```python
# This Python 3 environment comes with many helpful analytics
libraries installed
# It is defined by the kaggle/python Docker image:
https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/"
directory
# For example, running this (by clicking run or pressing Shift+Enter)
will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/)
that gets preserved as output when you create a version using "Save &
Run All"
# You can also write temporary files to /kaggle/temp/, but they won't
be saved outside of the current session

import matplotlib.pyplot as plt
import seaborn as sns
```

Getting the train and test data

```python
import gdown

url = "https://drive.google.com/uc?
id=1_FZIrNug8svcEK5QMDdV2MoHmcCny8kJ&export=download"
output = "train.csv"
gdown.download(url, output)

url = "https://drive.google.com/uc?
id=1_FAidr3sAiSWx6mPS26HMpWjVaiSTOXq&export=download"
output = "test.csv"
gdown.download(url, output)
```

```
Downloading...
From: https://drive.google.com/uc?
id=1_FZIrNug8svcEK5QMDdV2MoHmcCny8kJ&export=download
To: /content/train.csv
100%|██████████| 1.24G/1.24G [00:05<00:00, 219MB/s]
Downloading...
From: https://drive.google.com/uc?
id=1_FAidr3sAiSWx6mPS26HMpWjVaiSTOXq&export=download
```

```
To: /content/test.csv
100%|██████████| 524M/524M [00:03<00:00, 170MB/s]
```

{"type":"string"}

```
train_df = pd.read_csv("/content/train.csv")
test_df = pd.read_csv("/content/test.csv")
```

```
train_df
```

```
         Unnamed: 0  lepton_1_pT  lepton_1_eta  lepton_1_phi
lepton_2_pT  \
0                 0     0.841381      1.832647     -0.689286
0.781839
1                 1     0.663798      2.058290      0.681435
1.054036
2                 2     1.792225     -1.099978      0.088109
0.573157
3                 3     0.893018      0.297782     -1.274870
1.316164
4                 4     1.338997      0.350023     -1.518510
1.482963
...             ...          ...           ...           ...
...
3499995     3499995     1.052621      0.602641     -0.859267
1.498731
3499996     3499996     0.624401      0.361025      1.177020
0.737001
3499997     3499997     0.719730     -0.655623     -1.236807
0.769770
3499998     3499998     0.670955     -0.450620     -0.880438
0.539060
3499999     3499999     0.665091      1.751356     -0.656336
0.864334

         lepton_2_eta  lepton_2_phi  missing_energy_magnitude  \
0            0.572864      1.577097                  0.398978
1            0.575352     -1.001445                  0.462154
2           -0.472629      1.642084                  1.203374
3            1.593303      0.672115                  0.307014
4           -0.491807      0.340170                  0.415071
...               ...           ...                       ...
3499995      0.416403      1.495084                  1.104591
3499996      0.380580      1.728161                  1.307348
3499997      1.170407     -0.009082                  1.505161
3499998      0.937796      0.357333                  0.289037
3499999      0.853009      1.665205                  1.422063

         missing_energy_phi   MET_rel  axial_MET       M_R
M_TR_2  \
0                 -0.683847  0.001826   0.651397  0.865560  0.429017
```

```
1                  -0.833411  0.199734   0.215158  0.949988  0.618046

2                   1.506731  0.457695  -0.640507  1.157024  1.585432

3                  -1.189868  0.064561   0.430909  1.162625  0.548821

4                  -1.292034  0.240712   0.611775  1.307798  0.697804

...                      ...       ...        ...       ...       ...

3499995             0.307900  1.658127  -0.778934  1.022135  1.441749

3499996            -0.744138  1.962474  -0.641088  0.555763  1.201866

3499997             0.097434  0.407014   0.097485  1.010633  1.095738

3499998             0.624295  0.197286   0.139753  0.689692  0.490803

3499999             1.186270  1.643481  -0.445953  0.701854  1.163961


                R       MT2       S_R  M_Delta_R  dPhi_r_b
cos(theta_r1)  \
0        0.439840  0.000000  0.796105   0.342497  0.461542
0.005710
1        0.577324  0.000000  0.962927   0.333800  1.455247
0.101246
2        1.215963  0.000000  1.113292   0.645729  0.721326
0.613326
3        0.418897  0.163908  1.157707   0.298163  0.803802
0.038902
4        0.473487  0.429977  1.287935   0.330327  0.717237
0.003147
...           ...       ...       ...        ...       ...
...
3499995  1.251692  2.646003  1.051955   1.973445  1.203800
0.056984
3499996  1.919043  2.366463  0.630864   1.763709  1.075939
0.640265
3499997  0.962121  0.359156  1.073840   1.268585  1.242062
0.262156
3499998  0.631491  0.326569  0.664390   0.521536  0.502427
0.198597
3499999  1.471656  1.489170  0.797141   1.257939  1.238222
0.449188

         class
0          0.0
```

```
1          0.0
2          1.0
3          0.0
4          1.0
...        ...
3499995    1.0
3499996    0.0
3499997    1.0
3499998    0.0
3499999    0.0

[3500000 rows x 20 columns]
```

