[52]:
```python
# Count the frequency of each predicted value
value_counts = top_5_predictions_df['Predicted_Country_Destination'].
↪value_counts()

print("Predicted Country Destination Frequency:")
print(value_counts)
```

```
Predicted Country Destination Frequency:
Predicted_Country_Destination
DE       62096
```

```
AU        62080
IT        61742
CA        61700
ES        32923
FR        14404
GB        11792
US         2331
PT          536
other       461
NDF         349
NL           66
Name: count, dtype: int64
```

14 NDCG score_Voting

[53]:
```python
y_pred_prob = voting_model.predict_proba(X_val_split)  # Predict on validation
 ↪set
# Calculate the NDCG score
model_3_score = ndcg_score(
    y_true=y_val_encoded,
    y_score=y_pred_prob,
    k=5,
)
model_3_score = math.ceil(model_3_score * 100)
print(f"Model NDCG Score: {model_3_score}")
```

```
Model NDCG Score: 93
```

[54]:
```python
top_5_predictions_df.to_csv('predictions_df_voting.csv', index=False)
```

15 Building a Neural Network Model with Keras

A **Neural Network (NN)** is a system that mimics the way the brain works, with layers of nodes (neurons) to process data.

- **Input Layer**: The number of features in the data (`input_dim`).
- **Hidden Layers**: Layers with 128, 64 and 32 neurons, using **ReLU activation**, and **Dropout** for regularization.
- **Output Layer**: The number of classes (`output_dim`) with **softmax activation** for classification.
- **Adam Optimizer**: Helps adjust weights during training.
- **EarlyStopping**: Stops training when the model stops improving.

[55]:
```python
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping
```

```python
input_dim = X_train_split.shape[1]
output_dim = len(y_train_split.unique())


model_network = Sequential([
    Dense(128, activation='relu', input_dim=input_dim),
    Dropout(0.2),
    Dense(64, activation='relu'),
    Dropout(0.2),
    Dense(32, activation='relu'),
    Dense(output_dim, activation='softmax')
])
```

```
D:\Down_apps\AnaCodaa\Lib\site-packages\keras\src\layers\core\dense.py:87:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

[56]:
```python
model_network.compile(optimizer='adam', loss='sparse_categorical_crossentropy',␣
↪metrics=['accuracy'])
```

We need to balance batch size and epochs for effective training

[57]:
```python
history = model_network.fit(
    X_train_split, y_train_split,
    validation_data=(X_val_split, y_val_split),
    epochs=10,
    batch_size=32,
    callbacks=[EarlyStopping(patience=3, restore_best_weights=True)]
)
```

```
Epoch 1/10
5337/5337              17s 2ms/step -
accuracy: 0.8380 - loss: 0.6481 - val_accuracy: 0.8741 - val_loss: 0.4939
Epoch 2/10
5337/5337              12s 2ms/step -
accuracy: 0.8750 - loss: 0.4930 - val_accuracy: 0.8746 - val_loss: 0.4917
Epoch 3/10
5337/5337              12s 2ms/step -
accuracy: 0.8748 - loss: 0.4888 - val_accuracy: 0.8747 - val_loss: 0.4900
Epoch 4/10
5337/5337              12s 2ms/step -
accuracy: 0.8747 - loss: 0.4882 - val_accuracy: 0.8748 - val_loss: 0.4888
Epoch 5/10
5337/5337              12s 2ms/step -
accuracy: 0.8738 - loss: 0.4904 - val_accuracy: 0.8747 - val_loss: 0.4888
Epoch 6/10
```

```
5337/5337              12s 2ms/step -
accuracy: 0.8753 - loss: 0.4858 - val_accuracy: 0.8747 - val_loss: 0.4889
Epoch 7/10
5337/5337              12s 2ms/step -
accuracy: 0.8741 - loss: 0.4885 - val_accuracy: 0.8748 - val_loss: 0.4882
Epoch 8/10
5337/5337              12s 2ms/step -
accuracy: 0.8754 - loss: 0.4858 - val_accuracy: 0.8748 - val_loss: 0.4885
Epoch 9/10
5337/5337              12s 2ms/step -
accuracy: 0.8744 - loss: 0.4875 - val_accuracy: 0.8748 - val_loss: 0.4885
Epoch 10/10
5337/5337              12s 2ms/step -
accuracy: 0.8756 - loss: 0.4833 - val_accuracy: 0.8747 - val_loss: 0.4898
```

[58]:

