Self-case study 1 title: Network intrusion detection tags

Table of contents

7. Load and spliting dataset

In [1]:

```
### importing libraries
import pandas as pd
import numpy as np
from datetime import datetime as dt
import gc
from sklearn.model_selection import RandomizedSearchCV

from warnings import filterwarnings
filterwarnings('ignore')
```

In [2]:

```
## setting random seed
SEED = 42
np.random.seed(SEED)

pd.options.display.precision=12
pd.options.display.max_columns=45

root_path = 'E:/case study 1/intrusion detection/UNSW-NB15 - CSV Files/'
```

In [3]:

```
### loading cleaned and preprocessed dataframe from disk
df = pd.read_csv(root_path+'final_preprocessed_NIDS_dataset.csv')
print(f"Shape of dataframe: {df.shape}")
```

```
Shape of dataframe: (2059418, 33)
```

In [5]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2059418 entries, 0 to 2059417
Data columns (total 33 columns):
 #   Column            Dtype
---  ------            -----
 0   proto             object
 1   state             object
 2   dur               float64
```

```
 3   sbytes             int64
 4   dbytes             int64
 5   sttl               int64
 6   dttl               int64
 7   service            object
 8   Sload              float64
 9   Dload              float64
 10  Spkts              int64
 11  stcpb              int64
 12  dtcpb              int64
 13  smeansz            int64
 14  dmeansz            int64
 15  trans_depth        int64
 16  res_bdy_len        int64
 17  Sjit               float64
 18  Djit               float64
 19  Stime              int64
 20  Sintpkt            float64
 21  Dintpkt            float64
 22  tcprtt             float64
 23  ct_state_ttl       int64
 24  ct_flw_http_mthd   float64
 25  is_ftp_login       float64
 26  ct_srv_src         int64
 27  ct_srv_dst         int64
 28  ct_dst_ltm         int64
 29  ct_src_ ltm        int64
 30  ct_src_dport_ltm   int64
 31  ct_dst_src_ltm     int64
 32  Label              int64
dtypes: float64(10), int64(20), object(3)
memory usage: 518.5+ MB
```

8. Feature engineering and scaling

In [6]:

```
### uniques list for categories in proto features
unique_proto = list(df['proto'].unique())
### uniques list for categories in state feature
unique_state = list(df['state'].unique())
### uniques list for categories in service feature
unique_service = list(df['service'].unique())

def numerical_proto(x):
    '''this function will return index of a category present in the list'''
    return unique_proto.index(x)
def numerical_state(x):
    '''this function will return index of a category present in the list'''
    return unique_state.index(x)
def numerical_service(x):
    '''this function will return index of a category present in the list'''
    return unique_service.index(x)

### converting categorical features and with the index of their respective category in un
ique list
df['proto'] = df['proto'].apply(numerical_proto)
### converting categorical features and with the index of their respective category in un
ique list
df['state'] = df['state'].apply(numerical_state)
### converting categorical features and with the index of their respective category in un
ique list
df['service'] = df['service'].apply(numerical_service)
```

In [7]:

```
### adding an extra features by adding two features
df["sttl+dttl"] = np.array(df["sttl"]) + np.array(df["dttl"])
### adding an extra features by adding two features
df["sbytes+dbytes"] = np.array(df["sbytes"]) + np.array(df["dbytes"])
```

```
### adding an extra features by adding two features
df["Sload+Dload"] = np.array(df["Sload"]) + np.array(df["Dload"])
### adding an extra features by adding two features
df["stcpb+dtcpb"] = np.array(df["stcpb"]) + np.array(df["dtcpb"])
### adding an extra features by adding two features
df["smeansz+dmeansz"] = np.array(df["smeansz"]) + np.array(df["dmeansz"])
### adding an extra features by adding two features
df["Sjit+Djit"] = np.array(df["Sjit"]) + np.array(df["Djit"])
### adding an extra features by adding two features
df["Sintpkt+Dintpkt"] = np.array(df["Sintpkt"]) + np.array(df["Dintpkt"])
### adding an extra features by adding two features
df["trans_depth+res_bdy_len"] = np.array(df["trans_depth"]) + np.array(df["res_bdy_len"]
)
### adding an extra features by adding two features
df["ct_state_ttl+ct_flw_http_mthd"] = np.array(df["ct_state_ttl"]) + np.array(df["ct_flw
_http_mthd"])
### adding an extra features by adding two features
df["ct_srv_dst+ct_dst_ltm"] = np.array(df["ct_srv_dst"]) + np.array(df["ct_dst_ltm"])
### adding an extra features by adding two features
df["ct_src_ ltm+ct_src_dport_ltm"] = np.array(df["ct_src_ ltm"]) + np.array(df["ct_src_d
port_ltm"])
```

In [8]:

```
df.head(5)
```

Out[8]:

	proto	state	dur	sbytes	dbytes	sttl	dttl	service	Sload	Dload	Spkts	stcpb	dtcpb
0	0	0	0.001055	132	164	31	29	0	500473.937500000000	621800.937500000000	2	0	0
1	0	0	0.036133	528	304	31	29	1	87676.085940000004	50480.171880000002	4	0	0
2	0	0	0.001119	146	178	31	29	0	521894.531299999973	636282.375000000000	2	0	0
3	0	0	0.001209	132	164	31	29	0	436724.562500000000	542597.187500000000	2	0	0
4	0	0	0.001169	146	178	31	29	0	499572.250000000000	609067.562500000000	2	0	0

In [9]:

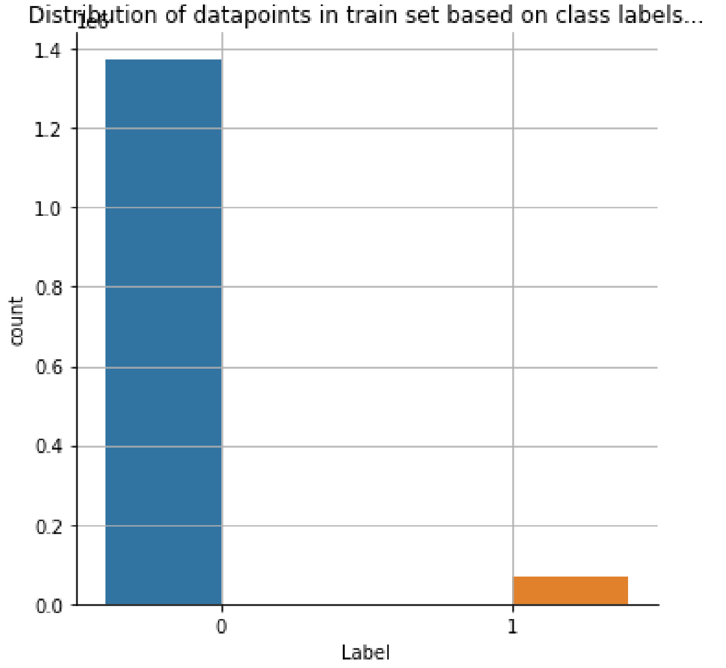
```
### spliting dataframe into train and test set
from sklearn.model_selection import train_test_split
train, test= train_test_split(df, test_size=0.3, stratify=df['Label'])
print(f"Shape of train: {train.shape}")
print(f"Shape of test: {test.shape}")
```

```
Shape of train: (1441592, 44)
Shape of test: (617826, 44)
```

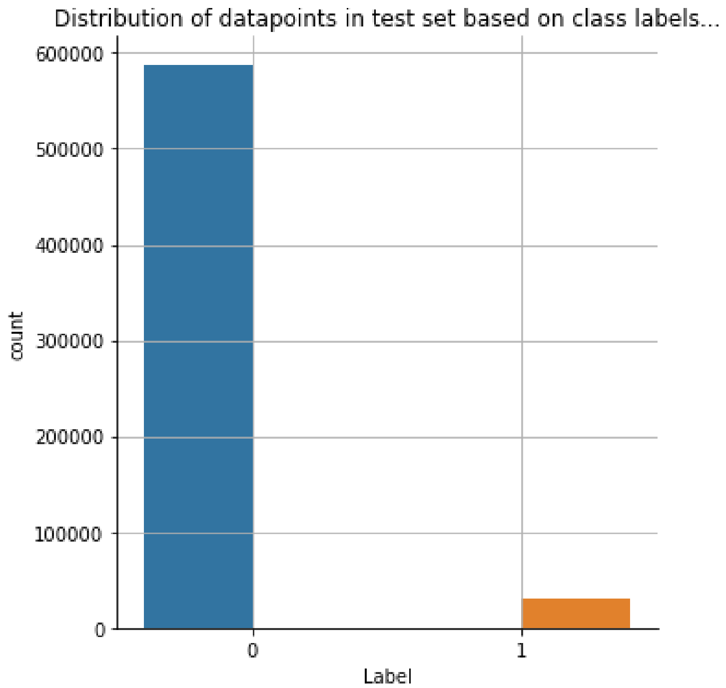
In [10]:

