Aim of the problem is to detect the presence or absence of cardiovascular disease in person based on the given features. Features available are:

- **Age | Objective Feature | age | int (days)**
- **Height | Objective Feature | height | int (cm) |**
- **Weight | Objective Feature | weight | float (kg) |**
- **Gender | Objective Feature | gender | categorical code |**
- **Systolic blood pressure | Examination Feature | ap_hi | int |**
- **Diastolic blood pressure | Examination Feature | ap_lo | int |**
- **Cholesterol | Examination Feature | cholesterol | 1: normal, 2: above normal, 3: well above normal |**
- **Glucose | Examination Feature | gluc | 1: normal, 2: above normal, 3: well above normal |**
- **Smoking | Subjective Feature | smoke | binary |**
- **Alcohol intake | Subjective Feature | alco | binary |**
- **Physical activity | Subjective Feature | active | binary |**
- **Presence or absence of cardiovascular disease | Target Variable | cardio | binary |**

In [1]:

```
# import the necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:

```
# read the csv file
cardio_df = pd.read_csv("cardio_train.csv", sep=";")
```

In [3]:

```
cardio_df.head()
```

Out[3]:

	id	age	gender	height	weight	ap_hi	ap_lo	cholesterol	gluc	smoke	alco	active	cardio
0	0	18393	2	168	62.0	110	80	1	1	0	0	1	0
1	1	20228	1	156	85.0	140	90	3	1	0	0	1	1
2	2	18857	1	165	64.0	130	70	3	1	0	0	0	1
3	3	17623	2	169	82.0	150	100	1	1	0	0	1	1
4	4	17474	1	156	56.0	100	60	1	1	0	0	0	0

PERFORM EXPLORATORY DATA ANALYSIS

In [4]:

```
# Drop id

cardio_df = cardio_df.drop(columns = 'id')
```

In [5]:

```
# since the age is given in days, we convert it into years

cardio_df['age'] = cardio_df['age']/365
```

In [6]:

```
cardio_df.head()
```

Out[6]:

	age	gender	height	weight	ap_hi	ap_lo	cholesterol	gluc	smoke	alco	active	cardio
0	50.391781	2	168	62.0	110	80	1	1	0	0	1	0
1	55.419178	1	156	85.0	140	90	3	1	0	0	1	1
2	51.663014	1	165	64.0	130	70	3	1	0	0	0	1
3	48.282192	2	169	82.0	150	100	1	1	0	0	1	1
4	47.873973	1	156	56.0	100	60	1	1	0	0	0	0

In [7]:

```
# checking the null values
cardio_df.isnull().sum()
```

Out[7]:

```
age            0
gender         0
height         0
weight         0
ap_hi          0
ap_lo          0
cholesterol    0
gluc           0
smoke          0
alco           0
active         0
cardio         0
dtype: int64
```

In [8]:

```
# Checking the dataframe information

cardio_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 70000 entries, 0 to 69999
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   age          70000 non-null  float64
 1   gender       70000 non-null  int64  
 2   height       70000 non-null  int64  
 3   weight       70000 non-null  float64
 4   ap_hi        70000 non-null  int64  
 5   ap_lo        70000 non-null  int64  
 6   cholesterol  70000 non-null  int64  
 7   gluc         70000 non-null  int64  
 8   smoke        70000 non-null  int64  
 9   alco         70000 non-null  int64  
 10  active       70000 non-null  int64  
 11  cardio       70000 non-null  int64  
dtypes: float64(2), int64(10)
memory usage: 6.4 MB
```

In [9]:

```
# Statistical summary of the dataframe
cardio_df.describe()
```

Out[9]:

	age	gender	height	weight	ap_hi	ap_lo	cholesterol	gluc	
count	70000.000000	70000.000000	70000.000000	70000.000000	70000.000000	70000.000000	70000.000000	70000.000000	700
mean	53.339358	1.349571	164.359229	74.205690	128.817286	96.630414	1.366871	1.226457	

	age	gender	height	weight	ap_hi	ap_lo	cholesterol	gluc
std	6.759594	0.476838	8.210126	14.395757	154.011419	188.472530	0.680250	0.572270
min	29.583562	1.000000	55.000000	10.000000	-150.000000	-70.000000	1.000000	1.000000
25%	48.394521	1.000000	159.000000	65.000000	120.000000	80.000000	1.000000	1.000000
50%	53.980822	1.000000	165.000000	72.000000	120.000000	80.000000	1.000000	1.000000
75%	58.430137	2.000000	170.000000	82.000000	140.000000	90.000000	2.000000	1.000000
max	64.967123	2.000000	250.000000	200.000000	16020.000000	11000.000000	3.000000	3.000000

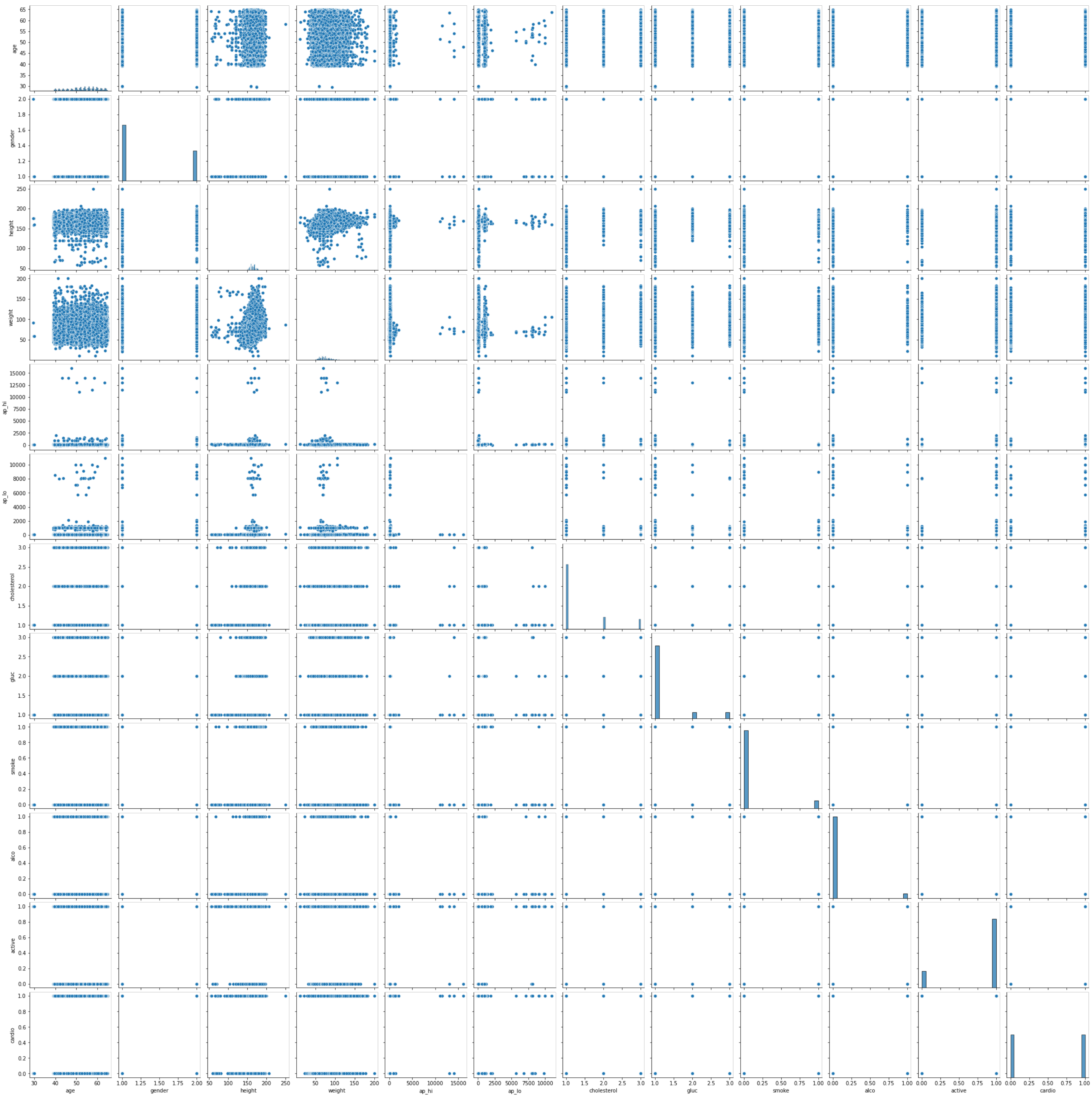
VISUALIZE DATASET

In [10]:

```
sns.pairplot(cardio_df)
```

Out[10]:

<seaborn.axisgrid.PairGrid at 0x7f94685c6278>



In [ ]:

```
In [ ]:
```

```

```

```
In [ ]:
```

```

```

CREATE TRAINING AND TESTING DATASET

In [11]:

```
# split the dataframe into target and features

df_target = cardio_df['cardio']
df_final = cardio_df.drop(columns =['cardio'])
```

In [12]:

```
cardio_df.columns
```

Out[12]:

```
Index(['age', 'gender', 'height', 'weight', 'ap_hi', 'ap_lo', 'cholesterol',
       'gluc', 'smoke', 'alco', 'active', 'cardio'],
      dtype='object')
```

In [13]:

```
df_final.shape
```

Out[13]:

```
(70000, 11)
```

In [14]:

```
df_target.shape
```

Out[14]:

```
(70000,)
```

In [15]:

```
#spliting the data in to test and train sets
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(df_final, df_target, test_size = 0.2
)
```

In [16]:

```
X_train.shape
```

Out[16]:

```
(56000, 11)
```

In [17]:

```
y_train.shape
```

Out[17]:

```
(56000,)
```

In [18]:

```
X_test.shape
```

Out[18]:

```
(14000, 11)
```

In [19]:

```
X_test.shape
```

Out[19]:

```
(14000, 11)
```

TRAIN AND TEST XGBOOST MODEL IN LOCAL MODE (NOTE THAT SAGEMAKER BUILT-IN ALGORITHMS ARE NOT USED HERE)

In [20]:

```
# install xgboost

!pip install xgboost
```

```
Requirement already satisfied: xgboost in /home/ec2-user/anaconda3/envs/python3/lib/pytho
n3.6/site-packages (1.3.3)
Requirement already satisfied: scipy in /home/ec2-user/anaconda3/envs/python3/lib/python3
.6/site-packages (from xgboost) (1.5.3)
Requirement already satisfied: numpy in /home/ec2-user/anaconda3/envs/python3/lib/python3
.6/site-packages (from xgboost) (1.19.5)
```

In [21]:

```
# use xgboost model in local mode

# note that we have not performed any normalization or scaling since XGBoost is not sensi
tive to this.
# XGboost is a type of ensemble algorithms and works by selecting thresholds or cut point
s on features to split a node.
# It doesn't really matter if the features are scaled or not.


from xgboost import XGBClassifier

# model = XGBClassifier(learning_rate=0.01, n_estimators=100, objective='binary:logistic'
)
model = XGBClassifier()

model.fit(X_train, y_train)
```

```
/home/ec2-user/anaconda3/envs/python3/lib/python3.6/site-packages/xgboost/sklearn.py:888:
UserWarning: The use of label encoder in XGBClassifier is deprecated and will be removed
in a future release. To remove this warning, do the following: 1) Pass option use_label_e
ncoder=False when constructing XGBClassifier object; and 2) Encode your labels (y) as int
egers starting with 0, i.e. 0, 1, 2, ..., [num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)
```

```
[18:47:57] WARNING: ../src/learner.cc:1061: Starting in XGBoost 1.3.0, the default evalua
tion metric used with the objective 'binary:logistic' was changed from 'error' to 'loglos
s'. Explicitly set eval_metric if you'd like to restore the old behavior.
```

Out[21]:

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.300000012, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=2, num_parallel_tree=1, random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=None)
```

In [22]:

```
# make predictions on test data

predict = model.predict(X_test)
```

In [23]:

```
predict
```

Out[23]:

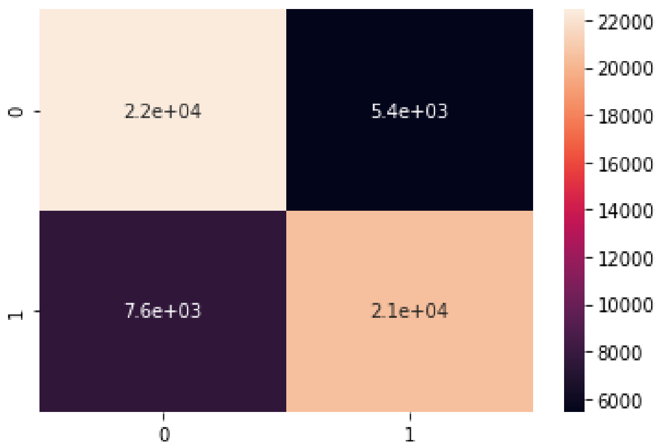
```
array([1, 0, 0, ..., 1, 0, 0])
```

In [24]:

```
# Assess trained model performance on training dataset
predict_train = model.predict(X_train)
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_train, predict_train)
plt.figure()
sns.heatmap(cm, annot=True)
```

Out[24]:

```
<AxesSubplot:>
```



In [25]:

```
# print metrics for training dataset

from sklearn.metrics import precision_score, recall_score, accuracy_score

print("Precision = {}".format(precision_score(y_train, predict_train)))
print("Recall = {}".format(recall_score(y_train, predict_train)))
print("Accuracy = {}".format(accuracy_score(y_train, predict_train)))
```

```
Precision = 0.7902157164869029
Recall = 0.7298537730814388
Accuracy = 0.7671607142857143
```

In [26]:

```
# print metrics for testing dataset

print("Precision = {}".format(precision_score(y_test, predict)))
print("Recall = {}".format(recall_score(y_test, predict)))
print("Accuracy = {}".format(accuracy_score(y_test, predict)))
```

```
Precision = 0.7381722915703498
Recall = 0.6970314318975553
Accuracy = 0.7299285714285715
```

In [27]:

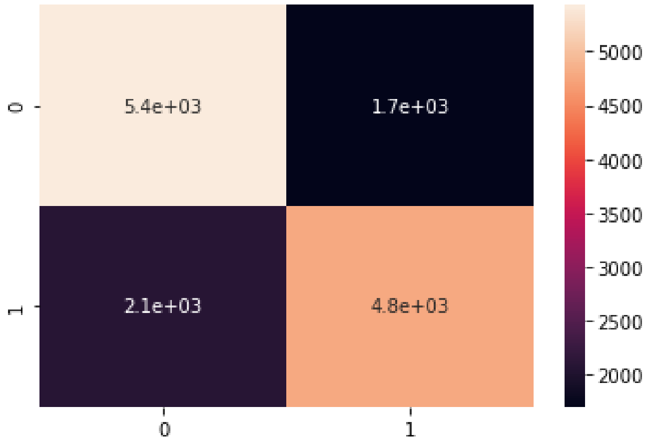
```
# plot the confusion matrix

from sklearn.metrics import confusion_matrix
```

```
cm = confusion_matrix(y_test, predict)
plt.figure()
sns.heatmap(cm, annot=True)
```

Out[27]:

```
<AxesSubplot:>
```



In [28]:

```
param_grid = {
        'gamma': [0.5, 1, 5],    # regularization parameter
        'subsample': [0.6, 0.8, 1.0], # % of rows taken to build each tree
        'colsample_bytree': [0.6, 0.8, 1.0], # number of columns used by each tree
        'max_depth': [3, 4, 5] # depth of each tree
        }
```

In [ ]:

```
y_predict_optim = grid.predict(X_test)
```

In [ ]:

```
y_predict_optim
```

In [ ]:

```
# print metrics for testing dataset

print("Precision = {}".format(precision_score(y_test, y_predict_optim)))
print("Recall = {}".format(recall_score(y_test, y_predict_optim)))
print("Accuracy = {}".format(accuracy_score(y_test, y_predict_optim)))
```

PERFORM DIMENSIONALITY REDUCTION USING PCA (USING SAGEMAKER)

In [30]:

```
# Boto3 is the Amazon Web Services (AWS) Software Development Kit (SDK) for Python
# Boto3 allows Python developer to write software that makes use of services like Amazon
S3 and Amazon EC2



import sagemaker
import boto3
from sagemaker import Session

# Let's create a Sagemaker session
sagemaker_session = sagemaker.Session()
bucket = Session().default_bucket()
prefix = 'pca'  # prefix is the subfolder within the bucket.
```

```
#Let's get the execution role for the notebook instance.
# This is the IAM role that you created when you created your notebook instance. You pass the role to the training job.
# Note that AWS Identity and Access Management (IAM) role that Amazon SageMaker can assume to perform tasks on your behalf (for example, reading training results, called model artifacts, from the S3 bucket and writing training results to Amazon S3).

role = sagemaker.get_execution_role()
```

In [31]:

```
import io # The io module allows for dealing with various types of I/O (text I/O, binary I/O and raw I/O).
import numpy as np
import sagemaker.amazon.common as smac # sagemaker common libary

# Code below converts the data in numpy array format to RecordIO format
# This is the format required by Sagemaker PCA

buf = io.BytesIO() # create an in-memory byte array (buf is a buffer I will be writing to)
df_matrix = df_final.to_numpy() # convert the dataframe into 2-dimensional array
smac.write_numpy_to_dense_tensor(buf, df_matrix)
buf.seek(0)

# When you write to in-memory byte arrays, it increments 1 every time you write to it
# Let's reset that back to zero
```

Out[31]:

```
0
```

In [32]:

```
import os

# Code to upload RecordIO data to S3

# Key refers to the name of the file

key = 'pca'

#following code uploads the data in record-io format to S3 bucket to be accessed later for training
boto3.resource('s3').Bucket(bucket).Object(os.path.join(prefix, 'train', key)).upload_fileobj(buf)

# Let's print out the training data location in s3
s3_train_data = 's3://{}/{}/train/{}'.format(bucket, prefix, key)


print('uploaded training data location: {}'.format(s3_train_data))
```

```
uploaded training data location: s3://sagemaker-us-east-2-542063182511/pca/train/pca
```

In [33]:

```
# create output placeholder in S3 bucket to store the PCA output

output_location = 's3://{}/{}/output'.format(bucket, prefix)
print('training artifacts will be uploaded to: {}'.format(output_location))
```

```
training artifacts will be uploaded to: s3://sagemaker-us-east-2-542063182511/pca/output
```

In [34]:

```
# This code is used to get the training container of sagemaker built-in algorithms
# all we have to do is to specify the name of the algorithm, that we want to use

# Let's obtain a reference to the pca container image
# Note that all  models are named estimators
# You don't have to specify (hardcode) the region, get_image_uri will get the current reg
```

```
ion name using boto3.Session


from sagemaker.amazon.amazon_estimator import get_image_uri


container = get_image_uri(boto3.Session().region_name, 'pca')
```

```
The method get_image_uri has been renamed in sagemaker>=2.
See: https://sagemaker.readthedocs.io/en/stable/v2.html for details.
Defaulting to the only supported framework/algorithm version: 1. Ignoring framework/algor
ithm version: 1.
```

In [ ]:

```

```

DEPLOY THE TRAINED PCA MODEL

In [36]:

```
# Deploy the model to perform inference

pca_reduction = pca.deploy(initial_instance_count = 1,
                                          instance_type = 'ml.m4.xlarge')
```

```
-------------!
```

In [37]:

```
from sagemaker.predictor import csv_serializer, json_deserializer


# Content type overrides the data that will be passed to the deployed model, since the de
ployed model expects data in text/csv format.

# Serializer accepts a single argument, the input data, and returns a sequence of bytes i
n the specified content type

# Deserializer accepts two arguments, the result data and the response content type, and
return a sequence of bytes in the specified content type.

# Reference: https://sagemaker.readthedocs.io/en/stable/predictors.html


# pca_reduction.content_type = 'text/csv'
pca_reduction.serializer = csv_serializer
pca_reduction.deserializer = json_deserializer
```

In [38]:

```
# make prediction on the test data

result = pca_reduction.predict(np.array(df_final))
```

```
The csv_serializer has been renamed in sagemaker>=2.
See: https://sagemaker.readthedocs.io/en/stable/v2.html for details.
The json_deserializer has been renamed in sagemaker>=2.
See: https://sagemaker.readthedocs.io/en/stable/v2.html for details.
```

In [ ]:

```
# We have pass in the container, the type of instance that we would like to use for train
ing
# output path and sagemaker session into the Estimator.
# We can also specify how many instances we would like to use for training


pca = sagemaker.estimator.Estimator(container,
```

```
                                                role,
                                                train_instance_count=1,
                                                train_instance_type='ml.c4.xlarge',
                                                output_path=output_location,
                                                sagemaker_session=sagemaker_session)

# We can tune parameters like the number of features that we are passing in, mode of algo
rithm, mini batch size and number of pca components


pca.set_hyperparameters(feature_dim=11,
                         num_components=6,
                         subtract_mean=False,
                         algorithm_mode='regular',
                         mini_batch_size=100)


# Pass in the training data from S3 to train the pca model


pca.fit({'train': s3_train_data})

# Let's see the progress using cloudwatch logs
```

In [ ]:

```
result # results are in Json format
```

In [40]:

```
# Since the results are in Json format, we access the scores by iterating through the sco
res in the predictions
predictions = np.array([r['projection'] for r in result['projections']])
```

In [41]:

```
predictions
```

Out[41]:

```
array([[-2.89103657e-01,  3.99437475e+00, -1.25495701e+01,
         6.42405853e+01,  3.68210945e+01, -2.17848068e+02],
       [ 1.09570193e+00, -4.77767706e+00,  1.23644390e+01,
         4.45821114e+01,  4.56663399e+01, -2.41025101e+02],
       [ 1.33668399e+00,  1.79976070e+00, -9.73582458e+00,
         5.34248428e+01,  5.57539673e+01, -2.23016754e+02],
       ...,
       [ 9.36102509e-01,  6.50153160e+00,  2.10844498e+01,
         4.50918350e+01,  7.45691071e+01, -2.82263916e+02],
       [ 1.15454197e-03, -8.17430115e+00, -2.97180176e+00,
         5.16770020e+01,  5.14335823e+01, -2.34024872e+02],
       [ 3.68915290e-01, -1.09633231e+00, -4.88934517e+00,
         6.41318741e+01,  4.39791260e+01, -2.28002136e+02]])
```

In [42]:

```
predictions.shape
```

Out[42]:

```
(70000, 6)
```

In [43]:

```
# Delete the end-point

pca_reduction.delete_endpoint()
```

TRAIN AND EVALUATE XGBOOST MODEL ON DATA AFTER DIMENSIONALITY REDUCTION (USING SAGEMAKER)

In [ ]:

```
predictions.shape
```

In [ ]:

```
# Convert the array into dataframe in a way that target variable is set as the first column and is followed by feature columns
# This is because sagemaker built-in algorithm expects the data in this format

train_data = pd.DataFrame({'Target':df_target})
train_data
```

In [ ]:

```
for i in range(predictions.shape[1]):
    train_data[i] = predictions[:,i]
```

In [ ]:

```
train_data.head()
```

In [ ]:

```
train_data_size = int(0.9 * train_data.shape[0])
train_data_size
```

In [ ]:

```
# shuffle the data in dataframe and then split the dataframe into train, test and validation sets.

import sklearn

train_data = sklearn.utils.shuffle(train_data)
train, test, valid = train_data[:train_data_size], train_data[train_data_size:train_data_size + 3500], train_data[train_data_size + 3500:]
```

In [ ]:

```
train.shape, test.shape,valid.shape
```

In [ ]:

```
X_test, y_test = test.drop(columns = ['Target']), test['Target']
```

In [ ]:

```
# save train_data and validation_data as csv files

train.to_csv('train.csv',header = False, index = False)
valid.to_csv('valid.csv',header = False, index = False)
```

In [ ]:

```
prefix = 'XGBoost-Classifier'
key = 'XGBoost-Classifier'
```

In [ ]:

```
# read the data from csv file and then upload the data to s3 bucket
with open('train.csv','rb') as f:
    # The following code uploads the data into S3 bucket to be accessed later for training
    boto3.Session().resource('s3').Bucket(bucket).Object(os.path.join(prefix, 'train', key)).upload_fileobj(f)

# Let's print out the training data location in s3
```

```
s3_train_data = 's3://{}/{}/train/{}'.format(bucket, prefix, key)
print('uploaded training data location: {}'.format(s3_train_data))
```

In [ ]:

```
# reading the data from csv file and then upload the data to s3 bucket
with open('valid.csv','rb') as f:
    # The following code uploads the data into S3 bucket to be accessed later for trainin
g
    boto3.Session().resource('s3').Bucket(bucket).Object(os.path.join(prefix, 'valid', k
ey)).upload_fileobj(f)

# Let's print out the validation data location in s3
s3_valid_data = 's3://{}/{}/valid/{}'.format(bucket, prefix, key)
print('uploaded validation data location: {}'.format(s3_valid_data))
```

In [ ]:

```
# creates output placeholder in S3 bucket to store the linear learner output

output_location = 's3://{}/{}/output'.format(bucket, prefix)
print('training artifacts will be uploaded to: {}'.format(output_location))
```

In [ ]:

```
# This code is used to get the training container of sagemaker built-in algorithms
# all we have to do is to specify the name of the algorithm, that we want to use

# Let's obtain a reference to the XGBoost container image
# Note that all  models are named estimators
# You don't have to specify (hardcode) the region, get_image_uri will get the current reg
ion name using boto3.Session


container = get_image_uri(boto3.Session().region_name, 'xgboost','0.90-2')
```

In [ ]:

```
# We have pass in the container, the type of instance that we would like to use for train
ing
# output path and sagemaker session into the Estimator.
# We can also specify how many instances we would like to use for training


Xgboost_classifier = sagemaker.estimator.Estimator(container,
                                       role,
                                       train_instance_count=1,
                                       train_instance_type='ml.m4.xlarge',
                                       output_path=output_location,
                                       sagemaker_session=sagemaker_session)

# To improve the performance of the model, a hyperparameters tuning job need to be run

Xgboost_classifier.set_hyperparameters(max_depth=3,
                           objective='multi:softmax',
                           num_class= 2,
                           eta = 0.5,
                           num_round = 150
                           )
```

In [ ]:

```
# Create "train", "validation" channels to feed in the model
# Source: https://docs.aws.amazon.com/sagemaker/latest/dg/sagemaker-algo-docker-registry-
paths.html


train_input = sagemaker.session.s3_input(s3_data = s3_train_data, content_type='csv',s3_
data_type = 'S3Prefix')
valid_input = sagemaker.session.s3_input(s3_data = s3_valid_data, content_type='csv',s3_
data_type = 'S3Prefix')
```

```
Xgboost_classifier.fit({'train': train_input, 'validation': valid_input})
```

In [ ]:

```

```

TASK #10: DEPLOY AND TEST THE TRAINED XGBOOST MODEL

In [ ]:

```
# Deploy the model to perfrom inference

Xgboost_classifier = Xgboost_classifier.deploy(initial_instance_count = 1,
                                               instance_type = 'ml.m4.xlarge')
```

In [ ]:

```
# Content type over-rides the data that will be passed to the deployed model, since the d
eployed model expects data in text/csv format, we specify this as content -type.
# Serializer accepts a single argument, the input data, and returns a sequence of bytes i
n the specified content type
#Reference: https://sagemaker.readthedocs.io/en/stable/predictors.html

from sagemaker.predictor import csv_serializer, json_deserializer

Xgboost_classifier.serializer = csv_serializer
```

In [ ]:

```
# make prediction

XGB_prediction = Xgboost_classifier.predict(np.array(X_test))
```

In [ ]:

```
XGB_prediction
```

In [ ]:

```
# custom code to convert the values in bytes format to array

def bytes_2_array(x):

    #makes entire prediction as string and splits based on ','
    l = str(x).split(',')

    #Since the first element contains unwanted characters like (b,',') we remove them
    l[0] = l[0][2:]
    #same-thing as above remove the unwanted last character (')
    l[-1] = l[-1][:-1]

    #iterating through the list of strings and converting them into float type
    for i in range(len(l)):
        l[i] = float(l[i])

    #converting the list to into array
    l = np.array(l).astype('float32')

    #reshape one-dimensional array to two-dimentaional array
    return l.reshape(-1,1)
```

In [ ]:

```
predicted_values = bytes_2_array(XGB_prediction)
```

In [ ]:

```
predicted_values
```

In [ ]:

```
y_test = np.array(y_test)
y_test = y_test.reshape(-1,1)
```

In [ ]:

```
y_test
```

In [ ]:

```
# plot metrics

from sklearn.metrics import precision_score, recall_score, accuracy_score

print("Precision = {}".format(precision_score(y_test, predicted_values, average='macro')
))
print("Recall = {}".format(recall_score(y_test, predicted_values, average='macro')))
print("Accuracy = {}".format(accuracy_score(y_test, predicted_values)))
```

In [ ]:

```
# plot confusion matrix

from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, predicted_values)
plt.figure()
sns.heatmap(cm, annot=True)
```

In [ ]:

```
# Delete the end-point

Xgboost_classifier.delete_endpoint()
```

In [ ]:

```
cardio_df [ cardio_df['ap_hi'] == 16020]
cardio_df [ cardio_df['age'] > 64.8]
```

In [ ]:

```
cardio_df.hist(bins = 30, figsize = (20,20), color = 'r')
# get the correlation matrix

corr_matrix = cardio_df.corr()
corr_matrix
# plotting the correlation matrix
plt.figure(figsize = (16,16))
sns.heatmap(corr_matrix, annot = True)
plt.show()
```

In [ ]:

```
xgb_model = XGBClassifier(learning_rate=0.01, n_estimators=100, objective='binary:logisti
c')
from sklearn.model_selection import GridSearchCV
grid = GridSearchCV(xgb_model, param_grid, refit = True, verbose = 4)
grid.fit(X_train, y_train)
```