```
1 pip install scikit-learn
    Requirement already satisfied: scikit-learn in /usr/local/lib/python3.7/dist-package
    Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-package
    Requirement already satisfied: scipy>=1.1.0 in /usr/local/lib/python3.7/dist-package
    Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/dist
    Requirement already satisfied: numpy>=1.14.6 in /usr/local/lib/python3.7/dist-packag
1 pip install sklearn-genetic
   Collecting sklearn-genetic
      Downloading sklearn_genetic-0.5.1-py3-none-any.whl (11 kB)
    Requirement already satisfied: scikit-learn>=0.23 in /usr/local/lib/python3.7/dist-p
    Requirement already satisfied: multiprocess in /usr/local/lib/python3.7/dist-package
   Collecting deap>=1.0.2
      Downloading deap-1.3.1-cp37-cp37m-manylinux_2_5_x86_64.manylinux1_x86_64.manylinux
                                         | 160 kB 13.9 MB/s
    Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages (from
    Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-package
    Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/dist
    Requirement already satisfied: scipy>=1.1.0 in /usr/local/lib/python3.7/dist-package
    Requirement already satisfied: dill>=0.3.4 in /usr/local/lib/python3.7/dist-packages
    Installing collected packages: deap, sklearn-genetic
    Successfully installed deap-1.3.1 sklearn-genetic-0.5.1
1 pip install sklearn-genetic-opt
   Collecting sklearn-genetic-opt
     Downloading sklearn_genetic_opt-0.8.1-py3-none-any.whl (30 kB)
    Requirement already satisfied: scikit-learn>=0.21.3 in /usr/local/lib/python3.7/dist
    Requirement already satisfied: tqdm>=4.61.1 in /usr/local/lib/python3.7/dist-package
    Requirement already satisfied: deap>=1.3.1 in /usr/local/lib/python3.7/dist-packages
    Requirement already satisfied: numpy>=1.14.5 in /usr/local/lib/python3.7/dist-packag
    Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/dist
    Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-package
    Requirement already satisfied: scipy>=1.1.0 in /usr/local/lib/python3.7/dist-package
    Installing collected packages: sklearn-genetic-opt
    Successfully installed sklearn-genetic-opt-0.8.1
1 #Import libraries
2 import numpy as np
3 import pandas as pd
4 import random
5 import matplotlib.pyplot
6 %matplotlib inline
7 import warnings
8 warnings.filterwarnings("ignore")
1 from sklearn.model selection import train test split
```

2 from sklearn.linear model import LogisticRegression

```
3 from sklearn.tree import DecisionTreeClassifier
4 from sklearn.metrics import accuracy_score
5 from sklearn import metrics
```

```
1 df = pd.read_csv('/content/KDDTrain+_20Percent.txt')
```

```
adding column names to data frame
 2
 3 columns = (['duration'
 4 , 'protocol_type'
 5, 'service'
 6,'flag'
7 ,'src_bytes'
8 , 'dst_bytes'
9 ,'land'
10 , 'wrong_fragment'
11 , 'urgent'
12 ,'hot'
13 , 'num_failed_logins'
14 , 'logged_in'
15 , 'num_compromised'
16 , 'root_shell'
17 , 'su_attempted'
18 , 'num root'
19 , 'num file creations'
20 , 'num shells'
21 , 'num_access_files'
22 , 'num outbound cmds'
23 , 'is_host_login'
24 , 'is_guest_login'
25 , 'count'
26 ,'srv_count'
27 , 'serror_rate'
28 ,'srv serror rate'
29 , 'rerror rate'
30 ,'srv_rerror_rate'
31 , 'same srv rate'
32 , 'diff srv rate'
33 ,'srv diff host rate'
34 , 'dst_host_count'
35 , 'dst host srv count'
36 ,'dst_host_same_srv_rate'
37 ,'dst_host_diff_srv_rate'
38 , 'dst host same src port rate'
39 ,'dst_host_srv_diff_host_rate'
40 , 'dst_host_serror_rate'
41 ,'dst host srv serror rate'
42 , 'dst host rerror rate'
43 , 'dst_host_srv_rerror_rate'
44 ,'attack'
45 ,'level'])
46
47 df.columns = columns
```

```
48
```

