



Right Message, Right Audience: Optimizing Airbnb's Campaign with Segmentation

Kirana Ananda

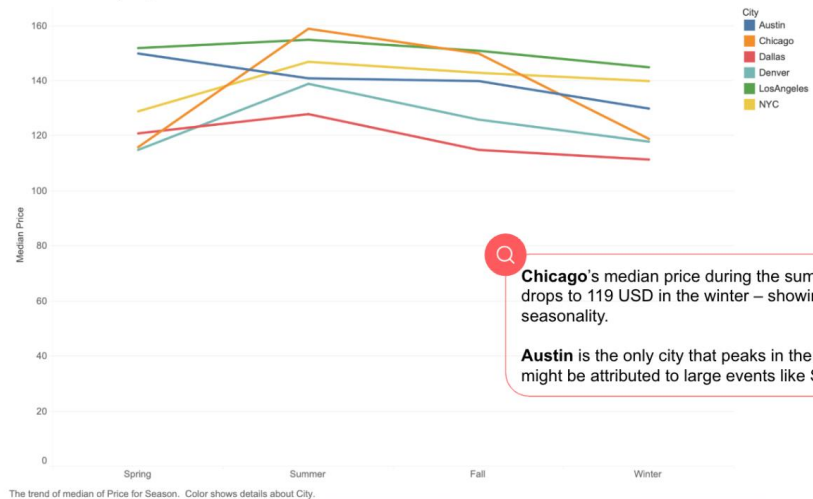


Q1'25 Recap



Seasonal demand influences shifts in pricing trends, this stood out particularly in

Median Price by City and Season



Chicago's median price during the summer is 159 USD, which drops to 119 USD in the winter – showing the most variance in seasonality.

Austin is the only city that peaks in the spring (at 150 USD) – which might be attributed to large events like SXSW which is on in March.

The trend of median of Price for Season. Color shows details about City.



Location-based marketing strategy, proof of concept starting out with Chicago

'Room type' and 'accommodates' have the highest influence on price across the key cities

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
season	3	359	120	266.25	< 2e-16 ***
city	5	1507	301	670.54	< 2e-16 ***
room_type	3	37435	12478	27760.85	< 2e-16 ***
season:city	15	453	30	67.22	< 2e-16 ***
season:room_type	9	87	10	21.49	< 2e-16 ***
city:room_type	15	999	67	148.13	< 2e-16 ***
season:city:room_type	44	57	1	2.88	6.07e-10 ***
Residuals	273671	123013	0		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6704 on 273671 degrees of freedom
Multiple R-squared: 0.2495, Adjusted R-squared: 0.2493
F-statistic: 967.9 on 94 and 273671 DF, p-value: < 2.2e-16

The new model (+accommodates) improves prediction accuracy by 22%.



Persona-based marketing strategy, creation of distinct personas based on additional variables that reflect stay characteristics.

Q2'25 strategic question:
Which of these properties is most appealing to you?



1



2



3



4



5



Data set in the analysis



1

City and neighborhood group

2

Price and price cluster (k-means)

3

Season

4

Room type and accommodates

5

Amenities

6

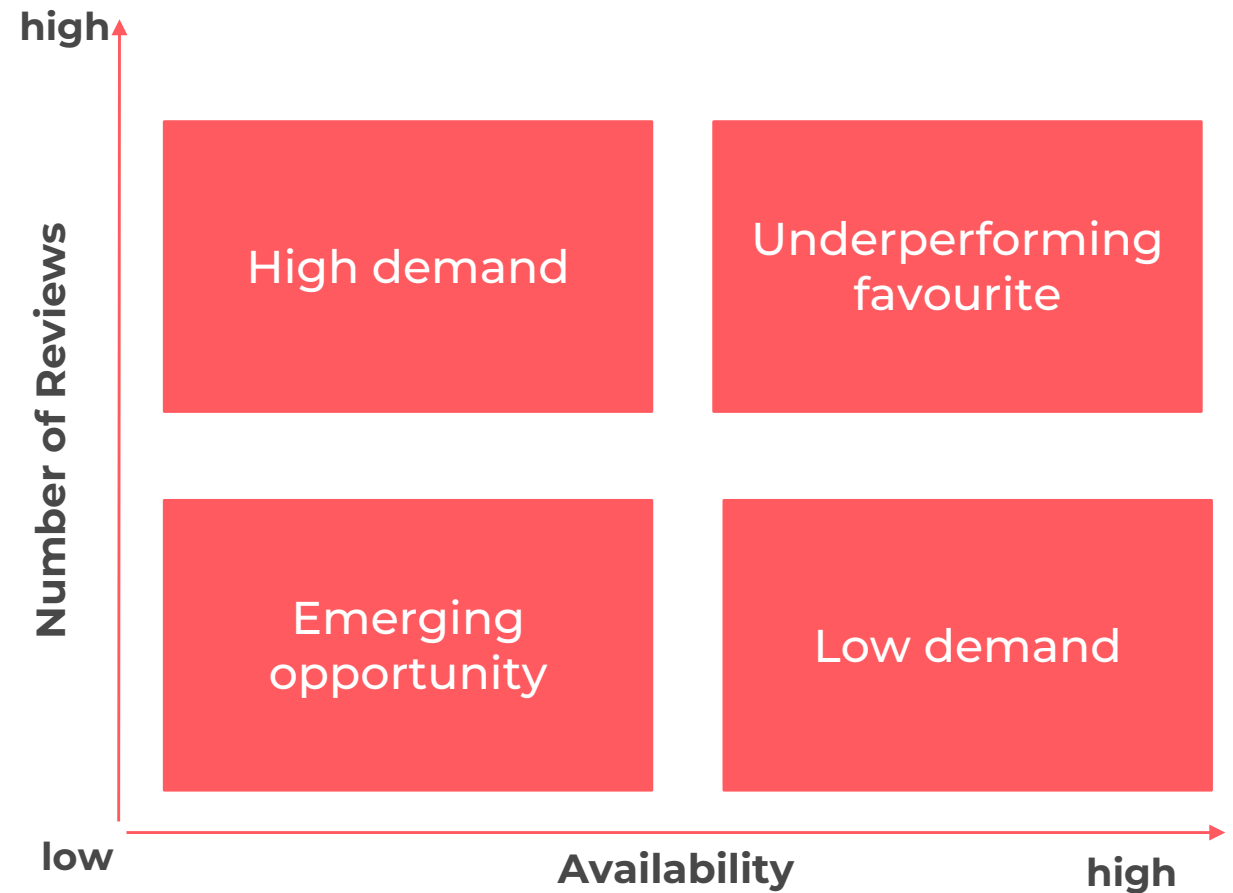
Text analysis

- Review dataset
- Neighborhood overview

7

Demand, a proxy based on
availability_365 and
number_of_reviews_ltm

Market Map



Data preparation



1

Restructure the 'amenities' column and exclude amenities type <100 occurrences.

```
[45]: # 3. More efficient approach to check amenities against keywords
for category, keywords in category_keywords.items():
    # Convert keywords to lowercase for case-insensitive matching
    keywords_lower = [keyword.lower() for keyword in keywords]

    for col in amenity_columns:
        # Get values from the amenity column, convert to lowercase
        amenity_values = amenities_expanded[col].fillna("").astype(str).str.lower()

        # Find rows where the amenity value matches any keyword in this category
        for keyword in keywords_lower:
            # Find matches where this keyword appears in the amenity value
            matches = amenity_values.str.contains(keyword, regex=False)
            # Set category flag to 1 for matches
            category_flags.loc[matches, category] = 1

[47]: category_flags
```

	Safety	WiFi	Kitchen	General Facilities	Bathroom	Clothing storage	Laundry at home	Heating & cooling system	Kitchen utensils	Bedroom	Recreation spot direct access	Waterfront	Kitchenette	Playground	Outside kitchen
0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
1	1	0	1	1	1	1	1	1	1	1	1	0	0	0	0
2	1	0	1	1	1	1	1	1	1	1	1	0	0	0	0
3	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
4	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
469524	1	1	1	0	0	0	0	1	1	0	0	0	0	0	0
469530	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0
469552	1	1	0	1	1	0	1	1	1	1	1	0	0	0	0
469553	1	1	0	1	1	0	1	1	1	1	1	0	0	0	0
469554	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0

153833 rows x 40 columns

2

Qualitatively categorize the 'amenities' from 514 to 40.

```
469555 rows x 3 columns

[25]: cleaned_df = cleaned_df.drop_duplicates(subset=['id'])

[27]: cleaned_df
```

	id	city	amenities
0	69810	Austin	["Cooking basics", "Bed linens", "Backyard", "...
1	70812	Austin	["Cooking basics", "Bed linens", "EV charger", "...
2	72833	Austin	["Courtyard view", "Cooking basics", "Bed line...
3	73005	Austin	["Clothing storage", "Central air conditioning", "...
4	73289	Austin	["Central air conditioning", "Cooking basics", "...
...	...	...	...
469524	1112482646283343030	Chicago	["Carbon monoxide alarm", "Fire extinguisher", "...
469530	1114571672303000146	Chicago	["First aid kit", "Carbon monoxide alarm", "Fi...
469552	1117438873812832956	Chicago	["Private entrance", "TV with standard cable", "...
469553	1117439997700638787	Chicago	["Private entrance", "TV with standard cable", "...
469554	1117896281364781567	Chicago	["Ceiling fan", "Fire pit", "Heating", "Lockbo...

