happy_countries

September 25, 2022

1 World happiness

1.1 Introduction

This lab uses a dataset on wine quality. The data set contains various chemical properties of wine, such as acidity, sugar, pH, and alcohol. It also contains a quality metric (3-9, with highest being better) and a color (red or white). The name of the file is `Wine_Quality_Data.csv`.

We will be using the chemical properties (i.e. everything but quality and color) to cluster the wine. Though this is unsupervised learning, there are interesting semi-supervised extensions relating clustering results onto color and quality.

[49]:
```
import numpy as np, pandas as pd, matplotlib.pyplot as plt, seaborn as sns, os
```

1.2 Exploratory analysis

- Import the data and examine the features.
- Note which are continuous, categorical, and boolean.
- Paiplots
- Correlation heatmaps

[50]:
```
# Import the data
data = pd.read_csv('Data2021.csv')
data.groupby("year")["Country name"].count()
```

[50]:
```
year
2005     27
2006     89
2007    102
2008    110
2009    114
2010    124
2011    146
2012    142
2013    137
2014    145
2015    143
2016    142
2017    147
```

```
2018    142
2019    144
2020     95
Name: Country name, dtype: int64
```

[51]:

```python
#data.groupby("Country name")["year"].count()["United States"]
data.loc[data["Country name"]=="North Macedonia"].T
```

[51]:

```
                                          1287             1288  \
Country name                   North Macedonia  North Macedonia
year                                      2007             2009
Life Ladder                              4,494            4,428
Log GDP per capita                       9,416            9,464
Social support                           0,811            0,734
Healthy life expectancy at birth        64,095           64,349
Freedom to make life choices             0,439            0,552
Generosity                               0,080           -0,042
Perceptions of corruption                0,870            0,844
Positive affect                          0,603            0,576
Negative affect                          0,251            0,370

                                          1289             1290  \
Country name                   North Macedonia  North Macedonia
year                                      2010             2011
Life Ladder                              4,180            4,898
Log GDP per capita                       9,496            9,518
Social support                           0,687            0,784
Healthy life expectancy at birth        64,502           64,661
Freedom to make life choices             0,513            0,607
Generosity                              -0,058           -0,087
Perceptions of corruption                0,856            0,865
Positive affect                          0,567            0,588
Negative affect                          0,314            0,363

                                          1291             1292  \
Country name                   North Macedonia  North Macedonia
year                                      2012             2013
Life Ladder                              4,640            5,186
Log GDP per capita                       9,513            9,541
Social support                           0,798            0,832
Healthy life expectancy at birth        64,811           64,942
Freedom to make life choices             0,613            0,641
Generosity                              -0,084            0,025
Perceptions of corruption                0,920            0,861
Positive affect                          0,642            0,578
Negative affect                          0,422            0,331
```

	1293	1294 \
Country name	North Macedonia	North Macedonia
year	2014	2015
Life Ladder	5,204	4,976
Log GDP per capita	9,576	9,613
Social support	0,793	0,766
Healthy life expectancy at birth	65,053	65,145
Freedom to make life choices	0,645	0,660
Generosity	0,035	-0,047
Perceptions of corruption	0,861	0,824
Positive affect	0,637	0,620
Negative affect	0,307	0,299

	1295	1296 \
Country name	North Macedonia	North Macedonia
year	2016	2017
Life Ladder	5,346	5,234
Log GDP per capita	9,640	9,650
Social support	0,871	0,800
Healthy life expectancy at birth	65,225	65,303
Freedom to make life choices	0,706	0,752
Generosity	0,080	-0,059
Perceptions of corruption	0,870	0,856
Positive affect	0,639	0,502
Negative affect	0,292	0,299

	1297	1298 \
Country name	North Macedonia	North Macedonia
year	2018	2019
Life Ladder	5,240	5,015
Log GDP per capita	9,677	9,711
Social support	0,849	0,815
Healthy life expectancy at birth	65,389	65,474
Freedom to make life choices	0,745	0,725
Generosity	-0,041	0,024
Perceptions of corruption	0,910	0,923
Positive affect	0,590	0,576
Negative affect	0,298	0,304

	1299
Country name	North Macedonia
year	2020
Life Ladder	5,054
Log GDP per capita	9,690
Social support	0,750
Healthy life expectancy at birth	65,560
Freedom to make life choices	0,787

```
Generosity                                0,131
Perceptions of corruption                 0,877
Positive affect                           0,605
Negative affect                           0,365
```

[52]:
```python
data.head(5).T
```

[52]:
```
                                          0            1            2  \
Country name                    Afghanistan  Afghanistan  Afghanistan
year                                   2008         2009         2010
Life Ladder                           3,724        4,402        4,758
Log GDP per capita                    7,370        7,540        7,647
Social support                        0,451        0,552        0,539
Healthy life expectancy at birth     50,800       51,200       51,600
Freedom to make life choices          0,718        0,679        0,600
Generosity                            0,168        0,190        0,121
Perceptions of corruption             0,882        0,850        0,707
Positive affect                       0,518        0,584        0,618
Negative affect                       0,258        0,237        0,275

                                          3            4
Country name                    Afghanistan  Afghanistan
year                                   2011         2012
Life Ladder                           3,832        3,783
Log GDP per capita                    7,620        7,705
Social support                        0,521        0,521
Healthy life expectancy at birth     51,920       52,240
Freedom to make life choices          0,496        0,531
Generosity                            0,162        0,236
Perceptions of corruption             0,731        0,776
Positive affect                       0,611        0,710
Negative affect                       0,267        0,268
```

[53]:
```python
data = data[data.year==2019]
data.drop("year", axis=1, inplace=True)
data.drop("Positive affect", axis=1, inplace=True)
data.drop("Negative affect", axis=1, inplace=True)
data = data[~data.index.duplicated()]
data.head(5).T
```

[53]:
```
                                         11       23       32         50  \
Country name                    Afghanistan  Albania  Algeria  Argentina
Life Ladder                           2,375    4,995    4,745      6,086
Log GDP per capita                    7,697    9,544    9,337     10,000
Social support                        0,420    0,686    0,803      0,896
Healthy life expectancy at birth     52,400   69,000   66,100     69,000
Freedom to make life choices          0,394    0,777    0,385      0,817
```

```
Generosity                                -0,108   -0,099    0,005     -0,211
Perceptions of corruption                  0,924    0,914    0,741      0,830

                                         65
Country name                        Armenia
Life Ladder                           5,488
Log GDP per capita                    9,522
Social support                        0,782
Healthy life expectancy at birth     67,200
Freedom to make life choices          0,844
Generosity                           -0,172
Perceptions of corruption             0,583
```

[54]:
```
data.shape
```

[54]:
```
(144, 8)
```

[55]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 144 entries, 11 to 1947
Data columns (total 8 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   Country name                      144 non-null    object
 1   Life Ladder                       144 non-null    object
 2   Log GDP per capita                138 non-null    object
 3   Social support                    144 non-null    object
 4   Healthy life expectancy at birth  139 non-null    object
 5   Freedom to make life choices      143 non-null    object
 6   Generosity                        137 non-null    object
 7   Perceptions of corruption         136 non-null    object
dtypes: object(8)
memory usage: 10.1+ KB
```

[56]:
```
data.dtypes
```

[56]:
```
Country name                        object
Life Ladder                         object
Log GDP per capita                  object
Social support                      object
Healthy life expectancy at birth    object
Freedom to make life choices        object
Generosity                          object
Perceptions of corruption           object
dtype: object
```

[57]:
```
data[data.index.duplicated()]
```

[57]:

```
Empty DataFrame
Columns: [Country name, Life Ladder, Log GDP per capita, Social support, Healthy
life expectancy at birth, Freedom to make life choices, Generosity, Perceptions
of corruption]
Index: []
```

[58]:

```python
# Convert numerical values to float

def convert_to_float(x):
    if isinstance(x, str):
        return float(x.replace(",",  "."))
    return x

for feature in list(data.columns):
    if feature != "Country name":
        data[feature] = data[feature].apply(convert_to_float)

data.dtypes
```

[58]:

```
Country name                        object
Life Ladder                        float64
Log GDP per capita                 float64
Social support                     float64
Healthy life expectancy at birth   float64
Freedom to make life choices       float64
Generosity                         float64
Perceptions of corruption          float64
dtype: object
```

[59]:

```python
stats = data.describe()
skew = data.skew()
skew.name = "skew"
stats = stats.append(skew)
stats.T
#pd.concat([stats, data.skew().T])
```

```
/var/folders/3k/ms4rjn056gx8yh5ch6ds4y8h0000gn/T/ipykernel_74523/4177248574.py:2
: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with
'numeric_only=None') is deprecated; in a future version this will raise
TypeError.  Select only valid columns before calling the reduction.
  skew = data.skew()
```

[59]:

```
                                  count       mean       std     min  \
Life Ladder                       144.0   5.570868  1.111850   2.375
Log GDP per capita                138.0   9.477029  1.143544   6.966
Social support                    144.0   0.816792  0.117761   0.420
Healthy life expectancy at birth  139.0  65.003914  6.650202  48.700
Freedom to make life choices      143.0   0.794552  0.116810   0.385
```

```
Generosity                        137.0  -0.019891  0.154101  -0.289
Perceptions of corruption         136.0   0.722654  0.185747   0.070

                                       25%      50%       75%     max  \
Life Ladder                        4.92750   5.5945   6.28125   7.780
Log GDP per capita                 8.56475   9.5945  10.44450  11.648
Social support                     0.75900   0.8440   0.91050   0.982
Healthy life expectancy at birth  59.80000  66.6000  69.25000  77.100
Freedom to make life choices       0.71700   0.8170   0.88900   0.970
Generosity                        -0.13000  -0.0450   0.06700   0.561
Perceptions of corruption          0.68150   0.7745   0.84950   0.963

                                      skew
Life Ladder                      -0.260997
Log GDP per capita               -0.326093
Social support                   -1.038382
Healthy life expectancy at birth -0.555264
Freedom to make life choices     -0.935375
Generosity                        1.026382
Perceptions of corruption        -1.475890
```

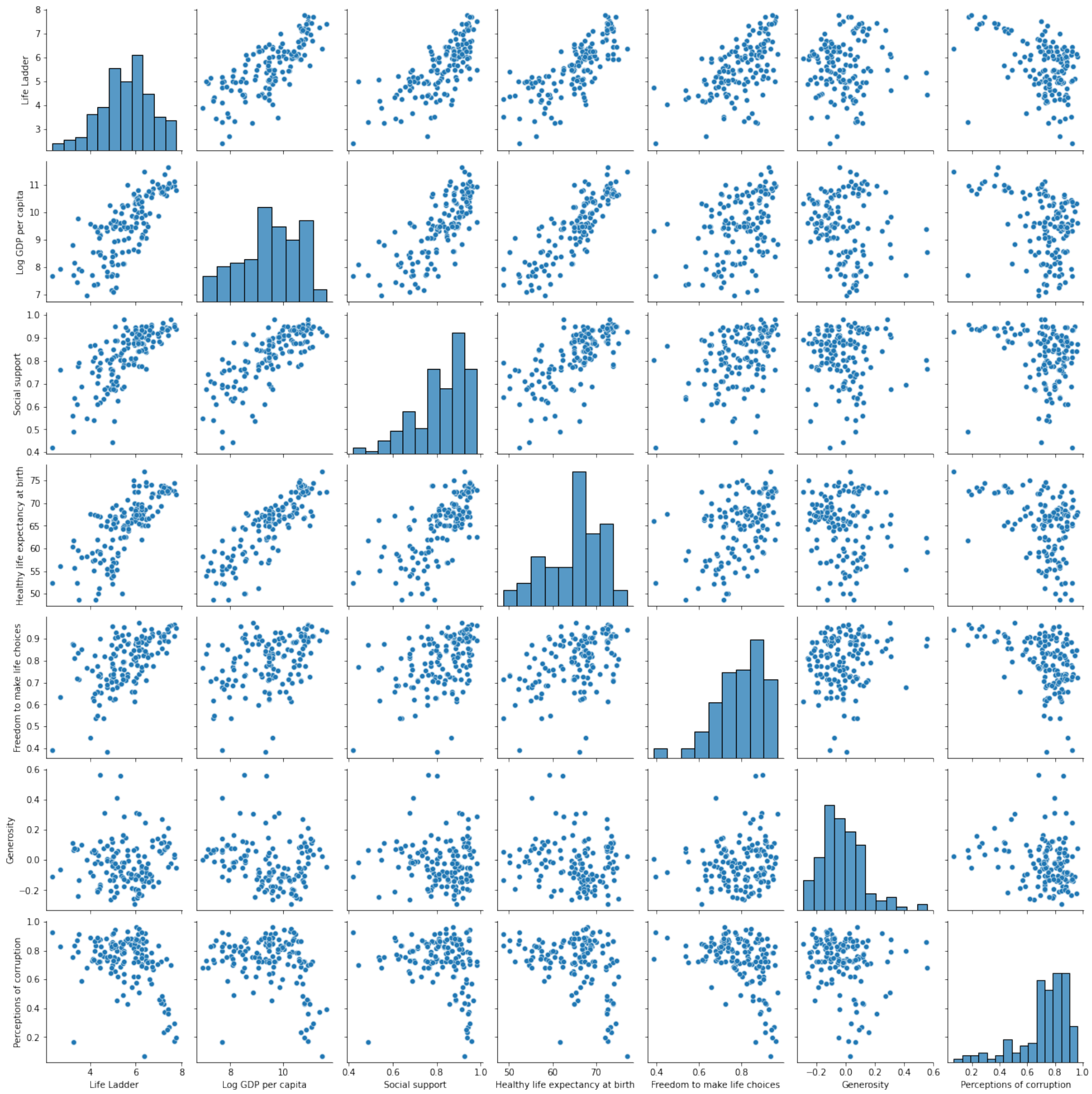
1.2.1 Filling NaNs

[60]:
```
means = data.describe().T["mean"]
data.fillna(value=means, inplace=True)
```

The distribution of quality values.

[61]:
```
sns.pairplot(data)
```

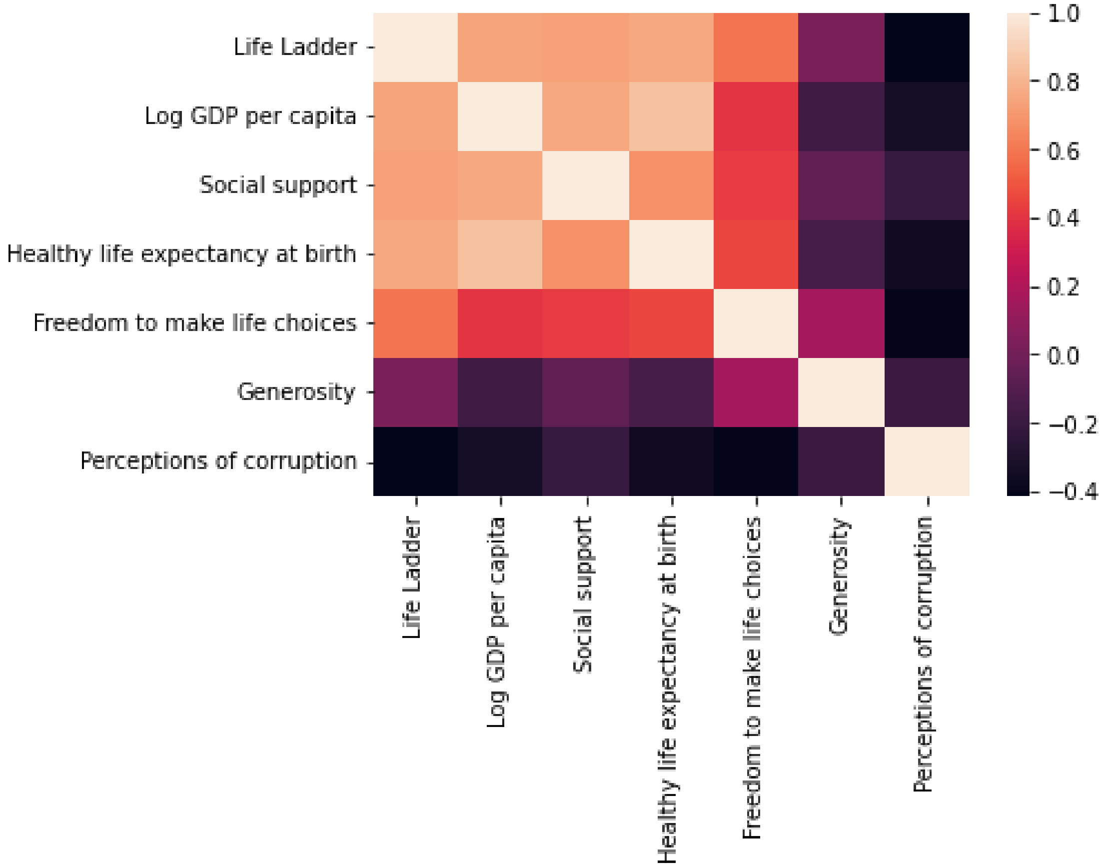
[61]:
```
<seaborn.axisgrid.PairGrid at 0x2b7ea1460>
```



1.2.2 Correlation heatmap

[62]:
```
float_columns = [x for x in data.columns if x not in ['Country name']]
sns.heatmap(data[float_columns].corr())
```

[62]: <AxesSubplot:>



[63]:
```
import pygal_maps_world.maps as maps
```

[64]:
```
# Translate country name to country code from pygal

