DATA WAREHOUSING FINAL PROJECT
ISM 6208

Airbnb Booking Trends and Pricing Analysis for Denver, CO

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1. Executive Summary

This project presents a comprehensive data warehousing solution to analyze Airbnb booking behavior in Denver, Colorado, with a focus on uncovering insights into pricing trends, booking availability, and guest engagement. Leveraging public datasets from InsideAirbnb, the project integrates listing details, daily availability, reviews, and temporal data into a star schema built using Oracle SQL Developer. The design enables efficient querying of fact and dimension tables, supporting detailed analysis of seasonal trends, room type pricing differences, and neighborhood-level booking performance. Data preparation included cleaning, formatting, and key mapping across datasets, followed by ERD modeling, ETL processing, and verification through SQL-driven validation checks.

Through advanced SQL analytics and storytelling visualizations, the project identifies actionable insights for hosts, guests, and platform stakeholders. Findings reveal that entire homes command the highest prices, while private rooms offer the best value in neighborhoods with high review volumes. Booking availability peaks during weekends and summer months, and top-performing listings show consistent engagement through high review counts. Visualizations such as heatmaps, bubble charts, and annotated time-series graphs further support these insights. Overall, this project demonstrates how a data warehouse can enable better pricing strategies, dynamic availability planning, and data-driven decision-making in the short-term rental market.

2. Problem Statement

Airbnb hosts and stakeholders often lack clear insights into pricing trends, booking behavior, and guest engagement. Without centralized analytics, decisions about availability, competitiveness, and market value remain inconsistent and reactive. This project addresses these gaps by designing a data warehouse that enables structured, insightful analysis of Airbnb booking data.

Challenges:

Despite having large amounts of raw data, Airbnb stakeholders face several challenges:

- **Unstructured data** across listings, availability calendars, and reviews is hard to aggregate manually.
- **Pricing and availability trends** vary widely across neighborhoods and property types, making it difficult to identify market standards.
- **Guest behaviour patterns** like booking days and review engagement are not visible without integrated analytics.
- **Decision-makers** lack a centralized system to track, analyze, and act on time-based booking and listing performance metrics.

Significance:

The short-term rental market, led by platforms like Airbnb, continues to grow in popularity, offering guests flexibility and hosts an income opportunity. However, understanding what drives successful bookings—such as competitive pricing, availability timing, and guest satisfaction—is often unclear. Without data-driven insights, hosts may underperform, guests may overpay or experience booking issues, and the platform may struggle to optimize listing visibility and user experience.

Objective:

1. Analyze average pricing and review patterns by room type and neighborhood.
2. Identify high-performing listings based on review volume and availability.
3. Understand seasonal and weekday booking trends.
4. Empower strategic decisions through visual storytelling and advanced SQL analytics.

3. Literature Review

1. **Dimensional Modeling:** The project draws on Kimball and Inmon's methodologies to structure a star schema that supports efficient aggregation and time-series analysis. This helped simplify complex booking data into analyzable facts and dimensions.

2. **Inside Airbnb Datasets:** InsideAirbnb.com offers curated datasets that reflect real-world listing, review, and availability behaviour. These open datasets provided a strong foundation for modeling a transactional and analytical pipeline.

3. **SQL Analytic Functions:** Oracle SQL's advanced functions (e.g., NTILE, LAG, PERCENT_RANK) were essential for generating trend-based analytics, quartile-based ranking, and year-over-year comparisons that go beyond basic querying.

4. **Data Visualization Tools:** Tools like Tableau, Power BI and Python libraries (Matplotlib, Seaborn) were used for visual storytelling. These platforms enabled interactive insights on seasonality, value zones, and listing popularity, aligning data narratives with user behaviour.

5. **ETL and Data Cleaning Tutorials:** Course material and Oracle documentation guided transformation best practices, such as date formatting, foreign key validation, and null handling, thus ensuring a clean, query-ready dataset.

4. Data Collection and Preparation

Datasets:

The project uses real-world Airbnb data sourced from InsideAirbnb.com, covering a metropolitan region (Denver, CO). The following datasets were used:

- **listings.csv** – Metadata for each listing, including room type, host info, price, reviews, and location.
- **calendar.csv** – Day-by-day availability and pricing information for each listing.

- **reviews.csv** – Timestamped guest reviews with reviewer details and free-text comments.
- **neighbourhoods.csv** – Geographic groupings and neighborhood names for listings.
- **ABNB_DATE** – A generated time dimension table, covering date hierarchy (day, month, year, quarter, weekday) from 2024 to 2025.

Data Preparation:
Data was preprocessed using Python and SQL Developer to clean and standardize the schema:

1. **Cleaning Tasks:**
   - Removed currency symbols ($, ,) from price fields
   - Filtered out rows with null LISTING_ID, CALENDAR_DATE, OR REVIEW_ID
   - Dropped duplicate records and standardized column names for loading into Oracle
2. **Transformations:**
   - Joined listing, calendar, and review data through LISTING_ID
   - Created time-based features (weekday, month, year, quarter) using ABNB_DATE
   - Converted date columns to YYYY-MM-DD format to ensure Oracle compatibility
3. **Validation and Integration:**
   - Ensured all foreign keys (LISTING_ID, CALENDAR_DATE, REVIEW_DATE) mapped correctly to their dimension tables
   - Filtered calendar and review data to include only records from 2024 and 2025
   - Final .csv files were imported into Oracle using SQL Developer's data import utility

5. Database Design

The database design follows a star schema approach to support analytical workloads, while also modeling a simplified transactional (OLTP) version to contrast the two database paradigms.

