lab2_2117902

October 16, 2024

1 Application of ML-based algorithm on The UNSW_NNB15 Datasets

1.1 Library

[1]:
```
#%pip install scikit-learn pandas numpy prettyprint cupy tqdm matplotlib␣
↪colorama
```

[2]:
```
# Importing necessary libraries
import pandas as pd
import numpy as np
from typing import Literal
from sklearn.metrics import roc_curve, precision_recall_curve, auc
from sklearn.preprocessing import LabelEncoder
from sklearn.decomposition import PCA
from sklearn.tree import DecisionTreeClassifier as DTC
from sklearn.neighbors import KNeighborsClassifier
from gc import collect
from time import sleep
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import cupy as cp
from tqdm import tqdm
import matplotlib.pyplot as plt
import seaborn as sns
from colorama import Style
```

1.2 Loading the data set

https://unsw-my.sharepoint.com/personal/z5025758_ad_unsw_edu_au/_layouts/15/onedrive.aspx?id=%2Fpers

[3]:
```
TRAIN_DATASET = 'UNSW_NB15_training-set.csv'
TEST_DATASET = 'UNSW_NB15_testing-set.csv'
```

[4]:
```
# Loading the csv data in a DataFrame
df_train = pd.read_csv(TRAIN_DATASET)
df_test = pd.read_csv(TEST_DATASET)
```

[5]:
```
df_train.head(5)
```

[5]:
```
   id       dur proto service state  spkts  dpkts  sbytes  dbytes       rate  \
0   1  0.121478   tcp       -   FIN      6      4     258     172  74.087490
1   2  0.649902   tcp       -   FIN     14     38     734   42014  78.473372
2   3  1.623129   tcp       -   FIN      8     16     364   13186  14.170161
3   4  1.681642   tcp     ftp   FIN     12     12     628     770  13.677108
4   5  0.449454   tcp       -   FIN     10      6     534     268  33.373826

   …  ct_dst_sport_ltm  ct_dst_src_ltm  is_ftp_login  ct_ftp_cmd  \
0  …                 1               1             0           0
1  …                 1               2             0           0
2  …                 1               3             0           0
3  …                 1               3             1           1
4  …                 1              40             0           0

   ct_flw_http_mthd  ct_src_ltm  ct_srv_dst  is_sm_ips_ports  attack_cat  \
0                 0           1           1                0      Normal
1                 0           1           6                0      Normal
2                 0           2           6                0      Normal
3                 0           2           1                0      Normal
4                 0           2          39                0      Normal

   label
0      0
1      0
2      0
3      0
4      0

[5 rows x 45 columns]
```

[6]:
```
def print_dataframe_shape(df:pd.DataFrame,name):print(f"The shape of {name} is:␣
↪{df.shape}")
```

[7]:
```
print_dataframe_shape(df_train,'Training Set')
print_dataframe_shape(df_test,'Testing Set')
```

```
The shape of Training Set is: (175341, 45)
The shape of Testing Set is: (82332, 45)
```

[8]:
```
# Creating a type of all the Features
Features = Literal['dur',
 'proto',
 'service',
 'state',
 'spkts',
```

```
 'dpkts',
 'sbytes',
 'dbytes',
 'rate',
 'sttl',
 'dttl',
 'sload',
 'dload',
 'sloss',
 'dloss',
 'sinpkt',
 'dinpkt',
 'sjit',
 'djit',
 'swin',
 'stcpb',
 'dtcpb',
 'dwin',
 'tcprtt',
 'synack',
 'ackdat',
 'smean',
 'dmean',
 'trans_depth',
 'response_body_len',
 'ct_srv_src',
 'ct_state_ttl',
 'ct_dst_ltm',
 'ct_src_dport_ltm',
 'ct_dst_sport_ltm',
 'ct_dst_src_ltm',
 'is_ftp_login',
 'ct_ftp_cmd',
 'ct_flw_http_mthd',
 'ct_src_ltm',
 'ct_srv_dst',
 'is_sm_ips_ports',
 'label']
```

1.2.1 Understanding the data

[9]:
```
y_label = 'label' # setting the label
features_list = df_train.columns.tolist()
```

[10]:
```
def separate(df:pd.DataFrame,):
    features = features_list.copy()
    features.remove(y_label)
```

```
    return df.drop(y_label,axis=1),df[y_label] # separate a DataFrame of the␣
↪features and the label
```

1.3 Preprocessing the Data

1.3.1 Cleaning the Data

Helper Function

[11]:
```
def standardize(df,column:Features): # Standardizing the values of a features␣
↪that has continuous values
    col_values = df[column].values

    mean = np.mean(col_values)
    std = np.std(col_values)
    col_values = col_values-mean
    col_values= col_values/std
    return pd.Series(col_values, name=column)



def min_max_scaling(df, column:Features): # MinMax scaling the values of a␣
↪features that has continuous values
    col_values = df[column].values
    min_value = np.min(col_values)
    max_value = np.max(col_values)
    scaled_values = (col_values - min_value) / (max_value - min_value)
    return pd.Series(scaled_values, name=column)

def state_to_mask(state_vector: np.ndarray): # Creating a Mask for feature that␣
↪has equally important state
    unique_val = np.unique(state_vector)
    size = len(unique_val)
    return { unique_val[mask]:mask for mask in range(size)}

def one_hot_encoding(state_mask:dict[int,str]): # Creating a function that␣
↪returns a one hot encoding from a Mask
    def wrapper(mask: str):
        v = np.zeros((1, len(state_mask)))
        mask = state_mask[mask]
        v[0][mask] = 1
        return v
    return wrapper

def one_hot_vector_distance(v1: np.ndarray, v2: np.ndarray): # Compute the␣
↪distance between two one hot encoding vector
    if v1.shape != v2.shape:
        raise
    if np.array_equal(v1, v2):
```

```
            return 0
        return 1

def str_encoder(df:pd.DataFrame,column:Features): # Set string to a equally␣
 ↪important state
    label_encoder = LabelEncoder()
    df[column] = label_encoder.fit_transform(df[column])
```

[12]:
```
def remove_uncessaryFeature(df: pd.DataFrame, features: list = []): # Function␣
 ↪to remove features
    try:
        return df.drop(features, axis=1)
    except KeyError :
        return df
```

Cleaning Function …

[13]:
```
features_to_normalize=['dur','spkts','stcpb','dtcpb','dpkts','dbytes','sbytes',
                       'rate',
   ␣
 ↪'sload','dload','sloss','dloss','sinpkt','dinpkt','sjit','djit','tcprtt','synack','smean','
features_to_ohe=['proto','service','state','is_ftp_login','ct_ftp_cmd','ct_flw_http_mthd','ct_
initial_features_to_remove = ['id','attack_cat']

text_featuresType = ['proto','service','state']

def preprocess_final(df:pd.DataFrame, normalize:␣
 ↪Literal['min_max_scaling','standardize']=standardize,features_to_remove:
 ↪list=[]):

    ftr = set(features_to_remove)
    df␣
 ↪=remove_uncessaryFeature(df,[*initial_features_to_remove,*features_to_remove])␣
 ↪# Removing uncessary feature

    # Set values to a equally important state
    for feature in set(features_to_ohe).difference(ftr).
 ↪union(text_featuresType):
        str_encoder(df,feature)

    #Normalize continuous feature
    for feature in set(features_to_normalize).difference(ftr):
        df[feature] = normalize(df,feature)

    return df
```

[14]:
```
def preprocess_partial(df:pd.DataFrame):

    # Removing uncessary feature
    df =remove_uncessaryFeature(df,['label',*initial_features_to_remove])

    # Set values to a equally important state
    for feature in text_featuresType:
        str_encoder(df,feature)

    #Normalize continuous feature
    for feature in features_to_normalize:
        df[feature] = standardize(df,feature)

    return df
```

1.4 Feature Selection

Looking for the features that has highest impact

[15]:
```
df_feature_analysis= preprocess_partial(df_train) # Creating a preprocessed␣
↪DataFrame to compute some Feature Engineering
```

Correlation Matrix

[16]:
```
# Find the highest correlation of a feature
def find_highest_correlation(corr_matrix:pd.DataFrame, target_feature:str):
    target_corr = corr_matrix[target_feature].drop(target_feature)
    highest_corr_feature = target_corr.idxmax()
    highest_corr_value = target_corr[highest_corr_feature]

    return highest_corr_feature, highest_corr_value
```

[17]:
```
corr_matrix = df_feature_analysis.corr().apply(abs) # Get the correlation␣
↪matrix with absolute values
corr_matrix
```

[17]:

	dur	proto	service	state	spkts	dpkts \
dur	1.000000	0.124502	0.008234	0.103443	0.254559	0.181182
proto	0.124502	1.000000	0.170032	0.172441	0.013469	0.026439
service	0.008234	0.170032	1.000000	0.144978	0.114403	0.077338
state	0.103443	0.172441	0.144978	1.000000	0.078701	0.098268
spkts	0.254559	0.013469	0.114403	0.078701	1.000000	0.390067
dpkts	0.181182	0.026439	0.077338	0.098268	0.390067	1.000000
sbytes	0.199731	0.005920	0.105188	0.049300	0.963791	0.188476
dbytes	0.144134	0.015812	0.035492	0.059759	0.206609	0.971907
rate	0.120966	0.013924	0.141709	0.432307	0.076358	0.098202
sttl	0.012196	0.049944	0.295302	0.584697	0.102723	0.192580
dttl	0.044159	0.113184	0.262970	0.375533	0.068246	0.053861

sload	0.081749	0.004759	0.166339	0.292570	0.051646	0.066710
dload	0.050603	0.046375	0.099581	0.150501	0.075897	0.139145
sloss	0.198597	0.011392	0.114522	0.060125	0.971069	0.204883
dloss	0.142963	0.020002	0.051495	0.071056	0.207798	0.978636
sinpkt	0.080055	0.562789	0.089971	0.095492	0.017587	0.022160
dinpkt	0.152142	0.052417	0.020190	0.076235	0.001678	0.006514
sjit	0.144413	0.016011	0.011469	0.045441	0.000384	0.000229
djit	0.157443	0.019388	0.090262	0.064747	0.017096	0.054371
swin	0.022047	0.138967	0.292887	0.367493	0.131813	0.183703
stcpb	0.013183	0.108571	0.237103	0.314361	0.107410	0.144119
dtcpb	0.014724	0.108630	0.237723	0.313922	0.102161	0.142667
dwin	0.017527	0.137605	0.300035	0.397710	0.133102	0.185555
tcprtt	0.053125	0.079193	0.140239	0.278469	0.039187	0.020915
synack	0.051093	0.073528	0.110995	0.261882	0.035507	0.015936
ackdat	0.049332	0.076362	0.155811	0.264946	0.038725	0.023899
smean	0.090028	0.042157	0.224861	0.070796	0.216592	0.014697
dmean	0.025336	0.077296	0.145641	0.256392	0.150237	0.441445
trans_depth	0.002071	0.020709	0.191839	0.056128	0.008834	0.029042
response_body_len	0.078915	0.006005	0.056951	0.025541	0.087217	0.442194
ct_srv_src	0.113709	0.203057	0.058269	0.385515	0.069127	0.079095
ct_state_ttl	0.186293	0.162433	0.205943	0.759825	0.086170	0.150023
ct_dst_ltm	0.086300	0.191101	0.047685	0.328748	0.060194	0.071909
ct_src_dport_ltm	0.094091	0.174965	0.038347	0.372309	0.068373	0.086695
ct_dst_sport_ltm	0.093923	0.165796	0.051106	0.408662	0.072484	0.094267
ct_dst_src_ltm	0.101760	0.175708	0.006774	0.429906	0.077553	0.094085
is_ftp_login	0.020641	0.018003	0.071051	0.051970	0.009951	0.013491
ct_ftp_cmd	0.020641	0.018003	0.071051	0.051970	0.009951	0.013491
ct_flw_http_mthd	0.024743	0.028809	0.266206	0.078856	0.006084	0.047974
ct_src_ltm	0.080871	0.168121	0.028599	0.323019	0.061584	0.075190
ct_srv_dst	0.115336	0.198594	0.048011	0.387446	0.069598	0.078342
is_sm_ips_ports	0.035370	0.585941	0.088847	0.094198	0.017770	0.021765

	sbytes	dbytes	rate	sttl	…	ct_dst_ltm	\
dur	0.199731	0.144134	0.120966	0.012196	…	0.086300	
proto	0.005920	0.015812	0.013924	0.049944	…	0.191101	
service	0.105188	0.035492	0.141709	0.295302	…	0.047685	
state	0.049300	0.059759	0.432307	0.584697	…	0.328748	
spkts	0.963791	0.206609	0.076358	0.102723	…	0.060194	
dpkts	0.188476	0.971907	0.098202	0.192580	…	0.071909	
sbytes	1.000000	0.009926	0.028468	0.020860	…	0.026661	
dbytes	0.009926	1.000000	0.059475	0.135515	…	0.042633	
rate	0.028468	0.059475	1.000000	0.407572	…	0.317229	
sttl	0.020860	0.135515	0.407572	1.000000	…	0.271383	
dttl	0.063009	0.023559	0.414546	0.032823	…	0.381678	
sload	0.018322	0.040430	0.602492	0.276475	…	0.076471	
dload	0.007829	0.104757	0.153051	0.397431	…	0.100953	
sloss	0.996109	0.017366	0.042923	0.044667	…	0.036965	

dloss	0.006804	0.996504	0.075259	0.162628	…	0.054538
sinpkt	0.006565	0.013618	0.075745	0.206571	…	0.072241
dinpkt	0.000024	0.007701	0.051539	0.003215	…	0.042781
sjit	0.002054	0.002422	0.063370	0.022676	…	0.046592
djit	0.003516	0.047354	0.085802	0.123435	…	0.057296
swin	0.050450	0.113148	0.515681	0.416843	…	0.412379
stcpb	0.043164	0.086894	0.408750	0.337305	…	0.326216
dtcpb	0.037988	0.086453	0.409046	0.334114	…	0.327530
dwin	0.050981	0.114269	0.518117	0.424320	…	0.415255
tcprtt	0.043624	0.003907	0.300794	0.039777	…	0.286773
synack	0.039739	0.000101	0.279271	0.042590	…	0.264577
ackdat	0.042883	0.007546	0.290051	0.032293	…	0.278326
smean	0.232348	0.036635	0.113232	0.010029	…	0.162651
dmean	0.004973	0.419965	0.273323	0.550389	…	0.203729
trans_depth	0.003428	0.030912	0.078556	0.063904	…	0.069216
response_body_len	0.001620	0.470905	0.022752	0.050454	…	0.016102
ct_srv_src	0.034395	0.045529	0.357704	0.346079	…	0.841280
ct_state_ttl	0.012053	0.089944	0.431534	0.672325	…	0.302420
ct_dst_ltm	0.026661	0.042633	0.317229	0.271383	…	1.000000
ct_src_dport_ltm	0.026490	0.052135	0.353589	0.344104	…	0.962052
ct_dst_sport_ltm	0.027281	0.056901	0.390721	0.379930	…	0.870644
ct_dst_src_ltm	0.032061	0.054633	0.383094	0.404346	…	0.852252
is_ftp_login	0.004515	0.010460	0.068140	0.124157	…	0.048527
ct_ftp_cmd	0.004515	0.010460	0.068140	0.124157	…	0.048527
ct_flw_http_mthd	0.002185	0.051403	0.109297	0.112833	…	0.085540
ct_src_ltm	0.027479	0.045594	0.310876	0.273252	…	0.886072
ct_srv_dst	0.034553	0.044531	0.362883	0.340678	…	0.852583
is_sm_ips_ports	0.006367	0.013147	0.072948	0.220429	…	0.069455

	ct_src_dport_ltm	ct_dst_sport_ltm	ct_dst_src_ltm	\
dur	0.094091	0.093923	0.101760	
proto	0.174965	0.165796	0.175708	
service	0.038347	0.051106	0.006774	
state	0.372309	0.408662	0.429906	
spkts	0.068373	0.072484	0.077553	
dpkts	0.086695	0.094267	0.094085	
sbytes	0.026490	0.027281	0.032061	
dbytes	0.052135	0.056901	0.054633	
rate	0.353589	0.390721	0.383094	
sttl	0.344104	0.379930	0.404346	
dttl	0.366308	0.389429	0.403465	
sload	0.100118	0.082462	0.155030	
dload	0.143573	0.153429	0.161192	
sloss	0.039158	0.041109	0.045857	
dloss	0.066411	0.072203	0.070905	
sinpkt	0.060851	0.057659	0.081595	
dinpkt	0.038731	0.039644	0.042856	

sjit	0.043927	0.045747	0.047338
djit	0.071165	0.075841	0.081518
swin	0.453084	0.497973	0.492118
stcpb	0.353927	0.389607	0.394579
dtcpb	0.354069	0.389581	0.394566
dwin	0.448574	0.493572	0.499716
tcprtt	0.264803	0.280883	0.290241
synack	0.244511	0.260560	0.265808
ackdat	0.256785	0.271092	0.283801
smean	0.169091	0.199021	0.152219
dmean	0.244463	0.264171	0.279326
trans_depth	0.069969	0.073894	0.084412
response_body_len	0.020611	0.021715	0.021633
ct_srv_src	0.866010	0.823583	0.967138
ct_state_ttl	0.353778	0.393091	0.427705
ct_dst_ltm	0.962052	0.870644	0.852252
ct_src_dport_ltm	1.000000	0.906793	0.869941
ct_dst_sport_ltm	0.906793	1.000000	0.838678
ct_dst_src_ltm	0.869941	0.838678	1.000000
is_ftp_login	0.064055	0.065305	0.062574
ct_ftp_cmd	0.064055	0.065305	0.062574
ct_flw_http_mthd	0.085699	0.086594	0.106129
ct_src_ltm	0.897438	0.803013	0.783753
ct_srv_dst	0.868850	0.830152	0.972370
is_sm_ips_ports	0.056858	0.053224	0.079765

	is_ftp_login	ct_ftp_cmd	ct_flw_http_mthd	ct_src_ltm \
dur	0.020641	0.020641	0.024743	0.080871
proto	0.018003	0.018003	0.028809	0.168121
service	0.071051	0.071051	0.266206	0.028599
state	0.051970	0.051970	0.078856	0.323019
spkts	0.009951	0.009951	0.006084	0.061584
dpkts	0.013491	0.013491	0.047974	0.075190
sbytes	0.004515	0.004515	0.002185	0.027479
dbytes	0.010460	0.010460	0.051403	0.045594
rate	0.068140	0.068140	0.109297	0.310876
sttl	0.124157	0.124157	0.112833	0.273252
dttl	0.107208	0.107208	0.223652	0.365404
sload	0.046194	0.046194	0.073920	0.084412
dload	0.027810	0.027810	0.039246	0.098149
sloss	0.005688	0.005688	0.002049	0.038795
dloss	0.007763	0.007763	0.048869	0.057412
sinpkt	0.014458	0.014458	0.018829	0.081130
dinpkt	0.002255	0.002255	0.046655	0.042445
sjit	0.005798	0.005798	0.088052	0.045108
djit	0.081014	0.081014	0.100563	0.062372
swin	0.129555	0.129555	0.207313	0.402189

stcpb	0.097536	0.097536	0.161696	0.318968
dtcpb	0.100410	0.100410	0.172032	0.317651
dwin	0.130834	0.130834	0.209360	0.403987
tcprtt	0.067715	0.067715	0.163332	0.278013
synack	0.056794	0.056794	0.144906	0.256475
ackdat	0.071807	0.071807	0.164719	0.269845
smean	0.043298	0.043298	0.017901	0.159718
dmean	0.023999	0.023999	0.129436	0.201604
trans_depth	0.016177	0.016177	0.226152	0.065314
response_body_len	0.004691	0.004691	0.065238	0.018091
ct_srv_src	0.089827	0.089827	0.120111	0.781051
ct_state_ttl	0.075058	0.075058	0.097270	0.296638
ct_dst_ltm	0.048527	0.048527	0.085540	0.886072
ct_src_dport_ltm	0.064055	0.064055	0.085699	0.897438
ct_dst_sport_ltm	0.065305	0.065305	0.086594	0.803013
ct_dst_src_ltm	0.062574	0.062574	0.106129	0.783753
is_ftp_login	1.000000	1.000000	0.022505	0.046326
ct_ftp_cmd	1.000000	1.000000	0.022505	0.046326
ct_flw_http_mthd	0.022505	0.022505	1.000000	0.074768
ct_src_ltm	0.046326	0.046326	0.074768	1.000000
ct_srv_dst	0.087511	0.087511	0.118709	0.777891
is_sm_ips_ports	0.015003	0.015003	0.024007	0.078886

	ct_srv_dst	is_sm_ips_ports
dur	0.115336	0.035370
proto	0.198594	0.585941
service	0.048011	0.088847
state	0.387446	0.094198
spkts	0.069598	0.017770
dpkts	0.078342	0.021765
sbytes	0.034553	0.006367
dbytes	0.044531	0.013147
rate	0.362883	0.072948
sttl	0.340678	0.220429
dttl	0.431188	0.091137
sload	0.141168	0.049327
dload	0.087247	0.035069
sloss	0.045459	0.009492
dloss	0.058605	0.016669
sinpkt	0.086988	0.941319
dinpkt	0.045648	0.011306
sjit	0.049711	0.013987
djit	0.082087	0.018827
swin	0.466245	0.115622
stcpb	0.373117	0.090374
dtcpb	0.374050	0.090525
dwin	0.473821	0.114671

```
tcprtt                0.316713          0.065994
synack                0.289605          0.061274
ackdat                0.310164          0.063635
smean                 0.171203          0.056094
dmean                 0.227964          0.060813
trans_depth           0.093901          0.017258
response_body_len     0.027303          0.005004
ct_srv_src            0.980323          0.088456
ct_state_ttl          0.364200          0.092616
ct_dst_ltm            0.852583          0.069455
ct_src_dport_ltm      0.868850          0.056858
ct_dst_sport_ltm      0.830152          0.053224
ct_dst_src_ltm        0.972370          0.079765
is_ftp_login          0.087511          0.015003
ct_ftp_cmd            0.087511          0.015003
ct_flw_http_mthd      0.118709          0.024007
ct_src_ltm            0.777891          0.078886
ct_srv_dst            1.000000          0.085149
is_sm_ips_ports       0.085149          1.000000

[42 rows x 42 columns]
```

[18]:

```
corr_feature={}
corr_tresh= 0.94

for feature in df_feature_analysis.columns:
    #Get the highest correlation for each feature
    f,score= find_highest_correlation(corr_matrix,feature)
    #Loading the feature and the score
    corr_feature[feature] = {'feature':f, 'score':score}

#Removing duplicates correlation since the corr matrix is a triangular matrix
for feature in df_feature_analysis.columns:
   try:
       t = corr_feature[feature]['feature']
       if corr_feature[t]['feature'] == feature:
           del corr_feature[t]
   except KeyError:
       continue

# Sorting by the highest correlation value
corr_feature = dict(sorted(corr_feature.items(), key=lambda item:␣
 ↪item[1]['score'], reverse=True))
# Filtering all correlation that is not above the threshold value
corr_feature = {f:corr_feature[f] for f in corr_feature.keys() if␣
 ↪corr_feature[f]['score'] >= corr_tresh }
corr_feature
```

[18]:
```
{'is_ftp_login': {'feature': 'ct_ftp_cmd', 'score': 1.0},
 'dbytes': {'feature': 'dloss', 'score': 0.996503594762374},
 'sbytes': {'feature': 'sloss', 'score': 0.9961094729147967},
 'swin': {'feature': 'dwin', 'score': 0.9901399299415929},
 'ct_srv_src': {'feature': 'ct_srv_dst', 'score': 0.9803230099911133},
 'dpkts': {'feature': 'dloss', 'score': 0.9786363765710283},
 'ct_dst_src_ltm': {'feature': 'ct_srv_dst', 'score': 0.9723704538697349},
 'spkts': {'feature': 'sloss', 'score': 0.9710686917738162},
 'ct_dst_ltm': {'feature': 'ct_src_dport_ltm', 'score': 0.9620518416459877},
 'tcprtt': {'feature': 'synack', 'score': 0.9494676611067793},
 'ackdat': {'feature': 'tcprtt', 'score': 0.941760373812716},
 'sinpkt': {'feature': 'is_sm_ips_ports', 'score': 0.941318900735516}}
```

[19]:
```
def compare_features(feature:list[Features],order_by:Features, ascending:
 ↪bool=True):
    if y_label not in feature:
        feature.append(y_label)
        print(feature)
    if order_by not in feature:
        raise ValueError('order_by must be in the feature parameter')

    if order_by == y_label:
        raise ValueError(f'cannot order_by the {y_label}')
    return df_train[feature].sort_values(by=order_by,axis=0,ascending=ascending)
```

is_ftp_login and **ct_ftp_cmd** *are exactly the same, so we can remove one them. For the rest we determined by looking directly at the df_train data and concludes that they are indeed highly correlated and prediction resulting removing will not affect that much*

[20]:
```
features_to_remove=['is_ftp_login']
#features_to_remove=['is_ftp_login','sbytes','dbytes','swin','dpkts','spkts']
```

PCA

[21]:
```
top_n_components =  30
```

[22]:
```
df_pca = df_feature_analysis.drop(features_to_remove,axis=1) #removing the␣
 ↪feature we did not need from the correlation analysis
feature_cov = np.dot(df_pca.transpose(), df_pca)/len(df_pca)
eigenvalues, eigenvectors = np.linalg.eig(feature_cov) # Getting the eigenvalues
pca_index= np.argsort(eigenvalues)[::-1][:top_n_components]
pca_feature = df_feature_analysis.columns[pca_index]
pca_feature # Getting  the most important features (principal components)␣
 ↪ordered by the highest eigenvalues
```

[22]:
```
Index(['dur', 'proto', 'service', 'state', 'spkts', 'dpkts', 'sbytes',
       'dbytes', 'rate', 'sttl', 'dttl', 'sload', 'dload', 'sloss', 'dloss',
       'sinpkt', 'dinpkt', 'sjit', 'djit', 'swin', 'stcpb', 'dtcpb', 'dwin',
```

```
         'tcprtt', 'synack', 'ackdat', 'smean', 'dmean', 'trans_depth',
         'response_body_len'],
        dtype='object')
```

[23]:
```
# Projecting the training dataset to the top_n_components SPACE to reduce the␣
↪features and keep the most information and variance
def toPCA_space(df:pd.DataFrame,pca_list,top_n_components=top_n_components):
    pca = PCA(n_components=top_n_components)
    pca.fit(df.values)
    pca_data = pca.transform(df.values)
    return pd.DataFrame(pca_data, columns=pca_list)
```

1.4.1 Final Preprocessing Step

Based on the various technique we decided to remove those features from the features that has equally important state

[24]:
```
features_to_ohe = list(set(features_to_ohe).difference(features_to_remove))
#features_to_ohe = []
features_to_ohe
```

[24]:
```
['is_sm_ips_ports',
 'state',
 'ct_state_ttl',
 'service',
 'ct_flw_http_mthd',
 'proto',
 'ct_ftp_cmd']
```

[ ]:
```
# Preprocessing the dataset and separate them to do the a Model training
X_train, Y_train =␣
↪separate(preprocess_final(df_train,features_to_remove=features_to_remove))
X_test, Y_test =␣
↪separate(preprocess_final(df_test,features_to_remove=features_to_remove))
X_train_PCA = toPCA_space(X_train,pca_feature.to_list(),)
X_test_PCA = toPCA_space(X_test,pca_feature.to_list(),)
```

[26]:
```
# NOTE uncommenting to put the dataset in the PCA space
#X_train = X_train_PCA
#X_test = X_test_PCA
print_dataframe_shape(X_train,'Training Set')
print_dataframe_shape(X_test,'Testing Set')
```

```
The shape of Training Set is: (175341, 41)
The shape of Testing Set is: (82332, 41)
```

[27]:
```python
#After this step those values are now unimportant
del df_train, df_test,df_feature_analysis,corr_matrix
collect()
```

