



In [1]:

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import numpy as np
import pandas as pd
import random
import math,time,sys
from matplotlib import pyplot
from datetime import datetime
#from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
#=====
def sigmoid1(gamma):      #convert to probability
    if gamma < 0:
        return 1 - 1/(1 + math.exp(gamma))
    else:
        return 1/(1 + math.exp(-gamma))

def sigmoid1i(gamma):     #convert to probability
    gamma = -gamma
    if gamma < 0:
        return 1 - 1/(1 + math.exp(gamma))
    else:
        return 1/(1 + math.exp(-gamma))

def sigmoid2(gamma):
    gamma /= 2
    if gamma < 0:
        return 1 - 1/(1 + math.exp(gamma))
    else:
        return 1/(1 + math.exp(-gamma))

def sigmoid3(gamma):
    gamma /= 3
    if gamma < 0:
        return 1 - 1/(1 + math.exp(gamma))
    else:
        return 1/(1 + math.exp(-gamma))

def sigmoid4(gamma):
    gamma *= 2
    if gamma < 0:
        return 1 - 1/(1 + math.exp(gamma))
    else:
        return 1/(1 + math.exp(-gamma))

def Vfunction1(gamma):
    return abs(np.tanh(gamma))

def Vfunction2(gamma):
    val = (math.pi)**(0.5)
    val /= 2
    val *= gamma
    val = math.erf(val)
    return abs(val)

def Vfunction3(gamma):
    val = 1 + gamma*gamma
    val = math.sqrt(val)
    val = gamma/val

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    return abs(val)

def Vfunction4(gamma):
    val=(math.pi/2)*gamma
    val=np.arctan(val)
    val=(2/math.pi)*val
    return abs(val)

def initialize(popSize,dim):
    population=np.zeros((popSize,dim))
    minn = 1
    maxx = math.floor(0.8*dim)
    if maxx<minn:
        minn = maxx

    for i in range(popSize):
        random.seed(i**3 + 10 + time.time() )
        no = random.randint(minn,maxx)
        if no == 0:
            no = 1
        random.seed(time.time()+ 100)
        pos = random.sample(range(0,dim-1),no)
        for j in pos:
            population[i][j]=1

        # print(population[i])
    return population

def fitness(solution, trainX, testX, trainy, testy):
    cols=np.flatnonzero(solution)
    val=1
    if np.shape(cols)[0]==0:
        return val
    clf=RandomForestClassifier(n_estimators=10)
    train_data=trainX[:,cols]
    test_data=testX[:,cols]
    clf.fit(train_data,trainy)
    val=1-clf.score(test_data,testy)

    #in case of multi objective []
    set_cnt=sum(solution)
    set_cnt=set_cnt/np.shape(solution)[0]
    val=omega*val+(1-omega)*set_cnt
    return val

def allfit(population, trainX, testX, trainy, testy):
    x=np.shape(population)[0]
    acc=np.zeros(x)
    for i in range(x):
        acc[i]=fitness(population[i],trainX,testX,trainy,testy)
        #print(acc[i])
    return acc

def toBinary(solution,dimension,trainX,testX,trainy,testy):
    # print("continuous",solution)

    Xnew = np.zeros(np.shape(solution))
    for i in range(dimension):
        temp = sigmoid1(solution[i])

        random.seed(time.time()+i)

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    if temp > 0.5: # sfunction
        Xnew[i] = 1
    else:
        Xnew[i] = 0
    # if temp > 0.5: # vfunction
    #     Xnew[i] = 1 - solution[i]
    # else:
    #     Xnew[i] = solution[i]

# Xnew = np.zeros(np.shape(solution))
# Xnew1 = np.zeros(np.shape(solution))
# Xnew2 = np.zeros(np.shape(solution))
# for i in range(dimension):
#     temp = sigmoid1(abs(solution[i]))
#     random.seed(time.time()+i)
#     r1 = random.random()
#     if temp > r1: # sfunction
#         Xnew1[i] = 1
#     else:
#         Xnew1[i] = 0

#     temp = sigmoid1i(abs(solution[i]))
#     if temp > r1: # sfunction
#         Xnew2[i] = 1
#     else:
#         Xnew2[i] = 0

# fit1 = fitness(Xnew1,trainX,testX,trainy,testy)
# fit2 = fitness(Xnew2,trainX,testX,trainy,testy)
# fitOld = fitness(solution,trainX,testX,trainy,testy)
# if fit1<fitOld or fit2<fitOld:
#     if fit1 < fit2:
#         Xnew = Xnew1.copy()
#     else:
#         Xnew = Xnew2.copy()
# return Xnew
# # else: CROSSOVER
# Xnew3 = Xnew1.copy()
# Xnew4 = Xnew2.copy()
# for i in range(dimension):
#     random.seed(time.time() + i)
#     r2 = random.random()
#     if r2>0.5:
#         tx = Xnew3[i]
#         Xnew3[i] = Xnew4[i]
#         Xnew4[i] = tx
# fit1 = fitness(Xnew3,trainX,testX,trainy,testy)
# fit2 = fitness(Xnew4,trainX,testX,trainy,testy)
# if fit1<fit2:
#     return Xnew3
# else:
#     return Xnew4
# print("binary",Xnew)
return Xnew

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#=====
def socialmimic(dataset, popSize, maxIter):

    #------
    df=pd.read_csv(dataset)

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(a,b)=np.shape(df)
#print(a,b)
data = df.values[:,0:b-1]
label = df.values[:,b-1]
dimension = np.shape(data)[1] #solution dimension
#-----

cross = 5
test_size = (1/cross)
trainX, testX, trainy, testy = train_test_split(data, label, stratify=label, tes
t_size=test_size)

clf=RandomForestClassifier(n_estimators=10)
clf.fit(trainX,trainy)
val=clf.score(testX,testy)
whole_accuracy = val
#print("Total Acc: ",val)

x_axis = []
y_axis = []
population = initialize(popSize,dimension)
GBESTSOL = np.zeros(np.shape(population[0]))
GBESTFIT = 1000

start_time = datetime.now()

for currIter in range(1,maxIter):
    newpop = np.zeros((popSize,dimension))
    fitList = allfit(population,trainX,testX,trainy,testy)
    y_axis.append(min(fitList))
    x_axis.append(currIter)
    bestInx = np.argmin(fitList)
    fitBest = min(fitList)
    Xbest = population[bestInx].copy()

    if fitBest<GBESTFIT:
        GBESTFIT = fitBest
        GBESTSOL = Xbest.copy()
        #print("",GBESTSOL.sum())

    for i in range(popSize):
        currFit = fitList[i]
        # print(currFit)
        difference = ( currFit - fitBest ) / currFit
        if difference == 0:
            random.seed(time.time())
            difference = random.uniform(0,1)
        newpop[i] = np.add(population[i],np.multiply(difference,populat
ion[i]))
        newpop[i] = toBinary(population[i],dimension,trainX,testX,train
y,testy)

    population = newpop.copy()
    # pyplot.plot(x_axis,y_axis)
    # pyplot.show()

#test accuracy
cols = np.flatnonzero(GBESTSOL)
val = 1
if np.shape(cols)[0]==0:

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        return GBESTSOL
    clf = RandomForestClassifier(n_estimators=10)
    train_data = trainX[:,cols]
    test_data = testX[:,cols]
    clf.fit(train_data,trainy)
    val = clf.score(test_data,testy)
    return GBESTSOL,val

#=====
=====
popSize = 20
maxIter = 10
omega = 0.9
datasetList = ["FinalData_3000"]
# datasetList = ["Breastcancer", "BreastEW", "CongressEW", "Exactly", "Exactly2", "HeartEW", "Ionosphere", "#KrVsKpEW", "Lymphography", "M-of-n", "PenglungEW", "Sonar", "SpectEW", "Tic-tac-toe", "Vote", "WaveformEW", "Wine", "Zoo"]

for dataset in datasetList:
    accuList = []
    featList = []
    for count in range(3001):
        if (dataset == "FinalData_3000") and count>1500:
            break
        #print(count)
        answer,testAcc = socialmimic("C:/Users/IYI/Desktop/matlab_yedek/aaa_mineral/minerals/birlestirilmis_3000/"+dataset+".csv",popSize,maxIter)
        print(answer.sum())
        accuList.append(testAcc)
        #print(featList.append(answer.sum()))
    inx = np.argmax(accuList)
    best_accuracy = accuList[inx]
    best_no_features = featList[inx]
    print(dataset,"best:",accuList[inx],featList[inx])

    with open("C:/Users/IYI/Desktop/matlab_yedek/aaa_mineral/minerals/birlestirilmis_3000/result_FinalData2.csv","a") as f:
        print(dataset,"% .2f" % (100*best_accuracy),best_no_features,file=f)

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IndexError                                Traceback (most recent call last)  
t)  
<ipython-input-1-847a4068c976> in <module>()  
    267     inx = np.argmax(accuList)  
    268     best_accuracy = accuList[inx]  
--> 269     best_no_features = featList[inx]  
    270     print(dataset,"best:",accuList[inx],featList[inx])  
    271
```

**IndexError:** list index out of range