test_df

```
         Unnamed: 0  lepton_1_pT  lepton_1_eta  lepton_1_phi
lepton_2_pT  \
0                 0     1.667973      0.064191     -1.225171
0.506102
1                 1     0.698336      1.689431     -1.134670
0.966594
2                 2     0.578286     -0.689652     -0.390094
0.480061
3                 3     0.798202      0.099358     -1.095839
0.531147
4                 4     1.466649      0.115517     -1.036161
0.877247
...             ...          ...           ...           ...
...
1499995     1499995     0.482755      1.204410      0.299445
0.780271
1499996     1499996     1.085361      0.861342     -1.356951
0.483685
1499997     1499997     1.339252     -1.753881      0.667430
1.279321
1499998     1499998     0.853325     -0.961783     -1.487277
0.678190
1499999     1499999     0.840389      1.419162     -1.218766
1.195631

         lepton_2_eta  lepton_2_phi  missing_energy_magnitude  \
0           -0.338939      1.672543                  3.475464
1            1.503367      0.880949                  0.242573
2           -0.632219      1.212005                  0.640473
3           -0.962327      1.500362                  1.273941
4            0.690861      1.130069                  0.890722
...               ...           ...                       ...
1499995      1.958697      0.938929                  0.887801
1499996      0.059381      0.292341                  0.340940
1499997     -0.125801     -1.025262                  0.996305
```

1499998	0.493580	1.647969	1.843867
1499999	1.695645	0.663756	0.490888

	missing_energy_phi	MET_rel	axial_MET	M_R	M_TR_2 \
0	-1.219136	0.012955	3.775174	1.045977	0.568051
1	-0.228654	0.364132	0.109350	0.668554	0.489941
2	-1.622401	0.872160	-0.186169	0.451853	0.669288
3	0.675408	1.803743	-0.845941	0.685836	1.234757
4	0.426515	1.283212	-0.563880	1.090046	1.327570
...	...	...	...	...	...
1499995	-1.404129	1.332697	-0.456543	0.551233	0.957969
1499996	0.761038	0.380255	0.038984	0.774140	0.660777
1499997	-1.425422	1.005658	-0.529824	1.616218	1.278956
1499998	0.276954	1.025105	-1.486535	0.892879	1.684429
1499999	-0.509186	0.704289	0.045744	0.825015	0.723530