name_data_format = {
    "cote d'ivoire": "ivory coast",
    "lao people's democratic republic": "laos",
    "macedonia": "north macedonia",
    "russia": "russian federation",
    "libya": "libyan arab jamahiriya",
    "vietnam": "viet nam",
    "cyprus": "north cyprus",
    "palestine": "palestinian territories",
    "south korea": "korea, republic of",
}

name_pygal_format = {}
for key, value in name_data_format.items():
    name_pygal_format[value] = key
```

```python
def format_name(name):
    name = name.lower()
    name = name_pygal_format.get(name, name)
    if " " not in name:
        return name
    name = name.split(",")[0].split(" (")[0]
    if "of china" in name:
        return " ".join(name.split()[:-3])
    return name
```

[65]:
```python
# Test
print("TEST: ", format_name("Hong Kong s.a.r. of China"))
print("TEST: ", format_name("South Korea"))
print("TEST: ", format_name("Ivory Coast"))
print("TEST: ", format_name("Russian Federation"))

codes = []
countries_pygal = []
for key, value in maps.COUNTRIES.items():
    countries_pygal.append(format_name(value))
    codes.append(key)
countries_data = list(map(format_name, list(data["Country name"])))

countries = countries_pygal
missmatched = []
not_found = []

for country_data in countries_data:
    if country_data not in countries_pygal:
        missmatched.append(country_data)
print(len(missmatched), missmatched)

for country_pygal in countries_pygal:
    if country_pygal not in countries_data:
        not_found.append(country_pygal)
#print(len(not_found), not_found)
```

```
TEST:  hong kong
TEST:  south korea
TEST:  cote d'ivoire
TEST:  russia
2 ['comoros', 'kosovo']
```

[66]:
```python
def encode(value):
    value = format_name(value)
    if value in ["comoros", "kosovo"]:
        print(f"WARNING: code for {value} generated manually")
```

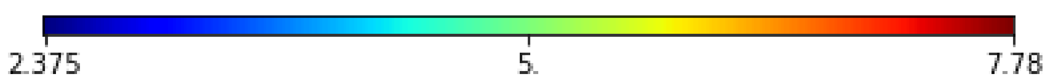
```
        return value[:3].lower()
    return codes[countries.index(value)]

country_code = data["Country name"].apply(encode)
data.set_index(country_code, inplace=True)
```

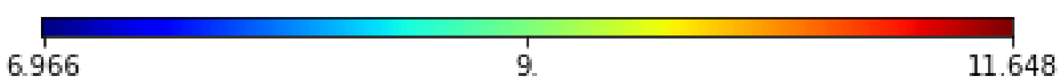
```
WARNING: code for comoros generated manually
WARNING: code for kosovo generated manually
```

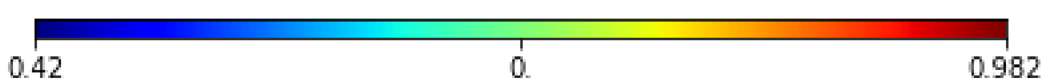
[67]:
```
from pygal.style import Style
import matplotlib

for feature in stats.columns:

    # style
    min_ = stats[feature]["min"]
    max_ = stats[feature]["max"]
    norm = matplotlib.colors.Normalize(vmin=min_, vmax=max_)
    cmap = matplotlib.cm.get_cmap("jet")

    def c_hex(value):
        r, g, b, q = cmap(norm(value))[0]
        return '#%02x%02x%02x' % (int(255*r), int(255*g), int(255*b))

    dat = data[[feature]].sort_values(by=feature)
    colors = reversed([c_hex(x) for x in dat.values])
    custom_style = Style(colors=tuple(colors))