153833 rows x 3 columns

3

Regrouping 40 to 27 amenities to ease clustering process.

```
[53]: count_ones
```

Safety	147997
WiFi	143285
Kitchen	138209
General Facilities	135235
Bathroom	132261
Clothing storage	117262
Laundry at home	140071
Heating & cooling system	149646
Kitchen utensils	119062
Bedroom	100320
Workspace	91182
Entertainment	132356
Check-in	113995
Parking	116507
Pets	49232
Outdoor activities	54262
BBQ	37427
Elevator	25233
Patio or balcony	52023
Backyard	42511
Pool	29257
Fireplace	23026
Housekeeping	17841
Sports	21073
Gym	20990
Family needs	32698
Hot tub	16663
View	20861
Lounge	8139
EV charger	6643
Recreation spot direct access	9814
Waterfront	2333
Kitchenette	1879
Playground	1836
Outdoor kitchen	3187
Movie theater	1334
Spa and wellness	1706
Water sports	844
Mini golf	444
Rooftop	439
dtype: int64	

4

Resampling n=5000 per cities (LA, NYC, Austin, Chicago, Denver, Dallas) to enter cluster analysis.

Criteria: grouping together if > 100k

Cluster analysis



1

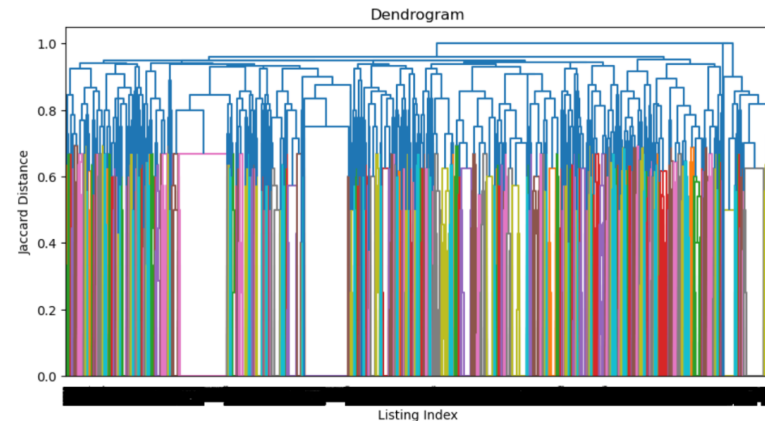
Cluster analysis with complete method using pairwise Jaccard distances*

```
[161]: X = check.drop(columns=['id', 'city']) # only binary features used for clustering
```

```
[163]: # Condensed distance array
dist_array = pdist(X, metric='jaccard')
```

```
[165]: # Hierarchical clustering
linkage_matrix = linkage(dist_array, method='complete')
```

```
# Plot dendrogram
plt.figure(figsize=(10, 5))
dendrogram(linkage_matrix)
plt.title("Dendrogram")
plt.xlabel("Listing Index")
plt.ylabel("Jaccard Distance")
plt.show()
```



* I tried ward and average method too, but ward is not suitable for dummy data and average produce monoton cluster. Complete method is chosen because I want to avoid merging very distant outliers.

2

Cross-checking the generated cluster**

7 (n=32) is outlier because this cluster shows no meaningful amenities.

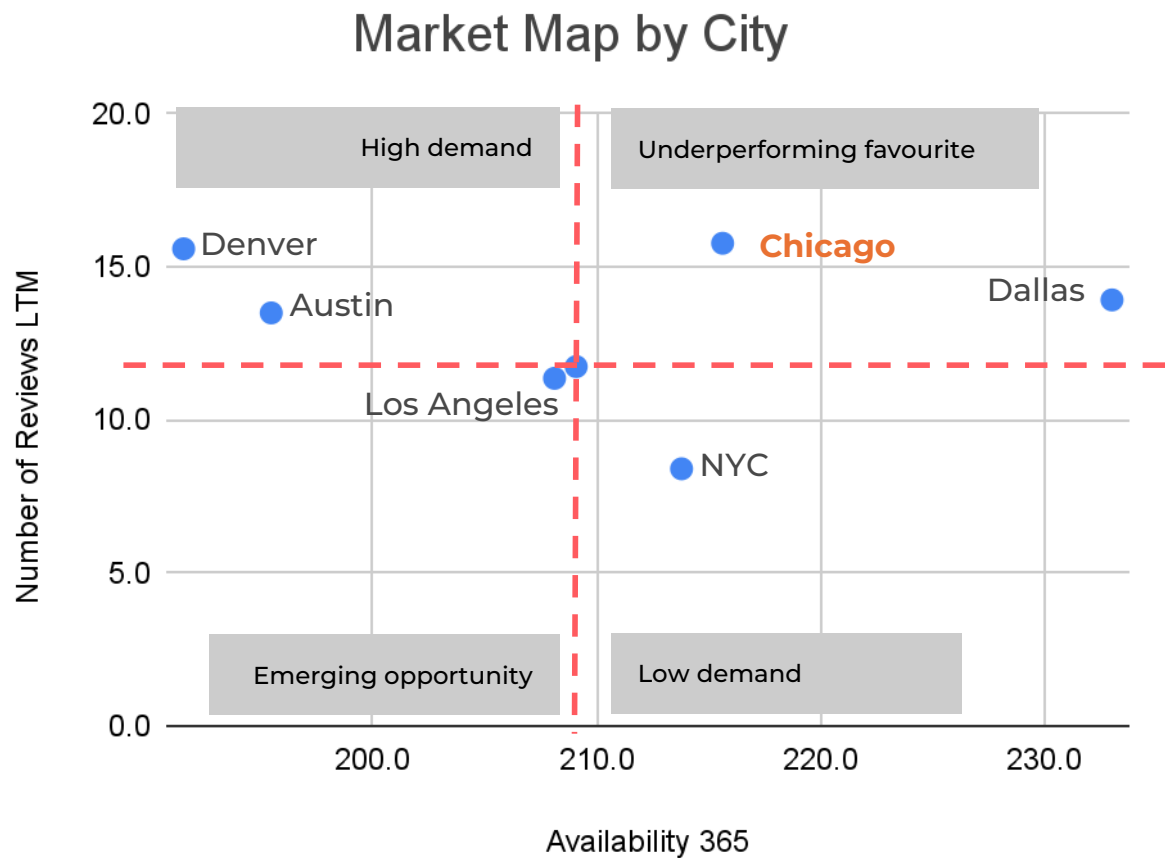
Row Labels	Grand Total	Family retreat	Workplace serenity	Patio paradise	Backyard bliss	Active leisure	BBQ escape	7	Pet haven
Basic airbnb	29966	2.72	4.09	3.45	2.79	1.76	1.95	#DIV/0!	3.08
Rooftop	172	-0.82	-0.54	-0.74	-0.75	-0.97	-1.00	#DIV/0!	-0.46
Mini golf	124	-0.81	-0.55	-0.74	-0.74	-1.22	-0.95	#DIV/0!	-0.46
Water sports	224	-0.81	-0.54	-0.74	-0.74	-1.11	-0.92	#DIV/0!	-0.46
Spa and wellness	314	-0.82	-0.54	-0.72	-0.72	-0.99	-0.94	#DIV/0!	-0.46
Movie theater	323	-0.81	-0.53	-0.72	-0.73	-1.05	-0.91	#DIV/0!	-0.45
Outdoor kitchen	705	-0.80	-0.55	-0.74	-0.67	-0.67	-0.81	#DIV/0!	-0.46
Playground	425	-0.72	-0.52	-0.70	-0.73	-1.16	-0.87	#DIV/0!	-0.46
Waterfront	487	-0.72	-0.53	-0.71	-0.71	-1.02	-0.88	#DIV/0!	-0.46
Recreation spot direct access	1819	-0.26	-0.49	-0.52	-0.60	-0.64	-0.65	#DIV/0!	-0.46
EV charger	1580	-0.65	-0.39	-0.52	-0.67	-0.30	-0.70	#DIV/0!	-0.43
Lounge	1851	-0.63	-0.51	-0.67	-0.59	-0.23	-0.34	#DIV/0!	-0.45
View	5389	0.22	-0.43	-0.43	0.06	0.20	0.27	#DIV/0!	-0.43
Hot tub	2430	-0.72	-0.31	-0.54	-0.47	-0.38	-0.41	#DIV/0!	-0.40
Family needs	8415	1.14	0.42	0.14	0.10	-0.03	0.40	#DIV/0!	-0.36
Gym	4315	-0.76	0.22	0.26	-0.58	1.54	-0.66	#DIV/0!	-0.35
Sports	4625	-0.56	-0.26	0.06	-0.29	1.09	-0.17	#DIV/0!	-0.05
Housekeeping	4073	1.20	-0.42	-0.61	-0.49	-0.38	-0.25	#DIV/0!	-0.44
Fireplace	5241	0.14	-0.01	-0.30	-0.21	-0.84	0.38	#DIV/0!	-0.37
Pool	6052	-0.52	0.05	0.95	-0.32	1.24	0.03	#DIV/0!	-0.07
Backyard	11386	0.50	-0.31	0.60	1.69	-0.51	1.32	#DIV/0!	-0.20
Patio or balcony	13818	1.30	-0.08	2.04	1.25	1.05	1.83	#DIV/0!	-0.12
Elevator	4538	-0.65	0.63	-0.29	-0.61	1.22	-0.77	#DIV/0!	-0.26
BBQ	9194	-0.03	-0.22	0.51	0.63	0.92	1.27	#DIV/0!	0.04
Outdoor activities	13413	1.07	-0.19	0.09	1.81	1.37	1.71	#DIV/0!	-0.05
Pets	10651	0.76	0.31	0.15	0.57	-0.30	0.29	#DIV/0!	3.09
Workspace	20802	2.04	2.21	1.43	1.74	1.41	1.76	#DIV/0!	1.90

** I tested 8 to 10 clusters, and 8 proved best, as it showed clearer distinctiveness. With more than 8, clusters have some similar strengths judged by their z-score.