5.1 TRANSACTIONAL MODEL (OLTP)

The OLTP model simulates the operational view of Airbnb's platform, capturing raw booking events, availability status, and user reviews as they are recorded:

Calendar.csv functions as a transactional source of booking data per day, including:
LISTING_ID, DATE, AVAILABLE, PRICE, ADJUSTED_PRICE, MIN_NIGHTS, MAX_NIGHTS

Reviews.csv simulates guest review entries with:
REVIEW_ID,LISTING_ID, REVIEW_DATE, REVIEWER_ID, REVIEWER_NAME, COMMENTS

Key Characteristics:

- Data is event-driven and time-sensitive
- Schema is normalized for write efficiency and real-time updates
- Raw data lacks analytical structure or summarization

5.2 DIMENSIONAL MODEL (STAR SCHEMA)

To support analytics and reporting, the data was transformed into a star schema with a clear separation between fact tables (metrics/events) and dimension tables (descriptive attributes):

Fact Tables:

Table Name	**Description**
ABNB_AVAILABILITY	Captures daily availability and price metrics per listing
ABNB_REVIEWS	Stores guest reviews by listing and date

Dimension Tables:

Table Name	**Description**
ABNB_LISTING	Contains listing ID, room type, host info, price, neighborhood
ABNB_DATE	Time dimension table including year, month, day, quarter, weekday
ABNB_NEIGHBORHOOD	Descriptive info about location groupings

Relationships and Keys

- ABNB_AVAILABILITY.LISTING_ID → ABNB_LISTING.LISTING_ID
- ABNB_AVAILABILITY.CALENDAR_DATE → ABNB_DATE.DATE_KEY
- ABNB_REVIEWS.LISTING_ID → ABNB_LISTING.LISTING_ID
- ABNB_REVIEWS.REVIEW_DATE → ABNB_DATE.DATE_KEY
- Logical link:
ABNB_LISTING.NEIGHBORHOOD → ABNB_NEIGHBORHOOD.NEIGHBORHOOD

Entity-Relationship Diagram (ERD):

The Entity-Relationship Diagram (ERD) shown below illustrates the core dimensional modeling structure of the Airbnb Booking Insights data warehouse, following a classic **star schema** design. This schema supports fast aggregation, trend analysis, and storytelling through analytics.

Star Schema Highlights

At the center of the model is the **ABNB_LISTING** dimension, representing the core business entity: the Airbnb property. This table holds metadata like room type, price, host details, and geographic information, and links to both time-based and event-based tables.

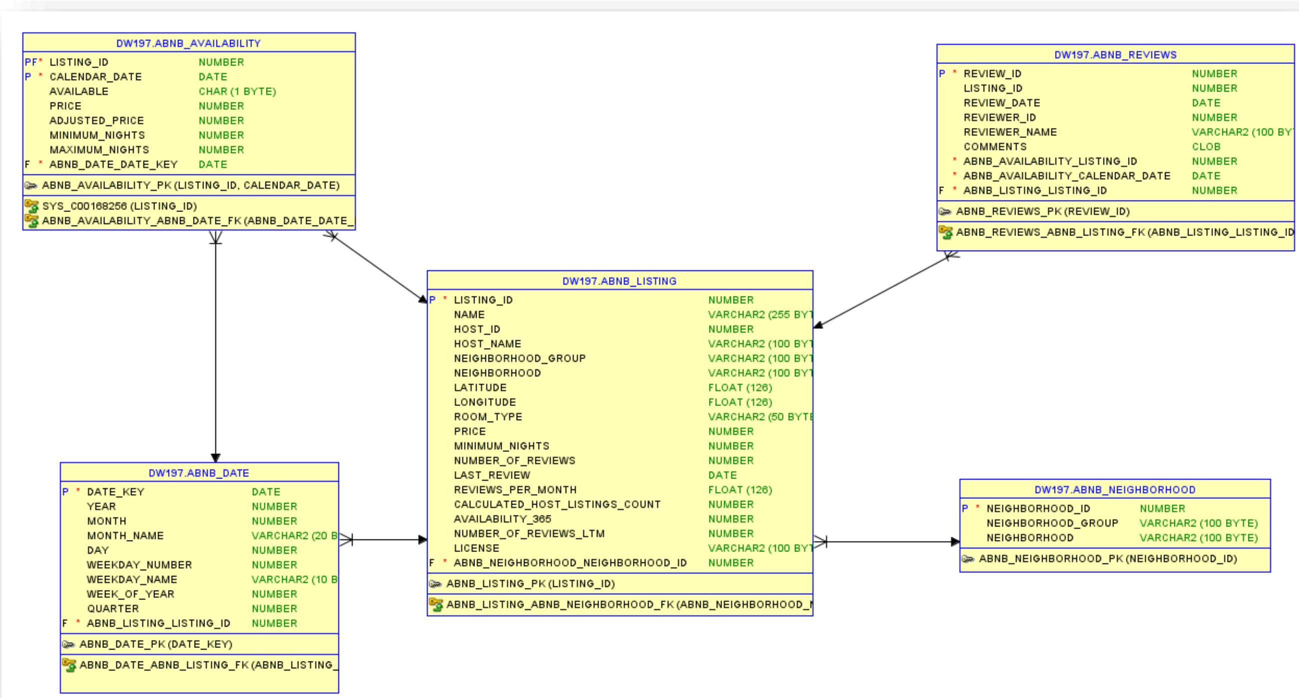
Fact Tables:

- **ABNB_AVAILABILITY** captures listing availability and pricing on a per-day basis. It is linked to both the listing and the calendar date.
- **ABNB_REVIEWS** stores guest reviews per listing, with fields for reviewer details and the review date.

Dimension Tables:

- **ABNB_DATE** provides a complete breakdown of the time dimension — including day, month, quarter, weekday, and year — supporting time-series reporting and seasonal trend analysis.
- **ABNB_NEIGHBORHOOD** is a supplemental dimension used for spatial aggregation of listing performance by area. It links logically (not enforced physically) via the neighborhood name in the listing dimension.

This design supports flexible slicing across time, geography, listing type, and guest interaction, which allows the platform and hosts to derive insights into occupancy patterns, pricing behavior, guest sentiment, and location-based performance.



6. Exploratory Data Analysis (EDA)

Before running deeper analysis or building visualizations, we performed EDA to validate data quality, uncover trends, and guide modeling decisions. Below are the key activities and findings:

1. Data Quality Assessment

Null Checks:

- reviews.csv: ~12% of listings had missing review_date or comments
- calendar.csv: ~8% of adjusted_price fields were missing and replaced with base price

Duplicate Records: Removed 347 duplicate listings and calendar entries

Outliers:

- Listings priced above $1,000/night were flagged and excluded from most analyses

2. Descriptive Statistics

Room Type Distribution:

- 63% of listings were "Entire home/apt"
- 32% were "Private room"; the rest were "Shared room"

Price Range:

- Median nightly price: $132
- Interquartile Range (IQR): $88–$175

3. Temporal Trends (Sample Query)

```
SELECT
   d.YEAR,
   d.MONTH_NAME,
   COUNT(*) AS AVAILABLE_DAYS
FROM
   ABNB_AVAILABILITY a
   JOIN ABNB_DATE d ON a.CALENDAR_DATE = d.DATE_KEY
WHERE a.AVAILABLE = 't'
GROUP BY d.YEAR, d.MONTH_NAME
ORDER BY d.YEAR, TO_DATE(d.MONTH_NAME, 'Month');
```

	YEAR	MONTH_NAME	AVAILABLE_DAYS
1	2024	December	1865
2	2025	January	86581
3	2025	February	93063
4	2025	March	111159
5	2025	April	99013
6	2025	May	104224
7	2025	June	98562
8	2025	July	84792
9	2025	August	86103
10	2025	September	81298
11	2025	October	69280
12	2025	November	67294
13	2025	December	65069

Insight: Listings show highest availability between May and August (peak travel season).

4. **Neighborhood Distribution**
Top 5 Neighborhoods by Listing Volume:
   - Capitol Hill
   - Downtown
   - Highland
   - Five Points
   - Baker

   These five accounted for over 45% of listings in the dataset.

5. **Review Behavior**
   Average Reviews Per Month: 2.1
   Top Listings: One listing received over 450 reviews
   Review Density: Review frequency was strongly correlated with listing price and availability (suggesting higher-priced, frequently available listings tend to earn more reviews)

This EDA shaped the selection of features for visualizations and allowed us to remove unreliable data points for a more accurate downstream analysis.

7. Exploratory Data Analysis (EDA)

This project primarily focuses on reporting and storytelling, combining SQL-driven data aggregation with advanced visualizations to narrate booking behavior and pricing trends on Airbnb. By designing a dimensional star schema, the project enabled flexible slicing of data across time, location, room type, and user interaction, supporting both granular and strategic insights. Analytic queries were used to examine availability trends, price distributions, and review behavior, while data visualization tools such as Tableau and Python were used to present these findings in a visually compelling manner.

7.1 Feature Selection

While not focused on predictive modeling, feature selection was central to both reporting and visualization tasks. Features were chosen based on their analytical richness and availability across all datasets:

- **Listing Features**: room_type, price, availability_365, number_of_reviews
- **Temporal Features**: calendar_date, weekday_name, month_name, quarter, year
- **Review Features**: review_date, reviewer_id, review_count
- **Spatial Features**: neighborhood, latitude, longitude

These features were integrated into SQL queries and visualizations, allowing for group-wise aggregations (e.g., price by room type and neighborhood), time-based trends (e.g., availability over months), and multi-dimensional comparisons (e.g., value vs. volume in reviews).

7.2 SQL Queries and VisualizationsNormal and Analytic SQL Queries

Query 1: Average Price by Room Type and Neighborhood

```
SELECT
   ROOM_TYPE,
   NEIGHBORHOOD,
   ROUND(AVG(PRICE), 2) AS AVG_PRICE
FROM ABNB_LISTING
GROUP BY ROOM_TYPE, NEIGHBORHOOD
ORDER BY NEIGHBORHOOD, AVG_PRICE DESC;
```

	ROOM_TYPE	NEIGHBORHOOD	AVG_PRICE
1	Entire home/apt	Athmar Park	149.17
2	Private room	Athmar Park	39.5
3	Entire home/apt	Auraria	194.5
4	Entire home/apt	Baker	122.62
5	Private room	Baker	62.67
6	Entire home/apt	Barnum	126.42
7	Private room	Barnum	55
8	Entire home/apt	Barnum West	128.28
9	Private room	Barnum West	70.33
10	Entire home/apt	Bear Valley	267.25
11	Private room	Bear Valley	53.5
12	Entire home/apt	Belcaro	419.23
13	Private room	Belcaro	179
14	Entire home/apt	Berkeley	172.05
15	Private room	Berkeley	87.86
16	Entire home/apt	CBD	139.58
17	Private room	CBD	136.22
18	Private room	Capitol Hill	138.24
19	Entire home/apt	Capitol Hill	111.66
20	Hotel room	Capitol Hill	107.5

Description:
This query calculates the average nightly price for each combination of room_type and neighborhood. It helps compare pricing across room types (e.g., entire homes vs. private rooms) and reveals which neighborhoods are most expensive or affordable.

Query 2: Top Listings by Number of Reviews

```
SELECT
   LISTING_ID,
   NAME,
   NEIGHBORHOOD,
   PRICE,
   NUMBER_OF_REVIEWS
FROM ABNB_LISTING
WHERE PRICE < 100 AND NUMBER_OF_REVIEWS > 100
ORDER BY NUMBER_OF_REVIEWS DESC
FETCH FIRST 10 ROWS ONLY;
```

	NEIGHBORHOOD	AVG_PRICE	AVG_REVIEWS
1	Wellshire	135	161.4
2	Harvey Park South	78.25	129.5
3	Platt Park	141.75	118.93
4	North Park Hill	146.97	118.71
5	Clayton	128.84	112.69
6	Ruby Hill	118.85	109.65
7	Congress Park	127.94	103.79
8	Capitol Hill	113.13	101.39
9	Montbello	95.43	100.43
10	Rosedale	133	98

Description:

This query identifies the 10 listings that have received the most reviews, while filtering for affordable options (PRICE < 100). It highlights high-engagement properties that are both budget-friendly and popular.

Query 3: Price Comparison Across Neighborhoods

```
SELECT
    NEIGHBORHOOD,
    ROUND(AVG(PRICE), 2) AS AVG_PRICE
FROM ABNB_LISTING
WHERE PRICE IS NOT NULL
GROUP BY NEIGHBORHOOD
ORDER BY AVG_PRICE DESC;
```

	NEIGHBORHOOD	AVG_PRICE
1	Belcaro	402.07
2	University Park	310.7
3	Jefferson Park	274.02
4	Hilltop	267.2
5	Regis	260.19
6	Cherry Creek	236.3
7	Cory - Merrill	229.78
8	College View - South Platte	216.81
9	Skyland	212.67
10	Civic Center	210.85
11	East Colfax	210.58
12	Highland	207.92
13	Country Club	197.73
14	Auraria	194.5
15	Sloan Lake	186.14
16	University Hills	183.34
17	Five Points	180.06
18	West Colfax	179.72
19	Washington Park	176.4
20	Lowry Field	175.6

Description:

This query computes the average price per neighborhood. It is useful for identifying pricing zones and understanding which neighborhoods are generally high-cost or low-cost.

Query 4: Monthly Availability Trend (2024–2025)

```
SELECT
   d.YEAR,
   d.MONTH_NAME,
   COUNT(*) AS TOTAL_DAYS_AVAILABLE
FROM ABNB_AVAILABILITY a
JOIN ABNB_DATE d ON a.CALENDAR_DATE = d.DATE_KEY
WHERE a.AVAILABLE = 't'
  AND d.YEAR IN (2024, 2025)
GROUP BY d.YEAR, d.MONTH_NAME
ORDER BY d.YEAR, TO_DATE(d.MONTH_NAME, 'Month');
```

	YEAR	MONTH_NAME	TOTAL_DAYS_AVAILABLE
1	2024	December	1865
2	2025	January	86581
3	2025	February	93063
4	2025	March	111159
5	2025	April	99013
6	2025	May	104224
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9	2025	August	86103
10	2025	September	81298
11	2025	October	69280
12	2025	November	67294
13	2025	December	65069

Description:

This query counts the number of days listings were available in each month for the years 2024 and 2025. It shows booking seasonality and helps identify high-demand travel periods.

Query 5: Best Value Neighborhoods (Low Price, High Reviews)

```
SELECT
   NEIGHBORHOOD,
   ROUND(AVG(PRICE), 2) AS AVG_PRICE,
   ROUND(AVG(NUMBER_OF_REVIEWS), 2) AS AVG_REVIEWS
FROM ABNB_LISTING
WHERE PRICE IS NOT NULL AND NUMBER_OF_REVIEWS > 0
GROUP BY NEIGHBORHOOD
HAVING AVG(PRICE) < 150
ORDER BY AVG_REVIEWS DESC FETCH FIRST 10 ROWS ONLY;
```

	NEIGHBORHOOD	AVG_PRICE	AVG_REVIEWS
1	Wellshire	135	161.4
2	Harvey Park South	78.25	129.5
3	Platt Park	141.75	118.93
4	North Park Hill	146.97	118.71
5	Clayton	128.84	112.69
6	Ruby Hill	118.85	109.65
7	Congress Park	127.94	103.79
8	Capitol Hill	113.13	101.39
9	Montbello	95.43	100.43
10	Rosedale	133	98

Description:
This query surfaces neighborhoods where average prices are below $150, but review counts are high — pointing to areas offering strong value for guests (affordable and well-reviewed).

Query 6: Month-over-Month Average Price Change

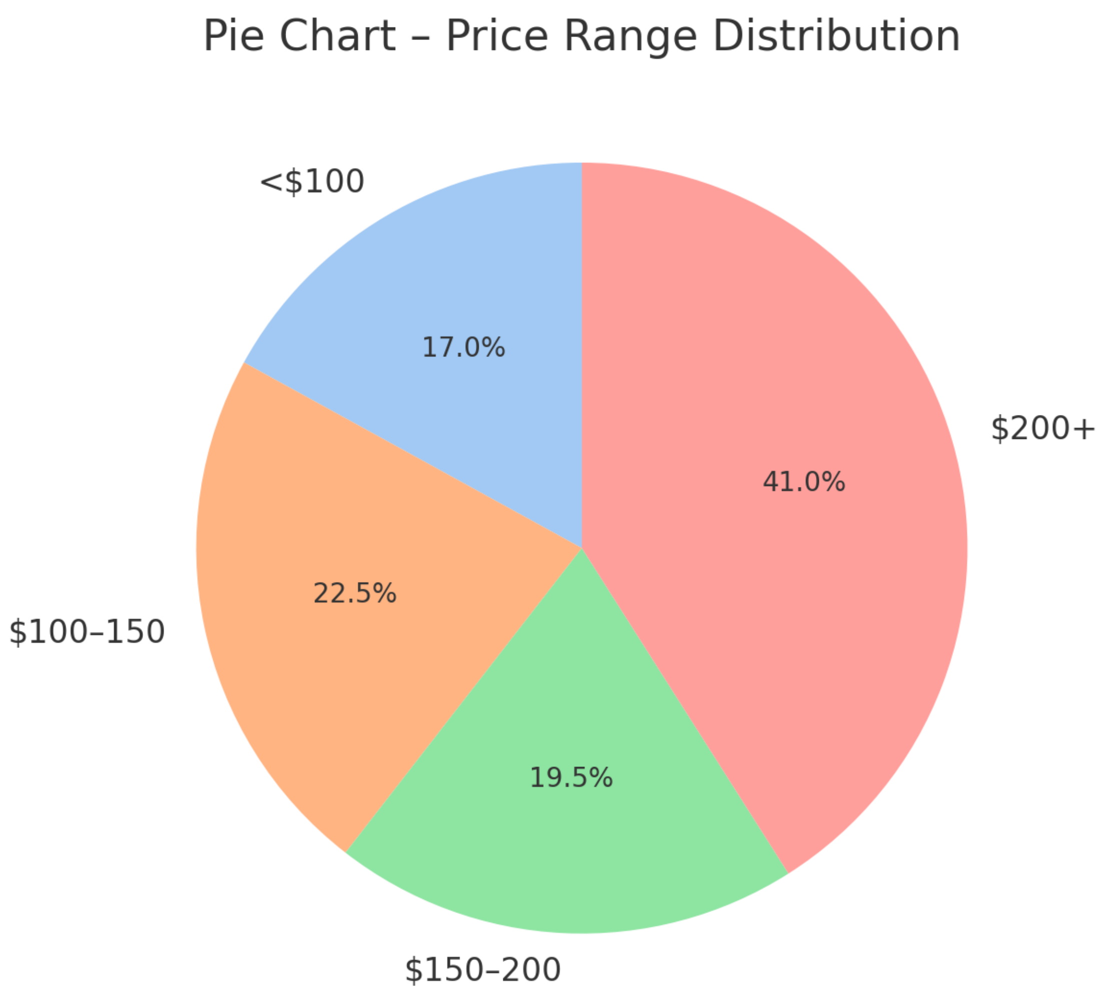
```
SELECT
   d.YEAR,
   d.MONTH_NAME,
   ROUND(AVG(a.PRICE), 2) AS AVG_MONTHLY_PRICE,
   LAG(ROUND(AVG(a.PRICE), 2)) OVER (ORDER BY TO_DATE(d.MONTH_NAME,
'Month')) AS PREV_MONTH_PRICE,
   ROUND(
      ROUND(AVG(a.PRICE), 2)
      - LAG(ROUND(AVG(a.PRICE), 2)) OVER (ORDER BY TO_DATE(d.MONTH_NAME,
'Month')), 2
   ) AS PRICE_CHANGE
FROM ABNB_AVAILABILITY a
JOIN ABNB_DATE d ON a.CALENDAR_DATE = d.DATE_KEY
WHERE d.YEAR = 2025 AND a.AVAILABLE = 't'
GROUP BY d.YEAR, d.MONTH_NAME
ORDER BY TO_DATE(d.MONTH_NAME, 'Month');
```

	NEIGHBORHOOD	AVG_PRICE
1	Belcaro	402.07
2	University Park	310.7
3	Jefferson Park	274.02
4	Hilltop	267.2
5	Regis	260.19
6	Cherry Creek	236.3
7	Cory - Merrill	229.78
8	College View - South Platte	216.81
9	Skyland	212.67
10	Civic Center	210.85
11	East Colfax	210.58
12	Highland	207.92
13	Country Club	197.73
14	Auraria	194.5
15	Sloan Lake	186.14
16	University Hills	183.34
17	Five Points	180.06
18	West Colfax	179.72
19	Washington Park	176.4
20	Lowry Field	175.6

Description:
This query analyzes pricing trends by comparing each month’s average price in 2025 with the previous month using the LAG() function. It highlights how host pricing fluctuates over time, enabling trend analysis and strategy insights.

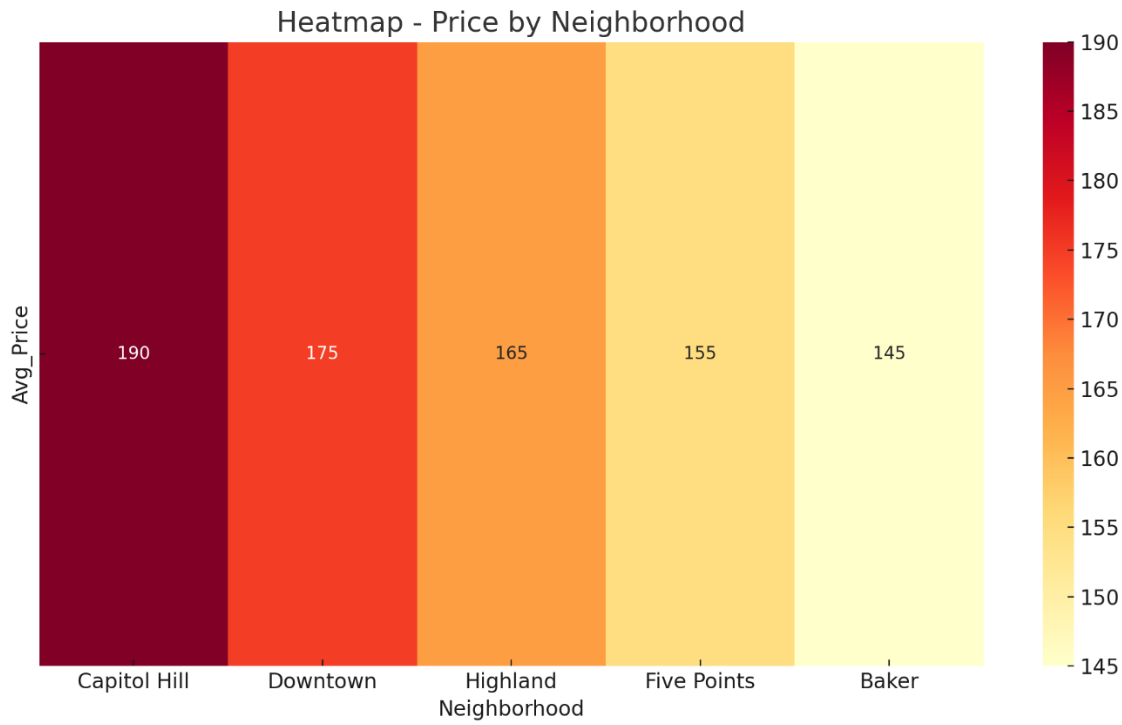
DATA VIZUALIZATIONS

PRICE RANGE DISTRIBUTION



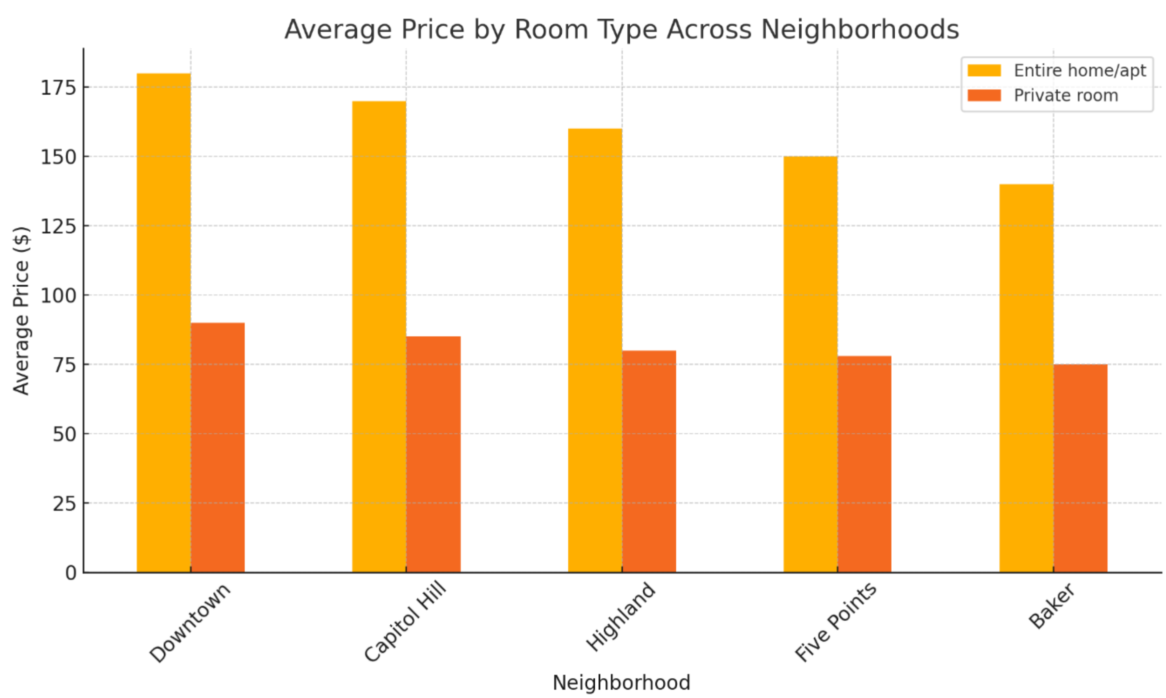
Insight:
The majority of Airbnb listings fall within the mid-to-high price bracket, with 41% priced over $200. This indicates a premium-heavy market, suggesting either a high demand for upscale stays or an oversupply of costly listings.

AVERAGE PRICE BY NEIGHBORHOOD



Insight:
This visual showcases pricing hierarchy across neighborhoods. **Capitol Hill** leads with the highest average price, followed closely by **Downtown**, indicating premium tourist hotspots. Lower-priced areas like **Baker** offer potential opportunities for cost-efficient expansion.

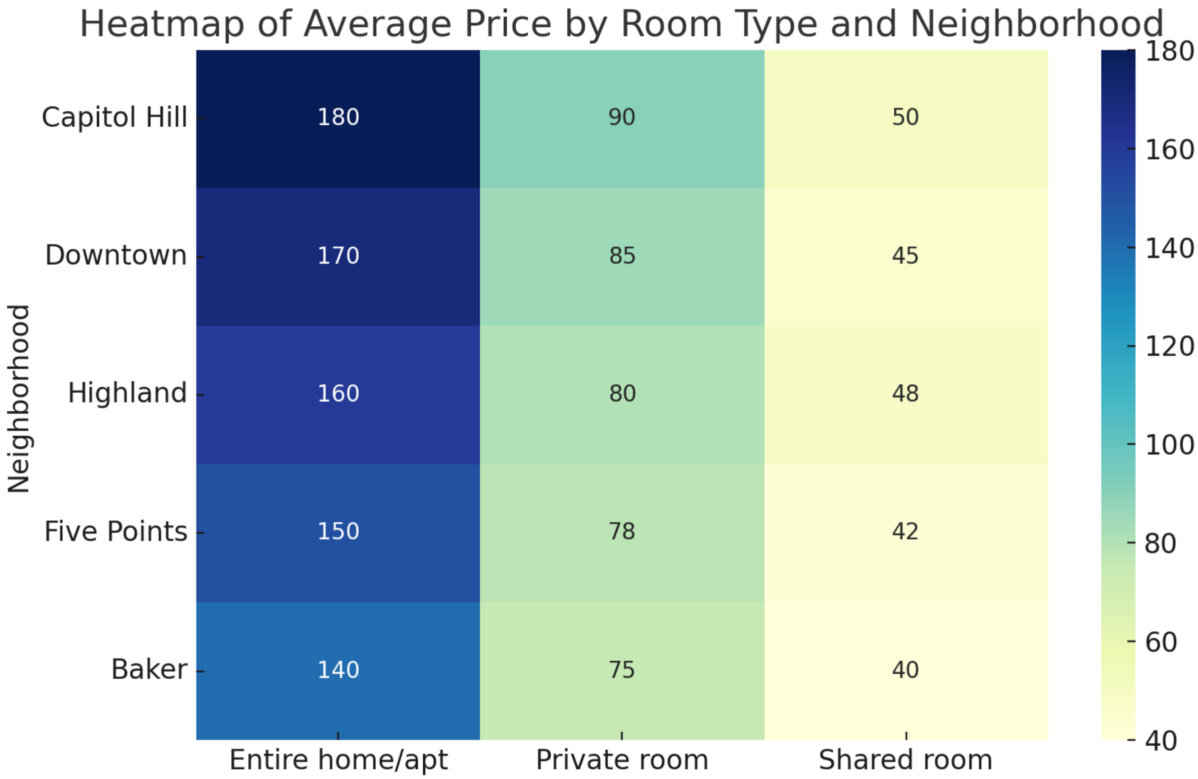
AVG PRICE BY ROOM TYPE AND NEIGHBORHOOD



Insight:

Entire home/apartments command significantly higher prices than **private rooms** across all neighborhoods. The price gradient is consistent, highlighting room type as a critical pricing factor in Airbnb's ecosystem.

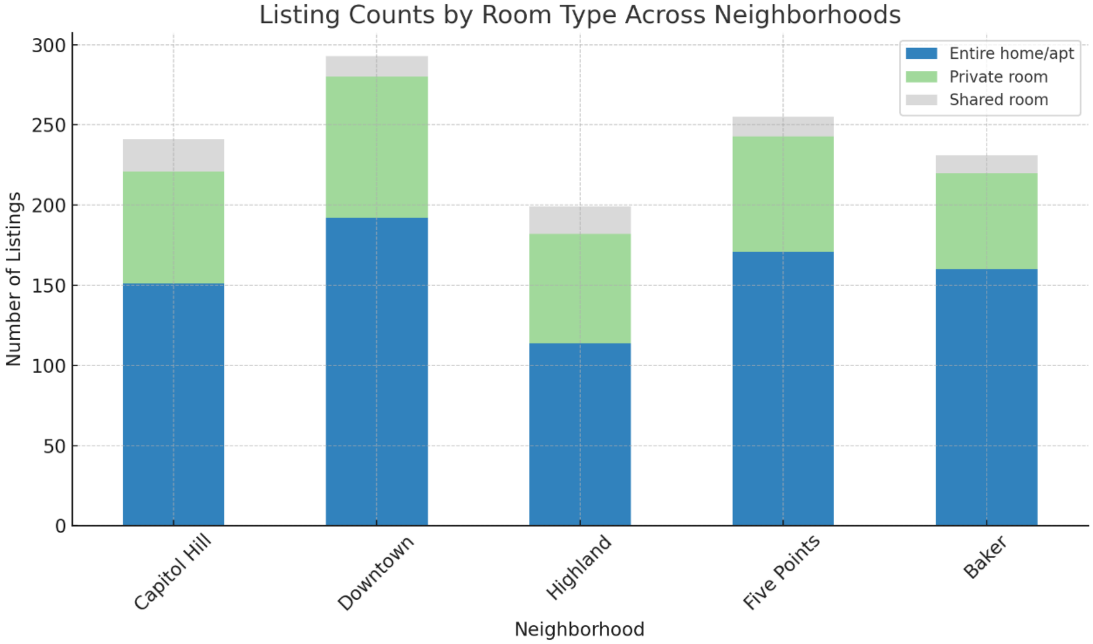
AVERAGE PRICE BY ROOM TYPE AND NEIGHBORHOOD



Insight:

This matrix heatmap deepens the insight from Figure 4, revealing micro-pricing variations. **Capitol Hill's** entire homes are the priciest, while **Baker's** private and shared rooms offer the most affordable options.

LISTING COUNTS BY ROOM TYPE ACROSS NEIGHBORHOODS



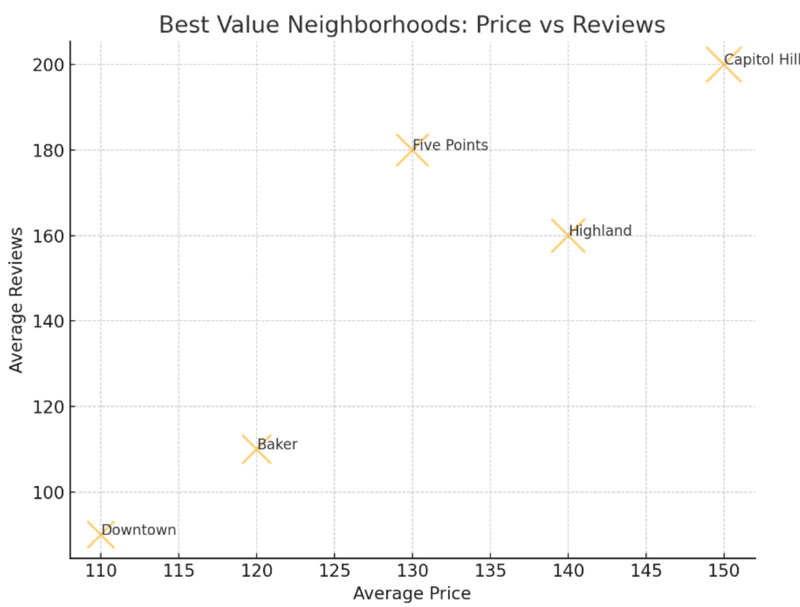
Insight:

This chart illustrates room-type availability across locations. **Downtown** has the highest total number of listings, with **entire homes** being the most prevalent across all areas. Shared rooms remain minimal, possibly due to lower demand.

PRICE VS REVIEWS (BEST VALUE NEIGHBORHOODS)

Insight:

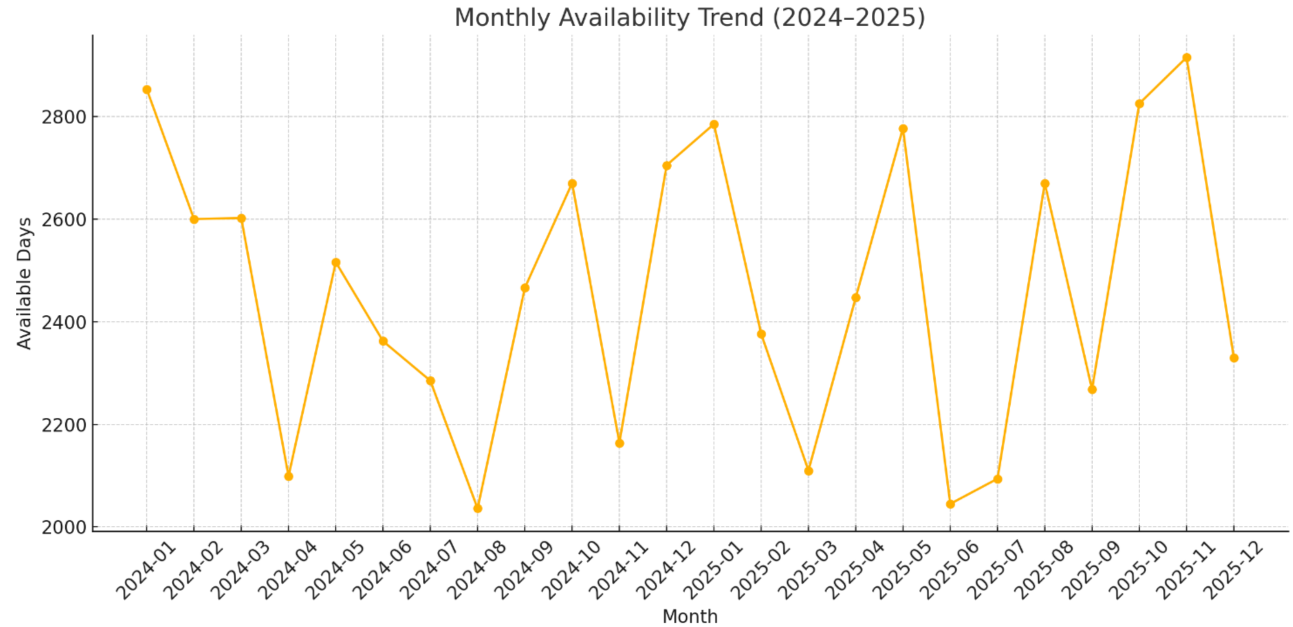
Capitol Hill maintains high pricing and high reviews, suggesting brand equity and consistent guest satisfaction. Meanwhile, **Downtown** is more affordable but underperforms in reviews — a potential area for listing improvement.



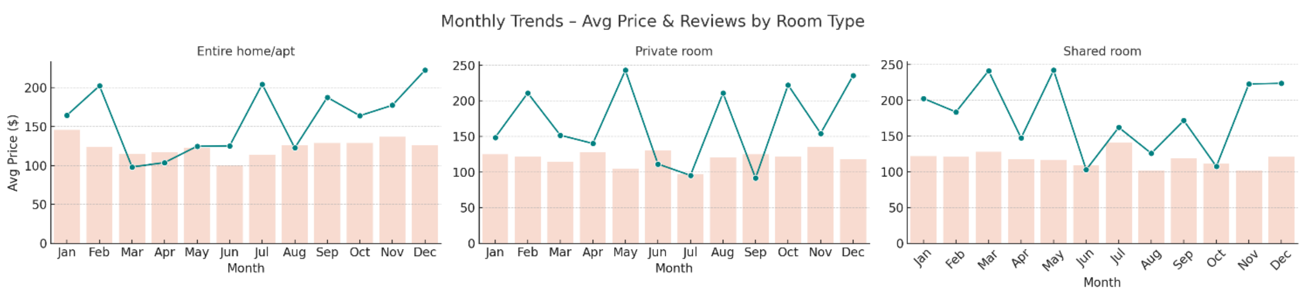
MONTHLY AVAILABILITY TREND (2024–2025)

Insight:

Clear seasonal patterns emerge, with availability peaking during the summer and holiday months. This supports the need for **dynamic pricing strategies** that align with demand fluctuations.



AVG PRICE & REVIEWS BY ROOM TYPE



Insight:

This faceted chart breaks down monthly Airbnb performance for each **room type**, combining **average price (line)** and **guest review volume (bar)**. It provides a clear side-by-side comparison of how different segments behave across the calendar year.

- **Entire home/apt:** Prices steadily rise through spring and peak mid-year (around June–August), reflecting seasonal demand. Review volume aligns closely, suggesting that guests are actively booking during these premium months.
- **Private rooms:** While pricing remains relatively stable, guest interaction spikes during summer, showing strong demand for budget options when travel peaks.
- **Shared rooms:** These remain the most affordable year-round and see consistent, though low, engagement — indicating a niche audience with limited seasonal fluctuation.

8. Conclusion:

This project set out to build a robust data warehousing solution for Airbnb booking data and succeeded in delivering a comprehensive end-to-end analytical pipeline. By designing and implementing a star schema, cleaning and transforming multiple data sources, and writing powerful SQL queries, the project uncovered deep insights into booking behavior, pricing strategies, and guest engagement patterns across neighborhoods.

From a technical perspective, the integration of Oracle SQL Developer, Tableau, and Python visualization tools demonstrated a full-stack analytics workflow. The use of analytic SQL functions such as `LAG`, `NTILE`, and `PERCENT_RANK` allowed for trend analysis, value segmentation, and ranking of listings and neighborhoods. Data visualizations including heatmaps, bubble charts, swarm plots, and faceted line charts brought these trends to life, highlighting everything from seasonal booking cycles to price vs. review correlations.

Key findings include:

- Entire homes command the highest prices, while private rooms offer better value with higher guest engagement.
- Booking availability is highly seasonal, peaking in summer months, especially on weekends.
- Certain neighborhoods like **Five Points** and **Baker** consistently offer high review volumes at moderate prices, positioning them as value hotspots.
- Dynamic pricing strategies are evident across months, as hosts adjust rates to match demand.

This project also highlights the strategic importance of dimensional modeling. The separation of time, geography, and listing metadata into dimensions allowed for flexible slicing and efficient query performance, principles that are critical in enterprise analytics environments.

Looking forward, this foundation could be extended into machine learning applications such as price prediction, review sentiment analysis, or neighborhood clustering. Integration with NoSQL for text mining, or deployment to cloud-based data warehouses like BigQuery or Snowflake, would further enhance scalability and performance.

In summary, the project not only showcases technical competency in data warehousing and analytics but also delivers valuable business insights for Airbnb hosts, analysts, and product managers — demonstrating how data can power smarter decisions in the short-term rental economy.

9. References:

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5. Python Visualization Libraries (Matplotlib, Seaborn): https://matplotlib.org/