49 #It gives an overview about a Dataframe columns 50 df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25191 entries, 0 to 25190
Data columns (total 42 columns):

```
Data columns (total 43 columns):
    Column
                                Non-Null Count Dtype
_ _ _
    _____
                                _____
0
    duration
                                25191 non-null int64
1
    protocol_type
                                25191 non-null object
 2
    service
                                25191 non-null object
 3
                                25191 non-null object
    flag
4
                                25191 non-null int64
    src_bytes
                                25191 non-null int64
5
    dst bytes
6
    land
                                25191 non-null int64
    wrong_fragment
7
                                25191 non-null int64
                                25191 non-null int64
8
    urgent
9
                                25191 non-null int64
    hot
10 num_failed_logins
                                25191 non-null int64
                                25191 non-null int64
11
    logged_in
                                25191 non-null int64
12 num_compromised
13 root_shell
                               25191 non-null int64
                               25191 non-null int64
14 su_attempted
15 num_root
                                25191 non-null int64
16 num_file_creations
                            25191 non-null int64
25191 non-null int64
17 num_shells
18 num_access_files
                               25191 non-null int64
19 num outbound cmds
                              25191 non-null int64
20 is_host_login
                              25191 non-null int64
                                25191 non-null int64
 21 is_guest_login
                               25191 non-null int64
22 count
23 srv_count
                               25191 non-null int64
                                25191 non-null float64
24 serror_rate
25 srv_serror_rate
                                25191 non-null float64
                               25191 non-null float64
 26 rerror_rate
                                25191 non-null float64
 27 srv_rerror_rate
 28 same_srv_rate
                                25191 non-null float64
                               25191 non-null float64
 29 diff srv rate
 30 srv_diff_host_rate
                             25191 non-null float64
 31 dst_host_count
                                25191 non-null int64
32 dst_host_srv_count
                              25191 non-null int64
                                25191 non-null float64
 33 dst_host_same_srv_rate
34 dst_host_diff_srv_rate
                                25191 non-null float64
 35 dst_host_same_src_port_rate 25191 non-null float64
 36 dst_host_srv_diff_host_rate 25191 non-null float64
 37 dst_host_serror_rate
                                25191 non-null float64
 38 dst_host_srv_serror_rate
                              25191 non-null float64
                                25191 non-null float64
 39 dst_host_rerror_rate
                                25191 non-null float64
40 dst_host_srv_rerror_rate
41 attack
                                25191 non-null object
42 level
                                25191 non-null int64
dtypes: float64(15), int64(24), object(4)
```

memory usage: 8.3+ MB

```
1 #By default the head function returns the first 5 rows
2 df.head()
```

	duration	<pre>protocol_type</pre>	service	flag	<pre>src_bytes</pre>	dst_bytes	land	wrong_fragmen
0	0	udp	other	SF	146	0	0	
1	0	tcp	private	S0	0	0	0	
2	0	tcp	http	SF	232	8153	0	
3	0	tcp	http	SF	199	420	0	
4	0	tcp	private	REJ	0	0	0	

5 rows × 43 columns



1 #By default the tail function returns the first 5 rows
2 df.tail()

	duration	<pre>protocol_type</pre>	service	flag	<pre>src_bytes</pre>	dst_bytes	land	wrong_fr
25186	0	tcp	exec	RSTO	0	0	0	
25187	0	tcp	ftp_data	SF	334	0	0	
25188	0	tcp	private	REJ	0	0	0	
25189	0	tcp	nnsp	S0	0	0	0	
25190	0	tcp	finger	S0	0	0	0	

5 rows × 43 columns



- 1 #Count the number of rows and column in the data set
- 2 df.shape

(25191, 43)

- 1 #Explore the data
- 2 df.columns

```
'dst_host_srv_rerror_rate', 'attack', 'level'],
dtype='object')
```

```
1 df = df.replace((np.inf, -np.inf, np.nan), 0).reset_index(drop=True)
 1 from sklearn.preprocessing import LabelEncoder
 3 protocol_type_encoder = LabelEncoder()
4 df['protocol_type']=protocol_type_encoder.fit_transform(df['protocol_type'].astype(str)
 6 service_encoder = LabelEncoder()
7 df['service']=service_encoder.fit_transform(df['service'].astype(str))
 9 flag_encoder = LabelEncoder()
10 df['flag']=flag_encoder.fit_transform(df['flag'].astype(str))
12 attack_encoder = LabelEncoder()
13 df['attack']=attack_encoder.fit_transform(df['attack'].astype(str))
15 label=df['attack']
 1 #splitting the model into training and testing set
 2 X_train, X_test, y_train, y_test = train_test_split(df,
                                                        label, test size=0.30,
 3
 4
                                                        random_state=101)
1 clf = DecisionTreeClassifier()
 3 # Train Decision Tree Classifer
 4 clf = clf.fit(X train,y train)
 6 #Predict the response for test dataset
 7 y pred = clf.predict(X test)
 8 print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
     Accuracy: 0.9997353797300873
 1 #training a logistics regression model
 2 logmodel = LogisticRegression()
 3 logmodel.fit(X_train,y_train)
 4 predictions = logmodel.predict(X test)
 5 print("Accuracy = "+ str(accuracy_score(y_test,predictions)))
```

Accuracy = 0.8641174913998412

```
1 #defining various steps required for the genetic algorithm
2 def initilization_of_population(size,n_feat):
3     population = []
4     for i in range(size):
5         chromosome = np.ones(n_feat,dtype=np.bool)
```

```
chromosome[:int(0.3*n feat)]=False
 6
 7
           np.random.shuffle(chromosome)
 8
           population.append(chromosome)
 9
       return population
10
11 def fitness_score(population):
       scores = []
12
13
       for chromosome in population:
           logmodel.fit(X_train.iloc[:,chromosome],y_train)
14
15
           predictions = logmodel.predict(X_test.iloc[:,chromosome])
16
           scores.append(accuracy_score(y_test,predictions))
       scores, population = np.array(scores), np.array(population)
17
18
       inds = np.argsort(scores)
       return list(scores[inds][::-1]), list(population[inds,:][::-1])
19
20
21 def selection(pop_after_fit,n_parents):
       population_nextgen = []
22
23
       for i in range(n_parents):
24
           population_nextgen.append(pop_after_fit[i])
25
       return population_nextgen
26
27 def crossover(pop_after_sel):
       population_nextgen=pop_after_sel
28
       for i in range(len(pop_after_sel)):
29
30
           child=pop after sel[i]
           child[3:7]=pop_after_sel[(i+1)%len(pop_after_sel)][3:7]
31
32
           population_nextgen.append(child)
33
       return population_nextgen
34
35 def mutation(pop_after_cross,mutation_rate):
       population_nextgen = []
36
37
       for i in range(0,len(pop_after_cross)):
           chromosome = pop_after_cross[i]
38
           for j in range(len(chromosome)):
39
40
               if random.random() < mutation_rate:</pre>
41
                   chromosome[j]= not chromosome[j]
           population_nextgen.append(chromosome)
42
43
       #print(population nextgen)
44
       return population_nextgen
45
46 def generations(size,n_feat,n_parents,mutation_rate,n_gen,X_train,
47
                                       X_test, y_train, y_test):
48
       best_chromo= []
49
       best_score= []
50
       population nextgen=initilization of population(size, n feat)
51
       for i in range(n_gen):
           scores, pop_after_fit = fitness_score(population_nextgen)
52
53
           print(scores[:2])
           pop after sel = selection(pop after fit,n parents)
54
           pop_after_cross = crossover(pop_after_sel)
55
56
           population_nextgen = mutation(pop_after_cross, mutation_rate)
57
           best chromo.append(pop after fit[0])
           best_score.append(scores[0])
58
59
       return best_chromo,best_score
```

## Print the selected features

```
1 from sklearn.svm import LinearSVC
 2 from __future__ import print_function
 3 from sklearn.preprocessing import LabelEncoder
 4 from sklearn import datasets, linear_model
 5
 6 from genetic_selection import GeneticSelectionCV
 9 def main():
       df = pd.read_csv('/content/KDDTrain+_20Percent.txt')
10
11
       df = df.replace((np.inf, -np.inf, np.nan), 0).reset_index(drop=True)
12
13
14
      ## adding column names to data frame
15
16
      columns = (['duration','protocol_type','service','flag','src_bytes','dst_bytes','la
17
       ,'logged_in','num_compromised','root_shell','su_attempted','num_root','num_file_cre
       ,'is_host_login','is_guest_login','count','srv_count','serror_rate','srv_serror_rat
18
       ,'diff_srv_rate','srv_diff_host_rate','dst_host_count','dst_host_srv_count','dst_hc
19
       ,'dst_host_same_src_port_rate','dst_host_srv_diff_host_rate','dst_host_serror_rate'
20
21
       ,'attack','level'])
22
23
       df.columns = columns
24
       protocol_type_encoder = LabelEncoder()
25
26
       df['protocol_type']=protocol_type_encoder.fit_transform(df['protocol_type'].astype(
27
28
       service encoder = LabelEncoder()
       df['service']=service_encoder.fit_transform(df['service'].astype(str))
29
30
31
       flag encoder = LabelEncoder()
32
       df['flag']=flag_encoder.fit_transform(df['flag'].astype(str))
33
34
       attack encoder = LabelEncoder()
       df['attack']=attack encoder.fit transform(df['attack'].astype(str))
35
36
37
      X = df
38
39
      y = df['attack']
40
41
       estimators = linear model.LogisticRegression(solver="liblinear", multi class="ovr")
42
       selectors = GeneticSelectionCV(estimators,
43
44
                                     cv=6,
45
                                     verbose=2,
46
                                     scoring="accuracy",
47
                                     max features=10,
48
                                     n population=60,
49
                                     crossover_proba=0.6,
                                     mutation_proba=0.05,
```

```
51
                                       n generations=15,
52
                                       crossover independent proba=0.6,
53
                                       mutation independent proba=0.05,
54
                                       tournament_size=4,
55
                                       n_gen_no_change=20,
56
                                       caching=True,
57
                                       n_{jobs=-2}
       selectors = selectors.fit(X, y)
58
59
       print(selectors.support_)
60
61
62
63 if __name__ == "__main__":
64
      main()
```

Selecting features with genetic algorithm. gen nevals avg

```
std
                                                                               min
0
        60
                [ 0.787703 5.683333 0.00862 ] [ 0.12829
                                                           3.196309 0.024058] [ 0.
                                                       [ 2764.098424
1
        38
                [-832.522646
                               7.716667 833.336318]
                                                                         2.608267
2
        46
               [-1499.219947
                                 8.066667 1500.0028
                                                      ]
                                                               [ 3571.041902
                                                                                 2.
3
        32
               [-499.10737
                               8.133333 500.002445]
                                                               [ 2179.654255
                                                                                 1.
4
                                                               [ 1280.31302
        36
                [-165.729093
                               8.616667 166.668888]
                                                                                 1.
5
       45
               [-332.407688
                               9.4
                                         333.335684]
                                                               [ 1795.226824
                                                                                 0.
                               9.316667 166.669031]
6
        38
               [-165.723174
                                                               [ 1280.31379
                                                                                 0.
7
        33
                               9.616667 1000.002024]
                                                               [ 3000.288355
               [-999.134936
                                                                                 0.
8
       42
               [-1332.4962
                                 9.966667 1333.335346]
                                                               [ 3399.674693
                                                                                 0.
9
        28
                [-832.445804
                              10.
                                         833.335298]
                                                               [ 2764.121592
                                                                                 0.
10
        38
                [-999.127851 10.05
                                        1000.001874]
                                                               [ 3000.290716
                                                                                 0.
       36
               [-665.761445 10.05
11
                                         666.668665]
                                                               [ 2494.680189
                                                                                 0.
12
       33
               [-832.443197
                              10.066667 833.335187]
                                                               [ 2764.122378
                                                                                 0.
        44
13
               [-1165.808066
                                10.1
                                           1166.668212]
                                                               [ 3210.538748
                                                                                 0.
14
        31
                [-165.71077]
                              10.016667 166.668277]
                                                               [ 1280.315405
                                                                                 0.
15
                                                               [ 2494.68082
        34
                [-665.759083
                              10.183333 666.668184]
                                                                                 0.
[False True False True False False True False False False False
False False False False False False False False False False False
False True False False False False False True False False True
False True False True False True False
```

1 from sklearn import datasets 2 from sklearn.ensemble import RandomForestClassifier 3 from sklearn.model\_selection import train\_test\_split 4 from sklearn.metrics import accuracy score 5 from sklearn.preprocessing import LabelEncoder 6 import pandas as pd 7 import numpy as np 8 import warnings 9 warnings.filterwarnings("ignore") 10 11 #Load the data 12 data = pd.read csv('/content/KDDTrain+ 20Percent.txt') 13 14 data = data.replace((np.inf, -np.inf, np.nan), 0).reset\_index(drop=True) 15 16 columns = (['duration','protocol\_type','service','flag','src\_bytes','dst\_bytes','land',

17 , 'logged\_in', 'num\_compromised', 'root\_shell', 'su\_attempted', 'num\_root', 'num\_file\_creatic

```
18 ,'is_host_login','is_guest_login','count','srv_count','serror_rate','srv_serror_rate','
19 , 'diff_srv_rate', 'srv_diff_host_rate', 'dst_host_count', 'dst_host_srv_count', 'dst_host_s
20 , 'dst_host_same_src_port_rate', 'dst_host_srv_diff_host_rate', 'dst_host_serror_rate', 'ds
21 ,'attack','level'])
22
23 data.columns = columns
24
25 protocol_type_encoder = LabelEncoder()
26 data['protocol_type']=protocol_type_encoder.fit_transform(data['protocol_type'].astype(
27
28 service_encoder = LabelEncoder()
29 data['service']=service_encoder.fit_transform(data['service'].astype(str))
30
31 flag_encoder = LabelEncoder()
32 data['flag']=flag_encoder.fit_transform(data['flag'].astype(str))
33
34 attack_encoder = LabelEncoder()
35 data['attack']=attack_encoder.fit_transform(data['attack'].astype(str))
37 n_samples = len(data)
38 X = data
39 y = data['attack']
40
41 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.7)
43 clf = RandomForestClassifier()
```

# data is fitted with the help of GASearchCV

```
1 from sklearn genetic import GASearchCV
 2 from sklearn_genetic.space import Continuous, Categorical, Integer
 3 from sklearn_genetic.plots import plot_fitness_evolution, plot_search_space
4 from sklearn.model selection import StratifiedKFold
 5 import matplotlib.pyplot as plt
 7 param_grid = {'min_weight_fraction_leaf': Continuous(0.01, 0.5, distribution='log-unifc
                 'bootstrap': Categorical([True, False]),
 8
 9
                 'max_depth': Integer(2, 30),
                 'max_leaf_nodes': Integer(2, 35),
10
                 'n estimators': Integer(100, 300)}
11
12
13 cv = StratifiedKFold(n_splits=3, shuffle=True)
14
15 evolved estimator = GASearchCV(estimator=clf,
16
                                  cv=cv,
17
                                   scoring='accuracy',
18
                                   population_size=10,
19
                                   generations=15,
20
                                  tournament_size=3,
21
                                   elitism=True,
22
                                   crossover_probability=0.6,
23
                                  mutation_probability=0.05,
```

```
param_grid=param_grid,
criteria='max',
algorithm='eaMuPlusLambda',
n_jobs=-1,
verbose=True,
keep_top_k=4)
```

## 1 evolved\_estimator.fit(X\_train,y\_train)

```
nevals
                fitness
                                  fitness std
                                                   fitness max
                                                                    fitness min
gen
0
        10
                 0.886952
                                  0.03248
                                                   0.952627
                                                                    0.863438
1
        14
                 0.923541
                                  0.0352381
                                                   0.954215
                                                                    0.869657
2
        12
                0.938454
                                  0.0305511
                                                   0.954215
                                                                    0.869657
3
        14
                0.953646
                                  0.000388286
                                                   0.954215
                                                                    0.953156
4
        11
                0.953857
                                  0.000360213
                                                   0.954215
                                                                    0.953421
5
        11
                0.953804
                                  0.000292621
                                                   0.954215
                                                                    0.953421
6
        14
                0.95399
                                  0.000237084
                                                   0.954215
                                                                    0.953553
7
        9
                0.954096
                                  0.00018192
                                                   0.954215
                                                                    0.953818
8
        16
                0.953844
                                  0.000453789
                                                   0.954215
                                                                    0.952759
9
        14
                0.954228
                                  0.000983952
                                                   0.956994
                                                                    0.953288
10
        12
                0.954082
                                  0.000144958
                                                   0.954215
                                                                    0.953818
11
        13
                0.953791
                                  0.000582242
                                                   0.954215
                                                                    0.952759
12
        12
                0.953778
                                  0.000458587
                                                   0.954215
                                                                    0.952891
13
        13
                0.954294
                                  0.000555776
                                                   0.955406
                                                                    0.953024
14
        10
                                  0.000442061
                0.954373
                                                   0.955406
                                                                    0.953553
15
        14
                 0.954625
                                  0.000524158
                                                   0.955406
                                                                    0.954215
```

GASearchCV(crossover\_probability=0.6,

'max\_leaf\_nodes': <sklearn\_genetic.space.space.Integer object
'min\_weight\_fraction\_leaf': <sklearn\_genetic.space.space.Cont
'n\_estimators': <sklearn\_genetic.space.space.Integer object a</pre>

population\_size=10, return\_train\_score=True, scoring='accuracy')

```
1 y_predicy_ga = evolved_estimator.predict(X_test)
2 accuracy_score(y_test,y_predicy_ga)
```

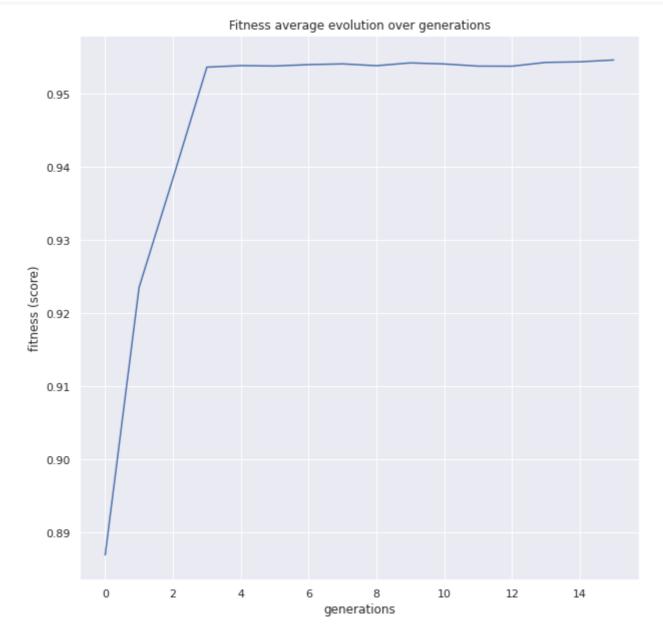
#### 0.95349892253601

'n\_estimators': 163}

```
1 evolved_estimator.best_params_
```

```
{'bootstrap': True,
  'max_depth': 16,
  'max_leaf_nodes': 32,
  'min_weight_fraction_leaf': 0.016579443235020405,
```

```
1 plot_fitness_evolution(evolved_estimator)
2 plt.show()
```



True False True	[0.9511711 [0.95474395 [0.95156808 [0.9511711 [0.95077412 [0.95236205 [0.9511711 [0.95394998 [0.95474395 [0.94998015	0.95514093 0.953553 0.95315601 0.95275903 0.95434696 0.95037713 0.9511711 0.95434696 0.95156808	0.952/5903] 0.953553 ] 0.94918618] 0.95514093] 0.95236205] 0.95474395] 0.95553791] 0.95514093] 0.95434696] 0.95315601]	[0.71835661 [0.69053078 [0.71357417	0.71916962 0.70720339 0.67033362 0.70152211 0.79555917 0.69906998 0.70668674 0.68857026
True True True False True True True True False	[0.95156808 [0.9511711 [0.95077412 [0.95236205 [0.9511711 [0.95394998 [0.95474395 [0.94998015	0.95315601 0.95275903 0.95434696 0.95037713 0.9511711 0.95434696 0.95156808	0.95514093] 0.95236205] 0.95474395] 0.95553791] 0.95514093] 0.95434696] 0.95315601]	[0.71835661 [0.69053078 [0.71357417 [0.78613067 [0.69562197 [0.7202816 [0.68723583	0.70720339 0.67033362 0.70152211 0.79555917 0.69906998 0.70668674 0.68857026
True True False True True True True False True False True	[0.9511711 [0.95077412 [0.95236205 [0.9511711 [0.95394998 [0.95474395 [0.94998015	0.95275903 0.95434696 0.95037713 0.9511711 0.95434696 0.95156808	0.95236205] 0.95474395] 0.95553791] 0.95514093] 0.95434696] 0.95315601]	[0.69053078 [0.71357417 [0.78613067 [0.69562197 [0.7202816 [0.68723583	0.67033362 0.70152211 0.79555917 0.69906998 0.70668674 0.68857026
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True True False True	[0.95394998 [0.95474395 [0.94998015	0.95434696 0.95156808	0.95434696] 0.95315601]	[0.7202816 [0.68723583	0.70668674 0.68857026
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True	[0.95315601	0.95553791	0.9511711 ]	[0.72318649	0.70953918
True	[0.95275903	0.95037713	0.94958317]	[0.70658398	0.70182562
True	[0.94720127	0.95593489	0.95394998]	[0.7381382	0.72267032
True	[0.95514093	0.95275903	0.95156808]	[0.7061708	0.6912694

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                 [0.95077412 0.95077412 0.95434696]
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                [0.95196507 0.95236205 0.95434696]
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True
                 [0.95156808 0.95672886 0.95394998]
                                                          [0.94114923 0.9274137
                                                                                  0.
```

### 1 evolved estimator.hof

```
{0: {'bootstrap': True,
  'max depth': 16,
  'max_leaf_nodes': 32,
  'min weight fraction leaf': 0.016579443235020405,
  'n estimators': 163},
1: {'bootstrap': True,
  'max depth': 16,
  'max leaf nodes': 32,
  'min_weight_fraction_leaf': 0.019245437578258293,
  'n estimators': 216},
2: {'bootstrap': True,
  'max_depth': 16,
  'max leaf nodes': 32,
  'min weight fraction leaf': 0.019245437578258293,
  'n estimators': 163},
 3: {'bootstrap': True,
  'max_depth': 16,
  'max_leaf_nodes': 29,
```

```
'min_weight_fraction_leaf': 0.019245437578258293,
'n_estimators': 163}}
```

```
1 chromo,score=generations(size=20,n_feat=43,n_parents=10,mutation_rate=0.10,
                       n_gen=15,X_train=X_train,X_test=X_test,y_train=y_train,y_test=y_t€
3 clf.fit(X_train.iloc[:,chromo[-1]],y_train)
4 predictions = clf.predict(X_test.iloc[:,chromo[-1]])
5 print("Accuracy score after genetic algorithm is= "+str(accuracy_score(y_test,predictic
    [0.8517069297947147, 0.8501190881252126]
    [0.9026879891119428, 0.9026879891119428]
    [0.9104003629352387, 0.9104003629352387]
    [0.8943518203470568, 0.8943518203470568]
    [0.9522513326528298, 0.9522513326528298]
    [0.9614381308835205, 0.9614381308835205]
    [0.973857321084269, 0.973857321084269]
    [0.9748780764432347, 0.9748780764432347]
    [0.9772598389474878, 0.9772598389474878]
    [0.9810026085970285, 0.9810026085970285]
    [0.9318362254735171, 0.9318362254735171]
    [0.909719859362595, 0.909719859362595]
    [0.9489622320517183, 0.9489622320517183]
    [0.9455597141884995, 0.9455597141884995]
    [0.9426675740047635, 0.9426675740047635]
   Accuracy score after genetic algorithm is= 0.9417602359079051
1 chromo,score=generations(size=20,n_feat=43,n_parents=10,mutation_rate=0.10,
                       n_gen=15,X_train=X_train,X_test=X_test,y_train=y_train,y_test=y_te
3 logmodel.fit(X_train.iloc[:,chromo[-1]],y_train)
4 predictions = logmodel.predict(X_test.iloc[:,chromo[-1]])
5 print("Accuracy score after genetic algorithm is= "+str(accuracy_score(y_test,predictic
    [0.8480775774072814, 0.8464897357377793]
    [0.8592491777248498, 0.8592491777248498]
    [0.86049676760803, 0.86049676760803]
    [0.9275263695134399, 0.9275263695134399]
    [0.9131790858568675, 0.9131790858568675]
    [0.9132925031189747, 0.9132925031189747]
    [0.8867528637858683, 0.8867528637858683]
    [0.8990586367245095, 0.8990586367245095]
    [0.9080753090620393, 0.9080753090620393]
    [0.8912328456391063, 0.8912328456391063]
    [0.9176590677101055, 0.9176590677101055]
    [0.9208914596801633, 0.9208914596801633]
    [0.9242372689123285, 0.9242372689123285]
    [0.9388680957241692, 0.9388680957241692]
    [0.9371668367925599, 0.9371668367925599]
    Accuracy score after genetic algorithm is= 0.9358058296472723
```

we can select the features with the help of the genetic selection function

```
1 from genetic selection import GeneticSelectionCV
  2 from sklearn.preprocessing import LabelEncoder
  3 from sklearn.tree import DecisionTreeClassifier
 4 import pandas as pd
  5 import numpy as np
 7 df = pd.read_csv('/content/KDDTrain+_20Percent.txt')
  9 df = df.replace((np.inf, -np.inf, np.nan), 0).reset_index(drop=True)
10
11 columns = (['duration','protocol_type','service','flag','src_bytes','dst_bytes','land',
12 , 'logged_in', 'num_compromised', 'root_shell', 'su_attempted', 'num_root', 'num_file_creatic
13 ,'is_host_login','is_guest_login','count','srv_count','serror_rate','srv_serror_rate','
14 ,'diff_srv_rate','srv_diff_host_rate','dst_host_count','dst_host_srv_count','dst_host_s
15 , 'dst_host_same_src_port_rate', 'dst_host_srv_diff_host_rate', 'dst_host_serror_rate', 'dst_host_s
16 , 'attack', 'level'])
17
18 df.columns = columns
19
20 protocol_type_encoder = LabelEncoder()
21 df['protocol_type']=protocol_type_encoder.fit_transform(df['protocol_type'].astype(str)
22
23 service_encoder = LabelEncoder()
24 df['service']=service_encoder.fit_transform(df['service'].astype(str))
26 flag encoder = LabelEncoder()
27 df['flag']=flag_encoder.fit_transform(df['flag'].astype(str))
29 attack encoder = LabelEncoder()
30 df['attack']=attack_encoder.fit_transform(df['attack'].astype(str))
31
32 x = df.drop('attack',axis=1)
33 Y = df['attack']
34 estimators = DecisionTreeClassifier()
35 models = GeneticSelectionCV(
36
             estimators, cv=5, verbose=0,
             scoring="accuracy", max_features=10,
37
             n population=100, crossover proba=0.6,
38
39
             mutation_proba=0.05, n_generations=15,
40
             crossover_independent_proba=0.5,
41
             mutation_independent_proba=0.04,
42
             tournament_size=3, n_gen_no_change=10,
             caching=True, n_jobs=-1)
43
44 \text{ models} = \text{models.fit}(x, Y)
45 print('Feature Selection:', x.columns[models.support_])
         Feature Selection: Index(['service', 'flag', 'src_bytes', 'is_host_login', 'same_srv
                       'dst host serror rate', 'level'],
                     dtype='object')
  1 #split dataset in features and target variable
  2 feature_cols = ['service', 'flag', 'src_bytes', 'is_host_login', 'same_srv_rate',
```

'diff srv rate'. 'dst host count'. 'dst host srv diff host rate'.

```
date_dist_late, dest_late, d
```

```
1 # Split dataset into training set and test set
2 x_train, x_test, Y_train, Y_test = train_test_split(x, Y, test_size=0.3, random_state=1
```

```
1 # Create Decision Tree classifer object
2 clf = DecisionTreeClassifier()
3
4 # Train Decision Tree Classifer
5 clf = clf.fit(x_train,Y_train)
6
7 #Predict the response for test dataset
8 Y_pred = clf.predict(x_test)
9
10 # Model Accuracy, how often is the classifier correct?
11 print("Accuracy:",metrics.accuracy_score(Y_test, Y_pred))
```

Accuracy: 0.9949722148716592