	R	MT2	S_R	M_Delta_R	dPhi_r_b	cos(theta_r1)
0	0.481928	0.000000	0.448410	0.205356	1.321893	0.377584
1	0.650313	0.683634	0.664825	0.510385	0.584092	0.031694
2	1.314412	0.559444	0.491753	0.559017	1.286520	0.400292
3	1.597630	1.864630	0.775854	1.556949	1.245781	0.538010
4	1.080762	1.588076	1.069615	1.258800	0.443045	0.415406
...	...	...	...	...	...	...
1499995	1.542171	1.982478	0.579808	1.481396	1.006600	0.189843
1499996	0.757443	0.331105	0.715807	0.447304	0.320159	0.371521
1499997	0.702218	0.541788	1.649413	1.139551	1.256152	0.159157
1499998	1.674084	3.366298	1.046707	2.646649	1.389226	

```
0.364599
1499999  0.778236  0.752942  0.838953   0.614048  1.210595
0.026692

[1500000 rows x 19 columns]
```

```
'''train_df = pd.read_csv('/kaggle/input/train-testcsv/train.csv')
test_df = pd.read_csv('/kaggle/input/train-testcsv/test.csv')'''

train_df.head(5)
```

```
   Unnamed: 0  lepton_1_pT  lepton_1_eta  lepton_1_phi  lepton_2_pT  \
0           0     0.841381      1.832647     -0.689286     0.781839
1           1     0.663798      2.058290      0.681435     1.054036
2           2     1.792225     -1.099978      0.088109     0.573157
3           3     0.893018      0.297782     -1.274870     1.316164
4           4     1.338997      0.350023     -1.518510     1.482963

   lepton_2_eta  lepton_2_phi  missing_energy_magnitude
missing_energy_phi  \
0      0.572864      1.577097                  0.398978           -
0.683847
1      0.575352     -1.001445                  0.462154           -
0.833411
2     -0.472629      1.642084                  1.203374
1.506731
3      1.593303      0.672115                  0.307014           -
1.189868
4     -0.491807      0.340170                  0.415071           -
1.292034

    MET_rel  axial_MET       M_R    M_TR_2         R       MT2
S_R  \
0  0.001826   0.651397  0.865560  0.429017  0.439840  0.000000
0.796105
1  0.199734   0.215158  0.949988  0.618046  0.577324  0.000000
0.962927
2  0.457695  -0.640507  1.157024  1.585432  1.215963  0.000000
1.113292
3  0.064561   0.430909  1.162625  0.548821  0.418897  0.163908
1.157707
4  0.240712   0.611775  1.307798  0.697804  0.473487  0.429977
1.287935

   M_Delta_R  dPhi_r_b  cos(theta_r1)  class
0   0.342497  0.461542       0.005710    0.0
1   0.333800  1.455247       0.101246    0.0
2   0.645729  0.721326       0.613326    1.0
3   0.298163  0.803802       0.038902    0.0
4   0.330327  0.717237       0.003147    1.0
```

```
test_df.head(5)
```

```
   Unnamed: 0  lepton_1_pT  lepton_1_eta  lepton_1_phi  lepton_2_pT  \
0           0     1.667973      0.064191     -1.225171     0.506102
1           1     0.698336      1.689431     -1.134670     0.966594
2           2     0.578286     -0.689652     -0.390094     0.480061
3           3     0.798202      0.099358     -1.095839     0.531147
4           4     1.466649      0.115517     -1.036161     0.877247

   lepton_2_eta  lepton_2_phi  missing_energy_magnitude
missing_energy_phi  \
0     -0.338939      1.672543                  3.475464           -
1.219136
1      1.503367      0.880949                  0.242573           -
0.228654
2     -0.632219      1.212005                  0.640473           -
1.622401
3     -0.962327      1.500362                  1.273941
0.675408
4      0.690861      1.130069                  0.890722
0.426515

    MET_rel  axial_MET       M_R    M_TR_2         R       MT2
S_R  \
0  0.012955   3.775174  1.045977  0.568051  0.481928  0.000000
0.448410
1  0.364132   0.109350  0.668554  0.489941  0.650313  0.683634
0.664825
2  0.872160  -0.186169  0.451853  0.669288  1.314412  0.559444
0.491753
3  1.803743  -0.845941  0.685836  1.234757  1.597630  1.864630
0.775854
4  1.283212  -0.563880  1.090046  1.327570  1.080762  1.588076
1.069615

   M_Delta_R  dPhi_r_b  cos(theta_r1)
0   0.205356  1.321893       0.377584
1   0.510385  0.584092       0.031694
2   0.559017  1.286520       0.400292
3   1.556949  1.245781       0.538010
4   1.258800  0.443045       0.415406
```

```
train_df.drop('Unnamed: 0',axis = 1,inplace = True)
```

```
test_df.drop('Unnamed: 0',axis = 1,inplace = True)
```

```
train_df.head(5)
```

```
   lepton_1_pT  lepton_1_eta  lepton_1_phi  lepton_2_pT  lepton_2_eta
\
0     0.841381      1.832647     -0.689286     0.781839      0.572864
```

```
1     0.663798      2.058290      0.681435     1.054036      0.575352

2     1.792225     -1.099978      0.088109     0.573157     -0.472629

3     0.893018      0.297782     -1.274870     1.316164      1.593303

4     1.338997      0.350023     -1.518510     1.482963     -0.491807


   lepton_2_phi  missing_energy_magnitude  missing_energy_phi
MET_rel  \
0      1.577097                  0.398978           -0.683847
0.001826
1     -1.001445                  0.462154           -0.833411
0.199734
2      1.642084                  1.203374            1.506731
0.457695
3      0.672115                  0.307014           -1.189868
0.064561
4      0.340170                  0.415071           -1.292034
0.240712

   axial_MET       M_R    M_TR_2         R       MT2       S_R
M_Delta_R  \
0   0.651397  0.865560  0.429017  0.439840  0.000000  0.796105
0.342497
1   0.215158  0.949988  0.618046  0.577324  0.000000  0.962927
0.333800
2  -0.640507  1.157024  1.585432  1.215963  0.000000  1.113292
0.645729
3   0.430909  1.162625  0.548821  0.418897  0.163908  1.157707
0.298163
4   0.611775  1.307798  0.697804  0.473487  0.429977  1.287935
0.330327

   dPhi_r_b  cos(theta_r1)  class
0  0.461542       0.005710    0.0
1  1.455247       0.101246    0.0
2  0.721326       0.613326    1.0
3  0.803802       0.038902    0.0
4  0.717237       0.003147    1.0
```

```
train_df.isnull().sum()
```

```
lepton_1_pT                 0
lepton_1_eta                0
lepton_1_phi                0
lepton_2_pT                 0
lepton_2_eta                0
```

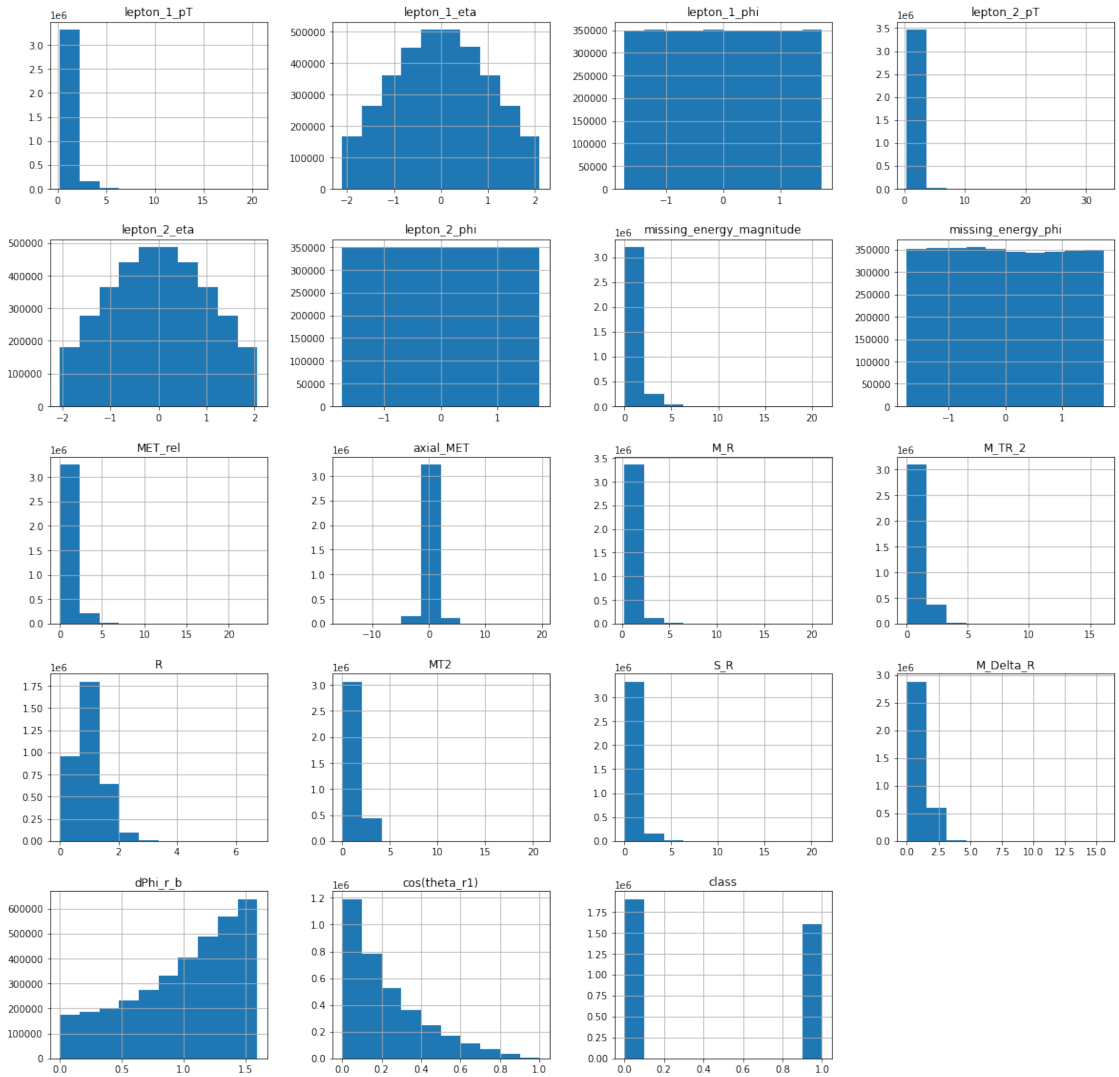
```
lepton_2_phi                0
missing_energy_magnitude    0
missing_energy_phi          0
MET_rel                     0
axial_MET                   0
M_R                         0
M_TR_2                      0
R                           0
MT2                         0
S_R                         0
M_Delta_R                   0
dPhi_r_b                    0
cos(theta_r1)               0
class                       0
dtype: int64
```

```
test_df.isnull().sum()
```

```
lepton_1_pT                 0
lepton_1_eta                0
lepton_1_phi                0
lepton_2_pT                 0
lepton_2_eta                0
lepton_2_phi                0
missing_energy_magnitude    0
missing_energy_phi          0
MET_rel                     0
axial_MET                   0
M_R                         0
M_TR_2                      0
R                           0
MT2                         0
S_R                         0
M_Delta_R                   0
dPhi_r_b                    0
cos(theta_r1)               0
dtype: int64
```

