Project 2: ML Modeling

For this project, classification models will be applied to predict the rating for Airbnb listings in the New York City area.

The original file containing the dataset can be found at this URL:
https://www.kaggle.com/datasets/arianazmoudeh/airbnbopendata

Part 1: Exploratory Data Analysis

Questions to answer:

1. Does the location of an Airbnb have an impact on the rating?
2. Does the number of reviews have any impact on the rating?
3. What impact does host verification, instant booking, and cancellation policy have on the rating?

Importing the modules

In [1]:
```
# importing the libraries to be used for EDA
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import statsmodels.api as sm
import seaborn as sns
from statsmodels.formula.api import ols
from pathlib import Path
```

Importing the dataset

In [2]:
```
# importing the dataset
df = pd.read_csv('C:/Users/19145/Documents/CS675_Jupyter_Notebooks/project_files/Airbnb_
df.shape
```

```
C:\Users\19145\anaconda3\lib\site-packages\IPython\core\interactiveshell.py:3165: DtypeW
arning: Columns (25) have mixed types.Specify dtype option on import or set low_memory=F
alse.
  has_raised = await self.run_ast_nodes(code_ast.body, cell_name,
```

Out[2]: (102599, 25)

The dataset will be sampled so that it will be easier to work with in jupyter.

In [3]:
```
# sample the dataset
# NOTE: This code is only executed once so that the same sample is used.
#
'''
df = df.sample(n=10000)

# Save the sampled dataset. This is only performed once.
filepath = Path('C:/Users/19145/Documents/CS675_Jupyter_Notebooks/project_files/airbnb_
filepath.parent.mkdir(parents=True, exist_ok=True)
```

```
df.to_csv(filepath, index=True)
'''
```

Out[3]:
```
"\ndf = df.sample(n=10000)\n\n# Save the sampled dataset. This is only performed once.\n
filepath = Path('C:/Users/19145/Documents/CS675_Jupyter_Notebooks/project_files/airbnb_o
pen_data_sampled.csv')  \nfilepath.parent.mkdir(parents=True, exist_ok=True)  \ndf.to_cs
v(filepath, index=True)\n"
```

In [4]:
```
# Import the sampled dataset
df = pd.read_csv('C:/Users/19145/Documents/CS675_Jupyter_Notebooks/project_files/airbnb_

# Display the first 10 rows of the dataset
df.head(10)
```

Out[4]:

	id	NAME	host id	host_identity_verified	host name	neighbourhood group	neighbourho
0	17460981	House on a quiet dead-end street in hip Ridgewood	63396104072	verified	Kelli	Queens	Glend
1	37211229	Entire 1 Bedroom apt	71565439330	verified	Kevin	Queens	Jama
2	16252548	It's All Yours: Big Beautiful 1 Bedroom in Harlem	50796166627	unconfirmed	Jahmil	Manhattan	Harl
3	23705284	Cozy Brooklyn Private Bedroom	28905384755	unconfirmed	Rachael Lee	Brooklyn	Bedfo Stuyves
4	49338632	2 Floor Condo in Williamsburg with Pvt Terrace	28447123313	verified	Thobey	Brooklyn	Williamsbu
5	43771448	Bright big bedroom in Brooklyn	77280159569	unconfirmed	Marie	Brooklyn	Kensingt
6	19873979	Private Room	51588895565	verified	Yvonne	Brooklyn	Borough P
7	29578995	City Saver in	2125505600	unconfirmed	James	Brooklyn	Sunset P

	id	NAME	host id	host_identity_verified	host name	neighbourhood group	neighbourho
		Brooklyn					
8	49615334	Cozy, cool, spacious Midtown!	19585442982	verified	Daniel	Manhattan	Murray H
9	19295721	Heaven away from Home!.	92208593104	unconfirmed	Majidudeen	Queens	Jama

10 rows × 26 columns

Data Dictionary

The sample above provides a view of the data in this dataset, including its features (columns):

id - Airbnb's unique identifier for the listing.

NAME - Name of the listing.

host id - Airbnb's unique identifier for the host/user.

host_identity_verified - t=true; f=false

host name - Name of the house. Usually just the first name(s).

neighbourhood group - The name of the bourough.

neighbourhood - The section of the bourough.

lat - latitude of the airbnb's location.

long - longitude of the airbnb's location.

country - Name of the country.

instant_bookable - (t=true; f=false). Whether the guest can automatically book the listing without the host requiring to accept their booking request. An indicator of a commercial listing.

cancellation_policy - Host's policy on cancellations.

room type - All homes are grouped into the following three room types:

Entire place Entire places are best if you're seeking a home away from home. With an entire place, you'll have the whole space to yourself. This usually includes a bedroom, a bathroom, a kitchen, and a separate, dedicated entrance. Hosts should note in the description if they'll be on the property or not (ex: ""Host occupies first floor of the home""), and provide further details on the listing.

Private rooms Private rooms are great for when you prefer a little privacy, and still value a local connection. When you book a private room, you'll have your own private room for sleeping and may share some spaces with others. You might need to walk through indoor spaces that another host or guest may occupy to get to your room.

Shared rooms Shared rooms are for when you don't mind sharing a space with others. When you book a shared room, you'll be sleeping in a space that is shared with others and share the entire space with other people. Shared rooms are popular among flexible travelers looking for new friends and budget-friendly stays."

Construction year - The year the building was built.

price - Daily price in local currency.

service fee - Fee for services provided by the host.

minimum nights - minimum number of night stays for the listing.

number of reviews - The number of reviews for the listing.

last review - The date of the most recent review.

reviews per month - The number of reviews the listing has over the lifetime of its listing.

review rate number - The rating for the listing (target variable).

calculated host listings count - The number of listings the host has in the city/region.

availability 365 - The availability of the listing x days in the future as determined by the calendar. NOTE: a listing may not be available because it has been booked by a guest or blocked by the host.

house_rules - The host's rules for the guests.

license - The license/permit/registration number.

Inspecting data types

In [5]:
```
# Return the data types of each feature.
df.dtypes
```

Out[5]:
```
id                                int64
NAME                             object
host id                           int64
host_identity_verified           object
host name                        object
neighbourhood group              object
```

```
neighbourhood                    object
lat                             float64
long                            float64
country                          object
country code                     object
instant_bookable                 object
cancellation_policy              object
room type                        object
Construction year               float64
price                           float64
service fee                     float64
minimum nights                  float64
number of reviews               float64
last review                      object
reviews per month               float64
review rate number              float64
calculated host listings count  float64
availability 365                float64
house_rules                      object
license                          object
dtype: object
```

Selecting features

Some of the features in this dataset seem unnecessary for what is to be accomplished. For example, we do not need to know the latitude and longitude of our listings since they are all located in the same geographic area (New York City). A new dataframe will be created that will exclude these features.

In [6]:
```
# Create a list for the necessary features
features = ['host_identity_verified', 'calculated host listings count', 'license',
            'neighbourhood group', 'instant_bookable', 'cancellation_policy', 'availabi
            'room type', 'Construction year', 'price', 'service fee', 'minimum nights',
            'reviews per month', 'review rate number']

# Create a new dataframe with the necessary features
df_subset_01 = df[features]
```

Some of the column names in this dataset could be improved to provide some better clarity. For example, the column 'neighbourhood group' contains the borough that the listing is located in. It would be much easier if this column was renamed 'borough' instead.

Also, the whitespaces in these column names should be replaced with underscores.

Cleaning of the data

In [7]:
```
# Rename some of the columns of the dataset.
df_subset_01.rename(columns={'host_identity_verified': 'id_verified',
                      'calculated host listings count': 'num_host_listings', 'neighbour
                        'availability 365': 'avail365', 'room type': 'room_type',
                      'Construction year': 'yr_built', 'service fee': 'service_fee', 'm
                      'number of reviews': 'num_reviews', 'reviews per month': 'monthly
                      'review rate number': 'rating'}, inplace=True)

df_subset_01.head(10)
```

```
C:\Users\19145\anaconda3\lib\site-packages\pandas\core\frame.py:4441: SettingWithCopyWar
ning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
guide/indexing.html#returning-a-view-versus-a-copy
  return super().rename(
```

Out[7]:

	id_verified	num_host_listings	license	borough	instant_bookable	cancellation_policy	avail365	ro
0	verified	1.0	NaN	Queens	False	flexible	0.0	h
1	verified	1.0	NaN	Queens	False	flexible	0.0	h
2	unconfirmed	1.0	NaN	Manhattan	True	flexible	0.0	h
3	unconfirmed	1.0	NaN	Brooklyn	False	strict	0.0	
4	verified	1.0	NaN	Brooklyn	True	moderate	0.0	h
5	unconfirmed	1.0	NaN	Brooklyn	False	strict	0.0	
6	verified	7.0	NaN	Brooklyn	False	strict	152.0	
7	unconfirmed	1.0	NaN	Brooklyn	False	moderate	0.0	h
8	verified	1.0	NaN	Manhattan	False	moderate	0.0	
9	unconfirmed	1.0	NaN	Queens	False	strict	365.0	h

Counting the number of unique values

In [8]:

```
# Count the number of unique values
unique = df_subset_01.nunique()
print("Here are the unique values in each column:")
print(unique)
```

```
Here are the unique values in each column:
id_verified               2
num_host_listings        75
license                   1
borough                   5
instant_bookable          2
cancellation_policy       3
avail365                437
room_type                 4
yr_built                 20
price                  1151
service_fee             231
min_nights               70
```

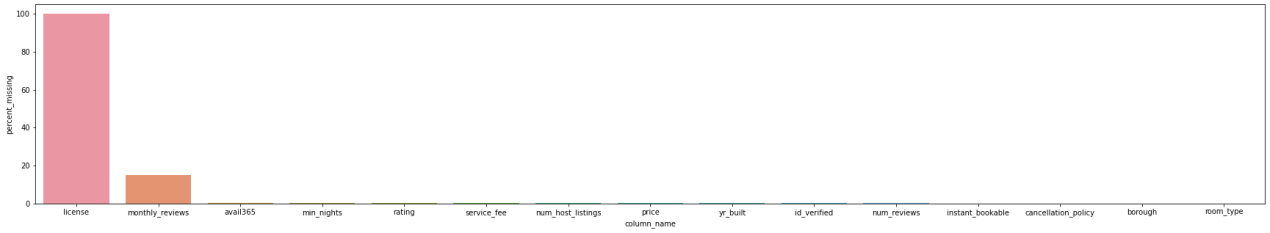
```
num_reviews             307
monthly_reviews         693
rating                    5
dtype: int64
```

Checking for missing values

In [9]:

```
# Count for missing values
print("The following is a summary of the missing values in our dataset:")
print(df_subset_01.isna().sum().sort_values(ascending=False))

# Calculate the percentage of missing values for each column
perc_missing = df_subset_01.isnull().sum() * 100 / len(df_subset_01)
df_missing_values = pd.DataFrame({'column_name': df_subset_01.columns,
                                  'percent_missing': perc_missing})
df_missing_values.sort_values('percent_missing', inplace=True, ascending=False)

# Construct a plot to display the percentages of missing values
fig, ax = plt.subplots(figsize=(30, 5))
sns.barplot(
    x='column_name',
    y='percent_missing',
    data=df_missing_values,
    ax=ax
)
plt.xlabel('column_name')
plt.ylabel('percent_missing')
plt.show()
```

```
The following is a summary of the missing values in our dataset:
license                 9999
monthly_reviews         1503
avail365                  46
min_nights                46
rating                    40
service_fee               33
num_host_listings         31
price                     29
yr_built                  28
id_verified               23
num_reviews               19
instant_bookable          16
cancellation_policy       10
borough                    3
room_type                  0
dtype: int64
```



The license column has nearly 100 percent of its values missing. Therefore, this column will be removed from the dataset. We also remove rows where borough, instant bookable, and cancellation information is missing since the count for those is relatively small.

In [10]:
```
# Remove the license column
df_subset_02 = df_subset_01.drop(['license'],axis=1)

# Remove specified rows
index_missing_val = df_subset_02[(df_subset_02['borough'].isna() == True) |
                                 (df_subset_02['instant_bookable'].isna() == True) |
                                 (df_subset_02['cancellation_policy'].isna() == True)].
df_subset_02.drop(index_missing_val, inplace=True)
df_subset_02.isna().sum()
```

Out[10]:
```
id_verified              21
num_host_listings        31
borough                   0
instant_bookable          0
cancellation_policy       0
avail365                 44
room_type                 0
yr_built                 26
price                    28
service_fee              33
min_nights               44
num_reviews              19
monthly_reviews        1503
rating                   38
dtype: int64
```

Checking for and removing duplicates

In [11]:
```
# Check for duplicates
df_subset_02[df_subset_02.duplicated()]
```

Out[11]:

	id_verified	num_host_listings	borough	instant_bookable	cancellation_policy	avail365	room_ty
1362	unconfirmed	2.0	Manhattan	True	strict	168.0	Priv ro
1579	verified	1.0	Brooklyn	False	moderate	31.0	En home/
2867	unconfirmed	12.0	Manhattan	False	strict	365.0	Priv ro
3564	unconfirmed	1.0	Queens	False	flexible	362.0	Priv ro
3906	verified	2.0	Manhattan	False	flexible	110.0	Priv ro
4060	verified	10.0	Manhattan	True	strict	350.0	En home/
4921	unconfirmed	1.0	Brooklyn	True	strict	13.0	Priv ro
5347	unconfirmed	12.0	Manhattan	False	strict	365.0	Priv ro
5622	verified	8.0	Brooklyn	False	flexible	144.0	En home/

	id_verified	num_host_listings	borough	instant_bookable	cancellation_policy	avail365	room_ty
5669	unconfirmed	1.0	Manhattan	True	strict	103.0	En home/
6095	unconfirmed	1.0	Brooklyn	True	flexible	0.0	Priv ro
6229	unconfirmed	2.0	Manhattan	False	moderate	0.0	Priv ro
6265	verified	3.0	Queens	True	flexible	140.0	Sha ro
6392	unconfirmed	1.0	Brooklyn	False	strict	364.0	Priv ro
6483	verified	1.0	Brooklyn	True	moderate	6.0	En home/
6789	verified	1.0	Brooklyn	True	flexible	0.0	Priv ro
6849	unconfirmed	1.0	Bronx	False	moderate	134.0	Priv ro
7001	unconfirmed	1.0	Queens	True	flexible	0.0	En home/
7131	verified	6.0	Manhattan	True	strict	312.0	En home/
7602	unconfirmed	1.0	Manhattan	False	flexible	56.0	En home/
7609	verified	1.0	Queens	True	flexible	126.0	Priv ro
7820	unconfirmed	1.0	Brooklyn	False	moderate	78.0	En home/
7876	verified	47.0	Manhattan	True	flexible	354.0	Priv ro
7986	verified	4.0	Brooklyn	False	strict	363.0	En home/
8080	verified	12.0	Manhattan	False	flexible	355.0	Priv ro
8154	unconfirmed	103.0	Queens	True	flexible	251.0	Priv ro
8224	verified	2.0	Brooklyn	False	flexible	0.0	Priv ro
8276	unconfirmed	1.0	Brooklyn	False	strict	270.0	En home/
8389	verified	1.0	Brooklyn	False	moderate	0.0	En home/
8668	verified	1.0	Manhattan	False	strict	34.0	Priv ro

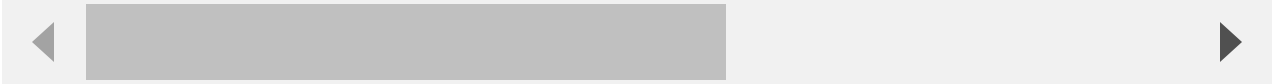
	id_verified	num_host_listings	borough	instant_bookable	cancellation_policy	avail365	room_ty
8923	verified	1.0	Manhattan	False	strict	203.0	En home/
9256	verified	1.0	Queens	False	moderate	0.0	En home/
9292	verified	3.0	Manhattan	False	moderate	62.0	Priv ro
9329	unconfirmed	1.0	Brooklyn	True	strict	35.0	En home/
9409	verified	2.0	Brooklyn	True	strict	0.0	En home/
9472	unconfirmed	3.0	Brooklyn	True	flexible	0.0	Sha ro
9507	unconfirmed	2.0	Queens	True	strict	124.0	Priv ro
9542	verified	96.0	Manhattan	True	flexible	206.0	En home/
9572	unconfirmed	1.0	Brooklyn	True	moderate	0.0	Priv ro
9628	verified	1.0	Manhattan	False	moderate	0.0	En home/
9659	unconfirmed	1.0	Manhattan	True	flexible	0.0	En home/
9698	unconfirmed	1.0	Brooklyn	False	moderate	355.0	En home/

In [12]:

```
# Drop duplicate listings
df_subset_02.drop_duplicates(subset=None, keep='first', inplace=True)

# Confirm duplicates have been removed
df_subset_02[df_subset_02.duplicated()]
```

Out[12]:

	id_verified	num_host_listings	borough	instant_bookable	cancellation_policy	avail365	room_type	yr_



Replacing missing values

The missing values for the remaining features will be replaced with default values.

