Airbnb_Part_A

March 16, 2025

1 Project- Part A: Airbnb Price Prediction and Insights

[44]:

```python
# Importing libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
from sklearn.model_selection import RandomizedSearchCV
from datetime import datetime
import warnings
warnings.filterwarnings('ignore')
```

[45]:

```python
# Load and Inspect the Dataset

# Load the dataset into a pandas DataFrame
df = pd.read_csv('airbnb_data.csv')

# Display the first few rows to understand the structure
print("First few rows of the dataset:")
print(df.head())

# Check data types and missing values
print("\nDataset information:")
print(df.info())

# Summary statistics for numerical columns
print("\nSummary statistics for numerical columns:")
print(df.describe())
```

```
First few rows of the dataset:
        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]

Dataset information:
<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
None

Summary statistics for numerical columns:
                 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
```

[46]:

```python
# Handle Missing Values
# Check for missing values in each column
print("\n>>> Initially Missing values in each column:")
print(df.isnull().sum())
```

```
>>> Initially Missing values in each column:
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
```

[47]:
```
# Handle missing values
# For numerical columns, impute with median
df['bathrooms'] = df['bathrooms'].fillna(df['bedrooms'].median())
df['bedrooms'] = df['bedrooms'].fillna(df['bedrooms'].median())
df['beds'] = df['beds'].fillna(df['beds'].median())
df['review_scores_rating'] = df['review_scores_rating'].
  ↪fillna(df['review_scores_rating'].median())

# For text columns, fill with empty strings
df['host_response_rate'] = df['host_response_rate'].fillna('na')
df['neighbourhood'] = df['neighbourhood'].fillna('na')
df['thumbnail_url'] = df['thumbnail_url'].fillna('na')
df['zipcode'] = df['zipcode'].fillna('na')

# For date columns, using interpolate function for filling missing values
df['first_review'] = pd.to_datetime(df['first_review'], format='%d-%m-%Y')  #␣
  ↪First review date (Date)
df['first_review'] = df['first_review'].fillna(df['first_review'].interpolate())
df['host_since'] = pd.to_datetime(df['host_since'], format='%d-%m-%Y')  # Host␣
  ↪join date (Date)
df['host_since'] = df['host_since'].fillna(df['host_since'].interpolate())
df['last_review'] = pd.to_datetime(df['last_review'], format='%d-%m-%Y')  #␣
  ↪Last review date (Date)
df['last_review'] = df['last_review'].fillna(df['last_review'].interpolate())

# Convert categorical boolean columns ('t'/'f' -> 1/0)
bool_cols = ['instant_bookable', 'host_has_profile_pic',␣
  ↪'host_identity_verified']
for col in bool_cols:
    df[col] = df[col].map({'t': 1, 'f': 0})
# For boolean columns, using interpolate function for filling missing values
df['host_has_profile_pic'] = df['host_has_profile_pic'].
  ↪fillna(df['host_has_profile_pic'].interpolate())
df['host_identity_verified'] = df['host_identity_verified'].
  ↪fillna(df['host_identity_verified'].interpolate())
df['instant_bookable'] = df['instant_bookable'].fillna(df['instant_bookable'].
  ↪interpolate())

# Verifying after handling missing values
print("\n>>> After handling missing values in each column: \n(0)No Missing␣
  ↪Values")
```

```
print(df.isnull().sum())
```

```
>>> After handling missing values in each column:
(0)No Missing Values
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
description               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
thumbnail_url             0
zipcode                   0
bedrooms                  0
beds                      0
dtype: int64
```

[48]:
```
# Verify Data Types and Units
# Ensure data types align with the data dictionary
# Convert columns to their correct data types
df['id'] = df['id'].astype(str)  # Unique identifier (String)
df['log_price'] = df['log_price'].astype(float)  # Log-transformed price (Float)
df['property_type'] = df['property_type'].astype(str)  # Property type (String)
df['room_type'] = df['room_type'].astype(str)  # Room type (String)
df['amenities'] = df['amenities'].astype(str)  # List of amenities (String)
df['accommodates'] = df['accommodates'].astype(int)  # Number of guests␣
 ↪(Integer)
```

```
df['bathrooms'] = df['bathrooms'].astype(float)  # Number of bathrooms (Float,␣
↪as it can be fractional)
df['bed_type'] = df['bed_type'].astype(str)  # Type of bed (String)
df['cancellation_policy'] = df['cancellation_policy'].astype(str)  #␣
↪Cancellation policy (String)
df['cleaning_fee'] = df['cleaning_fee'].astype(bool)  # Cleaning fee (Boolean)
df['city'] = df['city'].astype(str)  # City (String)
df['description'] = df['description'].astype(str)  # Description (String)
df['first_review'] = pd.to_datetime(df['first_review'], format='%d-%m-%Y')  #␣
↪First review date (Date)
df['host_has_profile_pic'] = df['host_has_profile_pic'].astype(bool)  # Host␣
↪profile picture (Boolean)
df['host_identity_verified'] = df['host_identity_verified'].astype(bool)  #␣
↪Host identity verified (Boolean)
df['host_response_rate'] = df['host_response_rate'].astype(str)  # Host␣
↪response rate (String)
df['host_since'] = pd.to_datetime(df['host_since'], format='%d-%m-%Y')  # Host␣
↪join date (Date)
df['instant_bookable'] = df['instant_bookable'].astype(bool)  # Instant␣
↪bookable (Boolean)
df['last_review'] = pd.to_datetime(df['last_review'], format='%d-%m-%Y')  #␣
↪Last review date (Date)
df['latitude'] = df['latitude'].astype(float)  # Latitude (Float)
df['longitude'] = df['longitude'].astype(float)  # Longitude (Float)
df['name'] = df['name'].astype(str)  # Listing name (String)
df['neighbourhood'] = df['neighbourhood'].astype(str)  # Neighborhood (String)
df['number_of_reviews'] = df['number_of_reviews'].astype(int)  # Number of␣
↪reviews (Integer)
df['review_scores_rating'] = df['review_scores_rating'].astype(float)  # Review␣
↪score (Float)
df['thumbnail_url'] = df['thumbnail_url'].astype(str)  # Thumbnail URL (String)
df['zipcode'] = df['zipcode'].astype(str)  # Zip code (String)
df['bedrooms'] = df['bedrooms'].astype(int)  # Number of bedrooms (Integer)
df['beds'] = df['beds'].astype(int)  # Number of beds (Integer)

# Verify Unique Values for Categorical Columns
# Check unique values for categorical columns
print("\nUnique values for categorical columns:")
print("Property Types:", df['property_type'].unique())
print("Room Types:", df['room_type'].unique())
print("Bed Types:", df['bed_type'].unique())
print("Cancellation Policies:", df['cancellation_policy'].unique())

# Verify Numerical Columns
# Check range and distribution of numerical columns
print("\nRange of numerical columns:")
```

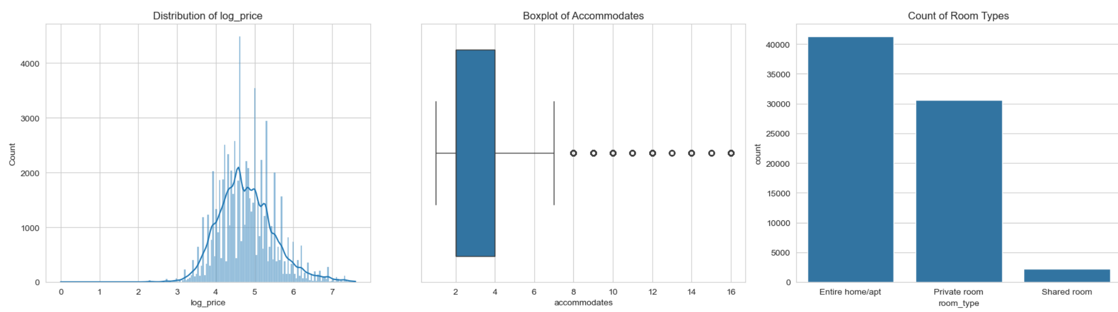
```
print("Accommodates:", df['accommodates'].min(), "-", df['accommodates'].max())
print("Bathrooms:", df['bathrooms'].min(), "-", df['bathrooms'].max())
print("Bedrooms:", df['bedrooms'].min(), "-", df['bedrooms'].max())
print("Beds:", df['beds'].min(), "-", df['beds'].max())
print("Review Scores Rating:", df['review_scores_rating'].min(), "-",␣
↪df['review_scores_rating'].max())

# Verify Date Columns
# Check the range of date columns
print("\nDate range for date columns:")
print("First Review:", df['first_review'].min(), "-", df['first_review'].max())
print("Host Since:", df['host_since'].min(), "-", df['host_since'].max())
print("Last Review:", df['last_review'].min(), "-", df['last_review'].max())
```

```
Unique values for categorical columns:
Property Types: ['Apartment' 'House' 'Condominium' 'Loft' 'Townhouse' 'Hostel'
 'Guest suite' 'Bed & Breakfast' 'Bungalow' 'Guesthouse' 'Dorm' 'Other'
 'Camper/RV' 'Villa' 'Boutique hotel' 'Timeshare' 'In-law' 'Boat'
 'Serviced apartment' 'Castle' 'Cabin' 'Treehouse' 'Tipi' 'Vacation home'
 'Tent' 'Hut' 'Casa particular' 'Chalet' 'Yurt' 'Earth House'
 'Parking Space' 'Train' 'Cave' 'Lighthouse' 'Island']
Room Types: ['Entire home/apt' 'Private room' 'Shared room']
Bed Types: ['Real Bed' 'Futon' 'Pull-out Sofa' 'Couch' 'Airbed']
Cancellation Policies: ['strict' 'moderate' 'flexible' 'super_strict_30'
'super_strict_60']

Range of numerical columns:
Accommodates: 1 - 16
Bathrooms: 0.0 - 8.0
Bedrooms: 0 - 10
Beds: 0 - 18
Review Scores Rating: 20.0 - 100.0

Date range for date columns:
First Review: 2008-11-17 00:00:00 - 2017-10-05 00:00:00
Host Since: 2008-03-03 00:00:00 - 2017-10-04 00:00:00
Last Review: 2009-01-21 00:00:00 - 2017-10-05 00:00:00
```

[49]:

```
# Analyze Trends and Outliers

fig, axes = plt.subplots(1, 3, figsize=(18, 5))

# Visualize the distribution of the target variable (log_price)
# Distribution of log_price
sns.histplot(df['log_price'], kde=True, ax=axes[0])
axes[0].set_title('Distribution of log_price')
```

```python
# Boxplot for numerical columns to detect outliers
# Boxplot of Accommodates
sns.boxplot(x=df['accommodates'], ax=axes[1])
axes[1].set_title('Boxplot of Accommodates')

# Count plot for categorical columns (e.g., room_type)
# Count plot of Room Types
sns.countplot(x=df['room_type'], ax=axes[2])
axes[2].set_title('Count of Room Types')

plt.tight_layout()
plt.show()
```