```
import matplotlib.pyplot as plt
import seaborn as sns
### plotting class distribution in train after splitting dataset
sns.catplot(data=train, x='Label', hue='Label', kind='count')
### adding title to the figure
plt.title('Distribution of datapoints in train set based on class labels...')
### adding grid to figure
plt.grid()
plt.show()

print('-'*70)
print('+'*70)
print('-'*70)

### plotting class distribution in test after splitting dataset
sns.catplot(data=test, x='Label', hue='Label', kind='count')
### adding title to the figure
```

```
plt.title('Distribution of datapoints in test set based on class labels...')
### adding grid to figure
plt.grid()
plt.show()
```




```
----------------------------------------------------------------------
++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
----------------------------------------------------------------------
```



In [11]:

```
### garbage collector
gc.collect()
```

Out[11]:

```
5703
```

- **Dataset has been distributed similar based on class label**

Let's distribute train and test data into X_train, X_test, y_train, y_test so that we can feed this into ML algorithms

In [12]:

```
### spliting dataframe into xtr and xte set to perform scaling on the features
X_tr = train.drop(['proto', 'state', 'service', 'Label'], axis=1)
X_te = test.drop(['proto', 'state', 'service', 'Label'], axis=1)

### spliting class lables from train and test set and reshapeing it to avoid any warning/
error
y_train = np.array(train['Label'])
y_test = np.array(test['Label'])
```

In [13]:

```
### scaling datasets using standardscaler
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
print(f"Scaling training data...")
train_scaled = scaler.fit_transform(X_tr)
print(f"Scaling test data...")
test_scaled = scaler.transform(X_te)
print(f"Completed!")
```

```
Scaling training data...
Scaling test data...
Completed!
```

In [14]:

```
### stacking data for train and set which will be input to the models
from scipy import sparse

X_train = sparse.csr_matrix(np.array(np.hstack((np.array(train[['proto', 'state', 'servi
ce']]), train_scaled)), dtype=np.float32))
X_test = sparse.csr_matrix(np.array(np.hstack((np.array(test[['proto', 'state', 'service
']]), test_scaled)), dtype=np.float32))
```

In [15]:

```
print(f"Shape of train dataset after stacking: {X_train.shape} and y_train: {y_train.shap
e}")
print(f"Shape of test dataset after stacking: {X_test.shape} and y_test: {y_test.shape}")
```

```
Shape of train dataset after stacking: (1441592, 43) and y_train: (1441592,)
Shape of test dataset after stacking: (617826, 43) and y_test: (617826,)
```

In [16]:

```
### Releasing memory by deleting variable and dataframes
### that will be no longer in use
del df
del train
del test
del train_scaled
del test_scaled
gc.collect()
```

Out[16]:

```
30
```

9. *Model training and hyperparameter tuning*

- ***Hyperparameter tuning on Naive_bayes as Base model and training with best hyperparameters***
- ***Hyperparameter tuning on Decision tree model and training with best hyperparameters***
- ***Hyperparameter tuning on Logistic regression model and training with best hyperparameters***
- ***Hyperparameter tuning on SVM model and training with best hyperparameters***
- ***Hyperparameter tuning on XGBoost model and training with best hyperparameters***
- ***Hyperparameter tuning on Random forest model and training with best hyperparameters***

In [17]:

```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import f1_score, precision_score,recall_score
def calculate_metrices(y_true, y_pred):
    '''this function will return auc and f1 score'''
    ### calculat auc
    auc = roc_auc_score(y_true, y_pred)
    ### calculate f1-score
    f1score = f1_score(y_true, y_pred)
    gc.collect()
    return auc, f1score
```

In [18]:

```
from sklearn.metrics import roc_curve

def plot_roc_auc_curve(y_train_true, y_train_pred, y_test_true, y_test_pred):
    '''this function will plot roc auc curve on train and test data'''
    ### geting fpr and tpr for train data
    fpr, tpr, _ = roc_curve(y_train_true, y_train_pred)
    ### ploting roc curve
    plt.plot(fpr, tpr, label='train')
    ### getting fpr and tpr for test data
    fpr, tpr, _ = roc_curve(y_test_true, y_test_pred)
    ### plotting roc curve
    plt.plot(fpr, tpr, label='test')
    ### adding axis-labels to the plot
    plt.xlabel("fpr")
    ### adding axis-labels to the plot
    plt.ylabel("tpr")
    ### adding title to the plot
    plt.title("ROC AUC curve")
    ### adding legend
    plt.legend()
    plt.grid()
    plt.show()
    gc.collect()
```

In [19]:

```
from sklearn.metrics import confusion_matrix

def plot_confusion_matrix(y_true, y_pred, title=''):
    '''this function will plot confusion matrix'''
    ### getting confusion matrix
    conf_mat = confusion_matrix(y_true, y_pred)
    ### ploting conf matrix using seaborn heatmap plot
    sns.heatmap(conf_mat, annot=True, fmt='d')
    ### adding title
    plt.title(f'Confusion matrix on {title}')
    ### adding axis-labels to the plot
    plt.xlabel("prdicted")
    ### adding axis-labels to the plot
    plt.ylabel("actual")
    plt.show()
    gc.collect()
```

In [20]:

```
def random_search_cv(estimator, param_distributions, algo_name='', X_train=X_train, y_tr
ain=y_train):
    """this function will return best score and best params after applying randomized sea
rch cv on train dataset"""
    st = dt.now()
    ### initializing randomized search cv with arguments
    clf = RandomizedSearchCV(estimator, param_distributions=param_distributions, scoring=
'f1', cv=5, n_jobs=-1)
    print(f"tunning hyperparameter on {algo_name} model...")
    ### fitting data to the randomizedsearchcv estimator
    clf.fit(X_train, y_train)
    print(f"tunning completed!")
    print(f"\ntime taken in hyperparameter tuning: {dt.now()-st}")
```

```
    gc.collect()
    ### returns best score and best params
    return clf.best_score_, clf.best_params_
```

In [21]:

```
def train_and_evaluate(estimator, X_train=X_train, y_train=y_train, X_test=X_test, y_tes
t=y_test):
    '''this function will train and evaluate dataset'''
    st = dt.now()
    ### fitting data to the estimator
    estimator.fit(X_train, y_train)
    print(f"training completed! and time taken: {dt.now()-st}")
    ### finding predictions on train data set
    y_tr_preds = estimator.predict(X_train )
    ### finding auc and f1score for train dataset
    tr_auc, tr_f1score = calculate_metrices(y_train, y_tr_preds)
    print(f"\nOn train data, AUC: {tr_auc}, f1-score: {tr_f1score}")
    ### finding predictions on test dataset
    y_te_preds = estimator.predict(X_test )
    ### finding auc and f1score on test dataset
    te_auc, te_f1score = calculate_metrices(y_test, y_te_preds)
    print(f"On test data, AUC: {te_auc}, f1-score: {te_f1score}")
    ### plotting confusion matrix on train and test dataset
    plot_confusion_matrix(y_train, y_tr_preds, title='train data')
    plot_confusion_matrix(y_test, y_te_preds, title='test data')
    ### plotting roc auc curve on train and test dataset
    plot_roc_auc_curve(y_train, y_tr_preds, y_test, y_te_preds)
    gc.collect()
    ### returns estimator, auc and f1score for train and test dataset
    return estimator, tr_auc, tr_f1score, te_auc, te_f1score
```

- ***Hyperparameter tuning on Naive_bayes as Base model***

In [22]:

```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.naive_bayes import GaussianNB
### initialising parameters
param_distributions = {'var_smoothing':[1e-06, 1e-05, 1e-04, 1e-03, 1e-02, 1e-01,1, 1e2]
}
### hyperparameter tunning on naive bayes model
best_score, best_params = random_search_cv(GaussianNB(), X_train=X_train.toarray(),
                                           param_distributions=param_distributions,
                                           algo_name='Naive bayes as base')
```

```
tunning hyperparameter on Naive bayes as base model...
tunning completed!

