In [84]:
```
import pandas as pd
import numpy as np

review=pd.read_csv('review_nc_asheville.csv')
listing=pd.read_csv('listing_nc_asheville.csv')

#1. Let us join the data first into one table
merged=pd.merge(listing,review,on='listing_id')
merged.head()
```

Out[84]:

	listing_id	zipcode	latitude	longitude	property_type	room_type	bathrooms	bedrooms	beds
0	38585	28804.0	35.65146	-82.62792	Private room in house	Private room	1.0	1.0	2.0
1	38585	28804.0	35.65146	-82.62792	Private room in house	Private room	1.0	1.0	2.0
2	38585	28804.0	35.65146	-82.62792	Private room in house	Private room	1.0	1.0	2.0
3	38585	28804.0	35.65146	-82.62792	Private room in house	Private room	1.0	1.0	2.0
4	38585	28804.0	35.65146	-82.62792	Private room in house	Private room	1.0	1.0	2.0

5 rows × 21 columns

The above result shows the dataframe - merged , after joining the review dataframe and listing dataframe using inner join.

In [26]:
```
#2. Let us get an idea of how the merged table looks like
merged.shape
merged.columns
merged.describe()
```

Out[26]:

	listing_id	zipcode	latitude	longitude	bathrooms	bedrooms
count	1.473390e+05	146155.000000	147339.000000	147339.000000	147156.000000	147339.000000
mean	1.141278e+07	28798.507372	35.583347	-82.559164	1.188256	1.336903
std	7.805519e+06	21.453325	0.038532	0.042917	0.491695	0.929120
min	3.858500e+04	28701.000000	35.407702	-82.770131	0.000000	0.000000
25%	4.045013e+06	28801.000000	35.573400	-82.588910	1.000000	1.000000
50%	1.170103e+07	28804.000000	35.587130	-82.558600	1.000000	1.000000
75%	1.793540e+07	28806.000000	35.604230	-82.534220	1.000000	2.000000
max	3.105452e+07	28815.000000	35.685558	-82.417304	12.500000	34.000000

The above table shows us the descriptive statistics of merged dataframe.

In [27]:
```
#3. Drop null values and fill null vlaues with relevant summary statist
merged.isnull().sum() # zipcode,bathrooms,beds,cancellation_policy and
merged.fillna({'bathrooms':merged['bathrooms'].mean(),'beds':merged['be
merged.dropna(how='any', inplace=True)
merged.isnull().sum()
```

Out[27]:
```
listing_id                  0
zipcode                     0
latitude                    0
longitude                   0
property_type               0
room_type                   0
bathrooms                   0
bedrooms                    0
beds                        0
minimum_nights              0
host_listings_count         0
instant_bookable            0
cancellation_policy         0
is_business_travel_ready    0
price_per_person            0
host_is_superhost           0
review_id                   0
date                        0
reviewer_id                 0
reviewer_name               0
sentiment                   0
dtype: int64
```

In [37]:
```
#4. Let us clean the data further using functions:
merged.dtypes
merged['zipcode'] = merged['zipcode'].astype(int)
merged['bathrooms'] = merged['bathrooms'].astype(int)
merged['bedrooms'] = merged['bedrooms'].astype(int)
merged['beds'] = merged['beds'].astype(int)
merged['price_per_person'] = merged['price_per_person'].round(2)
merged['sentiment'] = merged['sentiment'].round(2)
merged.sort_values('sentiment',ascending=False,inplace=True)
merged['instant_bookable_binary']=np.where(merged.instant_bookable == '
merged['is_business_travel_ready_binary']=np.where(merged.is_business_t
merged['host_is_superhost_binary']=np.where(merged.host_is_superhost ==
merged.head()
```

Out[37]:

	listing_id	zipcode	latitude	longitude	property_type	room_type	bathrooms	bedrooms
53681	6698737	28806	35.575910	-82.59421	Private room in bungalow	Private room	1	1
133625	22076023	28804	35.625548	-82.55522	House	Private room	1	1
129494	21131816	28806	35.612530	-82.59418	Private room in residential home	Private room	1	1
106655	17206606	28787	35.612180	-82.56962	House	Private room	1	1
25621	2477628	28801	35.589390	-82.56782	Entire residential home	Entire home/apt	1	2

5 rows × 26 columns

In the above data cleaning attempt, I converted integer values not needing a decimal point (like zipcode) to int. I also rounded floating point values to 2 decimal places for concise data. Then, I created binary values for columns having 't' and 'f' entries to be able to run regression on the data set later.

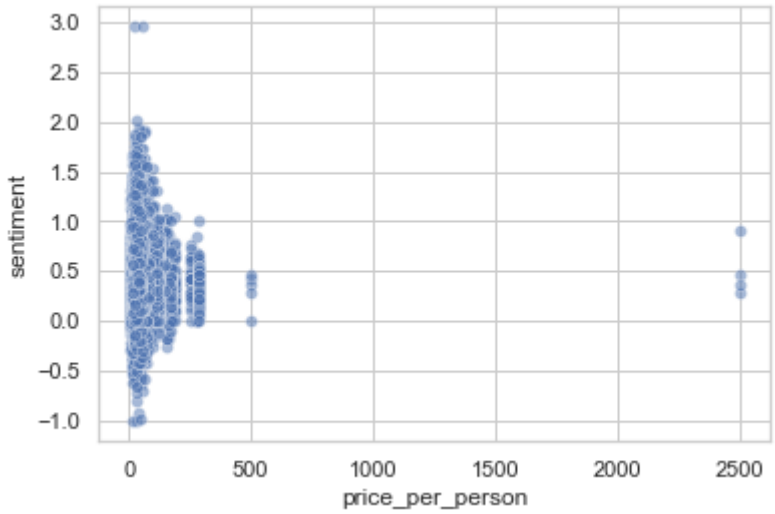
In [97]:
```
import seaborn

seaborn.set(style='whitegrid')

seaborn.scatterplot(x="price_per_person",
                    y="sentiment",
                    sizes=(40,400),
                    alpha=.5,
                    data=merged)

```

Out[97]: <AxesSubplot:xlabel='price_per_person', ylabel='sentiment'>



In the figure above, we can see a scatterplot between sentiment score and price_per_person. It shows as price increases, sentiment score steadily increases, atleast from negative to the positive scale. We can also see a few dots around 3.0 sentiment score at a lower price point, which we can safely categorize as OUTLIERS. People are basically giving a good score to hotels having a decent price and all other desired features as compared to super expensive hotels. There is another OUTLIER of expensive stays around $2500 having a positive sentiment score.

In [38]:
```
#5. Let us get further insights from the clean data set
mergedGroup1=merged.groupby('listing_id')[['review_id']].count()
mergedGroup1.rename(columns={'review_id':'No of Reviews per Listing'},i
mergedGroup1.sort_values('No of Reviews per Listing',ascending=False,in
mergedGroup1 #Number of reviews per listing in descending order
```

Out[38]:

listing_id	No of Reviews per Listing
695196	804
2411109	607
2296152	602
3314819	557
6054250	460
...	...
15922343	1
5822540	1
28335156	1
5477385	1
31054515	1

2520 rows × 1 columns

In [39]:
```
#6. Handling the date column and adding year using datetime
import datetime
merged['in_datetime']=pd.to_datetime(merged['date'],infer_datetime_form
merged['year']=merged['in_datetime'].dt.year #adding the Year column fo
merged.head()
```

Out[39]:

	listing_id	zipcode	latitude	longitude	property_type	room_type	bathrooms	bedrooms
53681	6698737	28806	35.575910	-82.59421	Private room in bungalow	Private room	1	1
133625	22076023	28804	35.625548	-82.55522	House	Private room	1	1
129494	21131816	28806	35.612530	-82.59418	Private room in residential home	Private room	1	1
106655	17206606	28787	35.612180	-82.56962	House	Private room	1	1
25621	2477628	28801	35.589390	-82.56782	Entire residential home	Entire home/apt	1	2

5 rows × 26 columns

In [41]:
```
#7. Further Insights
mergedGroup2=merged.groupby('year')[['review_id']].count()
mergedGroup2.rename(columns={'review_id':'No of reviews'},inplace=True)
mergedGroup2.sort_values('No of reviews',ascending=False,inplace=True)
mergedGroup2.head() # Top 5 year having maximum No of reviews
```

Out[41]:

year	No of reviews
2018	59610
2017	39914
2016	23118
2015	15658
2014	5958

In [42]:
```
#8. Further Insights
mergedGroup3=merged.groupby('year')[['sentiment']].mean()
mergedGroup3.rename(columns={'sentiment':'Average sentiment score'},inp
mergedGroup3.sort_values('Average sentiment score',ascending=False,inpl
mergedGroup3.head() # Top 5 year having highest average sentiment score
```

Out[42]:

year	Average sentiment score
2011	0.408462
2018	0.391177
2013	0.379784
2012	0.379170
2017	0.377514

In [43]:
```
#9. Further Insights
mergedGroup4=merged.groupby('reviewer_name')[['reviewer_id']].count()
mergedGroup4.rename(columns={'reviewer_id':'No of Reviews'},inplace=Tru
mergedGroup4.sort_values('No of Reviews',ascending=False,inplace=True)
mergedGroup4.head() # Top 5 reviewers based on No of reviews
```

Out[43]:

reviewer_name	No of Reviews
Sarah	1632
Michael	1325
David	1307
Emily	1163
John	1152

In [44]:
```
#10 Further insights
mergedGroup5=merged.groupby('year').agg(
             No_Of_Reviews=('review_id','count'),
             Sentiment_Score_Mean=('sentiment', 'mean'))
mergedGroup5.sort_values('No_Of_Reviews',ascending=False,inplace=True)
mergedGroup5.head() #Review count and Average sentiment score per year
```

Out[44]:

year	No_Of_Reviews	Sentiment_Score_Mean
2018	59610	0.391177
2017	39914	0.377514
2016	23118	0.371100
2015	15658	0.369193
2014	5958	0.367382

In [45]:
```
#11 Further insights
mergedGroup6=merged.groupby('zipcode').agg(
             No_Of_Reviews=('review_id','count'),
             Sentiment_Score_Mean=('sentiment', 'mean'))
mergedGroup6.sort_values('No_Of_Reviews',ascending=False,inplace=True)
mergedGroup6.head() # Top 5 zipcodes having highest No. of reviews and
```

Out[45]:

zipcode	No_Of_Reviews	Sentiment_Score_Mean
28806	46772	0.384252
28801	39344	0.376310
28803	18530	0.389688
28805	17131	0.376346
28804	15666	0.377582

In [46]:
```
#11 Further insights
mergedGroup7=merged.groupby('zipcode').agg(
             Sentiment_Score_Mean=('sentiment', 'mean'))
mergedGroup7.sort_values('Sentiment_Score_Mean',ascending=False,inplace
mergedGroup7.head() # Top 5 zipcodes in descending order of Average sen
```

Out[46]:

zipcode	Sentiment_Score_Mean
28815	0.437857
28732	0.392697
28803	0.389688
0	0.385625
28806	0.384252

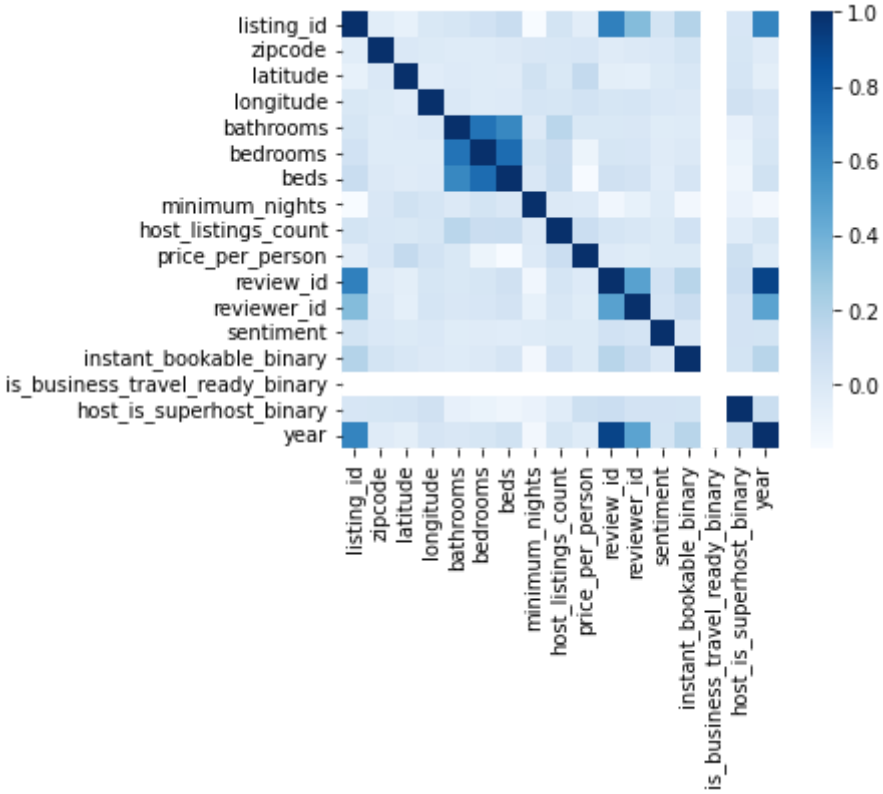
In [16]:
```
#B. running regression model to find out correlation between review sen
merged.corr()
```

Out[16]:

	listing_id	zipcode	latitude	longitude	bathrooms	bedrooms	beds	mi
listing_id	1.000000	-0.042081	-0.078539	0.004294	0.020234	0.054055	0.103379	
zipcode	-0.042081	1.000000	-0.001271	-0.015303	-0.025918	-0.023857	-0.011147	
latitude	-0.078539	-0.001271	1.000000	-0.036619	-0.019855	-0.022368	-0.030444	
longitude	0.004294	-0.015303	-0.036619	1.000000	-0.001133	-0.023790	-0.017681	
bathrooms	0.020234	-0.025918	-0.019855	-0.001133	1.000000	0.695541	0.605362	
bedrooms	0.054055	-0.023857	-0.022368	-0.023790	0.695541	1.000000	0.728002	
beds	0.103379	-0.011147	-0.030444	-0.017681	0.605362	0.728002	1.000000	
minimum_nights	-0.172713	0.009233	0.059826	0.031294	-0.009069	0.040210	0.008730	
host_listings_count	0.038915	0.010652	0.003392	0.021971	0.164730	0.098700	0.104487	
price_per_person	-0.047145	0.015280	0.125577	0.049678	0.003704	-0.104026	-0.166355	
review_id	0.639510	-0.029567	-0.049275	0.021070	0.005433	0.023901	0.063016	
reviewer_id	0.341550	-0.010659	-0.061874	0.029758	0.008580	0.016187	0.043226	
sentiment	0.041129	-0.002087	-0.014592	0.000526	-0.031878	-0.028017	-0.037566	
year	0.620539	-0.026941	-0.050081	0.026502	0.008229	0.023709	0.060082	

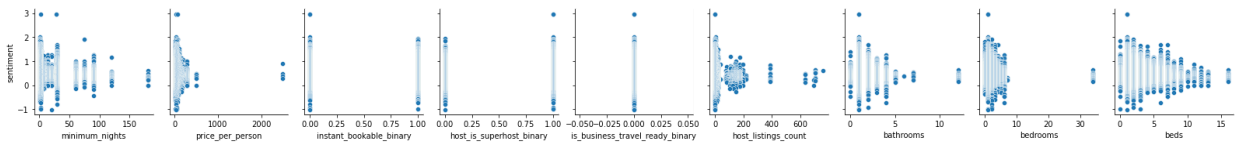
In [47]:
```
import seaborn as sns
corrmat = merged.corr()
sns.heatmap(corrmat, square = True, annot=False, cmap="Blues") # Blues,
```

Out[47]: <AxesSubplot:>



In [56]:
```
#pairplot to show sentiment vs various independent variables
sns.pairplot(data=merged, y_vars=['sentiment'], x_vars=['minimum_nights
```

Out[56]: <seaborn.axisgrid.PairGrid at 0x7fbbf4ec31f0>



In [57]:
```
merged.isnull().sum()
merged = merged.dropna(how='any')
merged.shape
# statsmodels:
import statsmodels.api as sm

Y1=merged['sentiment']
X1=merged[['minimum_nights','price_per_person','host_listings_count','i
X1=sm.add_constant(X1)
X1
model1 = sm.OLS(Y1, X1)
results1 = model1.fit()
results1.summary()
```

```
/opt/anaconda3/lib/python3.9/site-packages/statsmodels/tsa/tsatools.py:14
2: FutureWarning: In a future version of pandas all arguments of concat e
xcept for the argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

Out[57]:

OLS Regression Results

Dep. Variable:	sentiment	**R-squared:**	0.004
Model:	OLS	**Adj. R-squared:**	0.004
Method:	Least Squares	**F-statistic:**	73.78
Date:	Wed, 07 Sep 2022	**Prob (F-statistic):**	5.30e-122
Time:	01:18:40	**Log-Likelihood:**	37634.
No. Observations:	147163	**AIC:**	-7.525e+04
Df Residuals:	147154	**BIC:**	-7.516e+04
Df Model:	8		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.3885	0.002	204.981	0.000	0.385	0.392
minimum_nights	-0.0003	4.56e-05	-6.981	0.000	-0.000	-0.000
price_per_person	-0.0002	2.01e-05	-8.025	0.000	-0.000	-0.000
host_listings_count	-0.0001	4.69e-05	-3.003	0.003	-0.000	-4.9e-05
instant_bookable_binary	0.0014	0.001	1.383	0.167	-0.001	0.003
host_is_superhost_binary	0.0168	0.001	14.641	0.000	0.015	0.019
is_business_travel_ready_binary	2.636e-17	4.77e-19	55.222	0.000	2.54e-17	2.73e-17
bathrooms	-0.0056	0.002	-3.600	0.000	-0.009	-0.003
bedrooms	0.0019	0.001	2.210	0.027	0.000	0.004
beds	-0.0053	0.001	-8.694	0.000	-0.006	-0.004

Omnibus:	28958.948	**Durbin-Watson:**	0.008
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	123372.829
Skew:	0.917	**Prob(JB):**	0.00
Kurtosis:	7.094	**Cond. No.**	1.36e+18

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.66e-28. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

From the above regression, we can note that :

1. R squared value is very low at 0.004, which means the dependent variables are not able to explain the variance in the independent variable and can only explain 0.4% of the variance.
2. the column - 'instant_bookable_binary' is not a good fit to the model as it contains the value '0' within the interval of [0.025 - 0.975], which is the 95% confidence interval.
3. our Covariance type is 'nonrobust', which means we cannot minimize or eliminate variables.
4. for 5 of our independent variables, the coefficient of regression is NEGATIVE, which means if these variables increase, sentiment DECREASES and vice versa. (negative correlation)
5. for 3 of our independent variables, the coefficient of regression is POSITIVE, which means if these variables increase, sentiment INCREASES and vice versa (positive correlation)

In [63]:
```
#taking sample of the original data set

sampleMerged = merged.sample(frac=0.1, replace=False, random_state=1) #
sampleMerged.head()

Y2=sampleMerged['sentiment']
X2=sampleMerged[['minimum_nights','price_per_person','host_listings_cou
X2=sm.add_constant(X2)

model2 = sm.OLS(Y2, X2)
results2 = model2.fit()
results2.summary() #taking 10% fraction, R squared increased to 0.006 f
```

```
/opt/anaconda3/lib/python3.9/site-packages/statsmodels/tsa/tsatools.py:14
2: FutureWarning: In a future version of pandas all arguments of concat e
xcept for the argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

Out[63]:

OLS Regression Results

Dep. Variable:	sentiment	**R-squared:**	0.006
Model:	OLS	**Adj. R-squared:**	0.005
Method:	Least Squares	**F-statistic:**	10.18
Date:	Wed, 07 Sep 2022	**Prob (F-statistic):**	2.77e-14
Time:	01:20:55	**Log-Likelihood:**	3700.9
No. Observations:	14716	**AIC:**	-7384.
Df Residuals:	14707	**BIC:**	-7316.
Df Model:	8		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.3849	0.006	62.449	0.000	0.373	0.397
minimum_nights	-0.0003	0.000	-2.350	0.019	-0.001	-5.54e-05
price_per_person	-0.0002	7.48e-05	-2.936	0.003	-0.000	-7.3e-05
host_listings_count	-0.0003	0.000	-1.940	0.052	-0.001	2.73e-06
instant_bookable_binary	0.0031	0.003	0.973	0.330	-0.003	0.009
host_is_superhost_binary	0.0203	0.004	5.560	0.000	0.013	0.027
is_business_travel_ready_binary	-1.806e-18	6.61e-18	-0.273	0.785	-1.48e-17	1.12e-17
bathrooms	-0.0012	0.005	-0.240	0.811	-0.011	0.009
bedrooms	0.0019	0.003	0.704	0.481	-0.003	0.007
beds	-0.0069	0.002	-3.630	0.000	-0.011	-0.003

Omnibus:	2816.930	**Durbin-Watson:**	1.987

Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	10380.444
Skew:	0.931	**Prob(JB):**	0.00
Kurtosis:	6.669	**Cond. No.**	1.34e+18

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.6e-29. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

In [119]:

```
dummyData = pd.get_dummies(merged, columns=['room_type','property_type'
dummyData['instant_bookable_binary']=np.where(dummyData.instant_bookabl
dummyData['is_business_travel_ready_binary']=np.where(dummyData.is_busi
dummyData['host_is_superhost_binary']=np.where(dummyData.host_is_superh

dummyData.fillna({'bathrooms':dummyData['bathrooms'].mean(),'beds':dumm
dummyData.dropna(how='any', inplace=True)
dummyData.columns


Y10=dummyData['sentiment']
X10=dummyData[['minimum_nights','price_per_person','host_listings_count
       'property_type_Bed and breakfast', 'property_type_Boutique hotel
       'property_type_Bungalow', 'property_type_Cabin',
       'property_type_Camper/RV', 'property_type_Campsite',
       'property_type_Chalet', 'property_type_Condominium',
       'property_type_Cottage', 'property_type_Earth House',
       'property_type_Entire apartment', 'property_type_Entire bungalow
       'property_type_Entire cabin', 'property_type_Entire chalet',
       'property_type_Entire condominium',
       'property_type_Entire condominium (condo)',
       'property_type_Entire cottage', 'property_type_Entire guest suit
       'property_type_Entire guesthouse', 'property_type_Entire house',
       'property_type_Entire loft', 'property_type_Entire place',
       'property_type_Entire rental unit',
       'property_type_Entire residential home',
       'property_type_Entire townhouse', 'property_type_Entire vacation
       'property_type_Farm stay', 'property_type_Guest suite',
       'property_type_Guesthouse', 'property_type_House',
       'property_type_In-law', 'property_type_Loft', 'property_type_Oth
       'property_type_Private room', 'property_type_Private room in apa
       'property_type_Private room in bed and breakfast',
       'property_type_Private room in bungalow',
       'property_type_Private room in cabin',
       'property_type_Private room in castle',
       'property_type_Private room in condominium',
       'property_type_Private room in condominium (condo)',
       'property_type_Private room in cottage',
       'property_type_Private room in farm stay',
       'property_type_Private room in guest suite',
       'property_type_Private room in house',
       'property_type_Private room in loft',
       'property_type_Private room in rental unit',
       'property_type_Private room in residential home',
       'property_type_Private room in townhouse',
       'property_type_Room in bed and breakfast',
       'property_type_Room in boutique hotel', 'property_type_Room in h
       'property_type_Shared room in hostel',
       'property_type_Shared room in rental unit', 'property_type_Tent'
       'property_type_Tiny house', 'property_type_Townhouse',
       'property_type_Treehouse', 'property_type_Yurt']]

X10=sm.add_constant(X10)
X10
model1 = sm.OLS(Y10, X10)
results10 = model1.fit()
```

```
57 results10.summary()
```

breakfast						
property_type_Room in boutique hotel	3.696e+09	1.51e+09	2.453	0.014	7.43e+08	6.65e+09
property_type_Room in hotel	5.453e+08	2.22e+08	2.453	0.014	1.1e+08	9.81e+08
property_type_Shared room in hostel	5.453e+08	2.22e+08	2.453	0.014	1.1e+08	9.81e+08
property_type_Shared room in rental unit	3.455e-36	2.8e-36	1.232	0.218	-2.04e-36	8.95e-36
property_type_Tent	5.453e+08	2.22e+08	2.453	0.014	1.1e+08	9.81e+08
property_type_Tiny house	5.453e+08	2.22e+08	2.453	0.014	1.1e+08	9.81e+08
property_type_Townhouse	5.453e+08	2.22e+08	2.453	0.014	1.1e+08	9.81e+08
property_type_Treehouse	5.453e+08	2.22e+08	2.453	0.014	1.1e+08	9.81e+08
property_type_Yurt	5.453e+08	2.22e+08	2.453	0.014	1.1e+08	9.81e+08

In the above attempt, I tried to create a dummy dataframe using get_dummies() function from pandas to create binary values for each category in property_type and room_type. Finally, I added all these independent variables to my regression model in an attempt to find a better R squared value.

Result: R squared improved from 0.004 to 0.010, now explaining 1% of variance in this data set.

In [76]:
```
#Natural log on sentiment
#To take natural log, adding the sentiment column entirely by integer '
merged.sentiment = merged.sentiment + 2
merged['SentimentLog'] = np.log(merged['sentiment'])
Y4=merged['SentimentLog']
X4=merged[['minimum_nights','price_per_person','host_listings_count','i

X4=sm.add_constant(X4)
model4 = sm.OLS(Y4, X4)
results4 = model4.fit()
results4.summary()
```

```
/opt/anaconda3/lib/python3.9/site-packages/statsmodels/tsa/tsatools.py:14
2: FutureWarning: In a future version of pandas all arguments of concat e
xcept for the argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

Out[76]:

OLS Regression Results

Dep. Variable:	SentimentLog	**R-squared:**	0.004
Model:	OLS	**Adj. R-squared:**	0.004
Method:	Least Squares	**F-statistic:**	75.08
Date:	Wed, 07 Sep 2022	**Prob (F-statistic):**	3.15e-124
Time:	01:35:37	**Log-Likelihood:**	3.1201e+05
No. Observations:	147163	**AIC:**	-6.240e+05
Df Residuals:	147154	**BIC:**	-6.239e+05
Df Model:	8		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	1.8540	0.000	6311.663	0.000	1.853	1.855
minimum_nights	-4.868e-05	7.07e-06	-6.884	0.000	-6.25e-05	-3.48e-05
price_per_person	-2.453e-05	3.11e-06	-7.889	0.000	-3.06e-05	-1.84e-05
host_listings_count	-2.276e-05	7.27e-06	-3.129	0.002	-3.7e-05	-8.51e-06
instant_bookable_binary	0.0002	0.000	1.167	0.243	-0.000	0.000
host_is_superhost_binary	0.0027	0.000	14.990	0.000	0.002	0.003
is_business_travel_ready_binary	2.328e-17	1.74e-19	134.149	0.000	2.29e-17	2.36e-17
bathrooms	-0.0009	0.000	-3.632	0.000	-0.001	-0.000
bedrooms	0.0003	0.000	2.253	0.024	3.94e-05	0.001
beds	-0.0008	9.41e-05	-8.729	0.000	-0.001	-0.001

Omnibus:	21198.581	**Durbin-Watson:**	0.008
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	78646.161

Skew:	0.700	**Prob(JB):**	0.00
Kurtosis:	6.296	**Cond. No.**	8.03e+18

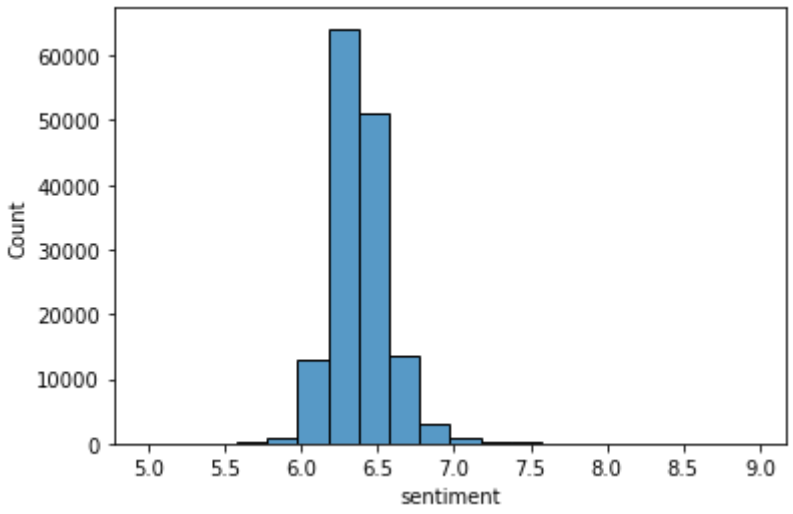
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 4.8e-30. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

In the above atempt, I took the log of the dependent variable - sentiment - in an attempt to get a better R Squared value. As sentiment values were negative, I had to add numeric 2 to all entries in the sentiment column as maximum negative value was greater than -2, hence if we add 2 to the entire column, all values in the column would be positive.

Result: there was no improvement in R squared value and it was still at 0.004

In [82]:
```
1 sns.histplot(data=merged, x="sentiment", bins=20)
```

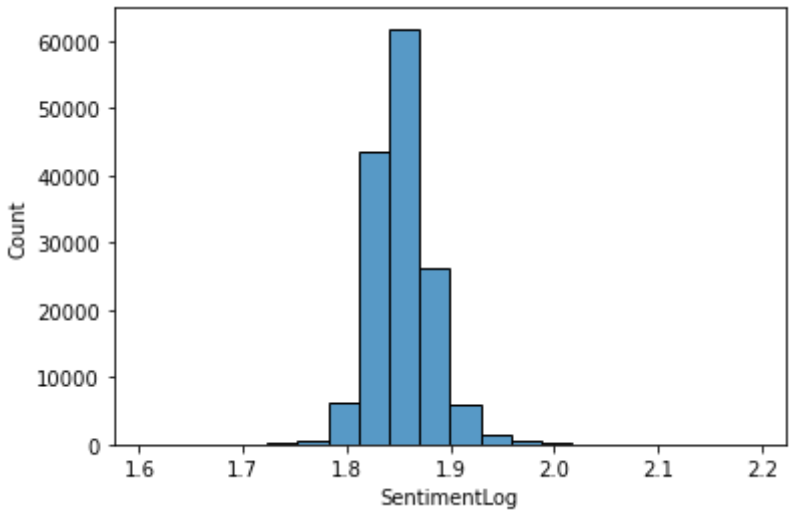
Out[82]:
```
<AxesSubplot:xlabel='sentiment', ylabel='Count'>
```



Histogram showing sentiment score in bins of 20

In [83]:
```
1 sns.histplot(data=merged, x="SentimentLog", bins=20)
```

Out[83]: <AxesSubplot:xlabel='SentimentLog', ylabel='Count'>



Histogram showing the LOG of sentiment score in bins of 20