There are no null values in the entire train and test data

```
train_df.hist(figsize=(20,20))
plt.show()
```




```
train_df.describe()

        lepton_1_pT  lepton_1_eta  lepton_1_phi   lepton_2_pT
lepton_2_eta  \
count  3.500000e+06  3.500000e+06  3.500000e+06  3.500000e+06
3.500000e+06
mean   1.000232e+00  3.599349e-04  3.409634e-04  9.992382e-01
3.546249e-04
std    6.873955e-01  1.003109e+00  1.001971e+00  6.537354e-01
1.002817e+00
min    2.548815e-01 -2.102919e+00 -1.734789e+00  4.285860e-01 -
2.059306e+00
25%    5.625003e-01 -7.569637e-01 -8.673235e-01  5.969753e-01 -
7.693463e-01
50%    7.913588e-01  6.139759e-04 -3.000550e-04  7.997329e-01
1.132228e-04
75%    1.204264e+00  7.581109e-01  8.681473e-01  1.161961e+00
7.698279e-01
```

```
max    2.055345e+01  2.101605e+00  1.734839e+00  3.303562e+01
2.059721e+00

       lepton_2_phi  missing_energy_magnitude  missing_energy_phi  \
count  3.500000e+06              3.500000e+06        3.500000e+06
mean  -2.609503e-04              9.994536e-01       -4.940216e-04
std    1.001447e+00              8.724024e-01        1.001655e+00
min   -1.734202e+00              7.199480e-04       -1.727112e+00
25%   -8.680870e-01              4.781798e-01       -8.663442e-01
50%   -3.504302e-04              7.734768e-01       -1.038813e-02
75%    8.670100e-01              1.206897e+00        8.681880e-01
max    1.734686e+00              2.106888e+01        1.740689e+00

            MET_rel     axial_MET           M_R        M_TR_2
R  \
count  3.500000e+06  3.500000e+06  3.500000e+06  3.500000e+06
3.500000e+06
mean   1.000944e+00 -8.176786e-05  1.000253e+00  9.996171e-01
9.998163e-01
std    8.897569e-01  1.000707e+00  6.286597e-01  5.839003e-01
4.711496e-01
min    7.693475e-08 -1.533509e+01  2.680643e-01  2.427395e-03
4.528082e-03
25%    3.689606e-01 -4.920890e-01  5.883102e-01  6.222096e-01
6.503162e-01
50%    8.017117e-01 -8.002724e-02  8.284981e-01  8.778247e-01
9.341271e-01
75%    1.374708e+00  3.489328e-01  1.210956e+00  1.219851e+00
1.283126e+00
max    2.338644e+01  1.959220e+01  2.107572e+01  1.616682e+01
6.731210e+00

                MT2           S_R     M_Delta_R      dPhi_r_b
cos(theta_r1)  \
count  3.500000e+06  3.500000e+06  3.500000e+06  3.500000e+06
3.500000e+06
mean   1.000160e+00  9.999674e-01  9.997972e-01  9.992375e-01
2.248649e-01
std    8.590315e-01  6.205179e-01  6.235858e-01  4.361374e-01
1.970049e-01
min    0.000000e+00  2.734135e-02  4.452858e-03  3.211849e-07
1.498080e-07
25%    1.708098e-01  5.984608e-01  5.134528e-01  6.874365e-01
6.910075e-02
50%    9.014440e-01  8.353698e-01  9.137308e-01  1.094097e+00
1.671680e-01
75%    1.612343e+00  1.207777e+00  1.383827e+00  1.369023e+00
3.301480e-01
max    2.068624e+01  2.115226e+01  1.561370e+01  1.591660e+00
1.000000e+00
```

```
              class
count  3.500000e+06
mean   4.572371e-01
std    4.981681e-01
min    0.000000e+00
25%    0.000000e+00
50%    0.000000e+00
75%    1.000000e+00
max    1.000000e+00
```

Splitting the dataset into train and test. Also dividing the data into feature set and label set. The label column is the 'class' column in the dataset. Train and test are given to us.

```
X_train = train_df.drop('class',axis = 1)
y_train = train_df['class']
X_test = test_df
```

```
from sklearn.preprocessing import StandardScaler
std = StandardScaler()
std.fit(X_train)
```

```
StandardScaler()
```

Model Building:

My approach was to apply the models which i have come across due course, so as to maximize my learning.

I used 'Hands On Machine Learning' book for referring to these models.

The rationale behind using each classifier is given when they are present in the notebook.

I looked at all these models:

1) Logistic Regression

2) Decision Tree

3) Random Forest

4) AdaBoost

5) Gradient Boosting

6) XGboost

7) Histogram Based Gradient Boosting

The rationale behing not using Support Vector Machines is that the basic vanilla SVM model itself took more than 1 hour for training. That is why I thought of not using SVM. This was the same case for Voting Classifier as well as Stacking Classifier.

Logistic Regression:

```
'''from sklearn.linear_model import LogisticRegression
model_logreg = LogisticRegression()
model_logreg.fit(X_train,y_train)
y_pred = model_logreg.predict(X_test)
y_pred=pd.DataFrame(y_pred)
y_pred=y_pred.astype('float64')
y_pred.to_csv(path_or_buf='y_pred_log_reg.csv',header=['class'],index_
label='Id')'''
```

```
"from sklearn.linear_model import LogisticRegression\nmodel_logreg =
LogisticRegression()\nmodel_logreg.fit(X_train,y_train)\ny_pred =
model_logreg.predict(X_test)\ny_pred=pd.DataFrame(y_pred)\
ny_pred=y_pred.astype('float64')\
ny_pred.to_csv(path_or_buf='y_pred_log_reg.csv',header=['class'],index
_label='Id')"
```

Decision Tree:

My rationale for using Decision tree clasiifier over logistic regression

Decison tree is a non linear model. Given the complexity of data, I believe a non linea rmodel will give better accuracy on the test data.

```
'''from sklearn.tree import DecisionTreeClassifier
model_dt = DecisionTreeClassifier()
model_dt.fit(X_train,y_train)
y_pred = model_dt.predict(X_test)
y_pred=pd.DataFrame(y_pred)
y_pred=y_pred.astype('float64')
y_pred.to_csv(path_or_buf='y_pred_dt.csv',header=['class'],index_label
='Id')'''
```

```
"from sklearn.tree import DecisionTreeClassifier\nmodel_dt =
DecisionTreeClassifier()\nmodel_dt.fit(X_train,y_train)\ny_pred =
model_dt.predict(X_test)\ny_pred=pd.DataFrame(y_pred)\
ny_pred=y_pred.astype('float64')\
ny_pred.to_csv(path_or_buf='y_pred_dt.csv',header=['class'],index_labe
l='Id')"
```

Accuracy is 0.7551

Cross Validation:

```
'''from sklearn.model_selection import GridSearchCV
param_grid = {'max_depth' : [1,2,3,4,5,6,7,8],
              'criterion' : ['gini','entropy']}
gs_dt = GridSearchCV(model_dt,param_grid = param_grid,cv = 5)
gs_dt.fit(X_train,y_train)
gs_dt.best_params_'''
```

```
"from sklearn.model_selection import GridSearchCV\nparam_grid =
{'max_depth' : [1,2,3,4,5,6,7,8],\n              'criterion' :
['gini','entropy']}\ngs_dt = GridSearchCV(model_dt,param_grid =
param_grid,cv = 5)\ngs_dt.fit(X_train,y_train)\ngs_dt.best_params_"
```

Best model

```
'''model_dt = DecisionTreeClassifier(max_depth = 8,criterion = 'gini')
model_dt.fit(X_train,y_train)
y_pred = model_dt.predict(X_test)
y_pred=pd.DataFrame(y_pred)
y_pred=y_pred.astype('float64')
y_pred.to_csv(path_or_buf='y_pred_dt.csv',header=['class'],index_label
='Id')'''
```

```
"model_dt = DecisionTreeClassifier(max_depth = 8,criterion = 'gini')\
nmodel_dt.fit(X_train,y_train)\ny_pred = model_dt.predict(X_test)\
ny_pred=pd.DataFrame(y_pred)\ny_pred=y_pred.astype('float64')\
ny_pred.to_csv(path_or_buf='y_pred_dt.csv',header=['class'],index_labe
l='Id')"
```

Accuracy is 0.78563

Random Forest:

The rationale behind using Random forest is: Decision trees have low bias and high variance. Desirable is low bias and low variance. Hence it is very prone to learn the features and might give less accuracy over the unseen test set which is 70% of the test set. Hence I used random forest as it aggregates many decision trees. Hence variance reduces by square root of the total no of trees used. Hence my assumption is that random forest would better generalize the data.

```
'''from sklearn.ensemble import RandomForestClassifier
model_rf = RandomForestClassifier(max_depth = 8, n_estimators = 100,
random_state = 42)
model_rf.fit(X_train,y_train)
y_pred = model_rf.predict(X_test)
y_pred=pd.DataFrame(y_pred)
y_pred=y_pred.astype('float64')
y_pred.to_csv(path_or_buf='y_pred_rf.csv',header=['class'],index_label
='Id')'''
```

```
"from sklearn.ensemble import RandomForestClassifier\nmodel_rf =
RandomForestClassifier(max_depth = 8, n_estimators = 100, random_state
= 42)\nmodel_rf.fit(X_train,y_train)\ny_pred =
model_rf.predict(X_test)\ny_pred=pd.DataFrame(y_pred)\
ny_pred=y_pred.astype('float64')\
ny_pred.to_csv(path_or_buf='y_pred_rf.csv',header=['class'],index_labe
l='Id')"
```

Accuracy came out to be: 0.75921

AdaBoost:

Now I wanted to try boosting algorithms as it aggregates a large number of weak classifiers (decision trees here) and learns from the result of previous classifier. Boosting is known to reduce bias. The misclassified examples are given more weight on subsequent trees and then trained. Hence what happens is that model tries to better learn the small differences in the training data.

So my assumption is that using boosting, my model would be both low bias as well as low variance. Low bias: Because the model trains from its mistakes from previous classifier Low Variance: It aggregates many decision trees as aggregation reduces variation(See explanation of random forest,an aggregation technique

Adaptive boosting

```
'''from sklearn.ensemble import AdaBoostClassifier
model_dt = DecisionTreeClassifier(max_depth = 8,criterion = 'gini')
model_rf = AdaBoostClassifier(model_dt, random_state = 42)
model_rf.fit(X_train,y_train)
y_pred = model_rf.predict(X_test)
y_pred=pd.DataFrame(y_pred)
y_pred=y_pred.astype('float64')
y_pred.to_csv(path_or_buf='y_pred_ada.csv',header=['class'],index_labe
l='Id')'''
```

```
"from sklearn.ensemble import AdaBoostClassifier\nmodel_dt =
DecisionTreeClassifier(max_depth = 8,criterion = 'gini')\nmodel_rf =
AdaBoostClassifier(model_dt, random_state = 42)\
nmodel_rf.fit(X_train,y_train)\ny_pred = model_rf.predict(X_test)\
ny_pred=pd.DataFrame(y_pred)\ny_pred=y_pred.astype('float64')\
ny_pred.to_csv(path_or_buf='y_pred_ada.csv',header=['class'],index_lab
el='Id')"
```

The accuracy is 0.7995

Gradient Boosting:

**This is a model which uses gradient descent to reach the optima. Here learning rate is a hyperparameter which can be tuned for faster or slower convergence. Unlike Adaboost, here all the trees are given equal weights.It builds trees on previous classifier's residuals thus capturing variance in data.

Compared to AdaBoost, gradient boosting does not penalize missed-classified cases but using loss function instead

My rationale for using Gradient Boosting is that I wnated to see that if taking loss into account,rather than increase weights of the misclassified, can it give me a model which gives better accuracy or not.

```
'''from sklearn.ensemble import GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier

model_gb = GradientBoostingClassifier(max_depth = 20,n_estimators =
100,random_state = 42)
model_gb.fit(X_train,y_train)
y_pred = model_gb.predict(X_test)
y_pred=pd.DataFrame(y_pred)
y_pred=y_pred.astype('float64')
y_pred.to_csv(path_or_buf='y_pred_gb.csv',header=['class'],index_label
='Id')'''
```

```
"from sklearn.ensemble import GradientBoostingClassifier\nfrom
sklearn.tree import DecisionTreeClassifier\n\nmodel_gb =
GradientBoostingClassifier(max_depth = 20,n_estimators =
100,random_state = 42)\nmodel_gb.fit(X_train,y_train)\ny_pred =
model_gb.predict(X_test)\ny_pred=pd.DataFrame(y_pred)\
ny_pred=y_pred.astype('float64')\
ny_pred.to_csv(path_or_buf='y_pred_gb.csv',header=['class'],index_labe
l='Id')"
```

By this time the boosting algorithms are giving me better accuracy on the test set compared to all previous algorithms. SO I would like to try out other boosting techniques given in the book and look for models giving me better accuracy.

Accuracy is 0.78539

Histogram Based Gradient Boosting Classifier:

Training the trees that are added to the ensemble can be dramatically accelerated by discretizing (binning) the continuous input variables to a few hundred unique values. Gradient boosting ensembles that implement this technique and tailor the training algorithm around input variables under this transform are referred to as histogram-based gradient boosting ensembles.

The only rationale to use this model was that it gave me better training speed when training using gradient boosting

```
'''from sklearn.ensemble import HistGradientBoostingClassifier
model_hgbc = HistGradientBoostingClassifier(learning_rate=0.01,
max_depth=100, max_iter=2000, max_leaf_nodes=100,random_state = 42)
model_hgbc.fit(X_train,y_train)
y_pred = model_hgbc.predict(X_test)
y_pred = model_hgbc.predict(X_test)
y_pred=pd.DataFrame(y_pred)
y_pred=y_pred.astype('float64')
y_pred.to_csv(path_or_buf='y_pred_hist.csv',header=['class'],index_lab
el='Id')'''
```

```
"from sklearn.ensemble import HistGradientBoostingClassifier\
nmodel_hgbc = HistGradientBoostingClassifier(learning_rate=0.01,
max_depth=100, max_iter=2000, max_leaf_nodes=100,random_state = 42)\
nmodel_hgbc.fit(X_train,y_train)\ny_pred = model_hgbc.predict(X_test)\
ny_pred = model_hgbc.predict(X_test)\ny_pred=pd.DataFrame(y_pred)\
ny_pred=y_pred.astype('float64')\
ny_pred.to_csv(path_or_buf='y_pred_hist.csv',header=['class'],index_la
bel='Id')"
```

Accuracy is 0.80234

Extreme Gradient Boosting:

****This model was not stated in the book but I got information about this model from internet****

Extreme gradient boosting or XGBoost is a more regularized form of Gradient Boosting. XGBoost uses regularization (L1 & L2), which improves model generalization capabilities.