time taken in hyperparameter tuning: 0:00:30.816331
```

In [23]:

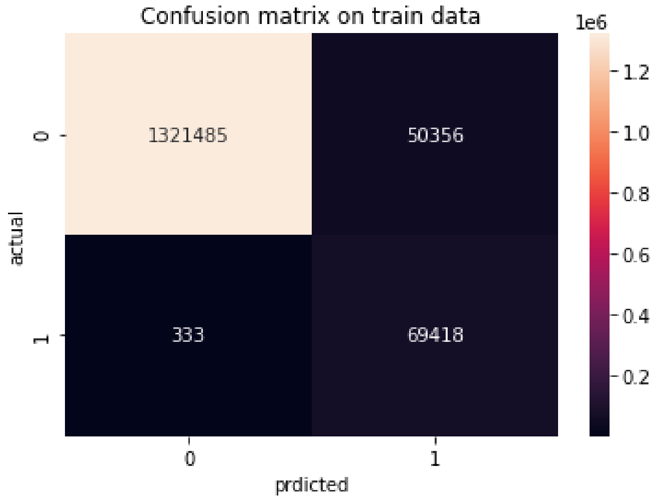
```
print(f"Best f1-score achieved by RandomizedSearchCV model: {best_score}")
var_smoothing = best_params['var_smoothing']
print(f"Best params are: {var_smoothing}")
```

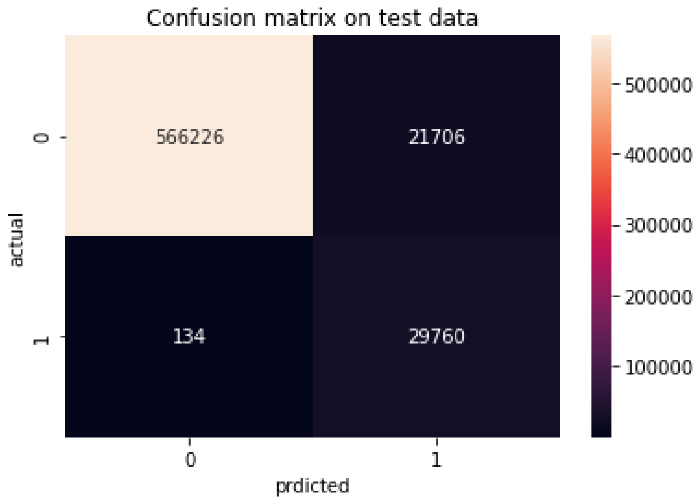
```
Best f1-score achieved by RandomizedSearchCV model: 0.7328908543994821
Best params are: 1e-06
```

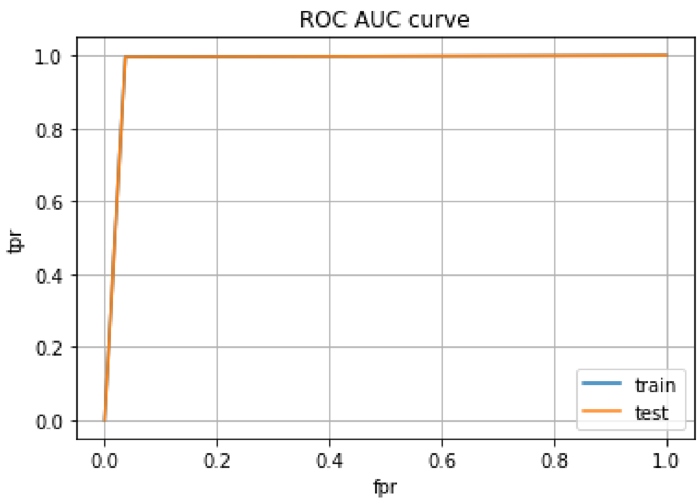
In [24]:

```
### training and evaluating naive bayes model on train and test dataset
base_model, nb_tr_auc, nb_tr_f1score, nb_te_auc, nb_te_f1score = train_and_evaluate(
                                                                    GaussianNB(var_smoothi
ng=var_smoothing),
                                                                    X_train=X_train.toarra
y(),
                                                                    X_test=X_test.toarray(
))
```

```
training completed! and time taken: 0:00:00.602158

On train data, AUC: 0.9792594985299837, f1-score: 0.732547157367102
On test data, AUC: 0.9792991297958374, f1-score: 0.7315634218289085
```







Observation

From the above scores and plots I found that our base model is giving very good auc, but but the f1 score is at 73% for both train and test dataset, it also a generalised model because there is very small difference in the scores

- ***Hyperparameter tuning on Decision tree model***

In [30]:

```
from sklearn.tree import DecisionTreeClassifier
```

```python
### initialising parameters
param_distributions = {
                        'max_depth':[3,5,7,9],
                        'criterion':['gini', 'entropy'],
                        'min_samples_split':[2,3,4,5,6],
                        'class_weight':['uniform', 'balanced']
                        }


### hyperparameter tunning on decision tree classifier model
best_score, best_params = random_search_cv(DecisionTreeClassifier(),
                                           param_distributions=param_distributions,
                                           algo_name='Decision tree')
```

```
tunning hyperparameter on Decision tree model...
tunning completed!

time taken in hyperparameter tuning: 0:04:10.001083
```

In [31]:

```python
print(f"Best f1-score achieved by RandomizedSearchCV model: {best_score}")
print(f"Best params are: {best_params}")
```

```
Best f1-score achieved by RandomizedSearchCV model: 0.8728672561267435
Best params are: {'min_samples_split': 5, 'max_depth': 9, 'criterion': 'entropy', 'class_
weight': 'balanced'}
```

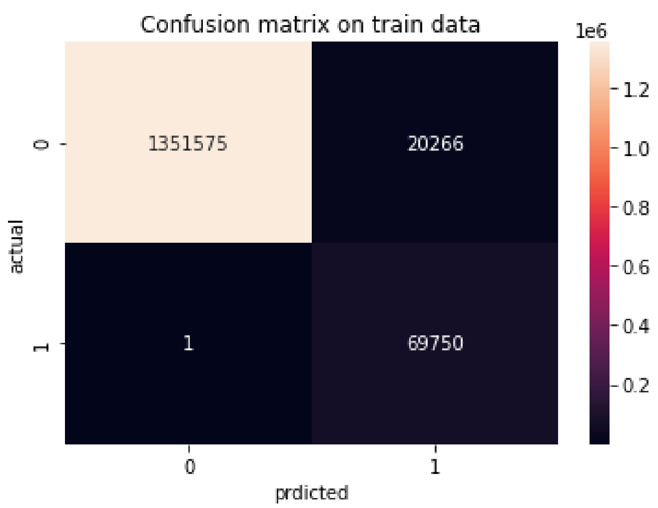
In [32]:

```python
### initialising best params
max_depth = best_params['max_depth']
criterion = best_params['criterion']
min_samples_split = best_params['min_samples_split']
class_weight = best_params['class_weight']
```

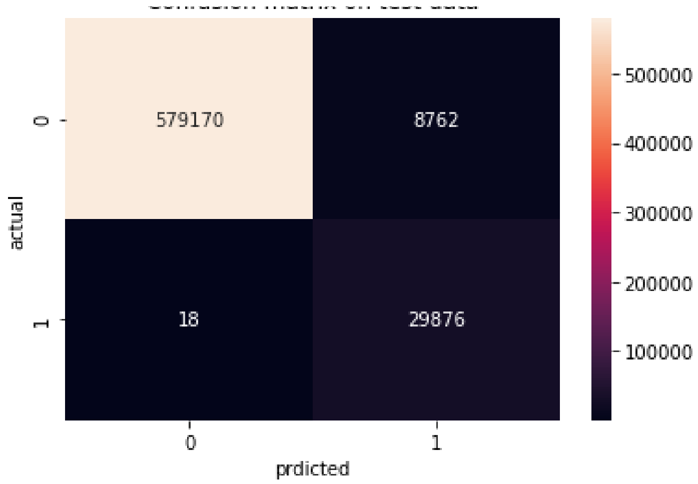
In [33]:

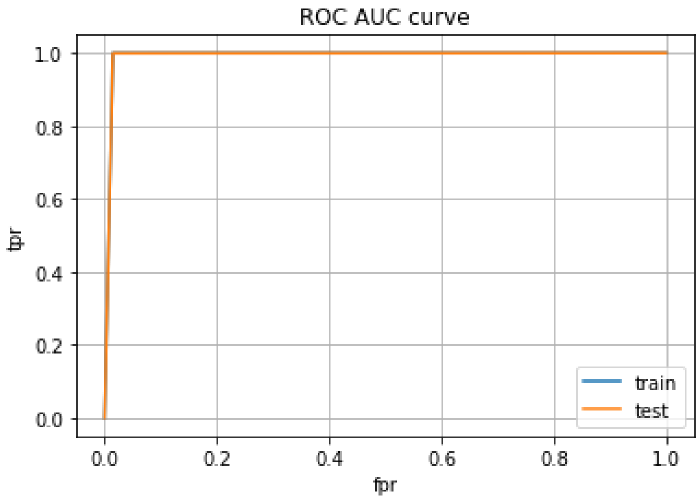
```python
### initializing estimator on best params
dec_tree_model = DecisionTreeClassifier(
                                max_depth=max_depth,
                                criterion=criterion,
                                min_samples_split=min_samples_split,
                                class_weight=class_weight,
                                )
### training and evaluating decision tree classifier model on train and test dataset
dec_tree_model, dec_tree_tr_auc, dec_tree_tr_f1score, dec_tree_te_auc, dec_tree_te_f1scor
e = train_and_evaluate(dec_tree_model)
```

