Introduction

This project aims to analyze prices and locations of Airbnbs using Airbnb data of Chicago, as well as other data sources about Chicago, mainly crime data. The following 12 suggested questions from the instructions should give an introduction to our project (in addition to the report):

1. **Which dataset(s) did you choose? Why?**
   We used essentially three types of data:
   - Airbnb *listings data* (each row is an Airbnb with a number of attributes including geographic information via longitude and latitude values).
   - *Crime data* (each row is a crime incident with a number of attributes, including geographic information via longitude and latitude values).
   - Chicago city data (labeled as "*population data*"; it contains geographic data of Chicago as GeoPandas polygons, including population data. This data serves as a common ground for merging Airbnb and crime data).
2. **How did you clean/transform the data? Why?**
   Thankfully, most of the data was already quite "clean." The main challenge was obtaining the correct geospheric projection of longitude-latitude pairs. In order to make meaningful joins of the data, they all need to be transformed to a common projection (we used this one: https://epsg.io/26916). Also, in the listings data, one Airbnb was listed with a price of $9999999, which we had to get rid of for obvious reasons. Afterward, we only did variable selection and filtering of rows for the EDA and modeling steps.
3. **How did you solve the problem of missing values? Why?**
   There were barely any missing values, which we dropped. We didn't think this would impact the analyses as it was much less than 1%.
4. **What questions did you ask of the data?**
   - Q1: Can we analyze and predict the locations of Airbnbs within Chicago?
   - Q2: What are the influencing factors behind Airbnb prices, and can we model this meaningfully?
5. **Why were these good questions?**
   - Relevance: Addresses a practical concern in the Airbnb market—location prediction and understanding price determinants are crucial for stakeholders.
   - Applicability: They provide insights for users, hosts, and policymakers in the Airbnb ecosystem.
   - Complexity: Many factors, such as crime rates, population data, and competition, making the study comprehensive.
   - Practical Impact: Outcomes could have practical implications for users looking to book Airbnbs, hosts setting prices, and authorities planning urban development.
6. **What were the answers to these questions?**
   - **ad (q1)** While we were able to analyze the average prices per grid cell (left plot), we discovered a high density of Airbnbs in the north of the map. However, this observation is only partially useful as an explanatory variable, as higher density in Airbnbs also results in higher competition and thus self-regulation in the prices. Conversely, we observed that the density of homicides is much higher in the southwest of Chicago. This, however, is one of the top 10 most relevant features, as we discovered in our combined model.
   - **ad (q2)** The analysis aims to predict Airbnb prices using different combinations of features. Three sets of features (10, 15, and 20) were evaluated with the Random Forest, Linear Regression, and XGBRegressor models. The results reveal an improvement in performance with an increasing number of features, especially with 20 features. The Random Forest model outperforms the others, showing a net with a positive r2_score, suggesting a better fit to the data. Potential reasons for these findings could include the inherent complexity of relationships between Airbnb location features and price. Adding more features may have allowed the models, particularly Random Forest, to better capture the variability in the data. However, this can also lead to overfitting to the training data, hence the need for validation on independent test datasets. Alternatively, the models' moderate performance may be explained by the essentially complex and dynamic nature of the Airbnb rental market, where many factors can influence prices and more likely models are needed to capture these nuances. Parameter adjustments, deeper exploration of features, and use of advanced techniques could also help improve Airbnb price prediction.
7. **How did you obtain them?**
   - **ad (q1)** was basically obtained by the visualizations we created.
   - **ad (q2)** has more "proof" as we have performance measures for our models.
8. **Do the answers make sense?**
   - Overall, most of the results were expected but actually, the **unimportance** of some features surprised us (e.g., the amount of people is not that relevant for predicting the price).
9. **Were there any difficulties in analyzing the data? What were the key insights obtained?**
   - One major problem was the size of the initial crime dataset.
   - The amenity column was a string of a list like "[]" and hat to be unpacked and then pivoted to a dummy dataframe to be analyzed properly.
   - Price had to be converted to float (was string before with $ sign)

   As for key insights:

   ● Higher Airbnb density in the north, but competition is a problem.

   ● Homicide density is a good predictor of prices.

   ● Random Forest model outperformed others in price prediction.
10. **What are potential biases in the data and analysis?**
    - We only tested our model for the city of Chicago and did not apply it to other cities, so we are not sure how well it generalizes. However, this would have extended the scope of this assignment a fair bit, so we accepted this Closed Classification World Assumption.
11. **Which Data Science tools and techniques were learned during this exercise?**
    - Associate Rule Learning, Geocoder, Uszipcode, K-Means-Clustering
12. **How was the work divided up between the members of the group?**
    - Overall, everyone was involved in all main processes (from finding datasets, finding questions, to preprocessing, EDA, model training, creating the slides and the report). We utilized tools that allowed us to work on projects simultaneously, we used WhatsApp for communication, had Zoom calls, or met in the old-fashioned way in the "Bib" to work on it together.

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In [1]:
```
!jupyter nbconvert --to html "main copy 2.ipynb" --output "AirBnB-Crime-Analysis.html"
```

```
[NbConvertApp] Converting notebook main copy 2.ipynb to html
[NbConvertApp] WARNING | Alternative text is missing on 28 image(s).
[NbConvertApp] Writing 6923446 bytes to AirBnB-Crime-Analysis.html
```

1. Load and Process Data

1.1. Airbnb data

In [7]:
```
with gzip.open(listings_csv_path, 'rt', encoding='utf-8') as f:
    file_content = f.read()

df_listings = pd.read_csv(listings_csv_path, compression='gzip', header=0, sep=',', quotechar='"')

# df_listings = pd.read_csv(listings_csv_path)
# df_listings.columns
```

In [8]:
```
# get rid of the dollar signs
df_listings = df_listings.dropna(subset=['price'])  # remove missings
df_listings['price'] = df_listings['price'].astype(str)
df_listings['price'] = df_listings['price'].str.replace('$', '').str.replace(',', '').astype(float)

# listings data as gdf
gdf_listings = gpd.GeoDataFrame(df_listings, geometry=gpd.points_from_xy(df_listings.longitude, df_listings.latitude))
gdf_listings.crs = 'EPSG:4326'
gdf_listings.to_crs(epsg=26916, inplace=True)  # common projection

# remove one outlier value (faulty data?)
gdf_listings = gdf_listings[gdf_listings['price'] <= 10000]

# only keep certain columns for now
# gdf_listings_filtered = gdf_listings[['geometry', 'accommodates', 'price', 'review_scores_location', 'review_scores_rating', 'reviews_per_month']].copy()
gdf_listings.columns
```

Out[8]:
```
Index(['id', 'listing_url', 'scrape_id', 'last_scraped', 'source', 'name',
       'description', 'neighborhood_overview', 'picture_url', 'host_id',
       'host_url', 'host_name', 'host_since', 'host_location', 'host_about',
       'host_response_time', 'host_response_rate', 'host_acceptance_rate',
       'host_is_superhost', 'host_thumbnail_url', 'host_picture_url',
       'host_neighbourhood', 'host_listings_count',
       'host_total_listings_count', 'host_verifications',
       'host_has_profile_pic', 'host_identity_verified', 'neighbourhood',
       'neighbourhood_cleansed', 'neighbourhood_group_cleansed', 'latitude',
       'longitude', 'property_type', 'room_type', 'accommodates', 'bathrooms',
       'bathrooms_text', 'bedrooms', 'beds', 'amenities', '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', 'calendar_updated', 'has_availability',
       'availability_30', 'availability_60', 'availability_90',
       'availability_365', 'calendar_last_scraped', 'number_of_reviews',
       'number_of_reviews_ltm', 'number_of_reviews_l30d', 'first_review',
       'last_review', 'review_scores_rating', 'review_scores_accuracy',
       'review_scores_cleanliness', 'review_scores_checkin',
       'review_scores_communication', 'review_scores_location',
       'review_scores_value', 'license', 'instant_bookable',
       'calculated_host_listings_count',
       'calculated_host_listings_count_entire_homes',
       'calculated_host_listings_count_private_rooms',
       'calculated_host_listings_count_shared_rooms', 'reviews_per_month',
       'geometry'],
      dtype='object')
```

In [9]:
```
#calculate correlations
print(gdf_listings['price'].corr(gdf_listings['beds']))
print(gdf_listings['price'].corr(gdf_listings['bedrooms']))
print(gdf_listings['price'].corr(gdf_listings['accommodates']))
print(gdf_listings['price'].corr(gdf_listings['number_of_reviews']))
print(gdf_listings['price'].corr(gdf_listings['review_scores_rating']))
print(gdf_listings['price'].corr(gdf_listings['review_scores_accuracy']))
print(gdf_listings['price'].corr(gdf_listings['review_scores_cleanliness']))
```

```
0.39983311251999737
0.4389075733734059
0.4951626630592687
-0.062269239294525O5
0.06397931465624156
0.05069734174196323 4
0.09205110004297448
```

1.2. Crime data

In [10]:
```
df_crime = pd.read_csv('crime.csv')
len(df_crime.index)
#It has 8 million rows! Need to reduce this for now to have quicker processing/visualizations.
```

Out[10]:
```
7975195
```

In [11]:
```
# rename columns for consistency
df_crime.rename(columns={'Latitude': 'latitude', 'Longitude': 'longitude'}, inplace=True)
df_crime.columns
```

Out[11]:
```
Index(['ID', 'Case Number', 'Date', 'Block', 'IUCR', 'Primary Type',
       'Description', 'Location Description', 'Arrest', 'Domestic', 'Beat',
       'District', 'Ward', 'Community Area', 'FBI Code', 'X Coordinate',
       'Y Coordinate', 'Year', 'Updated On', 'latitude', 'longitude',
       'Location'],
      dtype='object')
```

In [12]:
```
# types of crime
print(len(df_crime["Primary Type"].unique()))
df_crime["Primary Type"].unique()
```

```
36
```

Out[12]:
```
array(['ASSAULT', 'HOMICIDE', 'BURGLARY', 'BATTERY', 'THEFT',
       'CRIMINAL DAMAGE', 'DECEPTIVE PRACTICE', 'CRIMINAL SEXUAL ASSAULT',
       'OFFENSE INVOLVING CHILDREN', 'MOTOR VEHICLE THEFT', 'ROBBERY',
       'SEX OFFENSE', 'OTHER OFFENSE', 'WEAPONS VIOLATION', 'STALKING',
       'CRIMINAL TRESPASS', 'PROSTITUTION', 'ARSON', 'NARCOTICS',
       'KIDNAPPING', 'CONCEALED CARRY LICENSE VIOLATION',
       'INTERFERENCE WITH PUBLIC OFFICER', 'PUBLIC PEACE VIOLATION',
       'OBSCENITY', 'LIQUOR LAW VIOLATION', 'INTIMIDATION', 'GAMBLING',
       'HUMAN TRAFFICKING', 'CRIM SEXUAL ASSAULT',
       'OTHER NARCOTIC VIOLATION', 'NON-CRIMINAL', 'PUBLIC INDECENCY',
       'RITUALISM', 'DOMESTIC VIOLENCE',
       'NON-CRIMINAL (SUBJECT SPECIFIED)', 'NON - CRIMINAL'], dtype=object)
```

1.2.1 Filter

In [13]:
```
df_crime['Date'] = pd.to_datetime(df_crime['Date'], format='%m/%d/%Y %I:%M:%S %p')
df_crime_recent = df_crime[df_crime['Date'].dt.year >= 2018] # only take last n years for now

crimes_to_inspect = ["HOMICIDE"]  # a list of crime types from the "Primary Type" column
df_crime_recent = df_crime_recent[df_crime_recent["Primary Type"].isin(crimes_to_inspect)]
df_crime_recent = df_crime_recent[~df_crime_recent['Domestic']]

# randomly sample a fraction for reduced size
df_crime_recent_sampled = df_crime_recent # .sample(frac=0.30, random_state=1)

# remove strange location outliers
df_crime_recent_sampled = df_crime_recent_sampled[
    (df_crime_recent_sampled['latitude'] >= 41) &
    (df_crime_recent_sampled['latitude'] <= 42.5) &
    (df_crime_recent_sampled['longitude'] >= -88.5) &
    (df_crime_recent_sampled['longitude'] <= -87)]

gdf_crime = gpd.GeoDataFrame(df_crime_recent_sampled, geometry=[Point(xy) for xy in zip(df_crime_recent_sampled.longitude, df_crime_recent_sampled.latitude)])

# change projection
gdf_crime.set_crs(epsg=4326, inplace=True)  # set the original CRS to EPSG:4326
gdf_crime = gdf_crime.to_crs(epsg=26916)  # reproject to EPSG:26916

gdf_crime_filtered = gdf_crime[['ID', 'Date', 'IUCR', 'Primary Type',
                                'Description', 'Location Description', 'geometry']].copy()

gdf_crime_filtered = gdf_crime_filtered[gdf_crime_filtered['Description'] == 'FIRST DEGREE MURDER']
gdf_crime_filtered
```

Out[13]:

	ID	Date	IUCR	Primary Type	Description	Location Description	geometry
1	25953	2021-05-24 15:06:00	0110	HOMICIDE	FIRST DEGREE MURDER	STREET	POINT (437311.776 4640930.236)
2	26038	2021-06-26 09:24:00	0110	HOMICIDE	FIRST DEGREE MURDER	PARKING LOT	POINT (440917.058 4649491.537)
84	26262	2021-09-08 16:45:00	0110	HOMICIDE	FIRST DEGREE MURDER	CAR WASH	POINT (438307.241 4635964.141)
905	27854	2023-11-10 21:26:00	0110	HOMICIDE	FIRST DEGREE MURDER	STREET	POINT (444675.16 4652245.615)
922	27742	2023-06-24 01:23:00	0110	HOMICIDE	FIRST DEGREE MURDER	ALLEY	POINT (436898.424 4636352.921)
...	...	...	...	...	...	...	...
237287	25596	2020-11-06 02:22:00	0110	HOMICIDE	FIRST DEGREE MURDER	AUTO	POINT (444210.296 4624412.403)
237375	27289	2023-01-06 21:25:00	0110	HOMICIDE	FIRST DEGREE MURDER	HOUSE	POINT (445391.649 4626865.081)
237432	25460	2020-09-12 23:18:00	0110	HOMICIDE	FIRST DEGREE MURDER	STREET	POINT (436670.709 4637818.552)
237476	27015	2022-08-31 09:30:00	0110	HOMICIDE	FIRST DEGREE MURDER	GAS STATION	POINT (448344.068 4614689.311)
237594	27577	2023-06-20 12:42:00	0110	HOMICIDE	FIRST DEGREE MURDER	STREET	POINT (440097.024 4636285.554)

3738 rows × 7 columns

In [14]:
```
value_counts = gdf_crime_filtered['Location Description'].value_counts()
print(value_counts.head(20))
```

```
Location Description
STREET                        2151
AUTO                           290
ALLEY                          236
APARTMENT                      216
PORCH                          116
HOUSE                          113
YARD                           108
PARKING LOT                    101
GAS STATION                     43
PARK PROPERTY                   41
VACANT LOT                      37
RETAIL STORE                    29
GAS STATION DRIVE/PROP.         27
HALLWAY                         23
GARAGE                          19
CHA PARKING LOT                 18
RESTAURANT                      17
BARBER SHOP/BEAUTY SALON        14
HOTEL                           10
VESTIBULE                       10
Name: count, dtype: int64
```

1.3. Population data

Merge two data sets to get areas (districts) as well as their population.

