In [1]:
```python
import pandas as pd
! pip install langdetect
! pip install nltk
! pip install WordCloud
! pip install afinn
import nltk
```

```
Processing ./.cache/pip/wheels/c5/96/8a/f90c59ed25d75e50a8c10a1b1c2d4c402e4dacfa87f3aff36a/langdetect-1.0.9-py3-none-any.whl
Requirement already satisfied: six in /opt/conda/lib/python3.7/site-packages (from langdetect) (1.14.0)
Installing collected packages: langdetect
Successfully installed langdetect-1.0.9
Collecting nltk
  Using cached nltk-3.6.2-py3-none-any.whl (1.5 MB)
Requirement already satisfied: tqdm in /opt/conda/lib/python3.7/site-packages (from nltk) (4.45.0)
Requirement already satisfied: joblib in /opt/conda/lib/python3.7/site-packages (from nltk) (0.15.1)
Collecting regex
  Downloading regex-2021.7.6-cp37-cp37m-manylinux2014_x86_64.whl (721 kB)
     |████████████████████████████████| 721 kB 5.7 MB/s eta 0:00:01
Requirement already satisfied: click in /opt/conda/lib/python3.7/site-packages (from nltk) (7.1.2)
Installing collected packages: regex, nltk
Successfully installed nltk-3.6.2 regex-2021.7.6
Collecting WordCloud
  Using cached wordcloud-1.8.1-cp37-cp37m-manylinux1_x86_64.whl (366 kB)
Requirement already satisfied: pillow in /opt/conda/lib/python3.7/site-packages (from WordCloud) (7.1.2)
Requirement already satisfied: matplotlib in /opt/conda/lib/python3.7/site-packages (from WordCloud) (3.2.1)
Requirement already satisfied: numpy>=1.6.1 in /opt/conda/lib/python3.7/site-packages (from WordCloud) (1.18.4)
Requirement already satisfied: python-dateutil>=2.1 in /opt/conda/lib/python3.7/site-packages (from matplotlib->WordCloud) (2.8.1)
Requirement already satisfied: kiwisolver>=1.0.1 in /opt/conda/lib/python3.7/site-packages (from matplotlib->WordCloud) (1.2.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /opt/conda/lib/python3.7/site-packages (from matplotlib->WordCloud) (2.4.7)
Requirement already satisfied: cycler>=0.10 in /opt/conda/lib/python3.7/site-packages (from matplotlib->WordCloud) (0.10.0)
Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.7/site-packages (from python-dateutil>=2.1->matplotlib->WordCloud) (1.14.0)
Installing collected packages: WordCloud
Successfully installed WordCloud-1.8.1
Processing ./.cache/pip/wheels/9d/16/3a/9f0953027434eab5dadf3f33ab3298fa95afa8292fcf7aba75/afinn-0.1-py3-none-any.whl
Installing collected packages: afinn
Successfully installed afinn-0.1
```

In [2]:
```python
import matplotlib.pyplot as plt
plt.style.use('seaborn')
import seaborn as sns
```

In [4]:
```python
reviews = pd.read_csv('reviews after 2019.csv')
reviews = reviews.drop(columns = 'Unnamed: 0')
```

In [ ]:
```
REVIEWS CLEANING
```

In [ ]:
```
We will first remove the non-english comments using the LangDetect module
```

In [5]:
```python
from langdetect import detect
from langdetect import DetectorFactory
DetectorFactory.seed = 0

#testing language detection
detect('First class')
```

Out[5]: 'en'

In [6]:
```python
reviews.dropna(axis = 'index', subset=['comments'], inplace=True)
```

In [7]:
```python
#function detecting the language of each review
def language_detection(text):
    try:
        return detect(text)
    except:
        return None
```

In [8]:
```python
#inserting a new feature of the detected language
reviews['language'] = reviews['comments'].apply(language_detection)
```

In [12]:
```python
#removing the comments containing the expression 'the host cancelled the r
eservation. This is an automated posting'
reviews = reviews[~reviews.comments.str.contains((expression))]
```

In [13]:
```python
#verifying the number of comments that contain the expression
expression =  'This is an automated posting '
count=0
for comment in reviews.comments:
    if expression in comment:
        count+=1
print(count)
```

```
0
```

In [16]:
```python
#saving the new df to avoid long running time
#reviews.to_csv('processed_reviews.csv')
processed_reviews = pd.read_csv('processed_reviews.csv')
```

In [17]:
```python
processed_reviews.head()
```

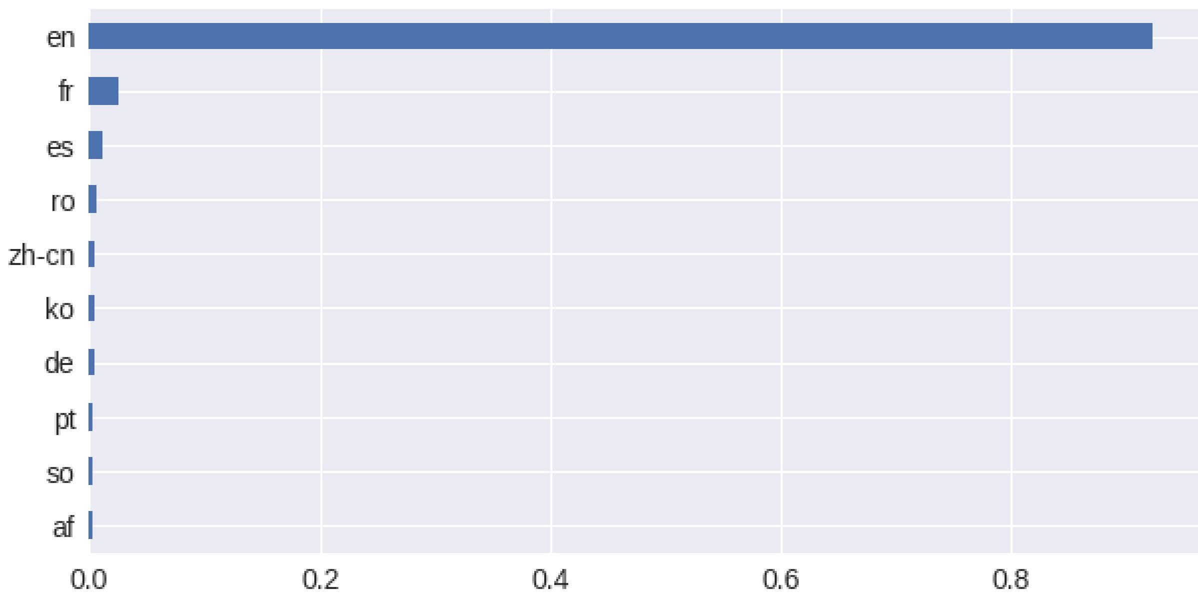
Out[17]:

	Unnamed: 0	Unnamed: 0.1	listing_id	id	date	comments	language
0	0	0	23691	438406815	2019-04-16	Great, cozy space. Would stay again	en
1	1	1	23691	442476822	2019-04-23	Great second visit- same level of hospitality ...	en
2	2	2	23691	516588467	2019-	Nice private space with full kitchen	en

					08-24	and all t...	
3	3	3	23691	522722658	2019-09-02	Yohan and Sarah's place was lovely. Very clean...	en
4	4	4	23691	542525855	2019-10-06	Great hosts, responsive and very accommodating!	en

In [18]:
```
#distribution of the languages
processed_reviews.language.value_counts(normalize=True).head(10).sort_valu
es().plot(kind = 'barh', figsize=(10,5), fontsize=14)
```

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff164714cd0>



In [19]:
```
#keeping the english language
processed_reviews_en = processed_reviews[(processed_reviews['language']=='
en')]
```

In [21]:
```
processed_reviews_en.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 193772 entries, 0 to 210631
Data columns (total 7 columns):
 #   Column        Non-Null Count   Dtype 
---  ------        --------------   ----- 
 0   Unnamed: 0    193772 non-null  int64 
 1   Unnamed: 0.1  193772 non-null  int64 
 2   listing_id    193772 non-null  int64 
 3   id            193772 non-null  int64 
 4   date          193772 non-null  object
 5   comments      193772 non-null  object
 6   language      193772 non-null  object
dtypes: int64(4), object(3)
memory usage: 11.8+ MB
```

In [ ]:
```
VISUALIZING THE DATA WITH WORDCLOUD
```

In [22]:
```
#visualizing the data with word cloud
from nltk.corpus import stopwords
from wordcloud import WordCloud
from collections import Counter
from PIL import Image
import re
import string
```

In [26]:
```
def plot_wordcloud(wordcloud, language):
    plt.figure(figsize=(12, 10))
    plt.imshow(wordcloud, interpolation = 'bilinear')
    plt.axis("off")
    plt.title(language + ' Comments\n', fontsize=18, fontweight='bold')
    plt.show()
```

In [24]:
```
import nltk
nltk.download('stopwords')
```

```
[nltk_data] Downloading package stopwords to /home/jovyan/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

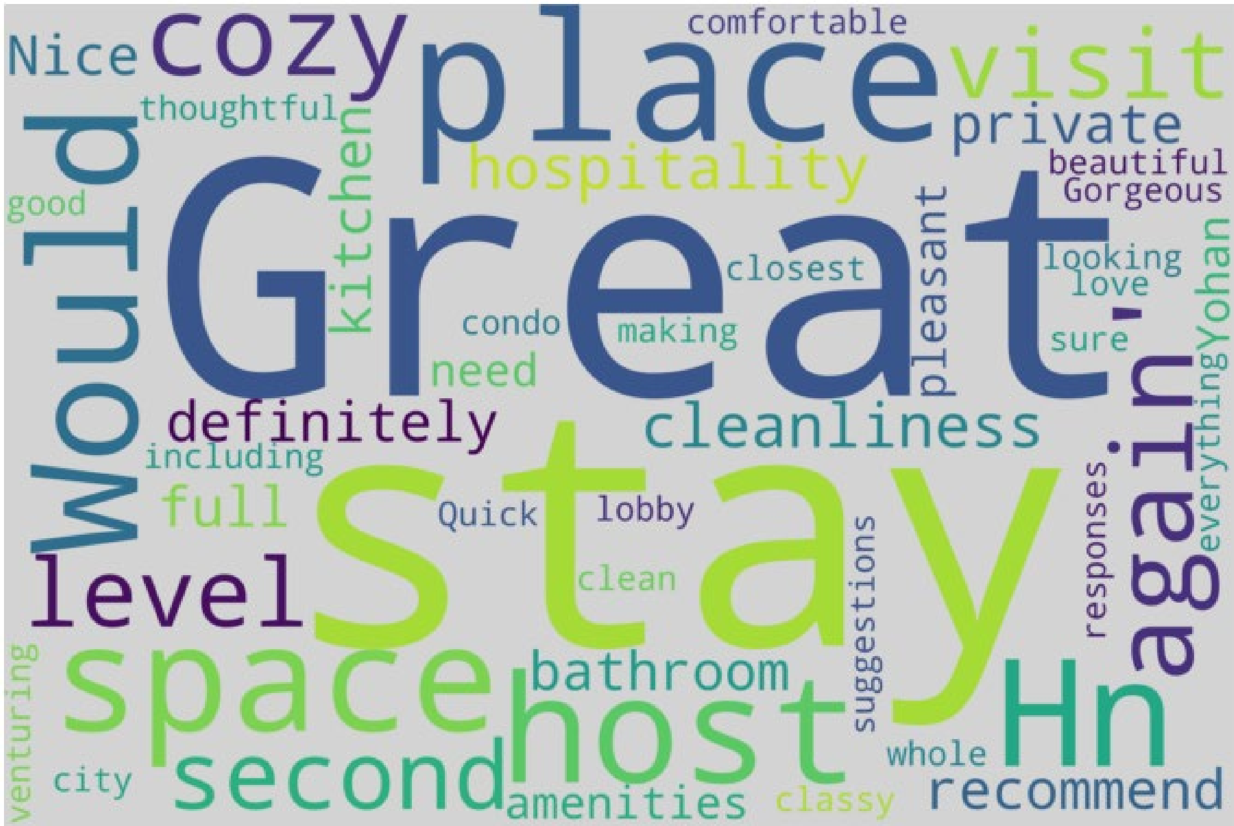
Out[24]: True

In [27]:
```
#list of the the stopwords
print(stopwords.words('english'))
```

['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've", "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him', 'his', 'himself', 'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them', 'their', 'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'll", 'these', 'those', 'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having', 'do', 'does', 'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'until', 'while', 'of', 'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through', 'during', 'before', 'after', 'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under', 'again', 'further', 'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', 'each', 'few', 'more', 'most', 'other', 'some', 'such', 'no', 'nor', 'not', 'only', 'own', 'same', 'so', 'than', 'too', 'very', 's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'now', 'd', 'll', 'm', 'o', 're', 've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't", 'doesn', "doesn't", 'hadn', "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn', "mightn't", 'mustn', "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn', "wasn't", 'weren', "weren't", 'won', "won't", 'wouldn', "wouldn't"]

In [31]:
```
wordcloud = WordCloud(max_font_size=None, max_words=200, background_color=
"lightgrey",
                      width=3000, height=2000,
                      stopwords=stopwords.words('english')).generate(str(p
rocessed_reviews_en.comments.values))

plot_wordcloud(wordcloud, 'English')
```

English Comments



In [50]:
```
processed_reviews_en = pd.read_csv('processed_reviews_en.csv')
```

In [32]:
```
# initialize afinn sentiment analyzer
#Afinn has preprocessed the text by removing the punctuation, converting a
ll the words to lower-case

from afinn import Afinn
af = Afinn()

# compute sentiment scores (polarity) and labels
sentiment_scores = [af.score(article) for article in processed_reviews_en.
comments]
sentiment_category = ['positive' if score > 0
                          else 'negative' if score < 0
                              else 'neutral'
                                  for score in sentiment_scores]
```

In [33]:
```
processed_reviews_en['sentiment_scores'] = sentiment_scores
processed_reviews_en['sentiment_category'] = sentiment_category
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:1: SettingWit
hCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
```

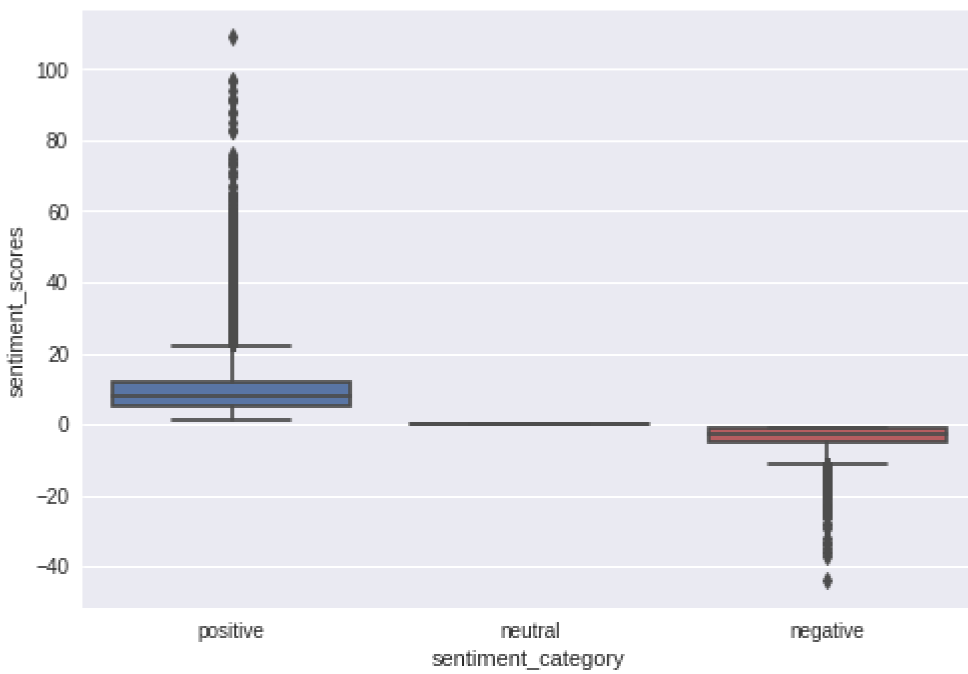
```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:2: SettingWit
hCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

In [34]:
```
processed_reviews_en.sentiment_scores.describe()
```

Out[34]:

```
count    193772.000000
mean          8.732350
std           6.265366
min         -44.000000
25%           5.000000
50%           8.000000
75%          12.000000
max         109.000000
Name: sentiment_scores, dtype: float64
```

In [37]:
```
sns.boxplot(y='sentiment_scores', x='sentiment_category', data = processed
_reviews_en)
plt.show()
```



In [38]:
```
#counting the number of comments that contain the expression 'the host can
celled the reservation. This is an automated postins'
expression =  'This is an automated posting'
count=0
for comment in processed_reviews_en.comments:
    if expression in comment:
        count+=1
print(count)
```

844

In [39]:
```
##removing the comments containing this expression
processed_reviews_en = processed_reviews_en[~processed_reviews_en.comments
.str.contains((expression))]
```

In [40]:
```
#checking the negative comments
columns_to_display = ['comments', 'sentiment_scores']
print(processed_reviews_en.sort_values(by='sentiment_scores')[columns_to_d
isplay].head(20))
```

```
                                                 comments  sentiment_scores
6943    I feel it is important to warn potential guest...             -44.0
49479   I don’t like writing negative reviews and I’ve...             -37.0
196214  My whole experience with this air bnb was terr...             -36.0
32004   TLDR: This is a pretty nice place, except for ...             -36.0
174610  this review is a frustrating one to write beca...             -35.0
165769  First of all: the location of the apartment is...             -34.0
119681  The host misrepresented themselves claiming th...             -33.0
15890   I will start off by saying Ice herself is a ve...             -32.0
78362   Maryam’s Airbnb was the worst experience I hav...             -29.0
125612  I hate negativity or leaving bad reviews, but ...             -28.0
86849   Please do yourselves a favour and scroll down ...             -28.0
33236   Do NOT stay here. The building is cheaply made...             -26.0
51039   We had a terrible stay here. The location and ...             -26.0
5751    **DANGER! 1. The house was not clean before ar...             -26.0
194205  The condo had no hand soap in the washroom, di...             -26.0
130298  Gabe's place is really bad. Dirty, dirty, dirt...             -25.0
39311   Where do I start?! The apartment was dirty and...             -25.0
43223   I regret to review this space with negative co...             -24.0
86589   DO NO STAY HERE. I originally booked here beca...             -24.0
83258   My stay here was not ideal at all. If you are ...             -24.0
```

One of the drawbacks to using the raw Afinn score is the that longer texts may yield higher values simply because they contain more words. To adjust for that, we can divide the score by the number of words in the text. The most straightforward way to count words in a Python string is to use the split method, which splits a string based on white spaces, and then count the length of the resulting list.

In [42]:
```
#removing the punctuation
import string
processed_reviews_en['comments'] = processed_reviews_en['comments'].str.tr
anslate(str.maketrans("","", string.punctuation))
```

In [43]:
```
#counting the words in each comment
def word_count(text_string):
    '''Calculate the number of words in a string'''
    return len(text_string.split())

processed_reviews_en['word_count'] = processed_reviews_en['comments'].appl
y(word_count)
```

In [44]:
```
processed_reviews_en.word_count.describe()
```

Out[44]:
```
count    192928.000000
mean         34.862384
std          40.680019
min           1.000000
```

```
25%         11.000000
50%         23.000000
75%         44.000000
max       1000.000000
Name: word_count, dtype: float64
```

In [45]:
```
#calculating the sentiment_scores_adjusted to the number of words in each comment
processed_reviews_en['sentiment_scores_adj'] = processed_reviews_en['sentiment_scores'] *100 / processed_reviews_en['word_count']
```

In [46]:
```
processed_reviews_en.sentiment_scores_adj.describe()
```

Out[46]:
```
count    192928.000000
mean         44.174017
std          38.090856
min        -300.000000
25%          20.000000
50%          33.333333
75%          57.142857
max         400.000000
Name: sentiment_scores_adj, dtype: float64
```

In [48]:
```
median_listing_scores = pd.DataFrame(processed_reviews_en.groupby('listing_id')['sentiment_scores_adj'].median())
```

In [1]:
```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import io
import seaborn as sns
import datetime
import math
import time
from scipy import stats
```

In [2]:
```
! pip install xgboost
import xgboost as xgb
```

```
Collecting xgboost
  Using cached xgboost-1.4.2-py3-none-manylinux2010_x86_64.whl (166.7 MB)
Requirement already satisfied: scipy in /opt/conda/lib/python3.7/site-pack
ages (from xgboost) (1.4.1)
Requirement already satisfied: numpy in /opt/conda/lib/python3.7/site-pack
ages (from xgboost) (1.18.4)
Installing collected packages: xgboost
Successfully installed xgboost-1.4.2
```

In [6]:
```
myListings_oneHot_v2 = pd.read_csv('myListings_oneHot_v2.csv')
```

DATA CLEANING AND EDA

In [8]:
```
#removing irrelevant features
myListings_oneHot_v2 = myListings_oneHot_v2.drop(columns = ['description',
 'review_scores_rating', 'review_scores_accuracy'\
                        ,'review_scores_cleanliness', 'review_scores_check
in', 'review_scores_communication', 'review_scores_location'\
                        , 'review_scores_value'])
```

In [9]:
```
myListings_oneHot_v2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9385 entries, 0 to 9384
Data columns (total 25 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   Unnamed: 0                      9385 non-null   int64
 1   id                              9385 non-null   int64
 2   host_id                         9385 non-null   int64
 3   host_since                      9385 non-null   object
 4   host_is_superhost               9385 non-null   int64
 5   neighbourhood_cleansed          9385 non-null   object
 6   accommodates                    9385 non-null   int64
 7   bathrooms_text                  9385 non-null   object
 8   bedrooms                        8666 non-null   float64
 9   beds                            9324 non-null   float64
 10  amenities                       9385 non-null   object
 11  price                           9385 non-null   int64
 12  minimum_nights                  9385 non-null   int64
```

```
 13  availability_365                9385 non-null   int64
 14  number_of_reviews               9385 non-null   int64
 15  number_of_reviews_ltm           9385 non-null   int64
 16  number_of_reviews_l30d          9385 non-null   int64
 17  first_review                    9385 non-null   object
 18  last_review                     9385 non-null   object
 19  instant_bookable                9385 non-null   int64
 20  calculated_host_listings_count  9385 non-null   int64
 21  reviews_per_month               9385 non-null   float64
 22  room_type_Entire home/apt       9385 non-null   int64
 23  room_type_Private room          9385 non-null   int64
 24  room_type_Shared room           9385 non-null   int64
dtypes: float64(3), int64(16), object(6)
memory usage: 1.8+ MB
```

In [10]:

```
#eliminating price outliers and keeping 99% of the observations
np.percentile(myListings_oneHot_v2.price, 99) #655
myListings_oneHot_v2 = myListings_oneHot_v2[-(myListings_oneHot_v2.price >
 655)]
```

In [11]:

```
#exploring the price after removing the outliers
myListings_oneHot_v2.price.describe()
```

Out[11]:

```
count    9385.000000
mean      113.572616
std        82.764345
min        13.000000
25%        60.000000
50%        93.000000
75%       140.000000
max       650.000000
Name: price, dtype: float64
```

In [12]:

```
#Converting bathroom-text to float
for i in range(0,len(myListings_oneHot_v2.bathrooms_text),1):
    myListings_oneHot_v2.bathrooms_text[i] = float(myListings_oneHot_v2.ba
throoms_text[i].split(" ")[0])
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:3: SettingWit
hCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  This is separate from the ipykernel package so we can avoid doing import
s until
```

In [13]:

```
myListings_oneHot_v2.bathrooms_text.value_counts()
```

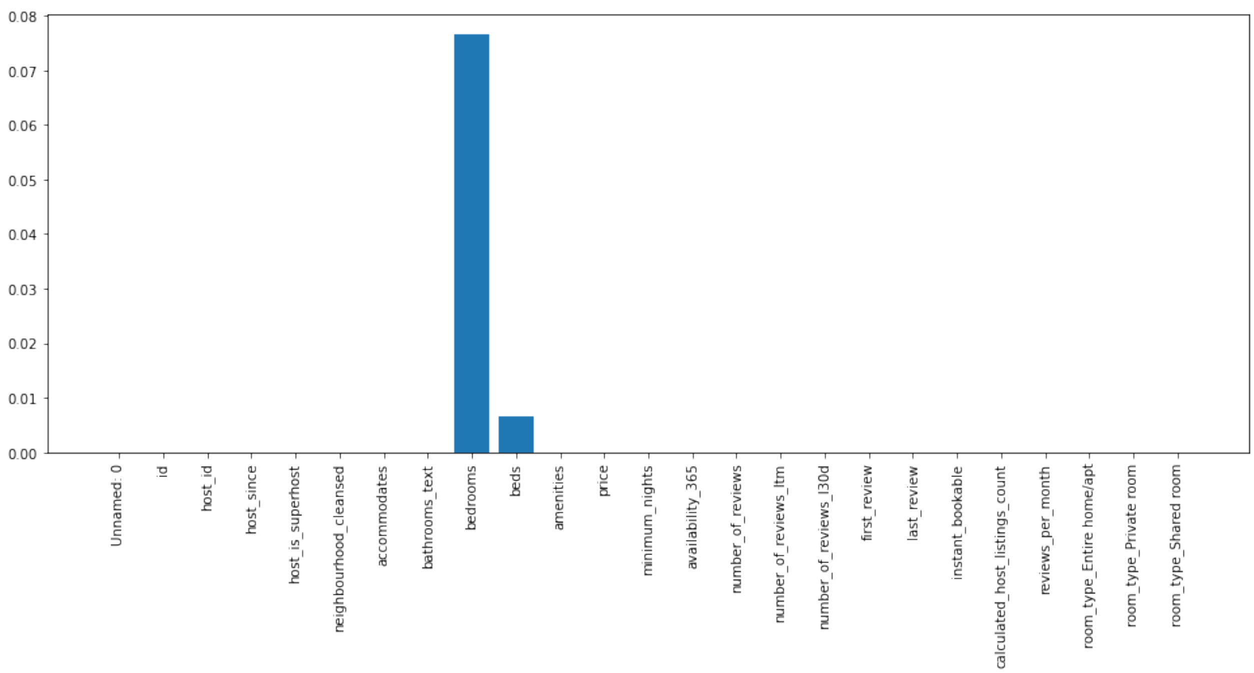
Out[13]:

```
1.0    7257
2.0    1186
1.5     639
2.5     147
3.0     111
3.5      35
4.0      10
```

```
Name: bathrooms_text, dtype: int64
```

In [14]:
```
# Looking at the proportion of missing values per feature
d = pd.isnull(myListings_oneHot_v2).sum()
d = {'features' : d.index, 'missing_values': d, 'proportion_missing_values
': (d/myListings_oneHot_v2.shape[0])}
d = pd.DataFrame(data=d).reset_index(drop=True)

# Figure representing the proportion of the missing values per feature
plt.figure(figsize=(16,6))
plt.xticks(rotation="vertical")
plt.bar(d.features, d.proportion_missing_values)
```

Out[14]:
```
<BarContainer object of 25 artists>
```



In [15]:
```
#removing irrelevant features
myListings_oneHot_v2 = myListings_oneHot_v2.drop(columns=['Unnamed: 0'])
```

In [16]:
```
#Filling the missing values in the numeric features with the median.
for col in myListings_oneHot_v2.columns[myListings_oneHot_v2.isnull().any(
)]:
    myListings_oneHot_v2[col] = myListings_oneHot_v2[col].fillna(myListing
s_oneHot_v2[col].median())
```

In [17]:
```
#converting host_since, first review, and last review to year
myListings_oneHot_v2.host_since = pd.to_datetime(myListings_oneHot_v2.host
_since)
myListings_oneHot_v2.last_review = pd.to_datetime(myListings_oneHot_v2.las
t_review)
myListings_oneHot_v2.first_review = pd.to_datetime(myListings_oneHot_v2.fi
rst_review)
for i in range(0,len(myListings_oneHot_v2.host_since)):
    myListings_oneHot_v2.host_since[i] = int(myListings_oneHot_v2.host_sin
ce[i].year)
    myListings_oneHot_v2.first_review[i] = int(myListings_oneHot_v2.first_
```

```
review[i].year)
    myListings_oneHot_v2.last_review[i] = int(myListings_oneHot_v2.last_re
view[i].year)
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:6: SettingWit
hCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

/opt/conda/lib/python3.7/site-packages/pandas/core/indexing.py:671: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self._setitem_with_indexer(indexer, value)
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:7: SettingWit
hCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  import sys
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:8: SettingWit
hCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

In [18]:

```
#labelEncoding of categorical_ordinal features
for ord_cat_feature in ['host_since', 'first_review', 'last_review']:
    myListings_oneHot_v2[ord_cat_feature] = myListings_oneHot_v2[ord_cat_f
eature].astype('category')
    myListings_oneHot_v2[ord_cat_feature] = myListings_oneHot_v2[ord_cat_f
eature].cat.codes
```

In [19]:

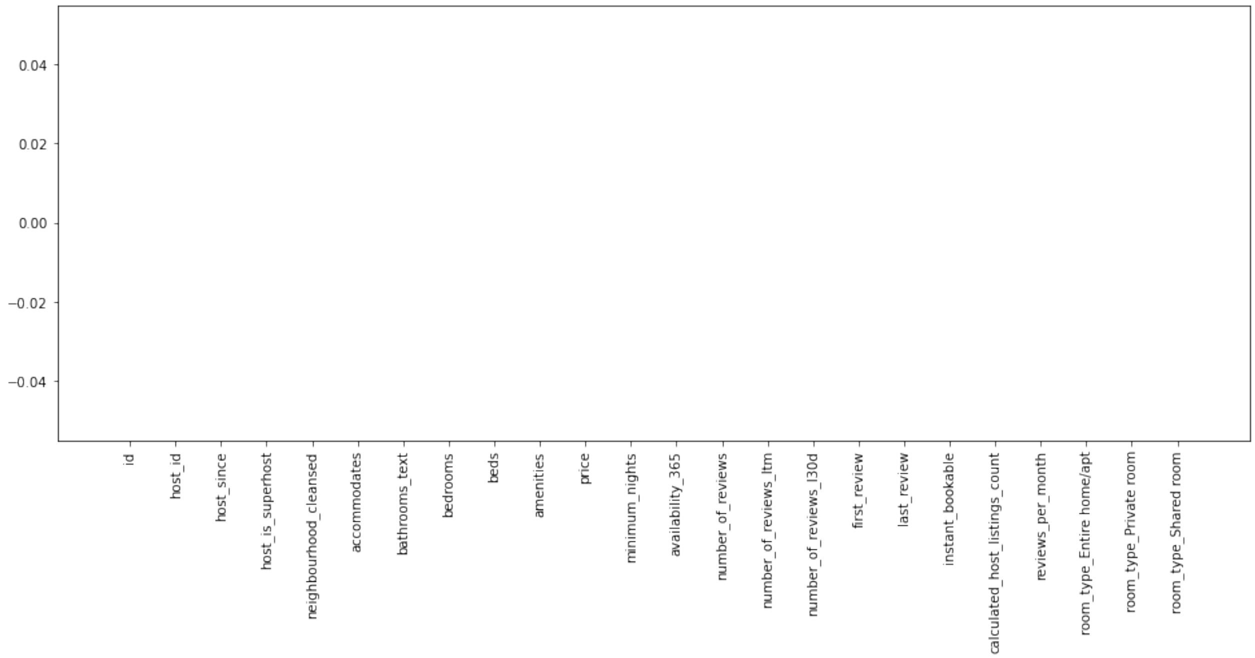
```
#cleaning amenities feature
myListings_oneHot_v2.amenities = myListings_oneHot_v2.amenities.str.replac
e('[', '')
myListings_oneHot_v2.amenities = myListings_oneHot_v2.amenities.str.replac
e(']', '')
myListings_oneHot_v2.amenities = myListings_oneHot_v2.amenities.str.replac
e('\"', '')
```

In [20]:

```
#ensuring there is no missing values
d = pd.isnull(myListings_oneHot_v2).sum()
d = {'features' : d.index, 'missing_values': d, 'proportion_missing_values
': (d/myListings_oneHot_v2.shape[0])}
d = pd.DataFrame(data=d).reset_index(drop=True)

# Figure representing the proportion of the missing values per feature
plt.figure(figsize=(16,6))
```

```python
plt.xticks(rotation="vertical")
plt.bar(d.features, d.proportion_missing_values)
```

Out[20]: <BarContainer object of 24 artists>



In [21]:
```python
#merging the listings and the review scores on the listing_id attribute
median_listing_scores = pd.read_csv('median_listing_scores.csv')
myListings_oneHot_v2 = myListings_oneHot_v2.merge(median_listing_scores, l
eft_on='id', right_on = 'listing_id', how='inner')
```

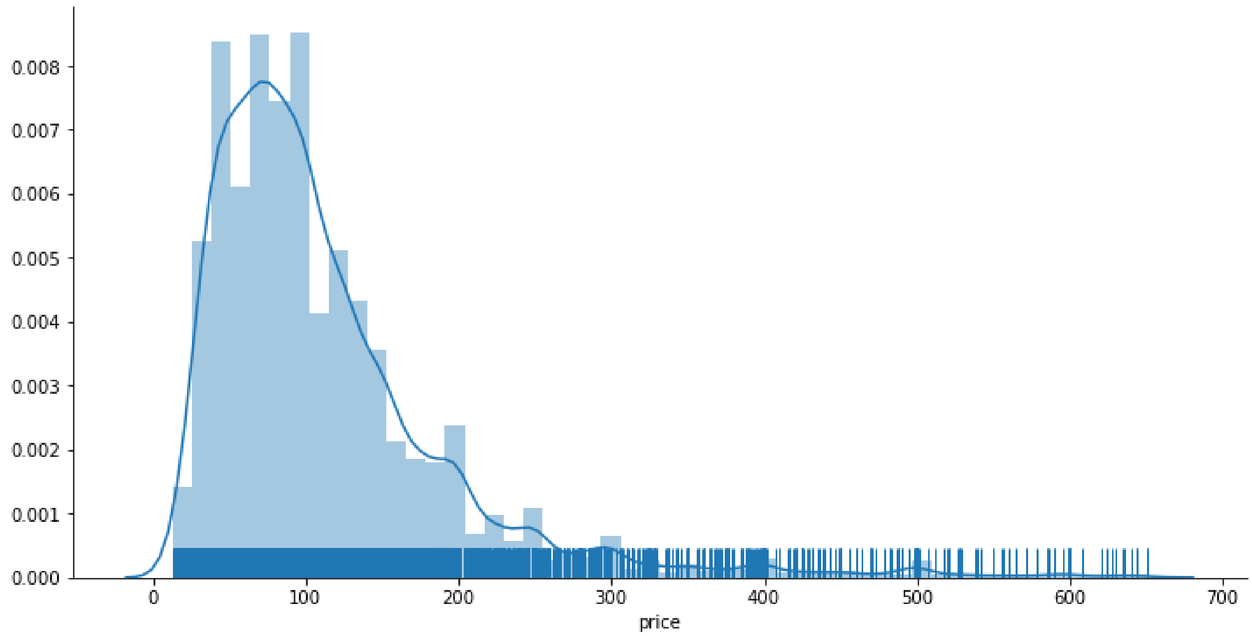
In [22]:
```python
#sentiment scores to numeric
myListings_oneHot_v2['sentiment_scores_adj'] = pd.to_numeric(myListings_on
eHot_v2['sentiment_scores_adj'], errors='coerce')
```

In [39]:
```python
 myListings_oneHot_v2[['accommodates', 'price', 'minimum_nights', 'number_
of_reviews', 'calculated_host_listings_count',\
                      'sentiment_scores_adj']].describe()
```

Out[39]:

	accommodates	price	minimum_nights	number_of_reviews	calculated_host_listings_cou
count	9181.000000	9181.000000	9181.000000	9181.000000	9181.00000
mean	3.123625	113.844570	23.557020	40.379806	5.0102
std	1.903233	82.817354	30.355241	63.654609	9.3242
min	1.000000	13.000000	1.000000	1.000000	1.00000
25%	2.000000	60.000000	5.000000	4.000000	1.00000
50%	2.000000	94.000000	28.000000	16.000000	2.00000
75%	4.000000	140.000000	28.000000	49.000000	4.00000
max	16.000000	650.000000	1000.000000	828.000000	72.00000

In [28]:
```
#univariate distributions : price
plt.figure(figsize=(12,6))
sns.distplot(myListings_oneHot_v2.price, rug=True)
sns.despine()
plt.show();
```

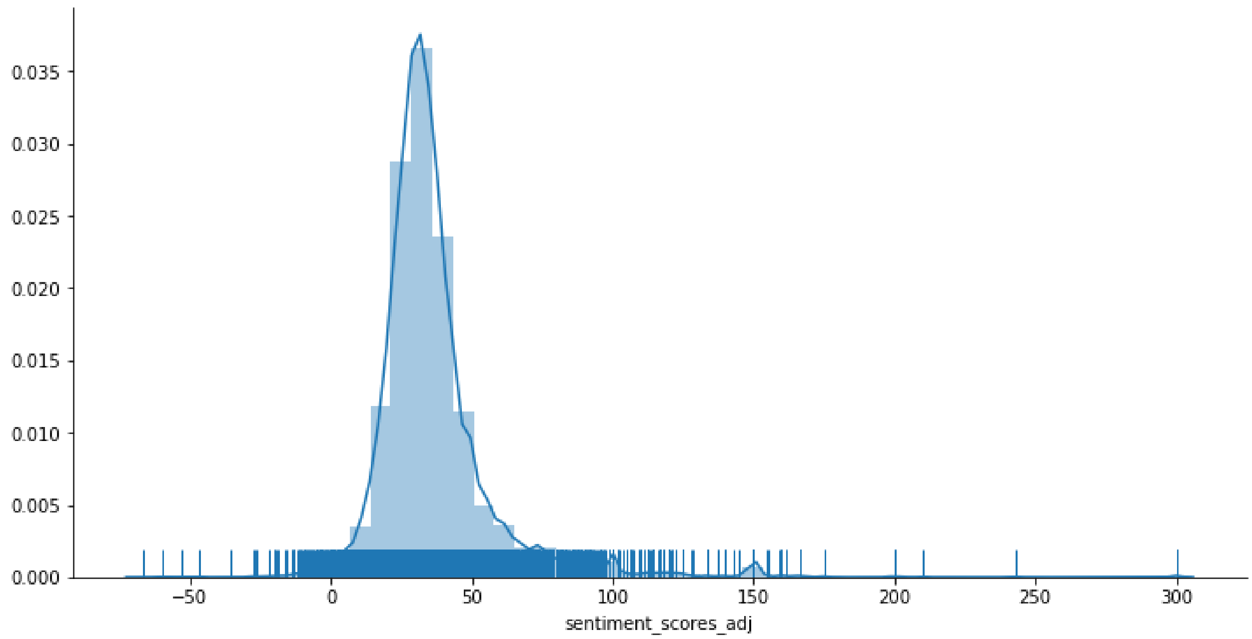


In [23]:
```
#checking the skewness of the price
from scipy.stats import skew
skew(myListings_oneHot_v2.price, axis=0, bias=False)
```

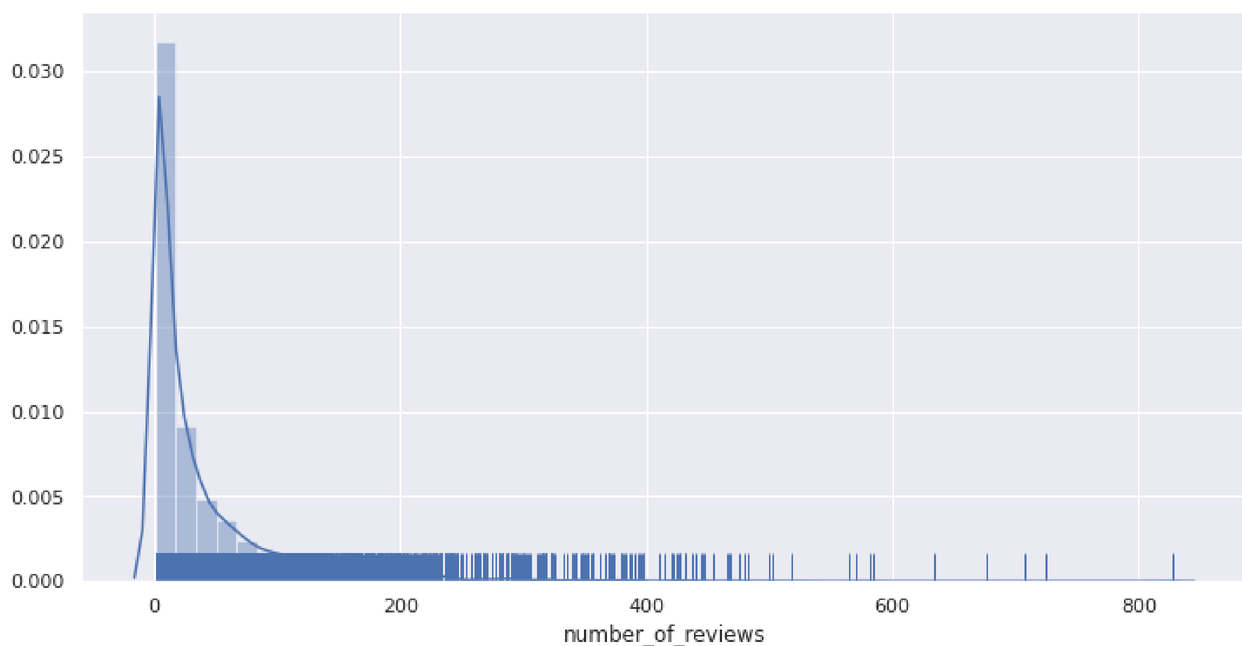
Out[23]: 2.349026837911659

The skew value is > 0 : The price distribution is skewed to the right (more weight on the left tail of the distribution)

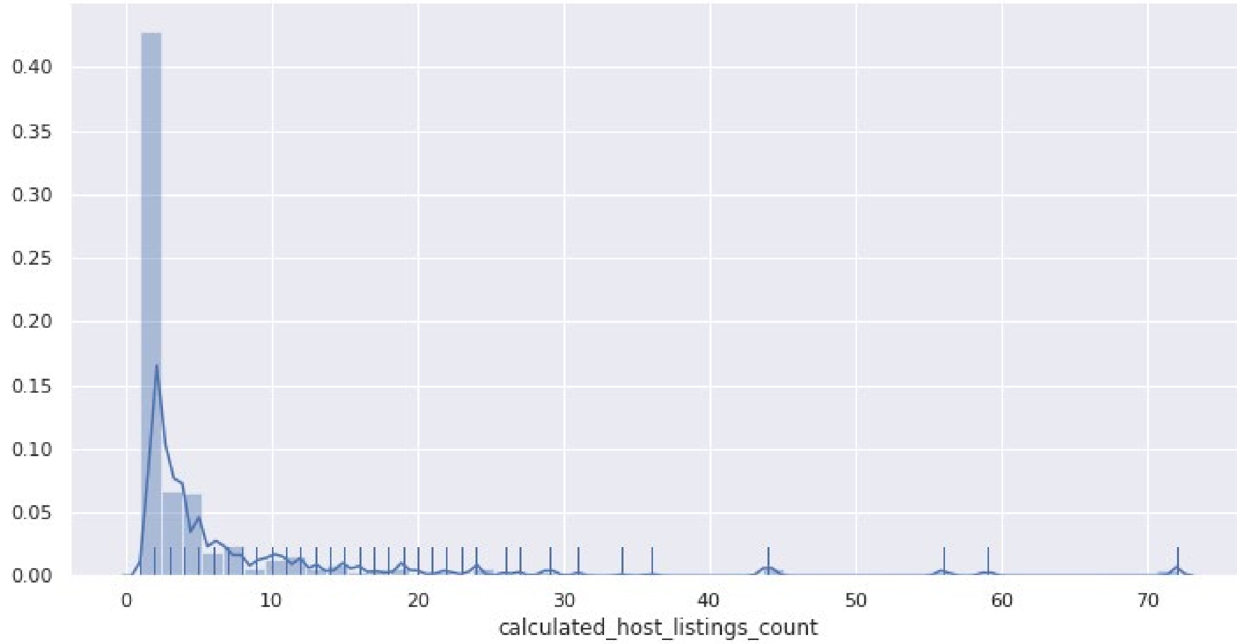
In [24]:
```
#univariate distributions : sentiment_scores_adj
plt.figure(figsize=(12,6))
sns.distplot(myListings_oneHot_v2.sentiment_scores_adj, rug=True)
sns.despine()
plt.show();
```



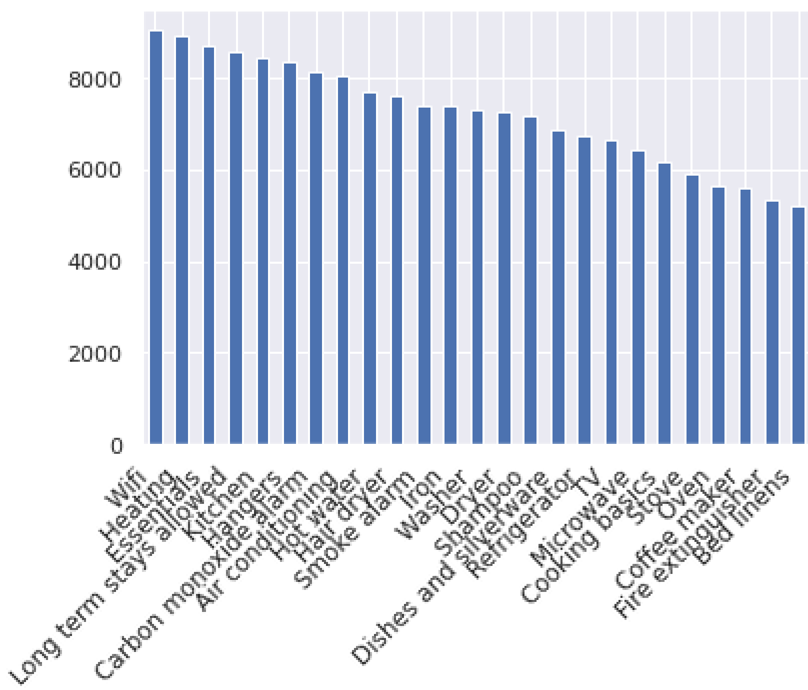
In [59]:
```
#univariate distributions : number_of_reviews
plt.figure(figsize=(12,6))
sns.distplot(myListings_oneHot_v2.number_of_reviews, rug=True)
sns.despine()
plt.show();
```



In [60]:
```
#univariate distributions: host_listings_count
plt.figure(figsize=(12,6))
sns.distplot(myListings_oneHot_v2.calculated_host_listings_count, rug=True
)
sns.despine()
plt.show();
```



In [61]:
```
#categorical distributions : the most frequent amenities
pd.Series(np.concatenate(myListings_oneHot_v2['amenities'].map(lambda amns
: amns.split(",")))).value_counts().head(25)\
    .plot(kind='bar')
ax = plt.gca()
ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right', fontsize
=12)
plt.show()
```



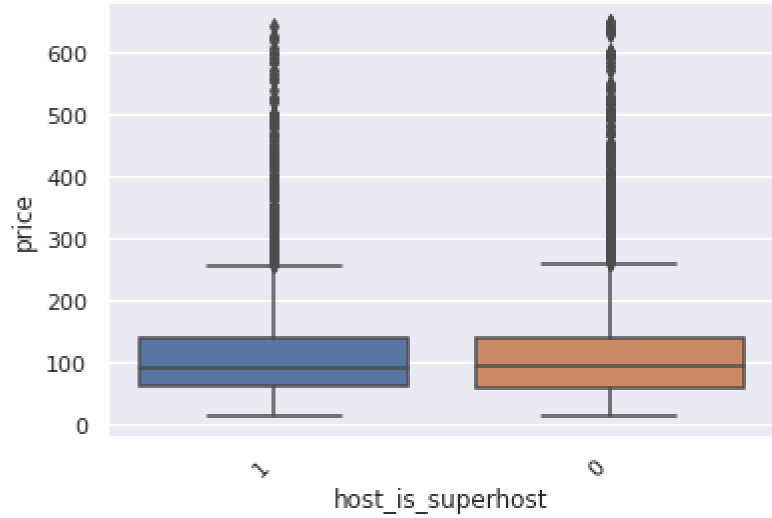
In [25]:
```
#categorical distributions : the most frequent neighborhood_cleansed
myListings_oneHot_v2.groupby(by='neighbourhood_cleansed').count()[['id']].
sort_values(by='id', ascending=False).head(20)
```

Out[25]:

neighbourhood_cleansed	id
Waterfront Communities-The Island	1602
Niagara	344
Church-Yonge Corridor	314
Annex	291
Bay Street Corridor	255
Trinity-Bellwoods	254
Dovercourt-Wallace Emerson-Junction	247
Moss Park	230
Willowdale East	222
Kensington-Chinatown	210
South Riverdale	186
Little Portugal	162
Palmerston-Little Italy	149
South Parkdale	141
York University Heights	108
Cabbagetown-South St.James Town	107
High Park-Swansea	100
North St.James Town	95
Dufferin Grove	94
Mimico (includes Humber Bay Shores)	93

In [63]:

```
#bivariate price boxplots:host_is_superhost
sort_price = myListings_oneHot_v2\
                    .groupby('host_is_superhost')['price']\
                    .mean()\
                    .sort_values(ascending=False)\
                    .index
sns.boxplot(y='price', x='host_is_superhost', data=myListings_oneHot_v2.lo
c[(myListings_oneHot_v2.price <= 655)],
            order=sort_price)
ax = plt.gca()
ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right')
plt.show();
```

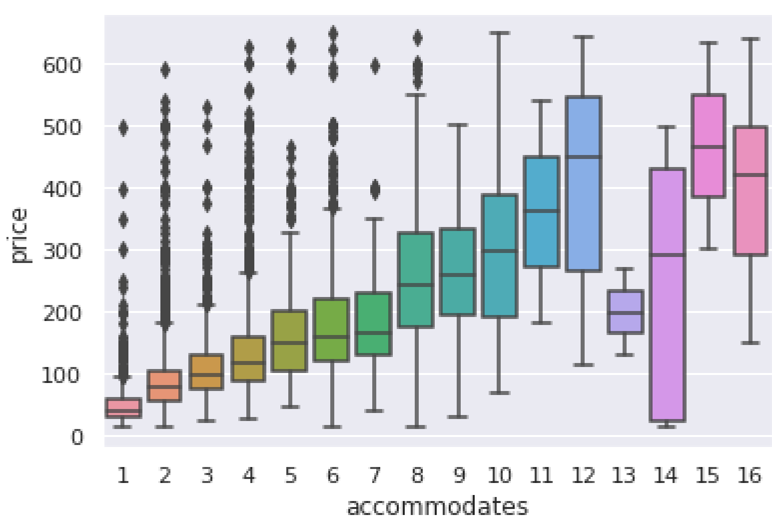


In [64]:
```
print(myListings_oneHot_v2.groupby('host_is_superhost')['price'].mean())
print(myListings_oneHot_v2.groupby('host_is_superhost')['price'].median())
```

```
host_is_superhost
0    112.789809
1    115.533862
Name: price, dtype: float64
host_is_superhost
0    95
1    91
Name: price, dtype: int64
```

The mean of superhosts prices is higher than non-superhosts, and interestingly the median of non-superhosts prices is higher

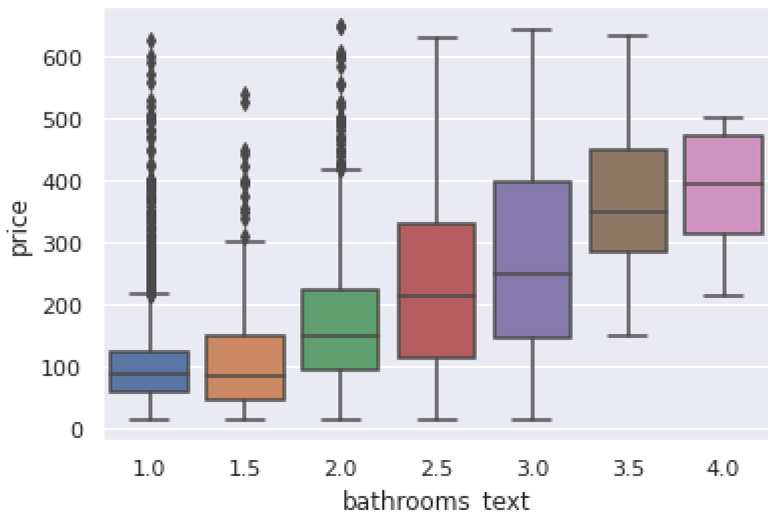
In [65]:
```
#bivariate price boxplots for numerical features: accommodates
sns.boxplot(y='price', x='accommodates', data = myListings_oneHot_v2)
plt.show()
```



It is clear that in general, the median price gets higher as the listing accommodates more guests. We can state the same for the number of bathrooms, bedrooms, and beds as per the following:

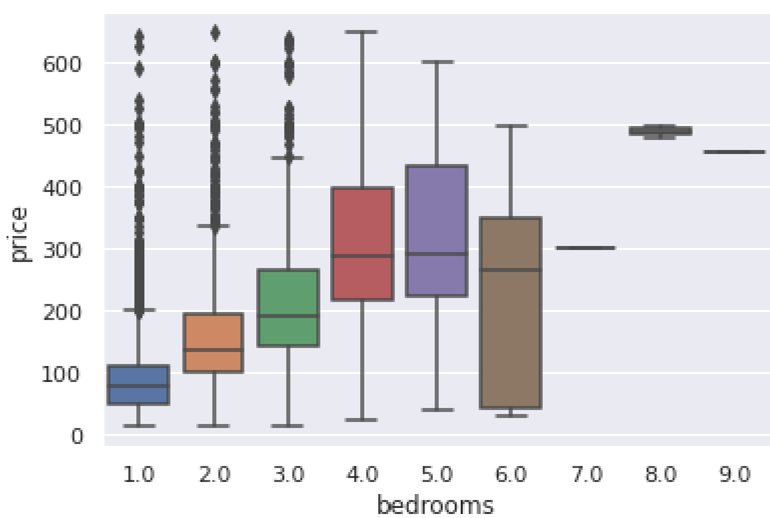
In [66]:
```
#bivariate price boxplots for numerical features: bathrooms_text
sns.boxplot(y='price', x='bathrooms_text', data = myListings_oneHot_v2)
```

```
plt.show()
```



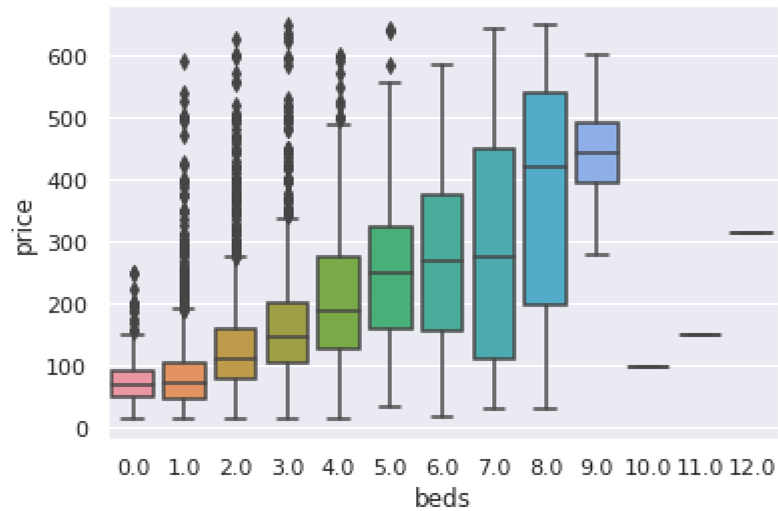
In [67]:

```
#bivariate price boxplots for numerical features: bedrooms
sns.boxplot(y='price', x='bedrooms', data = myListings_oneHot_v2)
plt.show()
```

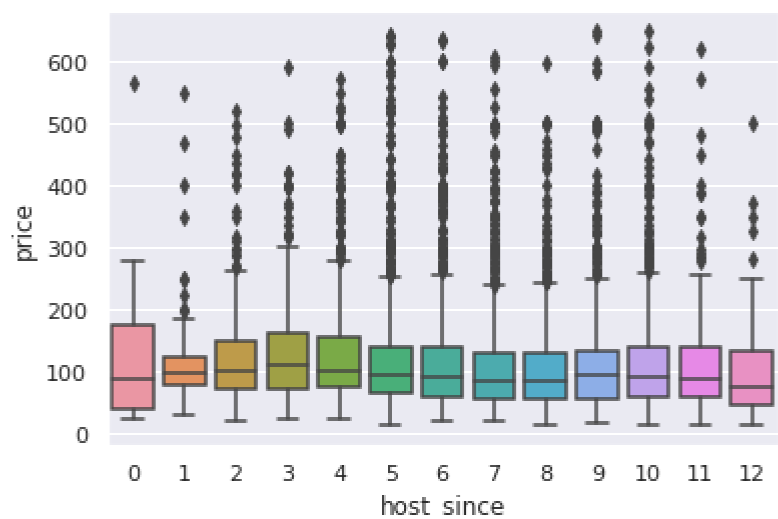


In [68]:

```
#bivariate price boxplots for numerical features: beds
sns.boxplot(y='price', x='beds', data = myListings_oneHot_v2)
plt.show()
```

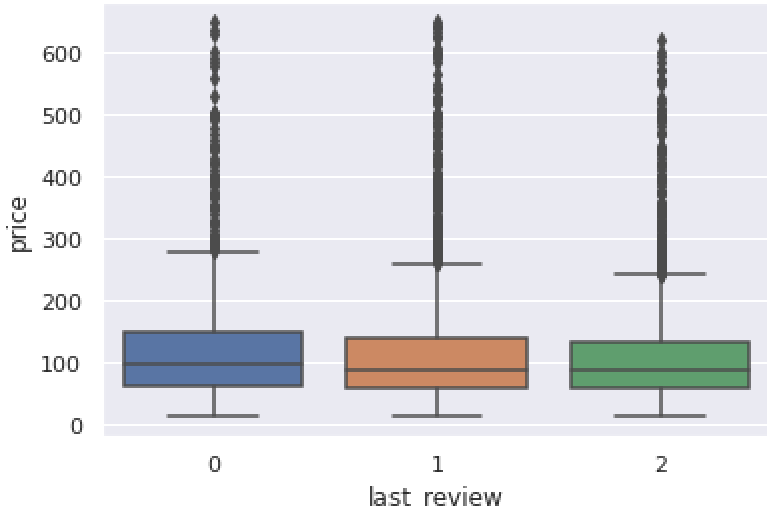


In [69]:
```
#bivariate price boxplots for numerical features: host_since
sns.boxplot(y='price', x='host_since', data = myListings_oneHot_v2)
plt.show()
```



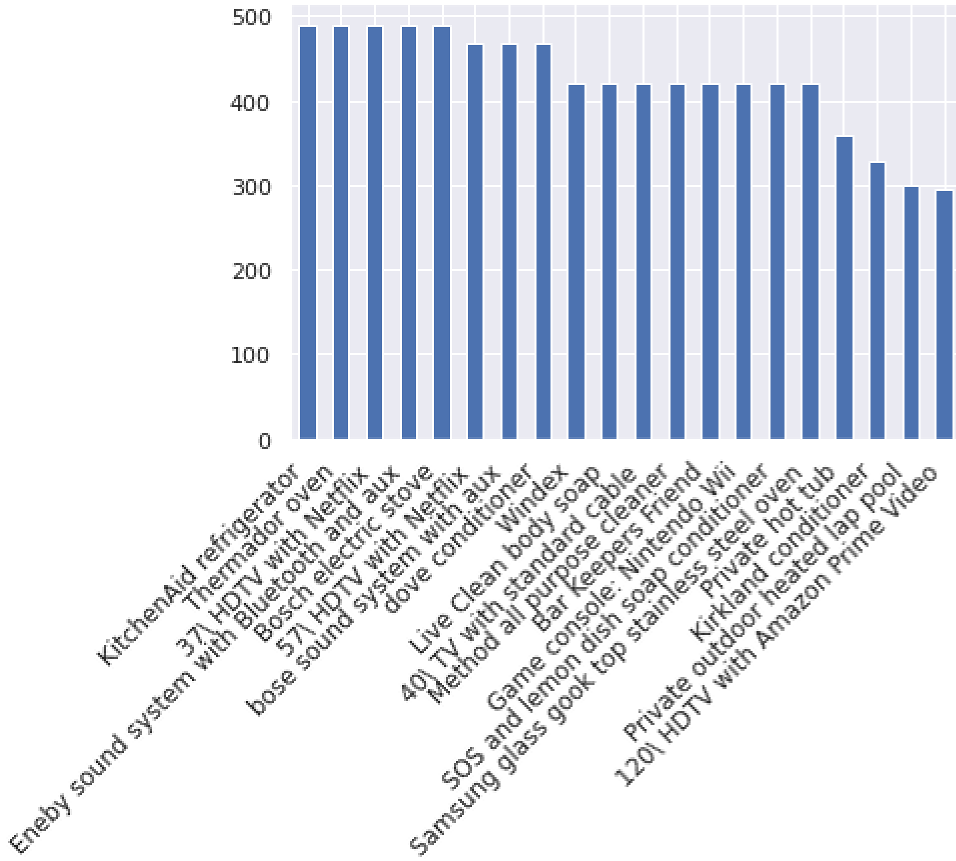
The number of years since the host started hosting on Airbnb does not seem to influence the price median

In [70]:
```
#bivariate price boxplots for numerical features: last_review
sns.boxplot(y='price', x='last_review', data = myListings_oneHot_v2)
plt.show()
```



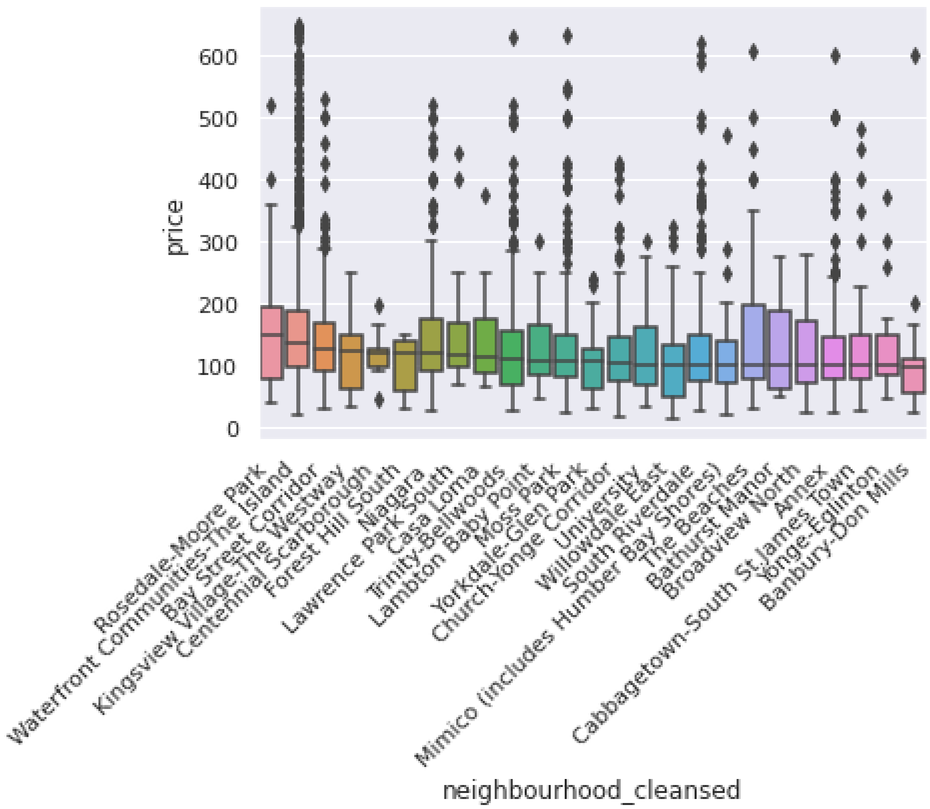
As the last_review gets older in time (2020 then 2019), the prices tend to be slighlty lower

In [71]:
```
#bivariate price boxplots for categorical features: top 20 amenities
amenities = np.unique(np.concatenate(myListings_oneHot_v2['amenities'].map
(lambda amns: amns.split(","))))
amenity_prices = [(amn, myListings_oneHot_v2[myListings_oneHot_v2['ameniti
es'].map(lambda amns: amn in amns)]['price'].mean()) for amn in amenities
if amn != ""]
amenity_srs = pd.Series(data=[a[1] for a in amenity_prices], index=[a[0] f
or a in amenity_prices])
amenity_srs.sort_values(ascending=False)[:20].plot(kind='bar')
ax = plt.gca()
ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right', fontsize
=12)
plt.show()
```



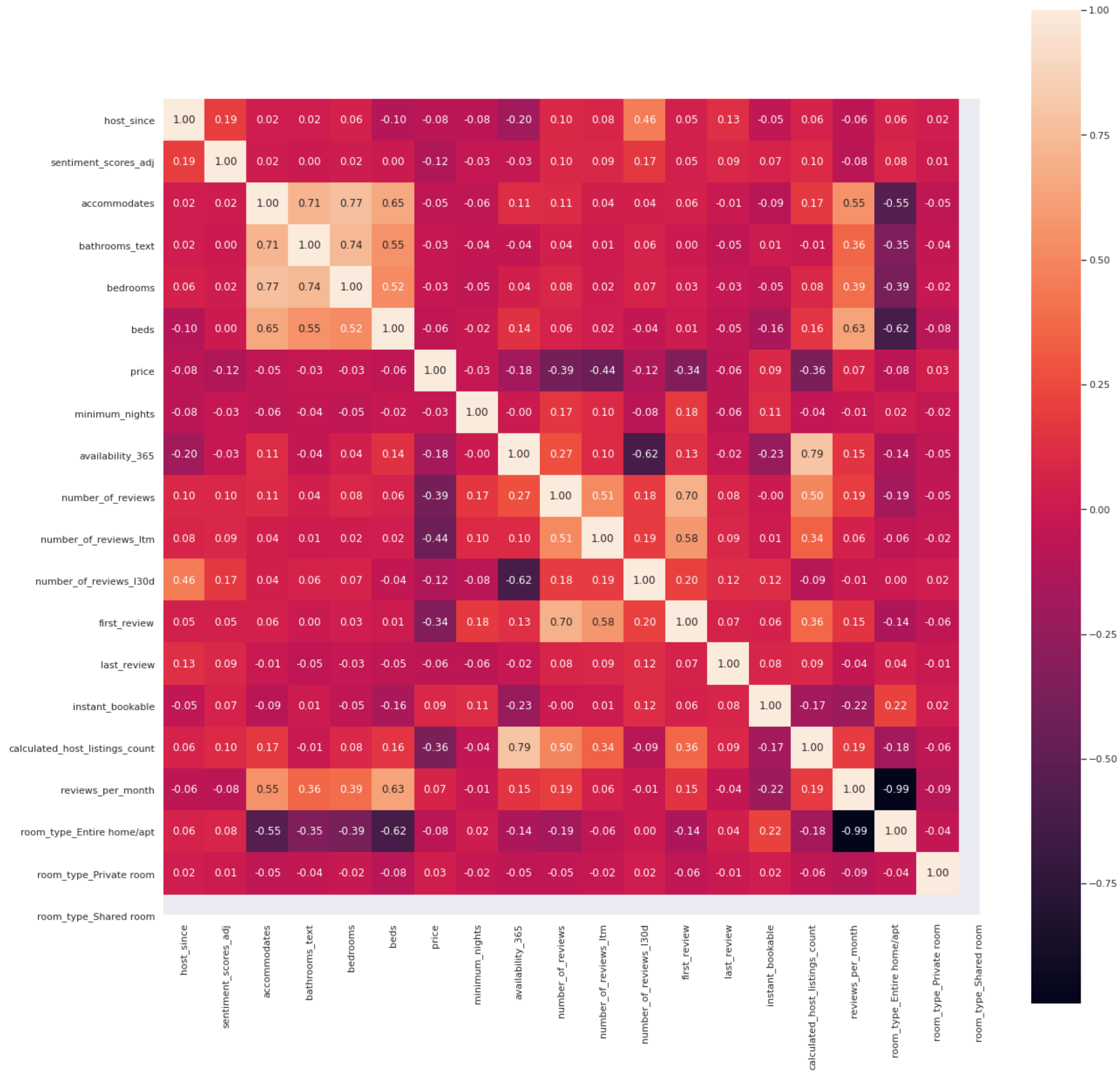
Certain amenities like a certain kind of refrigerators, ovens or HDTVs with Netflix are likely to raise the listing price

In [72]:
```
#bivariate price boxplots for numerical features: neighborhood_cleansed _
Top 25
sort_price = myListings_oneHot_v2\
                        .groupby('neighbourhood_cleansed')['price']\
                        .median()\
                        .sort_values(ascending=False)\
                        .index
sns.boxplot(y='price', x='neighbourhood_cleansed', data=myListings_oneHot_
v2,
              order=sort_price[:25])
ax = plt.gca()
ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right')
plt.show();
```



The closer the listing is to the lake, the main transit stations, the beach or to colleges, the higher the price

In [73]:
```
#heatmap of the correlation between the variables
#we will use the 'spearman' method as most of the attributes are discrete

col1 = ['host_since','sentiment_scores_adj','accommodates', 'bathrooms_tex
t', 'bedrooms', 'beds','price', 'minimum_nights', 'availability_365','numb
er_of_reviews', 'number_of_reviews_ltm', 'number_of_reviews_l30d', 'first_
review', 'last_review', 'instant_bookable',\
        'calculated_host_listings_count','reviews_per_month', 'room_type_E
ntire home/apt', 'room_type_Private room','room_type_Shared room']

corr = myListings_oneHot_v2[myListings_oneHot_v2.host_is_superhost == 1][c
ol1].corr(method = 'spearman')
plt.figure(figsize = (21,21))
sns.set(font_scale=1)
sns.heatmap(corr, cbar = True, annot=True, square = True, fmt = '.2f', xti
cklabels=col1, yticklabels=col1)
plt.show()
```

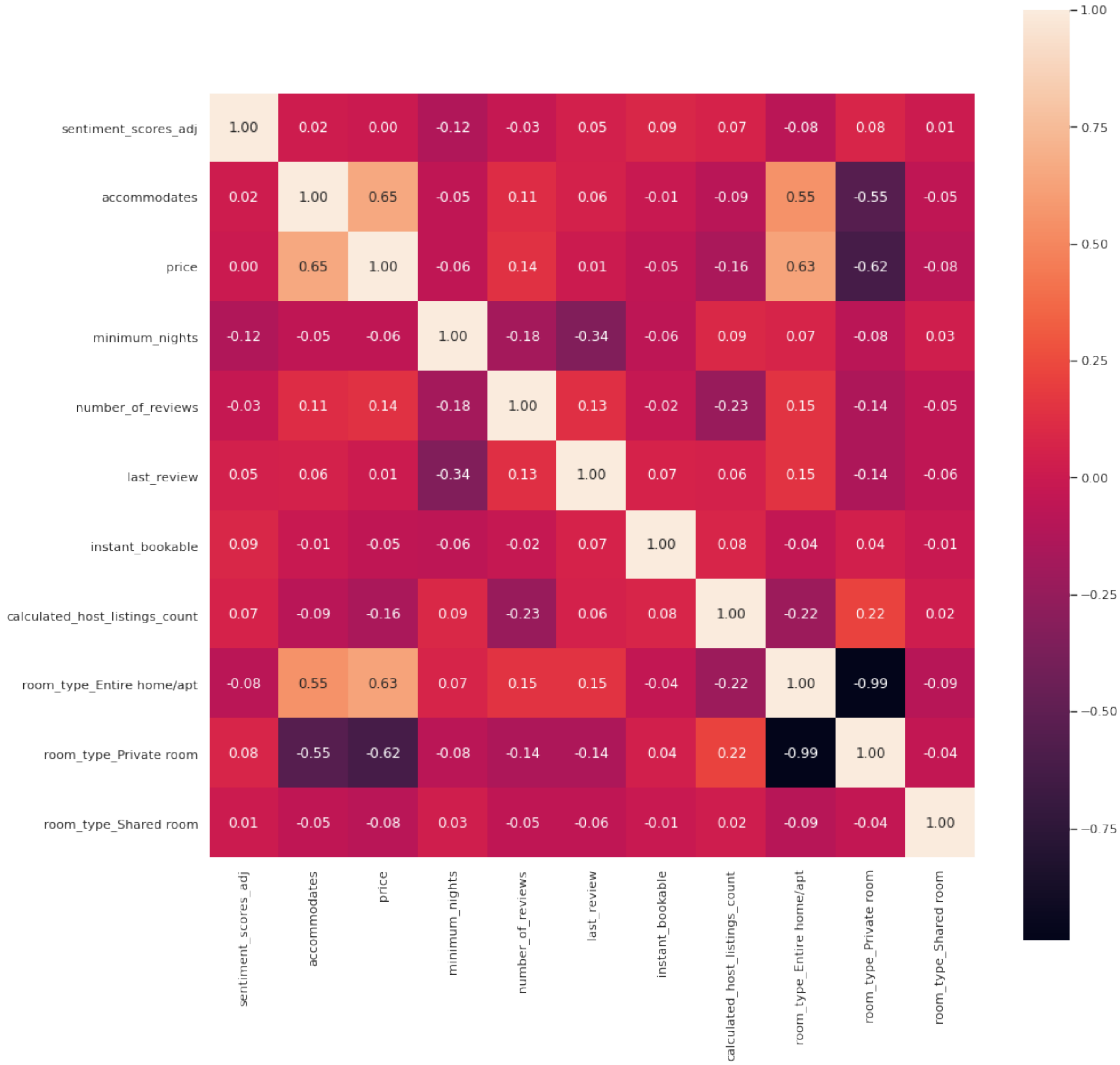


FEATURE SELECTIONThe Filter method will be used: the independent attributes that have a high corrrelation betweeen each others will be removed and one will be kept to resolve the mutli-collinearity issue. Treshold is 0.6. In the same time, a relative high collinearity exists between the dependent variable (price) and 2 other dependent variables (accommodates and bathrooms_text) The filter method is prefered to the wrapper and the hybrid methods as these ones are computation-costly.

In [26]:
```
#Feature selection : removing the relatively highly correlated variables
myListings_oneHot_v2 = myListings_oneHot_v2.drop(columns = ['bathrooms_text', 'bedrooms', 'availability_365', 'number_of_reviews_ltm', 'number_of_reviews_l30d', 'host_since', \
                                                   'first_review',
 'reviews_per_month', 'beds'])
```

In [27]:
```
#correlation between the numeric features after feature selection
col2 = ['sentiment_scores_adj','accommodates','price', 'minimum_nights', 'number_of_reviews', 'last_review', 'instant_bookable',\
        'calculated_host_listings_count','room_type_Entire home/apt', 'room_type_Private room','room_type_Shared room']

corr2 = myListings_oneHot_v2[myListings_oneHot_v2.host_is_superhost == 1][
```

```
col2].corr(method = 'spearman')
plt.figure(figsize = (15,15))
sns.set(font_scale=1)
sns.heatmap(corr2, cbar = True, annot=True, square = True, fmt = '.2f', xt
icklabels=col2, yticklabels=col2)
plt.show()
```



Corr = -0.99 between 'room_type_Entire home/apt'and 'room_type_Private room' as they are mutually exclusive

In [28]:
```
#Spearman test of hypothesis : if p > 0.05, we fail to reject the null hyp
othesis that the variables are uncorrelated
#In this, we will keep these variables
from scipy.stats import spearmanr

for i in range(0, len(myListings_oneHot_v2[myListings_oneHot_v2.host_is_su
perhost == 1][col2].columns),1):
    for j in range(0, len(myListings_oneHot_v2[myListings_oneHot_v2.host_i
s_superhost == 1][col2].columns),1):

        coef, p = spearmanr(myListings_oneHot_v2[myListings_oneHot_v2.host
_is_superhost == 1][col2].iloc[:, [i]], myListings_oneHot_v2[myListings_on
eHot_v2.host_is_superhost == 1][col2].iloc[:, [j]])
```

```
        if p > 0.05:
            print('p-value between',myListings_oneHot_v2[myListings_oneHot
_v2.host_is_superhost == 1][col2].columns[i], 'and', myListings_oneHot_v2[
myListings_oneHot_v2.host_is_superhost == 1][col2].columns[j], p)
```

```
p-value between sentiment_scores_adj and accommodates 0.2395371695679718
p-value between sentiment_scores_adj and price 0.9634530851247154
p-value between sentiment_scores_adj and number_of_reviews 0.1209782103404
6026
p-value between sentiment_scores_adj and room_type_Shared room 0.590396504
3932631
p-value between accommodates and sentiment_scores_adj 0.23953716956797194
p-value between accommodates and instant_bookable 0.5282505417104861
p-value between price and sentiment_scores_adj 0.9634530851247154
p-value between price and last_review 0.5531590277506034
p-value between minimum_nights and room_type_Shared room 0.071266749209771
5
p-value between number_of_reviews and sentiment_scores_adj 0.1209782103404
6026
p-value between number_of_reviews and instant_bookable 0.19139031986279192
p-value between last_review and price 0.5531590277506034
p-value between instant_bookable and accommodates 0.5282505417104861
p-value between instant_bookable and number_of_reviews 0.19139031986279204
p-value between instant_bookable and room_type_Shared room 0.6971331471978
1
p-value between calculated_host_listings_count and room_type_Shared room 0
.22506827556353237
p-value between room_type_Shared room and sentiment_scores_adj 0.590396504
3932631
p-value between room_type_Shared room and minimum_nights 0.071266749209771
5
p-value between room_type_Shared room and instant_bookable 0.6971331471978
1
p-value between room_type_Shared room and calculated_host_listings_count 0
.22506827556353237
```

TRANSFORMING CATEGORICAL-NOMINAL ATTRIBUTES: AMENITIES & NEIGORHOOD_CLEANSED

In [29]:

```
#Creating dummy amenities
from sklearn.feature_extraction.text import CountVectorizer

myListings_oneHot_v2.amenities = myListings_oneHot_v2.amenities.str.replac
e("[{}]", "").str.replace('"', "")
count_vectorizer =  CountVectorizer(tokenizer=lambda x: x.split(','))
amenities = count_vectorizer.fit_transform(myListings_oneHot_v2['amenities
'])
df_amenities = pd.DataFrame(amenities.toarray(), columns=count_vectorizer.
get_feature_names())
df_amenities
```

Out[29]:

	tresemm\u00e9 conditioner	tresemm\u00e9 shampoo	1 space	1. sonos 2. bryston/harbeth 3. rotel/totem sound system with bluetooth and aux	110\ hdtv with chromecast	120\ hdtv with amazon prime video	12\ hdtv with roku	2 spaces	ye

0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...
9176	0	0	0	0	0	0	0	0
9177	0	0	0	0	0	0	0	0
9178	0	0	0	0	0	0	0	0
9179	0	0	0	0	0	0	0	0
9180	0	0	0	0	0	0	0	0

9181 rows × 629 columns

In [30]:

```python
#creating dummy neighborhood_cleansed
df_neighborhood_cleansed =  pd.get_dummies(myListings_oneHot_v2['neighbour
hood_cleansed'])
df_neighborhood_cleansed
```

Out[30]:

	Agincourt North	Agincourt South-Malvern West	Alderwood	Annex	Banbury-Don Mills	Bathurst Manor	Bay Street Corridor	Bayview Village	Bayview Woods-Steeles	Be Nor
0	0	0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	
9176	0	0	0	0	0	0	0	0	0	
9177	0	0	0	0	0	0	0	0	0	
9178	0	0	0	0	0	0	1	0	0	
9179	0	0	0	0	0	0	1	0	0	
9180	0	0	0	0	0	0	1	0	0	

9181 rows × 139 columns

In [31]:

```python
#Concatenating myListings_oneHot_v2 with neighborhoods
```

```
listings_new = pd.concat([myListings_oneHot_v2, df_neighborhood_cleansed],
 axis=1)
```

In [32]:
```
# removing unnecessary attributes to the model
listings_new = listings_new.drop(columns = ['id','host_id', 'neighbourhood
_cleansed', 'amenities', 'listing_id'])
listings_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9181 entries, 0 to 9180
Columns: 151 entries, host_is_superhost to Yorkdale-Glen Park
dtypes: float64(1), int64(10), int8(1), uint8(139)
memory usage: 2.1 MB
```

In [33]:
```
#merge listings_new with the amenities dataframe
listings_new_ams = pd.concat([listings_new, df_amenities], axis=1, join='i
nner')
listings_new_ams
```

Out[33]:

	host_is_superhost	accommodates	price	minimum_nights	number_of_reviews	last_review	inst
0	0	3	72	28	217	0	
1	0	5	100	30	112	2	
2	1	2	70	28	85	2	
3	0	4	93	2	31	1	
4	1	2	101	28	58	2	
...	...	...	...	...	...	...	
9176	0	3	128	2	1	2	
9177	0	2	87	1	1	2	
9178	0	2	86	1	1	2	
9179	0	2	88	1	2	2	
9180	0	2	87	1	1	2	

9181 rows × 780 columns

In [228]:
```
listings_new = listings_new.to_csv('listings_new.csv')
listings_new = pd.read_csv('listings_new.csv')
```

In [34]:
```
listings_new.columns[:12]
```

Out[34]:
```
Index(['host_is_superhost', 'accommodates', 'price', 'minimum_nights',
       'number_of_reviews', 'last_review', 'instant_bookable',
       'calculated_host_listings_count', 'room_type_Entire home/apt',
       'room_type_Private room', 'room_type_Shared room',
```

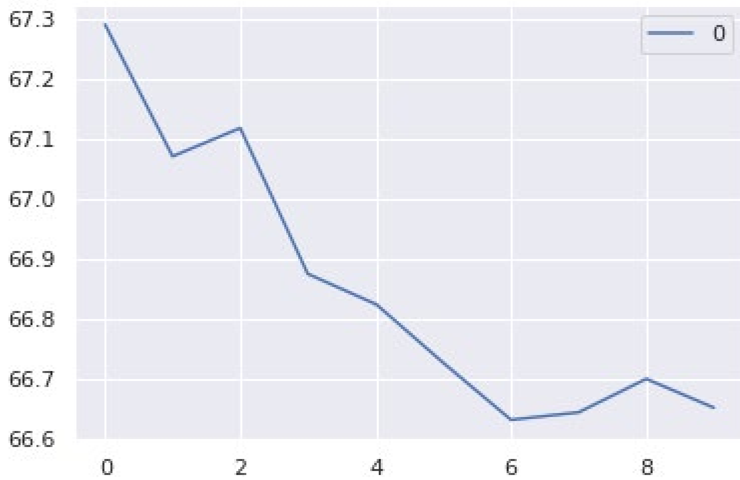
```
          'sentiment_scores_adj'],
         dtype='object')
```

BUILDING AND EVALUATING THE REGRESSION MODELSBuilding the FIRST model : Random forest on train/test and k-fold split of the superhost population, excluding the amenities & neighborhood_cleansed. We have 10 independent variables.

In [29]:
```
#determining the number of trees (n_estimators)
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.ensemble import RandomForestRegressor

rmse_val = []
y = listings_new_ams[listings_new_ams.host_is_superhost == 1]['price']
X = listings_new_ams[listings_new_ams.host_is_superhost == 1].drop(columns
 = ['price'], axis =1)
X = X.drop(columns = ['host_is_superhost'], axis =1) #X includes the entir
e features set

for k in range(50, 501, 50):

    rf = RandomForestRegressor(n_estimators=k,
                               criterion='mse',
                               random_state=0,
                               max_depth= 10)

    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.25, random_state=1)

    rf.fit(X_train, y_train)
    y_train_pred = rf.predict(X_train)
    y_test_pred = rf.predict(X_test)
    rmse_rf= (mean_squared_error(y_test,y_test_pred))**(1/2)
    rmse_val.append(rmse_rf) #store rmse values
    print('RMSE value for k= ' , k , 'is:', rmse_rf)



curve = pd.DataFrame(rmse_val) #elbow curve
curve.plot()
```

```
RMSE value for k=  50 is: 67.29100486991265
RMSE value for k=  100 is: 67.07133719463972
RMSE value for k=  150 is: 67.11843994344464
RMSE value for k=  200 is: 66.87548330165063
RMSE value for k=  250 is: 66.82535481660013
RMSE value for k=  300 is: 66.72707663526856
RMSE value for k=  350 is: 66.63231265237792
RMSE value for k=  400 is: 66.64477484964752
RMSE value for k=  450 is: 66.70057995811729
RMSE value for k=  500 is: 66.6525426750853
```

Out[29]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fac882f9dd0>
```



We can conclude that the optimal number of trees is curve [6] = 350

In [35]:

```
#1.First RF model: excluding amenities & neighborhood_cleansed
y = listings_new[listings_new.host_is_superhost == 1]['price']
X = listings_new[['host_is_superhost', 'accommodates', 'price', 'minimum_n
ights',
        'number_of_reviews', 'last_review', 'instant_bookable',
        'calculated_host_listings_count', 'room_type_Entire home/apt',
        'room_type_Private room', 'room_type_Shared room',
        'sentiment_scores_adj']]\
         [listings_new.host_is_superhost == 1].drop(columns = ['price'], ax
is =1)
X = X.drop(columns = ['host_is_superhost'], axis =1)
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3529 entries, 2 to 9166
Data columns (total 10 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   accommodates                    3529 non-null   int64  
 1   minimum_nights                  3529 non-null   int64  
 2   number_of_reviews               3529 non-null   int64  
 3   last_review                     3529 non-null   int8   
 4   instant_bookable                3529 non-null   int64  
 5   calculated_host_listings_count  3529 non-null   int64  
 6   room_type_Entire home/apt       3529 non-null   int64  
 7   room_type_Private room          3529 non-null   int64  
 8   room_type_Shared room           3529 non-null   int64  
 9   sentiment_scores_adj            3529 non-null   float64
dtypes: float64(1), int64(8), int8(1)
memory usage: 279.1 KB
```

In [36]:

```
#1.1 Random forest: evaluation technique = train/test split

time_start = time.perf_counter() #to compute the execution time to assess
the models efficiency


from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
```

```python
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.ensemble import RandomForestRegressor


X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25
, random_state=1)
rf = RandomForestRegressor(n_estimators=350,
                               criterion='mse',
                               random_state=None,
                               max_depth = 10)
rf.fit(X_train, y_train)
y_train_pred = rf.predict(X_train)
y_test_pred = rf.predict(X_test)
rmse_rf11= (mean_squared_error(y_test,y_test_pred))**(1/2)
mae_rf11= mean_absolute_error(y_test,y_test_pred)
r2_score11= r2_score(y_test, y_test_pred)
r2_score11_adj = 1 - ( 1-r2_score11 ) * ( len(y_test) - 1 ) / ( len(y_test
) - X_test.shape[1] - 1 )


print('RMSE test: %.3f' % rmse_rf11)
print('MAE test: %.3f' % mae_rf11)
print('R^2 test: %.3f' % r2_score11)
print('R^2 test adjusted: %.3f' % r2_score11_adj)

time_elapsed = (time.perf_counter() - time_start)
print('the execution time is: %.3f' % time_elapsed)
```

```
RMSE test: 69.948
MAE test: 44.247
R^2 test: 0.416
R^2 test adjusted: 0.410
the execution time is: 2.235
```

In [89]:
```python
#After repeating the process 20 times, we get the mean results as followin
g :

rmse_rf11 = 70.0732
mae_rf11 = 44.393
r2_score11 = 0.414
r2_score11_adj = 0.408
execTime_rf11 = 2.253
```

In [90]:
```python
#feature importances model 1.1: are computed as the mean and standard devi
ation of accumulation of the
#impurity decrease within each tree

coefs_df = pd.DataFrame()
coefs_df['attriute'] = X_train.columns
coefs_df['coefficient'] = rf.feature_importances_
coefs_df.sort_values('coefficient', ascending=False).head(10)
```

Out[90]:

	attriute	coefficient
0	accommodates	0.440018

9	sentiment_scores_adj	0.147923
2	number_of_reviews	0.131268
6	room_type_Entire home/apt	0.095657
1	minimum_nights	0.071285
5	calculated_host_listings_count	0.065067
3	last_review	0.026907
4	instant_bookable	0.017765
7	room_type_Private room	0.003994
8	room_type_Shared room	0.000116

In [93]:

```
#1.2 Random forsest : evaluation technique k-fold cross validation / k=5
#using the cross_val_score procedure: the trainset - validation set will b
e done automatically

time_start = time.perf_counter()

from sklearn.model_selection import cross_val_score

rmse_rf12 = (np.mean(abs(cross_val_score(RandomForestRegressor(n_estimator
s=350,
                                criterion='mse',
                                random_state=None,
                                max_depth=10), X, y, cv=5, scoring = 'neg_m
ean_squared_error'))))**(1/2)

mae_rf12 = np.mean(abs(cross_val_score(RandomForestRegressor(n_estimators=
350,
                                criterion='mse',
                                random_state=None,
                                max_depth=10), X, y, cv=5, scoring = 'neg_m
ean_absolute_error')))

r2_score12 = np.mean(abs(cross_val_score(RandomForestRegressor(n_estimator
s=350,
                                criterion='mse',
                                random_state=None,
                                max_depth=10), X, y, cv=5, scoring = 'r2'))
)

r2_score12_adj = 1 - ( 1-r2_score12 ) * ( (len(y)/10) - 1 ) / ( (len(y)/10
) - X.shape[1] - 1 )

print('RMSE test: %.3f' % rmse_rf12)
print('MAE test: %.3f' % mae_rf12)
print('R^2 test: %.3f' % r2_score12)
print('R^2 test adjusted: %.3f' % r2_score12_adj)

time_elapsed = (time.perf_counter() - time_start)
print('the execution time is: %.3f' % time_elapsed)
```

```
RMSE test: 69.351
```

```
MAE test: 45.078
R^2 test: 0.304
R^2 test adjusted: 0.284
the execution time is: 32.019
```

In [94]:
```
execTime_rf12 = 32.019
```

Building the SECOND model : Random forest on train/test and k-fold split of the superhost population, including the neighborhood_cleansed but excluding the amenities. We have 10 + 139 = 149 variables.

In [100]:
```
#2 including the neighborhood_cleansed & excluding amenities
y = listings_new[listings_new.host_is_superhost == 1]['price']
X = listings_new[listings_new.host_is_superhost == 1].drop(columns = ['pri
ce'], axis =1)
X = X.drop(columns = ['host_is_superhost'], axis =1)
```

In [96]:
```
#2.1 Random Forest : evaluation technique = train/test split

time_start = time.perf_counter()

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25
, random_state=1)
rf = RandomForestRegressor(n_estimators=350,
                               criterion='mse',
                               random_state=None,
                               max_depth=10)
rf.fit(X_train, y_train)
y_train_pred = rf.predict(X_train)
y_test_pred = rf.predict(X_test)
rmse_rf21= (mean_squared_error(y_test,y_test_pred))**(1/2)
mae_rf21= mean_absolute_error(y_test,y_test_pred)
r2_score21= r2_score(y_test, y_test_pred)
r2_score21_adj = 1 - ( 1-r2_score21 ) * ( len(y_test) - 1 ) / ( len(y_test
) - X_test.shape[1] - 1 )


print('RMSE test: %.3f' % rmse_rf21)
print('MAE test: %.3f' % mae_rf21)
print('R^2 test: %.3f' % r2_score21)
print('R^2 test adjusted: %.3f' % r2_score21_adj)

time_elapsed = (time.perf_counter() - time_start)
print('the execution time is: %.3f' % time_elapsed)
```

```
RMSE test: 67.287
MAE test: 41.331
R^2 test: 0.460
R^2 test adjusted: 0.350
the execution time is: 4.694
```

In [97]:
```
#After repeating the process 20 times, we get the mean results as followin
g :
rmse_rf21 = 67.39
mae_rf21 = 41.40
r2_score21 = 0.458
r2_score21_adj = 0.349
```

```
execTime_rf21 = 4.575
```

In [101]:
```
##feature importance model 2.1
coefs_df = pd.DataFrame()
coefs_df['attriute'] = X_train.columns
coefs_df['coefficient'] = rf.feature_importances_
coefs_df.sort_values('coefficient', ascending=False).head(10)
```

Out[101]:

	attriute	coefficient
0	accommodates	0.444430
6	room_type_Entire home/apt	0.100608
9	sentiment_scores_adj	0.078682
2	number_of_reviews	0.073077
1	minimum_nights	0.046440
5	calculated_host_listings_count	0.045680
3	last_review	0.028959
131	Waterfront Communities-The Island	0.024203
119	South Riverdale	0.019069
51	Etobicoke West Mall	0.016213

In [102]:
```
#2.2 Random forest : evaluation technique = k-fold cross validation / k=5

time_start = time.perf_counter()

rmse_rf22 = (np.mean(abs(cross_val_score(RandomForestRegressor(n_estimator
s=350,
                              criterion='mse',
                              random_state=None,
                              max_depth=10), X, y, cv=5, scoring = 'neg_m
ean_squared_error'))))**(1/2)

mae_rf22 = np.mean(abs(cross_val_score(RandomForestRegressor(n_estimators=
350,
                              criterion='mse',
                              random_state=None,
                              max_depth=10), X, y, cv=5, scoring = 'neg_m
ean_absolute_error')))

r2_score22 = np.mean(abs(cross_val_score(RandomForestRegressor(n_estimator
s=350,
                              criterion='mse',
                              random_state=None,
                              max_depth=10), X, y, cv=5, scoring = 'r2'))
)

r2_score22_adj = 1 - ( 1-r2_score22 ) * ( (len(y)/10) - 1 ) / ( (len(y)/10
) - X.shape[1] - 1)

print('RMSE test: %.3f' % rmse_rf22)
```

```
print('MAE test: %.3f' % mae_rf22)
print('R^2 test: %.3f' % r2_score22)
print('R^2 test adjusted: %.3f' % r2_score22_adj)

time_elapsed = (time.perf_counter() - time_start)
print('the execution time is: %.3f' % time_elapsed)
```

```
RMSE test: 66.459
MAE test: 42.197
R^2 test: 0.351
R^2 test adjusted: -0.126
the execution time is: 72.297
```

In [103]:
```
execTime_rf22 = 72.297
```

Building the THIRD model : Random forest on train/test and k-fold split of the superhost population, including the amenities & neighborhood_cleansed. We have 10 + 139 + 629 = 778 independent variables.

In [116]:
```
#3- including the neighborhood_cleansed & amenities
y = listings_new_ams[listings_new_ams.host_is_superhost == 1]['price']
X = listings_new_ams[listings_new_ams.host_is_superhost == 1].drop(columns
 = ['price'], axis =1)
X = X.drop(columns = ['host_is_superhost'], axis =1)
```

In [106]:
```
##3.1 Random forest : evaluation technique = train/test split

time_start = time.perf_counter()

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25
, random_state=1)
rf = RandomForestRegressor(n_estimators=350,
                               criterion='mse',
                               random_state=None,
                               max_depth=10)
rf.fit(X_train, y_train)
y_train_pred = rf.predict(X_train)
y_test_pred = rf.predict(X_test)
rmse_rf31= (mean_squared_error(y_test,y_test_pred))**(1/2)
mae_rf31= mean_absolute_error(y_test,y_test_pred)
r2_score31= r2_score(y_test, y_test_pred)
r2_score31_adj = 1 - ( 1-r2_score31 ) * ( len(y_test) - 1 ) / ( len(y_test
) - X_test.shape[1] - 1 )


print('RMSE test: %.3f' % rmse_rf31)
print('MAE test: %.3f' % mae_rf31)
print('R^2 test: %.3f' % r2_score31)
print('R^2 test adjusted: %.3f' % r2_score31_adj)

time_elapsed = (time.perf_counter() - time_start)
print('the execution time is: %.3f' % time_elapsed)
```

```
RMSE test: 66.492
MAE test: 39.349
R^2 test: 0.473
R^2 test adjusted: -3.472
the execution time is: 14.315
```

In [107]:
```
#After repeating the process 20 times, we get the mean results as followin
g :

rmse_rf31 = 66.709
mae_rf31 = 39.453
r2_score31 = 0.469
r2_score31_adj = -3.501
execTime_rf31 = 14.263
```

In [112]:
```
#feature importances model 3.1
coefs_df = pd.DataFrame()
coefs_df['attribute'] = X_train.columns
coefs_df['coefficient'] = rf.feature_importances_
coefs_df.sort_values('coefficient', ascending=False).head(30)
```

Out[112]:

	attribute	coefficient
0	accommodates	0.390359
6	room_type_Entire home/apt	0.093455
339	dishwasher	0.032630
2	number_of_reviews	0.026463
9	sentiment_scores_adj	0.025282
436	indoor fireplace	0.023791
256	bbq grill	0.020005
1	minimum_nights	0.016242
5	calculated_host_listings_count	0.015783
51	Etobicoke West Mall	0.013025
559	patio or balcony	0.011186
3	last_review	0.010301
131	Waterfront Communities-The Island	0.009618
119	South Riverdale	0.009063
415	gym	0.008419
398	full kitchen	0.007229
540	paid parking off premises	0.007137
418	hair dryer	0.006197
89	Moss Park	0.005937
565	pocket wifi	0.005462
592	safe	0.005354
113	Roncesvalles	0.005124
255	bathtub	0.005053

591	room-darkening shades	0.004882
378	free parking on premises	0.004837
323	crib	0.004709
282	breakfast	0.004628
350	elevator	0.004371
504	outlet covers	0.004268
433	hot tub	0.004250

In [113]:

```
#3.2 Random forest : evaluation technique = k-fold cross validation / k=5

time_start = time.perf_counter()

rmse_rf32 = (np.mean(abs(cross_val_score(RandomForestRegressor(n_estimator
s=350,
                              criterion='mse',
                              random_state=None,
                              max_depth=10), X, y, cv=5, scoring = 'neg_m
ean_squared_error'))))**(1/2)

mae_rf32 = np.mean(abs(cross_val_score(RandomForestRegressor(n_estimators=
350,
                              criterion='mse',
                              random_state=None,
                              max_depth=10), X, y, cv=5, scoring = 'neg_m
ean_absolute_error')))

r2_score32 = np.mean(abs(cross_val_score(RandomForestRegressor(n_estimator
s=350,
                              criterion='mse',
                              random_state=None,
                              max_depth=10), X, y, cv=5, scoring = 'r2'))
)

r2_score32_adj = 1 - ( 1-r2_score32 ) * ( (len(y)/10) - 1 ) / ( (len(y)/10
) - X.shape[1] - 1)

print('RMSE test: %.3f' % rmse_rf32)
print('MAE test: %.3f' % mae_rf32)
print('R^2 test: %.3f' % r2_score32)
print('R^2 test adjusted: %.3f' % r2_score32_adj)

time_elapsed = (time.perf_counter() - time_start)
print('the execution time is: %.3f' % time_elapsed)
```

```
RMSE test: 61.031
MAE test: 38.513
R^2 test: 0.461
R^2 test adjusted: 1.445
the execution time is: 229.163
```

In [114]:

```
execTime_rf32 = 229.163
```

Model 3.2 looks to provide the best results. It needs to be evaluated Model evaluation : -Effectiveness: We will select either the RMSE or the MAE as performance measures. RMSE is by definition robust to skewness but sensitive to outliers (as when optimizing it, it looks to optimize the mean), it assures to get unbiased forecasts. On the other hand, MAE protects outliers but is sensitive to skewed distributions (as when optimizing it, it looks to optimize the mediean). From above, our price distribution is skewed and outliers were removed (keeping 99% of the observations). Therefore, RMSE will be our primary performance measure. We will run competing algorithms to ensure our model is efficient: Linear Regression (and the 5 assumptions of the standard OLS), KNN, and XGBoost -Efficiency:. We will compute the execution time of each model and check our selected model performs -Stability: we will vary k- the number of folds- when running the cross validation and draw a curve with k in the X axis and RMSE in the Y axis. If the line goes up exponentially that means that the model is unstable. If the line goes up and down, this is a sign of overfitting (the model is doing a very good job on the training set but is highly biased on the testing set). The optimal case: the line goes up and at a certain k = a goes flat, in which case we can say the model is stable at k = aBuilding the FOURTH model: Linear regression-standard OLS. We will focus on the first model (no dummy variables) as the error was too high for the other two models

In [116]:
```
#4. First LR model: excluding amenities & neighborhood_cleansed

y = listings_new[listings_new.host_is_superhost == 1]['price']
X = listings_new[['host_is_superhost', 'accommodates', 'price', 'minimum_n
ights',
        'number_of_reviews', 'last_review', 'instant_bookable',
        'calculated_host_listings_count', 'room_type_Entire home/apt',
        'room_type_Private room', 'room_type_Shared room',
        'sentiment_scores_adj']]\
         [listings_new.host_is_superhost == 1].drop(columns = ['price'], ax
is =1)
X = X.drop(columns = ['host_is_superhost'], axis =1)
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3529 entries, 2 to 9166
Data columns (total 10 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   accommodates                    3529 non-null   int64
 1   minimum_nights                  3529 non-null   int64
 2   number_of_reviews               3529 non-null   int64
 3   last_review                     3529 non-null   int8
 4   instant_bookable                3529 non-null   int64
 5   calculated_host_listings_count  3529 non-null   int64
 6   room_type_Entire home/apt       3529 non-null   int64
 7   room_type_Private room          3529 non-null   int64
 8   room_type_Shared room           3529 non-null   int64
 9   sentiment_scores_adj            3529 non-null   float64
dtypes: float64(1), int64(8), int8(1)
memory usage: 279.1 KB
```

In [118]:
```
#4.1 Linear Regression_standars OLS: evaluation technique = train/test spl
it

time_start = time.perf_counter()

from sklearn.linear_model import LinearRegression

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25
```

```
, random_state=None)
lm = LinearRegression()

lm.fit(X_train, y_train)
y_train_pred = lm.predict(X_train)
y_test_pred = lm.predict(X_test)
rmse_lm41= (mean_squared_error(y_test,y_test_pred))**(1/2)
mae_lm41= mean_absolute_error(y_test,y_test_pred)
r2_score41= r2_score(y_test, y_test_pred)
r2_score41_adj = 1 - ( 1-r2_score41 ) * ( len(y_test) - 1 ) / ( len(y_test
) - X_test.shape[1] - 1 )


print('RMSE test: %.3f' % rmse_lm41)
print('MAE test: %.3f' % mae_lm41)
print('R^2 test: %.3f' % r2_score41)
print('R^2 test adjusted: %.3f' % r2_score41_adj)

time_elapsed = (time.perf_counter() - time_start)
print('the execution time is: %.3f' % time_elapsed)
```

```
RMSE test: 66.957
MAE test: 42.529
R^2 test: 0.313
R^2 test adjusted: 0.305
the execution time is: 0.012
```

In [119]:

```
#After repeating the process 20 times, we get the mean results as followin
g :

rmse_lm41 = 64.644
mae_lm41 = 41.516
r2_score41 = 0.416
r2_score41_adj = 0.4092
execTime_lm41 = 0.013
```

In [120]:

```
print(lm.intercept_)
print(lm.coef_)

#confirming the R^2
print(lm.score(X_test, y_test))
```

```
28.698229477498828
[ 2.55451484e+01 -5.30682494e-02 -2.08907430e-02 -8.42598633e+00
 -5.54899884e+00  8.27136558e-02  3.27870128e+01 -1.93538545e+00
 -3.08516274e+01  1.79117268e-02]
0.31269410606453873
```

In [122]:

```
#4.2 Linear Regression_standars OLS:  evaluation technique = k-fold cross
validation / k=5

time_start = time.perf_counter()

rmse_lm42 = (np.mean(abs(cross_val_score(lm, X, y, cv=5, scoring = 'neg_me
an_squared_error'))))**(1/2)
mae_lm42 = np.mean(abs(cross_val_score(lm, X, y, cv=5, scoring = 'neg_mean
```

```
_absolute_error')))
r2_score42 = np.mean(abs(cross_val_score(lm, X, y, cv=5, scoring = 'r2')))
r2_score42_adj = 1 - ( 1-r2_score42 ) * ( (len(y)/10) - 1 ) / ( (len(y)/10
) - X.shape[1] - 1 )

print('RMSE test: %.3f' % rmse_lm42)
print('MAE test: %.3f' % mae_lm42)
print('R^2 test: %.3f' % r2_score42)
print('R^2 test adjusted: %.3f' % r2_score42_adj)

time_elapsed = (time.perf_counter() - time_start)
print('the execution time is: %.3f' % time_elapsed)
```

```
RMSE test: 64.175
MAE test: 41.787
R^2 test: 0.413
R^2 test adjusted: 0.396
the execution time is: 0.089
```

In [172]:
```
execTime_lm42 = 0.089
```

VERIFYING THE STANDARD OLS ASSUMPTIONS1-Linear relationship between the predictors and the response variable 2-Normality of the error terms 3-No Multicollinearity among Predictors 4-Independence of the error terms 5-Homoscedasticity

In [123]:
```
#calculating the error terms
df_results = pd.DataFrame({'Actual': y_test, 'Predicted': y_test_pred})
df_results['Residuals'] = abs(df_results['Actual']) - abs(df_results['Pred
icted'])
df_results
```

Out[123]:

	Actual	Predicted	Residuals
3751	149	167.743441	-18.743441
5167	73	62.745462	10.254538
6446	175	256.343723	-81.343723
711	169	105.872428	63.127572
99	80	127.824853	-47.824853
...	...	...	...
7691	83	90.443190	-7.443190
4490	130	119.724670	10.275330
1649	60	179.657363	-119.657363
995	76	119.675170	-43.675170
731	148	138.430729	9.569271

883 rows × 3 columns

In [126]:
```
'''1-Linear relationship between the predictors and the response variable'
''
```

```
def linear_relationship(model):


    print('Checking with a scatter plot of actual vs. predicted.',
           'Predictions should follow the diagonal line.')



    # Plotting the actual vs predicted values
    sns.lmplot(x='Actual', y='Predicted', data=df_results, fit_reg=False,
height=7)

    # Plotting the diagonal line
    line_coords = np.arange(df_results.min().min(), df_results.max().max()
)
    plt.plot(line_coords, line_coords,  # X and y points
             color='darkorange', linestyle='--')
    plt.title('Actual vs. Predicted')
    plt.show()
```

In [127]:
```
linear_relationship(lm)
```

```
Checking with a scatter plot of actual vs. predicted. Predictions should f
ollow the diagonal line.
```

The spread is uneven around the diagonal line, which means the linearity assumption is not satisfied

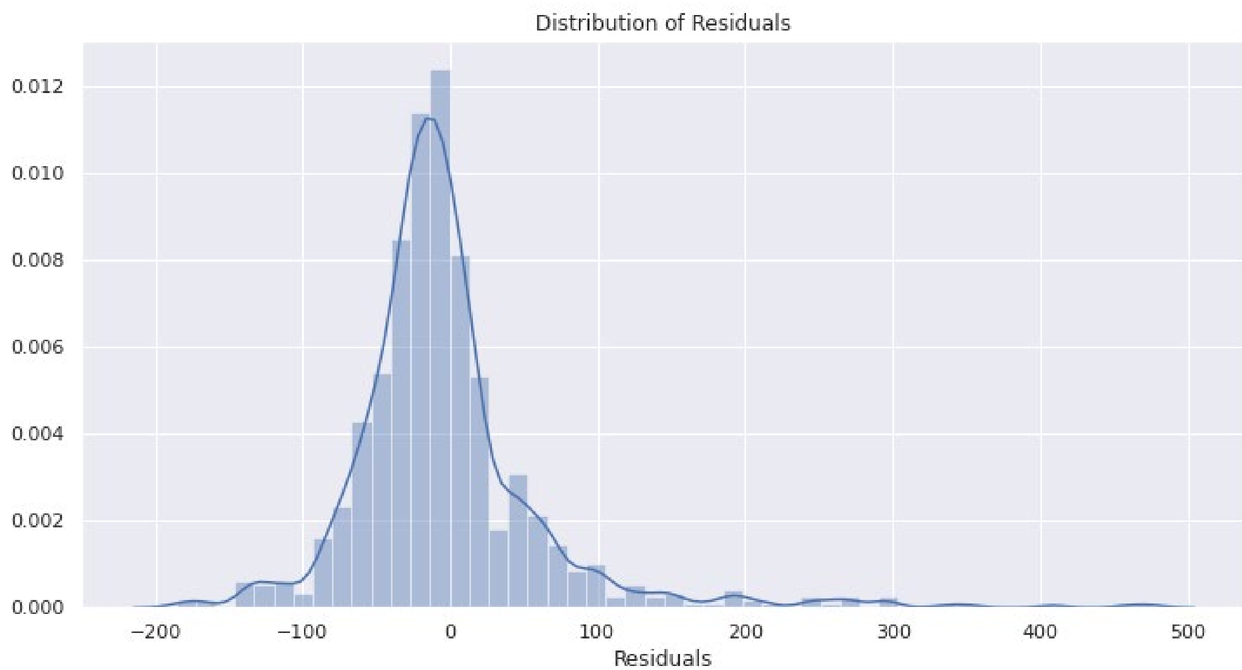
In [128]:

```python
'''2-Normality of the error terms'''

def normality_errors(model, p_value_thresh=0.05):

    from statsmodels.stats.diagnostic import normal_ad

    # Performing the test on the residuals using the Anderson-Darling test
    p_value = normal_ad(df_results['Residuals'])[1]
    print('p-value from the test (below 0.05 means non-normal) :', p_value
)

    # Reporting the normality of the residuals
    if p_value < p_value_thresh:
        print('Residuals are not normally distributed')
    else:
        print('Residuals are normally distributed')

    # Plotting the residuals distribution
    plt.subplots(figsize=(12, 6))
    plt.title('Distribution of Residuals')
    sns.distplot(df_results['Residuals'])
    plt.show()

    print()
    if p_value > p_value_thresh:
        print('Assumption satisfied')
    else:
        print('Assumption not satisfied')
```

In [129]:

```python
normality_errors(lm)
```

```
p-value from the test (below 0.05 means non-normal) : 0.0
Residuals are not normally distributed
```




```
Assumption not satisfied
```

```
In [130]: '''3-No Multicollinearity among Predictors'''

          from statsmodels.stats.outliers_influence import variance_inflation_factor

          vif = pd.DataFrame()
          vif["VIF Factor"] = [variance_inflation_factor(X.values, i) for i in range
          (X.shape[1])]
          vif["features"] = X.columns
          vif
```

Out[130]:

	VIF Factor	features
0	1.254906	accommodates
1	1.048103	minimum_nights
2	1.048863	number_of_reviews
3	1.103526	last_review
4	1.014365	instant_bookable
5	1.022610	calculated_host_listings_count
6	13.001662	room_type_Entire home/apt
7	4.674202	room_type_Private room
8	1.042497	room_type_Shared room
9	1.024004	sentiment_scores_adj

There is 1 feature whose VIF factor > 10, which indicates that multicollinearity might be present. Therefore, the assumption is not satisfied

```
In [131]: '''4- Independence of the error terms (absence of autocorrelation)'''
          #we will use the Durbin-Watson test
          #Values of 1.5 < d < 2.5 : no autocorrelation in the data

          import statsmodels.stats.stattools
          from statsmodels.stats.stattools import durbin_watson
          def independence_assumption(model):

              durbinWatson = durbin_watson(df_results['Residuals'])
              print('Durbin-Watson:', durbinWatson)
              if durbinWatson < 1.5:
                  print('Signs of positive autocorrelation', '\n')
                  print('Assumption not satisfied')
              elif durbinWatson > 2.5:
                  print('Signs of negative autocorrelation', '\n')
                  print('Assumption not satisfied')
              else:
                  print('Little to no autocorrelation', '\n')
                  print('Assumption satisfied')
```

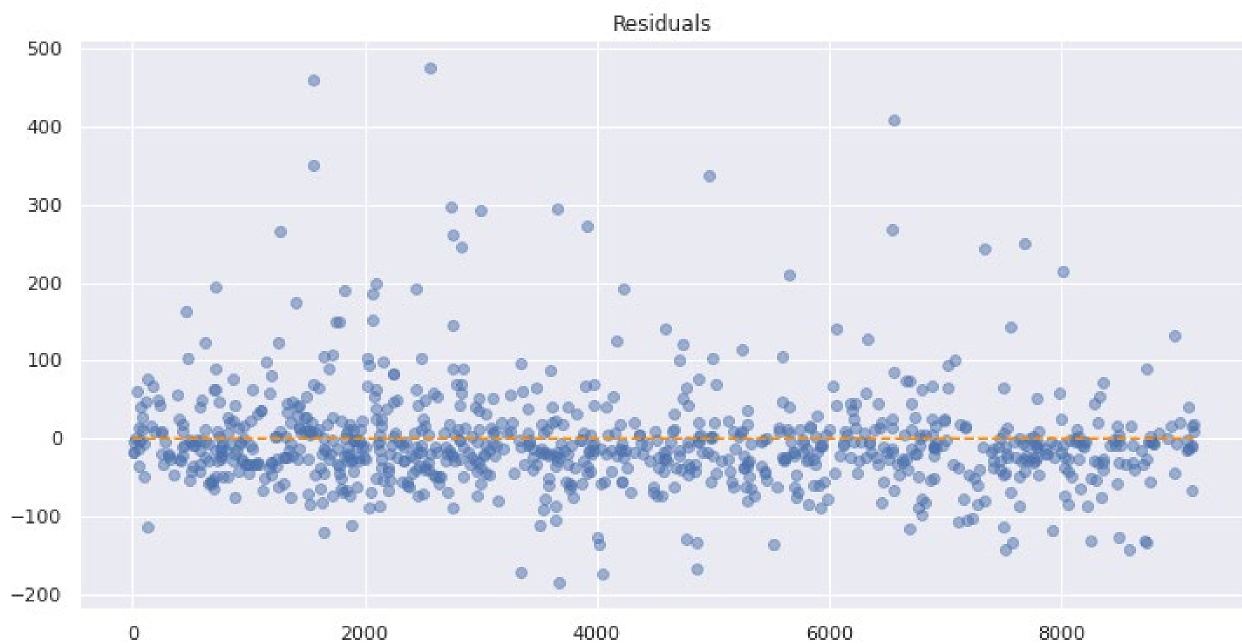
```
In [132]: independence_assumption(lm)
```

```
Durbin-Watson: 1.9742079446214784
Little to no autocorrelation
```

```
Assumption satisfied
```

In [137]:
```python
'''5- Homoscedasticity: Assumes that the errors exhibit constant variance'
''

def homoscedasticity(model):

    # Plotting the residuals
    plt.subplots(figsize=(12, 6))
    ax = plt.subplot(111)  # To remove spines
    plt.scatter(x=df_results.index, y=df_results.Residuals, alpha=0.5)
    plt.plot(np.repeat(0, df_results.index.max()), color='darkorange', lin
estyle='--')
    ax.spines['right'].set_visible(False)  # Removing the right spine
    ax.spines['top'].set_visible(False)  # Removing the top spine
    plt.title('Residuals')
    plt.show()
```

In [138]:
```python
homoscedasticity(lm)
```



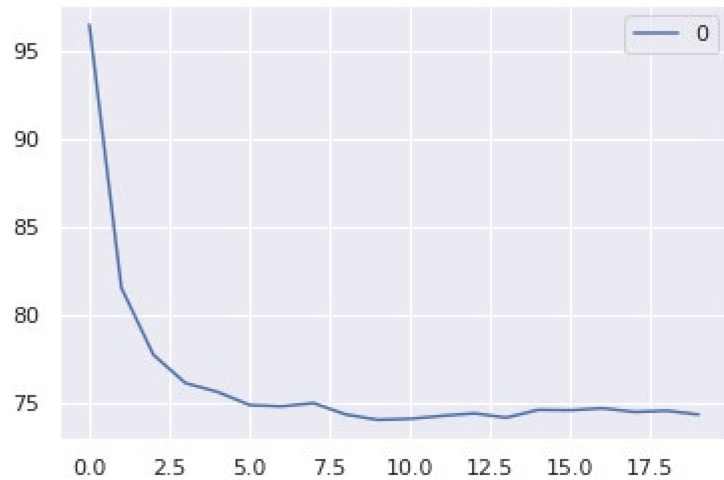
The variance across the residuals do not look to be uniform. So the homoscedasticity assumption is not satisfied. Conclusion on the LR assumptions: only 1 assumption is satisfied, which the independence of the residuals. Building the FIFTH model : K-Nearest Neighboors on train/test and k-fold split of the superhost population, excluding the amenities & neighborhood_cleansed. We have 10 independent variables.

In [139]:
```python
#5- First KNN model: excluding the amenites and the neighborhoods
y = listings_new[listings_new.host_is_superhost == 1]['price']
X = listings_new[['host_is_superhost', 'accommodates', 'price', 'minimum_n
ights',
       'number_of_reviews', 'last_review', 'instant_bookable',
       'calculated_host_listings_count', 'room_type_Entire home/apt',
       'room_type_Private room', 'room_type_Shared room',
       'sentiment_scores_adj']]\
        [listings_new.host_is_superhost == 1].drop(columns = ['price'], ax
is =1)
X = X.drop(columns = ['host_is_superhost'], axis =1)
```

In [168]:
```
##5.1 KNN: determining k
from sklearn import neighbors

rmse_val = []
for K in range(20):
    K = K+1
    knn = neighbors.KNeighborsRegressor(n_neighbors = K)

    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.25, random_state=0)
    knn.fit(X_train, y_train)
    y_train_pred = knn.predict(X_train)
    y_test_pred = knn.predict(X_test)
    rmse_knn51= (mean_squared_error(y_test,y_test_pred))**(1/2)
    rmse_val.append(rmse_knn51) #store rmse values
    print('RMSE value for k= ' , K , 'is:', rmse_knn51)

curve = pd.DataFrame(rmse_val) #elbow curve
curve.plot()
```

```
RMSE value for k=  1 is: 96.51492235828404
RMSE value for k=  2 is: 81.55687973394139
RMSE value for k=  3 is: 77.74978985550095
RMSE value for k=  4 is: 76.13989971750733
RMSE value for k=  5 is: 75.64372114148914
RMSE value for k=  6 is: 74.89374525213056
RMSE value for k=  7 is: 74.81866476750102
RMSE value for k=  8 is: 75.00165414370663
RMSE value for k=  9 is: 74.35972766257535
RMSE value for k=  10 is: 74.05352606417068
RMSE value for k=  11 is: 74.11131331280204
RMSE value for k=  12 is: 74.27923452090566
RMSE value for k=  13 is: 74.42173295580803
RMSE value for k=  14 is: 74.1769173768536 7
RMSE value for k=  15 is: 74.62120808531405
RMSE value for k=  16 is: 74.59921883604729
RMSE value for k=  17 is: 74.71413534585741
RMSE value for k=  18 is: 74.50039335813534
RMSE value for k=  19 is: 74.5701241307832
RMSE value for k=  20 is: 74.3563564240264
```

Out[168]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8422994f90>
```



The optimum k is 10

In [144]:
```
#5.1 KNN:evaluation technique = train/test split

time_start = time.perf_counter()

from sklearn import neighbors

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25
, random_state=None)
knn = neighbors.KNeighborsRegressor(n_neighbors = 10)


knn.fit(X_train, y_train)
y_train_pred = knn.predict(X_train)
y_test_pred = knn.predict(X_test)
rmse_knn51= (mean_squared_error(y_test,y_test_pred))**(1/2)
mae_knn51= mean_absolute_error(y_test,y_test_pred)
r2_score51= r2_score(y_test, y_test_pred)
r2_score51_adj = 1 - ( 1-r2_score51 ) * ( len(y_test) - 1 ) / ( len(y_test
) - X_test.shape[1] - 1 )

print('RMSE test: %.3f' % rmse_knn51)
print('MAE test: %.3f' % mae_knn51)
print('R^2 test: %.3f' % r2_score51)
print('R^2 test adjusted: %.3f' % r2_score51_adj)

time_elapsed = (time.perf_counter() - time_start)
print('the execution time is: %.3f' % time_elapsed)
```

```
RMSE test: 78.013
MAE test: 51.574
R^2 test: 0.127
R^2 test adjusted: 0.117
the execution time is: 0.065
```

In [145]:
```
#After repeating the process 20 times, we get the mean results as followin
g :

rmse_knn51 = 79.615
mae_knn51 =  52.91
```

```
r2_score51 =  0.147
r2_score51_adj = 0.138
execTime_knn51 = 0.066
```

In [147]:
```
##5.2 KNN:evaluation technique = k-fold cross validation / k=5

time_start = time.perf_counter()

rmse_knn52 = (np.mean(abs(cross_val_score(knn, X, y, cv=5, scoring = 'neg_
mean_squared_error'))))**(1/2)
mae_knn52 = np.mean(abs(cross_val_score(knn, X, y, cv=5, scoring = 'neg_me
an_absolute_error')))
r2_score52 = np.mean(abs(cross_val_score(knn, X, y, cv=5, scoring = 'r2'))
)
r2_score52_adj = 1 - ( 1-r2_score52 ) * ( (len(y)/10) - 1 ) / ( (len(y)/10
) - X.shape[1] - 1 )

print('RMSE test: %.3f' % rmse_knn52)
print('MAE test: %.3f' % mae_knn52)
print('R^2 test: %.3f' % r2_score52)
print('R^2 test adjusted: %.3f' % r2_score52_adj)

time_elapsed = (time.perf_counter() - time_start)
print('the execution time is: %.3f' % time_elapsed)
```

```
RMSE test: 78.095
MAE test: 52.166
R^2 test: 0.135
R^2 test adjusted: 0.110
the execution time is: 0.299
```

In [171]:
```
execTime_knn52 = 0.295
```

Building the SIXTH model: K-Nearest Neighboors on train/test and k-fold split of the superhost population, excluding the amenities & including neighborhood_cleansed. We have 10 + 139 = 149 independent variables.

In [148]:
```
#6. Second KNN model : including the neighborhood_cleansed & excluding ame
nities
y = listings_new[listings_new.host_is_superhost == 1]['price']
X = listings_new[listings_new.host_is_superhost == 1].drop(columns = ['pri
ce'], axis =1)
X = X.drop(columns = ['host_is_superhost'], axis =1)
```

In [150]:
```
#6.1 KNN:evaluation technique = train/test split

time_start = time.perf_counter()

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25
, random_state=None)
knn = neighbors.KNeighborsRegressor(n_neighbors = 10)


knn.fit(X_train, y_train)
y_train_pred = knn.predict(X_train)
y_test_pred = knn.predict(X_test)
rmse_knn61= (mean_squared_error(y_test,y_test_pred))**(1/2)
```

```
mae_knn61= mean_absolute_error(y_test,y_test_pred)
r2_score61= r2_score(y_test, y_test_pred)
r2_score61_adj = 1 - ( 1-r2_score61 ) * ( len(y_test) - 1 ) / ( len(y_test
) - X_test.shape[1] - 1 )

print('RMSE test: %.3f' % rmse_knn61)
print('MAE test: %.3f' % mae_knn61)
print('R^2 test: %.3f' % r2_score61)
print('R^2 test adjusted: %.3f' % r2_score61_adj)

time_elapsed = (time.perf_counter() - time_start)
print('the execution time is: %.3f' % time_elapsed)
```

```
RMSE test: 74.969
MAE test: 51.361
R^2 test: 0.164
R^2 test adjusted: -0.006
the execution time is: 0.629
```

In [151]:
```
#After repeating the process 20 times, we get the mean results as followin
g :

rmse_knn61 = 77.321
mae_knn61 = 51.278
r2_score61 = 0.151
r2_score61_adj = -0.02
execTime_knn61 = 0.631
```

In [153]:
```
#6.2 KNN:evaluation technique = k-fold cross validation / k=5

time_start = time.perf_counter()

rmse_knn62 = (np.mean(abs(cross_val_score(knn, X, y, cv=5, scoring = 'neg_
mean_squared_error'))))**(1/2)
mae_knn62 = np.mean(abs(cross_val_score(knn, X, y, cv=5, scoring = 'neg_me
an_absolute_error')))
r2_score62 = np.mean(abs(cross_val_score(knn, X, y, cv=5, scoring = 'r2'))
)
r2_score62_adj = 1 - ( 1-r2_score52 ) * ( (len(y)/10) - 1 ) / ( (len(y)/10
) - X.shape[1] - 1 )

print('RMSE test: %.3f' % rmse_knn62)
print('MAE test: %.3f' % mae_knn62)
print('R^2 test: %.3f' % r2_score62)
print('R^2 test adjusted: %.3f' % r2_score62_adj)

time_elapsed = (time.perf_counter() - time_start)
print('the execution time is: %.3f' % time_elapsed)
```

```
RMSE test: 78.030
MAE test: 52.191
R^2 test: 0.136
R^2 test adjusted: -0.500
the execution time is: 2.399
```

In [154]:
```
execTime_knn62 = 2.410
```

Building the SEVENTH model: K-Nearest Neighboors on train/test and k-fold split of the superhost population, including the amenities & neighborhood_cleansed. We have 10 + 139 + 629 = 778 independent variables.

In [155]:
```
#7- Third KNN model: including the neighborhood_cleansed & amenities
y = listings_new_ams[listings_new_ams.host_is_superhost == 1]['price']
X = listings_new_ams[listings_new_ams.host_is_superhost == 1].drop(columns
 = ['price'], axis =1)
X = X.drop(columns = ['host_is_superhost'], axis =1)
```

In [158]:
```
#7.1 KNN:evaluation technique = train/test split

time_start = time.perf_counter()

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25
, random_state=None)
knn = neighbors.KNeighborsRegressor(n_neighbors = 10)


knn.fit(X_train, y_train)
y_train_pred = knn.predict(X_train)
y_test_pred = knn.predict(X_test)
rmse_knn71= (mean_squared_error(y_test,y_test_pred))**(1/2)
mae_knn71= mean_absolute_error(y_test,y_test_pred)
r2_score71= r2_score(y_test, y_test_pred)
r2_score71_adj = 1 - ( 1-r2_score71 ) * ( len(y_test) - 1 ) / ( len(y_test
) - X_test.shape[1] - 1 )

print('RMSE test: %.3f' % rmse_knn71)
print('MAE test: %.3f' % mae_knn71)
print('R^2 test: %.3f' % r2_score71)
print('R^2 test adjusted: %.3f' % r2_score71_adj)

time_elapsed = (time.perf_counter() - time_start)
print('the execution time is: %.3f' % time_elapsed)
```

```
RMSE test: 75.875
MAE test: 49.724
R^2 test: 0.178
R^2 test adjusted: -5.971
the execution time is: 3.327
```

In [159]:
```
#After repeating the process 20 times, we get the mean results as followin
g :

rmse_knn71 = 79.749
mae_knn71 = 50.889
r2_score71 = 0.164
r2_score71_adj = -6.31
execTime_knn71 = 3.319
```

In [160]:
```
#7.2 KNN:evaluation technique = k-fold cross validation / k=5

time_start = time.perf_counter()

rmse_knn72 = (np.mean(abs(cross_val_score(knn, X, y, cv=5, scoring = 'neg_
mean_squared_error'))))**(1/2)
```

```
mae_knn72 = np.mean(abs(cross_val_score(knn, X, y, cv=5, scoring = 'neg_me
an_absolute_error')))
r2_score72 = np.mean(abs(cross_val_score(knn, X, y, cv=5, scoring = 'r2'))
)
r2_score72_adj = 1 - ( 1-r2_score52 ) * ( (len(y)/10) - 1 ) / ( (len(y)/10
) - X.shape[1] - 1 )

print('RMSE test: %.3f' % rmse_knn72)
print('MAE test: %.3f' % mae_knn72)
print('R^2 test: %.3f' % r2_score72)
print('R^2 test adjusted: %.3f' % r2_score72_adj)

time_elapsed = (time.perf_counter() - time_start)
print('the execution time is: %.3f' % time_elapsed)
```

```
RMSE test: 76.940
MAE test: 50.897
R^2 test: 0.160
R^2 test adjusted: 1.714
the execution time is: 14.315
```

In [162]:
```
execTime_knn72 = 14.315
```

Building the EIGHTH model : XGboost on train/test and k-fold split of the superhost population, including the amenities & neighborhood_cleansed. We have 10 + 139 + 629 = 788 independent variables.

In [205]:
```
#8. determining the best n_estimators (number of trees)
rmse_val = []
y = listings_new_ams[listings_new_ams.host_is_superhost == 1]['price']
X = listings_new_ams[listings_new_ams.host_is_superhost == 1].drop(columns
 = ['price'], axis =1)
X = X.drop(columns = ['host_is_superhost'], axis =1)

data_dmatrix = xgb.DMatrix(data=X,label=y)

for k in range(10, 101, 10):


    xg_reg = xgb.XGBRegressor(objective ='reg:squarederror', colsample_byt
ree = 1, learning_rate = 0.1,
                max_depth = 10, alpha = 10, n_estimators = k)

    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.25, random_state=None)

    xg_reg.fit(X_train, y_train)
    y_train_pred = xg_reg.predict(X_train)
    y_test_pred = xg_reg.predict(X_test)
    rmse_xg= (mean_squared_error(y_test,y_test_pred))**(1/2)
    rmse_val.append(rmse_xg) #store rmse values
    print('RMSE value for k= ' , k , 'is:', rmse_xg)



curve = pd.DataFrame(rmse_val) #elbow curve
curve.plot()
```

```
RMSE value for k=  10 is: 74.90908369935387
RMSE value for k=  20 is: 61.80075120809677
RMSE value for k=  30 is: 60.72929446583825
RMSE value for k=  40 is: 62.849795998210546
RMSE value for k=  50 is: 63.75287949745353
RMSE value for k=  60 is: 64.97407890290422
RMSE value for k=  70 is: 55.231055494892
RMSE value for k=  80 is: 66.51313868399963
RMSE value for k=  90 is: 59.475118733352964
RMSE value for k=  100 is: 65.77952427692121
```

Out[205]: <matplotlib.axes._subplots.AxesSubplot at 0x7f84593d4510>

In [164]:
```
#8.1 including the amenities and the neighborhoods
y = listings_new_ams[listings_new_ams.host_is_superhost == 1]['price']
X = listings_new_ams[listings_new_ams.host_is_superhost == 1].drop(columns
 = ['price'], axis =1)
X = X.drop(columns = ['host_is_superhost'], axis =1)
```

In [166]:
```
#8.1 XGboost:evaluation technique = train/test split

time_start = time.perf_counter()

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25
, random_state=None)

data_dmatrix = xgb.DMatrix(data=X,label=y)
xg_reg = xgb.XGBRegressor(objective ='reg:squarederror', colsample_bytree
= 1, learning_rate = 0.1,
                max_depth = 10, alpha = 10, n_estimators = 70)

xg_reg.fit(X_train, y_train)
y_train_pred = xg_reg.predict(X_train)
y_test_pred = xg_reg.predict(X_test)
rmse_xg81= (mean_squared_error(y_test,y_test_pred))**(1/2)
mae_xg81= mean_absolute_error(y_test,y_test_pred)
r2_score81= r2_score(y_test, y_test_pred)
r2_score81_adj = 1 - ( 1-r2_score81 ) * ( len(y_test) - 1 ) / ( len(y_test
) - X_test.shape[1] - 1 )

print('RMSE test: %.3f' % rmse_xg81)
```

```python
print('MAE test: %.3f' % mae_xg81)
print('R^2 test: %.3f' % r2_score81)
print('R^2 test adjusted: %.3f' % r2_score81_adj)

time_elapsed = (time.perf_counter() - time_start)
print('the execution time is: %.3f' % time_elapsed)
```

```
RMSE test: 64.633
MAE test: 39.128
R^2 test: 0.474
R^2 test adjusted: -3.463
the execution time is: 4.974
```

In [167]:
```python
#After repeating the process 20 times, we get the mean results as followin
g :

rmse_xg81 = 63.504
mae_xg81 = 37.3502
r2_score81 = 0.467
r2_score81_adj = -3.511
execTime_xg81 = 4.962
```

In [169]:
```python
##8.2 XGboost: evaluation technique = k-fold cross validation / k=5

time_start = time.perf_counter()

data_dmatrix = xgb.DMatrix(data=X,label=y)
xg = xgb.XGBRegressor(objective ='reg:squarederror', colsample_bytree = 1,
 learning_rate = 0.1,
                max_depth = 10, alpha = 10, n_estimators = 70)

rmse_xg82 = (np.mean(abs(cross_val_score(xg, X, y, cv=5, scoring = 'neg_me
an_squared_error'))))**(1/2)

mae_xg82 = np.mean(abs(cross_val_score(xg, X, y, cv=5, scoring = 'neg_mean
_absolute_error')))

r2_score82 = np.mean(abs(cross_val_score(xg, X, y, cv=5, scoring = 'r2')))

r2_score82_adj = 1 - ( 1-r2_score82 ) * ( (len(y)/10) - 1 ) / ( (len(y)/10
) - X.shape[1] - 1 )

print('RMSE test: %.3f' % rmse_xg82)
print('MAE test: %.3f' % mae_xg82)
print('R^2 test: %.3f' % r2_score82)
print('R^2 test adjusted: %.3f' % r2_score82_adj)

time_elapsed = (time.perf_counter() - time_start)
print('the execution time is: %.3f' % time_elapsed)
```

```
RMSE test: 63.350
MAE test: 39.067
R^2 test: 0.424
R^2 test adjusted: 1.475
the execution time is: 77.440
```

In [170]:
```
execTime_xg82 = 77.440
```

RESULTS SUMMARY OF ALL THE MODELS (Linear Regression results are mentioned for information only)

In [175]:
```
MODEL = ['RF1.1', 'RF1.2', 'RF2.1', 'RF2.2', 'RF3.1', 'RF3.2', 'LM4.1', 'L
M4.2', 'KNN5.1', 'KNN5.2', 'KNN6.1',\
        'KNN6.2', 'KNN7.1', 'KNN7.2', 'XGboost8.1', 'XGboost8.2']
RMSE = [rmse_rf11, rmse_rf12, rmse_rf21, rmse_rf22, rmse_rf31, rmse_rf32,
rmse_lm41, rmse_lm42, rmse_knn51, rmse_knn52,\
       rmse_knn61, rmse_knn62, rmse_knn71, rmse_knn72, rmse_xg81, rmse_xg8
2]
MAE = [mae_rf11, mae_rf12, mae_rf21, mae_rf22, mae_rf31, mae_rf32, mae_lm4
1, mae_lm42, mae_knn51, mae_knn52, mae_knn61,\
      mae_knn62, mae_knn71, mae_knn72, mae_xg81, mae_xg82]
Execution_time = [execTime_rf11, execTime_rf12, execTime_rf21, execTime_rf
22, execTime_rf31, execTime_rf32,\
                 execTime_lm41, execTime_lm42, execTime_knn51, execTime_kn
n52, execTime_knn61, execTime_knn62,\
                 execTime_knn71, execTime_knn72, execTime_xg81, execTime_x
g82]

RESULTS = pd.DataFrame(
    {'MODEL': MODEL,
     'RMSE': RMSE,
     'MAE': MAE,
     'Execution_time': Execution_time
    })
RESULTS.sort_values(by = 'RMSE')
```

Out[175]:

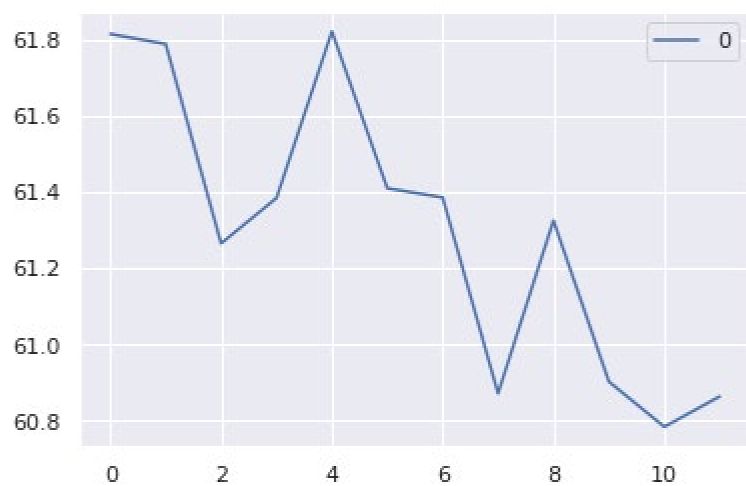
	MODEL	RMSE	MAE	Execution_time
5	RF3.2	61.030621	38.513456	229.163
15	XGboost8.2	63.350010	39.067468	77.440
14	XGboost8.1	63.504000	37.350200	4.962
7	LM4.2	64.174726	41.787063	0.089
6	LM4.1	64.644000	41.516000	0.013
3	RF2.2	66.458625	42.197432	72.297
4	RF3.1	66.709000	39.453000	14.263
2	RF2.1	67.390000	41.400000	4.575
1	RF1.2	69.350577	45.077613	32.019
0	RF1.1	70.073200	44.393000	2.253
13	KNN7.2	76.940187	50.897093	14.315
10	KNN6.1	77.321000	51.278000	0.631
11	KNN6.2	78.030164	52.190816	2.410
9	KNN5.2	78.094583	52.166204	0.295
8	KNN5.1	79.615000	52.910000	0.066
12	KNN7.1	79.749000	50.889000	3.319

STABILITY OF THE BEST MODEL 'RF 3.2'

In [267]:
```
#comparing the RMSE when the k-folds varies

y = listings_new_ams[listings_new_ams.host_is_superhost == 1]['price']
X = listings_new_ams[listings_new_ams.host_is_superhost == 1].drop(columns
 = ['price'], axis =1)
X = X.drop(columns = ['host_is_superhost'], axis =1)

rmse_val_stab = []
for k in range(3, 15, 1):

    rmse_stab = (np.mean(abs(cross_val_score(RandomForestRegressor(n_estim
ators=350,
                               criterion='mse',
                               random_state=None,
                               max_depth=10), X, y, cv=k, scoring = 'neg_m
ean_squared_error'))))**(1/2)


    rmse_val_stab.append(rmse_stab)
    print('RMSE value for k= ' , k , 'is:', rmse_stab)
```

```
RMSE value for k=  3 is: 61.813763773166286
RMSE value for k=  4 is: 61.787304505101645
RMSE value for k=  5 is: 61.26483259881595
RMSE value for k=  6 is: 61.38398833274411
RMSE value for k=  7 is: 61.82018224477345
RMSE value for k=  8 is: 61.409505299522415
RMSE value for k=  9 is: 61.38536875407887
RMSE value for k=  10 is: 60.87196723560409
RMSE value for k=  11 is: 61.32500454123509
RMSE value for k=  12 is: 60.90290232987636
RMSE value for k=  13 is: 60.784443590386076
RMSE value for k=  14 is: 60.864121688291284
```

Out[267]: <matplotlib.axes._subplots.AxesSubplot at 0x7f845937a350>



In [268]:
```
(max(rmse_val_stab)-min(rmse_val_stab)) / min(rmse_val_stab) *100
```

Out[268]: 1.7039535006144069

The model looks rather stable as the accuracy varies only by 1.71% between the max RMSE and the min RMSE. It reaches its maximum accuracy at rmse_val_stab[10] which corresponds to k=13Conclusion: our most effective regressor which includes the whole set of features & evaluated using the cross validation technique is the Random Forest regressor (350 trees). However, in terms of efficiency, it ranks last with almost 3min50s execution time. Nevertheless, this model will be used in predicting prices of the non_superhosts listings based on the knowledge of superhosts Top important features defining the price according to the best Random Forest model (in descendant order): Top 5 features: -how many guests the listing accommodates -whether the listing is an Entire home\apt -review scores -number of reviews -minimum nights required Top 5 amenities: -dishwasher -indoor fireplace -bbq grill -patio or balcony -paid parking off premises Top 5 neighborhoods: -Etobicoke West Mall -Waterfront Communities-the Island -South Riverdale -Moss Park -RonscevallesPRICE PREDICTION Predicting the non-superhosts prices by the best model RF3.2 (trained on the superhost subdataset)

In [50]:
```
#defining the X and y for the superhost subdataset and the non_superhost s
ubdataset
y_superhost = listings_new_ams[listings_new_ams.host_is_superhost == 1]['p
rice']
X_superhost = listings_new_ams[listings_new_ams.host_is_superhost == 1].dr
op(columns = ['price'], axis =1)
X_superhost = X_superhost.drop(columns = ['host_is_superhost'], axis =1)

y_non_superhost = listings_new_ams[listings_new_ams.host_is_superhost == 0
]['price']
X_non_superhost = listings_new_ams[listings_new_ams.host_is_superhost == 0
].drop(columns = ['price'], axis =1)
X_non_superhost = X_non_superhost.drop(columns = ['host_is_superhost'], ax
is =1)
```

In [51]:
```
#training the model on the superhost subdataset and predicting the price o
n the non-superhost subdataset

from sklearn.model_selection import KFold

model = RandomForestRegressor(n_estimators=350,
                              criterion='mse',
                              random_state=None,
                              max_depth=10)
cv = KFold(n_splits=13, random_state=None, shuffle=True) #13 is the optimu
m number of folds
for train_set, test_set in cv.split(X):
    model.fit(X_superhost.iloc[train_set], y_superhost.iloc[train_set])

y_non_superhost_pred = model.predict(X_non_superhost)
print(y_non_superhost_pred)
```

```
[ 62.96935133 157.40439179  88.27350656 ... 125.57819724 119.06651136
 114.6327278 ]
```

In [52]:
```
#RMSE between the predicted and the actual values of the non_superhosts pr
ices
rmse_non_superhost= (mean_squared_error(y_non_superhost,y_non_superhost_pr
ed))**(1/2)
rmse_non_superhost
```

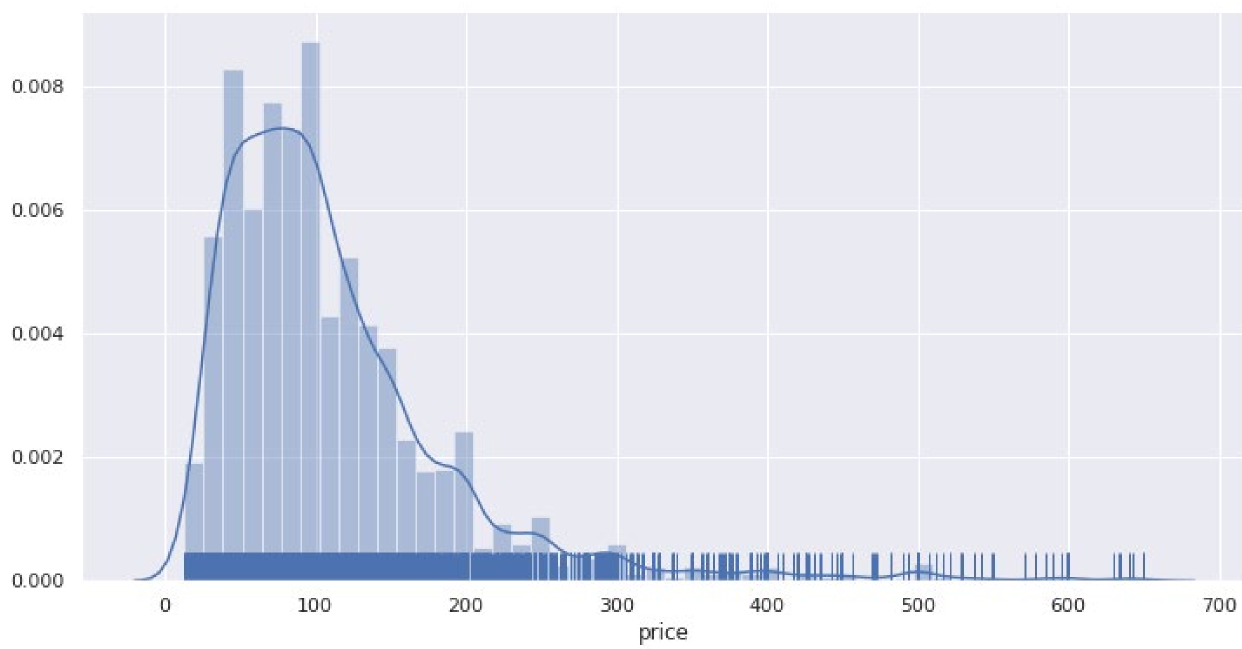
Out[52]: 63.80411313553884

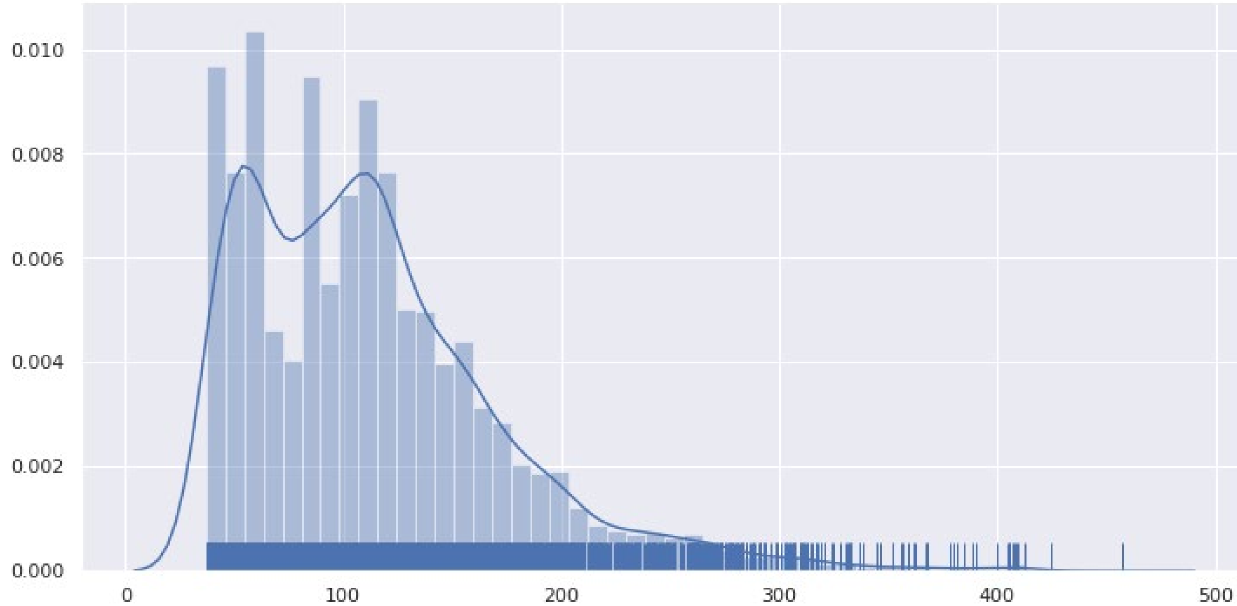
HYPOTHESIS TESTINGTo select the appropriate test of hypothesis, we will first check the normality of the predicted and the actual prices of the non_superhosts

In [180]:
```
#checking the mean and median of the actual and predicted prices
import statistics
from statistics import median
from statistics import mean

print('median actual price', median(y_non_superhost))
print('median predicted price', median(y_non_superhost_pred))
print('mean actual price', mean(y_non_superhost))
print('mean predicted price', mean(y_non_superhost_pred))
```

```
median actual price 95.0
median predicted price 105.47590797441141
mean actual price 112.78980891719745
mean predicted price 113.52129700739921
```

In [183]:
```
#plotting the actual values of the non_superhosts prices
plt.figure(figsize=(12,6))
sns.distplot(y_non_superhost, rug=True)
sns.despine()
plt.show();

#plotting the predicted values of the non_superhosts prices
plt.figure(figsize=(12,6))
sns.distplot(y_non_superhost_pred, rug=True)
sns.despine()
plt.show();
```





The data of both predicted and actual look non-normal. We will confirm with the Shapirow-Wilk normality test

In [184]:
```
#testing the normality of actual non_superhost_prices
from scipy.stats import shapiro

stat, p = shapiro(y_non_superhost)
print('Statistics=%.3f, p=%.3f' % (stat, p))

alpha = 0.05
if p > alpha:
    print('the data is normally distributed (fail to reject H0)')
else:
    print('the data is not normally distributed (reject H0)')
```

```
Statistics=0.800, p=0.000
the data is not normally distributed (reject H0)
```

```
/opt/conda/lib/python3.7/site-packages/scipy/stats/morestats.py:1676: User
Warning: p-value may not be accurate for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

In [186]:
```
#testing the normality of predicted non_superhost_prices

stat, p = shapiro(y_non_superhost_pred)
print('Statistics=%.3f, p=%.3f' % (stat, p))

alpha = 0.05
if p > alpha:
    print('the data is normally distributed (fail to reject H0)')
else:
    print('the data is not normally distributed (reject H0)')
```

```
Statistics=0.904, p=0.000
the data is not normally distributed (reject H0)
```

As the data is not normally distributed, we will use a non-parametric hypothesis test to compare two groups

In [187]:
```
#Mann-Whitney U Test : two-sided
#H0: the two population distributions are identical / Ha: the two populati
```

```
on distributions are different

from scipy.stats import mannwhitneyu
stat, p = mannwhitneyu(y_non_superhost, y_non_superhost_pred,
                        use_continuity=True,
                       alternative= 'two-sided')
print('Statistics=%.3f, p=%.3f' % (stat, p))
# interpret
alpha = 0.05
if p > alpha:
     print('Identical distributions (fail to reject H0)')
else:
    print('Different distributions (reject H0)')
```

```
Statistics=14586137.000, p=0.000
Different distributions (reject H0)
```

In [188]:

```
#Mann-Whitney U Test : one-sided
#H0: the actual non_superhosts price distributions is greater than the pre
dicted for superhosts
#Ha: the actual non_superhosts price distributions is less than the predic
ted for superhosts

from scipy.stats import mannwhitneyu
stat, p = mannwhitneyu(y_non_superhost, y_non_superhost_pred,
                        use_continuity=True,
                       alternative= 'less')
print('Statistics=%.3f, p=%.3f' % (stat, p))
# interpret
alpha = 0.05
if p > alpha:
     print('the actual non_superhosts price distributions is greater than
the predicted for superhosts (fail to reject H0)')
else:
    print('the actual non_superhosts price distributions is less than the
predicted for superhosts (reject H0)')
```

```
Statistics=14586137.000, p=0.000
the actual non_superhosts price distributions is less than the predicted f
or superhosts (reject H0)
```

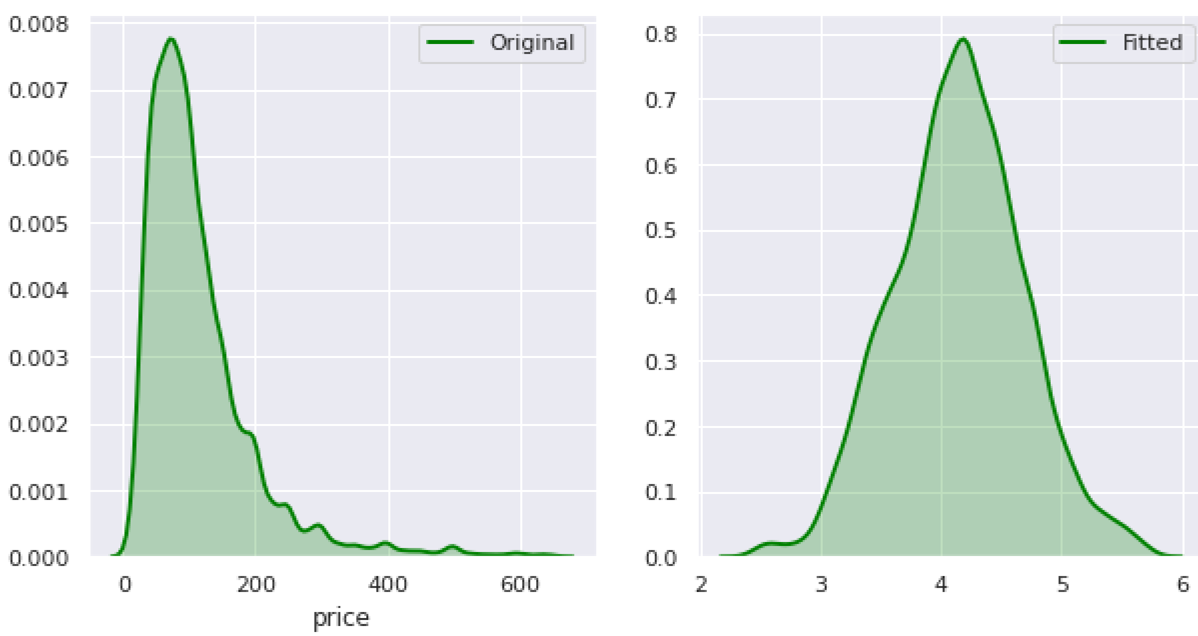
Conclusion: The distributions of the the actual prices of non_superhosts VS the prices that superhosts would apply for the same listings are different, and the distribution of the actual non_superhosts price distributions is less than the predicted for superhosts We can conclude that the superhosts utilize efficiently their market knowledge and experience to apply higher prices and generate more incomeLimitations: -The available features can be limited and fail to explain an important proportion of the price variance -The price is static. The results would be more realistic if the price in the dataset was dynamic and evolves in time -Working on the logarithmic price can improve the outcomeIMPROVING THE ACCURACYWe will transform the depenent variable using the Box-Cox transformation

In [120]:

```
# transform training data & save lambda value
fitted_price, fitted_lambda = stats.boxcox(listings_new_ams.price)


# creating axes to draw plots
fig, ax = plt.subplots(1, 2)
```

```python
# plotting the original data(non-normal)
sns.distplot(listings_new_ams.price, hist = False, kde = True,
             kde_kws = {'shade': True, 'linewidth': 2},
             label = "Original", color ="green", ax = ax[0])

# plotting the fitted data (normal)
sns.distplot(fitted_price, hist = False, kde = True,
             kde_kws = {'shade': True, 'linewidth': 2},
             label = "Fitted", color ="green", ax = ax[1])

# adding legends to the subplots
plt.legend(loc = "upper right")

# rescaling the subplots
fig.set_figheight(5)
fig.set_figwidth(10)

print(f"Lambda value used for Transformation: {fitted_lambda}")
```

```
Lambda value used for Transformation: -0.038657697373034636
```



In [121]:

```python
#adding the column 'fitted_price' to the listings_new_ams dataset
listings_new_ams['fitted_price'] = fitted_price
#dropping the original price from the fitted dataset
listings_new_ams_fitted = listings_new_ams.drop(columns= ['price'], axis =
 1)

#preparing the X and y of the superhost subdataset and the non_superhost s
ubdataset after fitting the price
y_superhost_fitted = listings_new_ams_fitted[listings_new_ams_fitted.host_
is_superhost == 1]['fitted_price']
X_superhost_fitted = listings_new_ams_fitted[listings_new_ams_fitted.host_
is_superhost == 1].drop(columns = ['fitted_price'], axis =1)
X_superhost_fitted = X_superhost_fitted.drop(columns = ['host_is_superhost
'], axis =1)

y_non_superhost_fitted = listings_new_ams_fitted[listings_new_ams_fitted.h
```

```
ost_is_superhost == 0]['fitted_price']
X_non_superhost_fitted = listings_new_ams_fitted[listings_new_ams_fitted.h
ost_is_superhost == 0].drop(columns = ['fitted_price'], axis =1)
X_non_superhost_fitted = X_non_superhost_fitted.drop(columns = ['host_is_s
uperhost'], axis =1)
```

In [126]:
```
#training the model on the superhost subdataset based on the fitted_price
and predicting the price on the non-superhost subdataset

from sklearn.model_selection import KFold

model = RandomForestRegressor(n_estimators=350,
                              criterion='mse',
                              random_state=None,
                              max_depth=10)
cv = KFold(n_splits=13, random_state=None, shuffle=True) #13 is the optimu
m number of folds
for train_set, test_set in cv.split(X):
    model.fit(X_superhost_fitted.iloc[train_set], y_superhost_fitted.iloc[
train_set])

y_non_superhost_pred_fitted = model.predict(X_non_superhost_fitted)
```

In [129]:
```
#RMSE between the predicted and the actual values of the non_superhosts fi
tted prices
rmse_non_superhost_fitted= (mean_squared_error(y_non_superhost_fitted,y_no
n_superhost_pred_fitted))**(1/2)
print('the RMSE after fitting the price: %.3f' % rmse_non_superhost_fitted
)

##MAE between the predicted and the actual values of the non_superhosts fi
tted prices
mae_non_superhost_fitted = mean_absolute_error(y_non_superhost_fitted,y_no
n_superhost_pred_fitted)
print('the MAE after fitting the price: %.3f' % mae_non_superhost_fitted)
```

```
the RMSE after fitting the price: 0.367
the MAE after fitting the price: 0.281
```

We are now going to check the normality and apply the hypothesis tests

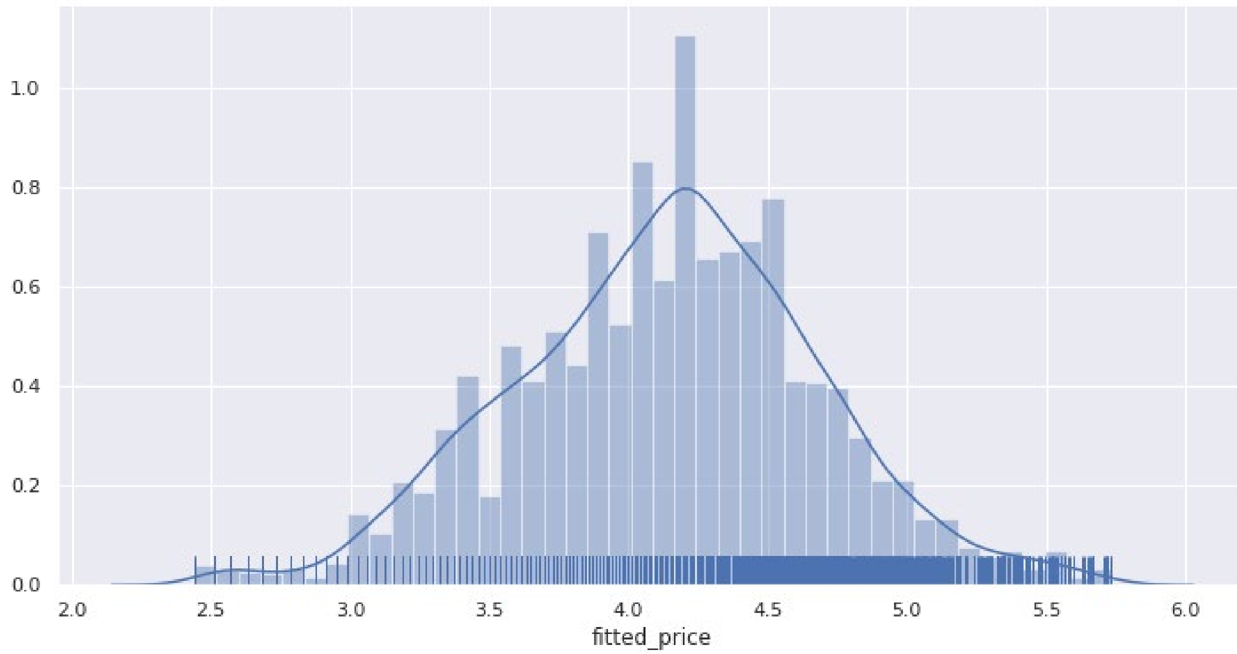
In [135]:
```
from scipy.stats import shapiro

stat, p = shapiro(y_non_superhost_fitted)
print('Statistics=%.3f, p=%.3f' % (stat, p))

alpha = 0.05
if p > alpha:
    print('the data is normally distributed (fail to reject H0)')
else:
    print('the data is not normally distributed (reject H0)')
```

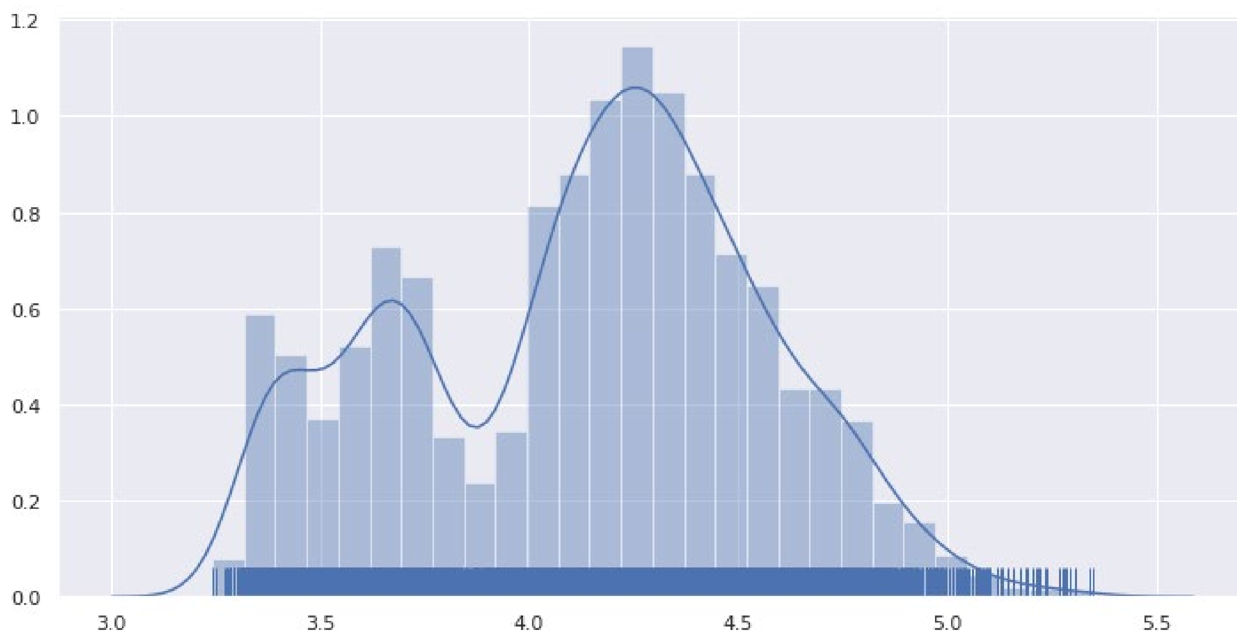
```
Statistics=0.997, p=0.000
the data is not normally distributed (reject H0)
```

```
/opt/conda/lib/python3.7/site-packages/scipy/stats/morestats.py:1676: User
Warning: p-value may not be accurate for N > 5000.
```

```
  warnings.warn("p-value may not be accurate for N > 5000.")
```

In [130]:
```
#plotting the actual values of the non_superhosts fitted prices
plt.figure(figsize=(12,6))
sns.distplot(y_non_superhost_fitted, rug=True, label = 'actual')
sns.despine()
plt.show();

#plotting the predicted values of the non_superhosts fitted prices
plt.figure(figsize=(12,6))
sns.distplot(y_non_superhost_pred_fitted, rug=True, label = 'predicted')
sns.despine()
plt.show();
```





In [131]:
```
#Mann-Whitney U Test : two-sided
#H0: the two population distributions are identical / Ha: the two populati
```

```
on distributions are different

from scipy.stats import mannwhitneyu
stat, p = mannwhitneyu(y_non_superhost_fitted, y_non_superhost_pred_fitted
,
                        use_continuity=True,
                       alternative= 'two-sided')
print('Statistics=%.3f, p=%.3f' % (stat, p))
# interpret
alpha = 0.05
if p > alpha:
     print('Identical distributions (fail to reject H0)')
else:
    print('Different distributions (reject H0)')
```

```
Statistics=16015826.000, p=0.803
Identical distributions (fail to reject H0)
```

In [132]:
```
from scipy.stats import kruskal

kruskal(y_non_superhost_fitted, y_non_superhost_pred_fitted)
```

Out[132]:
```
KruskalResult(statistic=0.062225625887874406, pvalue=0.8030122114382104)
```

PCA: the amount of variance explained by each of the principal components

In [81]:
```
listings_new_ams_scaled  = listings_new_ams.drop(columns = ['price', 'fitt
ed_price'])

from sklearn.preprocessing import StandardScaler

listings_new_ams_scaled = pd.DataFrame(StandardScaler().fit_transform(list
ings_new_ams_scaled))
```

In [86]:
```
listings_new_ams_scaled
```

Out[86]:

	0	1	2	3	4	5	6	7	8
0	-0.790178	-0.064959	0.146374	2.774816	-1.550439	1.534007	-0.322858	-1.424792	1.460999
1	-0.790178	0.985942	0.212264	1.125199	1.189088	-0.651888	-0.108352	0.701857	-0.684463
2	1.265538	-0.590409	0.146374	0.701012	1.189088	-0.651888	-0.322858	0.701857	-0.684463
3	-0.790178	0.460492	-0.710197	-0.147363	-0.180676	-0.651888	-0.430112	-1.424792	1.460999
4	1.265538	-0.590409	0.146374	0.276824	1.189088	-0.651888	1.178690	0.701857	-0.684463
...	...	...	...	...	...	...	...	...	...
9176	-0.790178	-0.064959	-0.710197	-0.618682	1.189088	1.534007	-0.430112	0.701857	-0.684463
9177	-0.790178	-0.590409	-0.743142	-0.618682	1.189088	-0.651888	0.535169	0.701857	-0.684463
9178	-0.790178	-0.590409	-0.743142	-0.618682	1.189088	-0.651888	0.535169	0.701857	-0.684463
9179	-0.790178	-0.590409	-0.743142	-0.602971	1.189088	-0.651888	0.535169	0.701857	-0.684463
9180	-0.790178	-0.590409	-0.743142	-0.618682	1.189088	-0.651888	0.535169	0.701857	-0.684463

9181 rows × 779 columns

In [114]:
```
#PCA
from sklearn.decomposition import PCA
pca = PCA(n_components=430)
principalComponents = pca.fit_transform(listings_new_ams_scaled)
explained_variance = pca.explained_variance_ratio_
#print(explained_variance)
```

In [138]:
```
#explained variance
sum_explained_variance = 0
for i in range(0, len(explained_variance),1):
    sum_explained_variance = sum_explained_variance + explained_variance[i
]
    i+=1
print(round(sum_explained_variance,3))
```

```
0.904
```