In [13]:

```
# Calculating the default values
all_min_nights = np.array(df_subset_02['min_nights'].dropna())
d_nights = round(np.mean(all_min_nights))

all_ratings = np.array(df_subset_02['rating'].dropna())
```

```
d_rating = round(np.mean(all_ratings))

all_prices = np.array(df_subset_02['price'].dropna())
d_price = round(np.mean(all_prices))

all_fees = np.array(df_subset_02['service_fee'].dropna())
d_fee = round(np.mean(all_fees))
```

In [14]:

```
# Assign default values for missing values
df_subset_02['monthly_reviews'].fillna(0, inplace=True)
df_subset_02['avail365'].fillna(0, inplace=True)
df_subset_02['min_nights'].fillna(d_nights, inplace=True)
df_subset_02['rating'].fillna(d_rating, inplace=True)
df_subset_02['num_host_listings'].fillna(0, inplace=True)
df_subset_02['yr_built'].fillna(0, inplace=True)
df_subset_02['id_verified'].fillna('missing', inplace=True)
df_subset_02['num_reviews'].fillna(0, inplace=True)
df_subset_02['price'].fillna(d_price, inplace=True)
df_subset_02['service_fee'].fillna(d_fee, inplace=True)

df_subset_02.isna().sum()
```

Out[14]:

```
id_verified            0
num_host_listings      0
borough                0
instant_bookable       0
cancellation_policy    0
avail365               0
room_type              0
yr_built               0
price                  0
service_fee            0
min_nights             0
num_reviews            0
monthly_reviews        0
rating                 0
dtype: int64
```

Changing Data Types

When observing the data for many of the numeric columns, they appear to be of the float data type when they should be int. This requires a data type conversion to be performed.

In [15]:

```
# Create a dictionary for the conversion of data types
convert_dict = {
    'num_host_listings': int,
    'avail365': int,
    'min_nights': int,
    'num_reviews': int,
    'monthly_reviews': float,
    'rating': int,
    'yr_built': int,
    'price': int,
    'service_fee': int
}

# Create a new dateframe containing the converted columns
df_subset_03 = df_subset_02.astype(convert_dict)
```

```
# Confirm the new data types
df_subset_03.dtypes
```

Out[15]:
```
id_verified             object
num_host_listings        int32
borough                 object
instant_bookable        object
cancellation_policy     object
avail365                 int32
room_type               object
yr_built                 int32
price                    int32
service_fee              int32
min_nights               int32
num_reviews              int32
monthly_reviews        float64
rating                   int32
dtype: object
```

View Descriptive Statistics

In [16]:
```
df_subset_03.describe()
```

Out[16]:

	num_host_listings	avail365	yr_built	price	service_fee	min_nights	num_reviews
count	9939.000000	9939.000000	9939.000000	9939.000000	9939.000000	9939.000000	9939.000000
mean	7.754502	140.815776	2007.235235	623.021833	124.595633	7.859342	27.880672
std	32.264418	134.788358	102.962455	329.787203	65.916611	20.245533	50.104251
min	0.000000	-10.000000	0.000000	50.000000	10.000000	-12.000000	0.000000
25%	1.000000	3.000000	2007.500000	341.000000	68.000000	1.000000	1.000000
50%	1.000000	97.000000	2012.000000	621.000000	124.000000	3.000000	7.000000
75%	2.000000	267.000000	2017.000000	907.000000	181.000000	5.000000	31.000000
max	332.000000	426.000000	2022.000000	1200.000000	240.000000	999.000000	618.000000

The descriptive statistics table shows that there are negative values for the avail365 and min_nights columns. This is indicated by the minimum value for each column. These values will be replaced with their respective rounded means.

In [17]:
```
# Get the mean values for both availability and minimum number of nights
avail_mean = round(df_subset_03['avail365'].mean())
min_night_mean = round(df_subset_03['min_nights'].mean())

# Get the number of rows in the dataframe
rows = df_subset_03.shape[0]

# Loop through the dataset and replace negative values for availability
for n in range(0, rows):
    val = df_subset_03.iloc[n, df_subset_03.columns.get_loc('avail365')]
    if val < 0:
```

```
        val = avail_mean
        df_subset_03.iloc[n, df_subset_03.columns.get_loc('avail365')] = val

for m in range(0, rows):
    val = df_subset_03.iloc[m, df_subset_03.columns.get_loc('min_nights')]
    if val < 0:
        val = min_night_mean
        df_subset_03.iloc[m, df_subset_03.columns.get_loc('min_nights')] = val
```

In [18]:
```
# Re-examine descriptive statistics to make sure no other alterations were made to any
df_subset_03.describe()
```

Out[18]:

	num_host_listings	avail365	yr_built	price	service_fee	min_nights	num_reviews
count	9939.000000	9939.000000	9939.000000	9939.000000	9939.000000	9939.000000	9939.000000
mean	7.754502	141.583962	2007.235235	623.021833	124.595633	7.863165	27.880672
std	32.264418	134.367980	102.962455	329.787203	65.916611	20.243760	50.104251
min	0.000000	0.000000	0.000000	50.000000	10.000000	1.000000	0.000000
25%	1.000000	4.000000	2007.500000	341.000000	68.000000	1.000000	1.000000
50%	1.000000	101.000000	2012.000000	621.000000	124.000000	3.000000	7.000000
75%	2.000000	267.000000	2017.000000	907.000000	181.000000	5.000000	31.000000
max	332.000000	426.000000	2022.000000	1200.000000	240.000000	999.000000	618.000000

The descriptive statistics table above confirms that the changes were successfully made.

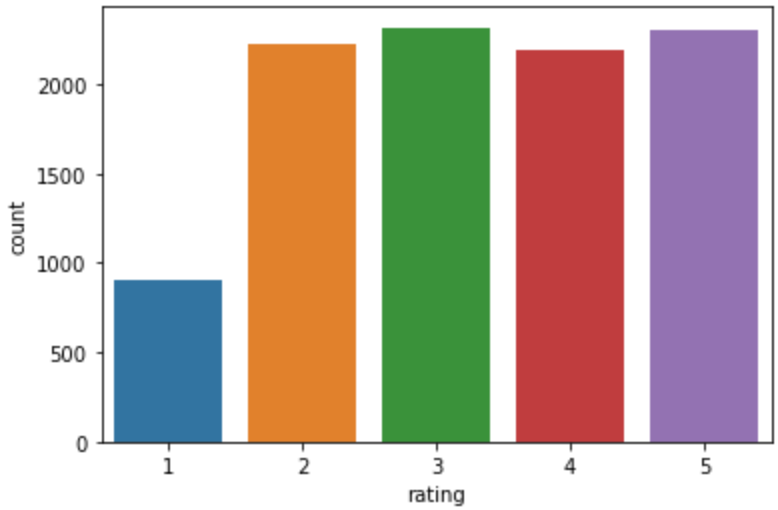
Plotting the target variable

The target variable for this dataset is the rating feature. The rating is the score for the listing ranging from 1 (Lowest) to 5 (Highest). Many guests would use this feature when deciding on a place to stay.

The rating feature will be plotted to identify any skewness in the data.

In [19]:
```
sns.countplot(x='rating', data=df_subset_03)
```

Out[19]:
```
<AxesSubplot:xlabel='rating', ylabel='count'>
```



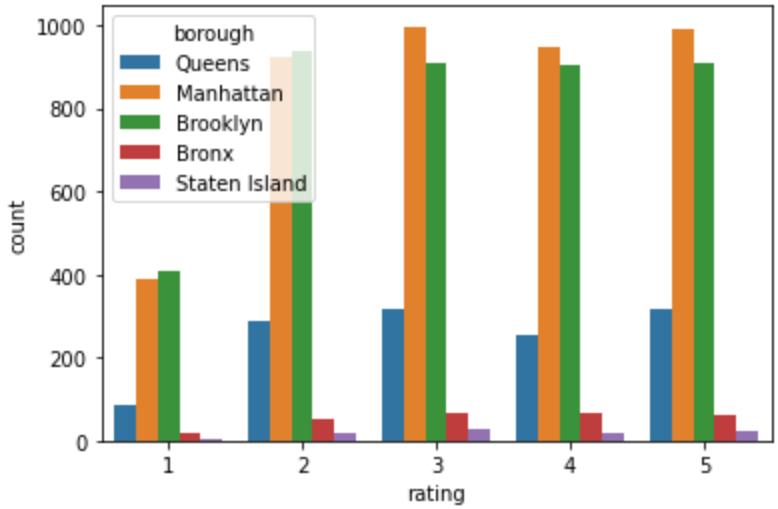
The plot above shows that the data is skewed to the right because the count of listings that received a rating of 1 is much lower that the rest. However, the count for all the other ratings appears to be more or less the same. This may indicate that making a prediction could be a challenge.

Q1: Does the location of an Airbnb have an impact on the rating?

To answer this question, the number of listings in each borough by rating will be plotted.

