

```
from math import e

class Node:

    def __init__(self, x, gradient, hessian, idxs, subsample_cols = 0.8 , min_leaf

        self.x, self.gradient, self.hessian = x, gradient, hessian
        self.idxs = idxs
        self.depth = depth
        self.min_leaf = min_leaf
        self.lambda_ = lambda_
        self.gamma = gamma
        self.min_child_weight = min_child_weight
        self.row_count = len(idxs)
        self.col_count = x.shape[1]
        self.subsample_cols = subsample_cols
        self.eps = eps
        self.column_subsample = np.random.permutation(self.col_count)[:round(self.s

        self.val = self.compute_gamma(self.gradient[self.idxs], self.hessian[self.i

        self.score = float('-inf')
        self.find_varsplit()
    def compute_gamma(self, gradient, hessian):

        return(-np.sum(gradient)/(np.sum(hessian) + self.lambda_))
    def find_varsplit(self):

        for c in self.column_subsample: self.find_greedy_split(c)
        if self.is_leaf: return
        x = self.split_col
        lhs = np.nonzero(x <= self.split)[0]
        rhs = np.nonzero(x > self.split)[0]
        self.lhs = Node(x = self.x, gradient = self.gradient, hessian = self.hessia
        self.rhs = Node(x = self.x, gradient = self.gradient, hessian = self.hessia

    def find_greedy_split(self, var_idx):

        x = self.x.values[self.idxs, var_idx]

        for r in range(self.row_count):
            lhs = x <= x[r]
            rhs = x > x[r]

            lhs_indices = np.nonzero(x <= x[r])[0]
            rhs_indices = np.nonzero(x > x[r])[0]
            if(rhs.sum() < self.min_leaf or lhs.sum() < self.min_leaf
```

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    or self.hessian[lhs_indices].sum() < self.min_child_weight): continue

    curr_score = self.gain(lhs, rhs)
    if curr_score > self.score:
        self.var_idx = var_idx
        self.score = curr_score
        self.split = x[r]
def weighted_quantile_sketch(self, var_idx):

    x = self.x.values[self.idxs, var_idx]
    hessian_ = self.hessian[self.idxs]
    df = pd.DataFrame({'feature':x, 'hess':hessian_})

    df.sort_values(by=['feature'], ascending = True, inplace = True)
    hess_sum = df['hess'].sum()
    df['rank'] = df.apply(lambda x : (1/hess_sum)*sum(df[df['feature'] < x['fea

    for row in range(df.shape[0]-1):
        # look at the current rank and the next ran
        rk_sk_j, rk_sk_j_1 = df['rank'].iloc[row:row+2]
        diff = abs(rk_sk_j - rk_sk_j_1)
        if(diff >= self.eps):
            continue

        split_value = (df['rank'].iloc[row+1] + df['rank'].iloc[row])/2
        lhs = x <= split_value
        rhs = x > split_value

        lhs_indices = np.nonzero(x <= split_value)[0]
        rhs_indices = np.nonzero(x > split_value)[0]
        if(rhs.sum() < self.min_leaf or lhs.sum() < self.min_leaf
           or self.hessian[lhs_indices].sum() < self.min_child_weight
           or self.hessian[rhs_indices].sum() < self.min_child_weight): continue

        curr_score = self.gain(lhs, rhs)
        if curr_score > self.score:
            self.var_idx = var_idx
            self.score = curr_score
            self.split = split_value

def gain(self, lhs, rhs):

    gradient = self.gradient[self.idxs]
    hessian = self.hessian[self.idxs]

    lhs_gradient = gradient[lhs].sum()
    lhs_hessian = hessian[lhs].sum()

    rhs_gradient = gradient[rhs].sum()
    rhs_hessian = hessian[rhs].sum()

```

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        rhs_gradient = -gradient[split_idx, self.var_idx]

        gain = 0.5 * ( lhs_gradient**2 / (lhs_hessian + self.lambda_) + (rhs_gradient**2 / (rhs_hessian + self.lambda_)) )
        return(gain)

    @property
    def split_col(self):

        return self.x.values[self.idx, self.var_idx]

    @property
    def is_leaf(self):

        return self.score == float('-inf') or self.depth <= 0

    def predict(self, x):
        return np.array([self.predict_row(xi) for xi in x])

    def predict_row(self, xi):
        if self.is_leaf:
            return(self.val)

        node = self.lhs if xi[self.var_idx] <= self.split else self.rhs
        return node.predict_row(xi)

