Data Minning Project

In [ ]:

```
#decision tree visualization
!pip install dtreeviz
```

```
Requirement already satisfied: dtreeviz in /usr/local/lib/python3.7/dist-pa
ckages (1.3.6)
Requirement already satisfied: graphviz>=0.9 in /usr/local/lib/python3.7/di
st-packages (from dtreeviz) (0.10.1)
Requirement already satisfied: pytest in /usr/local/lib/python3.7/dist-pack
ages (from dtreeviz) (3.6.4)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.7/dist-
packages (from dtreeviz) (3.2.2)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.7/dis
t-packages (from dtreeviz) (1.0.2)
Requirement already satisfied: pandas in /usr/local/lib/python3.7/dist-pack
ages (from dtreeviz) (1.3.5)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packa
ges (from dtreeviz) (1.21.6)
Requirement already satisfied: colour in /usr/local/lib/python3.7/dist-pack
ages (from dtreeviz) (0.1.5)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dis
t-packages (from matplotlib->dtreeviz) (0.11.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.
7/dist-packages (from matplotlib->dtreeviz) (1.4.2)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in
/usr/local/lib/python3.7/dist-packages (from matplotlib->dtreeviz) (3.0.8)
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/pytho
n3.7/dist-packages (from matplotlib->dtreeviz) (2.8.2)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.
7/dist-packages (from kiwisolver>=1.0.1->matplotlib->dtreeviz) (4.2.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-pa
ckages (from python-dateutil>=2.1->matplotlib->dtreeviz) (1.15.0)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dis
t-packages (from pandas->dtreeviz) (2022.1)
Requirement already satisfied: pluggy<0.8,>=0.5 in /usr/local/lib/python3.
7/dist-packages (from pytest->dtreeviz) (0.7.1)
Requirement already satisfied: setuptools in /usr/local/lib/python3.7/dist-
packages (from pytest->dtreeviz) (57.4.0)
Requirement already satisfied: atomicwrites>=1.0 in /usr/local/lib/python3.
7/dist-packages (from pytest->dtreeviz) (1.4.0)
Requirement already satisfied: more-itertools>=4.0.0 in /usr/local/lib/pyth
on3.7/dist-packages (from pytest->dtreeviz) (8.12.0)
Requirement already satisfied: attrs>=17.4.0 in /usr/local/lib/python3.7/di
st-packages (from pytest->dtreeviz) (21.4.0)
Requirement already satisfied: py>=1.5.0 in /usr/local/lib/python3.7/dist-p
ackages (from pytest->dtreeviz) (1.11.0)
Requirement already satisfied: scipy>=1.1.0 in /usr/local/lib/python3.7/dis
t-packages (from scikit-learn->dtreeviz) (1.4.1)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dis
t-packages (from scikit-learn->dtreeviz) (1.1.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/pytho
n3.7/dist-packages (from scikit-learn->dtreeviz) (3.1.0)
```

Data loading

In [ ]:
```
#imports
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import math
from scipy import stats
from dtreeviz.trees import *
from sklearn.cluster import KMeans
from sklearn.model_selection import train_test_split
from sklearn import preprocessing
from sklearn.preprocessing import  StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix,plot_confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_val_score
from sklearn.tree import plot_tree
from sklearn.naive_bayes import GaussianNB
from sklearn import svm
```

In [ ]:
```
df = pd.read_csv("dm.csv")
```

In [ ]:
```
df.head()
```

Out[ ]:

	first_name	Age	SystolicBP	DiastolicBP	BS	date	BodyTemp	HeartRate	BPS
0	Grange Cleen	19	120.0	80.0	19.0	7/31/2020	98.0	70	149.7
1	Elysee Smylie	40	160.0	100.0	18.0	5/12/2020	98.0	77	148.4
2	Ileana Fontel	32	140.0	90.0	18.0	7/15/2020	98.0	88	149.4
3	Perry Addicote	55	140.0	95.0	19.0	12/9/2019	98.0	77	133.7
4	Worthy Vaissiere	40	140.0	100.0	18.0	4/7/2020	98.0	90	129.4

Data cleaning:

1. missing handling
2. remove noise

3. duplicate records

In [ ]:
```
##detect the number of missing values
df.isnull().sum()
```

Out[ ]:
```
first_name     0
Age            0
SystolicBP     1
DiastolicBP    1
BS             1
date           0
BodyTemp       2
HeartRate      0
BPS            0
RiskLevel      0
dtype: int64
```

In [ ]:
```
##filling the missing value with mean
##"inplace=True" to modify and save the changes done for the wanted data in
df['SystolicBP'].fillna(int(df['SystolicBP'].mean()), inplace=True)
df['DiastolicBP'].fillna(int(df['DiastolicBP'].mean()), inplace=True)
df['BS'].fillna(int(df['BS'].mean()), inplace=True)
df['BodyTemp'].fillna(int(df['BodyTemp'].mean()), inplace=True)
df
```

Out[ ]:

	first_name	Age	SystolicBP	DiastolicBP	BS	date	BodyTemp	HeartRate
0	Grange Cleen	19	120.0	80.0	19.0	7/31/2020	98.0	70
1	Elysee Smylie	40	160.0	100.0	18.0	5/12/2020	98.0	77
2	Ileana Fontel	32	140.0	90.0	18.0	7/15/2020	98.0	88
3	Perry Addicote	55	140.0	95.0	19.0	12/9/2019	98.0	77
4	Worthy Vaissiere	40	140.0	100.0	18.0	4/7/2020	98.0	90
...	...	...	...	...	...	...	...	...
1025	Meggy Carcas	35	120.0	80.0	6.9	11/9/2019	98.0	78
1026	Elinore Fisby	12	120.0	95.0	6.9	5/11/2020	98.0	60
1027	Dee Gunderson	31	120.0	60.0	6.1	11/28/2019	98.0	76
1028	Andy Bech	35	120.0	60.0	6.1	1/12/2020	98.0	76

	first_name	Age	SystolicBP	DiastolicBP	BS	date	BodyTemp	HeartRate
1029	Arnuad Sarge	31	120.0	60.0	6.1	6/16/2020	98.0	76

1030 rows × 10 columns

In [ ]:

```
##Detecting outliers
df.describe()
```

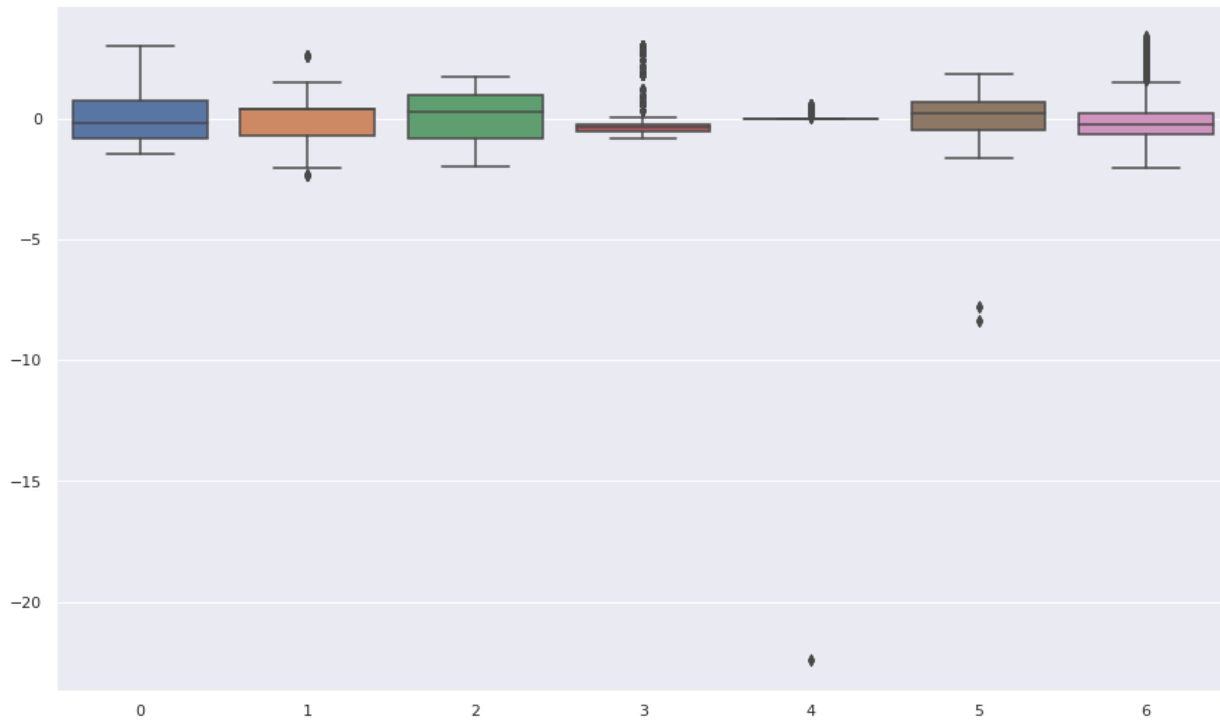
Out[ ]:

