```
import pandas as pd
df=pd.read_csv("Heart.csv")
```

```
print(df.to_string())
```

```
    Unnamed: 0  Age  Sex     ChestPain  RestBP  Chol  Fbs  RestECG  MaxHR  ExAng  Oldpeak  Slope   Ca        Thal  AHD
0            1   63    1       typical     145   233    1        2    150      0      2.3      3  0.0       fixed   No
1            2   67    1  asymptomatic     160   286    0        2    108      1      1.5      2  3.0      normal  Yes
2            3   67    1  asymptomatic     120   229    0        2    129      1      2.6      2  2.0  reversable  Yes
3            4   37    1    nonanginal     130   250    0        0    187      0      3.5      3  0.0      normal   No
4            5   41    0    nontypical     130   204    0        2    172      0      1.4      1  0.0      normal   No
5            6   56    1    nontypical     120   236    0        0    178      0      0.8      1  0.0      normal   No
6            7   62    0  asymptomatic     140   268    0        2    160      0      3.6      3  2.0      normal  Yes
7            8   57    0  asymptomatic     120   354    0        0    163      1      0.6      1  0.0      normal   No
8            9   63    1  asymptomatic     130   254    0        2    147      0      1.4      2  1.0  reversable  Yes
9           10   53    1  asymptomatic     140   203    1        2    155      1      3.1      3  0.0  reversable  Yes
10          11   57    1  asymptomatic     140   192    0        0    148      0      0.4      2  0.0       fixed   No
11          12   56    0    nontypical     140   294    0        2    153      0      1.3      2  0.0      normal   No
12          13   56    1    nonanginal     130   256    1        2    142      1      0.6      2  1.0       fixed  Yes
13          14   44    1    nontypical     120   263    0        0    173      0      0.0      1  0.0  reversable   No
14          15   52    1    nonanginal     172   199    1        0    162      0      0.5      1  0.0  reversable   No
15          16   57    1    nonanginal     150   168    0        0    174      0      1.6      1  0.0      normal   No
16          17   48    1    nontypical     110   229    0        0    168      0      1.0      3  0.0  reversable  Yes
17          18   54    1  asymptomatic     140   239    0        0    160      0      1.2      1  0.0      normal   No
18          19   48    0    nonanginal     130   275    0        0    139      0      0.2      1  0.0      normal   No
19          20   49    1    nontypical     130   266    0        0    171      0      0.6      1  0.0      normal   No
20          21   64    1       typical     110   211    0        2    144      1      1.8      2  0.0      normal   No
21          22   58    0       typical     150   283    1        2    162      0      1.0      1  0.0      normal   No
22          23   58    1    nontypical     120   284    0        2    160      0      1.8      2  0.0      normal  Yes
23          24   58    1    nonanginal     132   224    0        2    173      0      3.2      1  2.0  reversable  Yes
24          25   60    1  asymptomatic     130   206    0        2    132      1      2.4      2  2.0  reversable  Yes
25          26   50    0    nonanginal     120   219    0        0    158      0      1.6      2  0.0      normal   No
26          27   58    0    nonanginal     120   340    0        0    172      0      0.0      1  0.0      normal   No
27          28   66    0       typical     150   226    0        0    114      0      2.6      3  0.0      normal   No
28          29   43    1  asymptomatic     150   247    0        0    171      0      1.5      1  0.0      normal   No
29          30   40    1  asymptomatic     110   167    0        2    114      1      2.0      2  0.0  reversable  Yes
30          31   69    0       typical     140   239    0        0    151      0      1.8      1  2.0      normal   No
31          32   60    1  asymptomatic     117   230    1        0    160      1      1.4      1  2.0  reversable  Yes