```

```
class XGBoostTree:
```

```

    def fit(self, x, gradient, hessian, subsample_cols = 0.8 , min_leaf = 5, min_child_weight = 1):
        self.dtree = Node(x, gradient, hessian, np.array(np.arange(len(x))), subsample_cols, min_leaf, min_child_weight)
        return self

    def predict(self, x):
        return self.dtree.predict(X.values)

```

```
class XGBClassifier:
```

```

    def __init__(self):
        self.estimators = []

    @staticmethod
    def sigmoid(x):
        return 1 / (1 + np.exp(-x))

    # first order gradient logLoss
    def grad(self, preds, labels):
        preds = self.sigmoid(preds)
        return(preds - labels)

    # second order gradient logLoss
    def hess(self, preds, labels):
        preds = self.sigmoid(preds)

```

```
        return(preds * (1 - preds))
    @staticmethod
    def log_odds(column):
        binary_yes = np.count_nonzero(column == 1)
        binary_no = np.count_nonzero(column == 0)
        return(np.log(binary_yes/binary_no))

def fit(self, x, y, subsample_cols = 0.8 , min_child_weight = 1, depth = 5, min

    self.x, self.y = x, y.values
    self.depth = depth
    self.subsample_cols = subsample_cols
    self.eps = eps
    self.min_child_weight = min_child_weight
    self.min_leaf = min_leaf
    self.learning_rate = learning_rate
    self.boosting_rounds = boosting_rounds
    self.lambda_ = lambda_
    self.gamma = gamma

    self.base_pred = np.full((x.shape[0], 1), 1).flatten().astype('float64')

    for booster in range(self.boosting_rounds):
        Grad = self.grad(self.base_pred, self.y)
        Hess = self.hess(self.base_pred, self.y)
        boosting_tree = XGBoostTree().fit(self.x, Grad, Hess, depth = self.dept
        self.base_pred += self.learning_rate * boosting_tree.predict(self.x)
        self.estimators.append(boosting_tree)
def predict_proba(self, x):
    pred = np.zeros(x.shape[0])

    for estimator in self.estimators:
        pred += self.learning_rate * estimator.predict(x)

    return(self.sigmoid(np.full((x.shape[0], 1), 1).flatten().astype('float64'))

def predict(self, x):
    pred = np.zeros(x.shape[0])
    for estimator in self.estimators:
        pred += self.learning_rate * estimator.predict(x)

    predicted_probas = self.sigmoid(np.full((x.shape[0], 1), 1).flatten().astyp
    preds = np.where(predicted_probas > np.mean(predicted_probas), 1, 0)
    return(preds)
```

Double-click (or enter) to edit

```
import numpy as np
```

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sn
import warnings
warnings.filterwarnings('ignore')

data1=pd.read_csv('/content/drive/MyDrive/Half_Data/ack_h.csv')
data2=pd.read_csv('/content/drive/MyDrive/Half_Data/benign_traffic_h.csv')
data3=pd.read_csv('/content/drive/MyDrive/Half_Data/combo_h.csv')
data4=pd.read_csv('/content/drive/MyDrive/Half_Data/junk_h.csv')
data5=pd.read_csv('/content/drive/MyDrive/Half_Data/scan_h.csv')
data6=pd.read_csv('/content/drive/MyDrive/Half_Data/syn_h.csv')
data7=pd.read_csv('/content/drive/MyDrive/Half_Data/tcp_h.csv')
data8=pd.read_csv('/content/drive/MyDrive/Half_Data/udp_h.csv')
data9=pd.read_csv('/content/drive/MyDrive/Half_Data/udpplain_h.csv')

data1['class']='ack'
data2['class']='benign_traffic'
data3['class']='scan'
data4['class']='junk'
data5['class']='scan'
data6['class']='syn'
data7['class']='tcp'
data8['class']='udp'
data9['class']='udpplain'

data=pd.concat([data1,data2,data3,data4,data5,data6,data7,data8,data9],
               axis=0, sort=False, ignore_index=True)