In [15]:
```
df_population_census = pd.read_csv(population_census_csv_path)
df_population_census
```

Out[15]:

	CENSUS BLOCK	CENSUS BLOCK FULL	TOTAL POPULATION
0	310003002	170310310003002	104
1	310003003	170310310003003	46
2	310003004	170310310003004	40
3	310003005	170310310003005	58
4	310003006	170310310003006	75
...	...	...	...
46286	8419002052	170318419002052	0
46287	8419002053	170318419002053	32
46288	8419002054	170318419002054	131
46289	8419002055	170318419002055	79
46290	8419002056	170318419002056	20

46291 rows × 3 columns

In [16]:
```
df_population_census["TOTAL POPULATION"].sum() # corresponds to Chicago population
```

Out[16]:
```
2695598
```

In [17]:
```
df_population_census['CENSUS BLOCK FULL'] = df_population_census['CENSUS BLOCK FULL'].astype(str)
df_population_census['GEOID10_Subset'] = df_population_census['CENSUS BLOCK FULL'].str[:11]

df_census_grouped = df_population_census.groupby('GEOID10_Subset')['TOTAL POPULATION'].sum().reset_index()
df_census_grouped
```

Out[17]:

	GEOID10_Subset	TOTAL POPULATION
0	17031010100	4854
1	17031010201	6450
2	17031010202	2818
3	17031010300	6236
4	17031010400	5042
...	...	...
802	17031843700	2117
803	17031843800	2110
804	17031843900	3533
805	17031980000	0
806	17031980100	0

807 rows × 2 columns

In [18]:
```
df_census_boundaries = pd.read_csv(census_boundaries_csv_path)
df_census_boundaries['the_geom'] = df_census_boundaries['the_geom'].apply(wkt.loads)
gdf_census_boundaries = gpd.GeoDataFrame(df_census_boundaries, geometry='the_geom')
gdf_census_boundaries
```

Out[18]:

	the_geom	STATEFP10	COUNTYFP10	TRACTCE10	GEOID10	NAME10	NAMELSAD10	COMMAREA	COMMAREA_N	NOTES
0	MULTIPOLYGON (((-87.62405 41.73022, -87.62405 ...	17	31	842400	17031842400	8424.0	Census Tract 8424	44	44	NaN
1	MULTIPOLYGON (((-87.68608 41.82296, -87.68607 ...	17	31	840300	17031840300	8403.0	Census Tract 8403	59	59	NaN
2	MULTIPOLYGON (((-87.62935 41.8528, -87.62934 4...	17	31	841100	17031841100	8411.0	Census Tract 8411	34	34	NaN
3	MULTIPOLYGON (((-87.68813 41.85569, -87.68816 ...	17	31	841200	17031841200	8412.0	Census Tract 8412	31	31	NaN
4	MULTIPOLYGON (((-87.63312 41.87449, -87.63306 ...	17	31	839000	17031839000	8390.0	Census Tract 8390	32	32	NaN
...	...	...	...	...	...	...	...	...	...	...
796	MULTIPOLYGON (((-87.65746 41.93258, -87.65722 ...	17	31	70400	17031070400	704.0	Census Tract 704	7	7	NaN
797	MULTIPOLYGON (((-87.66349 41.93036, -87.6635 4...	17	31	70500	17031070500	705.0	Census Tract 705	7	7	NaN
798	MULTIPOLYGON (((-87.71436 41.983, -87.71472 41...	17	31	130300	17031130300	1303.0	Census Tract 1303	13	13	NaN
799	MULTIPOLYGON (((-87.71317 41.85523, -87.71357 ...	17	31	292200	17031292200	2922.0	Census Tract 2922	29	29	NaN
800	MULTIPOLYGON (((-87.71129 41.7934, -87.7109 41...	17	31	630900	17031630900	6309.0	Census Tract 6309	63	63	NaN

801 rows × 10 columns

In [19]:
```
# join the data
gdf_census_boundaries['GEOID10'] = gdf_census_boundaries['GEOID10'].astype(str)
gdf_population_merged = gdf_census_boundaries.merge(df_census_grouped, left_on='GEOID10', right_on='GEOID10_Subset', how='left')

# we only need a few columns
selected_columns = ['the_geom', 'GEOID10', 'TOTAL POPULATION']
gdf_population_merged = gdf_population_merged[selected_columns]

# obtain polygon area
gdf_population_merged.crs = 'EPSG:4326'
gdf_population_merged.to_crs(epsg=26916, inplace=True)
gdf_population_merged['Area_km2'] = gdf_population_merged['the_geom'].area / 1e6

# population density
gdf_population_merged['Population_Density'] = gdf_population_merged['TOTAL POPULATION'] / gdf_population_merged['Area_km2']
gdf_population_merged # FINAL POPULATION GDF
```

Out[19]:

	the_geom	GEOID10	TOTAL POPULATION	Area_km2	Population_Density
0	MULTIPOLYGON (((448099.985 4620011.369, 448099...	17031842400	3304	1.967197	1679.547464
1	MULTIPOLYGON (((443023.106 4630347.019, 443024...	17031840300	3950	0.830626	4755.450572
2	MULTIPOLYGON (((447758.91 4633624.092, 447759....	17031841100	7254	1.142409	6349.739874
3	MULTIPOLYGON (((442881.562 4633982.84, 442880....	17031841200	5262	0.624955	8419.804840
4	MULTIPOLYGON (((447463.312 4636034.682, 447468...	17031839000	7311	0.516078	14166.465239
...	...	...	...	...	...
796	MULTIPOLYGON (((445493.406 4642499.467, 445512...	17031070400	2984	0.324134	9206.075171
797	MULTIPOLYGON (((444991 4642257.173, 444990.349...	17031070500	2928	0.305194	9593.884111
798	MULTIPOLYGON (((440822.244 4648135.181, 440793...	17031130300	5064	0.720585	7027.623420
799	MULTIPOLYGON (((440802.854 4633948.727, 440770...	17031292200	2961	0.397729	7444.769197
800	MULTIPOLYGON (((440902.402 4627082.334, 440934...	17031630900	5363	0.659286	8134.552157

801 rows × 5 columns

In [20]:
```
# validity checks
print("Total Area of Chicago", gdf_population_merged["Area_km2"].sum())
print("Total Population of Chicago", gdf_population_merged["TOTAL POPULATION"].sum())
```

```
Total Area of Chicago 627.184916230284
Total Population of Chicago 2695598
```

--> the whole population got matched to a polygon (it matches the sum from before). Great!

The numbers for population and area roughly add up to the correct amount (https://en.wikipedia.org/wiki/Chicago)

1.4. Additional City data

In [21]:
```
# Parks
# https://data.cityofchicago.org/Parks-Recreation/Parks-Shapefiles-deprecated-November-2016-/5msb-wbxn/about_data
gdf_parks = gpd.read_file(population_data_path + 'Parks_Aug2012.shp')
gdf_parks.crs = 'EPSG:3435'
gdf_parks.to_crs(epsg=26916, inplace=True)  # common projection
gdf_parks.head(2)
```

Out[21]:

	PARK_NO	PARK	LOCATION	ZIP	ACRES	WARD	PARK_CLASS	LABEL	WHEELCHR_A	ALFRED_CAL	...	LAGOON	CAROUSEL	CROQUET	GOLF_COU_1	HARBOR	MODEL_TRAI	MODEL_YACH	NATURE_BIR	CRICKET_FI	geometry
0	1220.0	LEVIN (JOHN)	462 N PINE AVE	60644	5.76	37.0	COMMUNITY PARK	Levin	0	0	...	0	None	None	None	None	None	None	None	0	POLYGON ((436684.676 4637712.287, 436903.835 4...
1	1149.0	SAINT LOUIS	347 N ST LOUIS AVE	60624	0.37	28.0	MINI-PARK	Saint Louis	0	0	...	0	None	None	None	None	None	None	None	0	POLYGON ((440802.126 4637533.483, 440801.359 4...

2 rows × 77 columns

In [22]:
```
# Boulevards
# https://data.cityofchicago.org/Environment-Sustainable-Development/Open-Spaces-Boulevards-KML/uhyd-nthd/about_data --> select shp (not kml) file from this site
gdf_boulevards = gpd.read_file(population_data_path + 'DATA_ADMIN_OPNSP_BOULEVARDS.shp')
gdf_boulevards.crs = 'EPSG:3435'
gdf_boulevards.to_crs(epsg=26916, inplace=True)  # common projection
gdf_boulevards.head(2)
```

Out[22]:

	ID	SQ_FOOTAGE	ACREAGE	CA	SHAPE_AREA	SHAPE_LEN	geometry
0	0	918222.1731	21.08	23	918222.184638	35404.355558	MULTIPOLYGON (((441691.13 4638816.453, 441724....
1	0	102764.8106	2.36	24	102764.817307	3422.576960	MULTIPOLYGON (((441795.549 4640256.285, 441804...

In [23]:
```
# Riverwalks
# https://data.cityofchicago.org/Environment-Sustainable-Development/Open-Spaces-Riverwalk-KML/22bv-uv6r/about_data --> select shp (not kml) file from this site
gdf_riverwalks = gpd.read_file(population_data_path + 'DATA_ADMIN_OPNSP_RIVERWALK.shp')
gdf_riverwalks.crs = 'EPSG:3435'
gdf_riverwalks.to_crs(epsg=26916, inplace=True)  # common projection
gdf_riverwalks.head(2)
```

Out[23]:

	OBJECTID	ID	STATUS	SHAPE_LEN	geometry
0	1	0	1	713.002635	LINESTRING (441236.26 4649152.897, 441239.74 4...
1	2	0	1	7668.252237	LINESTRING (441279.926 4648940.097, 441291.436...

2. Exploratory Data Analysis (EDA)

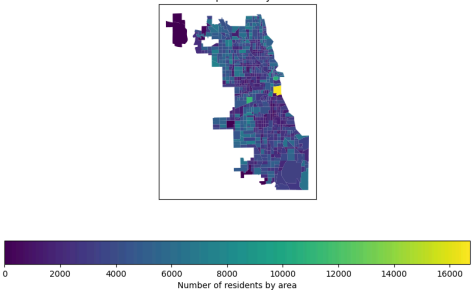
Now we have 3 main dataframes:

- `gdf_listings` (Airbnb data)
- `gdf_crime_filtered` (Crime data)
- `gdf_population_merged` (Population/geographic data)

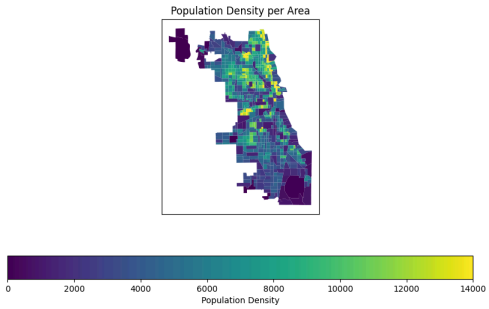
Moreover, 3 "side" dataframes: `gdf_parks`, `gdf_boulevards`, `gdf_riverwalks`

2.1. Geographic EDA

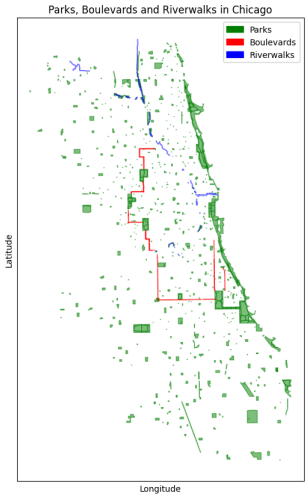
In [24]:
```
fig, ax = plt.subplots(1, 1, figsize=(10, 6))
gdf_population_merged.plot(column='TOTAL POPULATION', ax=ax, legend=True,
                           legend_kwds={'label': "Number of residents by area",
                                        'orientation': "horizontal"})
plt.title('Total Population by Area')

# remove x and y ticks
ax.set_xticks([])
ax.set_yticks([])
plt.show()
```



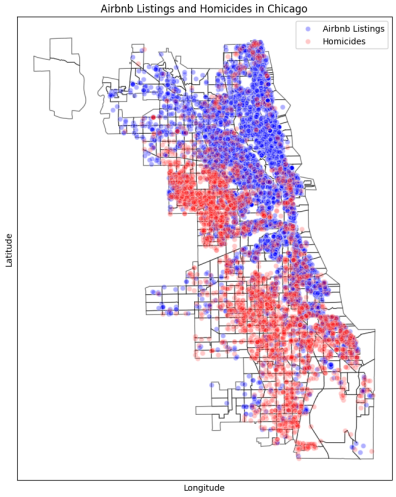
In [25]:
```
fig, ax = plt.subplots(1, 1, figsize=(10, 6))
gdf_population_merged.plot(column='Population_Density', ax=ax, legend=True,
                           vmin=0, vmax=14000,  # adjust scale
                           legend_kwds={'label': "Population Density",
                                        'orientation': "horizontal"})
plt.title('Population Density per Area')
# remove x and y ticks
ax.set_xticks([])
ax.set_yticks([])
plt.show()
```



