Submission_Arshdeep

February 15, 2025

0.1 Data Ingestion

0.1.1 Imports and Data Download

[1]:
```
import requests
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import re
import os
import pickle

from collections import Counter
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
from wordcloud import WordCloud
from scipy.stats import pointbiserialr

# from catboost import CatBoostRegressor
# import spacy
# from tqdm import tqdm

# !python -m spacy download en_core_web_sm
```

Connect to drive and download train and test data csv

[2]:
```
# FOLDER_ID = '13AZpzOC2HgYxUnChGCk8Q9g3mIJ8Q-Ku'
# API_KEY = "AIzaSyA8RPhv9HO9C3if71arj7F6uFtSs_IobYE"

# # List files in the folder
# url = f"https://www.googleapis.com/drive/v3/files?
↪q='{FOLDER_ID}'+in+parents&key={API_KEY}"
```

```
# response = requests.get(url)
# files = response.json()
# print(files)  # Print file details
```

[3]:
```
# # Download train_set.csv
# file_id = "1UeCuTCODvysuVNzQOhr7n9_OQ1pj1Baw"  # Get this from the files list
# download_url = f"https://www.googleapis.com/drive/v3/files/{file_id}?
↪alt=media&key={API_KEY}"
# file_response = requests.get(download_url)

# # Save the file
# with open("train_set", "wb") as f:
#     f.write(file_response.content)
```

[4]:
```
# # Download test_set.csv
# file_id = "12IdfMBzYpRc8Uyy5vsp5G4CZxOONrX8r"  # Get this from the files list
# download_url = f"https://www.googleapis.com/drive/v3/files/{file_id}?
↪alt=media&key={API_KEY}"
# file_response = requests.get(download_url)

# # Save the file
# with open("test_set", "wb") as f:
#     f.write(file_response.content)
```

0.2 Exploratory Data Analysis (EDA)

0.2.1 1.0 Describing Data

[5]:
```
train_df = pd.read_csv("train_set")
train_df.head()
```

[5]:
```
           id                region  price       type  sqfeet  beds  baths  \
0  7049965813         orange county   2632  apartment    1080     2    2.0
1  7036046796        visalia-tulare   1160  apartment     768     2    1.0
2  7037856890              portland   1262  apartment    1075     2    1.0
3  7046933042               boulder   1861  apartment    1076     2    2.0
4  7048650961  sioux falls / SE SD    626  apartment     720     1    1.0

   cats_allowed  dogs_allowed  smoking_allowed  wheelchair_access  \
0             1             1                0                  0
1             1             1                1                  0
2             1             1                0                  0
3             1             1                0                  0
4             1             1                0                  0

   electric_vehicle_charge  comes_furnished  laundry_options  \
0                        0                0       w/d in unit
```

```
1                        0                 0  laundry on site
2                        0                 0  laundry on site
3                        1                 0      w/d in unit
4                        0                 0      w/d in unit

      parking_options                                        description  \
0     attached garage  To schedule a tour We now book our tour appoin…
1             carport  Oak View is just minutes from Highway 99 and b…
2  off-street parking  ***Please Pardon Our Dust*** Do you want three…
3     detached garage  Luna Bella  Pet Friendly  Community in Lafayet…
4     detached garage  Creekstone Falls\t                           Prop…

       lat      long state
0  33.8123 -117.8530    ca
1  36.3008 -119.3440    ca
2  45.5273 -122.4800    or
3  39.9744 -105.0850    co
4  43.5179  -96.7924    sd
```

[6]:

```python
test_df = pd.read_csv("test_set")
test_df.head()
```

[6]:

```
           id                   region  price       type  sqfeet  beds  baths  \
0  7027550434   worcester / central MA   1750  apartment     936     2    1.0
1  7033922487       mcallen / edinburg    850  apartment    1200     2    2.5
2  7045296557  fort collins / north CO   1500  apartment    1029     2    1.0
3  7031700539             indianapolis    899  apartment     856     2    1.0
4  7048945590               cincinnati    595  apartment     350     0    1.0

   cats_allowed  dogs_allowed  smoking_allowed  wheelchair_access  \
0             1             0                1                  0
1             0             0                0                  0
2             1             1                0                  0
3             1             1                1                  0
4             0             0                0                  0

   electric_vehicle_charge  comes_furnished     laundry_options  \
0                        0                0                 NaN
1                        0                0         w/d in unit
2                        0                0         w/d in unit
3                        0                0     laundry in bldg
4                        0                0  no laundry on site

      parking_options                                        description  \
0                 NaN  VIEW OUR WEBSITE:  https://www.winncompanies.c…
1  off-street parking  2 bedrooms, 2.5 baths, refrigerator, stove, wa…
2  off-street parking  Brand New 2 bed 1 bath apartment will go FAST …
```

```
3                 NaN  Check out what these 2 bedrooms @ Teal Run hav…
4  off-street parking  Completely renovated with an urban flare. 3rd …

       lat      long state
0  42.2526  -71.8499    ma
1  26.2154  -98.2359    tx
2  40.3849 -105.0920    co
3  39.7886  -85.9779    in
4  39.1275  -84.5350    oh
```

[7]:
```python
train_df.shape
```

[7]: (346479, 19)

[8]:
```python
test_df.shape
```

[8]: (38498, 19)

[9]:
```python
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 346479 entries, 0 to 346478
Data columns (total 19 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   id                       346479 non-null  int64
 1   region                   346479 non-null  object
 2   price                    346479 non-null  int64
 3   type                     346479 non-null  object
 4   sqfeet                   346479 non-null  int64
 5   beds                     346479 non-null  int64
 6   baths                    346479 non-null  float64
 7   cats_allowed             346479 non-null  int64
 8   dogs_allowed             346479 non-null  int64
 9   smoking_allowed          346479 non-null  int64
 10  wheelchair_access        346479 non-null  int64
 11  electric_vehicle_charge  346479 non-null  int64
 12  comes_furnished          346479 non-null  int64
 13  laundry_options          275399 non-null  object
 14  parking_options          219914 non-null  object
 15  description              346477 non-null  object
 16  lat                      344728 non-null  float64
 17  long                     344728 non-null  float64
 18  state                    346479 non-null  object
dtypes: float64(3), int64(10), object(6)
memory usage: 50.2+ MB
```

[10]:
```python
train_df.describe()
```

[10]:

```
                 id         price        sqfeet           beds          baths  \
count  3.464790e+05  3.464790e+05  3.464790e+05  346479.000000  346479.000000
mean   7.040981e+09  1.615492e+03  1.067028e+03       1.904468       1.481110
std    8.798642e+06  6.586159e+04  2.018564e+04       3.256987       0.618514
min    7.003808e+09  0.000000e+00  0.000000e+00       0.000000       0.000000
25%    7.035975e+09  8.060000e+02  7.500000e+02       1.000000       1.000000
50%    7.043314e+09  1.039000e+03  9.500000e+02       2.000000       1.000000
75%    7.048429e+09  1.395000e+03  1.150000e+03       2.000000       2.000000
max    7.051292e+09  2.170191e+07  8.388607e+06    1100.000000      75.000000

        cats_allowed   dogs_allowed  smoking_allowed  wheelchair_access  \
count  346479.000000  346479.000000    346479.000000      346479.000000
mean        0.726780       0.707847         0.731987           0.081939
std         0.445614       0.454753         0.442925           0.274272
min         0.000000       0.000000         0.000000           0.000000
25%         0.000000       0.000000         0.000000           0.000000
50%         1.000000       1.000000         1.000000           0.000000
75%         1.000000       1.000000         1.000000           0.000000
max         1.000000       1.000000         1.000000           1.000000

       electric_vehicle_charge  comes_furnished            lat           long
count            346479.000000    346479.000000  344728.000000  344728.000000
mean                  0.012806         0.048040      37.237436     -92.706870
std                   0.112437         0.213852       5.542563      16.522223
min                   0.000000         0.000000     -43.533300    -163.894000
25%                   0.000000         0.000000      33.465200    -100.784000
50%                   0.000000         0.000000      37.658000     -87.772500
75%                   0.000000         0.000000      41.141000     -81.179600
max                   1.000000         1.000000     102.036000     172.633000
```

0.2.2 1.1 Checking variance of numerical columns

[11]:

```python
numerical_cols = ["price", "sqfeet", "beds", "baths", "lat", "long"]
for col in numerical_cols:
    print("Variance for",col,"column :", train_df[col].var())
```

```
Variance for price column : 4337748577.786544
Variance for sqfeet column : 407460235.51401496
Variance for beds column : 10.607963203245545
Variance for baths column : 0.38255925261972035
Variance for lat column : 30.720008881592843
Variance for long column : 272.98384804658565
```

Key Takeaways - Very high variance in price and sqfeet meaning possible outliers and wide range of values. - Low variance in bath and bedrooms ie. similar values - Low Lat variance, and high Long variance suggesting uneven dominance of some regions

0.2.3 1.2 Checking skewness of numerical columns

[12]:
```
for col in numerical_cols:
    print("Skewness for", col, "column:", train_df[col].skew())
```

```
Skewness for price column: 235.39303545130664
Skewness for sqfeet column: 388.96706906430643
Skewness for beds column: 304.2929719312646
Skewness for baths column: 10.648135085840252
Skewness for lat column: 0.249342430946829
Skewness for long column: -0.05552793176059056
```

Key Takeaways - Price, Sqfeet, Beds, and Baths are all highly right-skewed. - Latitude and Longitude are nearly symmetrical.

0.2.4 1.3 Checking for na values

[13]:
```
# missing values
train_df.isna().sum()
```

[13]:
```
id                            0
region                        0
price                         0
type                          0
sqfeet                        0
beds                          0
baths                         0
cats_allowed                  0
dogs_allowed                  0
smoking_allowed               0
wheelchair_access             0
electric_vehicle_charge       0
comes_furnished               0
laundry_options           71080
parking_options          126565
description                   2
lat                        1751
long                       1751
state                         0
dtype: int64
```

Key Takeaways: - laundry_options has 71,080 missing values, its Categorical, we can fill with mode (most common value) - parking_options has 126,565 missing values, its Categorical, we can fill with mode (most common parking value: off-street parking) - description has 2 missing values, which are insignificant, so we can drop them - lat has 1,751 missing values, its Numeric, we can fill it with region-wise median - long has 1,751 missing values, its Numeric, we can fill it with region-wise median

0.2.5 1.4 Checking for duplicate rows

[14]:
```
train_df.duplicated().sum()
```

[14]: 0

No duplicate rows

0.2.6 1.5 Checking value counts

[15]:
```
for col in ["region", "price", "type", "sqfeet", "beds", "baths",␣
↪"laundry_options", "parking_options", "state"]:
    print(train_df[col].value_counts(),"\n")
```

```
region
jacksonville      3830
columbus          3366
rochester         3306
fayetteville      3300
jackson           3299
                  …
southwest MS        11
southwest TX         9
st louis             7
fort smith, AR       5
kansas city          3
Name: count, Length: 404, dtype: int64

price
750         3782
850         3602
800         3602
1200        3470
950         3267
            …
13995          1
26             1
3943           1
11621360       1
3516           1
Name: count, Length: 3877, dtype: int64

type
apartment         286195
house              29978
townhouse          14329
condo               5598
duplex              4496
manufactured        3821
```

```
cottage/cabin         794
loft                  636
flat                  473
in-law                151
land                    6
assisted living         2
Name: count, dtype: int64

sqfeet
1000    9057
900     7633
1100    6333
800     6223
700     5982
        …
332        1
3260       1
3410       1
2822       1
2848       1
Name: count, Length: 3204, dtype: int64

beds
2       157981
1       105402
3        60415
4        10439
0         9857
5         2099
6          211
7           44
8           28
1100         2
1000         1
Name: count, dtype: int64

baths
1.0     178202
2.0     121309
1.5      24600
2.5      11858
3.0       5030
0.0       2821
4.0       1326
3.5        918
4.5        210
5.0        118
5.5         50
```

```
6.0         23
6.5          4
7.0          3
75.0         2
7.5          2
8.0          1
25.0         1
8.5          1
Name: count, dtype: int64

laundry_options
w/d in unit           118694
w/d hookups            67873
laundry on site        53006
laundry in bldg        32545
no laundry on site      3281
Name: count, dtype: int64

parking_options
off-street parking    115621
attached garage        36578
carport                35132
detached garage        15233
street parking         14331
no parking              2870
valet parking            149
Name: count, dtype: int64

state
ca    29821
fl    28696
tx    28052
nc    16732
mi    13091
ga    12426
oh    11585
tn    10392
co    10227
va     9953
ny     9057
sc     8943
pa     8932
il     8727
al     7332
or     7238
ks     7103
ia     6784
md     6712
```

```
mn      6690
la      6549
wa      6364
az      6092
wi      6005
in      5806
ok      5192
nj      5120
ky      4859
ut      4699
ms      4484
ma      4425
id      4010
ct      3387
nd      3063
ar      2858
nm      2609
nv      2550
ne      2447
dc      2245
ak      1949
mo      1941
de      1830
ri      1709
hi      1654
sd      1602
nh      1582
mt      1197
wv       740
vt       467
me       381
wy       170
Name: count, dtype: int64
```

Key Takeaways

region - Some regions have very few listings, these may not be reliable for model predictions due to limited data. - Some region names have inconsistent formatting ("fort smith, AR"), this included state, which is a different feature, need standardization

price - Some extreme values exist like 11621360 and 26, These are likely outliers and should be examined.

type (Property type) - Apartments dominate the dataset about 286k enteries, other property types contribute much less. - Rare categories (land, assisted living) have very few listings, so it could to a potential issue of One-hot encoding could create sparse data due to many of these categories

sqfeet - It could contain extreme outlier values and its skewed, we are using log_sqfeet for normalized curve

beds and **baths** - Extreme values lik 1000 beds, 75 baths are unrealistic and should be removed as outliers - Some of the properties with zero beds, are outliers

Identifying outliers

[16]:
```
train_df[(train_df["beds"] == 1000)]
```

[16]:
```
               id      region  price       type  sqfeet  beds  baths  \
25290  7036731908  youngstown    550  apartment     250  1000   25.0

       cats_allowed  dogs_allowed  smoking_allowed  wheelchair_access  \
25290             0             0                0                  0

       electric_vehicle_charge  comes_furnished laundry_options  \
25290                        0                0             NaN

      parking_options description      lat     long state
25290  street parking   2 bedroom  41.0252 -80.6687    oh
```

[17]:
```
train_df[(train_df["beds"] == 1100)]
```

[17]:
```
                id   region  price       type  sqfeet  beds  baths  \
51403   7046224868  chicago   2449  apartment    1000  1100   75.0
153122  7045590325  chicago   2449  apartment    1000  1100   75.0

        cats_allowed  dogs_allowed  smoking_allowed  wheelchair_access  \
51403              0             0                1                  0
153122             0             0                1                  0

        electric_vehicle_charge  comes_furnished laundry_options  \
51403                         0                0     w/d in unit
153122                        0                0     w/d in unit

       parking_options                                       description  \
51403          carport  Furnished or Unfurnished Units Includes Parkin…
153122         carport  Furnished or Unfurnished Units Includes Parkin…

            lat    long state
51403   42.0195 -87.665    il
153122  42.0195 -87.665    il
```

These above are outliers, they needs to be removed

[18]:
```
train_df[(train_df['beds'] == 0)].head(2)
```

[18]:
```
            id           region  price       type  sqfeet  beds  baths  \
14  7036089161  college station    589  apartment     480     0    1.0
45  7048022092          lincoln    499  apartment     495     0    1.0
```

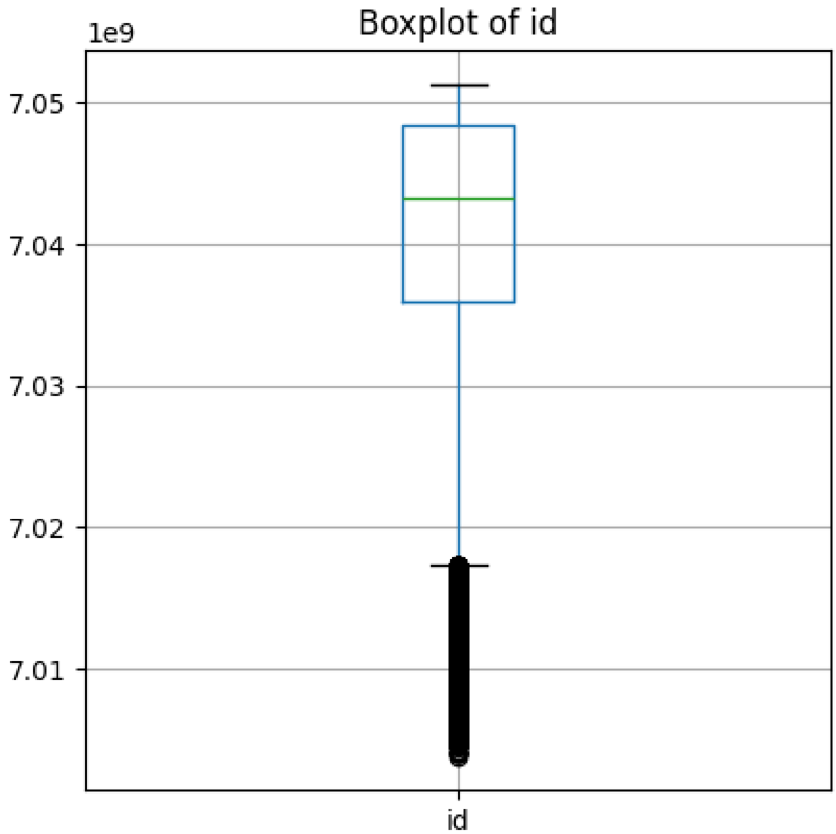
```
    cats_allowed  dogs_allowed  smoking_allowed  wheelchair_access  \
14             1             1                1                  0
45             1             0                0                  0

    electric_vehicle_charge  comes_furnished  laundry_options  \
14                        0                0              NaN
45                        0                0  laundry in bldg

       parking_options                                      description  \
14                 NaN  Join Us Today! @ The Gables  Located less than…
45  off-street parking  www.LNKhousing.com |  show contact info  |  sh…

        lat     long state
14  30.6190 -96.3185    tx
45  40.7893 -96.6938    ne
```

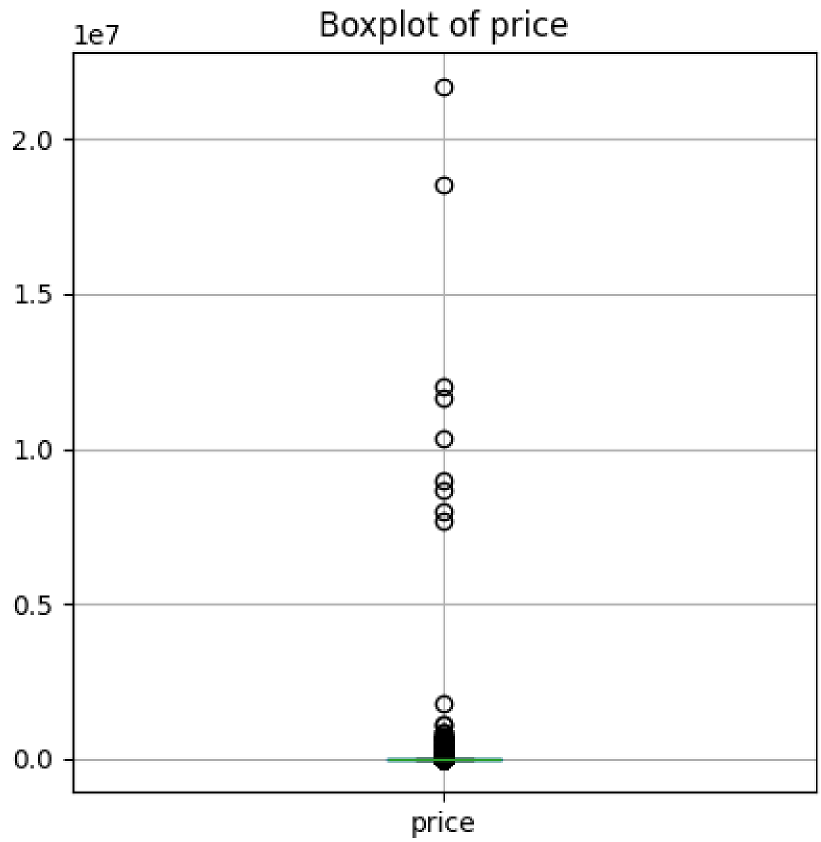
Zero beds properties are outliers, needs to removed

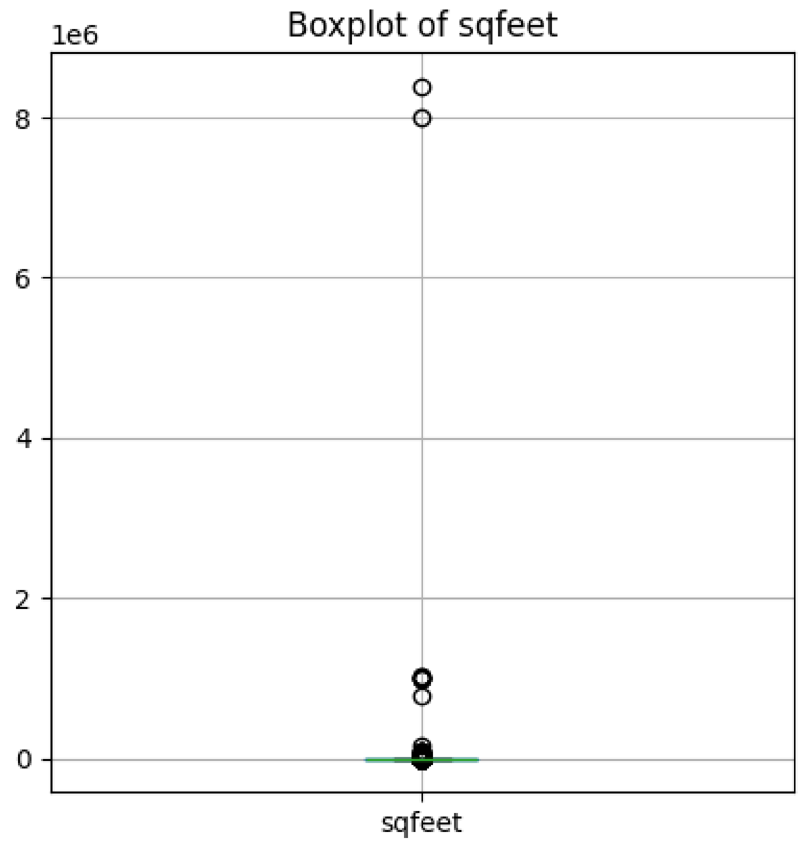
0.2.7 1.6 Detecting outliers using Boxplots (IQR method)

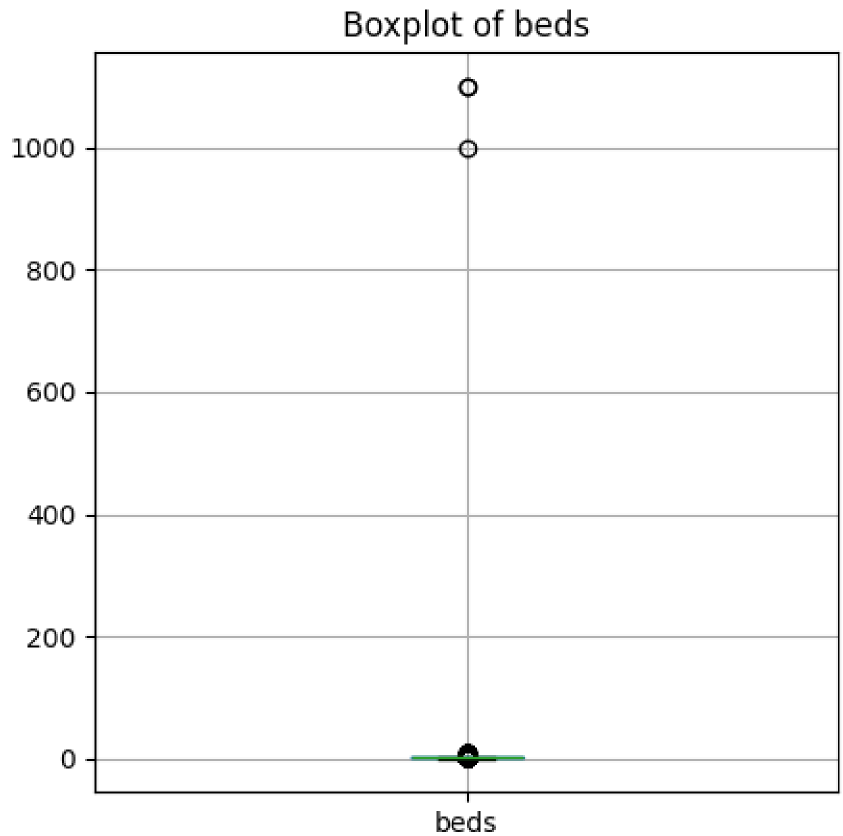
[19]:
```python
# Function to "Plot Box Plot" and it works only for the datatype of integer and␣
↪float columns.
def PBP (data):
    for col in data.select_dtypes(include=['int', 'float']).columns:
        fig, ax = plt.subplots(figsize=(5, 5))
        ax.set_title(f'Boxplot of {col}')
        bp=data.boxplot(column=col)
        plt.show()
        plt.close(fig)
```

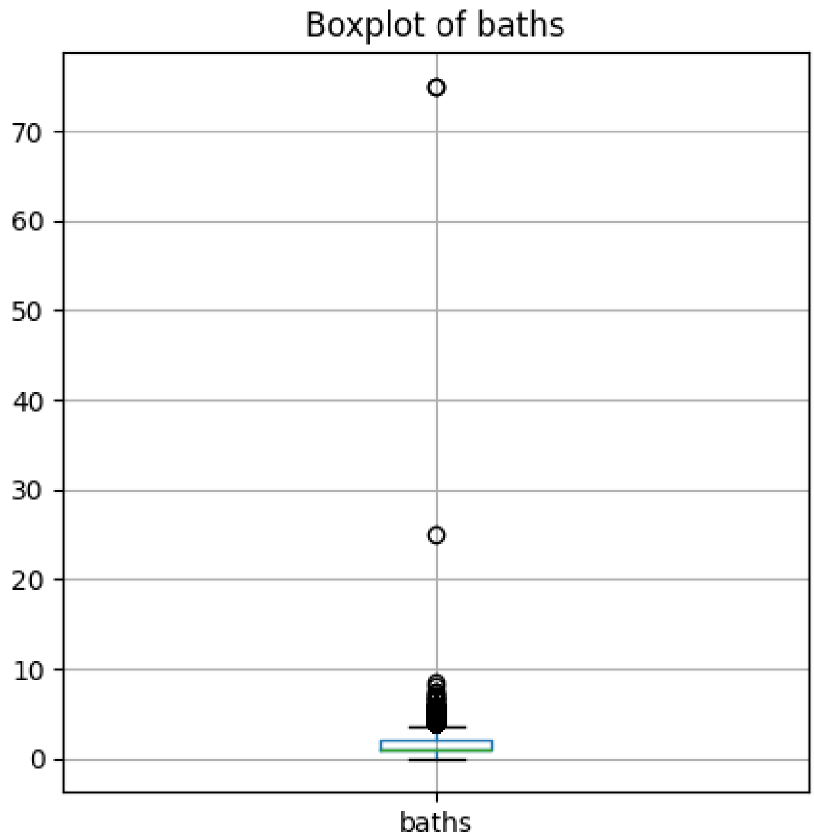
[20]:
```python
PBP(train_df)
```

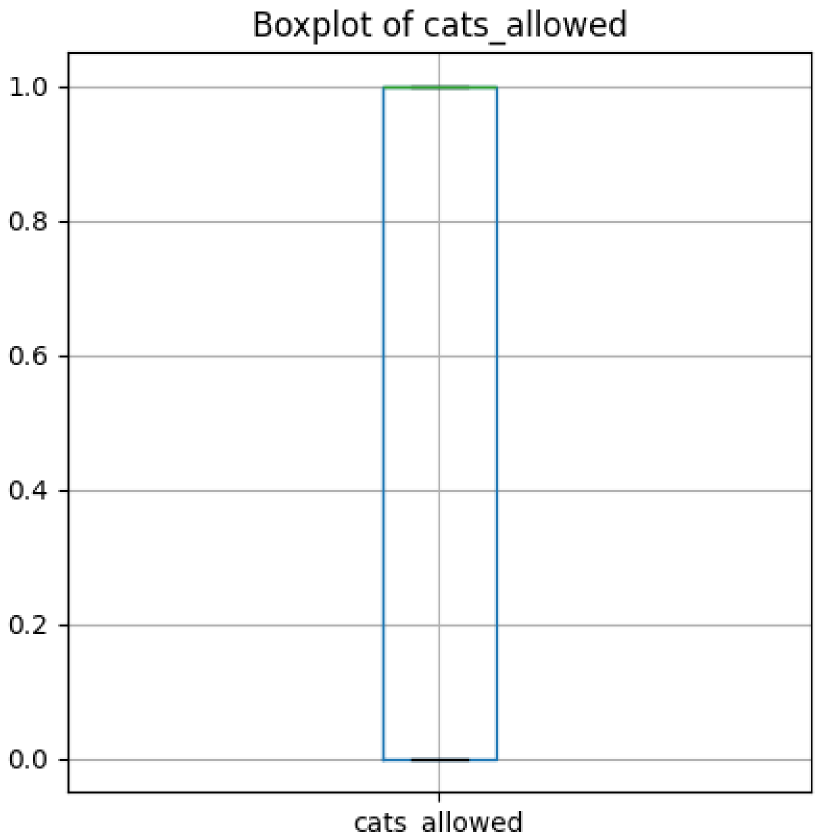

Boxplot of id
1e9
7.05
7.04
7.03
7.02
7.01
id

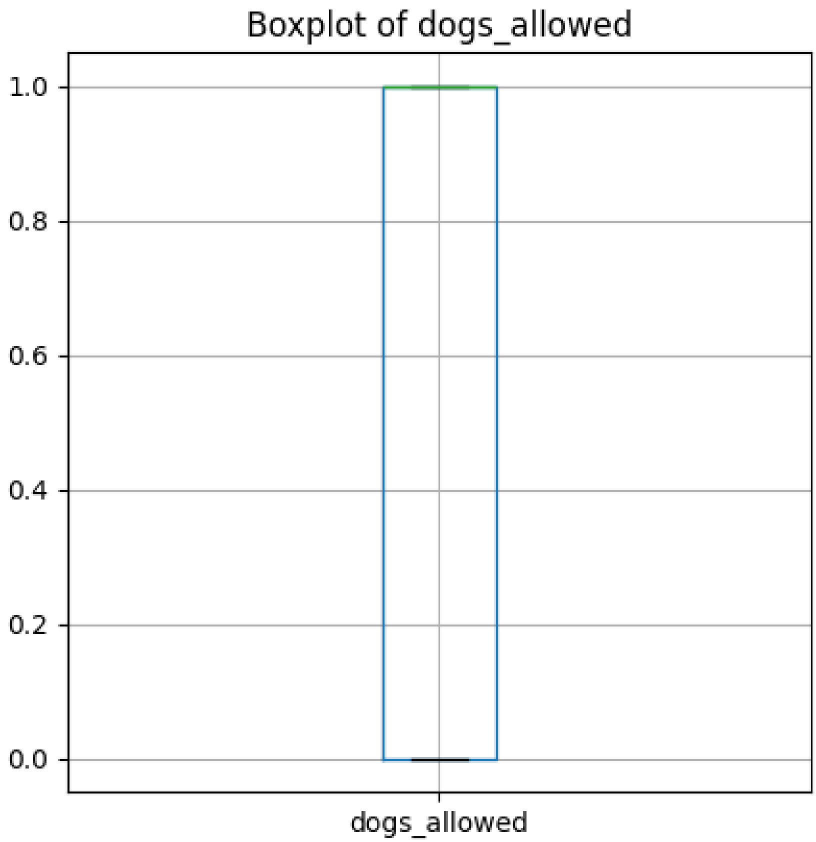

Boxplot of price
1e7
2.0
1.5
1.0
0.5
0.0
price

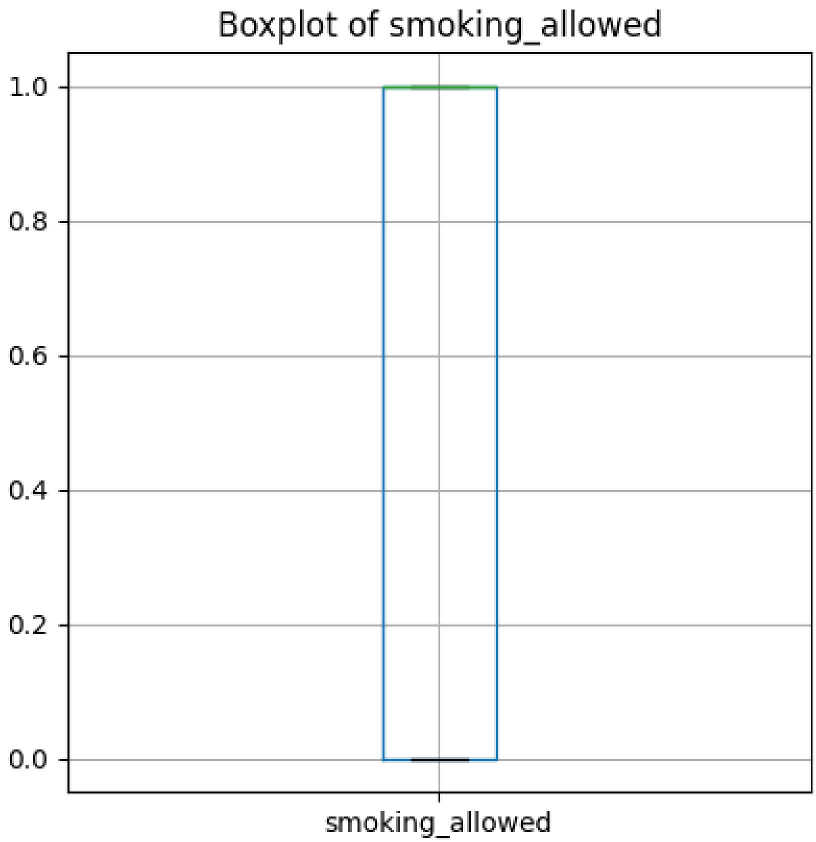

Boxplot of sqfeet
1e6
8
6
4
2
0
sqfeet

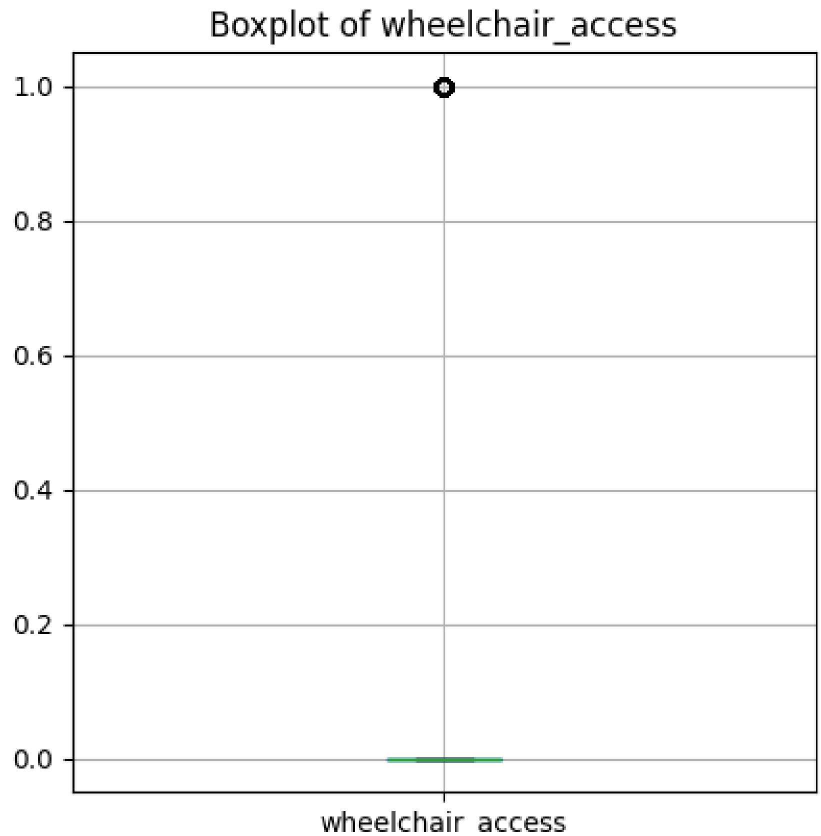

Boxplot of beds
1000
800
600
400
200
0
beds

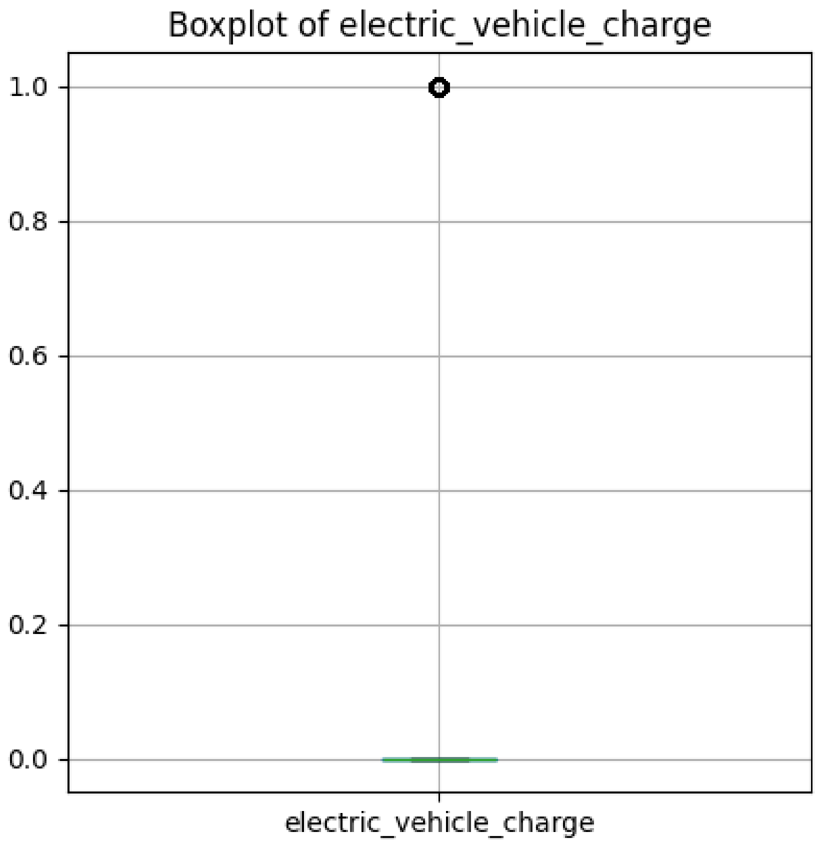

Boxplot of baths
70
60
50
40
30
20
10
0
baths

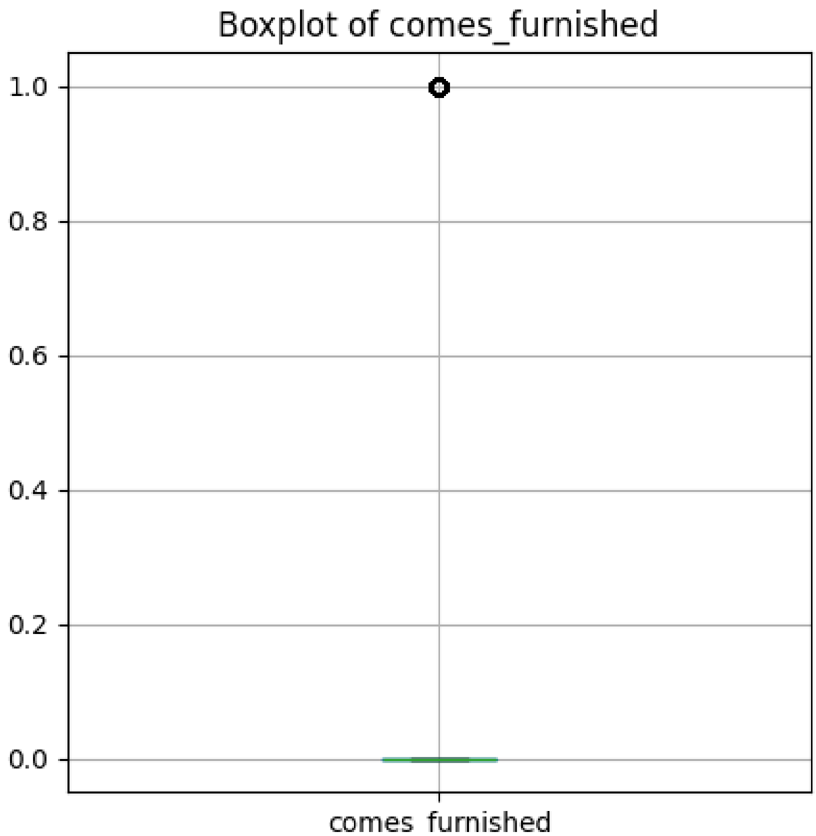

Boxplot of cats_allowed
1.0
0.8
0.6
0.4
0.2
0.0
cats_allowed

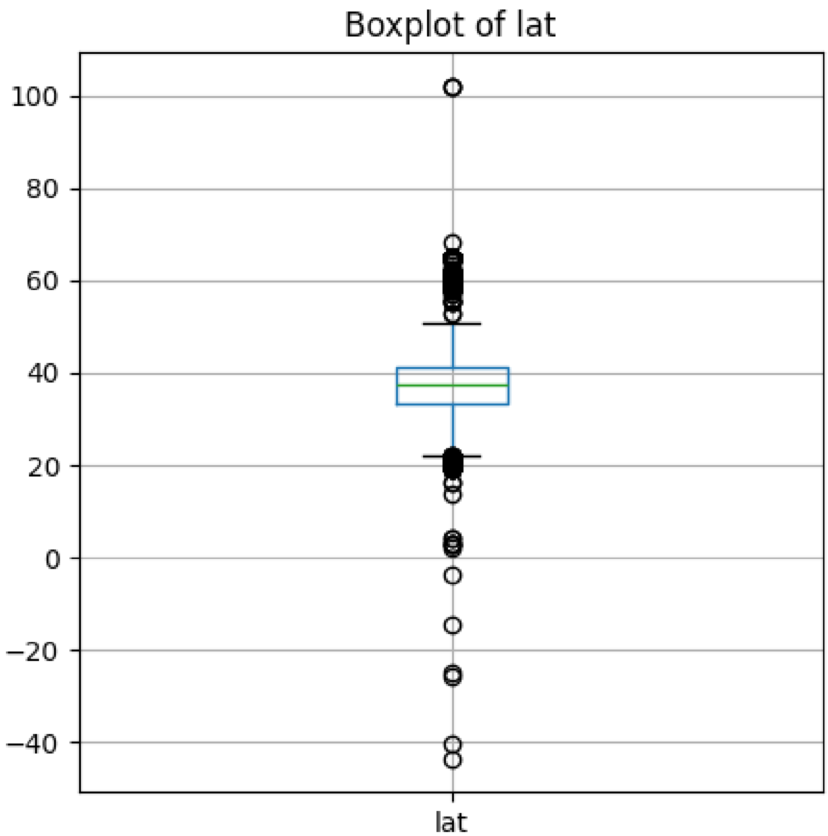

Boxplot of dogs_allowed
1.0
0.8
0.6
0.4
0.2
0.0
dogs_allowed

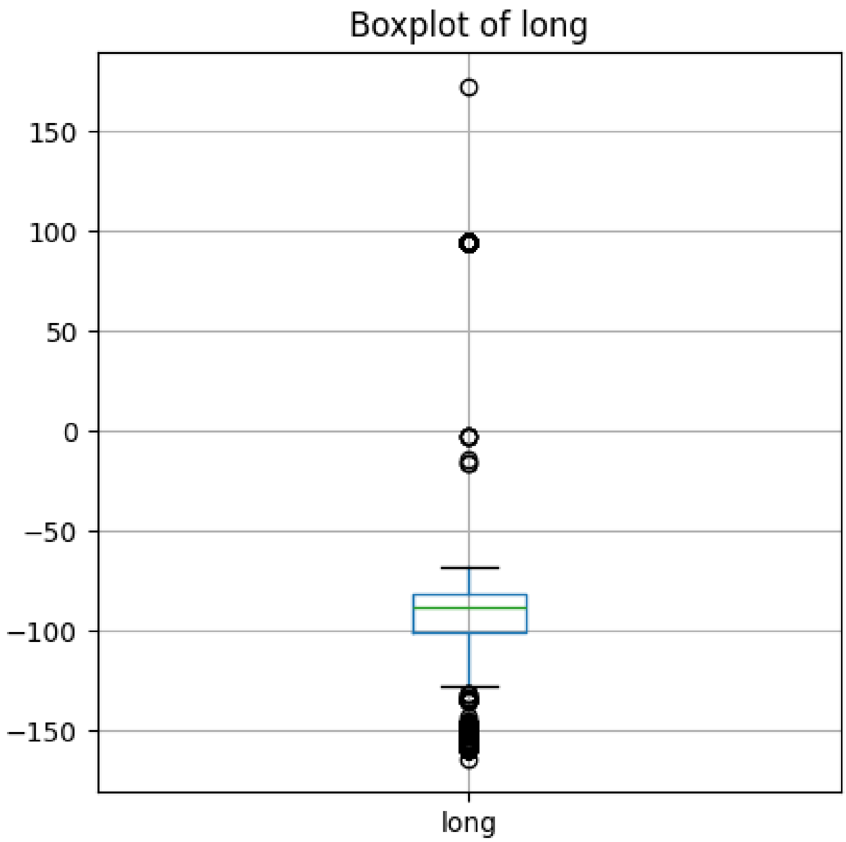

Boxplot of smoking_allowed
1.0
0.8
0.6
0.4
0.2
0.0
smoking_allowed


Boxplot of wheelchair_access
1.0
0.8
0.6
0.4
0.2
0.0
wheelchair_access


Boxplot of electric_vehicle_charge
1.0
0.8
0.6
0.4
0.2
0.0
electric_vehicle_charge


Boxplot of comes_furnished
1.0
0.8
0.6
0.4
0.2
0.0
comes_furnished


Boxplot of lat
100
80
60
40
20
0
−20
−40
lat



Key Takeaways for outliers - Price is over 500k per month for some properties and 0 - SqFeet for 2 properties is extremely large (skewed), and some of them are 0 - Properties with 0 beds, and 1000+ beds are outliers - Properties with 25+ baths are outliers, they are 1000sqfeet, so that's not physically possible

0.2.8 1.7 Histogram/Distribution plots

[21]:
```
# Function to Plot Distribution Plot
def PDP(data):
    columns = [col for col in data.columns]
    colors = sns.color_palette("dark", len(columns))

    for i, col in enumerate(data.select_dtypes(include=['int', 'float']).
↪columns):
        if data[col].value_counts().count() <= 10000:
            sns.histplot(data[col], kde=True, bins=15, color=colors[i %␣
↪len(colors)])
            plt.title(f'Distribution of {col}')
            plt.show()
```

[22]:
```
# PDP(train_df)
```

0.2.9 1.8 Word Cloud: Analyzing description

[23]:
```
def preprocess_text(text):
    if isinstance(text, str):  # Check if the value is a string
        text = text.lower()  # Convert to lowercase
        text = re.sub(r'[^\w\s]', '', text)  # Remove punctuation
        return text
    else:
        return ""  # Return empty string for NaN or non-string values

# description_cleaned = train_df['description'].dropna().apply(preprocess_text)
# description_cleaned
```

[24]:
```
# # Extract Key Terms using TF-IDF (removes standard English stopwords)
# vectorizer = TfidfVectorizer(stop_words="english", max_features=100)
# tfidf_matrix = vectorizer.fit_transform(description_cleaned)

# # Get feature names (important words)
# top_words = vectorizer.get_feature_names_out()

# # Combine text and remove additional stopwords
# text = " ".join(str(desc) for desc in description_cleaned)
# wordcloud = WordCloud(
#     width=800, height=400, background_color="white", max_words=200,
#     stopwords=vectorizer.get_stop_words()
# ).generate(text)

# # Display Word Cloud
# plt.figure(figsize=(10, 5))
# plt.imshow(wordcloud, interpolation="bilinear")
# plt.axis("off")
# plt.title("Cleaned Word Cloud of Description Text")
# plt.show()
```

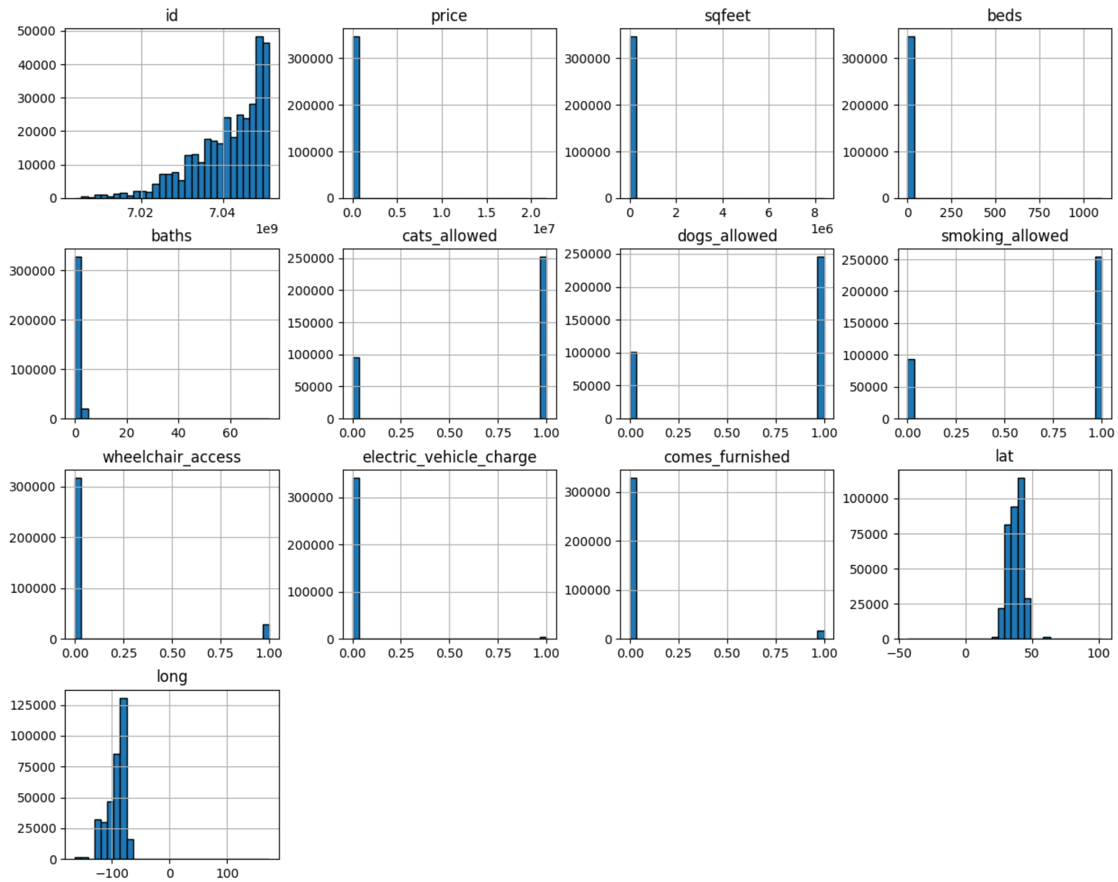
[25]:
```
# pd.set_option('display.max_colwidth', None)
# print(train_df['description'][100:110])
# pd.reset_option('display.max_colwidth')
```

0.2.10 1.9 Histogram of numerical features for comparison

[26]:
```
train_df.hist(figsize=(15, 12), bins=30, edgecolor="black")
```

[26]:
```
array([[<Axes: title={'center': 'id'}>,
        <Axes: title={'center': 'price'}>,
        <Axes: title={'center': 'sqfeet'}>,
```

```
  <Axes: title={'center': 'beds'}>],
 [<Axes: title={'center': 'baths'}>,
  <Axes: title={'center': 'cats_allowed'}>,
  <Axes: title={'center': 'dogs_allowed'}>,
  <Axes: title={'center': 'smoking_allowed'}>],
 [<Axes: title={'center': 'wheelchair_access'}>,
  <Axes: title={'center': 'electric_vehicle_charge'}>,
  <Axes: title={'center': 'comes_furnished'}>,
  <Axes: title={'center': 'lat'}>],
 [<Axes: title={'center': 'long'}>, <Axes: >, <Axes: >, <Axes: >]],
dtype=object)
```



Key Takeaway: - Price and sqfeet are skewed, normal and even distribution is desired, which we achieve after removing outlier and log base it

0.2.11 1.10 Plot of showing price variation in lat, long

[27]:
```
# Define price bins and corresponding colors
# price_bins = [0, 1000, 2000, 3000, 4000, 5000, np.inf]
# price_labels = ["<1000", "1000-2000", "2000-3000", "3000-4000", "4000-5000",␣
↪"5000+"]

# # Create a new column for price categories
# train_df["price_category"] = pd.cut(train_df["price"], bins=price_bins,␣
↪labels=price_labels, include_lowest=True)

# # Filter dataset based on latitude and longitude thresholds
# filtered_df = train_df[(train_df["lat"] >= 15) & (train_df["lat"] <= 65) &
#                          (train_df["long"] >= -125) & (train_df["long"] <=␣
↪-50)]

# # Scatter plot with custom price categories
# plt.figure(figsize=(10, 6))
# sns.scatterplot(x="lat", y="long", data=filtered_df, hue="price_category",␣
↪palette={"<1000": "#ccd1d9", "1000-2000": "#fff185", "2000-3000": "green",␣
↪"3000-4000": "blue", "4000-5000": "#af14fc", "5000+": "black"}, alpha=0.6)

# # Labels and title
# plt.xlabel("Latitude")
# plt.ylabel("Longitude")
# plt.title("Price Distribution by Location (Custom Binned Coloring)")
# plt.legend(title="Price Category", loc="upper right")
# plt.show()
```

0.3 Data Preprocessing

0.3.1 2.1 Removing Outlier in prices

Reason: - Mentioned above in the Box-plot - We can see from the price min and max values that most of the prices are in 0, 10^3 range. But, outliers are far away (10^7)

[28]:
```
train_df.shape
```

[28]:
```
(346479, 19)
```

[29]:
```
# Filtering properties using IQR
# Apply log transformation to normalize price
train_df["log_price"] = np.log1p(train_df["price"])

# Compute IQR on log-transformed prices
Q1_log = train_df["log_price"].quantile(0.25)
Q3_log = train_df["log_price"].quantile(0.75)
IQR_log = Q3_log - Q1_log
```

```
# Define new bounds using IQR (less strict)
lower_bound_log = Q1_log - (3 * IQR_log)
upper_bound_log = Q3_log + (3 * IQR_log)

# Convert bounds back to original scale
lower_bound = np.expm1(lower_bound_log)
upper_bound = np.expm1(upper_bound_log)

print('price range: ', lower_bound, upper_bound)

# Filter price using log-adjusted bounds
train_df = train_df[(train_df["price"] >= lower_bound) & (train_df["price"] <=
 ↪upper_bound)]

# Drop the temporary log-transformed price column after filtering
train_df.drop(columns=["log_price"], inplace=True)
```

```
price range:  154.89704526295714 7225.384554625592
```

[30]:
```
train_df.shape
```

[30]:
```
(344060, 19)
```

[31]:
```
# Removing zero price properties
train_df = train_df[(train_df["price"] > 0)]
```

[32]:
```
train_df.shape
```

[32]:
```
(344060, 19)
```

[33]:
```
# test
test_df["log_price"] = np.log1p(test_df["price"])

Q1_log = test_df["log_price"].quantile(0.25)
Q3_log = test_df["log_price"].quantile(0.75)
IQR_log = Q3_log - Q1_log

lower_bound_log = Q1_log - (3 * IQR_log)
upper_bound_log = Q3_log + (3 * IQR_log)

lower_bound = np.expm1(lower_bound_log)
upper_bound = np.expm1(upper_bound_log)

print('price range: ', lower_bound, upper_bound)

test_df = test_df[(test_df["price"] >= lower_bound) & (test_df["price"] <=
 ↪upper_bound)]
```

```
test_df.drop(columns=["log_price"], inplace=True)
```

```
price range:  154.12575647430336 7252.3151526412485
```

0.3.2 2.2 Removing Outlier in sqfeet

- Drop zero sqfeet enteries
- Drop extreme properties

Log values are used so tackle high skewness

[34]:
```
# Remove rows where sqfeet is 0
train_df = train_df[train_df["sqfeet"] > 0]
```

[35]:
```
test_df = test_df[test_df["sqfeet"] > 0]
```

[36]:
```
train_df.shape
```

[36]:
```
(344014, 19)
```

[37]:
```
# Removing IQR outside range for sqfeet
# Apply log transformation to normalize sqfeet due to skewness
train_df["log_sqfeet"] = np.log1p(train_df["sqfeet"])

# Compute IQR on log-transformed prices
Q1_sqfeet = train_df["log_sqfeet"].quantile(0.25)
Q3_sqfeet = train_df["log_sqfeet"].quantile(0.75)
IQR_sqfeet = Q3_sqfeet - Q1_sqfeet

# Define new bounds using IQR (less strict)
lower_bound_sqfeet = Q1_sqfeet - (3 * IQR_sqfeet)
upper_bound_sqfeet = Q3_sqfeet + (3 * IQR_sqfeet)

# Convert bounds back to original scale
lower_bound_sqfeet = np.expm1(lower_bound_sqfeet)
upper_bound_sqfeet = np.expm1(upper_bound_sqfeet)

print('sqfeet range: ', lower_bound_sqfeet, upper_bound_sqfeet)

# Filter price using log-adjusted bounds
train_df = train_df[(train_df["sqfeet"] >= lower_bound_sqfeet) &
 ↪(train_df["sqfeet"] <= upper_bound_sqfeet)]

# Drop the temporary log-transformed price column after filtering
train_df.drop(columns=["log_sqfeet"], inplace=True)

# Q1_sqfeet = train_df["sqfeet"].quantile(0.25)
# Q3_sqfeet = train_df["sqfeet"].quantile(0.75)
# IQR_sqfeet = Q3_sqfeet - Q1_sqfeet
```

```
# train_df = train_df[(train_df["sqfeet"] >= (Q1_sqfeet - 1.5 * IQR_sqfeet)) &␣
↪(train_df["sqfeet"] <= (Q3_sqfeet + 1.5 * IQR_sqfeet))]
# sqfeet range: 150.0 1750.0
```

```
sqfeet range:  207.6093534841274 4142.634911680846
```

[38]:
```
# test
test_df["log_sqfeet"] = np.log1p(test_df["sqfeet"])

Q1_sqfeet = test_df["log_sqfeet"].quantile(0.25)
Q3_sqfeet = test_df["log_sqfeet"].quantile(0.75)
IQR_sqfeet = Q3_sqfeet - Q1_sqfeet

lower_bound_sqfeet = Q1_sqfeet - (3 * IQR_sqfeet)
upper_bound_sqfeet = Q3_sqfeet + (3 * IQR_sqfeet)

lower_bound_sqfeet = np.expm1(lower_bound_sqfeet)
upper_bound_sqfeet = np.expm1(upper_bound_sqfeet)

test_df = test_df[(test_df["sqfeet"] >= lower_bound_sqfeet) &␣
↪(test_df["sqfeet"] <= upper_bound_sqfeet)]

# Drop the temporary log-transformed price column after filtering
test_df.drop(columns=["log_sqfeet"], inplace=True)
```

[39]:
```
train_df.shape
```

[39]: (342638, 19)

0.3.3 2.3 Removing Outliers in beds and baths

- 0 bed properties are outliers
- Properties with 1000+ beds and 25+ baths are outliers

[40]:
```
# Removing 0 bed properties
train_df = train_df[(train_df["beds"] > 0)]
test_df = test_df[(test_df["beds"] > 0)]
```

[41]:
```
train_df.shape
```

[41]: (332944, 19)

[42]:
```
## Remove outliers in beds
train_df = train_df[(train_df["beds"] < 1000)]
test_df = test_df[(test_df["beds"] < 1000)]
```

[43]:
```
train_df.shape
```

[43]: (332941, 19)

[44]:
```
## Remove properties with unrealistic baths
train_df = train_df[train_df["baths"] < 25]
test_df = test_df[test_df["baths"] < 25]
```

[45]:
```
train_df.shape
```

[45]: (332941, 19)

0.3.4 2.4 Drop missing Description

Reasoning: Only 2 rows were missing description out of 346,479, which is 0.0006% of the data. Removing them does not significantly impact the dataset.

[46]:
```
train_df.dropna(subset=["description"], inplace=True)
test_df.dropna(subset=["description"], inplace=True)
```

[47]:
```
train_df.shape
```

[47]: (332939, 19)

0.3.5 2.5 Filling Lat and Lng Missing Values

Reasoning: Ensuresuing missing values are filled with the median specific to their region, improving accuracy.

[48]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 332939 entries, 0 to 346478
Data columns (total 19 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   id                       332939 non-null  int64
 1   region                   332939 non-null  object
 2   price                    332939 non-null  int64
 3   type                     332939 non-null  object
 4   sqfeet                   332939 non-null  int64
 5   beds                     332939 non-null  int64
 6   baths                    332939 non-null  float64
 7   cats_allowed             332939 non-null  int64
 8   dogs_allowed             332939 non-null  int64
 9   smoking_allowed          332939 non-null  int64
 10  wheelchair_access        332939 non-null  int64
 11  electric_vehicle_charge  332939 non-null  int64
 12  comes_furnished          332939 non-null  int64
 13  laundry_options          263927 non-null  object
 14  parking_options          210920 non-null  object
```

```
 15   description             332939 non-null  object
 16   lat                     331258 non-null  float64
 17   long                    331258 non-null  float64
 18   state                   332939 non-null  object
dtypes: float64(3), int64(10), object(6)
memory usage: 50.8+ MB
```

[49]:
```
train_df["lat"] = train_df.groupby("region")["lat"].transform(lambda x: x.
 ↪fillna(x.median()))
train_df["long"] = train_df.groupby("region")["long"].transform(lambda x: x.
 ↪fillna(x.median()))

test_df["lat"] = test_df.groupby("region")["lat"].transform(lambda x: x.
 ↪fillna(x.median()))
test_df["long"] = test_df.groupby("region")["long"].transform(lambda x: x.
 ↪fillna(x.median()))
```

[50]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 332939 entries, 0 to 346478
Data columns (total 19 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   id                       332939 non-null  int64
 1   region                   332939 non-null  object
 2   price                    332939 non-null  int64
 3   type                     332939 non-null  object
 4   sqfeet                   332939 non-null  int64
 5   beds                     332939 non-null  int64
 6   baths                    332939 non-null  float64
 7   cats_allowed             332939 non-null  int64
 8   dogs_allowed             332939 non-null  int64
 9   smoking_allowed          332939 non-null  int64
 10  wheelchair_access        332939 non-null  int64
 11  electric_vehicle_charge  332939 non-null  int64
 12  comes_furnished          332939 non-null  int64
 13  laundry_options          263927 non-null  object
 14  parking_options          210920 non-null  object
 15  description              332939 non-null  object
 16  lat                      332939 non-null  float64
 17  long                     332939 non-null  float64
 18  state                    332939 non-null  object
dtypes: float64(3), int64(10), object(6)
memory usage: 50.8+ MB
```

0.3.6 2.6 Filling Missing Categorical Values (Laundary, Parking)

Reason: Filling missing values with the mode ensures that the most realistic and frequently used option is assigned.

[51]:
```
# train_df["laundry_options"].fillna(train_df["laundry_options"].mode()[0],␣
↪inplace=True)
# train_df["parking_options"].fillna(train_df["parking_options"].mode()[0],␣
↪inplace=True)
train_df["laundry_options"] = train_df["laundry_options"].
↪fillna(train_df["laundry_options"].mode()[0])
train_df["parking_options"] = train_df["parking_options"].
↪fillna(train_df["parking_options"].mode()[0])

test_df["laundry_options"] = test_df["laundry_options"].
↪fillna(test_df["laundry_options"].mode()[0])
test_df["parking_options"] = test_df["parking_options"].
↪fillna(test_df["parking_options"].mode()[0])
```

[52]:
```
train_df.info()
```

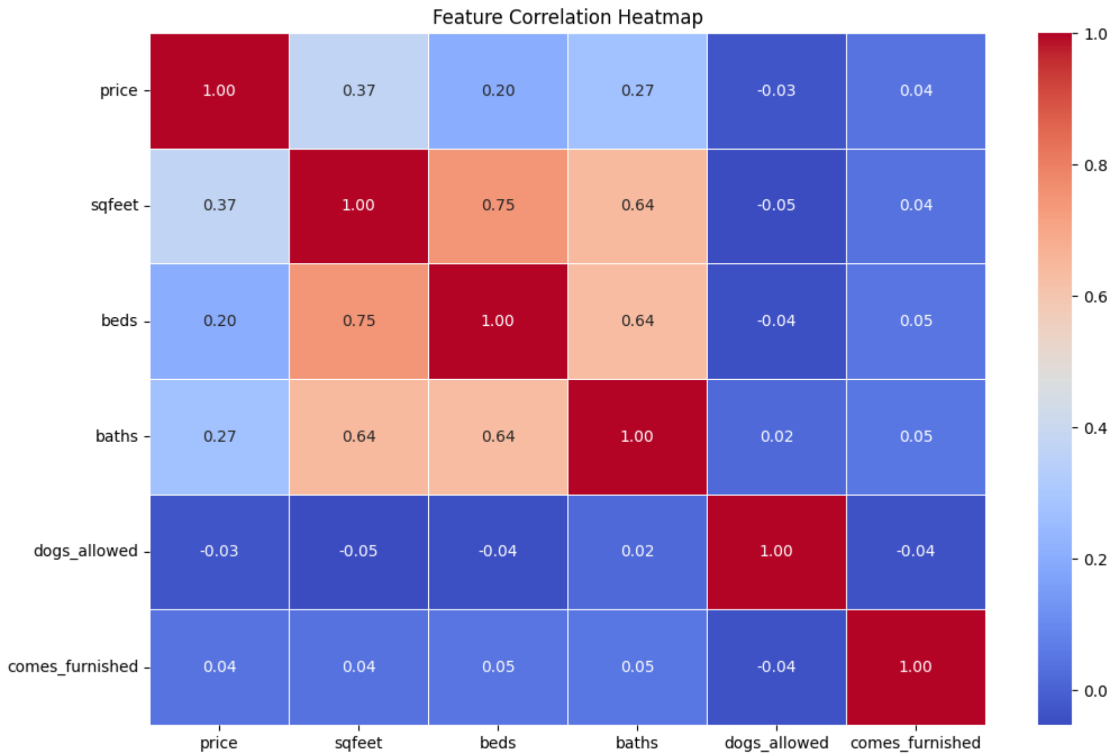
```
<class 'pandas.core.frame.DataFrame'>
Index: 332939 entries, 0 to 346478
Data columns (total 19 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   id                       332939 non-null  int64
 1   region                   332939 non-null  object
 2   price                    332939 non-null  int64
 3   type                     332939 non-null  object
 4   sqfeet                   332939 non-null  int64
 5   beds                     332939 non-null  int64
 6   baths                    332939 non-null  float64
 7   cats_allowed             332939 non-null  int64
 8   dogs_allowed             332939 non-null  int64
 9   smoking_allowed          332939 non-null  int64
 10  wheelchair_access        332939 non-null  int64
 11  electric_vehicle_charge  332939 non-null  int64
 12  comes_furnished          332939 non-null  int64
 13  laundry_options          332939 non-null  object
 14  parking_options          332939 non-null  object
 15  description              332939 non-null  object
 16  lat                      332939 non-null  float64
 17  long                     332939 non-null  float64
 18  state                    332939 non-null  object
dtypes: float64(3), int64(10), object(6)
memory usage: 50.8+ MB
```

[53]:
```
train_df.describe()
```

[53]:
```
                 id          price         sqfeet           beds  \
count  3.329390e+05  332939.000000  332939.000000  332939.000000
mean   7.040948e+09    1190.087316    1007.999162       1.947990
std    8.808727e+06     574.643847     363.995150       0.823293
min    7.003808e+09     157.000000     210.000000       1.000000
25%    7.035952e+09     820.000000     766.000000       1.000000
50%    7.043143e+09    1049.000000     950.000000       2.000000
75%    7.048411e+09    1399.000000    1153.000000       2.000000
max    7.051292e+09    7200.000000    4136.000000       8.000000

               baths   cats_allowed   dogs_allowed  smoking_allowed  \
count  332939.000000  332939.000000  332939.000000    332939.000000
mean        1.492473       0.727542       0.709310         0.735910
std         0.586911       0.445225       0.454081         0.440848
min         0.000000       0.000000       0.000000         0.000000
25%         1.000000       0.000000       0.000000         0.000000
50%         1.000000       1.000000       1.000000         1.000000
75%         2.000000       1.000000       1.000000         1.000000
max         7.500000       1.000000       1.000000         1.000000

       wheelchair_access  electric_vehicle_charge  comes_furnished  \
count      332939.000000            332939.000000    332939.000000
mean            0.079210                 0.012537         0.043963
std             0.270066                 0.111264         0.205013
min             0.000000                 0.000000         0.000000
25%             0.000000                 0.000000         0.000000
50%             0.000000                 0.000000         0.000000
75%             0.000000                 0.000000         0.000000
max             1.000000                 1.000000         1.000000

                 lat           long
count  332939.000000  332939.000000
mean       37.216456     -92.530496
std         5.546563      16.431466
min       -43.533300    -163.894000
25%        33.422600     -98.611700
50%        37.623600     -87.625700
75%        41.137900     -81.162800
max       102.036000     172.633000
```

[54]:
```
selected_cols = ["price", "sqfeet", "beds", "baths", "dogs_allowed",␣
 ↪"comes_furnished"]

# Compute the correlation matrix
corr_matrix = train_df[selected_cols].corr()
```

```
# Plot the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap="coolwarm", linewidths=0.5)
plt.title("Feature Correlation Heatmap")
plt.show()
```



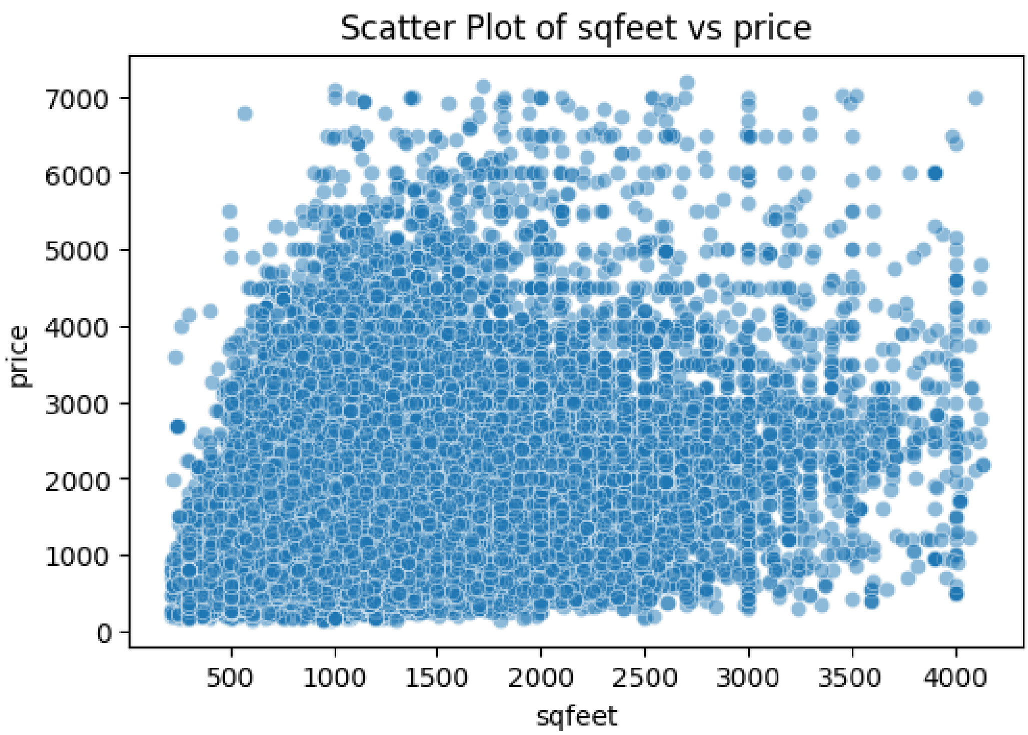
Key Insights - Square footage is the most important numerical feature for price prediction. - Bedrooms and bathrooms have weak correlations, meaning size matters more than room count. - Pet-friendliness and furnishing don't significantly impact rent.

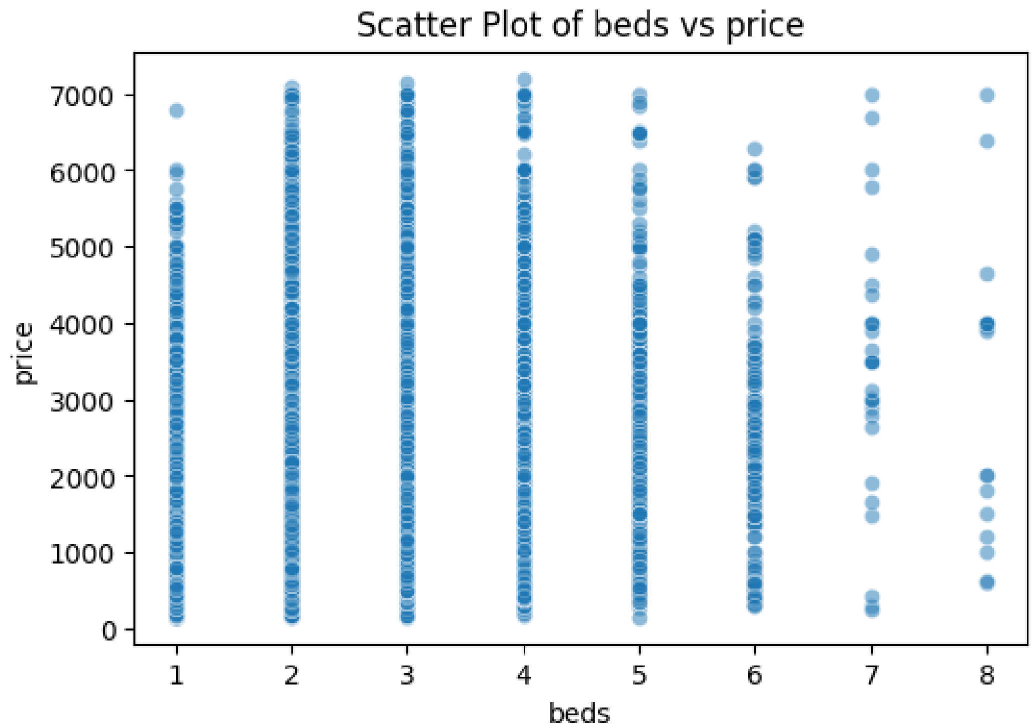
- Beds, baths, and sqfeet are highly correlated, meaning **multicollinearity** exists.
- We might remove beds or baths in some models (to avoid redundancy).
  - Predicting price using both beds and sqfeet might not add extra value.

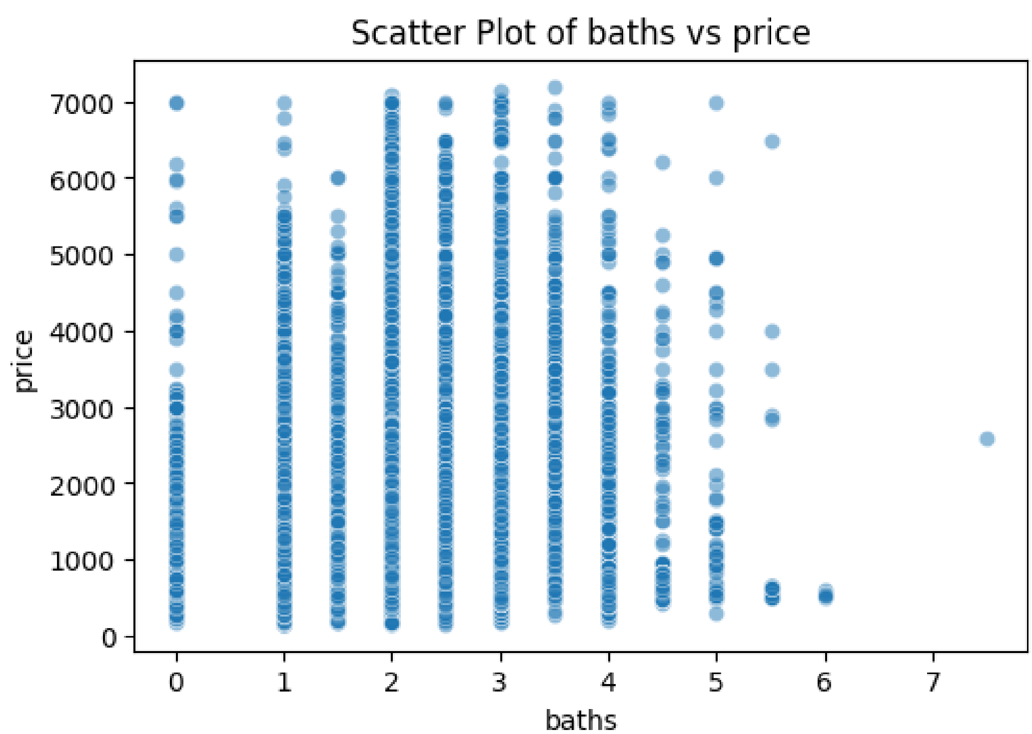
[55]:
```
def plot_scatter(df, columns, target="price"):
    plt.figure(figsize=(12, 8))
    for col in columns:
        plt.figure(figsize=(6, 4))
        sns.scatterplot(x=df[col], y=df[target], alpha=0.5)
        plt.xlabel(col)
        plt.ylabel(target)
        plt.title(f"Scatter Plot of {col} vs {target}")
```

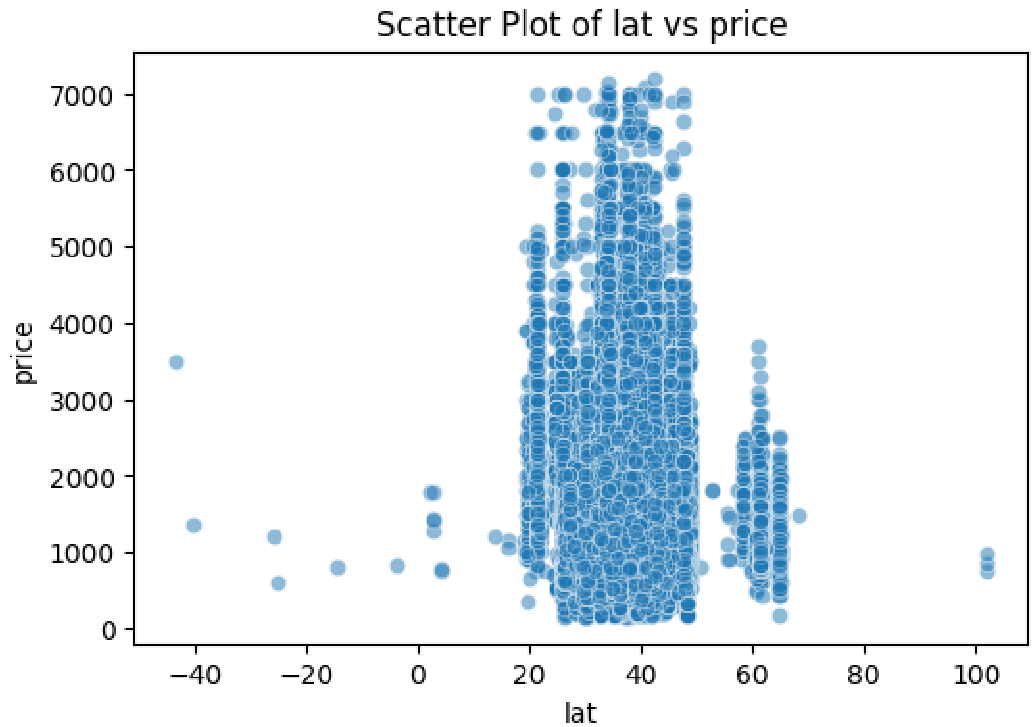
```
        plt.show()

numerical_cols = ["sqfeet", "beds", "baths", "lat", "long"]
plot_scatter(train_df, numerical_cols, target="price")
```

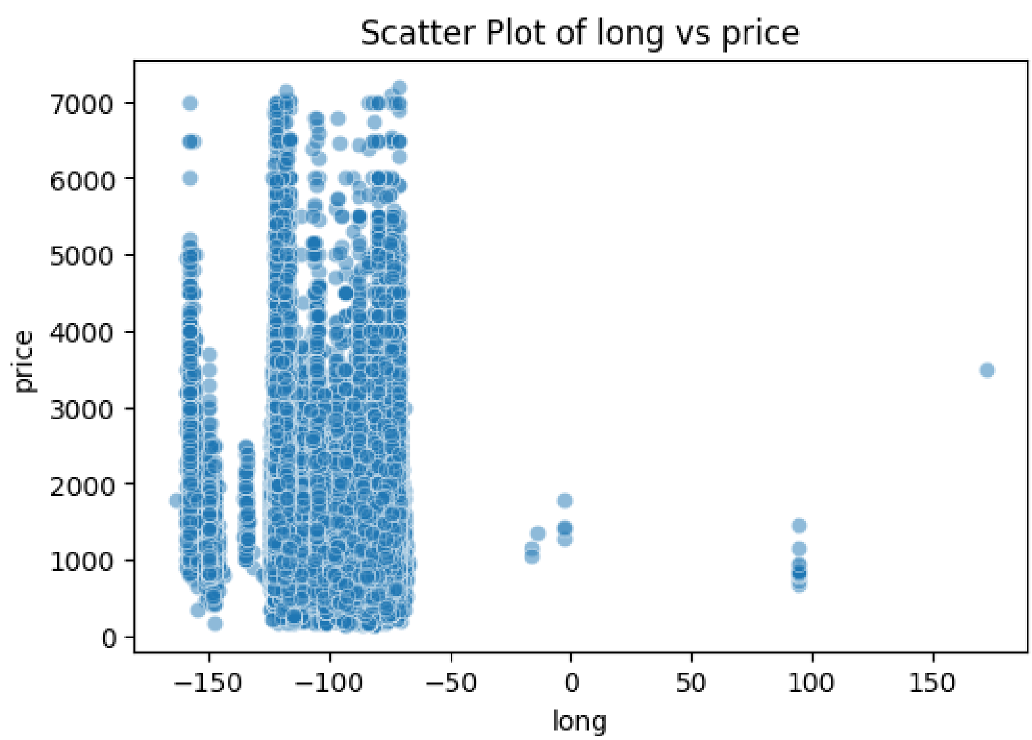
<Figure size 1200x800 with 0 Axes>




Scatter Plot of beds vs price
price
beds
0
1000
2000
3000
4000
5000
6000
7000
1
2
3
4
5
6
7
8

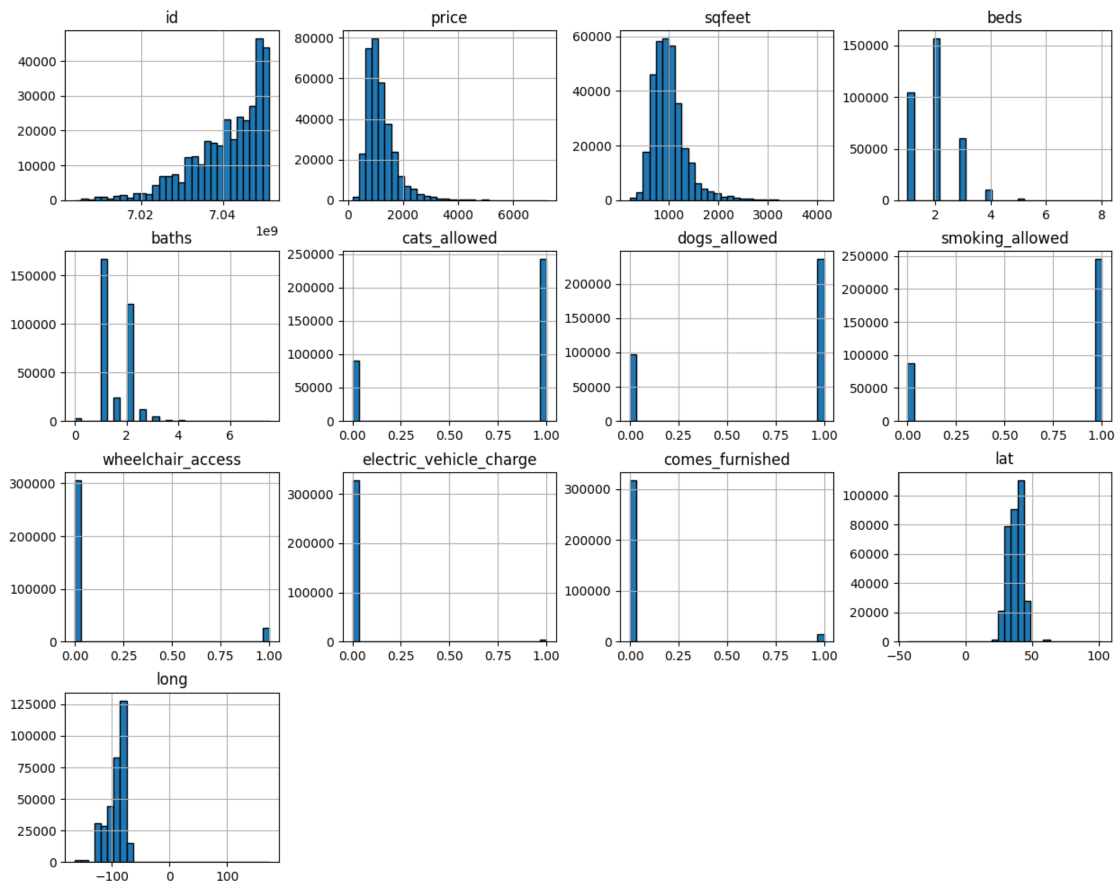

Scatter Plot of baths vs price
price
baths
0
1000
2000
3000
4000
5000
6000
7000
0
1
2
3
4
5
6
7


Scatter Plot of lat vs price
price
lat
0
1000
2000
3000
4000
5000
6000
7000
−40
−20
0
20
40
60
80
100


Scatter Plot of long vs price
price
long
0
1000
2000
3000
4000
5000
6000
7000
−150
−100
−50
0
50
100
150

[56]:
```
train_df.hist(figsize=(15, 12), bins=30, edgecolor="black")
```

[56]:
```
array([[<Axes: title={'center': 'id'}>,
        <Axes: title={'center': 'price'}>,
        <Axes: title={'center': 'sqfeet'}>,
        <Axes: title={'center': 'beds'}>],
       [<Axes: title={'center': 'baths'}>,
        <Axes: title={'center': 'cats_allowed'}>,
        <Axes: title={'center': 'dogs_allowed'}>,
        <Axes: title={'center': 'smoking_allowed'}>],
       [<Axes: title={'center': 'wheelchair_access'}>,
        <Axes: title={'center': 'electric_vehicle_charge'}>,
        <Axes: title={'center': 'comes_furnished'}>,
        <Axes: title={'center': 'lat'}>],
       [<Axes: title={'center': 'long'}>, <Axes: >, <Axes: >, <Axes: >]],
      dtype=object)
```



0.4 Feature Engineering

0.4.1 3.1 Creating new features

[57]:
```
# Price per sq
# Not included because of leaking issue (we want to predict price)
train_df["price_per_sqft"] = train_df["price"] / train_df["sqfeet"]
test_df["price_per_sqft"] = test_df["price"] / test_df["sqfeet"]
```

[58]:
```
# Total pets allowed
train_df["total_pets"] = train_df["cats_allowed"] + train_df["dogs_allowed"]
test_df["total_pets"] = test_df["cats_allowed"] + test_df["dogs_allowed"]
```

[59]:
```
# Luxury feature allowed (Wheelchair, electric, comes_furnihed)
train_df["luxury_features"] = (train_df["electric_vehicle_charge"] +␣
 ↪train_df["wheelchair_access"] + train_df["comes_furnished"])
test_df["luxury_features"] = (test_df["electric_vehicle_charge"] +␣
 ↪test_df["wheelchair_access"] + test_df["comes_furnished"])
```

[60]:
```
# 4. Location cluster feature based on Lat and Lng
# 12 general regions in US
coords = train_df[['lat', 'long']]
kmeans = KMeans(n_clusters=10, random_state=42)
train_df['geo_cluster'] = kmeans.fit_predict(coords)

coords = test_df[['lat', 'long']]
kmeans = KMeans(n_clusters=10, random_state=42)
test_df['geo_cluster'] = kmeans.fit_predict(coords)
```

[61]:
```
# Frequency encoding for region
region_freq = train_df['region'].value_counts(normalize=True)
train_df['region_freq'] = train_df['region'].map(region_freq)

region_freq = test_df['region'].value_counts(normalize=True)
test_df['region_freq'] = test_df['region'].map(region_freq)
```

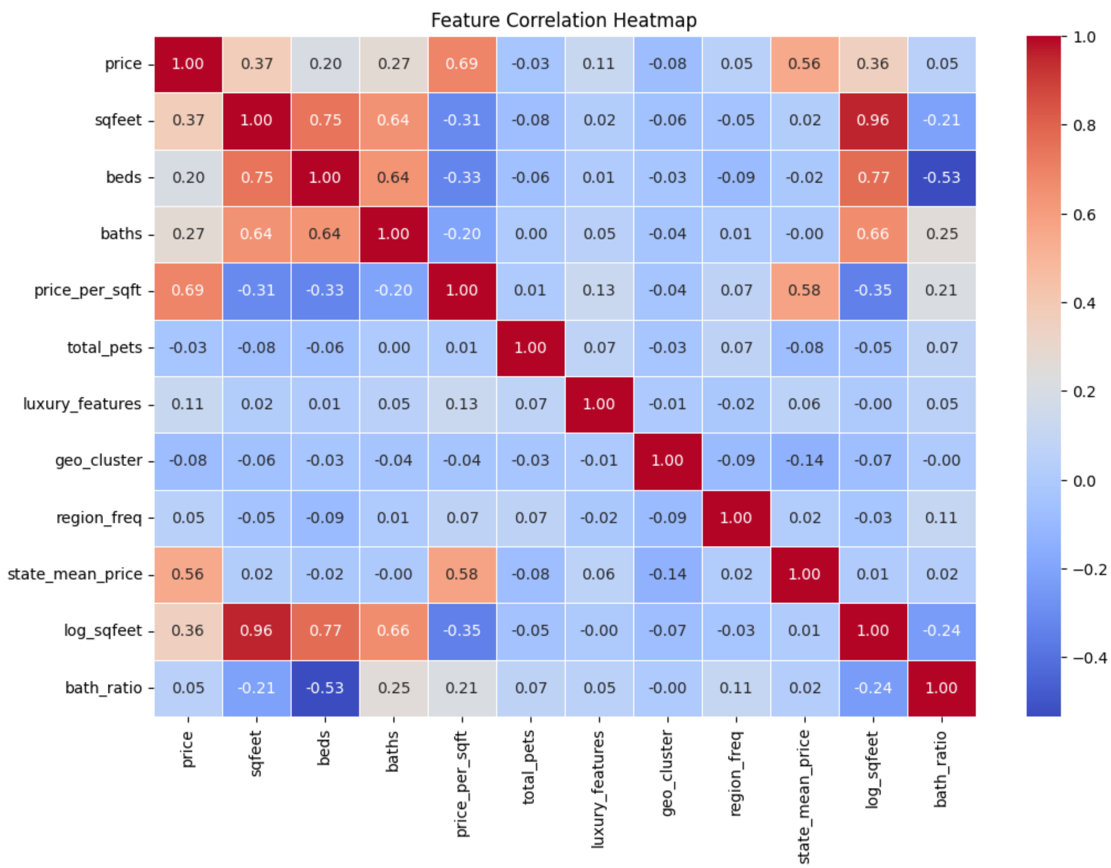
[62]:
```
# Apply log transformation to skewed features
train_df["log_price"] = np.log1p(train_df["price"])
train_df["log_sqfeet"] = np.log1p(train_df["sqfeet"])

test_df["log_price"] = np.log1p(test_df["price"])
test_df["log_sqfeet"] = np.log1p(test_df["sqfeet"])
```

[63]:
```
# Target encoding for state
state_mean_price = train_df.groupby('state')['price'].mean()
train_df['state_mean_price'] = train_df['state'].map(state_mean_price)

state_mean_price = test_df.groupby('state')['price'].mean()
```

```
test_df['state_mean_price'] = test_df['state'].map(state_mean_price)
```

[64]:
```
# Bath ratio
train_df['bath_ratio'] = train_df['baths'] / train_df['beds']

test_df['bath_ratio'] = test_df['baths'] / test_df['beds']
```

[65]:
```
selected_cols = ["price", "sqfeet", "beds", "baths", "price_per_sqft", "total_pets", "luxury_features", "geo_cluster", "region_freq", "state_mean_price", "log_sqfeet", "bath_ratio"]

# Compute the correlation matrix
corr_matrix = train_df[selected_cols].corr()

# Plot the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap="coolwarm", linewidths=0.5)
plt.title("Feature Correlation Heatmap")
plt.show()
```



```
[66]: # Dropping price_per_sqfeet due to unfair advantage in training and prediction
train_df.drop(columns=["price_per_sqft"], inplace=True)
test_df.drop(columns=["price_per_sqft"], inplace=True)
```

```
[67]: train_df.drop(columns=["state_mean_price"], inplace=True)
test_df.drop(columns=["state_mean_price"], inplace=True)
```

0.4.2 3.2 Text feature engineering - Description

Options - Using TF-IDF vectorization - Use BERT embedding (768 additional column for meaningful description, PCA/Autoencoders to reduce it to 100 again) - Using Spacy Named Entity Recognition (NER), we can have meaningful additional columns that could impact the price, but they were taking too much time (2+ hrs) - **Used:** Keyword-based Binary Flags, using insights word cloud above in the EDA

NER (unused)

```
[68]: # def preprocess_text(text):
#     text = text.lower()
#     text = re.sub(r'[^\w\s]', '', text)
#     return text

# train_df['description_cleaned'] = train_df['description'].
 ↪apply(preprocess_text)
```

```
[69]: # vectorizer = TfidfVectorizer(stop_words="english", max_features=100,␣
 ↪ngram_range=(1, 2))
# desc_features = vectorizer.fit_transform(train_df["description_cleaned"])
# # Convert to DataFrame and merge
# desc_df = pd.DataFrame(desc_features.toarray(), columns=[f"desc_{i}" for i in␣
 ↪range(100)])
```

```
[70]: # train_df = pd.concat([train_df.reset_index(drop=True), desc_df], axis=1)
# # Drop raw description column
# train_df.drop(columns=["description"], inplace=True)
```

```
[71]: # Load spaCy's pre-trained English model
# nlp = spacy.load("en_core_web_sm", disable=["tagger", "parser"])
```

```
[72]: # Define the entity labels we care about
# relevant_entities = {"FAC", "ORG", "GPE", "LOC", "MONEY"}  # Only these␣
 ↪entities

# Function to extract binary entity flags (FAST)
# def extract_entity_flags(texts):
#     entity_flags = []
```

```
#     for doc in tqdm(nlp.pipe(texts, batch_size=500), total=len(texts),␣
↪desc="Processing NER"):
#         entities_present = {label: 0 for label in relevant_entities}  #␣
↪Initialize all to 0
#         for ent in doc.ents:
#             if ent.label_ in relevant_entities:
#                 entities_present[ent.label_] = 1  # Mark as present
#         entity_flags.append(entities_present)

#     return entity_flags
```

[73]:
```
# train_df.drop(columns=["named_entities"], inplace=True)
# test_df.drop(columns=["named_entities"], inplace=True)
```

[74]:
```
# Convert descriptions to strings (avoid NaN issues)
# train_df['description'] = train_df['description'].astype(str)
# test_df['description'] = test_df['description'].astype(str)
```

[75]:
```
# Apply batch processing with progress tracking
# train_entity_flags = extract_entity_flags(train_df['description'])
# test_entity_flags = extract_entity_flags(test_df['description'])
```

[76]:
```
# Convert results to DataFrame and merge
# train_entity_df = pd.DataFrame(train_entity_flags)
# test_entity_df = pd.DataFrame(test_entity_flags)

# train_df = pd.concat([train_df, train_entity_df], axis=1)
# test_df = pd.concat([test_df, test_entity_df], axis=1)
```

[77]:
```
# pd.set_option('display.max_colwidth', None)
# print(train_df['description'][100:110])
# pd.reset_option('display.max_colwidth')
# train_df.head(10)[['named_entities', 'description']]
```

[78]:
```
# train_df.head()['named_entities']
```

[79]:
```
# train_df.shape
```

Keyword-based Binary Flags

[80]:
```
feature_keywords = {
    "has_outdoor": ["tennis", "court", "business center", "park", "community",␣
↪"clubhouse"],
    "has_pool": ["pool", "swimming"],
    "has_fitness_center": ["gym", "fitness center"],
    "mentions_price": ["rent", "deposit", "fee", "monthly"],
    "has_maintenance": ["emergency", "maintenance", "onsite"],
    "has_management": ["management", "managed", "professionally", "office"],
```

```
    "has_garbage_disposal": ["garbage", "disposal"],
    "has_closet": ["closet", "closets", "storage"],
    "has_kitchen": ["dining", "kitchen", "refrigerator"],
    "has_fan": ["fan", "air"],
    "has_offer": ["offer", "offers", "discount"],
    "has_appliances": ["appliances", "dryer", "laundry", "washer"]
}

# 'access', 'air', 'amenities', 'apartment', 'apartments',
# 'appliances', 'application', 'apply', 'area', 'availability',
# 'available', 'bath', 'beautiful', 'bedroom', 'bedrooms', 'ceiling',
# 'center', 'central', 'change', 'close', 'closet', 'closets',
# 'clubhouse', 'come', 'community', 'contact', 'court', 'deposit',
# 'details', 'dining', 'dishwasher', 'dogs', 'downtown', 'dryer',
# 'easy', 'enjoy', 'equal', 'features', 'fee', 'fitness', 'floor',
# 'flooring', 'free', 'friendly', 'ft', 'great', 'home', 'homes',
# 'housing', 'included', 'info', 'just', 'kitchen', 'large',
# 'laundry', 'lease', 'leasing', 'living', 'located', 'location',
# 'maintenance', 'management', 'minutes', 'month', 'new', 'offer',
# 'offers', 'office', 'online', 'onsite', 'opportunity', 'park',
# 'parking', 'patio', 'pet', 'pets', 'plans', 'pool', 'private',
# 'property', 'refrigerator', 'rent', 'room', 'schedule', 'select',
# 'shopping', 'space', 'spacious', 'sq', 'storage', 'subject',
# 'swimming', 'today', 'tour', 'unit', 'units', 'walkin', 'washer',
# 'water', 'welcome'

# Function to check for keyword presence
def keyword_flag(text, keywords):
    return bool(any(word in str(text).lower() for word in keywords))
```

[81]:
```
# Apply to dataset
for feature, words in feature_keywords.items():
    train_df[feature] = train_df['description'].apply(lambda x: keyword_flag(x,␣
 ↪words))
```

[82]:
```
train_df.shape
```

[82]: (332939, 38)

[83]:
```
train_df.head()
```

[83]:
```
           id              region  price       type  sqfeet  beds  baths  \
0  7049965813       orange county   2632  apartment    1080     2    2.0
1  7036046796      visalia-tulare   1160  apartment     768     2    1.0
2  7037856890            portland   1262  apartment    1075     2    1.0
3  7046933042             boulder   1861  apartment    1076     2    2.0
4  7048650961  sioux falls / SE SD    626  apartment     720     1    1.0
```

```
   cats_allowed  dogs_allowed  smoking_allowed  …  has_fitness_center  \
0             1             1                0  …                True
1             1             1                1  …               False
2             1             1                0  …               False
3             1             1                0  …               False
4             1             1                0  …                True

   mentions_price  has_maintenance has_management has_garbage_disposal  \
0            True            False          False                 True
1           False            False           True                False
2           False             True           True                False
3            True             True           True                False
4           False            False          False                False

  has_closet  has_kitchen  has_fan has_offer  has_appliances
0      False        False     True      True            True
1      False        False    False     False           False
2      False        False    False      True            True
3       True         True     True      True            True
4      False        False    False     False           False

[5 rows x 38 columns]
```

[84]:
```python
for feature, words in feature_keywords.items():
    test_df[feature] = test_df['description'].apply(lambda x: keyword_flag(x,␣
↪words))
```

[85]:
```python
test_df.shape
```

[85]:
```
(36947, 38)
```

0.4.3 3.3 Encode Categorical Variables (type, laundry, parking)

One-Hot Encoding for Nominal Categories (Type, Laundary, Parking Lot) For model to train, convert `laundry`, `parking`, … to numerical values

Laundry, Parking

[86]:
```python
# test_df['type'].unique()
```

[87]:
```python
# train_df['type'].unique()
```

[88]:
```python
train_df = pd.get_dummies(
    train_df, columns=["laundry_options", "parking_options"], drop_first=True
)

test_df = pd.get_dummies(
```

```
    test_df, columns=["laundry_options", "parking_options"], drop_first=True
)

# assisted living is not present in test df, ensuring both have same columns
test_df = test_df.reindex(columns=train_df.columns, fill_value=False)

train_df.shape
```

[88]: (332939, 46)

[89]:
```
train_df.head()
```

[89]:
```
           id              region  price       type  sqfeet  beds  baths  \
0  7049965813       orange county   2632  apartment    1080     2    2.0
1  7036046796      visalia-tulare   1160  apartment     768     2    1.0
2  7037856890            portland   1262  apartment    1075     2    1.0
3  7046933042             boulder   1861  apartment    1076     2    2.0
4  7048650961  sioux falls / SE SD   626  apartment     720     1    1.0

   cats_allowed  dogs_allowed  smoking_allowed  …  \
0             1             1                0  …
1             1             1                1  …
2             1             1                0  …
3             1             1                0  …
4             1             1                0  …

   laundry_options_laundry on site  laundry_options_no laundry on site  \
0                            False                               False
1                             True                               False
2                             True                               False
3                            False                               False
4                            False                               False

   laundry_options_w/d hookups laundry_options_w/d in unit  \
0                        False                        True
1                        False                       False
2                        False                       False
3                        False                        True
4                        False                        True

   parking_options_carport  parking_options_detached garage  \
0                    False                            False
1                     True                            False
2                    False                            False
3                    False                             True
4                    False                             True
```

```
  parking_options_no parking  parking_options_off-street parking  \
0                      False                               False
1                      False                               False
2                      False                                True
3                      False                               False
4                      False                               False

   parking_options_street parking  parking_options_valet parking
0                           False                          False
1                           False                          False
2                           False                          False
3                           False                          False
4                           False                          False

[5 rows x 46 columns]
```

[90]:
```
test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 36947 entries, 0 to 38497
Data columns (total 46 columns):
 #   Column                                Non-Null Count  Dtype
---  ------                                --------------  -----
 0   id                                    36947 non-null  int64
 1   region                                36947 non-null  object
 2   price                                 36947 non-null  int64
 3   type                                  36947 non-null  object
 4   sqfeet                                36947 non-null  int64
 5   beds                                  36947 non-null  int64
 6   baths                                 36947 non-null  float64
 7   cats_allowed                          36947 non-null  int64
 8   dogs_allowed                          36947 non-null  int64
 9   smoking_allowed                       36947 non-null  int64
 10  wheelchair_access                     36947 non-null  int64
 11  electric_vehicle_charge               36947 non-null  int64
 12  comes_furnished                       36947 non-null  int64
 13  description                           36947 non-null  object
 14  lat                                   36947 non-null  float64
 15  long                                  36947 non-null  float64
 16  state                                 36947 non-null  object
 17  total_pets                            36947 non-null  int64
 18  luxury_features                       36947 non-null  int64
 19  geo_cluster                           36947 non-null  int32
 20  region_freq                           36947 non-null  float64
 21  log_price                             36947 non-null  float64
 22  log_sqfeet                            36947 non-null  float64
 23  bath_ratio                            36947 non-null  float64
 24  has_outdoor                           36947 non-null  bool
```

```
 25  has_pool                           36947 non-null  bool
 26  has_fitness_center                 36947 non-null  bool
 27  mentions_price                     36947 non-null  bool
 28  has_maintenance                    36947 non-null  bool
 29  has_management                     36947 non-null  bool
 30  has_garbage_disposal               36947 non-null  bool
 31  has_closet                         36947 non-null  bool
 32  has_kitchen                        36947 non-null  bool
 33  has_fan                            36947 non-null  bool
 34  has_offer                          36947 non-null  bool
 35  has_appliances                     36947 non-null  bool
 36  laundry_options_laundry on site    36947 non-null  bool
 37  laundry_options_no laundry on site 36947 non-null  bool
 38  laundry_options_w/d hookups        36947 non-null  bool
 39  laundry_options_w/d in unit        36947 non-null  bool
 40  parking_options_carport            36947 non-null  bool
 41  parking_options_detached garage    36947 non-null  bool
 42  parking_options_no parking         36947 non-null  bool
 43  parking_options_off-street parking 36947 non-null  bool
 44  parking_options_street parking     36947 non-null  bool
 45  parking_options_valet parking      36947 non-null  bool
dtypes: bool(22), float64(7), int32(1), int64(12), object(4)
memory usage: 7.7+ MB
```

Type

[91]:
```python
type_counts = train_df["type"].value_counts()
type_counts
```

[91]:
```
type
apartment          274290
house               29242
townhouse           14195
condo                5378
duplex               4403
manufactured         3680
cottage/cabin         607
loft                  572
flat                  447
in-law                120
land                    3
assisted living         2
Name: count, dtype: int64
```

[92]:
```python
rare_types = type_counts[type_counts < 1000].index
rare_types
```

[92]: Index(['cottage/cabin', 'loft', 'flat', 'in-law', 'land', 'assisted living'],
dtype='object', name='type')

[93]:
```python
# Replace rare types with "other"
train_df["type"] = train_df["type"].replace(rare_types, "other")
test_df["type"] = test_df["type"].replace(rare_types, "other")
```

[94]:
```python
# One-hot encode after grouping
type_encoded_train = pd.get_dummies(train_df["type"], prefix="type")
type_encoded_test = pd.get_dummies(test_df["type"], prefix="type")
```

[95]:
```python
type_encoded_test = type_encoded_test.reindex(columns=type_encoded_train.
 ↪columns, fill_value=0)
```

[96]:
```python
train_df = pd.concat([train_df, type_encoded_train], axis=1)
test_df = pd.concat([test_df, type_encoded_test], axis=1)
```

[97]:
```python
# Drop original type column
train_df.drop(columns=["type"], inplace=True)
test_df.drop(columns=["type"], inplace=True)
```

[98]:
```python
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 332939 entries, 0 to 346478
Data columns (total 52 columns):
 #   Column                         Non-Null Count   Dtype
---  ------                         --------------   -----
 0   id                             332939 non-null  int64
 1   region                         332939 non-null  object
 2   price                          332939 non-null  int64
 3   sqfeet                         332939 non-null  int64
 4   beds                           332939 non-null  int64
 5   baths                          332939 non-null  float64
 6   cats_allowed                   332939 non-null  int64
 7   dogs_allowed                   332939 non-null  int64
 8   smoking_allowed                332939 non-null  int64
 9   wheelchair_access              332939 non-null  int64
 10  electric_vehicle_charge        332939 non-null  int64
 11  comes_furnished                332939 non-null  int64
 12  description                    332939 non-null  object
 13  lat                            332939 non-null  float64
 14  long                           332939 non-null  float64
 15  state                          332939 non-null  object
 16  total_pets                     332939 non-null  int64
 17  luxury_features                332939 non-null  int64
 18  geo_cluster                    332939 non-null  int32
 19  region_freq                    332939 non-null  float64
```

```
 20  log_price                          332939 non-null  float64
 21  log_sqfeet                         332939 non-null  float64
 22  bath_ratio                         332939 non-null  float64
 23  has_outdoor                        332939 non-null  bool
 24  has_pool                           332939 non-null  bool
 25  has_fitness_center                 332939 non-null  bool
 26  mentions_price                     332939 non-null  bool
 27  has_maintenance                    332939 non-null  bool
 28  has_management                     332939 non-null  bool
 29  has_garbage_disposal               332939 non-null  bool
 30  has_closet                         332939 non-null  bool
 31  has_kitchen                        332939 non-null  bool
 32  has_fan                            332939 non-null  bool
 33  has_offer                          332939 non-null  bool
 34  has_appliances                     332939 non-null  bool
 35  laundry_options_laundry on site    332939 non-null  bool
 36  laundry_options_no laundry on site 332939 non-null  bool
 37  laundry_options_w/d hookups        332939 non-null  bool
 38  laundry_options_w/d in unit        332939 non-null  bool
 39  parking_options_carport            332939 non-null  bool
 40  parking_options_detached garage    332939 non-null  bool
 41  parking_options_no parking         332939 non-null  bool
 42  parking_options_off-street parking 332939 non-null  bool
 43  parking_options_street parking     332939 non-null  bool
 44  parking_options_valet parking      332939 non-null  bool
 45  type_apartment                     332939 non-null  bool
 46  type_condo                         332939 non-null  bool
 47  type_duplex                        332939 non-null  bool
 48  type_house                         332939 non-null  bool
 49  type_manufactured                  332939 non-null  bool
 50  type_other                         332939 non-null  bool
 51  type_townhouse                     332939 non-null  bool
dtypes: bool(29), float64(7), int32(1), int64(12), object(3)
memory usage: 68.9+ MB
```

0.4.4 3.4 Region Encoding

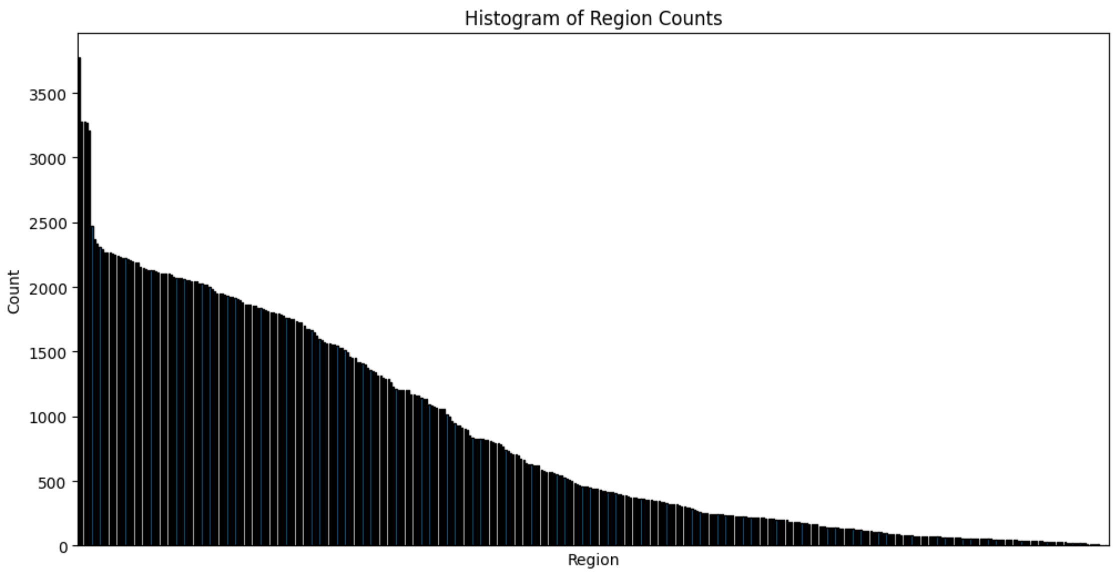
Used Kmeans clustering to encode region values into 10 categories, and then used coorelation matrix to determine the significant ones

[99]:
```
train_df['region'].value_counts()
```

[99]:
```
region
jacksonville      3772
fayetteville      3279
jackson           3279
columbus          3274
rochester         3212
```

```
                    …
southwest MS        11
st louis             7
southwest TX         7
fort smith, AR       3
kansas city          3
Name: count, Length: 404, dtype: int64
```

[100]:
```
# Plot histogram of region counts
plt.figure(figsize=(12, 6))
train_df["region"].value_counts().plot(kind="bar", edgecolor="black")

# Labels and title
plt.xlabel("Region")
plt.ylabel("Count")
plt.title("Histogram of Region Counts")
# plt.xticks(rotation=90)  # Rotate labels for better readability
plt.xticks([], [])
plt.show()
```



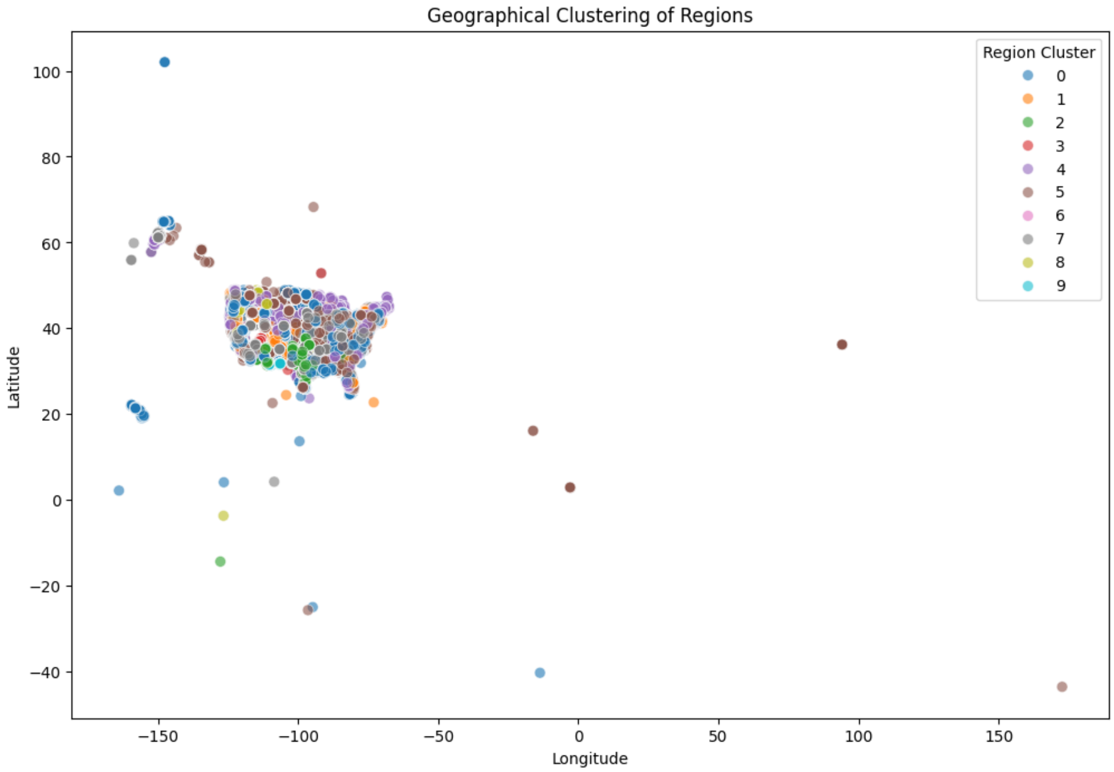
[101]:
```
# train_df.drop(columns=["region_cluster"], inplace=True, errors="ignore")
```

[102]:
```
 # Step 1: Compute region-level statistics
region_stats = train_df.groupby("region").agg({
    "sqfeet": "mean",
    "lat": "mean",
    "long": "mean"
}).reset_index()
```

```
region_stats_test = test_df.groupby("region").agg({
    "sqfeet": "mean",
    "lat": "mean",
    "long": "mean"
}).reset_index()

# Step 2: Apply K-Means clustering
num_clusters = 10  # Choose the number of clusters based on analysis

kmeans = KMeans(n_clusters=num_clusters, random_state=42)
region_stats["region_cluster"] = kmeans.fit_predict(region_stats[["sqfeet",␣
↪"lat", "long"]])

kmeans = KMeans(n_clusters=num_clusters, random_state=42)
region_stats_test["region_cluster"] = kmeans.
↪fit_predict(region_stats_test[["sqfeet", "lat", "long"]])

# Step 3: Merge the cluster labels back into train_df
train_df = train_df.merge(region_stats[["region", "region_cluster"]],␣
↪on="region", how="left")
test_df = test_df.merge(region_stats_test[["region", "region_cluster"]],␣
↪on="region", how="left")
```

[103]:

```
# Scatter plot of clusters based on latitude and longitude
plt.figure(figsize=(12, 8))
sns.scatterplot(x=train_df["long"], y=train_df["lat"],␣
↪hue=train_df["region_cluster"], palette="tab10", alpha=0.6, s=50)
plt.xlabel("Longitude")
plt.ylabel("Latitude")
plt.title("Geographical Clustering of Regions")
plt.legend(title="Region Cluster")
plt.show()
```



[104]:
```
train_df.shape
```

[104]: (332939, 53)

[105]:
```
# train_df['region_cluster'].value_counts()
```

[106]:
```
train_df.drop(columns=["region_cluster_x"], inplace=True, errors="ignore")
train_df.drop(columns=["region_cluster_y"], inplace=True, errors="ignore")

test_df.drop(columns=["region_cluster_x"], inplace=True, errors="ignore")
test_df.drop(columns=["region_cluster_y"], inplace=True, errors="ignore")
```

[107]:
```
train_df.shape
```

[107]: (332939, 53)

[108]:
```
train_df.head()
```

[108]:

	id	region	price	sqfeet	beds	baths	cats_allowed	\
0	7049965813	orange county	2632	1080	2	2.0	1	
1	7036046796	visalia-tulare	1160	768	2	1.0	1	
2	7037856890	portland	1262	1075	2	1.0	1	
3	7046933042	boulder	1861	1076	2	2.0	1	

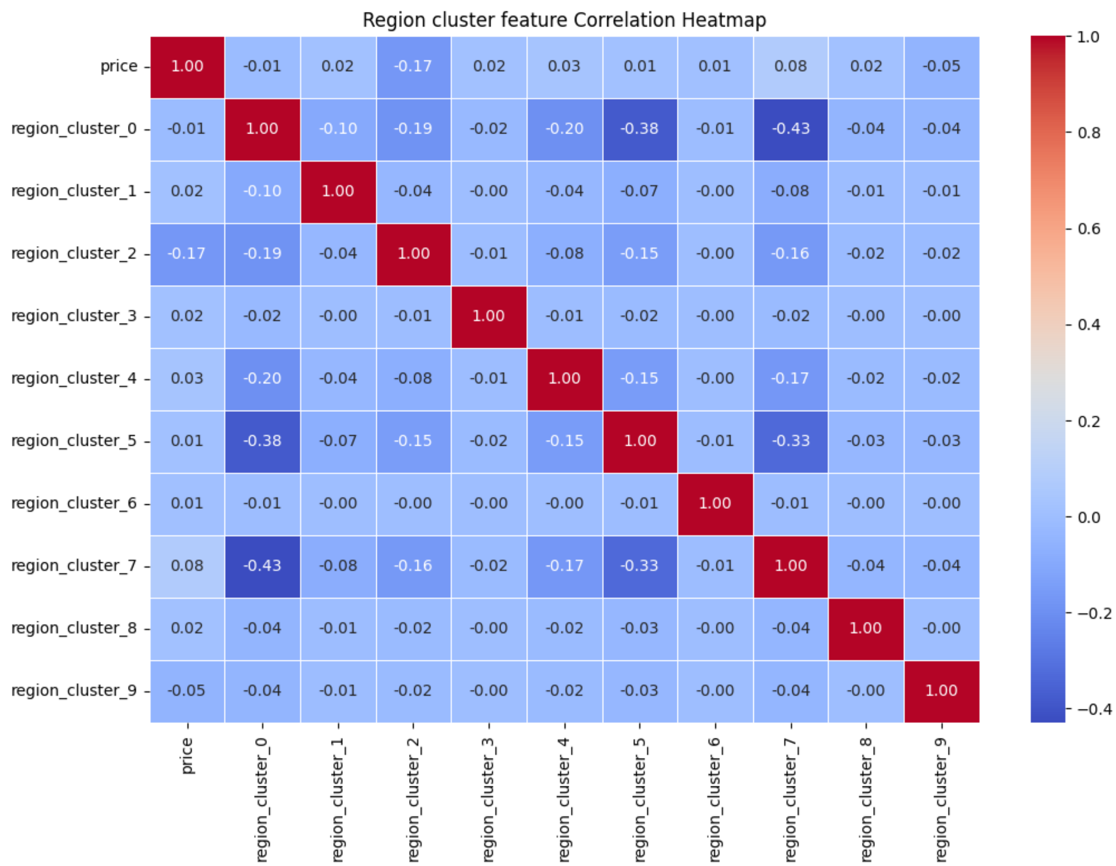
```
4  7048650961   sioux falls / SE SD    626     720     1    1.0              1

   dogs_allowed  smoking_allowed  wheelchair_access  …  \
0             1                0                  0  …
1             1                1                  0  …
2             1                0                  0  …
3             1                0                  0  …
4             1                0                  0  …

   parking_options_street parking  parking_options_valet parking  \
0                           False                          False
1                           False                          False
2                           False                          False
3                           False                          False
4                           False                          False

  type_apartment  type_condo  type_duplex type_house  type_manufactured  \
0           True       False        False      False              False
1           True       False        False      False              False
2           True       False        False      False              False
3           True       False        False      False              False
4           True       False        False      False              False

   type_other  type_townhouse  region_cluster
0       False           False               7
1       False           False               0
2       False           False               0
3       False           False               0
4       False           False               7

[5 rows x 53 columns]
```

[109]:
```python
# Apply one-hot encoding on region_cluster
region_cluster_encoded = pd.get_dummies(train_df["region_cluster"],␣
 ↪prefix="region_cluster")
region_cluster_encoded2 = pd.get_dummies(test_df["region_cluster"],␣
 ↪prefix="region_cluster")

# Drop the original column
train_df.drop(columns=["region_cluster"], inplace=True)
test_df.drop(columns=["region_cluster"], inplace=True)

# Merge one-hot encoded features back
train_df = pd.concat([train_df, region_cluster_encoded], axis=1)
test_df = pd.concat([test_df, region_cluster_encoded2], axis=1)
```

[110]:
```python
train_df.shape
```

[110]: (332939, 62)

[111]:
```python
selected_columns = [
    "price"
]

for i in range(10):
    selected_columns.append('region_cluster_' + str(i))

# Compute the correlation matrix
corr_matrix = train_df[selected_columns].corr()

# Plot the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap="coolwarm", linewidths=0.5)
plt.title("Region cluster feature Correlation Heatmap")
plt.show()
```



[112]:
```
# valuable: 2
# rest are insignificant
valuable = set([2])
for i in range(10):
    if i in valuable: continue
    train_df.drop(columns=["region_cluster_"+str(i)], inplace=True)
    test_df.drop(columns=["region_cluster_"+str(i)], inplace=True)
```

[113]:
```
train_df.shape
```

[113]: (332939, 53)

[114]:
```
test_df.shape
```

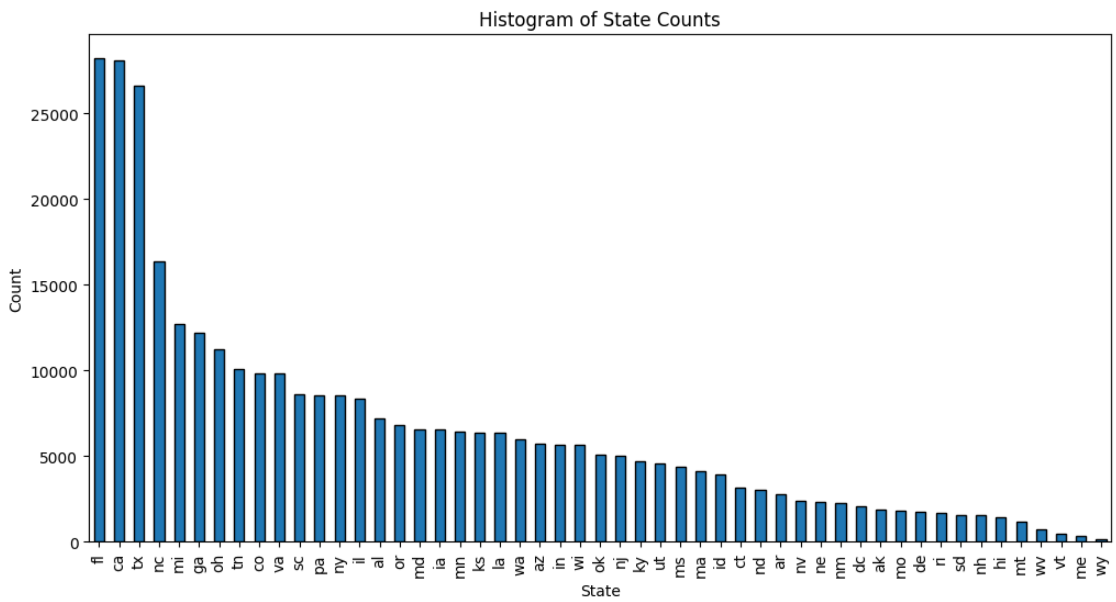
[114]: (36947, 53)

0.4.5 3.5 State Encoding

Used One-hot encoding to feature engineer the categorical state values, and then used coor matrix to determine significant ones

[115]:
```
# train_df['state'].value_counts()
```

[116]:
```
# Plot histogram of state counts
plt.figure(figsize=(12, 6))
train_df["state"].value_counts().plot(kind="bar", edgecolor="black")

# Labels and title
plt.xlabel("State")
plt.ylabel("Count")
plt.title("Histogram of State Counts")
plt.xticks(rotation=90)
# plt.xticks([], [])
plt.show()
```



[117]:
```
train_df.shape
```

[117]:
```
(332939, 53)
```

[118]:
```
# one-hot encode 'state'
state_encoded = pd.get_dummies(train_df["state"], prefix="state")
train_df = pd.concat([train_df, state_encoded], axis=1)

state_encoded2 = pd.get_dummies(test_df["state"], prefix="state")
state_encoded2 = state_encoded2.reindex(columns=state_encoded.columns,
 ↪fill_value=False)
test_df = pd.concat([test_df, state_encoded2], axis=1)
```

[119]:
```
train_df.shape
```

[119]:
```
(332939, 104)
```

[120]:
```
test_df.shape
```

[120]:
```
(36947, 104)
```

[121]:
```
train_df.head()
```

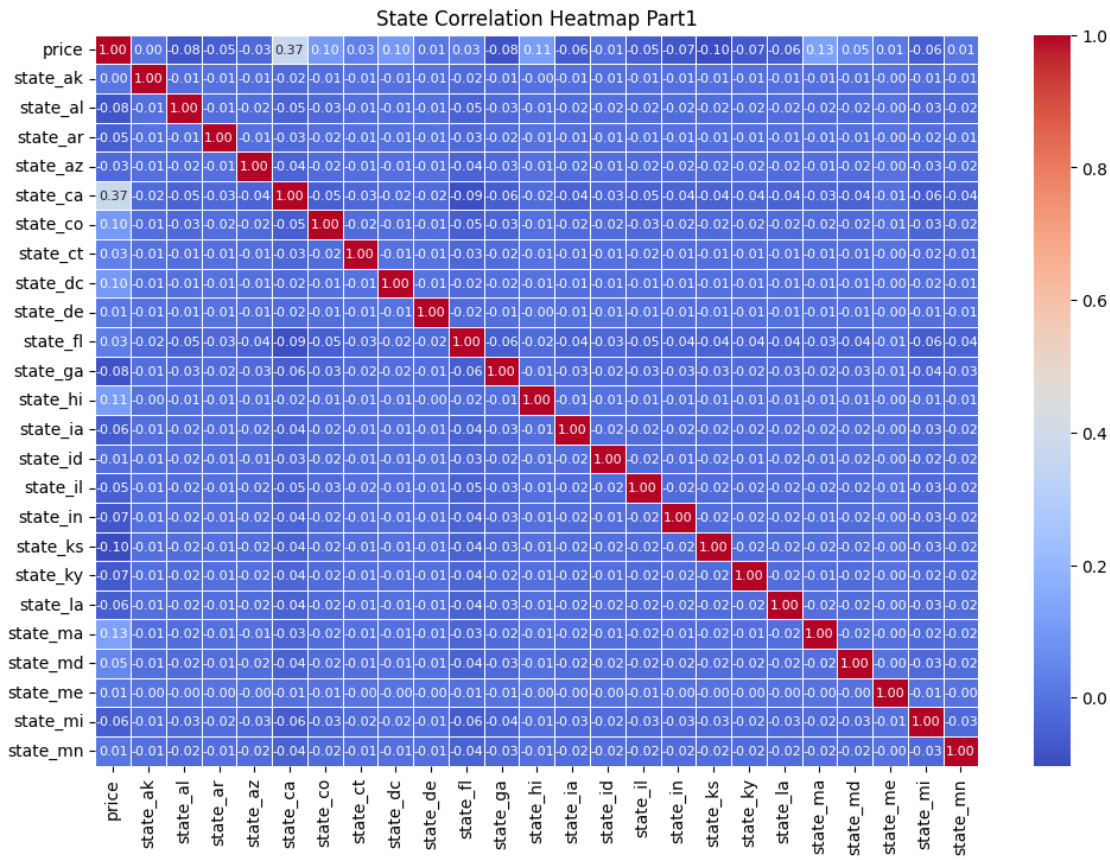
[121]:
```
           id           region  price  sqfeet  beds  baths  cats_allowed  \
0  7049965813    orange county   2632    1080     2    2.0             1
1  7036046796  visalia-tulare   1160     768     2    1.0             1
2  7037856890         portland   1262    1075     2    1.0             1
```

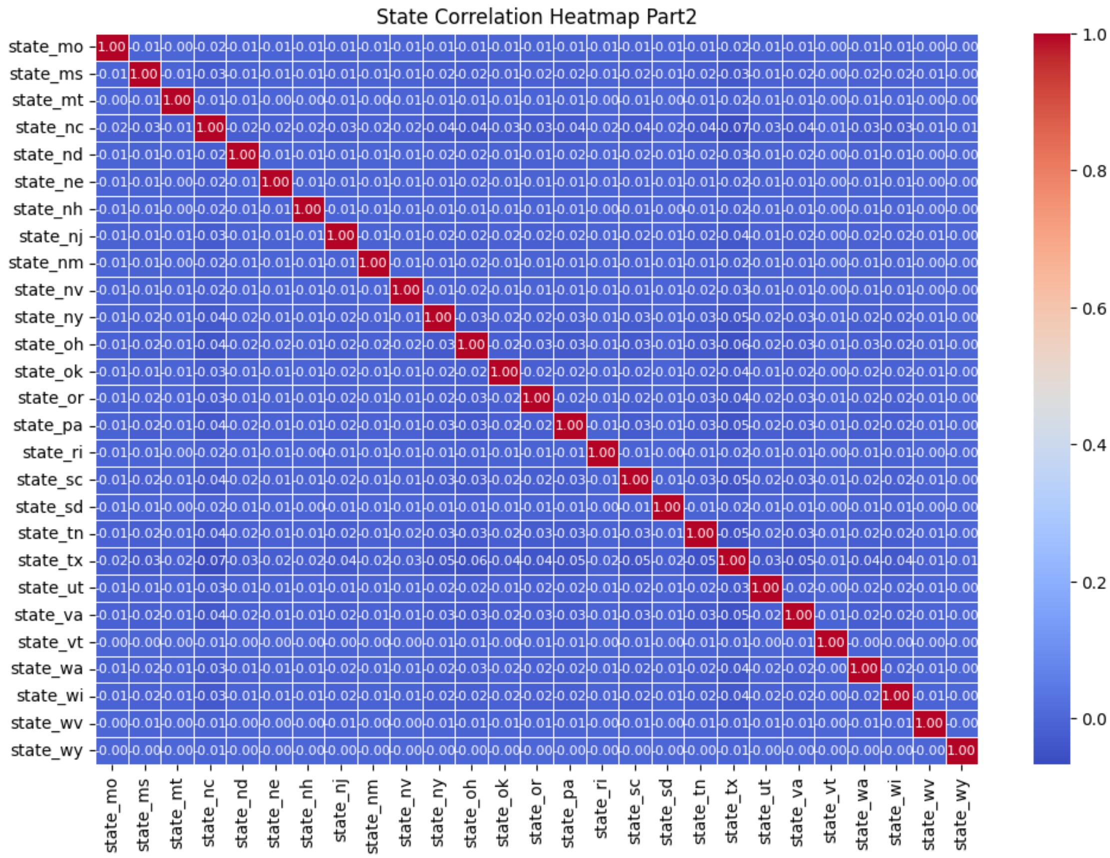
```
3  7046933042                boulder   1861    1076     2    2.0               1
4  7048650961  sioux falls / SE SD    626     720     1    1.0               1

   dogs_allowed  smoking_allowed  wheelchair_access  …  state_sd  state_tn  \
0             1                0                  0  …     False     False
1             1                1                  0  …     False     False
2             1                0                  0  …     False     False
3             1                0                  0  …     False     False
4             1                0                  0  …      True     False

  state_tx  state_ut  state_va state_vt  state_wa  state_wi  state_wv  \
0    False     False     False    False     False     False     False
1    False     False     False    False     False     False     False
2    False     False     False    False     False     False     False
3    False     False     False    False     False     False     False
4    False     False     False    False     False     False     False

   state_wy
0     False
1     False
2     False
3     False
4     False

[5 rows x 104 columns]
```

[122]:

```
selected_columns = [
    "price"
]

for col in train_df.columns:
    if col.startswith('state_'):
        selected_columns.append(col)

selected_columns_part1, selected_columns_part2 = selected_columns[:25],␣
 ↪selected_columns[25:]

corr_matrix = train_df[selected_columns_part1].corr()

plt.figure(figsize=(12, 8))
sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap="coolwarm", linewidths=0.
 ↪5, annot_kws={"size": 8})
plt.title("State Correlation Heatmap Part1")
plt.show()

corr_matrix2 = train_df[selected_columns_part2].corr()
```

```
plt.figure(figsize=(12, 8))
sns.heatmap(corr_matrix2, annot=True, fmt=".2f", cmap="coolwarm", linewidths=0.
↪5, annot_kws={"size": 8})
plt.title("State Correlation Heatmap Part2")
plt.show()
```





Key Takeaway - significant states: ca, co, dc, hi, ks, ma

[123]:
```
train_df.shape
```

[123]: (332939, 104)

[124]:
```
significant_states = set(['ca', 'co', 'dc', 'hi', 'ks', 'ma'])

for col in train_df.columns:
    if col.startswith('state_'):
        if col[-2:] in significant_states: continue

        train_df.drop(columns=[col], inplace=True)
        test_df.drop(columns=[col], inplace=True)
```

[125]:
```
train_df.shape
```

[125]: (332939, 59)

0.4.6 3.6. Normalize and Scale Numerical Data

Scale continous variables

[126]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 332939 entries, 0 to 332938
Data columns (total 59 columns):
 #   Column                              Non-Null Count   Dtype
---  ------                              --------------   -----
 0   id                                  332939 non-null  int64
 1   region                              332939 non-null  object
 2   price                               332939 non-null  int64
 3   sqfeet                              332939 non-null  int64
 4   beds                                332939 non-null  int64
 5   baths                               332939 non-null  float64
 6   cats_allowed                        332939 non-null  int64
 7   dogs_allowed                        332939 non-null  int64
 8   smoking_allowed                     332939 non-null  int64
 9   wheelchair_access                   332939 non-null  int64
 10  electric_vehicle_charge             332939 non-null  int64
 11  comes_furnished                     332939 non-null  int64
 12  description                         332939 non-null  object
 13  lat                                 332939 non-null  float64
 14  long                                332939 non-null  float64
 15  state                               332939 non-null  object
 16  total_pets                          332939 non-null  int64
 17  luxury_features                     332939 non-null  int64
 18  geo_cluster                         332939 non-null  int32
 19  region_freq                         332939 non-null  float64
 20  log_price                           332939 non-null  float64
 21  log_sqfeet                          332939 non-null  float64
 22  bath_ratio                          332939 non-null  float64
 23  has_outdoor                         332939 non-null  bool
 24  has_pool                            332939 non-null  bool
 25  has_fitness_center                  332939 non-null  bool
 26  mentions_price                      332939 non-null  bool
 27  has_maintenance                     332939 non-null  bool
 28  has_management                      332939 non-null  bool
 29  has_garbage_disposal                332939 non-null  bool
 30  has_closet                          332939 non-null  bool
 31  has_kitchen                         332939 non-null  bool
 32  has_fan                             332939 non-null  bool
 33  has_offer                           332939 non-null  bool
 34  has_appliances                      332939 non-null  bool
 35  laundry_options_laundry on site     332939 non-null  bool
 36  laundry_options_no laundry on site  332939 non-null  bool
 37  laundry_options_w/d hookups         332939 non-null  bool
```

```
 38  laundry_options_w/d in unit         332939 non-null  bool
 39  parking_options_carport             332939 non-null  bool
 40  parking_options_detached garage     332939 non-null  bool
 41  parking_options_no parking          332939 non-null  bool
 42  parking_options_off-street parking  332939 non-null  bool
 43  parking_options_street parking      332939 non-null  bool
 44  parking_options_valet parking       332939 non-null  bool
 45  type_apartment                      332939 non-null  bool
 46  type_condo                          332939 non-null  bool
 47  type_duplex                         332939 non-null  bool
 48  type_house                          332939 non-null  bool
 49  type_manufactured                   332939 non-null  bool
 50  type_other                          332939 non-null  bool
 51  type_townhouse                      332939 non-null  bool
 52  region_cluster_2                    332939 non-null  bool
 53  state_ca                            332939 non-null  bool
 54  state_co                            332939 non-null  bool
 55  state_dc                            332939 non-null  bool
 56  state_hi                            332939 non-null  bool
 57  state_ks                            332939 non-null  bool
 58  state_ma                            332939 non-null  bool
dtypes: bool(36), float64(7), int32(1), int64(12), object(3)
memory usage: 68.6+ MB
```

[127]:

```
scaler = StandardScaler()

# selecting numerical columns except the price
num_cols = train_df.select_dtypes(include=['int32', 'int64', 'float64']).columns
num_cols = num_cols.drop('price')
num_cols = num_cols.drop('log_price')

# keeping unscaled for Decision tree models
train_df_unscaled = train_df.copy()
test_df_unscaled = test_df.copy()

train_df[num_cols] = scaler.fit_transform(train_df[num_cols])
test_df[num_cols] = scaler.fit_transform(test_df[num_cols])
```

[128]:

```
train_df[num_cols].head()
```

[128]:

```
         id    sqfeet      beds     baths  cats_allowed  dogs_allowed  \
0  1.023725  0.197807  0.063173  0.864745      0.611957      0.640172
1 -0.556416 -0.659348  0.063173 -0.839095      0.611957      0.640172
2 -0.350927  0.184071  0.063173 -0.839095      0.611957      0.640172
3  0.679433  0.186818  0.063173  0.864745      0.611957      0.640172
4  0.874458 -0.791218 -1.151463 -0.839095      0.611957      0.640172
```

```
   smoking_allowed  wheelchair_access  electric_vehicle_charge  \
0        -1.669306          -0.293298                -0.112677
1         0.599051          -0.293298                -0.112677
2        -1.669306          -0.293298                -0.112677
3        -1.669306          -0.293298                 8.874963
4        -1.669306          -0.293298                -0.112677

   comes_furnished       lat      long  total_pets  luxury_features  \
0         -0.21444 -0.613742 -1.541101    0.644381        -0.336857
1         -0.21444 -0.165086 -1.631841    0.644381        -0.336857
2         -0.21444  1.498379 -1.822695    0.644381        -0.336857
3         -0.21444  0.497235 -0.764054    0.644381         2.145337
4         -0.21444  1.136100 -0.259375    0.644381        -0.336857

   geo_cluster  region_freq  log_sqfeet  bath_ratio
0    -0.694380     0.538839    0.381266    0.713428
1    -0.694380    -1.606406   -0.669772   -1.293978
2    -0.694380     0.661273    0.366957   -1.293978
3     2.255255     0.887508    0.369824    0.713428
4    -0.325675    -0.728080   -0.868689    0.713428
```

0.4.7 3.7 Dropping the features

[129]:
```
train_df.drop(columns=["region"], inplace=True)
train_df.drop(columns=["description"], inplace=True)
train_df.drop(columns=["state"], inplace=True)
train_df.drop(columns=["sqfeet"], inplace=True)

test_df.drop(columns=["region"], inplace=True)
test_df.drop(columns=["description"], inplace=True)
test_df.drop(columns=["state"], inplace=True)
test_df.drop(columns=["sqfeet"], inplace=True)

# unscaled

train_df_unscaled.drop(columns=["region"], inplace=True)
train_df_unscaled.drop(columns=["description"], inplace=True)
train_df_unscaled.drop(columns=["state"], inplace=True)
train_df_unscaled.drop(columns=["sqfeet"], inplace=True)

test_df_unscaled.drop(columns=["region"], inplace=True)
test_df_unscaled.drop(columns=["description"], inplace=True)
test_df_unscaled.drop(columns=["state"], inplace=True)
test_df_unscaled.drop(columns=["sqfeet"], inplace=True)
```

[130]:
```
train_df.info()
```

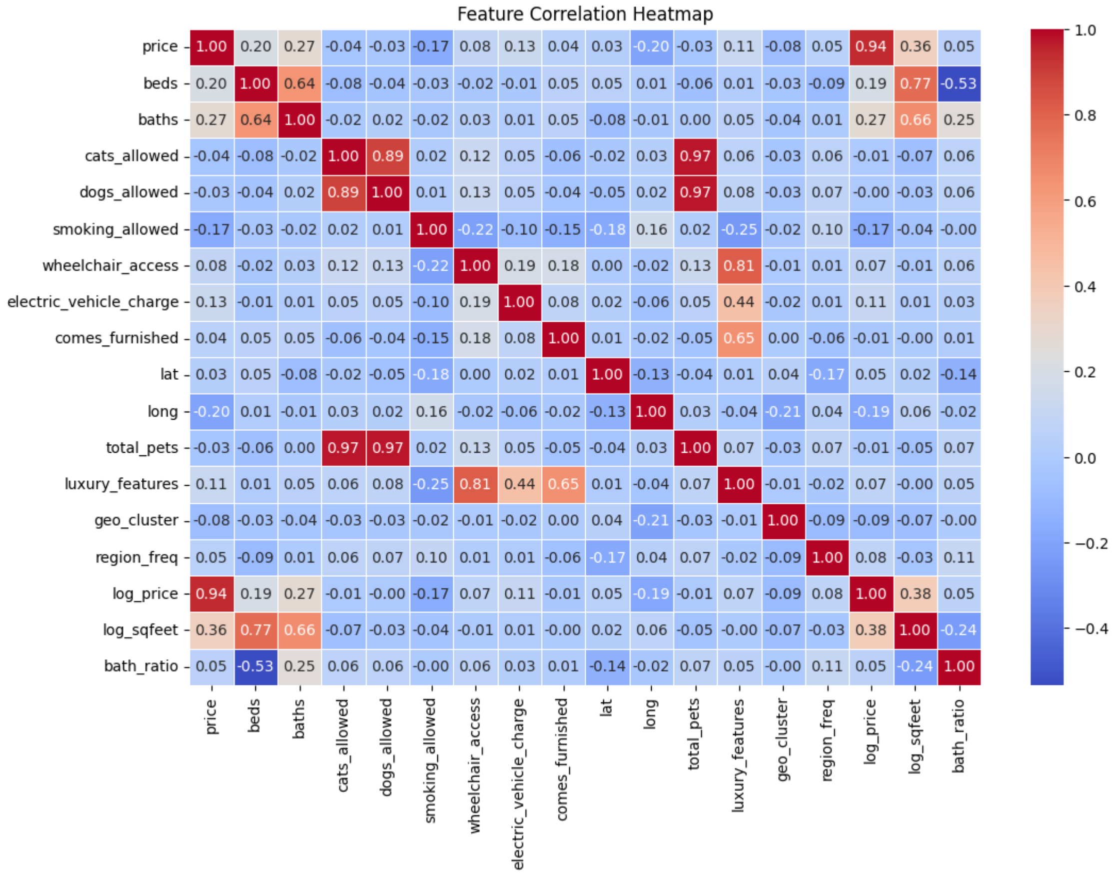
```
<class 'pandas.core.frame.DataFrame'>
```

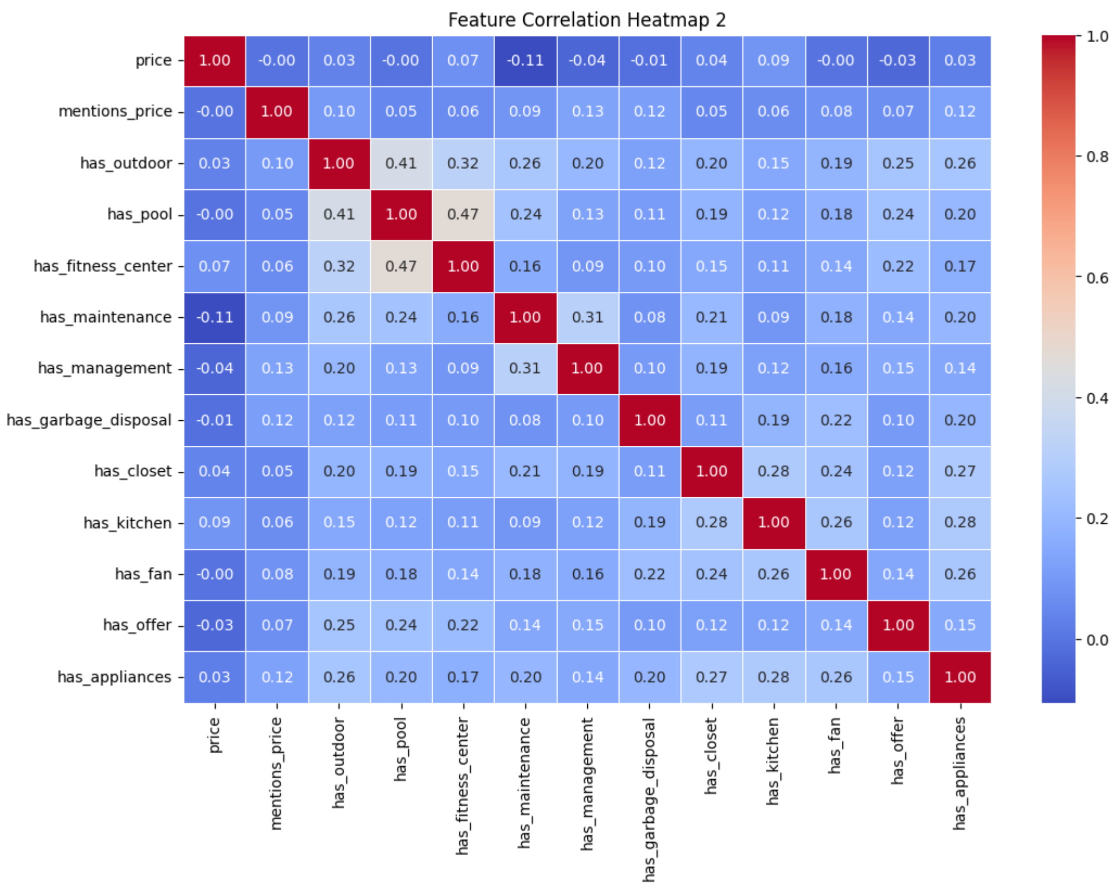
```
RangeIndex: 332939 entries, 0 to 332938
Data columns (total 55 columns):
 #   Column                              Non-Null Count   Dtype  
---  ------                              --------------   -----  
 0   id                                  332939 non-null  float64
 1   price                               332939 non-null  int64  
 2   beds                                332939 non-null  float64
 3   baths                               332939 non-null  float64
 4   cats_allowed                        332939 non-null  float64
 5   dogs_allowed                        332939 non-null  float64
 6   smoking_allowed                     332939 non-null  float64
 7   wheelchair_access                   332939 non-null  float64
 8   electric_vehicle_charge             332939 non-null  float64
 9   comes_furnished                     332939 non-null  float64
 10  lat                                 332939 non-null  float64
 11  long                                332939 non-null  float64
 12  total_pets                          332939 non-null  float64
 13  luxury_features                     332939 non-null  float64
 14  geo_cluster                         332939 non-null  float64
 15  region_freq                         332939 non-null  float64
 16  log_price                           332939 non-null  float64
 17  log_sqfeet                          332939 non-null  float64
 18  bath_ratio                          332939 non-null  float64
 19  has_outdoor                         332939 non-null  bool   
 20  has_pool                            332939 non-null  bool   
 21  has_fitness_center                  332939 non-null  bool   
 22  mentions_price                      332939 non-null  bool   
 23  has_maintenance                     332939 non-null  bool   
 24  has_management                      332939 non-null  bool   
 25  has_garbage_disposal                332939 non-null  bool   
 26  has_closet                          332939 non-null  bool   
 27  has_kitchen                         332939 non-null  bool   
 28  has_fan                             332939 non-null  bool   
 29  has_offer                           332939 non-null  bool   
 30  has_appliances                      332939 non-null  bool   
 31  laundry_options_laundry on site     332939 non-null  bool   
 32  laundry_options_no laundry on site  332939 non-null  bool   
 33  laundry_options_w/d hookups         332939 non-null  bool   
 34  laundry_options_w/d in unit         332939 non-null  bool   
 35  parking_options_carport             332939 non-null  bool   
 36  parking_options_detached garage     332939 non-null  bool   
 37  parking_options_no parking          332939 non-null  bool   
 38  parking_options_off-street parking  332939 non-null  bool   
 39  parking_options_street parking      332939 non-null  bool   
 40  parking_options_valet parking       332939 non-null  bool   
 41  type_apartment                      332939 non-null  bool   
 42  type_condo                          332939 non-null  bool   
 43  type_duplex                         332939 non-null  bool   
```

```
 44  type_house                          332939 non-null  bool
 45  type_manufactured                   332939 non-null  bool
 46  type_other                          332939 non-null  bool
 47  type_townhouse                      332939 non-null  bool
 48  region_cluster_2                    332939 non-null  bool
 49  state_ca                            332939 non-null  bool
 50  state_co                            332939 non-null  bool
 51  state_dc                            332939 non-null  bool
 52  state_hi                            332939 non-null  bool
 53  state_ks                            332939 non-null  bool
 54  state_ma                            332939 non-null  bool
dtypes: bool(36), float64(18), int64(1)
memory usage: 59.7 MB
```

[131]:

```
# selected_cols = ["price", "sqfeet", "beds", "baths", "lat", "long",␣
↪"price_per_sqft", "total_pets", "luxury_features", "region_cluster"]
selected_columns = [
    "price", "beds", "baths", "cats_allowed", "dogs_allowed",
    "smoking_allowed", "wheelchair_access", "electric_vehicle_charge",␣
↪"comes_furnished",
    "lat", "long", "total_pets", "luxury_features", "geo_cluster",
    "region_freq", "log_price", "log_sqfeet", "bath_ratio"
]

selected_columns2 = [
    "price", "mentions_price", "has_outdoor", "has_pool", "has_fitness_center",
    "has_maintenance", "has_management", "has_garbage_disposal", "has_closet",␣
↪"has_kitchen", "has_fan", "has_offer", "has_appliances"
]


# Compute the correlation matrix
corr_matrix = train_df[selected_columns].corr()
corr_matrix2 = train_df[selected_columns2].corr()

# Plot the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap="coolwarm", linewidths=0.5)
plt.title("Feature Correlation Heatmap")
plt.show()

plt.figure(figsize=(12, 8))
sns.heatmap(corr_matrix2, annot=True, fmt=".2f", cmap="coolwarm", linewidths=0.
↪5)
plt.title("Feature Correlation Heatmap 2")
plt.show()
```


Feature Correlation Heatmap
price
beds
baths
cats_allowed
dogs_allowed
smoking_allowed
wheelchair_access
electric_vehicle_charge
comes_furnished
lat
long
total_pets
luxury_features
geo_cluster
region_freq
log_price
log_sqfeet
bath_ratio



Key Takeaway - Cats and Dogs can be dropped, high correlation with total pets - `bath ratio`, `Wheelchair access`, `Comes furnished` can be dropped, low impact on price

[132]:
```
train_df.drop(columns=["cats_allowed"], inplace=True)
test_df.drop(columns=["cats_allowed"], inplace=True)
train_df_unscaled.drop(columns=["cats_allowed"], inplace=True)
test_df_unscaled.drop(columns=["cats_allowed"], inplace=True)
```

[133]:
```
train_df.drop(columns=["dogs_allowed"], inplace=True)
test_df.drop(columns=["dogs_allowed"], inplace=True)
train_df_unscaled.drop(columns=["dogs_allowed"], inplace=True)
test_df_unscaled.drop(columns=["dogs_allowed"], inplace=True)
```

[134]:
```
train_df.drop(columns=["bath_ratio"], inplace=True)
test_df.drop(columns=["bath_ratio"], inplace=True)
train_df_unscaled.drop(columns=["bath_ratio"], inplace=True)
test_df_unscaled.drop(columns=["bath_ratio"], inplace=True)
```

[135]:
```
train_df.drop(columns=["wheelchair_access"], inplace=True)
test_df.drop(columns=["wheelchair_access"], inplace=True)
train_df_unscaled.drop(columns=["wheelchair_access"], inplace=True)
test_df_unscaled.drop(columns=["wheelchair_access"], inplace=True)
```

[136]:
```
train_df.drop(columns=["comes_furnished"], inplace=True)
test_df.drop(columns=["comes_furnished"], inplace=True)
train_df_unscaled.drop(columns=["comes_furnished"], inplace=True)
test_df_unscaled.drop(columns=["comes_furnished"], inplace=True)
```

[137]:
```
train_df.drop(columns=["mentions_price"], inplace=True)
test_df.drop(columns=["mentions_price"], inplace=True)
train_df_unscaled.drop(columns=["mentions_price"], inplace=True)
test_df_unscaled.drop(columns=["mentions_price"], inplace=True)
```

[138]:
```
train_df.drop(columns=["has_pool"], inplace=True)
test_df.drop(columns=["has_pool"], inplace=True)
train_df_unscaled.drop(columns=["has_pool"], inplace=True)
test_df_unscaled.drop(columns=["has_pool"], inplace=True)
```

[139]:
```
train_df.drop(columns=["has_garbage_disposal"], inplace=True)
test_df.drop(columns=["has_garbage_disposal"], inplace=True)
train_df_unscaled.drop(columns=["has_garbage_disposal"], inplace=True)
test_df_unscaled.drop(columns=["has_garbage_disposal"], inplace=True)
```

[140]:
```
train_df.drop(columns=["has_fan"], inplace=True)
test_df.drop(columns=["has_fan"], inplace=True)
train_df_unscaled.drop(columns=["has_fan"], inplace=True)
test_df_unscaled.drop(columns=["has_fan"], inplace=True)
```

[141]:
```
train_df.head()
```

[141]:
```
         id  price      beds     baths  smoking_allowed  \
0  1.023725   2632  0.063173  0.864745        -1.669306
1 -0.556416   1160  0.063173 -0.839095         0.599051
2 -0.350927   1262  0.063173 -0.839095        -1.669306
3  0.679433   1861  0.063173  0.864745        -1.669306
4  0.874458    626 -1.151463 -0.839095        -1.669306

   electric_vehicle_charge       lat      long  total_pets  luxury_features  \
0                -0.112677 -0.613742 -1.541101    0.644381        -0.336857
1                -0.112677 -0.165086 -1.631841    0.644381        -0.336857
2                -0.112677  1.498379 -1.822695    0.644381        -0.336857
3                 8.874963  0.497235 -0.764054    0.644381         2.145337
4                -0.112677  1.136100 -0.259375    0.644381        -0.336857

   …  type_manufactured  type_other  type_townhouse  region_cluster_2  \
```

```
0  …             False       False          False            False
1  …             False       False          False            False
2  …             False       False          False            False
3  …             False       False          False            False
4  …             False       False          False            False

   state_ca  state_co  state_dc  state_hi  state_ks  state_ma
0      True     False     False     False     False     False
1      True     False     False     False     False     False
2     False     False     False     False     False     False
3     False      True     False     False     False     False
4     False     False     False     False     False     False

[5 rows x 46 columns]
```

[142]:
```
train_df_unscaled.head()
```

[142]:
```
           id  price  beds  baths  smoking_allowed  electric_vehicle_charge  \
0  7049965813   2632     2    2.0                0                        0
1  7036046796   1160     2    1.0                1                        0
2  7037856890   1262     2    1.0                0                        0
3  7046933042   1861     2    2.0                0                        1
4  7048650961    626     1    1.0                0                        0

       lat       long  total_pets  luxury_features  …  type_manufactured  \
0  33.8123 -117.8530           2                0  …              False
1  36.3008 -119.3440           2                0  …              False
2  45.5273 -122.4800           2                0  …              False
3  39.9744 -105.0850           2                1  …              False
4  43.5179  -96.7924           2                0  …              False

   type_other  type_townhouse  region_cluster_2  state_ca  state_co  state_dc  \
0       False           False             False      True     False     False
1       False           False             False      True     False     False
2       False           False             False     False     False     False
3       False           False             False     False      True     False
4       False           False             False     False     False     False

   state_hi  state_ks  state_ma
0     False     False     False
1     False     False     False
2     False     False     False
3     False     False     False
4     False     False     False

[5 rows x 46 columns]
```

[143]:

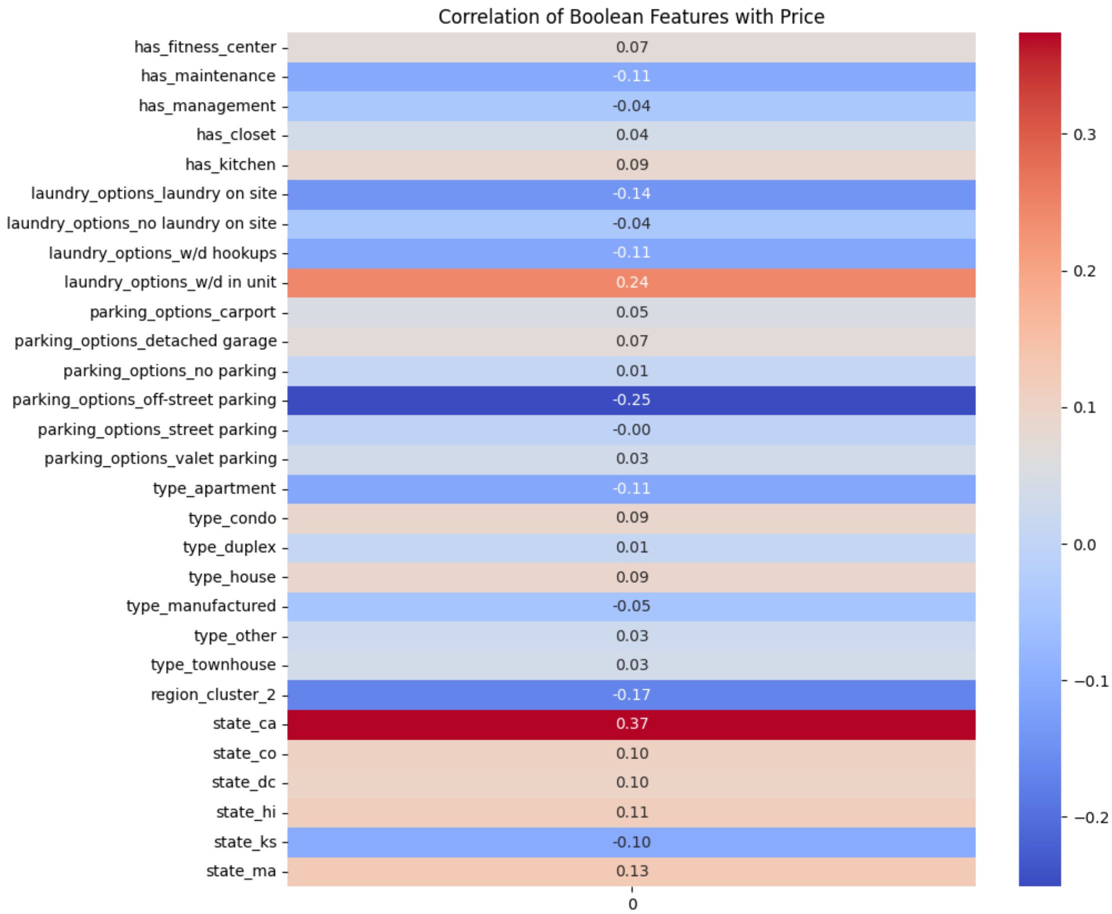
```
# Correlation value with price of following:
# region_freq: 0.05
# geo_cluster: 0.08
# total_pets: -0.03
# lat: 0.03
# has_offer: -0.03
# has_appliances: 0.03
# has_outdoor: 0.03

train_df.drop(columns=["total_pets"], inplace=True)
test_df.drop(columns=["total_pets"], inplace=True)
train_df_unscaled.drop(columns=["total_pets"], inplace=True)
test_df_unscaled.drop(columns=["total_pets"], inplace=True)

train_df.drop(columns=["has_offer"], inplace=True)
test_df.drop(columns=["has_offer"], inplace=True)
train_df_unscaled.drop(columns=["has_offer"], inplace=True)
test_df_unscaled.drop(columns=["has_offer"], inplace=True)

train_df.drop(columns=["has_appliances"], inplace=True)
test_df.drop(columns=["has_appliances"], inplace=True)
train_df_unscaled.drop(columns=["has_appliances"], inplace=True)
test_df_unscaled.drop(columns=["has_appliances"], inplace=True)

train_df.drop(columns=["has_outdoor"], inplace=True)
test_df.drop(columns=["has_outdoor"], inplace=True)
train_df_unscaled.drop(columns=["has_outdoor"], inplace=True)
test_df_unscaled.drop(columns=["has_outdoor"], inplace=True)
```

- This check correlation of boolean features with price
- Used Point-Biserial Correlation method

[144]:

```
# Select only boolean columns
bool_cols = train_df.select_dtypes(include=['bool']).columns

# Compute Point-Biserial correlation for each boolean column
bool_corr_results = {col: pointbiserialr(train_df[col], train_df["price"])[0]␣
 ↪for col in bool_cols}

# Convert to DataFrame for better visualization
bool_corr_df = pd.DataFrame(bool_corr_results.items(), columns=["Feature",␣
 ↪"Correlation with Price"])

# Convert boolean columns to int for visualization
bool_columns_as_int = train_df[bool_cols].astype(int)

# Create a heatmap
```

```python
plt.figure(figsize=(10, 10))
sns.heatmap(bool_columns_as_int.corrwith(train_df["price"]).to_frame(),␣
    ↪annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation of Boolean Features with Price")
plt.show()
```



Key Insights - Insignificant features that could be dropped - <0.04: type_townhouse, type_other, type_duplex, parking_options_valet parking, parking_options_street parking, parking_options_no parking - 0.04: laundry_options_no laundry on site, has_closet, has_management

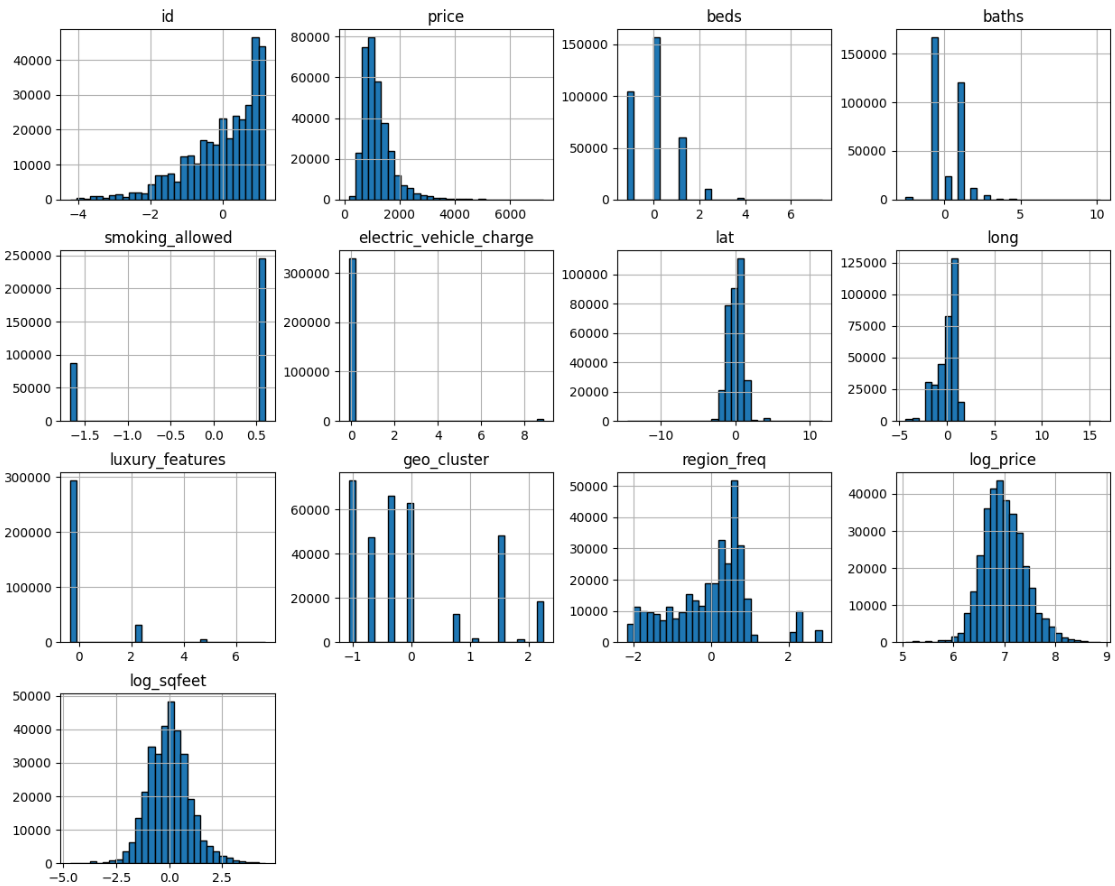
[145]:
```python
train_df.drop(columns=["type_townhouse"], inplace=True)
test_df.drop(columns=["type_townhouse"], inplace=True)
train_df_unscaled.drop(columns=["type_townhouse"], inplace=True)
test_df_unscaled.drop(columns=["type_townhouse"], inplace=True)

train_df.drop(columns=["type_other"], inplace=True)
test_df.drop(columns=["type_other"], inplace=True)
```

```
train_df_unscaled.drop(columns=["type_other"], inplace=True)
test_df_unscaled.drop(columns=["type_other"], inplace=True)

train_df.drop(columns=["type_duplex"], inplace=True)
test_df.drop(columns=["type_duplex"], inplace=True)
train_df_unscaled.drop(columns=["type_duplex"], inplace=True)
test_df_unscaled.drop(columns=["type_duplex"], inplace=True)

train_df.drop(columns=["parking_options_valet parking"], inplace=True)
test_df.drop(columns=["parking_options_valet parking"], inplace=True)
train_df_unscaled.drop(columns=["parking_options_valet parking"], inplace=True)
test_df_unscaled.drop(columns=["parking_options_valet parking"], inplace=True)

train_df.drop(columns=["parking_options_street parking"], inplace=True)
test_df.drop(columns=["parking_options_street parking"], inplace=True)
train_df_unscaled.drop(columns=["parking_options_street parking"], inplace=True)
test_df_unscaled.drop(columns=["parking_options_street parking"], inplace=True)

train_df.drop(columns=["parking_options_no parking"], inplace=True)
test_df.drop(columns=["parking_options_no parking"], inplace=True)
train_df_unscaled.drop(columns=["parking_options_no parking"], inplace=True)
test_df_unscaled.drop(columns=["parking_options_no parking"], inplace=True)

train_df.drop(columns=["laundry_options_no laundry on site"], inplace=True)
test_df.drop(columns=["laundry_options_no laundry on site"], inplace=True)
train_df_unscaled.drop(columns=["laundry_options_no laundry on site"],␣
↪inplace=True)
test_df_unscaled.drop(columns=["laundry_options_no laundry on site"],␣
↪inplace=True)

train_df.drop(columns=["has_closet"], inplace=True)
test_df.drop(columns=["has_closet"], inplace=True)
train_df_unscaled.drop(columns=["has_closet"], inplace=True)
test_df_unscaled.drop(columns=["has_closet"], inplace=True)

train_df.drop(columns=["has_management"], inplace=True)
test_df.drop(columns=["has_management"], inplace=True)
train_df_unscaled.drop(columns=["has_management"], inplace=True)
test_df_unscaled.drop(columns=["has_management"], inplace=True)
```

[146]:
```
train_df.hist(figsize=(15, 12), bins=30, edgecolor="black")
```

[146]:
```
array([[<Axes: title={'center': 'id'}>,
        <Axes: title={'center': 'price'}>,
        <Axes: title={'center': 'beds'}>,
        <Axes: title={'center': 'baths'}>],
       [<Axes: title={'center': 'smoking_allowed'}>,
```

```
 <Axes: title={'center': 'electric_vehicle_charge'}>,
 <Axes: title={'center': 'lat'}>,
 <Axes: title={'center': 'long'}>],
[<Axes: title={'center': 'luxury_features'}>,
 <Axes: title={'center': 'geo_cluster'}>,
 <Axes: title={'center': 'region_freq'}>,
 <Axes: title={'center': 'log_price'}>],
[<Axes: title={'center': 'log_sqfeet'}>, <Axes: >, <Axes: >,
 <Axes: >]], dtype=object)
```



Saving the cleaned and feature engineered data

[147]:
```python
# Save CSV inside the folder
train_df.to_csv("data/processed/train_cleaned_data.csv", index=False)
test_df.to_csv("data/processed/test_cleaned_data.csv", index=False)
```

0.5 Building Models

[148]:
```
# PBP(train_df)
```

[149]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 332939 entries, 0 to 332938
Data columns (total 33 columns):
 #   Column                               Non-Null Count   Dtype
---  ------                               --------------   -----
 0   id                                   332939 non-null  float64
 1   price                                332939 non-null  int64
 2   beds                                 332939 non-null  float64
 3   baths                                332939 non-null  float64
 4   smoking_allowed                      332939 non-null  float64
 5   electric_vehicle_charge              332939 non-null  float64
 6   lat                                  332939 non-null  float64
 7   long                                 332939 non-null  float64
 8   luxury_features                      332939 non-null  float64
 9   geo_cluster                          332939 non-null  float64
 10  region_freq                          332939 non-null  float64
 11  log_price                            332939 non-null  float64
 12  log_sqfeet                           332939 non-null  float64
 13  has_fitness_center                   332939 non-null  bool
 14  has_maintenance                      332939 non-null  bool
 15  has_kitchen                          332939 non-null  bool
 16  laundry_options_laundry on site      332939 non-null  bool
 17  laundry_options_w/d hookups          332939 non-null  bool
 18  laundry_options_w/d in unit          332939 non-null  bool
 19  parking_options_carport              332939 non-null  bool
 20  parking_options_detached garage      332939 non-null  bool
 21  parking_options_off-street parking   332939 non-null  bool
 22  type_apartment                       332939 non-null  bool
 23  type_condo                           332939 non-null  bool
 24  type_house                           332939 non-null  bool
 25  type_manufactured                    332939 non-null  bool
 26  region_cluster_2                     332939 non-null  bool
 27  state_ca                             332939 non-null  bool
 28  state_co                             332939 non-null  bool
 29  state_dc                             332939 non-null  bool
 30  state_hi                             332939 non-null  bool
 31  state_ks                             332939 non-null  bool
 32  state_ma                             332939 non-null  bool
dtypes: bool(20), float64(12), int64(1)
memory usage: 39.4 MB
```

[150]:
```
# train_df_unscaled.info()
```

0.5.1 1. Linear Regression with Log Price

[151]:
```
X_train = train_df.drop(columns=["log_price", "price"], axis=1)
y_train = train_df['log_price']

X_test = test_df.drop(columns=["log_price", "price"], axis=1)
y_test = test_df['log_price']
# X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

[152]:
```
# X_train.head()
```

[153]:
```
# X_train.info()
```

[154]:
```
# X_test.info()
```

[155]:
```
# y_train.head()
```

[156]:
```
# y_test.head()
```

[157]:
```
# Initialize and train the Linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)
```

[157]:
```
LinearRegression()
```

[158]:
```
# Make predictions
y_pred_log = model.predict(X_test)
y_pred_price = np.expm1(y_pred_log)
```

[159]:
```
mae = mean_absolute_error(np.expm1(y_test), np.expm1(y_pred_log))  # Convert␣
↪log_price back to price
mse = mean_squared_error(y_test, y_pred_log)
r2 = r2_score(y_test, y_pred_log)

print(f"Model Performance:")
print(f"Mean Absolute Error (MAE): {mae:.4f}")
print(f"Mean Squared Error (MSE): {mse:.4f}")
print(f"R² Score: {r2:.4f}")
```

```
Model Performance:
Mean Absolute Error (MAE): 276.5598
Mean Squared Error (MSE): 0.0936
R² Score: 0.4526
```

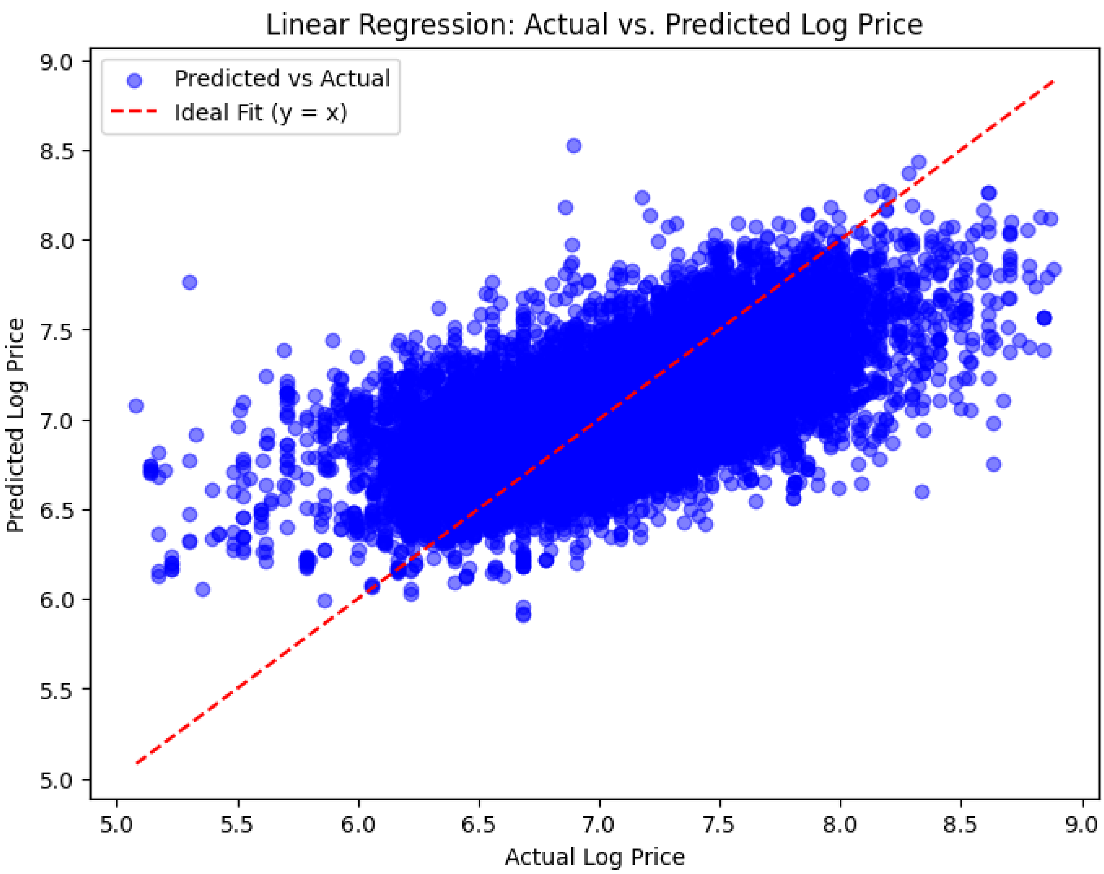
[160]:
```
predictions_df = pd.DataFrame({"Actual Price": np.expm1(y_test), "Predicted␣
↪Price": y_pred_price})
predictions_df.head(10)
```

[160]:

	Actual Price	Predicted Price
0	1750.0	1632.246281
1	850.0	1266.461175
2	1500.0	1732.105960
3	899.0	867.576709
4	899.0	1164.940140
5	805.0	1044.535686
6	1300.0	1311.517860
7	735.0	456.272787
8	1070.0	986.581301
9	805.0	766.473508

[161]:

```
# Scatter plot of actual vs. predicted log_price values
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred_log, alpha=0.5, label="Predicted vs Actual",␣
 ↪color="blue")

# Plot ideal prediction line (y = x) for reference
min_val = min(min(y_test), min(y_pred_log))
max_val = max(max(y_test), max(y_pred_log))
plt.plot([min_val, max_val], [min_val, max_val], linestyle="--", color="red",␣
 ↪label="Ideal Fit (y = x)")

# Labels and title
plt.xlabel("Actual Log Price")
plt.ylabel("Predicted Log Price")
plt.title("Linear Regression: Actual vs. Predicted Log Price")
plt.legend()
plt.show()
```



0.5.2 2. RandomForest with Price

[162]:
```
X_train = train_df_unscaled.drop(columns=["log_price", "price"], axis=1)
y_train = train_df_unscaled['price']

X_test = test_df_unscaled.drop(columns=["log_price", "price"], axis=1)
y_test = test_df_unscaled['price']
```

[163]:
```
 # Initialize and train the Random Forest Regressor model
randomforest_model = RandomForestRegressor(n_estimators=100, random_state=42,␣
 ↪n_jobs=-1)
randomforest_model.fit(X_train, y_train)
```

[163]:
```
RandomForestRegressor(n_jobs=-1, random_state=42)
```

[164]:
```
# Make predictions on the test set
randomforest_y_pred = randomforest_model.predict(X_test)
```

[165]:
```
# Calculate evaluation metrics
r2 = r2_score(y_test, randomforest_y_pred)
mae = mean_absolute_error(y_test, randomforest_y_pred)
mse = mean_squared_error(y_test, randomforest_y_pred)
rmse = np.sqrt(mse)

# Print results
print(f"Random Forest Model Evaluation Metrics for Price Prediction:")
print(f"  R² Score: {r2:.4f}  (Higher is better, max = 1)")
print(f"  MAE: ${mae:.2f} (Lower is better, avg absolute error)")
print(f"  MSE: {mse:.2f} (Lower is better, penalizes large errors)")
print(f"  RMSE: ${rmse:.2f} (Lower is better, interpretable error in price␣
↪units)")
```

```
Random Forest Model Evaluation Metrics for Price Prediction:
  R² Score: 0.8252  (Higher is better, max = 1)
  MAE: $115.20 (Lower is better, avg absolute error)
  MSE: 57591.04 (Lower is better, penalizes large errors)
  RMSE: $239.98 (Lower is better, interpretable error in price units)
```

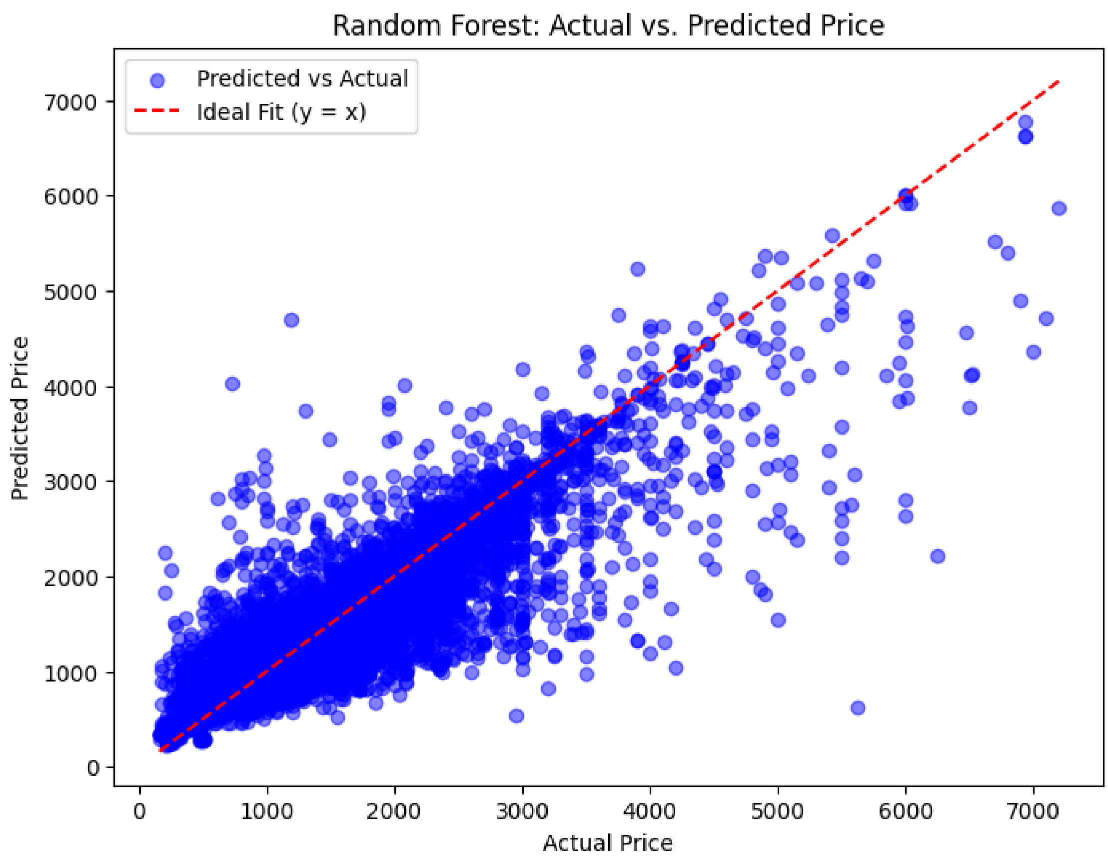
[166]:
```
predictions_df = pd.DataFrame({"Actual Price": y_test, "Predicted Price":␣
↪randomforest_y_pred})
predictions_df.head(10)
```

[166]:

	Actual Price	Predicted Price
0	1750	1595.50
1	850	878.65
2	1500	1508.04
3	899	699.56
4	899	972.25
5	805	950.99
6	1300	1268.31
7	735	633.95
8	1070	1072.17
9	805	796.78

[167]:
```
# Scatter plot of actual vs. predicted price values
plt.figure(figsize=(8, 6))
plt.scatter(y_test, randomforest_y_pred, alpha=0.5, label="Predicted vs␣
↪Actual", color="blue")

# Plot ideal prediction line (y = x) for reference
min_val = min(min(y_test), min(randomforest_y_pred))
max_val = max(max(y_test), max(randomforest_y_pred))
plt.plot([min_val, max_val], [min_val, max_val], linestyle="--", color="red",␣
↪label="Ideal Fit (y = x)")
```

```python
# Labels and title
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title("Random Forest: Actual vs. Predicted Price")
plt.legend()
plt.show()
```



[168]:

```python
# Save the trained model to disk in 'models' folder
os.makedirs("models", exist_ok=True)
model_path = "models/random_forest_price_model.pkl"
with open(model_path, "wb") as f:
    pickle.dump(randomforest_model, f)

print(f" Model saved successfully at: {model_path}")
```

```
Model saved successfully at: models/random_forest_price_model.pkl
```

0.5.3 3. XGBoost

[169]:
```
X_train = train_df_unscaled.drop(columns=["log_price", "price"], axis=1)
y_train = train_df_unscaled['price']

X_test = test_df_unscaled.drop(columns=["log_price", "price"], axis=1)
y_test = test_df_unscaled['price']
```

[170]:
```
xgb_model = XGBRegressor(n_estimators=360, learning_rate=0.1, random_state=42)
xgb_model.fit(X_train, y_train)
```

[170]:
```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.1, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             multi_strategy=None, n_estimators=360, n_jobs=None,
             num_parallel_tree=None, random_state=42, …)
```

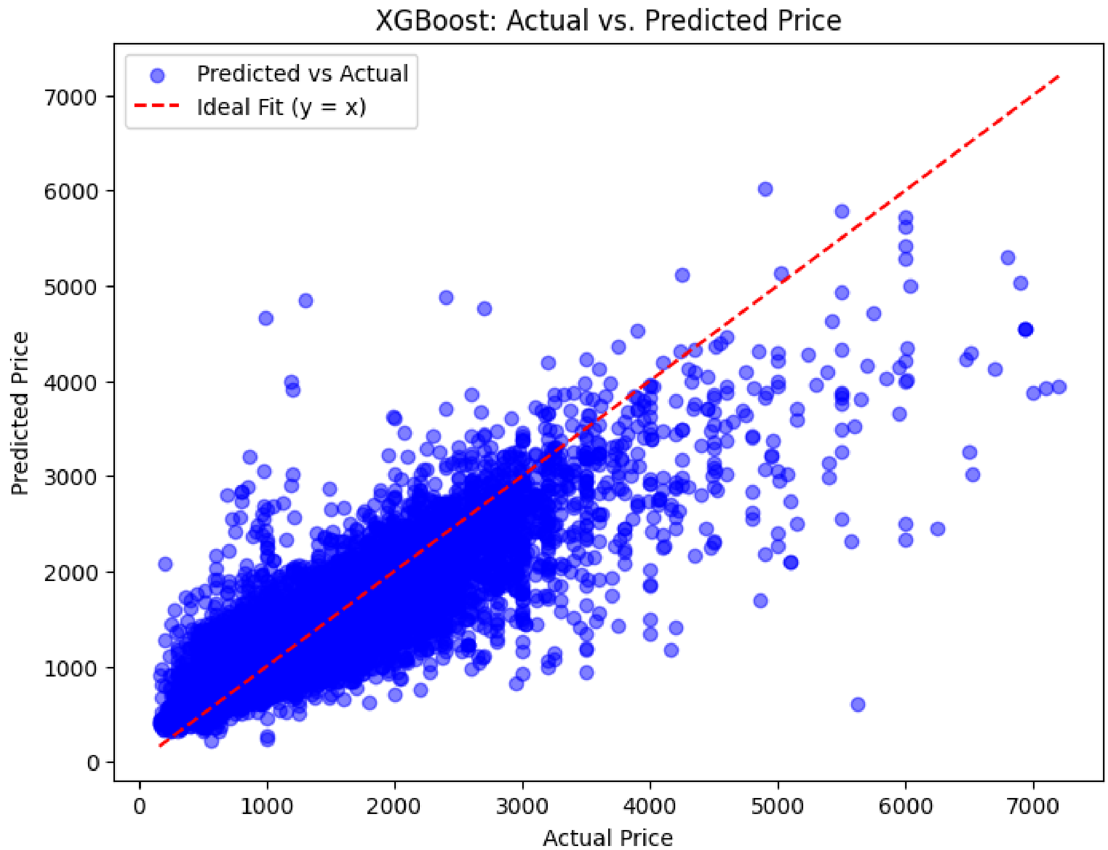
[171]:
```
# Make predictions on the test set
xgb_preds = xgb_model.predict(X_test)
```

[172]:
```
# Calculate evaluation metrics
r2 = r2_score(y_test, xgb_preds)
mae = mean_absolute_error(y_test, xgb_preds)
mse = mean_squared_error(y_test, xgb_preds)
rmse = np.sqrt(mse)

# Print results
print(f"XGBoost Model Evaluation Metrics for Price Prediction:")
print(f"  R² Score: {r2:.4f}  (Higher is better, max = 1)")
print(f"  MAE: ${mae:.2f} (Lower is better, avg absolute error)")
print(f"  MSE: {mse:.2f} (Lower is better, penalizes large errors)")
print(f"  RMSE: ${rmse:.2f} (Lower is better, interpretable error in price␣
 ↪units)")
```

```
XGBoost Model Evaluation Metrics for Price Prediction:
  R² Score: 0.7689  (Higher is better, max = 1)
  MAE: $169.61 (Lower is better, avg absolute error)
  MSE: 76130.66 (Lower is better, penalizes large errors)
  RMSE: $275.92 (Lower is better, interpretable error in price units)
```

[173]:
```
# Scatter plot of actual vs. predicted price values
plt.figure(figsize=(8, 6))
```

```
plt.scatter(y_test, xgb_preds, alpha=0.5, label="Predicted vs Actual",␣
↪color="blue")

# Plot ideal prediction line (y = x) for reference
min_val = min(min(y_test), min(xgb_preds))
max_val = max(max(y_test), max(xgb_preds))
plt.plot([min_val, max_val], [min_val, max_val], linestyle="--", color="red",␣
↪label="Ideal Fit (y = x)")

# Labels and title
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title("XGBoost: Actual vs. Predicted Price")
plt.legend()
plt.show()
```



0.5.4 4 CatBoost

This model can be used, due to time constraints not fully fine tuned

[204]:
```
# X_train = train_df_unscaled.drop(columns=["log_price", "price"], axis=1)
# y_train = train_df_unscaled['price']

# X_test = test_df_unscaled.drop(columns=["log_price", "price"], axis=1)
# y_test = test_df_unscaled['price']
```

[206]:
```
# categorical_features = X_train.select_dtypes(include=['object', 'category']).
↪columns.tolist()
# categorical_features
```

[206]: []

[207]:
```
# cat_model = CatBoostRegressor(
#     iterations=1000,  # Number of boosting iterations
#     learning_rate=0.05,  # Step size for optimization
#     depth=6,  # Depth of trees
#     loss_function='RMSE',  # Use RMSE as loss metric
#     cat_features=categorical_features,  # Specify categorical columns
#     verbose=200,  # Print progress every 200 iterations
#     random_seed=42
# )
# cat_model.fit(X_train, y_train)
```

```
0:      learn: 563.1665908      total: 157ms    remaining: 2m 36s
200:    learn: 320.6381840      total: 1.77s    remaining: 7.05s
400:    learn: 293.9706736      total: 3.3s     remaining: 4.94s
600:    learn: 280.2262182      total: 4.92s    remaining: 3.26s
800:    learn: 270.8888771      total: 6.44s    remaining: 1.6s
999:    learn: 263.5979647      total: 8s       remaining: 0us
```

[207]: <catboost.core.CatBoostRegressor at 0x271401ba7b0>

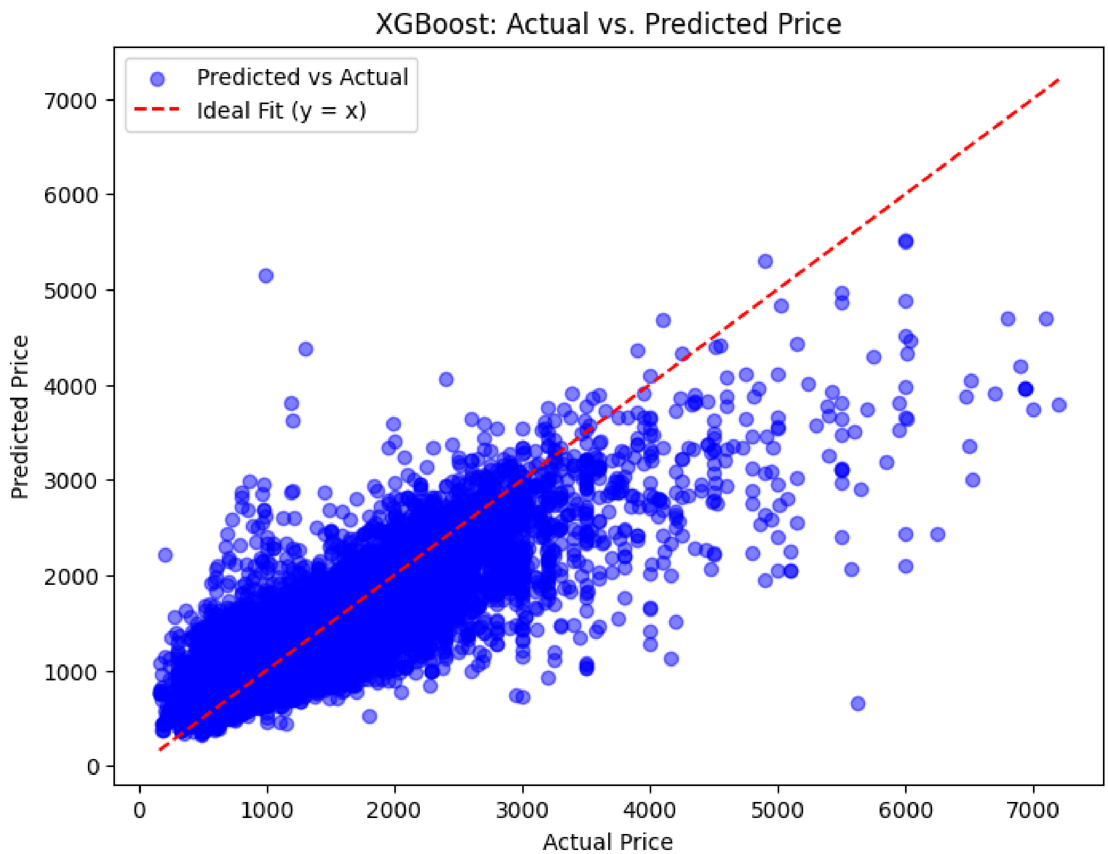
[208]:
```
# y_pred = cat_model.predict(X_test)
```

[209]:
```
# # Calculate evaluation metrics
# r2 = r2_score(y_test, y_pred)
# mae = mean_absolute_error(y_test, y_pred)
# mse = mean_squared_error(y_test, y_pred)
# rmse = np.sqrt(mse)

# # Print results
# print(f"Random Forest Model Evaluation Metrics for Price Prediction:")
# print(f" R² Score: {r2:.4f}  (Higher is better, max = 1)")
# print(f" MAE: ${mae:.2f} (Lower is better, avg absolute error)")
# print(f" MSE: {mse:.2f} (Lower is better, penalizes large errors)")
# print(f" RMSE: ${rmse:.2f} (Lower is better, interpretable error in price␣
↪units)")
```

```
Random Forest Model Evaluation Metrics for Price Prediction:
 R² Score: 0.7372  (Higher is better, max = 1)
 MAE: $184.98 (Lower is better, avg absolute error)
 MSE: 86584.84 (Lower is better, penalizes large errors)
 RMSE: $294.25 (Lower is better, interpretable error in price units)
```

[210]:

```
# # Scatter plot of actual vs. predicted price values
# plt.figure(figsize=(8, 6))
# plt.scatter(y_test, y_pred, alpha=0.5, label="Predicted vs Actual",␣
 ↪color="blue")

# # Plot ideal prediction line (y = x) for reference
# min_val = min(min(y_test), min(y_pred))
# max_val = max(max(y_test), max(y_pred))
# plt.plot([min_val, max_val], [min_val, max_val], linestyle="--", color="red",␣
 ↪label="Ideal Fit (y = x)")

# # Labels and title
# plt.xlabel("Actual Price")
# plt.ylabel("Predicted Price")
# plt.title("XGBoost: Actual vs. Predicted Price")
# plt.legend()
# plt.show()
```



0.5.5 Hyperparamater Tuning

Random Forest

[120]:
```
X_train = train_df_unscaled.drop(columns=["log_price", "price"], axis=1)
y_train = train_df_unscaled['price']

X_test = test_df_unscaled.drop(columns=["log_price", "price"], axis=1)
y_test = test_df_unscaled['price']
```

[133]:
```
param_grid = {
    "n_estimators": [100, 200, 300],  # Number of trees
    "max_features" : [2, 4, 6, 8]
    # "max_depth": [None, 10, 20],  # Depth of trees
    # "min_samples_split": [2, 5, 10],  # Minimum samples per split
    # "min_samples_leaf": [1, 2, 4],  # Minimum samples per leaf
}

randomforest_model = RandomForestRegressor(random_state=42, n_jobs=2)
```

[134]:
```python
grid_search = GridSearchCV(randomforest_model, param_grid, cv=5,
    scoring="neg_mean_squared_error", verbose=2)
grid_search.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 12 candidates, totalling 60 fits
[CV] END …max_features=2, n_estimators=100; total time=  12.1s
[CV] END …max_features=2, n_estimators=100; total time=  11.7s
[CV] END …max_features=2, n_estimators=100; total time=  11.7s
[CV] END …max_features=2, n_estimators=100; total time=  12.1s
[CV] END …max_features=2, n_estimators=100; total time=  12.4s
[CV] END …max_features=2, n_estimators=200; total time=  23.3s
[CV] END …max_features=2, n_estimators=200; total time=  23.7s
[CV] END …max_features=2, n_estimators=200; total time=  23.9s
[CV] END …max_features=2, n_estimators=200; total time=  24.7s
[CV] END …max_features=2, n_estimators=200; total time=  25.2s
[CV] END …max_features=2, n_estimators=300; total time=  36.4s
[CV] END …max_features=2, n_estimators=300; total time=  37.2s
[CV] END …max_features=2, n_estimators=300; total time=  35.8s
[CV] END …max_features=2, n_estimators=300; total time=  35.8s
[CV] END …max_features=2, n_estimators=300; total time=  37.7s
[CV] END …max_features=4, n_estimators=100; total time=  14.6s
[CV] END …max_features=4, n_estimators=100; total time=  14.3s
[CV] END …max_features=4, n_estimators=100; total time=  15.0s
[CV] END …max_features=4, n_estimators=100; total time=  15.2s
[CV] END …max_features=4, n_estimators=100; total time=  14.2s
[CV] END …max_features=4, n_estimators=200; total time=  29.0s
[CV] END …max_features=4, n_estimators=200; total time=  29.8s
[CV] END …max_features=4, n_estimators=200; total time=  29.3s
[CV] END …max_features=4, n_estimators=200; total time=  28.6s
[CV] END …max_features=4, n_estimators=200; total time=  29.0s
[CV] END …max_features=4, n_estimators=300; total time=  43.5s
[CV] END …max_features=4, n_estimators=300; total time=  43.2s
[CV] END …max_features=4, n_estimators=300; total time=  45.1s
[CV] END …max_features=4, n_estimators=300; total time=  42.5s
[CV] END …max_features=4, n_estimators=300; total time=  41.7s
[CV] END …max_features=6, n_estimators=100; total time=  16.9s
[CV] END …max_features=6, n_estimators=100; total time=  17.0s
[CV] END …max_features=6, n_estimators=100; total time=  17.2s
[CV] END …max_features=6, n_estimators=100; total time=  17.2s
[CV] END …max_features=6, n_estimators=100; total time=  16.9s
[CV] END …max_features=6, n_estimators=200; total time=  33.5s
[CV] END …max_features=6, n_estimators=200; total time=  34.4s
[CV] END …max_features=6, n_estimators=200; total time=  33.1s
[CV] END …max_features=6, n_estimators=200; total time=  33.6s
[CV] END …max_features=6, n_estimators=200; total time=  33.0s
[CV] END …max_features=6, n_estimators=300; total time=  50.1s
[CV] END …max_features=6, n_estimators=300; total time=  50.3s
[CV] END …max_features=6, n_estimators=300; total time=  49.5s
```

```
[CV] END …max_features=6, n_estimators=300; total time=  50.4s
[CV] END …max_features=6, n_estimators=300; total time=  49.8s
[CV] END …max_features=8, n_estimators=100; total time=  19.8s
[CV] END …max_features=8, n_estimators=100; total time=  19.3s
[CV] END …max_features=8, n_estimators=100; total time=  19.3s
[CV] END …max_features=8, n_estimators=100; total time=  19.5s
[CV] END …max_features=8, n_estimators=100; total time=  19.1s
[CV] END …max_features=8, n_estimators=200; total time=  39.5s
[CV] END …max_features=8, n_estimators=200; total time=  38.6s
[CV] END …max_features=8, n_estimators=200; total time=  40.8s
[CV] END …max_features=8, n_estimators=200; total time=  40.0s
[CV] END …max_features=8, n_estimators=200; total time=  40.2s
[CV] END …max_features=8, n_estimators=300; total time=  58.6s
[CV] END …max_features=8, n_estimators=300; total time=  58.4s
[CV] END …max_features=8, n_estimators=300; total time=  58.6s
[CV] END …max_features=8, n_estimators=300; total time=  58.6s
[CV] END …max_features=8, n_estimators=300; total time=  59.5s
```

[134]:
```
GridSearchCV(cv=5, estimator=RandomForestRegressor(n_jobs=2, random_state=42),
             param_grid={'max_features': [2, 4, 6, 8],
                         'n_estimators': [100, 200, 300]},
             scoring='neg_mean_squared_error', verbose=2)
```

[135]:
```python
best_params = grid_search.best_params_
print(f"Best Parameters: {best_params}")
```

```
Best Parameters: {'max_features': 8, 'n_estimators': 300}
```

[136]:
```python
best_model = RandomForestRegressor(**best_params, random_state=42, n_jobs=-1)
best_model.fit(X_train, y_train)
```

[136]:
```
RandomForestRegressor(max_features=8, n_estimators=300, n_jobs=-1,
                      random_state=42)
```

[137]:
```python
y_pred = best_model.predict(X_test)
```

[138]:
```python
# Calculate evaluation metrics
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)

# Print results
print(f"Random Forest Model Evaluation Metrics for Price Prediction:")
print(f"  R² Score: {r2:.4f}  (Higher is better, max = 1)")
print(f"  MAE: ${mae:.2f} (Lower is better, avg absolute error)")
print(f"  MSE: {mse:.2f} (Lower is better, penalizes large errors)")
```

```
print(f" RMSE: ${rmse:.2f} (Lower is better, interpretable error in price␣
↪units)")
```

```
Random Forest Model Evaluation Metrics for Price Prediction:
 R² Score: 0.7707  (Higher is better, max = 1)
 MAE: $155.70 (Lower is better, avg absolute error)
 MSE: 75541.06 (Lower is better, penalizes large errors)
 RMSE: $274.85 (Lower is better, interpretable error in price units)
```

[139]:

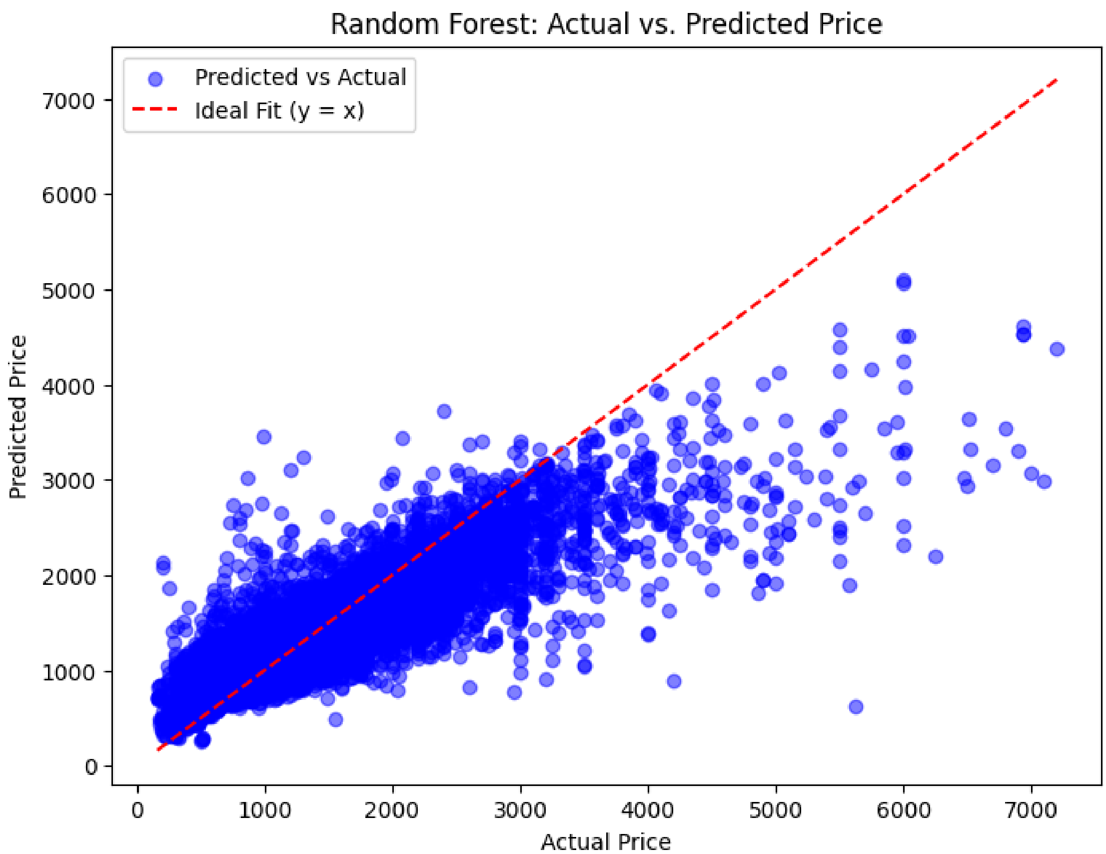
```
predictions_df = pd.DataFrame({"Actual Price": y_test, "Predicted Price":␣
↪y_pred})
predictions_df.head(10)
```

[139]:

	Actual Price	Predicted Price
0	1750	1589.240000
1	850	868.126667
2	1500	1376.696667
3	899	776.890000
5	899	1073.096667
6	805	976.110000
7	1300	1375.393333
8	735	678.626667
9	1070	1076.293333
10	805	935.386667

[140]:

```
# Scatter plot of actual vs. predicted price values
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred, alpha=0.5, label="Predicted vs Actual",␣
↪color="blue")

# Plot ideal prediction line (y = x) for reference
min_val = min(min(y_test), min(y_pred))
max_val = max(max(y_test), max(y_pred))
plt.plot([min_val, max_val], [min_val, max_val], linestyle="--", color="red",␣
↪label="Ideal Fit (y = x)")

# Labels and title
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title("Random Forest: Actual vs. Predicted Price")
plt.legend()
plt.show()
```


Random Forest: Actual vs. Predicted Price
Predicted vs Actual
Ideal Fit (y = x)
Predicted Price
Actual Price
0
1000
2000
3000
4000
5000
6000
7000