XGBoost delivers high performance as compared to Gradient Boosting. Its training is very fast and can be parallelized across clusters.

When to use XGBoost? When there is a larger number of training samples. Ideally, greater than 1000 training samples and less 100 features or we can say when the number of features < number of training samples. When there is a mixture of categorical and numeric features or just numeric features.

Citation: https://towardsdatascience.com/a-brief-introduction-to-xgboost-3eaee2e3e5d6#:~:text=XGBoost%20vs%20Gradient%20Boosting,can%20be%20parallelized%20across%20clusters.

```
'''import xgboost as xgb
model_xgb = xgb.XGBClassifier()
model_xgb.fit(X_train,y_train)
y_pred = model_xgb.predict(X_test)
```

```
y_pred=pd.DataFrame(y_pred)
y_pred=y_pred.astype('float64')
y_pred.to_csv(path_or_buf='y_pred_xgb_final.csv',header=['class'],inde
x_label='Id')'''
```

```
"import xgboost as xgb\nmodel_xgb = xgb.XGBClassifier()\
nmodel_xgb.fit(X_train,y_train)\ny_pred = model_xgb.predict(X_test)\
ny_pred=pd.DataFrame(y_pred)\ny_pred=y_pred.astype('float64')\
ny_pred.to_csv(path_or_buf='y_pred_xgb_final.csv',header=['class'],ind
ex_label='Id')"
```

Accuracy is : 0.80278

Cross Validation for Extreme Gradient Boosting:

I didn't know the practical (not theoritcal as theoretical range is very vague for cross validation) optimal range for the parameters of XGBoost. Hence the I referred the article on kaggle which I have given link below.

https://www.kaggle.com/code/prashant111/a-guide-on-xgboost-hyperparameters-tuning/notebook

```
'''from sklearn.model_selection import GridSearchCV
model_xgb = xgb.XGBClassifier(min_child_weight=7,learning_rate =
0.05,tree_method = 'gpu_hist',random_state = 42)
param_grid = {'n_estimators':[300,200,100],
              'max_depth': range(20,8,-2),
              'gamma':(1,9,1),
            'colsample_bytree' : range(0,1,3),
            'reg_lambda' : range(0,1,10),
            'reg_alpha' : range(0,20,5),
            'subsample' : 0.6
             }
gs_xgb = GridSearchCV(model_xgb,param_grid = param_grid,cv = 5,
verbose=3)
gs_xgb.fit(X_train,y_train)'''
```

```
"from sklearn.model_selection import GridSearchCV\nmodel_xgb =
xgb.XGBClassifier(min_child_weight=7,learning_rate = 0.05,tree_method
= 'gpu_hist',random_state = 42)\nparam_grid = {'n_estimators':
[300,200,100],\n              'max_depth': range(20,8,-2),\n
'gamma':(1,9,1),\n            'colsample_bytree' : range(0,1,3),\n
'reg_lambda' : range(0,1,10),\n            'reg_alpha' :
range(0,20,5),\n            'subsample' : 0.6\n             }\ngs_xgb
= GridSearchCV(model_xgb,param_grid = param_grid,cv = 5, verbose=3)\
ngs_xgb.fit(X_train,y_train)"
```

```
'''gs_xgb.best_params_'''
```

```
'gs_xgb.best_params_'
```

Extreme Gradient Boosting: Final Model

```
import xgboost as xgb
model_xgb = xgb.XGBClassifier(max_depth = 17,
                              gamma = 2.0,
                              n_estimators = 300,
                              learning_rate = 0.05,
                              min_child_weight = 7,
                              subsample = 0.6,
                              colsample_bytree = 0.67,
                              colsample_bylevel = 0.67,
                              colsample_bynode = 0.67,
                              reg_lambda = 0.9,
                              reg_alpha = 15.0,
                              n_jobs = -1,
                              random_state = 42)
model_xgb.fit(X_train,y_train)
y_pred = model_xgb.predict(X_test)
y_pred=pd.DataFrame(y_pred)
y_pred=y_pred.astype('float64')
y_pred.to_csv(path_or_buf='y_pred_xgb_final.csv',header=['class'],inde
x_label='Id')
```

Accuracy is : 0.80425

I didn't use stacking classifier as it took too much time