32          33   64    1    nonanginal     140   335    0        0    158      0      0.0      1  0.0      normal  Yes
33          34   59    1  asymptomatic     135   234    0        0    161      0      0.5      2  0.0  reversable   No
34          35   44    1    nonanginal     130   233    0        0    179      1      0.4      1  0.0      normal   No
35          36   42    1  asymptomatic     140   226    0        0    178      0      0.0      1  0.0      normal   No
36          37   43    1  asymptomatic     120   177    0        2    120      1      2.5      2  0.0  reversable  Yes
37          38   57    1  asymptomatic     150   276    0        2    112      1      0.6      2  1.0       fixed  Yes
38          39   55    1  asymptomatic     132   353    0        0    132      1      1.2      2  1.0  reversable  Yes
39          40   61    1    nonanginal     150   243    1        0    137      1      1.0      2  0.0      normal   No
40          41   65    0  asymptomatic     150   225    0        2    114      0      1.0      2  3.0  reversable  Yes
41          42   40    1       typical     140   199    0        0    178      1      1.4      1  0.0  reversable   No
42          43   71    0    nontypical     160   302    0        0    162      0      0.4      1  2.0      normal   No
43          44   59    1    nonanginal     150   212    1        0    157      0      1.6      1  0.0      normal   No
44          45   61    0  asymptomatic     130   330    0        2    169      0      0.0      1  0.0      normal  Yes
45          46   58    1    nonanginal     112   230    0        2    165      0      2.5      2  1.0  reversable  Yes
46          47   51    1    nonanginal     110   175    0        0    123      0      0.6      1  0.0      normal   No
47          48   50    1  asymptomatic     150   243    0        2    128      0      2.6      2  0.0  reversable  Yes
48          49   65    0    nonanginal     140   417    1        2    157      0      0.8      1  1.0      normal   No
49          50   53    1    nonanginal     130   197    1        2    152      0      1.2      3  0.0      normal   No
50          51   41    0    nontypical     105   198    0        0    168      0      0.0      1  1.0      normal   No
51          52   65    1  asymptomatic     120   177    0        0    140      0      0.4      1  0.0  reversable   No
52          53   44    1  asymptomatic     112   290    0        2    153      0      0.0      1  1.0      normal  Yes
53          54   44    1    nontypical     130   219    0        2    188      0      0.0      1  0.0      normal   No
54          55   60    1  asymptomatic     130   253    0        0    144      1      1.4      1  1.0  reversable  Yes
55          56   54    1  asymptomatic     124   266    0        2    109      1      2.2      2  1.0  reversable  Yes
56          57   50    1    nonanginal     140   233    0        0    163      0      0.6      2  1.0  reversable  Yes
```

```
#a) Find standard deviation, variance of every numerical attribute.
df = df.apply(pd.to_numeric, errors='coerce')
print(df.std())  #Standard Deviation
```

```
Unnamed: 0    87.612784
Age            9.038662
Sex            0.467299
ChestPain           NaN
RestBP        17.599748
Chol          51.776918
Fbs            0.356198
RestECG        0.994971
MaxHR         22.875003
ExAng          0.469794
Oldpeak        1.161075
Slope          0.616226
Ca             0.937438
```

```
Thal               NaN
AHD                NaN
dtype: float64
```

```
print(df.var())  #Variance
```

```
Unnamed: 0    7676.000000
Age             81.697419
Sex              0.218368
ChestPain             NaN
RestBP         309.751120
Chol          2680.849190
Fbs              0.126877
RestECG          0.989968
MaxHR          523.265775
ExAng            0.220707
Oldpeak          1.348095
Slope            0.379735
Ca               0.878791
Thal                  NaN
AHD                   NaN
dtype: float64
```

```
#b) Find covariance and perform Correlation analysis using Correlation coefficient.
print(df.cov())   #Covariance
```

```
                Unnamed: 0        Age       Sex  ChestPain      RestBP  \
Unnamed: 0  7676.000000  -1.874172 -2.900662        NaN  -33.966887
Age           -1.874172  81.697419 -0.411995        NaN   45.328678
Sex           -2.900662  -0.411995  0.218368        NaN   -0.530107
ChestPain           NaN        NaN       NaN        NaN         NaN
RestBP       -33.966887  45.328678 -0.530107        NaN  309.751120
Chol        -433.301325  97.787489 -4.836994        NaN  118.573339
Fbs           -1.231788   0.381614  0.007967        NaN    1.099207
RestECG      -13.096026   1.338797  0.010065        NaN    2.566455
MaxHR       -211.413907 -81.423065 -0.520184        NaN  -18.258005
ExAng         -0.016556   0.389220  0.032096        NaN    0.535473
Oldpeak      -12.246026   2.138850  0.055436        NaN    3.865638
Slope         -1.536424   0.901034  0.010808        NaN    1.273053
Ca             3.844223   3.066396  0.040964        NaN    1.639436
Thal                NaN        NaN       NaN        NaN         NaN
AHD                 NaN        NaN       NaN        NaN         NaN

                    Chol       Fbs    RestECG       MaxHR     ExAng    Oldpeak  \
Unnamed: 0  -433.301325 -1.231788 -13.096026 -211.413907 -0.016556 -12.246026
Age           97.787489  0.381614   1.338797  -81.423065  0.389220   2.138850
Sex           -4.836994  0.007967   0.010065   -0.520184  0.032096   0.055436
ChestPain           NaN       NaN        NaN         NaN       NaN        NaN
RestBP       118.573339  1.099207   2.566455  -18.258005  0.535473   3.865638
Chol        2680.849190  0.181496   8.811521   -4.064651  1.491345   2.799282
Fbs            0.181496  0.126877   0.024654   -0.063996  0.004295   0.002377
RestECG        8.811521  0.024654   0.989968   -1.897941  0.039670   0.131850
MaxHR         -4.064651 -0.063996  -1.897941  523.265775 -4.063307  -9.112209
ExAng          1.491345  0.004295   0.039670   -4.063307  0.220707   0.157216
Oldpeak        2.799282  0.002377   0.131850   -9.112209  0.157216   1.348095
Slope         -0.129598  0.013147   0.082126   -5.435501  0.074618   0.413219
Ca             5.791385  0.048394   0.119706   -5.686270  0.064162   0.322753
Thal                NaN       NaN        NaN         NaN       NaN        NaN
AHD                 NaN       NaN        NaN         NaN       NaN        NaN

                Slope        Ca  Thal  AHD
Unnamed: 0 -1.536424  3.844223   NaN  NaN
Age         0.901034  3.066396   NaN  NaN
Sex         0.010808  0.040964   NaN  NaN
ChestPain        NaN       NaN   NaN  NaN
RestBP      1.273053  1.639436   NaN  NaN
Chol       -0.129598  5.791385   NaN  NaN
Fbs         0.013147  0.048394   NaN  NaN
RestECG     0.082126  0.119706   NaN  NaN
MaxHR      -5.435501 -5.686270   NaN  NaN
ExAng       0.074618  0.064162   NaN  NaN
Oldpeak     0.413219  0.322753   NaN  NaN
Slope       0.379735  0.063747   NaN  NaN
Ca          0.063747  0.878791   NaN  NaN
Thal             NaN       NaN   NaN  NaN
AHD              NaN       NaN   NaN  NaN
```

```
print(df.corr())  #Corelation
```

```
              Unnamed: 0       Age       Sex  ChestPain    RestBP      Chol  \
Unnamed: 0    1.000000 -0.002367 -0.070849        NaN -0.022028 -0.095518
```

```
Age          -0.002367  1.000000 -0.097542        NaN  0.284946  0.208950
Sex          -0.070849 -0.097542  1.000000        NaN -0.064456 -0.199915
ChestPain          NaN       NaN       NaN        NaN       NaN       NaN
RestBP       -0.022028  0.284946 -0.064456        NaN  1.000000  0.130120
Chol         -0.095518  0.208950 -0.199915        NaN  0.130120  1.000000
Fbs          -0.039471  0.118530  0.047862        NaN  0.175340  0.009841
RestECG      -0.150232  0.148868  0.021647        NaN  0.146560  0.171043
MaxHR        -0.105488 -0.393806 -0.048663        NaN -0.045351 -0.003432
ExAng        -0.000402  0.091661  0.146201        NaN  0.064762  0.061310
Oldpeak      -0.120384  0.203805  0.102173        NaN  0.189171  0.046564
Slope        -0.028458  0.161770  0.037533        NaN  0.117382 -0.004062
Ca            0.046938  0.362605  0.093185        NaN  0.098773  0.119000
Thal               NaN       NaN       NaN        NaN       NaN       NaN
AHD                NaN       NaN       NaN        NaN       NaN       NaN

                    Fbs   RestECG     MaxHR     ExAng   Oldpeak     Slope  \
Unnamed: 0 -0.039471 -0.150232 -0.105488 -0.000402 -0.120384 -0.028458
Age         0.118530  0.148868 -0.393806  0.091661  0.203805  0.161770
Sex         0.047862  0.021647 -0.048663  0.146201  0.102173  0.037533
ChestPain        NaN       NaN       NaN       NaN       NaN       NaN
RestBP      0.175340  0.146560 -0.045351  0.064762  0.189171  0.117382
Chol        0.009841  0.171043 -0.003432  0.061310  0.046564 -0.004062
Fbs         1.000000  0.069564 -0.007854  0.025665  0.005747  0.059894
RestECG     0.069564  1.000000 -0.083389  0.084867  0.114133  0.133946
MaxHR      -0.007854 -0.083389  1.000000 -0.378103 -0.343085 -0.385601
ExAng       0.025665  0.084867 -0.378103  1.000000  0.288223  0.257748
Oldpeak     0.005747  0.114133 -0.343085  0.288223  1.000000  0.577537
Slope       0.059894  0.133946 -0.385601  0.257748  0.577537  1.000000
Ca          0.145478  0.128343 -0.264246  0.145570  0.295832  0.110119
Thal             NaN       NaN       NaN       NaN       NaN       NaN
AHD              NaN       NaN       NaN       NaN       NaN       NaN

                     Ca  Thal  AHD
Unnamed: 0  0.046938   NaN  NaN
Age         0.362605   NaN  NaN
Sex         0.093185   NaN  NaN
ChestPain        NaN   NaN  NaN
RestBP      0.098773   NaN  NaN
Chol        0.119000   NaN  NaN
Fbs         0.145478   NaN  NaN
RestECG     0.128343   NaN  NaN
MaxHR      -0.264246   NaN  NaN
ExAng       0.145570   NaN  NaN
Oldpeak     0.295832   NaN  NaN
Slope       0.110119   NaN  NaN
Ca          1.000000   NaN  NaN
Thal             NaN   NaN  NaN
AHD              NaN   NaN  NaN
```

```
#e) Perform the data discretization using equi frequency binning method on age attribute
bins = pd.cut(df['Age'], bins=5, labels=False)
df['Age'] = bins



print(df.head(5))
```

```
   Unnamed: 0  Age  Sex     ChestPain  RestBP  Chol  Fbs  RestECG  MaxHR  \
0           1    3    1       typical     145   233    1        2    150
1           2    3    1  asymptomatic     160   286    0        2    108
2           3    3    1  asymptomatic     120   229    0        2    129
3           4    0    1    nonanginal     130   250    0        0    187
4           5    1    0    nontypical     130   204    0        2    172

   ExAng  Oldpeak  Slope   Ca        Thal  AHD
0      0      2.3      3  0.0       fixed   No
1      1      1.5      2  3.0      normal  Yes
2      1      2.6      2  2.0  reversable  Yes
3      0      3.5      3  0.0      normal   No
4      0      1.4      1  0.0      normal   No
```

```
#c) How many independent features are present in the given dataset?
features = df.drop(columns=['AHD'])
# Get the number of independent features
independent_features = features.shape[1]
# .shape : returns a tuple representing its dimensions (number of rows, number of columns)
# features.shape[1] : retrieves the number of columns, which corresponds to the number of independent features.
print(independent_features)
```

```
14
```

```
#d)Can we identify unwanted features?
import pandas as pd
# Identify constant value columns
constant_cols = [col for col in df.columns if df[col].nunique() == 1]

# Identify duplicate columns
duplicate_cols = []
for i in range(len(df.columns)):
    col1 = df.columns[i]
    for col2 in df.columns[i+1:]:
        if df[col1].equals(df[col2]):
            duplicate_cols.append(col2)

# Combine all potentially unwanted columns
unwanted_cols = set(constant_cols + duplicate_cols)

print("Potentially unwanted columns:")
print(unwanted_cols)
```

```
Potentially unwanted columns:
{'Thal', 'AHD'}
```

```
#f) Normalize RestBP, chol, and MaxHR attributes (considering above dataset) using min-max normalization, Z-score normalization, and de
from sklearn.preprocessing import MinMaxScaler, StandardScaler, RobustScaler
# Select attributes to normalize
attributes_to_normalize = ['RestBP', 'Chol', 'MaxHR']


# Min-Max normalization
min_max_scaler = MinMaxScaler()
ans=df[attributes_to_normalize] = min_max_scaler.fit_transform(df[attributes_to_normalize])
print(ans)
```

```
[[0.48113208 0.24429224 0.60305344]
 [0.62264151 0.3652968  0.28244275]
 [0.24528302 0.23515982 0.44274809]
 [0.33962264 0.28310502 0.88549618]
 [0.33962264 0.17808219 0.77099237]
 [0.24528302 0.25114155 0.81679389]
 [0.43396226 0.32420091 0.67938931]
 [0.24528302 0.52054795 0.70229008]
 [0.33962264 0.29223744 0.58015267]
 [0.43396226 0.17579909 0.64122137]
 [0.43396226 0.15068493 0.58778626]
 [0.43396226 0.38356164 0.6259542 ]
 [0.33962264 0.29680365 0.54198473]
 [0.24528302 0.31278539 0.77862595]
 [0.73584906 0.16666667 0.69465649]
 [0.52830189 0.09589041 0.78625954]
 [0.1509434  0.23515982 0.74045802]
 [0.43396226 0.25799087 0.67938931]
 [0.33962264 0.34018265 0.51908397]
 [0.33962264 0.3196347  0.76335878]
 [0.1509434  0.19406393 0.55725191]
 [0.52830189 0.35844749 0.69465649]
 [0.24528302 0.36073059 0.67938931]
 [0.35849057 0.22374429 0.77862595]
 [0.33962264 0.1826484  0.46564885]
 [0.24528302 0.21232877 0.66412214]
 [0.24528302 0.48858447 0.77099237]
 [0.52830189 0.2283105  0.32824427]
 [0.52830189 0.27625571 0.76335878]
 [0.1509434  0.09360731 0.32824427]
 [0.43396226 0.25799087 0.61068702]
 [0.21698113 0.23744292 0.67938931]
 [0.43396226 0.47716895 0.66412214]
 [0.38679245 0.24657534 0.6870229 ]
 [0.33962264 0.24429224 0.82442748]
 [0.43396226 0.2283105  0.81679389]
 [0.24528302 0.11643836 0.3740458 ]
 [0.52830189 0.34246575 0.3129771 ]
 [0.35849057 0.51826484 0.46564885]
 [0.52830189 0.26712329 0.50381679]
 [0.52830189 0.2260274  0.32824427]
 [0.43396226 0.16666667 0.81679389]
 [0.62264151 0.40182648 0.69465649]
 [0.52830189 0.19634703 0.65648855]
 [0.33962264 0.46575342 0.7480916 ]
 [0.16981132 0.23744292 0.71755725]
 [0.1509434  0.11187215 0.39694656]
 [0.52830189 0.26712329 0.4351145 ]
```

```
       [0.43396226 0.66438356 0.65648855]
       [0.33962264 0.16210046 0.61832061]
       [0.10377358 0.16438356 0.74045802]
       [0.24528302 0.11643836 0.52671756]
       [0.16981132 0.37442922 0.6259542 ]
       [0.33962264 0.21232877 0.89312977]
       [0.33962264 0.28995434 0.55725191]
       [0.28301887 0.3196347  0.29007634]
       [0.43396226 0.24429224 0.70229008]
       [0.1509434  0.10502283 0.66412214]
```

```
# Z-score normalization
z_score_scaler = StandardScaler()
ans=df[attributes_to_normalize] = z_score_scaler.fit_transform(df[attributes_to_normalize])
print(ans)
```

```
     [[ 7.57525041e-01 -2.64900304e-01  1.71973294e-02]
      [ 1.61121989e+00  7.60415190e-01 -1.82190531e+00]
      [-6.65299701e-01 -3.42282606e-01 -9.02353991e-01]
      [-9.61698043e-02  6.39744770e-02  1.63735918e+00]
      [-9.61698043e-02 -8.25921990e-01  9.80536808e-01]
      [-6.65299701e-01 -2.06863578e-01  1.24326576e+00]
      [ 4.72960092e-01  4.12194834e-01  4.55078911e-01]
      [-6.65299701e-01  2.07591432e+00  5.86443385e-01]
      [-9.61698043e-02  1.41356778e-01 -1.14167145e-01]
      [ 4.72960092e-01 -8.45267566e-01  2.36138120e-01]
      [ 4.72960092e-01 -1.05806889e+00 -7.03789868e-02]
      [ 4.72960092e-01  9.15179793e-01  1.48561804e-01]
      [-9.61698043e-02  1.80047929e-01 -3.33107936e-01]
      [-6.65299701e-01  3.15466957e-01  1.02432497e+00]
      [ 2.29417576e+00 -9.22649867e-01  5.42655227e-01]
      [ 1.04208999e+00 -1.52236270e+00  1.06811312e+00]
      [-1.23442960e+00 -3.42282606e-01  8.05384176e-01]
      [ 4.72960092e-01 -1.48826852e-01  4.55078911e-01]
      [-9.61698043e-02  5.47613861e-01 -4.64472410e-01]
      [-9.61698043e-02  3.73503683e-01  9.36748650e-01]
      [-1.23442960e+00 -6.90502963e-01 -2.45531619e-01]
      [ 1.04208999e+00  7.02378464e-01  5.42655227e-01]
      [-6.65299701e-01  7.21724040e-01  4.55078911e-01]
      [ 1.76561750e-02 -4.39010483e-01  1.02432497e+00]
      [-9.61698043e-02 -7.87230839e-01 -7.70989517e-01]
      [-6.65299701e-01 -5.35738360e-01  3.67502595e-01]
      [-6.65299701e-01  1.80507626e+00  9.80536808e-01]
      [ 1.04208999e+00 -4.00319332e-01 -1.55917636e+00]
      [ 1.04208999e+00  5.93775086e-03  9.36748650e-01]
      [-1.23442960e+00 -1.54170828e+00 -1.55917636e+00]
      [ 4.72960092e-01 -1.48826852e-01  6.09854876e-02]
      [-8.36038670e-01 -3.22937030e-01  4.55078911e-01]
      [ 4.72960092e-01  1.70834838e+00  3.67502595e-01]
      [ 1.88395144e-01 -2.45554729e-01  4.98867069e-01]
      [-9.61698043e-02 -2.64900304e-01  1.28705392e+00]
      [ 4.72960092e-01 -4.00319332e-01  1.24326576e+00]
      [-6.65299701e-01 -1.34825253e+00 -1.29644741e+00]
      [ 1.04208999e+00  5.66959437e-01 -1.64675268e+00]
      [ 1.76561750e-02  2.05656874e+00 -7.70989517e-01]
      [ 1.04208999e+00 -7.14445506e-02 -5.52048726e-01]
      [ 1.04208999e+00 -4.19664907e-01 -1.55917636e+00]
      [ 4.72960092e-01 -9.22649867e-01  1.24326576e+00]
      [ 1.61121989e+00  1.06994440e+00  5.42655227e-01]
      [ 1.04208999e+00 -6.71157387e-01  3.23714436e-01]
      [-9.61698043e-02  1.61162051e+00  8.49172334e-01]
      [-1.12060362e+00 -3.22937030e-01  6.74019701e-01]
      [-1.23442960e+00 -1.38694368e+00 -1.16508294e+00]
      [ 1.04208999e+00 -7.14445506e-02 -9.46142150e-01]
      [ 4.72960092e-01  3.29468556e+00  3.23714436e-01]
      [-9.61698043e-02 -9.61341018e-01  1.04773646e-01]
      [-1.51899455e+00 -9.41995442e-01  8.05384176e-01]
      [-6.65299701e-01 -1.34825253e+00 -4.20684252e-01]
      [-1.12060362e+00  8.37797492e-01  1.48561804e-01]
      [-9.61698043e-02 -5.35738360e-01  1.68114734e+00]
      [-9.61698043e-02  1.22011203e-01 -2.45531619e-01]
      [-4.37647742e-01  3.73503683e-01 -1.77811715e+00]
      [ 4.72960092e-01 -2.64900304e-01  5.86443385e-01]
      [-1.23442960e+00 -1.44498040e+00  3.67502595e-01]
```

```
# Decimal scaling normalization
decimal_scaler = RobustScaler()
ans=df[attributes_to_normalize] = decimal_scaler.fit_transform(df[attributes_to_normalize])
print(ans)
```

```
     [[ 0.75       -0.125      -0.09230769]
      [ 1.5         0.703125   -1.38461538]
      [-0.5        -0.1875     -0.73846154]
```

```
[ 0.          0.140625    1.04615385]
[ 0.         -0.578125    0.58461538]
[-0.5        -0.078125    0.76923077]
[ 0.5         0.421875    0.21538462]
[-0.5         1.765625    0.30769231]
[ 0.          0.203125   -0.18461538]
[ 0.5        -0.59375     0.06153846]
[ 0.5        -0.765625   -0.15384615]
[ 0.5         0.828125    0.        ]
[ 0.          0.234375   -0.33846154]
[-0.5         0.34375     0.61538462]
[ 2.1        -0.65625     0.27692308]
[ 1.         -1.140625    0.64615385]
[-1.         -0.1875      0.46153846]
[ 0.5        -0.03125     0.21538462]
[ 0.          0.53125    -0.43076923]
[ 0.          0.390625    0.55384615]
[-1.         -0.46875    -0.27692308]
[ 1.          0.65625     0.27692308]
[-0.5         0.671875    0.21538462]
[ 0.1        -0.265625    0.61538462]
[ 0.         -0.546875   -0.64615385]
[-0.5        -0.34375     0.15384615]
[-0.5         1.546875    0.58461538]
[ 1.         -0.234375   -1.2       ]
[ 1.          0.09375     0.55384615]
[-1.         -1.15625    -1.2       ]
[ 0.5        -0.03125    -0.06153846]
[-0.65       -0.171875    0.21538462]
[ 0.5         1.46875     0.15384615]
[ 0.25       -0.109375    0.24615385]
[ 0.         -0.125       0.8       ]
[ 0.5        -0.234375    0.76923077]
[-0.5        -1.         -1.01538462]
[ 1.          0.546875   -1.26153846]
[ 0.1         1.75       -0.64615385]
[ 1.          0.03125    -0.49230769]
[ 1.         -0.25       -1.2       ]
[ 0.5        -0.65625     0.76923077]
[ 1.5         0.953125    0.27692308]
[ 1.         -0.453125    0.12307692]
[ 0.          1.390625    0.49230769]
[-0.9        -0.171875    0.36923077]
[-1.         -1.03125    -0.92307692]
[ 1.          0.03125    -0.76923077]
[ 0.5         2.75        0.12307692]
[ 0.         -0.6875     -0.03076923]
[-1.25       -0.671875    0.46153846]
[-0.5        -1.         -0.4       ]
[-0.9         0.765625    0.        ]
[ 0.         -0.34375     1.07692308]
[ 0.          0.1875     -0.27692308]
[-0.3         0.390625   -1.35384615]
[ 0.5        -0.125       0.30769231]
[-1.         -1.078125    0.15384615]
```