[27]: 20

1.5 Model

[28]:
```python
# Creating a Label class that store the metadata of binary classification
class LabelMetadata:

    def __init__(self,pos_class,␣
↪neg_class,pos_name,neg_name,prefered_class=None) -> None:
        self.PositiveClass:int = pos_class
        self.NegativeClass:int = neg_class
        self.NegativeName:str = neg_name
        self.PositiveName:str = pos_name
        self.PreferedClass= self.NegativeClass if prefered_class is None else␣
↪self.PositiveClass

        self.answer={
            self.PositiveClass: self.PositiveName,
            self.NegativeClass: self.NegativeName
        }

problem_label_class = LabelMetadata(0,1,'Normal','Attack')
```

[64]:
```python
# Base class of the Binary Classifier
class BinaryClassifier:

    # setting up the variables in the init function
    def __init__(self,label_class=problem_label_class):
        self.X = None
        self.Y = None
        self.Y_Pred:list = None
        self.Y_PredProba=[]
        self.label_class = label_class

    def fit(self):
      ...

    def predict(self):
      ...

    # Method to count the label class in a vector
    def _label_count(self,label_vectors):
      n = len(label_vectors)
```

```
    sum_one = list(label_vectors).count(1)
    sum_zero =n-sum_one
    return sum_zero,sum_one,n

  # Given the Y_test, calculate the True Positive,True Negative,False␣
↪Positive,False Negative and other info
  def _compute_analysis(self,y_test):
      self.TP=0
      self.TN=0
      self.FP=0
      self.FN=0


      for truth,pred in zip(y_test,self.Y_Pred):
          if truth ==self.label_class.NegativeClass and pred ==self.
↪label_class.NegativeClass:
            self.TN+=1
          elif truth ==self.label_class.PositiveClass and pred ==self.
↪label_class.PositiveClass:
            self.TP+=1
          elif truth ==self.label_class.NegativeClass and pred == self.
↪label_class.PositiveClass:
            self.FP+=1
          else:
            self.FN+=1
      self.roc_info = roc_curve(y_test, self.Y_PredProba)
      self.precision_recall_info = precision_recall_curve(y_test, self.
↪Y_PredProba)

  def plot_confusion_matrix(self):
    confusion_matrix = np.array([[self.TN, self.FP], [self.FN, self.TP]])

    plt.figure(figsize=(6, 4))
    sns.heatmap(confusion_matrix, annot=True, fmt='d', cmap='Blues',␣
↪cbar=False,
                xticklabels=['Predicted Negative', 'Predicted Positive'],
                yticklabels=['Actual Negative', 'Actual Positive'])

    plt.title('Confusion Matrix')
    plt.xlabel('Predicted Labels')
    plt.ylabel('True Labels')
    plt.show()

  def plot_roc_curve(self):
    fpr, tpr, thresholds_roc =self.roc_info
    plt.figure()
```

```
        plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area =␣
↪{auc(fpr, tpr):0.2f})')
        plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
        plt.xlabel('False Positive Rate')
        plt.ylabel('True Positive Rate')
        plt.title('ROC Curve')
        plt.legend(loc="lower right")
        plt.show()

    def plot_precision_recall_curve(self):
        precision, recall, thresholds_pr = self.precision_recall_info
        plt.figure()
        plt.plot(recall, precision, color='b', lw=2)
        plt.xlabel('Recall')
        plt.ylabel('Precision')
        plt.title('Precision-Recall Curve')
        plt.show()

    @property
    def accuracy(self):
        return (self.TP + self.TN)/(self.TP + self.TN +self.FP + self.FN)

    @property
    def f_score(self):
        return (2*self.precision * self.recall)/(self.precision+self.recall)

    @property
    def precision(self):
        return (self.TP)/(self.TP + self.FP)

    @property
    def recall(self):
        return self.TP/(self.TP + self.FN)
```

1.5.1 Decision Tree

Question

[30]:
```
# Encapsulate the concept of the best split into a Question object, since the␣
↪best split is a question of which value will determine the split
class Question:

    def __init__(self,feature:Features,value:float,information_gain:float):
        self.feature = feature
        self.value = value
        self.information_gain = information_gain

    def split(self,dataset:pd.DataFrame)->tuple[pd.DataFrame,pd.DataFrame]:
```

```python
        ...

    #Representing the object in a Question form
    def _repr(self,_type):
        return f'Is {Style.DIM}{self.feature}{Style.RESET_ALL} {Style.BRIGHT}{_type}{Style.RESET_ALL} to {Style.DIM}{self.value:0.5f}{Style.RESET_ALL} ? - Gain[{self.information_gain:.6f}]'

    def match(self,vector:pd.Series) -> bool:
        ...

    def __str__(self):
        return self.__repr__()

    # Dunder method to help the programming

    def __eq__(self, other):
        return self.information_gain == other.information_gain

    def __ne__(self, other):
        return self.information_gain != other.information_gain

    def __gt__(self, other):
        return self.information_gain > other.information_gain

    def __ge__(self, other):
        return self.information_gain >= other.information_gain

# When the feature has equally important state
class QuestionEqual(Question):

    # Splitting a dataset by asking if the feature is equal or not equal to the value
    def split(self, dataset:pd.DataFrame):
        return dataset[dataset[self.feature] == self.value], dataset[dataset[self.feature] != self.value]

    # Wether the feature of a single vector answer the questions
    def match(self,vector):
        return vector[self.feature] == self.value

    def __repr__(self):
        return super()._repr('equal')


class QuestionThresh(Question):
```

```
    # Splitting a dataset by asking if the feature is greater equal  or␣
↪strictly lower than the threshold(value)
    def split(self, dataset:pd.DataFrame):
       return dataset[dataset[self.feature] >= self.value],␣
↪dataset[dataset[self.feature] < self.value]

    # Wether the feature of a single vector answer the questions
    def match(self,vector):
        return vector[self.feature] >= self.value

    def __repr__(self):
        return super()._repr('greater or equal')
```

Node class

[31]:
```
# Base Node class
class Node:
    node_count=0
    def __init__(self):
        Node.node_count+=1

# Node that has other node basically a subtree
class TreeNode(Node):
    def __init__(self,question:Question,left:Node,right:Node):
        super().__init__()
        self.question = question
        """
        Satisfy the match
        """
        self.left=left
        """
        Dissatisfy the match
        """
        self.right = right

    # Ask the question of a certain vector and dirige to the child that has the␣
↪answer
    def match(self,vector) -> Node:
        return self.left if self.question.match(vector) else self.right

    def __repr__(self):
        return repr(self.question)

# Label that has the final answer of a series of question
class LeafNode(Node):

    def __init__(self,probabilities,label_class:LabelMetadata):
```

```
        super().__init__()
        self.proba = probabilities
        self.label_class = label_class
        self.answer:Literal[0,1,None] = self._compute_answer()

    # Compute an answer based on a binary probabilities
    def _compute_answer(self):
        label_0 = self.proba[0]
        label_1 = self.proba[1]

        if label_0 == label_1:
            return self.label_class.PreferedClass

        return 1 if label_1 > label_0 else 0

    @property
    def answer_proba(self):
        return self.proba[self.answer] # probability of a final answer

    def __repr__(self):
        return f'It is {Style.DIM}{self.label_class.answer[self.answer]}{Style.
↪RESET_ALL} with a probability of {self.answer_proba:.4f} %'
```

DecisionTree class

[32]:
```
x_train, x_val, y_train, y_val = train_test_split(X_train, Y_train, test_size=0.
↪2, random_state=42)
```

[63]:
```
ImpurityType=Literal['gini_index','entropy']



class DecisionTreeClassifier(BinaryClassifier):

    # Constructor of that set all the hyperparameters
    def __init__(self,max_height:int,min_information_gain:float,min_sample:
↪int,impurity:
↪ImpurityType='entropy',label_class=problem_label_class,ohe_feature=features_to_ohe):
↪
        super().__init__(label_class)
        self.max_height = max_height if max_height is not None else float('inf')
        self.min_information_gain = min_information_gain
        self.min_sample = min_sample
        self.impurity_type = impurity
        self.ohe_features = ohe_feature
        self.impurity = self._gini_impurity if impurity == 'gini_index' else self.
↪_entropy
        self.root: TreeNode = None
```

```
  # loading the dataset to fit the model
  def fit(self,x_train:pd.DataFrame,y_train:pd.DataFrame):
    self.X = x_train
    self.Y = y_train
    self.root_dataset = pd.concat([self.X,self.Y],axis=1)

  # Train a model using a training set and predict the values of a validation set if they are specified
  def train(self,x_val=None,y_val=None):

    self.root =self._build_tree(self.root_dataset)
    if x_val is None or y_val is None:
      return
    self.predict(x_val,y_val)

  # Return the representation of the Decision Tree Classifier
  def __str__(self) -> str:
     return self.__repr__()

  def __repr__(self):
    return f'DecisionTree(Max_Depth={self.max_height},Min_Inf_Gain={self.min_information_gain},Min_Sample={self.min_sample},Impurity={self.impurity_type})'

  # Predict values of a testing/validation test and compute analysis to aid several metrics
  def predict(self,x_to_test,y_to_test):
    self.Y_Pred = self._predict(x_to_test)
    self._compute_analysis(y_to_test)

  # from a dataframe, each vector will traverse the trained tree and have a computed answer, then load the self.Y_pred
  def _predict(self,x_to_test:pd.DataFrame):
    return x_to_test.apply(self._traverse_tree,axis=1).values

  # computes the entropy of a dataset
  def _entropy(self,labels:np.ndarray):
    try:
      probabilities = np.array(self._compute_target_probabilities(labels))
    except ZeroDivisionError:
      return float('inf')
    return -np.sum(probabilities * np.log2(probabilities))

  # compute the gini impurity of a dataset
  def _gini_impurity(self,labels:np.ndarray):
    try:
```

```
        probabilities = np.array(self._compute_target_probabilities(labels))
      except ZeroDivisionError:
        return float('inf')
      return (1 - np.sum(probabilities**2))

    # get the probabilities of the binary class
    def _compute_target_probabilities(self,labels_vectors):

      sum_zero, sum_one,n = self._label_count(labels_vectors)
      return [sum_zero/n,sum_one/n]

    # compute the information gain
    def _information_gain(self,current_information_gain:float,mean_impurity:
↪float):
      return current_information_gain - mean_impurity

    # build a tree recursively from a dataset, return a Leaf node if the a␣
↪condition match any hyperparameter otherwise go further into build another␣
↪TreeNode
    def _build_tree(self,dataset:pd.DataFrame,current_depth:int =0) ->TreeNode␣
↪| LeafNode:

        parent_gain = self.impurity(dataset['label'].values) # current gain of␣
↪the dataset
        current_n = len(dataset) # size of the current dataset

        if current_depth >= self.max_height or current_n < self.min_sample or␣
↪parent_gain < self.min_information_gain: # if the dataset has any of this␣
↪condition true then return a Leaf Node with an answer
          try:
            proba= self._compute_target_probabilities(dataset['label'].values)␣
↪# get the probability of each class
          except ZeroDivisionError: # if theres a zero division error, return a␣
↪node with the preferred class
            t =[0,0]
            t[self.label_class.NegativeClass]=1
            t[self.label_class.PositiveClass]=0
            proba =np.array(t)
          return LeafNode(proba,self.label_class)

        best_question=self._find_best_split(dataset,parent_gain) # Get the best␣
↪split by finding the best question

        left_dataset,right_dataset =self._split_dataset(dataset,best_question)␣
↪# split the dataset into matching or no the question
```

```
      left_child = self._build_tree(left_dataset,current_depth+1) # if matching build another tree
      right_child = self._build_tree(right_dataset,current_depth+1) # if not matching build another tree

      return TreeNode(best_question,left_child,right_child)

    def _traverse_tree(self,x_vector:pd.Series):
     current_node:LeafNode | TreeNode = self.root
     while isinstance(current_node,TreeNode): # Asking questions(TreeNode) till having an answer(LeafNode)
       current_node = current_node.match(x_vector)

     self.Y_PredProba.append(current_node.answer_proba) # loading the probability of an answer
     return current_node.answer # Final answer

    def print_tree(self,): # printing the tree
      self._print_tree(self.root,0)

    def _print_tree(self,node:Node| TreeNode, depth,answer =None):
      print(' '*depth,'' if answer is None else answer,node) # print the question
      if type(node) is TreeNode:
       self._print_tree(node.left,depth+1,'YES...')  # calling recursively to the left
       self._print_tree(node.right,depth+1,'NO...')  # calling recursively to the right

    def _split_dataset(self,dataset:pd.DataFrame,question:Question): # spliting the dataset into two based on the current best question
     return question.split(dataset)

    def _find_best_split(self,dataset:pd.DataFrame,current_gain:float)->Question: # Fining the best question

     best_question = None
     for feature in dataset.columns:
      if feature == y_label: # the dataset contain the y_label value so we skip it
       continue
      if feature in self.ohe_features:
        for values in dataset[feature].unique(): # going trough every unique value if the state are equally important
```

```
          best_question = self._compute_best_question(dataset,␣
↪current_gain,feature, values,best_question,QuestionEqual) # compute the␣
↪global best question
      else: # if the feature has continuous values
        val_unique_mean = dataset[feature].unique().mean() # splitting by␣
↪mean from the unique values
        val_mean = dataset[feature].mean() # splitting by the mean
        val_median = dataset[feature].median() # splitting by the median

        for values in [val_unique_mean,val_mean,val_median]:
          best_question = self._compute_best_question(dataset,␣
↪current_gain,feature, values,best_question,QuestionThresh) # compute the␣
↪global best question

    return best_question

  def _compute_best_question(self, dataset:pd.DataFrame, current_gain:
↪float,feature:Features, values:float,best_question:Question,Q_type:type)␣
↪->Question:

      N = len(dataset)

      # splitting
      if Q_type== QuestionEqual: # if its a one hot encoding feature(ohe/␣
↪equally important state)
        y_satisfaction,y_dissatisfaction  = dataset[dataset[feature]==␣
↪values].label.values,dataset[dataset[feature]!= values].label.values

      else: # if the feature is a continuous
        y_satisfaction, y_dissatisfaction = dataset[dataset[feature] >=␣
↪values].label.values, dataset[dataset[feature] < values].label.values

      #get the mean impurity from the previous split
      mean_impurity = (len(y_dissatisfaction)/N)*self.
↪impurity(y_dissatisfaction) + (len(y_satisfaction)/N)*self.
↪impurity(y_satisfaction)
      #calulating the information gain
      info_gain = self._information_gain(current_gain,mean_impurity)
      question =  Q_type(feature,values,info_gain) # creating a question

      if best_question is None:
        return question # return the question if none best question were given

      return question if question > best_question else best_question # return␣
↪the question that maximize the information gain
```

```
    # comparing decision tree model by the accuracy
    def __eq__(self, other):
        return self.accuracy == other.accuracy

    def __ne__(self, other):
        return self.accuracy  != other.accuracy

    def __gt__(self, other):
        return self.accuracy  > other.accuracy

    def __ge__(self, other):
        return self.accuracy  >= other.accuracy
```

1.5.2 K-Nearest Neighbors

[62]:
```
class KNNClassifier(BinaryClassifier):

    # Give the parameters aiding our KNN
    def __init__(self,ohe_feature:list[str] ,max_k:int=None,N_batch=100) ->␣
↪None:
        super().__init__()
        self.K = max_k
        self.N_batch = N_batch
        self.ohe_features =  ohe_feature
        self.ohe_func = cp.vectorize(self._to_one_hot_encoding) # creating a␣
↪vectorize function

    # loading the dataset and set a K value
    def fit(self,X_train:pd.DataFrame,Y_train:pd.DataFrame):
        self.X  = X_train
        self.Y = Y_train
        self.x_num, self.x_ohe = self._split(X_train) # split the numerical␣
↪values and ohe features
        if self.K is not None:
          self.K = self._to_odd_number( self.K-1) # ensure that the K is an odd␣
↪number
        else:
          self.K = self._to_odd_number(round(len(self.X)**0.5)) # give square␣
↪root of len of the training dataset for a K (by convention)

    def _to_odd_number(self, val):
        return val-1 if val%2 == 0 else val # return an odd number if its even

    def _split(self,df:pd.DataFrame):
        return df.drop(self.ohe_features,axis=1),df[self.ohe_features] # split␣
↪the numerical values and ohe features
```

```python
    def predict(self,x_test,y_test):
        dataframes_indices = self._predict(self._split(x_test)) # get the all K closest indices
        self.df_distances = pd.DataFrame(pd.concat(dataframes_indices).apply(self._prevote,axis=1)) # concatenate and transform the indices into its specified label
        self.df_distances.columns = ['label']
        self.Y_Pred = self.df_distances.label.apply(self._vote_majority).values # vote the label
        del dataframes_indices, self.df_distances
        collect()
        self._compute_analysis(y_test) # get an analysis of our prediction

    def _prevote(self,row):
        return [int(Y_train[i]) for i in  row.tolist()] # transform a row indices to its label

    def _predict(self,test:tuple):
        test_x_num, test_x_ohe = test
        N =len(test_x_num)
        batch_size =  N / self.N_batch # set the batch size
        dataframes_indices = []

        for i in tqdm(range(self.N_batch)): # iterate over each batch
             # free up the GPU RAM
            cp.get_default_memory_pool().free_all_blocks()
            # get the bornes from the batch index
            a,b= round(batch_size*i),round(batch_size*(i+1))
            # get the values from the interval
            num,ohe = test_x_num[a:b],test_x_ohe[a:b]
             # compute the distances between the current test batch and all the training set
            temp = self._compute_distance(num,self.x_num) + self.ohe_func(self._compute_distance(ohe,self.x_ohe))
            # get the top indices based on the closets distance
            top_K_indices = cp.argsort(temp, axis=1)[:, :self.K] # TODO check give the label now
            dataframes_indices.append(pd.DataFrame(top_K_indices.get()))
            del temp, top_K_indices
            collect() # free up the ram

            sleep(0.1)
        return dataframes_indices

    def _to_one_hot_encoding(x):
```

```
        return 0 if x == 0 else 1 # if the difference between the values is not 0␣
↪then we set it to 1 since they equally important state

    def _compute_distance(self,a,b):
        # compute the distance of all the vector in two matrix

      A = a.to_numpy(dtype='float32')
      B = b.to_numpy(dtype='float32')
      A = cp.asarray(A)
      B = cp.asarray(B)
      A_sq_norms = cp.sum(A ** 2, axis=1).reshape(-1, 1)  # Shape (n, 1)
      B_sq_norms = cp.sum(B ** 2, axis=1).reshape(1, -1)  # Shape (1, m)

      dot_product = cp.dot(A, B.T)  # Shape (n, m)
      euclidean_distances = A_sq_norms + B_sq_norms - 2 * dot_product
      del A_sq_norms,B_sq_norms, dot_product, A,B
      collect()
      return euclidean_distances


    def _vote_majority(self,label_vectors):
        # vote the label class based on majority occurrences

      sum_zero, sum_one,n = self._label_count(label_vectors) # BUG
      self.Y_PredProba.append(sum_one/n if sum_one > sum_zero  else sum_zero/n)
      return 1 if sum_one > len(label_vectors)-sum_one else 0
```

1.6 Training

[35]:
```
def print_accuracy(accuracy):
    return print(f'Accuracy: {accuracy:.4f}')

def my_model_validator(best_model : DecisionTreeClassifier,d,s,i,c): # function␣
↪to train and get the best model based on accuracy between two model
    model = DecisionTreeClassifier(d,i,s,c)
    model.fit(x_train, y_train)
    model.train(x_val,y_val)

    if best_model is None:
        return model

    if model > best_model:
        best_model = model

    return best_model
```

```
def scikit_learn_val(best_model,d,s,i,c):# function to train and get the best␣
↪model based on accuracy between two model
    model = DTC(criterion='gini' if c =='gini_index' else␣
↪'entropy',max_depth=d,min_impurity_decrease=i,min_samples_split=s)
    model.fit(x_train, y_train)
    y_pred = model.predict(x_val)
    accuracy = accuracy_score(y_val, y_pred)
    if best_model is None:
        return model,accuracy
    b_model,b_accuracy = best_model
    if accuracy > b_accuracy:
        b_model = model
        b_accuracy = accuracy

    return b_model,b_accuracy

def train()->tuple[DecisionTreeClassifier,DTC]: # return the best model based␣
↪on accuracy of scikit learn and my own by different combinaison of parameter
    max_depth= [6,10,12,14]
    min_samples_split= [50,100,300,500]
    min_impurity_decrease=[0.0, 0.001, 0.01]
    criterion:list[ImpurityType]= ['gini_index', 'entropy']

    my_best_model = None
    scikit_best_model = None
    for d in max_depth:
        for s in min_samples_split:
            for i in min_impurity_decrease:
                for c in criterion:
                    my_best_model = my_model_validator(my_best_model,d,s,i,c)
                    scikit_best_model␣
↪=scikit_learn_val(scikit_best_model,d,s,i,c)

    return my_best_model,scikit_best_model
```

[36]:
```
collect()
```

[36]: 0

Due two a constraint of time and ressource i was not able to train the model for all situation, so below are the best model for the highly correlated data removed without PCA

[37]:
```
#my_best_model,scikit_best_model= train()
#scikit_best_model,b_accuracy = scikit_best_model
#DTC(max_depth=14, min_samples_split=50)
#Accuracy: 0.9478
```

```
#DecisionTreeClassifier(Max_Depth=14,Min_Inf_Gain=0.
 ↪0,Min_Sample=50,Impurity=gini_index)
#Accuracy: 0.9457
```

1.7 Testing

1.7.1 Model Testing

Lets try another model of My DecisionTreeClassifier

[68]:
```
my_DTC = DecisionTreeClassifier(14,0.001,100,'gini_index',)
my_DTC.fit(X_train,Y_train)
my_DTC.train()
my_DTC.predict(X_test,Y_test)
print_accuracy(my_DTC.accuracy)
```

```
Accuracy: 0.7981
```

ScikitLearn DecisionTree

[74]:
```
scikit_DTC = DTC(max_depth=14,min_samples_split=50)
scikit_DTC.fit(X_train,Y_train)
Y_pred = scikit_DTC.predict(X_test)
accuracy = accuracy_score(Y_test, Y_pred)
print_accuracy(accuracy)
```

```
Accuracy: 0.7331
```

ScikitLearn KNN

[73]:
```
knn = KNeighborsClassifier(n_neighbors=419, algorithm='brute')
knn.fit(X_train, Y_train)
y_pred = knn.predict(X_test)
accuracy = accuracy_score(Y_test, y_pred)
print_accuracy(accuracy)
```

```
Accuracy: 0.8181
```

My KNN from scratch

[72]:
```
my_KNN = KNNClassifier(features_to_ohe,419,N_batch=102)
my_KNN.fit(X_train,Y_train)
my_KNN.predict(X_test,Y_test)
print_accuracy(my_KNN.accuracy)
```

```
100%|      | 102/102 [02:04<00:00,  1.22s/it]
```

```
Accuracy: 0.8219
```

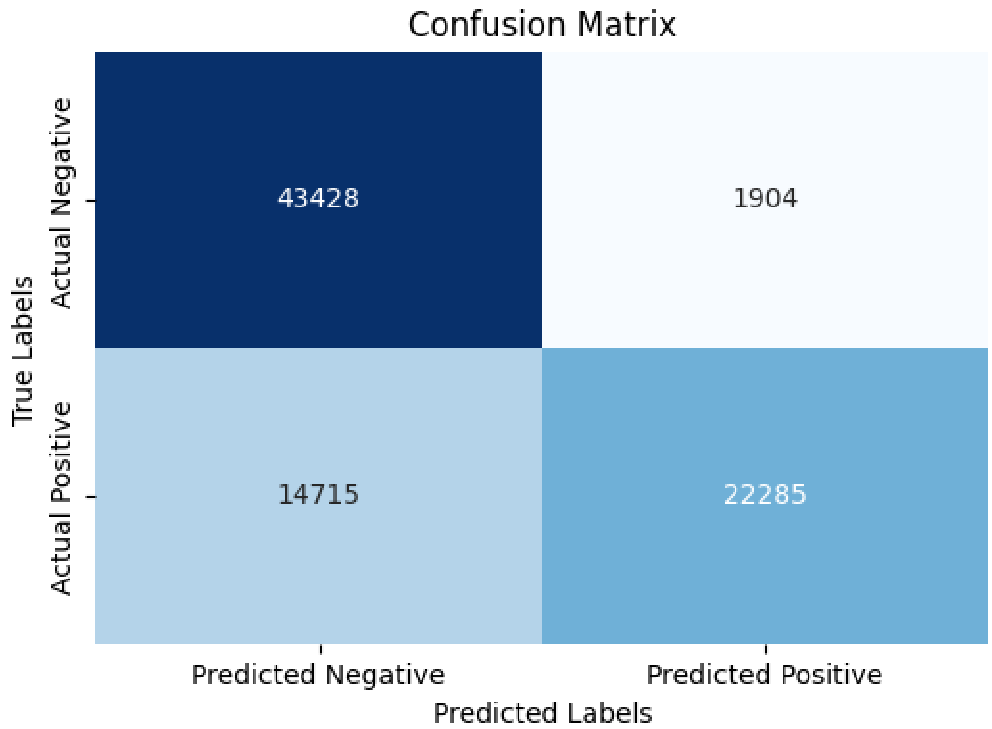
1.7.2 Model Selection

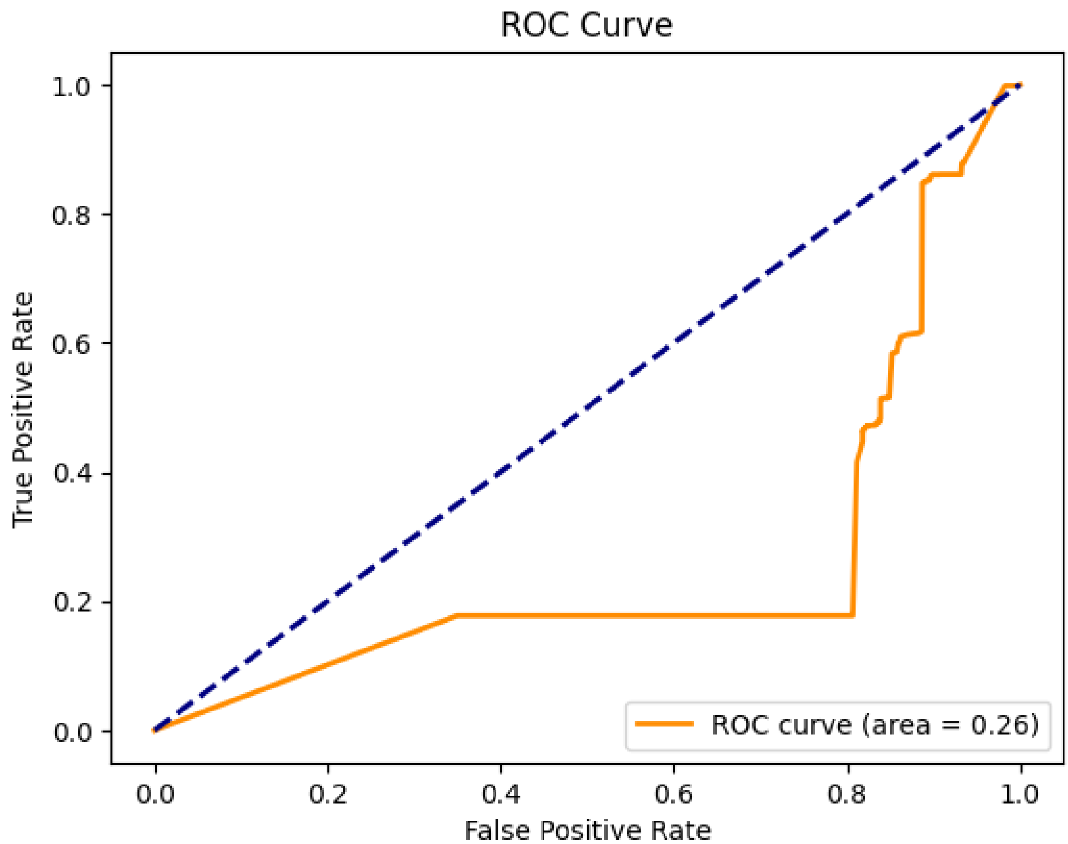
In this scenario, retaining the correlated features, rather than reducing the data to a 30-dimensional PCA space, resulted in my model generally outperforming the Scikit-learn implementation. For the Decision Tree algorithm, after training on the X_train and X_val datasets and selecting the optimal model for the X_test dataset, my model showed slightly better performance. Similarly, for the KNN algorithm, both models performed similarly, with mine achieving a slight edge. Moving forward, we will compare my models across additional metrics to identify the most effective one.

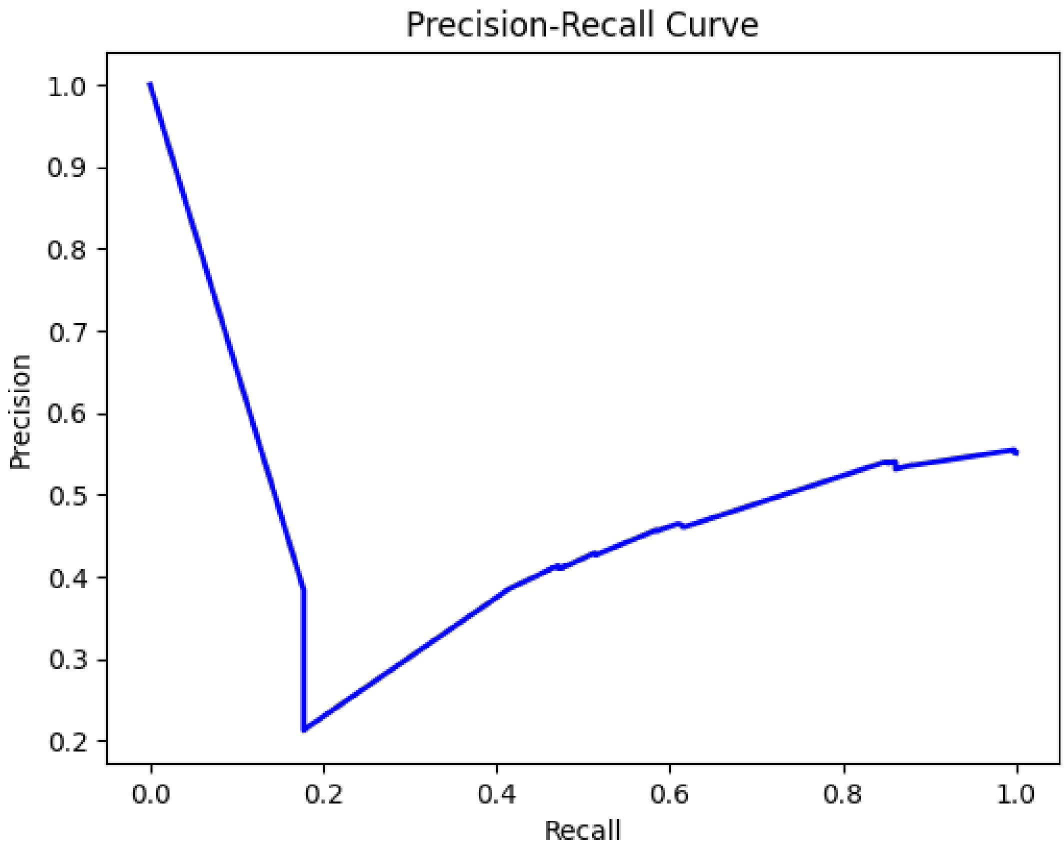
[69]:
```python
def show_metrics(model:BinaryClassifier):
  print(f"Accuracy: {model.accuracy*100:.5f} %")
  print(f'Precision: {model.precision*100:.5f} %')
  print(f'Recall: {model.recall*100:.5f} %')
  print(f'F-score: {model.f_score*100:.5f} %')
  print(f'')
  model.plot_confusion_matrix()
  print(f'')
  model.plot_roc_curve()
  print(f'')
  model.plot_precision_recall_curve()
  print(f'')
```

[71]:
```python
show_metrics(my_DTC)
```

```
Accuracy: 79.81465 %
Precision: 92.12865 %
Recall: 60.22973 %
F-score: 72.83989 %
```

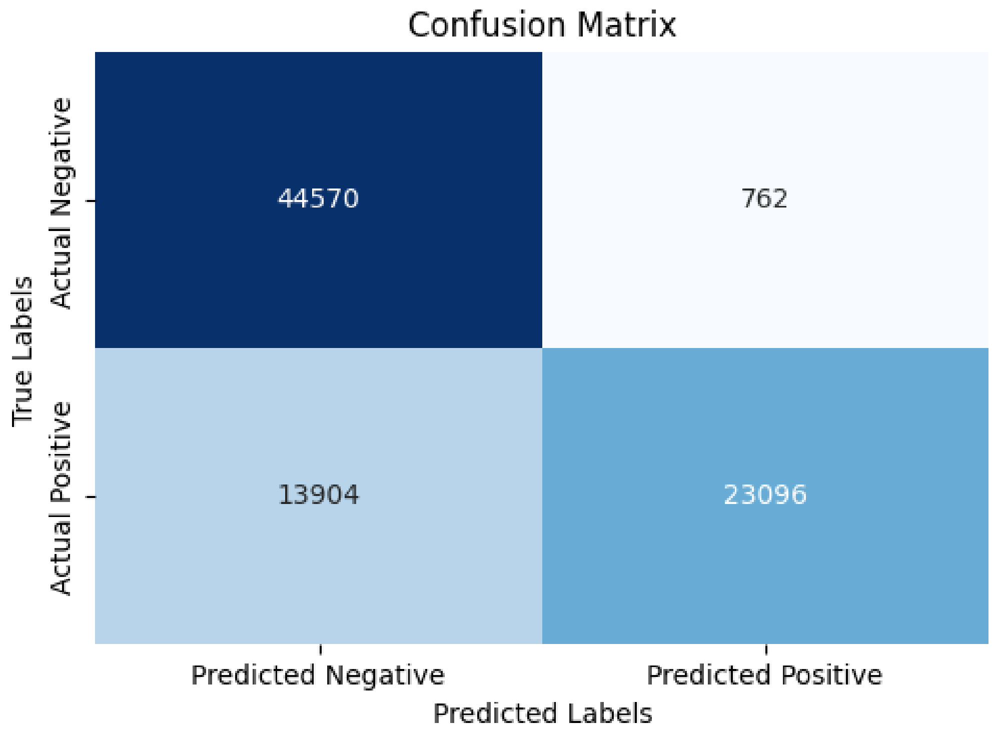

Confusion Matrix
True Labels
Actual Negative
Actual Positive
43428
1904
14715
22285
Predicted Negative
Predicted Positive
Predicted Labels

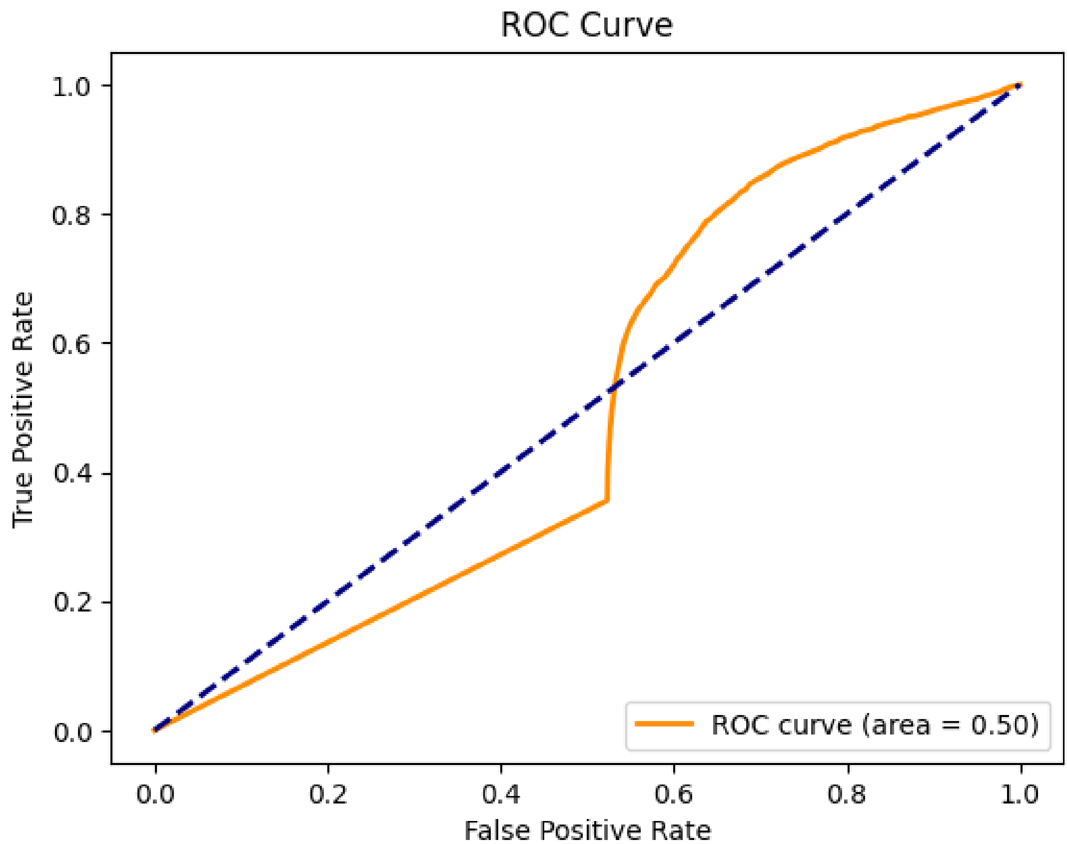

ROC Curve
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
ROC curve (area = 0.26)

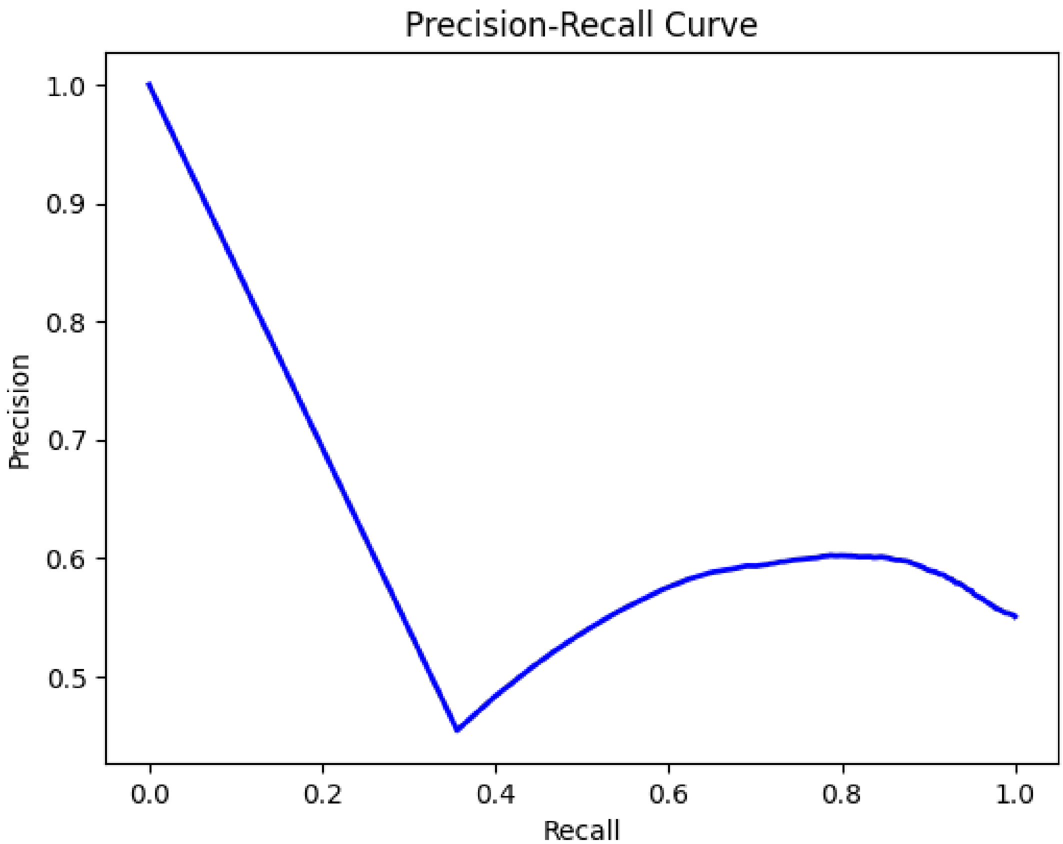


[75]:
```
show_metrics(my_KNN)
```

```
Accuracy: 82.18676 %
Precision: 96.80610 %
Recall: 62.42162 %
F-score: 75.90128 %
```


Confusion Matrix
Actual Negative
Actual Positive
True Labels
44570
762
13904
23096
Predicted Negative
Predicted Positive
Predicted Labels


ROC Curve
True Positive Rate
False Positive Rate
ROC curve (area = 0.50)
0.0
0.2
0.4
0.6
0.8
1.0

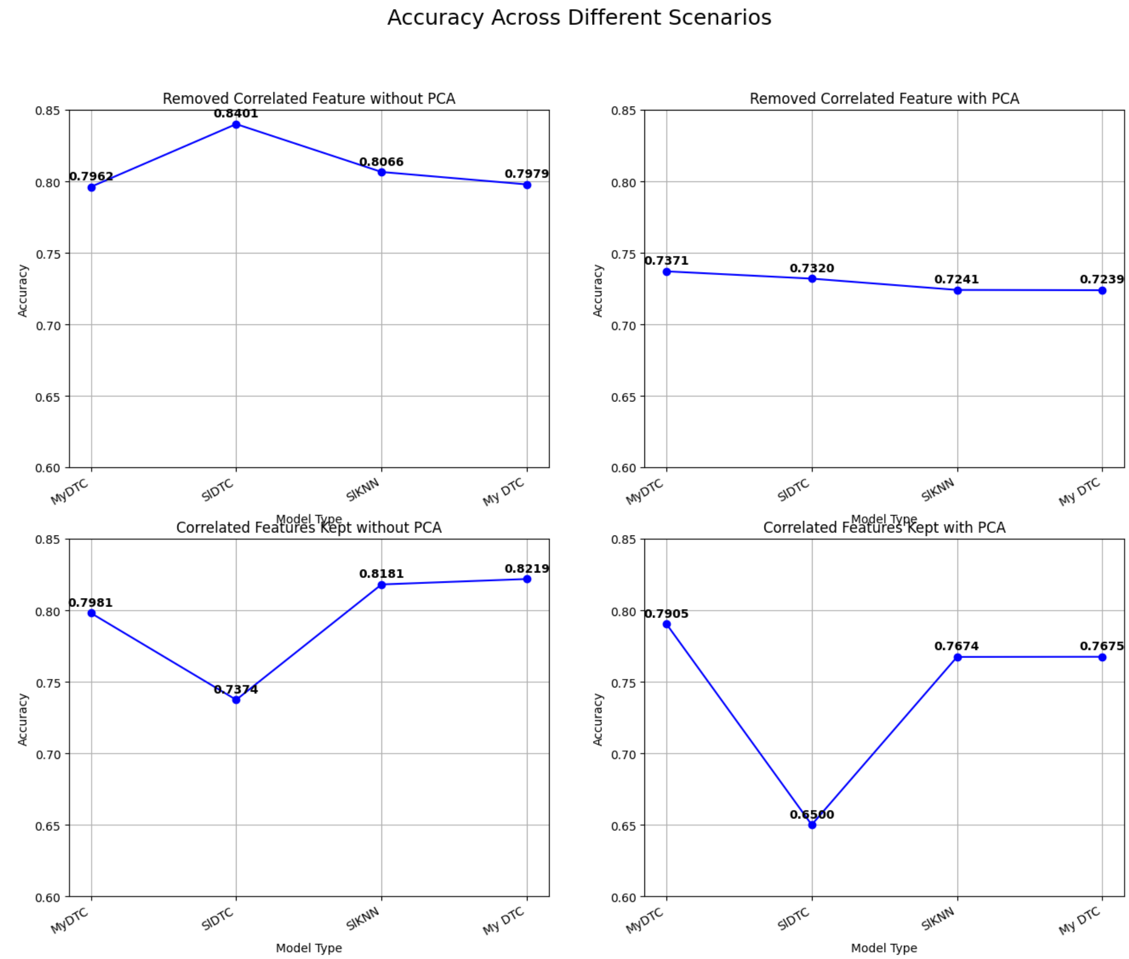


1.8 Conclusion

[88]:
```
# Data
scenarios = ['Removed w/o PCA', 'Removed w/ PCA', 'Kept w/o PCA', 'Kept w/ PCA']

# Accuracies for each scenario
removed_no_pca = [0.7962, 0.8401, 0.8066, 0.7979]
removed_pca = [0.7371, 0.7320, 0.7241, 0.7239]
kept_no_pca = [0.7981, 0.7374, 0.8181, 0.8219]
kept_pca = [0.7905, 0.6500, 0.7674, 0.7675]

# X-axis labels
x_labels = ['MyDTC', 'SlDTC', 'SlKNN', 'My DTC']

data = [removed_no_pca, removed_pca, kept_no_pca, kept_pca]

fig, axs = plt.subplots(2, 2, figsize=(16, 12))  # Increase figure size for␣
↪more space
```

```
fig.suptitle('Accuracy Across Different Scenarios', fontsize=18)

titles = ['Removed Correlated Feature without PCA',
          'Removed Correlated Feature with PCA',
          'Correlated Features Kept without PCA',
          'Correlated Features Kept with PCA']

for i, ax in enumerate(axs.flat):
    ax.plot(x_labels, data[i], marker='o', color='b')  # Use custom x_labels␣
 ↪for x-axis
    ax.set_title(titles[i])
    ax.set_xlabel('Model Type')
    ax.set_ylabel('Accuracy')
    ax.set_ylim([0.6, 0.85])  # Adjust the limits for y-axis for better␣
 ↪comparison
    ax.grid(True)

    ax.set_xticklabels(x_labels, rotation=30, ha='right')

    for j, v in enumerate(data[i]):
        ax.text(j, v + 0.005, f"{v:.4f}", ha='center', fontweight='bold')

plt.show()
```

```
<ipython-input-88-b3a3936fa8f9>:39: UserWarning: FixedFormatter should only be
used together with FixedLocator
  ax.set_xticklabels(x_labels, rotation=30, ha='right')
```



In the graphics above, we observe that when the highly correlated features were removed, the Scikit-learn model demonstrated better predictions, suggesting it performed faster and more efficiently with fewer features. However, overall, the mean accuracy across all scenarios was higher for my model compared to Scikit-learn's, with mine achieving 78% accuracy versus Scikit's 76%. While we could choose to remove the highly correlated features and retain the Scikit model for comparison, my model remains slightly better overall—and I prefer it, as it allowed for easier computation of additional metrics.

We ultimately concluded that the KNN model was the most effective due to its superior precision and F-score. For further details, please refer to the report!