```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

Example 1 – Binary Coding of nominal attribute

In [2]:

```
report_df = pd.read_csv('WH Report_preprocessed.csv')
BM = report_df.year == 2019
report2019_df = report_df[BM]
report2019_df.set_index('Name',inplace=True)
```

In [3]:

```
bc_Continent = pd.get_dummies(report2019_df.Continent)
bc_Continent.head(5)
```

Out[3]:

	Africa	Antarctica	Asia	Europe	North America	Oceania	South America
Name							
Afghanistan	0	0	1	0	0	0	0
Albania	0	0	0	1	0	0	0
Algeria	1	0	0	0	0	0	0
Argentina	0	0	0	0	0	0	1
Armenia	0	0	0	1	0	0	0

In [4]:

```
from sklearn.cluster import KMeans
dimensions = ['Life_Ladder', 'Log_GDP_per_capita', 'Social_support',
              'Healthy_life_expectancy_at_birth',
'Freedom_to_make_life_choices',
              'Generosity', 'Perceptions_of_corruption', 'Positive_affect',
'Negative_affect']
Xs = report2019_df[dimensions]
Xs = (Xs - Xs.min())/(Xs.max()-Xs.min())
Xs = Xs.join(bc_Continent/7)
kmeans = KMeans(n_clusters=3)
kmeans.fit(Xs)

for i in range(3):
    BM = kmeans.labels_==i
    print('Cluster {}: {}'.format(i,Xs[BM].index.values))
```

```
Cluster 0: ['Australia' 'Austria' 'Bahrain' 'Canada' 'Denmark' 'Estonia'
'Finland'
 'France' 'Germany' 'Iceland' 'Ireland' 'Israel' 'Luxembourg' 'Malta'
 'Netherlands' 'New Zealand' 'Norway' 'Singapore' 'Sweden' 'Switzerland'
 'United Arab Emirates' 'United Kingdom' 'United States' 'Uruguay'
```

```
 'Uzbekistan']
Cluster 1: ['Afghanistan' 'Algeria' 'Bangladesh' 'Benin' 'Burkina Faso'
'Cambodia'
 'Cameroon' 'Chad' 'Ethiopia' 'Gabon' 'Ghana' 'Guinea' 'Haiti' 'India'
 'Iraq' 'Jordan' 'Kenya' 'Lebanon' 'Liberia' 'Madagascar' 'Malawi' 'Mali'
 'Mauritania' 'Morocco' 'Myanmar' 'Nepal' 'Niger' 'Nigeria' 'Pakistan'
 'Rwanda' 'Senegal' 'Sierra Leone' 'Tanzania' 'Togo' 'Tunisia' 'Uganda'
 'Zambia' 'Zimbabwe']
Cluster 2: ['Albania' 'Argentina' 'Armenia' 'Azerbaijan' 'Belarus'
'Belgium'
 'Bolivia' 'Bosnia and Herzegovina' 'Botswana' 'Brazil' 'Bulgaria' 'Chile'
 'China' 'Colombia' 'Costa Rica' 'Croatia' 'Cyprus' 'Czech Republic'
 'Dominican Republic' 'Ecuador' 'El Salvador' 'Georgia' 'Greece'
 'Guatemala' 'Honduras' 'Hungary' 'Indonesia' 'Italy' 'Japan' 'Kazakhstan'
 'Kuwait' 'Latvia' 'Libya' 'Lithuania' 'Malaysia' 'Mexico' 'Moldova'
 'Mongolia' 'Montenegro' 'Nicaragua' 'Panama' 'Paraguay' 'Peru'
 'Philippines' 'Poland' 'Portugal' 'Romania' 'Saudi Arabia' 'Serbia'
 'Slovenia' 'South Africa' 'Spain' 'Sri Lanka' 'Tajikistan' 'Thailand'
 'Turkey' 'Turkmenistan' 'Ukraine' 'Vietnam']
```

In [5]:

```
clusters = ['Cluster {}'.format(i) for i in range(3)]