```
loss, accuracy = model_network.evaluate(X_val_split, y_val_split, verbose=1)
accuracy_ceiled = math.ceil(accuracy * 100)
print(f"Accuracy : {accuracy_ceiled}%")
```

```
1335/1335              2s 2ms/step -
accuracy: 0.8737 - loss: 0.4896
Accuracy : 88%
```

[59]:

```
probabilities = model_network.predict(df_test)

top_5_predictions = []
for i, user_probs in enumerate(probabilities):
    top_5_indices = user_probs.argsort()[-5:][::-1]
    top_5_countries = [country_map[idx] for idx in top_5_indices]

    for country in top_5_countries:
        top_5_predictions.append({
            'id': ids[i],
            'Predicted_Country_Destination': country
        })

top_5_predictions_df = pd.DataFrame(top_5_predictions)

top_5_predictions_df
```

```
1941/1941              3s 2ms/step
```

[59]:

	id	Predicted_Country_Destination
0	5uwns89zht	DE
1	5uwns89zht	AU
2	5uwns89zht	CA
3	5uwns89zht	ES
4	5uwns89zht	GB

```
…         …                                  …
310475   9uqfg8txu3                           DE
310476   9uqfg8txu3                           AU
310477   9uqfg8txu3                           CA
310478   9uqfg8txu3                           GB
310479   9uqfg8txu3                           ES

[310480 rows x 2 columns]
```

[60]:

```
# Count the frequency of each predicted value
value_counts = top_5_predictions_df['Predicted_Country_Destination'].
 ↪value_counts()

print("Predicted Country Destination Frequency:")
print(value_counts)
```

```
Predicted Country Destination Frequency:
Predicted_Country_Destination
DE       62096
AU       62096
CA       62073
ES       49836
GB       40035
FR       18063
IT       15986
US         235
other       34
NDF         13
NL           7
PT           6
Name: count, dtype: int64
```

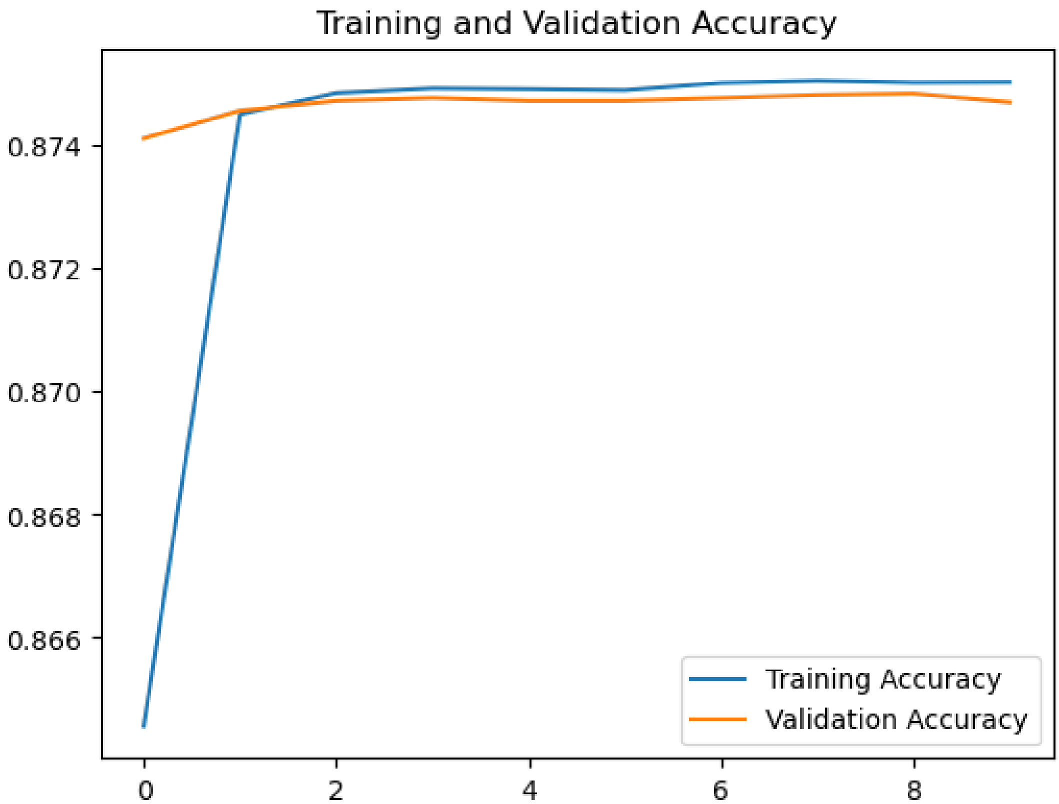
[61]:

```
y_pred_prob = model_network.predict(X_val_split)

model_1_score = ndcg_score(
    y_true=y_val_encoded,
    y_score=y_pred_prob,
    k=5
)
model_1_score = math.ceil(model_1_score * 100)
print(f"Model NDCG Score: {model_1_score}")
```

```
1335/1335              2s 1ms/step
Model NDCG Score: 93
```

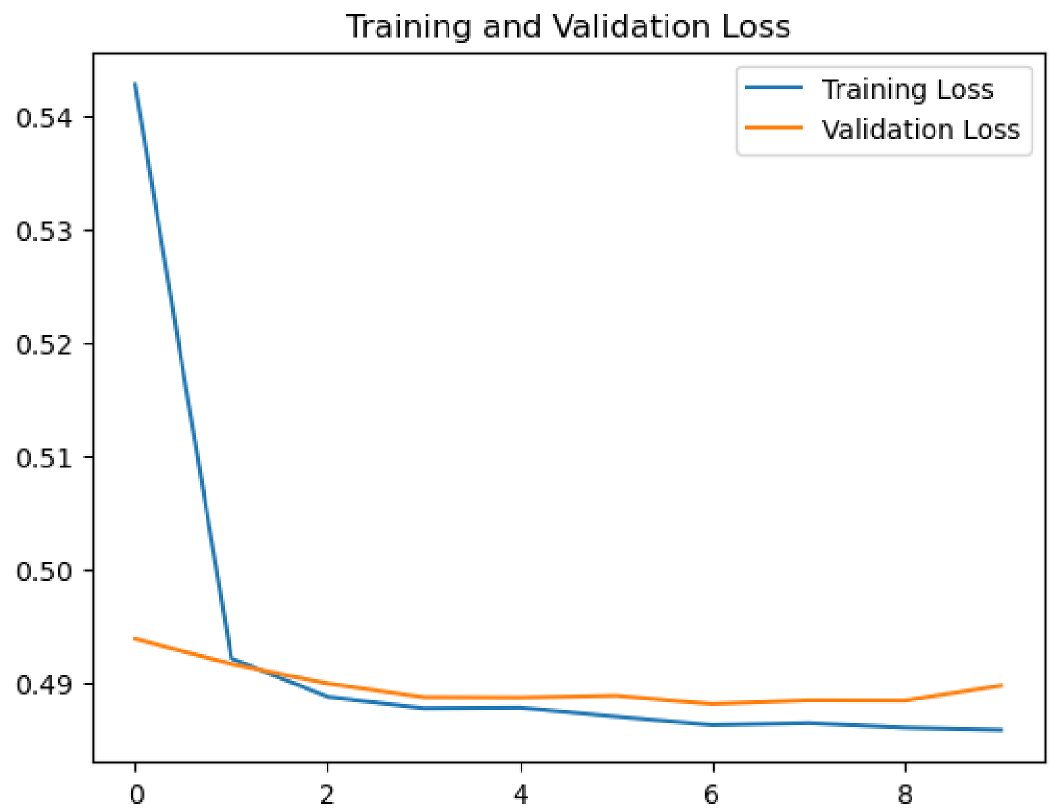
16 tracking the curves of training accuracy and validation accuracy

[62]:
```
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.legend()
plt.title('Training and Validation Accuracy')
plt.show()
```



17 tracking the curves of training loss and validation loss

[63]:
```
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.legend()
plt.title('Training and Validation Loss')
plt.show()
```



18 Flask Web Application for Predicting Country Destination

Saving the voting_model Model using Joblib

[64]:
```
import joblib
joblib.dump(voting_model, 'voting_model.pkl')
```

[64]:
```
['voting_model.pkl']
```

[65]:
```
df_train.columns
```

[65]:
```
Index(['gender', 'signup_method', 'signup_flow', 'language',
       'affiliate_channel', 'affiliate_provider', 'first_affiliate_tracked',
       'signup_app', 'first_device_type', 'first_browser',
       'country_destination', 'day_account_created', 'month_account_created',
       'year_account_created', 'day_first_active', 'month_first_active',
       'year_first_active', 'day_first_booking', 'month_first_booking',
       'year_first_booking', 'age_group', 'num_actions', 'num_devices',
       'total_secs'],
      dtype='object')
```

[66]:
```python
feature_names = [
    'gender', 'affiliate_channel',
     'first_affiliate_tracked', 'first_device_type','signup_method',
    'first_browser', 'day_account_created', 'month_account_created',
    'year_account_created', 'day_first_booking', 'month_first_booking',
    'year_first_booking', 'num_actions', 'total_secs',
    'age_group'
]

encoding_maps = {
    'gender': {'FEMALE': 0, 'MALE': 1, 'OTHER': 3},
    'affiliate_channel': {
        'direct': 0, 'sem-brand': 1, 'sem-non-brand': 2, 'seo': 3,
        'remarketing': 4, 'other': 5, 'content': 6
    },
    'first_affiliate_tracked': {
        'untracked': 0, 'omg': 1, 'linked': 2, 'tracked-other': 3,
        'product': 4, 'marketing': 5, 'local ops': 6
    },
    'first_device_type': {'desktop': 0, 'mobile': 1, 'tablet': 2, 'other': 3},
    'first_browser': {'chrome': 0, 'firefox': 1, 'safari': 2, 'edge': 3,␣
 ↪'other': 4},
    'age_group': {
        '18-25': 0, '26-35': 1, '36-45': 2, '46-55': 3,
        '56-65': 4, '66-75': 5, '76-85': 6, '86-100': 7
    },
    'signup_method': {
        'facebook': 0,
        'basic': 1,
        'google': 2
    }
}



country_map = {
    0: 'NDF', 1: 'US', 2: 'other', 3: 'FR', 4: 'CA', 5: 'GB', 6: 'ES', 7: 'IT',
    8: 'PT', 9: 'NL', 10: 'DE', 11: 'AU'
}
```

19 Flask Web Application for Prediction with Feature Encoding and Model Integration

[67]:
```
from flask import Flask, request, render_template

# Function to preprocess the input data
def preprocess_input_data(input_data):
    features = []

    for feature in feature_names:
        if feature in encoding_maps:
            value = input_data.get(feature, 'unknown')  # Default value␣
↪'unknown'
            features.append(encoding_maps[feature].get(value, -1))  # -1 for␣
↪missing values
        else:
            value = input_data.get(feature, 0)  # Default value 0
            features.append(float(value))

    return np.array(features).reshape(1, -1)

# Flask app
app = Flask(__name__)

@app.route('/')
def index():
    return render_template('index.html')

@app.route('/predict', methods=['POST'])
def predict():
    try:
        # Receive the input data
        input_data = request.form.to_dict()

        # Preprocess the data
        features = preprocess_input_data(input_data)

        # Make prediction using the model
        probabilities = voting_model.predict_proba(features)

        # Extract the top 5 countries with their probabilities
        top_5_indices = np.argsort(probabilities[0])[::-1][:5]  # Sort the␣
↪probabilities in descending order and select top 5
        top_5_countries = [country_map.get(idx, 'Unknown') for idx in␣
↪top_5_indices]
```

```
        return render_template(
            'index.html',
            prediction_text=f'Top 5 Predicted Countries: {", ".
 ↪join(top_5_countries)}'
        )
    except Exception as e:
        return render_template('index.html', prediction_text=f'Error: {str(e)}')

if __name__ == '__main__':
    app.run(port=5000)
```

```
 * Serving Flask app '__main__'
 * Debug mode: off
WARNING: This is a development server. Do not use it in a production deployment.
Use a production WSGI server instead.
 * Running on http://127.0.0.1:5000
Press CTRL+C to quit
127.0.0.1 - - [30/Dec/2024 09:08:51] "GET / HTTP/1.1" 200 -
127.0.0.1 - - [30/Dec/2024 09:08:52] "GET /favicon.ico HTTP/1.1" 404 -
127.0.0.1 - - [30/Dec/2024 09:09:43] "POST /predict HTTP/1.1" 200 -
```

==

I've developed a Flask application to test my model locally, and it's working successfully. The next step is to deploy it on a server to make it accessible to others

[68]:
```
X.columns
```

[68]:
```
Index(['gender', 'signup_method', 'affiliate_channel',
       'first_affiliate_tracked', 'first_device_type', 'first_browser',
       'day_account_created', 'month_account_created', 'year_account_created',
       'day_first_booking', 'month_first_booking', 'year_first_booking',
       'age_group', 'num_actions', 'total_secs'],
      dtype='object')
```

[ ]:
```

```