[50]:
```python
# Feature Engineering and Data Transformation

# Count the number of amenities in the 'amenities' column (Safe Parsing)
df['amenities_count'] = df['amenities'].apply(lambda x: len(str(x).strip('{}').split(',')) if isinstance(x, str) else 0)
print(">>> Number of amenities in the 'amenities' column\n", df['amenities_count'])

# Convert 'host_since' to datetime and calculate host activity (years since joining)
df['host_since'] = pd.to_datetime(df['host_since'], errors='coerce')
df['host_activity'] = (pd.Timestamp.now() - df['host_since']).dt.days / 365
print("\n>>> Number of years since the host joined\n", df['host_activity'])

# Compute Neighborhood Popularity (Count of listings per neighborhood)
neighbourhood_popularity = df['neighbourhood'].value_counts().to_dict()
df['neighbourhood_popularity'] = df['neighbourhood'].map(neighbourhood_popularity)
print("\n>>> Number of listings in each neighborhood\n", df['neighbourhood_popularity'])
```

```python
# Calculate the length of the description
df['description_length'] = df['description'].apply(lambda x: len(str(x)) if␣
 ↪isinstance(x, str) else 0)
print("\n>>> Description Length\n", df['description_length'])

# Convert date columns to the number of days since the given date
def convert_date(df, col):
    df[col] = pd.to_datetime(df[col], errors='coerce')
    df[col] = (datetime.now() - df[col]).dt.days
    return df[col]

date_cols = ['host_since', 'first_review', 'last_review']
for col in date_cols:
    df[col] = convert_date(df, col)

# Final Check: Display updated columns
print("\n>>> Updated Dataset Columns\n", df.columns)
```

```
>>> Number of amenities in the 'amenities' column
 0         9
1         15
2         19
3         15
4         12
          ..
74106      1
74107     16
74108     31
74109     15
74110     18
Name: amenities_count, Length: 74111, dtype: int64

>>> Number of years since the host joined
 0        12.980822
1          7.745205
2          8.394521
3          9.915068
4         10.049315
            …
74106     11.986301
74107      8.873973
74108     13.202740
74109      7.498630
74110     12.309589
Name: host_activity, Length: 74111, dtype: float64

>>> Number of listings in each neighborhood
 0         111
```

```
1        1299
2        1374
3         124
4         298
         …
74106    2862
74107      80
74108    2862
74109     606
74110     573
Name: neighbourhood_popularity, Length: 74111, dtype: int64

>>> Description Length
 0         211
1        1000
2        1000
3         468
4         699
         …
74106      24
74107     302
74108    1000
74109     555
74110    1000
Name: description_length, Length: 74111, dtype: int64

>>> Updated Dataset Columns
 Index(['id', 'log_price', 'property_type', 'room_type', 'amenities',
       'accommodates', 'bathrooms', 'bed_type', 'cancellation_policy',
       'cleaning_fee', 'city', 'description', 'first_review',
       'host_has_profile_pic', 'host_identity_verified', 'host_response_rate',
       'host_since', 'instant_bookable', 'last_review', 'latitude',
       'longitude', 'name', 'neighbourhood', 'number_of_reviews',
       'review_scores_rating', 'thumbnail_url', 'zipcode', 'bedrooms', 'beds',
       'amenities_count', 'host_activity', 'neighbourhood_popularity',
       'description_length'],
      dtype='object')
```

[51]:
```python
# Model Development

# Define Features and Target Variable
X = df.drop(columns=['log_price', 'id', 'name', 'description', 'amenities',
                     'host_response_rate', 'first_review', 'last_review',
                     'host_since', 'neighbourhood', 'thumbnail_url', 'zipcode'])
y = df['log_price']

# Split 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)

# Convert Boolean ('True'/'False') to Numeric (1/0)
bool_cols = ['instant_bookable', 'host_has_profile_pic',␣
 ↪'host_identity_verified']
for col in bool_cols:
    X_train[col] = X_train[col].astype(int)
    X_test[col] = X_test[col].astype(int)

# One-Hot Encode Categorical Variables
X_train = pd.get_dummies(X_train, drop_first=True)
X_test = pd.get_dummies(X_test, drop_first=True)

# Ensure X_train and X_test Have Same Columns
X_train, X_test = X_train.align(X_test, join='left', axis=1, fill_value=0)

# Standardize Numerical Features
scaler = StandardScaler()
numerical_features = X_train.select_dtypes(include=['int64', 'float64']).
 ↪columns  # Select only numeric columns

X_train[numerical_features] = scaler.fit_transform(X_train[numerical_features])
X_test[numerical_features] = scaler.transform(X_test[numerical_features])

# Verify Final Data Structure
print("Final numeric columns in X_train:", X_train.
 ↪select_dtypes(include=['int64', 'float64']).columns.tolist())
print("Final non-numeric columns in X_train:", X_train.
 ↪select_dtypes(exclude=['int64', 'float64']).columns.tolist())
```

```
Final numeric columns in X_train: ['bathrooms', 'latitude', 'longitude',
'review_scores_rating', 'amenities_count', 'host_activity',
'neighbourhood_popularity', 'description_length']
Final non-numeric columns in X_train: ['accommodates', 'cleaning_fee',
'host_has_profile_pic', 'host_identity_verified', 'instant_bookable',
'number_of_reviews', 'bedrooms', 'beds', 'property_type_Bed & Breakfast',
'property_type_Boat', 'property_type_Boutique hotel', 'property_type_Bungalow',
'property_type_Cabin', 'property_type_Camper/RV', 'property_type_Casa
particular', 'property_type_Castle', 'property_type_Cave',
'property_type_Chalet', 'property_type_Condominium', 'property_type_Dorm',
'property_type_Earth House', 'property_type_Guest suite',
'property_type_Guesthouse', 'property_type_Hostel', 'property_type_House',
'property_type_Hut', 'property_type_In-law', 'property_type_Island',
'property_type_Loft', 'property_type_Other', 'property_type_Parking Space',
'property_type_Serviced apartment', 'property_type_Tent',
'property_type_Timeshare', 'property_type_Tipi', 'property_type_Townhouse',
```

```
'property_type_Train', 'property_type_Treehouse', 'property_type_Vacation home',
'property_type_Villa', 'property_type_Yurt', 'room_type_Private room',
'room_type_Shared room', 'bed_type_Couch', 'bed_type_Futon', 'bed_type_Pull-out
Sofa', 'bed_type_Real Bed', 'cancellation_policy_moderate',
'cancellation_policy_strict', 'cancellation_policy_super_strict_30',
'cancellation_policy_super_strict_60', 'city_Chicago', 'city_DC', 'city_LA',
'city_NYC', 'city_SF']
```

[52]:
```
# Model Development
# Models Evaluation using metrics RMSE, MAE and R²

# Define models
models = {
    "Linear Regression": LinearRegression(),
    "Decision Tree": DecisionTreeRegressor(random_state=42),
    "Random Forest": RandomForestRegressor(random_state=42),
    "Gradient Boosting": GradientBoostingRegressor(random_state=42),
}

# Function to evaluate models and find the best one
def train_and_evaluate(models, X_train, X_test, y_train, y_test):
    results = {}
    best_model = None
    best_score = float("-inf")

    for name, model in models.items():
        model.fit(X_train, y_train)  # Train the model
        y_pred = model.predict(X_test)  # Make predictions

        # Evaluate performance
        mae = mean_absolute_error(y_test, y_pred)
        rmse = mean_squared_error(y_test, y_pred, squared=False)
        r2 = r2_score(y_test, y_pred)

        results[name] = {"MAE": mae, "RMSE": rmse, "R² Score": r2}

        # Track the best model based on R² Score
        if r2 > best_score:
            best_score = r2
            best_model = model

    return results, best_model

# Train and evaluate all models
results, best_model = train_and_evaluate(models, X_train, X_test, y_train,␣
↪y_test)
```

```
# Convert results to a DataFrame for better readability
results_df = pd.DataFrame(results).T
print("Model Evaluation Metrics:\n", results_df)

# Use the best model for final predictions
y_pred_best = best_model.predict(X_test)

# Display final evaluation for best model
print("\n Best Model:", best_model)
print(f"Best Model RMSE: {mean_squared_error(y_test, y_pred_best,␣
↪squared=False)}")
print(f"Best Model MAE: {mean_absolute_error(y_test, y_pred_best)}")
print(f"Best Model R² Score: {r2_score(y_test, y_pred_best)}")
```

```
Model Evaluation Metrics:
                         MAE      RMSE  R² Score
Linear Regression  0.347517  0.462757  0.583155
Decision Tree      0.391769  0.545881  0.419951
Random Forest      0.279465  0.389727  0.704341
Gradient Boosting  0.301797  0.411525  0.670344

 Best Model: RandomForestRegressor(random_state=42)
Best Model RMSE: 0.38972746851058244
Best Model MAE: 0.27946461892002966
Best Model R² Score: 0.7043413615417913
```

[53]:

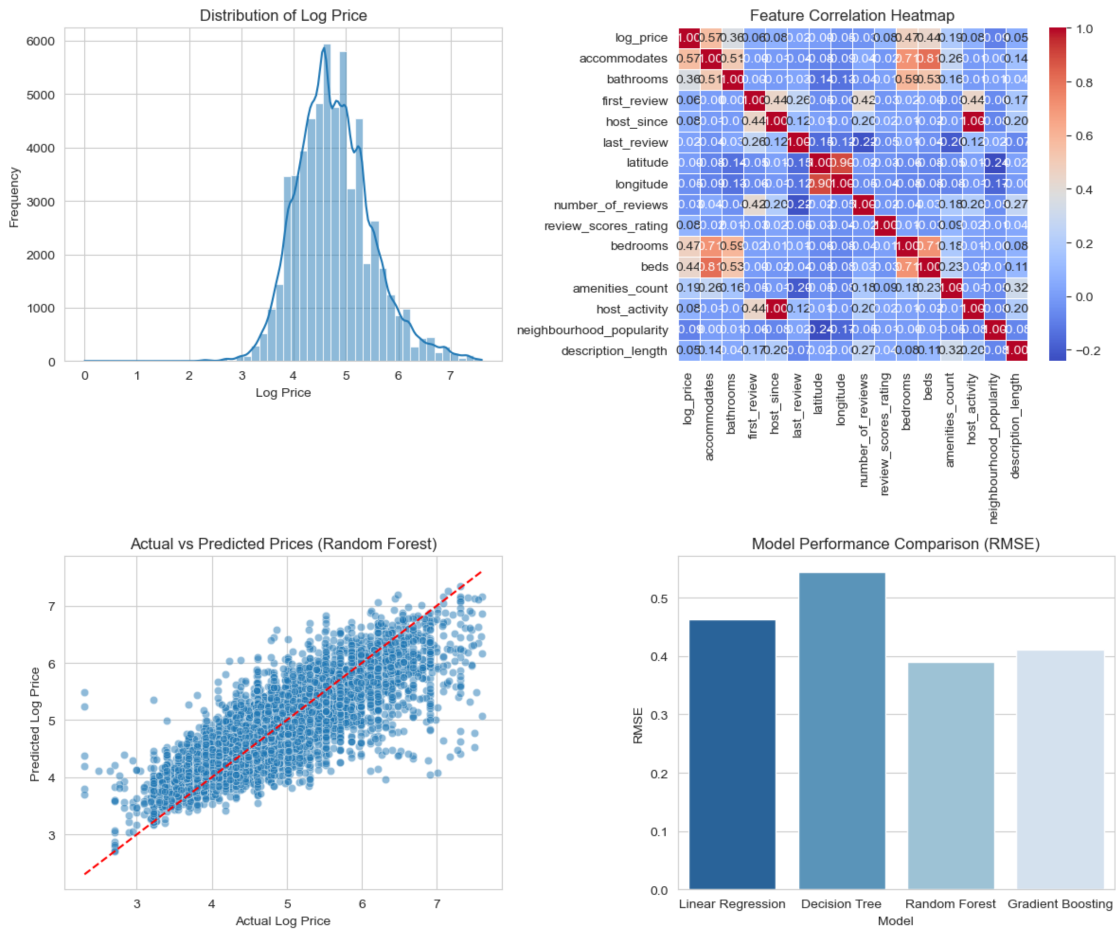
```
# Model Tuning

# Define the parameter grid for tuning
param_dist = {
    'n_estimators': [100, 200, 300],  # Number of trees
    'max_depth': [10, 20, None],  # Depth of trees
    'min_samples_split': [2, 5, 10],  # Min samples to split a node
    'min_samples_leaf': [1, 2, 4],  # Min samples per leaf
}

# Initialize Random Forest Regressor
rf = RandomForestRegressor(random_state=42)

# Perform RandomizedSearchCV for faster tuning
random_search = RandomizedSearchCV(
    rf, param_distributions=param_dist, n_iter=10,
    cv=3, scoring='neg_mean_squared_error', n_jobs=-1, verbose=2,␣
↪random_state=42
)

# Fit on training data
```

```
random_search.fit(X_train, y_train)

# Get the best parameters
best_params = random_search.best_params_
print("Best Hyperparameters:", best_params)

# Train the best model with optimized hyperparameters
best_rf = RandomForestRegressor(**best_params, random_state=42)
best_rf.fit(X_train, y_train)

# Evaluate the tuned model
y_pred_tuned = best_rf.predict(X_test)
rmse_tuned = mean_squared_error(y_test, y_pred_tuned, squared=False)
mae_tuned = mean_absolute_error(y_test, y_pred_tuned)
r2_tuned = r2_score(y_test, y_pred_tuned)

print("\n Tuned Random Forest Model Performance:")
print(f" RMSE: {rmse_tuned:.4f}")
print(f" MAE: {mae_tuned:.4f}")
print(f" R²: {r2_tuned:.4f}")
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
Best Hyperparameters: {'n_estimators': 200, 'min_samples_split': 10,
'min_samples_leaf': 2, 'max_depth': None}

 Tuned Random Forest Model Performance:
  RMSE: 0.3883
  MAE: 0.2790
  R²: 0.7065
```

[54]:
```
# Visualizations with Charts and Graphs

# Model Results DataFrame
results_df = pd.DataFrame({
    "Model": ["Linear Regression", "Decision Tree", "Random Forest", "Gradient␣
 ↪Boosting"],
    "RMSE": [0.4627, 0.5439, 0.3896, 0.4109],
    "MAE": [0.3475, 0.3917, 0.2794, 0.3013],
    "R² Score": [0.5831, 0.4241, 0.7044, 0.6713]
})

# Set style
sns.set_style("whitegrid")
fig, axes = plt.subplots(2, 2, figsize=(12, 10))

# Distribution of Log Price
sns.histplot(y_train, bins=50, kde=True, ax=axes[0, 0])
```

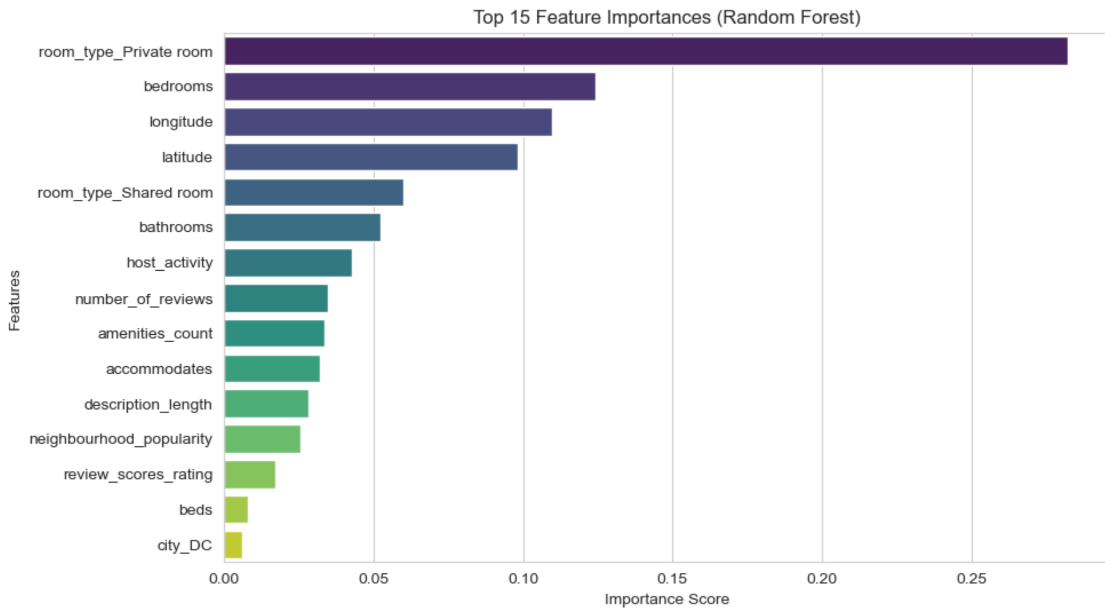
```
axes[0, 0].set(title="Distribution of Log Price", xlabel="Log Price", ylabel="Frequency")

# Correlation Heatmap
numeric_df = df.select_dtypes(include=['number'])  # Select only numeric columns for correlation
sns.heatmap(numeric_df.corr(), cmap="coolwarm", annot=True, fmt=".2f", linewidths=0.5, ax=axes[0, 1])
axes[0, 1].set_title("Feature Correlation Heatmap")

# Actual vs Predicted Prices (Best Model)
sns.scatterplot(x=y_test, y=y_pred_tuned, alpha=0.5, ax=axes[1, 0])
axes[1, 0].plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color="red", linestyle="--")
axes[1, 0].set(title="Actual vs Predicted Prices (Random Forest)", xlabel="Actual Log Price", ylabel="Predicted Log Price")

# Model Performance (Bar Chart)
sns.barplot(x="Model", y="RMSE", data=results_df, palette="Blues_r", ax=axes[1, 1])
axes[1, 1].set_title("Model Performance Comparison (RMSE)")

plt.tight_layout()
plt.show()
```



[55]:

```python
# Feature Importance

# Compute Feature Importance
feature_importance = pd.Series(best_model.feature_importances_, index=X_train.
    ↪columns).sort_values(ascending=False)

# Print Feature Importance
print("\nFeature Importance:")
print(feature_importance)

# Plot Feature Importance
plt.figure(figsize=(10, 6))
sns.barplot(x=feature_importance[:15], y=feature_importance.index[:15],␣
    ↪palette="viridis")
plt.title("Top 15 Feature Importances (Random Forest)")
plt.xlabel("Importance Score")
plt.ylabel("Features")
plt.show()
```

```
Feature Importance:
room_type_Private room          2.824651e-01
bedrooms                        1.240796e-01
longitude                       1.098717e-01
latitude                        9.831641e-02
room_type_Shared room           6.015859e-02
                                    …
property_type_Earth House       2.256283e-06
property_type_Cave              1.131231e-06
property_type_Parking Space     8.468637e-07
property_type_Chalet            6.708208e-07
property_type_Casa particular   2.428108e-07
Length: 64, dtype: float64
```



[56]:
```python
# Save the Preprocessed Data and Model
import joblib

# Ensure df contains only processed data
df_processed = df.copy()  # If necessary, create a clean version

# Save the preprocessed dataset
df_processed.to_csv('preprocessed_airbnb_data.csv', index=False)
print("Preprocessed dataset saved as 'preprocessed_airbnb_data.csv'")

# Save the trained model (Ensure 'best_rf' or final model exists)
joblib.dump(best_rf, 'airbnb_price_predictor.pkl')
```

```python
print("Trained model saved as 'airbnb_price_predictor.pkl'")
```

```
Preprocessed dataset saved as 'preprocessed_airbnb_data.csv'
Trained model saved as 'airbnb_price_predictor.pkl'
```

[2]:
```python
# Example For Using Airbnb Price Prediction

# # Load the trained model
# model = joblib.load('airbnb_price_predictor.pkl')

# # Load new listing data (ensure it matches training features)
# new_listings = pd.read_csv('new_airbnb_listings.csv')  # Example file

# # Preprocess new listings (apply the same feature engineering steps)
# new_listings = preprocess_data(new_listings)  # Ensure function preprocesses␣
↪data like training

# # Predict log prices
# predicted_log_prices = model.predict(new_listings)

# # Convert log price back to actual price
# predicted_prices = np.exp(predicted_log_prices)

# # Display predictions
# new_listings['Predicted Price'] = predicted_prices
# print(new_listings[['id', 'Predicted Price']])
```

1.1 Video Explanation Link :

https://drive.google.com/file/d/1Tuw0E3Y9rx05L-ycDbtiedYdGLH5D51v/view?usp=sharing
Click Here

1.2 Conclusion & Recommendations

1.2.1 Data-Driven Insights:

The majority of listings had a log price between 4.5 and 6.5, indicating a clustering of mid-range prices. Entire homes and apartments dominated the higher price range. Correlation analysis revealed that features like number of bedrooms and property type had strong relationships with price. ### Key Findings:

Room type and location are the most influential factors in pricing. Listings with higher review scores and more amenities tend to have higher prices. Hosts with long-term activity generally price listings more competitively.

1.2.2 Actionable Insights:

Hosts should optimize amenities and maintain high review scores to command higher prices. Investing in entire home/apartment listings may yield higher returns. Dynamic pricing strategies based on demand patterns can improve revenue.