Centroids = pd.DataFrame(0.0, index =  clusters,
                        columns = Xs.columns)
for i,clst in enumerate(clusters):
    BM = kmeans.labels_==i
    Centroids.loc[clst] = Xs[BM].mean(axis=0)

plt.figure(figsize=(10,4))
plt.subplot(1,2,1)
sns.heatmap(Centroids[dimensions], linewidths=.5,
            annot=True, cmap='binary')
plt.subplot(1,2,2)
sns.heatmap(Centroids[bc_Continent.columns],
            linewidths=.5, annot=True, cmap='binary')
plt.show()
```

To see this impact, remove the division by 7 run the clustering analysis, and create the heatmap of the centroid analysis to see this.

In [6]:

```
dimensions = ['Life_Ladder', 'Log_GDP_per_capita', 'Social_support',
             'Healthy_life_expectancy_at_birth',
'Freedom_to_make_life_choices',
             'Generosity', 'Perceptions_of_corruption', 'Positive_affect',
'Negative_affect']
Xs = report2019_df[dimensions]
Xs = (Xs - Xs.min())/(Xs.max()-Xs.min())
Xs = Xs.join(bc_Continent)
kmeans = KMeans(n_clusters=3)
kmeans.fit(Xs)

clusters = ['Cluster {}'.format(i) for i in range(3)]

Centroids = pd.DataFrame(0.0, index =  clusters,
```

```
                        columns = Xs.columns)
for i,clst in enumerate(clusters):
    BM = kmeans.labels_==i
    Centroids.loc[clst] = Xs[BM].mean(axis=0)

plt.figure(figsize=(10,4))
plt.subplot(1,2,1)
sns.heatmap(Centroids[dimensions], linewidths=.5, annot=True,
                    cmap='binary')
plt.subplot(1,2,2)
sns.heatmap(Centroids[bc_Continent.columns], linewidths=.5, annot=True,
                    cmap='binary')
plt.show()
```

The reason for this two-fold visual is that the normalized numerical values are between zero and one and the binary coded values are between 0 and 0.14; without the separation, the heatmap would only show the normalized numerical as those values have a larger scale. Run the normal non-separated heatmap and see that for yourself.

In [7]:

```
dimensions = ['Life_Ladder', 'Log_GDP_per_capita', 'Social_support',
              'Healthy_life_expectancy_at_birth',
'Freedom_to_make_life_choices',
              'Generosity', 'Perceptions_of_corruption', 'Positive_affect',
'Negative_affect']
Xs = report2019_df[dimensions]
Xs = (Xs - Xs.min())/(Xs.max()-Xs.min())
Xs = Xs.join(bc_Continent/7)
kmeans = KMeans(n_clusters=3)
kmeans.fit(Xs)

clusters = ['Cluster {}'.format(i) for i in range(3)]

Centroids = pd.DataFrame(0.0, index =  clusters,
                        columns = Xs.columns)
for i,clst in enumerate(clusters):
    BM = kmeans.labels_==i
    Centroids.loc[clst] = Xs[BM].mean(axis=0)


sns.heatmap(Centroids, linewidths=.5, annot=True,
                    cmap='binary')
plt.show()
```

Example 3 – Discretization of Numerical attributes

In [8]:

```
adult_df = pd.read_csv('adult.csv')
adult_df
```

Out[8]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capitalGain	capitalLoss	hoursPerWeek	nativeCountry	income
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=50K
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=50K
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
32556	27	Private	257302	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White	Female	0	0	38	United-States	<=50K
32557	40	Private	154374	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	0	0	40	United-States	>50K
32558	58	Private	151910	HS-grad	9	Widowed	Adm-clerical	Unmarried	White	Female	0	0	40	United-States	<=50K
32559	22	Private	201490	HS-grad	9	Never-	Adm-	Own-child	White	Male	0	0	20	United-States	<=50K

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capitalGain	capitalLoss	hoursPerWeek	nativeCountry	income
						married	clerical								
32560	52	Self-emp-inc	287927	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	White	Female	15024	0	40	United-States	>50K

32561 rows × 15 columns

In [9]:

```
adult_df = pd.read_csv('adult.csv')
sns.boxplot(data=adult_df, y='sex', x='hoursPerWeek',hue='income')
```

Out[9]:

In [10]:

```
adult_df.hoursPerWeek.plot.hist()
plt.show()
```

In [11]:

```
adult_df['discretized_hoursPerWeek']=adult_df.hoursPerWeek.apply(lambda v:
'>40' if v>40 else ('40' if v==40 else '<40'))
```

In [12]:

```
adult_df.groupby(['sex','income']).discretized_hoursPerWeek.value_counts().
unstack()[['<40','40', '>40']].plot.barh()
plt.show()
```

Types of Discretization

In [13]:

```
pd.cut(adult_df.age, bins = 5).value_counts().sort_index().plot.bar()
plt.show()
```

In [14]:

```
pd.qcut(adult_df.age,q=5,
        duplicates='drop').value_counts().sort_index().plot.bar()
plt.show()
```

Example – Construct one transformed attribute from two attributes

In [15]:

```
person_df = pd.read_csv('500_Person_Gender_Height_Weight_Index.csv')
person_df.Index = person_df.Index.replace({0:'Extremely Weak', 1: 'Weak',2:
'Normal',3:'Overweight', 4:'Obesity',5:'Extreme Obesity'})
person_df.columns = ['Gender', 'Height', 'Weight', 'Condition']
```

In [16]:

```
person_df
```

Out[16]:

	Gender	Height	Weight	Condition
0	Male	174	96	Obesity
1	Male	189	87	Normal
2	Female	185	110	Obesity
3	Female	195	104	Overweight
4	Male	149	61	Overweight
...	...	...	...	...
495	Female	150	153	Extreme Obesity
496	Female	184	121	Obesity
497	Female	141	136	Extreme Obesity
498	Male	150	95	Extreme Obesity
499	Male	173	131	Extreme Obesity

500 rows × 4 columns

In [17]:

```
sns.scatterplot(data = person_df, x='Height',y='Weight',
                hue='Condition',style='Gender')
plt.legend(bbox_to_anchor=(1.05, 1))
plt.show()
```

In [18]:

```
person_df['BMI'] = person_df.apply(lambda
r:r.Weight/((r.Height/100)**2),axis=1)
```

In [19]:

```
person_df
```

Out[19]:

	Gender	Height	Weight	Condition	BMI
0	Male	174	96	Obesity	31.708284
1	Male	189	87	Normal	24.355421
2	Female	185	110	Obesity	32.140248
3	Female	195	104	Overweight	27.350427
4	Male	149	61	Overweight	27.476240
...	...	...	...	...	...
495	Female	150	153	Extreme Obesity	68.000000
496	Female	184	121	Obesity	35.739603
497	Female	141	136	Extreme Obesity	68.407022
498	Male	150	95	Extreme Obesity	42.222222
499	Male	173	131	Extreme Obesity	43.770256

500 rows × 5 columns

In [20]:

```
person_df.BMI.hist()
```

Out[20]:

In [21]:

```
person_df.BMI.plot.box()
```

Out[21]:

In [22]:

```
person_df['Random'] = np.random.random(len(person_df))

plt.figure(figsize=(12,2.5))
sns.scatterplot(data = person_df, x='BMI',y='Random',
                hue='Condition')
plt.ylim([-0.25,1.25])
plt.xticks(np.linspace(10,80,15))
plt.yticks([])
plt.grid()
plt.legend(bbox_to_anchor=(1.01, 1))
plt.show()
```

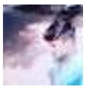
Log Transformation

In [23]:

```
country_df = pd.read_csv('GDP 2019 2020.csv')
country_df.set_index('Country Name',inplace=True)
country_df
```

Out[23]:

Country Name	Country Code	2019	2020
Afghanistan	AFG	1.929110e+10	1.980707e+10
Angola	AGO	8.941719e+10	6.230691e+10
Albania	ALB	1.528661e+10	1.479962e+10
Argentina	ARG	4.450000e+11	3.830000e+11
Armenia	ARM	1.367280e+10	1.264546e+10
...	...	...	...
Vanuatu	VUT	9.303380e+08	8.547936e+08
Samoa	WSM	8.522502e+08	8.070272e+08
South Africa	ZAF	3.510000e+11	3.020000e+11
Zambia	ZMB	2.330869e+10	1.932005e+10



ReplyForward