In [26]:
```
# plot all three
fig, ax = plt.subplots(figsize=(10, 10))

gdf_parks.plot(ax=ax, color='green', edgecolor='green', alpha=0.5)
gdf_boulevards.plot(ax=ax, color='red', edgecolor='red', alpha=0.5)
gdf_riverwalks.plot(ax=ax, color='blue', edgecolor='blue', alpha=0.5)
ax.set_xlabel('Longitude')
ax.set_ylabel('Latitude')
ax.set_xticks([])
ax.set_yticks([])
ax.set_aspect('equal')
plt.title('Parks, Boulevards and Riverwalks in Chicago')
# plt.legend(['Parks', 'Boulevards', 'Riverwalks'])
park_patch = mpatches.Patch(color='green', label='Parks')
boulevard_patch = mpatches.Patch(color='red', label='Boulevards')
riverwalk_patch = mpatches.Patch(color='blue', label='Riverwalks')
plt.legend(handles=[park_patch, boulevard_patch, riverwalk_patch])

plt.show()
```



In [27]:
```
from matplotlib import colors


fig, ax = plt.subplots(figsize=(10, 10))

gdf_population_merged.plot(ax=ax, color='white', edgecolor='black', alpha=0.5)
gdf_listings.plot(ax=ax, color='blue', edgecolor='white', alpha=0.3)
gdf_crime_filtered.plot(ax=ax, color='red', edgecolor='white', alpha=0.2)
ax.set_xlabel('Longitude')
ax.set_ylabel('Latitude')
ax.set_xticks([])
ax.set_yticks([])
ax.set_aspect('equal')
# plot legend with original color not alpha
plt.legend(['Airbnb Listings', 'Homicides'], loc='upper right')
plt.title('Airbnb Listings and Homicides in Chicago')
plt.show()
```



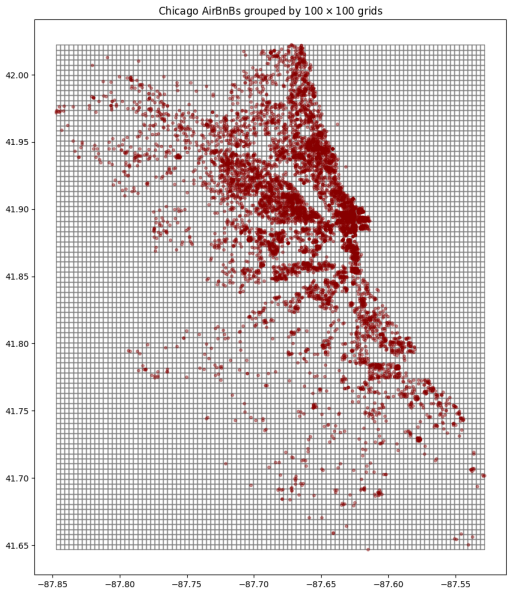
In [29]:
```
gdf_listings['geohash'] = gdf_listings.apply(lambda row: geohash.encode(row['latitude'], row['longitude'], precision=5), axis=1)


geometry = [Point(xy) for xy in zip(gdf_listings['longitude'], gdf_listings['latitude'])]
geo_df = gpd.GeoDataFrame(gdf_listings, geometry=geometry)

# Define the boundaries of the  grid
num_of_columns, num_of_rows = 100, 100
minx, miny, maxx, maxy = geo_df.geometry.total_bounds
dx = (maxx - minx) / num_of_columns  # width of grid cell
dy = (maxy - miny) / num_of_rows  # height of grid cell


grid = []
for x in range(num_of_columns):
    for y in range(num_of_rows):
        xmin = minx + x * dx
        xmax = minx + (x+1) * dx
        ymin = miny + y * dy
        ymax = miny + (y+1) * dy
        grid.append(Polygon([(xmin,ymin), (xmax,ymin), (xmax,ymax), (xmin,ymax)]))
grid = gpd.GeoDataFrame(grid, columns=['geometry'], crs=geo_df.crs)


joined = gpd.sjoin(geo_df, grid, how='left', predicate='within')
joined.head(3)
```

Out[29]:

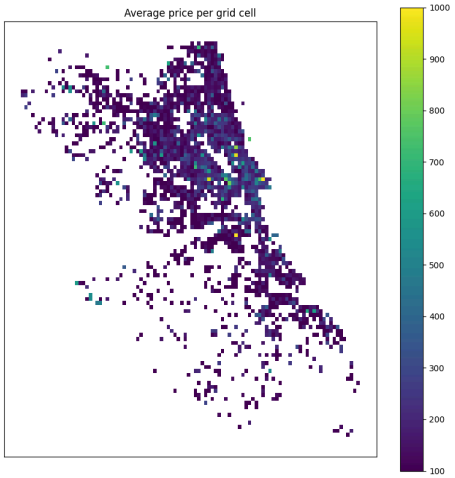
	id	listing_url	scrape_id	last_scraped	source	name	description	neighborhood_overview	picture_url	host_id	...	license	instant_bookable	calculated_host_listings_count	calculated_host_listings_count_entire_homes	calculated_hc
0	2384	https://www.airbnb.com/rooms/2384	20230912032549	2023-09-12	city scrape	Condo in Chicago · ★4.99 · 1 bedroom · 1 bed · ...	You are invited stay in the guest room of my v...	The apartment is less than one block from beau...	https://a0.muscache.com/pictures/acf6b3c0-47f2...	2613	...	R17000015609	f	1	0	
1	7126	https://www.airbnb.com/rooms/7126	20230912032549	2023-09-12	city scrape	Rental unit in Chicago · ★4.70 · 1 bedroom · 1...	A very small studio in a wonderful neighborhoo...	Ukrainian Village was just named "Hottest Neig...	https://a0.muscache.com/pictures/51073/16c81c7...	17928	...	R21000075737	f	1	1	
2	10945	https://www.airbnb.com/rooms/10945	20230912032549	2023-09-12	city scrape	Rental unit in Chicago · ★4.65 · 2 bedrooms · ...	Beautiful first floor apartment in Historic Ol...	NaN	https://a0.muscache.com/pictures/58d1a420-a24b...	33004	...	2209984	t	7	7	

3 rows × 78 columns

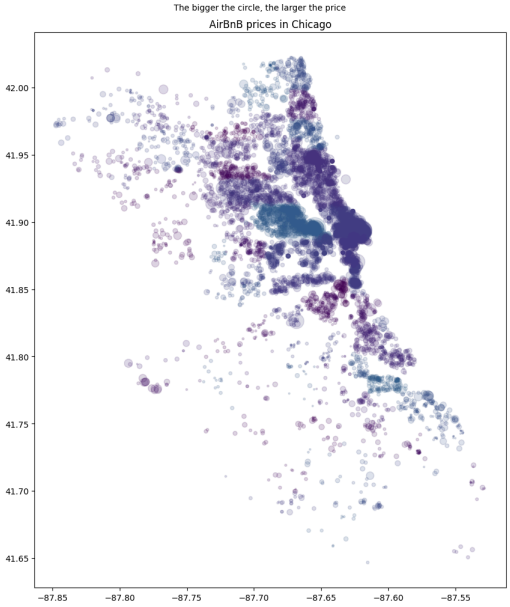
In [30]:
```
# Plot 1
fig, ax = plt.subplots(1, 1, figsize=(14, 12))
grid.plot(ax=ax, facecolor='none', edgecolor='grey')  # plot grid
joined.plot(ax=ax, markersize=10, color='darkred', alpha=0.4)  # plot the scatters
plt.title('Chicago AirBnBs grouped by $100\\times100$ grids')
plt.show()
```



In [31]:
```
# Plot 2
joined.groupby(joined.index_right)['price'].mean()
average_price = joined.groupby(joined.index_right)['price'].mean()

# join the average prices back to the grid
grid['price'] = average_price

# plot the grid with colors according to the average price
fig, ax = plt.subplots(1, 1, figsize=(10, 10))
vmin = 100
vmax = 1000
grid.plot(column='price', ax=ax, legend=True, vmin=vmin, vmax=vmax)
plt.title('Average price per grid cell')

# remove x and y ticks
ax.set_xticks([])
ax.set_yticks([])
plt.show()
```

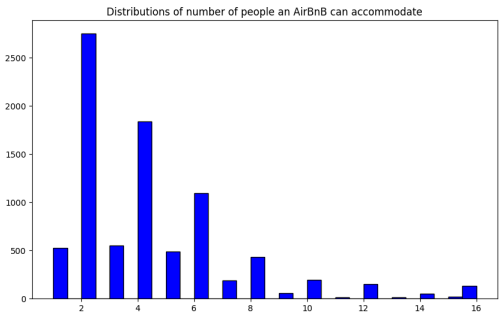


In [32]:
```
# Plot 3
fig, ax = plt.subplots(1, 1, figsize=(14, 12))

# create a color map
cmap = plt.get_cmap('viridis')
colors = cmap(joined['neighbourhood_cleansed'].astype('category').cat.codes)

# create a size variable that is proportional to the price_float value
sizes = joined['price'] / joined['price'].max() * 1200

# plot the scatters
joined.plot(ax=ax, markersize=sizes, color=colors, alpha=.17)
plt.title('AirBnB prices in Chicago')
plt.suptitle('The bigger the circle, the larger the price', fontsize=10, y=0.92)
plt.show()
```



2.2. Non-Geographic EDA

In [33]:
```
metric = df_listings["accommodates"] # gdf_population_merged['Population_Density']

plt.figure(figsize=(10, 6))
plt.hist(metric, bins=30, color='blue', edgecolor='black')
plt.title('Distributions of number of people an AirBnB can accommodate')
plt.show()
```



In [34]:
```
gdf_listings.groupby('neighbourhood_cleansed')['price'].mean().sort_values(ascending=False)
```

Out[34]:
```
neighbourhood_cleansed
Clearing           351.176471
Near North Side    337.975915
West Town          277.413793
Near South Side    261.841463
Loop               250.688034
                      ...
Calumet Heights     66.468750
West Lawn           66.000000
West Englewood      61.722222
Fuller Park         59.000000
New City            56.982143
Name: price, Length: 77, dtype: float64
```

In [35]:
```
gdf_listings[['neighbourhood_cleansed', 'price', 'bedrooms', 'beds', 'accommodates']].groupby('neighbourhood_cleansed').median().sort_values(by='price')
```

Out[35]:

neighbourhood_cleansed	price	bedrooms	beds	accommodates
Calumet Heights	29.0	1.0	1.0	1.0
Fuller Park	31.0	2.5	1.0	2.0
New City	31.5	2.0	1.0	2.0
South Chicago	33.0	2.0	1.0	2.0
East Side	42.0	2.0	1.0	2.0
...	...	...	...	...
Loop	186.5	1.0	1.0	3.0
Burnside	200.0	2.0	2.0	6.0
Ohare	200.0	1.0	1.0	3.0
Near South Side	246.5	2.0	3.0	6.0
Clearing	463.0	4.0	5.0	10.0

77 rows × 4 columns

In [36]:
```
top_10_nbds = gdf_listings['neighbourhood_cleansed'].value_counts()[:10].index
top_10_nbds
```

Out[36]:
```
Index(['Near North Side', 'West Town', 'Lake View', 'Near West Side',
       'Logan Square', 'Loop', 'Lincoln Park', 'Near South Side',
       'Lower West Side', 'Uptown'],
      dtype='object', name='neighbourhood_cleansed')
```

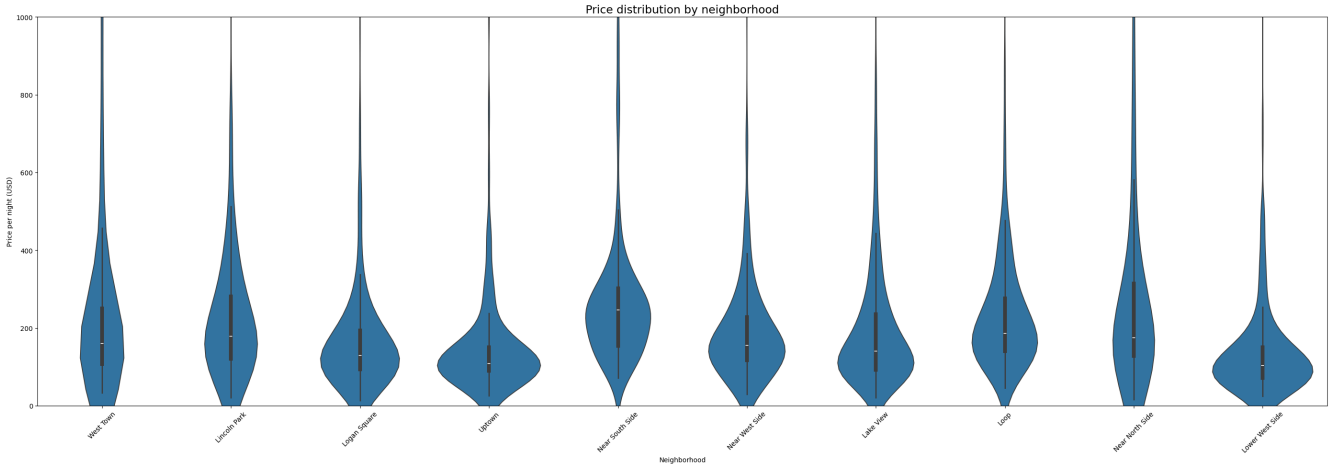
In [37]:
```
df_top10 = gdf_listings.loc[gdf_listings['neighbourhood_cleansed'].isin(top_10_nbds)]
df_top10.head(3)
```

Out[37]:

	id	listing_url	scrape_id	last_scraped	source	name	description	neighborhood_overview	picture_url	host_id	...	review_scores_value	license	instant_bookable	calculated_host_listings_count	calculated_host_listings_count_entire
1	7126	https://www.airbnb.com/rooms/7126	20230912032549	2023-09-12	city scrape	Rental unit in Chicago · ★4.70 · 1 bedroom · 1...	A very small studio in a wonderful neighborhoo...	Ukrainian Village was just named "Hottest Neig...	https://a0.muscache.com/pictures/51073/16c81c7...	17928	...	4.75	R21000075737	f	1	
2	10945	https://www.airbnb.com/rooms/10945	20230912032549	2023-09-12	city scrape	Rental unit in Chicago · ★4.65 · 2 bedrooms · ...	Beautiful first floor apartment in Historic Ol...	NaN	https://a0.muscache.com/pictures/58d1a420-a24b...	33004	...	4.65	2209984	t	7	
3	12140	https://www.airbnb.com/rooms/12140	20230912032549	2023-09-12	city scrape	Boutique hotel in Chicago · ★4.93 · 1 bedroom ...	Bed and Breakfast license issued by the City o...	The Guest House is in the heart of Chicago's m...	https://a0.muscache.com/pictures/miso/Hosting-...	46734	...	4.87	R20000055258	f	1	

3 rows × 77 columns

In [38]:
```
plt.figure(figsize=(28,10))
sns.violinplot(data=df_top10, x='neighbourhood_cleansed', y='price')
plt.rcParams['font.size'] = 14
plt.xticks(rotation=45)
plt.xlabel('Neighborhood')
plt.ylabel('Price per night (USD)')
plt.title('Price distribution by neighborhood')
plt.ylim(0, 1000)
plt.tight_layout()
plt.show()
```



In [39]:
```
gdf_listings[['neighbourhood_cleansed', 'price', 'bedrooms', 'beds', 'accommodates']].groupby('neighbourhood_cleansed').median().sort_values(by='price')
```

Out[39]:

neighbourhood_cleansed	price	bedrooms	beds	accommodates
Calumet Heights	29.0	1.0	1.0	1.0
Fuller Park	31.0	2.5	1.0	2.0
New City	31.5	2.0	1.0	2.0
South Chicago	33.0	2.0	1.0	2.0
East Side	42.0	2.0	1.0	2.0
...	...	...	...	...
Loop	186.5	1.0	1.0	3.0
Burnside	200.0	2.0	2.0	6.0
Ohare	200.0	1.0	1.0	3.0
Near South Side	246.5	2.0	3.0	6.0
Clearing	463.0	4.0	5.0	10.0

77 rows × 4 columns

3. In-Depth Analysis & Modeling - Airbnb Locations

Here, we create a final dataset which is based on "population". When computing further statistics for each district, it's important to account for the district's size ("normalization").

In [40]:
```
# listings data as gdf
gdf_listings = gpd.GeoDataFrame(df_listings, geometry=gpd.points_from_xy(df_listings.longitude, df_listings.latitude))
gdf_listings.crs = 'EPSG:4326'
gdf_listings.to_crs(epsg=26916, inplace=True)  # common projection

# remove one outlier value (faulty data?)
gdf_listings = gdf_listings[gdf_listings['price'] <= 10000]

# only keep certain columns for now
gdf_listings_filtered = gdf_listings[['geometry', 'accommodates', 'price', 'review_scores_location',
                                      'review_scores_rating', 'reviews_per_month']].copy()

gdf_listings_filtered
```

Out[40]:

	geometry	accommodates	price	review_scores_location	review_scores_rating	reviews_per_month
0	POINT (451158.383 4626394.394)	1	114.0	4.96	4.99	2.15
1	POINT (443579.828 4639081.416)	2	92.0	4.89	4.70	2.92
2	POINT (446939.361 4640199.221)	4	170.0	4.99	4.65	0.63
3	POINT (446147.997 4641494.278)	3	329.0	5.00	4.93	0.15
4	POINT (445578.398 4641764.099)	3	61.0	4.90	4.29	0.26
...	...	...	...	...	...	...
8523	POINT (442786.466 4636164.59)	13	438.0	NaN	NaN	NaN
8524	POINT (444431.643 4630673.558)	1	32.0	NaN	NaN	NaN
8525	POINT (445444.069 4623685.767)	4	24.0	NaN	NaN	NaN
8526	POINT (447616.595 4635477.377)	2	127.0	NaN	NaN	NaN
8527	POINT (445525.754 4644263.788)	8	366.0	NaN	NaN	NaN

8528 rows × 6 columns

In [42]:
```
# join Airbnb and population data
gdf_joined = gpd.sjoin(gdf_listings_filtered, gdf_population_merged, how="inner", predicate="within")
statistics = gdf_joined.groupby('GEOID10').agg(  # compute various descriptive statistics
    Airbnb_Count=('price', 'count'),
    Median_Price=('price', 'median'),
    Average_Price=('price', 'mean'),
    Median_Review_Score=('review_scores_rating', 'median'))
statistics = statistics.join(gdf_population_merged.set_index('GEOID10')['Area_km2'])

# calculate Airbnbs per km²
statistics['Airbnb_per_km2'] = statistics['Airbnb_Count'] / statistics['Area_km2']

# join back
gdf_population_merged_stats = gdf_population_merged.merge(statistics, on='GEOID10', how='left')
gdf_population_merged_stats.drop(columns=['Area_km2_y'], inplace=True)
gdf_population_merged_stats.rename(columns={'Area_km2_x': 'Area_km2'}, inplace=True)

# add crime counts
gdf_joined_crime = gpd.sjoin(gdf_crime_filtered, gdf_population_merged_stats, how="inner", predicate="within")
gdf_crime_counts = gdf_joined_crime.groupby('GEOID10').size().reset_index(name='Crime_Count')

# merge back
gdf_population_final = gdf_population_merged_stats.merge(gdf_crime_counts, on='GEOID10', how='left')
gdf_population_final.rename(columns={'Crime_Count_x': 'Crime_Count'}, inplace=True)
gdf_population_final['Crime_Count'].fillna(0, inplace=True)
gdf_population_final['Crimes_per_km2'] = gdf_population_final['Crime_Count'] / gdf_population_final['Area_km2']  # crime density column
gdf_population_final
```

Out[42]:

	the_geom	GEOID10	TOTAL POPULATION	Area_km2	Population_Density	Airbnb_Count	Median_Price	Average_Price	Median_Review_Score	Airbnb_per_km2	Crime_Count	Crimes_per_km2
0	MULTIPOLYGON (((448099.985 4620011.369, 448099...	17031842400	3304	1.967197	1679.547464	2.0	170.5	170.500000	4.540	1.016675	23.0	11.691765
1	MULTIPOLYGON (((443023.106 4630347.019, 443024...	17031840300	3950	0.830626	4755.450572	12.0	105.5	114.250000	4.890	14.446938	6.0	7.223469
2	MULTIPOLYGON (((447758.91 4633624.092, 447759....	17031841100	7254	1.142409	6349.739874	56.0	156.5	218.214286	4.800	49.019222	6.0	5.252059
3	MULTIPOLYGON (((442881.562 4633982.84, 442880....	17031841200	5262	0.624955	8419.804840	20.0	106.5	105.950000	4.850	32.002299	10.0	16.001149
4	MULTIPOLYGON (((447463.312 4636034.682, 447468...	17031839000	7311	0.516078	14166.465239	47.0	211.0	249.851064	4.805	91.071518	1.0	1.937692
...	...	...	...	...	...	...	...	...	...	...	...	...
796	MULTIPOLYGON (((445493.406 4642499.467, 445512...	17031070400	2984	0.324134	9206.075171	13.0	137.0	208.692308	4.750	40.106896	0.0	0.000000
797	MULTIPOLYGON (((444991 4642257.173, 444990.349...	17031070500	2928	0.305194	9593.884111	15.0	165.0	169.533333	4.670	49.148996	0.0	0.000000
798	MULTIPOLYGON (((440822.244 4648135.181, 440793...	17031130300	5064	0.720585	7027.623420	7.0	200.0	281.857143	4.930	9.714329	0.0	0.000000
799	MULTIPOLYGON (((440802.854 4633948.727, 440770...	17031292200	2961	0.397729	7444.769197	3.0	469.0	391.666667	4.830	7.542826	5.0	12.571377
800	MULTIPOLYGON (((440902.402 4627082.334, 440934...	17031630900	5363	0.659286	8134.552157	1.0	108.0	108.000000	4.470	1.516791	6.0	9.100748

801 rows × 12 columns

In [43]:
```
gdf_population_final_nonan = gdf_population_final.dropna(subset=['Median_Price', 'Crime_Count'])  # drop some missings

X = gdf_population_final_nonan[['Crimes_per_km2']]
y = gdf_population_final_nonan['Airbnb_per_km2']
X = sm.add_constant(X)  # add a constant to the model (the intercept)

model = sm.OLS(y, X).fit()

print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          Airbnb_per_km2   R-squared:                       0.010
Model:                             OLS   Adj. R-squared:                  0.009
Method:                  Least Squares   F-statistic:                     6.958
Date:                 Wed, 29 Oct 2025   Prob (F-statistic):            0.00854
Time:                         15:33:12   Log-Likelihood:                -3554.6
No. Observations:                  672   AIC:                             7113.
Df Residuals:                      670   BIC:                             7122.
Df Model:                            1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         34.8744      2.240     15.566      0.000      30.475      39.273
Crimes_per_km2    -0.4042      0.153     -2.638      0.009      -0.705      -0.103
==============================================================================
Omnibus:                      689.677   Durbin-Watson:                   1.797
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            37897.668
Skew:                           4.683   Prob(JB):                         0.00
Kurtosis:                      38.578   Cond. No.                         17.7
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

4. In-Depth Analysis & Modeling - Airbnb Prices

In a first step, we will extend the gdf_listings by some further data. We add 3 columns:

- `crime_count` which tells us how many homicides occured in a 2km radius
- `distance_to_center` which gives the distance to the city center
- `has_park_within_100m` which gives a boolean indicator whether there is a park nearby

In [44]:
```
if 'buffer' not in gdf_listings.columns:
    gdf_listings['buffer'] = gdf_listings['geometry'].buffer(2000)  # 2000 meters = 2km

if 'gdf_listings_buffer' not in locals():
    gdf_listings_buffer = gdf_listings[['id', 'buffer']].copy()
    gdf_listings_buffer.set_geometry('buffer', inplace=True)

# Perform the spatial join
joined = gpd.sjoin(gdf_listings_buffer, gdf_crime_filtered, how='left', predicate='intersects')

# Count the crimes and merge with the original dataframe
crime_count = joined.groupby('id').size().reset_index(name='crime_count_temp')
gdf_listings = gdf_listings.merge(crime_count, on='id', how='left')

# Update crime_count column
gdf_listings['crime_count'] = gdf_listings['crime_count_temp'].fillna(0)
gdf_listings.drop(['buffer', 'crime_count_temp'], axis=1, inplace=True, errors='ignore')
```

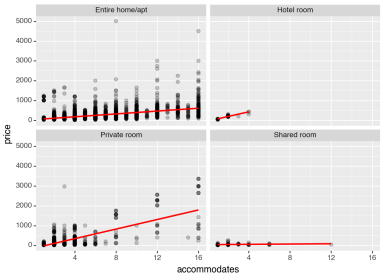
In [45]:
```
gdf_listings[["id", "crime_count"]].head(3)
```

Out[45]:

	id	crime_count
0	2384	62
1	7126	56
2	10945	31

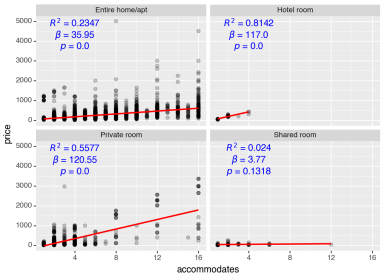
In [46]:
```
# Get distance to city center for each airbnb

# Create a Point object for the given coordinates
center_point = Point(448156, 4635454)

# Calculate distances and add/update the column in gdf_listings
if 'distance_to_center' in gdf_listings.columns:
    # Update the column if it already exists
    gdf_listings['distance_to_center'] = gdf_listings['geometry'].distance(center_point)
else:
    # Create the column if it does not exist
    gdf_listings = gdf_listings.assign(distance_to_center=gdf_listings['geometry'].distance(center_point))
```

In [47]:
```
def plot_price_relationships(x:str, facet:str, ax_scaling:str='free', outlier_cutoff:float=6000):
    g =(ggplot(gdf_listings[gdf_listings['price'] <= outlier_cutoff], # filter out the outlier
               aes(x=x, y='price', color=facet)) +
               geom_point(color='black', alpha=0.2, size=2, stroke=0.4) +
               geom_smooth(method='lm', color='r', se=False) +
               facet_wrap(facets=facet, scales=ax_scaling)
    )
    return g

plot_price_relationships(x='accommodates', facet='room_type', ax_scaling='fixed')
```



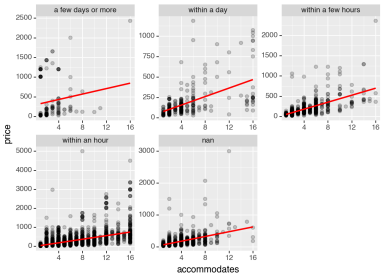
Out[47]:
```
<Figure Size: (640 x 480)>
```

In [48]:
```
def plot_price_relationships_r2(x:str, facet:str, df:pd.DataFrame=gdf_listings, ax_scaling:str='free', outlier_cutoff:float=6000):
    import warnings
    warnings.filterwarnings("ignore")
    df = df[df['price'] <= outlier_cutoff]

    # calculate R^2 for each facet
    facets = df[facet].unique()
    r2_values = {}
    for f in facets:
        model = smf.ols(formula=f'price ~ {x}', data=df[df[facet] == f]).fit()
        # r2_values[f] = f"R2 = {round(model.rsquared, 4)}"
        # r2_values[f] = f"$R^2$ = {round(model.rsquared, 4)}\n$\\beta$ = {round(model.params[x],2)}\n$p$ = {round(model.pvalues[x],4)}"
        r2_values[f] = f"$R^2$ = {round(model.rsquared, 4)}\n$\\beta$ = {round(model.params[x],2)}\n$p$ = {round(model.pvalues[x],4)}"