In [20]:
```
sns.countplot(x='rating', hue='borough', data=df_subset_03)
```

Out[20]:
```
<AxesSubplot:xlabel='rating', ylabel='count'>
```



The plot above shows that the number of listings in the boroughs of Brooklyn and Manhattan based on rating are much higher than the rest. This does not tell us anything significant about how it impacts the rating because the patterns are very identical.

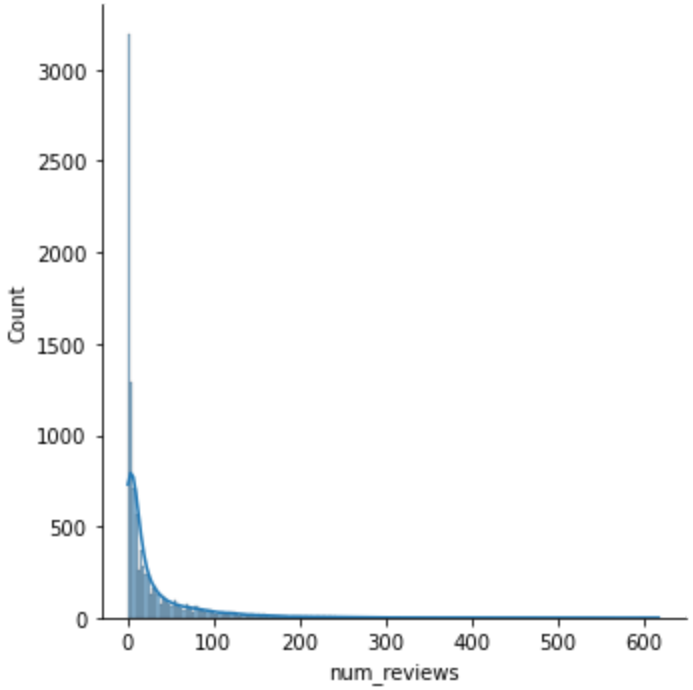
Q2: Do the number of reviews having any impact on the rating?

To determine if the number of reviews that a listing receives has any impact on its ratings, we will calculate the number of listings that were reviewed by rating, followed by the percentage of reviews of listings based on the rating.

First, we will observe the distribution of reviews.

In [21]:
```
# Plot the overall distribution of reviews
sns.displot(x='num_reviews', data=df_subset_03, kde=True)
```

Out[21]: <seaborn.axisgrid.FacetGrid at 0x1bdaff3c430>

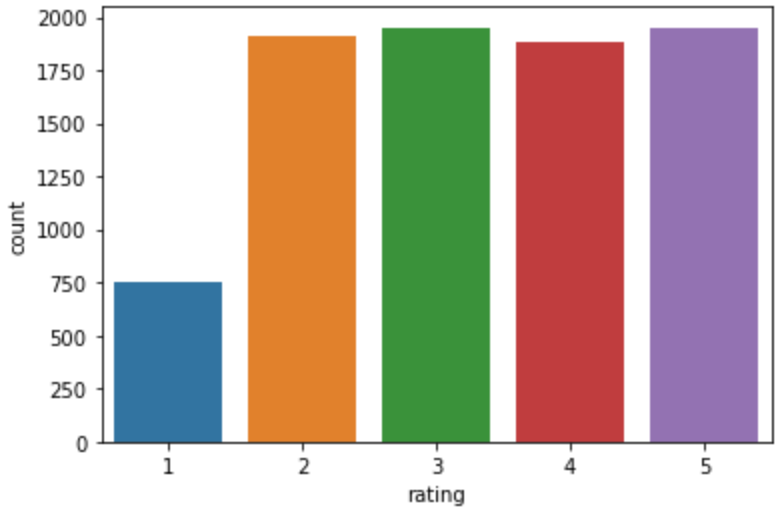


The plot shows that there is a extremely narrow distribution skewed to the left, close to where no reviews were written for a good majority of the listings. This can be based on the fact that many people do not feel comfortable with writing reviews.

Next, the number of listings that received reviews will be observed.

In [22]:
```
# Filter dataset for listings that received reviews.
df_filter_reviews = df_subset_03[(df_subset_03['num_reviews'] > 0)]

# Plot the dataset
sns.countplot(data=df_filter_reviews, x='rating')
```

Out[22]: <AxesSubplot:xlabel='rating', ylabel='count'>



The plot shows that all listings with a rating greater than 1 received just about the same number of reviews. This does not provide any indication that the number of reviews have an impact on the rating.

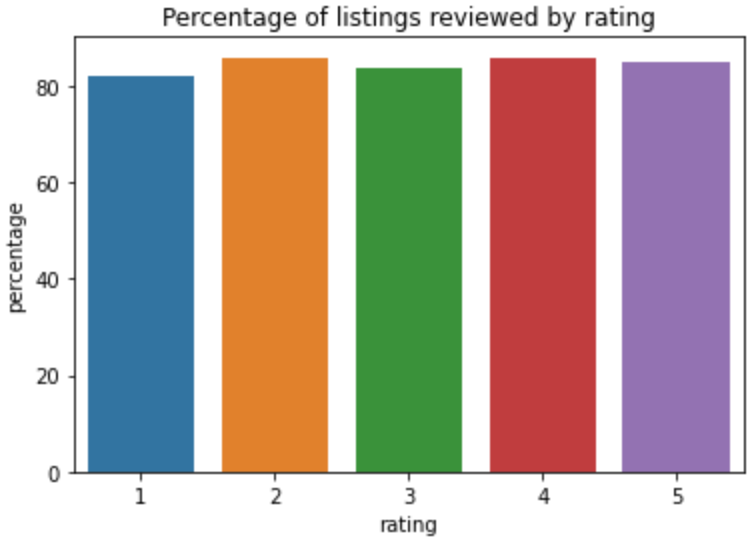
We could observe the percentage of listings that received reviews based on rating.

In [23]:

```
# List of ratings
ratings_list = df_subset_03['rating'].unique().tolist()
ratings_list.sort()

# Create list for the percentages
percent_reviewed = []

# For each rating, calculate the percentage of listings with that rating that received
for n in ratings_list:
    sum_listings_reviewed = len(df_subset_03[(df_subset_03['rating'] == n) & (df_subset
    length = len(df_subset_03[(df_subset_03['rating'] == n)])
    percentage_reviewed_by_rating = sum_listings_reviewed * 100 / length
    percent_reviewed.append(round(percentage_reviewed_by_rating))

ratings_reviewed_df = pd.DataFrame({'rating': ratings_list, 'percentage': percent_revie
sns.barplot(data=ratings_reviewed_df, x='rating', y='percentage').set(title='Percentage
```

Out[23]:

```
[Text(0.5, 1.0, 'Percentage of listings reviewed by rating')]
```



The plot shows that all the listings by rating received about the same percentage of reviews. This also tells us that more people were willing to leave a review than what was originally believed from the distribution plot.

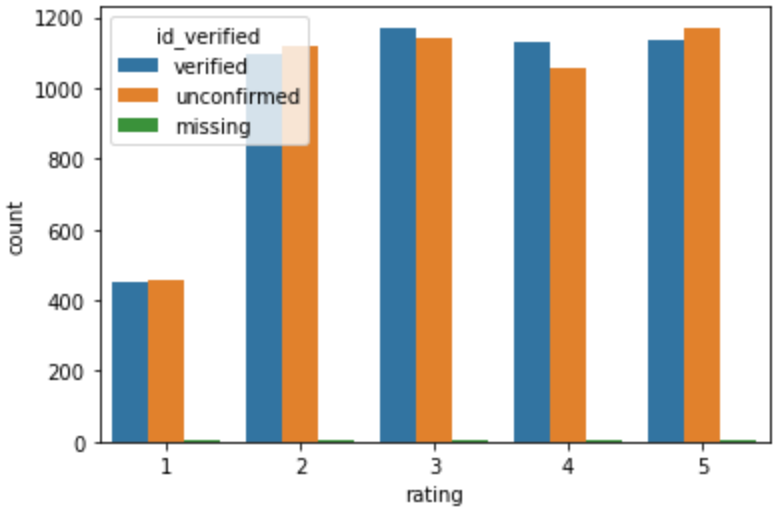
Q3: What impact does host verification, instant booking, and cancellation policy have on the rating?

Let's look at the categorical features and investigate their impact.

