finalprojectML_finalversion

April 3, 2025

[3]:
```python
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Load Dataset
df = pd.read_csv("Airbnb_data - airbnb_data.csv")
df.head()

# Check data info and statistical summary
df.info()

df.describe()

# Check null values in the dataset per column
df.isnull().sum()

# Dropping the null values from the dataset
df.dropna(inplace = True)
# check for any missing values after performing the .dropna function
df.isnull().sum()

# Dropping columns that are not necessary for further analysis
cols_to_drop = ["id", "description", "thumbnail_url"]
df.drop(columns= cols_to_drop, inplace = True)

df.columns

# Cleaning columns and converting to appropriate numerical data types
df["host_response_rate"] = df["host_response_rate"].str.rstrip("%")

# Setting up all "Date" columns datatype to date and adding a new column to␣
↪calculate the total tenure
# List of columns to convert
date_cols = ["first_review", "host_since", "last_review"]
df[date_cols] = df[date_cols].apply(pd.to_datetime, format='%d-%m-%Y')
```

```python
df["host_tenure"] = 2025 - df["host_since"].dt.year
df.dtypes


# Removing outliers using Interquartile range(IQR)
def remove_outliers(df, column):
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]

# Apply to columns with potential outliers
df = remove_outliers(df, "log_price")
df = remove_outliers(df, "accommodates")
df = remove_outliers(df, "bathrooms")
df = remove_outliers(df, "bedrooms")
df = remove_outliers(df, "beds")
# final shape of the dataset after removing outliers
df.shape
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 74111 entries, 0 to 74110
Data columns (total 29 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   id                      74111 non-null  int64
 1   log_price               74111 non-null  float64
 2   property_type           74111 non-null  object
 3   room_type               74111 non-null  object
 4   amenities               74111 non-null  object
 5   accommodates            74111 non-null  int64
 6   bathrooms               73911 non-null  float64
 7   bed_type                74111 non-null  object
 8   cancellation_policy     74111 non-null  object
 9   cleaning_fee            74111 non-null  bool
 10  city                    74111 non-null  object
 11  description             74111 non-null  object
 12  first_review            58247 non-null  object
 13  host_has_profile_pic    73923 non-null  object
 14  host_identity_verified  73923 non-null  object
 15  host_response_rate      55812 non-null  object
 16  host_since              73923 non-null  object
 17  instant_bookable        74111 non-null  object
 18  last_review             58284 non-null  object
 19  latitude                74111 non-null  float64
 20  longitude               74111 non-null  float64
```

```
 21   name                    74111 non-null  object
 22   neighbourhood           67239 non-null  object
 23   number_of_reviews       74111 non-null  int64
 24   review_scores_rating    57389 non-null  float64
 25   thumbnail_url           65895 non-null  object
 26   zipcode                 73143 non-null  object
 27   bedrooms                74020 non-null  float64
 28   beds                    73980 non-null  float64
dtypes: bool(1), float64(7), int64(3), object(18)
memory usage: 15.9+ MB
```

[3]:
```
(17138, 27)
```

[6]:
```
# Performing Feature engineering
neighborhood_counts = df['neighbourhood'].value_counts()

# Compute the average review score
neighborhood_avg_review = df.groupby('neighbourhood')['review_scores_rating'].
 ↪mean()

# Normalize and combine these factors into a popularity score
df['neighborhood_popularity'] = df['neighbourhood'].map(lambda x:
                                (neighborhood_counts[x] - neighborhood_counts.
 ↪min())
                                / (neighborhood_counts.max() -␣
 ↪neighborhood_counts.min()))

df['neighborhood_avg_review'] = df['neighbourhood'].map(lambda x:
                                (neighborhood_avg_review[x] -␣
 ↪neighborhood_avg_review.min())
                                / (neighborhood_avg_review.max() -␣
 ↪neighborhood_avg_review.min()))

# Weighted score: 70% listings count + 30% average review score
df['neighborhood_popularity'] = (df['neighborhood_popularity'] * 0.7) +\
                                (df['neighborhood_avg_review'] * 0.3)

df[['neighbourhood', 'neighborhood_popularity']].head().reset_index(drop=True)
```

[6]:

	neighbourhood	neighborhood_popularity
0	Noe Valley	0.322683
1	Downtown	0.315679
2	Richmond District	0.317702
3	Alphabet City	0.386873
4	Sherman Oaks	0.311005

[7]:
```
# Create a new column for number of amenities
df['num_amenities'] = df['amenities'].apply(lambda x: len(x.split(',')) if␣
↪isinstance(x, str) else 0)

# Verify the new feature
df[['amenities', 'num_amenities']].head()
```

[7]:
```
                                            amenities  num_amenities
5   {TV,"Wireless Internet",Heating,"Smoke detecto…             10
7   {TV,"Cable TV","Wireless Internet","Wheelchair…             26
8   {TV,"Cable TV","Wireless Internet","Pets live …             21
10  {Internet,"Wireless Internet","Air conditionin…             15
20  {"Cable TV",Internet,"Wireless Internet","Air …             21
```

[11]:
```
# Convert 'host_response_rate' from percentage string to numeric
df['host_response_rate'] = df['host_response_rate'].astype(str).str.rstrip('%').
↪astype(float) / 100

# Create a feature for the number of days the host has been on Airbnb
df['host_since'] = pd.to_datetime(df['host_since'])
df['host_days_active'] = (pd.to_datetime('today') - df['host_since']).dt.days

# Verify the new features
df[['host_response_rate', 'host_days_active']].head()
```

[11]:
```
    host_response_rate  host_days_active
5                  1.0              2856
7                  1.0              4337
8                  1.0              3590
10                 1.0              4389
20                 1.0              3369
```

[282]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
```

[13]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 17138 entries, 5 to 74103
Data columns (total 31 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   log_price               17138 non-null  float64
 1   property_type           17138 non-null  object
 2   room_type               17138 non-null  object
 3   amenities               17138 non-null  object
```

```
 4   accommodates             17138 non-null  int64
 5   bathrooms                17138 non-null  float64
 6   bed_type                 17138 non-null  object
 7   cancellation_policy      17138 non-null  object
 8   cleaning_fee             17138 non-null  bool
 9   city                     17138 non-null  object
 10  first_review             17138 non-null  datetime64[ns]
 11  host_has_profile_pic     17138 non-null  object
 12  host_identity_verified   17138 non-null  object
 13  host_response_rate       17138 non-null  float64
 14  host_since               17138 non-null  datetime64[ns]
 15  instant_bookable         17138 non-null  object
 16  last_review              17138 non-null  datetime64[ns]
 17  latitude                 17138 non-null  float64
 18  longitude                17138 non-null  float64
 19  name                     17138 non-null  object
 20  neighbourhood            17138 non-null  object
 21  number_of_reviews        17138 non-null  int64
 22  review_scores_rating     17138 non-null  float64
 23  zipcode                  17138 non-null  object
 24  bedrooms                 17138 non-null  float64
 25  beds                     17138 non-null  float64
 26  host_tenure              17138 non-null  int32
 27  neighborhood_popularity  17138 non-null  float64
 28  neighborhood_avg_review  17138 non-null  float64
 29  num_amenities            17138 non-null  int64
 30  host_days_active         17138 non-null  int64
dtypes: bool(1), datetime64[ns](3), float64(10), int32(1), int64(4), object(12)
memory usage: 4.0+ MB
```

[7]:

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
```

[11]:

```
# Convert categorical features using one-hot encoding
# df = pd.get_dummies(df, columns=['city', 'neighbourhood', 'zipcode'],␣
↪drop_first=True)

# Convert boolean columns to numeric
bool_cols = ['host_has_profile_pic', 'host_identity_verified',␣
↪'instant_bookable']
df[bool_cols] = df[bool_cols].replace({'t': 1, 'f':0})

# Defining the target variable
```

```
y = df['log_price']

# removing some columns that are not necessary for further analysis
X = df.drop(columns=['log_price', 'name'])

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

[ ]:

```
```

[13]:

```
# Set Target variable
y = df['log_price']
X = df.drop(columns=['log_price', 'name', 'first_review', 'last_review',␣
↪'host_since'])

# Step 2: One-hot encode categorical features
X = pd.get_dummies(X, drop_first=True)
```

[37]:

```
# Split dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Train the regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Predict on the test set
y_pred = model.predict(X_test)
```

[39]:

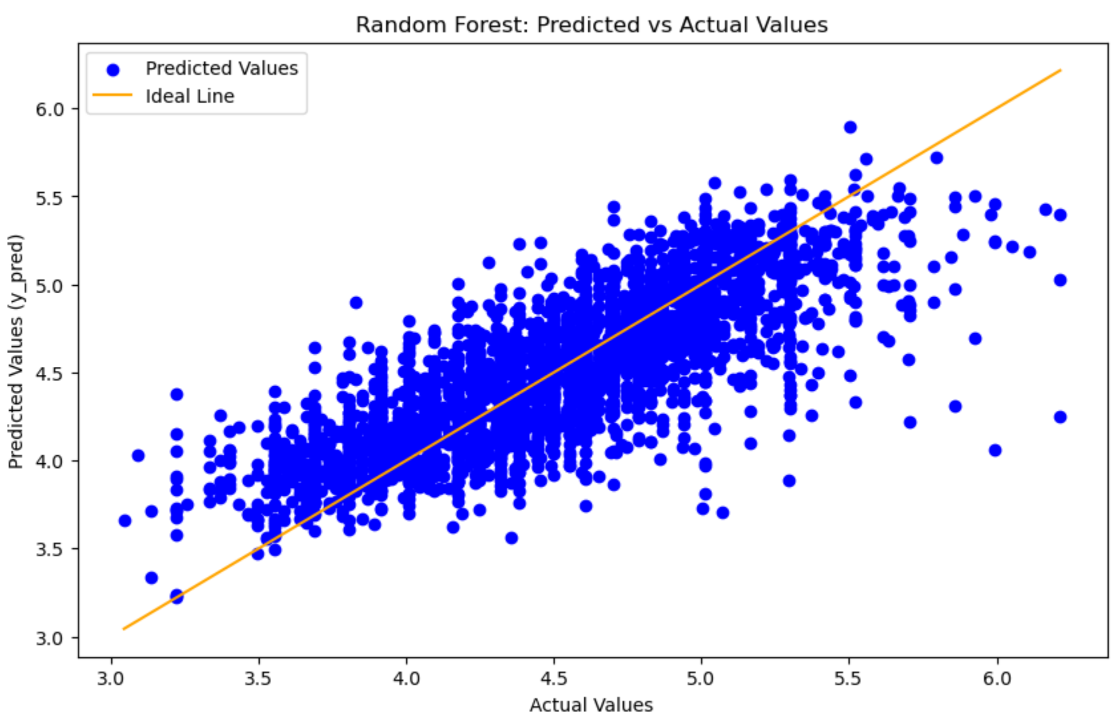
```
# Evaluate the model
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2 = r2_score(y_test, y_pred)

print(f"Root Mean Squared Error: {rmse}")
print(f"R-squared: {r2}")
```

```
Root Mean Squared Error: 350959.20981379034
R-squared: -484684051173.5906
```

[41]:

```
y = df['log_price']
X = df.drop(columns=['log_price', 'name','first_review', 'last_review',␣
↪'host_since'])

X = pd.get_dummies(X, drop_first=True)
```

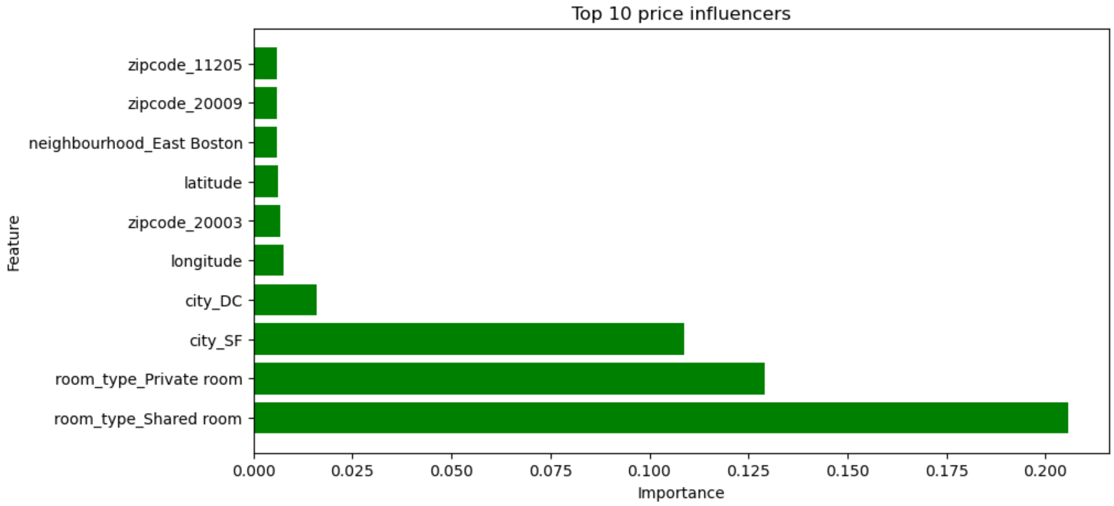
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
 ↪random_state=42)

# Train the Random Forest regression model
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# Predict
y_pred = rf_model.predict(X_test)


# Visualize actual vs predicted
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, color='blue', label='Predicted Values')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)],
 ↪color='orange', linestyle='-', label='Ideal Line')
plt.title('Random Forest: Predicted vs Actual Values')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values (y_pred)')
plt.legend()
plt.show()
```



[43]:
```
from xgboost import XGBRegressor

xgb = XGBRegressor(random_state=42)

# Fitting the model
xgb.fit(X_train, y_train)

# Predict
y_pred = xgb.predict(X_test)

# Evaluating the model
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2 = r2_score(y_test, y_pred)

print(f"Root Mean Squared Error: {rmse}")
print(f"R-squared: {r2}")
```

```
Root Mean Squared Error: 0.3020380694249631
R-squared: 0.6410211901258474
```

[45]:
```
# Create a DataFrame of feature importance
feature_importance = pd.DataFrame({'Feature': X_train.columns, 'Importance':␣
↪xgb.feature_importances_})

# Sort by importance and show top 10
top_10_features = feature_importance.sort_values(by='Importance',␣
↪ascending=False).head(10)
plt.figure(figsize=(10, 5))
plt.barh(top_10_features['Feature'], top_10_features['Importance'],␣
↪color='green')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.title('Top 10 price influencers')
plt.show()
```



Insights When hosting “Shared rooms” or “Private rooms,” revisit the pricing strategy to stay ahead of the competition.

For places near tourist hotspots or downtown areas, emphasize the awesome location—that alone can justify a higher price.

Highlight unique number of amenities and features to stand out in the most popular neighborhoods!

link for the Video Presentation of the Project https://drive.google.com/file/d/11h-w5p4qMNS0iG1VE83sGvCNaR-mLrkI/view?usp=sharing