    # map
    worldmap = maps.World(style=custom_style)

    for idx, row in dat.iterrows():
        worldmap.tittle = feature
        worldmap.add("", {idx:  row[feature]})

    worldmap.render_to_png(f"map_{feature.split()[0]}.png")
```

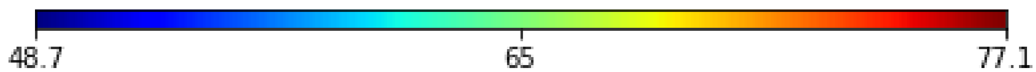
[68]:
```
%matplotlib inline

import matplotlib as mpl
from matplotlib import cm

for feature in stats.columns:
    gradient = np.linspace(0, 1, 256)
    gradient = np.vstack((gradient, gradient))

    min_ = stats[feature]["min"]
    max_ = stats[feature]["max"]
```

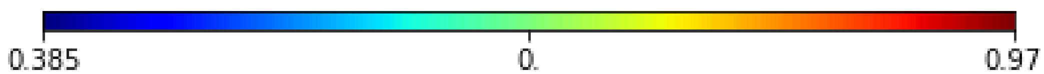
```python
def plot_color_gradients(cmap_list):
    # Create figure and adjust figure height to number of colormaps
    nrows = len(cmap_list)
    figh = 0.35 + 0.15 + (nrows + (nrows - 1) * 0.1) * 0.22
    fig, axs = plt.subplots(nrows=nrows + 1, figsize=(6.4, figh))
    fig.subplots_adjust(top=1 - 0.35 / figh, bottom=0.15 / figh,
                        left=0.2, right=0.99)

    for ax, name in zip(axs, cmap_list):
        ax.imshow(gradient, aspect='auto', cmap=plt.get_cmap(name))

    # Turn off *all* ticks & spines, not just the ones with colormaps.
    for ax in axs:
        ax.set_axis_off()
    axs[0].set_axis_on()
    axs[0].set_yticks(())
    axs[0].set_xticks((0, 128, 256))
    #axs[0].set_xticklabels((str(min_)[:2], str(np.mean(min_, max_))[:2], str(max_)[:2]))
    axs[0].set_xticklabels((str(min_), str(stats[feature]["mean"])[:2], str(max_)))

# Save colormap list for later.
plot_color_gradients(['jet'])
plt.savefig(f"cbar_{feature.split()[0]}.png")
#plt.show()
```

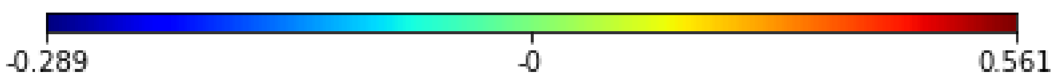


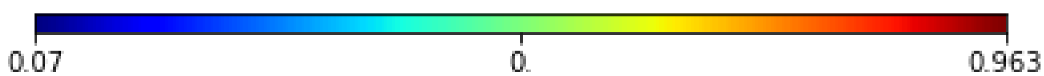












1.3 Cleaning

- Examine the correlation and skew of the relevant variables–everything except color and quality (without dropping these columns from our data).
- Perform any appropriate feature transformations and/or scaling.
- Examine the pairwise distribution of the variables with pairplots to verify scaling and normalization efforts.

And an examination of the skew values in anticipation of transformations.

[69]:
```
skew_columns = (data[float_columns].skew().sort_values(ascending=False))
skew_columns = skew_columns.loc[skew_columns < -0.7]
skew_columns
```

[69]:
```
Freedom to make life choices   -0.938571
Social support                 -1.038382
Perceptions of corruption      -1.517732
dtype: float64
```

[70]:
```
# Perform log transform on skewed columns
for col in skew_columns.index.tolist():
    data[col] = np.log1p(data[col])
```

Perform feature scaling.

[71]:
```
from sklearn.preprocessing import StandardScaler

sc = StandardScaler()
data[float_columns] = sc.fit_transform(data[float_columns])
data.head(5).T
```

[71]:
```
Country name                                 af        al        dz         ar  \
Country name                        Afghanistan   Albania   Algeria  Argentina
Life Ladder                           -2.884402 -0.519745  -0.74538   0.464928
Log GDP per capita                    -1.595861  0.060042 -0.125541   0.468863
Social support                        -3.634898 -1.079317 -0.080716   0.667857
Healthy life expectancy at birth      -1.936031  0.613821  0.168365   0.613821
Freedom to make life choices          -3.732758 -0.113843  -3.82932   0.218013
Generosity                            -0.588342 -0.528246  0.166204  -1.276114
Perceptions of corruption              1.011805  0.966646  0.145659   0.577718

Country name                             am
Country name                        Armenia
Life Ladder                       -0.074792
Log GDP per capita                 0.040318
Social support                    -0.255089
Healthy life expectancy at birth   0.337331
Freedom to make life choices       0.437912
Generosity                        -1.015696
Perceptions of corruption         -0.678813
```

1.4 K-Means

- Fit a K-means clustering model with two clusters.
- Examine the clusters.

[86]:
```
from sklearn.cluster import KMeans

km = KMeans(n_clusters=5, random_state=42)
km = km.fit(data[float_columns])

data['kmeans'] = km.predict(data[float_columns])
```

[87]:
```
(data[['Country name','kmeans']]
 .groupby(['kmeans'])
 .size()
 .to_frame()
 .rename(columns={0:'number'}))
```

[87]:
```
        number
kmeans
0           15
1           23
```

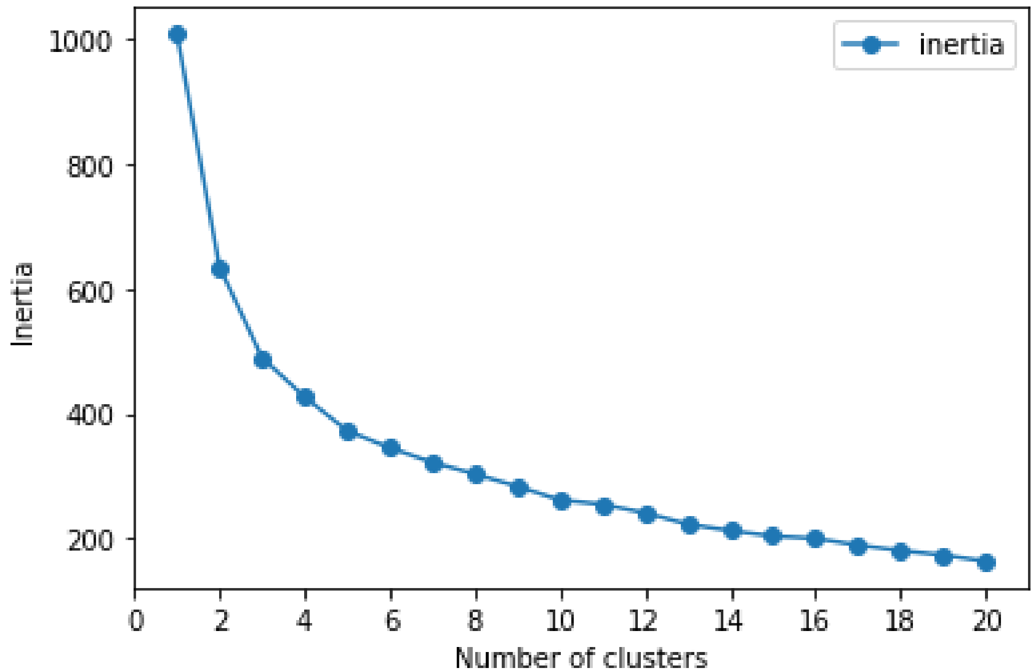
2	57
3	19
4	29

1.5 K-Means

- Now fit K-Means models with cluster values ranging from 1 to 20.
- For each model, store the number of clusters and the inertia value.
- Plot cluster number vs inertia. Does there appear to be an ideal cluster number?

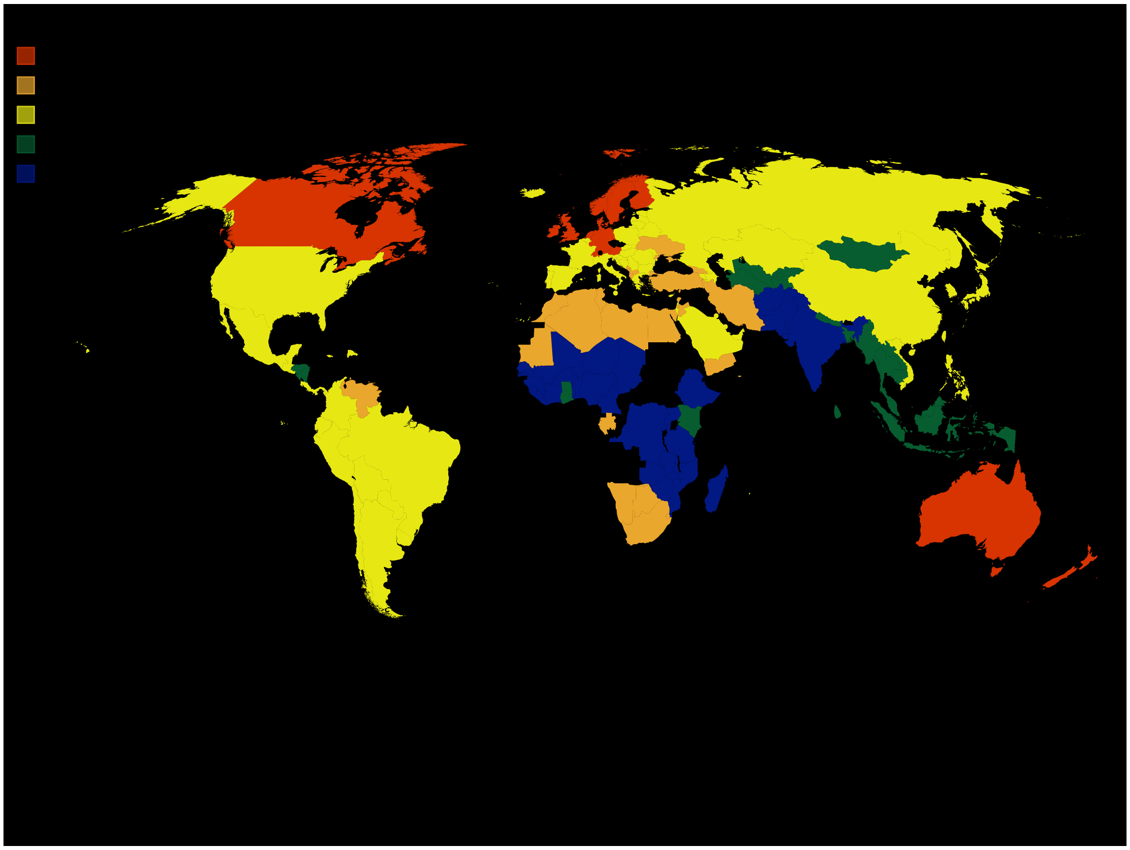
[74]:
```
## Create and fit a range of models
km_list = list()

for nclust in range(1,21):
    km = KMeans(n_clusters=nclust, random_state=42)
    km = km.fit(data[float_columns])

    km_list.append(pd.Series({'clusters': nclust,
                              'inertia': km.inertia_,
                              'model': km}))
```

[75]:
```
plot_data = (pd.concat(km_list, axis=1)
             .T
             [['clusters','inertia']]
             .set_index('clusters'))

ax = plot_data.plot(marker='o',ls='-')
ax.set_xticks(range(0,21,2))
ax.set_xlim(0,21)
ax.set(xlabel='Number of clusters', ylabel='Inertia');
```



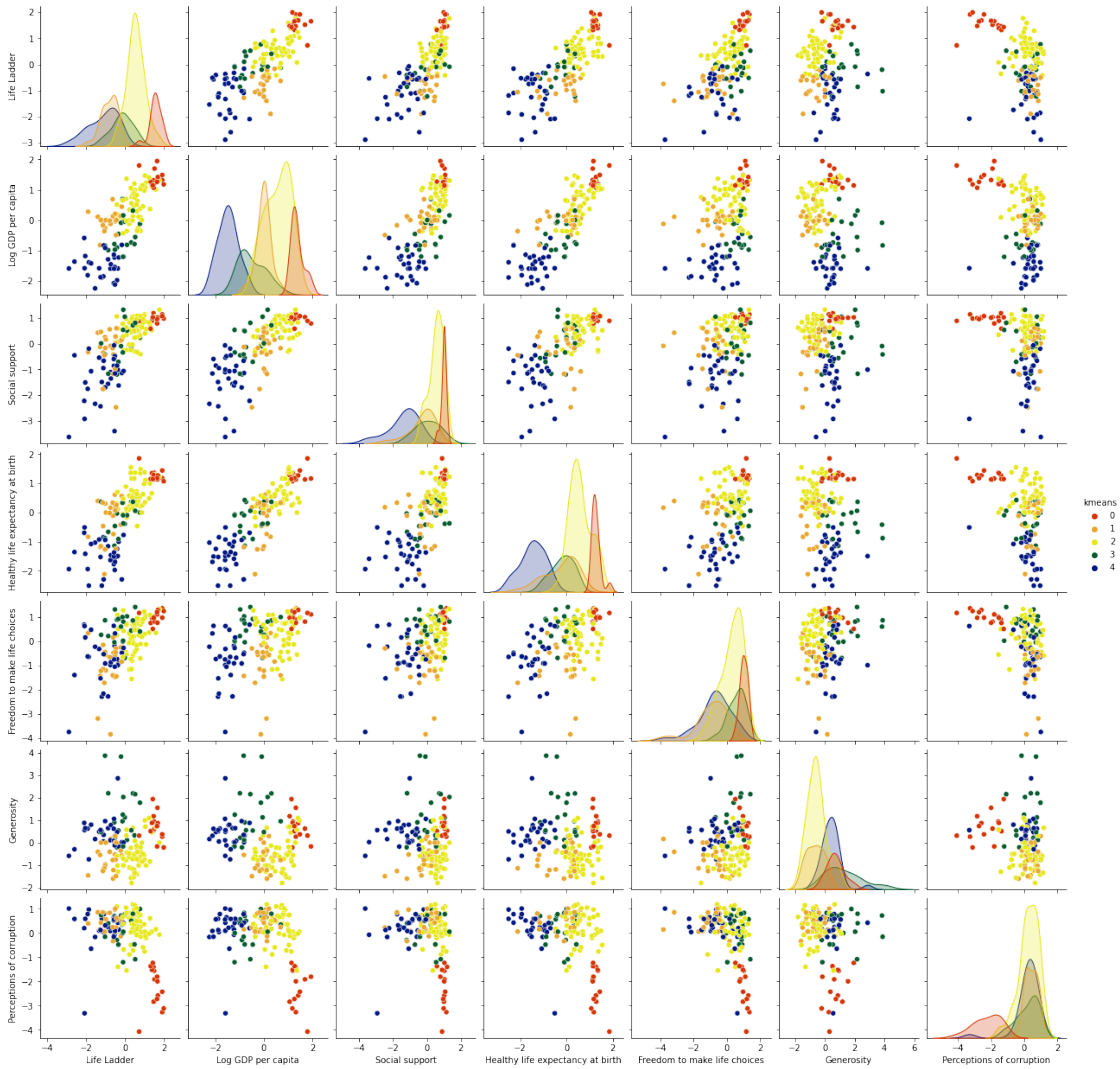
[103]:
```
# map KMeans
worldmap = maps.World(style=mystyle)
kmeans_values = sorted(list(data.kmeans.unique()))

for val in kmeans_values:
    data_dict = data.loc[data["kmeans"]==val].to_dict()["kmeans"]
    worldmap.add(str(val), data_dict)

worldmap.render_to_png(f"map_kmeans.png")
worldmap
```

[103]:



[104]:
```
from pygal.style import DefaultStyle

method="kmeans"
data = data[~data.index.duplicated()]
colors = mystyle.colors[:5]
palette = sns.color_palette(colors)
sns.pairplot(data[ float_columns + [method]], hue=method, palette=palette)
```

[104]: `<seaborn.axisgrid.PairGrid at 0x2d406ac70>`



1.6 Agglomerative clustering

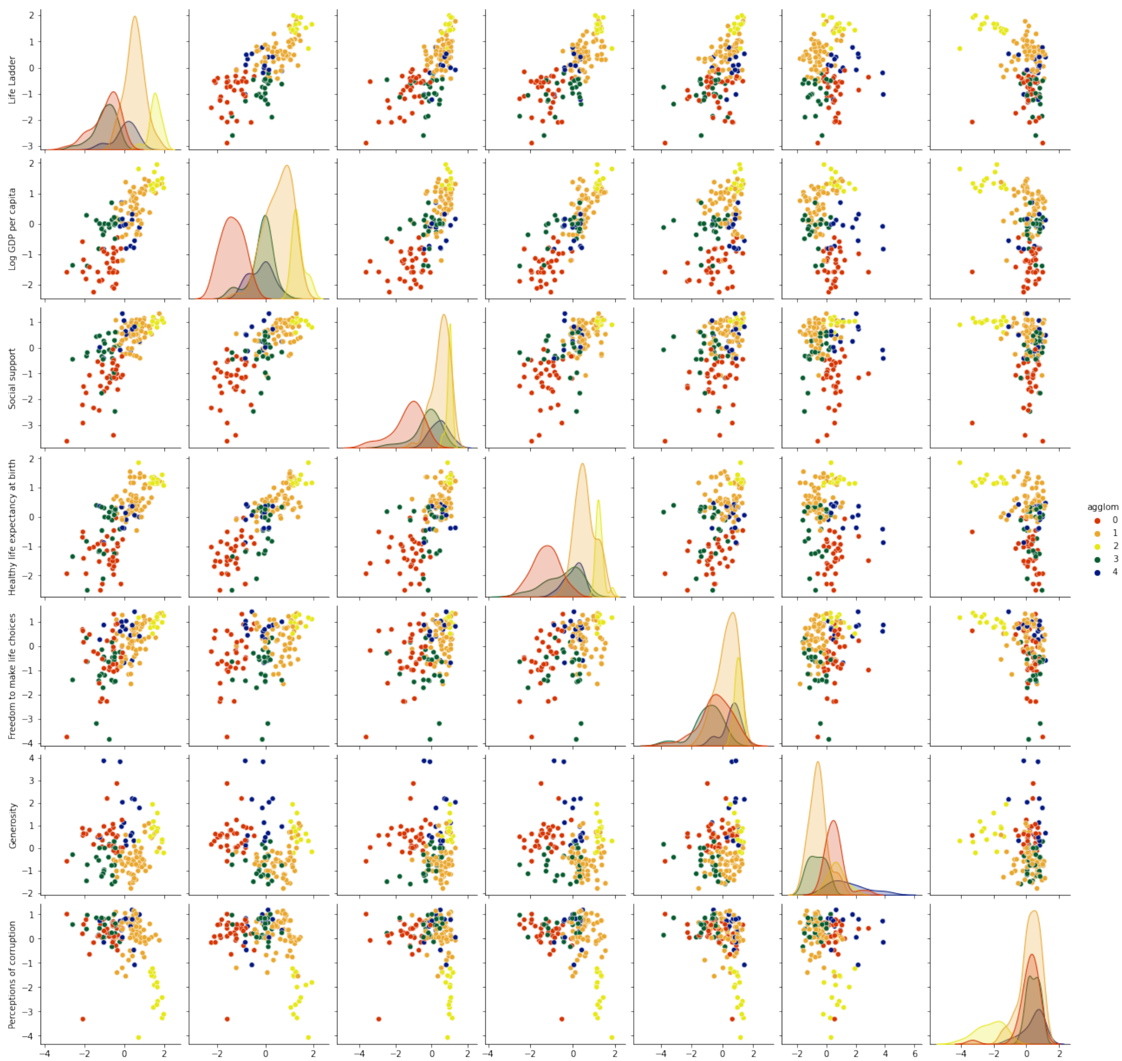
- Fit an agglomerative clustering model with two clusters.
- Compare the results to those obtained by K-means with regards to wine color by reporting the number of red and white observations in each cluster for both K-means and agglomerative clustering.
- Visualize the dendrogram produced by agglomerative clustering. *Hint:* SciPy has a module called `cluster.hierarchy` that contains the `linkage` and `dendrogram` functions required to create the linkage map and plot the resulting dendrogram.

[91]:
```
from sklearn.cluster import AgglomerativeClustering

ag = AgglomerativeClustering(n_clusters=5, linkage='ward',␣
↪compute_full_tree=True)
```

```python
ag = ag.fit(data[float_columns])
data['agglom'] = ag.fit_predict(data[float_columns])
```

[105]:
```python
method="agglom"
data = data[~data.index.duplicated()]
colors = mystyle.colors[:5]
palette = sns.color_palette(colors)
sns.pairplot(data[ float_columns + [method]], hue=method, palette=palette)
```

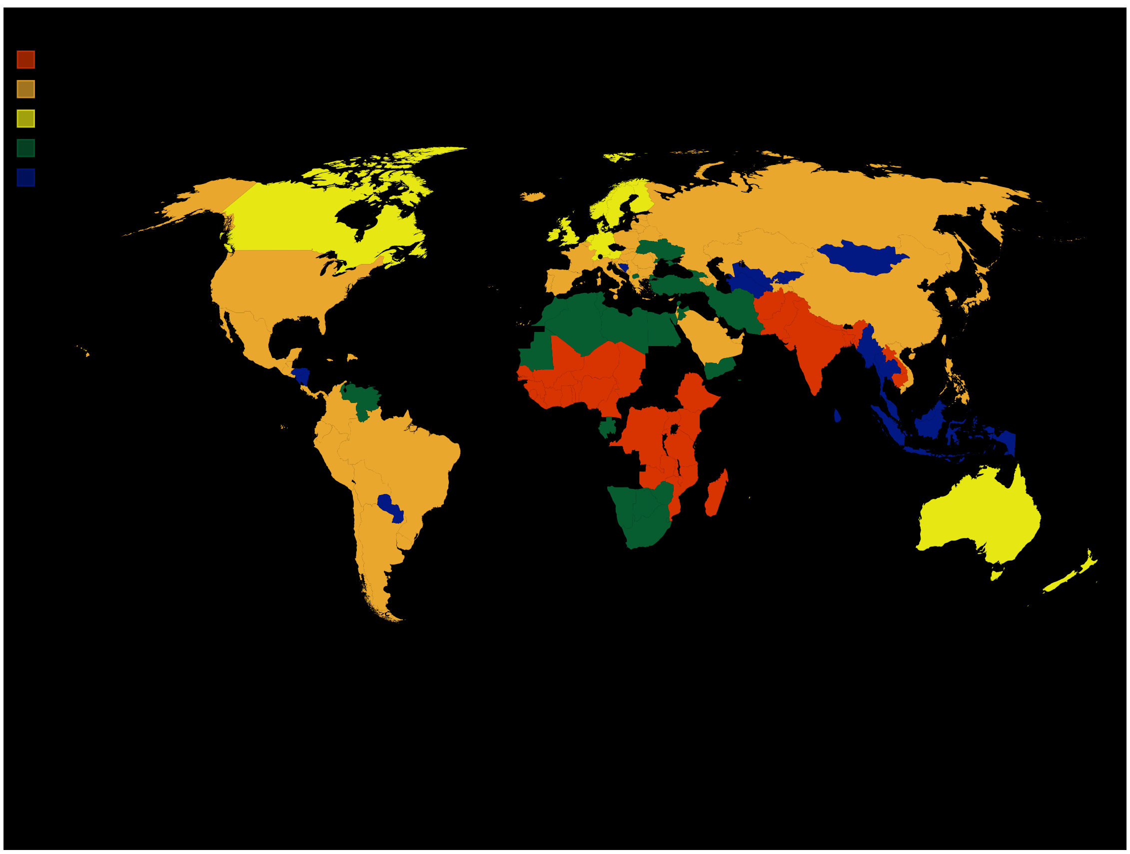
[105]:
```
<seaborn.axisgrid.PairGrid at 0x2d6d9df40>
```



Note that cluster assignment is arbitrary, the respective primary cluster numbers for red and white may not be identical to the ones below and also may not be the same for both K-means and agglomerative clustering.

[101]:
```python
from pygal.style import Style
mystyle = Style(colors=("#d73402", "#eaa72d", "#e7e813", "#075d30", "#021882"))

# map
worldmap = maps.World(style=mystyle)

# map Agglo
method = "agglom"
worldmap = maps.World(style=mystyle)
kmeans_values = sorted(list(data[method].unique()))

for val in kmeans_values:
    data_dict = data.loc[data[method]==val].to_dict()[method]
    worldmap.add(str(val), data_dict)

worldmap.render_to_png(f"map_{method}.png")
worldmap
```

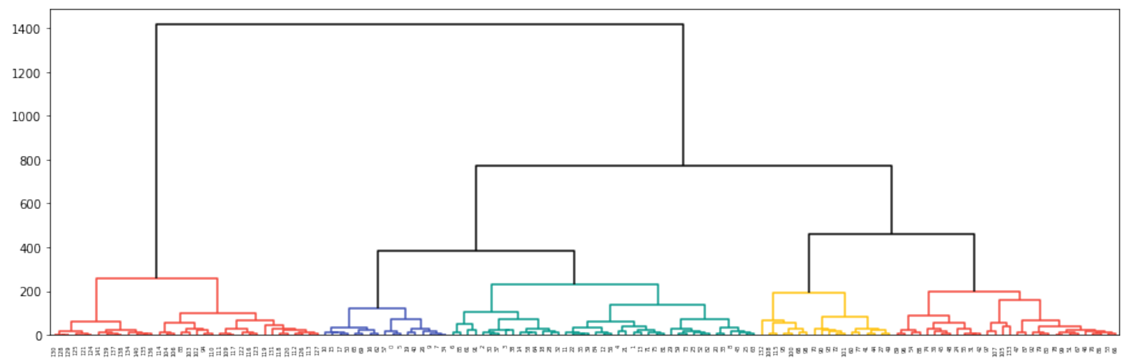
[101]:



Though the cluster numbers are not identical, the clusters are very consistent within a single wine variety (red or white).

And here is a plot of the dendrogram created from agglomerative clustering.

[95]:
```python
# First, we import the cluster hierarchy module from SciPy (described above) to␣
↪obtain the linkage and dendrogram functions.
from scipy.cluster import hierarchy
from pygal.style import DefaultStyle

Z = hierarchy.linkage(ag.children_, method='ward')

fig, ax = plt.subplots(figsize=(16,5))

# Some color setup
colors = DefaultStyle.colors[:4]
hierarchy.set_link_color_palette(colors)

den = hierarchy.dendrogram(Z, orientation='top',
                           p=100, truncate_mode='level',
                           color_threshold=300,
                           show_leaf_counts=False, ax=ax,
                           above_threshold_color="black")
```

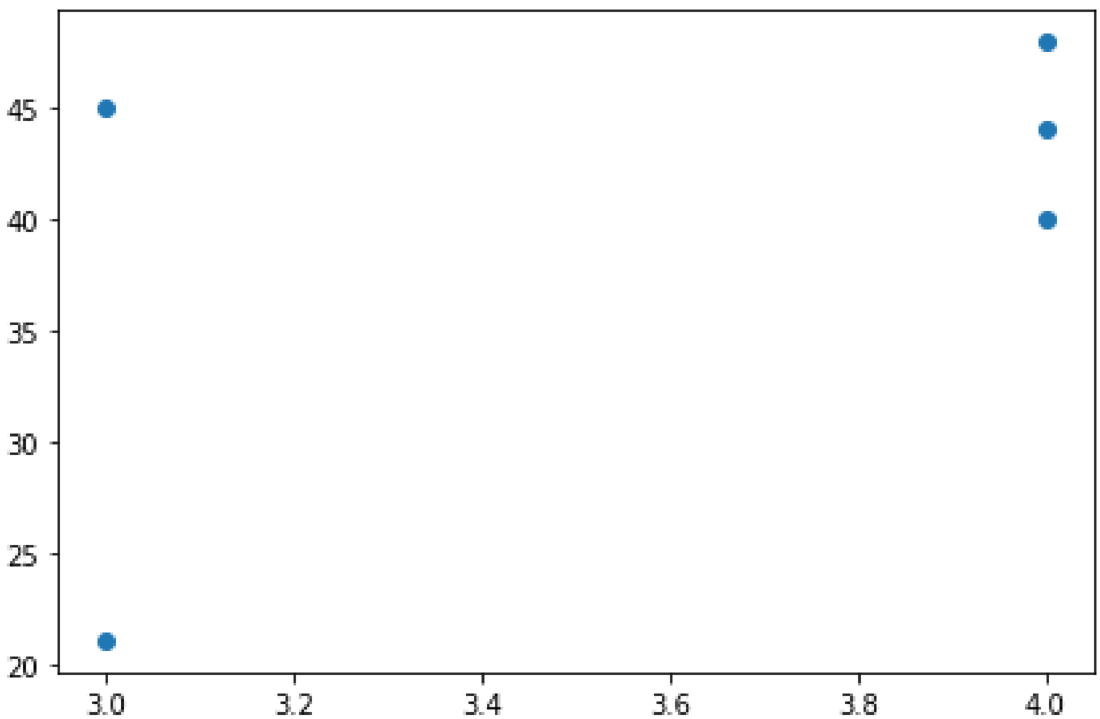


1.7 DBSCAN

[82]:
```python
from sklearn.cluster import DBSCAN

outliers = {}
clusters = {}

for eps in [i/10 for i in range(10, 50, 1)]:
    for neigh in [i for i in range(4, 10, 1)]:
        dbscan = DBSCAN(min_samples=neigh, eps=eps)
        db = dbscan.fit(data[float_columns])
        data['dbscan'] = db.fit_predict(data[float_columns])
        noutlier = data[data["dbscan"]==-1].count().iloc[0]
        ncluster = len(list(data["dbscan"].unique())) - 1
        if ncluster > 2 and noutlier < 50:
```

```
            outliers[(eps, neigh)] = noutlier
            clusters[(eps, neigh)] = ncluster

print(outliers)
print(clusters)

y = [outliers[key] for key in outliers.keys()]
x = [clusters[key] for key in outliers.keys()]

plt.scatter(x, y, marker="o")
plt.xlabel = "Number of outliers"
plt.ylabel = "Number of clusters"
plt.tight_layout()

#dbscan_values = sorted(list(data[method].unique()))
#dbscan_values
```

```
{(1.3, 4): 40, (1.3, 5): 44, (1.3, 6): 48, (1.4, 9): 45, (1.5, 4): 21}
{(1.3, 4): 4, (1.3, 5): 4, (1.3, 6): 4, (1.4, 9): 3, (1.5, 4): 3}
```

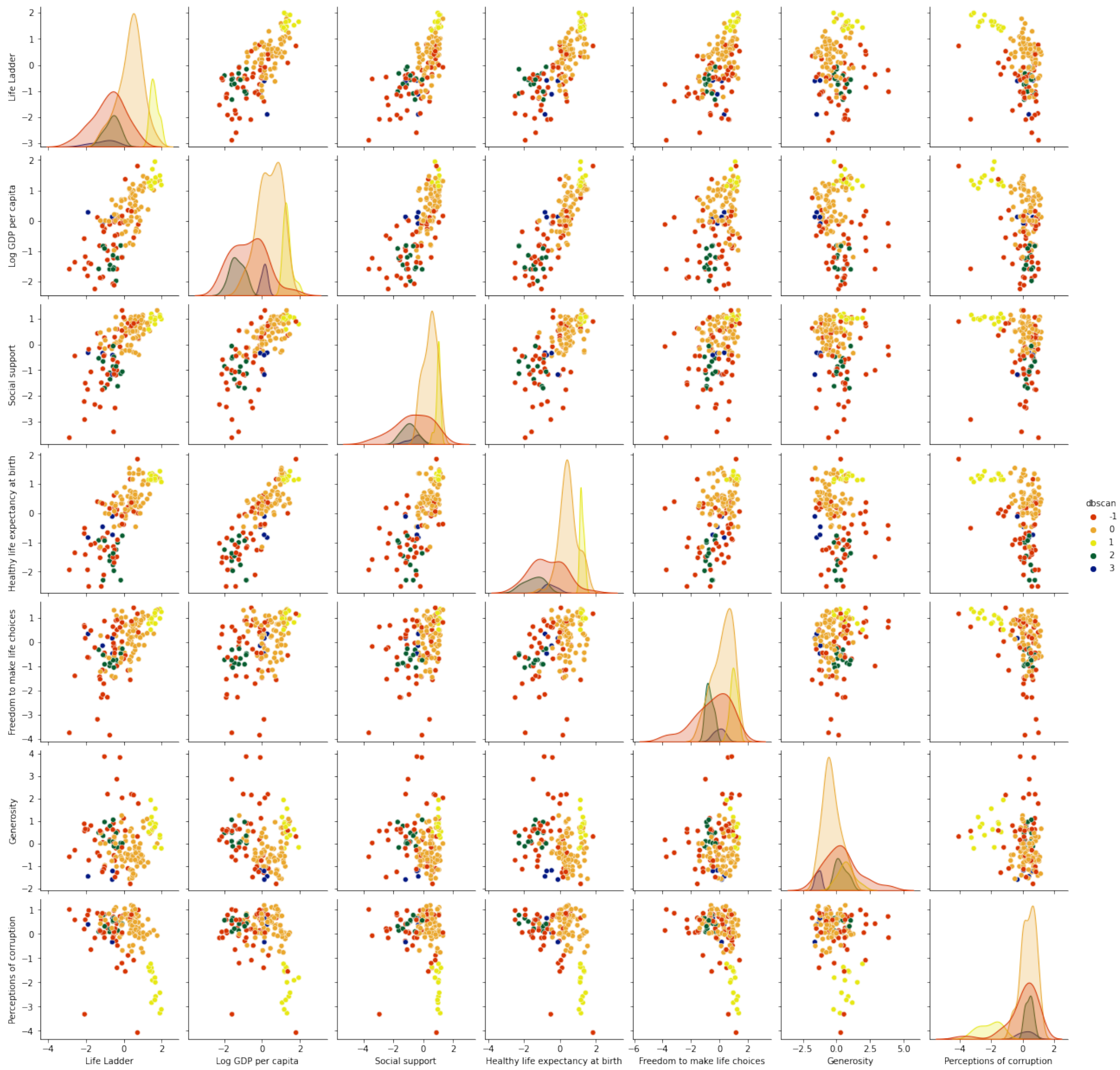


[96]:
```
dbscan = DBSCAN(min_samples=5, eps=1.3)
db = dbscan.fit(data[float_columns])
data['dbscan'] = db.fit_predict(data[float_columns])
data.groupby("dbscan").count()
```

[96]:
```
        Country name  Life Ladder  Log GDP per capita  Social support  \
dbscan
-1                44           44                  44              44
 0                69           69                  69              69
 1                14           14                  14              14
 2                12           12                  12              12
 3                 4            4                   4               4

        Healthy life expectancy at birth  Freedom to make life choices  \
dbscan
-1                                    44                            44
 0                                    69                            69
 1                                    14                            14
 2                                    12                            12
 3                                     4                             4

        Generosity  Perceptions of corruption  kmeans  agglom
dbscan
-1              44                         44      44      44
 0              69                         69      69      69
 1              14                         14      14      14
 2              12                         12      12      12
 3               4                          4       4       4
```

[106]:
```python
from pygal.style import DefaultStyle

method="dbscan"
dbscan_values = data[method].unique()
#data = data[~data.index.duplicated()]
colors = mystyle.colors[:len(dbscan_values)]
palette = sns.color_palette(colors)
sns.pairplot(data[float_columns + [method]], hue=method, palette=palette)
```

[106]: <seaborn.axisgrid.PairGrid at 0x2df055f10>



[102]:

```
# map
method = "dbscan"
worldmap = maps.World(style=mystyle)
dbscan_values = sorted(list(data[method].unique()))

for val in dbscan_values:
    data_dict = data.loc[data[method]==val].to_dict()[method]
    worldmap.add(str(val), data_dict)

worldmap.render_to_png(f"map_{method}.png")
worldmap
```

[102]: