Airbnb

February 24, 2025

Part A: Airbnb Price Prediction and Insights

Deliverables

1. Data Exploration and Preprocessing

[241]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.simplefilter(action='ignore')

# Load the dataset
df = pd.read_csv("Airbnb_data.csv")

# Display the first 5 rows
df.head()
```

[241]:
```
         id  log_price property_type        room_type  \
0   6901257   5.010635     Apartment  Entire home/apt
1   6304928   5.129899     Apartment  Entire home/apt
2   7919400   4.976734     Apartment  Entire home/apt
3  13418779   6.620073         House  Entire home/apt
4   3808709   4.744932     Apartment  Entire home/apt

                                           amenities  accommodates  bathrooms  \
0  {"Wireless Internet","Air conditioning",Kitche…             3        1.0
1  {"Wireless Internet","Air conditioning",Kitche…             7        1.0
2  {TV,"Cable TV","Wireless Internet","Air condit…             5        1.0
3  {TV,"Cable TV",Internet,"Wireless Internet",Ki…             4        1.0
4  {TV,Internet,"Wireless Internet","Air conditio…             2        1.0

   bed_type cancellation_policy  cleaning_fee  …   latitude   longitude  \
0  Real Bed              strict          True  …  40.696524  -73.991617
1  Real Bed              strict          True  …  40.766115  -73.989040
2  Real Bed            moderate          True  …  40.808110  -73.943756
3  Real Bed            flexible          True  …  37.772004 -122.431619
4  Real Bed            moderate          True  …  38.925627  -77.034596
```

```
                                       name     neighbourhood  \
0            Beautiful brownstone 1-bedroom  Brooklyn Heights
1  Superb 3BR Apt Located Near Times Square    Hell's Kitchen
2                          The Garden Oasis            Harlem
3        Beautiful Flat in the Heart of SF!      Lower Haight
4                Great studio in midtown DC  Columbia Heights

  number_of_reviews review_scores_rating  \
0                 2                100.0
1                 6                 93.0
2                10                 92.0
3                 0                  NaN
4                 4                 40.0

                                       thumbnail_url zipcode bedrooms  beds
0  https://a0.muscache.com/im/pictures/6d7cbbf7-c…   11201      1.0   1.0
1  https://a0.muscache.com/im/pictures/348a55fe-4…   10019      3.0   3.0
2  https://a0.muscache.com/im/pictures/6fae5362-9…   10027      1.0   3.0
3  https://a0.muscache.com/im/pictures/72208dad-9…   94117      2.0   2.0
4                                                NaN   20009      0.0   1.0

[5 rows x 29 columns]
```

[243]:

```python
# Check dataset info
df.info()

# Check summary statistics for numerical columns
df.describe()
```

```
<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
```

[243]:

```
                 id     log_price  accommodates     bathrooms      latitude  \
count  7.411100e+04  74111.000000  74111.000000  73911.000000  74111.000000
mean   1.126662e+07      4.782069      3.155146      1.235263     38.445958
std    6.081735e+06      0.717394      2.153589      0.582044      3.080167
min    3.440000e+02      0.000000      1.000000      0.000000     33.338905
25%    6.261964e+06      4.317488      2.000000      1.000000     34.127908
50%    1.225415e+07      4.709530      2.000000      1.000000     40.662138
75%    1.640226e+07      5.220356      4.000000      1.000000     40.746096
max    2.123090e+07      7.600402     16.000000      8.000000     42.390437

          longitude  number_of_reviews  review_scores_rating      bedrooms  \
count  74111.000000       74111.000000          57389.000000  74020.000000
mean     -92.397525          20.900568             94.067365      1.265793
std       21.705322          37.828641              7.836556      0.852143
min     -122.511500           0.000000             20.000000      0.000000
25%     -118.342374           1.000000             92.000000      1.000000
50%      -76.996965           6.000000             96.000000      1.000000
75%      -73.954660          23.000000            100.000000      1.000000
max      -70.985047         605.000000            100.000000     10.000000

               beds
count  73980.000000
mean       1.710868
std        1.254142
min        0.000000
25%        1.000000
50%        1.000000
75%        2.000000
```

```
max       18.000000
```

[245]:
```python
# Check number of missing values in each column
df.isnull().sum()
```

[245]:
```
id                           0
log_price                    0
property_type                0
room_type                    0
amenities                    0
accommodates                 0
bathrooms                  200
bed_type                     0
cancellation_policy          0
cleaning_fee                 0
city                         0
description                  0
first_review             15864
host_has_profile_pic       188
host_identity_verified     188
host_response_rate       18299
host_since                 188
instant_bookable             0
last_review              15827
latitude                     0
longitude                    0
name                         0
neighbourhood             6872
number_of_reviews            0
review_scores_rating     16722
thumbnail_url             8216
zipcode                    968
bedrooms                    91
beds                       131
dtype: int64
```

[247]:
```python
# Fill missing values for numerical columns with median
num_cols = ['bathrooms', 'bedrooms', 'beds', 'review_scores_rating']
df[num_cols] = df[num_cols].fillna(df[num_cols].median())
# Verify changes
df[num_cols].isnull().sum()
```

[247]:
```
bathrooms               0
bedrooms                0
beds                    0
review_scores_rating    0
dtype: int64
```

[249]:
```
# Convert non-null values to string first, then remove '%' and convert to float
df['host_response_rate'] = df['host_response_rate'].astype(str).str.rstrip('%')

# Convert column to numeric, setting errors='coerce' to handle any unexpected␣
↪values
df['host_response_rate'] = pd.to_numeric(df['host_response_rate'],␣
↪errors='coerce')

# Fill missing values with median
df['host_response_rate'].fillna(df['host_response_rate'].median(), inplace=True)

# Verify changes
df['host_response_rate'].isnull().sum()
```

[249]: 0

[251]:
```
# Convert dates to datetime format
df['host_since'] = pd.to_datetime(df['host_since'])
df['first_review'] = pd.to_datetime(df['first_review'])
df['last_review'] = pd.to_datetime(df['last_review'])

# Fill missing dates with the most common date
df['host_since'].fillna(df['host_since'].mode()[0], inplace=True)
df['first_review'].fillna(df['first_review'].mode()[0], inplace=True)
df['last_review'].fillna(df['last_review'].mode()[0], inplace=True)

# Create a new feature: How long the host has been on Airbnb
df['host_years'] = 2025 - df['host_since'].dt.year

# Verify changes
df[['host_since', 'first_review', 'last_review', 'host_years']].isnull().sum()
```

[251]:
```
host_since      0
first_review    0
last_review     0
host_years      0
dtype: int64
```

[253]:
```
# List of boolean columns
bool_cols = ['host_has_profile_pic', 'host_identity_verified',␣
↪'instant_bookable']

# Convert 't' to True and 'f' to False
for col in bool_cols:
    df[col] = df[col].map({'t': True, 'f': False})

# Fill missing values with False and convert to integer (0 or 1)
```

```
df[bool_cols] = df[bool_cols].fillna(False).astype(int)

# Verify changes
df[bool_cols].isnull().sum()
```

[253]:
```
host_has_profile_pic      0
host_identity_verified    0
instant_bookable          0
dtype: int64
```

[255]:
```
df['neighbourhood'].fillna("Unknown", inplace=True) # Fill with "Unknown"
df['zipcode'].fillna(df['zipcode'].mode()[0], inplace=True) #Fill with mode

# Verify changes
df[['neighbourhood', 'zipcode']].isnull().sum()
```

[255]:
```
neighbourhood    0
zipcode          0
dtype: int64
```

[257]:
```
# Dropping some columns which are not much useful
df.drop(columns=['thumbnail_url', 'description'], inplace=True)

# Verify remaining missing values
df.isnull().sum()
```

[257]:
```
id                        0
log_price                 0
property_type             0
room_type                 0
amenities                 0
accommodates              0
bathrooms                 0
bed_type                  0
cancellation_policy       0
cleaning_fee              0
city                      0
first_review              0
host_has_profile_pic      0
host_identity_verified    0
host_response_rate        0
host_since                0
instant_bookable          0
last_review               0
latitude                  0
longitude                 0
name                      0
```

```
neighbourhood            0
number_of_reviews        0
review_scores_rating     0
zipcode                  0
bedrooms                 0
beds                     0
host_years               0
dtype: int64
```

[259]:
```python
# Define function to remove outliers using 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 numerical 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")

# Verify shape after removing outliers
df.shape
```

[259]:
```
(34576, 28)
```

[261]:
```python
#Feature Engineering such as neighborhood popularity, number of amenities, and␣
↪host activity metrics
# Compute the number of listings per neighborhood
neighborhood_counts = df['neighbourhood'].value_counts()

# Compute the average review score per neighborhood
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)

# Fill NaNs with the mean value
df['neighborhood_popularity'].fillna(df['neighborhood_popularity'].mean(),␣
↪inplace=True)

# Verify the new feature
df[['neighbourhood', 'neighborhood_popularity']].head()
```

[261]:

```
       neighbourhood  neighborhood_popularity
0   Brooklyn Heights                 0.247012
5         Noe Valley                 0.256796
6            Unknown                 0.906962
7           Downtown                 0.248859
8  Richmond District                 0.243277
```

[262]:

```
# 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()
```

[262]:

```
                                           amenities  num_amenities
0  {"Wireless Internet","Air conditioning",Kitche…              9
5  {TV,"Wireless Internet",Heating,"Smoke detecto…             10
6  {TV,Internet,"Wireless Internet","Air conditio…             21
7  {TV,"Cable TV","Wireless Internet","Wheelchair…             26
8  {TV,"Cable TV","Wireless Internet","Pets live …             21
```

[265]:

```
# 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()
```

[265]:
```
   host_response_rate  host_days_active
0                 1.0              4718
5                 1.0              2819
6                 1.0              2915
7                 1.0              4300
8                 1.0              3553
```

2. Model Development

[268]:
```
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

# Convert 'amenities' to numeric (count of amenities)
df['num_amenities'] = df['amenities'].apply(lambda x: len(x.split(',')) if␣
 ↪isinstance(x, str) else 0)
df = df.drop(columns=['amenities'])

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

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

# Define target variable (log-transformed price)
y = df['log_price']
X = df.drop(columns=['log_price', 'id', 'name'])  # Drop non-relevant columns

# 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)
```

[270]:
```
X_train = pd.get_dummies(X_train, drop_first=True)
X_test = pd.get_dummies(X_test, drop_first=True)
```

[90]:
```
# Ensure X_train and X_test have the same columns
X_train, X_test = X_train.align(X_test, join='left', axis=1, fill_value=0)
```

[38]:
```
# Linear Regression Model
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)
y_pred_lr = lr_model.predict(X_test)
```

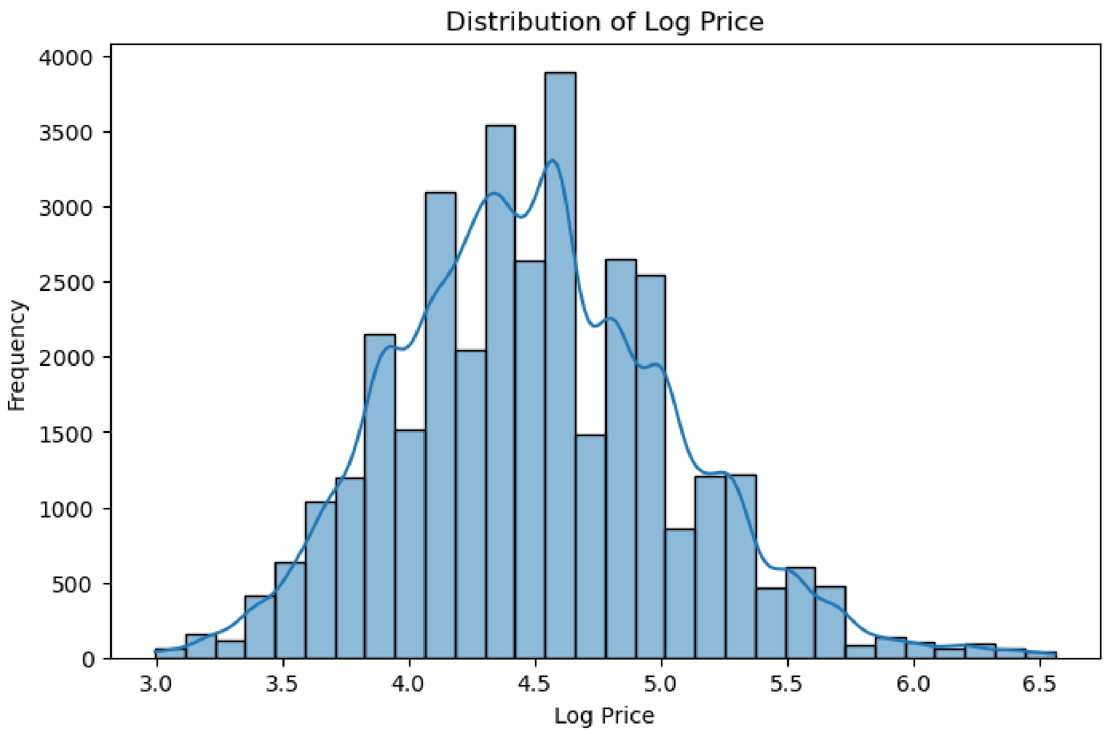
```
# Random Forest Model
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
y_pred_rf = rf_model.predict(X_test)
```

3. Model Evaluation

[42]:
```
def evaluate_model(y_test, y_pred, model_name):
    print(f" {model_name} Performance:")
    print(f" RMSE: {np.sqrt(mean_squared_error(y_test, y_pred)):.2f}")
    print(f" MAE: {mean_absolute_error(y_test, y_pred):.2f}")
    print(f" R² Score: {r2_score(y_test, y_pred):.2f}")
    print("-" * 40)

# Evaluate both models
evaluate_model(y_test, y_pred_lr, "Linear Regression")
evaluate_model(y_test, y_pred_rf, "Random Forest Regressor")
```

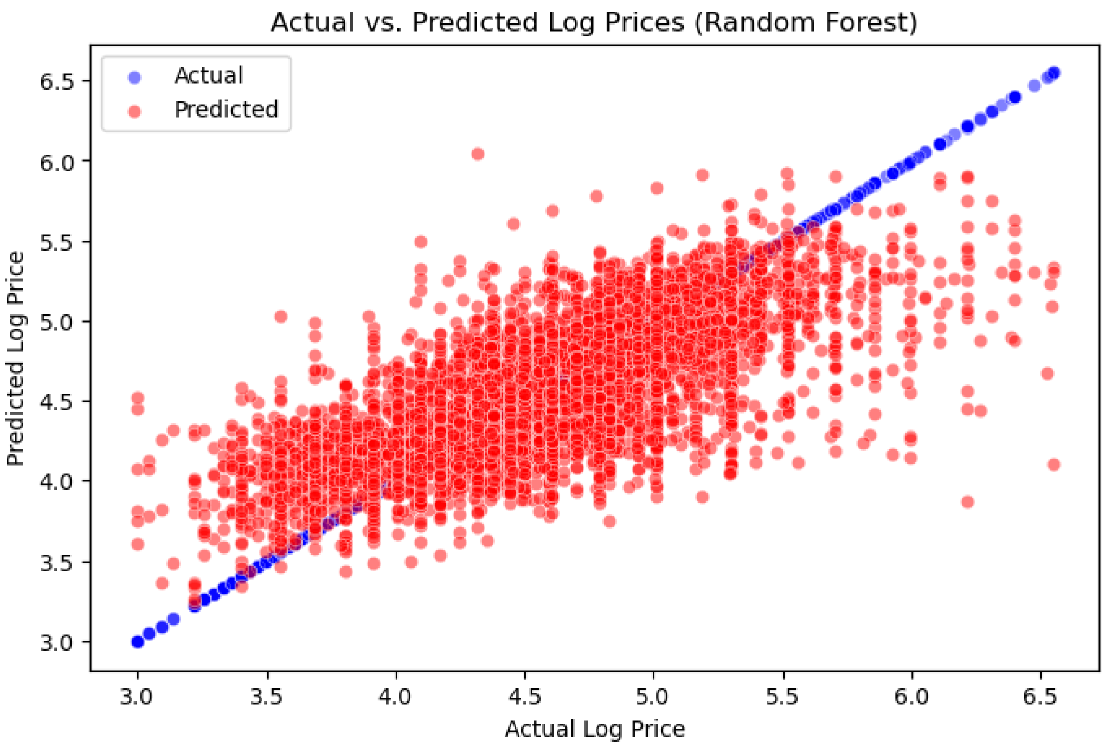
```
 Linear Regression Performance:
 RMSE: 0.54
 MAE: 0.43
 R² Score: 0.02
----------------------------------------
 Random Forest Regressor Performance:
 RMSE: 0.37
 MAE: 0.28
 R² Score: 0.54
----------------------------------------
```

[66]:
```
# Visualizations
plt.figure(figsize=(8, 5))
sns.histplot(df['log_price'], bins=30, kde=True)
plt.title("Distribution of Log Price")
plt.xlabel("Log Price")
plt.ylabel("Frequency")
plt.show()
```

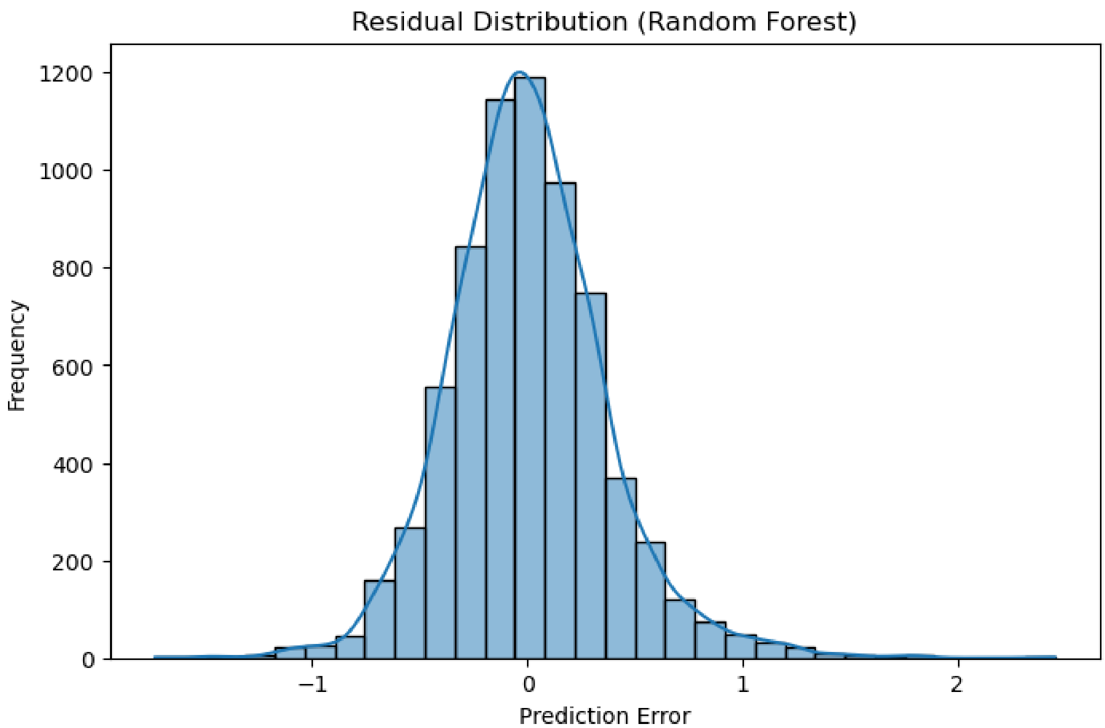


[68]:
```
plt.figure(figsize=(10, 5))
sns.scatterplot(x=df['neighborhood_popularity'], y=df['log_price'])
plt.title("Neighborhood Popularity vs. Log Price")
plt.xlabel("Neighborhood Popularity")
plt.ylabel("Log Price")
plt.show()
```

[272]:
```
plt.figure(figsize=(8, 5))

# Plot actual values in one color and predicted values in another
sns.scatterplot(x=y_test, y=y_test, color="blue", alpha=0.5, label="Actual")  #␣
 ↪Blue for actual values
sns.scatterplot(x=y_test, y=y_pred_rf, color="red", alpha=0.5,␣
 ↪label="Predicted")  # Red for predicted values

plt.title("Actual vs. Predicted Log Prices (Random Forest)")
plt.xlabel("Actual Log Price")
plt.ylabel("Predicted Log Price")
plt.legend()  # Show the legend
plt.show()
```



[74]:
```
residuals = y_test - y_pred_rf

plt.figure(figsize=(8, 5))
sns.histplot(residuals, bins=30, kde=True)
plt.title("Residual Distribution (Random Forest)")
plt.xlabel("Prediction Error")
plt.ylabel("Frequency")
plt.show()
```



[86]:
```
# Tuning the Model
from sklearn.model_selection import GridSearchCV

param_grid = {
    'max_depth': [None, 10, 30],
    'min_samples_split': [2, 5, 10]
}
grid_search = GridSearchCV(RandomForestRegressor(n_estimators=100,␣
 ↪random_state=42, n_jobs=-1),
                           param_grid, cv=3, scoring='r2', n_jobs=-1)
grid_search.fit(X_train, y_train)

best_rf = grid_search.best_estimator_
y_pred_best_rf = best_rf.predict(X_test)

evaluate_model(y_test, y_pred_best_rf, "Grid Search Tuned RF")
```

```
Grid Search Tuned RF Performance:
RMSE: 0.37
MAE: 0.28
R² Score: 0.54
----------------------------------------
```

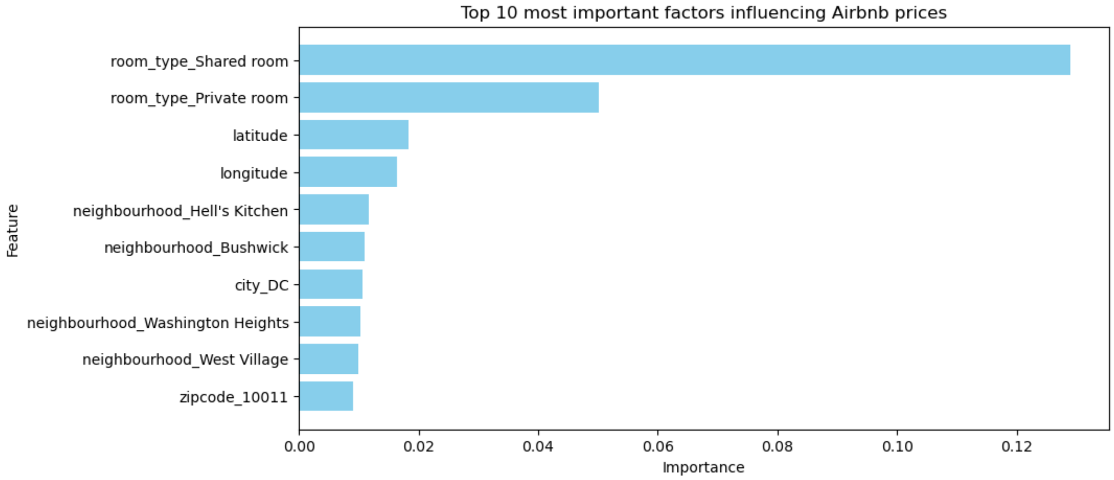
[98]:

```
from xgboost import XGBRegressor

# Define XGBoost model with default parameters
xgb = XGBRegressor(random_state=42)

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

# Predict on test data
y_pred_xgb = xgb.predict(X_test)

# Evaluate XGBoost
evaluate_model(y_test, y_pred_xgb, "XGBoost Regressor")
```

```
XGBoost Regressor Performance:
RMSE: 0.36
MAE: 0.27
R² Score: 0.56
----------------------------------------
```

[276]:

```
# Insights about the factors influencing Airbnb prices

# 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='skyblue')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.title('Top 10 most important factors influencing Airbnb prices')
plt.gca().invert_yaxis()  # Invert y-axis to show the highest at the top
plt.show()
```


Top 10 most important factors influencing Airbnb prices
room_type_Shared room
room_type_Private room
latitude
longitude
neighbourhood_Hell's Kitchen
neighbourhood_Bushwick
city_DC
neighbourhood_Washington Heights
neighbourhood_West Village
zipcode_10011
Feature
0.00
0.02
0.04
0.06
0.08
0.10
0.12
Importance