Host verification

In [24]:
```
sns.countplot(data=df_subset_03, x='rating', hue='id_verified')
```

Out[24]:
```
<AxesSubplot:xlabel='rating', ylabel='count'>
```

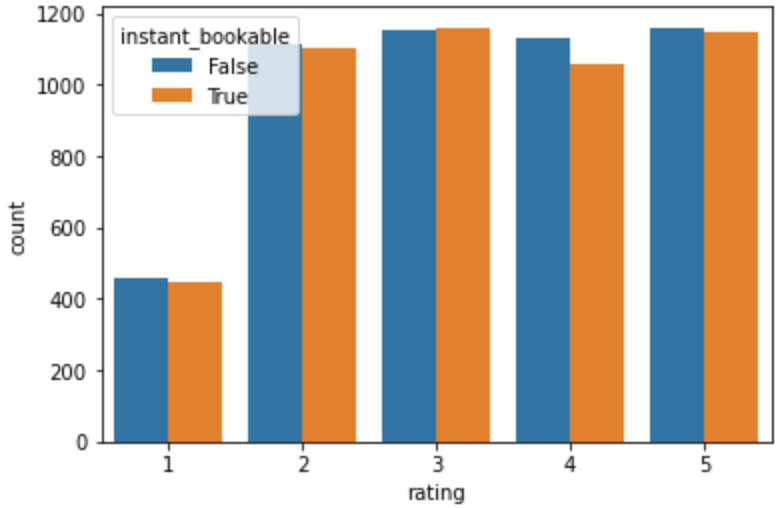


For host verification, there seems to be a little influence on the rating. For listings with a rating of 3 or 4, there is a slightly higher number of listings with confirmed verifications than those whose host verification status is unconfirmed. For listings with other ratings, it appears the number of unconfirmed verifications are higher. Even though it appears to be a slight difference, it is an interesting development.

Instant Booking Status

In [25]:
```
sns.countplot(data=df_subset_03, x='rating', hue='instant_bookable')
```

Out[25]: <AxesSubplot:xlabel='rating', ylabel='count'>

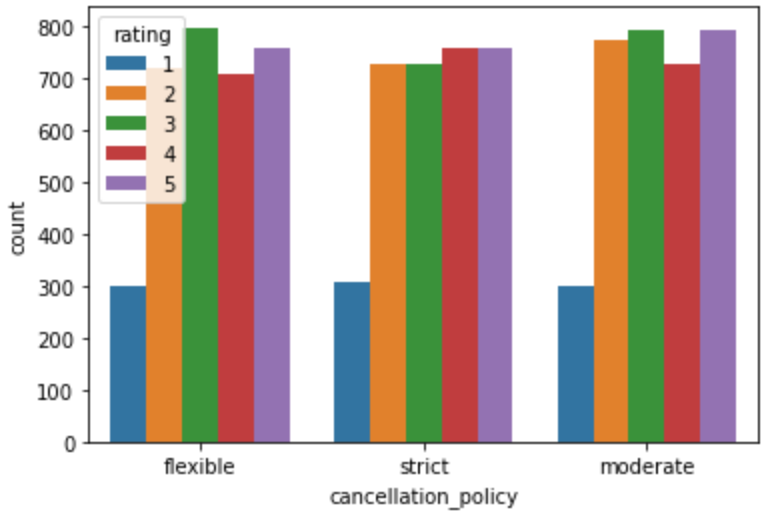


The booking status date shows that there is a greater number of listings that do not offer instant booking. The difference between listings that do not offer instant booking and those that do is most apparent with listings with a rating of 4. This could indicate that predicting the rating based on booking status would be easier for the model than it would be for the other features that were examined so far.

Cancellation Policy

In [26]:
```
sns.countplot(data=df_subset_03, x='cancellation_policy', hue='rating')
```

Out[26]: <AxesSubplot:xlabel='cancellation_policy', ylabel='count'>



Listings with a rating of 3 offer more flexible cancellations than the other listings, while listings with a rating of 4 or 5 offer more strict cancellations. This could also play a role in determining the rating.

Part 2: Feature Engineering

One Hot Encoding

The OHE process will transform categorical variables into numeric ones so that they can be used by the model. The old columns will then be replaced with the new columns in the dataset.

Id_verified

In [27]:
```
dummy = pd.get_dummies(df_subset_03['id_verified'])
dummy.head()
```

Out[27]:

	missing	unconfirmed	verified
0	0	0	1
1	0	0	1
2	0	1	0
3	0	1	0
4	0	0	1

In [28]:
```
df_subset_03 = pd.concat([df_subset_03, dummy], axis=1).drop('id_verified', axis=1)
df_subset_03.rename(columns={'missing':'host_missing', 'unconfirmed':'host_unconfirmed'
df_subset_03.head()
```

Out[28]:

	num_host_listings	borough	instant_bookable	cancellation_policy	avail365	room_type	yr_built	pri
0	1	Queens	False	flexible	0	Entire home/apt	2012	2
1	1	Queens	False	flexible	0	Entire home/apt	2022	9
2	1	Manhattan	True	flexible	0	Entire home/apt	2019	11
3	1	Brooklyn	False	strict	0	Private room	2018	9
4	1	Brooklyn	True	moderate	0	Entire home/apt	2004	6

instant_bookable

In [29]:
```
dummy1 = pd.get_dummies(df_subset_03['instant_bookable'], drop_first=True)
dummy1.head()
```

Out[29]:

	True
0	0
1	0
2	1
3	0
4	1

In [30]:

```
df_subset_03 = pd.concat([df_subset_03, dummy1], axis=1).drop('instant_bookable', axis=
df_subset_03.rename(columns={True:'instant_booking'}, inplace=True)
df_subset_03.head()
```

Out[30]:

	num_host_listings	borough	cancellation_policy	avail365	room_type	yr_built	price	service_fee	m
0	1	Queens	flexible	0	Entire home/apt	2012	232	46	
1	1	Queens	flexible	0	Entire home/apt	2022	996	199	
2	1	Manhattan	flexible	0	Entire home/apt	2019	1127	225	
3	1	Brooklyn	strict	0	Private room	2018	971	194	
4	1	Brooklyn	moderate	0	Entire home/apt	2004	653	131	

Cancellation_policy

In [31]:

```
dummy2 = pd.get_dummies(df_subset_03['cancellation_policy'])
dummy2.head()
```

Out[31]:

	flexible	moderate	strict
0	1	0	0
1	1	0	0
2	1	0	0
3	0	0	1
4	0	1	0

In [32]:

```
df_subset_03 = pd.concat([df_subset_03, dummy2], axis=1).drop('cancellation_policy', ax
df_subset_03.rename(columns={'moderate':'cancel_moderate', 'strict':'cancel_strict', 'f
df_subset_03.head()
```

Out[32]:

	num_host_listings	borough	avail365	room_type	yr_built	price	service_fee	min_nights	num_revie
0	1	Queens	0	Entire home/apt	2012	232	46	5	
1	1	Queens	0	Entire home/apt	2022	996	199	1	
2	1	Manhattan	0	Entire home/apt	2019	1127	225	3	
3	1	Brooklyn	0	Private room	2018	971	194	3	
4	1	Brooklyn	0	Entire home/apt	2004	653	131	1	

borough

In [33]:
```
dummy3 = pd.get_dummies(df_subset_03['borough'])
dummy3
```

Out[33]:

	Bronx	Brooklyn	Manhattan	Queens	Staten Island
0	0	0	0	1	0
1	0	0	0	1	0
2	0	0	1	0	0
3	0	1	0	0	0
4	0	1	0	0	0
...	...	...	...	...	...
9995	0	1	0	0	0
9996	0	0	1	0	0
9997	0	0	1	0	0
9998	0	0	1	0	0
9999	0	0	0	1	0

9939 rows × 5 columns

In [34]:
```
df_subset_03 = pd.concat([df_subset_03, dummy3], axis=1).drop('borough', axis=1)
df_subset_03.head()
```

Out[34]:

	num_host_listings	avail365	room_type	yr_built	price	service_fee	min_nights	num_reviews	monthl
0	1	0	Entire home/apt	2012	232	46	5	1	

	num_host_listings	avail365	room_type	yr_built	price	service_fee	min_nights	num_reviews	monthl
1	1	0	Entire home/apt	2022	996	199	1	1	
2	1	0	Entire home/apt	2019	1127	225	3	5	
3	1	0	Private room	2018	971	194	3	1	
4	1	0	Entire home/apt	2004	653	131	1	0	

5 rows × 22 columns

room_type

In [35]:
```
dummy4 = pd.get_dummies(df_subset_03['room_type'])
dummy4
```

Out[35]:

	Entire home/apt	Hotel room	Private room	Shared room
0	1	0	0	0
1	1	0	0	0
2	1	0	0	0
3	0	0	1	0
4	1	0	0	0
...	...	...	...	...
9995	0	0	0	1
9996	1	0	0	0
9997	1	0	0	0
9998	1	0	0	0
9999	0	0	1	0

9939 rows × 4 columns

In [36]:
```
df_subset_03 = pd.concat([df_subset_03, dummy4], axis=1).drop('room_type', axis=1)
df_subset_03.head()
```

Out[36]:

	num_host_listings	avail365	yr_built	price	service_fee	min_nights	num_reviews	monthly_reviews	r
0	1	0	2012	232	46	5	1	0.08	
1	1	0	2022	996	199	1	1	0.09	

	num_host_listings	avail365	yr_built	price	service_fee	min_nights	num_reviews	monthly_reviews	r
2	1	0	2019	1127	225	3	5	0.31	
3	1	0	2018	971	194	3	1	0.21	
4	1	0	2004	653	131	1	0	0.00	

5 rows × 25 columns

Splitting the dataset

The dataset will be split between the input (feature) variables and the target variable (rating). Then, the dataset will be divided into training data and testing data. The training data will be applied to the model so that it can perform machine learning on the dataset, then it will apply what it learned to the testing data by making predictions on the dataset.

The features to be used in the model will be the ones that were examined during the EDA.

In [37]:
```
# Split the dataset into features and the target variable
feature_cols = ['Bronx', 'Brooklyn', 'Queens', 'Manhattan', 'Staten Island', 'host_veri
                'host_missing', 'instant_booking', 'cancel_moderate', 'cancel_strict',
X = df_subset_03[feature_cols] # Features
y = df_subset_03.rating # Target

# import the training and testing modules
from sklearn.model_selection import train_test_split

# 80% of the dataset will be used for training, leaving 20% for testing
X_train, X_test, y_train, y_test =train_test_split(X,y,test_size= 0.20, random_state=16
```

Standardization

In [38]:
```
# import the standard scaler
from sklearn.preprocessing import StandardScaler

# Scale the input data
sc_X = StandardScaler()
X_train = sc_X.fit_transform(X_train)
X_test = sc_X.fit_transform(X_test)
```

Import and train the Gaussian NB model

The first model that will be used to make predictions is the Gaussian NB model. NB stands for Naive Bayes, which is one of the more popular models used for performing classifications.

In [39]:
```
# Import the Gaussian NB model
from sklearn.naive_bayes import GaussianNB

# Instantiate the model
```

```
gnb = GaussianNB()

# Perform the predictions
y_pred = gnb.fit(X_train, y_train).predict(X_test)

# Display results
result = pd.DataFrame({'Actual' : y_test, 'Predicted' : y_pred})
result
```

Out[39]:

	Actual	Predicted
3381	2	2
4642	4	2
230	5	2
8034	1	2
3879	4	2
...	...	...
9065	4	2
9425	2	2
3753	1	4
697	2	2
3762	1	2

1988 rows × 2 columns

In [40]:

```
from sklearn import metrics

# Print number of mislabled points
print("Number of mislabeled points out of a total %d points: %d" % (X_test.shape[0], (y
# Print accuracy score
gnb_accuracy = metrics.accuracy_score(y_test, y_pred)
print("Accuracy: " + str(gnb_accuracy))
```

```
Number of mislabeled points out of a total 1988 points: 1538
Accuracy: 0.22635814889336017
```

Mislabeled points: 1538 out of 1988 points

Accuracy: 0.22635814889336017

The number of mislabeled data points and the accuracy score indicate that the model did not perform well on the testing data. This is probably due to the lack of impact the features examined in the EDA had on the rating.

To confirm this, we could look at the prior probabilities for each ratings.

Prior probabilities for each rating

In [41]:

```
# Get the class labels from the model
class_labels = gnb.classes_
```

```
# Get the probabilities for each class
class_prob = gnb.class_prior_

# Create a Dataframe for the class probabilities
class_prob_df = pd.DataFrame({'class': class_labels, 'probability': class_prob})
class_prob_df
```

Out[41]:

	class	probability
0	1	0.087662
1	2	0.224249
2	3	0.230663
3	4	0.222488
4	5	0.234939

The dataframe above shows that the similar probabilities for all listings based on rating (with the exception of those with a rating of 1) would have an effect on the model's ability to make a correct prediction. This was a hypothesis that was stated earlier in the EDA when counting the number of listings based on rating.

Evaluating Gaussian NB Model

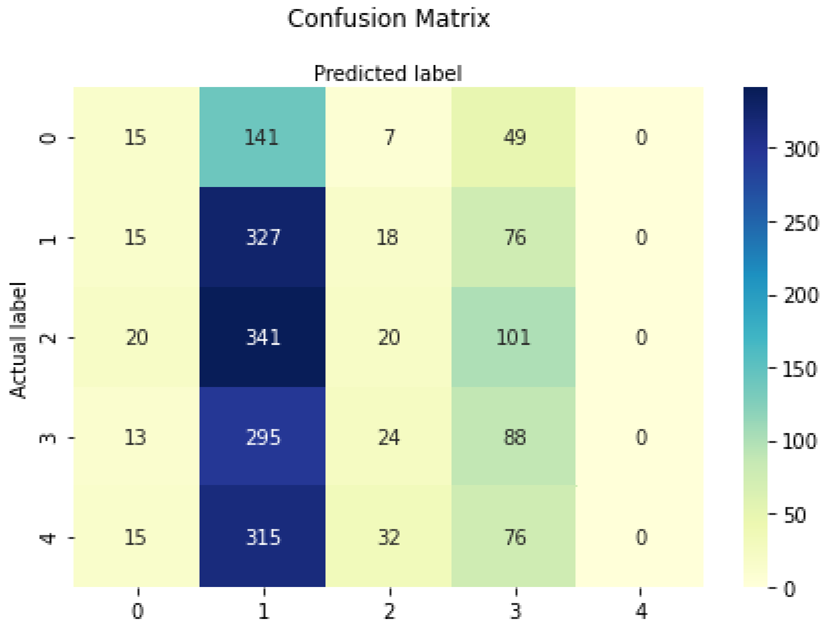
Confusion Matrix

In [42]:

```
# import the metrics class
from sklearn import metrics

# passing actual and predicted values
cnf_matrix = metrics.confusion_matrix(y_test, y_pred)

class_names = gnb.classes_ # name of classes
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)

# create heatmap
sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion Matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

Out[42]:

```
Text(0.5, 257.44, 'Predicted label')
```



The confusion matrix shows that there were a high number of predictions for listings having a rating of 2 (the model represented this as class label '1'). This means that the model showed some bias towards this label for some reason. Also, the model did not predict any listing to have a rating of 5 (or class label '4').

Classification report

In [43]:
```
from sklearn.metrics import classification_report
target_names = ['1', '2', '3', '4', '5']
print(classification_report(y_test, y_pred, target_names=target_names))
```

```
              precision    recall  f1-score   support

           1       0.19      0.07      0.10       212
           2       0.23      0.75      0.35       436
           3       0.20      0.04      0.07       482
           4       0.23      0.21      0.22       420
           5       0.00      0.00      0.00       438

    accuracy                           0.23      1988
   macro avg       0.17      0.21      0.15      1988
weighted avg       0.17      0.23      0.15      1988

C:\Users\19145\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1245: Unde
finedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\19145\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1245: Unde
finedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\19145\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1245: Unde
finedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

As stated before, the Gaussian NB model had an accuracy of 23%. In regards to each rating, it had the highest accuracy for listings with a rating of 2. This was evident in the confusion matrix.

Precision: Measures the percentage of listings that actually received the rating that they were predicted to have. There is a tie among listings with ratings of 2 and 4.

Recall: Measures the percentage of listings whose rating the model was able to identify. It had the highest recall for listings with a rating of 2 (75%).

Improve Gaussian NB Model

To improve the model, the amount of testing data will be increased to 30% (70% of the data will be used for training).

In [44]:
```
# 70% of the dataset will be used for training, leaving 30% for testing
X_train, X_test, y_train, y_test =train_test_split(X,y,test_size= 0.30, random_state=16

# Scale the input data
sc_X = StandardScaler()
X_train = sc_X.fit_transform(X_train)
X_test = sc_X.fit_transform(X_test)

# Instantiate the model
gnb_01 = GaussianNB()

# Perform the predictions
y_pred = gnb_01.fit(X_train, y_train).predict(X_test)

# Display results
result_01 = pd.DataFrame({'Actual' : y_test, 'Predicted' : y_pred})
result_01
```

Out[44]:

	Actual	Predicted
3381	2	2
4642	4	4
230	5	3
8034	1	2
3879	4	3
...	...	...
7204	3	4
133	3	2
3658	4	2
5007	5	2
9125	3	3

2982 rows × 2 columns

In [45]:
```
# Print number of mislabled points
print("Number of mislabeled points out of a total %d points: %d" % (X_test.shape[0], (y
# Print accuracy score
```

```
gnb_01_accuracy = metrics.accuracy_score(y_test, y_pred)
print("Accuracy: " + str(gnb_01_accuracy))
```

```
Number of mislabeled points out of a total 2982 points: 2327
Accuracy: 0.21965124077800133
```