```
training completed! and time taken: 0:00:26.648015

On train data, AUC: 0.9926064071239479, f1-score: 0.8731465196191954
On test data, AUC: 0.9922473942263232, f1-score: 0.8718846670168681
```



Confusion matrix on test data





In [34]:

```
gc.collect()
```

Out[34]:

```
15
```

Observation

From the above scores and plots we I found that this model is performing good compared to base model and it generalised model because the difference in the train and test f1-scores is nearly 0.5%.

It is quite good in predicting abnormal class but there is a large number of normal class predicted as abnormal/malicious

- ***Hyperparameter tuning on Logistic regression model***

In [35]:

```
from sklearn.linear_model import SGDClassifier
### initialising parameters
param_distributions = {
                        'penalty':['l1', 'l2', 'elasticnet'],
                        'alpha':[0.0001, 0.001, 0.01, 0.1, 1, 10],
                        'max_iter':[500, 1000, 2000, 3000],
                        'epsilon':[0.1],
                        'learning_rate':['optimal', 'constant', 'invscaling', 'adaptive'
],
                        'eta0':[0.001, 0.01, 1],
                        'class_weight':[None, 'balanced']
                        }
### hyperparameter tunning on logistic regression model
best_score, best_params = random_search_cv(SGDClassifier(loss='log'),
                                           param_distributions=param_distributions,
```

```
                                        algo_name='logistic regression')
```

```
tunning hyperparameter on logistic regression model...
tunning completed!

time taken in hyperparameter tuning: 0:02:36.200115
```

In [36]:

```python
print(f"Best f1-score achieved by RandomizedSearchCV model: {best_score}")
print(f"Best params are: {best_params}")
```

```
Best f1-score achieved by RandomizedSearchCV model: 0.8475722265108994
Best params are: {'penalty': 'l2', 'max_iter': 500, 'learning_rate': 'adaptive', 'eta0':
0.01, 'epsilon': 0.1, 'class_weight': 'balanced', 'alpha': 0.0001}
```

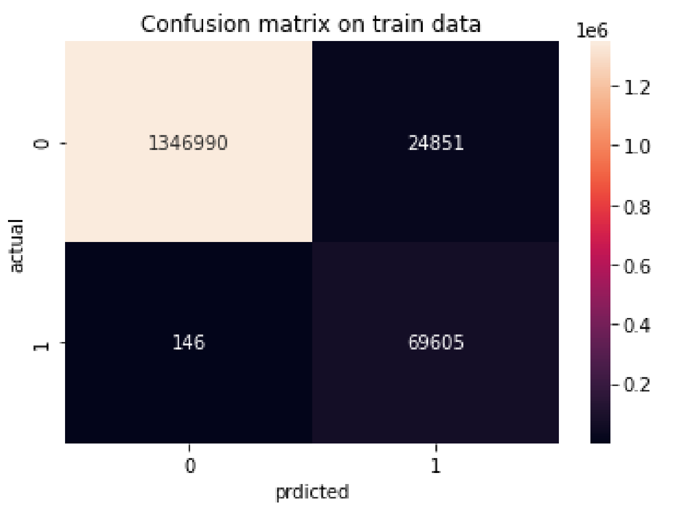
In [37]:

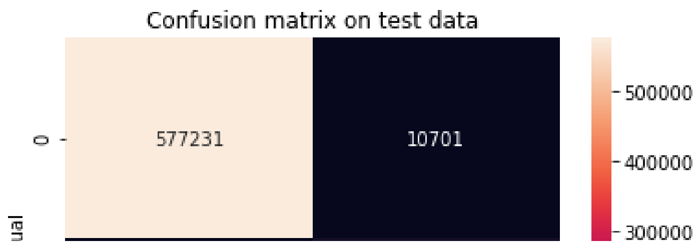
```python
### initialising best params
penalty = best_params['penalty']
max_iter = best_params['max_iter']
learning_rate = best_params['learning_rate']
eta0 = best_params['eta0']
epsilon = best_params['epsilon']
class_weight = best_params['class_weight']
alpha = best_params['alpha']
```

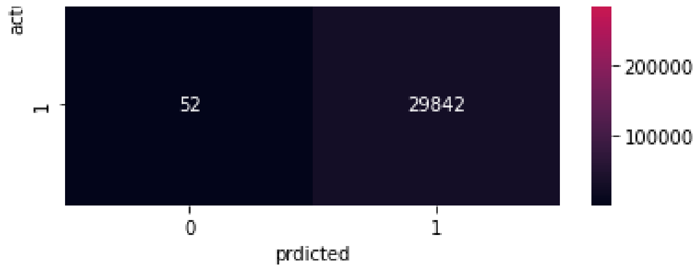
In [38]:

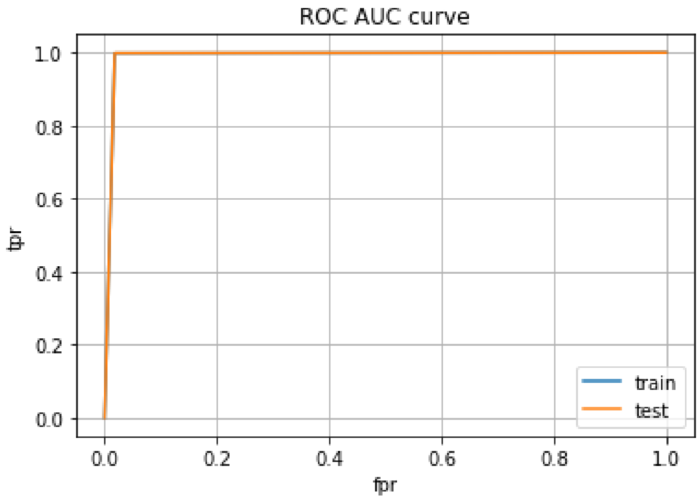
```python
### initialising estimators on best params
lr_model = SGDClassifier(loss='log',
                    penalty=penalty,
                    max_iter=max_iter,
                    learning_rate=learning_rate,
                    eta0=eta0,
                    epsilon=epsilon,
                    class_weight=class_weight,
                    alpha=alpha)
### training and evaluating logistic regression model on train and test dataset
lr_model, lr_tr_auc, lr_tr_f1score, lr_te_auc, lr_te_f1score = train_and_evaluate(lr_mode
l)
```

```
training completed! and time taken: 0:00:30.413081

On train data, AUC: 0.9898958834714043, f1-score: 0.8477714104758018
On test data, AUC: 0.9900297180133149, f1-score: 0.8473387566193904
```









In [39]:

```
gc.collect()
```

Out[39]:

```
15
```

Observation

From the above scores and plots we I found that this model is performing good compared to base model and it generalised model because the difference in the train and test f1-scores is nearly 0.5%.

it doesn't perform vell compared to Decision tree, but yes it is quite good in predicting abnormal class but there is a large number of normal class predicted as abnormal/malicious

- ## ***Hyperparameter tuning on SVM model***

In [40]:

```
### initialising parameters
param_distributions = {
                        'penalty':['l1', 'l2', 'elasticnet'],
                        'alpha':[0.0001, 0.001, 0.01, 0.1, 1, 10],
                        'max_iter':[500, 1000, 2000, 3000],
                        'epsilon':[0.1],
                        'learning_rate':['optimal', 'constant', 'invscaling', 'adaptive'
],
                        'eta0':[0.001, 0.01, 1],
                        'class_weight':[None, 'balanced']
                        }
### hyperparameter tunning on svm model
best_score, best_params = random_search_cv(SGDClassifier(loss='hinge'),
                                           param_distributions=param_distributions,
                                           algo_name='SVM')
```

```
tunning hyperparameter on SVM model...
tunning completed!

time taken in hyperparameter tuning: 0:02:13.112533
```

In [41]:

```
print(f"Best f1-score achieved by RandomizedSearchCV for SVM model: {best_score}")
print(f"Best params are: {best_params}")
```

```
Best f1-score achieved by RandomizedSearchCV for SVM model: 0.8376444411567329
Best params are: {'penalty': 'l2', 'max_iter': 3000, 'learning_rate': 'invscaling', 'eta0
': 1, 'epsilon': 0.1, 'class_weight': None, 'alpha': 0.01}
```

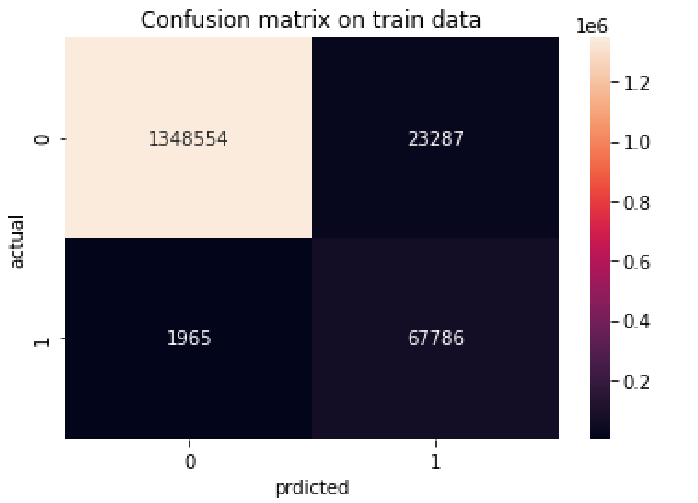
In [42]:

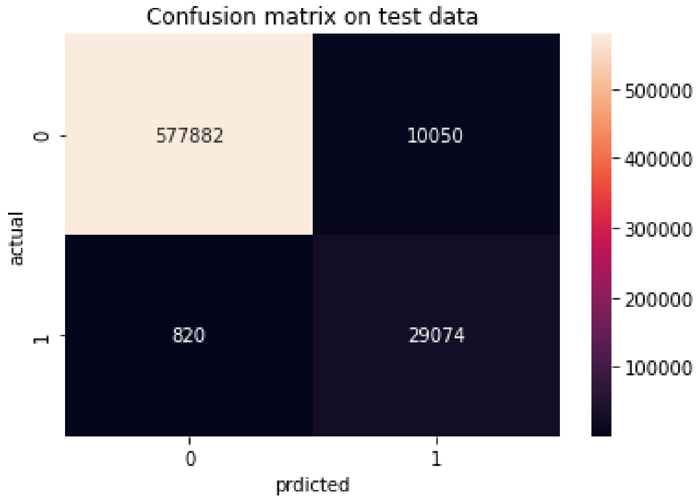
```
### initialising best params
penalty = best_params['penalty']
max_iter = best_params['max_iter']
learning_rate = best_params['learning_rate']
eta0 = best_params['eta0']
epsilon = best_params['epsilon']
class_weight = best_params['class_weight']
alpha = best_params['alpha']
```

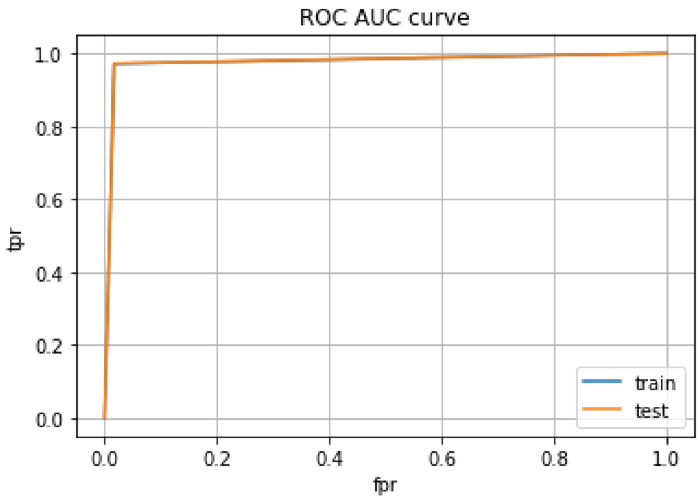
In [43]:

```
### initialising estimators on best params
svm_model = SGDClassifier(loss='hinge',
                    penalty=penalty,
                    max_iter=max_iter,
                    learning_rate=learning_rate,
                    eta0=eta0,
                    epsilon=epsilon,
                    class_weight=class_weight,
                    alpha=alpha)
### training and evaluating svm model on train and test dataset
svm_model, svm_tr_auc, svm_tr_f1score, svm_te_auc, svm_te_f1score = train_and_evaluate(sv
m_model)
```

```
training completed! and time taken: 0:00:04.913125

On train data, AUC: 0.9774266807972193, f1-score: 0.8429836342834404
On test data, AUC: 0.9777379664335677, f1-score: 0.8425048538062534
```







In [44]:

```
gc.collect()
```

Out[44]:

```
15
```

Observation

From the above scores and plots we I found that this model is performing good compared to base model and it generalised model because the difference in the train and test f1-scores is nearly 0.5%.

it doesn't perform well and it is not as good as in prediction compared to logistic regression because the misclassified datapoints are higher compared to logisitic regression.

- ***Hyperparameter tuning on XGBoost model***

In [45]:

```
from xgboost import XGBClassifier
### initialising parameters
param_distributions = {
                        'n_estimators':[50, 100, 150, 200, 250, 300],
                        'max_depth':[3,5,7,9,11],
                        'learning_rate':[1e-03, 1e-02, 1e-01, 1, 1e01, 1e02],
                        'booster':['gbtree', 'gblinear', 'dart'],
                        'tree_method':['exact', 'approx', 'hist', 'gpu_hist'],
                        'sampling_method':['uniform', 'gradient_based'],

                        }
### hyperparameter tunning on xgboost classifier model
best_score, best_params = random_search_cv(XGBClassifier(),
                                           param_distributions=param_distributions,
                                           algo_name='XGBoost')
```

```
tunning hyperparameter on XGBoost model...
tunning completed!

time taken in hyperparameter tuning: 4:26:11.475976
```

In [46]:

```
print(f"Best f1-score achieved by RandomizedSearchCV for xgboost model: {best_score}")
print(f"Best params are: {best_params}")
```

```
Best f1-score achieved by RandomizedSearchCV for xgboost model: 0.9451469962996683
Best params are: {'tree_method': 'approx', 'sampling_method': 'uniform', 'n_estimators':
300, 'max_depth': 9, 'learning_rate': 1, 'booster': 'dart'}
```

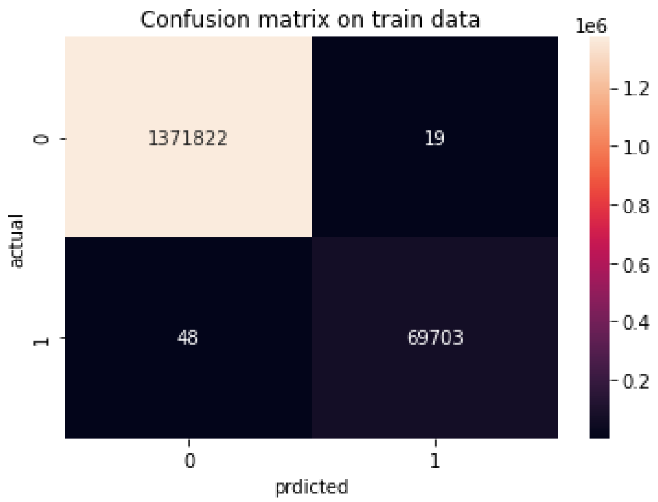
In [47]:

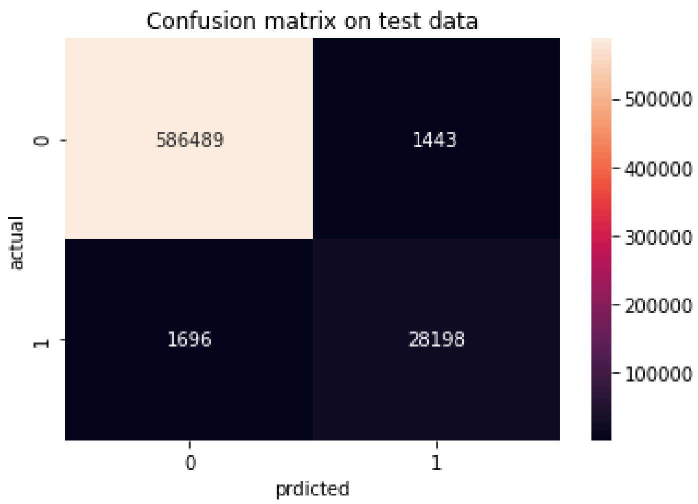
```
### initialising best params
tree_method = best_params['tree_method']
sampling_method = best_params['sampling_method']
n_estimators = best_params['n_estimators']
learning_rate = best_params['learning_rate']
max_depth = best_params['max_depth']
booster = best_params['booster']
```

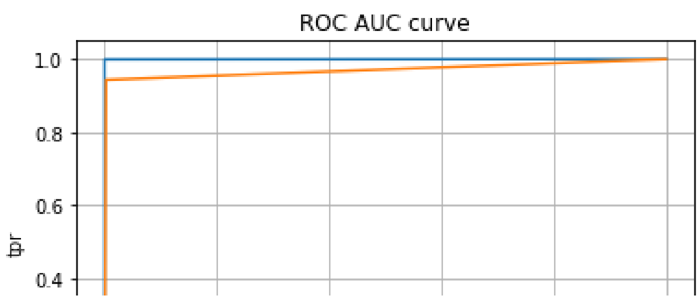
In [48]:

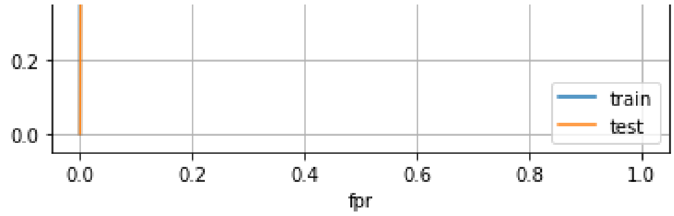
```
### initialising estimators on best params
xgb_model = XGBClassifier(n_estimators = n_estimators,
                          max_depth = max_depth,
                          learning_rate = learning_rate,
                          booster = booster,
                          tree_method = tree_method,
                          sampling_method = sampling_method,
                          n_jobs = -1
                          )
### training and evaluating xgboost classifier model on train and test dataset
xgb_model, xgb_tr_auc, xgb_tr_f1score, xgb_te_auc, xgb_te_f1score = train_and_evaluate(xg
b_model)
```

```
training completed! and time taken: 0:33:48.633681

On train data, AUC: 0.9996489939107732, f1-score: 0.9995196202849297
On test data, AUC: 0.9704059208974176, f1-score: 0.9472747123540775
```









Observation

From the above scores and plots we I found that this model is performing very good compared to base, decision tree, logistic regression and svm model, and it not as generalised compared to the previous ones

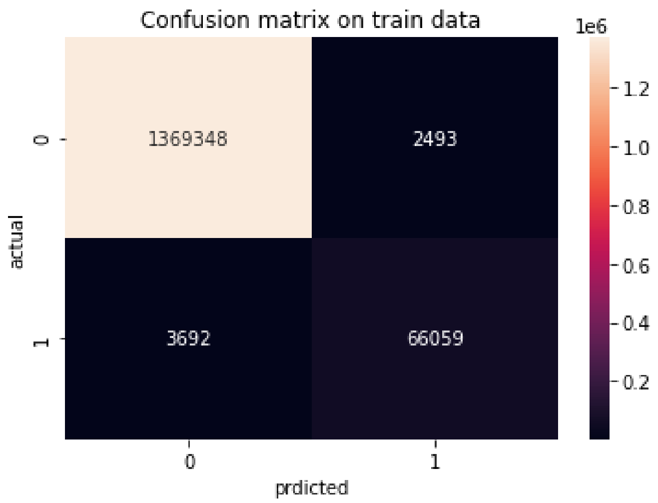
because the difference in the train and test f1-scores is nearly 5%. And we can see that the misclassified points in test data is greater than train dataset

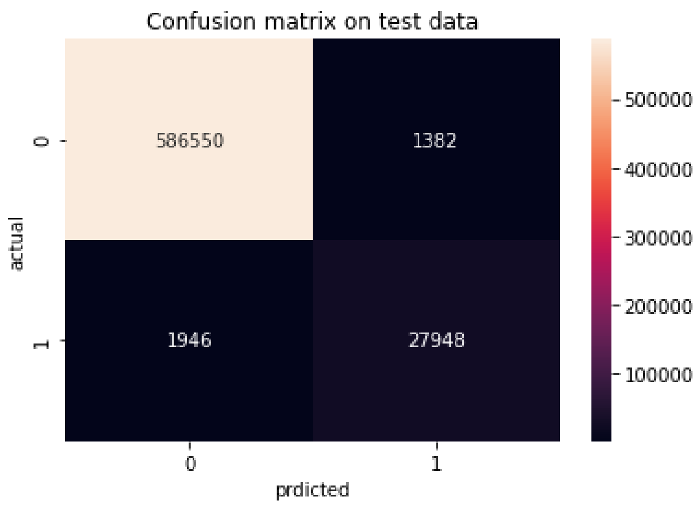
- ***XGBoost classifier with default parameters***

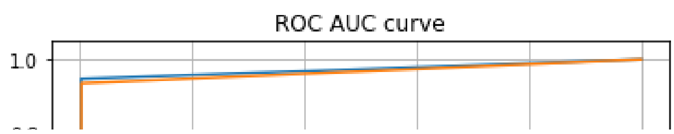
In [49]:

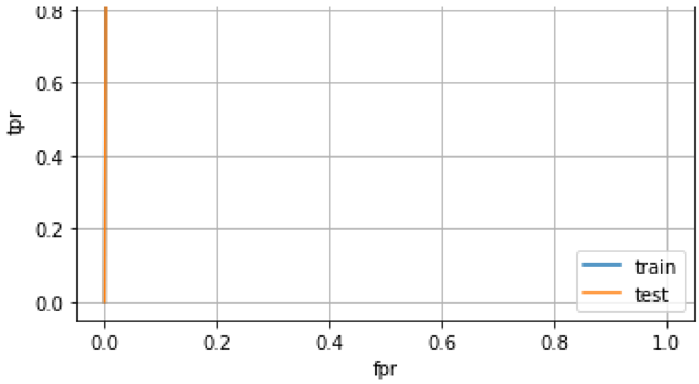
```
### training and evaluating xgboost classifier model with default parameters on train and test dataset
def_xgb_model = XGBClassifier(n_jobs=-1)
def_xgb_model, def_xgb_tr_auc, def_xgb_tr_f1score, def_xgb_te_auc, def_xgb_te_f1score = train_and_evaluate(def_xgb_model)
```

```
training completed! and time taken: 0:03:51.762440

On train data, AUC: 0.9726257966163565, f1-score: 0.9552793504117771
On test data, AUC: 0.966276356553211, f1-score: 0.9438065649061191
```









In [50]:

```
gc.collect()
```

Out[50]:

```
15
```

Observation

From the above scores and plots we I found that this model with default parameters is performing very good, and it generalised because the difference in the train and test f1-scores is nearly 1% which is quite low. And having auc and f1-score better than previous algorithms.

- ***Hyperparameter tuning on Random Forest model***

In [51]:

```
from sklearn.ensemble import RandomForestClassifier
### initialising parameters
param_distributions = {
                            'n_estimators': [70, 85, 100, 130, 150, 200],
                            'criterion': ['gini', 'entropy'],
                            'max_depth':[2,4,6,8,10],
                            'min_samples_split': [1,2,3,4,5,6],
                            'min_samples_leaf':[1,2,3,4,5],
                            'max_features': ['auto', 'sqrt', 'log2'],
                            'class_weight': [None, 'balanced', 'balanced_subsample'],
                            'bootstrap':[True, False],
                            'ccp_alpha': [0.005, 0.01, 0.2, 0.3,0.5],
                            'max_samples': [0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0
]
                            }
### hyperparameter tunning on random forest classifier model
best_score, best_params = random_search_cv(RandomForestClassifier(),
                                           param_distributions=param_distributions,
                                           algo_name='Random forest classifier')
```

```
tunning hyperparameter on Random forest classifier model...
tunning completed!

time taken in hyperparameter tuning: 0:43:36.822935
```

In [52]:

```
print(f"Best f1-score achieved by RandomizedSearchCV random forest model: {best_score}")
print(f"Best params are: {best_params}")
```

```
Best f1-score achieved by RandomizedSearchCV random forest model: 0.8322643125623266
Best params are: {'n_estimators': 70, 'min_samples_split': 3, 'min_samples_leaf': 4, 'max
_samples': 0.5, 'max_features': 'auto', 'max_depth': 10, 'criterion': 'gini', 'class_weig
ht': 'balanced', 'ccp_alpha': 0.01, 'bootstrap': False}
```

In [53]:

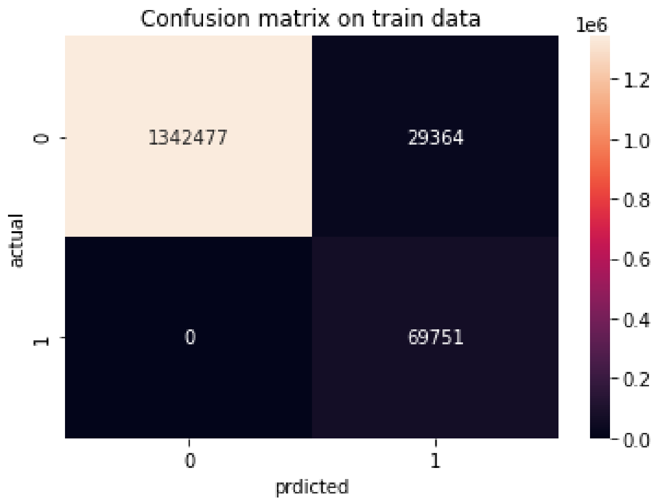
```
### initialising best params
```

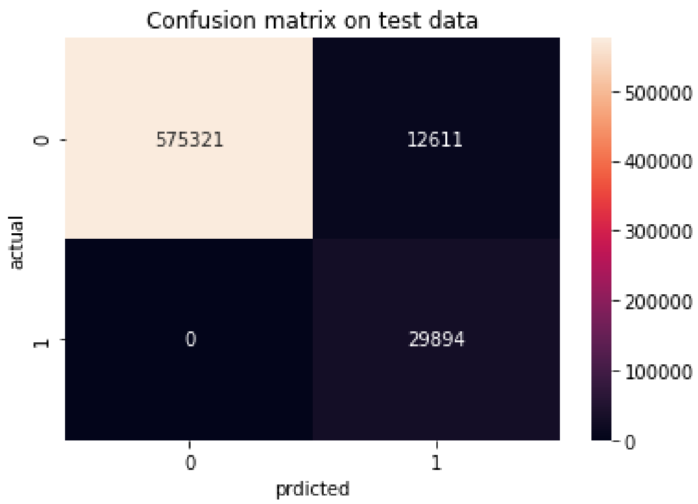
```
n_estimators = best_params['n_estimators']
criterion = best_params['criterion']
max_depth = best_params['max_depth']
min_samples_split = best_params['min_samples_split']
min_samples_leaf = best_params['min_samples_leaf']
max_features = best_params['max_features']
class_weight = best_params['class_weight']
bootstrap = best_params['bootstrap']
ccp_alpha = best_params['ccp_alpha']
max_samples = best_params['max_samples']
```

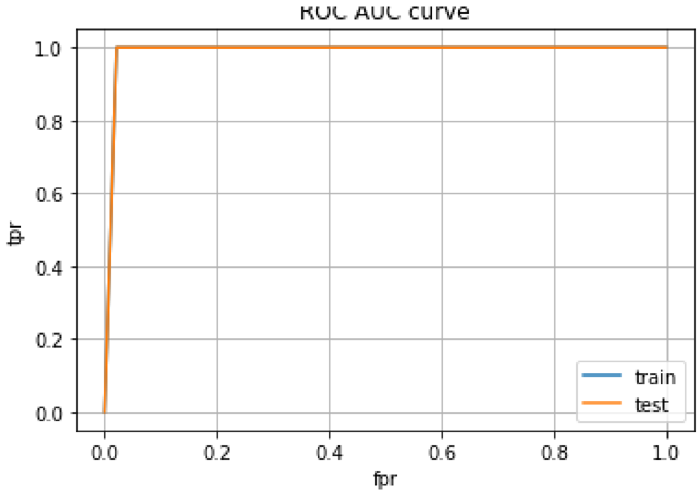
In [54]:

```
### initialising estimators on best params
rf_model = RandomForestClassifier(
                    n_estimators = n_estimators,
                    criterion = criterion,
                    max_depth = max_depth,
                    min_samples_split = min_samples_split,
                    min_samples_leaf = min_samples_leaf,
                    max_features = max_features,
                    class_weight = class_weight,
                    bootstrap = bootstrap,
                    ccp_alpha = ccp_alpha,
                    max_samples = max_samples,
                    n_jobs = -1
                    )

### training and evaluating random forest classifier model on train and test dataset
rf_model, rf_tr_auc, rf_tr_f1score, rf_te_auc, rf_te_f1score = train_and_evaluate(rf_mode
l)
```

```
training completed! and time taken: 0:02:28.770943

On train data, AUC: 0.9892975935257804, f1-score: 0.8261106439425343
On test data, AUC: 0.9892751202520019, f1-score: 0.8258125112225306
```







Observation

From the above scores and plots we I found that this model is performing good compared to base model but not others, and it is generalized model because the difference in the train and test f1-scores is less than 0.1%, but compared to other models the f1-score is quite low.

the False negatives is 0 but the false positives is very large, which classifies normal traffics as abnorm/malicious

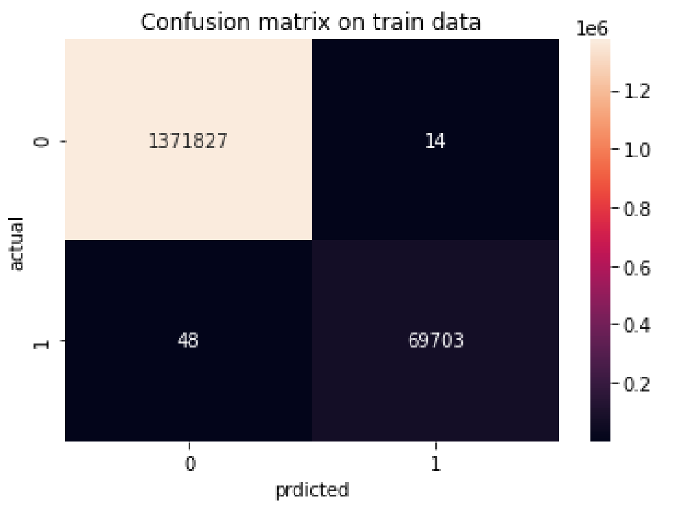
Hence, we can conclude that the it works very well on one class but not on the other class

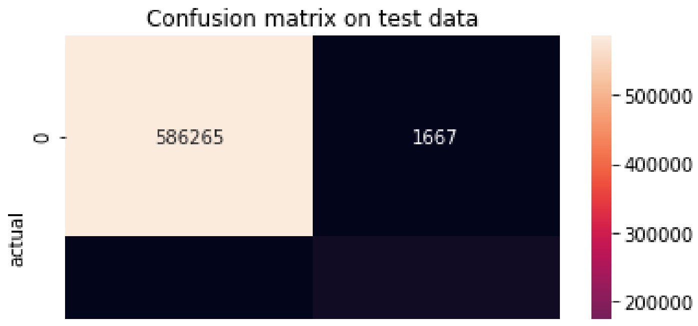
- ***Random Forest Classifier with default parameters***

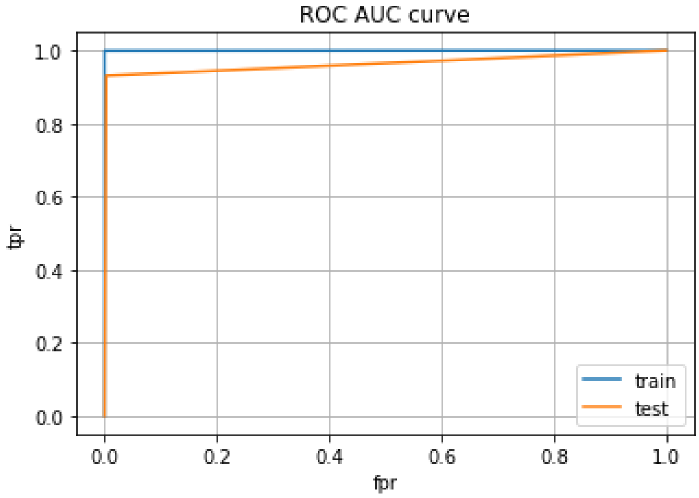
In [55]:

```
### training and evaluating random forest classifier model with default parameters on tra
in and test dataset
def_rf_model = RandomForestClassifier(n_jobs=-1)
def_rf_model, def_rf_tr_auc, def_rf_tr_f1score, def_rf_te_auc, def_rf_te_f1score = train
_and_evaluate(def_rf_model)
```

```
training completed! and time taken: 0:07:02.002404

On train data, AUC: 0.9996508162794004, f1-score: 0.9995554535807496
On test data, AUC: 0.9641105186824225, f1-score: 0.9372327171094723
```







Observation

From the above scores and plots we I found that this model is performing very good compared to tunned random forest but it is overfitted because the difference in the train and test f1-scores is nearly 6%. It works well on train data but not on the test data, we see the confusion matrix.

10. Summary of all the estimators with their respective scores and auc

In [57]:

```
columns = ['train auc', 'test auc', 'train f1-score', 'test f1-score']
scores = [
          [nb_tr_auc, nb_te_auc, nb_tr_f1score, nb_te_f1score],
          [dec_tree_tr_auc, dec_tree_tr_f1score, dec_tree_te_auc, dec_tree_te_f1score],
          [lr_tr_auc, lr_te_auc, lr_tr_f1score, lr_te_f1score],
          [svm_tr_auc, svm_te_auc, svm_tr_f1score, svm_te_f1score],
          [xgb_tr_auc, xgb_te_auc, xgb_tr_f1score, xgb_te_f1score],
          [def_xgb_tr_auc, def_xgb_te_auc, def_xgb_tr_f1score, def_xgb_te_f1score],
          [rf_tr_auc, rf_te_auc, rf_tr_f1score, rf_te_f1score],
          [def_rf_tr_auc, def_rf_te_auc, def_rf_tr_f1score, def_rf_te_f1score],
         ]

index = ['Naive Bayes Classifier (Base model)',
         'Decision Tree Classifier',
         'Logistic Regression',
         'Support Vector Machine (SVM)',
         'XGBoost Classifier',
         'XGBoost with default parameters',
         'Random Forest Classifier',
         'Random Forest Classifier with default parameters',
]

score_df = pd.DataFrame(data=scores, columns=columns, index=index)
score_df
```

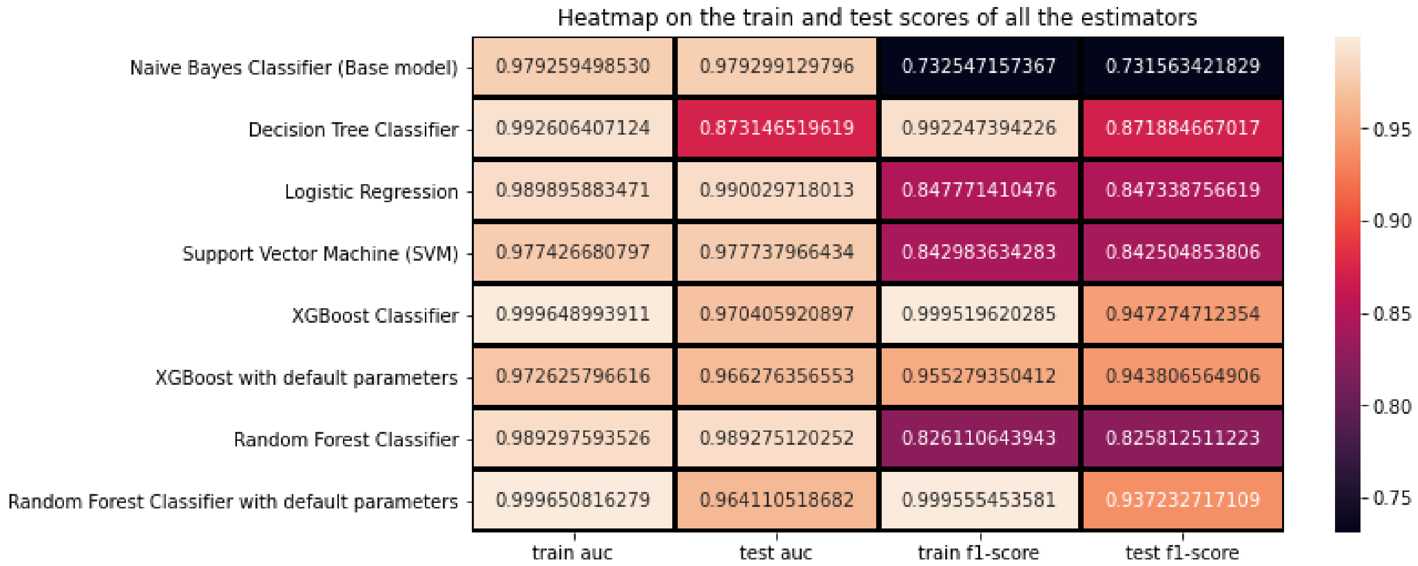
Out[57]:

	train auc	test auc	train f1-score	test f1-score
Naive Bayes Classifier (Base model)	0.979259498530	0.979299129796	0.732547157367	0.731563421829
Decision Tree Classifier	0.992606407124	0.873146519619	0.992247394226	0.871884667017
Logistic Regression	0.989895883471	0.990029718013	0.847771410476	0.847338756619
Support Vector Machine (SVM)	0.977426680797	0.977737966434	0.842983634283	0.842504853806

	train auc	test auc	train f1-score	test f1-score
XGBoost Classifier	0.999648993911	0.970405920897	0.999519620285	0.947274712354
XGBoost with default parameters	0.972625796616	0.966276356553	0.955279350412	0.943806564906
Random Forest Classifier	0.989297593526	0.989275120252	0.826110643943	0.825812511223
Random Forest Classifier with default parameters	0.999650816279	0.964110518682	0.999555453581	0.937232717109

In [58]:

```
plt.figure(figsize=(10,5))
sns.heatmap(score_df, fmt='.12f', annot=True, linecolor='black', linewidths='2', )
plt.title('Heatmap on the train and test scores of all the estimators')
plt.show()
```



comparison between baseline model and selected model scores

In [79]:

```
score_df.loc[['Naive Bayes Classifier (Base model)', 'XGBoost with default parameters'],]
```

Out[79]:

	train auc	test auc	train f1-score	test f1-score
Naive Bayes Classifier (Base model)	0.979259498530	0.979299129796	0.732547157367	0.731563421829
XGBoost with default parameters	0.972625796616	0.966276356553	0.955279350412	0.943806564906

Observation

from the above heatmap we found that XGBoost and Random Forest had perfromed well from our base model Naive bayes

but the xgboost with default parameters have very similar auc and f1-score for both train and test data.

Hence, I can conclude that our XGBoost model with default parameters is like generalized model from all the models with best auc and f1-score.

11. Saving models, scaling vectors and the unique categories in proto, service, state feature, engineered features name in pickle file

In [63]:

```
### saving uniques categorical value in respective feature list to disk
with open('unique_categories.pkl', 'wb') as f:
    pickle.dump([unique_proto,unique_service,unique_state], f)
```

In [68]:

```
### saving scaler vector to disk
```

```
### saving scaler vector to disk
with open('scaler.pkl', 'wb') as f:
    pickle.dump(scaler, f)
```

In [71]:

```
### storing models in the form of key, value pair in dictionary
estimators_dict = {
                    'base_model':base_model,
                   'def_xgb_model':def_xgb_model,
                   'def_rf_model':def_rf_model,
                   'dec_tree_model':dec_tree_model,
                   'lr_model': lr_model,
                   'svm_model':svm_model,
                   'xgb_model':xgb_model,
                   'rf_model':rf_model
                  }
### for each key and its model in dictionary
for name, model_name in estimators_dict.items():
    ### saving key and its model in the disk
    with open(name+'.pkl', 'wb') as f:
        pickle.dump(model_name, f)
```

In [73]:

```
c### features name on that feature engineering to be perform
feature_eng =  [["sttl", "dttl"],
                ["sbytes", "dbytes"],
                ["Sload", "Dload"],
                ["stcpb", "dtcpb"],
                ["smeansz", "dmeansz"],
                ["Sjit", "Djit"],
                ["Sintpkt", "Dintpkt"],
                ["trans_depth", "res_bdy_len"],
                ["ct_state_ttl", "ct_flw_http_mthd"],
                ["ct_srv_dst", "ct_dst_ltm"],
                ["ct_src_", "ct_src_dport_ltm"]]
### saving in the disk
with open('feature_eng.pkl', 'wb') as f:
    pickle.dump(feature_eng, f)
```

END