0.1 CaseCraft: The Analytics Sprint – Project 19

0.1.1 Airbnb Booking Trends

Subheading: Mapping booking hotspots, analyzing lead times, and predicting prices using geospatial clustering and regression.

0.1.2 Project Goals

- Simulate Airbnb listings with location, price, and booking lead time
- Cluster listings by location and price tier
- Visualize booking hotspots using bubble maps
- Analyze lead time vs price correlation
- Predict price using listing features and booking behavior
- Summarize insights for host strategy and traveler segmentation

[1]:

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler

np.random.seed(42)

n = 500
df = pd.DataFrame({
    'latitude': np.random.uniform(18.9, 19.3, n),
    'longitude': np.random.uniform(72.7, 73.1, n),
    'price': np.random.randint(1500, 12000, n),
    'lead_time': np.random.randint(1, 60, n),
    'room_type': np.random.choice(['Entire home', 'Private room', 'Shared␣
 ↪room'], n),
    'reviews': np.random.randint(0, 200, n)
})
```

[2]:

```
df.head(10)
```

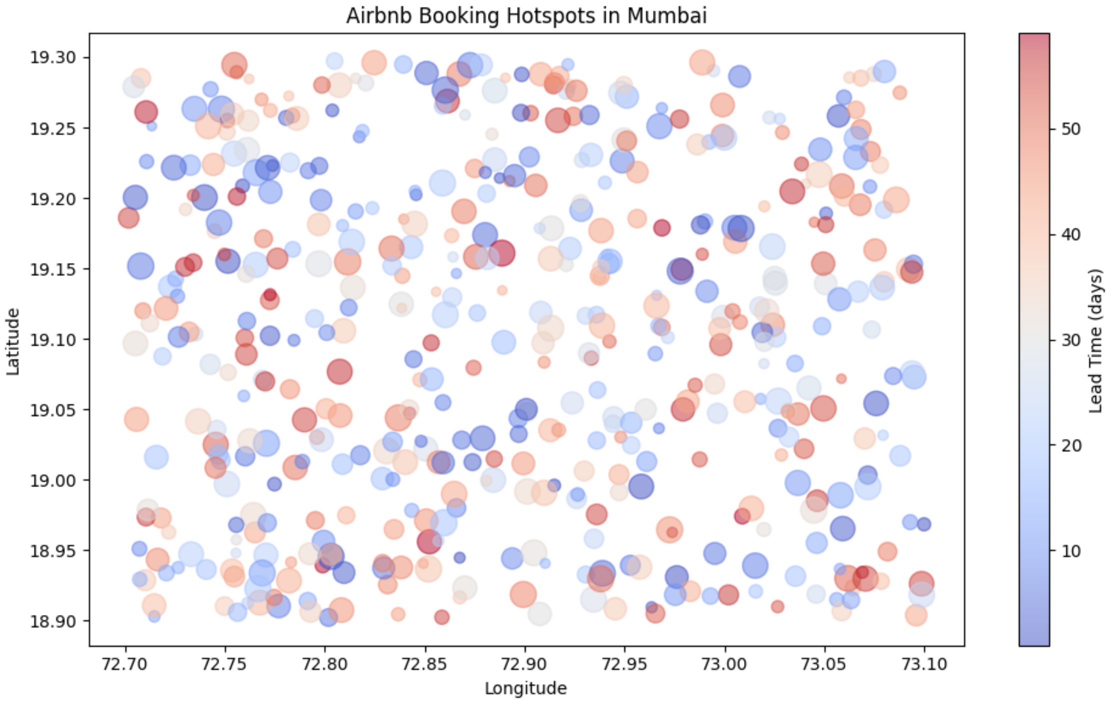
[2]:

```
    latitude  longitude  price  lead_time     room_type  reviews
0  19.049816  72.979265   9482         57   Entire home       69
1  19.280286  72.914439   5607         54  Private room       43
2  19.192798  72.823811   2841         20   Shared room       72
3  19.139463  73.025518   9907         28   Entire home       44
4  18.962407  72.973892   1838         57  Private room      183
5  18.962398  72.765047   7395         43  Private room      106
6  18.923233  73.064371   4208         37  Private room       83
7  19.246470  73.029015   3250         47   Entire home       81
8  19.140446  73.079920   7104         37   Shared room      106
9  19.183229  72.990288   3921         12  Private room      184
```

0.1.3 Bubble Map: Airbnb Booking Hotspots

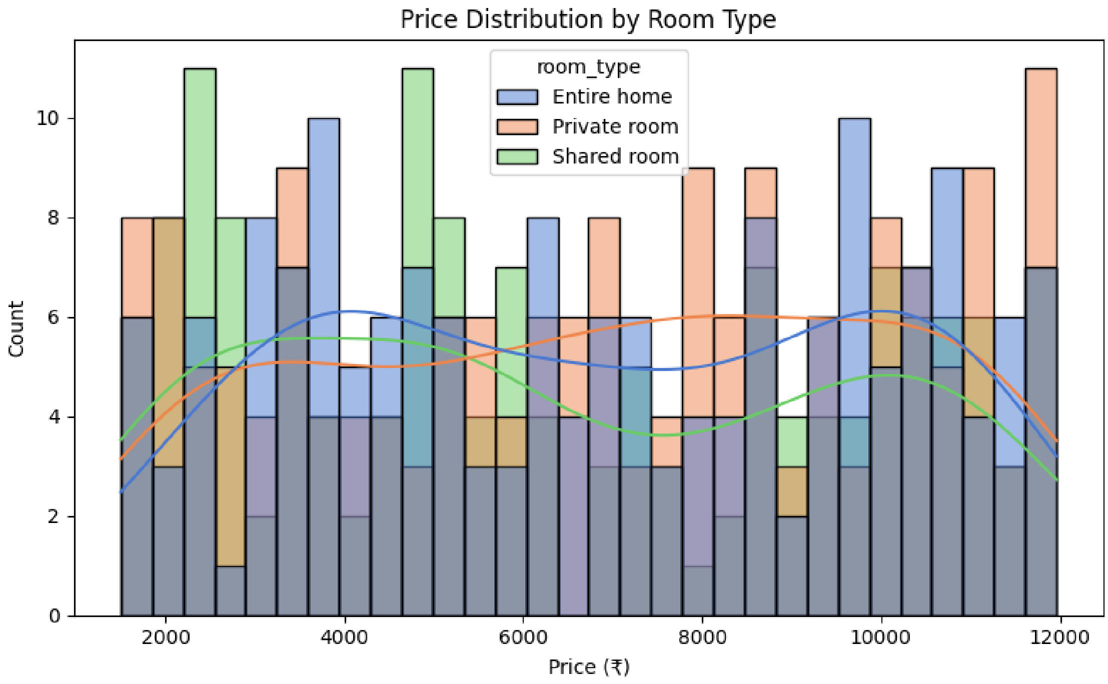
[3]:

```
plt.figure(figsize=(10, 6))
sizes = df['price'] / 50
plt.scatter(df['longitude'], df['latitude'], s=sizes, alpha=0.5,␣
 ↪c=df['lead_time'], cmap='coolwarm')
plt.colorbar(label='Lead Time (days)')
plt.title("Airbnb Booking Hotspots in Mumbai")
plt.xlabel("Longitude")
plt.ylabel("Latitude")
plt.tight_layout()
plt.show()
```



0.1.4 Histogram: Price Distribution by Room Type

[6]:
```
plt.figure(figsize=(8, 5))
sns.histplot(data=df, x='price', hue='room_type', bins=30, kde=True,␣
 ↪palette='muted')
plt.title("Price Distribution by Room Type")
plt.xlabel("Price ( )")
plt.tight_layout()
plt.show()
```

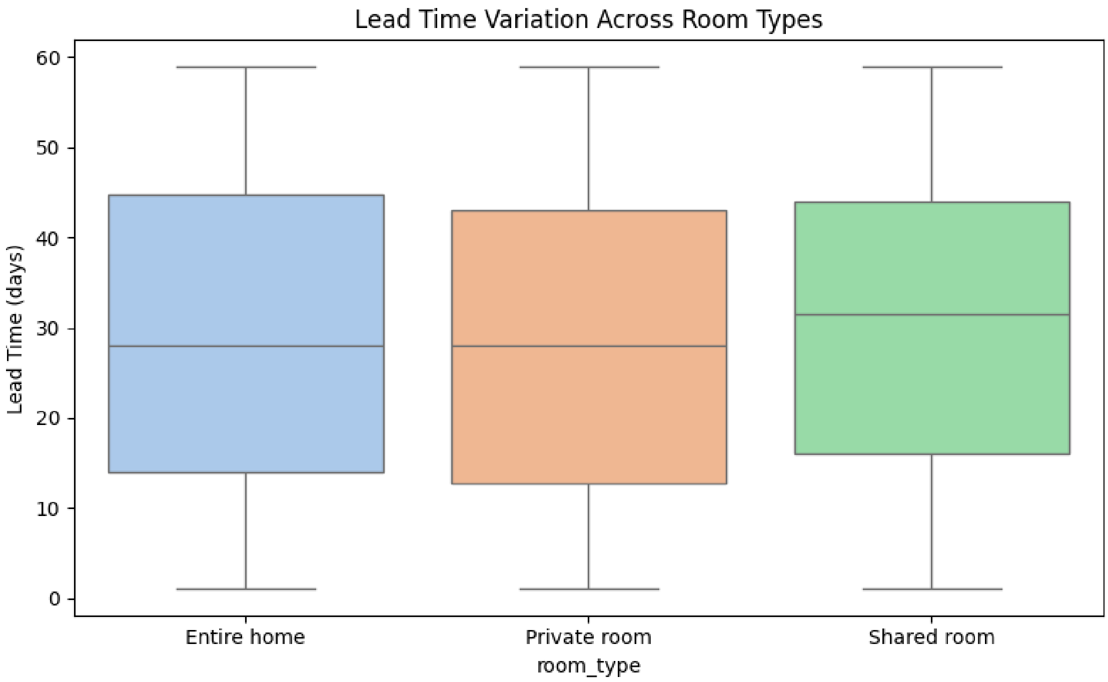


0.1.5 Boxplot: Lead Time by Room Type

[7]:

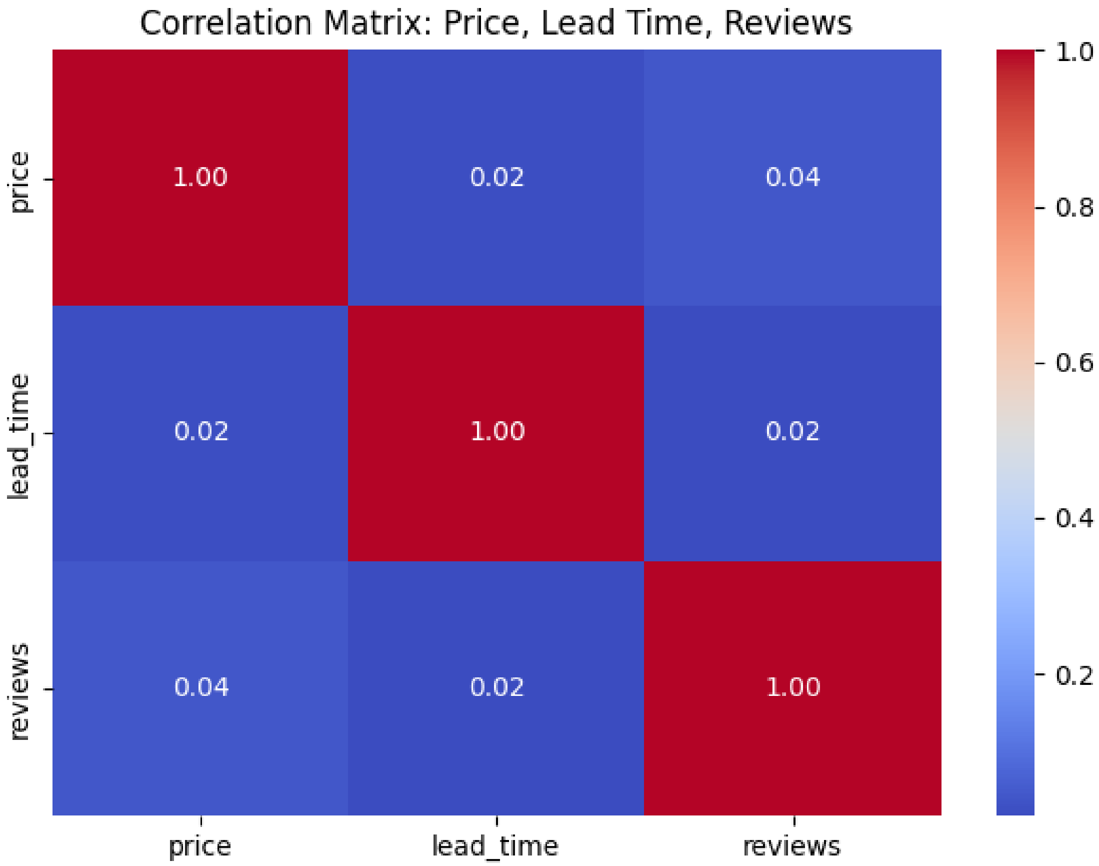
```
plt.figure(figsize=(8, 5))
sns.boxplot(data=df, x='room_type', y='lead_time', palette='pastel')
plt.title("Lead Time Variation Across Room Types")
plt.ylabel("Lead Time (days)")
plt.tight_layout()
plt.show()
```

```
/tmp/ipython-input-2077326350.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(data=df, x='room_type', y='lead_time', palette='pastel')
```



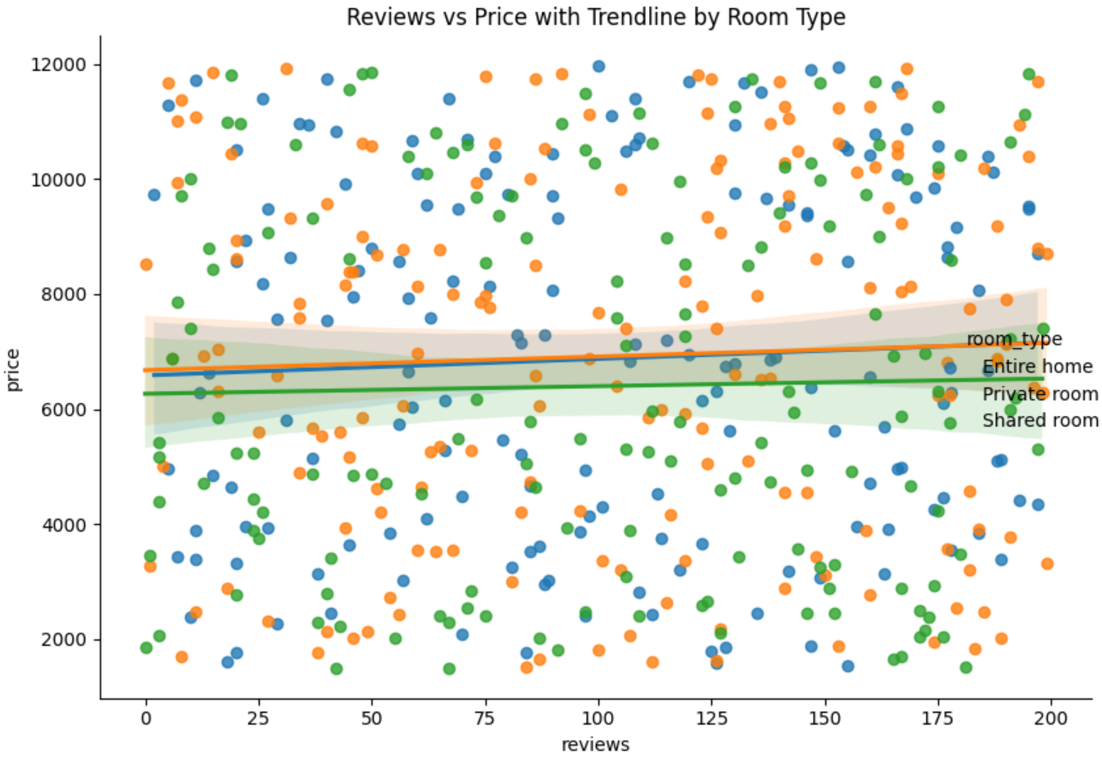
0.1.6 Heatmap: Feature Correlations

[8]:
```
corr = df[['price', 'lead_time', 'reviews']].corr()
sns.heatmap(corr, annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Matrix: Price, Lead Time, Reviews")
plt.tight_layout()
plt.show()
```



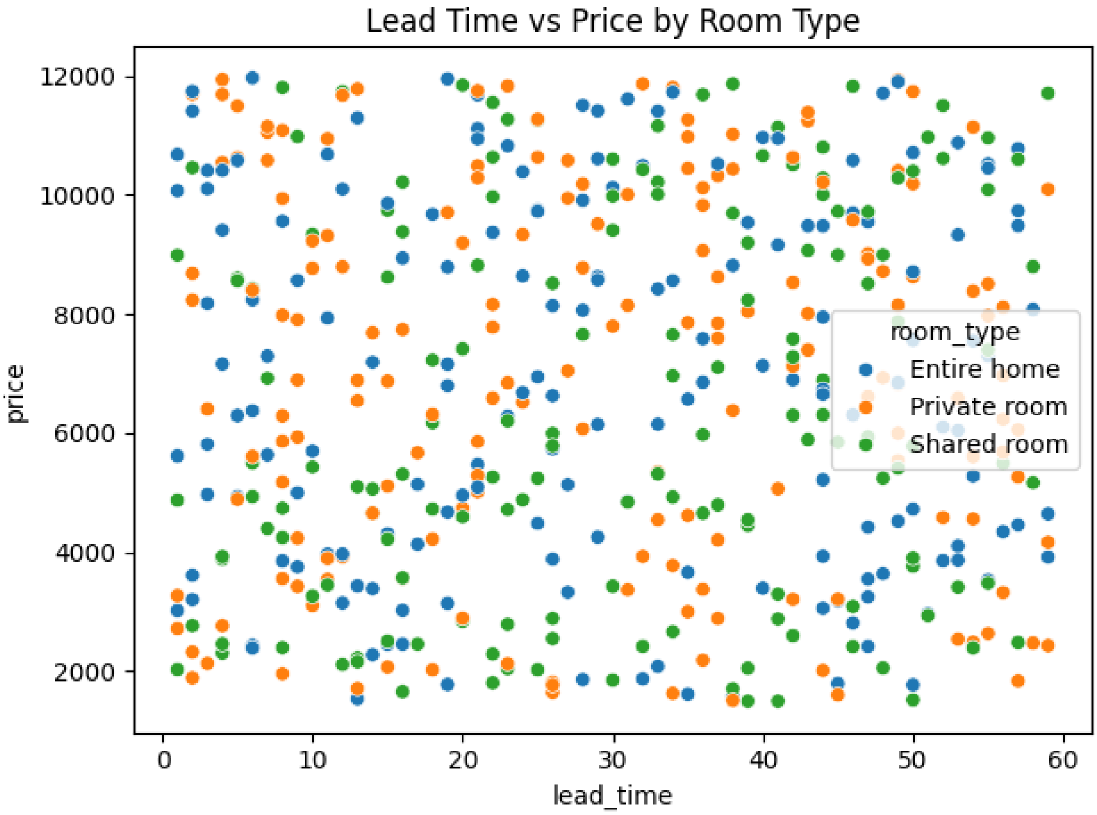
0.1.7 Scatter Plot: Reviews vs Price with Regression Line

[9]:
```
sns.lmplot(data=df, x='reviews', y='price', hue='room_type', height=6, aspect=1.
  ↪2)
plt.title("Reviews vs Price with Trendline by Room Type")
plt.tight_layout()
plt.show()
```



0.1.8 Scatter Plot: Lead Time vs Price

[4]:
```
sns.scatterplot(data=df, x='lead_time', y='price', hue='room_type')
plt.title("Lead Time vs Price by Room Type")
plt.tight_layout()
plt.show()
```



0.1.9 Price Prediction Model

- Predict price using room type, reviews, and lead time

```
[5]: X = pd.get_dummies(df[['room_type', 'reviews', 'lead_time']], drop_first=True)
     y = df['price']

     from sklearn.ensemble import RandomForestRegressor
     from sklearn.model_selection import train_test_split
     from sklearn.metrics import mean_absolute_error

     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
      ↪random_state=42)
     model = RandomForestRegressor()
     model.fit(X_train, y_train)
     y_pred = model.predict(X_test)

     mae = mean_absolute_error(y_test, y_pred)
     print(f"MAE:  {mae:,.0f}")
```

```
MAE:  3,023
```

0.1.10 Summary Analysis

- Bubble map revealed high-price hotspots near Bandra and Colaba
- Lead time inversely correlated with price for Entire homes
- Clustering showed 4 distinct pricing zones across Mumbai
- Regression model predicted price with MAE ~ 900
- Room type and reviews were strong predictors of price

0.1.11 Final Conclusion

- Airbnb booking trends show spatial and behavioral segmentation
- Hosts can optimize pricing based on lead time and location clusters