Mislabeled points: 2327 out of 2982 points

Accuracy: 0.21965124077800133

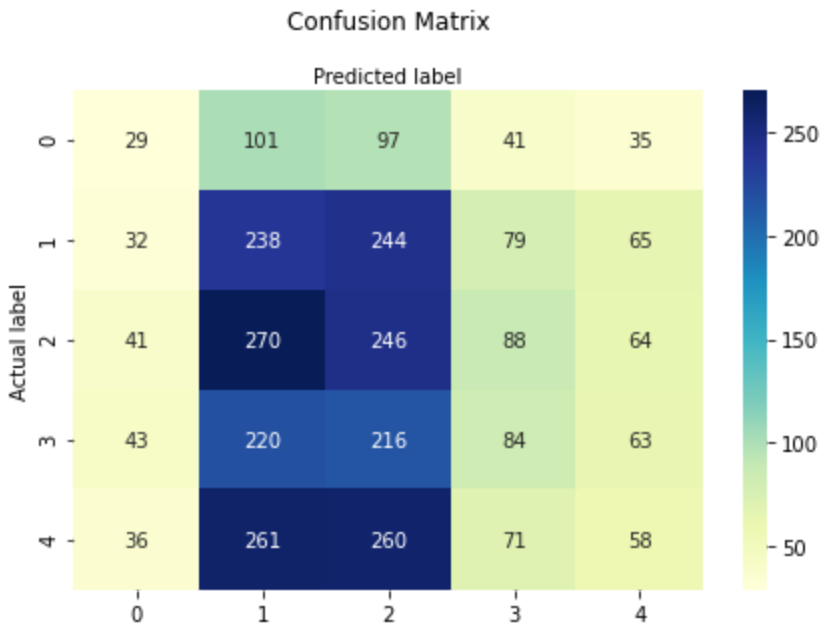
Judging from the Accuracy score, the model performed slightly worse with the increase in testing data. This means that more testing data did not improve the model.

Confusion Matrix

In [46]:

```
# passing actual and predicted values
cnf_matrix = metrics.confusion_matrix(y_test, y_pred)

class_names = gnb_01.classes_ # name of classes
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)

# create heatmap
sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion Matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

Out[46]: `Text(0.5, 257.44, 'Predicted label')`



The confusion matrix now shows that the majority of predictions were for listings with ratings of 2-3. Also, the model was able to predict listings with a rating of 5, as it was not able to do so in its previous run.

Classification Report

In [47]:
```
from sklearn.metrics import classification_report
target_names = ['1', '2', '3', '4', '5']
print(classification_report(y_test, y_pred, target_names=target_names))
```

```
              precision    recall  f1-score   support

           1       0.16      0.10      0.12       303
           2       0.22      0.36      0.27       658
           3       0.23      0.35      0.28       709
           4       0.23      0.13      0.17       626
           5       0.20      0.08      0.12       686

    accuracy                           0.22      2982
   macro avg       0.21      0.20      0.19      2982
weighted avg       0.21      0.22      0.20      2982
```

The precision of the model improve to 21%. This can be contributed to being able to identify listings with the highest rating. It also shows a more balanced amount of precision among listings based on rating.

For recall, it was highest for listings with ratings of 2-3.

Import and train the Decision Tree model

The second model that will be used to classify the dataset is the Decision Tree. This model uses a tree-like structure to make predictions on data. This includes branching out until it has enough data to make a decision in regards to a data point.

In [48]:
```
# Import the Decision Tree Classifier
from sklearn.tree import DecisionTreeClassifier
```

Splitting the dataset

In [49]:
```
# Perform another splitting of the dataset, including more features
feature_cols_dt = ['Bronx', 'Brooklyn', 'Queens', 'Manhattan', 'Staten Island', 'host_v
                'host_missing', 'instant_booking', 'cancel_moderate', 'cancel_strict',
                   'price', 'service_fee', 'min_nights', 'num_reviews', 'monthly_review
X1 = df_subset_03[feature_cols_dt] # Features
y1 = df_subset_03.rating # Target
```

Training and Testing data

In [50]:
```
# assign test data size to 20%
X1_train, X1_test, y1_train, y1_test = train_test_split(X1, y1, test_size = 0.20, rando
```

Build the Decision Tree model

In [51]:
```
# Create the Decision Tree Classifier
dtc = DecisionTreeClassifier()
```

```
# Train the Decision Tree Classifier
dtc = dtc.fit(X1_train, y1_train)

# Make the predictions
y1_pred = dtc.predict(X1_test)
```

Evaluate the Decision Tree

Accuracy

In [52]:

```
# Print the accuracy of the classifier
print("Accuracy: ", metrics.accuracy_score(y1_test, y1_pred))
```

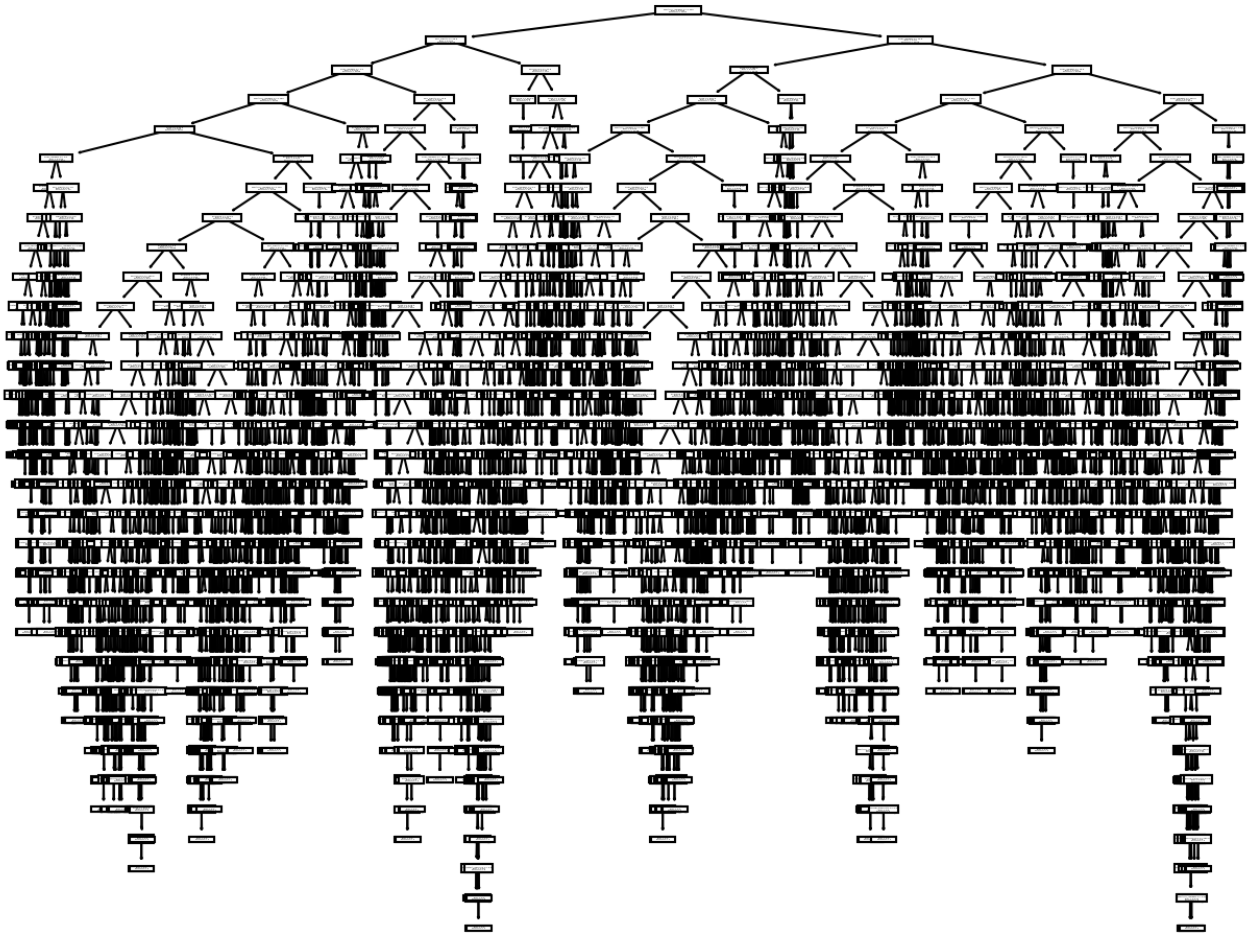
```
Accuracy:  0.2454728370221328
```

The Accuracy returned a score of approximately 26%, which is better than the Naive Bayes model, but is still poor.

Visualize the Decision Tree

In [53]:

```
# Import module for visualizing the Decision Tree
from sklearn.tree import plot_tree
plt.figure(figsize=(10,8), dpi=150)
plot_tree(dtc, feature_names=feature_cols_dt);
```



The Decision Tree produced by the model is a messy one. It is difficult to determine anything from this visualization, especially information regarding how decisions are made when trying to reach a prediction. Therefore, the classifier will have to be modified in an attempt to improve acccuracy.

Retrain the Model

In [54]:
```
# Create the Decision Tree Classifier
# The splitting strategy and max levels of branching will be modified
dtc = DecisionTreeClassifier(max_depth=3)

