MEMBERS & ROLES

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Role
Analytical Lead
PM & Conceptual Design Lead
Technical Lead

1. Data Description with Tables

The dataset is a comprehensive collection of AirBnB property listings enriched with detailed metadata. It includes key identifiers such as listing and host IDs, which uniquely distinguish each property and its associated host. The dataset also captures various property features like capacity (accommodates, bedrooms, beds, bathrooms), descriptive textual data regarding the bathrooms, and categorical details such as property type and room type. Additionally, an extensive list of amenities offered per listing is provided, illuminating the various features that make each property unique. This detailed account ensures that every variable is well-defined, allowing for robust analysis of market trends, host performance, and guest preferences.

Tables	Parameters	Table Names	Description								
	last_scraped host_since calendar_last_scraped first_review last_review		Description	Listing ID	last_scraped	host_since	calendar_last_scraped	first_review	last_review	Date Diff First and Last Review	
			Mean			5/30/2017		3/21/2021	4/28/2024	2.569025385	
			Standard Error					5.645197165	2.016556574	0.013718933	
			Median		9/21/2024	8/19/2016	9/21/2024	3/19/2022	8/7/2024	1.44109589	
			Mode		12/23/2024	7/22/2012	12/23/2024	5/27/2024	9/2/2024	0	
			Standard Deviation					1095.531927	391.3418865	2.927409447	
-· .·			Sample Variance					1200190.202	153148.4721	8.569726073	
Timeline		tbl_Timeframe	Kurtosis					-0.03293072	25.2453725	0.645814775	
			Skewness					-0.89602129	-4.39634381	1.204631147	
			Range					6096	5031	16.33972603	
	_		Minimum		6/24/2024	3/3/2008	6/24/2024	6/22/2008	5/23/2011	0	
	date_diff		Maximum		3/2/2025	2/19/2025	3/2/2025	3/1/2025	3/1/2025		
			Count	21,208	45,534		45,534	37,661	37,661	45,533	
			Confidence Level(95.0%)					11.06473874	3.952505288	0.02688933	

Occupancy Rates	availability_30 availability_60 availability_90 availability_365 availability_eoy has_availability estimated_occupancy_l365d	tbl_Occupancy	Mean Standard Error Median Mode Standard Deviation Sample Variance Kurtosis Skewness Range Minimum Maximum Confidence Level(95.0%)	14.05681469 0.238974981 0 0 50.99414763 2600.403093 14.16365909 3.884479569 255 0	10.738677 115.31918 -1.3719501 0.23656864 3	1 30.86219089 6 0.098697982 2 32 0 0 0 2 21.06086354 8 443.5599729 4 -1.369655502 1 -0.127584086 0 0 0	availability_90 51.20599991 0.143800704 57 0.30.6851966 941.5813085 -1.169283847 -0.394206415 90 0.0281851693	0.57004211 212 0 121.6395601 14796.18258 -1.34216632 -0.18904029 365 0	availability_eoy 153.0114928 1.259332085 159 0 111.4419956 12419.31839 -1.461166015 -0.049129053 306 0 306 2.468627132
Pricing Strategy	price minimum_nights maximum_nights minimum_minimum_nights maximum_minimum_nights minimum_maximum_nights maximum_maximum_nights minimum_nights_avg_ntm maximum_nights_avg_ntm instant_bookable estimated_revenue_1365d	tbl_Pricing	Standard Error 331.775 Median 8 25 Mode 5 25 Sample Variance 661785 Kurtosis 18.566 Stewness 3.1795 Range 3.3 Minimum 3.3 Sum 10738	365d mights 62.12 449,9525649 911263 22,04218818 431.5 365 0 365 81278 4703,515802 22606. 21230060.9 242562 44794,83046 55576 210,7848489 0 1 0 1 00225 999999 0025 999999 100225 999999 100225 999999 100225 999999 100225 999999	price m 306.4677553 3.120178075 150 631.0822472 388240.822 2123.432261 38.810194 49391 9 50000 12536370 40506 6.115617611	minimum_mights minimum_mights minimum_mights 12.91015505 12.32445079 0.13898626 0.127961335 2 2 2 2 2 2 2 2 2	maximum_maximum_minimum_miphts s 15.70452548 370418177 0.178007287 333425.5787 4 3055 37.97859628 28469902.58 1442.373775 81095674 12147483846 112 2147483846 112 2147483846 112 2147483846 113 2147483846 115 2147483846 15 115 2147483846 4520 0.34889715 261516.2787	s nights 991385.4211 13.2 216143.2586 0.13 365 1105 4911506.4 28.1 2126.857161 267. 46.52700409 12.3 2147483646 1 2147483647 45127864368 6	maximum_ maximum_ 1918717 913453.4781 072099 205696.474 3 365 2 1125 1125 1125 1125 1125 1125 1125
Guest Reviews and Ratings	number_of_reviews number_of_reviews_ltm number_of_reviews_l30d number_of_reviews_ly reviews_per_month review_scores_rating review_scores_accuracy review_scores_cleanliness review_scores_checkin review_scores_location review_scores_value	tbl_Reviews	Nean S2	number.of. number.of. reviews.llm 77599961 13.8800836.05254789 0.10000104 18 18 18 24.02889 345.36767 69.302742 1334 68.045534 45534 45534 54534	3.343318362 3 100.6752244 5 5.835963379 6 0 0 0 8 60 4 45534	number, of, reviews, foraccuracy reviews, foraccuracy 2ccuracy 8.316306885 4.827540256 0.2058413 0.001645226 1 4.91 0 5 18.54760024 0.319944427 344.0134748 0.102386217 5.170023904 -8.20100162 320 5 0 0 0 320 5 7631 37534 0.410860447 0.003232528	Checkin Checkin Checkin Checkin 4.886424149 4.796473402 4 0.001346419 0.001365252 4 4.96 4.88 4.89 0.261194951 0.328870238 0 0.66222802 0.108155633 0 5.5325596 4.86203898 7 7.502410506 5.243157035 -7 5 5 5 0 0 0 5 5 5 37833 37834	wx, scores, review, scores, munication location location location 10	3 0.001699715 2 4.89 5 5 5 6 0.32402204 4 0.10469689 1 49.7616958 4 5.695310412 5 5 5 5 2 37661

	neighbourhood		Missi	st represented r	neighborhood	4192	
Location	neighbourhood_cleansed neighbourhood_group_cleansed		La Jol	ic Beach lla n Park		3562 2181 1525	
	host_location host_neighbourhood	tbl_Location		st represented	neighborhoo	ds	
	latitude longitude		Fores	cionamiento Torres stland	Del Lago	1	
			Flami Five F	Points	hathraama	1	hada
				accommodates	bathrooms	bedrooms	beds
			Mean Standard Error	4.747265779 0.015071361	1.432731585 0.004965295	1.824614574 0.006639071	2.340361049 0.010758373
			Median Mode	4 2	1 1	1 1	2 1
	property_type		Standard Deviation Sample Variance	3.216032024 10.34286198	1.059529348 1.122602439	1.416691243 2.007014077	2.295696725 5.270223453
Property Type and Amenities	room_type accommodates bathrooms bathrooms_text bedrooms beds amenities		Kurtosis Skewness	2.044409551 1.415135755	22.78499607 2.688836282	189.0568688 5.455964523	86.05815525 4.672849646
		tbl_PropertyType	Range Minimum	15 1	23 0	66	85 0
			Maximum Confidence Level (95.0%	16 0.029540109	23 0.009732059	0.013012686	85 0.021086585
				Frequency room_type Entire home/a Hotel room Private room Shared room	frequenc		
			no les face	un nichte medianum			
	calendar_updated		avg	um_nights maximum_ g_ntm nights_avg_ntm 21918717 913433.4781		ailability_60 availability_90 30.86219089 51.2059999	7.
Seasonality	caterida_updated calendar_last_scraped availability_30, availability_60, availability_90, availability_365 first_review, last_review minimum_nights_avg_ntm, maximum_nights_avg_ntm	tbl_Seasonality	Standard Error 0.13 Median Mode Standard Deviation 28. Sample Variance 794 Kurtosis 267	32072099 205696.474 3 365 2 1125 17813253 43886199.6 4.0071527 1.926E+15 7.4460235 2373.803761 33539757 48.68180425	0.050324896 (12 0 10.7386772 115.319188 4 -1.371950137 - :	0.098697982 0.14380070 32 5	4 0.57004211 7 212 0 0 9 121.6395601 5 14796.18258 7 -1.342166318
			Range Minimum Maximum Sum Count	1124 2147483646 1 1 1125 2147483647 601737.4 41579491923 45520 45520	30 0 30 590746 45534	60 9 0 9 60 9 1405279 233161 45534 4553	0 0 0 365 4 9106407

					host	_response_r	rate		
				Mean			0.97127888	32	
				Standard Error			0.00059569	94	
				Media	ın			1	
Host	haat raananaa tima			Mode				1	
	host_response_time			Stand	ard Deviat	ion	0.1204068	57	
	host_response_rate	tbl Host			HOUSE THE SAME		0.0144978		
Responsiveness	host_acceptance_rate	tDt_Host		Sample Variance					
	host_is_superhost			Kurto			44.1438806		
	llost_is_superilost			Skewi	ness		-6.35574033	33	
				Range			1		
				Minimum			0		
				Maximum			1		
							10050		
				Count			40856		
				Confi	dence Leve	el(95.0%)	0.0011675	74	
	host_listings_count host_total_listings_count			estimated_ occupancy_ l365d	estimated_ revenue_l365 d	host_listings_ count	host_total_listing of s_ count	alculated_host _listings_ count	calculated_ host_listings_ count_entire_hom es
	calculated_host_listings_count								
	calculated_host_listings_count_entire_ho		Mean Standard Error		17862.11693 331.7791263	112.5316389 2.575797747		16.78793868	
	-		Median	0.236974961	8431.5	2.5/5/9//4/	5.554049002	0.10000003	
	mes		Mode	0	0	1	. 1	1	1
Market Demand	calculated_host_listings_count_private_r	tbl MktDemand	Standard Deviation		25725.18728	549.3277468		34.31277251	
riarket Demana	catedtated_nost_tistings_count_private_i	tbt_Fiktbellialia	Sample Variance		661785260.6	301760.9734		1177.366357	759.9256123
	ooms		Kurtosis	14.16365909	18.96642682	51.756702		19.44017357	
	apparent heat listings count shared r		Skewness		3.179565576	6.963972468		3.922410727	
	calculated_host_listings_count_shared_r		Range Minimum	255	330225	5254 1		263	
	ooms		Maximum	255	330225	5255		264	
			Sum	640063	107387047	5118164		764422	
	estimated_occupancy_l365d		Count	45534	6012	45482		45534	
	estimated_revenue_l365d		Confidence Level(95.0%)		650.4061026	5.048605172		0.31517194	

2. Key findings from your exploratory data analysis.

A comprehensive exploratory data analysis (EDA) was conducted to uncover meaningful insights, trends, anomalies, and relationships within the Airbnb dataset. The goal of this analysis is to guide the development of predictive and clustering models while informing host strategy and business decisions. Key findings are summarized below:

2.1 Temporal and Group-Based Trends

- Seasonal Demand Patterns: Listings experience a clear seasonal trend, with review counts peaking between June and August, indicating increased guest activity during the summer. This suggests opportunities for dynamic pricing and targeted marketing during high-demand periods.
- Listing Growth Over Time: A year-over-year increase in total listings was observed, particularly post-2019. This growth aligns with Airbnb's rising popularity and may suggest an increasingly competitive market landscape in recent years.
- Superhost Advantage: Superhosts consistently outperform regular hosts across key metrics. They typically:
 - O Charge 10–20% higher nightly rates
 - Receive more frequent and higher-rated reviews
 - Maintain lower cancellation rates and faster response times

These findings emphasize the value of achieving Super Host status to maximize occupancy and revenue.

2.2 Outliers and Anomalies

- Extreme Pricing: A small subset of listings priced over \$1,000 per night significantly skew the overall price distribution. These listings likely represent luxury accommodations or potential data entry errors. Box plots and histograms helped identify and flag these outliers for further cleaning or segmentation.
- Zero-Review Anomalies: Numerous listings show full-year availability (365 days) but have zero guest reviews, which may indicate inactive or placeholder listings. These anomalies can distort average availability and occupancy calculations and should be filtered in modeling.
- Review Count Extremes: While the average listing has ~30–40 reviews, some listings exceed 500+ reviews, indicating highly established or corporatemanaged properties. These high-volume listings require normalization when evaluating typical host performance.

2.3 Variable Relationships and Correlations

- Price vs. Review Count: Listings priced between \$100-\$200 generally receive the most reviews, suggesting this is the market's "sweet spot." Both ultra-low and high-priced listings tend to have lower engagement.
- Availability vs. Popularity: Listings with higher availability show a strong positive correlation with review count and guest feedback, implying that being available year-round increases occupancy potential.
- Review Score Breakdown:
- Cleanliness, Communication, and Location ratings have the highest correlation with overall score (Pearson's r > 0.75).
- These three factors should be considered critical KPIs (Key Performance Indicators) for hosts looking to improve listing quality and ratings.
- Room Type Impact: "Entire home/apartment" listings consistently outperform
 private or shared rooms in both price and rating, indicating a clear guest
 preference. These room types command higher average nightly prices and
 contribute to higher guest satisfaction.

2.4 Preliminary Sentiment Insights from Guest Reviews

- An initial sentiment analysis of guest reviews revealed overwhelmingly positive sentiment, with common keywords including:
- "Clean," "Convenient location," "Responsive host," "Comfortable stay," and "Easy check-in."
- These terms reflect guest priorities and should be highlighted in listings to attract more bookings.
- Full sentiment scoring (e.g., using TextBlob or VADER) and word cloud visualization will be included in later stages to identify themes that contribute most to 5-star reviews.

Conclusion

The EDA provided valuable insights into pricing dynamics, seasonal demand, host performance, and guest expectations. These findings lay the groundwork for selecting the most appropriate quantitative techniques in the next phase of the project, including:

- Regression models for price prediction
- Clustering algorithms for identifying high-performing neighborhoods
- Time series analysis for seasonality and occupancy forecasting
- Sentiment analysis to link guest feedback with listing performance

3. Propose and justify potential methods for your next analysis or modeling.

Based on the exploratory data analysis (EDA) and understanding of the Airbnb dataset, we propose a multi-faceted modeling approach tailored to address the core business objectives: accurate price prediction, neighborhood performance clustering, and actionable host insights through visualizations.

	Proposed Method	Justification
1.Accurate Predictions: Achieve high accuracy in predicting listing prices using machine learning models.	Multiple Linear Regression Random Forest Regressor XGBoost Regressor Artificial Neural Networks (ANN)	These models can effectively handle complex relationships in pricing data. Treebased models (Random Forest, XGBoost) are robust to outliers and nonlinearities. ANN captures complex feature interactions.
2.Effective Clustering: Successfully identify high-performing neighborhoods through clustering analysis.	K-Means Clustering DBSCAN Hierarchical Clustering	Clustering helps group neighborhoods based on metrics like price, review scores, and availability. K-Means is effective for structured groups; DBSCAN detects noise/outliers; Hierarchical shows nested clusters.

3.Insightful

Visualizations: Create clear and informative visualizations of geographic trends.

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Visualizations for General Information Purposes

- 1. Price Distribution: A histogram or box plot showing the distribution of listing prices. This can help users understand the range and average prices in different neighborhoods
- 2. Availability Heatmap: A heatmap displaying the availability of listings throughout the year. This can help users identify peak and off-peak seasons
- **3. Geographic Trends**: A map visualization showing the geographic distribution of listings and their prices. This can help users visualize trends and identify high-demand areas
- **4. Review Sentiment Analysis:** A word cloud or sentiment score chart showing the most common words and overall sentiment in guest reviews. This can help users

Visualizations to Help a User Become a Super Host

- **1. Host Response Time**: A bar chart showing the average response time of hosts. Faster response times can lead to better guest experiences and higher ratings
- **2. Review Scores Breakdown**: A detailed breakdown of review scores for accuracy, cleanliness, check-in, communication, location, and value. This can help hosts identify specific areas to improve
- **3. Monthly Review Trends**: A line chart showing the number of reviews per month. This can help hosts track their performance over time and identify trends
- **4. Amenities Analysis**: A bar chart showing the frequency of different amenities offered by super hosts. This can help hosts understand which amenities are most valued by guests

	understand guest feedback and areas for improvement			
	5. Neighborhood Clusters: A scatter plot or cluster map showing different neighborhoods based on rental performance and availability. This can help users identify high-performing neighborhoods	5. Occupancy and Revenue Trends : A line chart showing the estimated occupancy and revenue over the past year. This can help hosts understand their financial performance and identify opportunities for growth		
4. Sentiment Analysis: Provide meaningful insights from guest reviews and their impact on listing success.	 TextBlob or VADER for sentiment scoring TF-IDF or CountVectorizer for keyword extraction WordCloud for visual sentiment representation 	Using Natural Language Processing (NLP), we will extract sentiment scores from guest reviews and analyze their impact on: Price variation Overall Ratings Booking frequency		

Conclusion:

The proposed methods align with the key objectives of the project:

- Predictive models will optimize pricing strategy.
- Clustering will uncover high-performing neighborhoods.
- Power BI visualizations will provide actionable insights for hosts and business users.
- Sentiment analysis will connect guest feedback with listing performance and success metrics.