	Age	SystolicBP	DiastolicBP	BS	BodyTemp	HeartRate	
count	1030.000000	1030.000000	1030.000000	1030.000000	1030.000000	1030.000000	103
mean	29.991262	113.141748	76.429126	8.821505	98.285825	74.203883	8
std	13.417093	18.340302	13.883184	3.429944	8.769676	8.661162	1
min	10.000000	70.000000	49.000000	6.000000	-98.000000	2.000000	4
25%	19.000000	100.000000	65.000000	6.900000	98.000000	70.000000	7
50%	27.000000	120.000000	80.000000	7.500000	98.000000	76.000000	8
75%	40.000000	120.000000	90.000000	8.000000	98.000000	80.000000	9
max	70.000000	160.000000	100.000000	19.000000	103.000000	90.000000	15

In [ ]:

```
#representing the range and outliers to see by eye to check for further pos
adj = StandardScaler()
d_scaled = adj.fit_transform(df[["Age","SystolicBP",   "DiastolicBP",  "BS"
sns.set(rc={'figure.figsize':(15,9)})
sns.boxplot(data=d_scaled)
```

Out[ ]: `<matplotlib.axes._subplots.AxesSubplot at 0x7fa42af4e590>`



In [ ]:
```
#eleminating the outliers presented in the previous boxplots using zscore o
df = df[(np.abs(stats.zscore(df[["SystolicBP" ,"DiastolicBP" , "BS" , "Body
```

In [ ]:
```
df.describe()
```

Out[ ]:

	Age	SystolicBP	DiastolicBP	BS	BodyTemp	HeartRate	
count	1008.000000	1008.000000	1008.000000	1008.000000	1008.000000	1008.000000	100
mean	29.858135	112.922619	76.320437	8.662946	98.680952	74.389881	8
std	13.395619	18.060858	13.812746	3.217368	1.381634	7.475599	1
min	10.000000	70.000000	49.000000	6.000000	98.000000	60.000000	4
25%	19.000000	100.000000	65.000000	6.900000	98.000000	70.000000	7
50%	26.500000	120.000000	80.000000	7.500000	98.000000	76.000000	8
75%	38.250000	120.000000	90.000000	8.000000	98.000000	80.000000	9
max	70.000000	160.000000	100.000000	19.000000	103.000000	90.000000	14

In [ ]:
```
#drop duplicate records
df.drop_duplicates(inplace=True)
```

```
/usr/local/lib/python3.7/dist-packages/pandas/util/_decorators.py:311: Sett
ingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
```

```
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  return func(*args, **kwargs)
```

Data cleaning (irrelevant attributes, correlated attributes)

1. irrelevant attributes
2. correlated attributes

In [ ]:

```
#Correlated attributes are usually removed because they are similar in beha
# in prediction calculations,so keeping attributes with similar impacts is
#Removing correlated attributes saves space and time of calculation of comp
#Moreover, it also makes processes easier to design, analyze, understand an
```

In [ ]:

```
#irrelevant attribute
# drop to remove column
# column_name - Name of the column to be deleted
# axis=1 - Specifies the axis to be deleted. Axis 1 means column and 0 mean
# inplace=true specifies the drop operation to be in same dataframe rather
df.drop("first_name", axis=1, inplace=True)
df.drop("date", axis=1, inplace=True)
df.head()
```

```
/usr/local/lib/python3.7/dist-packages/pandas/core/frame.py:4913: SettingWi
thCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  errors=errors,
```

Out[ ]:

	Age	SystolicBP	DiastolicBP	BS	BodyTemp	HeartRate	BPS	RiskLevel
3	55	140.0	95.0	19.0	98.0	77	133.7	high risk
4	40	140.0	100.0	18.0	98.0	90	129.4	high risk
5	55	140.0	95.0	19.0	98.0	77	135.7	high risk
6	42	140.0	100.0	18.0	98.0	90	128.4	high risk
7	50	130.0	100.0	16.0	98.0	75	130.8	mid risk

In [ ]:

```
#correlated attributes
# Create correlation matrix
cor_matrix = df.corr().abs()
cor_matrix
```

Out[ ]:

	Age	SystolicBP	DiastolicBP	BS	BodyTemp	HeartRate	BPS
Age	1.000000	0.408410	0.390869	0.467103	0.252150	0.057464	0.440110
SystolicBP	0.408410	1.000000	0.777529	0.385091	0.277262	0.037383	0.369904

	Age	SystolicBP	DiastolicBP	BS	BodyTemp	HeartRate	BPS
DiastolicBP	0.390869	0.777529	1.000000	0.413283	0.259882	0.071435	0.398179
BS	0.467103	0.385091	0.413283	1.000000	0.110127	0.117833	0.909689
BodyTemp	0.252150	0.277262	0.259882	0.110127	1.000000	0.102279	0.147639
HeartRate	0.057464	0.037383	0.071435	0.117833	0.102279	1.000000	0.088566
BPS	0.440110	0.369904	0.398179	0.909689	0.147639	0.088566	1.000000

In [ ]:

```
# Select upper triangle of correlation matrix
upper_tri = cor_matrix.where(np.triu(np.ones(cor_matrix.shape),k=1).astype(
upper_tri
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: Deprecation
Warning: `np.bool` is a deprecated alias for the builtin `bool`. To silence
this warning, use `bool` by itself. Doing this will not modify any behavior
and is safe. If you specifically wanted the numpy scalar type, use `np.bool
_` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/
devdocs/release/1.20.0-notes.html#deprecations
```

Out[ ]:

	Age	SystolicBP	DiastolicBP	BS	BodyTemp	HeartRate	BPS
Age	NaN	0.40841	0.390869	0.467103	0.252150	0.057464	0.440110
SystolicBP	NaN	NaN	0.777529	0.385091	0.277262	0.037383	0.369904
DiastolicBP	NaN	NaN	NaN	0.413283	0.259882	0.071435	0.398179
BS	NaN	NaN	NaN	NaN	0.110127	0.117833	0.909689
BodyTemp	NaN	NaN	NaN	NaN	NaN	0.102279	0.147639
HeartRate	NaN	NaN	NaN	NaN	NaN	NaN	0.088566
BPS	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [ ]:

```
# Find index of feature columns with correlation greater than or equal 0.8
to_drop = [column for column in upper_tri.columns if any(upper_tri[column]
to_drop
```

Out[ ]:

```
['BPS']
```

In [ ]:

```
# Now we are droping the columns which are in the list 'to_drop' from the d
df.drop(to_drop, axis=1, inplace=True)
df.head()
```

```
/usr/local/lib/python3.7/dist-packages/pandas/core/frame.py:4913: SettingWi
thCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  errors=errors,
```

Out[ ]:

	Age	SystolicBP	DiastolicBP	BS	BodyTemp	HeartRate	RiskLevel
3	55	140.0	95.0	19.0	98.0	77	high risk
4	40	140.0	100.0	18.0	98.0	90	high risk
5	55	140.0	95.0	19.0	98.0	77	high risk
6	42	140.0	100.0	18.0	98.0	90	high risk
7	50	130.0	100.0	16.0	98.0	75	mid risk

Data cleaning:

1. discretization

In [ ]:

```
#discretization refers to the process of converting or partitioning continu
#to discretized or nominal attributes/features/variables/intervals.
```

In [ ]:

```
##define a new dataframe
dd = pd.DataFrame()
```

In [ ]:

```
#using it as a reference
df['Age'].min(), df['Age'].max()
```

Out[ ]:

```
(10, 70)
```

In [ ]:

```
#The uses of "qcut" (Quantile-based discretization function) for a result t
#q represent the quantiles as the number of bins so it must always be the s
dd['Age_bin'] = pd.qcut(df['Age'], q=[0, .20, .40, .60, .80, 1.00], labels=
                                                                     'Middl
dd
```

Out[ ]:

	Age_bin
3	Old Adults
4	Middle-aged Adults
5	Old Adults
6	Middle-aged Adults
7	Old Adults
...	...
1025	Middle-aged Adults

	Age_bin
1026	Teenager
1027	Middle-aged Adults
1028	Middle-aged Adults
1029	Middle-aged Adults

1008 rows × 1 columns

In [ ]:
```
df['BodyTemp'].min(), df['BodyTemp'].max()
```

Out[ ]:
```
(98.0, 103.0)
```

In [ ]:
```
#in "cut" the bins must be dfined by the user by being familiar with data a
#"duplicates" If bin edges are not unique, raise ValueError or drop non-uni
dd['BodyTemp_bin'] = pd.cut(df['BodyTemp'], bins=[85,97,100,110], labels=['
                               duplicates= 'drop')

dd
```

Out[ ]:

	Age_bin	BodyTemp_bin
3	Old Adults	Normal
4	Middle-aged Adults	Normal
5	Old Adults	Normal
6	Middle-aged Adults	Normal
7	Old Adults	Normal
...	...	...
1025	Middle-aged Adults	Normal
1026	Teenager	Normal
1027	Middle-aged Adults	Normal
1028	Middle-aged Adults	Normal
1029	Middle-aged Adults	Normal

1008 rows × 2 columns

In [ ]:
```
df['HeartRate'].min(), df['HeartRate'].max()
```

Out[ ]:
```
(60, 90)
```

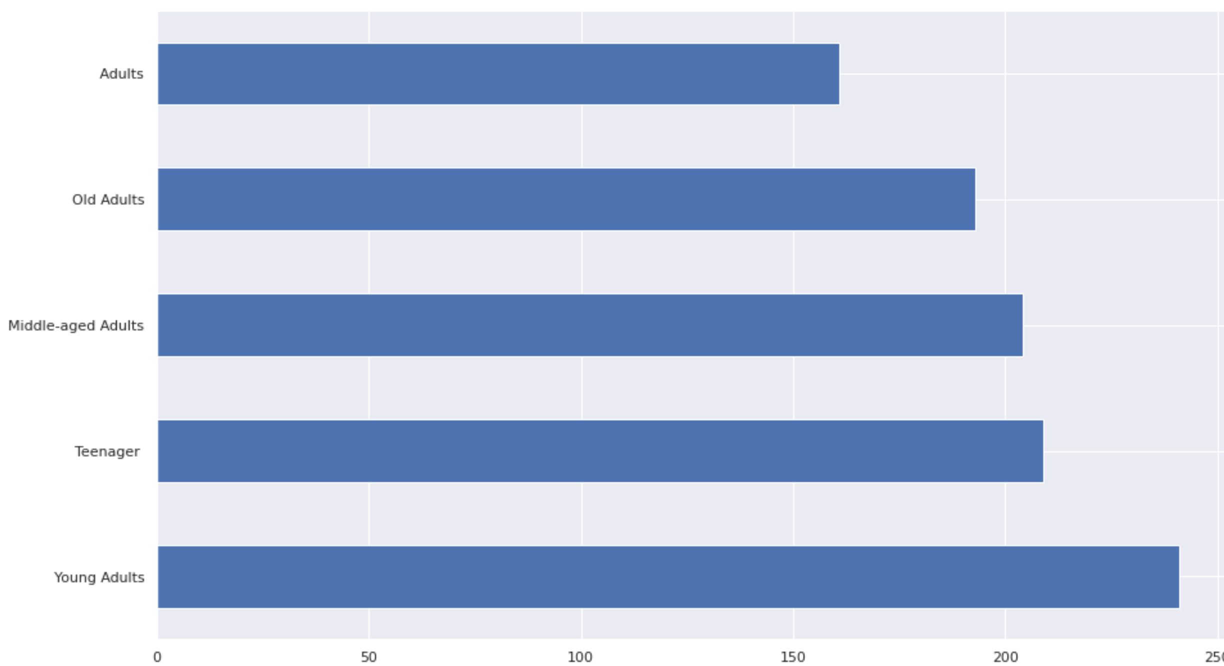
In [ ]:
```
dd['HeartRate_bin'] = pd.cut(df['HeartRate'], bins=[40,60,80,100], labels=[
dd
```

Out[ ]:

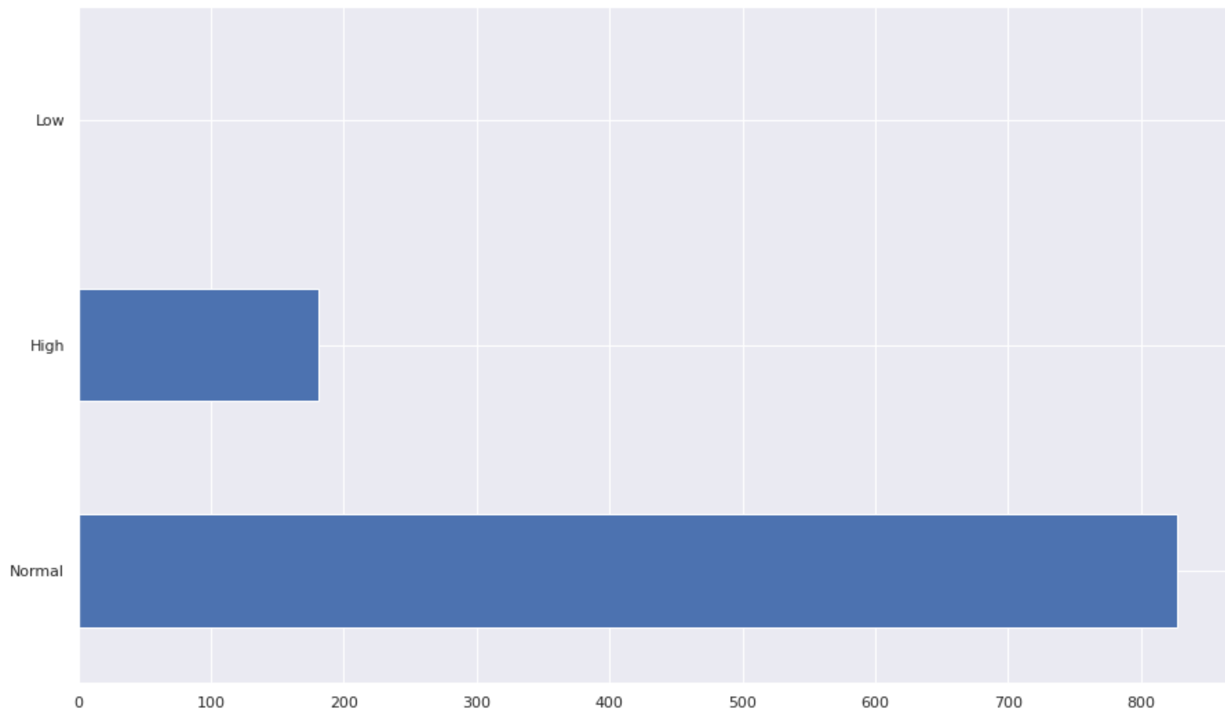
	Age_bin	BodyTemp_bin	HeartRate_bin
3	Old Adults	Normal	Normal
4	Middle-aged Adults	Normal	High
5	Old Adults	Normal	Normal
6	Middle-aged Adults	Normal	High
7	Old Adults	Normal	Normal
...	...	...	...
1025	Middle-aged Adults	Normal	Normal
1026	Teenager	Normal	Low
1027	Middle-aged Adults	Normal	Normal
1028	Middle-aged Adults	Normal	Normal
1029	Middle-aged Adults	Normal	Normal

1008 rows × 3 columns

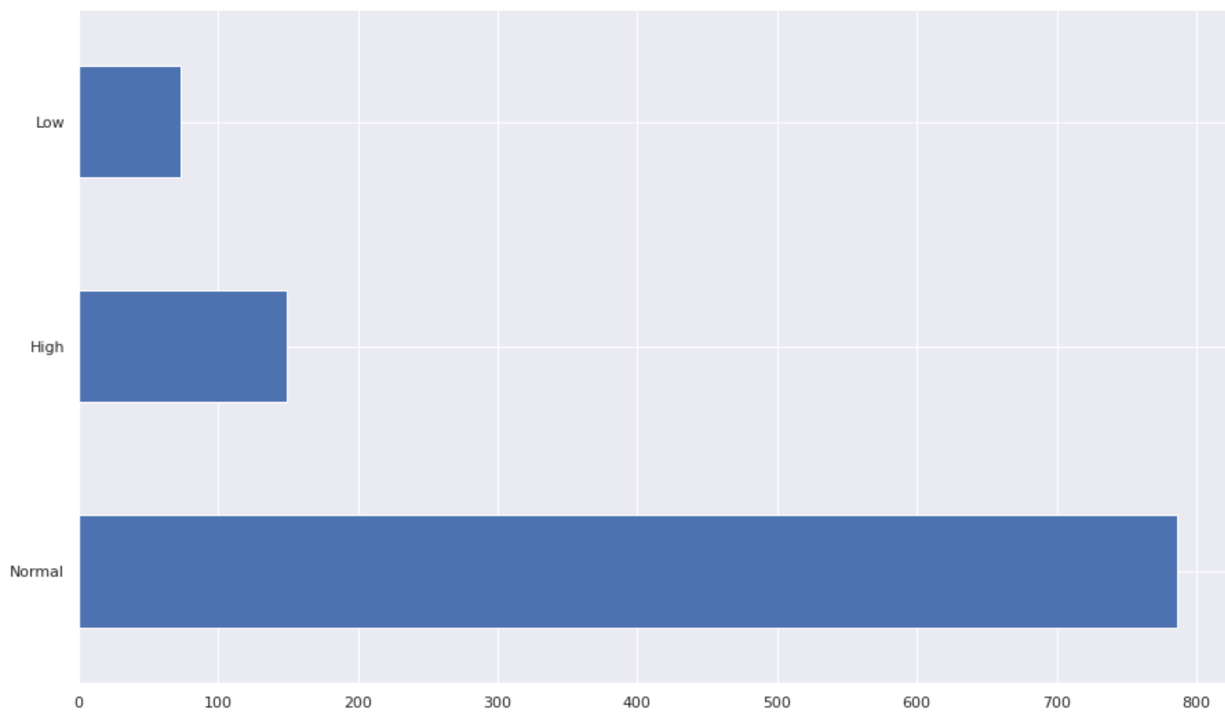
In [ ]:
```
#"kind" represent the chosen bar plot with a defualt of "line" while "barh"
dd['Age_bin'].value_counts().plot(kind='barh')
plt.show()
```



In [ ]:
```
dd['BodyTemp_bin'].value_counts().plot(kind='barh')
plt.show()
```



In [ ]:
```
dd['HeartRate_bin'].value_counts().plot(kind='barh')
plt.show()
```



In [ ]:
```
dd.head()
```

Out[ ]:

	Age_bin	BodyTemp_bin	HeartRate_bin
3	Old Adults	Normal	Normal
4	Middle-aged Adults	Normal	High

	Age_bin	BodyTemp_bin	HeartRate_bin
5	Old Adults	Normal	Normal
6	Middle-aged Adults	Normal	High
7	Old Adults	Normal	Normal

KNN

1. split data
2. apply algorithm
3. accuracy check (confusion matrix prefered)

In [ ]:
```
#Split the data into 80% train and 20% test subsets. "shuffle = True" shuff
X_train, X_test, y_train, y_test = train_test_split(df.iloc[:,:-1], df.iloc
```

In [ ]:
```
#choosing the most suitable number of K
K = math.sqrt(len(df))
K= round(K)
K
```

Out[ ]: 32

In [ ]:
```
#Standardize features by removing the mean and scaling to unit variance. Th
adj = StandardScaler()
#Fit to data, then transform it, equivalent to fit.transform but more effic
X_train = adj.fit_transform(X_train)
#Perform standardization by centering and scaling.
X_test  = adj.transform(X_test)
#Classifier implementing the k-nearest neighbors vote, with n_neighbors def
knn = KNeighborsClassifier(n_neighbors=15,metric="manhattan")
#Fit the k-nearest neighbors classifier from the training dataset.
knn.fit(X_train, y_train)
```

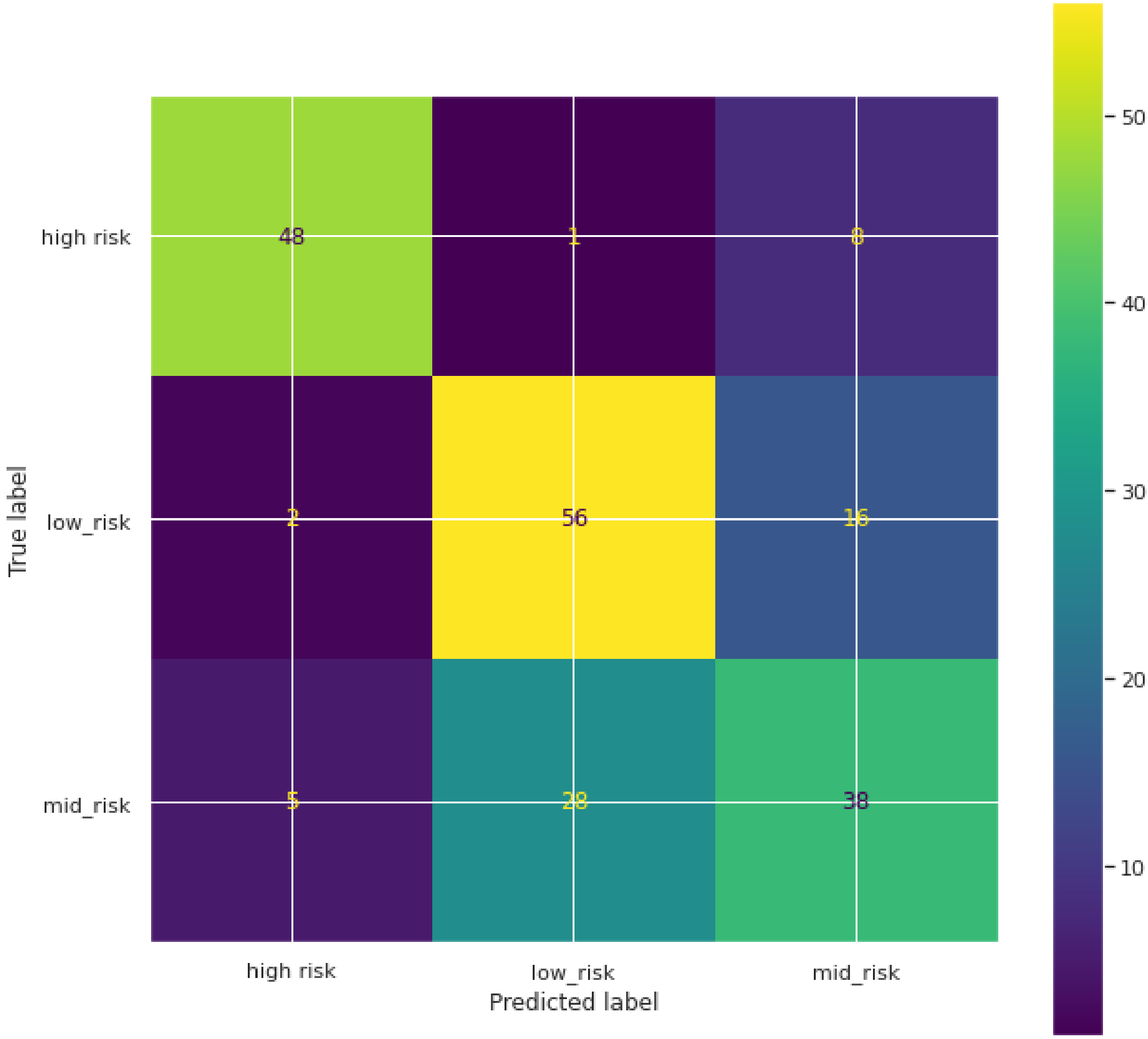
Out[ ]: KNeighborsClassifier(metric='manhattan', n_neighbors=15)

In [ ]:
```
#Predict the class labels for the provided data.
y_pred = knn.predict(X_test)
y_pred
#To evaluate the result, we will use accuracy_score
print(accuracy_score(y_test,y_pred))
```

0.7029702970297029

In [ ]:
```
#Create figure and set of subplots. "figsize=(width, height)"
fig, ax = plt.subplots(figsize=(10, 10))
#A funcution that evaluates classification accuracy by computing the confus
plot_confusion_matrix(knn, X_test, y_test, display_labels=["high risk" , 'l
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87: Fut
ureWarning: Function plot_confusion_matrix is deprecated; Function `plot_co
nfusion_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one of
the class methods: ConfusionMatrixDisplay.from_predictions or ConfusionMatr
ixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
```



Decision Tree

1. apply algorithm
2. accuracy check (confusion matrix prefered)

In [ ]:

```
#A non-parametric supervised learning that predicts the value of a target v
# The deeper the tree, the more complex the decision rules and the fitter t
```

In [ ]:

```
#Encode target labels with value between 0 and n_classes-1.
le = preprocessing.LabelEncoder()
le.fit(y_train)
y_train = le.transform(y_train)
le.fit(y_test)
y_test = le.transform(y_test)
```

```
dtc = DecisionTreeClassifier(random_state = 0)
dtc.fit(X_train,y_train)
```

Out[ ]: DecisionTreeClassifier(random_state=0)

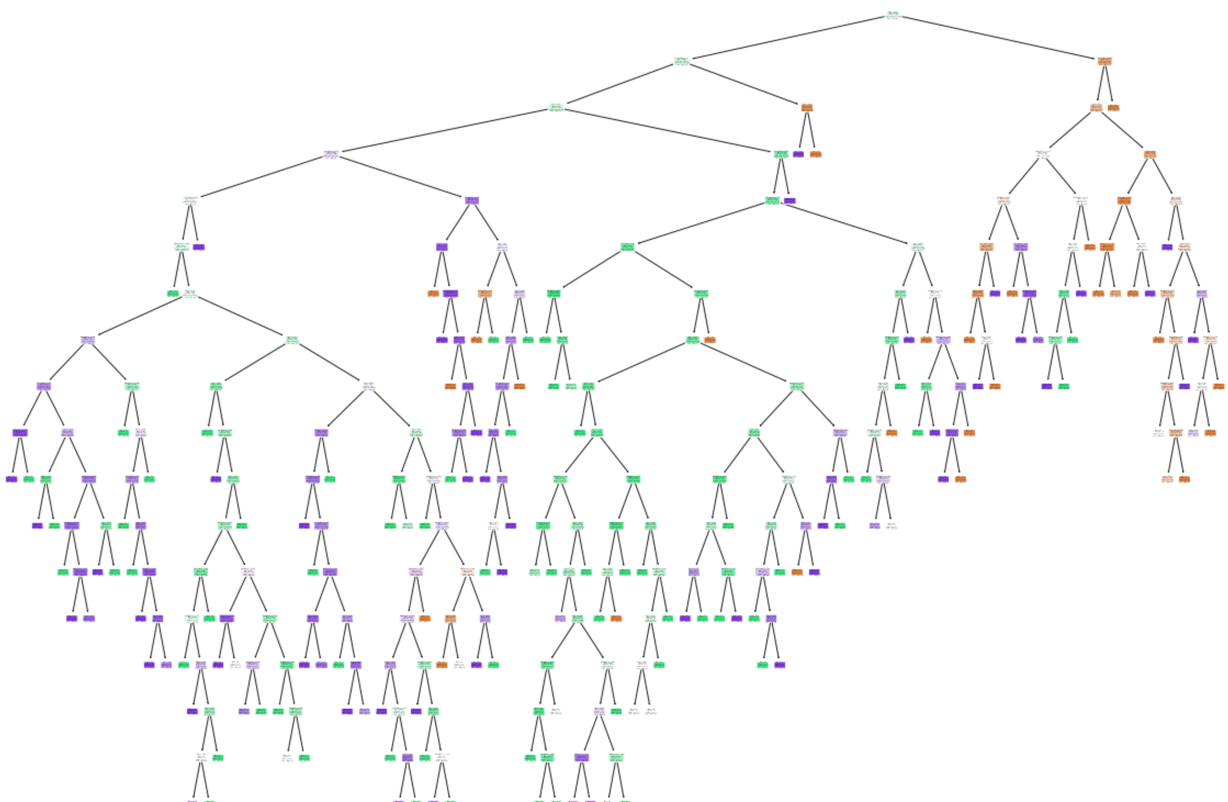
In [ ]:
```
dtc.score(X_test, y_test)
```

Out[ ]: 0.806930693069307

In [ ]:
```
#Evaluate a score by cross-validation."cv" determine the split strategy wit
dt_accuracy = np.mean(cross_val_score(dtc, X_train, y_train, cv=10, scoring
print("Mean accuracy: ", dt_accuracy)
```

Mean accuracy: 0.8412345679012345

In [ ]:
```
fig = plt.figure(figsize=(20, 14))
#"filled"=True paint the nodes with a default of false, "rounded"=True draw
_ = plot_tree(dtc, filled=True, rounded=True, class_names=['high_risk', 'mi
fig.savefig("decistion_tree.png")
```



In [ ]:
```
#vizaulizing the decision tree. "Classs_names" represent the low mid high r
viz = dtreeviz(dtc, X_train, y_train,
                target_name="Heart Risk",
                feature_names=['Age', 'SystolicBP', 'DiastolicBP', 'BS', 'B
                class_names=['0', '1', '2'])
viz.save("decision_tree.svg")
```

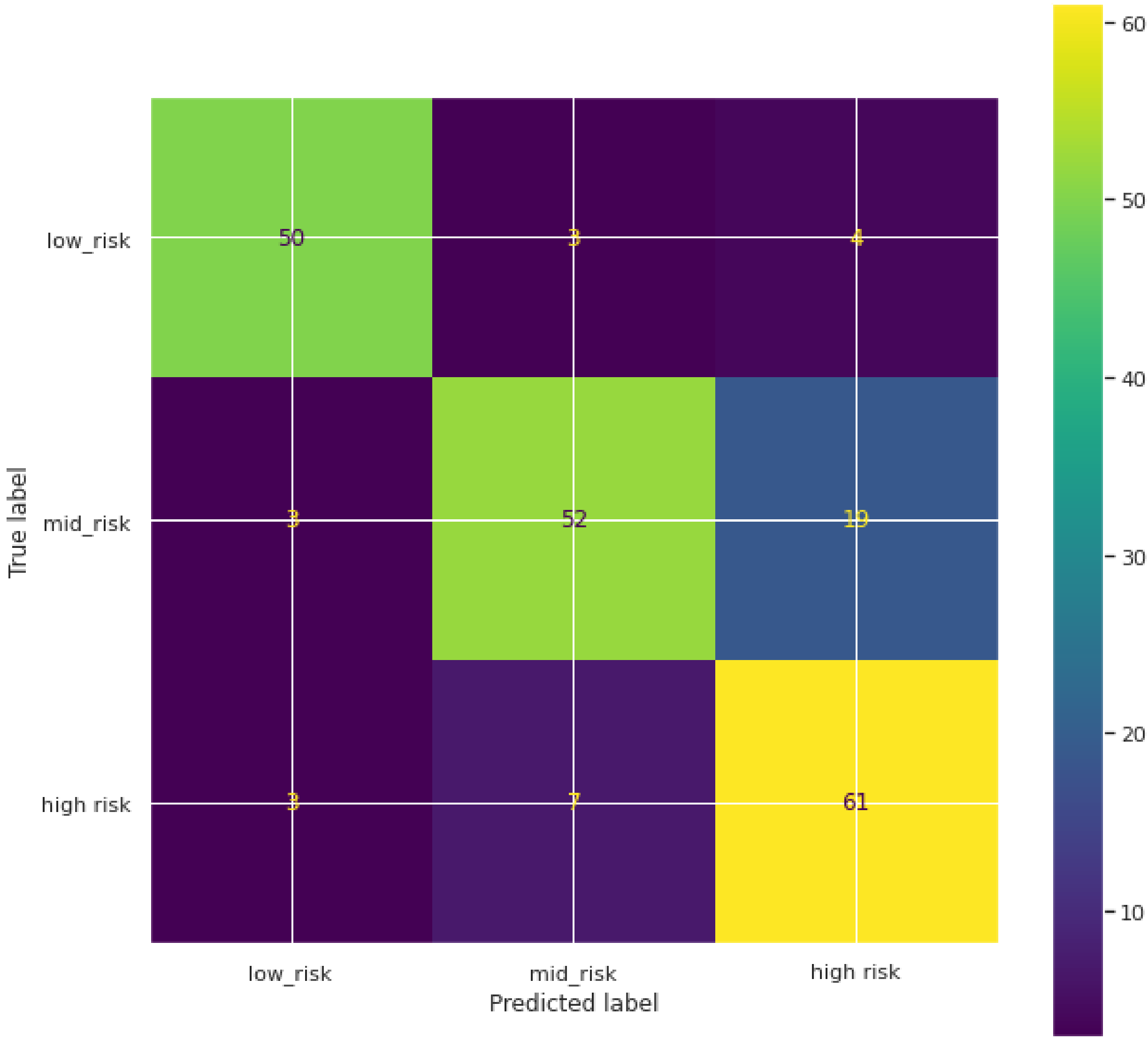
/usr/local/lib/python3.7/dist-packages/sklearn/base.py:451: UserWarning: X

```
does not have valid feature names, but DecisionTreeClassifier was fitted wi
th feature names
  "X does not have valid feature names, but"
/usr/local/lib/python3.7/dist-packages/numpy/core/fromnumeric.py:3208: Visi
bleDeprecationWarning: Creating an ndarray from ragged nested sequences (wh
ich is a list-or-tuple of lists-or-tuples-or ndarrays with different length
s or shapes) is deprecated. If you meant to do this, you must specify 'dtyp
e=object' when creating the ndarray.
  return asarray(a).size
/usr/local/lib/python3.7/dist-packages/matplotlib/cbook/__init__.py:1376: V
isibleDeprecationWarning: Creating an ndarray from ragged nested sequences
(which is a list-or-tuple of lists-or-tuples-or ndarrays with different len
gths or shapes) is deprecated. If you meant to do this, you must specify 'd
type=object' when creating the ndarray.
  X = np.atleast_1d(X.T if isinstance(X, np.ndarray) else np.asarray(X))
findfont: Font family ['Arial'] not found. Falling back to DejaVu Sans.
findfont: Font family ['Arial'] not found. Falling back to DejaVu Sans.
findfont: Font family ['Arial'] not found. Falling back to DejaVu Sans.
```

In [ ]:

```
fig, ax = plt.subplots(figsize=(10, 10))
plot_confusion_matrix(dtc, X_test, y_test, display_labels=['low_risk', 'mid
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87: Fut
ureWarning: Function plot_confusion_matrix is deprecated; Function `plot_co
nfusion_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one of
the class methods: ConfusionMatrixDisplay.from_predictions or ConfusionMatr
ixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
```



Naive Bayes

In [ ]:
```
#The likelihood of the features is assumed to be Gaussian with parameters e
gnb = GaussianNB()
gnb.fit(X_train, y_train)
```

Out[ ]:
```
GaussianNB()
```

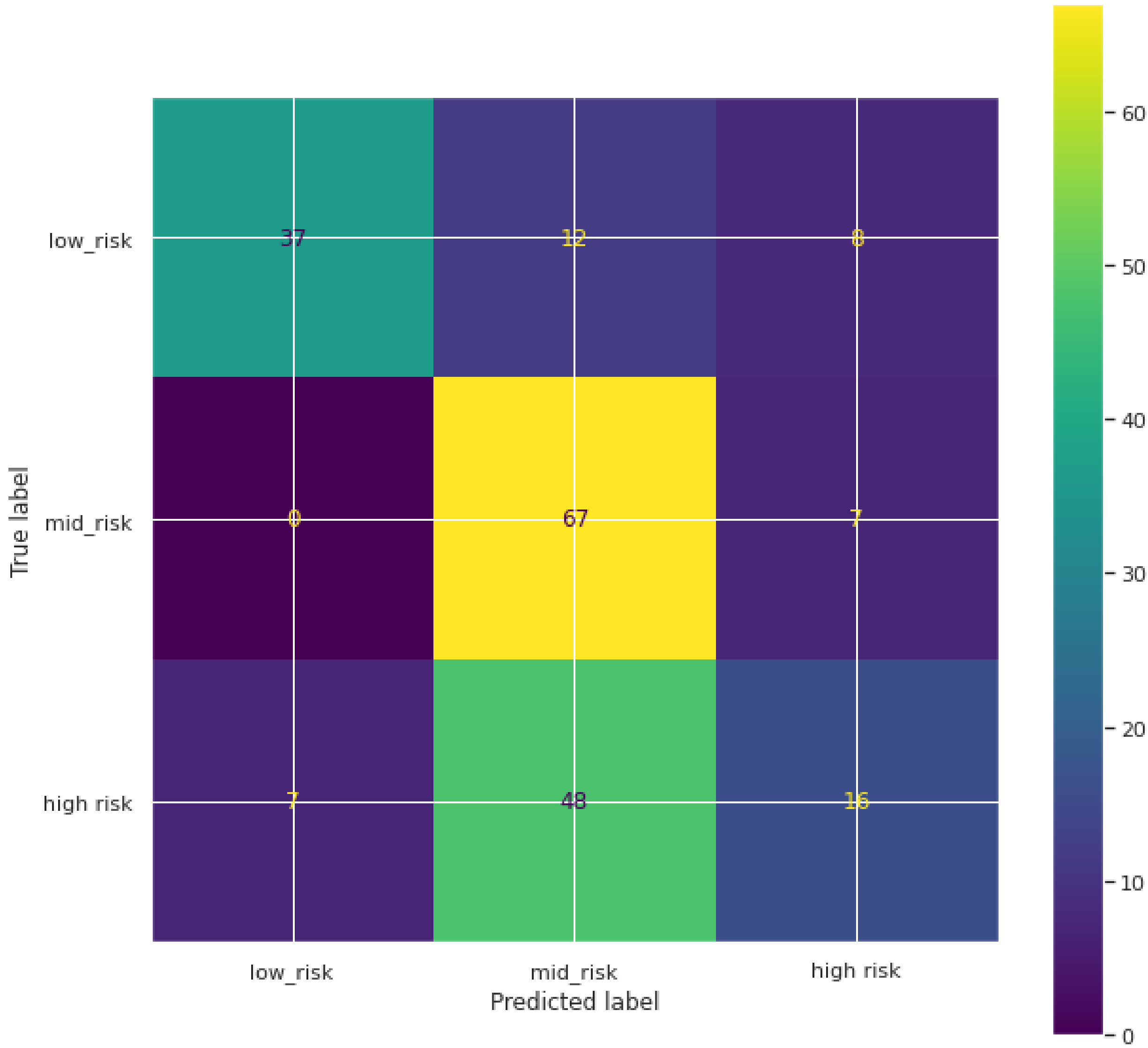
In [ ]:
```
dt_accuracy = np.mean(cross_val_score(dtc, X_train, y_train, cv=10, scoring
print("Mean accuracy: ", dt_accuracy)
```

```
Mean accuracy:  0.8412345679012345
```

In [ ]:
```
fig, ax = plt.subplots(figsize=(10, 10))
plot_confusion_matrix(gnb, X_test, y_test, display_labels=['low_risk', 'mid
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87: Fut
ureWarning: Function plot_confusion_matrix is deprecated; Function `plot_co
nfusion_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one of
the class methods: ConfusionMatrixDisplay.from_predictions or ConfusionMatr
```

```
ixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
```



Kmeans

In [ ]:
```
df_c = pd.read_csv("Country-data.csv")
df_c.head()
```

Out[ ]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_
0	Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	5
1	Albania	16.6	28.0	6.55	48.6	9930	4.49	76.3	1
2	Algeria	27.3	38.4	4.17	31.4	12900	16.10	76.5	2
3	Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	6
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.44	76.8	2

In [ ]:
```
df_c.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 167 entries, 0 to 166
Data columns (total 10 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   country     167 non-null    object
 1   child_mort  167 non-null    float64
 2   exports     167 non-null    float64
 3   health      167 non-null    float64
 4   imports     167 non-null    float64
 5   income      167 non-null    int64
 6   inflation   167 non-null    float64
 7   life_expec  167 non-null    float64
 8   total_fer   167 non-null    float64
 9   gdpp        167 non-null    int64
dtypes: float64(7), int64(2), object(1)
memory usage: 13.2+ KB
```

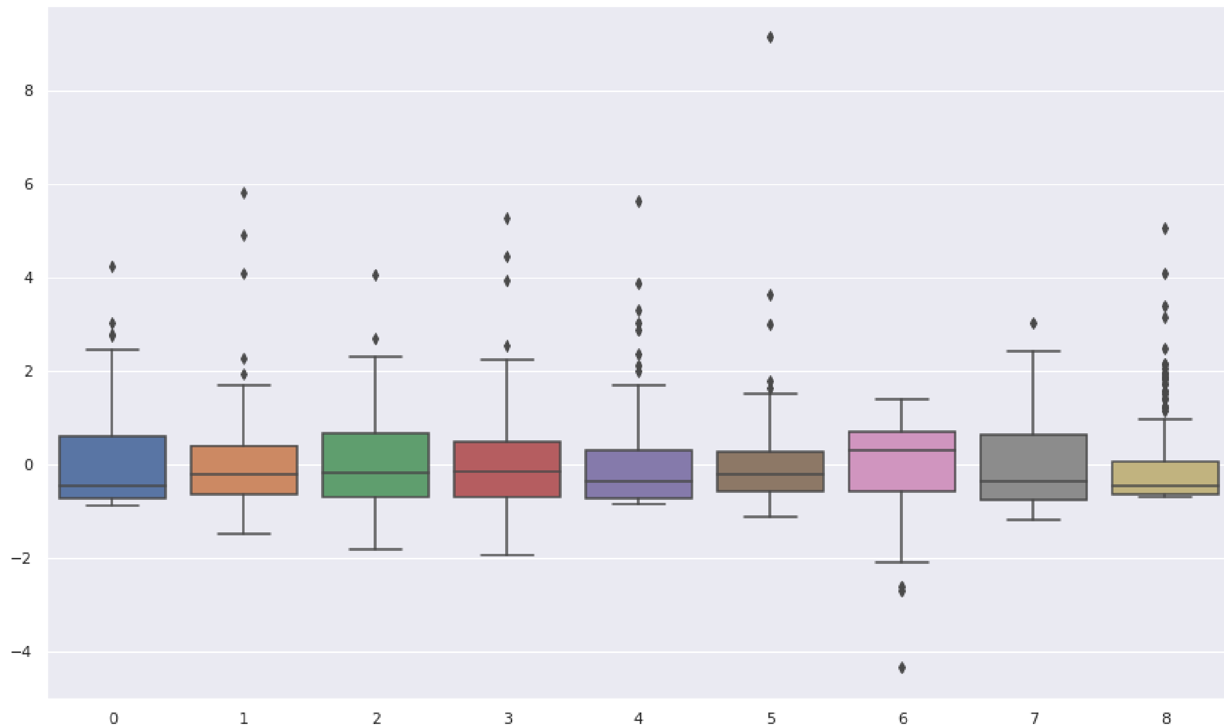
In [ ]:
```
df_c.describe()
```

Out[ ]:

	child_mort	exports	health	imports	income	inflation	life_ex
count	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	167.000
mean	38.270060	41.108976	6.815689	46.890215	17144.688623	7.781832	70.555
std	40.328931	27.412010	2.746837	24.209589	19278.067698	10.570704	8.893
min	2.600000	0.109000	1.810000	0.065900	609.000000	-4.210000	32.100
25%	8.250000	23.800000	4.920000	30.200000	3355.000000	1.810000	65.300
50%	19.300000	35.000000	6.320000	43.300000	9960.000000	5.390000	73.100
75%	62.100000	51.350000	8.600000	58.750000	22800.000000	10.750000	76.800
max	208.000000	200.000000	17.900000	174.000000	125000.000000	104.000000	82.800

In [ ]:
```
adj = StandardScaler()
d_scaled = adj.fit_transform(df_c[["child_mort",        "exports",       "he
sns.set(rc={'figure.figsize':(15,9)})
sns.boxplot(data=d_scaled)
```

Out[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f039745be90>
```



In [ ]:

```
#eleminating the outliers presented in the previous boxplots using zscore o
df_c = df_c[(np.abs(stats.zscore(df_c[["child_mort",    "exports",      "he
```

In [ ]:

```
df_c.describe()
```

Out[ ]:

	child_mort	exports	health	imports	income	inflation	life_exp
count	153.000000	153.000000	153.000000	153.000000	153.000000	153.000000	153.0000
mean	37.224183	38.670582	6.774706	45.735725	14365.222222	7.024150	70.4575
std	36.358238	20.352828	2.539936	19.143349	13406.165312	6.949213	8.2292
min	2.600000	0.109000	1.970000	0.065900	609.000000	-4.210000	46.5000
25%	8.700000	23.800000	4.970000	30.900000	3340.000000	1.770000	65.3000
50%	20.300000	35.000000	6.320000	43.300000	9920.000000	5.140000	72.5000
75%	62.000000	50.600000	8.500000	58.600000	20400.000000	10.100000	76.5000
max	150.000000	103.000000	14.200000	108.000000	57600.000000	39.200000	82.8000

In [ ]:

```
df_c.drop_duplicates(inplace = True)
```

```
/usr/local/lib/python3.7/dist-packages/pandas/util/_decorators.py:311: Sett
ingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
```

```
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  return func(*args, **kwargs)
```

In [ ]:

```
#correlated attributes
# Create correlation matrix
cor_matrix = df_c.corr().abs()
cor_matrix
```

Out[ ]:

	child_mort	exports	health	imports	income	inflation	life_expec	total_
child_mort	1.000000	0.292012	0.284920	0.115421	0.616987	0.291671	0.870294	0.887
exports	0.292012	1.000000	0.091612	0.601012	0.426994	0.067629	0.237220	0.284
health	0.284920	0.091612	1.000000	0.162576	0.312409	0.341229	0.271964	0.228
imports	0.115421	0.601012	0.162576	1.000000	0.007693	0.231058	0.020562	0.105
income	0.616987	0.426994	0.312409	0.007693	1.000000	0.241964	0.693767	0.571
inflation	0.291671	0.067629	0.341229	0.231058	0.241964	1.000000	0.312152	0.354
life_expec	0.870294	0.237220	0.271964	0.020562	0.693767	0.312152	1.000000	0.788
total_fer	0.887719	0.284961	0.228688	0.105601	0.571882	0.354268	0.788974	1.000
gdpp	0.524979	0.271026	0.466815	0.043599	0.915745	0.346857	0.639576	0.473

In [ ]:

```
# Select upper triangle of correlation matrix
upper_tri = cor_matrix.where(np.triu(np.ones(cor_matrix.shape),k=1).astype(
upper_tri
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: Deprecation
Warning: `np.bool` is a deprecated alias for the builtin `bool`. To silence
this warning, use `bool` by itself. Doing this will not modify any behavior
and is safe. If you specifically wanted the numpy scalar type, use `np.bool
_` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/
devdocs/release/1.20.0-notes.html#deprecations
```

Out[ ]:

	child_mort	exports	health	imports	income	inflation	life_expec	total_
child_mort	NaN	0.292012	0.284920	0.115421	0.616987	0.291671	0.870294	0.887
exports	NaN	NaN	0.091612	0.601012	0.426994	0.067629	0.237220	0.284
health	NaN	NaN	NaN	0.162576	0.312409	0.341229	0.271964	0.228
imports	NaN	NaN	NaN	NaN	0.007693	0.231058	0.020562	0.105
income	NaN	NaN	NaN	NaN	NaN	0.241964	0.693767	0.571
inflation	NaN	NaN	NaN	NaN	NaN	NaN	0.312152	0.354

	child_mort	exports	health	imports	income	inflation	life_expec	total_
life_expec	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.788
total_fer	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
gdpp	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N

In [ ]:

```
# Find index of feature columns with correlation greater than or equal 0.8
to_drop = [column for column in upper_tri.columns if any(upper_tri[column]
to_drop
```

Out[ ]:

```
['life_expec', 'total_fer', 'gdpp']
```

In [ ]:

```
# Now we are droping the columns which are in the list 'to_drop' from the d
df_c.drop(to_drop, axis=1, inplace=True)
df_c.head()
```

Out[ ]:

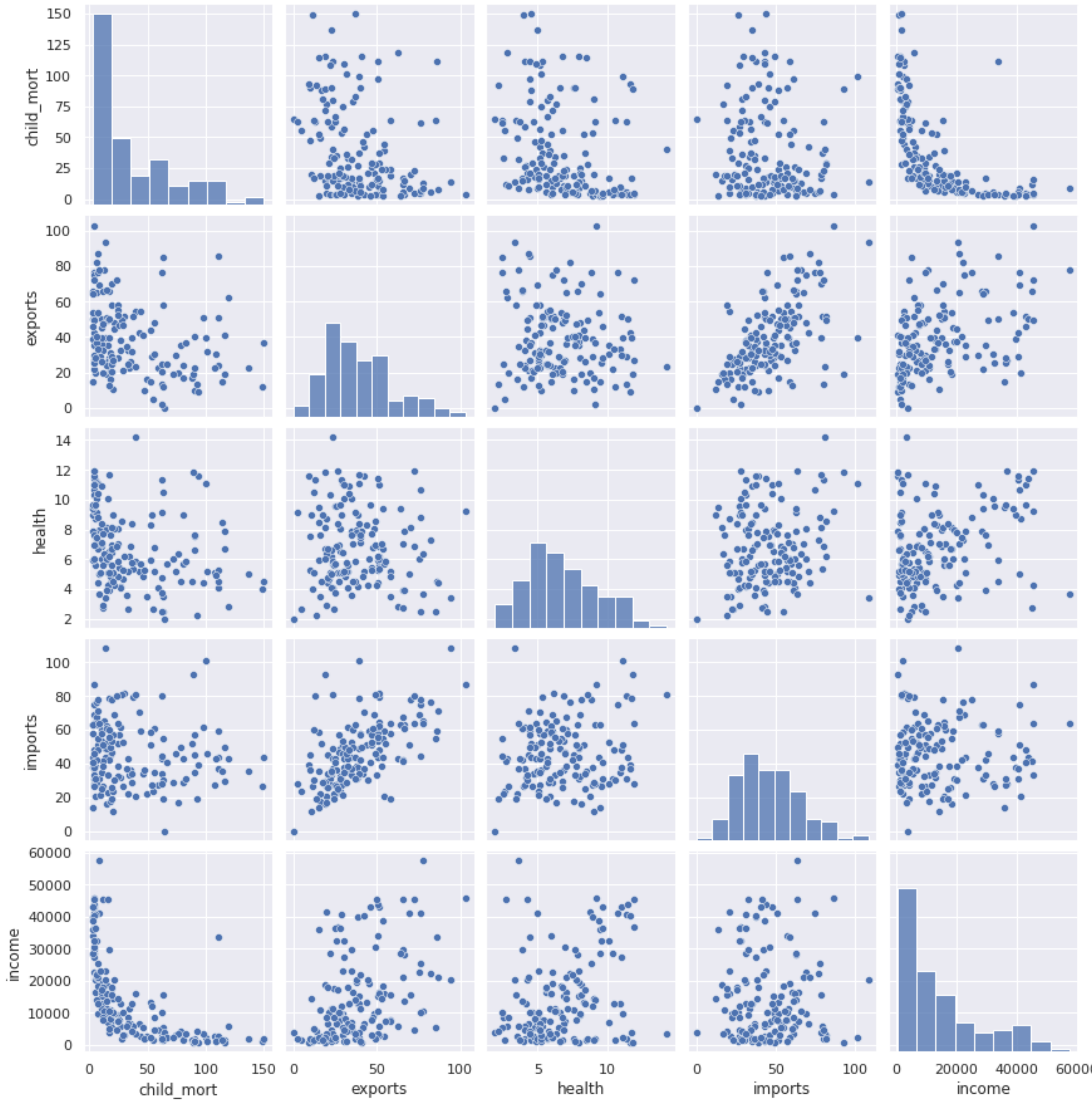
	country	child_mort	exports	health	imports	income	inflation
0	Afghanistan	90.2	10.0	7.58	44.9	1610	9.44
1	Albania	16.6	28.0	6.55	48.6	9930	4.49
2	Algeria	27.3	38.4	4.17	31.4	12900	16.10
3	Angola	119.0	62.3	2.85	42.9	5900	22.40
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.44

In [ ]:

```
#A pairplot plot a pairwise relationships creates a grid of Axes each varia
#and in the x-axis across a single column. Visualize the correlation your d
sns.pairplot(df_c.iloc[:,1:-1])
```

Out[ ]:

```
<seaborn.axisgrid.PairGrid at 0x7f039746fa90>
```



In [ ]:

```
#preprocessing for data to get the best centers
#Transform features by scaling each feature of range 0:1.
scaler = MinMaxScaler()
scaler.fit(df_c.iloc[:,1:-1])
df_c.iloc[:,1:-1]= scaler.transform(df_c.iloc[:,1:-1])
scaler.fit(df_c.iloc[:,1:-1])
df_c.iloc[:,1:-1] = scaler.transform(df_c.iloc[:,1:-1])
df_c.head()
```

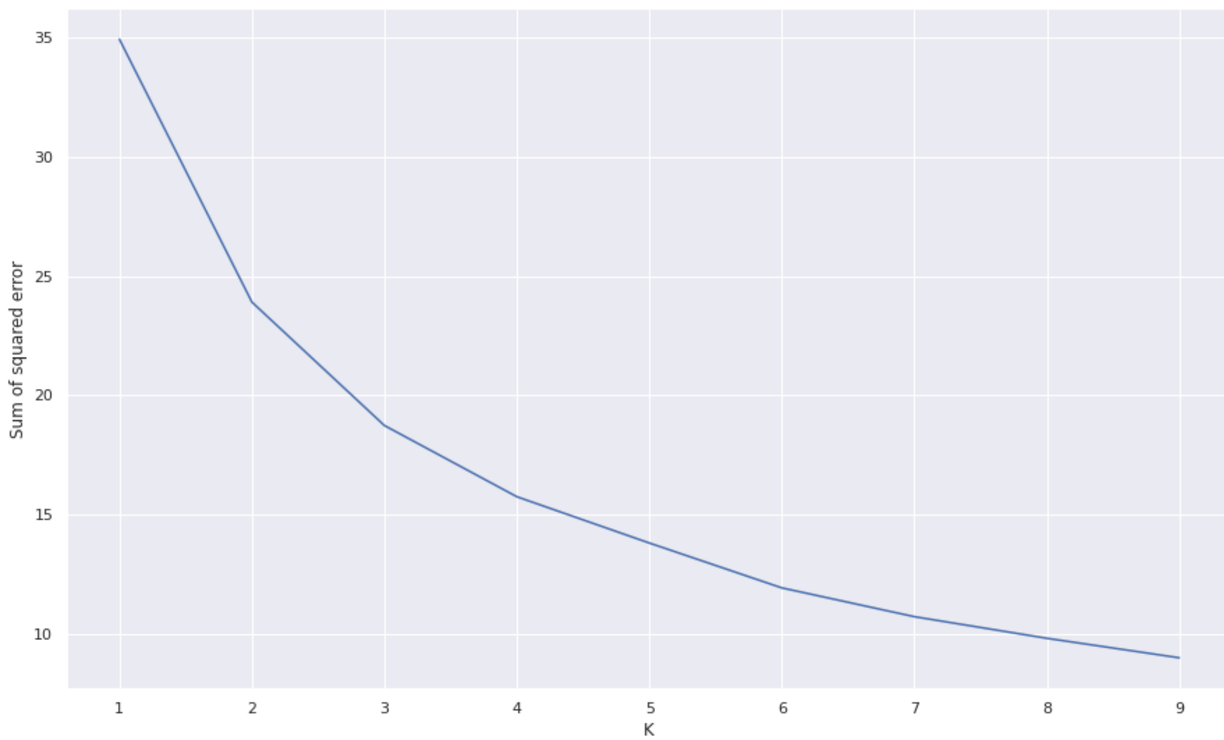
Out[ ]:

	country	child_mort	exports	health	imports	income	inflation
0	Afghanistan	0.594301	0.096131	0.458708	0.415384	0.017564	9.44
1	Albania	0.094980	0.271073	0.374489	0.449664	0.163552	4.49
2	Algeria	0.167571	0.372151	0.179886	0.290308	0.215666	16.10
3	Angola	0.789688	0.604436	0.071954	0.396854	0.092839	22.40

	country	child_mort	exports	health	imports	income	inflation
4	Antigua and Barbuda	0.052239	0.441156	0.331971	0.545093	0.324455	1.44

In [ ]:
```
#Determine optimal cluster k number with elbow method.
sse = []
k_rng = range(1,10)
for k in k_rng:
    km = KMeans(n_clusters=k)
    km.fit(df_c.iloc[:,1:-1])
    sse.append(km.inertia_)
#Show Elbow plot.
plt.xlabel('K')
plt.ylabel('Sum of squared error')
plt.plot(k_rng,sse)
```

Out[ ]: [<matplotlib.lines.Line2D at 0x7f03995e1750>]



In [ ]:
```
#The KMeans algorithm clusters data by trying to separate samples in n grou
km = KMeans(n_clusters=3)
y_predicted = km.fit_predict(df_c.iloc[:,1:-1])
y_predicted
df_c['cluster']=y_predicted
df_c.head()
```

Out[ ]:

	country	child_mort	exports	health	imports	income	inflation	cluster
0	Afghanistan	0.594301	0.096131	0.458708	0.415384	0.017564	9.44	2
1	Albania	0.094980	0.271073	0.374489	0.449664	0.163552	4.49	0

	country	child_mort	exports	health	imports	income	inflation	cluster
2	Algeria	0.167571	0.372151	0.179886	0.290308	0.215666	16.10	0
3	Angola	0.789688	0.604436	0.071954	0.396854	0.092839	22.40	2
4	Antigua and Barbuda	0.052239	0.441156	0.331971	0.545093	0.324455	1.44	0

In [ ]:

```
#to get the centers
km.cluster_centers_
```

Out[ ]:

```
array([[0.14282094, 0.41598039, 0.36203686, 0.45236553, 0.20337242],
       [0.01738174, 0.46458237, 0.56522965, 0.4077165 , 0.65172964],
       [0.57515637, 0.22785894, 0.33334663, 0.37483667, 0.02805749]])
```

In [ ]:

```
#Visualising a few of the clusters.
df1 = df_c[df_c.cluster==0]
df2 = df_c[df_c.cluster==1]
df3 = df_c[df_c.cluster==2]
plt.scatter(df1["child_mort"],df1['exports'],color='green')
plt.scatter(df2["child_mort"],df2['exports'],color='red')
plt.scatter(df3["child_mort"],df3['exports'],color='black')
#Plot the clusters,"s" for centroid size, "color", "marker" are traits for
plt.scatter(km.cluster_centers_[:,0],km.cluster_centers_[:,1],s=200,color='
plt.legend()
```

Out[ ]:

```
<matplotlib.legend.Legend at 0x7f03980a6e50>
```