This data analysis is on a dataset from Data Camp which is centered on data gotten from chocolate bars from different country of origin, stating the bar name, bean origin,cocopa percent, ratings, reviews, amongst others.

First, we import our packages to use

In [2]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from datetime import datetime
import dateutil.parser

pd.set_option('display.max_columns', 15)
pd.set_option('expand_frame_repr', True)

sns.set_palette('hls')
%matplotlib inline
```

Lets read in the data

In [3]:
```
chocolate_bars = pd.read_csv('chocolate_bars.csv', index_col= 'id', parse_dates=T
chocolate_bars
```

Out[3]:

	manufacturer	company_location	year_reviewed	bean_origin	bar_name	cocoa_percent
id						
2454	5150	U.S.A.	2019	Tanzania	Kokoa Kamili, batch 1	76.0
2458	5150	U.S.A.	2019	Dominican Republic	Zorzal, batch 1	76.0
2454	5150	U.S.A.	2019	Madagascar	Bejofo Estate, batch 1	76.0
2542	5150	U.S.A.	2021	Fiji	Matasawalevu, batch 1	68.0
2546	5150	U.S.A.	2021	Venezuela	Sur del Lago, batch 1	72.0
...	...	...	...	...	...	...
1205	Zotter	Austria	2014	Blend	Raw	80.0
1996	Zotter	Austria	2017	Colombia	APROCAFA, Acandi	75.0
2036	Zotter	Austria	2018	Blend	Dry Aged, 30 yr Anniversary bar	75.0
2170	Zotter	Austria	2018	Congo	Mountains of the Moon	70.0
2170	Zotter	Austria	2018	Belize	Maya Mtn	72.0

2530 rows × 10 columns

Lets now clean our data; checking the info, missing values and duplicates, lets drop the missing values, duplicates and check the measures of central tendency

In [3]:
```
chocolate_bars.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2530 entries, 2454 to 2170
Data columns (total 10 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   manufacturer      2530 non-null   object 
 1   company_location  2530 non-null   object 
 2   year_reviewed     2530 non-null   int64  
 3   bean_origin       2530 non-null   object 
 4   bar_name          2530 non-null   object 
 5   cocoa_percent     2530 non-null   float64
 6   num_ingredients   2443 non-null   float64
 7   ingredients       2443 non-null   object 
 8   review            2530 non-null   object 
 9   rating            2530 non-null   float64
dtypes: float64(3), int64(1), object(6)
memory usage: 217.4+ KB
```

In [4]:
```
#dropping the missing values
cb1= chocolate_bars.dropna()
cb1
```

Out[4]:

	manufacturer	company_location	year_reviewed	bean_origin	bar_name	cocoa_percent
id						
2454	5150	U.S.A.	2019	Tanzania	Kokoa Kamili, batch 1	76.0
2458	5150	U.S.A.	2019	Dominican Republic	Zorzal, batch 1	76.0
2454	5150	U.S.A.	2019	Madagascar	Bejofo Estate, batch 1	76.0
2542	5150	U.S.A.	2021	Fiji	Matasawalevu, batch 1	68.0
2546	5150	U.S.A.	2021	Venezuela	Sur del Lago, batch 1	72.0
...	...	...	...	...	...	...
1205	Zotter	Austria	2014	Blend	Raw	80.0
1996	Zotter	Austria	2017	Colombia	APROCAFA, Acandi	75.0
2036	Zotter	Austria	2018	Blend	Dry Aged, 30 yr Anniversary bar	75.0
2170	Zotter	Austria	2018	Congo	Mountains of the Moon	70.0
2170	Zotter	Austria	2018	Belize	Maya Mtn	72.0

2443 rows × 10 columns

In [19]:
```
#dropping the duplicates as well
cb2= cb1.drop_duplicates()
cb2
```

Out[19]:

	manufacturer	company_location	year_reviewed	bean_origin	bar_name	cocoa_percen
id						
2454	5150	U.S.A.	2019	Tanzania	Kokoa Kamili, batch 1	76.(
2458	5150	U.S.A.	2019	Dominican Republic	Zorzal, batch 1	76.(
2454	5150	U.S.A.	2019	Madagascar	Bejofo Estate, batch 1	76.(
2542	5150	U.S.A.	2021	Fiji	Matasawalevu, batch 1	68.(
2546	5150	U.S.A.	2021	Venezuela	Sur del Lago, batch 1	72.(
...	...	...	...	...	...	..

Our data is better now, no more missing values and duplicates. We can now use this data to gain insights

In [8]:
```
#checking the measures of central tendecies to see what we can depict from our da
cb2.describe()
```

Out[8]:

	year_reviewed	cocoa_percent	num_ingredients	rating
count	2443.000000	2443.000000	2443.000000	2443.00000
mean	2014.485878	71.496725	3.041343	3.21009
std	3.957507	5.156974	0.913728	0.42837
min	2006.000000	42.000000	1.000000	1.00000
25%	2012.000000	70.000000	2.000000	3.00000
50%	2015.000000	70.000000	3.000000	3.25000
75%	2018.000000	74.000000	4.000000	3.50000
max	2021.000000	100.000000	6.000000	4.00000

In [9]:
```
#checking for the categorical data as well
cd=cb2.dtypes[cb2.dtypes=='object'].index
cb2[cd].describe()
```

Out[9]:

	manufacturer	company_location	bean_origin	bar_name	ingredients	review
count	2443	2443	2443	2443	2443	2443
unique	542	67	62	1567	21	2403
top	Soma	U.S.A.	Venezuela	Madagascar	B,S,C	spicy, cocoa
freq	56	1118	246	52	999	4

Now,lets answer the questions

In [12]:
```
#1; Average rating by country of origin; we use 'groupby' here
avr= cb2.groupby('bean_origin').rating.mean()
avr
```

Out[12]:
```
bean_origin
Australia    3.250000
Belize       3.243243
Blend        3.085069
Bolivia      3.180380
Brazil       3.259740
               ...
U.S.A.       3.217742
Uganda       3.097222
Vanuatu      3.062500
Venezuela    3.239837
Vietnam      3.287671
Name: rating, Length: 62, dtype: float64
```

In [14]:
```
#to reset the index, morelike to make the outpt a dataframe to aid plots
avr2=avr.reset_index()
avr2
```

Out[14]:

	bean_origin	rating
0	Australia	3.250000
1	Belize	3.243243
2	Blend	3.085069
3	Bolivia	3.180380
4	Brazil	3.259740
...	...	...
57	U.S.A.	3.217742
58	Uganda	3.097222
59	Vanuatu	3.062500
60	Venezuela	3.239837
61	Vietnam	3.287671

62 rows × 2 columns

In [64]:
```
#2; Bars reviewed by country
bars_reviewed= cb2.groupby('bean_origin').bar_name.count()
bars_reviewed
```

Out[64]:
```
bean_origin
Australia      3
Belize        74
Blend        144
Bolivia       79
Brazil        77
            ...
U.S.A.        31
Uganda        18
Vanuatu       12
Venezuela    246
Vietnam       73
Name: bar_name, Length: 62, dtype: int64
```

In [65]:
```
#we also reset index here to allow for easy plots
bars_reviewed2= cb2.groupby('bean_origin').bar_name.count().reset_index()
bars_reviewed2
```

Out[65]:

	bean_origin	bar_name
0	Australia	3
1	Belize	74
2	Blend	144
3	Bolivia	79
4	Brazil	77
...	...	...
57	U.S.A.	31
58	Uganda	18
59	Vanuatu	12
60	Venezuela	246
61	Vietnam	73

62 rows × 2 columns

In [66]:
```
bars_reviewed2.rename(columns={'bar_name':'total_bars'},inplace=True)
bars_reviewed2
```

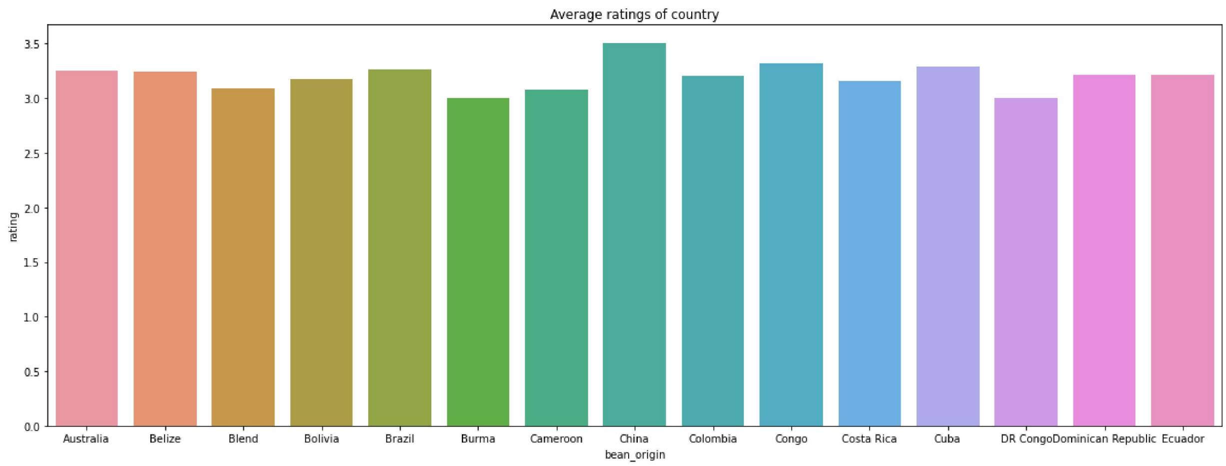
Out[66]:

	bean_origin	total_bars
0	Australia	3
1	Belize	74
2	Blend	144
3	Bolivia	79
4	Brazil	77
...	...	...
57	U.S.A.	31
58	Uganda	18
59	Vanuatu	12
60	Venezuela	246
61	Vietnam	73

62 rows × 2 columns

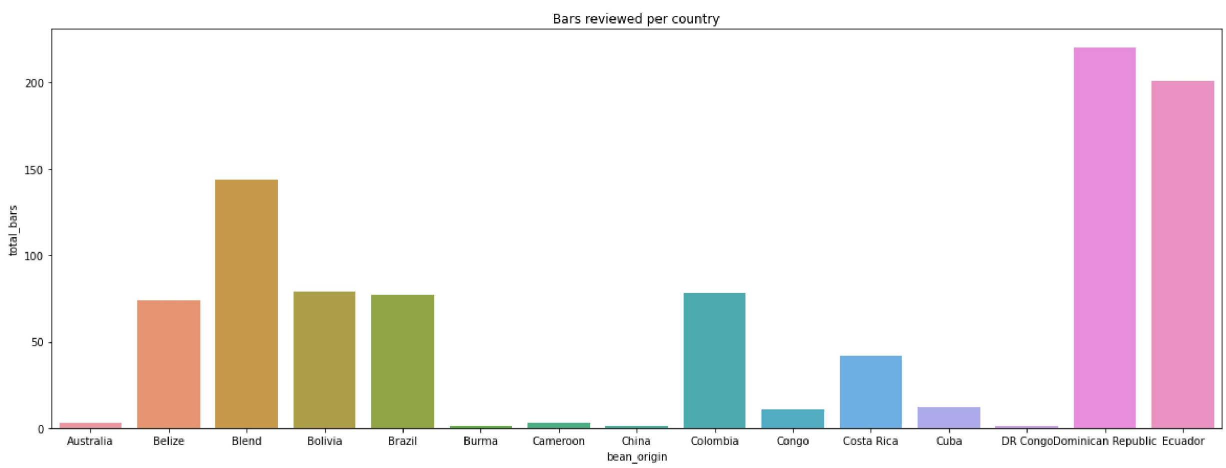
In [67]:
```
#3: Graph for question 1
plt.figure(figsize=(20,7))
plt.title('Average ratings of country')
sns.barplot(x='bean_origin', y='rating', data=avr2[0:15])
```

Out[67]:
```
<AxesSubplot:title={'center':'Average ratings of country'}, xlabel='bean_origi
n', ylabel='rating'>
```



In [68]:
```
#3b; Graph for question 2
plt.figure(figsize=(20,7))
plt.title('Bars reviewed per country')
sns.barplot(x='bean_origin', y='total_bars', data=bars_reviewed2[0:15])
```

Out[68]:
```
<AxesSubplot:title={'center':'Bars reviewed per country'}, xlabel='bean_origi
n', ylabel='total_bars'>
```



To check for the quality of the chocolate bars, the cocoa percent and the rating could be said to inform the quality. However, it is pertinent to check the relationship between these two variables to know if they can be used independently of each other. Since the whole data cannot be used at once, we will extract the chocolate bars with higher ratings (rating > 3.5) or with higher cocoa percentage (cocoa_percent >=75%) to determine this correlation.

In [28]:
```
#4; cocoa bean origin an indicator for quality?
#extracting chocolate bars with a rating above 3.5
cbr= cb2.loc[(cb2.rating > 3.5)]
cbr
```

Out[28]:

id	manufacturer	company_location	year_reviewed	bean_origin	bar_name	cocoa_percent	r
2454	5150	U.S.A.	2019	Madagascar	Bejofo Estate, batch 1	76.0	
797	A. Morin	France	2012	Peru	Peru	63.0	
1011	A. Morin	France	2013	Ecuador	Equateur	70.0	
1015	A. Morin	France	2013	Venezuela	Chuao	70.0	
1019	A. Morin	France	2013	Peru	Chanchamayo Province	63.0	
...	...	...	...	...	...	...	
2048	Zoto (Chocolatoa)	Belgium	2018	Nicaragua	El Castillero, batch ca1705, 3 turns	70.0	
647	Zotter	Austria	2011	Peru	Peru	70.0	
875	Zotter	Austria	2012	Dominican Republic	Loma Los Pinos, Yacao region, D.R.	62.0	
879	Zotter	Austria	2012	Dominican Republic	Santo Domingo	70.0	
1996	Zotter	Austria	2017	Colombia	APROCAFA, Acandi	75.0	

406 rows × 10 columns

In [34]:
```
#extracting the chocolate bars with cocoa percent greater or equal to 75
cbc=cb2.loc[(cb2.cocoa_percent >= 75)]
cbc
```

Out[34]:

id	manufacturer	company_location	year_reviewed	bean_origin	bar_name	cocoa_percent	nu
2454	5150	U.S.A.	2019	Tanzania	Kokoa Kamili, batch 1	76.0	
2458	5150	U.S.A.	2019	Dominican Republic	Zorzal, batch 1	76.0	
2454	5150	U.S.A.	2019	Madagascar	Bejofo Estate, batch 1	76.0	
2546	5150	U.S.A.	2021	Uganda	Semuliki Forest, batch 1	80.0	
705	Adi aka Fijiana (Easy In Ltd)	Fiji	2011	Fiji	Vanua Levu, Toto-A	80.0	
...	...	...	...	...	...	...	
1824	Zart Pralinen	Austria	2016	Tanzania	Kakao Kamili, Kilombero Valley	85.0	
1880	Zart Pralinen	Austria	2016	Trinidad	San Juan Estate, Gran Couva	78.0	
1716	Zokoko	Australia	2016	Solomon Islands	Guadalcanal	78.0	
879	Zotter	Austria	2012	Bolivia	El Ceibo Coop	90.0	
1205	Zotter	Austria	2014	Blend	Raw	80.0	

284 rows × 10 columns

In [36]:
```
#extracting chocolate bars with both criteria
cbf=  cb2.loc[
    (cb2.cocoa_percent >=75)
    &(cb2.rating > 3.5)
]
cbf
```

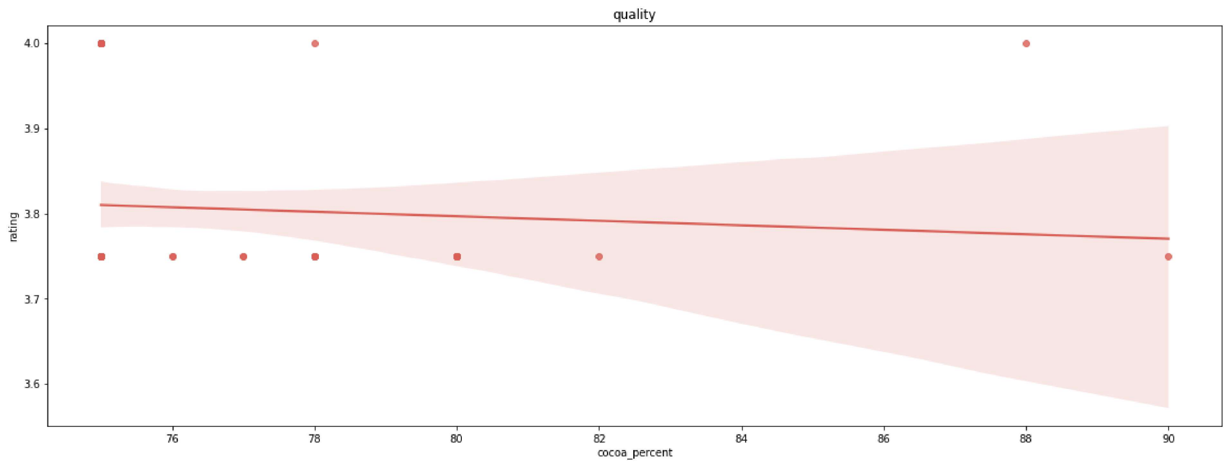
Out[36]:

id	manufacturer	company_location	year_reviewed	bean_origin	bar_name	cocoa_percent	nu
2454	5150	U.S.A.	2019	Madagascar	Bejofo Estate, batch 1	76.0	
636	Akesson's (Pralus)	U.K.	2011	Indonesia	Bali (west), Sukrama Family, Melaya area	75.0	
572	AMMA	Brazil	2010	Brazil	Monte Alegre, 3 diff. plantations	75.0	
331	Askinosie	U.S.A.	2009	Philippines	Davao	77.0	
24	Bonnat	France	2006	Blend	Carribean, Trinite	75.0	
...	...	...	...	...	...	...	
2326	Taste Artisan	U.S.A.	2019	Peru	Piura	75.0	
1117	Videri	U.S.A.	2013	Blend	Dark, Central and S. America	90.0	
1916	Wm	U.S.A.	2016	Ghana	Ghana, 2013, batch 129	75.0	
1716	Zokoko	Australia	2016	Solomon Islands	Guadalcanal	78.0	
1996	Zotter	Austria	2017	Colombia	APROCAFA, Acandi	75.0	

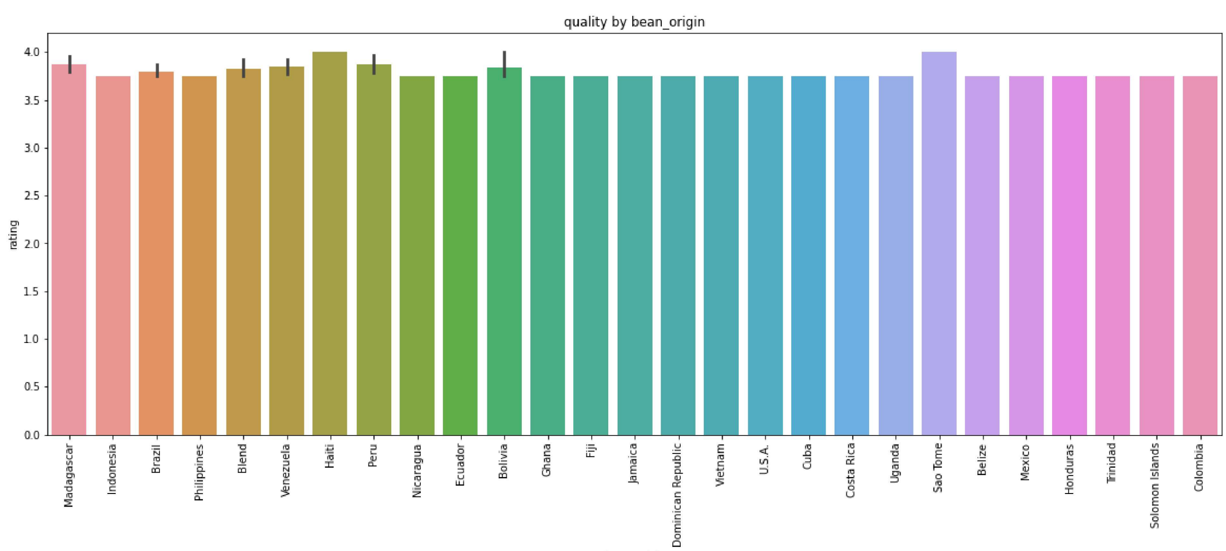
75 rows × 10 columns

In [75]:
```
#visualizing the chocolate bars with both criteria
plt.figure(figsize=(20,7))
plt.title('quality')
sns.regplot(x= 'cocoa_percent', y= 'rating', data=cbf)
```

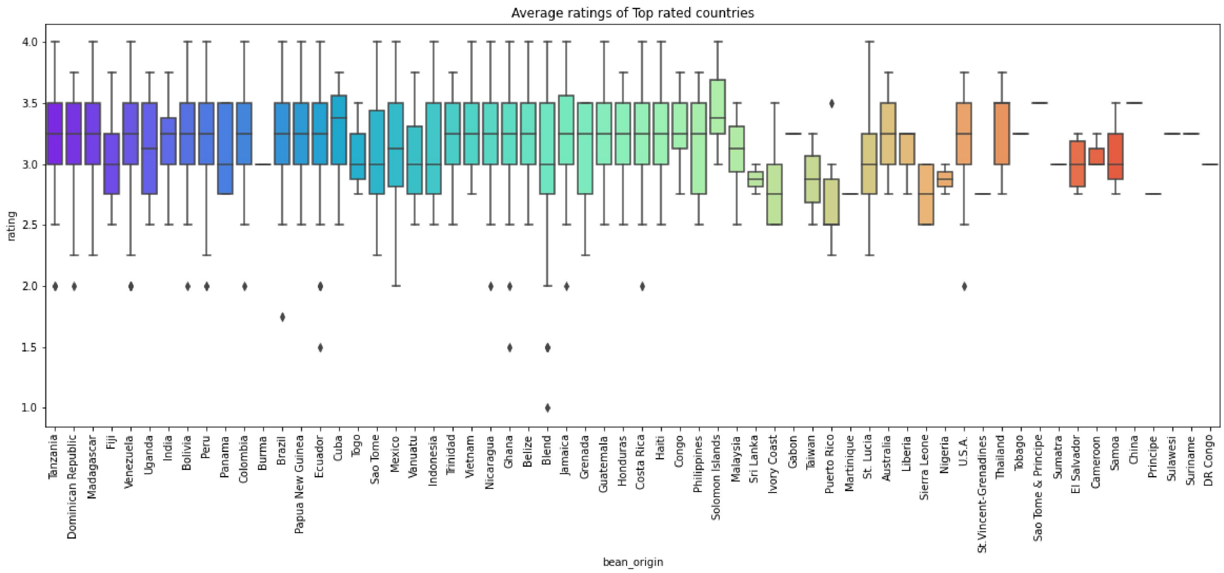
Out[75]:
```
<AxesSubplot:title={'center':'quality'}, xlabel='cocoa_percent', ylabel='ratin
g'>
```



In [44]:
```
plt.figure(figsize=(20,7))
plt.title('quality by bean_origin')
sns.barplot(x= cbf['bean_origin'], y= cbf['rating'])
plt.xticks(rotation=90);
```



In [69]:
```
plt.figure(figsize=(20,7))
plt.title('Average ratings of Top rated countries')
sns.boxplot(x='bean_origin', y='rating', data=cb2, palette= 'rainbow')
plt.xticks(rotation=90);
```



From this visualization above, especially the scatter plot,it shows an insignificant level of correlation which depicts that both variables can be used independent of eachother and that the higher the cocoa percent,the more the quality of the chocolate bars and it was also rated higher as such

In [71]:
```
#from the '.describe' above, it was evident that bean origin 'venezuela' was the
#reasonable to check it straight to check if the bean origin defines the quality

cbv= cb2[cb2.bean_origin== 'Venezuela']
cbv
```

Out[71]:

	manufacturer	company_location	year_reviewed	bean_origin	bar_name	cocoa_percent	n
id							
2546	5150	U.S.A.	2021	Venezuela	Sur del Lago, batch 1	72.0	
1015	A. Morin	France	2013	Venezuela	Chuao	70.0	
1315	A. Morin	France	2014	Venezuela	Carenero, Criollo	70.0	
1315	A. Morin	France	2014	Venezuela	Sur del Lago, Criollo	70.0	
1319	A. Morin	France	2014	Venezuela	Puerto Cabello,	70.0	

In [72]:
```
#to get the information regarding the chocolate bars from Venezuela
cbv.describe()
```

Out[72]:

	year_reviewed	cocoa_percent	num_ingredients	rating
count	246.000000	246.000000	246.000000	246.000000
mean	2012.756098	71.762195	3.162602	3.239837
std	3.823326	4.507290	0.946521	0.458923
min	2006.000000	58.000000	2.000000	2.000000
25%	2010.000000	70.000000	2.000000	3.000000
50%	2013.000000	70.000000	3.000000	3.250000
75%	2015.000000	75.000000	4.000000	3.500000
max	2021.000000	91.000000	5.000000	4.000000

From this table above, it is evident that bean origin doesnt define the quality of the chocolate bars because if it does, it would be expected that the maximum cocoa percent will be 100 which is the maximum of the whole data but this isnt the case

In [70]:
```
#5b; The average cocoa content from chocolate bars with higher ratings (ratings>
cbr.describe()
```

Out[70]:

	year_reviewed	cocoa_percent	num_ingredients	rating
count	406.000000	406.000000	406.000000	406.000000
mean	2014.073892	70.996305	3.029557	3.818350
std	3.991900	3.597065	0.880019	0.111563
min	2006.000000	50.000000	2.000000	3.750000
25%	2011.000000	70.000000	2.000000	3.750000
50%	2014.000000	70.000000	3.000000	3.750000
75%	2017.000000	72.000000	3.000000	4.000000
max	2021.000000	90.000000	5.000000	4.000000

In [73]:
```
#6;Comparethe average rating of bars with and without Lecithin
#first we call out the unique ingredients then proceed to separate those with Lec

cb2.ingredients.unique()
```

Out[73]:
```
array(['B,S,C', 'B,S,C,L', 'B,S', 'B,S,C,V', 'B,S,C,V,L', 'B,S,C,V,L,Sa',
       'B,S,C,V,Sa', 'B,S,V,L', 'B,S*', 'B', 'B,S*,C', 'B,S,L', 'B,S,V',
       'B,S*,C,L', 'B,S*,C,Sa', 'B,S*,Sa', 'B,S,C,Sa', 'B,S*,V,L', 'B,C',
       'B,S*,C,V', 'B,S,C,L,Sa'], dtype=object)
```

In [59]:
```
#lets call out those with Lecithin using the 'isin' command

cbl= cb2.loc[
    (cb2.ingredients.isin(['B,S,C,L', 'B,S,C,V,L', 'B,S,C,V,L,SA', 'B,S,V,L', 'B,
]
cbl
```

Out[59]:

id	manufacturer	company_location	year_reviewed	bean_origin	bar_name	cocoa_percent	nu
797	A. Morin	France	2012	Bolivia	Bolivia	70.0	
797	A. Morin	France	2012	Peru	Peru	63.0	
1011	A. Morin	France	2013	Panama	Panama	70.0	
1015	A. Morin	France	2013	Colombia	Colombie	70.0	
1011	A. Morin	France	2013	Madagascar	Madagascar, Criollo	70.0	
...	...	...	...	...	...	...	
697	Zokoko	Australia	2011	Bolivia	Alto Beni	68.0	
701	Zokoko	Australia	2011	Papua New Guinea	Tokiala	66.0	
701	Zokoko	Australia	2011	Bolivia	Tranquilidad, Baures	72.0	
1780	Zokoko	Australia	2016	Blend	Goddess Blend	65.0	
1716	Zokoko	Australia	2016	Solomon Islands	Guadalcanal	78.0	

489 rows × 10 columns

In [60]:
```
#to see the average rating of chocolate bars with lecithin
cbl.describe()
```

Out[60]:

	year_reviewed	cocoa_percent	num_ingredients	rating
count	489.000000	489.000000	489.000000	489.000000
mean	2012.274029	69.945808	4.361963	3.152352
std	4.277582	6.179987	0.514010	0.486813
min	2006.000000	42.000000	3.000000	1.000000
25%	2009.000000	66.000000	4.000000	2.750000
50%	2012.000000	70.000000	4.000000	3.250000
75%	2015.000000	74.000000	5.000000	3.500000
max	2021.000000	91.000000	5.000000	4.000000

In [61]:
```
# ectracting the chocolate bars without lecithin
cbnl= cb2.loc[
    (cb2.ingredients.isin(['B,S,C', 'B,S', 'B,S,C,V', 'B,S,C,V,SA', 'B,S*', 'B',
]
cbnl
```

Out[61]:

id	manufacturer	company_location	year_reviewed	bean_origin	bar_name	cocoa_percent
2454	5150	U.S.A.	2019	Tanzania	Kokoa Kamili, batch 1	76.0
2458	5150	U.S.A.	2019	Dominican Republic	Zorzal, batch 1	76.0
2454	5150	U.S.A.	2019	Madagascar	Bejofo Estate, batch 1	76.0
2542	5150	U.S.A.	2021	Fiji	Matasawalevu, batch 1	68.0
2546	5150	U.S.A.	2021	Venezuela	Sur del Lago, batch 1	72.0
...	...	...	...	...	...	...
1205	Zotter	Austria	2014	Blend	Raw	80.0
1996	Zotter	Austria	2017	Colombia	APROCAFA, Acandi	75.0
2036	Zotter	Austria	2018	Blend	Dry Aged, 30 yr Anniversary bar	75.0
2170	Zotter	Austria	2018	Congo	Mountains of the Moon	70.0
2170	Zotter	Austria	2018	Belize	Maya Mtn	72.0

1938 rows × 10 columns

In [62]:
```
#To check the average rating of chocolate bars without lecithin
cbnl.describe()
```

Out[62]:

	year_reviewed	cocoa_percent	num_ingredients	rating
count	1938.000000	1938.000000	1938.000000	1938.000000
mean	2015.051600	71.887513	2.693498	3.227038
std	3.680506	4.786860	0.626360	0.411253
min	2006.000000	55.000000	1.000000	1.500000
25%	2012.000000	70.000000	2.000000	3.000000
50%	2015.000000	70.000000	3.000000	3.250000
75%	2018.000000	74.000000	3.000000	3.500000
max	2021.000000	100.000000	4.000000	4.000000

```
In summary, chocolate bars without lecithin was rated higher than those with
lecithin. It means people really preferred their chocolate bars without lecithin
Another insight is that bean origin does not define the quality of the chocolate
bars, the cocoa perceunt does and thus the ratings.
```