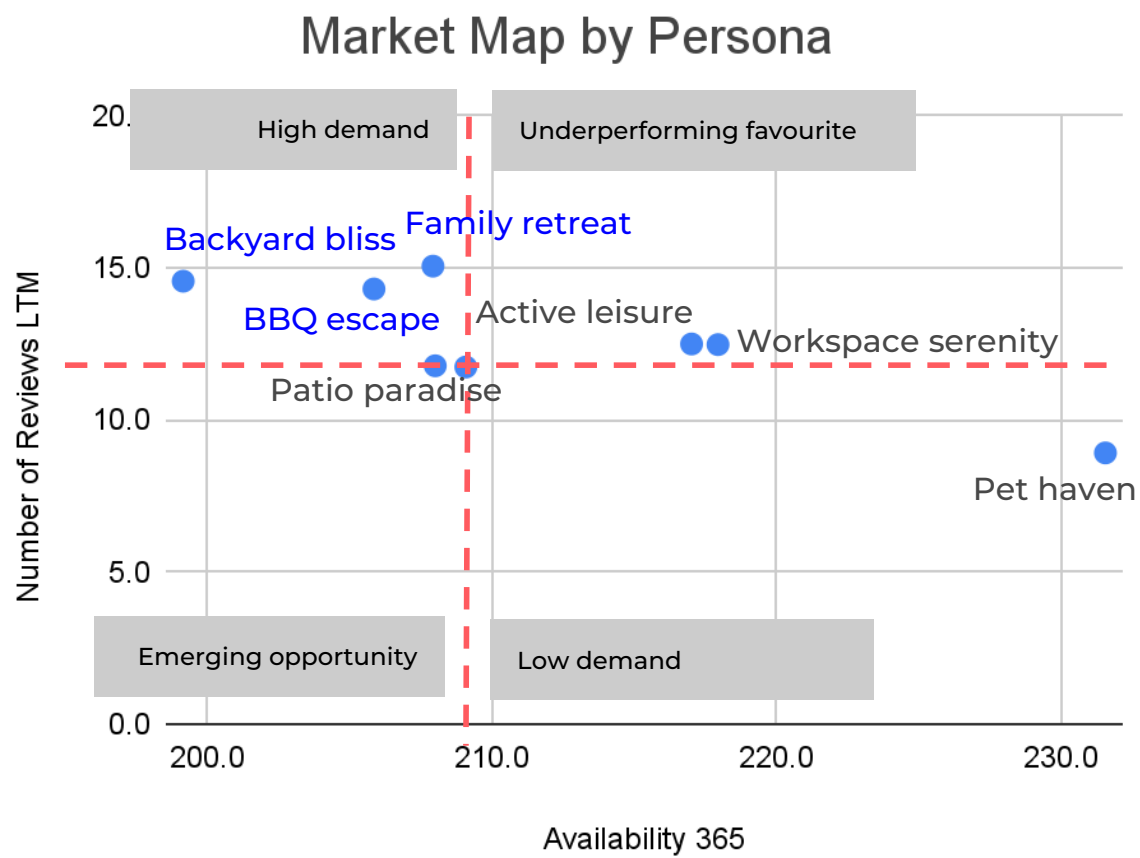
Market Overview



1 Baseline for location-based marketing



2 Baseline for persona-based marketing



Chicago Overview

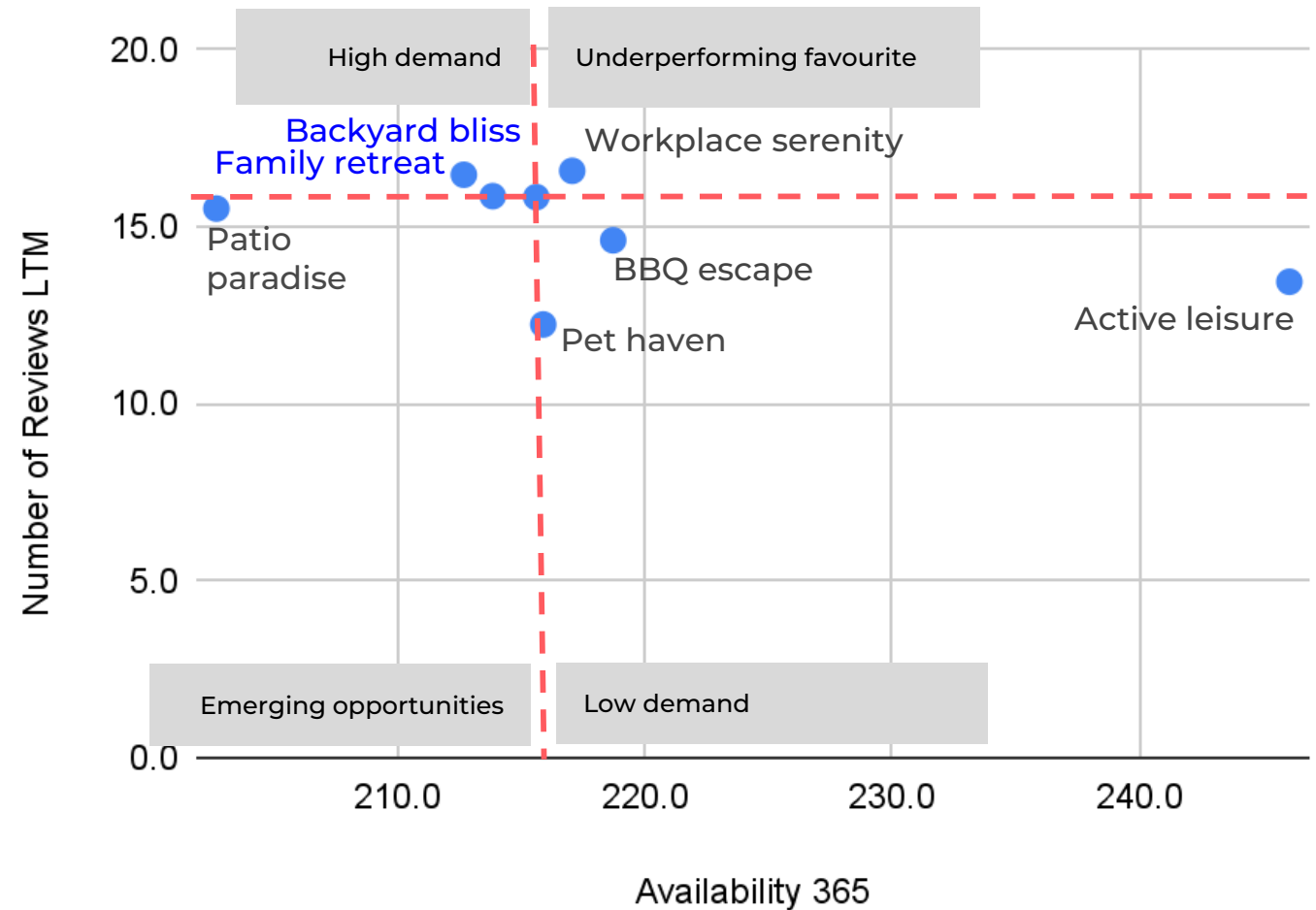


Mission