data.groupby('class')['class'].count()
data
```

| | MI_dir_L5_weight | MI_dir_L5_mean | MI_dir_L5_variance | MI_dir_L3_weight |
|--------|------------------|----------------|--------------------|------------------|
| 0 | 1.000000 | 566.000000 | 0.000000e+00 | 1.000000 |
| 1 | 1.996585 | 566.000000 | 5.820000e-11 | 1.997950 |
| 2 | 2.958989 | 566.000000 | 0.000000e+00 | 2.975291 |
| 3 | 3.958979 | 566.000000 | 0.000000e+00 | 3.975285 |
| 4 | 4.914189 | 566.000000 | 1.160000e-10 | 4.948239 |
| ... | ... | ... | ... | ... |
| 813555 | 107.013362 | 451.270414 | 4.019486e+04 | 177.665918 |
| 813556 | 108.012301 | 452.221506 | 3.991953e+04 | 178.664861 |
| 813557 | 108.716218 | 453.157691 | 3.964675e+04 | 179.370847 |
| 813558 | 109.580657 | 454.077947 | 3.937690e+04 | 180.236616 |

813559

109.981077

454.986486

3.910882e+04

180.644259

813560 rows × 116 columns



```
from google.colab import drive
drive.mount('/content/drive')
```

Drive already mounted at /content/drive; to attempt to forcibly remount, call

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
data["class"]= le.fit_transform(data["class"])
from sklearn.model_selection import train_test_split
```

```
target = "class"
```

```
y = data[target]
```

```
x = data.drop(target,axis = 1)
```

```
x.shape
```

```
(813560, 115)
```

```
x.head()
```

| | MI_dir_L5_weight | MI_dir_L5_mean | MI_dir_L5_variance | MI_dir_L3_weight | MI_c |
|----------|------------------|----------------|--------------------|------------------|------|
| 0 | 1.000000 | 566.0 | 0.000000e+00 | 1.000000 | |
| 1 | 1.996585 | 566.0 | 5.820000e-11 | 1.997950 | |
| 2 | 2.958989 | 566.0 | 0.000000e+00 | 2.975291 | |
| 3 | 3.958979 | 566.0 | 0.000000e+00 | 3.975285 | |
| 4 | 4.914189 | 566.0 | 1.160000e-10 | 4.948239 | |

5 rows × 115 columns

**Remove correlated features**

Remove correlated features

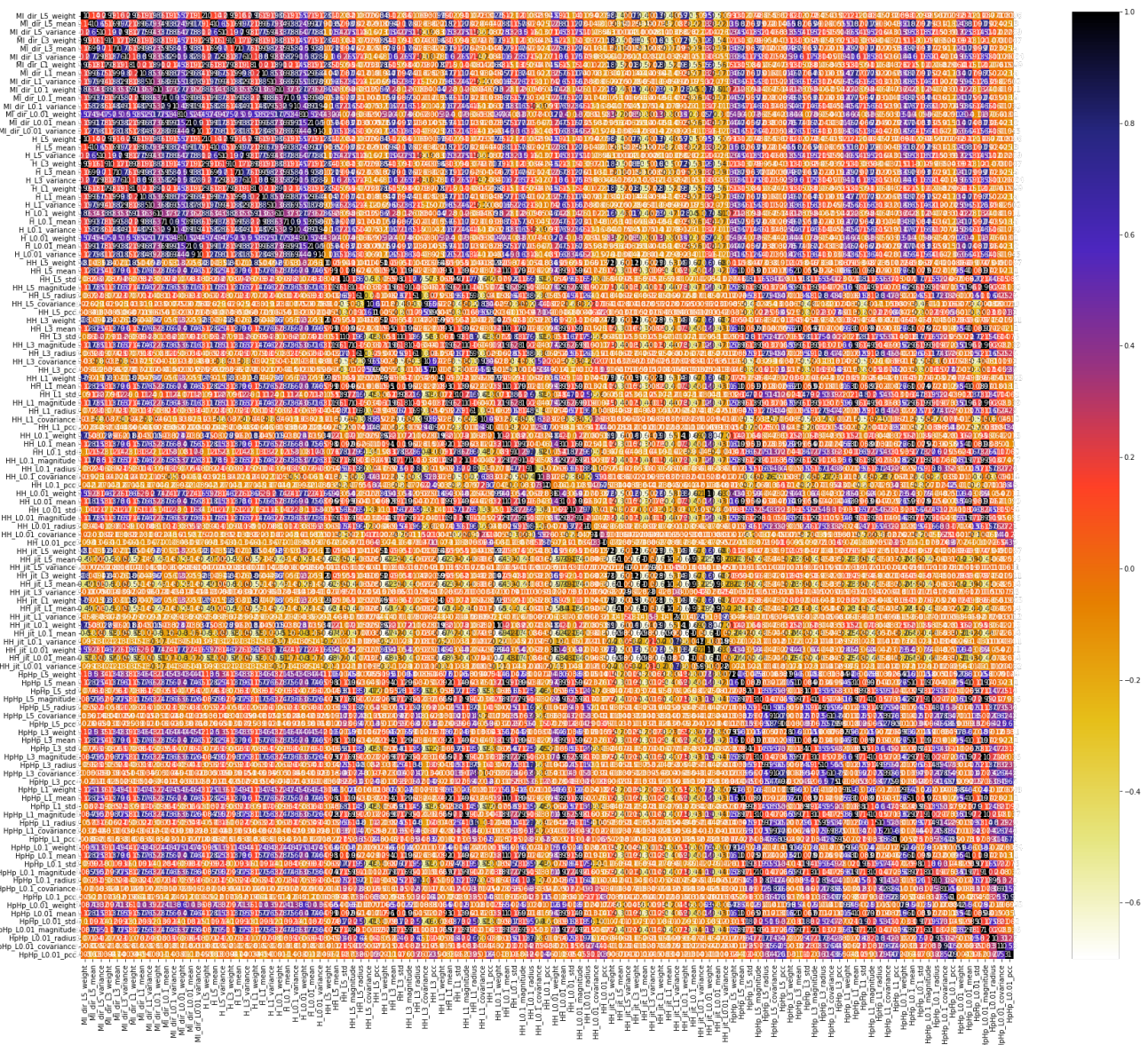
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.3,random_state=