    # create a new dataframe for R^2 values
    r2_df = pd.DataFrame(list(r2_values.items()), columns=[facet, 'R2'])
    g = (ggplot(df, aes(x=x, y='price', color=facet)) +
         geom_point(color='black', alpha=0.2, size=2, stroke=0.4) +
         geom_smooth(method='lm', color='r', se=False) +
         geom_text(data=r2_df, mapping=aes(label='R2'), color='b', x=len(df[x].unique())/4, y=outlier_cutoff-1700) +
         facet_wrap(facets=facet, scales=ax_scaling))
    return g

plot_price_relationships_r2(x='accommodates', facet='room_type', ax_scaling='fixed')
```



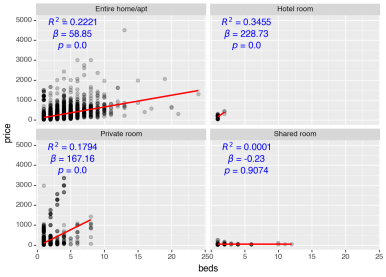
Out[48]:
```
<Figure Size: (640 x 480)>
```

In [49]:
```
facet = 'host_response_time'
plot_price_relationships(x='accommodates', facet=facet)
```



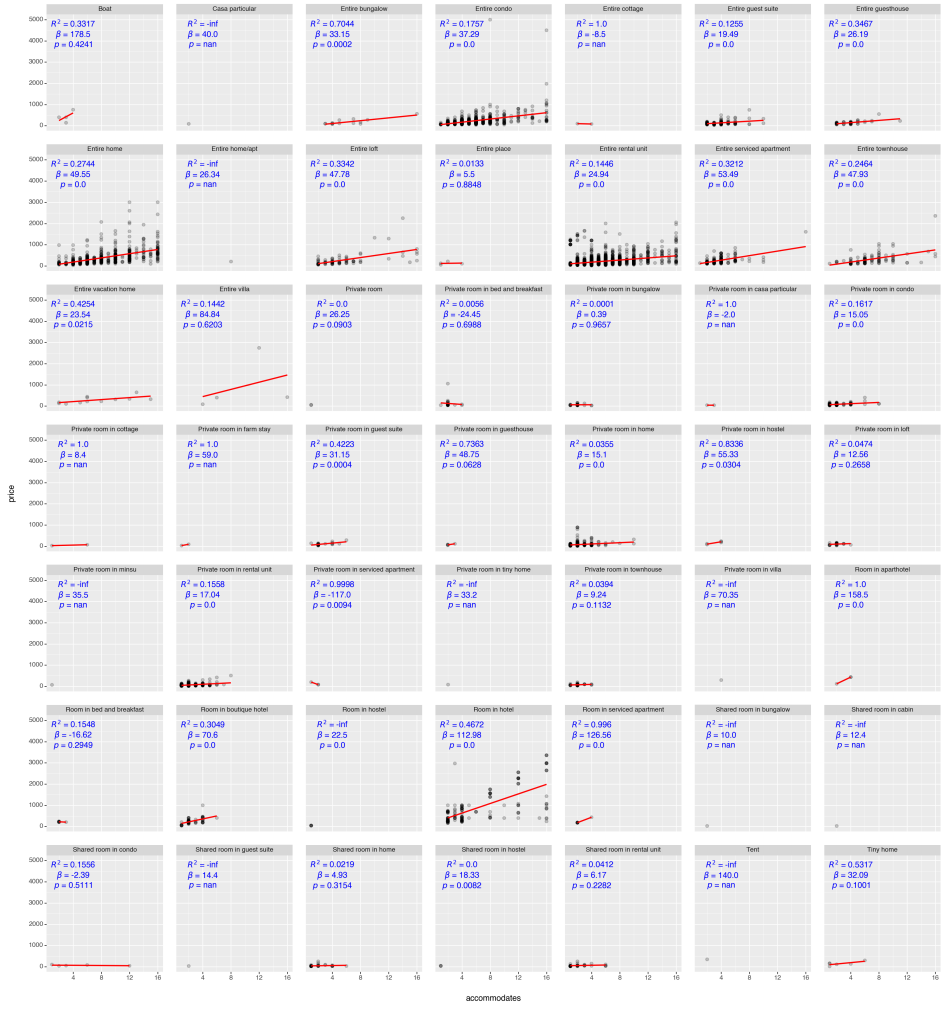
Out[49]: <Figure Size: (640 x 480)>

In [50]:
```
plot_price_relationships_r2(x='beds', facet='room_type', ax_scaling='fixed')
```



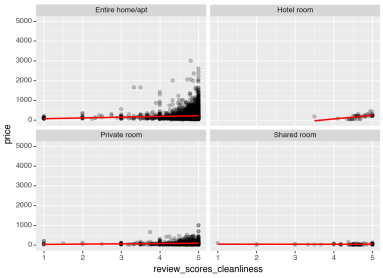
Out[50]: <Figure Size: (640 x 480)>

In [51]:
```
plot_price_relationships_r2(x='accommodates', facet='property_type', ax_scaling='fixed') + theme(aspect_ratio=1, figure_size=(25, 20))
```



Out[51]: <Figure Size: (2500 x 2000)>

In [52]:
```
facet = 'room_type'
plot_price_relationships_r2(x='review_scores_cleanliness', facet=facet, ax_scaling='fixed')
```



Out[52]: <Figure size: (640 x 480)>

4.1 K-means clustering

- `StandardScaler` : subtracting mean, dividing by stdev $\rightarrow x_{scaled} = \frac{x - \bar{x}}{\sigma}$
- `MinMaxScaler` : scaling to squish values btw 0 and 1 $\rightarrow x_{scaled} = (\frac{x - x_{min}}{x_{max} - x_{min}}) \times (x_{max} - x_{min}) - x_{min}$

4.1.1 Data Processing steps

In [53]:
```
property_type = gdf_listings['property_type'].tolist()
pt_dict = {}
for pt in property_type:
    if pt in pt_dict:
        pt_dict[pt] += 1
    else:
        pt_dict[pt] = 1
sorted(pt_dict.items(), key=lambda item: item[1], reverse=False)
```

Out[53]:
```
[('Private room in tiny home', 1),
 ('Shared room in bungalow', 1),
 ('Shared room in guest suite', 1),
 ('Casa particular', 1),
 ('Entire home/apt', 1),
 ('Private room in villa', 1),
 ('Shared room in cabin', 1),
 ('Private room in minsu', 1),
 ('Tent', 1),
 ('Private room in farm stay', 2),
 ('Private room in cottage', 2),
 ('Private room', 2),
 ('Entire cottage', 2),
 ('Private room in casa particular', 2),
 ('Shared room in hostel', 3),
 ('Room in aparthotel', 3),
 ('Private room in serviced apartment', 3),
 ('Entire place', 4),
 ('Entire villa', 4),
 ('Boat', 4),
 ('Private room in hostel', 5),
 ('Room in hostel', 5),
 ('Private room in guesthouse', 5),
 ('Shared room in condo', 5),
 ('Tiny home', 6),
 ('Room in serviced apartment', 9),
 ('Room in bed and breakfast', 9),
 ('Entire vacation home', 12),
 ('Entire bungalow', 14),
 ('Private room in guest suite', 25),
 ('Private room in loft', 28),
 ('Private room in bed and breakfast', 29),
 ('Private room in bungalow', 30),
 ('Shared room in rental unit', 37),
 ('Shared room in home', 48),
 ('Entire guesthouse', 54),
 ('Private room in townhouse', 65),
 ('Room in boutique hotel', 81),
 ('Entire loft', 83),
 ('Entire townhouse', 109),
 ('Entire guest suite', 163),
 ('Private room in condo', 168),
 ('Room in hotel', 170),
 ('Entire serviced apartment', 184),
 ('Private room in home', 554),
 ('Entire home', 624),
 ('Private room in rental unit', 727),
 ('Entire condo', 887),
 ('Entire rental unit', 4352)]
```

In [54]:
```
def convert_object_to_numeric(dataframe:pd.DataFrame):
    df = dataframe.copy()
    for col in df.columns:
        try:
            df[col] = df[col].astype('int64')
        except TypeError:
            try:
                df[col] = df[col].astype('float64')
            except TypeError:
                pass
        except ValueError:
            try:
                df[col] = df[col].astype('float64')
            except ValueError:
                pass
    return df

numerical_df = convert_object_to_numeric(gdf_listings)
numerical_df = numerical_df.select_dtypes(include=['int64', 'float64'])
```

In [55]:
```
numerical_df2 = numerical_df.copy()
numerical_df2.drop(['neighbourhood_group_cleansed','bathrooms','calendar_updated','reviews_per_month',
                    'review_scores_rating', 'review_scores_accuracy', 'review_scores_cleanliness',
                   'review_scores_checkin', 'review_scores_communication', 'review_scores_location', 'review_scores_value',
                    'latitude', 'longitude', 'availability_30'], axis=1, inplace=True)
numerical_df2['bedrooms'].fillna(1, inplace=True)
numerical_df2['beds'].fillna(1, inplace=True)
print(numerical_df2['bedrooms'].isna().sum())
print(numerical_df2['beds'].isna().sum())
```

```
0
0
```

In [56]:
```
numerical_df3 = numerical_df2[['accommodates', 'bedrooms', 'beds', 'availability_60', 'availability_90', 'availability_365', 'number_of_reviews', 'price']]
numerical_df3.shape
```

Out[56]: (8528, 8)

4.1.2 The Model

In [57]:
```
stds = StandardScaler()
mmxs = MinMaxScaler()

df_std = pd.DataFrame(stds.fit_transform(numerical_df3))
df_mmx = pd.DataFrame(mmxs.fit_transform(numerical_df3))
df_std.columns, df_mmx.columns = numerical_df3.columns, numerical_df3.columns
display(df_std.head())
display(df_mmx.head())
```

	accommodates	bedrooms	beds	availability_60	availability_90	availability_365	number_of_reviews	price
0	-1.103415	-0.716494	-0.727375	-0.710123	-0.200745	0.847434	2.055314	-0.318389
1	-0.770721	-0.716494	-0.727375	0.508041	0.618873	1.044915	5.222512	-0.400637
2	-0.105332	0.179307	-0.140187	-0.271584	0.094318	-0.542832	0.289430	-0.109030
3	-0.438027	-0.716494	-0.727375	0.654220	0.717227	-0.392746	-0.359959	0.485399
4	-0.438027	-0.716494	-0.727375	-1.538475	-1.446564	0.547263	-0.052354	-0.516532

	accommodates	bedrooms	beds	availability_60	availability_90	availability_365	number_of_reviews	price
0	0.000000	0.000000	0.000000	0.283333	0.522222	0.882192	0.068127	0.013469
1	0.066667	0.000000	0.000000	0.700000	0.800000	0.950685	0.151561	0.010564
2	0.200000	0.083333	0.043478	0.433333	0.622222	0.400000	0.021609	0.020864
3	0.133333	0.000000	0.000000	0.750000	0.833333	0.452055	0.004502	0.041859
4	0.133333	0.000000	0.000000	0.000000	0.100000	0.778082	0.012605	0.006470

In [58]:
```
# X = numerical_df3.values
X = df_std.values

# kmeans = KMeans(n_clusters=8, init='k-means++', n_init='warn', max_iter=300, tol=0.0001, verbose=1, random_state=None, copy_x=True, algorithm='lloyd')
kmeans = KMeans(n_clusters=4, random_state=0)
kmeans.fit(X)
```

Out[58]:
```
KMeans(n_clusters=4, random_state=0)
```

In [59]:
```
numerical_df3['cluster'] = kmeans.labels_
df_std['cluster'] = kmeans.labels_
numerical_df3.head()
```

	accommodates	bedrooms	beds	availability_60	availability_90	availability_365	number_of_reviews	price	cluster
0	1	1.0	1.0	17	47	322	227	114	1
1	2	1.0	1.0	42	72	347	505	92	1
2	4	2.0	2.0	26	56	146	72	170	1
3	3	1.0	1.0	45	75	165	15	329	1
4	3	1.0	1.0	0	9	284	42	61	0

In [60]:
```
# drop overlapping columns from the right dataframe before the merge
joined = pd.read_csv(airbnb_data_path + "listings.csv.gz")
joined = joined.dropna(subset=['price']) # remove missings
joined['price'] = joined['price'].astype(str)
joined['price'] = joined['price'].str.replace('$', '').str.replace(',', '').astype(float)
columns_to_drop = [col for col in joined.columns if col in numerical_df2.columns and col not in ['id', 'price']]

joined_drop = joined.drop(columns=columns_to_drop, inplace=False)

joined2 = numerical_df2.merge(joined_drop, on=['id', 'price'])
print(joined_drop.shape)
print(joined2.columns)
print(joined2.shape)
print(len(kmeans.labels_))
```

```
(8528, 50)
Index(['id', 'scrape_id', 'host_id', 'host_listings_count',
       'host_total_listings_count', 'accommodates', 'bedrooms', 'beds',
       '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', 'availability_60', 'availability_90',
       'availability_365', 'number_of_reviews', 'number_of_reviews_ltm',
       'number_of_reviews_l30d', 'calculated_host_listings_count',
       'calculated_host_listings_count_entire_homes',
       'calculated_host_listings_count_private_rooms',
       'calculated_host_listings_count_shared_rooms', 'crime_count',
       'distance_to_center', 'listing_url', 'last_scraped', 'source', 'name',
       'description', 'neighborhood_overview', 'picture_url', 'host_url',
       'host_name', 'host_since', 'host_location', 'host_about',
       'host_response_time', 'host_response_rate', 'host_acceptance_rate',
       'host_is_superhost', 'host_thumbnail_url', 'host_picture_url',
       'host_neighbourhood', 'host_verifications', 'host_has_profile_pic',
       'host_identity_verified', 'neighbourhood', 'neighbourhood_cleansed',
       'neighbourhood_group_cleansed', 'latitude', 'longitude',
       'property_type', 'room_type', 'bathrooms', 'bathrooms_text',
       'amenities', 'calendar_updated', 'has_availability', 'availability_30',
       'calendar_last_scraped', 'first_review', 'last_review',
       'review_scores_rating', 'review_scores_accuracy',
       'review_scores_cleanliness', 'review_scores_checkin',
       'review_scores_communication', 'review_scores_location',
       'review_scores_value', 'license', 'instant_bookable',
       'reviews_per_month'],
      dtype='object')
(8528, 77)
8528
```

In [76]:
```
# drop overlapping columns from the right dataframe before the merge
columns_to_drop = [col for col in joined.columns if col in numerical_df3.columns and col not in ['accommodates', 'bedrooms', 'beds', 'availability_60',
                                                                                                 'availability_90', 'availability_365', 'number_of_reviews', 'price']]
joined_drop = joined.drop(columns=columns_to_drop, inplace=False)


joined3 = numerical_df3.merge(joined_drop, on=['accommodates', 'bedrooms', 'beds', 'availability_60', 'availability_90', 'availability_365', 'number_of_reviews', 'price'])
joined3 = pd.concat([joined2, numerical_df3['cluster']], axis=1)
joined3.columns
```

Out[76]:
```
Index(['id', 'scrape_id', 'host_id', 'host_listings_count',
       'host_total_listings_count', 'accommodates', 'bedrooms', 'beds',
       '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', 'availability_60', 'availability_90',
       'availability_365', 'number_of_reviews', 'number_of_reviews_ltm',
       'number_of_reviews_l30d', 'calculated_host_listings_count',
       'calculated_host_listings_count_entire_homes',
       'calculated_host_listings_count_private_rooms',
       'calculated_host_listings_count_shared_rooms', 'crime_count',
       'distance_to_center', 'listing_url', 'last_scraped', 'source', 'name',
       'description', 'neighborhood_overview', 'picture_url', 'host_url',
       'host_name', 'host_since', 'host_location', 'host_about',
       'host_response_time', 'host_response_rate', 'host_acceptance_rate',
       'host_is_superhost', 'host_thumbnail_url', 'host_picture_url',
       'host_neighbourhood', 'host_verifications', 'host_has_profile_pic',
       'host_identity_verified', 'neighbourhood', 'neighbourhood_cleansed',
       'neighbourhood_group_cleansed', 'latitude', 'longitude',
       'property_type', 'room_type', 'bathrooms', 'bathrooms_text',
       'amenities', 'calendar_updated', 'has_availability', 'availability_30',
       'calendar_last_scraped', 'first_review', 'last_review',
       'review_scores_rating', 'review_scores_accuracy',
       'review_scores_cleanliness', 'review_scores_checkin',
       'review_scores_communication', 'review_scores_location',
       'review_scores_value', 'license', 'instant_bookable',
       'reviews_per_month', 'cluster'],
      dtype='object')
```

In [77]:
```
# joined2['cluster'] = joined2['cluster'].astype('str')
joined3['cluster'] = joined3['cluster'].astype('str')
joined3.cluster.value_counts()
```

Out[77]:
```
cluster
1    3551
0    2621
2    1908
3     448
Name: count, dtype: int64
```

In [ ]:
```
custom_color_sequence = ["blue", "red", "fuchsia", "green"]

# ensure coords are merged correctly by id if possible, otherwise align by index
if 'id' in joined3.columns and 'id' in joined.columns:
    coords = joined[['id', 'latitude', 'longitude']].drop_duplicates(subset='id')
    # merge coords into joined3
    if 'latitude' in joined3.columns and 'longitude' in joined3.columns:
        joined3 = joined3.drop(columns=['latitude', 'longitude'])
    joined3 = joined3.merge(coords, on='id', how='left')
else:
    # fallback: align by index (both reset to avoid misalignment)
    joined3 = pd.concat([joined3.reset_index(drop=True), joined[['latitude', 'longitude']].reset_index(drop=True)], axis=1)

# drop rows without valid coordinates
joined3 = joined3.dropna(subset=['latitude', 'longitude']).copy()

# ensure numeric types
joined3['latitude'] = joined3['latitude'].astype(float)
joined3['longitude'] = joined3['longitude'].astype(float)

# ensure cluster column exists and is string/categorical
if 'cluster' in joined3.columns:
    joined3['cluster'] = joined3['cluster'].astype(str)
else:
    joined3['cluster'] = '0'

# use price for marker size so higher price => bigger dot
if 'price' not in joined3.columns:
    joined3['price'] = 0

print("Interactive geoplot:\ndot color -> cluster\ndot size -> price (higher price, bigger dot)")

try:
    fig = px.scatter_mapbox(
        joined3,
        lat="latitude",
        lon="longitude",
        hover_name="beds",
        hover_data=["price", "beds"],
        color="cluster",
        color_discrete_sequence=custom_color_sequence,
        size="price",
        size_max=15,
        zoom=10,
        height=500,
        opacity=0.65
    )
except (KeyError, Exception) as e:
    fig = px.scatter_mapbox(
        joined3,
        lat="latitude",
        lon="longitude",
        hover_name="beds",
        hover_data=["price", "beds"],
        color="cluster",
        color_discrete_sequence=px.colors.qualitative.Safe,
        size="price",
        size_max=15,
        zoom=10,
        height=500,
        opacity=0.65
    )

fig.update_layout(mapbox_style="open-street-map")
fig.update_layout(margin={"r":0, "t":0, "l":0, "b":0})
fig.show()
```

In [85]:
```
#let's see what factors contributed to the clusters
cmap='YlGnBu'
print('true values:')
display(numerical_df3.groupby('cluster').mean().style.background_gradient(cmap=cmap))

print('scaled values:')
display(df_std.groupby('cluster').mean().style.background_gradient(cmap=cmap))
```

true values:

cluster	accommodates	bedrooms	beds	availability_60	availability_90	availability_365	number_of_reviews	price
0	3.178176	1.416635	1.641358	6.774132	14.731782	113.337657	45.734834	139.520031
1	2.782878	1.223599	1.417066	44.522388	73.160800	268.811884	40.435089	142.023655
2	6.790881	2.731132	3.513627	40.481656	67.002096	250.603774	62.592243	233.807128
3	12.595982	4.642857	6.816964	36.087054	59.794643	226.265625	32.328125	853.475446

scaled values:

cluster	accommodates	bedrooms	beds	availability_60	availability_90	availability_365	number_of_reviews	price
0	-0.378748	-0.343272	-0.350777	-1.208395	-1.258649	-0.800839	-0.009803	-0.222981
1	-0.510262	-0.516194	-0.482479	0.630948	0.656929	0.427288	-0.070182	-0.213621
2	0.823177	0.834256	0.748596	0.434057	0.455018	0.283458	0.182250	0.129516
3	2.754501	2.546782	2.688276	0.219923	0.218724	0.091205	-0.162543	2.446175

4.2 Associate Rule Learning (unsupervised co-occurence analysis)

In [86]:
```
gdf_listings.columns
```

Out[86]:
```
Index(['id', 'listing_url', 'scrape_id', 'last_scraped', 'source', 'name',
       'description', 'neighborhood_overview', 'picture_url', 'host_id',
       'host_url', 'host_name', 'host_since', 'host_location', 'host_about',
       'host_response_time', 'host_response_rate', 'host_acceptance_rate',
       'host_is_superhost', 'host_thumbnail_url', 'host_picture_url',
       'host_neighbourhood', 'host_listings_count',
       'host_total_listings_count', 'host_verifications',
       'host_has_profile_pic', 'host_identity_verified', 'neighbourhood',
       'neighbourhood_cleansed', 'neighbourhood_group_cleansed', 'latitude',
       'longitude', 'property_type', 'room_type', 'accommodates', 'bathrooms',
       'bathrooms_text', 'bedrooms', 'beds', 'amenities', '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', 'calendar_updated', 'has_availability',
       'availability_30', 'availability_60', 'availability_90',
       'availability_365', 'calendar_last_scraped', 'number_of_reviews',
       'number_of_reviews_ltm', 'number_of_reviews_l30d', 'first_review',
       'last_review', 'review_scores_rating', 'review_scores_accuracy',
       'review_scores_cleanliness', 'review_scores_checkin',
       'review_scores_communication', 'review_scores_location',
       'review_scores_value', 'license', 'instant_bookable',
       'calculated_host_listings_count',
       'calculated_host_listings_count_entire_homes',
       'calculated_host_listings_count_private_rooms',
       'calculated_host_listings_count_shared_rooms', 'reviews_per_month',
       'geometry', 'crime_count', 'distance_to_center'],
      dtype='object')
```

In [87]:
```
gdf_listings['amenities'] = gdf_listings['amenities'].astype('str')
amenities = gdf_listings['amenities']

ls_amen = amenities.apply(lambda x: len(x.strip('[]').split(','))).to_list() # strip and split required as amenities col actually contains lists in str format
max_len = max(ls_amen)
idx = ls_amen.index(max_len)

print(f"the longest list contains {max_len} amenities")

len(gdf_listings['amenities'].iloc[idx].strip('[]').split(',')) == max_len
```

```
the longest list contains 97 amenities
```

Out[87]:
```
True
```

In [88]:
```
# preprocessing -> converting amenities column to actual lists
gdf_listings['amenities_list'] = gdf_listings['amenities'].apply(lambda x: x.strip('[]').split(','))

gdf_listings['amenities_list'][:5]
```

Out[88]:
```
0    ["Fire extinguisher",  "Long term stays allowe...
1    ["Fire extinguisher",  "Long term stays allowe...
2    ["Fire extinguisher",  "Dishes and silverware"...
3    ["Fire extinguisher",  "Free street parking", ...
4    ["Fire extinguisher",  "Long term stays allowe...
Name: amenities_list, dtype: object
```

In [89]:
```
amenities_df = pd.DataFrame(gdf_listings['amenities_list'].apply(set))


amenities_ls = gdf_listings['amenities_list']
flattened_list = [elem for sub_ls in amenities_ls for elem in sub_ls]


amenities_columns = pd.DataFrame(columns=list(set(sorted(flattened_list))))


amenities_df = pd.concat([amenities_df, amenities_columns], axis=1)

amenities_df.fillna(0, inplace=True)

for idx, row in amenities_df.iterrows(): #omit first column which contains the lists
    # get the amenities for the current row
    amenities = amenities_ls.loc[idx]

    for amenity in amenities:
        # if the amenity is in the DataFrame columns, set its value to 1
        if amenity in amenities_df.columns:
            amenities_df.loc[idx, amenity] = 1
```

In [90]:
```
amenities_df.shape
```

Out[90]:
```
(8528, 2801)
```

In [91]:
```
amenities_dummies = amenities_df.drop(columns=['amenities_list'])

amenities_dummies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8528 entries, 0 to 8527
Columns: 2800 entries,  to  "58\" HDTV with Disney+"
dtypes: int64(2800)
memory usage: 182.2 MB
```

Metrics used in associate rule mining are the following:

- **Support**

It indicates how frequently an item set appears in the data set.

Let $frq(A)$ be the number of occurrences (frequency) from the total number of transactions $frq(T) = T$:

$$supp(A) = \frac{frq(A)}{T}$$

- **Confidence**

It says how likely item set B is purchased when item set A is purchased

$$conf(A \rightarrow B) = \frac{supp(A,B)}{supp(A)}$$

with $supp(A,B) = \frac{frq(A,B)}{frq(T)}$ and $supp(A) = \frac{frq(A)}{frq(T)}$ it holds that:

$$conf(A \rightarrow B) = \frac{supp(A,B)}{supp(A)} = \frac{\frac{frq(A,B)}{frq(T)}}{\frac{frq(A)}{frq(T)}} = \frac{frq(A,B)}{frq(A)}$$

- **Lift**

Lift: It says how likely item set B is purchased when item set A is purchased while controlling for how popular item set B is.

Lift is the ratio of the observed support to that expected if A and B were independent or equivalently the ratio of the confidence of the rule to the expected confidence of the RHS item set by independence.

$$lift(A \rightarrow B) = \frac{conf(A,B)}{supp(B)} = \frac{supp(A,B)}{supp(A) \times supp(B)}$$

Note:

$$lift(A \rightarrow B) == lift(B \rightarrow A)$$

In [92]:
```
def support(df, cols):
  if type(cols) != list:
    cols = [cols]
    #cols = np.array(cols)
  #print(cols)
  bool_mask = df[cols].isin([1]).all(axis=1)
  frqA = len(df[bool_mask])
  T = len(df[cols])
  return frqA/T

# item set of 3 different products
# print(support(retail, ["Bread", "Yogurt", "Egg"]))
# # also works with single item sets
# support(retail,'Bread')


def confidence(df, A, B):
  if type(A)==list and type(B)==list:
    AB = A + B
  elif type(A)==list and type(B)!=list:
    AB = A
    AB.append(B)
  elif type(A)!=list and type(B)==list:
    AB = B
    AB.append(A)
  elif type(A)!=list and type(B)!=list:
    AB = [A, B]
  return support(df, AB) / support(df, A)

# print(confidence(retail, "Bread", "Egg"))

# confidence(retail, ["Bread"], ["Dog_Food","Flowers"])


def lift(df, A, B):
  return confidence(df, A, B) / support(df, B)

# lift(retail, "Bread", "Egg")
```

In [ ]:
```
# Calculate support for each amenity
support_values = {amenity: support(amenities_dummies, amenity) for amenity in amenities_dummies.columns}

# Filter amenities with support > 10%
filter_amenities = [amenity for amenity, support in support_values.items() if support > 0.15]
print("number of features with support > 15%:", len(filter_amenities))

amenities_names = amenities_dummies[filter_amenities].columns

lift_vals = {}

for i, a1 in enumerate(amenities_names):
    for a2 in amenities_names[i:]:
        if a1 != a2:
            # print(f"lift of {a1} and {a2} is {lift(amenities_dummies, a1, a2)}")
            lift_value = lift(amenities_dummies, a1, a2)
            combo = f"{a1} & {a2}"
            lift_vals[combo] = lift_value
```

In [ ]:
```
highest_lift = sorted(lift_vals.items(), key=lambda item: item[1], reverse=True)[:10]
pd.DataFrame(highest_lift, columns=['Itemsets', 'Lift']).style.background_gradient(cmap=cmap)
```

- If the lift is equal to 1, it means that the antecedent and the consequent are independent of each other. When two events are independent of each other, no rule can be drawn involving those two events.
- If the lift is greater than 1, it means that the antecedent and the consequent are positively correlated. This indicates that the occurrences of the antecedent and the consequent are dependent on one another, and the rule could be useful for predicting the consequent in future data sets.
- If the lift is less than 1, it means that the antecedent and the consequent are negatively correlated.

So, a lift value of 4.182987 means that the antecedent and the consequent are positively correlated and occur together more than 4 times as often as would be expected if they were independent. This suggests a strong association between the antecedent and the consequent.

further analysis of the amenities column

In [94]:
```
amenities_dummies['price'] = gdf_listings['price']

# removing outlier
amenities_dummies = amenities_dummies[amenities_dummies['price'] <= 25000]

average_price = {}
median_price = {}
for col in amenities_dummies.columns:
    if col != 'price' and amenities_dummies[col].sum() > 3:
        average_price[col] = amenities_dummies[amenities_dummies[col] == 1]['price'].mean()
        median_price[col] = amenities_dummies[amenities_dummies[col] == 1]['price'].median()
```

In [95]:
```
amenities_count = pd.DataFrame(amenities_dummies[amenities_dummies.columns[:-1]].sum().sort_values(ascending=False), columns=['count'])
amenities_count.reset_index(inplace=True)
amenities_count.rename(columns={'index': 'amenity'}, inplace=True)
amenities_count.head()
```

Out[95]:

	amenity	count
0	"Smoke alarm"	8312
1	"Kitchen"	7853
2	"Carbon monoxide alarm"	7724
3	"Essentials"	7711
4	"Wifi"	7522

In [96]:
```
avg = pd.DataFrame(sorted(average_price.items(), key=lambda item: item[1], reverse=True), columns=['amenity', 'average_price'])
med = pd.DataFrame(sorted(median_price.items(), key=lambda item: item[1], reverse=True), columns=['amenity', 'median_price'])

avg = avg.merge(amenities_count, on='amenity')
med = med.merge(amenities_count, on='amenity')


combined = avg.merge(med, on=['amenity', 'count'], suffixes=('_avg', '_med'))
combined['diff'] = abs(combined['average_price'] - combined['median_price'])
combined = combined.sort_values(by='diff', ascending=False)
combined.head(20).style.background_gradient(cmap='RdYlGn_r', subset=['average_price', 'median_price', 'count', 'diff'])
```

Out[96]:

	amenity	average_price	count	median_price	diff
7	"HDTV with premium cable	642.000000	5	128.000000	514.000000
3	"Sonos sound system"	845.818182	11	402.000000	443.818182
8	and wardrobe"	636.083333	12	220.500000	415.583333
13	"TV with Apple TV	569.500000	6	179.000000	390.500000
14	"Sound system with aux"	535.357143	14	225.000000	310.357143
2	"Viking refrigerator"	849.166667	6	573.000000	276.166667
25	"Children\u2019s books and toys for ages 2-5 years old	437.600000	5	180.000000	257.600000
19	"48\" HDTV with Fire TV	498.750000	4	242.500000	256.250000
15	"Private sauna"	529.550000	20	297.500000	232.050000
29	"48\" HDTV with Amazon Prime Video	432.307692	13	210.000000	222.307692
67	"Free driveway parking on premises"	332.000000	19	120.000000	212.000000
21	"75\" HDTV with Amazon Prime Video	473.153846	13	264.000000	209.153846
9	"Wifi"	621.178571	28	417.500000	203.678571
36	DVD player	408.500000	14	205.500000	203.000000
73	"Treseme conditioner"	327.625000	8	126.000000	201.625000
32	"65\" HDTV with standard cable	429.500000	6	228.000000	201.500000
18	"Standalone high chair"	511.600000	10	311.000000	200.600000
33	"Building staff"	415.899654	578	219.500000	196.399654
93	"Indoor fireplace: electric	311.000000	9	115.000000	196.000000
52	"Bosch stainless steel gas stove"	361.400000	5	176.000000	185.400000

Features which we also want to consider in predicting the price

In [97]:
```
# SELECTING THE AMENITIES WHICH HAVE A DIFFERENCE OF 10% OR LESS BETWEEN THE AVERAGE AND MEDIAN PRICE
features_df = combined[combined['diff'] <= ((combined['average_price']+ combined['median_price'])/2) * 0.1] \
        .sort_values(by=['median_price', 'average_price', 'count'], ascending=False)
features_df.head(20).style.background_gradient(cmap='RdYlGn_r', subset=['average_price', 'median_price', 'count', 'diff'])
```

Out[97]:

	amenity	average_price	count	median_price	diff
4	"Private outdoor kitchen"	750.857143	7	771.000000	20.142857
6	"Thermador refrigerator"	666.777778	9	663.000000	3.777778
10	"Thermador stainless steel oven"	611.500000	6	654.500000	43.000000
17	"Shared hot tub - available seasonally"	515.142857	7	504.000000	11.142857
16	"Thermador stainless steel gas stove"	523.285714	14	494.000000	29.285714
27	"Viking stainless steel oven"	436.750000	8	468.500000	31.750000
26	"Wolf stainless steel gas stove"	437.250000	4	436.000000	1.250000
28	"Wolf stainless steel oven"	436.000000	4	433.500000	2.500000
51	"75\" HDTV with Roku"	363.000000	5	361.000000	2.000000
78	"Shared pool - available seasonally"	322.636364	11	349.000000	26.363636
54	"Exercise equipment: stationary bike	360.600000	5	344.000000	16.600000
65	"85\" HDTV with Amazon Prime Video	333.250000	4	343.500000	10.250000
70	"Shared pool - available all year	329.666667	9	325.000000	4.666667
76	"Free parking garage on premises"	324.266667	15	307.000000	17.266667
72	"Paid parking lot on premises \u2013 30 spaces"	327.750000	4	299.000000	28.750000
103	open specific hours"	302.739130	23	298.000000	4.739130
113	"70\" HDTV with Amazon Prime Video	295.125000	8	285.000000	10.125000
120	"KitchenAid stainless steel gas stove"	288.125000	8	281.000000	7.125000
204	"Fast wifi \u2013 109 Mbps"	253.800000	5	278.000000	24.200000
189	"Golf course view"	260.600000	10	270.500000	9.900000

In [98]:
```
features = features_df['amenity'][:20].tolist()
print('the following features will be considered by the feature selector:\n')
for feature in features:
    print(feature)
```

```
the following features will be considered by the feature selector:

"Private outdoor kitchen"
"Thermador refrigerator"
"Thermador stainless steel oven"
"Shared hot tub - available seasonally"
"Thermador stainless steel gas stove"
"Viking stainless steel oven"
"Wolf stainless steel gas stove"
"Wolf stainless steel oven"
"75\" HDTV with Roku"
"Shared pool - available seasonally"
"Exercise equipment: stationary bike
"85\" HDTV with Amazon Prime Video
"Shared pool - available all year
"Free parking garage on premises"
"Paid parking lot on premises \u2013 30 spaces"
open specific hours"
"70\" HDTV with Amazon Prime Video
"KitchenAid stainless steel gas stove"
"Fast wifi \u2013 109 Mbps"
"Golf course view"
```

4.3 Supervised learning

Trying to predict Airbnb prices and see which features are relevant.

4.3.1 Data processing

In [99]:
```
room_types = pd.get_dummies(gdf_listings['room_type'])
room_types = room_types.astype(int)

# num_df_for_ml = pd.concat([numerical_df2, room_types, amenities_df[features]], axis=1)
num_df_for_ml = pd.concat([numerical_df2, room_types], axis=1)

num_df_for_ml.drop(['id', 'host_id', 'scrape_id'], inplace=True, axis=1)
num_df_for_ml
```

Out[99]:

	host_listings_count	host_total_listings_count	accommodates	bedrooms	beds	price	minimum_nights	maximum_nights	minimum_minimum_nights	maximum_minimum_nights	...	calculated_host_listings_count	calculated_host_listings_count_entire_homes	calculated_host_listings_count_private_rooms	calcula
0	1	1	1	1.0	1.0	114	3	60	3	3	...	1	0	1	
1	2	2	2	1.0	1.0	92	32	60	2	32	...	1	1	0	
2	7	82	4	2.0	2.0	170	4	1125	2	4	...	7	7	0	
3	1	1	3	1.0	1.0	329	2	10	2	2	...	1	0	1	
4	10	13	3	1.0	1.0	61	32	395	32	45	...	4	4	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
8523	3	3	13	5.0	8.0	438	30	365	30	30	...	3	3	0	
8524	13	18	1	1.0	1.0	32	2	365	2	2	...	9	0	9	
8525	1	1	4	3.0	3.0	24	32	365	32	32	...	1	1	0	
8526	4565	5836	2	1.0	1.0	127	32	1125	32	366	...	645	645	0	
8527	28	31	8	3.0	4.0	366	1	365	2	2	...	28	27	1	

8528 rows × 30 columns

In [100…
```
na_col = num_df_for_ml.isnull().sum()
```

4.3.2 Train-test split

In [101…
```
def create_split(df:pd.DataFrame, valid_size:float):
    # Separate features and target variable
    X = df.drop(columns='price')
    y = df['price']

    # Split the data into train and validation sets
    X_train, X_valid, y_train, y_valid = train_test_split(X, y, test_size=valid_size)

    return X_train, y_train, X_valid, y_valid
```

In [102…
```
X_train, y_train, X_test, y_test = create_split(num_df_for_ml, valid_size=0.2)
```

4.3.3 Choosing suitable ML

In [103…
```
#We choose to train Random Forest Regressor for this task. Then we will compare it with simple Linear regression.

ml_methods = []

ml_methods.append(RandomForestRegressor)
ml_methods.append(LinearRegression)
ml_methods.append(XGBRegressor)
```

In [104…
```
def predict_price(X_train: pd.DataFrame, y_train: pd.DataFrame, X_test: pd.DataFrame, model_class: type, cv: int = 5) -> tuple:
    y_pred = None
    trained_model = None

    # Initialize the model
    trained_model = model_class()

    # Fit the model on the entire training data
    trained_model.fit(X_train, y_train)

    y_pred = trained_model.predict(X_test)

    return y_pred, trained_model
```

4.3.4 Feature Selection

In [105…
```
def create_split_with_features(df: pd.DataFrame, valid_size: float, num_features: int):
    # Separate features and target variable
    X = df.drop(columns='price')
    y = df['price']

    # Feature selection
    selector = RFE(RandomForestRegressor(), n_features_to_select=num_features)
    selector.fit(X, y)
    X_selected = selector.transform(X)
    features = [col for col, selected in zip(X.columns, selector.support_) if selected]

    print("Num Features: %s" % (selector.n_features_))
    print("Selected Features: %s" % (features))

    # Split the data into train and validation sets
    X_train, X_valid, y_train, y_valid = train_test_split(X_selected, y, test_size=valid_size)

    return X_train, y_train, X_valid, y_valid
```

4.3.5 Scale features

In [106…
```
def scale_features(X_train, X_test):
    scaler = StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_scaled = scaler.transform(X_test)
    return X_train_scaled, X_test_scaled
```

In [107…
```
# Create split with 10 features
X_train_10, y_train, X_test_10, y_test = create_split_with_features(num_df_for_ml, valid_size=0.2, num_features=10)
X_train_10_scaled, X_test_10_scaled = scale_features(X_train_10, X_test_10)

# Create split with 15 features
X_train_15, y_train, X_test_15, y_test = create_split_with_features(num_df_for_ml, valid_size=0.2, num_features=15)
X_train_15_scaled, X_test_15_scaled = scale_features(X_train_15, X_test_15)

# Create split with 20 features
X_train_20, y_train, X_test_20, y_test = create_split_with_features(num_df_for_ml, valid_size=0.2, num_features=20)
X_train_20_scaled, X_test_20_scaled = scale_features(X_train_20, X_test_20)
```

```
Num Features: 10
Selected Features: ['host_listings_count', 'host_total_listings_count', 'accommodates', 'bedrooms', 'availability_60', 'availability_365', 'number_of_reviews', 'calculated_host_listings_count_private_rooms', 'crime_count', 'distance_to_center']
Num Features: 15
Selected Features: ['host_listings_count', 'host_total_listings_count', 'accommodates', 'bedrooms', 'beds', 'minimum_nights', 'maximum_minimum_nights', 'availability_60', 'availability_90', 'availability_365', 'number_of_reviews', 'number_of_reviews_ltm', 'calculated_host_listings_
count_private_rooms', 'crime_count', 'distance_to_center']
Num Features: 20
Selected Features: ['host_listings_count', 'host_total_listings_count', 'accommodates', 'bedrooms', 'beds', 'minimum_nights', 'maximum_nights', 'maximum_minimum_nights', 'maximum_maximum_nights', 'minimum_nights_avg_ntm', 'availability_60', 'availability_90', 'availability_365', 'n
umber_of_reviews', 'number_of_reviews_ltm', 'calculated_host_listings_count', 'calculated_host_listings_count_entire_homes', 'calculated_host_listings_count_private_rooms', 'crime_count', 'distance_to_center']
```

5. Metrics & Evaluation

In [108…
```
suitable_metrics = []

suitable_metrics.append(sklearn.metrics.mean_squared_error)
suitable_metrics.append(sklearn.metrics.mean_absolute_error)
def rmse(y_true, y_pred):
    return np.sqrt(sklearn.metrics.mean_squared_error(y_true, y_pred))
suitable_metrics.append(rmse)
suitable_metrics.append(sklearn.metrics.r2_score)
```

In [109…
```
def compare_metrics(y_true:pd.DataFrame, y_pred:pd.DataFrame) -> dict:
    scores = {}  # dict of metric name -> metric value/score

    for metric in suitable_metrics:
        metric_name = metric.__name__

        score = metric(y_true, y_pred)

        scores[metric_name] = score

    return scores

def print_scores(scores: dict, model_name: str):
  print(f"\nScores:\t{model_name}\n==============================")
  for metric_name, metric_value in scores.items():
    print(f"{metric_name}: {metric_value}")
```

In [110…
```
def compare_models(X_train, y_train, X_test):
    # Train Random Forest model with selected features
    y_pred_rf, _ = predict_price(X_train, y_train, X_test, RandomForestRegressor)

    # Train Linear Regression model with selected features
    y_pred_lin, _ = predict_price(X_train, y_train, X_test, LinearRegression)

    # Train XGBRegressor model with selected features
    y_pred_xgb, _ = predict_price(X_train, y_train, X_test, XGBRegressor)

    return y_pred_rf, y_pred_lin, y_pred_xgb
```

In [111…
```
def plot_metrics_evolution(metric_values, model_names, feature_counts, metric_name):
    plt.figure(figsize=(10, 6))

    for i, model_values in enumerate(metric_values):
        plt.plot(feature_counts, model_values, label=model_names[i])

    plt.title(f'{metric_name} Evolution for different Models')
    plt.xlabel('Number of Features')
    plt.ylabel(metric_name)
    plt.legend()
    plt.show()
```

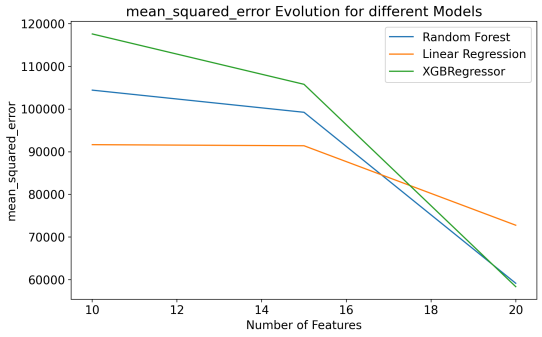
In [112…
```
# Performance with 10 features
y_pred_rf_10, y_pred_lin_10, y_pred_xgb_10 = compare_models(X_train_10_scaled, y_train, X_test_10_scaled)

metrics_scores_sel_10 = compare_metrics(y_test, y_pred_rf_10)
metrics_scores_lin_10 = compare_metrics(y_test, y_pred_lin_10)
metrics_scores_xgb_10 = compare_metrics(y_test, y_pred_xgb_10)

print("\nPerformance with 10 features:")
print_scores(metrics_scores_sel_10, model_name='Random Forest')
print_scores(metrics_scores_lin_10, model_name='Linear Regression')
print_scores(metrics_scores_xgb_10, model_name='XGBRegressor')

# Performance with 15 features
y_pred_rf_15, y_pred_lin_15, y_pred_xgb_15 = compare_models(X_train_15_scaled, y_train, X_test_15_scaled)

metrics_scores_sel_15 = compare_metrics(y_test, y_pred_rf_15)
metrics_scores_lin_15 = compare_metrics(y_test, y_pred_lin_15)
metrics_scores_xgb_15 = compare_metrics(y_test, y_pred_xgb_15)

print("\nPerformance with 15 features:")
print_scores(metrics_scores_sel_15, model_name='Random Forest')
print_scores(metrics_scores_lin_15, model_name='Linear Regression')
```

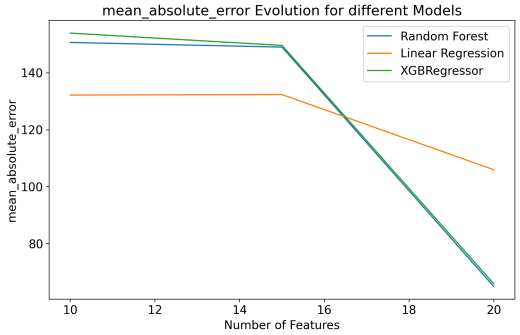
```
print_scores(metrics_scores_xgb_15, model_name='XGBRegressor')

# Performance with 20 features
y_pred_rf_20, y_pred_lin_20, y_pred_xgb_20 = compare_models(X_train_20_scaled, y_train, X_test_20_scaled)

metrics_scores_sel_20 = compare_metrics(y_test, y_pred_rf_20)
metrics_scores_lin_20 = compare_metrics(y_test, y_pred_lin_20)
metrics_scores_xgb_20 = compare_metrics(y_test, y_pred_xgb_20)

print("\nPerformance with 20 features:")
print_scores(metrics_scores_sel_20, model_name='Random Forest')
print_scores(metrics_scores_lin_20, model_name='Linear Regression')
print_scores(metrics_scores_xgb_20, model_name='XGBRegressor')
```

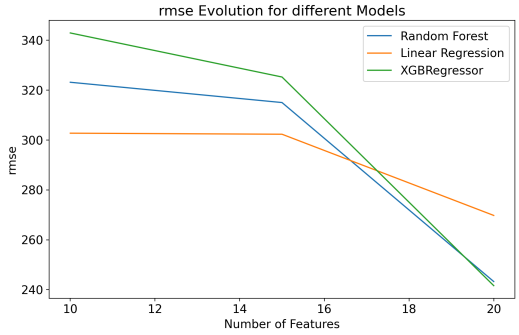
```
Performance with 10 features:

Scores: Random Forest
==============================
mean_squared_error: 104447.81797981133
mean_absolute_error: 150.66330680890924
rmse: 323.18387642302224
r2_score: -0.14396838533101963

Scores: Linear Regression
==============================
mean_squared_error: 91665.45641880699
mean_absolute_error: 132.1907565448995
rmse: 302.7630367445917
r2_score: -0.003969122555574744

Scores: XGBRegressor
==============================
mean_squared_error: 117616.5673486465
mean_absolute_error: 153.93811519763673
rmse: 342.9527188230147
r2_score: -0.2881995741070944

Performance with 15 features:

Scores: Random Forest
==============================
mean_squared_error: 99254.21574860252
mean_absolute_error: 149.0247545078993
rmse: 315.0463707910353
r2_score: -0.08708527495684315

Scores: Linear Regression
==============================
mean_squared_error: 91411.98373552356
mean_absolute_error: 132.36038787901123
rmse: 302.34414784401497
r2_score: -0.0011929541126947107

Scores: XGBRegressor
==============================
mean_squared_error: 105811.64457099648
mean_absolute_error: 149.61657350954948
rmse: 325.28701875739
r2_score: -0.1589057438471273

Performance with 20 features:

Scores: Random Forest
==============================
mean_squared_error: 59179.96684787109
mean_absolute_error: 64.99874870671208
rmse: 243.26932985452788
r2_score: 0.35182933996775245

Scores: Linear Regression
==============================
mean_squared_error: 72783.37247557897
mean_absolute_error: 105.99522740954987
rmse: 269.78393665223837
r2_score: 0.20283756328994906

Scores: XGBRegressor
==============================
mean_squared_error: 58382.248561906626
mean_absolute_error: 65.97328994114821
rmse: 241.62418869373624
r2_score: 0.3605663774396181 7
```

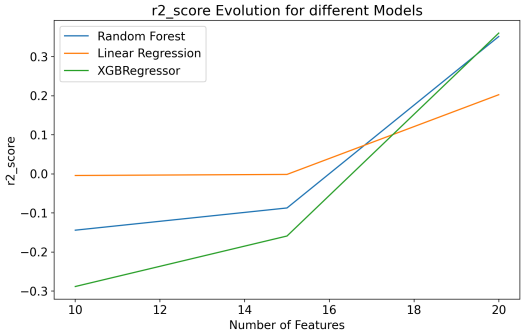
In [113…

```
# Plotting Metrics Evolution
metric_names = ['mean_squared_error', 'mean_absolute_error', 'rmse', 'r2_score']
feature_counts = [10, 15, 20]

for metric_name in metric_names:
    plot_metrics_evolution(
        [[metrics_scores_sel_10[metric_name], metrics_scores_sel_15[metric_name], metrics_scores_sel_20[metric_name]],
         [metrics_scores_lin_10[metric_name], metrics_scores_lin_15[metric_name], metrics_scores_lin_20[metric_name]],
         [metrics_scores_xgb_10[metric_name], metrics_scores_xgb_15[metric_name], metrics_scores_xgb_20[metric_name]]],
        ['Random Forest', 'Linear Regression', 'XGBRegressor'],
        feature_counts,
        metric_name
    )
```



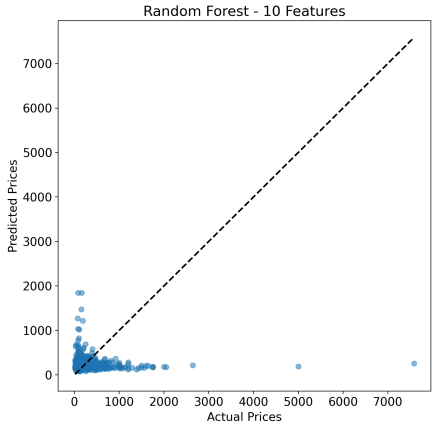


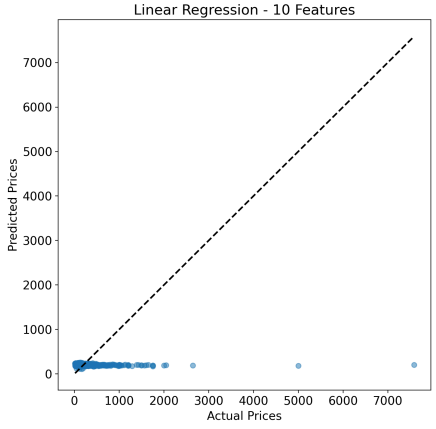


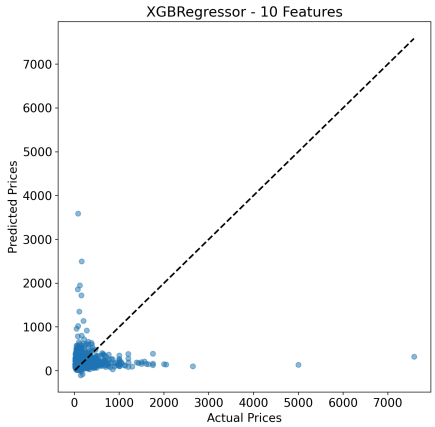


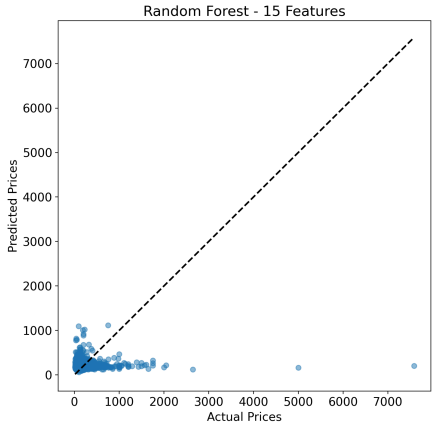
In [114…
```python
def plot_actual_vs_predicted(y_true, y_pred, title):
    plt.figure(figsize=(8, 8))
    plt.scatter(y_true, y_pred, alpha=0.5)
    plt.plot([min(y_true), max(y_true)], [min(y_true), max(y_true)], '--k', linewidth=2)
    plt.title(title)
    plt.xlabel('Actual Prices')
    plt.ylabel('Predicted Prices')
    plt.show()
```

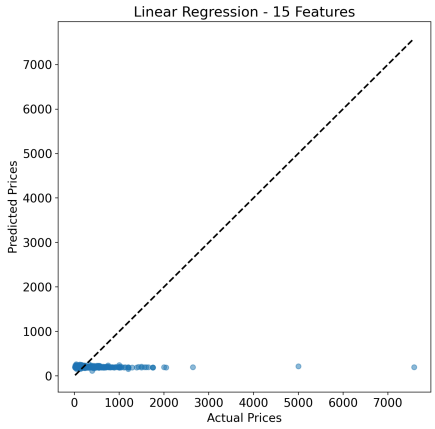
In [115…
```python
plot_actual_vs_predicted(y_test, y_pred_rf_10, 'Random Forest - 10 Features')
plot_actual_vs_predicted(y_test, y_pred_lin_10, 'Linear Regression - 10 Features')
plot_actual_vs_predicted(y_test, y_pred_xgb_10, 'XGBRegressor - 10 Features')

plot_actual_vs_predicted(y_test, y_pred_rf_15, 'Random Forest - 15 Features')
plot_actual_vs_predicted(y_test, y_pred_lin_15, 'Linear Regression - 15 Features')
plot_actual_vs_predicted(y_test, y_pred_xgb_15, 'XGBRegressor - 15 Features')

plot_actual_vs_predicted(y_test, y_pred_rf_20, 'Random Forest - 20 Features')
plot_actual_vs_predicted(y_test, y_pred_lin_20, 'Linear Regression - 20 Features')
plot_actual_vs_predicted(y_test, y_pred_xgb_20, 'XGBRegressor - 20 Features')
```

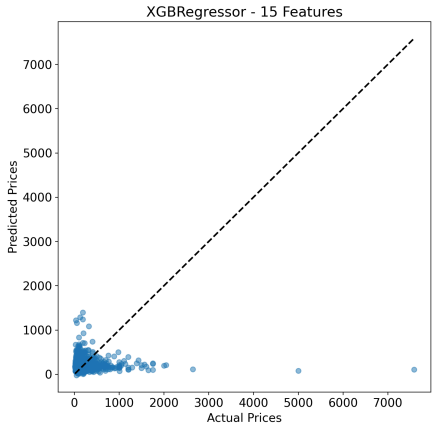


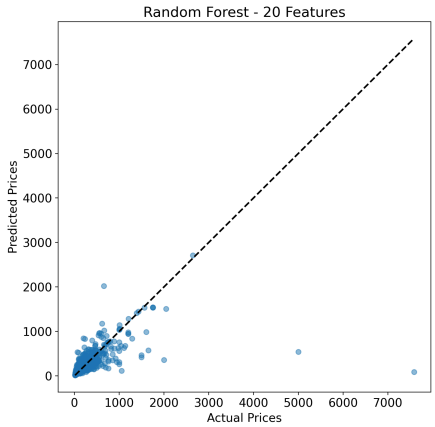


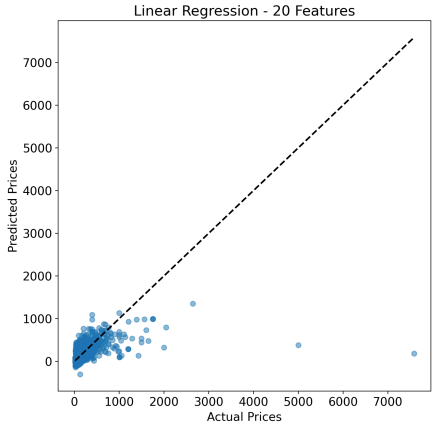

XGBRegressor - 10 Features
Predicted Prices
Actual Prices
0
1000
2000
3000
4000
5000
6000
7000

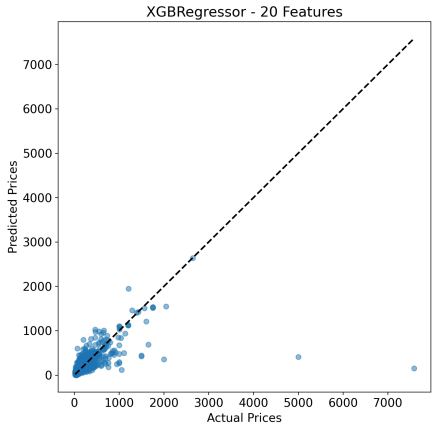

Random Forest - 15 Features
Predicted Prices
Actual Prices
0
1000
2000
3000
4000
5000
6000
7000


Linear Regression - 15 Features
Predicted Prices
Actual Prices
0
1000
2000
3000
4000
5000
6000
7000


XGBRegressor - 15 Features
Predicted Prices
Actual Prices
0
1000
2000
3000
4000
5000
6000
7000







Analysis

The analysis aims to predict Airbnb prices using different combinations of features. Three sets of features (10, 15, and 20) were evaluated with the Random Forest, Linear Regression, and XGBRegressor models. The results reveal an improvement in performance with increasing number of features, especially with 20 features. The Random Forest model outperforms the others, showing a net with a positive r2_score, suggesting a better fit to the data.

Potential reasons for these findings could include the inherent complexity of relationships between Airbnb location features and price. Adding more features may have allowed the models, particularly Random Forest, to better capture the variability in the data. However, this can also lead to overfitting to the training data, hence the need for validation on independent test datasets.

Alternatively, the models' moderate performance may be explained by the essentially complex and dynamic nature of the Airbnb rental market, where many factors can influence prices and more likely models are needed to capture these nuances. Parameter adjustments, deeper exploration of features, and use of advanced techniques could also help improve Airbnb price prediction.