# Train the Decision Tree Classifier
dtc = dtc.fit(X1_train, y1_train)

# Make the predictions
y1_pred = dtc.predict(X1_test)
```

Print the Accuracy of the re-trained model

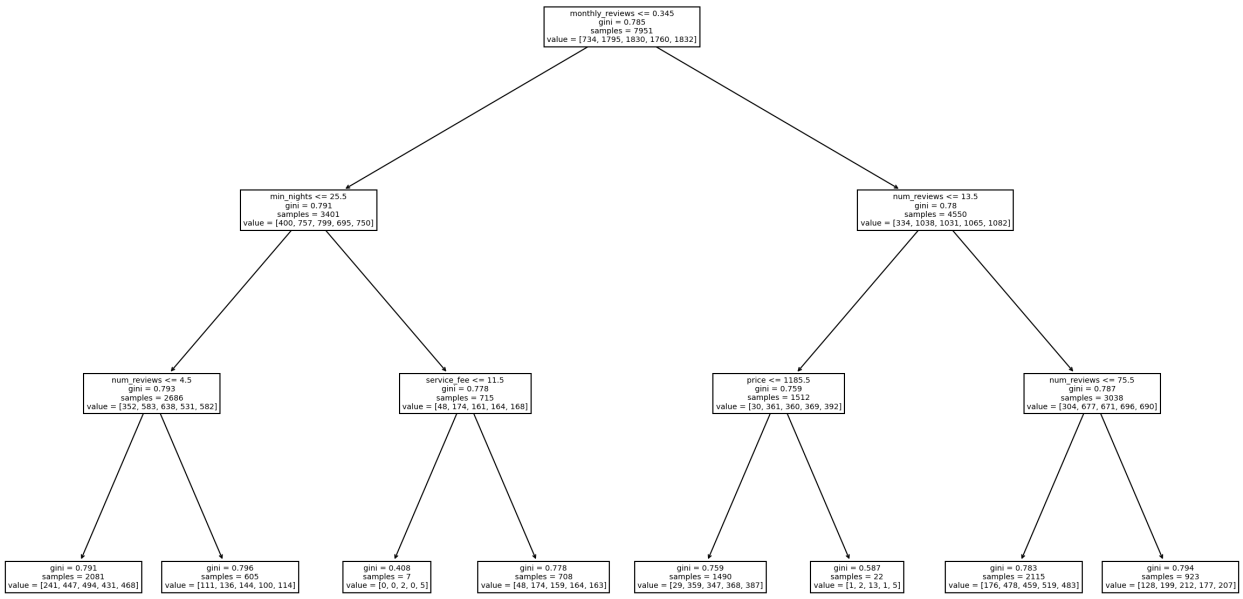
In [55]:
```
# Print the accuracy of the classifier
print("Accuracy: ", metrics.accuracy_score(y1_test, y1_pred))
```

```
Accuracy:  0.22334004024144868
```

The reduced Accuracy score of approximately 22% shows that reducing the levels did not improve the model's performance.

Another visualization of the Decision Tree

In [56]:
```
# Import module for visualizing the Decision Tree
from sklearn.tree import plot_tree
plt.figure(figsize=(20,12), dpi=150)
plot_tree(dtc, feature_names=feature_cols_dt);
```



This shortened version of the Decision Tree allows the viewing of insights into how the tree is constructed. The root node is a test of the monthly reviews attribute. According to the model, the monthly reviews attribute received the highest importance in predicting a rating. Based on its value (being less than or equal to 0.345), it would make a decision on what attribute (or feature) to examine less. For example, depending on the value, either the minimum nights attribute would be examined next, or the number of reviews attribute would be examined.

When it comes to guests making a decision about an Airbnb listing, this model suggests that observing the average number of reviews a listing receives a month would be their first metric towards making a decision. This makes sense since the number of reviews per month represent the frequency of occupancy at a listing.

Examine Coefficients

In [57]:
```
feature_names = X1.columns
importance = dtc.feature_importances_

coefficients_df = pd.DataFrame({'feature': feature_names,
                                'importance': importance})
coefficients_df
```

Out[57]:

	feature	importance
0	Bronx	0.000000
1	Brooklyn	0.000000
2	Queens	0.000000
3	Manhattan	0.000000
4	Staten Island	0.000000

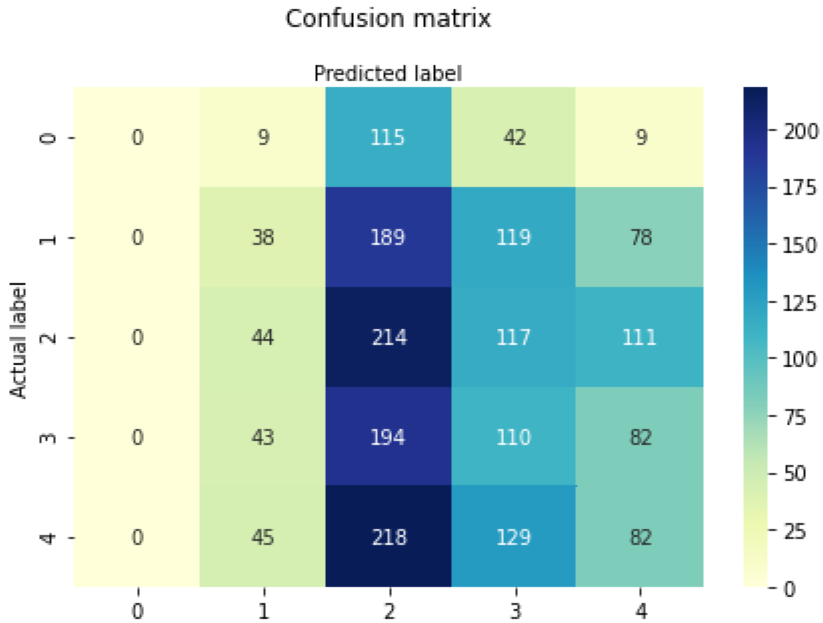
	feature	importance
5	host_verified	0.000000
6	host_unconfirmed	0.000000
7	host_missing	0.000000
8	instant_booking	0.000000
9	cancel_moderate	0.000000
10	cancel_strict	0.000000
11	cancel_flexible	0.000000
12	avail365	0.000000
13	price	0.128927
14	service_fee	0.076172
15	min_nights	0.109040
16	num_reviews	0.491834
17	monthly_reviews	0.194027

From the list of coefficients, it is clearly indicated that the model did not include any of the categorical variables, choosing to focus on the numeric variables instead to make its predictions. This would suggest that a guest would be more swayed by quantitative metrics as opposed to qualitative ones.

Confusion Matrix

In [58]:
```
# passing actual and predicted values
cnf_matrix = metrics.confusion_matrix(y1_test, y1_pred)

class_names = dtc.classes_
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)

# create heatmap
sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

Out[58]:
```
Text(0.5, 257.44, 'Predicted label')
```



According to the Confusion Matrix, the Decision Tree predicted the value '3' for the majority of its ratings (this is given the class label of '2'). It also showed a failure to predict '1' for any listings' rating (this is given the class label of '0'). This bias contributed to the poor accuracy of the model, as was the case with the Gaussian NB model.

Classification Report

In [59]:

```
target_names = ['1', '2', '3', '4', '5']
print(classification_report(y1_test, y1_pred, target_names=target_names))
```

```
              precision    recall  f1-score   support

           1       0.00      0.00      0.00       175
           2       0.21      0.09      0.13       424
           3       0.23      0.44      0.30       486
           4       0.21      0.26      0.23       429
           5       0.23      0.17      0.20       474

    accuracy                           0.22      1988
   macro avg       0.18      0.19      0.17      1988
weighted avg       0.20      0.22      0.20      1988

C:\Users\19145\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1245: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\19145\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1245: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\19145\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1245: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Precision: Outside of listings with a rating of '1', the Decision Tree shared equal precision rates of 23% for listings with a ratings of '3' and '5' and 21% for listings with a rating of '2' and '4'.

Recall: The Decision Tree model was able to identify listings with a rating of '3' more than any other listing at a rate of 44%.

Conclusion

The best explanation for why each model performed so poorly when trying to predict the rating for an Airbnb listing was that the count of listings by rating was pretty much the same. This was reflected when performing EDA on a few of the dataset's features. It was difficult to determine any feature that would have a profound impact on what rating the listing received. Even though the Decision Tree was able to indicate how the numeric features had a clear significant impact on the rating, it still resulted in a low accuracy score for its predictions.

In [ ]: