airbnb_prediction_model (1)

July 8, 2023

[1]:
```
import warnings
warnings.filterwarnings("ignore")
from sklearn.exceptions import FitFailedWarning
```

[2]:
```
import pandas as pd
import numpy as np
df = pd.read_csv('train.csv')
df.head(5)
```

[2]:
```
         id                                     name  \
0  22267382  Modern and Cozy Large Studio in Brooklyn
1   2473861          Royal Harlem TRIPLEX Home 5 Beds
2  25079703                 Sunny East Village Studio
3   9342478         Beautiful, airy, light-filled room
4   4866426        Private Room in Prime Brooklyn Spot

                                             summary  \
0  Modern large studio with new amenities and app…
1  Harlem is back and so gorgeous! Visit and expl…
2  Clean, hip and well designed sun drenched East…
3  Private, spacious, comfortable room in 2-bed f…
4  Comfy, quiet and big private room in a three b…

                                               space  \
0  Our place is a little quiet sanctuary in the h…
1  Harlem is back and so gorgeous! Visit and expl…
2  This is a rare East Village studio with it's h…
3  Big closet, two big windows, tall ceiling and …
4  This big old apartment that we love and take c…

                                         description experiences_offered  \
0  Modern large studio with new amenities and app…                none
1  Harlem is back and so gorgeous! Visit and expl…                none
2  Clean, hip and well designed sun drenched East…                none
3  Private, spacious, comfortable room in 2-bed f…                none
4  Comfy, quiet and big private room in a three b…                none
```

```
                         neighborhood_overview  \
0  BAM, Barclays, Brooklyn City Point, Fort Green…
1  HARLEM is a piece of real NY history overflowi…
2  East Village is one of the last remaining neig…
3  One block from Morgan L stop. Super cool area…
4  I absolutely love this neighborhood - right at…

                                            notes  \
0                                             NaN
1  HARLEM RESTAURANTS Red Rooster Harlem -- excel…
2                                             NaN
3                                             NaN
4  Just a note about the space: The window in you…

                                          transit  \
0                          Subway: 2,3,4,5,A,C,B,Q,G
1  PUBLIC TRANSPORTATION: Conveniently near all p…
2                                             NaN
3                                             NaN
4  Super convenient to almost all subway lines. A…

                                           access  …  \
0  Washer/Dryer Dishwasher Internet Gym Roof Top …  …
1                           The WHOLE ENTIRE HOUSE  …
2  You'll have access to the entire space - it's …  …
3                                             NaN  …
4  Your room has a very comfortable queen sized b…  …

  review_scores_communication review_scores_location  review_scores_value  \
0                        10.0                   10.0                 10.0
1                         9.0                    9.0                  9.0
2                        10.0                   10.0                 10.0
3                         NaN                    NaN                  NaN
4                        10.0                   10.0                 10.0

  instant_bookable is_business_travel_ready cancellation_policy  \
0                t                        f            flexible
1                t                        f            moderate
2                f                        f            moderate
3                f                        f            flexible
4                f                        f            flexible

  require_guest_profile_picture require_guest_phone_verification  \
0                             f                                f
1                             f                                f
2                             f                                f
3                             f                                f
```

```
4                              f                                f

  calculated_host_listings_count  reviews_per_month
0                               1               0.59
1                               3               2.47
2                               1               0.89
3                               1                NaN
4                               1               3.14

[5 rows x 65 columns]
```

[3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 33538 entries, 0 to 33537
Data columns (total 65 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   id                              33538 non-null  int64
 1   name                            33526 non-null  object
 2   summary                         32266 non-null  object
 3   space                           23038 non-null  object
 4   description                     33230 non-null  object
 5   experiences_offered             33538 non-null  object
 6   neighborhood_overview           19948 non-null  object
 7   notes                           13447 non-null  object
 8   transit                         20796 non-null  object
 9   access                          19304 non-null  object
 10  interaction                     18670 non-null  object
 11  house_rules                     19983 non-null  object
 12  host_id                         33538 non-null  int64
 13  host_name                       33533 non-null  object
 14  host_since                      33533 non-null  object
 15  host_location                   33424 non-null  object
 16  host_about                      20374 non-null  object
 17  host_response_time              17345 non-null  object
 18  host_response_rate              17345 non-null  object
 19  host_acceptance_rate            0 non-null      float64
 20  host_is_superhost               33533 non-null  object
 21  host_neighbourhood              28832 non-null  object
 22  host_listings_count             33533 non-null  float64
 23  host_verifications              33538 non-null  object
 24  host_has_profile_pic            33533 non-null  object
 25  host_identity_verified          33533 non-null  object
 26  neighbourhood_cleansed          33538 non-null  object
 27  neighbourhood_group_cleansed    33538 non-null  object
 28  city                            33499 non-null  object
```

```
 29  state                             33528 non-null  object
 30  zipcode                           33053 non-null  object
 31  market                            33448 non-null  object
 32  country_code                      33538 non-null  object
 33  country                           33538 non-null  object
 34  property_type                     33538 non-null  object
 35  room_type                         33538 non-null  object
 36  accommodates                      33538 non-null  int64
 37  bathrooms                         33478 non-null  float64
 38  bedrooms                          33505 non-null  float64
 39  beds                              33507 non-null  float64
 40  bed_type                          33538 non-null  object
 41  amenities                         33538 non-null  object
 42  square_feet                       341 non-null    float64
 43  price                             33538 non-null  int64
 44  guests_included                   33538 non-null  int64
 45  extra_people                      33538 non-null  object
 46  minimum_nights                    33538 non-null  int64
 47  maximum_nights                    33538 non-null  int64
 48  number_of_reviews                 33538 non-null  int64
 49  first_review                      26591 non-null  object
 50  last_review                       26593 non-null  object
 51  review_scores_rating              25874 non-null  float64
 52  review_scores_accuracy            25844 non-null  float64
 53  review_scores_cleanliness         25859 non-null  float64
 54  review_scores_checkin             25829 non-null  float64
 55  review_scores_communication       25849 non-null  float64
 56  review_scores_location            25830 non-null  float64
 57  review_scores_value               25827 non-null  float64
 58  instant_bookable                  33538 non-null  object
 59  is_business_travel_ready          33538 non-null  object
 60  cancellation_policy               33538 non-null  object
 61  require_guest_profile_picture     33538 non-null  object
 62  require_guest_phone_verification  33538 non-null  object
 63  calculated_host_listings_count    33538 non-null  int64
 64  reviews_per_month                 26591 non-null  float64
dtypes: float64(14), int64(9), object(42)
memory usage: 16.6+ MB
```

[4]:
```
def convert_tf(x):
    if x == 't':
        return 1
    elif x =='f':
        return 0
    else:
        pass
df['host_is_superhost'] = df['host_is_superhost'].apply(convert_tf)
```

[5]:

```python
df['host_is_superhost']
```

[5]:

```
0        0.0
1        0.0
2        0.0
3        0.0
4        1.0
        …
33533    0.0
33534    0.0
33535    0.0
33536    0.0
33537    0.0
Name: host_is_superhost, Length: 33538, dtype: float64
```

[6]:

```python
df['market'].value_counts()
```

[6]:

```
New York                     33425
Other (Domestic)                10
Catskills and Hudson Valley      2
Los Angeles                      2
Adirondacks                      2
Boston                           1
San Francisco                    1
Jamaica South Coast              1
New Orleans                      1
Agra                             1
Paris                            1
Kyoto                            1
Name: market, dtype: int64
```

[7]:

```python
df.select_dtypes(include=['int', 'float']).drop(columns=['id', 'host_id'])
```

[7]:

```
       host_acceptance_rate  host_is_superhost  host_listings_count  \
0                       NaN                0.0                  1.0
1                       NaN                0.0                  4.0
2                       NaN                0.0                  1.0
3                       NaN                0.0                  1.0
4                       NaN                1.0                  1.0
…                      …                 …                   …
33533                   NaN                0.0                  1.0
33534                   NaN                0.0                  3.0
33535                   NaN                0.0                  1.0
33536                   NaN                0.0                  4.0
33537                   NaN                0.0                  1.0

       accommodates  bathrooms  bedrooms  beds  square_feet  price  \
```

```
0                    2        1.0        1.0   1.0          NaN    145
1                    8        1.0        3.0   5.0          NaN    175
2                    2        1.0        0.0   1.0          NaN    180
3                    1        1.0        1.0   1.0          NaN     42
4                    2        1.0        1.0   1.0          NaN     80
…                 …        …        …    …         …     …
33533                2        1.0        1.0   1.0          NaN    110
33534                8        3.0        4.0   4.0          NaN   1195
33535                1        NaN        1.0   1.0          NaN     50
33536                2        1.0        1.0   1.0          NaN     60
33537                8        2.0        3.0   4.0          NaN    325

       guests_included  …  number_of_reviews  review_scores_rating  \
0                    2  …                  6                 100.0
1                    3  …                137                  91.0
2                    1  …                  3                 100.0
3                    1  …                  0                   NaN
4                    1  …                144                  97.0
…                  …  …                …                   …
33533                1  …                 19                  87.0
33534                1  …                 86                  95.0
33535                1  …                  0                   NaN
33536                1  …                  1                 100.0
33537                4  …                 56                  95.0

       review_scores_accuracy  review_scores_cleanliness  \
0                        10.0                       10.0
1                         9.0                        9.0
2                        10.0                        9.0
3                         NaN                        NaN
4                        10.0                       10.0
…                         …                          …
33533                     9.0                        8.0
33534                    10.0                        9.0
33535                     NaN                        NaN
33536                    10.0                       10.0
33537                     9.0                        9.0

       review_scores_checkin  review_scores_communication  \
0                       10.0                         10.0
1                        9.0                          9.0
2                        9.0                         10.0
3                        NaN                          NaN
4                       10.0                         10.0
…                        …                            …
33533                    9.0                          9.0
33534                   10.0                         10.0
```

```
33535                   NaN                          NaN
33536                  10.0                         10.0
33537                  10.0                         10.0

       review_scores_location  review_scores_value  \
0                        10.0                 10.0
1                         9.0                  9.0
2                        10.0                 10.0
3                         NaN                  NaN
4                        10.0                 10.0
…                         …                    …
33533                     9.0                  8.0
33534                    10.0                  9.0
33535                     NaN                  NaN
33536                    10.0                 10.0
33537                    10.0                  9.0

       calculated_host_listings_count  reviews_per_month
0                                   1               0.59
1                                   3               2.47
2                                   1               0.89
3                                   1                NaN
4                                   1               3.14
…                               …                 …
33533                               1               0.44
33534                               1               2.28
33535                               1                NaN
33536                               3               0.10
33537                               1               2.76

[33538 rows x 22 columns]
```

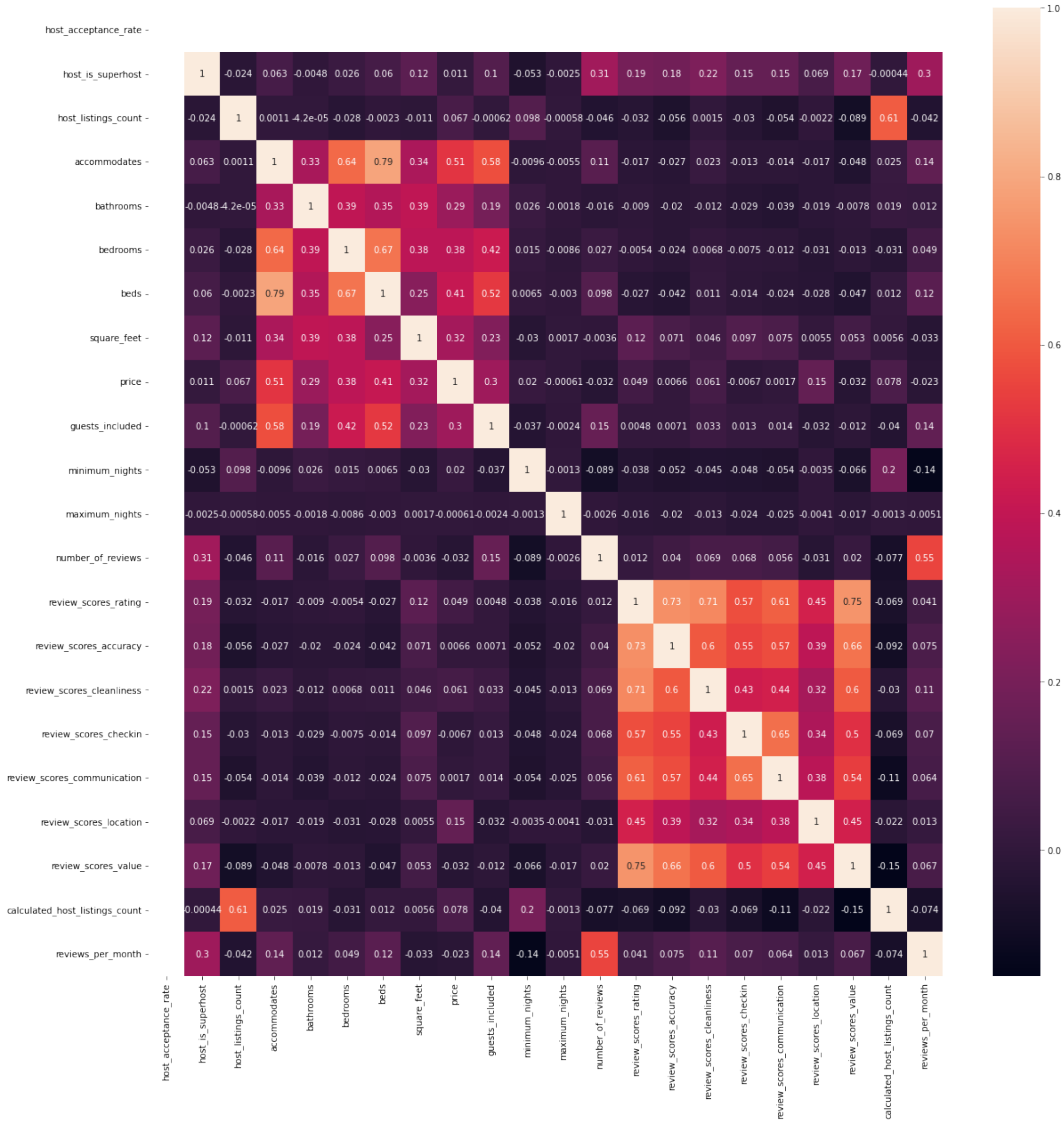
[8]:

```
baseline_features =['accommodates',
                    'bathrooms',
                    'bedrooms',
                    'beds',
                    'guests_included',
                    'number_of_reviews',
                    'reviews_per_month',
                    'neighbourhood_group_cleansed',
                    'room_type',
                    'host_is_superhost',
                    'property_type'
                   ]
```

[9]:

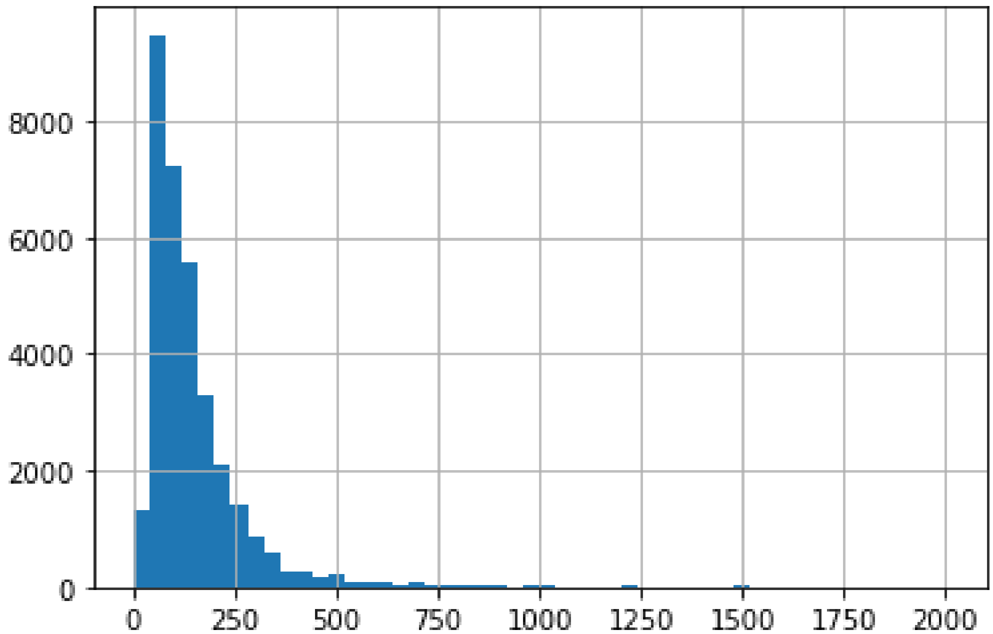
```
import pandas as pd
import seaborn as sns
```

```python
import matplotlib.pyplot as plt

# create a sample dataframe
plt.figure(figsize=(20,20))
# calculate the correlation matrix
corr_matrix = df.select_dtypes(include=['int', 'float']).drop(columns=['id', 'host_id']).corr()

# plot the correlation heatmap
sns.heatmap(corr_matrix, annot=True)

# show the plot
plt.show()
```



[10]:
```
df['price'].hist(bins = 50)
```

[10]: <AxesSubplot:>



[11]:
```
considering_features = ['host_is_superhost', 'state' ,'country',␣
 ↪'property_type', 'accommodates', 'bedrooms', 'number_of_reviews',
            'review_scores_rating']
```

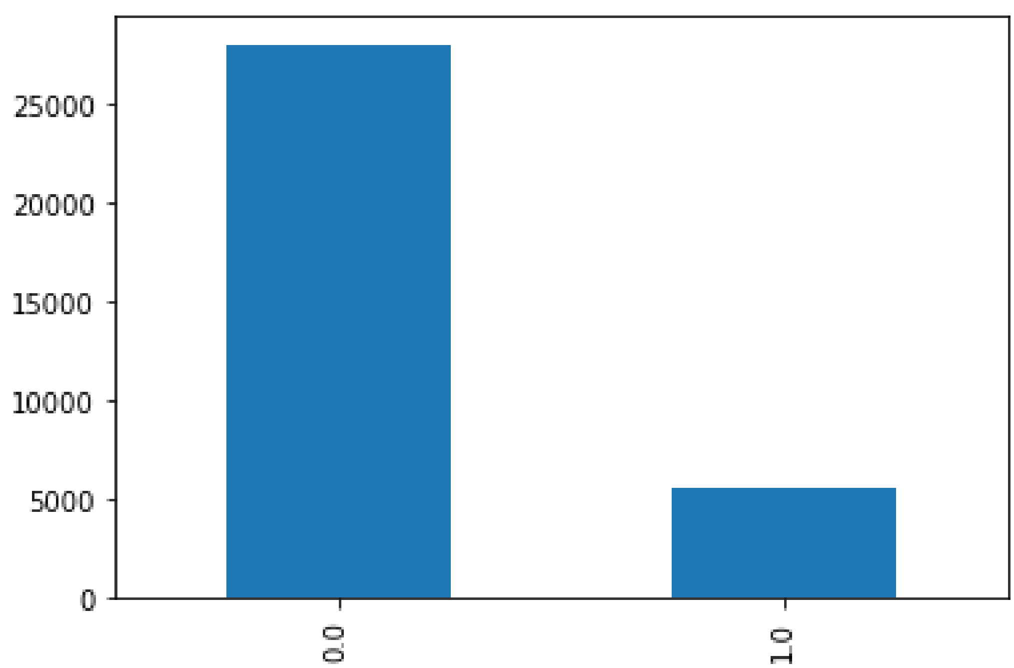
[12]:
```
basic_feature = ['host_is_superhost', 'state' , 'bedrooms',␣
 ↪'number_of_reviews', 'review_scores_rating', 'accommodates']

for bf in basic_feature:
    print(bf +": " ,df[bf].unique(), df[bf].dtype)
```

```
host_is_superhost:  [ 0.  1. nan] float64
state:  ['NY' 'Ny' 'New York' nan 'MP' 'NJ' 'ny' 'CA'] object
bedrooms:  [ 1.  3.  0.  2.  5.  4. nan  6.  9.  7.  8. 10.] float64
number_of_reviews:  [  6 137   3   0 144  12   1  30   2  10 118 173  16   8  66
29 171 108
 157  47  27  19 127  24   7  25  70  31  17 107  11  41 102   4 104  84
  85 134   5  76  73   9 167  22  83  72 313  14  35  23  45 153 142  68
  20 208  91  13  26  50  42  88  21  92  98  18  89  52  40  36 103  59
  15 176  28  44  55  53 106  32  43  57  64  58  69 213  38  51 205 156
```

```
 121 113 123  78  56  39  49  95 128 146 115  65 135 166  34  37  75 241
  97  67 162  63 226 120  93 125  90  33  71 177 112  74 151 129 141 109
 204  86  99 187 277 193 150 139 184 138  81 296 110 100  46 170 278 212
 119  54  96 169 229  87  62 246  82  60 131  61 333 161 154 230 168 221
 209 111 190 197 207  80 114 155 165 132 158  48 305 195 174 116 101 200
  94 317 202  77  79 244 273 206 201 194 266 242 140 149 240 243 186 303
 145 311 126 191 147 269 117 260 124 164 231 122 188 233 245 409 557 214
 133 105 216 315 143 136 160 319 175 182 282 308 180 159 222 224 210 181
 284 529 172 152 163 215 268 239 196 218 203 397 263 290 198 265 347 217
 178 148 276 130 473 225 179 256 228 270 236 237 238 234 227 192 283 348
 306 338 261 232 247 264 267 250 211 354 356 185 199 359 301 418 279 343
 255 189 259 275 300 324 326 455 272 183 421 219 334 312 410 262 288 391
 375 293 341 358 252 251 258 285 253 220 294 297 405 362 463 287 307 394
 304 412 401 235 249 248 309 393 286 482 378 289] int64
review_scores_rating:  [100.  91.  nan  97.  93.  96.  80.  90.  73.  98.  92.
95.  94.  99.
  84.  89.  88.  83.  85.  60.  75.  86.  20.  50.  69.  87.  40.  79.
  76.  70.  82.  74.  78.  65.  77.  45.  64.  67.  81.  57.  72.  53.
  66.  71.  58.  55.  68.  62.  47.  30.] float64
accommodates:  [ 2  8  1  6  4 16  5 12  3  7  9 10 13 11 14 15] int64
```

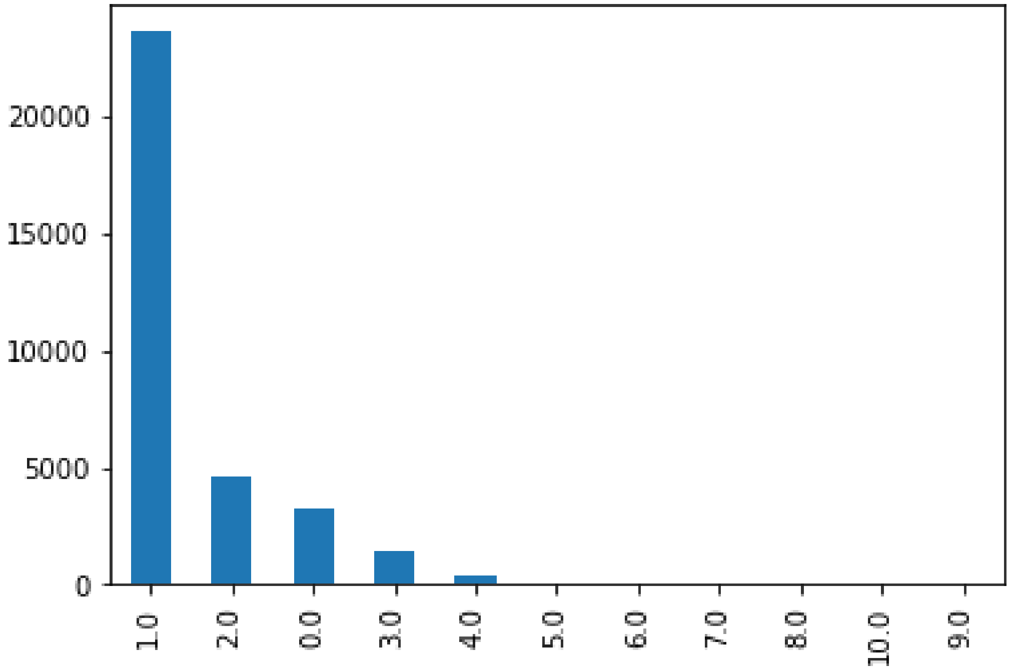
[13]:
```
df['host_is_superhost'].value_counts().plot(kind='bar')
```

[13]: <AxesSubplot:>



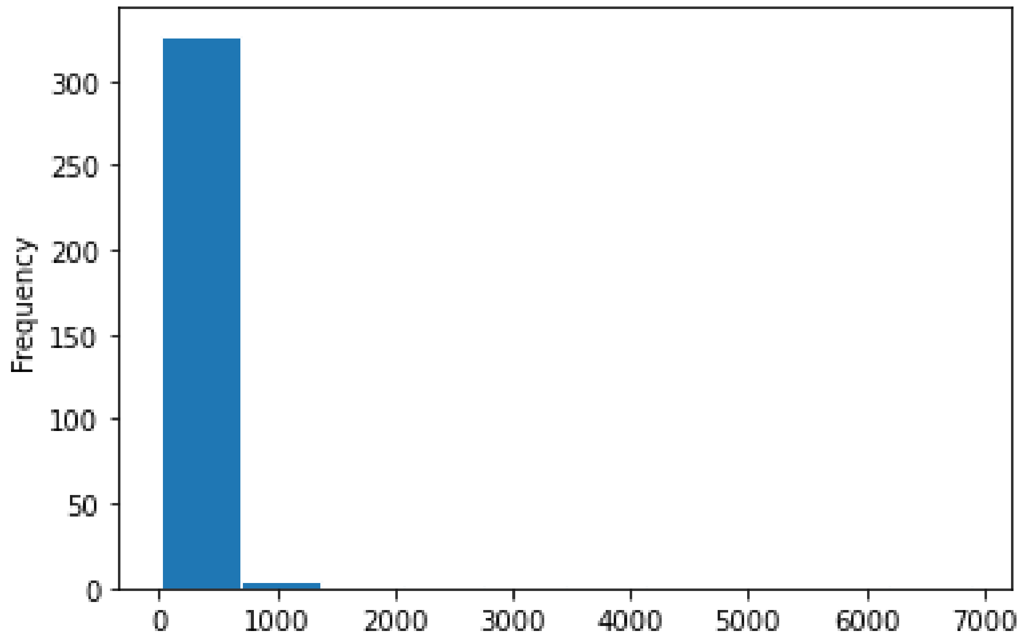
[14]:
```
df['bedrooms'].value_counts().plot(kind='bar')
```

[14]: <AxesSubplot:>



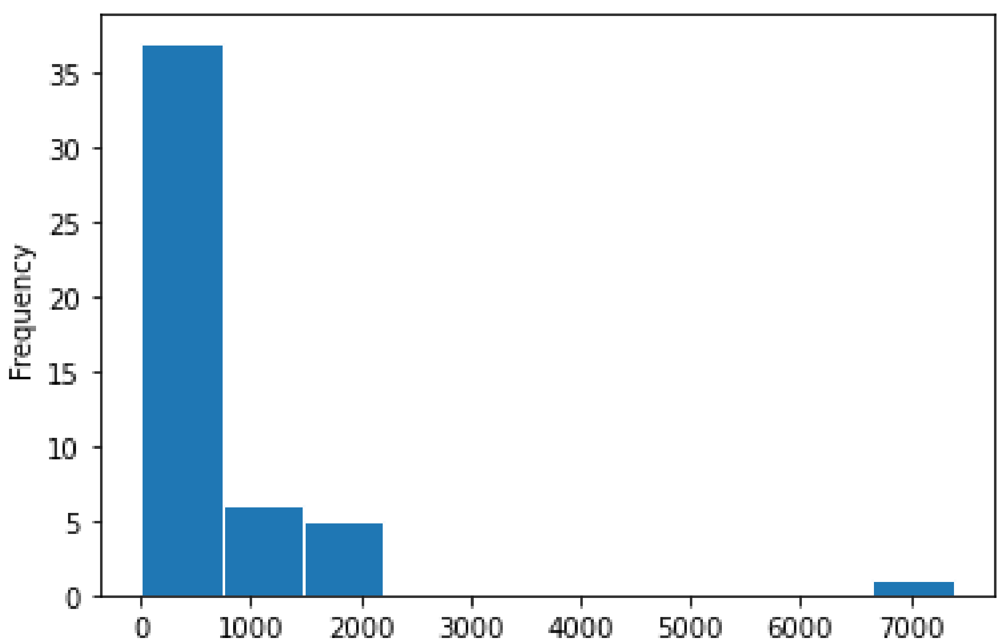
[15]:
```
df['number_of_reviews'].value_counts().plot(kind='hist', ec= 'w')
```

[15]: <AxesSubplot:ylabel='Frequency'>



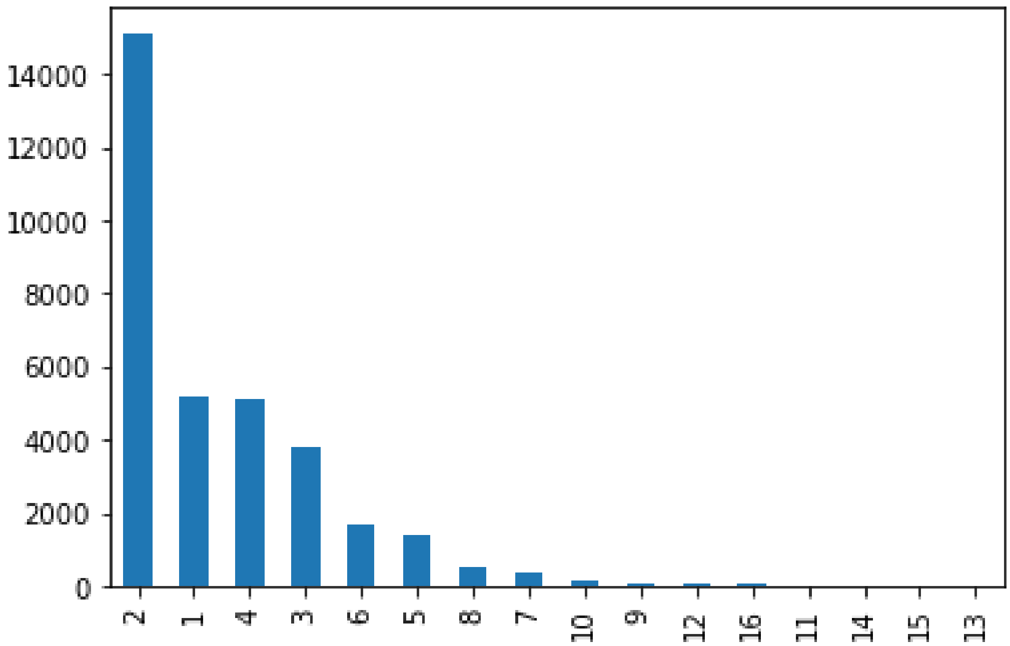
[16]:
```
df['review_scores_rating'].value_counts().plot(kind='hist', ec= 'w')
```

[16]: <AxesSubplot:ylabel='Frequency'>



[17]:
```
df['accommodates'].value_counts().plot(kind='bar')
```

[17]: <AxesSubplot:>



[18]:
```
df.select_dtypes(include=['int', 'float']).drop(columns=['id', 'host_id'])
```

[18]:

	host_acceptance_rate	host_is_superhost	host_listings_count	\
0	NaN	0.0	1.0	
1	NaN	0.0	4.0	
2	NaN	0.0	1.0	
3	NaN	0.0	1.0	
4	NaN	1.0	1.0	
…	…	…	…	
33533	NaN	0.0	1.0	
33534	NaN	0.0	3.0	
33535	NaN	0.0	1.0	
33536	NaN	0.0	4.0	
33537	NaN	0.0	1.0	

	accommodates	bathrooms	bedrooms	beds	square_feet	price	\
0	2	1.0	1.0	1.0	NaN	145	
1	8	1.0	3.0	5.0	NaN	175	
2	2	1.0	0.0	1.0	NaN	180	
3	1	1.0	1.0	1.0	NaN	42	
4	2	1.0	1.0	1.0	NaN	80	

```
…            …        …       …    …          …     …
33533            2       1.0       1.0   1.0         NaN    110
33534            8       3.0       4.0   4.0         NaN   1195
33535            1       NaN       1.0   1.0         NaN     50
33536            2       1.0       1.0   1.0         NaN     60
33537            8       2.0       3.0   4.0         NaN    325

       guests_included  …  number_of_reviews  review_scores_rating  \
0                    2  …                  6                 100.0
1                    3  …                137                  91.0
2                    1  …                  3                 100.0
3                    1  …                  0                   NaN
4                    1  …                144                  97.0
…                  …  …                  …                     …
33533                1  …                 19                  87.0
33534                1  …                 86                  95.0
33535                1  …                  0                   NaN
33536                1  …                  1                 100.0
33537                4  …                 56                  95.0

       review_scores_accuracy  review_scores_cleanliness  \
0                        10.0                       10.0
1                         9.0                        9.0
2                        10.0                        9.0
3                         NaN                        NaN
4                        10.0                       10.0
…                         …                          …
33533                     9.0                        8.0
33534                    10.0                        9.0
33535                     NaN                        NaN
33536                    10.0                       10.0
33537                     9.0                        9.0

       review_scores_checkin  review_scores_communication  \
0                       10.0                         10.0
1                        9.0                          9.0
2                        9.0                         10.0
3                        NaN                          NaN
4                       10.0                         10.0
…                        …                            …
33533                    9.0                          9.0
33534                   10.0                         10.0
33535                    NaN                          NaN
33536                   10.0                         10.0
33537                   10.0                         10.0

       review_scores_location  review_scores_value  \
```

```
0                        10.0                   10.0
1                         9.0                    9.0
2                        10.0                   10.0
3                         NaN                    NaN
4                        10.0                   10.0
…                        …                      …
33533                     9.0                    8.0
33534                    10.0                    9.0
33535                     NaN                    NaN
33536                    10.0                   10.0
33537                    10.0                    9.0

       calculated_host_listings_count  reviews_per_month
0                                   1               0.59
1                                   3               2.47
2                                   1               0.89
3                                   1                NaN
4                                   1               3.14
…                                 …                 …
33533                               1               0.44
33534                               1               2.28
33535                               1                NaN
33536                               3               0.10
33537                               1               2.76

[33538 rows x 22 columns]
```

[19]:
```python
missing = df.isna().sum()

missing /= df.shape[0]
missing *=100
missing = missing.to_frame().rename(columns={0:'Precent Of Missing Values'})
missing
```

[19]:

	Precent Of Missing Values
id	0.000000
name	0.035780
summary	3.792713
space	31.307770
description	0.918361
…	…
cancellation_policy	0.000000
require_guest_profile_picture	0.000000
require_guest_phone_verification	0.000000
calculated_host_listings_count	0.000000
reviews_per_month	20.713817

```
[65 rows x 1 columns]
```

[20]:
```python
missing.loc[baseline_features]
```

[20]:
```
                               Precent Of Missing Values
accommodates                                    0.000000
bathrooms                                       0.178902
bedrooms                                        0.098396
beds                                            0.092432
guests_included                                 0.000000
number_of_reviews                               0.000000
reviews_per_month                              20.713817
neighbourhood_group_cleansed                    0.000000
room_type                                       0.000000
host_is_superhost                               0.014908
property_type                                   0.000000
```

[21]:
```python
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.datasets import fetch_openml
from sklearn.model_selection import train_test_split
from xgboost import XGBRegressor
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import RandomizedSearchCV
```

0.0.1 XGB

Search Best param for XGBoost

[22]:
```python
# df['room_type']=df['room_type'].str.split('/', expand=True)[0].str.split('␣
↪',expand=True)[0]
# df['room_type'].value_counts()
```

[96]:
```python
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler


class Impute_Standardize(BaseEstimator, TransformerMixin):
    def __init__(self, strategy='mean', fill_value=None):
        self.strategy = strategy
        self.fill_value = fill_value
        self.imputer = SimpleImputer(strategy=self.strategy,
                                     fill_value=self.fill_value)
        self.scaler = StandardScaler()
```

```
    def fit(self, X, y=None):
        self.imputer.fit(X)
        self.scaler.fit(X)
        return self

    def transform(self, X, y=None):
        X_imputed = self.imputer.transform(X)
        X_imputed = pd.DataFrame(X_imputed, columns=self.imputer.
 ↪get_feature_names_out())
        X_scaled = self.scaler.transform(X_imputed)
        return X_scaled
```

[93]:
```
preprocessor = ColumnTransformer([('ohe', OneHotEncoder(),
                              ('neighbourhood_group_cleansed',␣
 ↪'room_type','property_type','host_is_superhost')),

                             ('imp-mode',␣
 ↪SimpleImputer(strategy='most_frequent'),
                              ('bathrooms', 'bedrooms', 'beds')),

                             ('imp-mean', Impute_Standardize(strategy='mean'),
                              ('review_scores_accuracy')),

                             ('imp-cons', SimpleImputer(strategy='constant',␣
 ↪fill_value=0),
                              ('reviews_per_month')),

                             ('std', StandardScaler(), ('accommodates',
                                                         'guests_included',
                                                         'number_of_reviews'))])
```

[91]:
```
baseline_features =['accommodates',
                    'bathrooms',
                    'bedrooms',
                    'beds',
                    'guests_included',
                    'number_of_reviews',
                    'reviews_per_month',
                    'neighbourhood_group_cleansed',
                    'room_type',
                    'host_is_superhost',
                    'property_type',
                    'review_scores_accuracy'
                   ]
```

[95]:
```
one_hot_features = ['neighbourhood_group_cleansed',
                    'room_type',
                    'property_type',
                    'host_is_superhost',
                    'bathrooms',
                    'bedrooms',
                    'beds']


impute_standardize_mean = ['review_scores_accuracy']

simple_imputer = ['reviews_per_month']

standard_scaler = ['accommodates',
                   'guests_included',
                   'number_of_reviews']
```

[105]:
```
df_x, df_y = df.drop(columns=['price']), df['price']


one_hot_features = ['neighbourhood_group_cleansed', 'room_type',␣
 ↪'property_type',
                    'host_is_superhost', 'bathrooms', 'bedrooms', 'beds']

impute_standardize_mean = ['review_scores_accuracy']
simple_imputer = ['reviews_per_month']
standard_scaler = ['accommodates', 'guests_included', 'number_of_reviews']

one_hot_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore', sparse=False))
])

impute_standardize_mean_transformer = Pipeline(steps=[
    ('imputer', Impute_Standardize(strategy='mean'))
])

simple_imputer_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='constant'))
])

standard_scaler_transformer = Pipeline(steps=[
    ('scaler', StandardScaler())
])

preprocessor = ColumnTransformer(transformers=[
    ('ohe', one_hot_transformer, one_hot_features),
```

```
    ('ism', impute_standardize_mean_transformer, impute_standardize_mean),
    ('si', simple_imputer_transformer, simple_imputer),
    ('ss', standard_scaler_transformer, standard_scaler)
])

model = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', XGBRegressor())
])

X_train, X_test, y_train, y_test = train_test_split(df_x, df_y, test_size=0.2,␣
 ↪random_state=42)

param_grid = {
    'classifier__learning_rate': [0.01, 0.05, 0.1, 0.2],
    'classifier__n_estimators': range(50, 200, 10),
    'classifier__max_depth': range(3, 10),
    'classifier__colsample_bytree': [0.5, 0.7, 1],
    'classifier__gamma': [0, .25, 1.0],
    'classifier__subsample': [0.5, 0.7, 1],
    'classifier__reg_lambda': [0, 1.0, 10.0]
}


random_search = RandomizedSearchCV(
    model,
    param_distributions=param_grid,
    n_iter=10,
    cv=5,
    n_jobs=-1
)

# random_search.fit(X_train, y_train)

# print('Best parameters:', random_search.best_params_)
# print('Best score:', -random_search.best_score_)
```

[114]:
```
from sklearn.model_selection import RandomizedSearchCV, train_test_split
from sklearn.pipeline import Pipeline, make_pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.impute import SimpleImputer
from xgboost import XGBRegressor
import pandas as pd
import numpy as np

one_hot_features = ['neighbourhood_group_cleansed',
```

```python
                    'room_type',
                    'property_type',
                    'host_is_superhost',
                    'bathrooms',
                    'bedrooms',
                    'beds']

impute_standardize_mean = ['review_scores_accuracy']

simple_imputer = ['reviews_per_month']

standard_scaler = ['accommodates',
                   'guests_included',
                   'number_of_reviews']

df_x, df_y = df.drop(columns=['price']), df['price']

one_hot_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

impute_standardize_mean_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent'))
])

simple_imputer_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='constant'))
])

standard_scaler_transformer = Pipeline(steps=[
    ('simple_imputer', SimpleImputer(strategy='most_frequent')),
    ('imputer', StandardScaler())
])

preprocessor = ColumnTransformer(transformers=[
    ('ohe', one_hot_transformer, one_hot_features),
    ('ism', impute_standardize_mean_transformer, impute_standardize_mean),
    ('si', simple_imputer_transformer, simple_imputer),
    ('ss', standard_scaler_transformer, standard_scaler)
])

# preprocessor.fit_transform(df)

model = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', XGBRegressor())
```

```
])

X_train, X_test, y_train, y_test = train_test_split(df_x, df_y, test_size=0.2,␣
↪random_state=42)

param_grid = {
    'classifier__learning_rate': [0.01, 0.05, 0.1, 0.2],
    'classifier__n_estimators': range(50, 200, 10),
    'classifier__max_depth': range(3, 10),
    'classifier__colsample_bytree': [0.5, 0.7, 1],
    'classifier__gamma': [0, .25, 1.0],
    'classifier__subsample': [0.5, 0.7, 1],
    'classifier__reg_lambda': [0, 1.0, 10.0]
}

random_search = RandomizedSearchCV(
    model,
    param_distributions=param_grid,
    n_iter=10,
    cv=5,
    n_jobs=-1
)

random_search.fit(X_train, y_train)

print('Best parameters:', random_search.best_params_)
```

```
Best parameters: {'classifier__subsample': 1, 'classifier__reg_lambda': 1.0,
'classifier__n_estimators': 120, 'classifier__max_depth': 8,
'classifier__learning_rate': 0.05, 'classifier__gamma': 0.25,
'classifier__colsample_bytree': 0.5}
```

[115]:
```
# best_xgb_model = Pipeline([
#     ('preproc', preprocessor),
#     ('classifier', XGBRegressor(
#         subsample= 0.7,
#         reg_lambda= 1.0,
#         n_estimators= 80,
#         max_depth= 5,
#         learning_rate = 0.05,
#         gamma = 0.25,
#         colsample_bytree=1)
#     )
# ])
```

[116]:
```
best_xgb_model = random_search.best_estimator_
```

[117]:
```
df_x, df_y = df.drop(columns=['price']), df['price']

# split the data into training and testing sets
xgb_X_train, xgb_X_test, xgb_y_train, xgb_y_test = train_test_split(df_x, df_y,␣
↪test_size=0.2, random_state=42)


# Fit the pipeline to the training data
best_xgb_model.fit(xgb_X_train, xgb_y_train)

xgb_y_pred_train = best_xgb_model.predict(xgb_X_train)
print('train_RMSE', mean_squared_error(xgb_y_pred_train, xgb_y_train)**0.5)

xgb_y_pred_test = best_xgb_model.predict(xgb_X_test)
print('test_RMSE', mean_squared_error(xgb_y_pred_test, xgb_y_test)**0.5)
```

```
train_RMSE 78.69322389542123
test_RMSE 95.10140155751522
```

[118]:
```
best_xgb_model.fit(df_x,df_y)

xgb_y_pred = best_xgb_model.predict(df_x)
print('train_RMSE', mean_squared_error(xgb_y_pred, df_y)**0.5)
```

```
train_RMSE 80.2805870671499
```

Apply on Test set

[119]:
```
test = pd.read_csv('test.csv')
test.head()
```

[119]:
```
         id                                           name  \
0  19307997              Super Lux 2BR in Downtown Manhattan
1  20176193        Vintage Eclectic Brownstone Pad in Brooklyn
2  19485371                       Spacious Harlem Hideaway
3  13079990                  Spacius private room in Brooklyn
4  22339757  *Dg) Delightful Private Room 20 min to Manhattan

                                             summary  \
0  Prepare to be WOWED! This spectacularly bright…
1  Ideal for romantic, creative types, this is an…
2  Postive Vibes . This is our Harlem tree house,…
3  Newly renovated apartment, its a 3 bedroom apa…
4  Hi my home is only 2 blocks from the subway st…

                                               space  \
0  Top of the line Wolf and Sub-Zero appliances, …
1  Not your typical New York abode, my apartment …
```

```
2  The private room is very spacious and cozy. Th…
3  3 bedroom apartment, 1 full bathroom, living r…
4                                                NaN

                                         description experiences_offered  \
0  Prepare to be WOWED! This spectacularly bright…                none
1  Ideal for romantic, creative types, this is an…                none
2  Postive Vibes . This is our Harlem tree house,…                none
3  Newly renovated apartment, its a 3 bedroom apa…                none
4  Hi my home is only 2 blocks from the subway st…                none

                               neighborhood_overview  \
0                                                NaN
1  Bed Stuy is a diverse historic neighborhood wi…
2  You are in a Cultural Haven full of restaurant…
3                                                NaN
4                                                NaN

                                               notes  \
0                                                NaN
1  This is an actual unique living experience whe…
2  We also keep cucumber water in the fridge feel…
3                                                NaN
4                                                NaN

                                             transit  \
0                                                NaN
1  Close to buses and subways there is also free …
2  Train, uber or a taxi. (Extremely taxi accessi…
3  There is the Mta 3 train Sutter stop, also the…
4                                                NaN

                                              access  …  \
0                                                NaN  …
1  Entrance hallway, living room, bedroom, kitche…  …
2                Private Room, Kitchen And Bathroom  …
3                                                NaN  …
4                                                NaN  …

  review_scores_communication review_scores_location  review_scores_value  \
0                         NaN                    NaN                  NaN
1                        10.0                   10.0                 10.0
2                        10.0                   10.0                 10.0
3                         9.0                    8.0                  9.0
4                         8.0                    8.0                  8.0

  instant_bookable is_business_travel_ready          cancellation_policy  \
```

```
0                 f                        f                     flexible
1                 f                        f                     flexible
2                 t                        f                     flexible
3                 f                        f                     flexible
4                 t                        f  strict_14_with_grace_period

  require_guest_profile_picture require_guest_phone_verification  \
0                             f                                f
1                             f                                f
2                             f                                f
3                             f                                f
4                             f                                f

  calculated_host_listings_count  reviews_per_month
0                              1                NaN
1                              1               1.48
2                              1               0.37
3                              1               0.23
4                              9               1.53

[5 rows x 64 columns]
```

[120]:
```
xgb_y_pred = best_xgb_model.predict(df_x)
print('train_RMSE', mean_squared_error(xgb_y_pred, df_y)**0.5)
```

```
train_RMSE 80.2805870671499
```

[121]:
```
xgb_df_predict_y = best_xgb_model.predict(test)
output_df = pd.DataFrame()
output_df['Id'] = test['id']
output_df['Predicted'] = xgb_df_predict_y
output_df.to_csv('xgb_prediction.csv', index = False)
```

0.0.2 RandomForest

[153]:
```
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.datasets import fetch_openml
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error
```

Search Best Param__

[158]:

```
# df_x, df_y = df.drop(columns=['price']), df['price']

# categorical_transformer = Pipeline(steps=[
#     ('imputer', SimpleImputer(strategy='most_frequent')),
#     ('onehot', OneHotEncoder(handle_unknown='ignore'))
# ])

# preprocessor = ColumnTransformer(transformers=[
#     ('ohe', categorical_transformer, baseline_features)
# ])

# rf_model = Pipeline([
#     ('preproc', preprocessor),
#     ('classifier', RandomForestRegressor())
# ])

# param_grid = {
#     'classifier__n_estimators': [10, 50, 100],
#     'classifier__max_depth': [None, 10, 20],
# }

# random_search = RandomizedSearchCV(
#     rf_model,
#     param_distributions=param_grid,
#     n_iter=10,
#     cv=5,
#     n_jobs=-1,
#     random_state=42
# )

# random_search.fit(df_x, df_y)

# print(random_search.best_params_)
```

[154]:

```
df_x, df_y = df.drop(columns=['price']), df['price']

categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

preprocessor = ColumnTransformer(transformers=[
    ('ohe', categorical_transformer, baseline_features)
])

rf_model = Pipeline([
    ('preproc', preprocessor),
```

```
    ('classifier', RandomForestRegressor(n_estimators=50,max_depth=10))
])

# split the data into training and testing sets
rf_X_train, rf_X_test, rf_y_train, rf_y_test = train_test_split(df_x, df_y,␣
 ↪test_size=0.2, random_state=42)

# Fit the pipeline to the training data
rf_model.fit(rf_X_train, y_train)
```

[154]:

```
Pipeline(steps=[('preproc',
                 ColumnTransformer(transformers=[('ohe',
                                                  Pipeline(steps=[('imputer',
SimpleImputer(strategy='most_frequent')),
                                                                  ('onehot',
OneHotEncoder(handle_unknown='ignore'))]),
                                                  ['accommodates', 'bathrooms',
                                                   'bedrooms', 'beds',
                                                   'guests_included',
                                                   'number_of_reviews',
                                                   'reviews_per_month',
'neighbourhood_group_cleansed',
                                                   'room_type'])])),
                ('classifier',
                 RandomForestRegressor(max_depth=10, n_estimators=50))])
```

[157]:

```
rf_y_pred_train = rf_model.predict(rf_X_train)
print('train_RMSE', mean_squared_error(rf_y_pred_train, rf_y_train)**0.5)

rf_y_pred_test = rf_model.predict(rf_X_test)
print('test_RMSE', mean_squared_error(rf_y_pred_test, rf_y_test)**0.5)
```

```
train_RMSE 84.37952399596651
test_RMSE 99.68500273229499
```

[ ]: