```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
pk=pd.read csv('apple quality prediction 1.csv')
pk.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4000 entries, 0 to 3999
Data columns (total 9 columns):
    Column
                 Non-Null Count
                                Dtype
_ _ _
0
    A id
                 4000 non-null
                                int64
1
    Size
                 4000 non-null
                                float64
2
                 4000 non-null
                                float64
    Weight
3
                 4000 non-null
                                float64
    Sweetness
    Crunchiness 4000 non-null
4
                                float64
5
    Juiciness
                 4000 non-null
                                float64
                 4000 non-null
                                float64
    Ripeness
6
    Acidity
7
                 4000 non-null
                                float64
    Quality
                 4000 non-null
                                object
dtypes: float64(7), int64(1), object(1)
memory usage: 281.4+ KB
pk.head(20)
         Size Weight Sweetness Crunchiness Juiciness
   A_id
Ripeness \
      0 -3.970049 -2.512336
                             5.346330
                                         -1.012009
                                                    1.844900
0.329840
      1 -1.195217 -2.839257
                             3.664059
                                          1.588232
                                                     0.853286
0.867530
      2 -0.292024 -1.351282 -1.738429
                                         -0.342616
                                                    2.838636 -
0.038033
      3 -0.657196 -2.271627 1.324874
                                         -0.097875 3.637970 -
3.413761
      4 1.364217 -1.296612 -0.384658
                                         -0.553006
                                                    3.030874 -
1.303849
      5 -3.425400 -1.409082 -1.913511
                                         -0.555775 -3.853071
5
1.914616
      6 1.331606 1.635956
                             0.875974
                                         -1.677798
                                                    3.106344 -
1.847417
      7 -1.995462 -0.428958
                             1.530644
                                         -0.742972
                                                    0.158834
0.974438
      8 -3.867632 -3.734514
                             0.986429
                                         -1.207655
                                                     2.292873
4.080921
      9 -0.727983 -0.442820 -4.092223
                                          0.597513
                                                     0.393714
1.620857
```

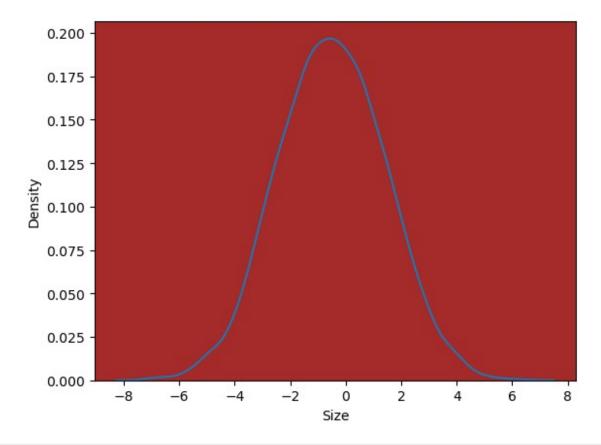
```
10
      10 -2.699336 -1.329507 -1.418507
                                             -0.625546
                                                         2.371074
3.403165
11
      11 2.450960 -0.564177
                               -1.635041
                                              0.942400
                                                         -2.087317
1.214322
      12 -0.170812 -1.867271
                                                         -3.094555 -
                               -1.771845
                                              2.413155
0.624884
13
      13 -1.345531 -1.623701
                                2.044144
                                              1.754813
                                                         0.997567
0.434180
                                              0.894581
                                                         -1.300061
14
      14 2.839581 -0.344798
                               -1.019797
0.582379
15
      15 -2.659887 -2.795684
                                4.230404
                                              0.697550
                                                         2.180911 -
0.088775
16
      16 -1.468952 -1.950360
                               -2.214373
                                              0.909759
                                                         2.864449
3.965956
17
      17 -0.074370 -4.714750
                                0.249768
                                              2.935319
                                                         1.409755 -
2.643810
18
      18 -0.302364 1.724396
                               -2.442337
                                              3.465108
                                                         0.449792 -
0.074362
      19 -2.108050 0.356467
                               -1.156193
                                              4.326723
                                                         1.561543 -
4.630174
     Acidity Quality
0
   -0.491590
                good
   -0.722809
1
                good
2
    2.621636
                 bad
3
    0.790723
                good
    0.501984
4
                good
5
   -2.981523
                 bad
6
   2.414171
                good
7
   -1.470125
                good
8
   -4.871905
                 bad
9
    2.185608
                 bad
10 -2.810808
                 bad
11
   1.294324
                good
12 -2.076114
                 bad
13 1.724026
                good
14 1.709708
                good
15 -1.083621
                good
16 -0.558209
                 bad
   1.250970
17
                good
18 2.493782
                 bad
19 -1.376657
                good
pk.describe()
                            Size
                                       Weight
                                                  Sweetness
                                                             Crunchiness
              A_id
count
       4000.000000
                    4000.000000 4000.000000
                                                4000.000000
                                                              4000.000000
mean
       1999.500000
                       -0.503015
                                     -0.989547
                                                  -0.470479
                                                                 0.985478
```

```
std
       1154.844867
                        1.928059
                                      1.602507
                                                    1.943441
                                                                 1.402757
min
          0.000000
                       -7.151703
                                     -7.149848
                                                   -6.894485
                                                                 -6.055058
25%
        999.750000
                                     -2.011770
                                                   -1.738425
                                                                 0.062764
                       -1.816765
                       -0.513703
                                     -0.984736
50%
       1999.500000
                                                   -0.504758
                                                                 0.998249
75%
       2999.250000
                        0.805526
                                      0.030976
                                                   0.801922
                                                                  1.894234
max
       3999.000000
                        6.406367
                                      5.790714
                                                    6.374916
                                                                 7.619852
         Juiciness
                        Ripeness
                                       Acidity
       4000.000000
                     4000.000000
                                   4000.000000
count
          0.512118
                        0.498277
                                      0.076877
mean
          1.930286
                        1.874427
std
                                      2.110270
min
         -5.961897
                       -5.864599
                                     -7.010538
25%
         -0.801286
                       -0.771677
                                     -1.377424
50%
          0.534219
                        0.503445
                                      0.022609
          1.835976
                        1.766212
                                      1.510493
75%
max
          7.364403
                        7.237837
                                      7.404736
pk.dtypes
A id
                  int64
               float64
Size
Weight
               float64
               float64
Sweetness
Crunchiness
               float64
               float64
Juiciness
Ripeness
               float64
Acidity
               float64
Quality
                object
dtype: object
std=pk.select dtypes(include=['float']).std()
standard_error=std/np.sqrt(len(pk))
std
Size
               1.928059
Weight
               1.602507
Sweetness
               1.943441
Crunchiness
               1.402757
Juiciness
               1.930286
Ripeness
               1.874427
Acidity
               2.110270
dtype: float64
```

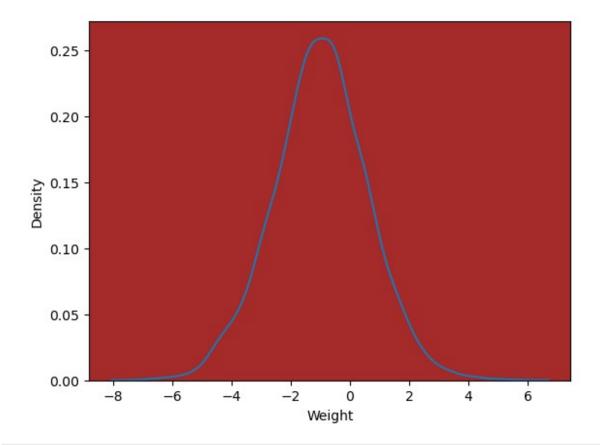
```
standard error
Size
               0.030485
Weight
               0.025338
               0.030728
Sweetness
Crunchiness
               0.022180
Juiciness
               0.030520
               0.029637
Ripeness
Acidity
               0.033366
dtype: float64
```

Data have less variability

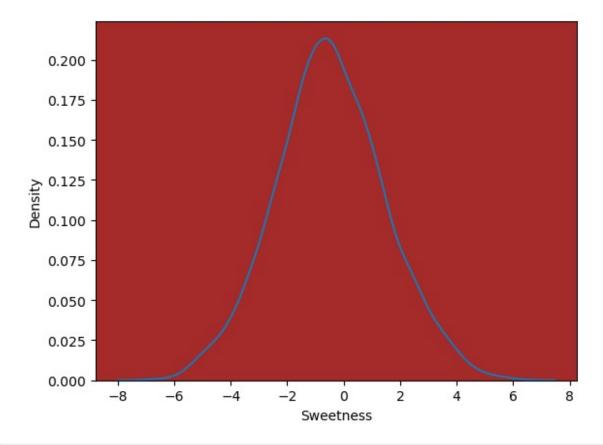
```
pk.select dtypes(include=['float']).skew()
Size
              -0.002437
Weight
               0.003102
Sweetness
               0.083850
Crunchiness
               0.000230
              -0.113421
Juiciness
              -0.008764
Ripeness
              0.055783
Acidity
dtype: float64
pk.select dtypes(include=['float']).kurt()
Size
              -0.083341
Weight
               0.359050
Sweetness
               0.014472
Crunchiness
               0.722020
Juiciness
               0.028735
Ripeness
              -0.071850
Acidity
              -0.093451
dtype: float64
for i in
['Size','Weight','Sweetness','Crunchiness','Juiciness','Ripeness','Aci
dity']:
    sns.kdeplot(data=pk,x=i)
    plt.gca().set facecolor('brown')
    plt.show()
C:\Users\Admin\anaconda3\Lib\site-packages\seaborn\ oldcore.py:1119:
FutureWarning: use inf as na option is deprecated and will be removed
in a future version. Convert inf values to NaN before operating
instead.
 with pd.option context('mode.use inf as na', True):
```



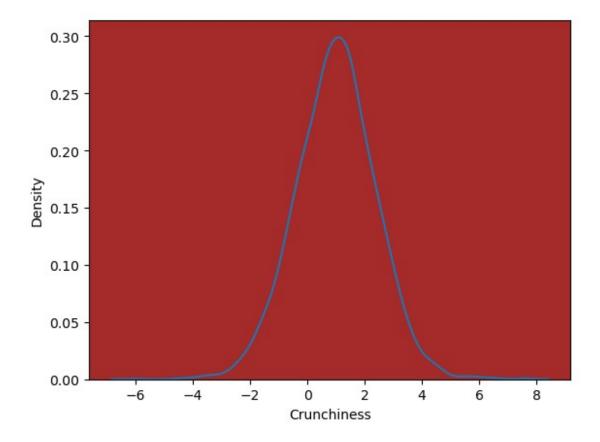
C:\Users\Admin\anaconda3\Lib\site-packages\seaborn_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.



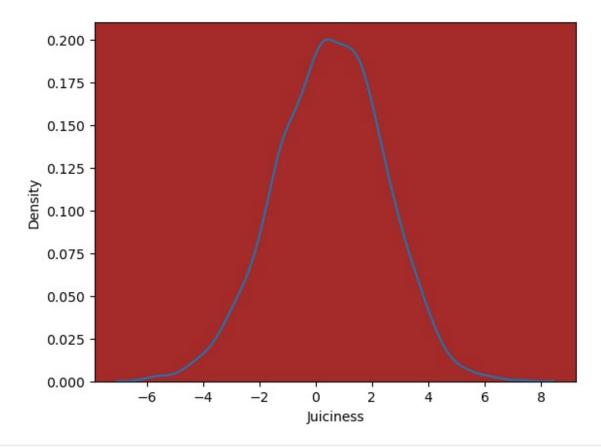
C:\Users\Admin\anaconda3\Lib\site-packages\seaborn_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.



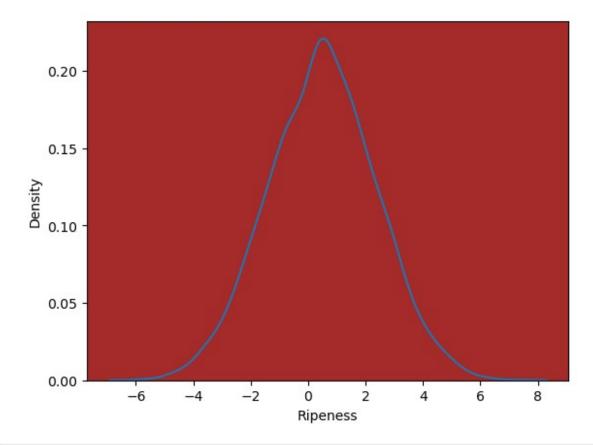
C:\Users\Admin\anaconda3\Lib\site-packages\seaborn_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.



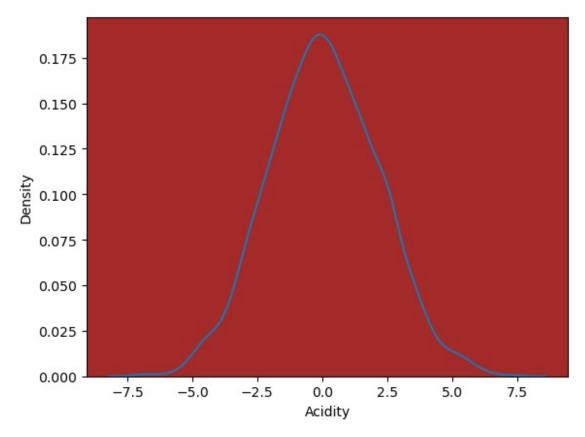
C:\Users\Admin\anaconda3\Lib\site-packages\seaborn_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.



C:\Users\Admin\anaconda3\Lib\site-packages\seaborn_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.

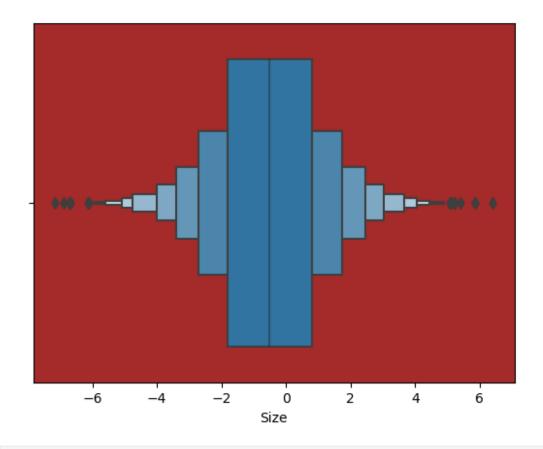


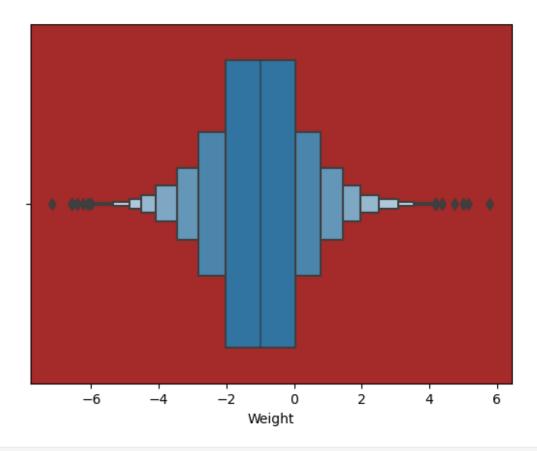
C:\Users\Admin\anaconda3\Lib\site-packages\seaborn_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.

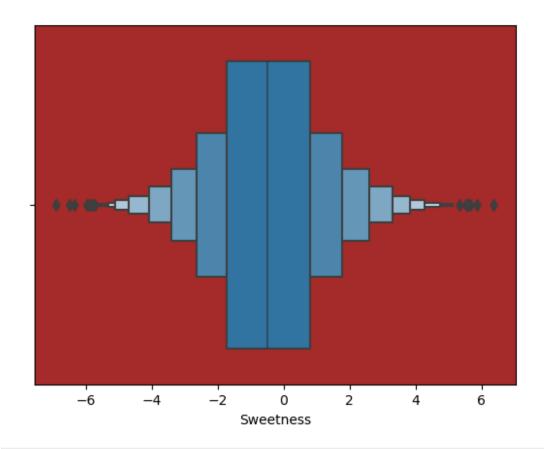


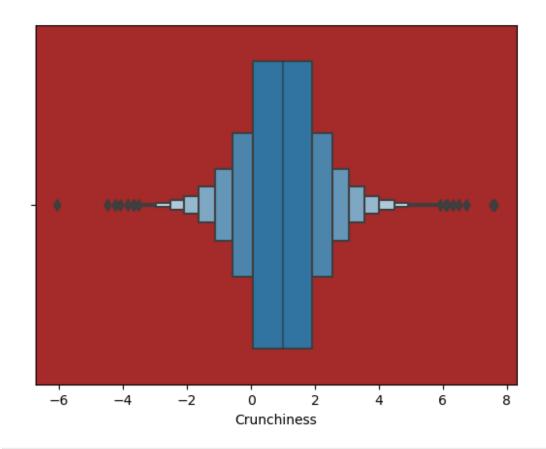
```
for i in
['Size','Weight','Sweetness','Crunchiness','Juiciness','Ripeness','Aci
dity']:
    sns.boxenplot(data=pk,x=i)
    plt.gca().set_facecolor('brown')
    plt.show()

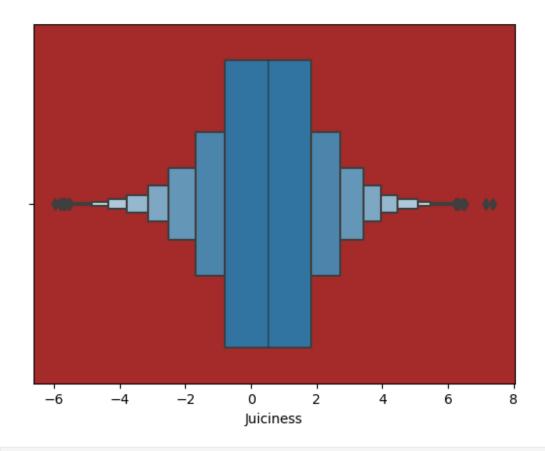
C:\Users\Admin\anaconda3\Lib\site-packages\seaborn\
categorical.py:1794: FutureWarning: use_inf_as_na option is deprecated
and will be removed in a future version. Convert inf values to NaN
before operating instead.
    with pd.option_context('mode.use_inf_as_na', True):
```

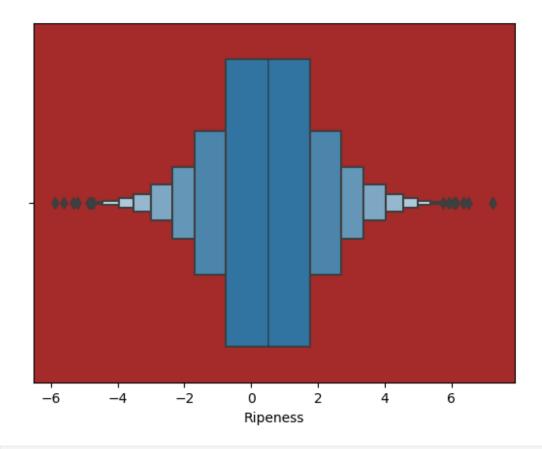


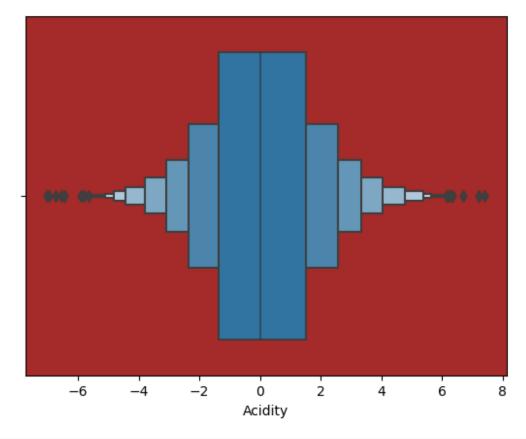






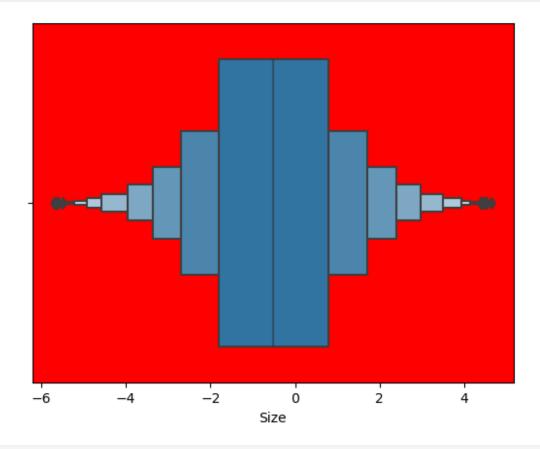




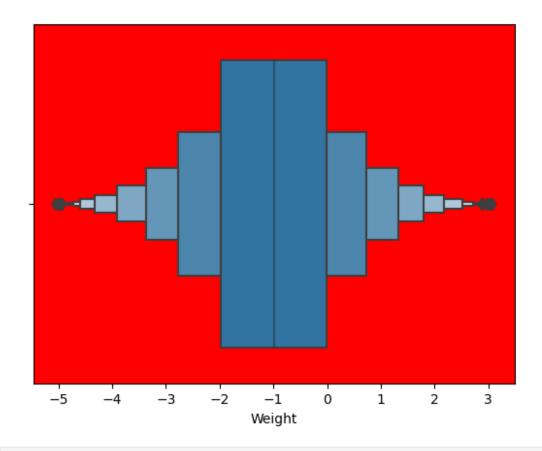


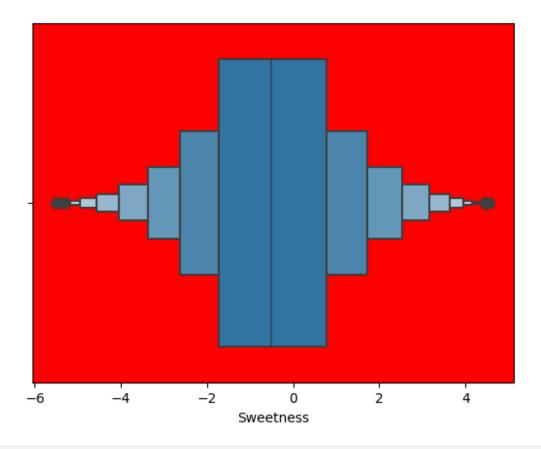
```
def treat_outlier(col):
    Q1=pk[col].quantile(0.25)
    Q3=pk[col].quantile(0.75)
    IQR=Q3-Q1
    UL=Q3+1.5*IQR
    LL=Q1-1.5*IQR
    upperotlier=pk[col]>UL
    loweroutlier=pk[col]<LL</pre>
    median=pk[col].median()
    pk.loc[upperotlier,col]=median
    pk.loc[loweroutlier,col]=median
in['Size','Weight','Sweetness','Crunchiness','Juiciness','Ripeness','A
cidity']:
    treat outlier(i)
for i
in['Size','Weight','Sweetness','Crunchiness','Juiciness','Ripeness','A
cidity']:
    sns.boxenplot(data=pk,x=i)
    plt.gca().set_facecolor('red')
    plt.show()
```

with pd.option context('mode.use inf as na', True):

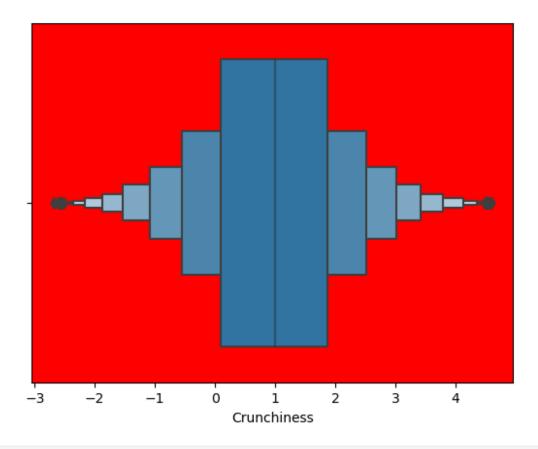


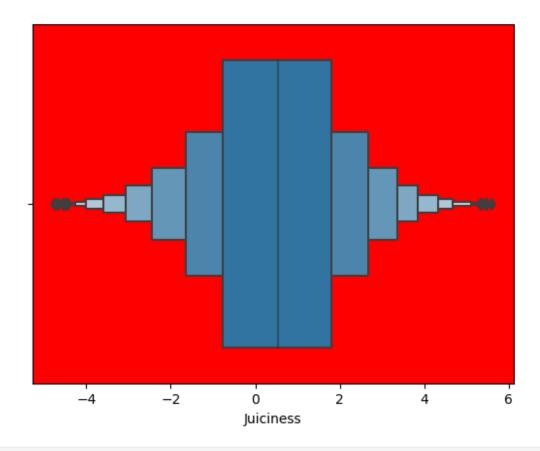
C:\Users\Admin\anaconda3\Lib\site-packages\seaborn\
categorical.py:1794: FutureWarning: use_inf_as_na option is deprecated
and will be removed in a future version. Convert inf values to NaN
before operating instead.

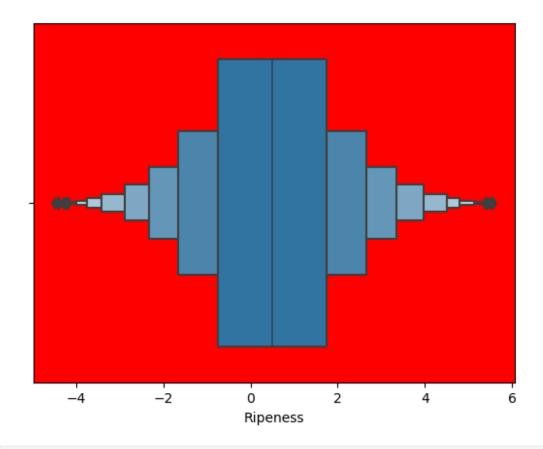


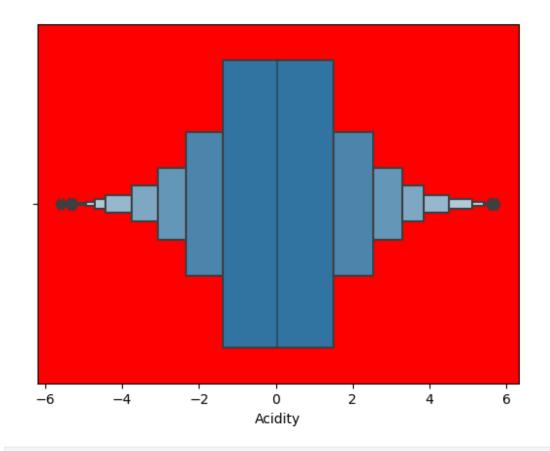


C:\Users\Admin\anaconda3\Lib\site-packages\seaborn\
categorical.py:1794: FutureWarning: use_inf_as_na option is deprecated
and will be removed in a future version. Convert inf values to NaN
before operating instead.









from scipy.stats import zscore zscore(pk.select dtypes(include=['float']))>+3 Size Weight Sweetness Crunchiness Juiciness Ripeness Acidity False 1 False False False False False False False False 3 False 3995 False False False False False False False 3996 False False False False False False False 3997 False False False False False False False

3998	False	False	False	False	False	False
False						
3999	False	False	False	False	False	False
False						

[4000 rows x 7 columns]

zscore(pk.select_dtypes(include=['float']))<-3</pre>

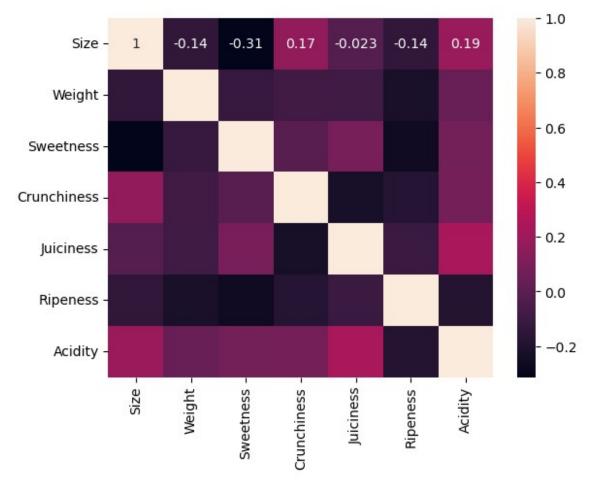
	Size	Weight	Sweetness	Crunchiness	Juiciness	Ripeness
Acidi [.]	ty	_				
0	False	False	False	False	False	False
False						
1	False	False	False	False	False	False
False						
2	False	False	False	False	False	False
False						
3	False	False	False	False	False	False
False	_	_	_		_	_
4	False	False	False	False	False	False
False						
2005	- 1	- 1	- 1	- 1	- 1	- 1
3995	False	False	False	False	False	False
False	F-1	F-1	E-1	E-1	E.1	F.1
3996	False	False	False	False	False	False
False	Fp] co	Годоо	Годоо	Годоо	Годоо	F21.00
3997 False	False	False	False	False	False	False
3998	False	False	False	False	False	False
False	ratse	ratse	ratse	ratse	ratse	ratse
3999	False	False	False	False	False	False
False	ratse	racse	racse	ratse	ratse	ratse

[4000 rows x 7 columns]

```
pk[['Size','Weight','Sweetness','Crunchiness','Juiciness','Ripeness','
Acidity']].corr()
```

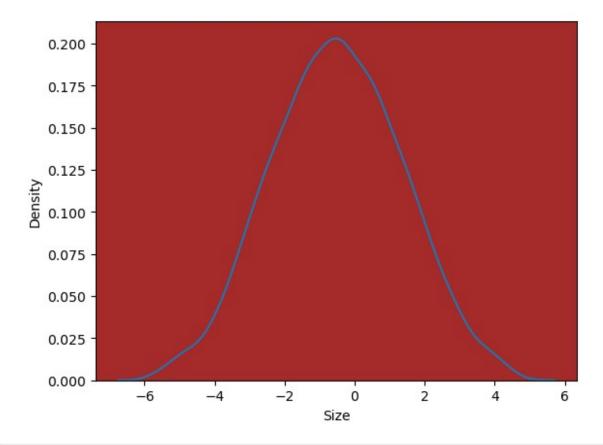
		Size	Weight	Sweetness	Crunchiness	Juiciness	
Ripeness	\						
Size		1.000000	-0.140180	-0.312955	0.165760	-0.022888	-
0.139821							
Weight		-0.140180	1.000000	-0.120500	-0.086807	-0.090456	-

```
0.221947
            -0.312955 -0.120500
                                  1.000000
                                              -0.014191
                                                         0.089395 -
Sweetness
0.258363
Crunchiness 0.165760 -0.086807 -0.014191
                                               1.000000
                                                         -0.227767 -
0.181666
                                              -0.227767
Juiciness
            -0.022888 -0.090456
                                 0.089395
                                                         1.000000 -
0.108158
Ripeness
            -0.139821 -0.221947
                                 -0.258363
                                              -0.181666
                                                         -0.108158
1.000000
Acidity
             0.192140 0.039086
                                 0.071963
                                               0.077810
                                                         0.234223 -
0.188371
             Acidity
             0.192140
Size
Weight
             0.039086
Sweetness
             0.071963
Crunchiness
             0.077810
Juiciness
             0.234223
Ripeness
            -0.188371
Acidity
             1.000000
sns.heatmap(pk[['Size','Weight','Sweetness','Crunchiness','Juiciness',
'Ripeness', 'Acidity']].corr(),annot=True)
<Axes: >
```

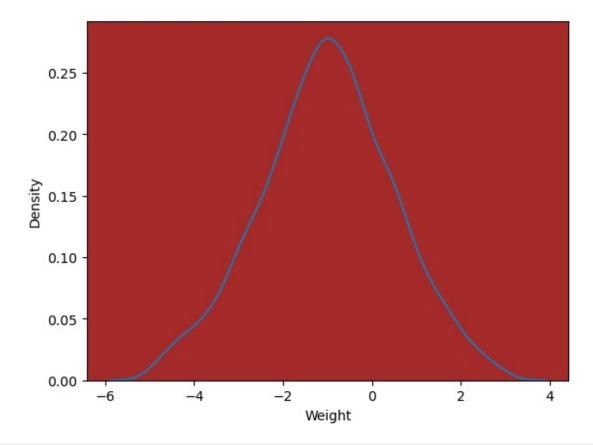


```
for i in
['Size','Weight','Sweetness','Crunchiness','Juiciness','Ripeness','Aci
dity']:
    sns.kdeplot(data=pk,x=i)
    plt.gca().set_facecolor('brown')
    plt.show()

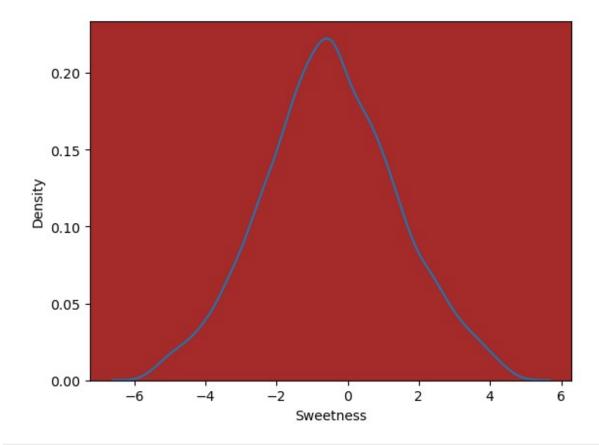
C:\Users\Admin\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed
in a future version. Convert inf values to NaN before operating
instead.
    with pd.option_context('mode.use_inf_as_na', True):
```



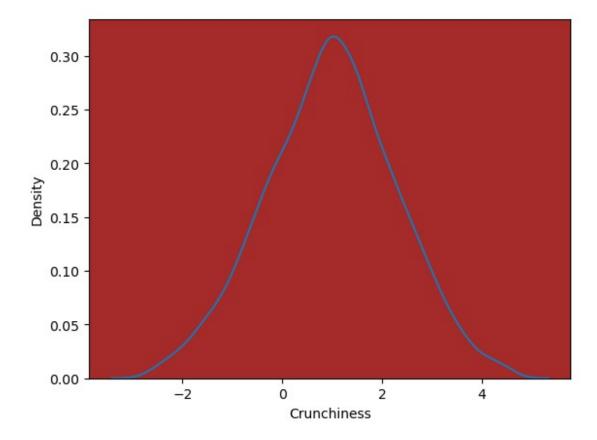
C:\Users\Admin\anaconda3\Lib\site-packages\seaborn_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.



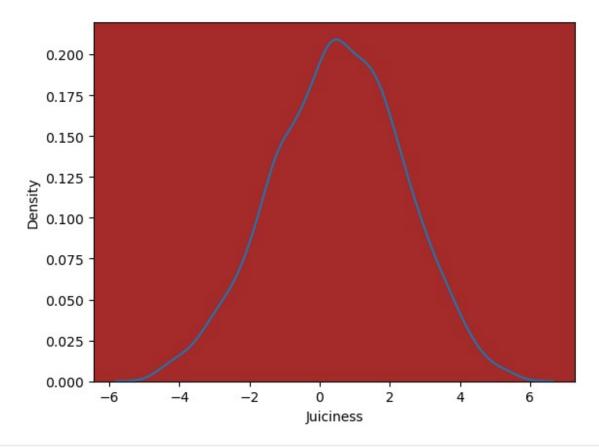
C:\Users\Admin\anaconda3\Lib\site-packages\seaborn_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.



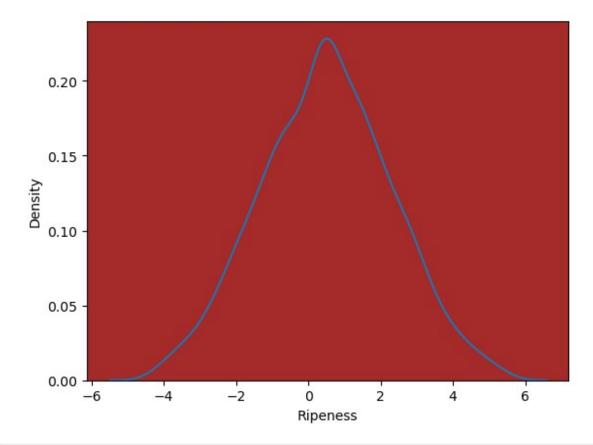
C:\Users\Admin\anaconda3\Lib\site-packages\seaborn_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.



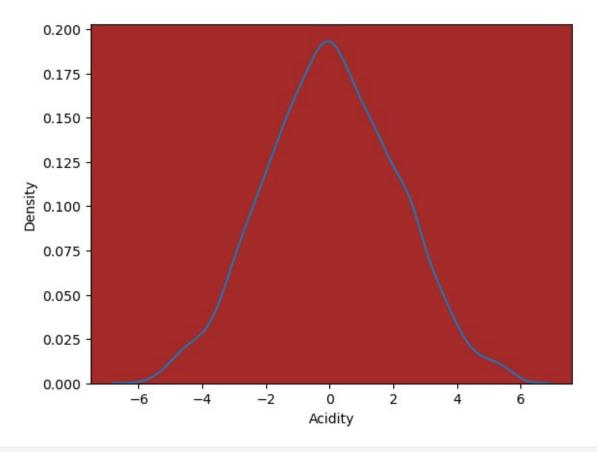
C:\Users\Admin\anaconda3\Lib\site-packages\seaborn_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.



C:\Users\Admin\anaconda3\Lib\site-packages\seaborn_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.



C:\Users\Admin\anaconda3\Lib\site-packages\seaborn_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.



pk						
A_id Ripeness		Weight	Sweetness	Crunchiness	Juiciness	
•	-	-2.512336	-0.504758	-1.012009	1.844900	
	-1.195217	-2.839257	3.664059	1.588232	0.853286	
	-0.292024	-1.351282	-1.738429	-0.342616	2.838636	-
	-0.657196	-2.271627	1.324874	-0.097875	3.637970	-
4 4	1.364217	-1.296612	-0.384658	-0.553006	3.030874	-
1.303849						
	0.059386	-1.067408	-3.714549	0.473052	1.697986	
	-0.293118	1.949253	-0.204020	-0.640196	0.024523	-
	-2.634515	-2.138247	-2.440461	0.657223	2.199709	
	-4.008004	-1.779337	2.366397	-0.200329	2.161435	
0.214488						

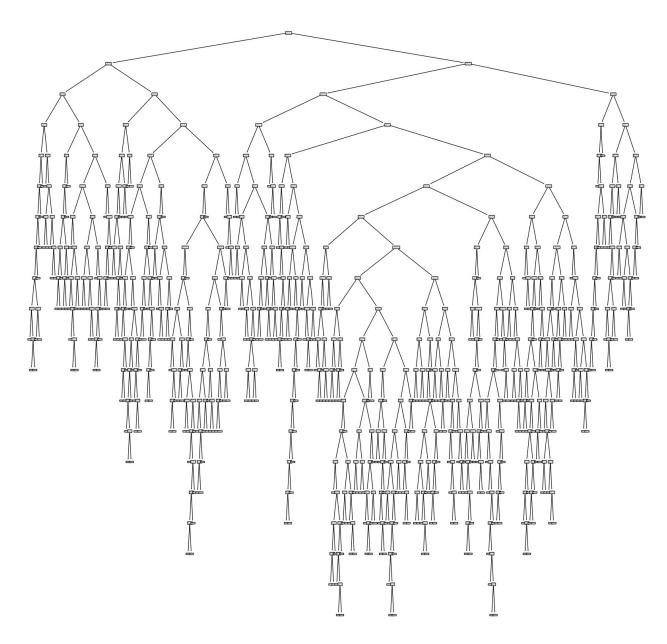
```
3999 3999
            0.278540 -1.715505 0.121217 -1.154075
                                                           1.266677 -
0.776571
       Acidity Quality
0
     -0.491590
                  good
1
     -0.722809
                  good
2
      2.621636
                   bad
3
      0.790723
                  good
4
      0.501984
                  good
3995 0.137784
                   bad
3996
     1.854235
                  good
3997 -1.334611
                   bad
3998 -2.229720
                  good
3999 1.599796
                  good
[4000 rows x 9 columns]
pk.isnull().sum()
A id
Size
               0
Weight
               0
Sweetness
               0
Crunchiness
Juiciness
               0
               0
Ripeness
Acidity
               0
Quality
               0
dtype: int64
from sklearn.preprocessing import LabelEncoder,PowerTransformer
LE=LabelEncoder()
pk['Quality']=LE.fit_transform(pk['Quality'])
pk['Quality']
0
        1
1
        1
2
        0
3
        1
4
        1
3995
        0
3996
        1
3997
        0
3998
        1
3999
        1
Name: Quality, Length: 4000, dtype: int32
```

```
pk=pk.drop('A id',axis=True)
PT=PowerTransformer()
x=pk.drop('Quality',axis=1)
y=pk['Quality']
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.20,rand
om state=42)
from sklearn.linear model import LogisticRegression
LR=LogisticRegression()
LR.fit(x_train,y_train)
LogisticRegression()
model_pred=LR.predict(x_test)
y test
555
        1
3491
        0
527
        0
3925
        1
2989
        0
1922
        0
        1
865
3943
        1
1642
        1
2483
        1
Name: Quality, Length: 800, dtype: int32
LR.score(x_train,y_train)
0.7334375
LR.score(x_test,y_test)
0.74375
from sklearn.metrics import
classification_report,confusion_matrix,accuracy_score,f1_score
accuracy_score(model_pred,y_test)
0.74375
confusion_matrix(model_pred,y_test)
```

```
array([[297, 101],
       [104, 298]], dtype=int64)
print(classification_report(model_pred,y_test))
              precision
                            recall f1-score
                                                support
           0
                    0.74
                              0.75
                                         0.74
                                                    398
           1
                    0.75
                              0.74
                                         0.74
                                                    402
                                         0.74
                                                    800
    accuracy
                    0.74
                              0.74
                                         0.74
                                                    800
   macro avg
weighted avg
                    0.74
                              0.74
                                         0.74
                                                    800
pd.DataFrame(y test).value counts()
Quality
           401
0
1
           399
Name: count, dtype: int64
pd.DataFrame(model pred).value counts()
1
     402
     398
Name: count, dtype: int64
from sklearn.neighbors import KNeighborsClassifier
KNN=KNeighborsClassifier(n neighbors=7)
KNN.fit(x_train,y_train)
KNeighborsClassifier(n neighbors=7)
KNN_pred=KNN.predict(x_test)
y_test
555
        1
3491
        0
527
        0
3925
        1
2989
        0
1922
        0
865
        1
3943
        1
        1
1642
2483
        1
Name: Quality, Length: 800, dtype: int32
```

```
accuracy_score(y_test,KNN_pred)
0.89
confusion_matrix(y_test,KNN_pred)
array([[359, 42],
       [ 46, 353]], dtype=int64)
print(classification_report(y_test,KNN_pred))
              precision
                            recall f1-score
                                               support
           0
                   0.89
                              0.90
                                        0.89
                                                    401
           1
                   0.89
                              0.88
                                        0.89
                                                    399
                                        0.89
                                                    800
    accuracy
   macro avg
                   0.89
                              0.89
                                        0.89
                                                    800
weighted avg
                   0.89
                              0.89
                                        0.89
                                                    800
from sklearn.tree import DecisionTreeClassifier
DTC=DecisionTreeClassifier(max_depth=31)
DTC.fit(x_train,y_train)
DecisionTreeClassifier(max depth=31)
DTC_pred=DTC.predict(x_test)
y_test
555
        1
3491
        0
527
        0
3925
        1
2989
        0
1922
        0
865
        1
3943
        1
1642
        1
2483
Name: Quality, Length: 800, dtype: int32
accuracy_score(DTC_pred,y_test)
0.81125
print(classification_report(y_test,DTC_pred))
```

```
precision
                             recall f1-score
                                                 support
            0
                    0.80
                               0.82
                                          0.81
                                                      401
                               0.80
                                                      399
            1
                    0.82
                                          0.81
                                                      800
                                          0.81
    accuracy
                    0.81
   macro avg
                               0.81
                                          0.81
                                                      800
weighted avg
                    0.81
                               0.81
                                          0.81
                                                      800
confusion_matrix(y_test,DTC_pred)
array([[330, 71],
       [80, 319]], dtype=int64)
from sklearn import tree
plt.figure(figsize=(20,20))
tree.plot_tree(DTC)
plt.show()
```



```
from sklearn.ensemble import RandomForestClassifier
RFC=RandomForestClassifier(n_estimators=89)
RFC.fit(x_train,y_train)
RandomForestClassifier(n_estimators=89)
RFC_pred=RFC.predict(x_test)
y_test
555     1
3491     0
```

```
527
        0
3925
        1
2989
        0
1922
        0
865
        1
        1
3943
1642
        1
2483
        1
Name: Quality, Length: 800, dtype: int32
accuracy_score(y_test,RFC_pred)
0.89375
confusion_matrix(y_test,RFC_pred)
array([[356, 45],
       [ 40, 359]], dtype=int64)
print(classification report(y test,RFC pred))
              precision
                            recall f1-score
                                               support
           0
                   0.90
                              0.89
                                        0.89
                                                    401
           1
                   0.89
                              0.90
                                        0.89
                                                    399
                                        0.89
                                                   800
    accuracy
                   0.89
                              0.89
                                        0.89
                                                   800
   macro avg
                              0.89
weighted avg
                   0.89
                                        0.89
                                                   800
from sklearn.model selection import RandomizedSearchCV,GridSearchCV
parameters={'n estimators':
[1,7,9,11,19,21,25,29,31,51,71,89,99,101,119,201,251], 'criterion':
['gini','entropy'],
            'max_depth':range(1,10)}
RSCV=RandomizedSearchCV(estimator=RFC,scoring='accuracy',param distrib
utions=parameters,cv=10)
RSCV.fit (x_train,y_train)
RandomizedSearchCV(cv=10,
estimator=RandomForestClassifier(n estimators=89),
                   param distributions={'criterion': ['gini',
'entropy'],
                                         'max depth': range(1, 10),
                                         'n estimators': [1, 7, 9, 11,
19, 21,
```

```
25, 29, 31,
51, 71, 89,
                                                     99, 101, 119,
201.
                                                     251]},
                 scoring='accuracy')
RSCV.best params
{'n estimators': 119, 'max depth': 9, 'criterion': 'entropy'}
RSCV.best score
0.847499999999999
GSCV=GridSearchCV(estimator=RFC,scoring='accuracy',param grid=paramete
rs, cv=10)
GSCV.fit(x train,y train)
GridSearchCV(cv=10, estimator=RandomForestClassifier(n estimators=89),
            'n_estimators': [1, 7, 9, 11, 19, 21, 25, 29,
31, 51,
                                       71, 89, 99, 101, 119, 201,
251]},
            scoring='accuracy')
GSCV.best_params_
{'criterion': 'gini', 'max depth': 9, 'n estimators': 89}
GSCV.best_score_
0.8534375000000001
```