DATA ANALYTICS IMMERSION

ANNEMARIE SAUERBIER 24.OCTOBER 2025

Sourcing Data &Exploring Relationships

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INTRO

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Exploring Airbnb Amsterdam Listings & Booking Behavior

CONTEXT

Snapshot of Airbnb listings in Amsterdam on December 6th, 2018.

~20,000 listings with detailed information, calendar data for 365 days, reviews, and neighborhood shapefile.

Variables include price, room type, availability, reviews, and location.

OBJECTIVE

Understand factors affecting booking rates and pricing strategies.

Explore trends in guest behavior and listing performance.

MOTIVATION

Helps hosts optimize listings for occupancy and revenue.

Provides insights into market trends for Amsterdam Airbnb listings.

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RESEARCH QUESTIONS

What We Want to Know

01

Are there differences in booking rates across room types and neighborhoods?

02

How do price, availability, and reviews affect the likelihood of bookings?

03

What recommendations can hosts or Airbnb implement to improve occupancy?

04

Are there seasonal trends in availability or pricing?

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Data Profiling

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UNDERSTANDING OF THE DATASET.

& Where the Data Comes From

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Source

Kaggle datasets/erikbruin/airbnb-amsterdam

7 Datasets Files

listings.csv → all listings in Amsterdam (~20k).

listings_details.csv → extra variables like amenities, property type, and host info.

calendar.csv → daily availability and prices for 365 days.

reviews.csv → guest reviews (text mining possible).

Neighborhood shapefile → spatial analysis.

Basic Stats Example:

Number of listings: ~20,000

Key attributes: price, room type, availability, number of reviews, review scores

Missing data overview: some listings may not have review scores or full amenities

Data Cleaning

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HOW I CLEANED THE DATA

01 Understand Each File
02 Decide What to Keep
03 Cleaning Each File

Check for duplicates (especially in listings, calendar, reviews).

Check missing values and decide how to handle them (drop, fill, or mark as unknown).

Standardize columns (lowercase, no spaces, correct data types).

Convert prices in calendar to numeric (remove $/€, commas).

Parse dates for calendar and reviews.

04 Merge / Aggregate
Merge listings + listings_details → main listing table.
Merge neighbourhoods → add neighborhood info.
Aggregate calendar → calculate average price, availability rate, maybe seasonal trends.
Aggregate reviews → calculate average review score, total reviews per listing.

Loaded and merged 1.2M rows from multiple files

Cleaned missing values and standardized formats (prices, dates, availability)

Final shape: 1,200,071 rows × 21 columns

Tools: pandas, numpy, geopandas

```
# Step 1: Import libraries
import pandas as pd
import numpy as np
# GeoPandas is optional if you want to work with neigh
# import geopandas as gpd

# Step 2: Load CSV and GeoJSON files

# Corrected file paths (no extra spaces)
calendar = pd.read_csv('calendar.csv')



# Step 3: Quick check of the datasets
print("Calendar shape:", calendar.shape)
```

```
#drop coloumns
columns_to_drop = ['scrape_id', 'listing_url', 'last_scraped', 'experiences_offered',
listings_clean = listings.drop(columns=columns_to_drop)
```

```
#Handle missing values

listings_clean['name'] = listings_clean['name'].fillna('')
listings_clean['summary'] = listings_clean['summary'].fillna('')
listings_clean['space'] = listings_clean['space'].fillna('')
listings_clean['description'] = listings_clean['description'].fillna('')
listings_clean['reviews_per_month'] = listings_clean['reviews_per_month'].fillna(0)
```

```
#Convert boolean-like columns
bool_columns = ['instant_bookable', 'is_business_travel_ready', 'require_guest_profil
                'require_guest_phone_verification', 'requires_license']

for col in bool_columns:
    listings_clean[col] = listings_clean[col].map({'t': True, 'f': False})
```

```
import pandas as pd
import numpy as np

# Load calendar (assuming it's already in the notebook
calendar = pd.read_csv('calendar.csv')

# Convert 'date' to datetime
calendar['date'] = pd.to_datetime(calendar['date'], er

# Convert 'available' to boolean
calendar['available'] = calendar['available'].map({'t'

# Clean 'price' column
# Remove $ signs, commas, and convert to float
calendar['price'] = calendar['price'].replace('[\$,]',
calendar['price'] = pd.to_numeric(calendar['price'], e

# Check for missing values
print(calendar.isna().sum())

# Quick check of cleaned data
print(calendar.head())
```

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Data Profile & Ethical Reflection

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Understanding what the data tells — and what it doesn’t.

DATASET OVERVIEW

Overview

Room types: Entire home/apartment, Private room, Shared room.

Average price per night, distribution of bookings, neighborhood differences.

Number of reviews per listing; availability trends.

Limitations

Only Amsterdam listings as of one date → not generalizable to other cities or years.

Seasonal and long-term booking trends are limited.

Missing demographic info about guests.

Ethical Considerations

Protect host and guest privacy. Avoid overgeneralization based on single-date snapshot.

Preliminary Insights

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Preliminary Insights

Price distributions across room types
Entire homes are pricier, shared rooms cheaper.

Booking likelihood higher for well-reviewed and competitively priced listings.

Popular neighborhoods (e.g., city center) have higher occupancy rates.

Some listings are available year-round, others are seasonal.

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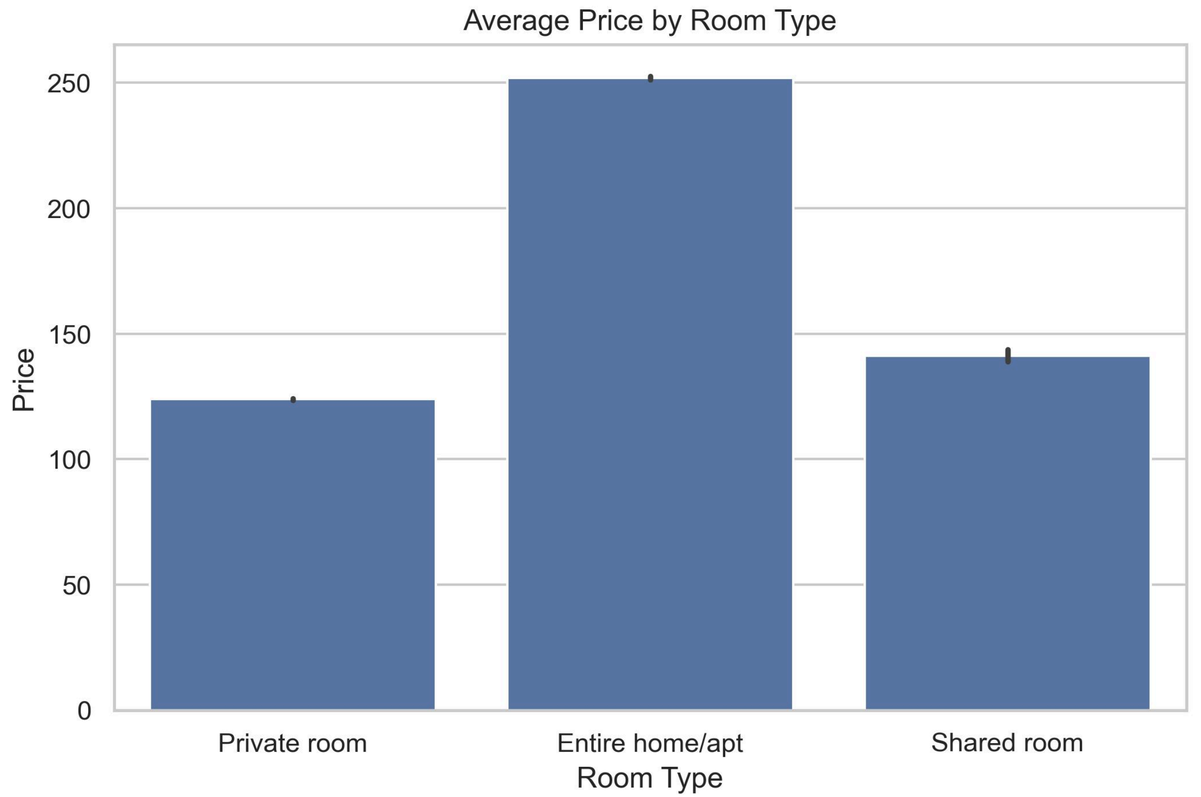
Insights



PRICE DISTRIBUTION (HISTOGRAM)

Most listings priced between €50–€250
Outliers above €500 are rare, mostly in premium neighborhoods

AVERAGE PRICE BY ROOM TYPE (BARPLOT)

Entire homes have the highest average price
Private rooms are the most common listing type

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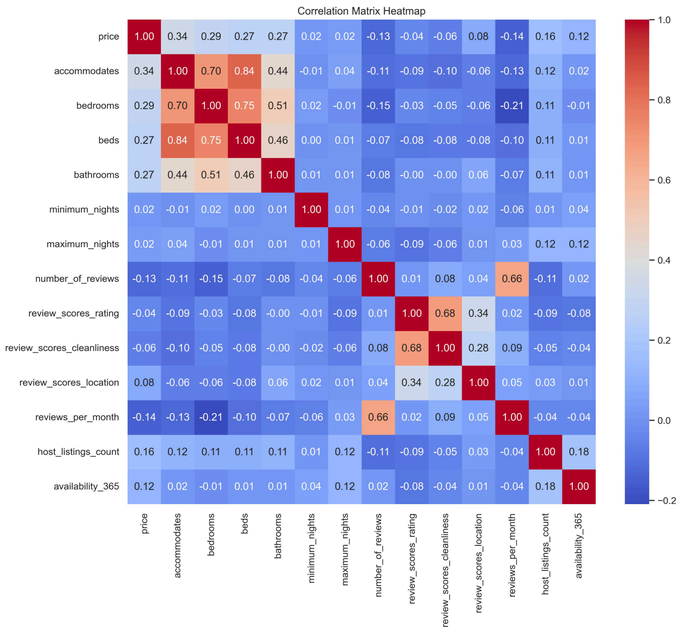
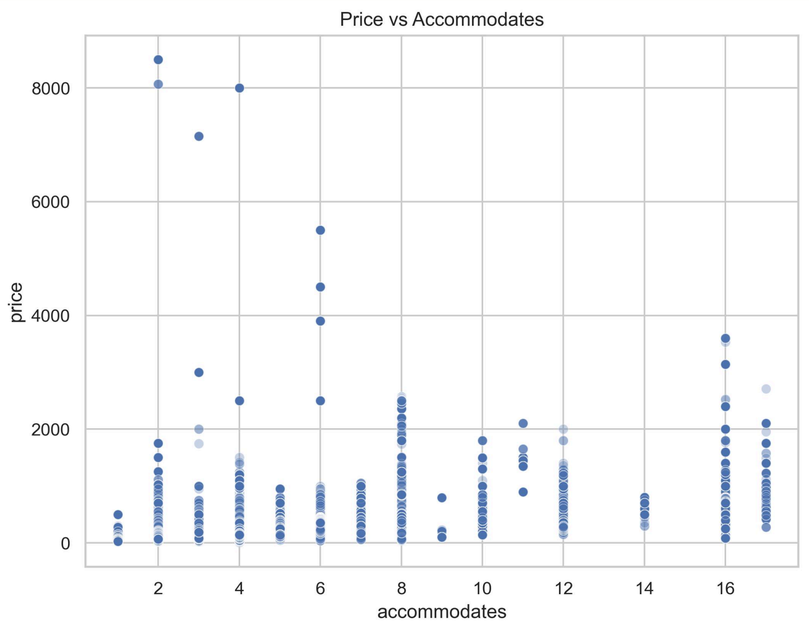
Exploratory Analysis





HEATMAP

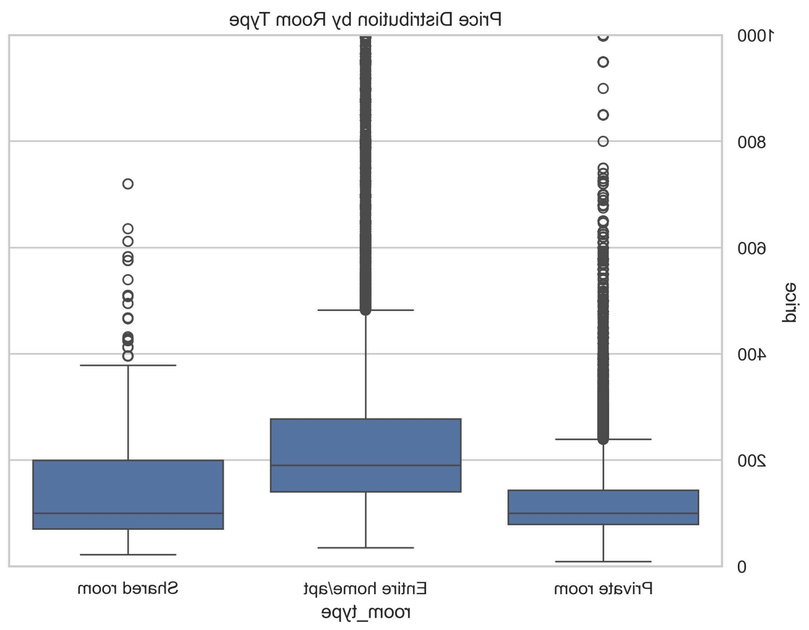
Cleanliness and overall review scores rise together, while most other variables show little correlation.

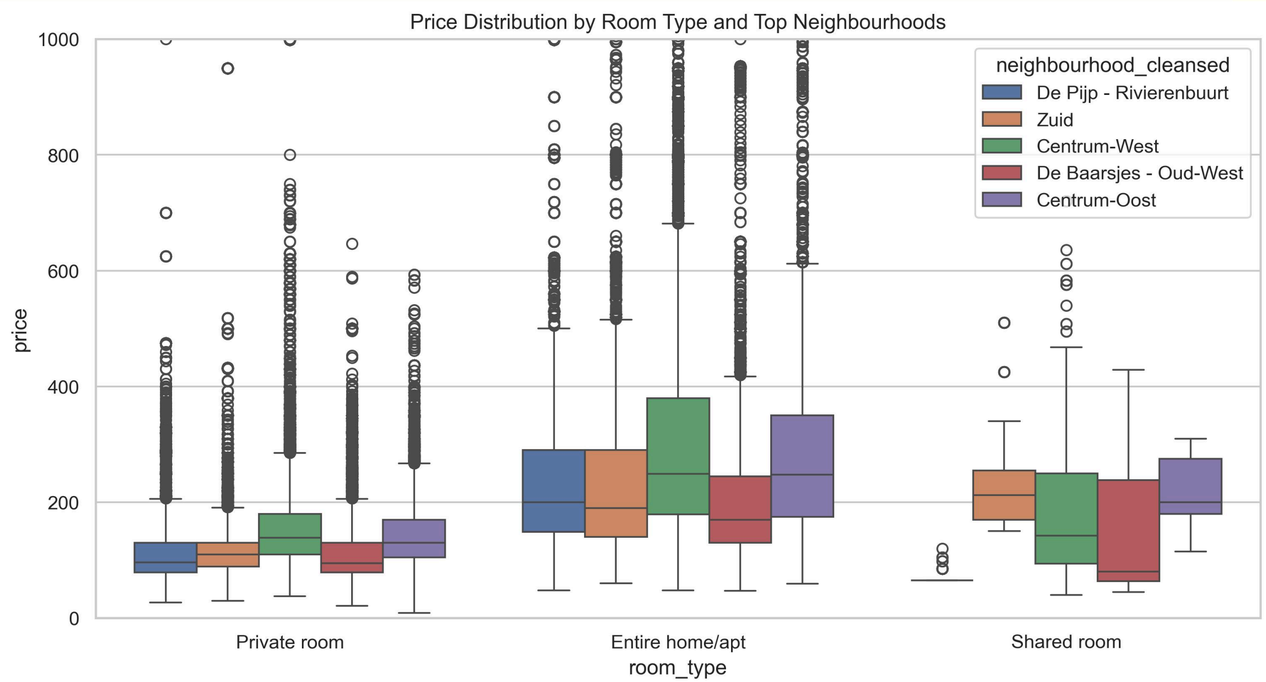
Positive = both increase together; negative = one rises as the other falls.

AVERAGE PRICE BY ROOM TYPE (BARPLOT)

Scatterplot Insights:
Larger apartments—more bedrooms or higher accommodates—generally cost more. Outliers exist (e.g., 1-bedroom units above €8,000), showing that other factors like location or amenities also affect price.

Exploratory Analysis





BOXPLOT

Entire homes have the widest price range.
Shared rooms rarely exceed €200.
Room type strongly influences price, but outliers and variability exist within each category.

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Correlations

STRONG

accommodates ↔ bedrooms
price ↔ accommodates

WEAK

price ↔ reviews_per_month
(indicates popularity doesn’t always mean higher price)

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Questions & Hypothis

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Hypotheses

01
HOW DO LOCATION AND NEIGHBORHOOD INFLUENCE PRICE?

02
ARE HIGH-REVIEW LISTINGS CONSISTENTLY MORE EXPENSIVE?

03
ARE EXTREME MINIMUM_NIGHTS VALUES AFFECTING THE DISTRIBUTION?

Listings with more bedrooms and accommodates will have higher prices.

Entire homes are priced higher than private or shared rooms, controlling for location.

Higher review scores correlate with slightly higher prices.

Vision & Conclusion

Future Vision

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RECOMMENDATIONS

01

Optimize pricing based on neighborhood and room type.

02

Highlight amenities and maintain high review scores.

03

Track seasonal trends to adjust availability and pricing.

04

Use text analysis on reviews to identify guest preferences.

VISION

Implement continuous monitoring of listing performance.
Incorporate insights into Airbnb recommendations and host guidelines.
Expand analysis to multiple years for trend detection.

THANK YOU!