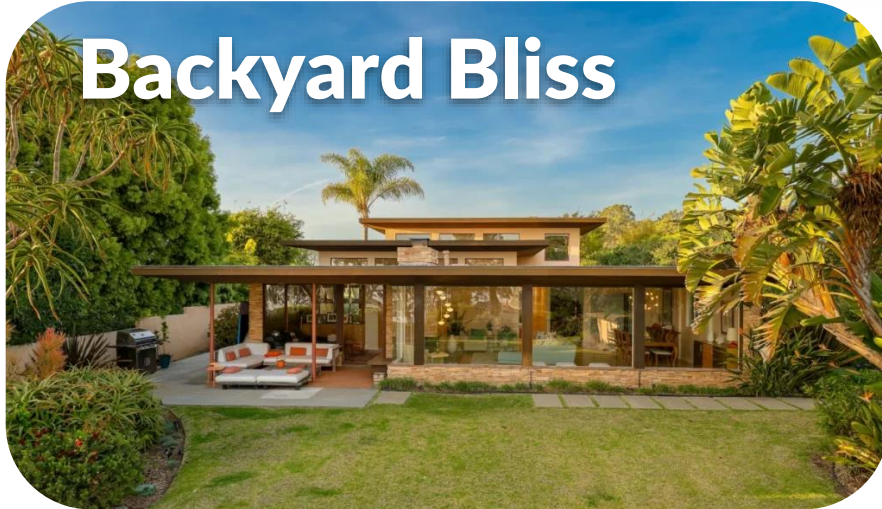
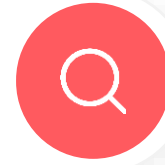


Create a segmented marketing strategy, focusing on the high demand personas to lift Chicago from an 'underperforming favourite' to a 'high demand' city

Market Map in Chicago

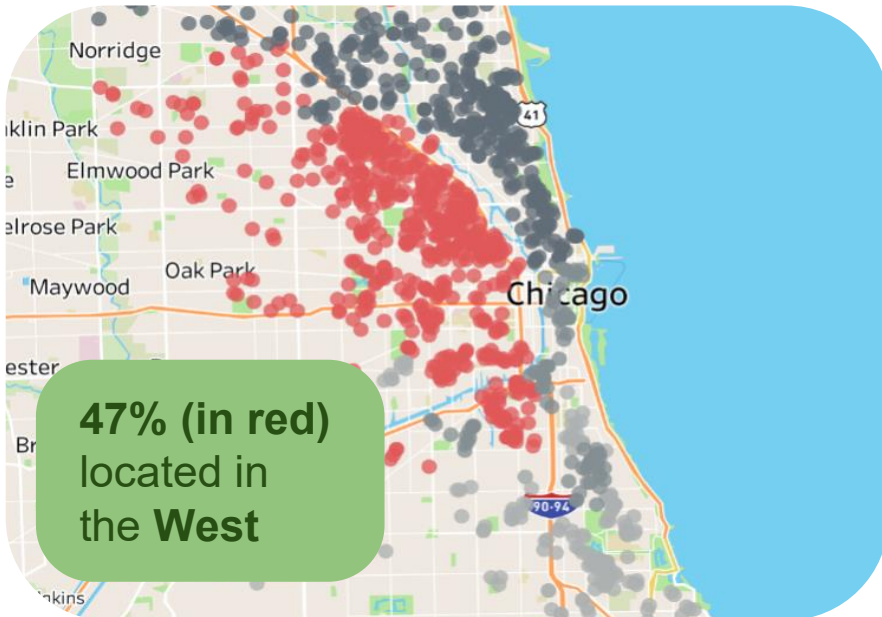
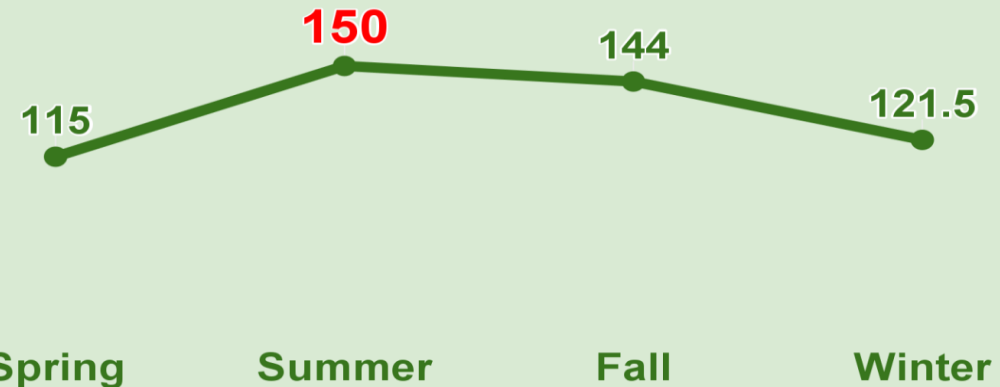


Persona



Median Price: 132 USD; 74% under 200 USD per night

Price spikes in the summer



76%
entire
home/ap
t



Accommodates
4

“Serenity”

Key amenities:

- Backyard
- Outdoor activities
- Patio/balcony view

Persona



Family Retreat



Median Price: 165 USD; 60% under 200 USD per night



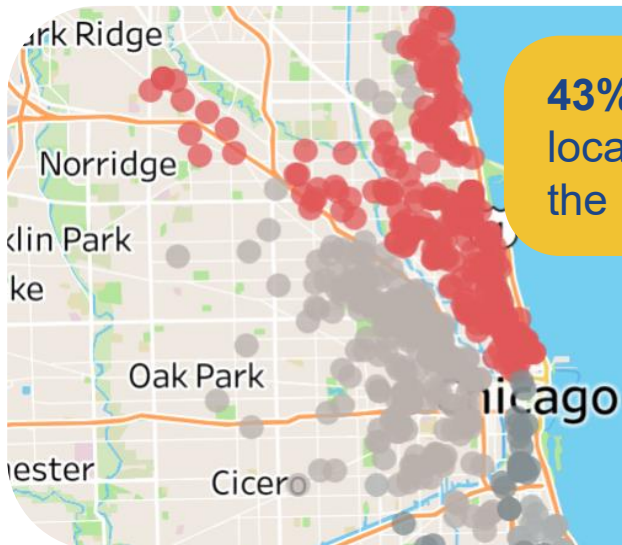
Price spikes in the summer

Spring

Summer

Fall

Winter



43% (in red)
located in
the North



82%
entire
home/ap
t



Accommodates

5

“Great”

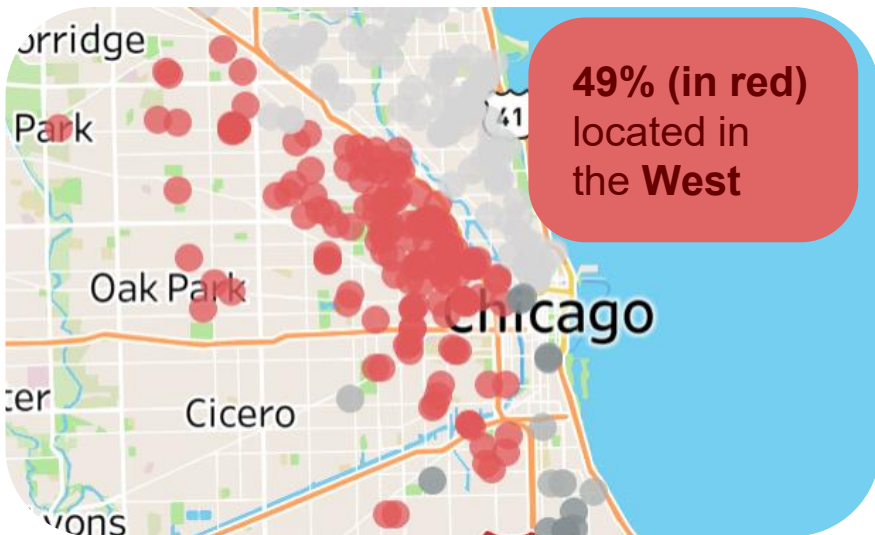
Key amenities:

- Housekeeping
- Playground
- Direct access to recreation spot

Persona



Median Price: 181 USD; 56% under 200 USD per night



81%
entire
home/ap
t



Accommodates

5

“Comfortable”

Key amenities:

- BBQ
- Lounge

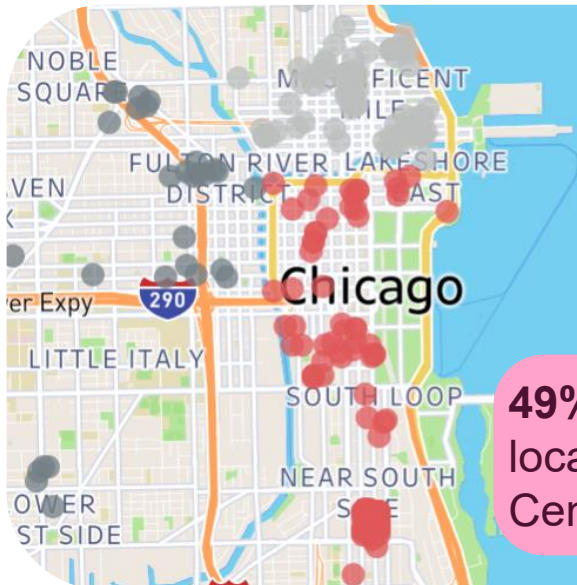
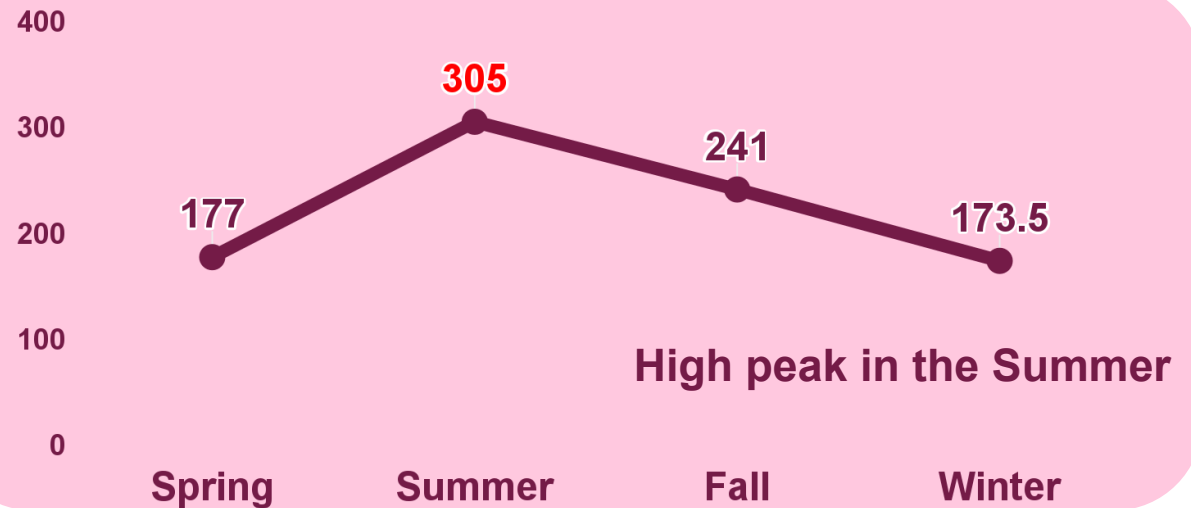
Persona



Active Leisure



Median Price: 213.5 USD; 45% under 200 USD per night



49% (in red)
located in the
Central Loop



99%
entire
home/ap
t



Accommodates

5

Key amenities:

- Sports
- Hot tub
- Pool
- Spa and Wellness

Content Plan



- Seasonal blog series highlighting key trends, attractions, activities
- Omni-channel social campaigns with UGC highlighting seasonal experiences

Workspace serenity

The cheapest type of property, ideal for the 'work from anywhere' productive escape

Patio paradise

Book early for an unforgettable fall breeze in Chicago!

Summer

Winter

Spring

Fall

Backyard bliss

Experience 'summer in the city' with your friends and family

Active leisure

Stay active in Winter with the best price!

Family retreat

Family outdoor fun, sunny escapes, taking advantage of the summer attractions

BBQ Escape

Perfect for a summer staycation

Thank You

Kirana Ananda