x_train.shape, x_test.shape

((569492, 115), (244068, 115))
```

check the pearson correlation on "X_train" data only

```
import seaborn as sns
plt.figure(figsize=(30,25))
cor = x_train.corr()
sns.heatmap(cor, annot=True, cmap=plt.cm.CMRmap_r)
plt.show()
```



select highly correlated features

```
def correlation(dataset, threshold):
    col_corr = set()
    corr_matrix = dataset.corr()
    for i in range(len(corr_matrix.columns)):
        for j in range(i):
            if abs(corr_matrix.iloc[i,j]) > threshold:
                colname = corr_matrix.columns[i]
                col_corr.add(colname)
    return col_corr

corr_features = correlation(x_train, 0.8)
len(set(corr_features))
print("correlated features: ", len(set(corr_features)))

correlated features:  95

print("correlated features are: ", corr_features )

correlated features are:  {'H_L5_weight', 'HH_L0.01_mean', 'HpHp_L1_magnitude'

x_train.shape

(569492, 115)
```



```
x_train_noncorr = x_train.drop(corr_features, axis=1)
```

```
x_train_noncorr.shape
```

```
(569492, 20)
```

```
x_test_noncorr = x_test.drop(corr_features, axis =1)
```

```
x_test_noncorr.shape
```

```
(244068, 20)
```

```
y_train.shape
```

```
(569492,)
```

```
x_train.shape, y_train.shape
```

```
((569492, 115), (569492,))
```

```
x_train_noncorr.shape, x_test_noncorr.shape
```

```
((569492, 20), (244068, 20))
```

```
import datetime
```

```
start = datetime.datetime.now()
```

```
model_ncr = XGBClassifier()
```

```
model_ncr.fit(x_train_noncorr, y_train)
```

```
end = datetime.datetime.now()
```

```
print("Total execution time on 20 features: ", end-start)
```

```
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score
```

```
y_pred_ncr = model_ncr.predict(x_test_noncorr)
```

```
print("Accuracy score on 20 features: ", accuracy_score(y_test, y_pred_ncr)*100)
```

```
print("Confusion matrix:\n ", confusion_matrix(y_test, y_pred_ncr))
```

```
print("Corect prediction are: ", sum(y_test == y_pred_ncr))
```

```
print("Incorrect predictions are :", sum(y_test!= y_pred_ncr))
```

```
Accuracy score on 20 features: 54.44444444444444
```

```
Confusion matrix:
```

```
[[27  0  0]
```

```
 [ 2 22  0]
```

```
 [ 0 39  0]]
```

```
Correct prediction are: 40
```

```
Correct prediction are: 49  
Incorrect predictions are : 41
```

```
confusion_m = pd.crosstab(y_test,model_ncr.predict(x_test_noncorr))  
  
print("Accuracy is: ",(np.diag(confusion_m).sum()/confusion_m.sum().sum())*100)  
  
fig = plt.figure(figsize=(10,5))  
  
sn.heatmap(confusion_m,annot=True,cmap='Blues')
```